

Sea State, Trim, and Specific Fuel Consumption in Short Sea Shipping: An Empirical Analysis Using Operational Voyage Data

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ABSTRACT

Trim optimization is widely promoted as a low-cost lever for reducing ship fuel consumption, yet most estimates of its benefit come from calm-water simulations or empirical models, leaving open whether the effect survives where sea state, wind and speed vary jointly with trim. This study analyzes 139 voyages of a Ro-Ro/Container vessel on a fixed interisland route (Puerto del Rosario–Las Palmas de Gran Canaria, Canary Islands), combining loading-computer hydrostatics, flow-meter fuel records, AIS-derived speed and course, and hourly sea-state observations. A naive comparison across trim bins reproduces the $\approx 4\%$ saving commonly cited for moderate stern trim, but the difference is not significant (Welch t-test, $p = 0.80$) and is no longer identifiable once significant wave height (H_s) and speed over ground are controlled for ($p > 0.7$ in every specification). Over the interquartile trim range these operations explore, the 95% confidence interval for the trim effect spans -1.4% to $+1.7\%$ of specific consumption, excluding savings of the magnitude reported under controlled conditions. Trim is itself confounded with sea state: bow-down voyages occur, on average, in significantly higher sea states than moderate stern-trim voyages ($p = 0.009$). Added resistance from wave height is significant in head seas ($p < 0.001$) but indistinguishable from zero in beam seas ($p = 0.42$). For this vessel and route, trim adjustments within the range routinely used are therefore secondary to weather-driven resistance, while the wider envelope simulated under controlled conditions remains beyond the resolution of operational data, with direct implications for how trim optimization tools are calibrated and how their recommendations are presented onboard.

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1. Introduction.

Since 1 January 2019, the implementation of the Fuel Oil Consumption Data Collection System (DCS) has been required by the International Maritime Organization (IMO) under Regulation 27 of MARPOL Annex VI, introduced by Resolution MEPC.278(70), for ships of 5,000 gross tonnage (GT) and above, which together account for around 85% of the emissions generated by international shipping traffic (IMO, 2016, 2018). Despite the gradual improvement in per-ship fuel consumption, total CO₂ emissions continue to rise as the fleet grows (IMO, 2024); this has led the IMO to establish carbon neutrality by 2050 as its target, with intermediate milestones set at a 20–30% reduction by 2030 and 70–80% by 2040, relative to 2008 levels (IMO, 2023). This framework rests on four complementary instruments: the Energy Efficiency Design Index (EEDI),

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the Energy Efficiency Existing Ship Index (EEXI), the Carbon Intensity Indicator (CII), and the Ship Energy Efficiency Management Plan (SEEMP) (IMO, 2021, 2022a, 2022b), which address, respectively, the design of newbuildings, the technical retrofitting of the existing fleet, and the continuous monitoring of actual operational performance.

For ships already in service, the room for maneuver lies primarily with the officer of the watch, who plans the loading and stability with the aid of a loading computer type-approved under the criteria of the International Code on Intact Stability, 2008 (2008 IS Code) (IMO, 2008). This software confirms that the weight distribution meets the stability criteria, but it does not evaluate the resulting effect on resistance: for a given loading condition, several ballast distributions may be equally "safe" while producing different trims and, in turn, different levels of fuel consumption, because hydrodynamic resistance varies non-linearly with trim (Shivachev et al., 2020; De Carlini et al., 2025). It is within this regulatory margin (adjusting trim without compromising stability) that trim optimization is positioned as an operational energy-efficiency measure, prompting a detailed examination of the relevant literature.

This body of literature, drawn mostly from towing-tank tests, empirical models (Guldhammer & Harvald, 1974; Holtrop & Mennen, 1982), and, more recently, computational fluid dynamics (CFD) using RANS codes, consistently shows that trim variations of only a few centimeters can appreciably alter resistance, with fuel savings commonly reported at between 2% and 5%, and up to 15% under specific conditions for container ships and LNG carriers (Coraddu et al., 2017; Shivachev et al., 2020; Zwart et al., 2023; De Carlini et al., 2025). These "white-box" (physics-based) or "gray-box" (hybrid, combining physical knowledge with statistical fitting) models share a common feature: the effect of trim is estimated under controlled or simulated conditions of draft, speed, and sea state. In parallel, recent data-driven approaches have increasingly focused on predicting fuel consumption through machine learning models that explicitly incorporate high-dimensional meteorological factors (Yang et al., 2024). What they do not resolve is whether this effect remains identifiable under the real-world operation of an in-service vessel, where trim is not assigned under controlled conditions but is instead chosen by the officer of the watch according to the loading condition and, presumably, the prevailing sea state as well. This covariation between trim and weather (officers navigate differently when conditions worsen) introduces a risk of confounding that is rarely addressed explicitly in fleet studies based on operational data: a simple comparison of fuel consumption across trim ranges may, in fact, reflect a difference in the weather conditions under which the voyages within each range were sailed, rather than an effect of trim itself. It is precisely the distinction between correlation and controlled effect that the present study puts to the test, leading to the study's primary objective: to determine whether longitudinal trim has an identifiable effect on specific fuel consumption once sea state and speed are statistically controlled for, using real navigational data from an in-service merchant vessel.

To answer this question, 139 commercial voyages of a Ro-Ro vessel operating on a fixed inter-island route (Puerto del

Rosario – Las Palmas de Gran Canaria) are analyzed, combining hydrostatic data from the loading computer, actual fuel consumption from the flow meter, speed, heading, and weather observations. The analysis further incorporates the relative direction of waves and wind with respect to the ship's heading, a variable that the literature recognizes as relevant to added resistance but that is rarely quantified alongside trim using purely operational data. The remainder of the article is organized as follows: Section 2 describes the vessel under study, the data collection and cleaning process, and the analytical framework applied; Section 3 presents the results, ranging from the simple comparison across trim ranges and the evidence of confounding with sea state to the multivariable regression, the directional effect of waves, and a sensitivity analysis; Section 4 discusses these results in light of the literature and their implications for the design of onboard decision support systems (DSS); and Section 5 concludes.

2. Materials and Methods.

Answering the question raised in Section 1 requires two distinct components. First, a dataset is needed in which trim, speed, and sea state are jointly and coherently recorded for the same set of voyages, without which controlling for weather conditions when evaluating trim becomes impossible. Second, an analytical framework must be implemented to explicitly test whether trim covaries with these other variables prior to attributing any effect to it, while also cross-referencing this central result against independent sources of evidence within the same dataset. This section addresses both components: Sections 2.1–2.3 describe the vessel, the route, and the process of constructing and cleaning the dataset; Section 2.4 outlines the complete analytical framework, organized into the same sequence as the presentation of the results; and Section 2.5 presents the robustness checks and limitations framing the interpretation of the findings.

2.1. Case study: why the observed trim range is narrow.

The vessel under study is a roll-on/roll-off (Ro-Ro) cargo ship engaged in short sea shipping, with a length between perpendiculars of 128.00 m, a beam of 22.65 m, a deadweight of 7,388.8 t, and a gross tonnage of 10,585 GT. Its propulsive plant, a diesel engine coupled to a controllable pitch propeller (CPP), typically operates between 75% and 80% MCR, delivering service speeds of 18 to 20 knots depending on sea state. The vessel operates a regular liner service in the Canary Islands over distances ranging from 50 to 150 nautical miles; this study is restricted to the voyages between Puerto del Rosario (PRO) and Las Palmas de Gran Canaria (LPA). This route exhibits a high frequency of port calls and rapid cargo turnover, requiring frequent alternation among fully loaded, partially loaded, and ballast conditions, which in turn induces natural trim variability across voyages (throughout this article, trim is defined as the difference between aft and forward draft, such that positive values denote trim by the stern and negative values trim by the head; ITTC, 2024).

This variability, however, is subject to practical constraints that warrant clarification prior to presenting the results. Although the vessel's ballasting system comprises 16 tanks with a total capacity of 4,140.6 m³ / 4,244.1 t, not all of them represent operational degrees of freedom for dynamic trim adjustment during transit. Two tanks are operated continuously and automatically by an anti-heeling system independent of voyage planning, while side tanks are managed exclusively in port and remain isolated at sea. In practice, the effective margin for dynamic trim adjustment during navigation is restricted to double-bottom tanks and the fore/aft peak tanks, a subset considerably smaller than the total system capacity. This structural constraint explains why, as shown in Section 3.1, the range of trim observed under actual operational conditions is substantially narrower than that typically examined in the CFD studies cited in Section 1.

2.2. Building the voyage database.

From this case study, a dataset covering 139 PRO–LPA voyages completed between 31 July 2025 and 29 July 2026 was constructed. Each voyage required the integration of four distinct data sources (Global Fishing Watch, NAPA, onboard flow meters, and Puertos del Estado); the methodology applied to each source governs the scope and validity of the conclusions presented in Section 3. Vessel position and movement were extracted from Automatic Identification System (AIS) signal records retrieved via the Global Fishing Watch platform (Global Fishing Watch, 2026). Navigated distance was calculated using the haversine formula between consecutive waypoints, bounded between 1 nautical mile after departure and 1 nautical mile prior to arrival to isolate open-sea transit from port maneuvering operations. From these records, both speed over the ground (SOG) and vessel heading at the monitoring checkpoint were derived, the latter being required to compute the relative direction of waves and wind (Section 2.4). Hydrostatic parameters, including draft and trim, were extracted from the vessel's loading computer software, (NAPA Ltd., 2016), with preference given to the trim values reported directly by the system over simple draft differences. Mean draft was also calculated from the forward and aft drafts to serve as a control variable for loading condition in Section 3.1, independent of trim. Fuel consumption was obtained from a third source: onboard flow meters monitoring the consumption of Heavy Fuel Oil (HFO), specifically grade IFO 380. Voyage consumption was calculated from the difference between initial and final readings, converted to mass using the standard density factor at 15°C ($\rho=0.9816 \text{ t/m}^3$), and expressed as specific consumption per nautical mile (t/nm) and per hour (t/h). Finally, meteorological data, including wind direction and speed together with significant wave height (H_s) and wave direction, were acquired from the SIMAR point 4046010 via the PORTUS platform (Puertos del Estado, 2026) by cross-referencing hourly meteorological records with the navigation window of each voyage, a fusion of AIS-derived and meteorological data consistent with approaches shown to improve the reliability of ship fuel-consumption models (Du et al., 2022).

The primary dataset further captures the voyage date, utilized in Section 3.7 for monthly data aggregation, and an indicator flag specifying whether the vessel followed the standard direct route or executed a weather-induced diversion, an aspect addressed in Section 3.8.

2.3. Data quality control.

Prior to any analysis, a strict exclusion criterion was applied: any voyage with incomplete or inconsistent records across any of the four aforementioned sources was discarded entirely, and only steady-state open-sea transit segments were isolated, removing port wait times and maneuvering operations (X. Li et al., 2022). This screening yielded the final sample of 139 complete voyages, with wind data available for 138 of them.

A subsequent review of extreme values identified an additional voyage (V135, 20 July 2026) exhibiting a specific fuel consumption of 0.1880 t/nm (approximately 6.7 standard deviations above the sample mean) without justification from the recorded meteorological or speed variables for that day. Rather than silently discarding this record, it is documented as a data quality anomaly pending verification against the original engine room logbook and excluded from the primary analysis reported in Section 3; all results are additionally reported with this outlier included (Section 3.9), allowing the reader to assess its impact on the conclusions.

2.4. Analytical framework.

With the dataset constructed, the analysis is structured into six distinct blocks mapped to the subsections of Section 3, arranged from general observations to specific evaluations.

The first block is purely descriptive: prior to estimating any model, summary statistics are calculated for each variable alongside the Pearson correlation matrix between specific fuel consumption and the remaining numerical parameters as (trim, mean draft, significant wave height H_s , wind speed, speed over the ground SOG, and distance). The objective of this preliminary step is to identify, without assuming a specific functional relationship, which variables display the strongest and weakest associations with fuel consumption prior to model estimation (Section 3.1).

The second block quantifies the relationship between speed and consumption, which naval architecture theory (Adland et al., 2020) models as a simple power law, as expressed in Equation (1):

$$\text{Consumption (t/h)} = a \text{ SOG}^k \quad (1)$$

where k is the exponent of the power law. The exponent k was estimated via simple linear regression of log (consumption) on log (SOG), with the resulting slope providing the estimate of k . Although this block does not directly answer the core research question, it provides a baseline magnitude against which the strength or weakness of the remaining associations can be interpreted (Section 3.2).

The third block represents the core of the study and addresses the question raised in Section 1 through a two-step test of whether trim, by itself, moves specific fuel consumption within

the range these operations explore. The first step formally replicates the simple comparison motivating this study by grouping voyages into trim intervals and testing mean differences using Welch's t-test and a one-way analysis of variance (ANOVA). The second step evaluates whether trim covaries with sea state (thereby assessing whether the simple comparison is subject to confounding) by comparing mean H_s across trim subgroups, also using Welch's t-test (Section 3.3).

The fourth block subjects this central question to simultaneous statistical control for speed and weather conditions via multivariable regression. To achieve this, parameterizing wave height alone is insufficient: the physics of added resistance dictates that weather impact depends not only on magnitude but also on the direction from which waves encounter the vessel. Consequently, from the meteorological wave and wind directions recorded at the SIMAR point and the vessel's heading at the monitoring checkpoint, the relative angle of incidence was computed for each voyage, as defined in Equation (2):

$$\theta_{\text{rel}} = \min\{|\theta_{\text{meteo}} - \theta_{\text{heading}}| \bmod 360, 360 - |\theta_{\text{meteo}} - \theta_{\text{heading}}| \bmod 360\}. \quad (2)$$

The relative angle defined above satisfies $\theta_{\text{rel}} = 0^\circ$ for head seas or head winds, and $\theta_{\text{rel}} = 180^\circ$ for following seas or following winds.

This variable was utilized both in quadrant form (head $0-45^\circ$, bow $45-90^\circ$, beam/quarterming $90-135^\circ$, following $135-180^\circ$) and as a continuous trigonometric term, $\cos(\theta_{\text{rel}})$, taking a value of +1 for head seas and -1 for following seas. It also served to construct the composite regressor for directional added resistance shown in Equation (3):

$$R_{\text{dir}} = H_s^2 \cos(\theta_{\text{rel, wave}}) \quad (3)$$

which parsimoniously approximates directional added resistance (Shivachev et al., 2020) in line with hybrid "gray-box" models combining physical principles with statistical calibration (Coraddu et al., 2017; Zwart et al., 2023). It should be noted that the term $H_s^2 \cos(\theta_{\text{rel, wave}})$ is adopted in this study as a simplified proxy (a first-order empirical regressor) to capture directional added resistance trends, rather than as an exact analytical formulation of wave energy transfer and hull diffraction.

Using the collected dataset, four nested specifications were estimated via ordinary least squares (OLS), all employing specific fuel consumption (t/nm) as the dependent variable. Model A formally replicates the simple bivariate comparison expressed in Equation (4):

$$\text{Consumption} \sim \text{Trim} \quad (4)$$

Model B incorporates controls for speed and sea state, without a priori excluding a non-linear "U-shaped" relationship for trim (Equation 5):

$$\text{Consumption} \sim \text{Trim} + \text{Trim}^2 + \text{SOG} + H_s \quad (5)$$

Model C replaces H_s with the directional added resistance term defined in Equation (3) (Equation 6):

$$\text{Consumption} \sim \text{Trim} + \text{SOG} + H_s^2 \cos(\theta_{\text{rel, wave}}) \quad (6)$$

And Model D adds wind parameters to verify whether they alter the conclusions of the preceding models (Equation 7):

$$\begin{aligned} \text{Consumption} \sim & \text{Trim} + \text{SOG} + H_s + H_s^2 \cos(\theta_{\text{rel, wave}}) \\ & + \text{Wind} + \cos(\theta_{\text{rel, wind}}) \end{aligned} \quad (7)$$

All models were estimated both with and without voyage V135 (Section 2.3). The same relative direction variable, applied separately to each quadrant and evaluated via simple linear regression ($H_s \rightarrow \text{consumption}$) within each quadrant, further allows for the decomposition of the H_s effect by wave direction (Section 3.5).

The fifth block re-examines wind specifically, prompted by an observation that justifies an additional calculation: the wind reported by the SIMAR point represents true (meteorological) wind, the wind that would blow over a fixed point at sea, which does not necessarily correspond to the wind acting upon the superstructure of the moving vessel. To obtain the apparent wind, the true wind vector was vectorially combined with the vessel's velocity vector (heading and SOG), yielding an apparent wind speed and relative apparent wind angle for each voyage, following the same angular convention as in the preceding block. This calculation requires no additional data beyond those described in Section 2.2, involving merely a different combination of existing variables, and enables a comparison of the explanatory power of true versus apparent wind regarding fuel consumption, both in terms of simple correlation and by substituting one for the other within the previously specified regression models (Section 3.6).

The sixth and final block leverages two variables from the dataset that, while not part of the primary research question on trim, allow for testing whether the observed pattern remains consistent with independent lines of evidence within the same sample. First, voyages were aggregated by calendar month to compute the correlation between monthly mean H_s and monthly mean fuel consumption, evaluating whether the weather effect identified on a voyage-by-voyage basis holds at a higher level of temporal aggregation (Section 3.7). Second, Welch's t-test was applied to compare H_s , distance traveled, and specific fuel consumption between voyages following the standard direct route and those incorporating weather-induced diversions, providing an indirect assessment of the effectiveness of this practice (Section 3.8).

2.5. Diagnostics and limitations.

Four robustness checks accompany the regression models specified in the fourth block. First, the variance inflation factor (VIF) was calculated for each regressor in Model D to rule out the possibility that the lack of statistical significance for trim resulted from multicollinearity with other predictors. Second, the risk of confounding between trim and sea state (the primary issue motivating Model B over Model A) was independently evaluated using Welch's t-test on mean H_s across

trim subgroups, as well as through bivariate correlation analysis between both parameters. Third, the residuals of the physics-based model (Model C) were inspected against trim to confirm that no residual pattern remained attributable to this variable once SOG and the directional added resistance term from Equation (3) ($H_s^2 \cdot \cos \theta$) were included. Fourth, all regression outputs (blocks three and four) were recalculated with voyage V135 included (Section 2.3), with both specifications reported in Section 3.9.

Prior to presenting the results, the methodological scope and boundaries of this research design warrant explicit clarification. This investigation is observational rather than experimental: trim was neither randomly assigned nor systematically varied for research purposes, but was instead determined by the officer of the watch according to operational criteria not fully captured within the dataset. The same condition applies to the decision to follow the standard direct route versus executing a weather-induced diversion (sixth block), which likewise was not subject to controlled assignment. Consequently, the estimated models describe conditional associations and serve to rule out a simple linear trim effect within the observed range, but do not establish causality in a strict econometric sense. Furthermore, the range of trim actually observed (-0.92 m to +1.20 m) is, for the reasons outlined in Section 2.1, relatively narrow, and all empirical findings pertain to a single vessel operating on a specific route, limitations addressed in Section 4.4 alongside the prospective avenues for future research derived from them.

3. Results.

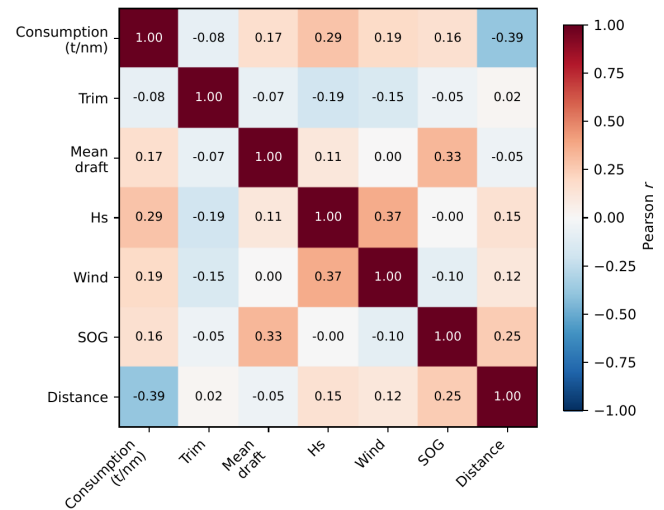
3.1. Descriptive overview and correlation structure.

The interquartile range of trim spans 0.08 m to 0.42 m by the stern, so half the voyages lie within it, and only 14% of the sample exhibits trim by the head (negative): actual operations explore a substantially narrower trim range than that covered by the CFD studies cited in Section 1, which typically simulate between 3 and 7 trim variations on both sides of the design condition. Table 1 summarizes the main variables across the 139-voyage sample.

Prior to estimating any econometric model, the pairwise relationships among all available variables warrant examination. Figure 1 displays the Pearson correlation matrix between specific fuel consumption and the six core numerical variables of the study.

Three primary insights emerge from Figure 1. First, trim is by far the variable least correlated with fuel consumption ($r=-0.08$) across the entire matrix, even weaker than its correlation with H_s ($r=-0.19$), which foreshadows the confounding issue documented in Section 3.3. Second, distance traveled (nautical miles) exhibits the strongest correlation with specific fuel consumption in the table ($r=-0.39$): longer routes (corresponding to voyages with greater weather-induced diversions or differing traffic conditions during port approach) tend to dilute consumption per mile, a purely arithmetic-operational artifact to keep in mind when interpreting subsequent results. Third, mean draft (a proxy for loading condition) displays a moderate

Figure 1: Pearson correlation matrix (r) between specific fuel consumption and main operational and meteorological variables ($n = 138-139$).



Source: Authors.

correlation with consumption ($r=0.17$) and notably with speed ($r=0.33$): heavier loaded vessels navigate slightly faster on this route, likely driven by schedule constraints, but shows virtually no correlation with trim ($r=-0.07$), ruling out the possibility that trim acts as a proxy for loading condition in the regression models presented in Section 3.4.

3.2. Speed as the dominant driver of consumption.

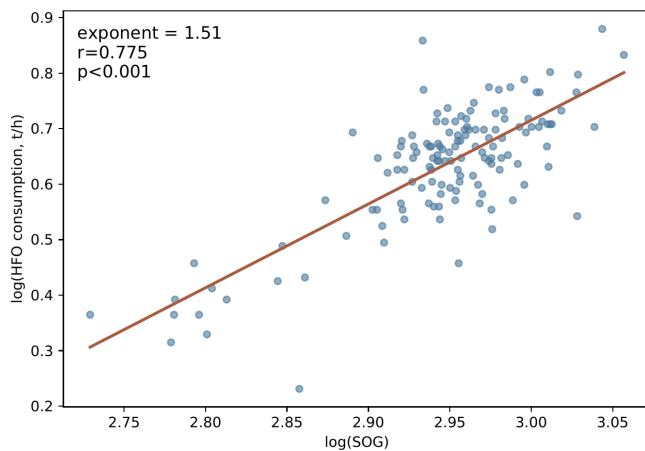
The variable exhibiting the strongest and most robust relationship with fuel consumption is not meteorological, but kinematic: speed over the ground (SOG). Figure 2 illustrates the relationship between SOG and hourly fuel consumption (t/h) on a logarithmic scale, fitting the simple power law defined in Equation (1) ($\text{consumption} \propto \text{SOG}^k$).

The log-log fit yields an exponent $k=1.51$ ($r=0.775$, $p<0.001$), substantially exceeding any other correlation coefficient reported in this article and standing as statistically the most robust parameter in the entire dataset. This exponent is lower than the cubic value ($k \approx 3$) predicted by classical power-speed laws across a vessel's full speed range, yet this outcome is to be expected: the sample spans a relatively narrow SOG interval (15.3 to 21.3 knots, centered around the service speed). Within this bounded speed band, the power-speed curve flattens relative to the full operational envelope, a behavior consistent with empirical findings in operational speed ranges below design speed (Berthelsen & Nielsen, 2021), while hourly fuel consumption incorporates auxiliary loads that remain largely insensitive to vessel speed. Furthermore, in vessels equipped with controllable pitch propellers (CPP) operating at constant engine RPM, the reduction in propulsive efficiency when operating off-design pitch in narrow service speed ranges further flattens the brake power curve

Table 1: Descriptive statistics of the main variables ($n = 139$).

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
Trim (m)	0.268	0.280	-0.920	0.230	1.200
Mean draft (m)	5.709	0.129	5.420	5.720	5.950
H_s (m)	2.134	0.791	0.806	1.998	4.807
Wind (kn)	15.17	5.74	2.83	16.56	28.77
SOG (kn)	19.05	1.04	15.32	19.17	21.26
Distance (nm)	91.90	4.87	78.59	92.45	106.26
HFO Consumption (t/nm)	0.1130	0.0111	0.0902	0.1124	0.1880

Figure 2: Speed–consumption relationship on a log–log scale ($n = 138$, excluding V135). The slope of the fitted line represents the exponent k of the power law consumption $(t/h) \propto \text{SOG}^k$.



Source: Authors.

relative to fixed-pitch installations. In any case, the empirical finding is clear: within the actual operational margin available to an officer of the watch on this route, a minor speed adjustment exerts a statistically associated impact on consumption that no other variable (including weather conditions) comes close to matching.

3.3. Naive trim comparison and evidence of confounding.

Table 2 summarizes specific consumption and mean wave height across trim bins:

Table 2: Specific consumption and mean wave height by trim bin.

Trim bin	n	Mean consumption (t/nm)	Mean H_s (m)
≤ 0 m	19	0.1152	2.63
0–0.15 m	32	0.1136	2.14
0.15–0.30 m	33	0.1153	2.17
0.30–0.45 m	27	0.1108	1.90
0.45–0.60 m	10	0.1097	2.00
> 0.60 m	18	0.1109	1.96

The moderate stern-trim bin (0.30–0.45 m) exhibits a consumption 3.9% lower than that of the head-trim bin (≤ 0 m), a

difference that at first glance appears to replicate the fuel savings cited in the trim optimization literature (Section 1). However, panel (b) of Figure 3 displays the exact same trajectory as panel (a): mean H_s is not constant across bins, being nearly 40% higher in the ≤ 0 m bin than in the 0.30–0.45 m bin (2.63 m vs. 1.90 m; Welch's t-test: $t=2.77$, $p=0.009$). Trim and sea state do not vary independently in these operational data.

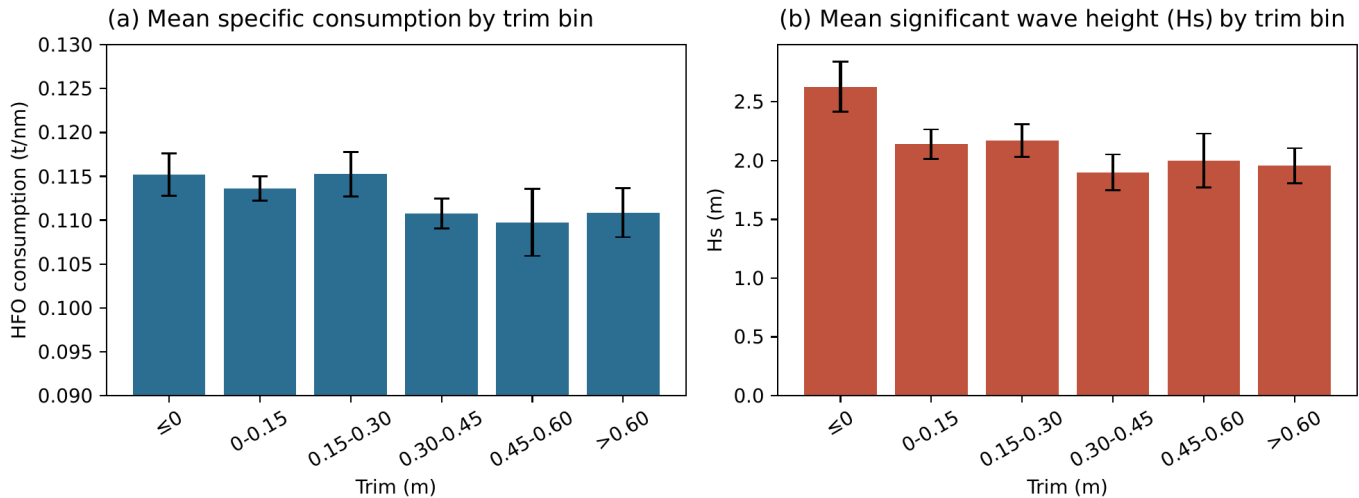
Under direct statistical testing, the apparent difference is not confirmed. Grouping the sample into the [0.30 m, 0.60 m] interval versus all remaining voyages (the standard benchmark in the literature) yields an observed difference of merely 0.6% (0.1125 t/nm vs. 0.1132 t/nm), which is not statistically significant (Welch's t-test: $t=-0.259$, $p=0.797$, $n=139$). Similarly, a one-way analysis of variance (ANOVA) across the six trim bins in Table 2 fails to reject the null hypothesis of equal means ($F=0.959$, $p=0.445$): the variation in fuel consumption across trim intervals cannot be distinguished from sampling variability at this sample size.

3.4. Multivariable regression: does trim survive controlling for weather and speed?

Table 3 presents four nested OLS regression specifications (Equations 4–7; Section 2.4), estimated excluding voyage V135 and the single voyage lacking wind data ($n=137$).

The trim coefficient fails to reach statistical significance in any of the four specifications (p -values ranging from 0.22 to 0.97) and actually reverses sign across models depending on the covariates included, behavior consistent with an estimate dominated by sampling variability rather than with a stable effect of either sign within this range. In contrast, speed over the ground and the directional added resistance term (Equation 3; $H_s^2 \cdot \cos \theta$, or H_s entered separately) remain statistically significant at the 1% level across all specifications in which they are included, consistent with the hierarchy of magnitudes suggested in Figure 1 and quantified in Section 3.2. The highest variance inflation factor (VIF) among the regressors in Model D is 3.9 (H_s), remaining well below the conventional threshold of 5; thus, the lack of statistical significance for trim (VIF=1.09) cannot be attributed to multicollinearity with remaining predictors. Non-significance here is a statement about resolution rather than about magnitude. The 95% confidence interval for the trim coefficient in Model D spans -0.0048 to +0.0056 t/nm per meter of trim, that is, between -4.2% and +5.0% of mean specific consumption per meter. Applied to the interquartile trim range these operations actually explore (0.08–0.42 m), the

Figure 3: (a) Mean specific consumption by trim bin. (b) Mean significant wave height (H_s) by trim bin. The same downward trend emerges in both panels.



Source: Authors.

Table 3: OLS regression coefficients (dependent variable: HFO consumption, t/nm). P-values reported for each coefficient.

Regressor	Model A (Eq. 4)	Model B (Eq. 5)	Model C (physics-based, Eq. 6)	Model D (full, Eq. 7)
Trim	-0.0034 ($p = 0.222$)	-0.0008 ($p = 0.836$)	-0.0009 ($p = 0.744$)	+0.0004 ($p = 0.871$)
Trim ²	—	-0.0002 ($p = 0.969$)	—	—
SOG	—	+0.0022 ($p = 0.002$)	+0.0024 ($p = 0.001$)	+0.0025 ($p = 0.001$)
H_s	—	+0.0039 ($p < 0.001$)	—	+0.0017 ($p = 0.342$)
$H_s^2 \cos(\theta_{\text{wave}})$	—	—	+0.0008 ($p < 0.001$)	+0.0004 ($p = 0.248$)
Wind (kn)	—	—	—	+0.00014 ($p = 0.354$)
$\cos(\theta_{\text{wind}})$	—	—	—	+0.0028 ($p = 0.065$)
R^2 / Adj. R^2	0.011 / 0.004	0.180 / 0.156	0.171 / 0.152	0.218 / 0.182
n	137	137	137	137

same interval narrows to -1.4% to +1.7%, which excludes savings of the order reported in Section 1 for adjustments confined to that window. Applied to the full observed envelope (2.12 m) it widens to -9.0% to +10.6% and excludes nothing. The data therefore constrain the trim effect only over the narrow range in which this vessel is routinely operated, and remain uninformative about the wider trim envelope simulated in the CFD literature.

3.5. Directional effect of sea state.

Figure 4 illustrates specific fuel consumption against H_s , disaggregated by relative wave direction:

In head seas ($0-60^\circ$, $n=72$), the $H_s \rightarrow$ consumption slope is 0.00427 t/nm per meter of H_s (standard error 0.00123; $r=0.383$; $p=0.0009$). In beam seas ($60-120^\circ$, $n=60$), the slope is -0.0017 t/nm per meter of H_s (standard error 0.00211; $r=-0.105$; $p=0.424$), which is statistically indistinguishable from zero. The subsample for following seas ($n=6$) is too small to yield a reliable parameter estimate (slope 0.0034, $p=0.733$).

Figure 5 decomposes this same effect across relative direction quadrants:

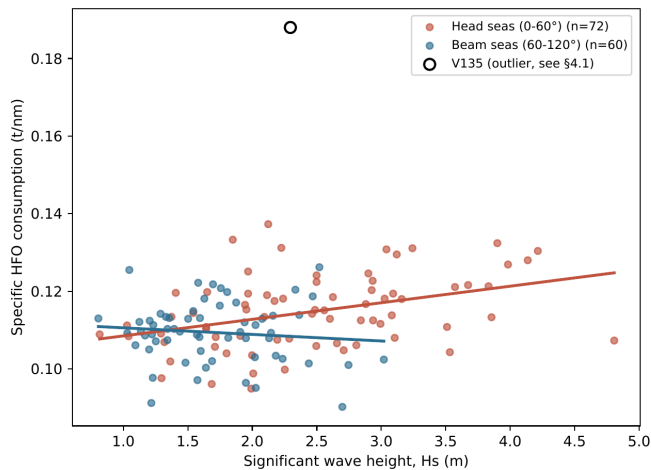
The four-quadrant decomposition reinforces this pattern: for both wind and waves, mean consumption decreases in an approximately monotonic fashion from the head quadrant toward the beam. The following quadrant for waves ($n=3$) and the beam quadrant ($n=14$) contain small sample sizes and are thus presented as indicative rather than conclusive.

3.6. The wind experienced onboard: true versus apparent wind.

The preceding analysis utilizes true wind speed and direction as reported by the SIMAR point, that is, the wind vector acting upon a fixed geographic location. However, this is not the wind vector actually impinging upon the vessel's superstructure: aerodynamic resistance is driven by apparent wind, which results from the vector addition of true wind and the vessel's velocity vector. Given that the vessel operates at a service speed (≈ 19 knots) comparable to the average wind speed in the area (≈ 15 knots), these two vectors can be expected to differ substantially, as empirically confirmed below.

Figure 6 compares the relative angle distributions of both vectors:

Figure 4: Specific fuel consumption versus H_s , separated by relative wave direction. The open circle corresponds to voyage V135 (excluded from the regression fit).



Source: Authors.

The vector transformation yields a pronounced shift. While true wind is distributed relatively evenly between head and beam conditions (median 83° , close to pure beam winds), apparent wind concentrates overwhelmingly toward the bow (median 35°): across 137 of the 138 voyages with wind data, the vessel experiences a head or bow wind component regardless of true wind direction. Apparent wind speed is also systematically higher than true wind speed (mean 25.6 kn vs. 15.2 kn) due to the vector addition of the vessel's speed over the ground.

This distinction affects the explanatory power of the wind parameter. The correlation between apparent wind speed and specific fuel consumption ($r=0.241$, $p=0.0045$) is more than double that of true wind speed ($r=0.152$, $p=0.077$, not statistically significant at the 5% level). After controlling for H_s and SOG, the model residuals remain correlated with apparent wind speed ($r=0.153$, $p=0.075$) but show no correlation with true wind speed ($r=0.051$, $p=0.555$): part of the unexplained variance under the true wind formulation did not reflect random noise, but rather the parameterization of an inappropriate physical variable. Substituting true wind with apparent wind in a regression specification alongside trim, SOG, and H_s renders the new wind term marginally significant ($p=0.069$), substantially closer to statistical significance than true wind in Model D of Table 3 ($p=0.354$), without introducing problematic collinearity with SOG ($r=-0.01$) or other predictors ($VIF=1.15$).

Figure 7 illustrates this relationship:

Trim, once again, remains statistically insignificant in all specifications substituting apparent wind for true wind ($p=0.978$). What does change is the physical interpretation regarding wind resistance: rather than wind exerting a negligible operational impact, as suggested by Table 3, true wind represents the wrong parameterization for capturing aerodynamic resistance on a vessel operating at speeds comparable to prevailing local wind velocities.

3.7. Seasonal variation.

The dataset covers a full year (31 July 2025 to 29 July 2026), enabling an evaluation of whether the pattern observed at the individual voyage level holds at a monthly scale. Figure 8 illustrates the monthly evolution of mean H_s alongside mean specific fuel consumption.

Both series exhibit close covariation: winter months (December to March) concentrate both the highest mean H_s (2.6–3.3 m) and the highest specific consumption (0.113–0.119 t/nm), whereas summer months (August, May) present the lowest values for both parameters. The correlation between monthly mean H_s and monthly mean fuel consumption reaches $r=0.70$, noticeably higher than the correlation observed on a voyage-by-voyage basis ($r=0.29$, Section 3.1), a standard pattern when aggregating noisy operational data. Monthly averaging filters out individual voyage noise, rendering the underlying seasonal signal more apparent. This consistency between voyage-level and monthly scales reinforces the interpretation that H_s represents a genuine determinant of fuel consumption rather than a sample-specific artifact.

3.8. Evidence on the effectiveness of weather routing.

Voyages are recorded either as following the standard direct route ($n=98$, excluding voyage V135) or as incorporating a weather-induced diversion ($n=40$, labeled "Various" in the primary logbook). This distinction enables an indirect yet informative assessment of whether diversions achieve their intended purpose.

Figure 9 compares both voyage groups:

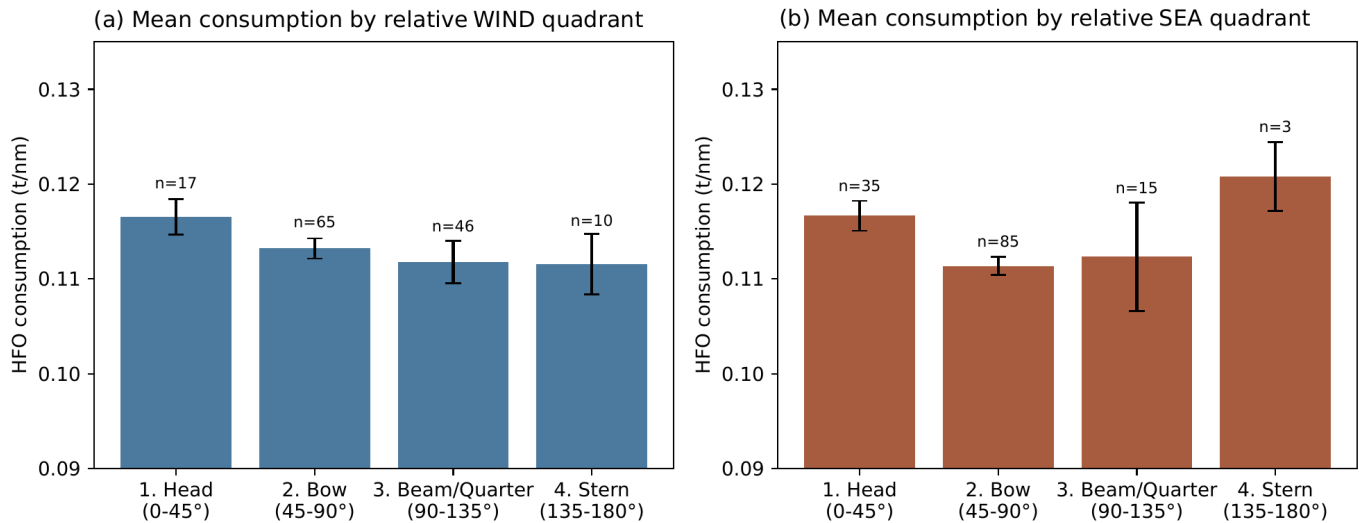
Voyages incorporating diversions were conducted, as expected, under significantly worse sea conditions (mean H_s 2.38 m vs. 2.03 m; Welch's t-test: $t=2.27$, $p=0.026$) and covered significantly greater distances (95.8 nm vs. 90.4 nm; $t=6.93$, $p<0.001$), consistent with the geometry of altered tracklines. Despite departing under rougher weather and navigating additional distance, the specific consumption of weather-diverted voyages is not significantly different from, and is in fact marginally lower than, that of direct voyages (0.1116 t/nm vs. 0.1128 t/nm; $t=-0.73$, $p=0.465$).

This outcome supports two interpretations, which the available data cannot conclusively disentangle: either weather routing effectively mitigates initial adverse sea conditions (preventing specific consumption from surging despite higher H_s and greater distance) or officers of the watch execute diversions selectively in cases where altered routes remain efficient, resorting to other unmeasured measures (such as speed reduction or delayed departure) during severely adverse conditions. In either scenario, the pattern remains consistent with weather routing acting as an effective operational tool in this fleet, an effect that, unlike trim, is detectable within the resolution of these operational data.

3.9. Robustness checks.

The findings presented in Section 3.4 remain stable when voyage V135 is included in the estimation: the trim coefficient remains statistically insignificant across all model specifications (p -values ranging from 0.35 to 0.91). Furthermore,

Figure 5: Mean specific consumption by relative quadrant for (a) wind and (b) waves. Sample size n indicated above each bar; error bars represent standard errors.



Source: Authors.

the R^2 values for Models B, C, and D exhibit a moderate reduction (from 0.180 to 0.110, from 0.171 to 0.073, and from 0.218 to 0.131, respectively), as expected when incorporating an observation with an exceptionally large residual.

Figure 10 illustrates the model fit and residual diagnostics:

The overall goodness-of-fit of Model C ($R^2=0.171$) is modest in absolute terms, consistent with expectations for a three-regressor model estimated on fleet data from a single vessel; Figure 10(a) displays considerable scatter around the 1:1 identity line. This outcome does not invalidate the central finding regarding trim (which relies on the absence of statistical significance rather than overall model explanatory power), but it does indicate that a substantial fraction of specific consumption variability on this route remains uncaptured by the available operational variables.

4. Discussion.

This study has examined 139 commercial voyages of a Ro-Ro vessel on the Puerto del Rosario–Las Palmas de Gran Canaria route to answer a specific research question: whether longitudinal trim exerts an identifiable effect on specific fuel consumption once sea state and speed are statistically controlled for. In doing so, the analytical framework has systematically leveraged the remaining variables within the dataset (speed, draft, wave and wind direction, calendar date, and routing type) to contextualize this finding.

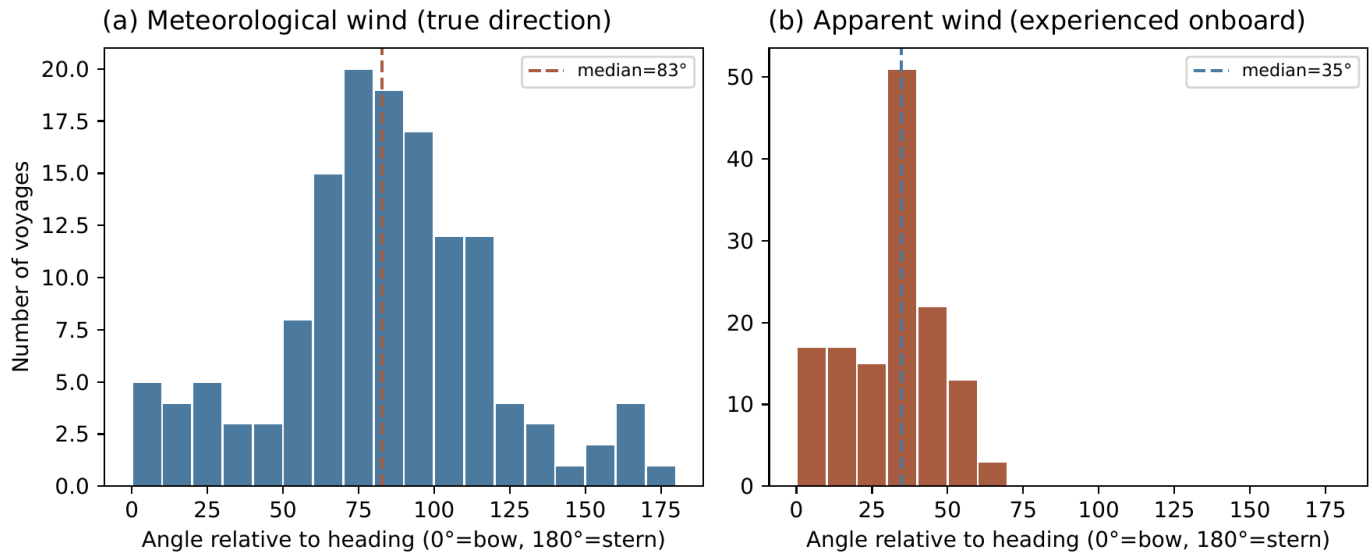
Taken together, the empirical results presented in Section 3 delineate a distinct hierarchy among the determinants of specific fuel consumption on this short sea route. It is precisely this hierarchy (rather than any single isolated result) that structures the discussion that follows. Specifically, while traditional towing-tank and simulation models predict clear economic gains

from trim optimization, real-world operational data in short-sea shipping indicate that such fine-tuning adjustments are largely subordinate to broader kinematic and environmental constraints. Empirical evidence from short-sea shipping indicates that speed is the operational variable through which fuel costs are actually managed, with sailing speeds responding measurably to fuel prices across Baltic and Norwegian coastal fleets (Ollila et al., 2025). Whether minor hydrostatic variations survive statistical control alongside that dominant lever is the question the present analysis addresses. The following subsections unpack these findings, examining their methodological underpinnings, their divergence from naive operational metrics, and their practical implications for the design of next-generation onboard decision-support systems.

4.1. A hierarchy of determinants: speed, weather, and the detectability of trim.

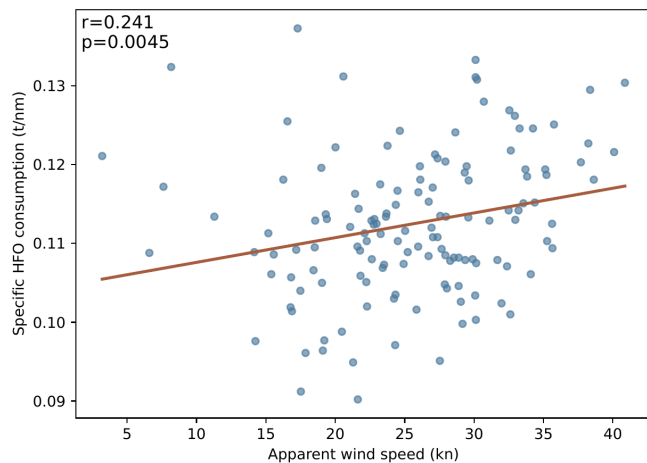
The ordering that emerges from Section 3 is unambiguous: speed first, sea state second, trim last. While unsurprising from a naval architecture perspective (propulsive power scales nonlinearly with vessel speed), it carries substantial practical relevance for the design of onboard efficiency tools: on this route and for this vessel, precise speed management offers, according to the available statistical evidence, significantly greater potential than trim management. Sea state occupies the second tier, exerting an effect that depends markedly on its relative direction to the vessel's heading, a pattern further validated at the monthly scale. Wind speed occupies an intermediate position whose role becomes apparent only when distinguishing between true meteorological wind and the wind vector actually experienced aboard: substituting one for the other nearly doubles its correlation with consumption, serving as a reminder that the variable readily available in a database does not always correspond to

Figure 6: Distribution of relative wind angle relative to vessel heading: (a) true wind, median 83° ; (b) apparent wind, computed by combining true wind with the vessel's velocity vector, median 35° ($n = 138$).



Source: Authors.

Figure 7: Specific fuel consumption versus apparent wind speed ($n = 137$, excluding V135).



Source: Authors.

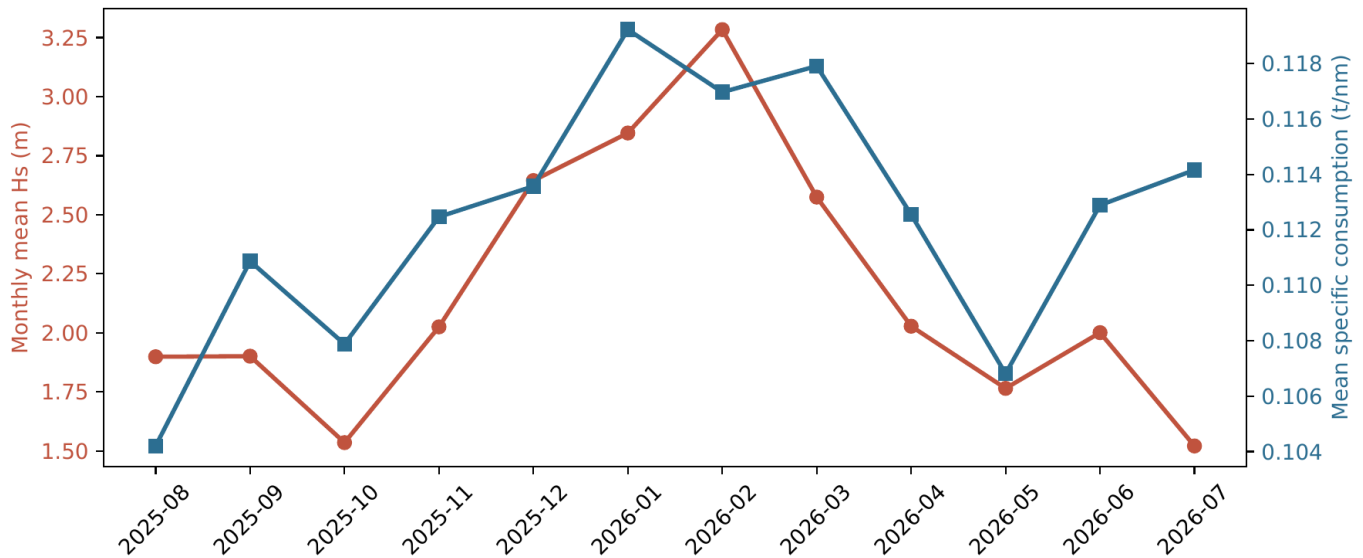
the physically governing parameter. Trim, conversely, does not emerge from background sampling variability under any model specification within the range these operations explore, regardless of the wind parameterization employed, despite being the variable that originally motivated this investigation, an outcome that constrains what can be inferred from observational data of this kind rather than what trim can physically achieve.

This hierarchy does not contradict the CFD- and towing-tank-based trim optimization literature cited in Section 1, which consistently documents fuel savings of 2–5% under controlled draft, speed, and calm-water conditions. Rather, it demonstrates that within the trim range actually observed under real-world vessel operations (-0.92 m to $+1.20$ m, concentrated between 0 m and 0.45 m), such an effect cannot be identified in a statistically robust manner once controlled for the environmental conditions with which trim covaries in practice. The magnitudes at stake are correspondingly small: once added resistance from wind and waves is incorporated explicitly, dynamic trim optimization of a VLCC over a full route has been estimated to save on the order of 0.04% of fuel relative to calm-water trim optimization (J. Li et al., 2022). Both propositions can simultaneously hold true: a physical effect of trim on resistance may exist, yet that effect remains, in this operational context, too minor relative to meteorological and operational noise, as well as the variability in speed itself, to be detected within a sample of $n=137$ voyages spanning the narrow trim envelope permitted by actual operations.

4.2. Why the naive trim comparison is misleading.

The finding in Section 3.3 (that a simple comparison across trim bins ostensibly replicates fuel savings comparable to those reported in the literature, yet fails to survive direct statistical testing or control for sea state) constitutes perhaps the most transferable insight of this study, a conclusion further corroborated by Figure 1: across the entire correlation matrix, trim displays the weakest association with fuel consumption while

Figure 8: Monthly evolution of mean significant wave height (H_s) and mean specific fuel consumption (excluding voyage V135; months with fewer than 3 voyages omitted).



Source: Authors.

simultaneously exhibiting one of the strongest covariations with H_s . Any operational fleet study evaluating trim performance that fails to report formal significance testing and omits verification of whether trim covaries with ambient voyage weather risks mistaking a sampling artifact for a causal effect. This risk is far from hypothetical in these data: mean draft, another hydrostatic parameter reflecting loading condition, exhibits no confounding with trim ($r=-0.07$), ruling out a generic issue common to all hydrostatic variables and pointing instead to a mechanism specific to how trim is selected in daily practice, presumably in response to prevailing conditions.

4.3. Implications for onboard decision-support systems.

The distinction between an association observed in operational data and an effect that survives statistical control carries direct practical implications for the design of onboard decision-support systems (DSS). The literature on DSS adoption highlights that technology effectiveness hinges not only on algorithmic precision, but also on the socio-technical dynamics established with the officer of the watch: when a tool operates as a "black box," prescribing a specific trim without transparent justification, interaction tends to polarize between distrust and automation bias (Schwarz et al., 2023), whereas preserving the mariner's perceived autonomy is essential for successful technology adoption (Zoubir et al., 2025). A DSS trained on historical operational fleet data that fails to correct for the confounding mechanisms documented in Section 3.3 could, in practice, learn to recommend trim conditions that statistically coincide with fair weather, a recommendation that is useless, or directly misleading, at the worst possible time. This is a specification re-

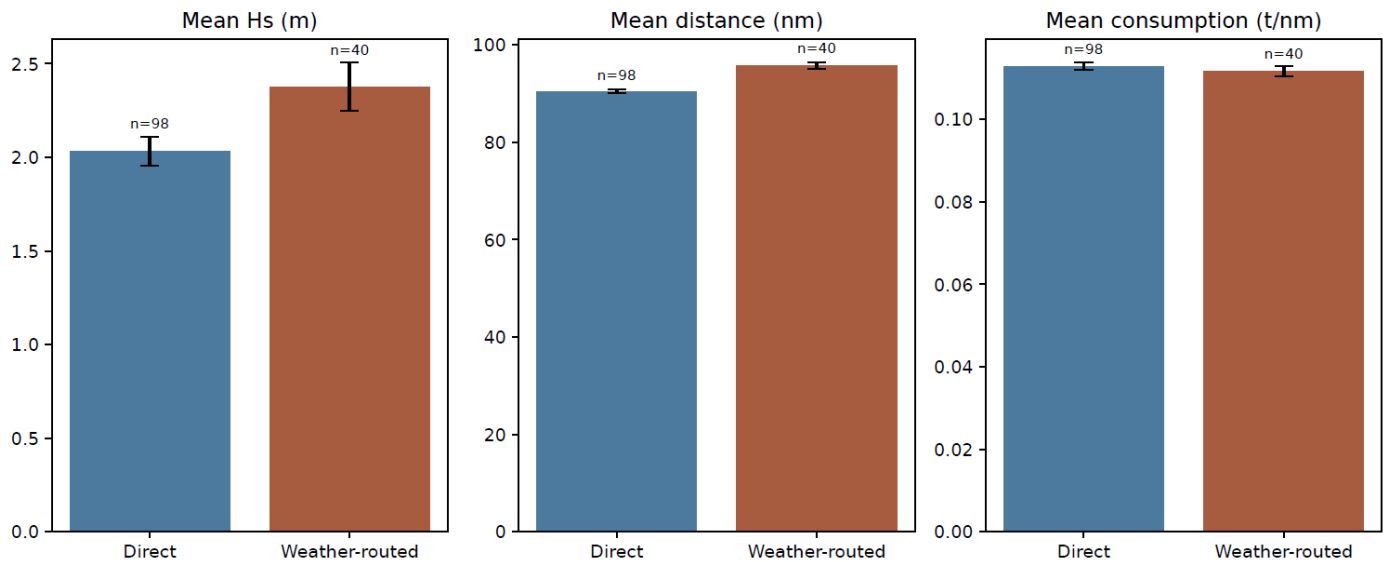
quirement rather than an argument against trim optimization as such: it identifies the correction that a trim optimization module must incorporate for its recommendations to remain reliable in the conditions where fuel savings matter most: explicit control for sea state and speed, or calibration on data in which trim is varied independently of them.

Conversely, the findings presented in Sections 3.5 to 3.8 point toward areas offering genuine potential for enhancement within existing onboard tools. The relative direction of the wave with respect to vessel heading (readily available in real time by fusing AIS data with meteorological forecasting) accounts for greater fuel consumption variability than trim within the observed trim envelope, and could be integrated into route advice systems with relative ease. Furthermore, the seasonal pattern identified in Section 3.7 demonstrates that a substantial fraction of fuel consumption variability on this regular line is predictable weeks in advance rather than solely on a voyage-by-voyage basis, opening avenues for seasonally aware maintenance scheduling and fuel procurement planning. Finally, the empirical evidence on weather routing presented in Section 3.8, while indirect, indicates that this operational practice (currently executed informally by vessel officers) could be formalized and systematically evaluated within a DSS framework rather than left entirely to individual watchkeeping.

4.4. Limitations and future work.

In addition to the methodological constraints noted in Section 2.5 (observational design, narrow trim range, single vessel and route), several avenues for future research emerge from this analysis. First, the data anomaly documented in voyage

Figure 9: Comparison between direct-route voyages and weather-diverted voyages: mean wave height, distance traveled, and mean specific fuel consumption (excluding voyage V135; error bars represent standard errors).



Source: Authors.

V135 (Section 2.3) underscores the necessity of implementing systematic data quality audits on flow meter logs prior to operationalizing such databases. Second, the absence of current data from the SIMAR dataset leaves an additional potential confounding factor unexamined within the Fuerteventura–Gran Canaria channel; incorporating oceanic reanalysis products would yield a more comprehensive model and could help clarify the negative correlation between distance traveled and specific consumption noted in Section 3.1, tentatively attributed here to route-specific operational artifacts but requiring deeper investigation. Third, the comparison between direct routes and weather-diverted voyages (Section 3.8) remains observational, preventing the exclusion of officer decision bias (diverting only when such maneuvers prove cost-effective) as the driving mechanism behind the observed pattern; a quasi-experimental research design comparing voyages with similar H_s but differing diversion choices would yield a more conclusive evaluation. Finally, and most ambitiously, only a dedicated field measurement campaign featuring deliberate, controlled trim variations (within the safety boundaries of the 2008 IS Code) across fixed intervals of H_s and SOG would experimentally isolate the physical effect of trim from ambient sea state, an objective that observational data cannot achieve by design. Such a campaign, combined with a physics-based or hybrid model calibrated outside the confounded operational envelope, is the natural route toward a trim optimization tool for vessels of this class: the present study delimits the conditions such a tool would have to satisfy, not the gains it could ultimately deliver.

5. Conclusions.

Speed over the ground shows the strongest association with specific fuel consumption ($r=0.775$ on a log-log scale), substan-

tially ahead of sea state ($r=0.29$) and longitudinal trim ($r=-0.08$, not statistically significant).

A simple comparison across trim bins ostensibly reproduces fuel savings on the order of those reported in the literature; however, this difference fails to achieve statistical significance when tested directly on individual voyage data ($p=0.80$) or via a one-way analysis of variance across bins ($p=0.45$). Under actual operational conditions, trim covaries with sea state ($p=0.009$), offering a more parsimonious alternative explanation for the observed differences across trim intervals.

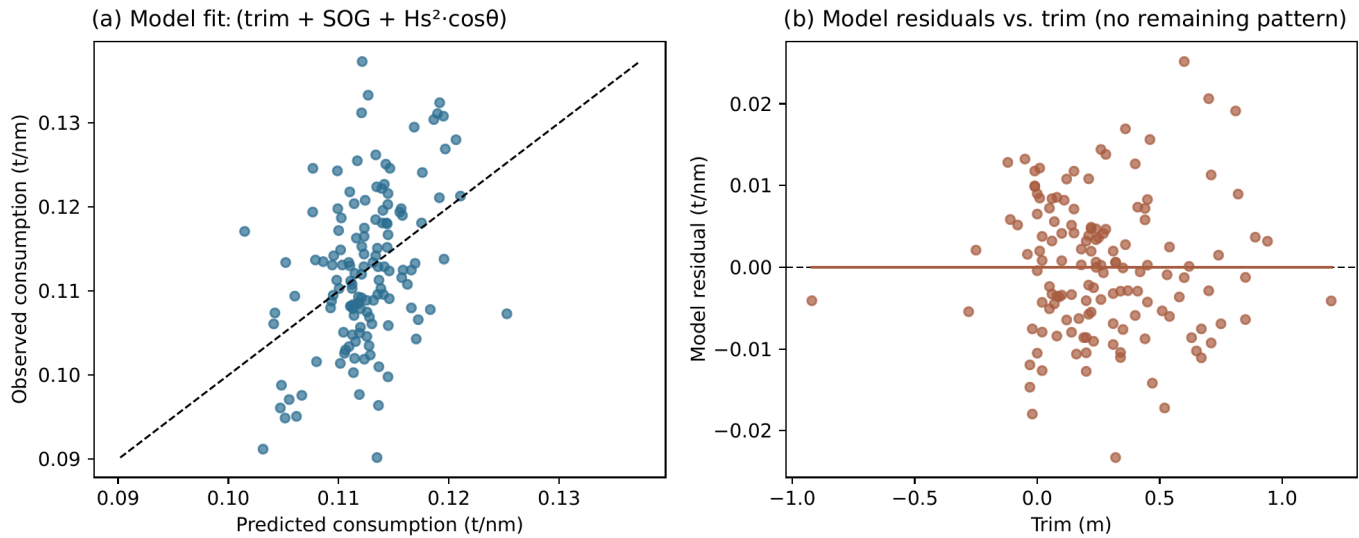
Across four distinct multivariable regression specifications, the trim coefficient never reaches statistical significance (p-values ranging from 0.22 to 0.97), whereas speed and a physically motivated directional added resistance term (Equation 3; $H_s^2 \cdot \cos \theta$) remain consistently significant.

The relative direction of waves relative to vessel heading markedly modulates the impact of wave height on fuel consumption (statistically significant in head seas, $p<0.001$; non-significant in beam seas, $p=0.42$), a pattern further corroborated at a monthly scale ($r=0.70$ between monthly mean H_s and monthly mean fuel consumption).

True meteorological wind accounts for little consumption variability by itself, representing an inappropriate parameterization: apparent wind (the vector actually impinging upon the vessel, resulting from combining true wind with vessel velocity) nearly doubles its correlation with fuel consumption ($r=0.241$ vs. $r=0.152$) and concentrates overwhelmingly from the bow (median 35° vs. 83° for true wind), due to operating at service speeds comparable to local mean wind speeds.

Voyages incorporating weather routing diversions take place under rougher sea states and cover greater distances, yet do not display significantly higher specific fuel consumption than direct voyages, an indication, albeit non-conclusive, that this in-

Figure 10: (a) Observed versus predicted specific consumption for Model C, excluding V135. (b) Residuals of Model C plotted against trim (residual–trim correlation ≈ 0).



Source: Authors.

formal practice proves effective.

Taken together, these findings do not invalidate the CFD- and towing-tank-based trim optimization literature, but they do advise caution when directly extrapolating idealized fuel savings to the real-world operation of a specific vessel without verifying whether the trim effect survives statistical control for sea state and speed, a methodological step rarely reported explicitly in fleet studies, and whose absence carries direct implications for the design of explainable onboard decision-support systems. The practical implication is not that trim optimization should be abandoned for vessels of this type, but that its potential must be established, and its recommendations calibrated, outside the confounded operational envelope in which trim and weather covary in daily practice.

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