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Research Article

Analysis of weather and ship-type effects on fuel efficiency and emissions for green maritime operations

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Abstract. This research is an endeavour to develop an explainable machine learning framework to quantify the combined effect of ship type, fuel type, distance and weather conditions affecting fuel consumption and CO_2 emissions for green maritime operations. The data collected from the voyage-level records for various vessel categories was pre-processed and used to train three supervised regression models: Linear Regression, Random Forest, and Extreme Gradient Boosting (XGBoost). The models were tested based on the coefficient of determination (R2) and mean squared error for training and test data sets separately for fuel consumption and CO_2 emission. Results show that all models are able to capture the main trends, but the Random Forest was able to provide the most accurate and robust predictions, with values of test R2 exceeding 0.94 and the lowest values of error for both target variables. In order to improve the interpretability, SHapley Additive exPlanations (SHAP) analysis and feature importance measures were used for the Random Forest models. Distance becomes the main factor, whereas ship type, fuel type, and weather variables have a secondary but significant impact on fuel consumption and emissions. The proposed approach offers a transparent and computationally efficient aid for supporting operational optimization, fuel choice evaluation, and policy design in the context of maritime decarbonization.

Keywords: Machine Learning, SHapley Additive exPlanations, Emission, Fuel Efficiency, Green Maritime

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1. Introduction

Shipping is a very important facilitator of international trade and, at the same time, a very important and increasing contributor to emissions of greenhouse gas (GHG). International shipping already a significant portion of the world's CO_2 emissions, and this portion can increase significantly by mid-century unless more drastic mitigation efforts are implemented, as seaborne commerce will increase (*2023 IMO Strategy on Reduction of GHG Emissions from Ships*, n.d.; H. P. Nguyen et al., 2024). Safety Ships that burn heavy fuel oil or marine diesel also emit CO_2 and sulfur oxide, nitrogen oxide, and particulate matter (PM), which degrade the quality of air in port cities and coastal areas. In reaction, the International Maritime Organization (IMO) has implemented a Revised GHG Strategy to achieve net-zero GHG emissions in internationally-registered shipping by or near 2050, with an interim checkpoint of 2030 and a further checkpoint of 2040, and demands a reduction in the carbon intensity of transport work (Ampah et al., 2021; IMO, 2021; Le et al., 2023). The future net-zero scheme that IMO is pursuing should be used to turn the same ambitions into actionable steps by imposing GHG-intensity fuel standards and price controls, increasing the adoption of zero and near-zero-emission fuels and technologies into practice (Garcia et al., 2021; P. C. Wu & Lin, 2020; Zannis et al., 2022). To meet such objectives, cleaner fuels and new ship designs are not only prerequisites but operational efficiency improvements and resilient means of measuring how various parameters drive fuel consumption and emissions under real-world operations are also required (Agarwala, 2021; Majidi Nezhad et al., 2024).

The technical/operational and environmental variables provide a complex interaction in fuel consumption and relative amounts of emissions produced by ships. Some of the determinants are sailing speed, draft, and displacement, the condition of hull and propeller, the main engine load, auxiliary systems, and some external factors such as wind, waves, currents, and sea state.(V. G. Nguyen et al., 2023; Sui et al., 2020) The use of the noon report and data on the routes has evidenced that unfavorable weather and head seas can significantly increase the fuel consumption, and the ineffectiveness of hull and poor choice of speed worsen efficiency. Ship type and ship size are also important, with the various types of vessels (such as a container vessel, a bulk carrier, an offshore service vessel, a fishing trawler) having different speed regimes, loading profiles, and duty patterns, which result in different energy and emission profiles (Fan et al., 2022; Rudzki et al., 2022). Most of these relationships can be seen in traditional statistical models, but they can rarely deal with nonlinear interactions and heterogeneous operating modes. Here, machine-learned methods that directly model fuel consumption and emissions of different types of ships and at a greater variety of operational circumstances have

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been shown to be a promising method to achieve more accurate estimates of fuel consumption and emissions (Abaei et al., 2022; Gupta et al., 2022).

The rapidly developing domain of machine learning is an attractive option in modeling and forecasting of complex engineering problems like nanofluids characterization (Kumar K et al., 2024), biodiesel-diesel powered engines (Sharma & Sharma, 2021), solar farms (Zhang et al., 2023), wind energy, etc., among others. There is thus an increasing interest in machine learning (ML) in maritime studies to predict ship fuel consumption, energy efficiency, and emissions. More recent designs have used the algorithms of Random Forests, Gradient Boosting, XGBoost, support vector machines, and deep neural networks on large-scale operational data, where supposedly much better predictive accuracy can be obtained than with traditional regression models (Guo et al., 2022; Hu et al., 2019; Patil et al., 2024; Uyanik et al., 2019; Uyanık et al., 2020). Ship energy consumption forecasting has been done based on ensemble and stacking, through the incorporation of several base learners, and approaches like SHapley Additive explanations (SHAP) have the potential to measure the contributions of inputs like speed, mean draft, and trim. Other results show that ML models can predict CO_2 emissions of ships when they are trained under conditions of more comprehensive monitoring, reporting, and verification types of data to support operational decisions and audit carbon (Ma et al., 2023; Z. Wu et al., 2025). These developments indicate that ML offers reliable and customizable tools to model the contribution of weather, fuel type, and ship characteristics to fuel efficiency and emissions- information that may be necessary to design green operation strategies and climate policies effective in the maritime environment.

Nevertheless, the literature still has some remarkable gaps, especially in the explainable machine learning of the green maritime operations. Most of the high-performing ML models that are applied to ship fuel and emission prediction are black boxes that provide little understanding of why specific predictions are given and how different features interact (*Fuel Efficiency and CO2 Emission Data Sources - International Council on Clean Transportation*, n.d.). Although a few more recent studies have also taken into account explainable AI (XAI) methods, including SHAP, to decipher the fuel consumption models, the majority concentrate on a limited range of variables (e.g. speed, draft, or engine load) and on specific categories of ships (e.g. container ships or passenger ships) as opposed to investigating systematically the implications of both environmental factors (e.g. weather and sea state) and ship-type differences on emissions (Maulud et al., 2020; Wang et al., 2024). Additionally, few works are targeted at relatively small and practical-oriented datasets in which variables like ship type, fuel type, distance, and weather category are used to generate simple and yet interpretable models applicable at early-stage planning or educational stages. It is therefore necessary to conduct studies with a balance between predictive performance and transparency, explicitly comparing several ML algorithms on identical datasets and applying XAI tools to clarify the marginal and joint impacts of both operational and environmental conditions on maritime emissions.

The present study is an attempt to fill this research gap to formulate and interpret ML models to predict fuel consumption and CO_2 emissions using operational records of ships that are distinguished by type of ship, voyage distance, fuel type, and weather conditions. The first one is to develop and compare three supervised learning models, linear regression, Random Forest, and XGBoost, to measure their effectiveness in predicting fuel consumption and emissions at different operating conditions in the form of the coefficient of determination and mean squared error. The second is to use explicable techniques of ML, specifically feature importance analysis and SHAP-based interpretation, to find out which combinations of ship type, fuel, and distance and weather have the strongest effect on fuel efficiency and emissions, and how these effects vary among algorithms. The study will help make more informed decisions regarding operational changes, fuel selection, and route optimization to minimize emissions and promote the wider decarbonization and net-zero goals of maritime operations to support the wider aim of the maritime industry.

2. Materials and methods

2.1 Data collection

In this paper, open-source operational shipping data have been taken through the Kaggle platform and used to develop and test the machine learning models (Gholizadeh et al., 2020). The dataset consists of records at the voyage level of the various types of vessels that include the information of the category of the ship, the distance covered in the voyage, the type of fuel used, the weather or the state of the sea prevailing during the voyage, and the estimated fuel consumption and CO_2 emissions. The variables provide a concise but significant picture of the key technical and environmental factors of the energy consumption of ships, which is why the dataset can be used to create supervised regression models. By utilizing an openly available dataset, maximum transparency and reproducibility of the analysis will be guaranteed, as well as other researchers will be able to extend, refine, or benchmark other algorithms on the same data. The data was downloaded in a spreadsheet format, which was pre-processed to deal with missing data and categorical encodings, and then divided into a training and a testing set and served as the foundation of creating linear regression, Random Forest, and XGBoost models along with explainable ML analysis.

2.2 Machine learning

2.2.1 Linear regression

Linear regression (LR) gives a clear baseline regression to determine the fuel consumption and emissions of the ship as a linear regression of the explanatory variables that include ship type, distance, type of fuel, and weather conditions. LR in its ordinary least squares formulation assumes that the conditional mean of the response is a weighted average of the predictors, the coefficients being between observed and predicted values being minimized (Talekar & Agrawal, 2020). Assuming LR is linear, independent, homoscedastic, and the errors are roughly normally distributed, the parameter estimates are unbiased and efficient, and it is straightforward to conduct hypothesis tests and construct confidence intervals. Even with some of the assumptions loosened, LR can still be useful in determining the direction and approximate magnitude of effects, e.g., whether stormy weather has a systematic effect that enhances emissions or how varying types of fuels cause the average response to change (Villegas-Mier et al., 2022). The application of LR to this study is that it can be used as an interpretable benchmarking predictive performance and the added value of more flexible non-linear models. The simple functional shape of it enables the direct comparison of the estimated coefficients with the domain knowledge of the fields of naval architecture and marine engineering, which helps to provide a scientifically based interpretation of the effects of operational and environmental variables on the fuel consumption and CO_2 emissions.

2.2.2 Random Forest

Random Forest (RF) is an ensemble learning algorithm that trains a huge number of decision trees on bootstrap sets of the training data and combines their predictions, regression-based problems by averaging them. At every split, each tree in the forest is also trained on a subset of the observations and on a random subset of the predictor variables, discouraging correlation between trees and minimizing overfitting (Liu et al., 2023; Qiu et al., 2021). This stochastic structure enables RF to model nonlinear, complex interactions between variables, e.g., ship type, distance, fuel type, and weather state, without explicit specification of interaction terms. Statistically, Random Forests estimate the conditional expectation of the response, as well as giving internal quantifications of uncertainty and variable importance, such as the mean decrease in impurity or permutation-based importance (Akbar et al., 2024). RF has been demonstrated to be effective in maritime applications when there are heterogeneous operational data and noise, missing values, and mixed data types are prevalent. RF is a powerful nonparametric tool that, in this work, can be used as a supplement to linear regression to investigate the nonlinear and interaction effects, and yet still maintains some level of interpretability in the form of feature importance profiles and partial dependence structures.

2.2.3 Extreme Gradient Boosting

Extreme Gradient Boosting (XGBoost) is an efficient implementation of the gradient boosting decision tree approach. The algorithm constructs a series of shallow regression trees one after another, with each tree being built to fit the residual of the last ensemble through gradient-based optimization of a given loss function, e.g., squared error in regression. XGBoost uses regularization words on tree intricacy (such as penalties on the number of leaves and the size of leaf weight), contraction by means of learning rates, column and row subsampling, and complex handling with missing values, all of which bolster generalization and control overfitting (Gabaldón et al., 2021; Wojtuch et al., 2021). The architecture will allow XGBoost to fit the most nonlinear relationships and higher-order interactions among both operational and environmental factors, which is why it is well applicable to identify subtle trends in fuel consumption and emission data. Furthermore, the framework reveals a rich set of hyperparameters that can be optimized to make the bias-variance trade-off of datasets of varying size and noise levels (Fryer et al., 2021; Mokhtari et al., 2019). In the current work, the XGBoost will serve as a powerful ensemble regressor in estimating fuel and CO_2 emissions and also give fine-grained scores of importance that can subsequently be analyzed using explainable machine learning tools, which will be a potent supplement to both linear regression and Random Forest.

2.3 SHapley Additive exPlanations

SHapley Additive exPlanations SHAP is a converged system of explaining the output of the complex machine learning models grounded on the principles of cooperative game theory. The key point is to consider every input feature as a player in a prediction game and assign it Shapley value, which is the prediction of its average marginal contribution of all possible feature subsets [40,41]. Practically, SHAP provides approximate values of such values with both model-specific and model-agnostic algorithms, giving additive explanations where the combination of the feature contribution and a base value recreates the model output on an observation. This additive form allows interpretation globally, summarizing SHAP values across the data to get feature importance scores and interaction trends, and interpretation locally, explaining single predictions as contributions of each feature. SHAP has also been applied to study maritime, where the parameters of operation, or sensor values that are leading to anomalies, risk scores, or emission estimates are analyzed to convert black-box models into more explainable decision support tools [42].

3. Results and discussion

3.1 Model prediction

Python-based scientific libraries were widely used in data analysis, model development, and interpretation in this study. The raw operational dataset was imported and preprocessed with the library pandas to perform tasks such as renaming columns, type conversion, removing missing values, and creating feature-target matrices for further modeling. The scikit-learn library was used to split data into training and testing subsets, apply one-hot encoding to categorical variables using ColumnTransformer and OneHotEncoder, and implement baseline and ensemble regressors, including LinearRegression, RandomForestRegressor. The XGBoost library was used for a gradient boosted tree model with improved nonlinear fitting capability and evaluation metrics such as R2 and mean squared error using sklearn.metrics. Model explainability was accomplished using the shap library, which was used to generate SHAP values to quantify feature contributions and generate summary plots. Visualization of correlations, distributions, violin plots, and scatter plots with error bands was performed with matplotlib and seaborn, allowing for a thorough graphical analysis of data patterns, model performance, and error behavior of the model in training and test data.

3.1.1 Fuel consumption model

Figure 1 illustrates violin plots of the fuel consumption and CO_2 emission in relation to fuel type and weather conditions. Figure 1a presents the distribution of fuel consumption for HFO and diesel in calm, moderate, and stormy weather; the width of each violin stands for the probability density of observations, while the box within the violin is the interquartile range and median. Calm

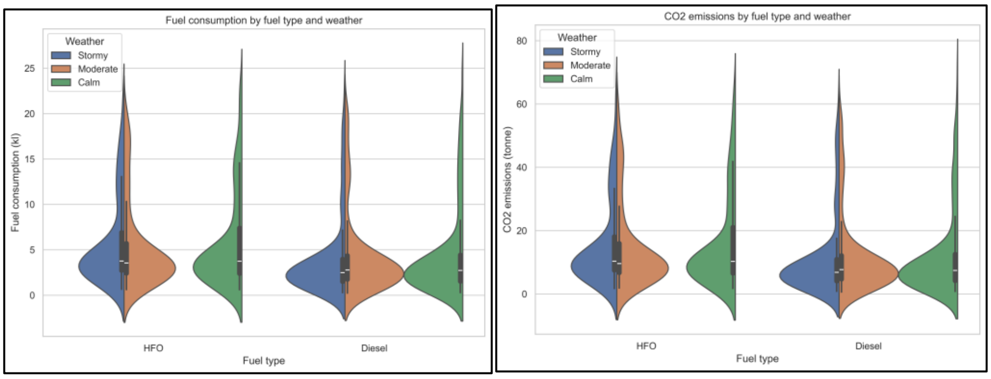


Figure 1 Violin plots for (a) fuel consumption (b) CO2 emission

conditions typically have lower and more concentrated fuel use, while moderate and stormy weather produces wider and longer tails, which could be seen as higher and more variable fuel use, especially for HFO-fuelled operations. Figure 1a presents similar distributions for the CO_2 emissions, which show similar patterns to those for the fuel consumption, as the CO_2 emissions relate to fuel use and emission factors. HFO usually produces higher emission levels and wider distribution than diesel, especially in unfavourable weather. Together, the plots illustrate the combined effects of fuel choice and sea state on both the central tendency and spread of both energy use and climate-relevant emissions.

The results of this study comparing the predictive performance of three machine learning models for fuel consumption are shown in Figure 2: Linear Regression (LR), XGBoost, and Random Forest (RF). Each panel contains predicted vs. actual fuel consumption with an ideal 1:1 line and + 15% error bands, as well as distinct markers for training (blue) and test (red) samples and a text box containing a performance summary. For LR (Figure 2a), the train R2 is 0.942 with a train MSE of 1.341, and the test R2 is 0.947, and the test MSE is 1.419, which shows a reasonably good linear fit with a noticeable scatter around the ideal line for higher consumption

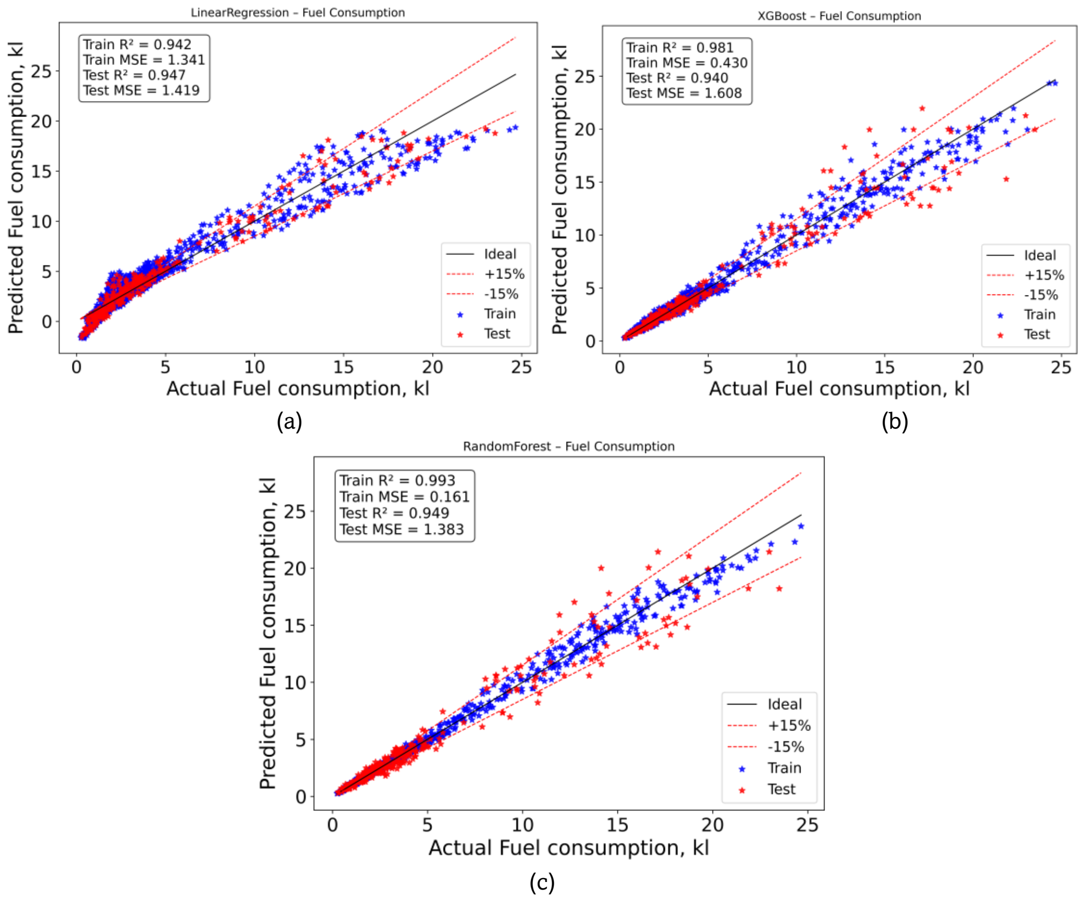


Figure 2 Fuel consumption model actual vs predicted values for (a) LR, (b) XGBoost, (c) RF ML

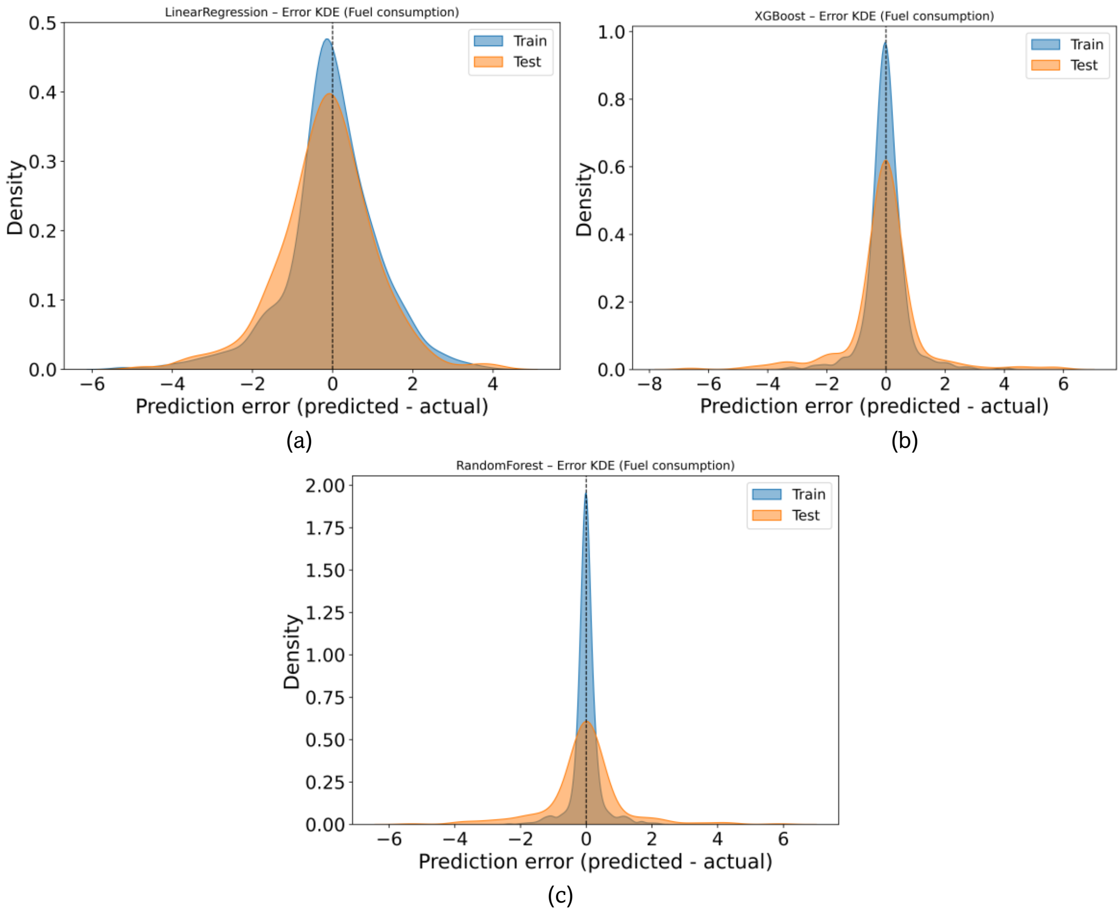


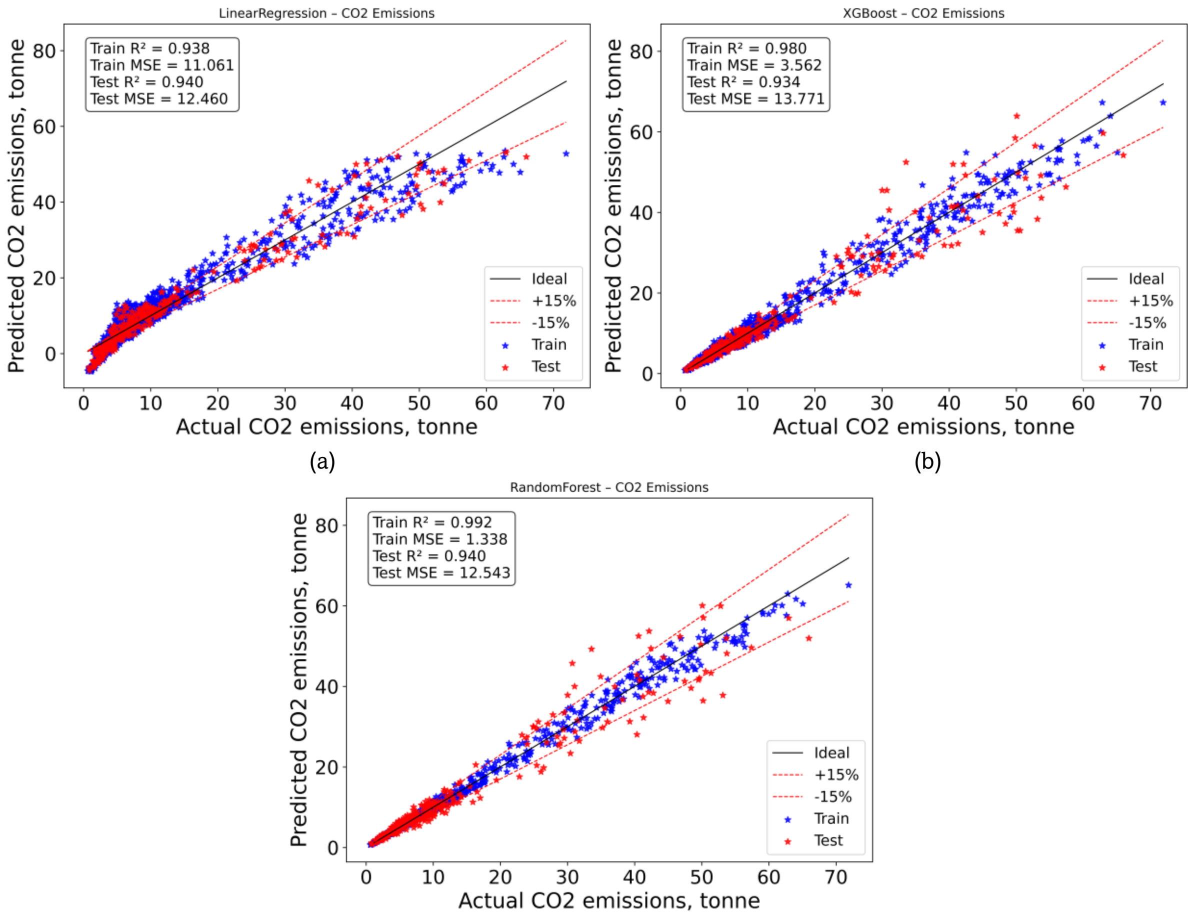
Figure 3 Fuel consumption model error KDE for (a) LR, (b) XGBoost, (c) RF ML

levels. XGBoost gets better in-sample fit, train R2 is 0.981, train MSE is 0.430, test R2 is 0.940, test MSE is 1.608, as depicted in Figure 2b, which indicates that the model is slightly overfitted and the dispersion of test points is somewhat wider than that of the training set, especially beyond 10 kl. RF has the best overall balance with a very high train R2 = 0.993 and low train MSE = 0.161, and has a strong test R2 = 0.949 with the lowest test MSE = 1.383 amongst the three models. As depicted in Figure 2c, RF predictions are clustered the closest to the ideal line and are mostly within the +15% bounds for the train and test set, while LR and XGBoost predictions have more deviations for larger consumption values. Overall, the figure shows that all models capture the main trend, but the ensemble-based RF model captures the most accurate and stable fuel consumption estimates.

Figure 3 is a kernel density estimate of the prediction errors for the three fuel consumption models and gives a distributional picture of model bias and variation for both training and test data. In all the panels, the horizontal axis is the error (predicted vs actual fuel consumption), and the vertical axis is the estimated probability density with the dashed vertical line at zero denoting perfect predictions. For Linear Regression, the distributions for the Training and Test errors are centred near 0 but fairly broad, with significant mass outside + 2kl, indicating moderate random error and some under- and over-prediction, as depicted in Figure 3a. The XGBoost model has a much sharper peak of the training error around zero, indicating an excellent in-sample fit, while the test error curve is wider with heavier tails, which indicates mild overfitting and sensitivity to unseen data (Figure 3b). The Random Forest model shown in Figure 3c reveals the smallest and narrowest error distributions for both train and test sets, and most of the errors are around zero, and there is very little probability mass outside the + 2kl range. Overall, the KDE plots support the results of the scatter plots: Random Forest gives the most stable and least biased predictions of fuel consumption, followed by XGBoost and then Linear Regression.

3.1.2 Carbon-di-oxide model

The performance of the three CO_2 emission models is compared in Figure 4 by plotting the predicted versus the actual emissions along with the ideal 1:1 line and the plus or minus 15% error bands. In Figure 4a, the Linear Regression model achieves a train R2 of 0.938 and test R2 of 0.940 with train and test MSE values of 11.061 and 12.46 tonne, respectively. The spread of points around the ideal line is moderate, with a noticeable spread for higher emission levels, suggesting that the linear approximation captures the general trend but is not capable of capturing nonlinearities. Figure 4b presents the XGBoost model, which gives a better fit to the in-sample data, with a train R2 of 0.980, train MSE of 3.562 tonne, slightly lower test R2 of 0.934, and test MSE of 13.771. This pattern indicates a slight overfitting as the training points are near the ideal line, whereas the test points are more spread out, particularly outside the range of 30 tonnes. Figure 4c illustrates the Random Forest model, which gives the best overall balance with train R2 of 0.992 and train MSE of 1.338 tonne, and test R2 of 0.940 with test MSE of 12.543 tonne. The Random Forest scatter cloud in Figure 4c is compact and symmetric around the ideal line across the emission range, and the majority of observations are within the +-15%



(a) (b)
(c)

Figure 4 CO_2 emission model actual vs predicted values for (a) LR, (b) XGBoost, (c) RF ML

bounds. Overall, Figure 4 illustrates that all three models are able to accurately estimate the CO_2 emissions; however, Random Forest allows for the most accurate and stable predictions, while XGBoost is able to give a higher accuracy in training at the expense of higher error in the test data.

Figure 5 shows kernel density estimates of the CO_2 emission prediction errors for the three machine learning models, which could be used to compare the bias and dispersion. In Figure 5a, corresponding to the Linear Regression, both train and test error distributions are centred around zero and have relatively broad asymmetric shapes with noticeable tails below -10 and above +10 tonnes. This means that LR sometimes under- or over-estimates emissions by big margins, particularly for certain operating conditions. Figure 5b is the XGBoost model, where there is a much sharper and taller peak in the training error distribution around zero, indicating a very good in-sample fit, but the test error distribution is much broader with heavier tails, indicating slightly overfitting and somewhat larger errors on unseen voyages. The Random Forest results in Figure 5c show the narrowest and most symmetric train and test distributions with most probability mass concentrated very close to zero and very little of the distribution extending beyond + 5 tonnes. The high central peaks and rapid decay of the tails in Figure 5c imply that RF gives smaller and more consistent residuals compared to LR and XGBoost across the dataset. Overall, Figure 5 proves that all models are roughly unbiased, but Random Forest provides the most reliable predictions on the CO_2 emissions and is followed by XGBoost and Linear Regression, which have the highest variability in the magnitude of errors.

3.2 Feature evaluation and model interpretation

RF model made the best predictions of fuel consumption among all three algorithms, which were the most robust. Thus, it was selected to undergo explainable machine learning analysis and a quantitative measure of feature importance in Figure 6. The SHAP summary plot in Figure 6a shows the effect of each input feature on the RF fuel-consumption prediction of individual samples, and the horizontal axis is the value of the SHAP values. Distance is evidently the dominant factor, with high-distance observations (depicted in pink) related to high SHAP values and low-distance observations (in blue) related to negative contributions, which confirms the fact that long voyages have a strong positive impact on forecasted fuel consumption. The categorical variables that exhibit non-negligible positive SHAP effects include ship type (Tanker Ship) and ship type (Surfer Boat), which means that the ship types are likely to use more fuel than the reference categories (when the distance and weather are held constant). Fuel type (Diesel) will usually have slightly negative SHAP values compared to fuel type (HFO), indicating that diesel will be more fuel efficient. The weather conditions impact relatively smaller and interpretable changes: stormy and calm weather change predictions upwards and

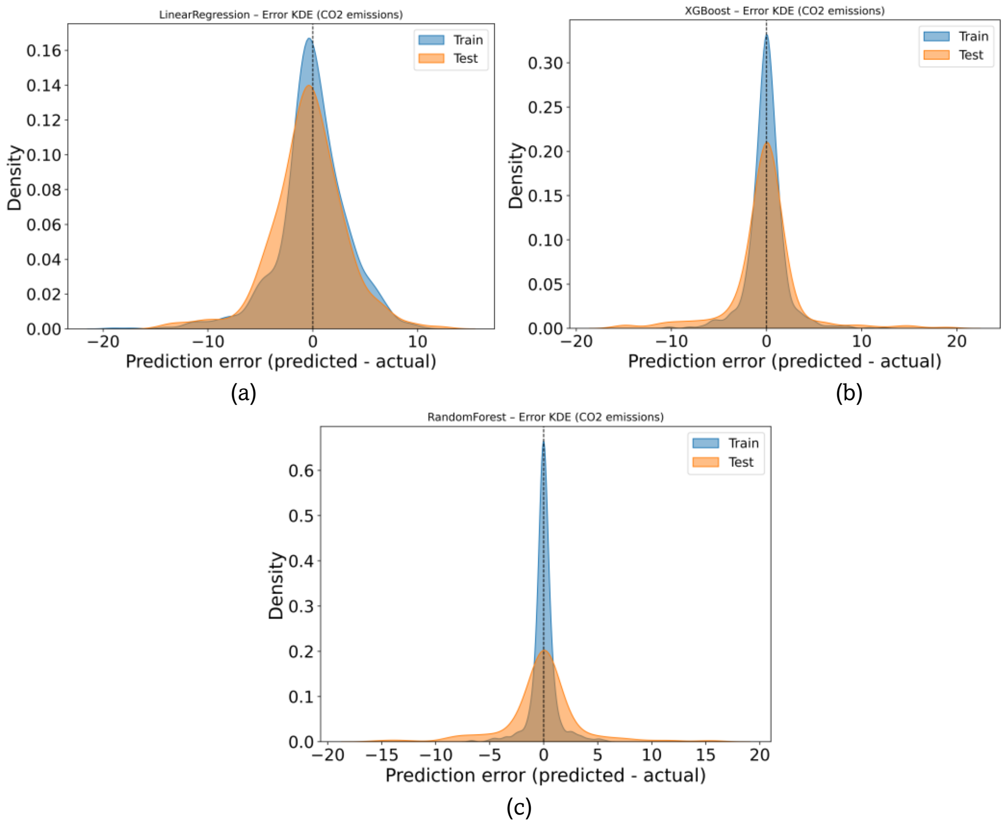


Figure 5 CO_2 emissions model error KDE for (a) LR, (b) XGBoost, (c) RF ML

downwards, respectively, whereas moderate weather is in between. Figure 6b shows the corresponding bar-chart of feature-importance of RF that confirms the SHAP results with distance ranking as the significantly larger dominant predictor, then ship-type indicators, and weather category as the other insignificant predictor with a small contribution. These explicable ML diagnostics combined are an indication that the RF model is in line with physical expectations and gives clear evidence of how the combination of operational and environmental factors collectively influences fuel consumption.

The model interpretation of the CO_2 emission was based on the same Random Forest-SHAP model, and the findings are summarised in Figure 7. Just like the fuel-consumption case, the RF model of CO_2 emission was chosen as it gave the optimal trade-off in accuracy and generalisation during the regression analysis. Figure 7a, the SHAP summary plot indicates that distance is once again the major influential predictor in the case of emission prediction. Of predicted emissions: high-distance journeys (pink points) are connected with large positive SHAP values, whereas low-distance instances (blue) detect the prediction down, indicating the nearly proportional relationship between travelled distance, fuel consumption, and CO_2 emission. Of categorical features, ship type

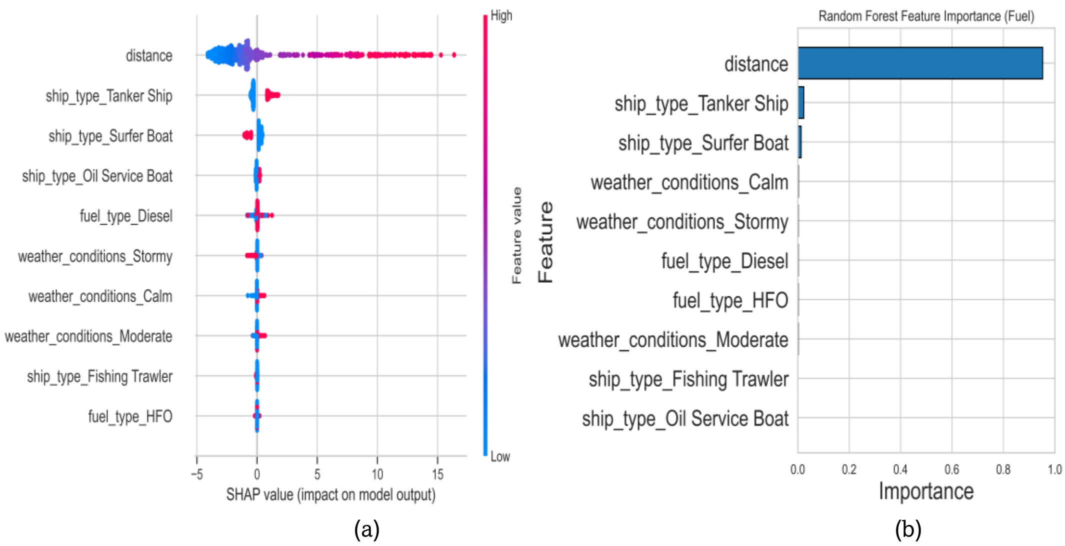
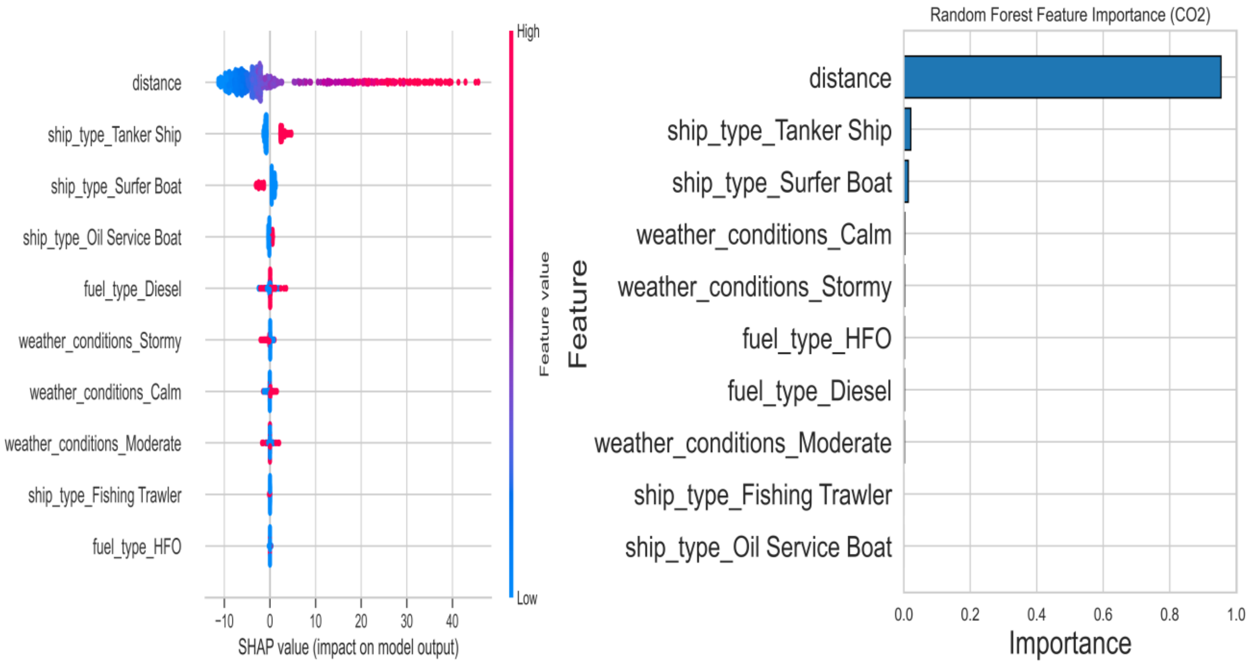


Figure 6 Explaianable ML-based fuel consumption model analysis (a) shap value (b) feature importance



(a)

(b)

Figure 7 Explaianable ML-based CO_2 model analysis (a) shap value (b) feature importance

(Tanker Ship) and ship type (Surfer Boat) also have positive SHAP contributions that clearly show that, all other factors being equal, these two categories of ships have higher emissions than the reference ship types, which correlate with their higher fuel requirement. The smaller, but interpretable, effects can be observed in Fuel type (HFO) and fuel type (Diesel), and as a result of its higher emission factor, the HFO tends to positively shift the emissions upwards as compared to diesel. Weather conditions have secondary impacts: stormy and calm conditions have less effect (after all) on predicted emissions by changing resistance and engine load. These observations are also statistically supported by the Random Forest feature-importance plot of Figure 7b, which ranks distance way high above the rest of the variables, then in increasing order come the tanker and surfer ship types, the weather, and fuel-type indicators. The combination of the SHAP and importance analysis reveals that the CO_2 model is physically plausible and transparent in the allocation of the emissions to distance, vessel type, fuel preference, and sea condition.

4. Conclusion

This paper introduced a full machine learning & explainable AI pipeline for estimating ship fuel consumption and CO_2 emission based on a small operational data set combining ship type, voyage distance, fuel type, and weather conditions. Linear Regression, XGBoost, and Random Forest models were developed and thoroughly tested to show that ensemble-based methods are significantly more accurate than the simple linear baseline, especially for high levels of fuel use and emission. Among them, Random Forest ensured the best predictive accuracy and most balanced generalisation behaviour for both of the targets, with narrow error distributions and good agreement with the one-to-one ideal in the validation plots. Building on this model that performed best, the global and local interpretability of the model was explored using SHAP-value analysis and feature-importance metrics. These analyses showed a consistent result that distance was the major determinant of fuel consumption and CO_2 emissions, but tanker and high-speed service vessels, heavy fuel oil, and stormy weather conditions were related to systematically higher predicted values. Calm weather and diesel fuel were associated with relatively low consumption and emissions, in accordance with physical and operational expectations.

The results confirm the ability of interpretable machine learning to offer not only accurate forecasts but also a quantitative understanding of the driving forces behind ship energy and emission performance, namely operational and environmental factors. The methodology is easily transferable to richer datasets and more predictors (for example, speed, draft, or engine load) and can aid scenario analysis and green-routing strategies and decision-making for meeting the net-zero emission goals of the maritime sector.

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