

# Data-Driven Explainable Artificial Intelligence for Energy Efficiency in Short-Sea Shipping

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**Abstract:** The maritime industry is under pressure to increase energy efficiency for climate change mitigation. Navigational data, combining vessel operational and environmental measurements from onboard instruments and external sources, are critical for achieving this goal. Shortsea shipping presents a unique challenge due to the significant influence of surrounding landscape characteristics. With high-resolution onboard data increasingly accessible through IoT devices, appropriate data representations and AI/ML analytical tools are needed for effective decision support. The aim of this study is to investigate the fuel consumption estimation model's role in developing an energy efficiency decision support tool. ML models that lacking explainability may neglect important factors and essential constraints, such as the need to meet arrival time requirements. Onboard weather measurements are compared to external forecasts, and our findings demonstrate the necessity of eXplainable Artificial Intelligence (XAI) techniques for effective decision support. Real-world data from a short-sea passenger vessel in southern Sweden, consisting of 1754 voyages over 15 months 1, are used to support our conclusions.

## Data Description and Preparation

The ship's onboard data were received from our industry partner CetaSol AB [1] in Gothenburg. It has been gathered from January 2020 to March 2021, it has a 3Hz frequency and records about the ship's position, course direction, and speed. It is also including some operational and meteorological data, such as fuel rate, engine speed, torque, acceleration, wind speed and direction.

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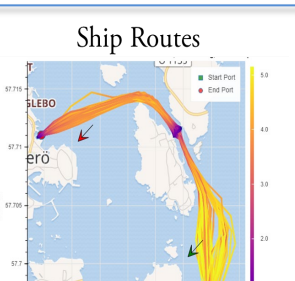
<https://www.marinetraffic.com>

Ship Type Passenger,

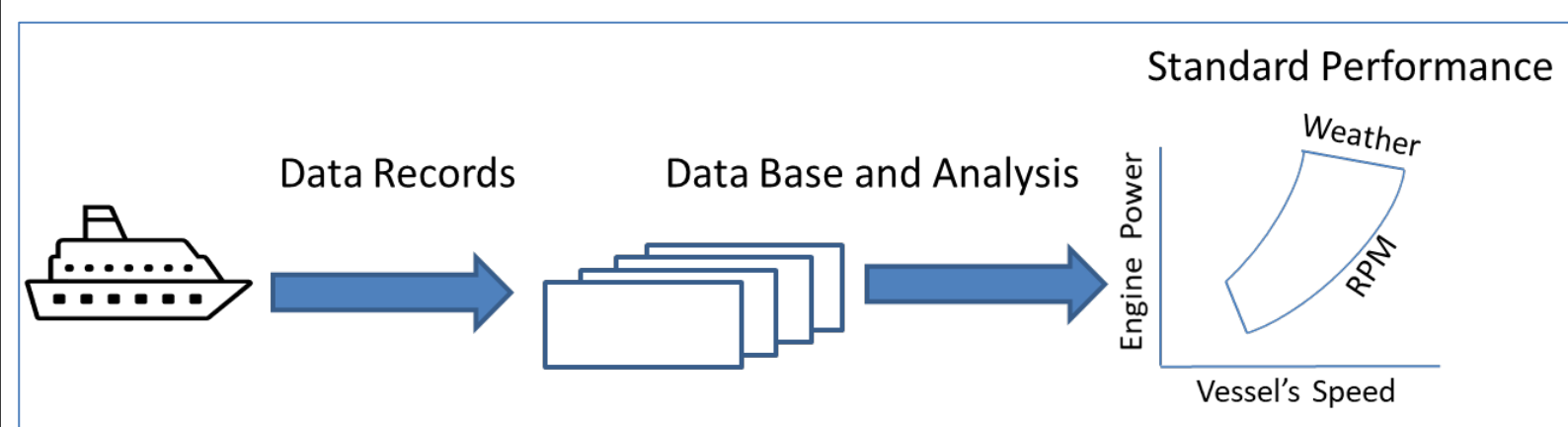
Length × Breadth 19 X 6.41m

Speed recorded (Average): 4.2 m/s

Flag Sweden (SE)



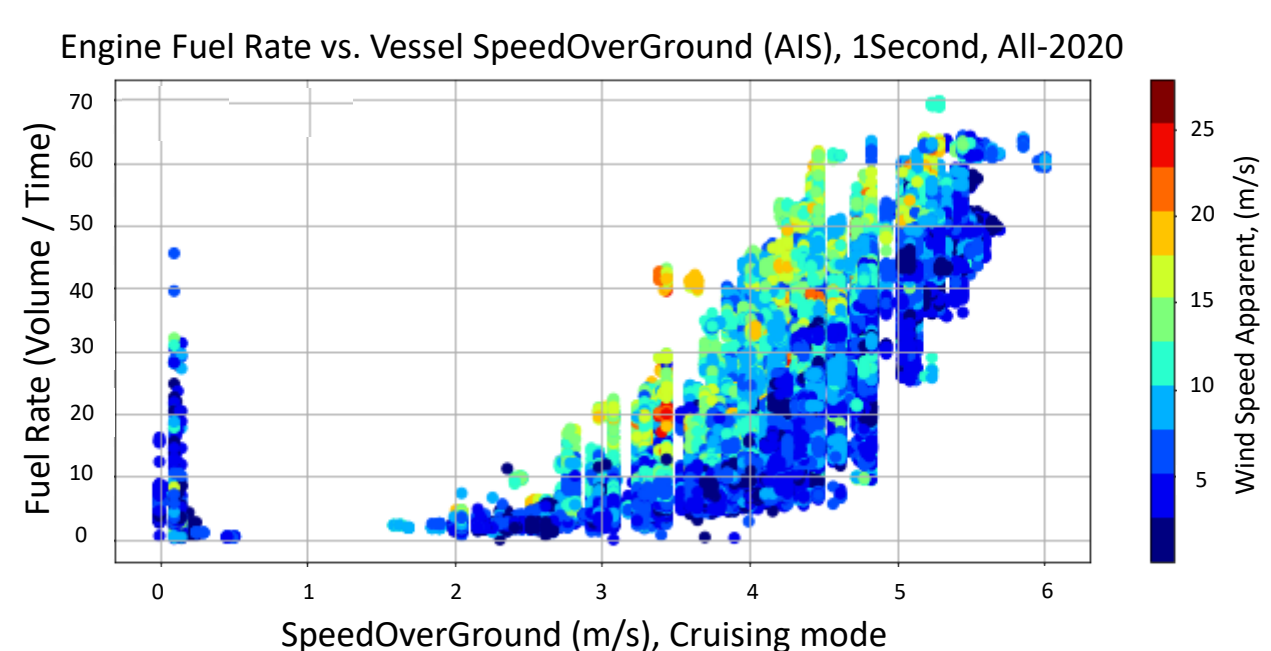
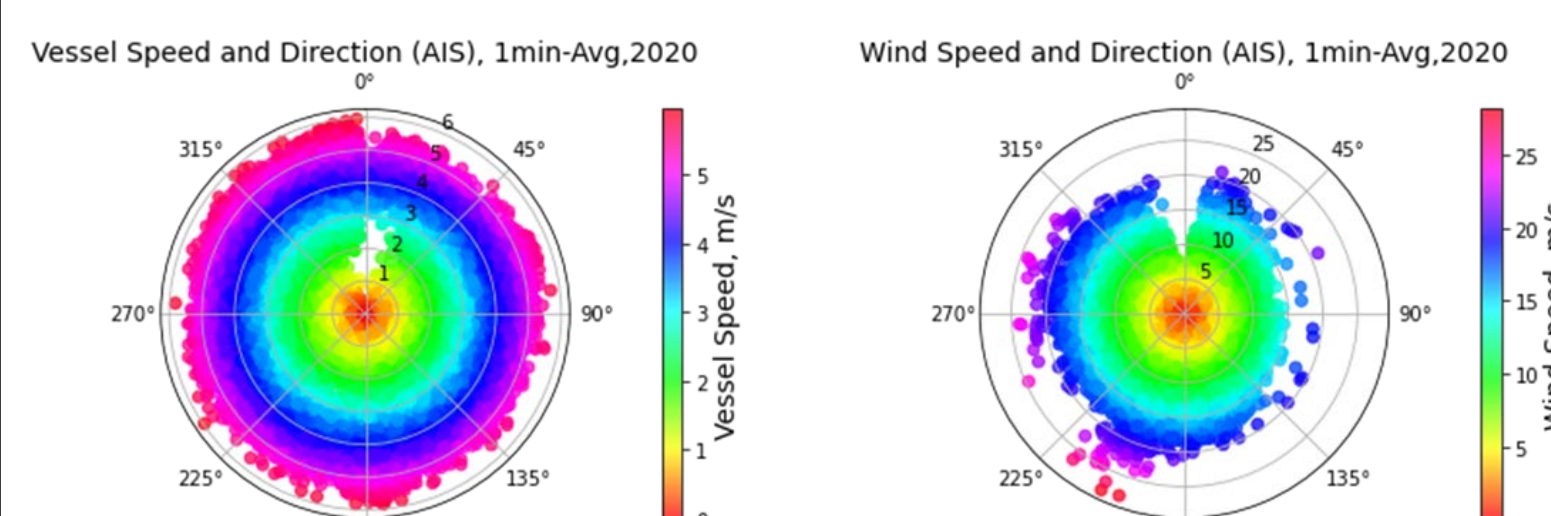
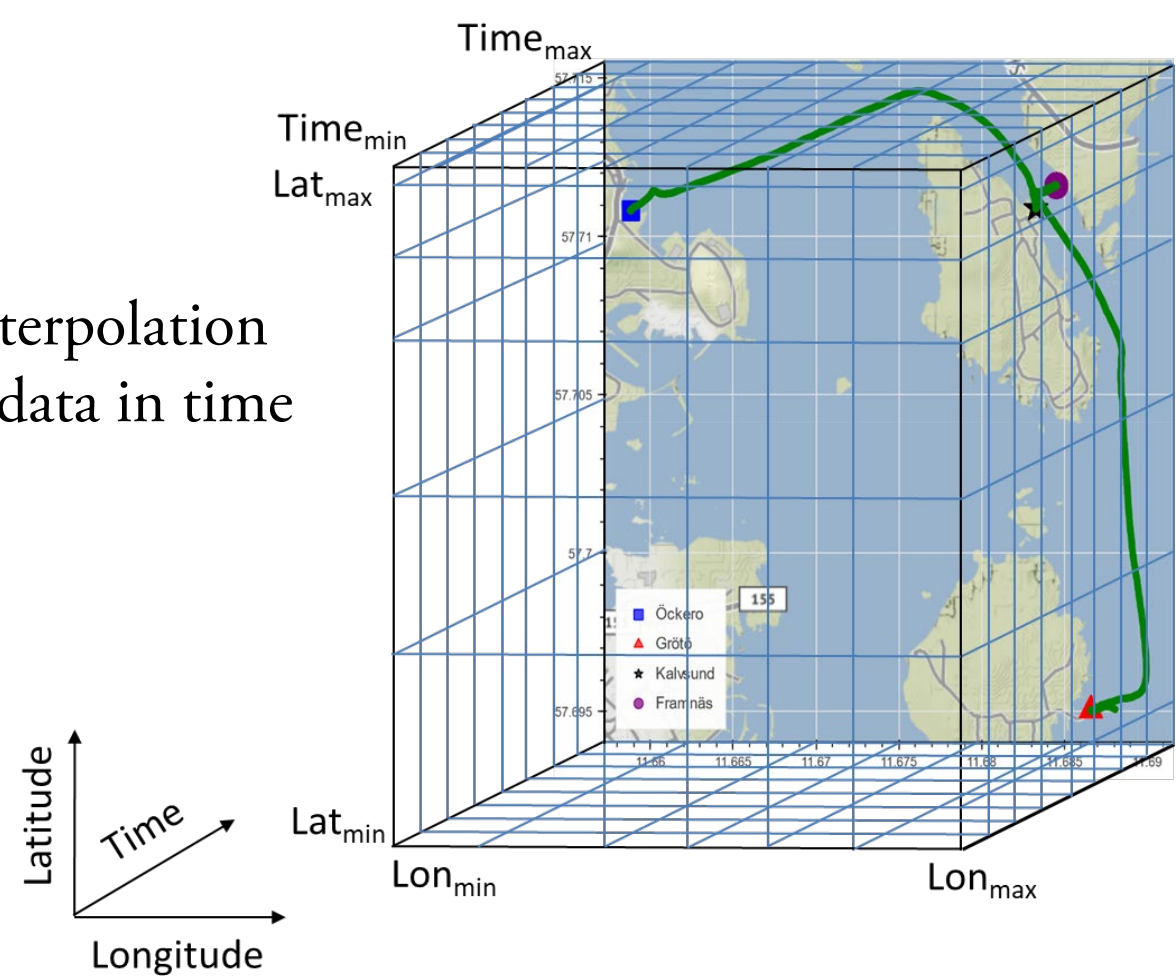
## Data Preprocessing



Other weather variables such as wave height and sea current speed and direction have been collected from external sources, Copernicus Marine Service [2] and StormGlass [3] APIs.

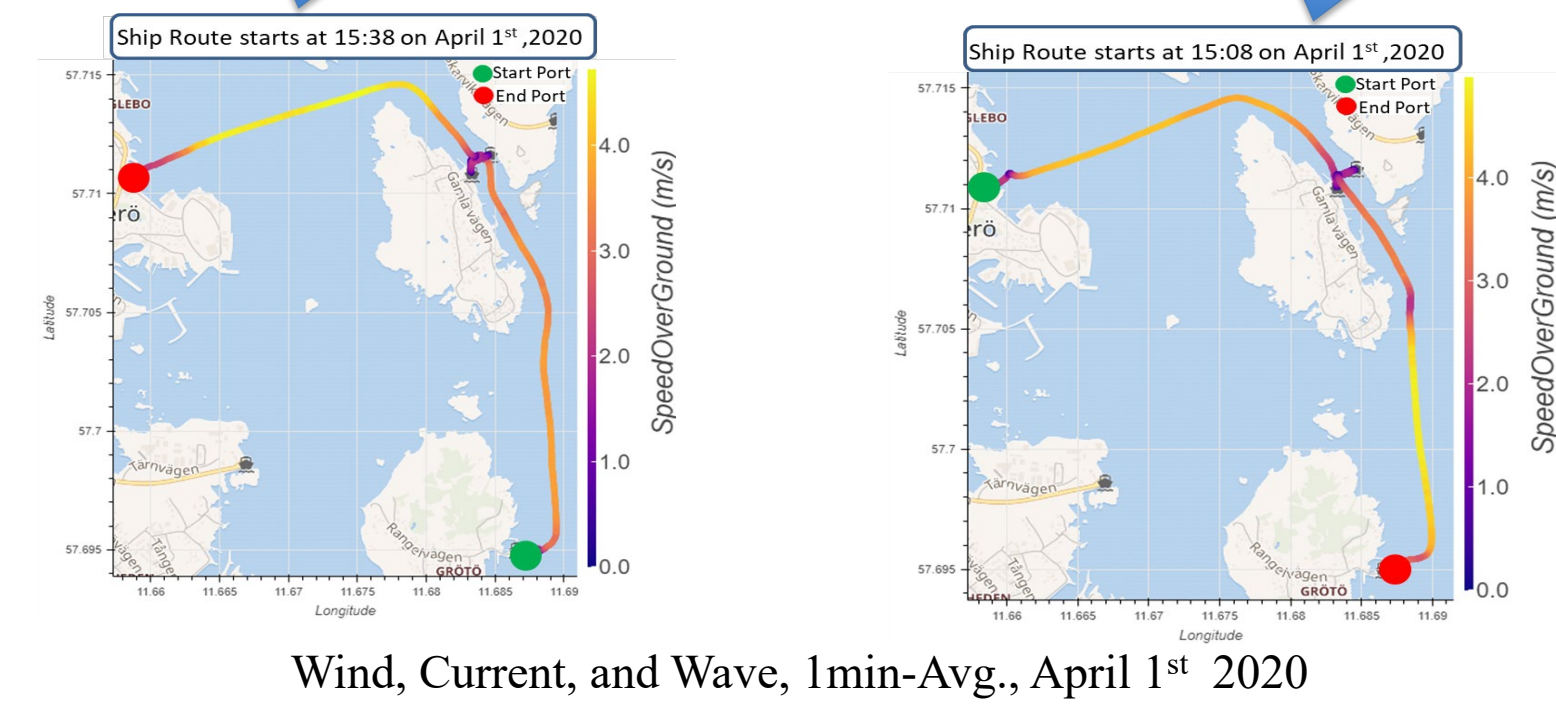
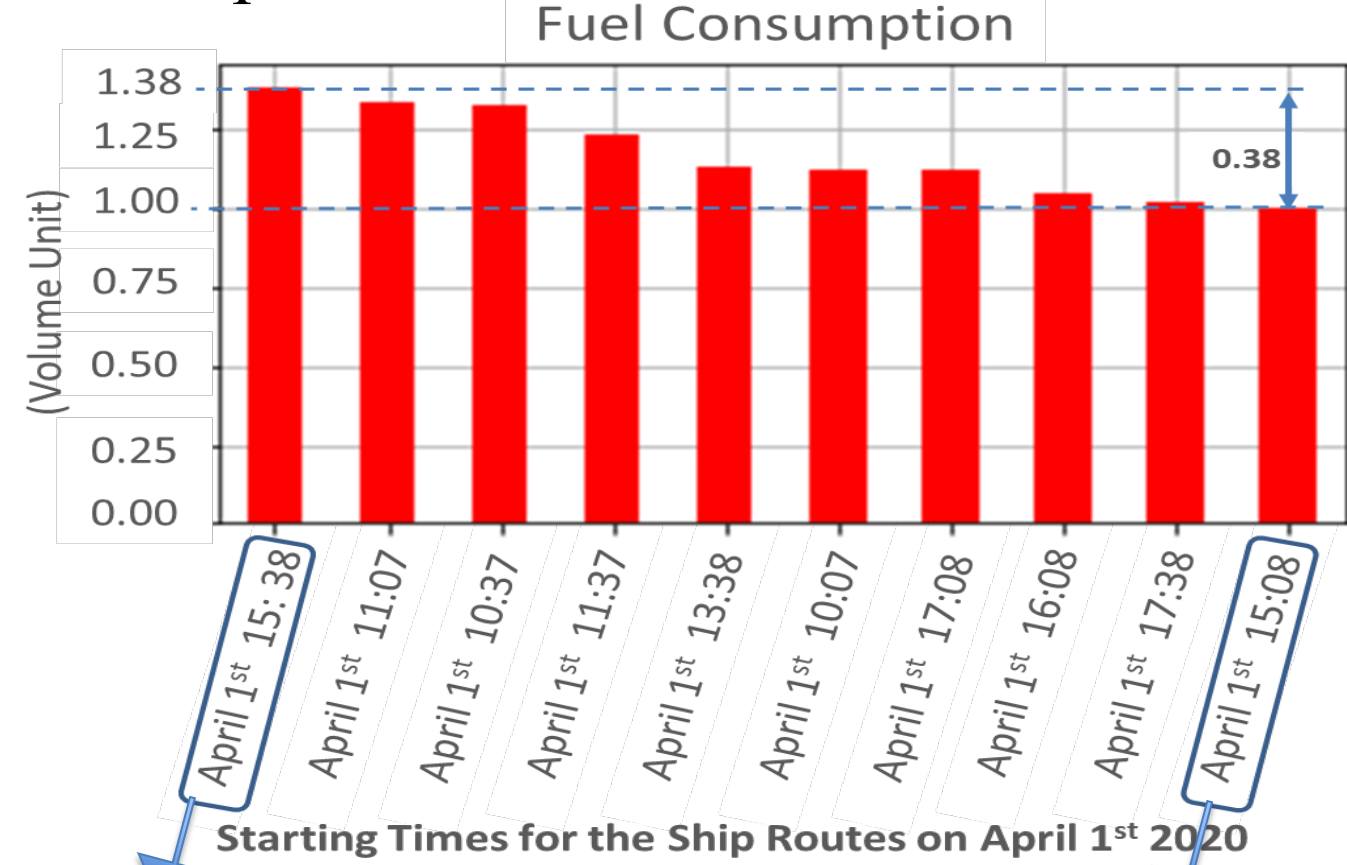
Validating Weather Data with the Standard Performance of Ships

Trilinear interpolation of weather data in time and space

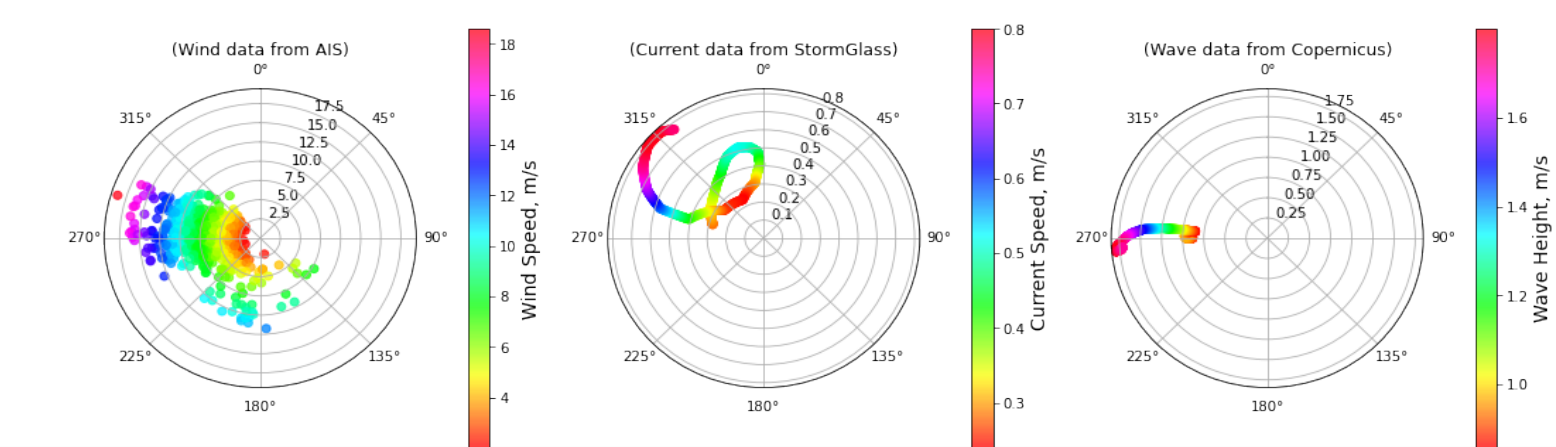


## Motivation

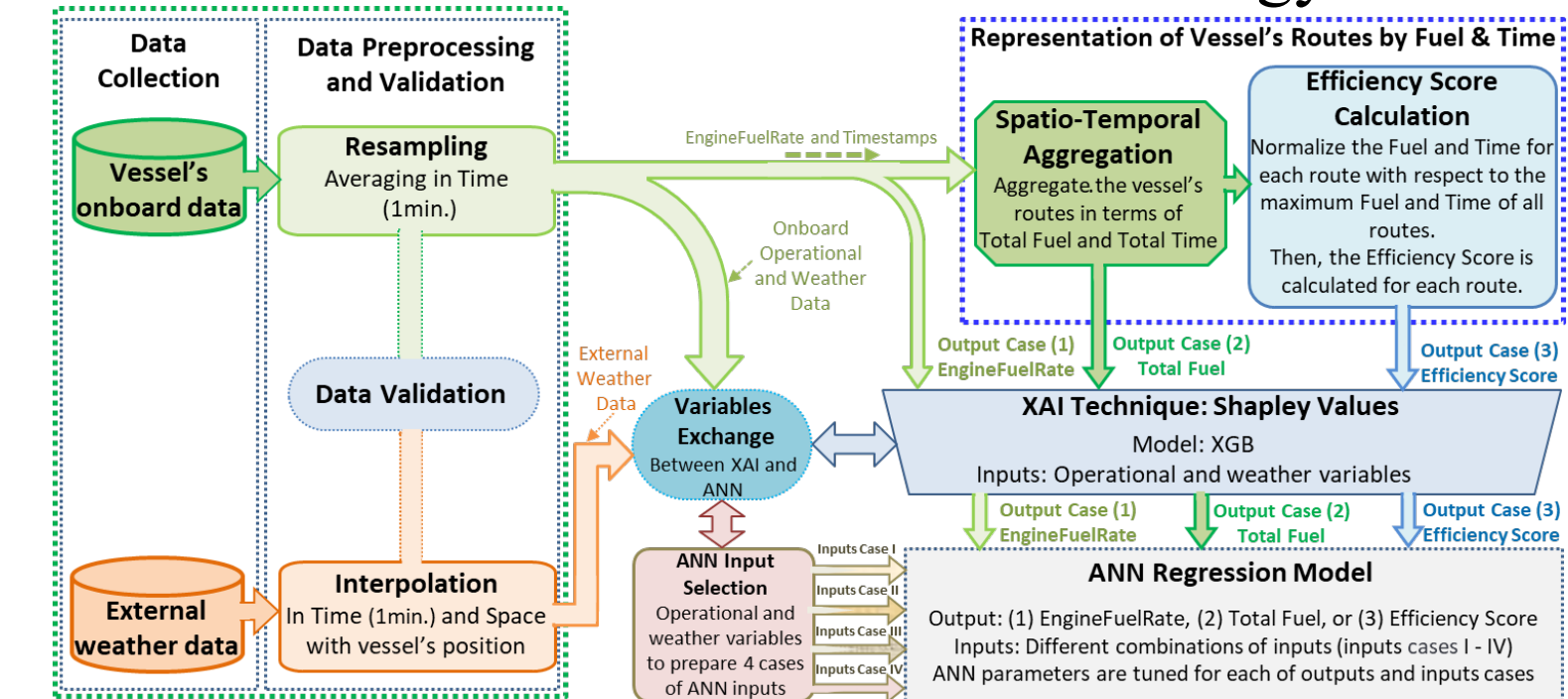
What are the critical factors influencing the vessel's fuel consumption in SSS?



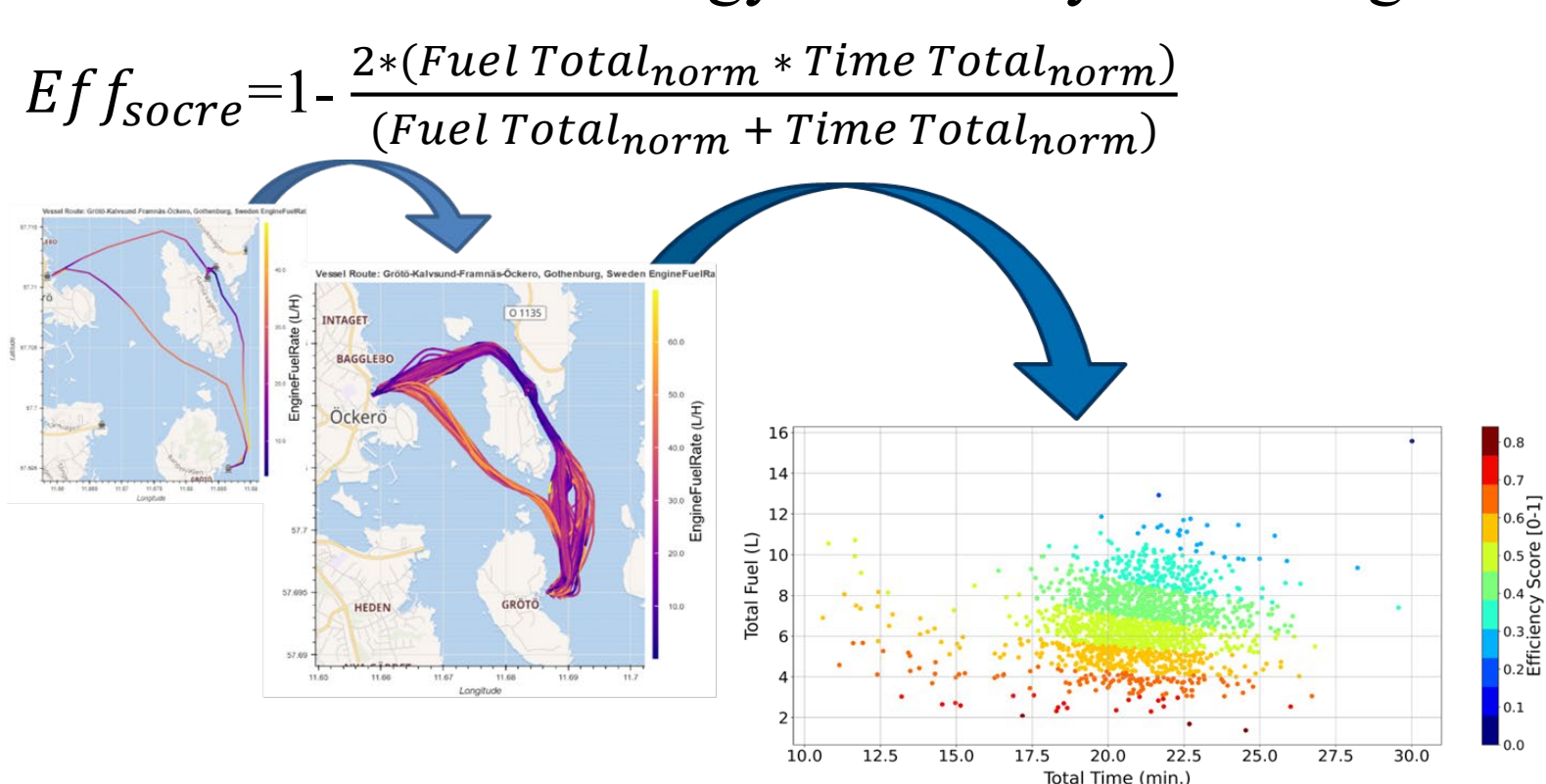
Wind, Current, and Wave, 1min-Avg., April 1<sup>st</sup> 2020



## The Workflow of the Methodology

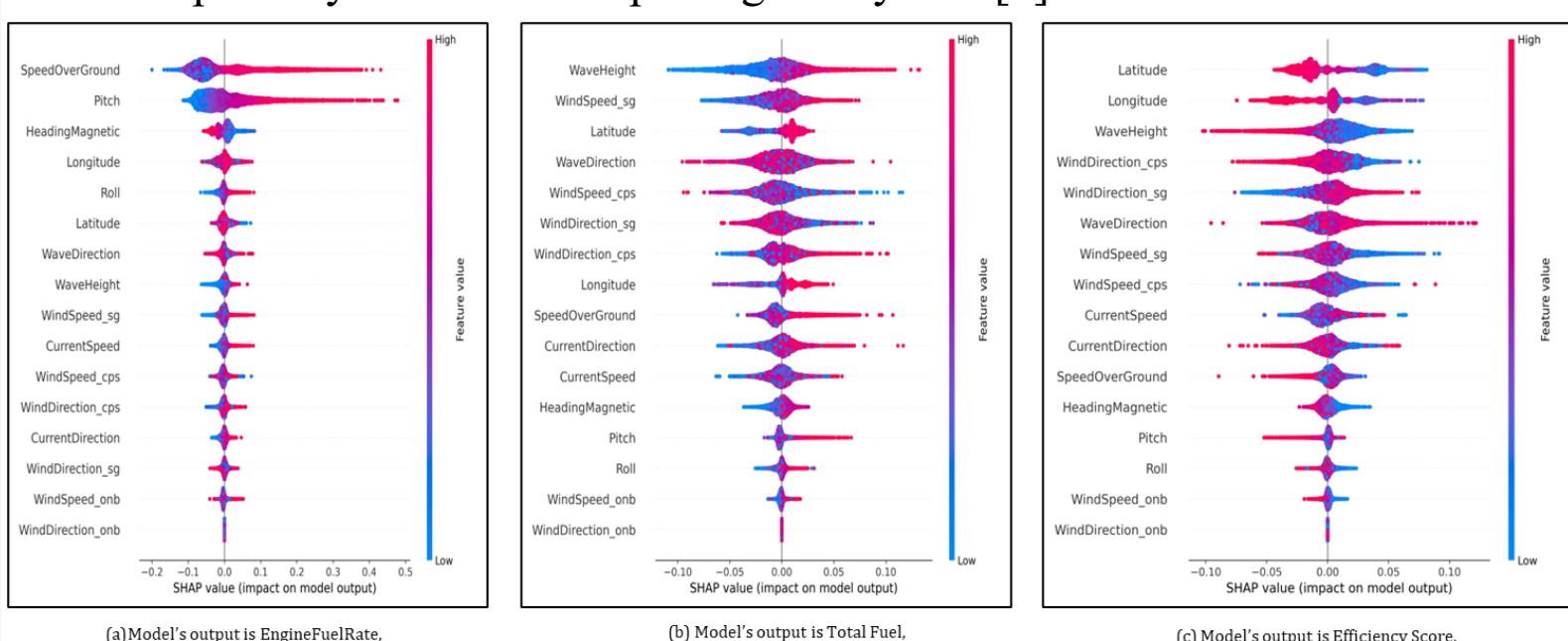


## Vessel's Energy Efficiency Modeling



## Applying XAI

Shapley additive explanations (SHAP) is an Explainable AI (XAI) technique, which is publicly available as a package in Python [4].



Beeswarm plots of SHAP values for XGBoost regression model with different outputs, (a) EngineFuelRate, (b) Total Fuel and (c) Efficiency Score.

## Results

Results of the estimation model (ANN) with different cases for inputs and outputs

Inputs Description		Inputs of ANN	
Inputs Case	Inputs	No.# of Inputs	Inputs of ANN
I	Navigation and Weather (Weather=wind speed and direction from onboard data)	6	[latitude, longitude, speedOverGround, headingMagnetic, windSpeed_onboard, windDirection_onboard]
II	Navigation and Weather (wind, wave, current, all from external sources)	12	[latitude, longitude, speedOverGround, headingMagnetic, waveheight, wavedirect, windSpeed_cds, windSpeed_sg, windDirection_cds, windDirection_sg, currentSpeed, currentDirection]
III	Navigation and Weather (wind onboard, wave & current from external sources)	10	[latitude, longitude, speedOverGround, headingMagnetic, windSpeed_onboard, windDirection_onboard, waveheight, wavedirect, currentSpeed, currentDirection]
IV	Navigation and Weather (wind, wave, current) (onboard & external sources)	14	[latitude, longitude, speedOverGround, headingMagnetic, windSpeed_onboard, windDirection_onboard, windSpeed_cds, windSpeed_sg, windDirection_cds, windDirection_sg, waveheight, wavedirect, currentSpeed, currentDirection]

(a) ANN Regression, where the output is **EngineFuelRate**

Inputs Case	Inputs	No.# ANN Inputs	ANN Layers #	ANN Neurons #	RMSE	R2	MAE
I	Navigation and Weather (Weather=wind speed and direction from onboard data)	6	10	100	0.0852	0.7153	0.0631
II	Navigation and Weather (wind, wave, current, all from external sources)	12	4	100	0.0730	0.7909	0.0544
III	Navigation and Weather (wind onboard, wave & current from external sources)	10	5	100	0.0714	0.8001	0.0531
IV	Navigation and Weather (wind, wave, current) (onboard & external sources)	14	4	100	<b>0.0698</b>	<b>0.8088</b>	<b>0.0516</b>

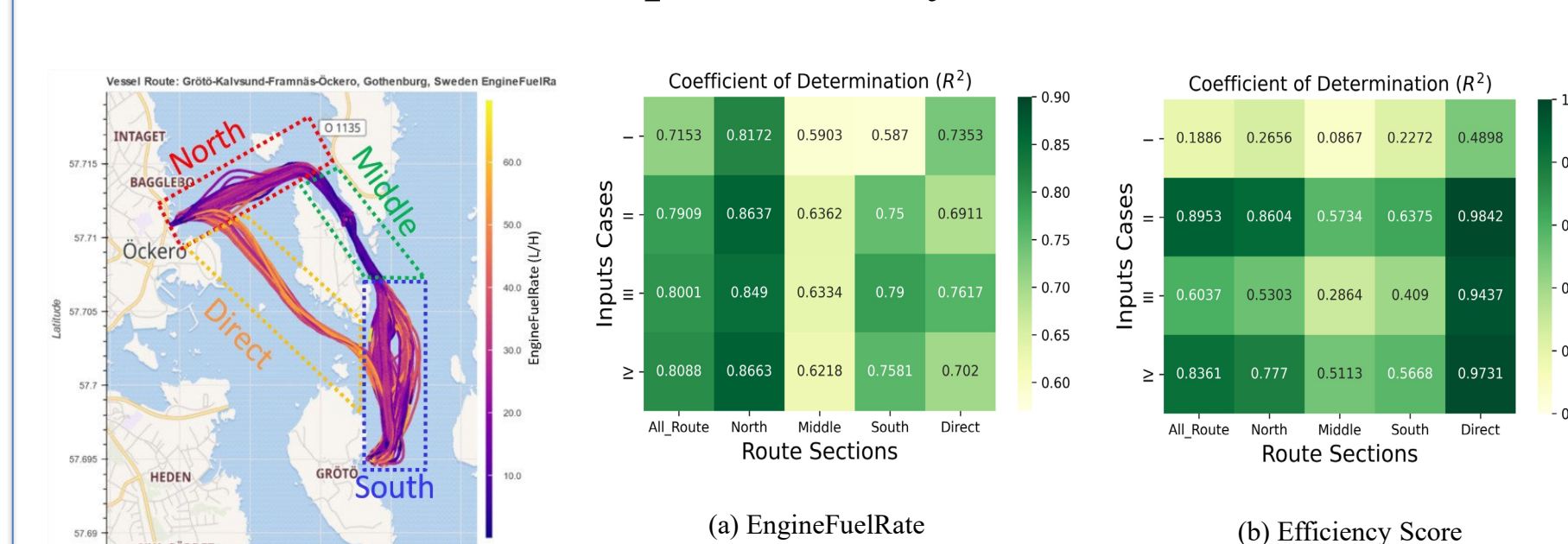
(b) ANN Regression, where the output is **Total Fuel**

Inputs Case	Inputs	No.# ANN Inputs	ANN Layers #	ANN Neurons #	RMSE	R2	MAE
I	Navigation and Weather (Weather=wind speed and direction from onboard data)	6	4	100	0.0980	0.2074	0.0776
II	Navigation and Weather (wind, wave, current, all from external sources)	12	5	100	<b>0.0317</b>	<b>0.9170</b>	<b>0.0221</b>
III	Navigation and Weather (wind onboard, wave & current from external sources)	10	5	100	0.0562	0.7398	0.0409
IV	Navigation and Weather (wind, wave, current) (onboard & external sources)	14	5	100	0.0351	0.8986	0.0249

(c) ANN Regression, where the output is **Efficiency Score**

Inputs Case	Inputs	No.# ANN Inputs	ANN Layers #	ANN Neurons #	RMSE	R2	MAE
I	Navigation and Weather (Weather=wind speed and direction from onboard data)	6	3	50	0.0807	0.1886	0.0634
II	Navigation and Weather (wind, wave, current, all from external sources)	12	5	100	<b>0.0290</b>	<b>0.8953</b>	<b>0.0204</b>
III	Navigation and Weather (wind onboard, wave & current from external sources)	10	4	100	0.0564	0.6037	0.0431
IV	Navigation and Weather (wind, wave, current) (onboard & external sources)	14	5	100	0.0363	0.8361	0.0267

## Spatial Analysis



The vessel routes are mapped by latitude and longitude, and distributed in different sections of geographical directions

## Conclusion

- By using a practical real-world example of a small passenger vessel, this study showcases how XAI with ML techniques can facilitate decision-making.
- In this case, we analyze the process of developing a fuel estimation module, which is a crucial component of the vessel's energy efficiency decision support tool.
- The outcomes presented in this study have the potential to enhance operation and energy management in short-sea shipping.
- Based on the discussed results, it is evident that the proposed approach of aggregating data and estimating the Efficiency Score, instead of directly working with the EngineFuelRate onboard signal, is more effective in facilitating decision making.
- The resulting model is based on a more comprehensive understanding of the critical factors that impact fuel consumption, both temporally and spatially, resulting in more dependable counterfactual predictions.
- Moreover, the quantitative evaluation indicates that estimating the Efficiency Score produces more precise and less biased outcomes than estimating the measured EngineFuelRate.
- Moving forward**, the developed model will be integrated with the vessel's energy optimization framework to provide decision support to captains on suitable trajectories and speed profiles based on current and forecasted weather conditions, thereby enhancing energy efficiency.
- Real-world implementation and the evaluation of its value for short-sea shipping are planned in the near future

Related Links:

[1] CetaSol AB <https://cetasol.com>

Weather Data:

[2] <https://marine.copernicus.eu/>

[3] <https://stormglass.io/>

[4] Shap package. [Online]. Available: <https://github.com/slundberg/shap>

QR to link of the paper



**https link of the paper:**

[Data-Driven Explainable Artificial Intelligence for Energy Efficiency in Short-Sea Shipping | SpringerLink](https://www.sciencedirect.com/journal/data-driven-explainable-artificial-intelligence-for-energy-efficiency-in-short-sea-shipping)



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