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THE SMART ARCHIPELAGO: AN AI FRAMEWORK FOR ENERGY RESILIENCE IN EASTERN INDONESIA

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Abstract. *As the world's largest archipelagic country, Indonesia relies on maritime logistics for energy distribution, particularly in the eastern region, which is vulnerable to extreme weather. This study validates the feasibility of The Smart Archipelago framework, an artificial intelligence (AI)-based decision support system designed to enhance the resilience of energy logistics. The case study focuses on a disruption event in the Ambon-Sorong shipping route in May 2023, analyzing three main modules: integration of oceanographic, meteorological, and operational data; predictive analytics through the comparison of four machine learning models (Logistic Regression, SVM, Random Forest, LightGBM); and a prescriptive module based on economic feasibility analysis. Results show that the tuned SVM achieved the best performance on the test set (F1-score 0.63), while tuned Logistic Regression demonstrated the highest stability in cross-validation. The gross cost-benefit ratio reached 429% for a single idealized avoidance scenario; however, after adjusting for prediction uncertainty based on the model's precision (0.62), the model-adjusted ROI is approximately 291%, which remains economically favorable. Sensitivity analysis across conservative to optimistic operational assumptions confirmed the robustness of this economic justification. These results are supported by a heuristic recommendation system based on key variables such as wave height and current speed. These findings confirm the potential of The Smart Archipelago to be implemented on multi-year historical data as a step toward predictive and adaptive maritime logistics systems.*
Keywords: *disruption prediction, energy resilience, maritime logistics, machine learning, ROI.*

INTRODUCTION

As the world's largest archipelagic country, Indonesia relies on maritime logistics to ensure energy distribution reaches remote regions. This challenge is even more complex in the eastern areas, which are dominated by underdeveloped, frontier, and outermost (3T) regions, where sea routes serve as the backbone of energy supply but port infrastructure, monitoring systems, and logistics resilience remain limited.

Data from Statistics Indonesia show that Yos Sudarso Port in Ambon handled more than 20 thousand tons of cargo and 238 vessel visits in just one month (June 2023). However, the vulnerability of this region to extreme weather was evident in mid-May 2023, when Ambon Port Authority (KSOP Ambon) suspended all voyages in the Banda and Seram Seas due to waves reaching up to 4 meters (Kompas.id, 2023) and extreme rainfall (Badan Meteorologi, Klimatologi, dan Geofisika, 2023), potentially causing significant operational losses.

Pertamina International Shipping (PIS) has begun digitalization efforts through vessel performance monitoring and the use of low-emission fuels, but these systems remain reactive without a risk-based decision support system capable of proactively predicting and responding to disruptions. Artificial intelligence (AI) using machine learning approaches has been proven to enhance logistics resilience in various global maritime sectors (Munim et al., 2020). Addressing this gap, this study proposes The Smart Archipelago framework, a three-module system consisting of multi-source data integration, predictive analytics, and a prescriptive module. These specific algorithms were selected because they represent a necessary progression from highly interpretable baseline models to advanced ensemble methods, which have recently been proven effective in maritime risk and operational delay forecasting (Balas & Balas, 2025; Maternová et al., 2023; Muhajirin et al., 2025; Zhang et al., 2025; Zhu et al., 2023). Supported by hyperparameter optimization, the output then feeds into a prescriptive module that generates operational recommendations based on key variable thresholds such as wave height and current speed, with the potential to evolve into risk probability-based recommendations.

This approach is validated through an empirical case study of the Ambon-Sorong shipping route disruption in May 2023 as a proof of concept to assess the technical and economic feasibility of the framework.

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The validation results are then projected onto large dataset scenarios to measure scalability potential and readiness for full implementation. This research is expected not only to provide strategic recommendations for PIS but also to contribute to strengthening national energy resilience policies through the application of maritime logistics digitalization that is contextual and adaptive to the geographical conditions of Eastern Indonesia.

METHODOLOGY

This research employs an empirical case study approach on the Ambon-Sorong shipping route to validate The Smart Archipelago framework as an AI-based decision support system for logistics. The empirical dataset covers 31 days (May 2023) obtained from credible sources: oceanographic data from Copernicus Marine Environment Monitoring Service (CMEMS) including wave height and ocean currents, meteorological data from the Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG) including rainfall and wind speed, port operational data from PT Pelabuhan Indonesia and Statistics Indonesia, as well as economic/logistics data from fuel price reports and maritime industry demurrage tariffs.

The analysis follows the three main modules of the framework. First, the Data Integration Module, which validates disruption events through the combination of oceanographic, meteorological, and port operational data. Second, the Predictive Analytics Module, which compares four classification models: Logistic Regression, Support Vector Machine (SVM), Random Forest, and Light Gradient Boosting Machine (LightGBM), with hyperparameter tuning using GridSearchCV, evaluation based on F1-score, and 5-fold cross-validation.

These four models were selected to represent diverse paradigms in the machine learning that proven effective in recent maritime risk assessments (Zhang et al., 2025). Specifically, the linear approach of Logistic Regression provides a highly interpretable baseline for identifying maritime risk factors (Maternová et al., 2023; Muhajirin et al., 2025). The margin-based SVM is included for its robust precision in handling non-linear boundaries related to vessel schedule disruptions (Muhajirin et al., 2025). The tree-based ensemble, Random Forest, is proven to effectively capture complex interactions in dynamic environmental data without overfitting (Zhu et al., 2023). Finally, the gradient boosting framework of LightGBM was selected for its high computational efficiency and accuracy in complex hydrodynamic and marine risk predictions (Balas & Balas, 2025). This strategic selection ensures the evaluation balances interpretability, accuracy, and generalization capability under various data conditions. To test scalability potential, a synthetic dataset distribution and realistic variation of the empirical data were used. Third, the Prescriptive Module calculates an economic feasibility by comparing reactive and proactive scenarios, and develops a heuristic recommendation system based on key variables from predictive model.

Energy Supply Chain Resilience

Energy supply chain resilience refers to the system's ability to respond to and recover from technical or environmental disruptions (Hossain et al., 2023). In Indonesia, especially in the 3T regions, reliance on maritime transportation makes extreme weather and limited infrastructure major risk (Badan Pusat Statistik, 2023). Fuel distribution disruptions can trigger domino effects on industrial, transportation, and public service sectors (International Energy Agency [IEA], 2022). This condition highlights the need for a predictive approach such as The Smart Archipelago.

Application of Artificial Intelligence (AI) in Maritime Logistics

The application of artificial intelligence (AI) in the maritime sector includes ocean weather prediction, route optimization, and predictive maintenance (Munim et al., 2020). Machine learning models can process oceanographic and meteorological data to predict risks. Kim et al. (2023), through the Explainable AI (XAI) method, demonstrated that relative wind speed is the second most important factor after vessel speed in influencing shaft power. These findings reinforce the relevance of using oceanographic and meteorological

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variables in this framework.

Pertamina International Shipping (PIS) Logistics Strategy and Innovation Gaps

PT Pertamina International Shipping (PIS) has carried out digitalization initiatives, including vessel performance monitoring and the use of low-emission fuels (PT Pertamina International Shipping, 2024). However, the current system remains descriptive and has yet to utilize risk-based predictive analytics. Maritime risk management literature emphasizes the need to transition from reactive to proactive strategies through the integration of real-time data and predictive models (Hossain et al., 2023). This approach is also supported by Munim et al. (2020), who highlighted the role of predictive models in improving the efficiency and resilience of maritime logistics. This gap opens opportunities for developing The Smart Archipelago as a system that monitors, predicts, and provides prescriptive recommendations.

Comparative Studies of International AI-Based Maritime Logistics Implementation The Maritime and Port Authority of Singapore (MPA, 2024) integrates ocean weather and current predictions into vessel traffic management, reducing voyage delays. In Norway, the autonomous ship Yara Birkeland utilizes AI and oceanographic data for safe and efficient navigation (DNV, 2021). Implementation in Indonesia needs to be adapted to the local context, which is why The Smart Archipelago is designed to be modular and context-specific for 3T regions.

RESULTS AND DISCUSSION

This section presents the research findings obtained from empirical case study of the maritime disruption event in May 2023. All results are presented objectively and follow the architecture of the three modules of The Smart Archipelago, namely data integration, predictive analytics, and the prescriptive module. The results are provided to establish the quantitative basis for further interpretation in the Discussion section.

Results

Empirical Validation of Disruption Event

The multi-source data analysis successfully validated the occurrence of an extreme weather event that coincided with official voyage delay reports in May 2023. Three layers of evidence reinforce this finding:

- Oceanographic Anomalies: Data from the Copernicus Marine Service (CMEMS) showed a significant surge in wave height reaching up to 4.0 meters on 12-13 May (Figure 1). Ocean current map visualizations (Figure 2) indicated a shift from relatively stable patterns on 10 May to chaotic, high-velocity currents concentrated in specific bathymetric choke points on 12 May, particularly in the Seram-Misool strait and northern Buru Island.
- Meteorological Anomalies: Data from BMKG Ambon confirmed extreme rainfall of 133 mm on 12 May and an increase in wind speed up to 5 knots, significantly exceeding the monthly daily average.
- Operational Confirmation: National media reports (Kompas.id, 2023) confirmed that the Ambon Port Authority suspended voyages in the Banda and Seram Seas following severe weather warnings from BMKG.

From a geoscience perspective, the extreme oceanographic anomalies recorded by CMEMS are directly influenced by the local geomorphology and complex bathymetry of the Maluku region. The Banda and Seram Seas act as a central region of water mass circulation that receives massive flows from the Pacific Ocean (Siwasiwan et al., 2025). Spatial analysis of Figure 2 reveals that as these flows are squeezed between large island clusters, peak current velocities, indicated by the deep red contours, become highly concentrated in narrow maritime corridors such as the coastal waters near the Onin Peninsula and the Seram-Misool strait. When extreme monsoon winds sweep through these areas (Nanlohy et al., 2021), they interact with the steep underwater topography to create severe turbulent mixing and water column instability (Purba et al., 2025). This topographic steering and funneling effect drastically amplifies kinetic energy, resulting in the chaotic eddies and the extreme 4.0-meter wave spikes along the Ambon-Sorong route. Consequently, this physical evidence provides a robust geoscientific justification for the severe maritime disruption event.

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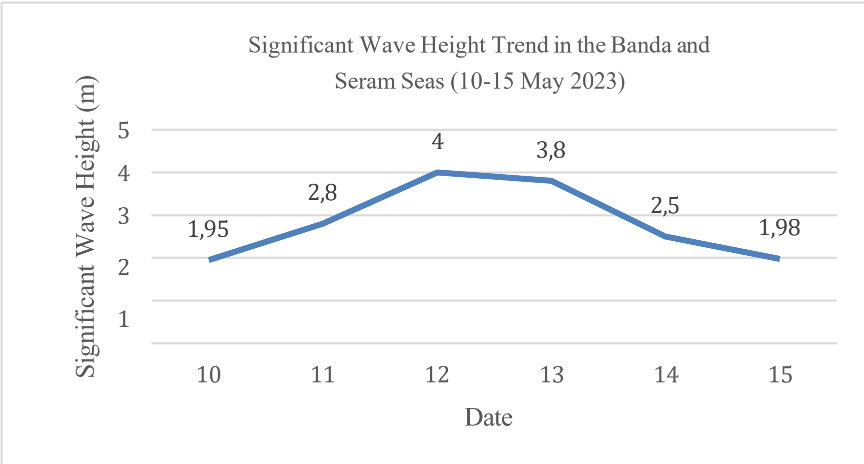

Figure 1. Trend of significant wave height in the Banda and Seram Seas, 10-15 May 2023 (Source: Copernicus Marine Environment Monitoring Service, processed by the author)

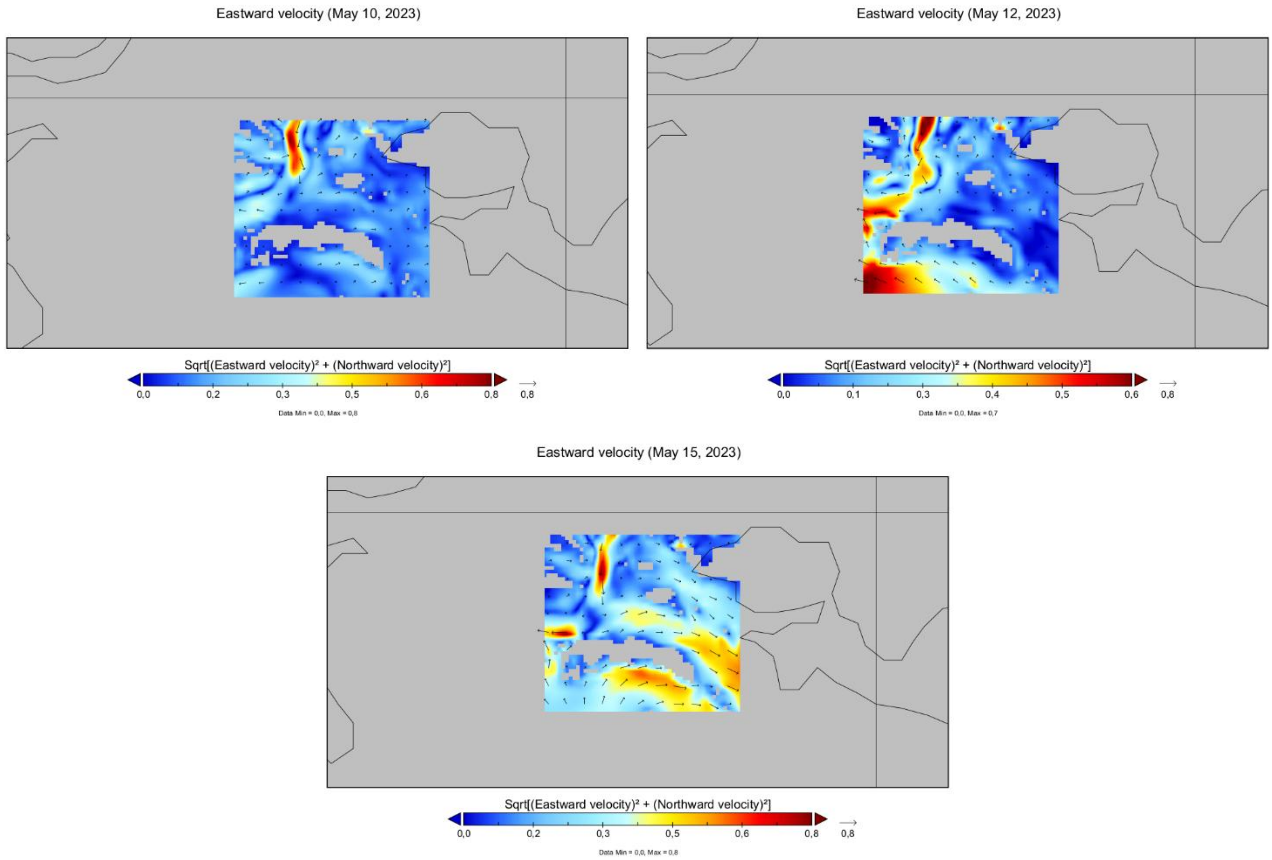

Figure 2. Visualization of ocean current maps in the Seram and Banda Seas; (a) relatively stable currents on 10 May 2023, (b) chaotic and extreme currents concentrating in bathymetric choke points on 12 May 2023, and (c) returning to normal conditions on 15 May 2023 (Source: Copernicus Marine Environment Monitoring Service, processed by the author)

Predictive Modeling Results

Four classification algorithms were tested to predict voyage disruption risk: Logistic Regression, Support Vector Machine (SVM), Random Forest, and LightGBM. Each model was optimized using GridSearchCV

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(cv=5) with F1-score as the main metric. Evaluation was conducted in two stages: (a) cross-validation to measure model stability, and (b) testing on the test set to measure prediction performance on unseen data.

Cross-Validation Result (CV=5)

Table 1. Cross-Validation (CV=5) Result for Selected Machine Learning Models

Model	Mean F1-score	Std Dev
Logistic Regression	0.4645	0.0930
SVM	0.4168	0.1354
Random Forest	0.4171	0.1028
LightGBM	0.4063	0.0712

Cross-validation result show that tuned Logistic Regression has the highest average F1-score and the smallest deviation, indicating more consistent performance compared to other models.

Test Set Results

Table 2. Performance Comparison of Machine Learning Models on Test Data After Tuning

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	0.5500	0.6410	0.4464	0.5263	0.6080
SVM	0.5800	0.6207	0.6429	0.6316	N/A
Random Forest	0.5400	0.6000	0.5357	0.5660	0.5552
LightGBM	0.5400	0.6087	0.5000	0.5490	0.5357

On the test data, tuned SVM recorded the highest F1-score (0.6316), indicating better prediction performance on new data. Nevertheless, tuned Logistic Regression remains the most stable model across cross-validation folds, making it relevant for feature importance interpretation.

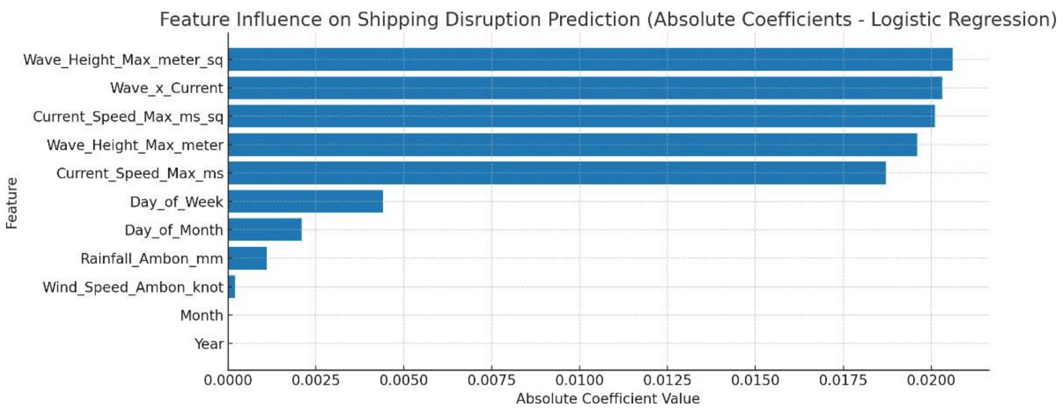

Figure 3. Visualization of feature importance for Logistic Regression model on May 2023 empirical dataset

Economic Feasibility Analysis (ROI)

The economic feasibility calculation of this framework was conducted by comparing reactive and proactive scenarios for a standard 30,000 DWT tanker vessel on the Ambon-Sorong route

Gross Cost-Benefit Estimation

In an idealized scenario where a disruption is perfectly predicted and successfully avoided, the economic parameters are as follows: assuming a 48-hour delay at a demurrage rate of USD 6,350 per day. This rate serves as a representative baseline for MR class tankers (30,000 to 50,000 DWT) in the regional spot market to illustrate the economic framework and should be adjusted to actual contractual rates in implementation. Under this assumption, the avoided potential loss amounts to USD 12,700. The additional proactive cost for a

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route diversion 10% longer, calculated using the average May 2023 VLSFO price of USD 571 per metric ton (Ship & Bunker, 2023), is estimated at approximately USD 2,400. This yields a gross cost-benefit ratio of 429% for a single perfectly predicted avoidance event.

Model-Adjusted ROI

However, this idealized figure assumes perfect prediction. To account for prediction uncertainty, an expected value framework and cost-sensitive evaluation strategy (Vanderschueren et al., 2022) were applied. This approach calculates the net economic benefit per decision by weighting outcomes with the model's confusion matrix. Given the best-performing model precision of 0.6207 (tuned SVM), approximately 38% of triggered alarms would be false positives, resulting in unnecessary diversion costs:

$$
\begin{aligned}
\mathrm{E[Net\ Benefit\ per\ alarm]} &= (\mathrm{Precision}\ \times \mathrm{Avoided\ Loss}) - ((1-\mathrm{Precision})\ \times \mathrm{Diversion\ Cost}) \\
&= (0.6207\ \times 12{,}700) - ((0.3793) \times 2{,}400) \\
&= 7{,}882.89 - 910.32 \\
&= \mathrm{USD}\ 6{,}973
\end{aligned}
$$

This yields a model-adjusted ROI of approximately 291 percent per alarm, which remains economically favorable but more accurately reflects the system's current predictive capability. Furthermore, with a recall of 0.6429, approximately 36% of actual disruption events would remain undetected, representing residual operational risk.

Sensitivity Analysis

To assess the robustness of the economic justification under varying operational conditions, a sensitivity analysis was conducted across three scenarios (Table 3).

Table 3. Sensitivity Analysis of Model-Adjusted ROI Under Varying Operational Scenarios

Scenario	Delay Duration (hours)	Demurrage Rate (USD/day)	Avoided Loss (USD)	Diversion Cost (USD)	Model-Adj. ROI (%)
Conservative	24	5,000	5,000	2,400	91%
Base Case	48	6,350	12,700	2,400	291%
Optimistic	72	7,500	22,500	2,400	544%

Note: Model-Adjusted ROI is calculated as $[(\mathrm{Precision}\ \times \mathrm{Avoided\ Loss}) - ((1-\mathrm{Precision})\ \times \mathrm{Diversion\ Cost}]\ /$ $\mathrm{Diversion\ Cost} \times 100\%$, following the expected value framework for classifier-based decisions (Vanderschueren et al., 2022). All scenarios use precision = 0.6207 from the tuned SVM model.

These estimates represent marginal operational benefits per avoidance decision and do not include system development, deployment, or maintenance cost. Furthermore, the results demonstrate that the framework maintains positive economic returns even under conservative assumptions (ROI ≈ 91%), confirming its viability across a range of plausible conditions.

Discussion

This section discusses the interpretation of the empirical results obtained, linking the findings from the case study to the three-module framework of The Smart Archipelago. The discussion focuses on validating the logic of the framework, examining the technical and economic implications of the modeling results, and projecting the system's performance and scalability.

Concept Validity and Framework Logic

The empirical findings from this case study strongly validate the three-module architecture of The Smart Archipelago:

- Data Integration Module: Triangulating oceanographic data (CMEMS), meteorological data (BMKG),

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and operational events (news reports) proved crucial in forming a complete and accountable risk picture. This approach is consistent with the findings of Munim et al. (2020), which emphasize the importance of multi-source integration in predicting maritime logistics disruptions and optimizing operational efficiency.

- Predictive Analytics Module: Testing four classification algorithms (Logistic Regression, SVM, Random Forest, LightGBM) demonstrated that machine learning can consistently identify oceanographic factors as the main predictors of voyage disruptions. Based on cross-validation evaluation (CV=5), tuned Logistic Regression achieved the highest performance stability (Mean F1-score = 0.4645, deviation 0.0930) and was therefore selected for feature importance interpretation.
  However, in the test set evaluation, tuned SVM recorded the highest F1-score (0.6316), indicating superior predictive performance on new data. This finding suggests that model selection can be tailored to operational priorities, for example, SVM for short-term prediction accuracy and Logistic Regression for transparent risk factor interpretation. The feature importance results from Logistic Regression confirmed that oceanographic variables such as Wave Height (squared), Wave × Current interaction, and Current Speed (squared) contributed the most to risk prediction, consistent with Kim et al. (2023), which found that oceanographic variables significantly influence vessel operational performance.
- Prescriptive Module: The gross cost-benefit ratio of 429% represents the idealized upper-bound estimate for a single perfectly predicted avoidance event. After adjusting for the model's prediction uncertainty (precision = 0.6207), the model-adjusted ROI is approximately 291% under base-case assumptions, which still provides strong economic justification for implementing the prescriptive module. Sensitivity analysis (Table 3) further demonstrates that the framework maintains positive returns even under conservative scenarios (ROI ≈ 91%), while also revealing that approximately 36% of actual disruptions remain undetected at the current recall level (0.6429), representing residual risk that future model improvements should address.
  In this study, the prescriptive module was implemented through a heuristic recommendation system that translates risk prediction outputs from the SVM model into three levels of operational recommendations:
  - High Risk – advised to delay the voyage, consider route diversion, and prepare for mitigation of logistics impacts.
  - Moderate Risk – continue the voyage with heightened alertness, ensuring vessel and crew readiness to face worsening sea conditions.
  - Low Risk – proceed as planned with routine monitoring of weather and sea conditions.

  Risk classification is based on a combination of threshold values for key features such as *Tinggi_Gelombang_Max_meter, Kecepatan_Arus_Max_ms*, and *Kecepatan_Angin_Ambon_knot*. These rules are designed to align with operational logic in the field, enabling rapid and data-driven mitigation decisions. The integration of this prescriptive module proves that The Smart Archipelago framework can not only predict risks but also provide actionable guidance that can be directly implemented in maritime logistics operations.

Limitations, Performance Projection, and Scalability Vision

Although the model trained on the 31-day empirical dataset serves as an effective proof of concept, its small size limits its generalizability for full-scale use. With approximately 31 data points split into training and test sets, the resulting test set contains a limited number of samples, which means the reported metrics (F1-score, precision, recall) carry inherent statistical uncertainty and can undermine model stability (Cheng et al., 2025). Additionally, the economic feasibility analysis represents marginal operational benefit per avoidance decision and does not account for system development, data infrastructure, or deployment costs. These challenges underscore the need for larger-scale historical data collection to build more reliable and statistically robust predictive models.

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This performance projection is consistent with the initial simulation conducted during the conceptual phase using a synthetic dataset (>500 data points) designed to represent annual operation variation. It is important to note that this synthetic dataset was not used as part of the empirical validation but as a conceptual simulation to test the scalability potential of the framework. In that simulation, ensemble models such as Random Forest demonstrated substantially higher prediction performance, suggesting that The Smart Archipelago framework has the potential to become increasingly effective as more real historical data is incorporated into training. However, the specific magnitude of performance improvement on real-world multi-year data remains to be empirically validated in future studies. Therefore, the strategic step recommended for Pertamina International Shipping (PIS) is to apply this framework to multi-year operational historical data (1-2 years) to build a production-ready predictive engine while integrating it into maritime logistics SOPs to sustainably enhance energy distribution resilience.

Alignment with Sustainable Development Goals (SDGs)

The Smart Archipelago framework not only addresses operational and economic challenges but also contributes to achieving several targets of the United Nations Sustainable Development Goals, particularly in the context of maritime energy logistics for 3T regions.

Table 4. Alignment of The Smart Archipelago framework with SDGs

SDG	Relevant Targets	Contribution of The Smart Archipelago
SDG 7 – Affordable and Clean Energy	7.1 Ensure universal access to affordable, reliable, and modern energy services	Improves energy supply chain resilience in remote and vulnerable areas by reducing distribution disruptions.
SDG – 9 Industry, Innovation, and Infrastructure	9.1 Develop quality, reliable, sustainable, and resilient infrastructure	Integrates AI- driven decision support to modernize maritime logistics infrastructure and enhance operational efficiency.
SDG 13 – Climate Action	13.1 Strengthen resilience and adaptive capacity to climate-related hazards	Provides predictive and prescriptive tools to mitigate operational risks caused by extreme weather, reducing emissions from unnecessary delays.

CONCLUSIONS AND SUGGESTION

Conclusion

This study demonstrates that The Smart Archipelago framework is effective in predicting and responding to energy logistics disruptions in 3T maritime regions, validated through an empirical case study on the Ambon-Sorong route (May 2023). The framework's three main modules, namely Data Integration, Predictive Analytics, and Prescriptive, were proven both technically and economically. The predictive module showed that tuned SVM achieved the best performance on the test data (F1-score 0.6316), while tuned Logistic Regression provided the most consistent results in cross-validation. Feature importance analysis confirmed that oceanographic factors, particularly wave height and current speed, are the main risk triggers. The prescriptive module demonstrated a gross cost-benefit ratio of 429% under idealized conditions; after adjusting for prediction uncertainty (precision = 0.62), the model-adjusted ROI is approximately 291%, with sensitivity analysis confirming economic viability across conservative to optimistic scenarios (91%-544%). These results are supported by a three-tier heuristic risk recommendation system.

These findings indicate that the framework has strong potential for broad implementation, with predictive performance expected to improve substantially when trained on multi-year historical data, though the specific magnitude of improvement requires future empirical validation. Furthermore, application of The Smart Archipelago aligns with the Sustainable Development Goals, particularly SDG 7 on affordable and Clean

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Energy, SDG 9 on Industry, Innovation, and Infrastructure, and SDG 13 on Climate Action. By enabling predictive and adaptive maritime energy logistics, this framework strengthens critical infrastructure resilience and supports climate adaptation strategies at both national and regional levels.

Suggestions

Practical Recommendations

1. PIS is advised to integrate The Smart Archipelago into maritime logistics SOPs, using 1-2 years of operational data as the basis for a production-ready predictive model.
2. Conduct a pilot project on strategic routes in the 3T regions to test the framework's performance directly and assess its economic impact on energy distribution efficiency.
3. Validate the recommendation system with operational experts to ensure its relevance and usability in the field.

Academic Recommendations

1. Expand the dataset by including navigation variables from AIS data to enrich model features and improve prediction accuracy.
2. Apply advanced model interpretation methods such as SHAP or LIME to enhance transparency and user trust in the system.
3. Explore combinations of ensemble models and deep learning to potentially improve predictive performance on large-scale maritime datasets.

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