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Towards Risk-Informed Evaluation of Baltic Sea Winter Navigability Using Machine Learning

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This paper addresses the critical challenges of winter navigation in the Baltic Sea, a region known for its complex and rapidly changing ice conditions. These challenges increase the risk of maritime accidents, operational delays, and safety hazards for various vessels. To mitigate these risks, the paper presents novel tool for navigability assessment through route planning. These are based on the Winter Navigation Risk Index (WiNRI), an innovative data-driven model that combines a rich dataset of 329 historical accident reports with expert insights and machine learning techniques. WiNRI assesses navigability by evaluating multiple factors, such as vessel type, ice conditions, and environmental parameters. Using a modified Dijkstra algorithm, the safe route predictions are generated and hazardous areas through dynamic risk maps highlighted. These visual tools enable real-time assessment and better decision-making for ship operators, icebreakers, and maritime authorities, ultimately enhancing maritime safety in the Baltic Sea

Keywords: ice routing, risk index, WiNRI, winter navigation, decision support systems, machine learning.

1. Introduction

There are various levels of assessing and mitigating risks associated with maritime traffic depending on the temporal and spatial scale of the assessment. *Strategic risk assessment*, uses long-term observations and historical data to identify persistent patterns of hazardous conditions and is typically expressed through aggregated indicators, such as accident frequencies or risk heatmaps, to support policy-making, infrastructure planning, and fleet-level decisions, Valdez Banda et al. (2015); Goerlandt et al. (2017).

Operational risk assessment is carried out for a specific operations performed in a narrow time and space window, reflecting current environmental conditions, traffic, and vessel characteristics. This supports real-time or near-real-time decisions, such as navigation warnings, traffic restrictions, or icebreaker assistance, Lensu and Goerlandt (2019); Liu et al. (2024).

Tactical risk assessment is integrated into voyage planning, for a specific route, accounting for the vessel's objectives, constraints, and evolving environmental conditions along the planned trajectory, Życzkowski et al. (2025). Tactical decision-making therefore requires a representation of risk that can be evaluated along alternative routes and directly integrated into the route finding process, which is the optimisation of ship routes with respect to dynamically changing environmental conditions and ship's response to those.

Previous studies on weather routing, including applications in ice-covered waters, have primarily focused on optimising travel time, fuel consumption, emissions, or route availability, rarely accounting for safety or risk associated with the conditions along the anticipated routes. Conventionally, these are considered indirectly, through operational constraints, ice class requirements, or environmental thresholds, Li et al. (2021); Zvyagina and Zvyagin (2022). For an extensive scientific literature review on routing methods suitable for ice-covered waters, see for example Lehtola et al. (2019). Additionally, beyond these theoretical solutions, there exist two well-established industry standards that support the decision-making process on the polar waters: *the Polar Operational Limit Assessment Risk Indexing System* POLARIS, International Maritime Organization (2016) and *the Arctic Ice Regime Shipping System* AIRSS, Transport Canada (2018). In contrast, the proposed Winter Navigation Risk Index (WiNRI) provides a continuous risk estimate in the range from 0 to 1, which can be directly integrated into routing algorithms as a component of the cost function, while accounting for a broader set of explanatory variables, including environmental conditions such as wind as well as detailed ship characteristics.

The literature lacks routing solutions suitable for ice-covered but non-polar waters, such as the Baltic Seas, in which an empirically derived, ice-related navigational risk index is explicitly incorporated into the routing process as a component of the cost function, enabling direct risk minimisation at the scale of an individual voyage.

Therefore, this paper introduces a *deterministic ice routing algorithm* employing Winter Navigation Risk Index (WiNRI), which is explicitly included in the cost function of the route optimisation process. WiNRI is based on a Baltic Sea database integrating accident and near-miss records with detailed environmental factors and ship characteristics, covering a period of 25 years, Fintraffic (2025); Lensu and Goerlandt (2019).

2. Methodology

The methodological framework adopted in this study builds upon the deterministic routing approach previously developed by the author and described in detail in Życzkowski et al. (2025).

The present study extends this framework by integrating the Winter Navigation Risk Index (WiNRI) into the routing process.

2.1. *Discrete Sailing Environment and Navigability Bitmap*

The proposed routing framework is built upon the **Discrete Sailing Environment (DSE)**, a mathematical representation of the navigational area discretized into a regular geographical grid. The navigational domain is defined as

$$\begin{aligned} Area(\varphi_1, \varphi_n; \lambda_1, \lambda_m) = \\ \{(\varphi, \lambda) \mid \varphi_1 \leq \varphi \leq \varphi_n, \quad \lambda_1 \leq \lambda \leq \lambda_m\}. \end{aligned} \tag{1}$$

The domain is discretized into grid points $P_{i,j} = (\varphi_i, \lambda_j)$, where $i = 1, \dots, n$ and $j = 1, \dots, m$ with constant spacing between the parallels and meridians. The grid is represented as a bitmap of navigability, where each cell is classified as navigable (sea) or non-navigable (land and excluded areas). Let $\mathcal{N}(P_{i,j}) \in \{0, 1\}$ denote the navigability indicator: $\mathcal{N}(P_{i,j}) = 1$ for navigable points and $\mathcal{N}(P_{i,j}) = 0$ otherwise. In practice, land is identified directly from environmental rasters (e.g., missing values in ice datasets) and additionally protected by a safety buffer (in grid steps) to avoid routes that pass too close to the coastline.

2.2. *Movement Model and Feasible Transitions*

Ship movements are restricted to a predefined neighbourhood, following a discrete movement model. Each vertex $P_{i,j}$ can transition to a set of neighbouring points $P_{i+p,j+q}$, where the pair (p, q) belongs to a predefined transition set $\mathcal{T}$. In the most general form (used in our earlier routing studies), up to 56 transitions are possible:

$$\begin{aligned} (p, q) \in \mathcal{T} = \Big\{ & (\pm1, 0), (0, \pm1), (\pm1, \pm1), (\pm2, \pm1), \\ & (\pm1, \pm2), (\pm2, \pm3), (\pm3, \pm1), (\pm3, \pm2), (\pm1, \pm3), \\ & (\pm4, \pm1), (\pm1, \pm4), (\pm3, \pm4), (\pm4, \pm3), \\ & (\pm1, \pm8), (\pm8, \pm1) \Big\}. \end{aligned} \tag{2}$$

A directed transition from $P_{i,j}$ to $P_{i+p,j+q}$ is permitted only if: A) both endpoints are navigable: $\mathcal{N}(P_{i,j}) = 1$ and $\mathcal{N}(P_{i+p,j+q}) = 1$ and B) the straight-line segment connecting the points does not intersect any non-navigable cell. The latter condition prevents "shortcut" through the land even if both endpoints are at sea. A practical implementation uses a discrete line-of-sight test and rejects transitions intersecting land or the buffered coastline.

2.3. *Graph Construction*

The DSE with feasible transitions defines a following directed graph:

$$G = (V, E), \tag{3}$$

where: V is the set of vertices representing all navigable grid points $P_{i,j}$ and E is the set of directed edges $e = (u, v)$ between permissible neighbouring points. Each edge is assigned a geometric length $d(e)$ in nautical miles, computed from the grid resolution and local latitude. Given a ship speed V_{ship} in knots, the traversal time of an edge is estimated as follows, yielding $\Delta t(e)$ in minutes:

$$\Delta t(e) = \frac{d(e)}{V_{\text{ship}}} \cdot 60, \tag{4}$$

For each feasible edge $e = (u, v)$ of the routing graph and for each environmental time slot s $\mathrm{WiNRI}_s(e)$ is calculated using Eq. (8). These values are then embedded into the routing objective function (6) as a time-weighted penalty, so that the shortest-path search minimizes a combined measure of travel time and accumulated risk index.

2.4. *Time-Weighted Risk Objective Function*

The ship route is considered an ordered sequence of edges $P = \{e_0, e_1, \ldots, e_{K-1}\}$ connecting successive grid nodes. The cumulative voyage time prior to entering edge e_k is:

$$t_k = \sum_{i=0}^{k-1} \Delta t(e_i) \tag{5}$$

To jointly penalize travel time and exposure to high risk conditions, the route cost function is defined as follows:

$$J(P) = \sum_{k=0}^{K-1} \Delta t(e_k)\Big(1 + \mathrm{WiNRI}_{s(t_k)}(e_k)\Big), \tag{6}$$

where $s(t_k)$ maps the current voyage time to the corresponding environmental time slot. For $\mathrm{WiNRI} = 0$, the cost function (6) reduces to minimum-time routing, while larger WiNRI values progressively penalize paths that remain longer in high-risk regions.

2.5. *Shortest Path Search on the WiNRI–Weighted Graph*

Such a defined cost function is then optimized to find a path $P^\star$ between the start node A and destination node B:

$$P^\star = \arg\min_{P:A\to B} J(P). \tag{7}$$

Since the edges' weights depend on the time slot determined by the accumulated travel time, the problem becomes a time-dependent shortest path problem. We solve it using a modified Dijkstra algorithm that propagates both cumulative cost and elapsed time, updating the active time slot during relaxation, as presented below.

Algorithm 1: Time–Dependent Dijkstra with ML–Predicted WiNRI Edge Weights

Input: Graph $G = (V, E)$; start node A; destination node B; edge lengths $d(e)$; ship speed V_{ship}; WiNRI values $\mathrm{WiNRI}_s(e)$; slot mapping $s(t)$.
Output: Optimal path $P^\star$ minimizing (6).
Initialize $\mathrm{dist}[v] \leftarrow +\infty$ and $\mathrm{time}[v] \leftarrow +\infty$ for all v;
$\mathrm{dist}[A] \leftarrow 0$, $\mathrm{time}[A] \leftarrow 0$;
Push $(0, 0, A)$ into priority queue Q;
while Q *not empty* **do**
    Pop (c, t, u) with minimal c;
    if $u = B$ **then**
        break
    foreach $e = (u, v) \in E$ **do**
        $\Delta t \leftarrow \dfrac{d(e)}{V_{\text{ship}}} \cdot 60$;
        $t' \leftarrow t + \Delta t$;
        $s \leftarrow s(t)$;
        $c' \leftarrow c + \Delta t \cdot \Big(1 + \mathrm{WiNRI}_s(e)\Big)$;
        if $c' < \mathrm{dist}[v]$ **then**
            $\mathrm{dist}[v] \leftarrow c'$;
            $\mathrm{time}[v] \leftarrow t'$;
            Push (c', t', v) into Q;
return $P^\star$;

2.6. *Winter Navigation Risk Index development*

WiNRI is derived from historical vessel observations and accident records using supervised machine learning. The modelling effort was based on an integrated database of winter navigation events collected over approximately 25 years for the Northern Baltic Sea (2000–2024), comprising 329 observations, including 162 accident cases and 167 non-accident cases.

The objective of the learning task was to construct the following predictor:

$$\mathrm{WiNRI} = f_\theta(\mathbf{x}), \tag{8}$$

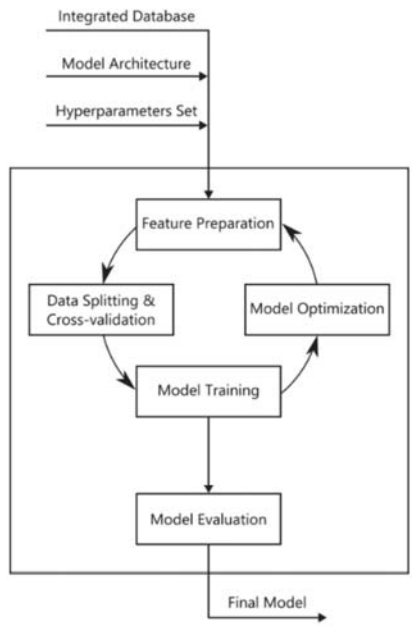

Fig. 1.: Machine learning model workflow

$$\mathbf{x}(e, s) = \big[\theta_w,\ U,\ h,\ B,\ L,\ \mathrm{Age},\ \mathrm{POLARIS},\ \big], \tag{9}$$

Therein $\mathbf{x}$ is a vector of relevant environmental and vessel characteristics, $\mathrm{WiNRI} \in [0, 1]$ representing the expected risk level, where 0 denotes low, while 1 means high risk. For operational consistency, navigation outside the ice regime was *a priori* assigned 0. The vector $\mathbf{x}$ contains eight of the most informative features predicting winter navigational risk in the study area. These belong to environmental and ship's characteristics, as follows: wind direction and wind speed, θ_w and U, ice thickness h, ice type type; ship breadth (B), length (L), age (Age), safety index $\mathrm{POLARIS})$, Vanhatalo et al. (2021); Montewka et al. (2015); Kotovirta et al. (2009)

Process of WiNRI model development is depicted in Figure 1 and described in details in the following section.

The input consisted of an Integrated Database E describing both accident and non-accident events observed during winter navigation in the Northern Baltic Sea over a multi-decade period. The binary target variable was defined as $y \in \{0, 1\}$, where $y = 1$ indicates an accident and $y = 0$ indicates safe passage under comparable ice conditions.

Missing values were inputed in a round-robin manner based on other available predictors. Continuous variables were standardized (z-score normalization), while categorical variables remained integer-encoded. The preprocessed dataset was split into disjoint training and testing subsets using a 9:1 ratio. The training subset was further partitioned into $k = 5$ folds for cross-validation, enabling robust hyperparameter tuning and model selection.

For each candidate architecture and each hyperparameter configuration $\theta \in \Theta_j$, the model was trained and evaluated using 5-fold cross-validation. The score was defined as:

$$CV(\theta) = \frac{1}{k}\sum_{i=1}^{k} Q\big(ML_j(\theta), \mathcal{D}_i\big), \qquad (10)$$

where $Q(\cdot)$ denotes the performance metric. ROC–AUC was selected due to its threshold-independent capability to discriminate between rare accident events and the majority of non-accident cases. The optimal configuration for each model class was determined as follows:

$$\theta^* = \arg\max_{\theta \in \Theta_j} CV(\theta). \qquad (11)$$

Three machine learning models were evaluated as follows: Random Forest, AdaBoost, and XGBoost. Among those the **XGBoost** achieved the highest overall discrimination performance and was therefore selected as the predictive model used in the WiNRI framework. XGBoost is based on gradient boosting, where successive decision trees are fitted to the negative gradients of the loss function, while explicit regularization terms are employed to control model complexity and mitigate overfitting.

In total, approximately 35,000 hyperparameter configurations were evaluated during the grid search. The optimal XGBoost model was obtained with the following hyperparameter set:

$$\begin{aligned} n_{\text{estimators}} &= 60, \\ \text{max\_depth} &= 5, \\ \text{colsample\_bytree} &= 0.85, \\ \text{subsample} &= 0.9, \\ \text{min\_child\_weight} &= 1, \\ \text{learning\_rate} &= 0.1, \\ \text{reg\_alpha} &= 0.0, \\ \text{reg\_gamma} &= 0.1, \\ \text{reg\_lambda} &= 2.0. \end{aligned}$$

3. Results

To demonstrate the practical applicability of the proposed WiNRI-based ice-routing methodology, two complementary case studies were conducted for identical environmental conditions corresponding to 20 February 2024 in the Bothnian Bay. These scenarios were selected due to the limited availability of validated datasets suitable for this type of analysis at the current stage of the research. Both cases illustrate the impact of incorporating ice-related navigational risk into the routing process, while addressing two different reference scenarios.

In addition, we present spatial WiNRI heatmaps covering the entire analysed sea area. These maps illustrate the overall behaviour of the WiNRI index under the prevailing ice conditions and demonstrate that WiNRI is not solely a function of the ice regime, but also depends explicitly on vessel-specific characteristics. As a result, identical environmental conditions may yield different spatial risk distributions for different ships.

The first case study is of a demonstrative nature and focuses on a direct comparison between the route recommended by the WiNRI-based ice-routing algorithm and the geometrically shortest route between the same start and end positions. The second case study constitutes a validation exercise, in which the WiNRI-based recommended route is compared with a real ship trajectory recorded in the Automatic Identification System (AIS) on the same date. By considering identical ice and meteorological conditions for both cases, full consistency of the routing framework and input data is ensured.

The routing task was defined between fixed start and end positions located in the northern and southern parts of the Bothnian Bay and solved using the objective function as presented in Equation 6, which simultaneously penalises travel time and increased ice-related navigational risk.

3.1. *Case study I: Demonstrative WiNRI-based ice routing*

As part of the demonstrative case study, the proposed routing methodology was applied to a general cargo vessel *DONGEBORG* depicted in Fig. 2, operating in the Bothnian Bay. The spatial characteristics of the WiNRI-based route in relation to prevailing ice conditions are illustrated in Fig. 3. In contrast to the geometrically shortest path (indicated in black), the recommended route deliberately deviates from the direct connection between the start and end points in order to bypass areas associated with elevated WiNRI values. This behaviour reflects the influence of the adopted objective function, which explicitly accounts for ice-related navigational risk in addition to travel time.

The main quantitative characteristics of the WiNRI-based routing solution are summarised in Table 3. The resulting route has a total length of 334.75 NM and a passage time of approximately 33.5 h, corresponding to a mean operational speed of 10 kn. Importantly, the WiNRI values along the route remain within the low-to-moderate range ($\text{WiNRI}_{\text{min}} = 0.462$, $\text{WiNRI}_{\text{max}} = 0.886$), indicating that the algorithm successfully avoids segments associated with the highest ice-related risk under the given environmental conditions.

A direct comparison between the WiNRI-based route and the geometrically shortest route is provided in Table 2. While the shortest route is marginally shorter in terms of distance and travel time, it completely neglects the spatial distribution of ice-related risk. The WiNRI-based route, on the other hand, exhibits a higher number of course changes ($\Delta\psi > 5°$), which reflects intentional manoeuvring to circumvent locally hazardous ice regions visible in Fig. 3. This results in an increased cumulative routing cost when evaluated using the WiNRI-weighted objective function, but leads to a route that is better aligned with safe winter navigation practice.

Overall, the combined interpretation of Fig. 3, Table 3, and Table 2 demonstrates that incorporating the WiNRI index into the routing process introduces a systematic trade-off between route efficiency and navigational safety. The proposed approach favours moderate increases in travel distance and passage time in exchange for a substantial reduction in exposure to elevated ice-related risk, highlighting the operational relevance of WiNRI as a decision-support indicator for ice navigation.

3.2. *Case study II: Validation against AIS-recorded voyage*

The second case study constitutes a validation exercise based on real operational data. The

Fig. 2.: Cargo vessel *m/s DONGEBORG* (IMO 9163697, MMSI 245413000, length 133 m, beam 16 m).

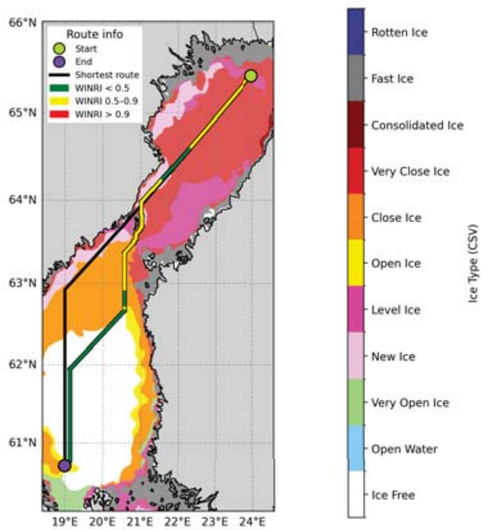

Fig. 3.: Comparison of the recommended WiNRI-based route with prevailing ice conditions.

WiNRI-based recommended route is compared with an actual ship trajectory recorded 20 February 2024 for the general cargo vessel *ANTARCTIC ENABLER*, see Fig. 4. The comparison was performed for environmental conditions prevailing in the Bothnian Bay on 20 February 2024, with both routes visualised in Fig. 5.

Based on the analysis of those two trajectories the impact of incorporating the WiNRI index into winter navigation routing algorithm can be clearly observed. Although the WiNRI-based

Table 1.: Summary of the demonstrative WiNRI-based ice-routing case study (cargo vessel *DONGEBORG*).

Parameter	Value
Start position (lat, lon)	65.42°N, 23.98°E
End position (lat, lon)	60.70°N, 19.00°E
Total objective cost	2874.153
Total travel time	2008.49 min (33.47 h)
Total distance travelled	334.75 NM
Mean operational speed	10.00 kn
WiNRI (edge) min / mean / max	0.462 / 0.702 / 0.886

Table 2.: Comparison of the routes recommended by the WiNRI-based ice-routing algorithm and the shortest-route baseline (20 February 2024).

Metric	WiNRI-based route	Shortest route
Total distance [NM]	333.7	332.3
Total travel time [h]	33.47	33.2
Average speed [kn]	10.0	10.0
Course changes ($\Delta\psi > 5°$)	19	2
Cumulative WiNRI cost	43.711	33.201

route is slightly longer in terms of total distance (288.36 NM) than the recorded AIS route (279.6 NM), the corresponding passage time increases only marginally (24.7 h versus 24.0 h, respectively). This indicates that the incorporation of ice-related risk into the routing objective does not lead to a significant degradation of time efficiency.

A key result of the comparison is the substantially lower cumulative WiNRI cost associated with the recommended route. As reported in Table 4, the total WiNRI-weighted cost for the algorithm-generated route amounts to 29.0 h, compared with 37.4 h for the recorded AIS trajectory. This reduction reflects a systematic avoidance of areas characterised by elevated WiNRI values, as also visible in Fig. 5, where the recommended route bypasses regions of consolidated ice.

In terms of manoeuvring characteristics, the WiNRI-based route exhibits a slightly higher number of course changes ($\Delta\psi > 5°$) compared to the recorded voyage. This behaviour is consistent with active route adaptation aimed at reducing exposure to hazardous ice conditions, rather than following a more direct but risk-prone trajectory.

Overall, the results demonstrate that the proposed WiNRI-based routing methodology is capable of significantly reducing the cumulative ice-related navigational risk while maintaining a passage time comparable to that observed in real operations. This confirms the practical relevance of the WiNRI index as a decision-support indicator for winter navigation, particularly in ice-covered waters where safety considerations must be balanced against operational efficiency.

Fig. 4.: Cargo vessel *m/s ANTARCTIC ENABLER* (IMO 9319064, general cargo ship, Finland flag, length overall 159 m, breadth 24 m).

3.3. *WiNRI heatmaps.*

For both case studies, spatial heatmaps of the WiNRI index were generated using ice conditions at 12:00 UTC on 20 February 2024 (Figs. 6 and 7). These maps provide an additional layer of decision support that complements the explicitly recommended routes increasing situational awareness by highlighting areas of locally increased ice-related navigational risk, enabling an informed, experience-based selection of an alternative routes while maintaining an acceptable safety level.

WiNRI heatmaps are not universal but are explicitly dependent on the characteristics of the

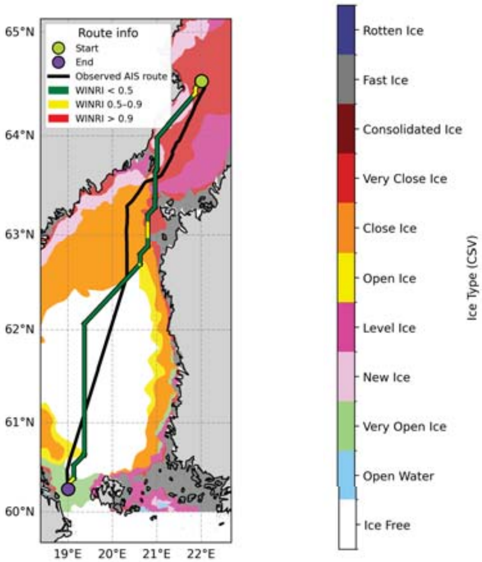

Fig. 5.: Comparison of the WiNRI-based recommended route and the actual AIS-based route (validation case). The coloured line represents the route generated using the WiNRI index, while the black line denotes the trajectory executed by the vessel and recorded in AIS data.

Table 3.: Summary of the demonstrative WiNRI-based ice-routing case study (cargo vessel *ANTARCTIC ENABLER*).

Parameter	Value
Start position (lat, lon)	64.53°N, 22.01°E
End position (lat, lon)	60.26°N, 19.00°E
Total objective cost	1742.1
Total travel time	1483.9 min (24.7 h)
Total distance travelled	288.13 NM
Mean operational speed	11.7 kn
WiNRI (edge) min / mean / max	0.172 / 0.371 / 0.772

considered vessel. This vessel dependency is clearly visible when comparing the heatmaps obtained for the *DONGEBORG* (Fig. 6) and the *ANTARCTIC ENABLER* (Fig. 7), despite identical environmental conditions.

For instance, some areas that feature low WiNRI (green) for one ship, are characterised by

Table 4.: Comparison of the recorded voyage of the *ANTARCTIC ENABLER* and the route recommended by the WiNRI-based ice-routing algorithm (20 February 2024).

Metric	Recorded route	WiNRI-based route
Total distance [NM]	279.6	288.4
Total travel time [h]	24.0	24.7
Average speed [kn]	11.7	11.7
Course changes ($\Delta\psi > 5^{\circ}$)	19	21
Cumulative WiNRI cost	37.4	29.0

higher values of WiNRI for another.

These spatial differences confirm that the WiNRI index inherently accounts for ship-specific parameters, such as hull dimensions and ice capability, and therefore produces risk assessments and route recommendations tailored to a particular vessel under given ice and weather conditions. Consequently, the WiNRI framework supports not only automated route optimisation but also informed human decision-making in winter navigation by providing risk-aware, vessel-dependent spatial context.

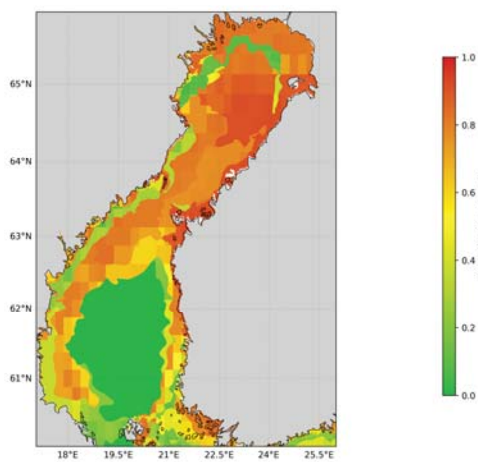

Fig. 6.: Spatial distribution of the WiNRI derived from ice conditions at 12:00 UTC on 20 February 2024 for the cargo vessel *DONGEBORG*.

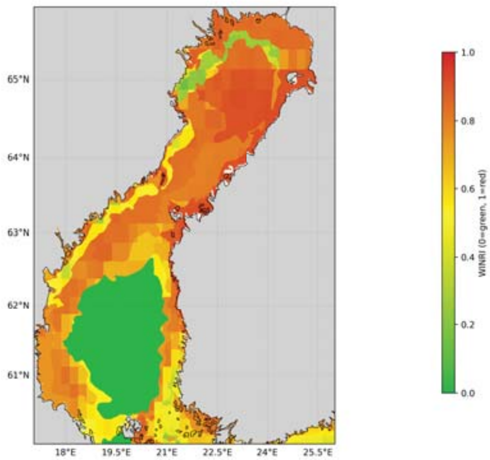

Fig. 7.: Spatial distribution of the WiNRI derived from ice conditions at 12:00 UTC on 20 February 2024 for the cargo vessel *ANTARCTIC ENABLER*.

Discussion

Despite the promising results, several limitations of the proposed approach should be acknowledged.

First, the routing framework relies on a discretised spatial grid derived from meteorological and ice data stored in NetCDF files. This grid-based representation inherently limits the smoothness of the generated trajectories and prevents the full representation of continuous ship motion. Increasing the spatial resolution of the computational grid and exploring adaptive or multi-scale grid structures could improve trajectory smoothness and local route optimisation.

Second, the graph structure allows a finite set of possible transitions between neighbouring grid nodes, which constrains manoeuvring flexibility and may lead to angular route segments that do not fully reflect real ship dynamics.

Third, the current implementation assumes a constant vessel speed along the entire route, independent of local ice conditions, wind, or manoeuvring intensity. This needs to be addressed in future work by adoption of a suitable ship performance model accounting for relevant factors, see for example Montewka et al. (2018).

The framework is presently limited to the Baltic Sea region and does not explicitly quantify the level of navigational risk associated with high WiNRI values; instead, it provides relative risk-aware route recommendations without defining operational risk thresholds. Future work could focus on expanding the WiNRI boundaries beyond this sea area. This would strengthen the applicability of the proposed WiNRI-based routing approach as a comprehensive decision-support system for winter navigation in ice-covered waters.

Finally, the method is intended as a route recommendation tool and does not replace the navigator's expert judgement or account for tactical, short-term decision-making on board.

Conclusions

This paper presented a time-weighted WiNRI-based ice-routing framework that integrates machine learning–based risk prediction with a deterministic, graph-based route optimisation algorithm. Within the proposed framework, WiNRI serves as a quantitative risk metric incorporated directly into the cost function of the routing algorithm. In this role, the index can support route selection by explicitly accounting for ice-related navigational risk along candidate routes. At the same time, WiNRI is not intended to replace existing operational decision-support frameworks such as POLARIS or AIRSS, but rather to complement them by providing an additional data-driven indicator that can be integrated into route optimisation procedures.

The primary objective of the study was to develop and demonstrate a practical decision-support tool for winter navigation that explicitly accounts for ice-related navigational risk while maintaining operational efficiency.

The results obtained in this study suggest that the proposed routing methodology is capable of incorporating the WiNRI index directly into the objective function and providing interpretable route recommendations for ice-covered waters. Through two complementary case studies conducted for identical environmental conditions on 20 February 2024 in the Bothnian Bay, the framework demonstrated its ability to generate routes characterised by reduced cumulative ice-related risk, while maintaining passage times comparable to both the geometrically shortest route and real AIS-recorded voyages.

The results indicate that the inclusion of the WiNRI index leads to systematic and interpretable trade-offs between navigational safety and travel efficiency. The WiNRI-based routes intentionally deviate from purely geometric solutions, guiding vessels through areas associated with lower ice-related risk. This behaviour was consistently observed in both the demonstrative and validation case studies, suggesting that WiNRI may serve as a useful decision-support indicator for seasonal ice navigation.

Nevertheless, further validation across a broader range of environmental conditions, ice regimes, and vessel types would be beneficial to fully assess the robustness and operational applicability of the proposed framework.

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