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Tian, W., Zhang, C., Fu, S. et al (2026). Predicting High-Resolution Gridded Sea Ice Concentration by Integrating LightGBM and Kriging Algorithms. Journal of Marine Science and Technology, 14(12).
<http://dx.doi.org/10.3390/jmse14121092>

N.B. When citing this work, cite the original published paper.

Article

Predicting High-Resolution Gridded Sea Ice Concentration by Integrating LightGBM and Kriging Algorithms

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Abstract

High-resolution spatiotemporal sea ice concentration (SIC) estimates are essential for Arctic navigation and ice analysis, but existing observational products are often too coarse, and physics-based models are computationally expensive. This study proposes a data-driven framework that couples Light Gradient Boosting Machine (LightGBM) temporal prediction with Kriging-based spatial interpolation to reconstruct SIC fields over the Northern Sea Route sector. LightGBM is trained on a grid-based SIC time series with engineered features representing persistence, seasonality, and short-term variability, enabling multi-horizon forecasting across large spatial grids. The predicted SIC fields are then refined using Ordinary Kriging (OK) and Co-Kriging (CK) with Gaussian and spherical semi-variogram models. Prediction performance is evaluated using root mean square error, and interpolation accuracy is assessed through cross-validation. Results show that, for high-latitude regions and resolutions finer than $0.25^\circ \times 0.25^\circ$, OK with a spherical semi-variogram achieves lower interpolation errors than CK and Gaussian-based alternatives. By sequentially coupling temporal learning and spatial refinement, the proposed framework improves temporal continuity, spatial structure, and error quantification, providing high-resolution SIC information suitable for large-scale Arctic ice analysis and navigation support.

Keywords: Arctic navigation; sea ice concentration; spatial interpolation; kriging algorithm; correlation analysis

1. Introduction

Arctic sea ice has continued to decline over the satellite observation period, although the rate of summer minimum sea-ice loss has slowed in recent years and shows signs of stabilization over the last two decades [1–3]. This trend is expected to lead to a sustained increase in maritime activity in Arctic waters [4,5]. Ensuring the safe and efficient operation of ships in this highly dynamic and ice-covered environment remains a major challenge [6]. Accurate prediction of sea ice concentration (SIC) is a key requirement, as it enables route planning strategies that reduce exposure to dense or hazardous ice conditions and mitigate the risk of ice-induced blockage.

Physical sea ice–ocean models have traditionally been employed for SIC forecasting. However, their effectiveness for operational applications such as ship route planning is constrained by several factors [7,8]. These models are computationally demanding, limiting their applicability for large-scale or high-resolution forecasting. In addition, rapid climate



Academic Editor: Anatoly Gusev

Received: 13 May 2026

Revised: 1 June 2026

Accepted: 4 June 2026

Published: 12 June 2026

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change has altered key ice properties, increasing model uncertainty, while sensitivity to initial and boundary conditions complicates calibration and operational robustness [9,10]. These limitations motivate the exploration of alternative, data-driven forecast approaches. Machine learning (ML) techniques have recently gained attention as an efficient alternative for SIC prediction. By learning directly from historical SIC observations and hydrological variables, ML models can represent nonlinear relationships that are difficult to capture using physics-based formulations [11]. Several studies have reported improvements in prediction accuracy and computational efficiency relative to traditional models [12]. Nevertheless, many existing ML-based SIC forecasting approaches focus on limited spatial domains or small numbers of grid points, restricting their applicability to Arctic navigation problems that require wide-area, grid-based predictions [13]. To address this issue, feature-engineered ML approaches capable of handling a large number of grids have been proposed [14]. Feature-engineered ML approaches construct physically and statistically meaningful predictors, such as oceanic or atmospheric covariates, before model training. LightGBM is an efficient gradient-boosting decision-tree algorithm designed for fast training, low memory usage, and large-scale tabular datasets, making it suitable for grid-based SIC prediction over a large Arctic domain [15].

In parallel with advances in temporal forecasting, the spatial resolution of SIC data remains a limiting factor for navigation-oriented applications. Observational and reanalysis SIC products are typically available at resolutions on the order of $0.25^\circ \times 0.25^\circ$, which is insufficient for detailed route planning in ice-infested waters. Spatial refinement through interpolation is therefore required. Interpolation methods are commonly classified as non-geostatistical or geostatistical [16]. While non-geostatistical approaches such as inverse distance weighting, trend surface analysis, and machine learning-based interpolation are widely used, geostatistical methods, particularly Kriging, provide a rigorous framework for modelling spatial autocorrelation and generating unbiased estimates with minimum variance [17–19]. Optimal Interpolation (OI) is another widely used statistical interpolation method in meteorology and oceanography. OI and Kriging are mathematically related estimation techniques, as both are based on covariance or spatial-correlation assumptions. However, OI is commonly used when a dynamic or climatological background field and associated error statistics are available, whereas Kriging estimates the spatial field mainly from the observed or predicted data themselves through an empirical semi-variogram. In this study, no additional dynamic sea-ice or ocean background model is introduced. Therefore, Kriging is adopted as a suitable geostatistical approach for the present data-driven spatial refinement framework. Despite extensive research on spatial interpolation, geostatistical methods have been applied only sparingly to SIC, and their performance for refined SIC reconstruction in polar regions remains insufficiently explored. A further limitation of existing studies is that temporal SIC forecasting and spatial interpolation are typically treated as independent problems. This separation can introduce inconsistencies between predicted temporal evolution and reconstructed spatial structure.

Previous studies have demonstrated that Ordinary Kriging (OK) generally outperforms non-geostatistical methods such as IDW and spline interpolation [20]. This advantage is also related to its statistical-estimation foundation: Kriging, similar to Optimal Interpolation, belongs to the class of best linear unbiased estimators under specified spatial covariance assumptions, whereas deterministic methods such as inverse distance weighting use prescribed interpolation weights and do not provide the same minimum-variance unbiased-estimation property [21]. Co-Kriging (CK) can further improve interpolation accuracy when suitable auxiliary variables are available and strongly correlated with the target variable [22,23]. However, several studies indicate that CK does not universally outperform OK, and its performance depends on covariance structure assumptions and

sampling configurations [24,25]. Consequently, the relative merits of OK and CK must be evaluated in the context of specific data characteristics.

From an engineering and operational perspective, reliable SIC products must exhibit both temporal continuity and spatial coherence. Therefore, this study presents a unified spatiotemporal framework for sea ice concentration (SIC) prediction that integrates feature-engineered LightGBM-based temporal forecasting with Kriging-based spatial interpolation within a single, consistent methodology, providing temporal prediction accuracy across forecast horizons and spatial grids, and spatial interpolation accuracy across different resolutions and Kriging configurations. First, a scalable machine-learning approach is developed to predict SIC time series over the NSR (Northern Sea Route) sector, enabling systematic evaluation of temporal prediction accuracy across multiple forecast horizons and grid locations. Building on the temporally predicted SIC fields, the study conducts a comprehensive assessment of geostatistical interpolation methods, examining the performance of Ordinary Kriging and Co-Kriging under different spatial resolutions and semi-variogram models. By explicitly coupling temporal prediction and spatial refinement, the proposed framework enables an integrated evaluation of spatiotemporal reconstruction accuracy, demonstrating how high-resolution SIC fields can be obtained while maintaining temporal continuity and spatial coherence. The results provide new insights into the combined use of machine learning and geostatistical methods for high-precision SIC reconstruction in polar regions.

2. Methods

The proposed method introduces a hybrid data-driven framework that integrates machine learning and geostatistics for Arctic sea ice prediction. The core idea of the proposed method is to first resolve the temporal evolution of SIC at each coarse-grid location using a feature-engineered Light Gradient Boosting Machine (LightGBM) model and subsequently enforce spatial coherence and refinement through Kriging-based interpolation. By separating temporal dynamics, learning from spatial dependency modelling, while coupling them in a consistent workflow, the method addresses the limitations of treating time and space independently and enables the generation of SIC fields with enhanced temporal continuity and spatial resolution.

2.1. Overview of the Proposed Framework

The proposed methodology reconstructs SIC fields through a sequential spatiotemporal strategy, in which temporal evolution and spatial dependence are modelled separately but coupled within a unified framework. The framework consists of four main components: data input and preprocessing, temporal feature engineering and prediction using LightGBM, spatial dependency modelling and interpolation using Ordinary Kriging (OK) or Co-Kriging (CK), and generation of high-resolution spatiotemporal SIC outputs, including two operators, i.e., a temporal prediction operator based on machine learning and a spatial interpolation operator based on geostatistics. The overall workflow and interaction between the two operators are illustrated schematically in Figure 1.

Let $X(p, t)$ denote SIC at spatial location p and time t . The objective is to reconstruct future high-resolution SIC fields that are consistent in both time and space. The temporal prediction stage is represented by a machine-learning operator F , which maps engineered feature vectors Y_t to future SIC values on a coarse grid:

$$\hat{X}(p_i, t + \tau) = \mathcal{F}(Y_t(p_i)), \quad p_i \in \mathcal{G}_c, \quad (1)$$

where $\mathcal{G}_c$ denotes the coarse-resolution grid and τ is the forecast time horizon. The spatial interpolation stage is represented by a geostatistical operator $\mathcal{K}$, which maps temporally predicted SIC values from the coarse grid to a finer grid $\mathcal{G}_f$:

$$\hat{X}_f(p_0, t + \tau) = \mathcal{K}(\hat{X}(\cdot, t + \tau)), \quad p_0 \in \mathcal{G}_f. \quad (2)$$

The complete spatiotemporal reconstruction is therefore expressed as,

$$\hat{X}_f(p, t + \tau) = \mathcal{K}(\mathcal{F}(X_t(p), Y_t(p))), \quad (3)$$

where $\mathcal{K}$ denotes operator composition. In this formulation, temporal variability is resolved by machine learning, while spatial coherence and ice-field structure are imposed through geostatistical modelling. This sequential design assumes a practical separation between coarse-grid temporal forecasting and spatial refinement. It improves computational efficiency, but it does not resolve the feedback between local thermodynamic SIC evolution and advective ice redistribution driven by winds and ocean currents.

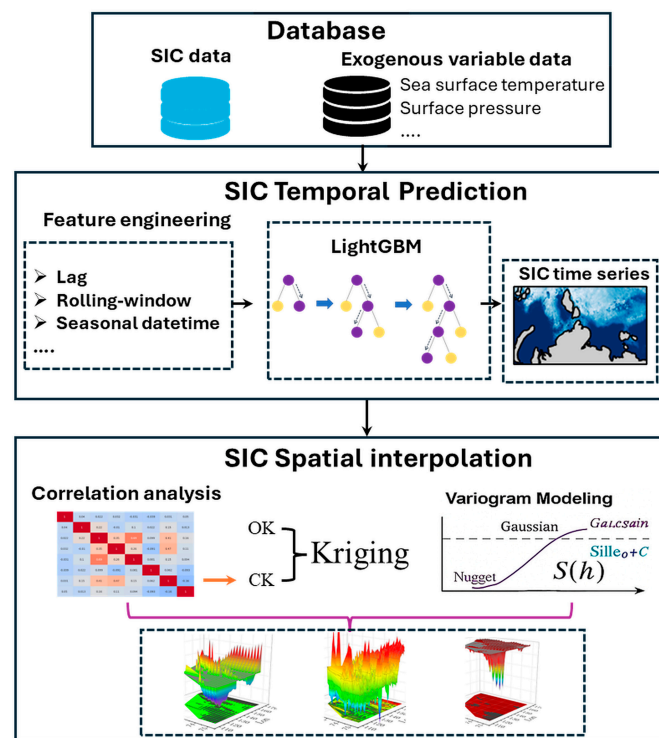


Figure 1. Framework of the proposed spatiotemporal sea ice concentration (SIC) prediction method.

2.2. Temporal Prediction of Sea Ice Concentration Using LightGBM

Temporal prediction of sea ice concentration is of critical importance for ships navigating the NSR, particularly during summer when ships are more active. Temporal evolution of SIC is governed by strong persistence, seasonal forcing, and modulation by ocean–ice interactions. To represent these characteristics efficiently over NSR, temporal SIC prediction is formulated as a supervised regression problem using a feature-engineered Light Gradient Boosting Machine (LightGBM). In data-driven forecasting, the predictive performance of machine learning models is strongly influenced by the quality of feature representation. From a mathematical perspective, feature engineering can be interpreted as the explicit construction of an input space that encodes physically and statistically meaningful characteristics of the target process. In this study, a feature-engineered LightGBM model is developed to predict SIC time series over NSR. LightGBM is an ensemble learning

framework based on gradient boosting decision trees. Unlike conventional level-wise tree growth strategies, LightGBM adopts a leaf-wise growth algorithm, which expands the leaf associated with the maximum loss reduction at each iteration (Figure 2). Combined with histogram-based feature binning and gradient-based one-sided sampling, this strategy significantly improves computational efficiency and memory usage, making LightGBM suitable for large-scale, grid-based SIC forecasting.

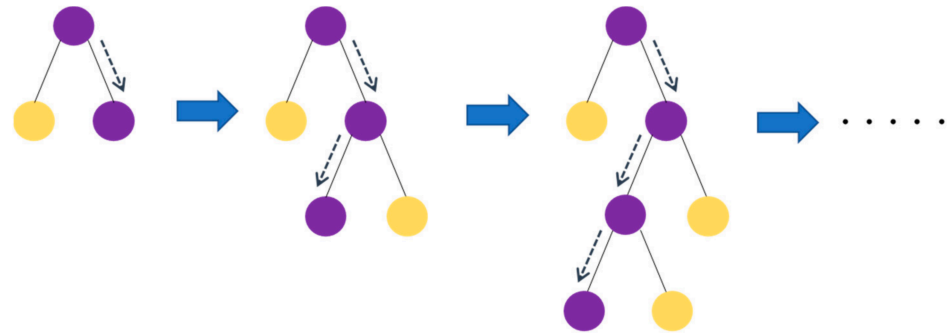


Figure 2. Leaf-wise tree growth strategy.

For simply explanation of temporal forecast using the LightGBM method, let X_t denote the sea ice concentration at time t . Temporal prediction is formulated as a supervised regression problem in which future SIC values are estimated from engineered features derived from historical observations and auxiliary variables. The LightGBM model learns a nonlinear mapping of the form

$$\hat{X}_t = f_{\theta}(Y_t), \quad (4)$$

As in Equation (1), Y_t is the feature vector at time t , $f_{\theta}(\cdot)$ denotes the LightGBM predictor parameterized by θ , and $\hat{X}_t$ is the predicted SIC.

Construction of the feature vector Y_t : To capture the dominant temporal characteristics of SIC evolution, the selection of relevant features for the feature vector Y_t is a crucial step in developing accurate sea ice concentration (SIC) forecasting models. Sea level pressure, temperature, and wind speed have been extensively considered in previous SIC prediction studies [26]. Additionally, research has demonstrated that factors such as cloud cover, radiation, and vertical flux also influence sea ice dynamics and thermodynamics [27].

Based on the existing literature, we selected several exogenous variables that may be useful for sea ice concentration prediction, including sea surface temperature (SST), surface pressure (SP), mean sea level pressure (MSLP), 2-m air temperature (T2M), and 2-m dewpoint temperature (D2M).

These exogenous variables are treated as known inputs over the forecast horizon and incorporated into the feature vector to represent sea ice thermodynamic interactions. The following seasonal effect and time lag autocorrelation features should also be considered.

Seasonal datetime features: Seasonal variability associated with the annual freeze–melt cycle preserves periodic continuity between December and January and avoids artificial discontinuities introduced by integer month encoding. It is represented using trigonometric transformations of the calendar month m as

$$SO = \left[\sin\left(\frac{2\pi m}{12}\right), \cos\left(\frac{2\pi m}{12}\right) \right]. \quad (5)$$

Lag and rolling-window features: Temporal persistence and memory effects in SIC are represented using lagged observations and rolling statistics. The rolling feature smooths short-term variability and approximates the thermal inertia of the ice–ocean system. Lag

features include SIC values at one-, two-, and three-day offsets, and a rolling mean to include the rolling feature vector as

$$R = [X_{t-1}, X_{t-2}, X_{t-3}, X_t^{rolling}], \text{ with } X_t^{rolling} = \frac{1}{3} \sum_{k=1}^3 X_{t-k}. \quad (6)$$

The concept of LightGBM for SIC forecasting is illustrated in Figure 3. LightGBM employs a leaf-wise tree growth strategy combined with histogram-based splitting, enabling efficient learning of nonlinear relationships across large datasets. Model hyperparameters are optimized using a grid search with parallel computation. Conventional error metrics such as Mean Absolute Error (MAE) assess prediction accuracy independently at each grid point and do not explicitly account for spatial coherence. However, SIC fields exhibit strong spatial continuity, and localized inconsistencies can reduce the physical realism of predictions. To address this limitation, a spatially regularized loss function is introduced by augmenting MAE with a gradient-based penalty. To enhance spatial consistency of temporal predictions, the training objective augments Mean Absolute Error (MAE) with a spatial gradient penalty:

$$\mathcal{L} = \alpha \frac{1}{N} \sum_{t=1}^N (|\hat{X}_t((i, j)) - X_t(i, j)| + \beta (\hat{X}_t((i, j)) - X_t(i-1, j) + \hat{X}_t((i, j)) - X_t(i, j-1))) , \quad (7)$$

where (i, j) denote grid indices for various time and α, β balance temporal accuracy and spatial smoothness, N is the number of training samples and α and β control the relative importance of pointwise accuracy and spatial smoothness.

Time	SST	SP	MSLP	SIC _{t-1}	SIC _{t-2}	SIC _{t-3}	SIC _{rolling mean}	SIC _t
...	...	...	...	...	...	...	...	...
Date ₁	271.461	102,020.062	102,043.937	0.826	...	...	...	0.821
Date ₂	271.459	102,137.125	102,161.750	0.821	0.826	...	...	0.815
Date ₃	271.457	101,825.562	101,849.500	0.815	0.821	0.826	...	0.811
Date ₄	271.459	101,934.251	101,959.062	0.811	0.815	0.821	...	0.798
Date ₅	271.461	101,836.937	101,860.312	0.798	0.811	0.815	0.857	0.791
Date ₆	271.459	102,995.752	103,020.312	0.791	0.798	0.811	0.851	?

Figure 3. Concept of prediction using relevant features in the LightGBM model.

This formulation promotes temporally accurate SIC predictions while reducing unrealistic spatial discontinuities, producing SIC forecasts that are more consistent with the spatial structure of Arctic ice fields. The hyperparameters in Equation (4) should be determined for the LightGBM by minimizing the loss function in Equation (8). Since the predictive performance of the established LightGBM will be very sensitive to the choice of those hyperparameters, a grid search strategy is employed to identify an optimal configuration and to exhaustively evaluate combinations of key parameters, including the number of leaves, maximum tree depth, subsampling ratio, number of estimators, and learning rate. Parallel computation is used to reduce computational cost. The final determined values of those hyperparameters, which achieve a balance between model complexity and generalization capability, are shown in Table 1 for the LightGBM model.

Table 1. Hyperparameter setting of LightGBM.

Parameter	Impact	Value Range	Optimal Value
num_leaves	Controls the complexity of the model, with higher values leading to more complex models and potentially overfitting	1–200	81
max_depth	Limits the depth of the trees, balancing exploration of complex interactions with the risk of overfitting	1–20	15
subsample	Controls the proportion of training data used to train each tree, introducing randomness and reducing overfitting	0.4–1	0.629
n_estimators	Controls the number of trees, influencing the complexity of model	1–300	153
learning_rate	Controls the step size of the gradient descent algorithm, influencing the speed of convergence and the model's sensitivity to outliers	0.01–0.3	0.23

2.3. Spatial Interpolation of Sea Ice Concentration Using Kriging

The temporally predicted sea ice concentration fields remain defined on the coarse spatial grid. To obtain high-resolution SIC fields suitable for navigation-oriented analysis and spatially detailed ice characterization, geostatistical interpolation is applied to each forecast time slice using Kriging-based methods [28]. Ordinary Kriging (OK) and Co-Kriging (CK) are considered to evaluate their suitability for refined SIC reconstruction under different spatial resolutions. For SIC data of a specific spatial resolution given by the data, the procedure consists of selecting SIC samples, computing empirical semi-variances, fitting theoretical semi-variogram models, solving the Kriging system, and estimating SIC at unknown locations as weighted linear combinations of known values. The interpolation procedure consists of the following steps:

1. SIC samples at the selected resolution are used as interpolation input, and target interpolation points are defined according to the required spatial accuracy;
2. Pairwise distances between sampling points are computed using geographic coordinates, and empirical semi-variances are calculated from SIC differences;
3. A theoretical semi-variogram model is fitted to describe the spatial dependence structure of the SIC field;
4. The fitted semi-variogram is used to construct the Kriging system of equations;
5. The system is solved to obtain optimal interpolation weights;
6. SIC at unknown locations is estimated as a weighted linear combination of known SIC values.

2.3.1. Semi-Variogram Modelling and Physical Interpretation

An essential characteristic of sea ice concentration fields is spatial autocorrelation, whereby SIC values at nearby locations tend to be more similar than those farther apart. This spatial dependence arises from physical processes such as ice drift, thermodynamic growth and melt, and large-scale atmospheric forcing. In geostatistics, spatial autocorrelation is quantified using the semi-variogram, which describes how the variance of SIC differences increases with distance as,

$$\gamma(d) = \frac{1}{2} \text{Var} [X(p) - X(p + d)], \quad (8)$$

where d denotes the spatial separation distance. Figure 4 shows a typical spatial relationship of the semi-variogram model. The change rate of distance between each point is described by the semi-variance. The model needs to set up three parameters, i.e., the nugget C_0 , the sill C , and the range r . The discontinuity or vertical jump at the starting point indicates that the spatial variable is discontinuous and has highly irregular spatial variability. In geostatistics, this discontinuity is known as the nugget effect [29]. When the distance is r , the semi-variogram tends to the sill value.

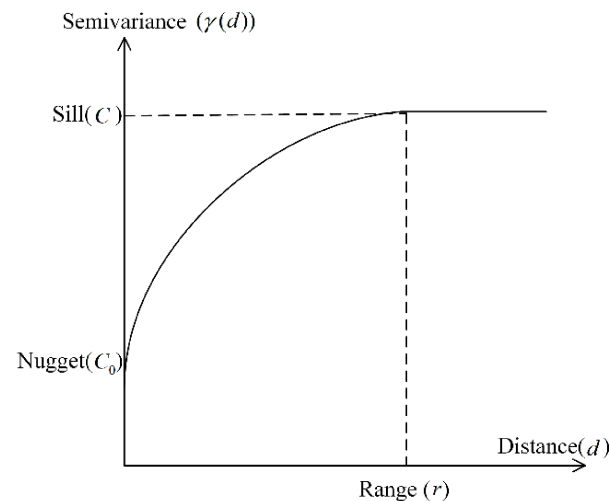


Figure 4. Typical semi-variogram model.

The nugget represents microscale variability, measurement uncertainty, or unresolved sub-grid ice processes such as ridging and lead formation. The sill corresponds to the total variance of the SIC field, while the range defines the characteristic spatial scale beyond which SIC values become effectively uncorrelated. Observations separated by distances greater than the range are therefore considered spatially independent. In this study, after many attempts at fitting the theoretical semi-variances (Cubic, Exponential, Gaussian, Five-sphere, Spherical, Sinusoidal hole effect, Markov second order, Markov third order), Gaussian and spherical functions are adopted for the SIC semi-variogram models as follows:

1. Gaussian model: If the variance of the source data is smooth, the Gaussian model is usually used to calculate the semi-variogram value.

$$\gamma(d) = \begin{cases} 0 & d = 0 \\ C_0 + C(1 - \exp(-\frac{d^2}{r^2})) & d > 0 \end{cases} \quad (9)$$

2. Spherical model: If the study area is in a high latitude, the Spherical model is usually used.

$$\gamma(d) = \begin{cases} 0 & d = 0 \\ C_0 + C(\frac{3d}{2r} - \frac{d^3}{2r^3}) & 0 < d \leq r \\ C_0 + C & d > r \end{cases} \quad (10)$$

2.3.2. Kriging as a Best Linear Unbiased Prediction (BLUP) Problem

Kriging can be interpreted within the framework of statistical estimation theory. If the SIC field is modelled as a random field and the estimation of it is expressed as a linear system containing random error, the Best Linear Unbiased Prediction (BLUP) under the Gauss–Markov theorem is obtained by choosing the estimator that minimizes the estimation variance subject to unbiasedness constraints [30]. Let p_0 denote an unknown target location and denote neighbouring sampling points. The linear estimator of SIC at p_0 is written as

$$\hat{X}(p_0) = \sum_{k=1}^K \lambda_i X(p_k), \quad (11)$$

where λ_i are interpolation weights to be determined. Under the assumptions of second-order stationarity and isotropy, the mean of the SIC field is spatially invariant, and the

covariance between any two locations depends only on their separation distance. Since the true covariance function is generally unknown, the semi-variogram is used as its proxy,

$$\gamma(p_k, p_l) = \gamma(|p_k - p_l|). \quad (12)$$

The BLUP formulation leads to the minimization of the estimation variance $\text{Var}(\hat{X}(p_0) - X(p_0))$, which subjects to the unbiasedness constraint. Introducing a Lagrange multiplier μ , the resulting Ordinary Kriging system is given by

$$\sum_{l=1}^L \lambda_l \gamma(p_k, p_l) + \mu = \gamma(p_k, p_0), k = 1, \dots, K, \text{ with constraints } \sum_{l=1}^L \lambda_l = 1. \quad (13)$$

Solving this linear system yields the optimal weights λ_l , which are substituted into Equation (9) to obtain the unbiased minimum-variance estimate $\hat{X}(p_0)$.

2.3.3. Co-Kriging Formulation

Co-Kriging extends the BLUP framework by incorporating one or more auxiliary variables that are spatially correlated with the primary variable [31]. Let $X(p)$ denote an auxiliary field correlated with SIC. The CK estimator is expressed as

$$\hat{X}(p_0) = \sum_{k=1}^K \lambda_k X(p_k) + \sum_{l=1}^L \omega_l Z(p_l), \quad (14)$$

where λ_k and ω_l are weights for the primary and auxiliary variables, respectively. To ensure unbiasedness, the following constraints are imposed:

$$\sum_{k=1}^K \lambda_k = 1, \sum_{l=1}^L \omega_l = 0 \quad (15)$$

The resulting coupled system incorporates both variograms and cross-variograms and is solved to obtain the CK estimate $\hat{X}(p_0)$.

The prediction and interpolation performance is evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), as follows:

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |\hat{X}(p_i) - X(p_i)|, \quad (16)$$

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (\hat{X}(p_i) - X(p_i))^2 \quad (17)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{X}(p_i) - X(p_i))^2} \quad (18)$$

The sequential coupling of temporal ML prediction and spatial Kriging interpolation mirrors the multiscale nature of sea ice processes, with temporal evolution governed by local thermodynamics and spatial structure imposed by large-scale forcing. This separation improves spatiotemporal consistency and robustness of high-resolution SIC reconstruction.

3. Data Source and Exogenous Variables Selection

3.1. Case Study Region and Data Source

The Northern Sea Route (NSR) is a major Arctic shipping corridor that extends from the North Cape of Norway across the northern coast of Eurasia and Siberia and exits to the Pacific Ocean through the Bering Strait. Within the NSR, the East Siberian Sea and the Laptev Sea form a key bottleneck where sea-ice conditions change rapidly and strongly affect navigation, as shown in Figure 5. Therefore, this study takes the sea area between [113° E–170° E, 70° N–75° N] as the research area. Sea ice concentration products are commonly retrieved from passive microwave satellite observations using dedicated

algorithms [32]. Daily sea ice concentration (SIC) and associated covariates were obtained from the Copernicus Climate Data Store product “ERA5 hourly data on single levels from 1940 to present”, provided by the Copernicus Climate Change Service (C3S) [33]. In this study, the ERA5 variable “sea ice area fraction” was used as SIC, because it represents the fraction of a grid box covered by sea ice. The associated covariates extracted from the same ERA5 product included sea surface temperature (SST), surface pressure (SP), mean sea level pressure (MSLP), 2-m air temperature (T2M), and 2-m dewpoint temperature (D2M). In this work, ERA5 SIC at $0.25^\circ \times 0.25^\circ$ is treated as the base dataset and is used in two ways. First, for time series prediction, SIC together with the covariates are collocated on the $0.25^\circ \times 0.25^\circ$ grid over 1 January 2021 to 1 August 2022. Second, for spatial interpolation, SIC fields in the full year 2021 (January–December 2021) are interpolated and evaluated month by month to account for seasonal variability in spatial dependence and to ensure robust semi-variogram fitting.

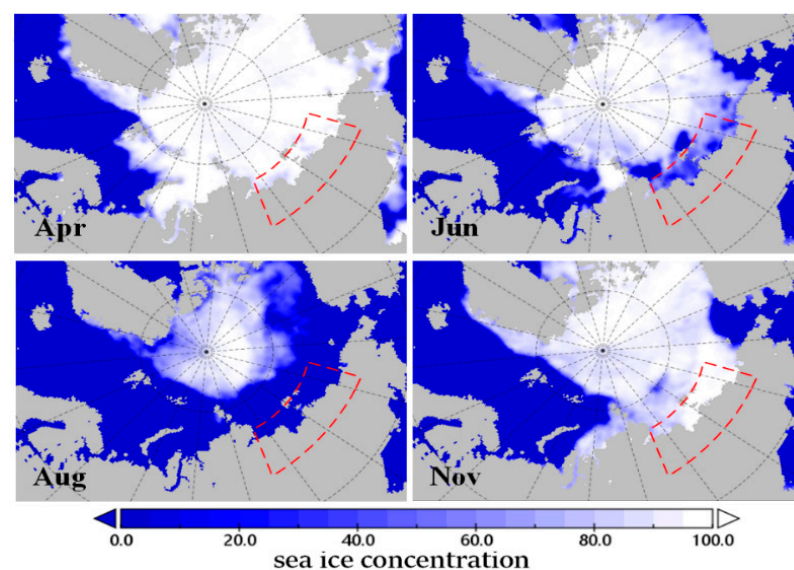


Figure 5. Distribution of SIC in April, June, August, and November in 2021 (the red box indicates the study area.).

For resolution-sensitivity tests in the interpolation module, ERA5 SIC at $0.5^\circ \times 0.5^\circ$ is additionally used as a coarser source field to interpolate toward $0.25^\circ \times 0.25^\circ$. To evaluate the finest-resolution interpolation outcomes, an independent higher-resolution SIC product at $0.05^\circ \times 0.05^\circ$ from a CMEMS reanalysis is used as a benchmark. All datasets are processed over the same study domain with consistent masking of land points and strict spatiotemporal collocation to ensure fair evaluation.

3.2. Exogenous Variables Selection

A preliminary covariate screening step was conducted to identify suitable exogenous inputs for SIC prediction. This analysis aims to reduce the dimensionality of the input feature space and retain variables that show physically interpretable and statistically meaningful relationships with SIC. The selected covariates are then combined with lag, rolling-window, and seasonal datetime features to form the complete feature vector used in the temporal prediction module.

To support this screening, Pearson correlation analysis was employed to assess the strength and direction of the relationships between SIC and candidate exogenous variables. Since the time series prediction of SIC mainly targets the summer navigation season, the correlation analysis was performed primarily using summer data from June to September 2021.

Table 2 summarizes the mean correlation coefficients between SIC and several atmospheric variables over the entire study region. A pronounced negative relationship is observed between SIC and SST, with a mean correlation of -0.606 , indicating that higher SST generally coincides with lower ice concentration. In contrast, SP and MSLP exhibit moderate positive correlations with SIC (0.459 and 0.412 , respectively), suggesting that higher pressure conditions are associated with increased SIC at the regional mean scale. The remaining near-surface thermodynamic variables show comparatively weak linkages: 2-m air temperature (T2M) and 2-m dew-point temperature (D2M) have small negative correlations (-0.227 and -0.128), implying a limited linear influence on SIC when averaged across the domain. Thus, we choose SST, SP, and MSLP as exogenous variables for further research, which is consistent with related research. The 5th Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) points out that various factors have a great influence on local SIC, such as temperature change [34], humidity transport [35], sea surface pressure [36], etc. Cruz-García et al. [37] also showed that the SIC anomaly in the Barents Sea had a strong negative correlation with the local marine sea ice surface temperature (SST) anomaly.

Table 2. Mean correlation coefficients between different variables with SIC.

Variable	Mean Correlation Coefficient with SIC
Sea surface temperature (SST)	-0.606
Surface pressure (SP)	0.459
Mean sea level pressure (MSLP)	0.412
2-m air temperature (T2M)	-0.227
2-m dewpoint temperature (D2M)	-0.128

Finally, the complete feature vector for SIC forecasting can be summarized as

$$Y_t = \left\{ X_{t-1}, X_{t-2}, X_{t-3}, X_{\text{rolling}}(t), SST_t, SP_t, MSLP_t, \sin\left(\frac{2\pi m}{12}\right), \cos\left(\frac{2\pi m}{12}\right) \right\}. \quad (19)$$

According to the correlation analysis results in Table 2, in this study, SP, SST, and MSLP data were selected as the covariate ranges of the CK method, and the SIC was spatially interpolated based on them. Considering the large fluctuation range of SIC data in the navigable area of the NSR in a year, in order to ensure the reliability of the interpolation data, the sea ice conditions of each month are separately interpolated.

According to the obtained correlation data, SST, SP, MSLP, and SIC are analyzed by the Pearson correlation coefficient for each month, where a indicates that the obtained ocean surface temperature value has only one variable, and does not meet the requirements of covariate value in collaborative Kriging. As can be seen from Table 3, the correlation coefficient between SST and SIC is larger than that between SP, MSLP, and SIC in January, May, June, August, October, and November, and at the same time, they reach a 0.01 significance level. Except for January, which had a correlation coefficient of 0.44 , all other months have a correlation coefficient larger than 0.5 . In February, April, and December, the correlation coefficients between SP and SIC (absolute values larger than 0.3) are all larger than the correlation coefficients between MSLP and SIC and also reach the significant level of 0.01 . The absolute values of the correlation coefficients between the three covariables and SIC in March and September are all smaller than 0.3 . Therefore, no auxiliary variable showed a sufficiently strong linear correlation with SIC to support Co-Kriging in March and September. Based on the above analysis, the covariable of January, May, June, August, October, and November is SST, the covariable of February, April, and December is SP, and CK is not used in March and September [38].

Table 3. Pearson correlation analysis of SIC and other variables.

Month	SST	SP	MSLP	Most Related
January	0.44 **	−0.310 **	−0.411 **	SST
February	a	0.307 **	0.257 **	SP
March	0.047 **	0.257 **	0.102 **	None
April	a	0.306 **	0.274 **	SP
May	−0.789 **	0.327 **	0.350 **	SST
June	−0.810 **	0.557 **	0.594 **	SST
July	−0.513 **	0.569 **	0.592 **	MSLP
August	−0.539 **	−0.181 **	−0.246 **	SST
September	−0.002	0.052 **	0.121 **	None
October	−0.866 **	0.699 **	0.747 **	SST
November	−0.520 **	0.416 **	0.410 **	SST
December	a	0.406 **	0.373 **	SP

Note **: represents a significant association at the 0.01 level (bilateral); a means there is only one constant.

4. Results on the Case Studies

4.1. Temporal Prediction of SIC

Based on the geographic resolution of the data, it contains information from 229×21 geographic grids. To reduce computational effort, all land grids are excluded, and a hypothesis is made that if the sea ice concentration is zero for five consecutive days from 22 July 2022 to 26 July 2022, the grid is considered ice-free for the next six days, and no sea ice prediction is required. After removing the grids that satisfy the above assumptions and the land grid, the number of geographic grids that need to be predicted is reduced from the original 4809 to 1730, significantly reducing the computational effort. The missing or invalid values (e.g., $SIC < 0$ or $SIC > 1$) were interpolated using the nearest neighbour method. Missing data, albeit extremely rare in this dataset, are addressed using a forward fill approach. Also known as the Last Observation Carried Forward (LOCF), this method replaces a missing value with the most recent observed value from the preceding time step, thereby preserving the continuity of the time series [39]. Finally, the training set spanned 1 January 2021 to 26 July 2022, encompassing daily SIC measurements across 1730 grids, while the following 6 days (27 July 2022 to 1 August 2022) are served as the testing set.

For the six-day forecasting of each grid, we performed recursive forecasting to realize multi-step forecasting, which means a single model is used repeatedly to forecast all six steps. Moreover, considering that ships often need to plan their routes before sailing for many days ahead, the predicted value for time step $t + 1$ serves as an input when making predictions for the subsequent time step $t + 2$, and so forth. In this multi-step prediction, a rolling window feature is adopted by feeding each newly predicted value into the model for the next time step. If the true observations are used instead of the model's predictions in the rolling window stage, it would introduce data leakage, leading to high accuracy that does not align with real conditions. Consequently, this would inflate the estimated performance of the model and undermine its reliability and applicability in operational settings, such as planning maritime routes over multiple days. The 6-day forecast result is shown in Figure 6, which has enough accuracy for ship route planning.

Figure 7 shows the geographic distribution of RMSE, while the average forecast RMSE for the whole area is 0.097. From the geographic distribution of RMSE, the ice-edge regions exhibit very low RMSE values, primarily because SIC in these areas is close to zero; consequently, the absolute prediction errors are small, and the resulting RMSE is correspondingly low. Likewise, regions with severe ice conditions also show low prediction RMSE, because SIC in consolidated ice typically does not vary substantially over short

time scales; therefore, LightGBM can leverage the strong temporal persistence in the recent historical time series to produce accurate estimates.

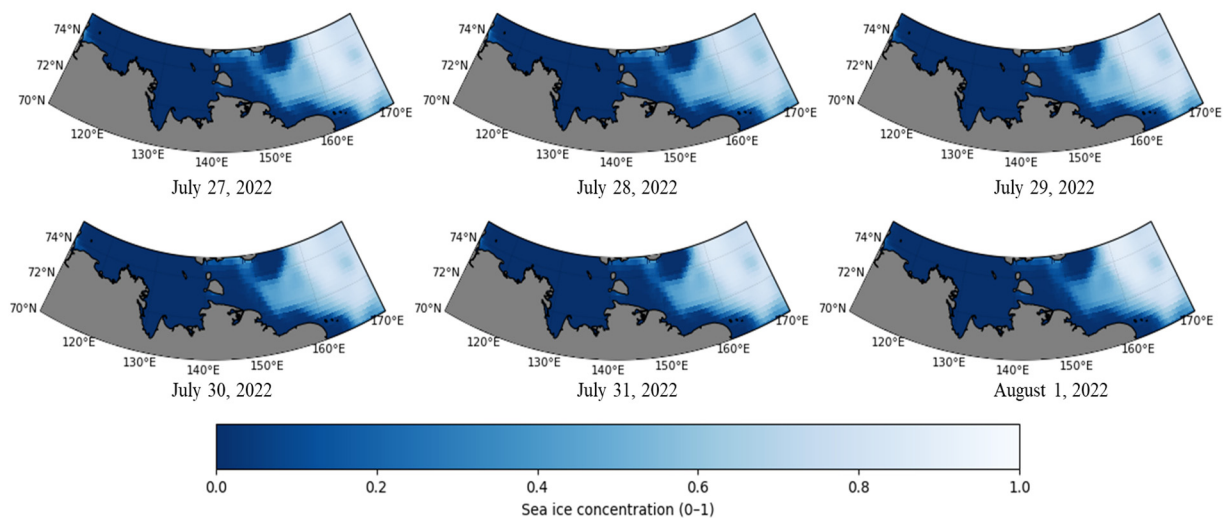


Figure 6. The 6-day temporal prediction of SIC.

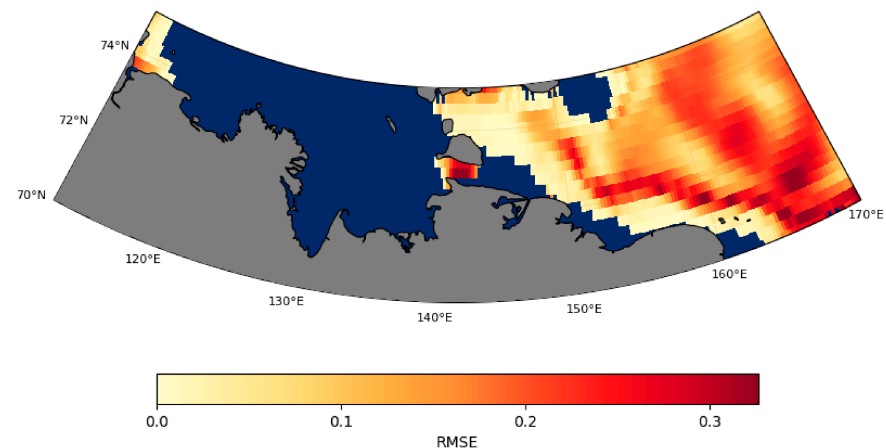


Figure 7. The geographic distribution of prediction RMSE.

The average RMSE for 1-day to 6-day forecasts is computed across all geographic grids, as shown in Figure 8. When using one year of historical data to predict the following day's sea ice concentration, the average RMSE can be as low as 0.031. This indicates that, if real-time sea ice data are available, the prediction results would be highly reliable, supporting real-time route planning in ice-covered regions. Notably, even when applying the feature-engineered LightGBM method to predict 6 days of sea ice concentration, the outcomes remain acceptable.

4.2. Interpolation Results Analysis

Kriging requires all data to have the same variability and be normally distributed to some extent. In this study, normal Q-Q plots are used to visually examine whether the monthly SIC samples approximately follow a normal distribution. A Q-Q plot, or quantile-quantile plot, compares the quantiles of the sample data with the corresponding quantiles of a theoretical distribution. If the sample distribution is close to the theoretical normal distribution, the points in the Q-Q plot should approximately follow a straight reference line. The monthly Q-Q plots of SIC are shown in Figure 9. From Figure 9, the normal distribution of January to April, June, and October to December has a better verification effect. The test results in May and July are not as good as those in other months, but they basically

meet the normal distribution assumption. In general, except for August and September, the SIC data in other months basically satisfy the second-order stationary assumption required by the Kriging interpolation method. Due to the climatic conditions in August and September, the SIC in coastal waters is mostly 0, showing a slightly normal distribution, and the interpolation accuracy will be focused on in the subsequent interpolation.

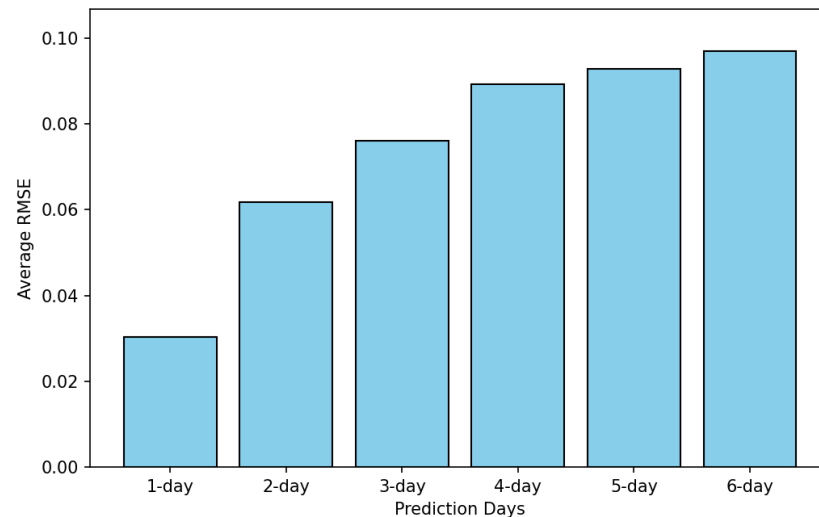


Figure 8. Average RMSE of SIC forecasts from 1 day ahead to 6 days ahead.

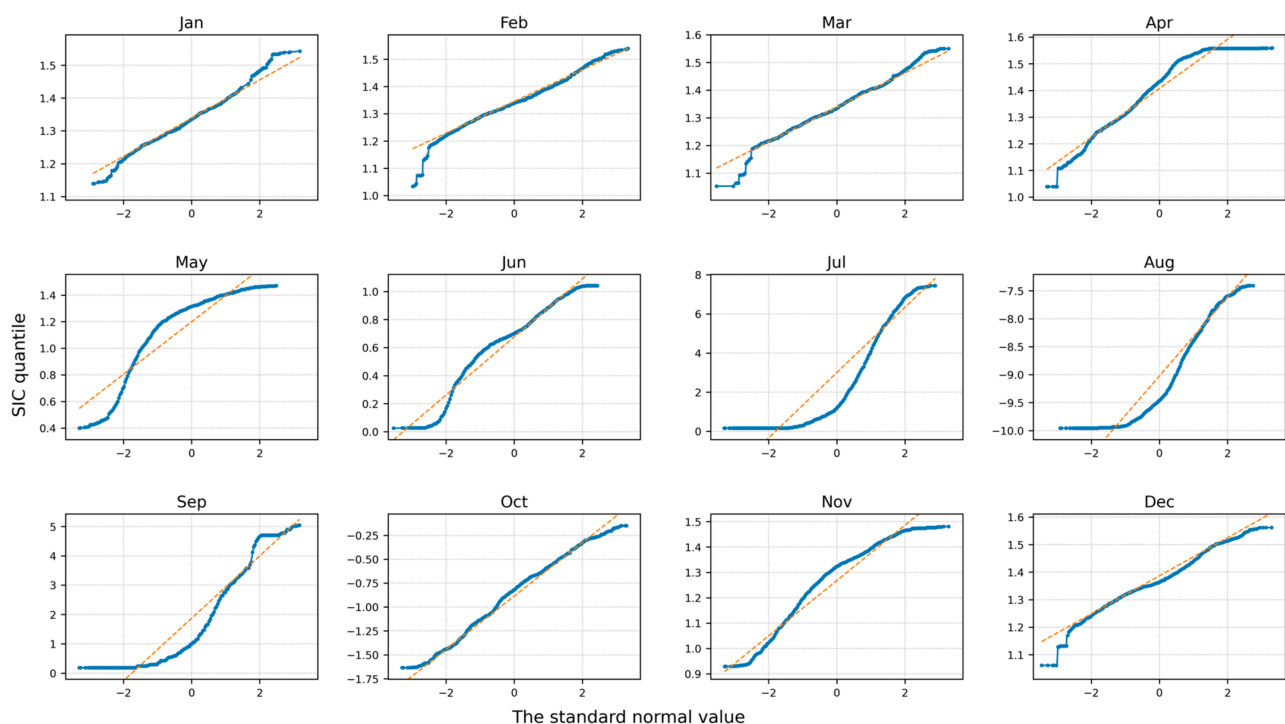


Figure 9. Normal Q-Q chart of SIC for 12 months in 2021 (the blue solid lines represent empirical SIC quantiles, and the orange dashed lines represent theoretical normal reference lines).

4.2.1. Interpolation Test 1: Spatial Resolution of $0.5^\circ \times 0.5^\circ$

Since SIC has a strong seasonal periodic characteristic, this study further evaluates interpolation by analyzing the errors from month to month. Table 4 shows the data accuracy of $0.25^\circ \times 0.25^\circ$ spatial resolution obtained by SIC data interpolation based on $0.5^\circ \times 0.5^\circ$ spatial resolution. Table 4 shows that the Gaussian model (OK) in January–March, September and December yields an MAE of <0.009 , in April, May to July, and October to November

an MAE of <0.07 . The Spherical model (OK) in January–April and September–December yields an MAE of <0.06 , in May–August an MAE of <0.01 . The Gaussian model (CK) in January–May, April–May, August and November–December yields an MAE of <0.09 . The Spherical model (CK) in January–April and December yields an MAE of <0.01 . MAE of both models is maintained at a low level. According to the above analysis, it is found that when the Gaussian model is selected, CK fine interpolation of SIC is better than OK. When the Spherical model is selected, OK is superior to CK in fine interpolation of SIC. In addition, the comparative analysis of source data shows that the main influencing factor of the accuracy difference is the SIC data fluctuation amplitude in each month. The smaller the data variance is, the higher the interpolation accuracy is. MSE is the most used regression loss function to measure the difference between the observed and the interpolated SIC. By analyzing the data in Table 4, it can be found that both the OK algorithm and CK algorithm have good convergence performance in interpolation prediction.

Table 4. Accuracy of the target spatial resolution of $0.25^\circ \times 0.25^\circ$ data based on the $0.5^\circ \times 0.5^\circ$ original data.

	Month	MAE		MSE		RMSE	
		Gaussian model	Spherical model	Gaussian model	Spherical model	Gaussian model	Spherical model
OK	January	0.00646	0.00326	0.00013	0.00005	0.01131	0.00707
	February	0.00601	0.00352	0.0001	0.00006	0.01004	0.00757
	March	0.00801	0.00368	0.00015	0.00006	0.01225	0.00757
	April	0.01039	0.00138	0.00023	0.00002	0.0156	0.00387
	May	0.03285	0.01227	0.00363	0.00078	0.06024	0.02786
	June	0.06976	0.02161	0.00975	0.00143	0.09872	0.03784
	July	0.06837	0.02428	0.00882	0.00158	0.09391	0.03981
	August	0.01913	0.00733	0.00118	0.00032	0.03441	0.018
	September	0.00554	0.00169	0.00061	0.0002	0.02476	0.01398
	October	0.04063	0.00434	0.00299	0.00016	0.05467	0.01268
	November	0.01727	0.00589	0.00069	0.00013	0.02628	0.01119
	December	0.00619	0.00344	0.0001	0.00005	0.00984	0.00708
CK	January	0.00891	0.00890	0.00021	0.00021	0.01449	0.01447
	February	0.00222	0.00746	0.00006	0.00017	0.00775	0.01309
	March	--	--	--	--	--	--
	April	0.00225	0.00982	0.00005	0.00024	0.00707	0.01563
	May	0.00003	0.03486	0	0.00499	0	0.07064
	June	0.0131	0.08017	0.00081	0.01748	0.02846	0.13221
	July	0.01568	0.10848	0.00071	0.02331	0.02664	0.15267
	August	0.00444	0.02477	0.0007	0.00194	0.02646	0.04407
	September	--	--	--	--	--	--
	October	0.01543	0.07399	0.00068	0.01137	0.02608	0.10662
	November	0.0058	0.01671	0.00011	0.00074	0.01049	0.02728
	December	0.00221	0.00727	0.00004	0.00014	0.00632	0.01199

Generally, the error of interpolation in winter is smaller than that in summer, which is similar to the results obtained by Smith et al. [40] using numerical models. This is mainly because the variation range of sea ice data in winter is small, while that in summer is large. In addition, Goessling et al. [41] demonstrated that the predictability of sea ice is low on the monthly time scale of the entire Arctic from summer to autumn. Figure 10 shows the RMSE comparison of target interpolation resolution $0.25^\circ \times 0.25^\circ$. It can be seen from the figure that the algorithm interpolation error is the smallest and stable in the Gaussian model (CK), and the interpolation error is kept in a low range for the 10 months of interpolation. It can also be seen from the figure that the performance of the algorithm is not only related to

the covariable but also closely related to the variation function. When an inappropriate algorithm or theoretical model is selected, RMSE has a large oscillation amplitude and low interpolation accuracy, which is mainly reflected in the fact that the interpolation error of the Spherical model (CK) is much larger than that of the Gaussian model (CK) and Spherical model (OK). In addition, the prediction effect of early and late summer is worse than that of other months, which is similar to the sea ice prediction results by Horvath et al. [42], who used a Bayesian logistic regression algorithm. The overall performance can be ordered as follows: Gaussian model (CK) > Spherical model (OK) > Gaussian model (OK) > Spherical model (CK).

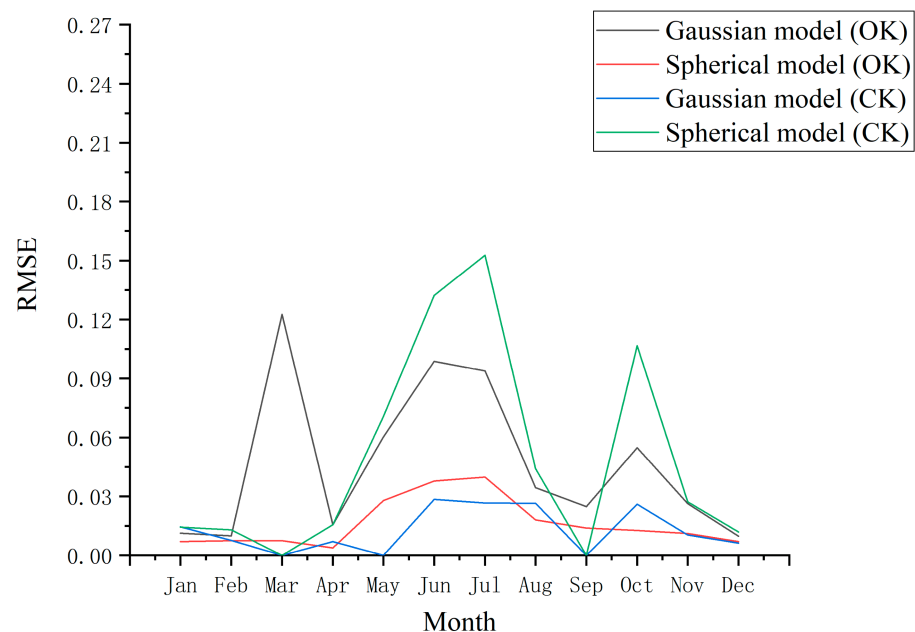


Figure 10. Monthly RMSE comparison for SIC interpolation from $0.5^\circ \times 0.5^\circ$ to $0.25^\circ \times 0.25^\circ$ using different models.

4.2.2. Interpolation Test 2: Spatial Resolution of $0.25^\circ \times 0.25^\circ$

Figure 11 shows the distribution of selected original SIC data with a spatial resolution of $0.25^\circ \times 0.25^\circ$, and the corresponding SIC distribution with a spatial resolution of $0.125^\circ \times 0.125^\circ$ after using OK interpolation. The selected months, January, April, July, and October, represent stable winter ice, spring transition, summer ice fluctuation, and autumn freeze-up conditions, respectively. By comparison with the original SIC data, when the source data is stable with small fluctuations, the interpolation accuracy is high. For example, in January and April, the interpolation results obtained by both the Gaussian model (OK) and the Spherical model (OK) fluctuate within a small range and are highly consistent with the source data. When the source data fluctuates greatly, such as in July and October, the Spherical model (OK) performs better than the Gaussian model (OK). Even if the source data fluctuates greatly, the Spherical model (OK) can still capture its data characteristics, and the interpolation results are highly consistent with the source data.

As can be seen from Figure 12, the Gaussian model (CK) shows larger interpolation fluctuations in April, July, and October. The reason is that the source data in these months have large fluctuations, and the Gaussian model is not good at high-resolution interpolation in high-latitude regions. In the Spherical model (CK), the overall interpolation result fluctuates within a smaller range in the selected months, which is consistent with the OK algorithm. When the spatial resolution of data interpolation is $0.125^\circ \times 0.125^\circ$, the performance of the Spherical model (CK) is better than that of the Gaussian model (CK).

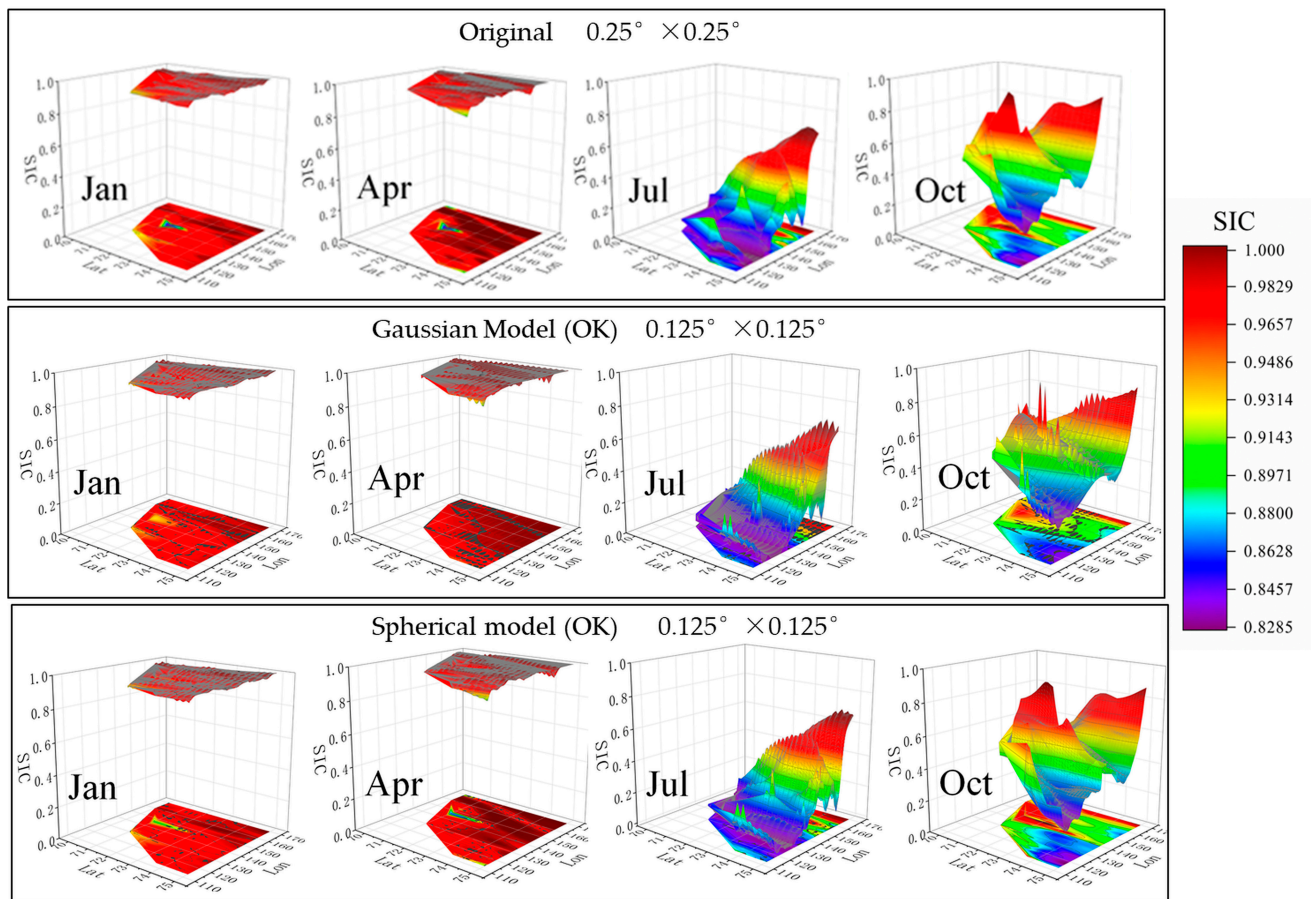


Figure 11. Distribution of original SIC data and OK interpolation for January, April, July, and October.

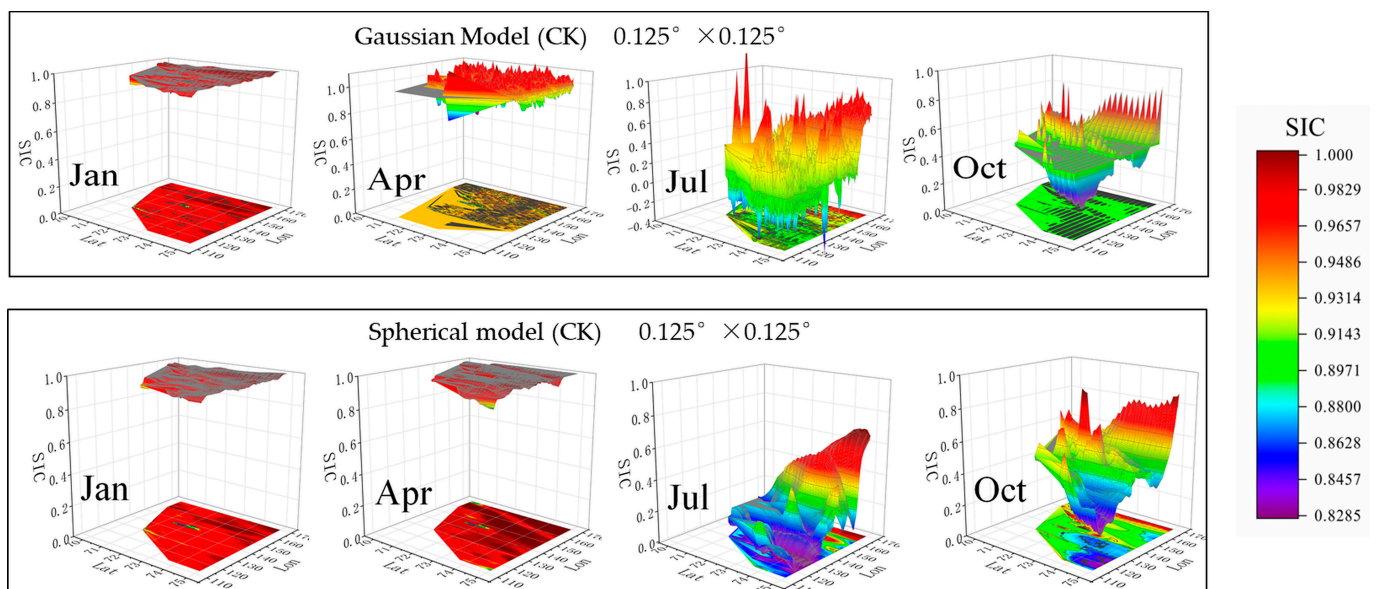


Figure 12. Distribution of CK interpolation for January, April, July, and October.

Through the above analysis and comparison, the performance of the Spherical model is superior to that of the Gaussian model when the interpolation resolution of $0.125^\circ \times 0.125^\circ$ is obtained after the interpolation resolution of $0.25^\circ \times 0.25^\circ$. The reason is that when the interpolation resolution is improved, the physical distance at high latitudes is more in line with the spherical model and can better leverage the advantages of high latitudes. In addition, when Wei et al. [14] used LSTM to forecast sea ice, it was found that due to

the large errors in ice concentration and ice margin, the prediction precision in October was low, and the Spherical model (OK) in this study performed well in interpolating fine prediction in October, which also reflects the satisfactory performance of the interpolation algorithm. Comprehensive analysis shows that the overall performance of the four models is ordered as follows: Spherical model (OK) > Spherical model (CK) > Gaussian model (OK) > Gaussian model (CK).

4.2.3. Interpolation Test 3: Spatial Resolution of $0.05^\circ \times 0.05^\circ$

Table 5 shows the data accuracy of $0.05^\circ \times 0.05^\circ$ based on the spatial resolution of $0.25^\circ \times 0.25^\circ$ SIC data interpolation. By comparing the interpolation errors of the Gaussian model (OK) and the Spherical model (OK), the MAE of the Spherical model in 12 months is much smaller than that of the Gaussian model. The MAE of the Gaussian model (OK) with the maximum interpolation error in 12 months is about 0.18221 in October, while that of the Spherical model (OK) is about 0.04749. The interpolation accuracy is about 3.84 times that of the Gaussian model (OK). In addition, the MAE of the spherical model (OK) is within a very small range, and the interpolation accuracy is about 3.43, 3.67, and 7.25 times higher than that of the Gaussian model (OK) from March to May, respectively. By comparing the interpolation errors of the Gaussian model (CK) and the Spherical model (CK), the MAE of the Spherical model in 12 months is smaller than that of the Gaussian model. The MAE of the Gaussian model (CK) is about 0.18029 in July, with the maximum interpolation error in 12 months, while that of the Spherical model (CK) is about 0.01746. The interpolation accuracy is about 10.33 times higher than that of the Gaussian model (CK). By comparing the interpolation errors of the Spherical model (OK) and the Spherical model (CK), the size of the interpolation errors of the Spherical model (OK) fluctuates. In April-June, August, and November-December, the MAE of the Spherical model (OK) is smaller than that of the Spherical model (CK), and in the remaining months, the MAE is larger than that of the Spherical model (CK). Moreover, the absolute MAE of the two models in all months is smaller than 0.022. The spherical semi-variogram model yields a much smaller fitting-loss value than the Gaussian model, consistent with the results from the $0.25^\circ \times 0.25^\circ$ to $0.125^\circ \times 0.125^\circ$ interpolation test.

Table 5. Based on the spatial resolution of $0.25^\circ \times 0.25^\circ$ original data interpolation, the accuracy comparison of the target spatial resolution of $0.05^\circ \times 0.05^\circ$ data was obtained.

	Month	MAE		MSE		RMSE	
		Gaussian model	Spherical model	Gaussian model	Spherical model	Gaussian model	Spherical model
OK	January	0.00884	0.00634	0.00023	0.00015	0.01511	0.01214
	February	0.00719	0.00512	0.00018	0.00013	0.01335	0.01137
	March	0.01223	0.00356	0.00036	0.00009	0.01908	0.00955
	April	0.01124	0.00306	0.00042	0.00009	0.02052	0.00967
	May	0.02924	0.00403	0.00295	0.00015	0.05432	0.01220
	June	0.08162	0.03512	0.01347	0.00302	0.11604	0.05491
	July	0.08107	0.03303	0.01299	0.00272	0.11399	0.05215
	August	0.01697	0.00864	0.00189	0.00098	0.04345	0.03133
	September	0.00798	0.00318	0.00069	0.00035	0.02628	0.01860
	October	0.18221	0.04749	0.05124	0.00532	0.22637	0.07295
	November	0.02095	0.01205	0.00089	0.00040	0.02991	0.02009
	December	0.01270	0.00445	0.00038	0.00009	0.01943	0.00964

Table 5. Cont.

		MAE		MSE		RMSE	
CK	January	0.01460	0.00376	0.00051	0.00009	0.02257	0.00927
	February	0.01676	0.00392	0.00075	0.00010	0.02732	0.00978
	March	—	—	—	—	—	—
	April	0.01870	0.01862	0.00075	0.00075	0.02745	0.02738
	May	0.06111	0.06116	0.00921	0.00921	0.09596	0.09596
	June	0.08480	0.03728	0.01613	0.00314	0.12702	0.05608
	July	0.18029	0.01746	0.04296	0.00087	0.20727	0.02950
	August	0.01900	0.01624	0.00248	0.00182	0.04983	0.04269
	September	—	—	—	—	—	—
	October	0.04948	0.02616	0.00747	0.00271	0.08640	0.05201
	November	0.02961	0.02955	0.00152	0.00152	0.03897	0.03894
	December	0.01496	0.01616	0.00047	0.00052	0.02172	0.02275

Figure 13 shows the monthly RMSE of SIC fields refined to a spatial resolution of $0.05^\circ \times 0.05^\circ$. As indicated in Figure 13, Ordinary Kriging (OK) with a spherical semi-variogram achieves the lowest RMSE in winter and the transition seasons, when sea-ice coverage is relatively extensive. This method also adapts well to month-to-month variability in SIC, achieving stable performance across the annual cycle. This behaviour is consistent with the additional refinement experiment in which SIC is downscaled from $0.25^\circ \times 0.25^\circ$ to $0.125^\circ \times 0.125^\circ$, where the spherical model likewise outperforms the Gaussian model.

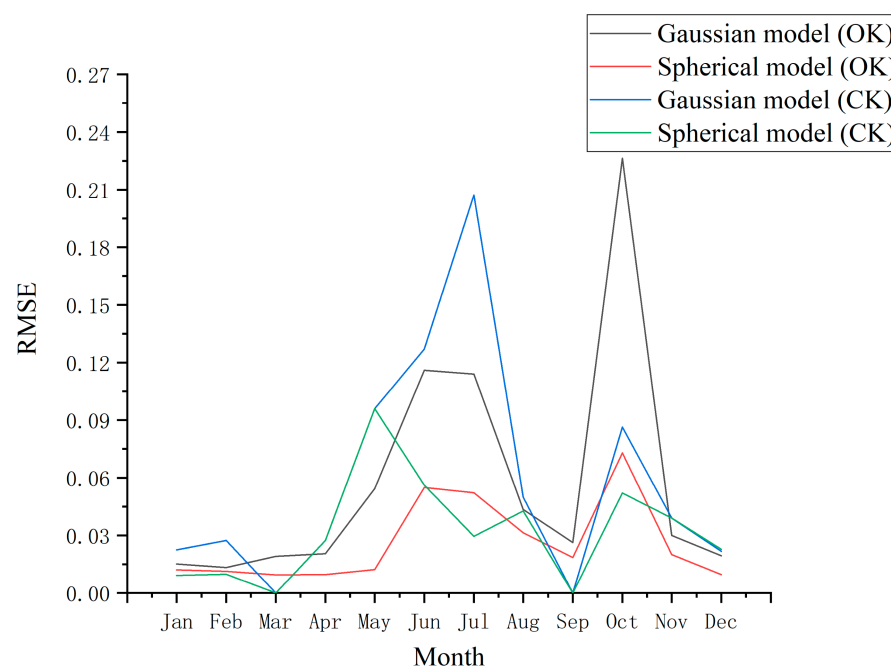


Figure 13. Monthly RMSE comparison for SIC interpolation from $0.25^\circ \times 0.25^\circ$ to $0.05^\circ \times 0.05^\circ$ using OK and CK with Gaussian and spherical semi-variogram models.

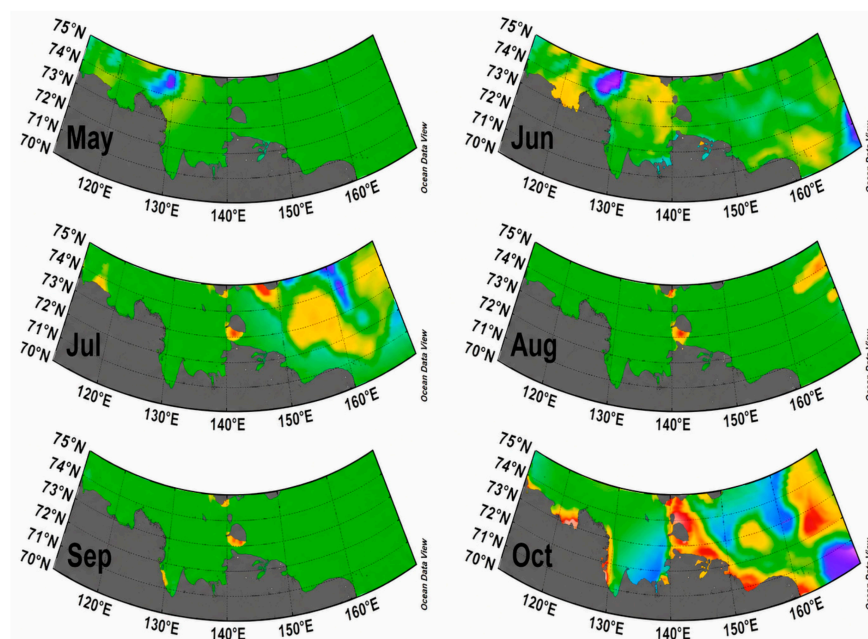
By comparing the refinement results for the two target resolutions (0.125° and 0.05°), we find that the advantage of the spherical semi-variogram becomes more pronounced as the target grid becomes finer. Moreover, OK generally performs better than Co-Kriging (CK) in the studied domain. Although previous studies report that CK can outperform OK when the covariates exhibit stable and moderate-to-strong spatial correlation with the primary variable, the added benefit of CK is not consistently observed here because the covariate–SIC relationships are strongly seasonal and can be weak or spatially uniform

in certain months, which reduces the robustness of cross-variogram estimation and limits the improvement from CK. However, Lim and Wu [25] show that Co-Kriging (CK) is not universally superior to Ordinary Kriging (OK) across different formulations and application cases. In our $0.25^\circ \times 0.25^\circ$ to $0.05^\circ \times 0.05^\circ$ refinement evaluation, the overall performance of the tested configurations can be ranked as follows: Spherical (OK) > Spherical (CK) > Gaussian (OK) > Gaussian (CK).

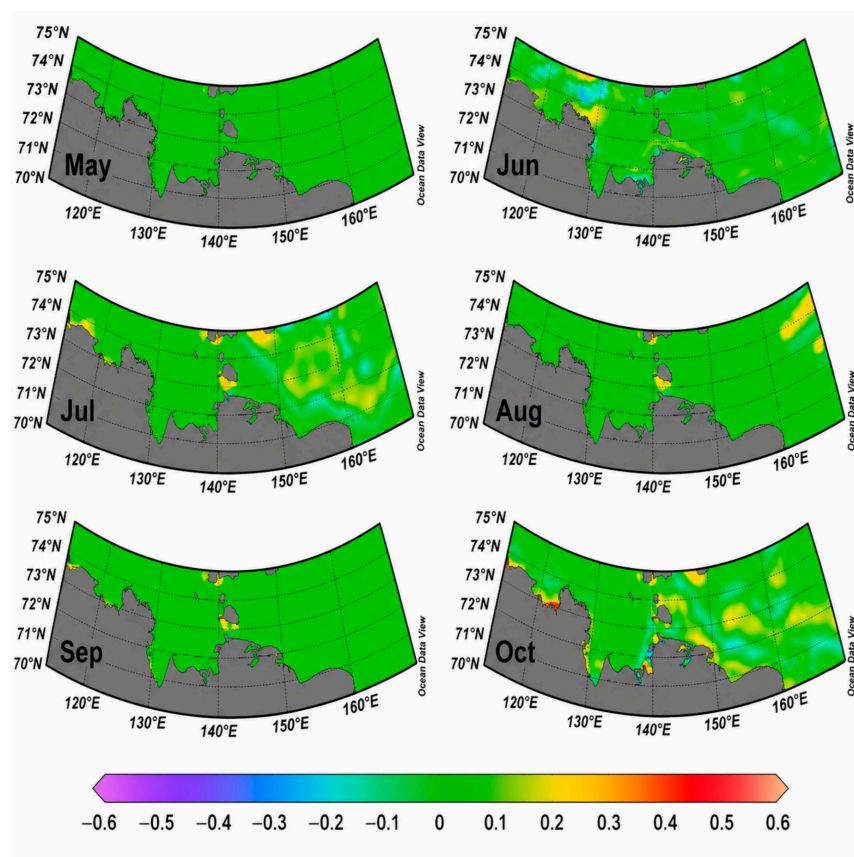
To understand the spatial interpolation error distribution in the study area, Figures 14 and 15 show the spatial distribution of the difference between the observed value of OK and CK interpolation resolution of $0.05^\circ \times 0.05^\circ$ and the interpolation result, respectively. Figures 14 and 15 are drawn using Ocean Data View 5.8.2 [43] software. The colour bar in the figure indicates that if the result is smaller than 0, the interpolation result is higher than the observed value; otherwise, it is smaller than the observed value. These two figures only show the results for the May–October period, since differences for the remaining months are generally close to zero. The results show that the concentration error of the coastal margin ice area near the Eurasian continent is more frequent. Physically, sea ice advection, ocean heat transport, and polar air–sea interaction are extremely active in coastal marginal ice areas [44], making sea ice dynamics relatively complex and more changeable. As can be seen from Figure 14, most of the error values are within $-0.1 \sim 0.1$, and the interpolation effect of the Spherical model is much better than that of the Gaussian model. In Figure 14a, the absolute value of error from May to July and October reaches 0.6, which is a relatively high interpolation error range. In addition, the areas with the absolute value of error larger than 0.1 in July are mostly concentrated in the East Siberian Sea and are far away from the coastal areas, which has little impact on sailing ships. The areas with the absolute value of error larger than 0.1 in October are mostly distributed in the coastal areas of Eurasia and the New Siberian Islands, which would have a great impact on the nearby navigating ships. Compared with the area with larger errors in Figure 14b, the accuracy of June, July, and October in Figure 14b has been greatly improved, and in all 12 months, the maximum absolute error is around 0.4.

It can be seen from Figure 15a that the absolute values of interpolation errors in July are all larger than 0.1, and most of them are around -0.15 , which is higher than the observed values. However, there is a wide water area where the error is larger than 0.2 in the East Siberian Sea. Overall, the effect of July interpolation in the Gaussian model (CK) is not good. By comparing Figure 15a,b, the interpolation effect of the Spherical model is better than that of the Gaussian model, and the result is similar to that of the OK algorithm. The analysis reflects the potential of kriging in predicting SIC for an entire year by performing an error analysis on three sets of trials.

Interpolation errors are generally lower in winter, when the SIC field is spatially more homogeneous and exhibits stronger and more stable spatial autocorrelation. Higher errors occur during spring melt and autumn freeze-up, when the marginal ice zone migrates rapidly and SIC gradients intensify, leading to stronger small-scale variability that is more difficult to reproduce through spatial refinement. In this context, Gaussian semi-variograms tend to fit smoothly varying SIC fields, whereas spherical models, with a finite correlation range, better capture the spatial dependence structure at high latitudes, which explains their improved performance when refining to finer grids.

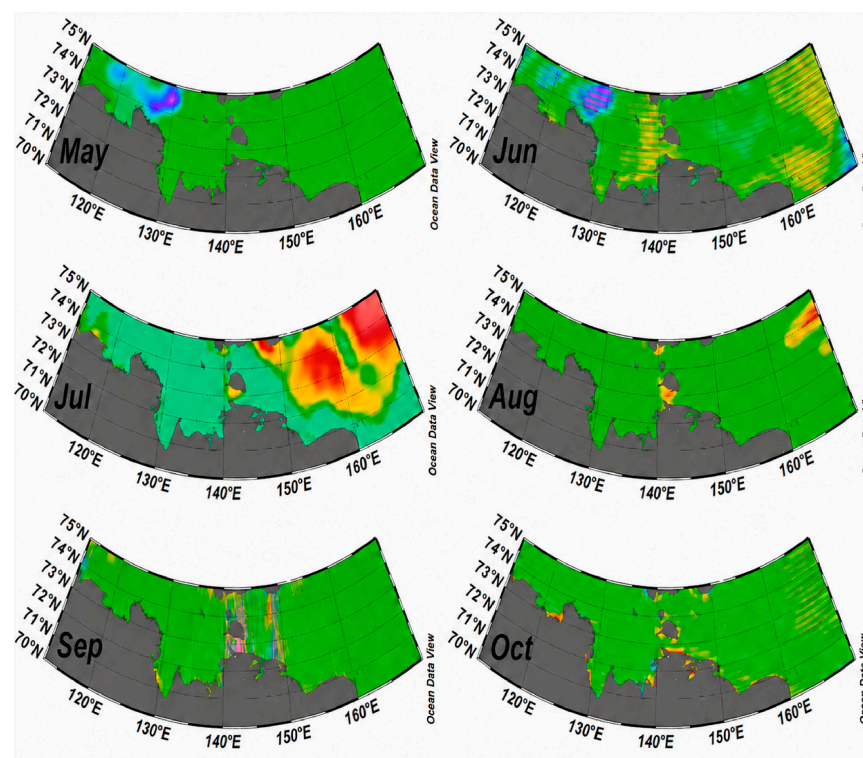


(a) Gaussian Model (OK)

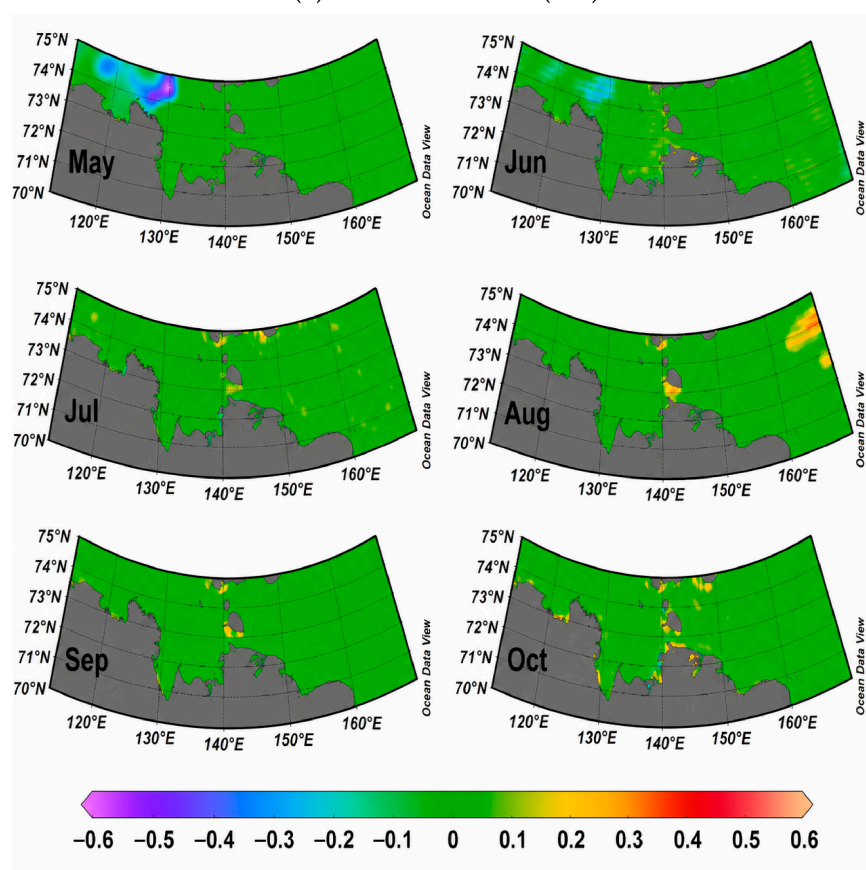


(b) Spherical model (OK)

Figure 14. The spatial distribution of the difference between the observations and the interpolation results with the interpolation resolution of $0.05^\circ \times 0.05^\circ$ for the May–October period, which is obtained by the OK algorithm based on data of $0.25^\circ \times 0.25^\circ$.



(a) Gaussian Model (CK)



(b) Spherical model (CK)

Figure 15. The spatial distribution of the difference between the observations and the interpolation results with the target interpolation resolution of $0.05^\circ \times 0.05^\circ$ for the May–October period, which is obtained by the CK algorithm based on data of $0.25^\circ \times 0.25^\circ$.

4.3. Spatiotemporal Prediction of SIC During Summer

In this section, we perform a spatiotemporal test by sequentially coupling the LightGBM temporal forecasts with Kriging-based spatial refinement and then comparing the refined SIC fields with the independent 0.05° benchmark dataset. Since the spherical Co-Kriging (CK) configuration provides the best interpolation performance in July, we choose this method to conduct spatial interpolation on predicted SIC information. The daily SIC prediction on the coarse $0.25^\circ \times 0.25^\circ$ grid over the NSR subregion will be downscaled from 0.25° to 0.05° , using the auxiliary variable identified earlier (MSLP) as covariates in the CK. Semi-variogram (and cross-variogram) parameters are fitted following the same monthly strategy as in the interpolation module, with July statistics used as the dominant reference to match the timing of the test window. Figure 16 presents the daily geographical distribution of SIC errors over the selected NSR sector for the 6-day evaluation period from 27 July to 1 August 2022. The domain-mean RMSE remains relatively stable across the period, ranging from 0.0885 (27 July) to 0.105 (1 August), indicating consistent short-term performance with a modest degradation toward the end of the forecast window. Spatially, the largest errors are not uniformly distributed but concentrate in the eastern part of the study region, where SIC gradients are strong and the marginal ice zone is present. The results show that the spatiotemporal prediction is accurate enough for further application.

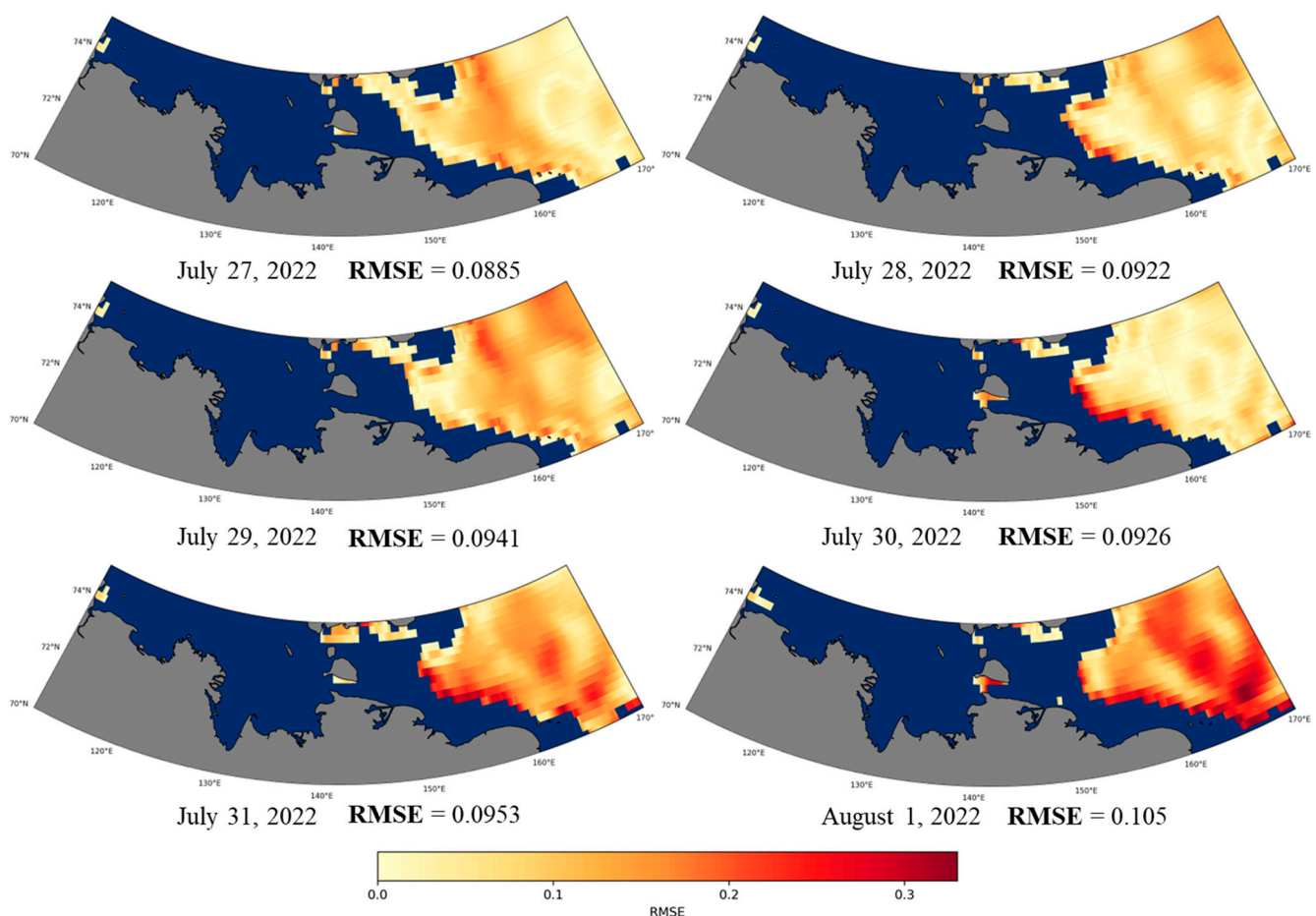


Figure 16. The RMSE distribution of the 6-day prediction of SIC.

5. Conclusions

This study develops a unified, data-driven spatiotemporal framework for reconstructing high-resolution gridded Arctic sea ice concentration (SIC) fields over the Northern Sea Route (NSR) sector by sequentially coupling feature-engineered LightGBM-based temporal

forecasting with Kriging-based spatial interpolation. The workflow first generates temporally consistent SIC estimates on a coarse grid and then downscales each forecast time slice to a finer grid while preserving spatial coherence, thereby providing SIC information that is more suitable for further applications.

For the temporal module, the LightGBM model is trained with daily SIC and exogenous covariates (SST, SP, and MSLP) from 1 January 2021 to 26 July 2022 and is evaluated for a six-day forecast window (27 July to 1 August 2022) using a recursive multi-step strategy with rolling-window features to avoid information leakage. The model achieves an area-mean RMSE of 0.097 for the six-day forecasts, and the one-day lead RMSE is as low as 0.031. For the spatial module, systematic experiments across multiple target resolutions and seasons show that interpolation performance depends strongly on both the semi-variogram formulation and the availability and stability of covariates. Co-Kriging is not universally superior to Ordinary Kriging; for high-latitude domains and target resolutions finer than $0.25^\circ \times 0.25^\circ$, spherical semi-variograms generally outperform Gaussian formulations and often yield lower interpolation errors. A coupled summer case study further demonstrates the end-to-end capability of the framework: after spatial refinement to $0.05^\circ \times 0.05^\circ$ resolution and benchmarking against an independent high-resolution product, the domain-mean error remains stable across the six-day period (0.0885–0.105), with the largest errors concentrated in the eastern marginal ice zone where SIC gradients are strongest.

The sequential coupling of LightGBM and Kriging provides a practical pathway for generating high-resolution SIC fields by applying geostatistical refinement to temporally consistent SIC estimates, with quantifiable prediction and interpolation errors. Future work should incorporate additional physically meaningful covariates and richer evaluation protocols to better characterize the coupled spatiotemporal uncertainty and further explore real-time SIC prediction by combining machine learning and Kriging, including potential application to remote sensing SIC products.

Author Contributions: Conceptualization, W.T. and C.Z.; methodology, S.F.; software, W.T.; validation, W.T., F.Z. and H.H.; formal analysis, C.Z.; investigation, W.T.; resources, S.F.; data curation, W.T.; writing—original draft preparation, W.T.; writing—review and editing, S.F.; visualization, F.Z.; supervision, H.H.; project administration, W.T.; funding acquisition, W.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Swedish Lighthouse Competence Center grant (FY26-04); the Fund of Guangxi Science and Technology Program (GuikeLT2504240033); the Guangxi Natural Science Foundation (2025GXNSFHA069259; 2026GXNSFHA00640291); the Guangxi Science and Technology Major Program (GuikeJB2502850005); and the Guangxi Maritime Economy Talent Development Support Special Program (2025XHRC06).

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy/ethical restrictions.

Conflicts of Interest: Author Haofan Hu was employed by the company Shipping Specialized Carriers Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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