



1 Similar-Year Feature Construction Improves Deep-Learning 2 Arctic Sea Ice Forecasts

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13 **Abstract.** Seasonal Arctic sea ice prediction is important for understanding Arctic climate change and its impacts.
14 Existing deep-learning models commonly use the multi-year mean climatology of the forecast period as a historical-
15 evolution background. This provides stable seasonal information, but has limited ability to represent interannual
16 differences in sea ice evolution. We propose a dynamic similar-year feature construction method based on sea ice
17 spatial similarity and incorporate it into the SwinUNet forecasting framework. Using sea ice concentration (SIC) at
18 forecast initialization and the Intersection over Union (IoU) of sea ice extent (SIE), the method identifies the most
19 similar historical year since 1979 and extracts its SIC evolution over the forecast period as the historical-evolution
20 feature. Continuous SIC and sea ice thickness (SIT) from the preceding four months are also included, combining
21 recent conditions with historical same-period evolution. Using NSIDC SIC and PIOMAS SIT data from 1979 to 2024,
22 four-month Arctic sea ice forecasts are conducted at pentad intervals. The Similarity scheme is compared with
23 Continuous and Climatology features in SwinUNet, as well as Persistence and ECMWF SEAS5. Similarity generally
24 outperforms Continuous and Climatology. Over the first 12 forecast periods, it reduces MAE by 5.41% and 6.97%,
25 improves ACC by 1.63% and 4.03%, and increases BACC by 0.09% and 0.42%, respectively. Relative to Persistence
26 and SEAS5, the annual-mean MAE decreases by 22.19% and 42.24%, while BACC improves by 4.67% and 8.43%.
27 These results show that dynamic similar-year features can enhance SwinUNet skill without increasing model
28 complexity.

29 1 Introduction

30 Arctic sea ice is an important component of the global climate system. Its changes not only substantially affect surface
31 energy exchange and atmospheric circulation, but also have direct implications for Arctic ecosystems and navigation
32 safety. Over the past several decades, continuous global warming has led to a significant decline in Arctic sea ice
33 extent (SIE) and thickness, accompanied by increasing interannual variability in sea ice conditions (Serreze and
34 Stroeve, 2015; Notz and Stroeve, 2016). These rapid changes pose increasing challenges to the predictability of future
35 sea ice evolution, particularly beyond the range of short-term forecasts (Bushuk et al., 2020; Bonan et al., 2019).



Therefore, accurate prediction of sea ice concentration (SIC) on subseasonal-to-seasonal timescales remains challenging. Improving predictive skill at these timescales is important for extending the useful lead time of sea ice forecasts, enhancing climate prediction, and supporting human activities such as Arctic navigation.

Traditional sea ice prediction has mainly relied on dynamical numerical models, such as the Pan-Arctic Ice Ocean Modeling and Assimilation System (PIOMAS), the Los Alamos Sea Ice Model (CICE), and the operational seasonal prediction system SEAS5 of the European Centre for Medium-Range Weather Forecasts (ECMWF) (Zhang and Rothrock, 2003; Hunke and Lipscomb, 2010; Stockdale et al., 2018). These models predict future sea ice conditions by coupling atmospheric, oceanic, and sea ice processes. Although substantial progress has been made in recent years, their predictive capability remains affected by factors such as forcing errors and model parameterization schemes. This limitation is particularly evident during the rapid summer sea ice melt season, when forecast skill tends to decline markedly (Bushuk et al., 2019; Wayand et al., 2019; Bushuk et al., 2024).

With the development of deep-learning techniques, their applications to sea ice prediction have gradually expanded. Early studies applied long short-term memory (LSTM) networks to SIC prediction. For example, Chi and Kim (2017) used an LSTM model to predict SIC one month ahead, demonstrating the potential of deep-learning methods to predict sea ice conditions based on historical sea ice information. Subsequently, convolutional neural networks (CNNs) were applied to SIC prediction, where spatial feature extraction improved the representation of the spatial distribution of sea ice (Kim et al., 2020). Building on these approaches, spatiotemporal deep-learning models such as ConvLSTM further combined convolutional operations with recurrent memory mechanisms to predict SIC (Liu et al., 2021). In recent years, U-Net and Transformer architectures have also been applied to seasonal sea ice prediction. IceNet employs a CNN-based U-Net architecture to predict the probability of SIE over the following six months (Andersson et al., 2021), while Transformer-based models such as SwinUNet further enhance the representation of spatiotemporal dependencies in sea ice prediction (Ren et al., 2025).

Sea ice prediction covers a range of timescales. Short-term forecasts typically focus on sea ice evolution over the following days to several weeks, during which the current sea ice state exhibits strong persistence and short-term atmospheric and oceanic conditions are the primary factors influencing sea ice changes (Guemas et al., 2016). As the forecast lead time extends to the subseasonal scale (approximately 1–2 months) and seasonal scale (approximately 3–6 months), the influence of the initial sea ice state gradually weakens (Blanchard-Wrigglesworth et al., 2011). To address this issue, existing deep-learning models commonly introduce historical sea ice evolution during the same period as the forecast period on the basis of recent sea ice conditions. The multi-year mean climatology has been widely adopted because it can characterize the stable seasonal cycle (Andersson et al., 2021; Ren et al., 2025). Although climatology provides stable seasonal background information, it essentially represents a multi-year mean state and therefore has limited ability to characterize anomalous evolution in individual years.

To retain the year-specific characteristics contained in historical observations, the principle of historical similarity has been introduced in statistical forecasting studies. This approach identifies historical years with states similar to the current conditions and uses their subsequent evolution as a reference for future changes. Previous studies have shown that similar-year methods can achieve good predictive performance in some medium- to long-range forecasting tasks



and, to some extent, outperform climatology-based forecasts (Delle Monache et al., 2013; Ding et al., 2019; Menary et al., 2021; Rader et al., 2023). Based on this concept, this study introduces the principle of historical similarity into a deep-learning framework for sea ice prediction. Unlike conventional similar-year methods, which directly use the subsequent evolution of similar years for analog-based prediction, the proposed approach dynamically constructs historical same-period evolution features for the forecast period. Specifically, the most similar year is dynamically identified from historical records according to the spatial distribution of SIC at the forecast initialization time, and the corresponding SIC evolution sequence during the forecast period is extracted. This sequence replaces the multi-year mean climatology and is jointly input into the SwinUNet model with recent SIC and sea ice thickness (SIT) features. In this framework, the historical similar year is no longer used as a direct prediction, but rather as a year-specific feature, enabling the deep-learning model to learn the nonlinear relationship between future sea ice changes and the current sea ice state together with historically similar evolution patterns. This study conducts experiments on seasonal Arctic sea ice prediction over a four-month forecast period. Three feature-construction strategies, namely Continuous, Climatology, and Similarity, are systematically compared. The proposed approach is further evaluated against the Persistence baseline and the operational seasonal prediction system SEAS5 of the ECMWF.

2 Data

2.1 NSIDC Sea Ice Concentration Data

This study uses SIC data from 1979 to 2024 as the experimental dataset. The data are provided by the National Snow and Ice Data Center (NSIDC) and are derived from satellite observations, including daily SIC observations from the Nimbus-7 Scanning Multichannel Microwave Radiometer (SMMR), as well as the Special Sensor Microwave Imager (SSM/I) and Special Sensor Microwave Imager/Sounder (SSMIS) aboard the Defense Meteorological Satellite Program (DMSP) satellites (DiGirolamo et al., 2022). The data are provided on a North Polar Stereographic projection with a spatial resolution of 25 km. Missing values in the central pole-hole region caused by limitations in satellite observation geometry were interpolated in this study. The daily SIC data were then averaged into 5-day pentad means, which were used as both model inputs and reference data for forecast verification.

2.2 PIOMAS Sea Ice Thickness Data

SIT data were obtained from the reanalysis product of the Pan-Arctic Ice Ocean Modeling and Assimilation System (PIOMAS). PIOMAS is a coupled sea ice–ocean numerical model that assimilates SIC and sea surface temperature (SST) data to improve the simulation of sea ice conditions (Zhang and Rothrock, 2003). Previous studies have shown that PIOMAS SIT is in good agreement with in situ, airborne, and satellite observations (Schweiger et al., 2011). The dataset provides daily products with a spatial resolution of approximately 18 km. In this study, the PIOMAS SIT data were reprojected onto the same North Polar Stereographic projection as the NSIDC SIC data and resampled to the



106 same 25 km spatial resolution. The temporal resolution of both datasets was then converted to the pentad scale to
 107 ensure consistency in their spatial and temporal dimensions. The processed SIT data were used as an additional sea
 108 ice state feature alongside SIC. Together with the current SIC and the SIC sequence from the historical similar year,
 109 these features were jointly input into the SwinUNet model to provide additional constraints on the initial sea ice state
 110 for future SIC prediction.

111 **3 Method**

112 **3.1 SwinUNet Model**

113 The SwinUNet model combines the Swin Transformer with a U-Net encoder–decoder architecture (Cao et al., 2023),
 114 extracting local and cross-window features through window self-attention and shifted window mechanisms (Liu et al.,
 115 2021), while preserving features at different spatial scales via multi-scale encoding and skip connections. The Arctic
 116 sea ice field exhibits significant spatial heterogeneity and multi-scale variation characteristics (Serreze and Stroeve,
 117 2015), and this architecture has been applied to Arctic sea ice prediction with favorable performance (Ren et al., 2025).
 118 Building upon the application of Ren et al. (2025) in seasonal-scale sea ice prediction, this study further adopts this
 119 architecture and conducts subseasonal-to-seasonal scale sea ice prediction by incorporating the dynamic similar-year
 120 features proposed herein.

121 As illustrated in Figure 1, the model overall consists of four parts: Encoder, Bottleneck, Decoder, and Output Head.
 122 The input sequence is assembled from two complementary 24 pentad windows: the most recent 24 pentads and a 24-
 123 pentad evolution window identified from the dynamically selected similar year, as introduced in the next section. First,
 124 the input multivariate sea ice data sequence is converted into token features through Patch Embedding. For each pentad,
 125 sine and cosine seasonal encodings are constructed based on its intra-annual temporal position and input into the model
 126 as additional temporal features to represent the seasonal phase corresponding to different time steps. The encoder
 127 comprises 4 Swin Transformer stages, achieving multi-scale sea ice feature extraction by progressively reducing
 128 spatial resolution and increasing feature channels. Each stage consists of several Swin Transformer Blocks, and down
 129 sampling between adjacent stages is implemented via Patch Merging.

130 Balancing model computational cost and prediction performance, the network depths of the 4 stages in the encoder
 131 are set to 2, 2, 6, and 2, respectively, with corresponding attention heads of 3, 6, 12, and 24, and a window size of 7.
 132 Down sampling is performed between stages using 3 Patch Merging modules, each reducing the spatial resolution to
 133 1/2 of its original size while increasing the feature channels. After the 4 encoding stages, the features enter the
 134 bottleneck layer, which consists of 2 Swin Transformer Blocks used to further extract high-level features.

135 Subsequently, the encoded multi-scale features enter the decoder, where spatial resolution is progressively restored
 136 via Patch Expanding. The green Up Stage 4, Up Stage 3, Up Stage 2, and Up Stage 1 modules in Figure 1 correspond
 137 to the combinations of Patch Expanding and Swin Transformer Blocks in the decoder, where Patch Expanding is
 138 responsible for the stepwise upsampling of feature maps. At each decoding level, features from the corresponding
 139 encoding stage are concatenated with the upsampled features via skip connections to recover spatial details lost during



140 encoding and fuse sea ice features at different scales. After stepwise upsampling, the feature map restores the spatial
 141 scale of the initial Patch Embedding.
 142 Finally, the output head first uses Patch Expanding to further restore the spatial resolution, and then converts the
 143 feature channels into the output channels corresponding to the target prediction period via Output Projection. In the
 144 seasonal prediction setting of this study, the model produces SIC fields spanning the forthcoming 24 pentads. The
 145 prediction results are then restored to the target SIC data's spatial resolution using bilinear interpolation, and the output
 146 is constrained to 0–1 using the Sigmoid function to obtain the final SIC prediction results. This SwinUNet structure
 147 is maintained across all forecasting experiments in this study to ensure comparability among different historical feature
 148 input schemes.

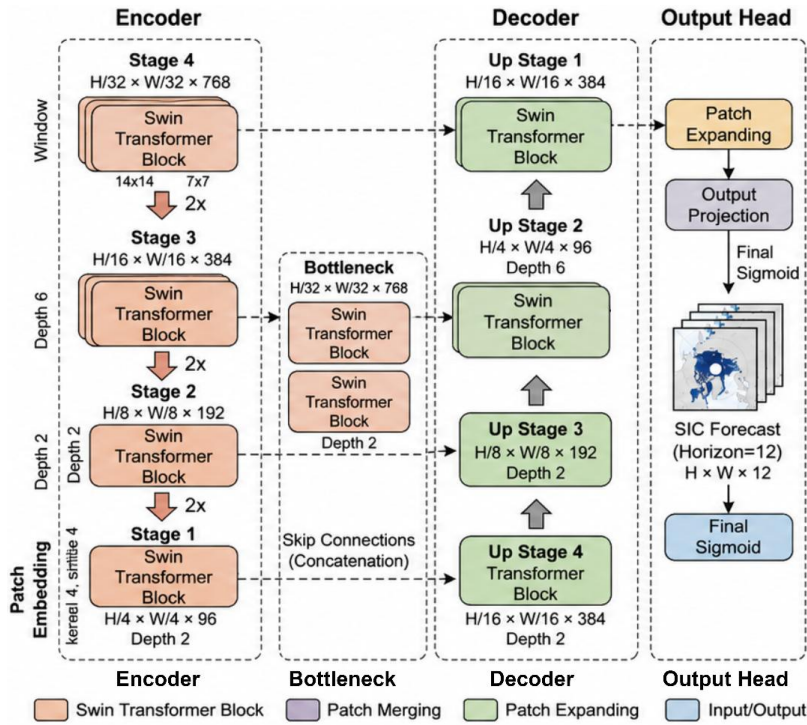


Figure 1: SwinUNet Architecture for SIC Forecasting.

3.2 Dynamic Similar-Year Feature Construction Scheme

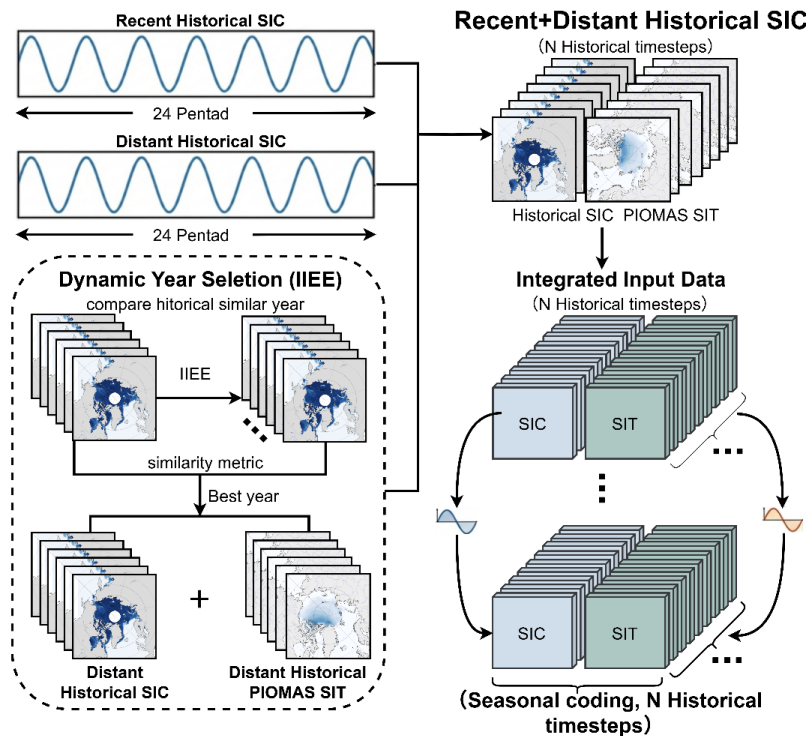
Unlike previous models that adopt the multi-year mean climatology of the forecast period as the historical contemporaneous evolution window (Andersson et al., 2021; Ren et al., 2025), this study dynamically constructs historical contemporaneous evolution windows based on historical SIC data since 1979. For each prediction sample, the Intersection over Union (IoU) similarity between the spatial distribution of SIC at the current initialization time and that of historical years for the same period is first calculated, and the historical year with the highest similarity is selected as the similar year k^* :



$$k^* = \arg \max_{k \in \{1, \dots, K\}} \text{IoU}(S_{t_0}, S_{t_0-k}), \quad (1)$$

where S_{t_0} and S_{t_0-k} represent the SIC field at the initialization time and that of the same period in the k -th year, respectively. To highlight the spatial distribution characteristics of sea ice, the SIC field is first binarized using a 15% SIC threshold; that is, grids with an SIC greater than 0.15 are defined as sea ice, and grids with an SIC less than or equal to 0.15 are defined as open water. On this basis, the Intersection over Union (IoU) is employed to measure the consistency of the spatial distribution of sea ice between the current year and historical years for the same period. Its values range from 0 to 1, where higher values indicate a higher degree of spatial overlap and stronger similarity. K denotes the number of historical years that can be retraced prior to the forecast year, and $\arg$ represents the independent variable corresponding to the maximum value. k^* is the year with the largest IoU among all candidate historical years—namely, the historical year whose sea ice spatial distribution is most similar to the current initialization time—and is determined as the similar year for that prediction sample.

Subsequently, the contemporaneous sea ice evolution sequence corresponding to the selected similar year and the forecast period is extracted to construct the historical contemporaneous evolution window. For example, if the current prediction sample is initialized at the 2nd pentad of August in a given year, the similar year is identified based on the IoU similarity of the SIC spatial distribution between the current time and the same period of historical years, and the SIC evolution sequence from the 3rd pentad of August of that similar year through the subsequent forecast period is extracted to serve as the historical contemporaneous evolution background for the current prediction sample. For the 4-month-ahead forecasts conducted in this study, corresponding historical SIC sequences of 24 pentads are extracted. Similar to Ren et al. (2025), this study further incorporates PIOMAS SIT features to enhance the model's representation capability for the sea ice state and its evolutionary process, thereby providing additional sea ice state features to mitigate the Spring Predictability Barrier (SPB). Specifically, the pentad-by-pentad SIC and SIT over the four months preceding the initialization time are used as recent historical state features, which are jointly input into the model together with the historical contemporaneous SIC evolution features of the forecast period corresponding to the similar year, with temporal encodings utilized to represent the seasonal phase at different time steps. As shown in Figure 2, the left side illustrates the dynamic similar-year identification and the extraction process of the predicted contemporaneous SIC evolution features, while the right side displays the construction and temporal encoding of input features such as recent historical SIC, SIT, and similar-year historical SIC, which are fed into the model as different channels. For each prediction sample, the similar-year retrieval utilizes only historical data available prior to the forecast initialization time to prevent future data leakage.



187
188 **Figure 2: Schematic illustration of Dynamic Similar-Year Feature Construction: Selection of similar-year input time**
189 **series (left) and integration with seasonal coding and ice thickness data (right).**

190 **3.3 Evaluation metrics**

191 To comprehensively evaluate the model prediction performance, this study employs the Mean Absolute Error (MAE),
192 Binary Accuracy (BACC) based on the Integrated Ice Edge Error (IIEE), and the Detrended Anomaly Correlation
193 Coefficient (Detrended ACC). Specifically, MAE is used to evaluate the prediction accuracy of SIC, BACC is used
194 to evaluate the prediction accuracy of the sea ice edge location, and Detrended ACC is used to evaluate the predictive
195 capability for the interannual variability of SIE.

196 To ensure the consistency of evaluation results, before calculating various metrics, a valid ocean mask is first
197 constructed using the historical maximum SIE for each month since 1979 to uniformly constrain the model prediction
198 results, limiting statistical analysis solely to regions where sea ice coverage has historically been possible. The Mean
199 Absolute Error (MAE) is used to measure the average deviation between the predicted SIC and the observed values,
200 with a smaller value indicating higher prediction accuracy. The Binary Accuracy (BACC) is calculated based on the
201 Integrated Ice Edge Error (IIEE). First, the predicted SIC and observed values are converted into binary sea ice
202 distributions using a SIC threshold of 0.15; then, the inconsistent area of the ice edge location between the prediction
203 and observation (IIEE) is calculated. Subsequently, taking the area of the historical maximum SIE coverage region



for the corresponding month as the normalization baseline, BACC is defined as:

$$BACC = \left(1 - \frac{IIEE}{A}\right) \times 100\% \quad (2)$$

where *IIEE* denotes the inconsistent area of the sea ice edge location between the prediction and observation, and *A* represents the area of the historical maximum SIE coverage region for the corresponding month. The closer BACC is to 100%, the more consistent the predicted ice-edge location is with the observed result. This study also uses the Anomaly Correlation Coefficient (ACC) to evaluate the model's predictive capability for interannual variations in sea ice. Specifically, we remove linear trends from the predicted and observed SIE sequences, respectively, and then calculate the correlation coefficient between the resulting anomaly sequences. Detrended ACC more objectively reflects the model's ability to characterize interannual anomalous changes in sea ice and cross-season forecasting skill. All evaluation metrics are calculated on the test set and evaluated using the same historical maximum SIE mask to ensure comparability across prediction models.

4 Experiments and results

4.1 Model training

All models in this study were trained on a computing platform equipped with an NVIDIA L20 GPU (48 GB VRAM). The training, validation, and test sets were constructed using SIC and PIOMAS SIT data from 1979 to 2024, divided chronologically such that the training, validation, and test sets account for 60%, 10%, and 30% of the total samples, respectively. The model prediction results presented herein are all derived from the test set, corresponding to the years 2012–2024. The model inputs consist of SIC and SIT, adopting the similar-year mixed time-lag feature fusion strategy based on SIC-based IoU similarity proposed in Section 3.2. This strategy utilizes the recent historical features of the current year along with the historical contemporaneous evolution features of the forecast period to jointly construct the input features. For seasonal forecasting, the model inputs employ 5-day pentad mean fields to predict the SIC sequence for the next 4 months (24 pentads).

During the training process, a joint loss function proposed by Ren et al. (2025) was adopted, combining the Mean Squared Error (MSE) and the Normalized Integrated Ice Edge Error (NIIEE). Here, MSE is used to constrain the pixel-level prediction error of SIC, while NIIEE measures the spatial discrepancy between the predicted and true sea ice distributions, thereby enhancing the model's capability to preserve the spatial structure of the sea ice edge. The overall loss function is defined as:

$$L = L_{MSE} + 0.01L_{NIIEE} \quad (3)$$

where the weight coefficient 0.01 is used to balance the contributions of NIIEE and MSE during optimization, resulting in a post-balancing NIIEE-to-MSE ratio of approximately 2:1. During model training, the batch size was set to 8, and the initial learning rate was set to 1×10^{-4} . The Adam optimizer was employed for parameter updating, and an Early Stopping strategy was implemented to terminate training prematurely if the validation loss failed to decrease for 10 consecutive epochs, thereby preventing model overfitting.



To evaluate the contribution of the proposed dynamic similar-year feature construction scheme to seasonal-scale sea ice prediction, this study compared the predictive performance of different historical contemporaneous evolution feature construction strategies on SIC over the next four months: (1) Continuous: using only consecutive pentad-by-pentad sea ice observations from the four months preceding the initialization time as historical evolution features; (2) Climatology: using consecutive sea ice observations from the four months prior to the initialization time as short-term historical features, while employing the multi-year mean sea ice evolution sequence corresponding to the forecast period as the historical contemporaneous evolution feature; and (3) Similarity: the method proposed in this study, which—within the same feature construction framework as (2)—dynamically selects a similar year based on sea ice spatial similarity and substitutes the multi-year mean sea ice evolution sequence with the sea ice evolution sequence of the corresponding period in the similar year to construct the historical contemporaneous evolution feature. As shown in Table 1, apart from the historical feature construction strategies, all three sets of experiments adopted the identical SwinUNet architecture, training strategy, and evaluation scheme to ensure that performance differences among experiments stemmed primarily from the distinct historical feature construction strategies.

Table 1. Experimental Settings for Different Historical Feature Construction Schemes

Experiment	Recent Historical Features	Historical Contemporaneous Evolution Features	Unified Parameter Settings
Continuous	Pentad-by-pentad SIC + SIT for the 4 months preceding initialization	None	● Input temporal resolution: 1 pentad ● Forecast duration: 24 pentads ● Batch Size: 8
Climatology	Pentad-by-pentad SIC + SIT for the 4 months preceding initialization	Multi-year mean SIC of the forecast period	● Optimizer: Adam ● Loss function: ● Training epochs: Maximum 100
Similarity	Pentad-by-pentad SIC + SIT for the 4 months preceding initialization	SIC of the corresponding forecast period in the similar year	● Early Stopping: 10 epochs

4.2 Comparison of Sea Ice Prediction Results Among Different Schemes

Figures 3(a, c, e) display the prediction performance of the three methods—Continuous, Climatology, and Similarity—across 24 forecast lead times. Overall, as the forecast lead time extends, the prediction skill of all three methods exhibits a declining trend, manifested by an overall increase in MAE and an overall decrease in ACC and BACC. The advantage of Similarity over Climatology is primarily reflected in the early stage of forecasting: at the 6th pentad, its MAE, ACC, and BACC are lower by 0.63%, higher by 0.31%, and higher by 0.55% compared to



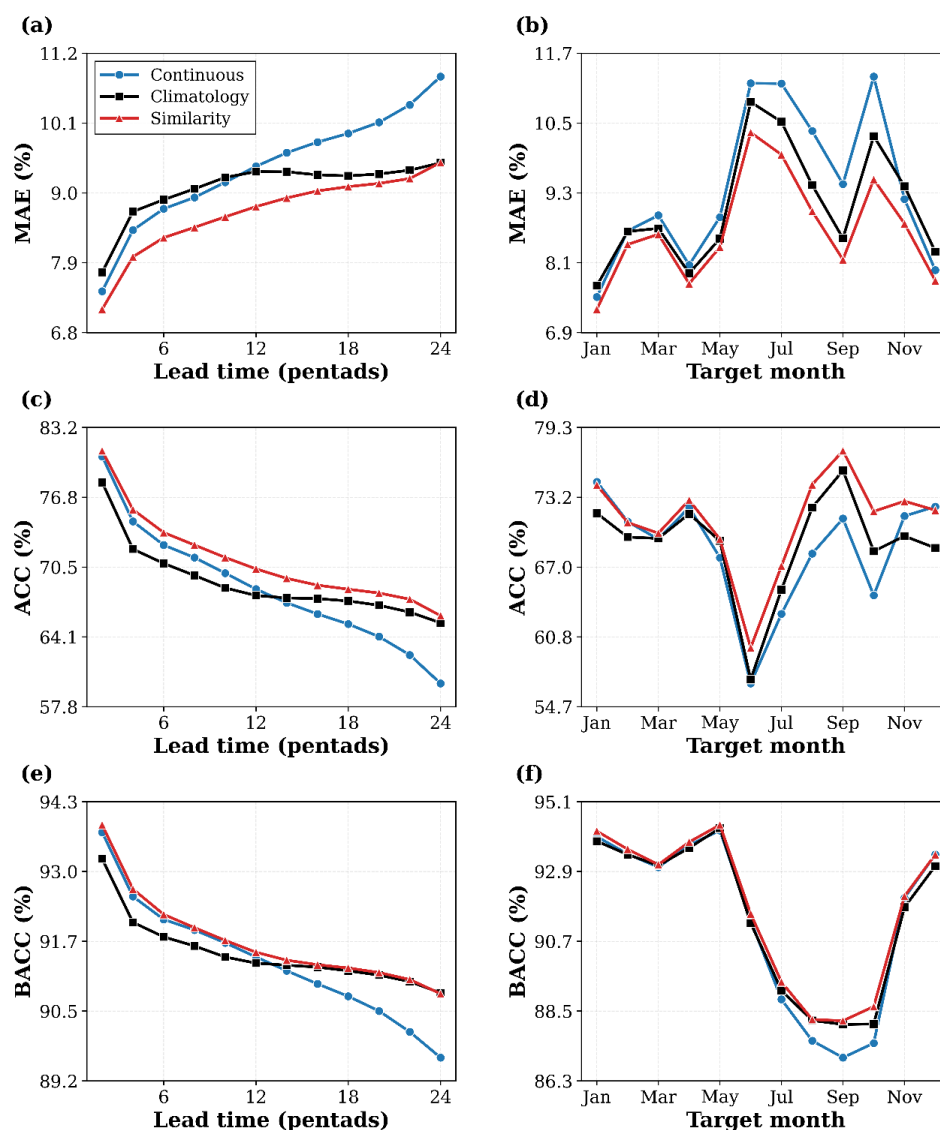
258 Climatology, respectively. As the forecast lead time extends, this advantage gradually diminishes, and by the 24th
 259 pentad, the corresponding differences narrow to -0.09% , $+0.98\%$, and $+0.02\%$, where the BACC at the 23rd–24th
 260 lead pentads becomes essentially comparable to or slightly lower than that of Climatology (-0.01% and -0.02% ,
 261 respectively). This indicates that in the early forecast stage, Similarity can more fully utilize the shared evolutionary
 262 characteristics between the current sea ice state and historical similar years. With increasing forecast lead time, the
 263 cumulative influence of ocean-atmosphere variability and uncertainties in dynamic and thermodynamic processes
 264 intensifies, while the constraint of the initial sea ice state on subsequent evolution gradually weakens, leading to a
 265 decline in the effectiveness of the interannual state characteristics contained in the similar year. Consequently, the
 266 performance advantage of Similarity over Climatology progressively diminishes with increasing lead time, whereas
 267 the stable seasonal evolution background provided by the multi-year mean climatology retains certain predictive value
 268 at longer lead times.

269 Meanwhile, the advantages of Climatology and Similarity over Continuous gradually expand as the forecast lead time
 270 increases. At the 6th pentad, the MAE and ACC of Similarity are lower by 0.39% and higher by 0.91% compared to
 271 Continuous, respectively; by the 24th pentad, these differences widen to -1.16% and $+5.06\%$. This result primarily
 272 stems from the more pronounced performance degradation of Continuous in long-range forecasting. Continuous relies
 273 solely on the consecutive sea ice state prior to the initialization time; as the forecast lead time increases, the time
 274 interval between its historical input and the target period continuously expands, making it difficult to provide an
 275 effective seasonal evolution background for long-range forecasting. In contrast, both Climatology and Similarity
 276 incorporate historical contemporaneous evolution features corresponding to the forecast period—the former provides
 277 a multi-year mean seasonal background, while the latter further provides interannual evolution characteristics of
 278 specific historical similar years, thereby offering more sustained evolutionary constraints at longer forecast lead times.
 279 From the perspective of the growth rate of prediction errors with lead time, the monthly average MAE corresponding
 280 to leads 1–24 pentads increases by 3.85% , 2.73% , and 2.25% for Continuous, Similarity, and Climatology,
 281 respectively; the ratios of MAE at the 24th pentad relative to the 6th pentad are 1.27, 1.19, and 1.11, respectively. It
 282 can be seen that the prediction error of Continuous grows the fastest with lead time, Climatology is the most stable,
 283 and Similarity lies between the two. Overall, although the advantage of Similarity over Climatology gradually
 284 weakens at longer lead times, it can still maintain favorable prediction performance throughout the entire forecast
 285 period by dynamically introducing historical similar-year evolution features, and generally outperforms the two
 286 baseline feature construction schemes.

287 From the perspective of different target months (Figures 3b, d, f), cross-seasonal prediction exhibits clear seasonal
 288 dependence, with higher prediction accuracy during the stable winter freezing stage and maximum forecasting
 289 difficulty during the rapid melt-freeze transition stage. For January–March, Similarity records an MAE of 8.13% and
 290 an ACC of 71.73% , whereas for June, September, and October, the values are 9.35% for MAE and 69.70% for ACC.
 291 June experiences the highest annual MAE (10.33%) and lowest ACC (59.88%) for Similarity. Across all target months,
 292 Similarity yields the lowest MAE among the three schemes. Its annual average ACC and BACC reach the highest
 293 levels overall (71.08% for ACC and 91.76% for BACC), although the ACC for January, February, and December is



294 slightly lower than that of Continuous.



295
 296 **Figure 3. Comparison of SIC prediction performance of the SwinUNet model under different input strategies (Continuous,**
 297 **Climatology, and Similarity). (a) Mean Absolute Error (MAE) under different forecast lead times (1–24 pentads); (b) MAE**
 298 **for different target months; (c) Anomaly Correlation Coefficient (ACC) under different forecast lead times; (d) ACC for**
 299 **different target months; (e) Binary Accuracy (BACC) calculated based on the Integrated Ice Edge Error (IIEE) under**
 300 **different forecast lead times; (f) BACC for different target months.**

301 Figure 4 further illustrates the heatmap distribution of the MAE, ACC, and BACC gains of Similarity relative to
 302 Continuous and Climatology across target months and forecast lead times. Among all 288 "target month–forecast lead
 303 time" combinations, compared to Continuous, Similarity performs better in 253 (87.8%), 220 (76.4%), and 227 (78.8%)
 304 combinations for MAE, ACC, and BACC, respectively; compared to Climatology, it performs better in 245 (85.1%),



248 (86.1%), and 219 (76.0%) combinations, respectively. Similarity performs weaker than Climatology in long-lead-
 time predictions for some target months in September–October, and weaker than Continuous in short-to-medium lead-
 time predictions for some target months in December and January.

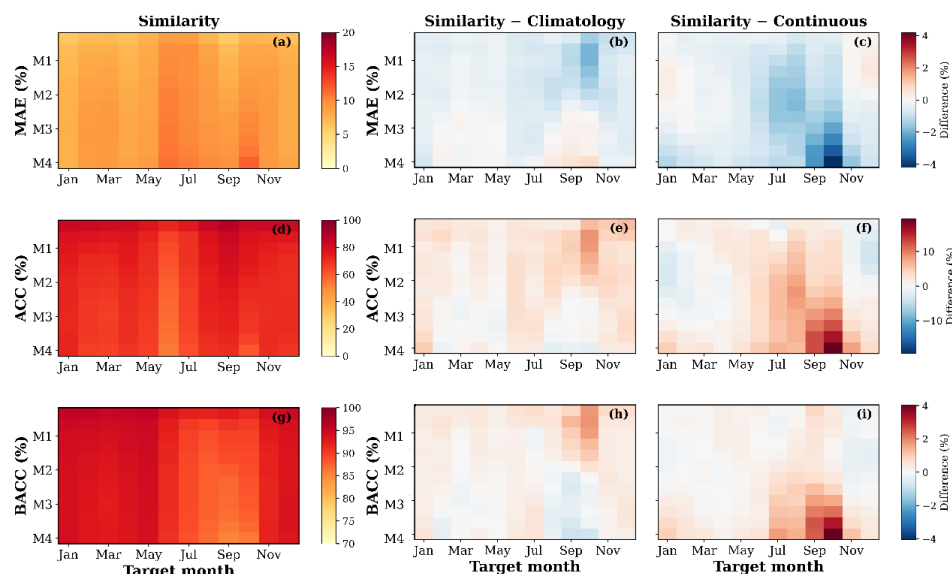


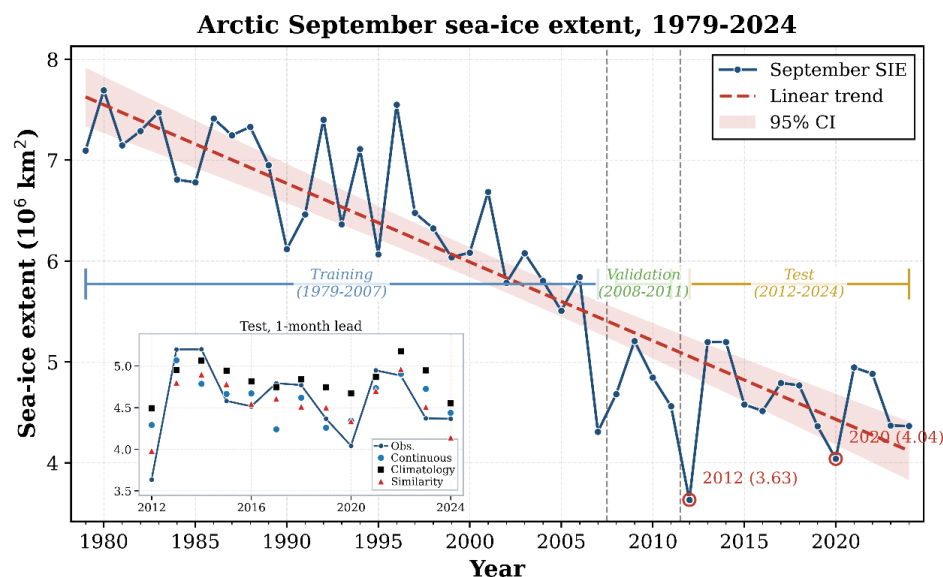
Figure 4. Prediction performance of Similarity and its performance differences relative to Climatology and Continuous. The first column (a, d, g) represents the MAE, ACC, and BACC of Similarity across different target months and forecast lead times, respectively; the second column (b, e, h) represents the differences of Similarity relative to Climatology; and the third column (c, f, i) represents the differences of Similarity relative to Continuous. The horizontal axis indicates target months, and the vertical axis indicates forecast lead times, where each forecast lead time is represented by the average result of two adjacent pentads and denoted by M1–M4 representing forecast lead times at different monthly scales.

Averaged across all target months and 24 forecast lead times, Similarity yields an MAE of 8.68%, representing reductions of 7.62% and 4.38% compared to Continuous (9.39%) and Climatology (9.08%), respectively; its ACC reaches 71.08%, showing increases of 3.69% and 2.92% relative to Continuous (68.55%) and Climatology (69.06%), respectively; and its BACC is 91.76%, exceeding Continuous and Climatology by 0.37% and 0.23%, respectively. When averaging only over the first 12 forecast lead times, Similarity achieves an MAE of 8.21%, which is 5.41% and 6.97% lower than Continuous (8.68%) and Climatology (8.83%), respectively; its ACC reaches 74.08%, representing improvements of 1.63% and 4.03% over Continuous (72.89%) and Climatology (71.21%), respectively; and its BACC stands at 92.37%, outperforming Continuous and Climatology by 0.09% and 0.42%, respectively.

To further analyze the performance of different historical feature construction schemes in typical anomalous years, this study selects 2012 and 2020 as representative years (Figure 5) and computes the spatial distribution of the Mean Absolute Error (MAE) for September across the different schemes for these two years (see Figure 6). Unlike the multi-year average results presented earlier, the metrics of the Continuous model at a 1-month lead time are comparable to or superior to those of Climatology and Similarity. For M1 in both years, Similarity records the lowest MAE (2012: 4.28%, 2020: 4.74%), followed by Continuous (5.25% and 4.87%), both of which significantly outperform Climatology (5.81% and 5.83%). Therefore, at short lead times during anomalous years, climatology tends to degrade



330 predictive skill. As the forecast lead time increases, the advantages of Similarity and Climatology over Continuous
 331 become more pronounced, with Similarity exhibiting lower MAE values than the other two models in the Beaufort
 332 Sea, East Siberian Sea, and Laptev Sea.



333
 334 **Figure 5. Two anomalous years of September SIE (2012, 2020) identified among all test set years (2012–2024). The bottom-**
 335 **left inset shows the comparison between observations and the September average SIE predicted one month in advance by**
 336 **the three schemes.**

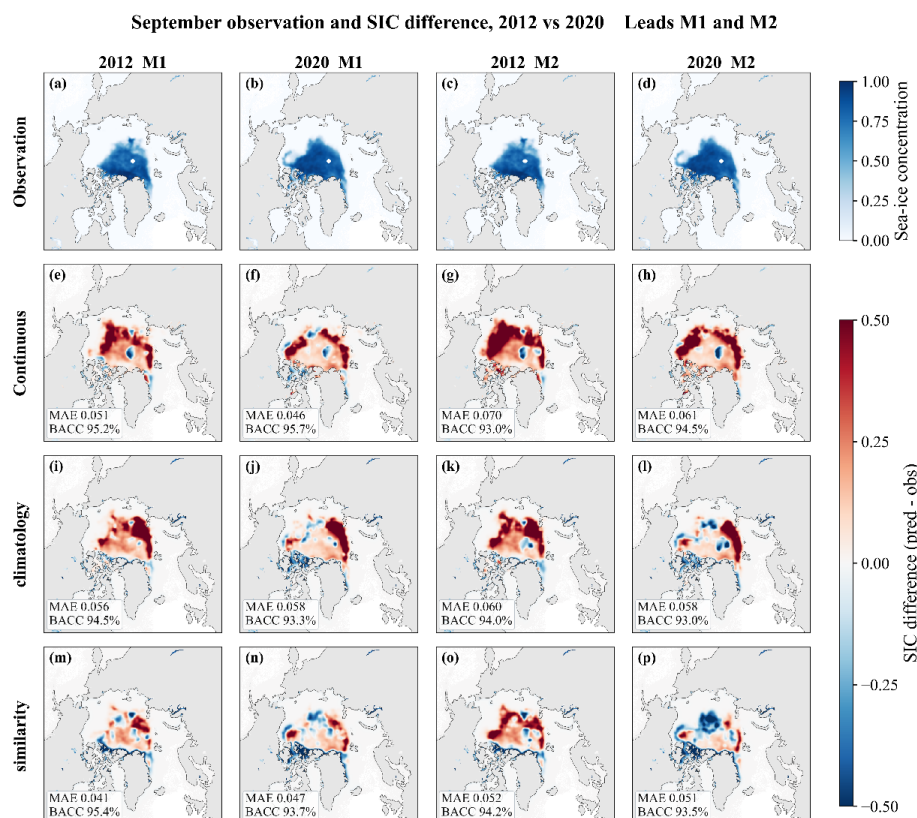


Figure 6. Spatial distribution of Mean Absolute Error (MAE) for predicted SIC in September of 2012 and 2020, shown for lead 1–2 months (M1–M2) across three SwinUNet configurations: Continuous (continuous temporal input), Climatology (climatology constraint), and Similarity (similar-year constraint).

4.3 Comparison of Different Prediction Models

This study denotes the SwinUNet model constructed by incorporating dynamic similar-year features as SwinUNet-SIM. To further verify the predictive capability of SwinUNet-SIM, it is compared with two typical sea ice prediction methods, including the Persistence model and the operational seasonal forecasting system SEAS5 provided by the ECMWF (Johnson et al., 2019). The Persistence model is an anomaly persistence model that assumes anomalies remain constant over time and estimates the target SIC values by adding the current anomaly to the climatological mean state of the target time; this model is widely used as a baseline for sea ice forecasting (Wang et al., 2016). SEAS5 represents the current predictive performance level of operational sea ice seasonal forecasting systems (Wang et al., 2019). The three models are evaluated using the Mean Absolute Error (MAE), Anomaly Correlation Coefficient (ACC), and Binary Accuracy (BACC) based on the Integrated Ice Edge Error (IIEE), and their spatial prediction capabilities are further analyzed in conjunction with the 15% SIC ice edge line.



Figure 7 presents the prediction results of the three models across different target months under various forecast lead times (Lead M1–M4). Overall statistical results indicate that SwinUNet-SIM achieves the best comprehensive prediction performance. Its annual average MAE is 22.19% lower than that of Persistence and 42.24% lower than that of SEAS5. Meanwhile, SwinUNet-SIM achieves the highest ice edge prediction accuracy, with its annual average BACC higher than that of Persistence and SEAS5 by 4.67% and 8.43%, respectively. In general, upon entering the rapid summer melting stage, the ice edge prediction error increases significantly, with SEAS5 exhibiting the most pronounced decline. An analysis of the average performance in summer (June–September) reveals that the summer average MAE of SwinUNet-SIM is 15.08%, which is lower than those of Persistence (15.41%) and SEAS5 (23.11%); its summer average BACC reaches 89.98%, representing increases of 6.46% and 13.37% over Persistence (83.52%) and SEAS5 (76.61%), respectively.

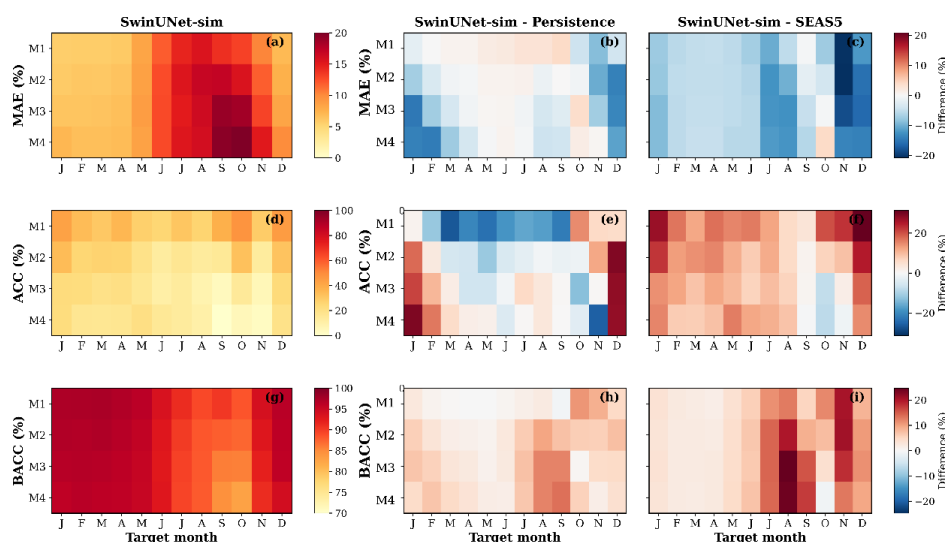


Figure 7. Prediction performance of SwinUNet-SIM and its performance differences relative to Persistence and SEAS5. The first column (a, d, g) represents the MAE, ACC, and BACC of SwinUNet-SIM across different target months and forecast lead times, respectively; the second column (b, e, h) represents the differences of SwinUNet-SIM relative to Persistence; and the third column (c, f, i) represents the differences of SwinUNet-SIM relative to SEAS5. The horizontal axis indicates target months, and the vertical axis indicates forecast lead times, where each forecast lead time is represented by the average result of two adjacent pentads and denoted by M1–M4 representing forecast lead times at different monthly scales.

To demonstrate the generalization capability of SwinUNet-SIM in predicting recent SIE, Figure 8 plots the observed and predicted SIE for September from 2021 to 2024. The SIE in September 2023 ($4.37 \times 10^6 \text{ km}^2$) was the sixth lowest recorded in the Arctic since 1979, while the SIE in September 2022 ($4.90 \times 10^6 \text{ km}^2$) was the highest since 2015. Across all four years, SwinUNet-SIM is able to well capture the spatial variations of the September sea ice edge; whether in low or relatively high sea ice years, its predicted ice edge significantly outperforms those of the other two models. The four-month-ahead BACC predicted by SwinUNet-SIM is on average 8.63% higher than that of Persistence and 15.35% higher than that of SEAS5. Therefore, the SwinUNet-SIM model exhibits favorable generalization capability in predicting the SIE from 2021 to 2024.

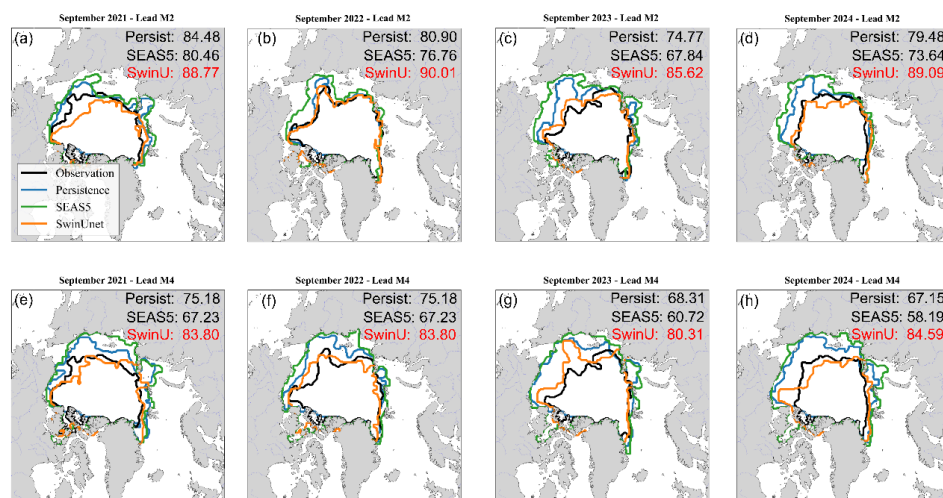


Figure 8. Predicted September SIEs and their BACCs of 2021–2024 for 2 and 4-month leads by Persistence, SEAS5 and SwinUNet-SIM. (a)–(d) 2 month lead, (e)–(h) 4 month lead.

4.4 Interannual Variability of the Prediction Capability of the Similar-Year Scheme

As described in Section 3.2, similar years are dynamically selected for each pentad initialization point, and Figure 9 illustrates the similar years identified for each pentad initialization point in the test set along with their corresponding similarities. The results show that the average time interval between the initialization year and the identified similar year is 7.45 ± 5.31 years, with a 1-year time difference being the most common, accounting for 12.7%. The average similarity value is 0.87 ± 0.057 . Further analysis shows that similarity varies seasonally: similarity values during the summer half-year are generally lower, whereas those during the winter half-year are higher, indicating differences in the degree of matchable spatial states of sea ice between seasons and historical years. The similar years identified across different pentads are relatively dispersed in time and are not restricted to the most recent years preceding the current year, suggesting that similar-year identification does not simply rely on temporal proximity, but is capable of retrieving historical scenarios from a broader historical period that are more structurally similar to the current sea ice state. Most of the identified similar years fall after 2000, which may reflect interdecadal variability in the Arctic sea ice state and the continuous decline in SIE.

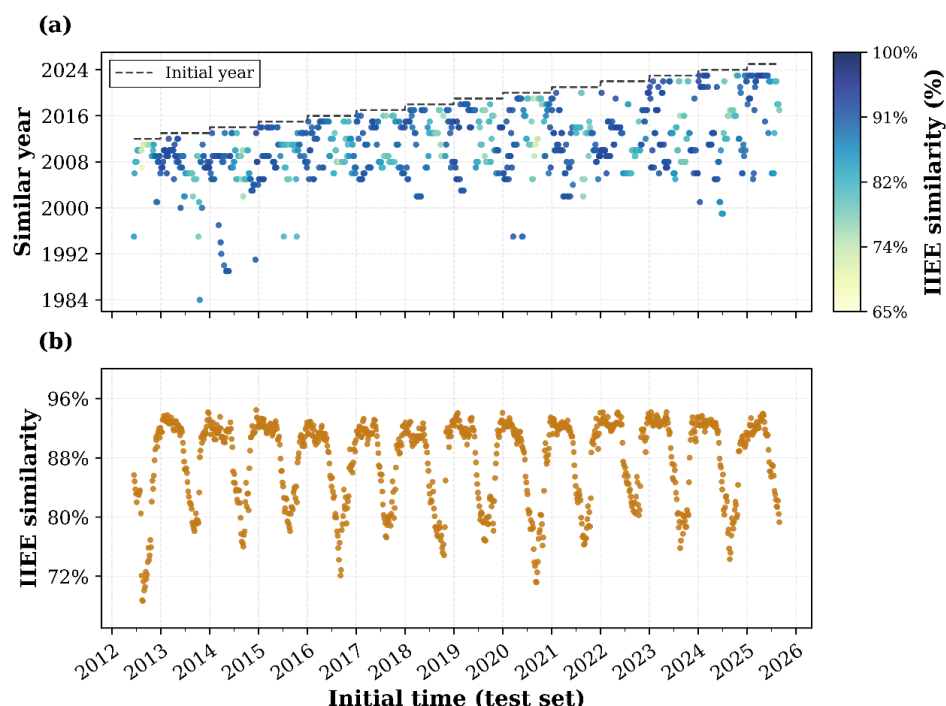


Figure 9. Dynamic similar-year identification results in the test set. (a) Historical similar years corresponding to different forecast initialization times, with colors representing the IoU similarity between the current year and the selected similar year, and the dashed line indicating the forecast initialization year; (b) Corresponding IoU similarity values.

Figure 10 presents the BACC difference (Similarity – Climatology) between Similarity and Climatology across 1–4 month forecast lead times as a function of the target forecast years (2012–2024). The differences across all four forecast lead times exhibit an upward trend over time, indicating that the advantage of Similarity over the fixed climatology configuration expands year by year throughout the testing period. This is consistent with the mechanism of the similar-year method: as the data series lengthens, the historical samples available for retrieval increase, which may enrich candidate scenarios for similar-year selection and thereby help enhance the representativeness of similar-year features in recent years. Linear regression indicates that the increase in the difference is largest for the first month (Lead 6) at $0.130\% \cdot a^{-1}$, followed by $0.114\% \cdot a^{-1}$ for the second month (Lead 12), $0.096\% \cdot a^{-1}$ for the third month (Lead 18), and $0.115\% \cdot a^{-1}$ for the fourth month (Lead 24). Among them, the third and fourth months exhibit higher correlations (R^2 approximately 0.53–0.56), whereas the first month shows the largest slope, reflecting that shorter lead times are more sensitive to similar-year features.

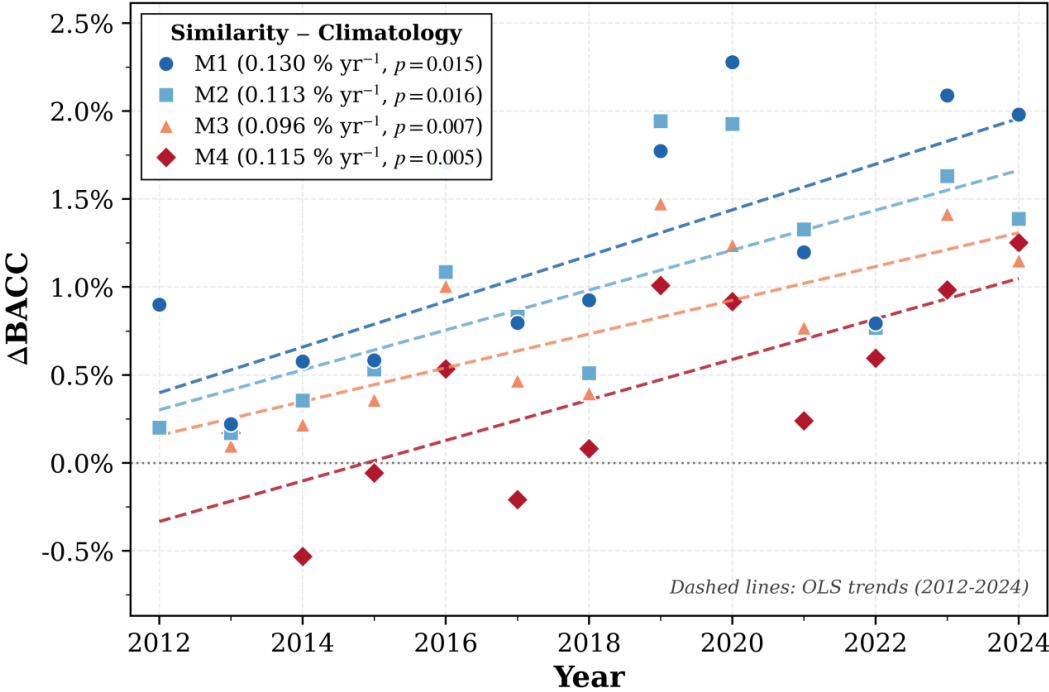


Figure 10. BACC difference (ΔBACC) of Similarity relative to Climatology and its interannual variation. Different symbols and colors represent forecast lead times of 1–4 months (M1–M4), respectively. Each scatter point represents the BACC difference between Similarity and Climatology for the corresponding year and forecast lead time, with positive values indicating that the prediction performance of Similarity outperforms Climatology, and negative values indicating inferior performance. The dashed lines represent the ordinary least squares (OLS) linear trends during the 2013–2024 period, with the corresponding annual rates of change ($\% \text{ yr}^{-1}$) and their significance test p values given in the legend.

5 Conclusions

Existing deep learning models typically incorporate the multi-year mean climatology of the forecast period as the historical contemporaneous evolution background to provide stable seasonal variation information; however, their averaged features struggle to capture interannual differences in sea ice evolution. To address this issue, this study proposes a dynamic similar-year (Similarity) feature construction scheme based on sea ice spatial similarity. It integrates recent SIC and thickness features with historical contemporaneous evolution features for the forecast period dynamically constructed via the similar-year method as joint model inputs, thereby establishing a sea ice prediction framework using SwinUNet. Based on NSIDC Arctic SIC and PIOMAS SIT data from 1979 to 2024, seasonal-scale sea ice predictions are systematically evaluated and compared with other input feature construction approaches (Continuous and Climatology), the baseline model (Persistence), and the operational forecasting system (ECMWF SEAS5). The dynamic similar-year feature construction scheme can dynamically select the most similar year according to the spatial distribution of sea ice at the initialization time, making the historical contemporaneous evolution features input to the model more consistent with the current sea ice state compared to the climatological mean. Consequently, this



effectively enhances sea ice prediction accuracy. Over the four-month (1–24 pentad) forecasts, the similar-year scheme reduces MAE by 4.38%, increases ACC by 2.92%, and increases BACC by 0.23% relative to the climatology scheme. When considering only the first 12 pentads, the similar-year scheme reduces MAE by 6.97%, increases ACC by 4.03%, and increases BACC by 0.42% compared to the climatology scheme.

The predictive gains provided by the similar-year approach are primarily manifested in the early forecast stage. As the forecast lead time further increases, the advantage of Similarity over Climatology gradually diminishes. Because similar years are dynamically retrieved from historical data based on the spatial state of sea ice at initialization, their subsequent sea ice evolution provides year-specific seasonal backgrounds corresponding to the initial state for the current forecast. Compared to the multi-year climatology describing average seasonal evolution, this feature offers a more targeted historical evolution reference in the early forecast stage. With increasing lead time, the constraint of the initial similarity between the current year and the historical similar year on subsequent sea ice evolution progressively weakens, and different years may produce distinct evolutionary trajectories under the action of ocean-atmosphere forcing and sea ice thermodynamic and dynamic processes. Therefore, the predictive advantage of Similarity over Climatology gradually wanes, and the performance gap between the two tends to narrow.

Compared with traditional forecasting methods and operational seasonal forecasting systems, the proposed model exhibits superior predictive capability. Relative to the Persistence model, the proposed SwinUNet-SIM model achieves a 22.19% reduction in annual average MAE and a 4.67% increase in BACC; compared to ECMWF SEAS5, it reduces MAE by 42.24% and increases BACC by 8.43%. Independent validation on typical years from 2021 to 2024 further demonstrates that the model can more accurately reconstruct the September sea ice edge position, exhibiting favorable generalization capability and stability.

The similar years identified for test samples (2012–2024) are predominantly distributed after 2000, which may be related to the continuous decline of Arctic sea ice and its interdecadal state transition since the 21st century. However, the similar years are not restricted to the most recent period; instead, they successfully retrieve historical scenarios that are more structurally similar to the current sea ice state from a broader historical period, indicating that the method does not simply rely on temporal proximity. Further analysis shows that as the test years progress, the overall predictive advantage of the Similarity scheme over the traditional Climatology scheme exhibits an enhancing trend. This suggests that with the continuous accumulation of historical samples, dynamic similar-year retrieval can more fully exploit historical contemporaneous sea ice evolution features, providing a more targeted prediction reference under recent low-sea-ice conditions.

Overall, the long-term historical feature construction method based on similar years proposed in this study makes full use of historical sea ice evolution characteristics. Without increasing model complexity, it effectively enhances the representativeness of historical contemporaneous evolution features and improves seasonal sea ice prediction accuracy. This method is not only applicable to SwinUNet but can also be extended to other spatiotemporal prediction models such as ConvLSTM and Transformer, providing a novel perspective for constructing sea ice seasonal prediction systems with enhanced physical consistency and interannual adaptability. Future work can further incorporate multi-source environmental factors such as SIT, sea surface temperature, and atmospheric circulation to build a multi-



466 variable similar-year retrieval mechanism, and explore integration with operational seasonal forecasting models to
 467 further enhance cross-seasonal sea ice prediction capabilities.

468 **Code and data availability**

469 The source code for the SwinUNet seasonal Arctic sea ice forecast model developed in this study, including the
 470 similar-year feature construction modules, has been archived on Zenodo (<https://doi.org/10.5281/zenodo.23297957>)
 471 (Wang, 2026). NSIDC sea ice concentration data are publicly available from the NASA National Snow and Ice Data
 472 Center Distributed Active Archive Center (DiGirolamo et al., 2022). PIOMAS sea ice thickness data are publicly
 473 available from the Polar Science Center, University of Washington (Zhang & Rothrock, 2003; Schweiger et al., 2011).
 474 Training the full model and running the four-month pentad forecasts require access to GPU computing resources.

475 **Author contributions**

476 MW designed the similar-year feature method, developed the model code, and carried out the experiments. YR
 477 contributed to the SwinUNet forecasting framework. JS supervised the study and acquired the funding. MW
 478 prepared the manuscript with contributions from all co-authors.

479 **Competing interests**

480 The authors declare that they have no conflict of interest.

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486 **Financial support**

487 This research has been supported by the National Key Research and Development Program of China (grant no.
 488 2023YFC2809101) and the the Laoshan Laboratory Technology Innovation Project (No. LSKJ202202301).

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