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SEA ICE EXTENT FORECASTING USING STATISTICAL AND DEEP LEARNING MODELS

*The **subject matter** of the article is the forecasting of time series of sea ice extent using statistical and deep learning methods. Sea ice extent is one of the most important indicators of climate change. Today, there are trends towards melting glaciers, which leads to a rise in sea level and, in turn, creates a significant threat of flooding of coastal regions around the globe. In addition, melting glaciers affect the flora and fauna of the Arctic and Antarctic regions, as well as economic stability in the world, covering economic development and food security. The spheres of agriculture, tourism, logistics are directly dependent on climate change, therefore, forecasting future changes is critically important for stability and sustainable development. The article analyzes the main trends in the change in sea ice extent. The **goal** of the study is to increase the reliability of long-term forecasting by designing a framework that covers the full forecasting cycle from data analysis to the use of predictive statistical methods and deep learning techniques. The **tasks** of the article are to conduct a comparative analysis of statistical methods and deep learning methods and their evaluation for the task of forecasting the area of sea ice distribution. The study used forecasting **methods** based on statistical models and deep learning. A study was conducted on the use of different approaches to forecasting future changes in a time series based on statistical methods, deep learning methods and ensemble models. The **results** obtained allow to evaluate the performance of models in the short term and an approach to long-term forecasting was formed. The use of autoregressors and deep learning methods is proposed to create a reliable long-term forecast. The comparison of the performance of the methods was carried out for the Northern and Southern Hemispheres. **Conclusions**. The scientific novelty of the results obtained is as follows: the method of forecasting time series of sea ice distribution using statistical methods and deep learning methods has been further developed. It was propose a generalizable forecasting framework that links time-series characteristics to model class selection and ensemble construction. The use of ensemble approaches allows us to ensure both the consideration of the main trends and the recognition of hidden patterns. The results obtained allow for a comprehensive assessment of time series for the Northern and Southern Hemispheres and indicate the feasibility of using both statistical forecasting methods for data with clearly defined patterns, such as the Arctic region, and deep learning methods to recognize hidden patterns observed in time series data for the Antarctic region.*

Keywords: *sea ice extent; forecasting; autoregressors; deep learning; ensemble models.*

1. Introduction

1.1. Motivation

According to Copernicus data, the monthly Arctic Sea Ice Extent reached a record low for the period in February 2025. The average area was 13.7 million km^2, the lowest monthly value in the 47-year observation period [1].

Sea ice has a significant impact on climate processes and is one of the key indicators of climate change. Today, many studies are aimed at the interdependence of sea ice surface area with weather phenomena in different parts of the globe. Sea ice also has a significant impact on ecosystems [2].

The existence of flora and fauna of the Arctic regions is completely dependent on the spread of glaciers in the region, as it is a necessary condition for the survival of certain species.

Another important aspect is the rise of Sea level. The melting of large volumes of sea ice changes the balance of the hydrosphere, causing a change in the chemical composition of the water and can cause flooding of coastal regions. Given that a significant part of the world's population lives on the coasts, in potentially dangerous areas, this can cause climate migrations.

Melting glaciers pose many challenges to humanity, including economic losses, directly threatening agriculture, tourism, etc [3].

Thus, the development planning of many cities is associated with the risks of flooding as a result of rising Sea levels, and to create reliable, stable infrastructure, understanding potential threats is extremely relevant.

The research topic is consistent with the Sustainable Development Goals, in particular Goal 13 – Climate Action, SDG 14 – Life Below Water, and SDG 15 – Life on Land.

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1.2. State-of-the-Art

The task of time series forecasting remains relevant, especially with the emergence of new forecasting methods. Artificial intelligence tools, in particular machine learning and deep learning, are able to capture patterns quite well and create highly accurate short-term forecasts [4]. However, many methods experience attenuation, and as a result, the created model is unsuitable for long-term forecasting [5, 6]. This problem is inherent not only to classical machine learning methods, but also to deep learning methods, although less pronounced.

At the same time, statistical forecasting methods capture only general trends and are not always able to predict complex patterns.

Given the problems, let us analyze the main trends in forecasting climate data using statistical autoregressors, as well as methods based on artificial intelligence technologies.

The article [7] reveals post-processing methods based on supervised machine learning for improving the skill of sea ice concentration forecasts from the TOPAZ4 prediction system. It is used deep learning approach for short-term forecasting.

The work [8] describes opportunities and challenges of advancing Arctic Sea Ice Remote Sensing with AI and Deep Learning.

There are several approaches in Time Series forecasting including autoregressors, recurrent and convolutional neural networks. Article [9] analyzes the data of extreme precipitation observed in East Malaysia as a result of climate change. Article [10] examines the impact of climate change on dengue disease in Singapore by analyzing a time series. Article [11] is devoted to the study of short-term forecasting of sea ice concentration. Study [12] analyzes the opportunities and challenges in the field of remote sensing of Arctic sea ice using artificial intelligence technologies and, in particular, machine learning.

Paper [13] analyzes the fluctuations in sea ice area within the Arctic Circle using big data and the SARIMA model. Paper [14] discusses the forecasting of sea ice extent using NNAR, SARIMA, and SARIMAX methods. Study [15] is based on a comparison of the effectiveness of the SARIMA and SARIMAX models for predicting the time series of particulate carbon on the Sunda Shelf.

Paper [16] evaluates deep learning models for one-month forecasting of pan-Arctic ice thickness. Paper [17] considers the use of the long short-term memory method for the task of predicting sea ice thickness.

The majority of studies use long short-term memory approach. Also, some articles are investigating Bi-LSTM, although its use is controversial and debate continues. Study [18] proposes a WGAN-LSTM deep learning approach to improve sea ice thickness forecasting. Paper [19] proposes an optimization of the LSTM method for predicting sea ice melt.

Thus, in this research it will be appropriate to use following forecasting methods:

– SARIMA;
– LSTM;
– Bi-LSTM.

The study [20] examines physics-free neural architectures versus physics-based statistical models for long-term Arctic forecasts by employing a Fourier Neural Operator (FNO) and a Convolutional Neural Network (CNN) together with the seasonal time series model SARIMAX, which includes physical predictors, including temperature anomalies and ice thickness.

The research [21] investigated the thickness of laboratory-grown sea ice using linear regression and three machine learning algorithms: decision trees, random forests, and fully connected neural networks. To comprehensively track the growth of thin sea ice using different parameters, a combination of up to 13 radar and physical parameters was introduced into four multivariate models in two time series datasets.

The study [22] presents a comprehensive benchmarking framework for classifying sea ice types, as the lack of a standardized benchmark and comparative study hinders a clear consensus on the best models. Both traditional and deep learning approaches are considered. Deep learning models offer a promising direction for improving the efficiency and consistency of sea ice classification.

1.3. Objective and approach

The purpose of this study is to determine the most accurate methods for predicting sea ice extent based on historical data.

In previous work [23] it was provided statistical and data-driven analysis of Sea Ice Extent data. Based on this research, the following hypothesis can be formed.

Hypothesis. The time series of sea ice extent in the Northern Hemisphere is non-stationary and shows a clear downward trend. Thus, it is advisable to forecast data using classical autoregression methods taking into account seasonal patterns. At the same time, the time series corresponding to the sea ice extent in the Southern Hemisphere is stationary and may contain hidden patterns. It is advisable to use machine learning approaches to forecast data.

It is determined to provide a research comparing different approaches and find the best solution to achieve the highest efficiency of the model. To test the hypothesis, we will consider the following forecasting methods: SARIMA, LSTM, Bi-LSTM and ensemble models combining SARIMA with LSTM and Bi-LSTM.

The following tasks should be solved for achieving our purpose:

– to analyze existing approaches to forecasting Sea Ice Extent;

– based on previous research, to formulate a hypothesis regarding the application of different forecasting methods;

– to conduct a comparative analysis of statistical and deep learning methods, as well as ensemble models;

– to perform a hypothesis test regarding forecasting Sea Ice Extent;

– to formulate an approach for long-term forecasting.

Thus, *the rest of the paper* are structured as follows. Section 2 describes the dataset and mathematical framework of the study. Statistical forecasting methods and deep learning methods are analyzed. An approach for creating ensemble forecasting models is described. Section 3 presents the results of the experiments. The data are presented in tabular and graphical forms for better visualization. Hypothesis testing is performed and the results of the study are described. Section 4 presents the conclusions.

2. Methodology

2.1. Dataset

The dataset [24] published on Kaggle by National Snow and Ice Data Center [25] provides measurements of total sea ice extent, defined as the area of ocean with at least 15% sea ice concentration, covering both the Northern (Arctic) and Southern (Antarctic) hemispheres. The data is derived from satellite passive-microwave radiometers, specifically the Scanning Multichannel Microwave Radiometer (SMMR) on NASA's Nimbus 7 satellite (1978–1987), a sequence of Special Sensor Microwave Imagers (SSMIs) on DMSP satellites (1987–2007), and the Special Sensor Microwave Imager Sounder (SSMIS) on DMSP F17 (2008–2012, with potential updates beyond this period).

The dataset has some limitations due to the nature of satellite data, including low spatial resolution, underestimation of thin or new ice, and higher uncertainties during the summer melt season.

2.2. SARIMA

There are several approaches to time series forecasting. However, given the topic of the study and the need for long-term forecasting, we will focus on seasonal autoregression and deep learning algorithms.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is an extension of the ARIMA model that explicitly supports univariate time series data with a seasonal component. This algorithm can be described as:

$$\mathrm{SARIMA}(p, d, q) \times (P, D, Q)_s, \tag{1}$$

where:

p – order of the non-seasonal AR (AutoRegressive) part;

d – degree of non-seasonal differencing;

q – order of the non-seasonal MA (Moving Average) part;

P – order of the seasonal AR part;

D – degree of seasonal differencing;

Q – order of the seasonal MA part;

s – length of the seasonal cycle (12 for monthly data with yearly seasonality).

Let's define Backshift Operator B for compactly expressing differencing and lag structures:

$$B^k y_t = y_{t-k}. \tag{2}$$

Differencing Operators are divided into:

– Non-seasonal differencing:

$$\nabla^d y_t = (1 - B)^d y_t, \tag{3}$$

– Seasonal differencing:

$$\nabla_s^D y_t = (1 - B^s)^D y_t. \tag{4}$$

Thus, the fully differenced series can be described as:

$$z_t = \nabla^d \nabla_s^D y_t. \tag{5}$$

SARIMA models the differenced series zt as:

$$\Phi_P(B^s)\phi_p(B) z_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t, \tag{6}$$

where:

$\phi_p(B) = 1 - \phi_1 B - \ldots - \phi_p B^p$ (non-seasonal AR);

$\theta_q(B) = 1 + \theta_1 B + \ldots + \theta_q B^q$ (non-seasonal MA);

$\Phi_P(B^s) = 1 - \Phi_1 B^s - \ldots - \Phi_P B^{Ps}$ (seasonal AR);

$\Theta_Q(B^s) = 1 + \Theta_1 B^s + \ldots + \Theta_Q B^{Qs}$ (seasonal MA)

$\varepsilon_t \sim WN(0, \sigma^2)$ (white noise error term).

Final equation in expanded form:

$$\Phi(B^s)\phi(B)\nabla^d \nabla_s^D y_t = \Theta(B^s)\theta(B)\varepsilon_t. \tag{7}$$

Parameters ϕ, θ, Φ, Θ are typically estimated via Maximum Likelihood Estimation (MLE) or non-linear least squares. Once fitted, SARIMA can be used to generate forecasts by projecting the model forward using past data and residuals.

2.3. LSTM

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network. This type is designed to

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model sequences and store long-term dependencies. The network architecture solves the problem of gradient vanishing that is inherent in standard RNNs. This is done by implementing a more complex memory structure.

The state of a memory cell passes through the entire sequence with minimal changes, which allows information to be stored over time.

An LSTM uses three gates to control the flow of information into, out of, and within a cell state: forget gate, input gate and output gate.

The role of forget gate is to Decide what information from the cell state should be forgotten. The input gate decides what new information to add to the cell state. And output gate determines what part of the cell state becomes the output.

Thus, LSTM is effective for long sequences because it can capture long-range dependencies in time series.

2.4. Bi-LSTM

A Bidirectional LSTM consists of two separate LSTMs. One processes the input forward (as in normal LSTM), the other processes it backward (from t=T to 1).

Forward LSTM can be described as:

$$\overrightarrow{h}_t = \mathrm{LSTM}_{fwd}(x_t, \overrightarrow{h}_{t-1}). \quad (8)$$

Backward LSTM:

$$\overleftarrow{h}_t = \mathrm{LSTM}_{bwd}\left(x_t, \overleftarrow{h}_{t+1}\right). \quad (9)$$

Combined output:

$$h_t = \left[\overrightarrow{h}_t; \overleftarrow{h}_t\right]. \quad (10)$$

Each output h_t is the concatenation of the hidden states from both directions at time t.

2.5. Ensemble models

In the SARIMA+LSTM ensemble, the LSTM is typically used to model the non-linear residuals r_t from the SARIMA model, as SARIMA captures linear patterns but struggles with non-linearities.

Thus, the final forecast is the sum of the SARIMA forecast and the LSTM residual prediction:

$$\hat{y}_t = \hat{y}_t^{SARIMA} + \hat{r}_t^{LSTM}. \quad (11)$$

The ensemble model can be represented as:

$$\hat{y}_t = \phi(B)\Phi(B^S)(1-B)^D y_t + f_{LSTM}(r_{t-1}, \ldots, r_{t-k}), \quad (12)$$

where f_{LSTM} represents the non-linear function learned by the LSTM to model residuals.

Advantages of this approach are following: SARIMA captures linear trends and seasonality, LSTM captures non-linear patterns in the residuals, improving forecast accuracy for complex time series.

The SARIMA+Bi-LSTM ensemble is similar to SARIMA+LSTM, but replaces the LSTM with a Bi-LSTM to capture bidirectional dependencies in the residuals or input sequence.

Prediction combining provides as:

$$\hat{y}_t = \hat{y}_t^{SARIMA} + \hat{r}_t^{Bi-LSTM}, \quad (13)$$

Thus, this ensemble model can be represented as:

$$\hat{y}_t = \phi(B)\Phi(B^S)(1-B)^d(1-B^S)^D y_t + f_{Bi-LSTM}(r_{t-k}, \quad (14)$$

where $f_{Bi\text{-}LSTM}$ is the non-linear function learned by the Bi-LSTM, incorporating both forward and backward temporal dependencies.

Advantages of this approach are following: Bi-LSTM's bidirectional processing captures more complex patterns, especially in time series with strong dependencies in both past and future directions. It is suitable for datasets where context from future time steps (within the input window) improves residual modeling.

In summary, the SARIMA+LSTM and SARIMA+Bi-LSTM ensembles combine the linear modeling of SARIMA with the non-linear, sequential learning of LSTM or Bi-LSTM. The key mathematical difference lies in the bidirectional processing of Bi-LSTM, which enhances the model's ability to capture complex temporal dependencies. Both ensembles are powerful for time series forecasting, with the choice depending on the data's complexity and computational constraints.

3. Case study and results

Metrics were used to evaluate the performance of the models, namely, the mean absolute error, the mean square error, the weighted mean square error, and the R^2 estimate. The data were divided into training and validation samples. The model was trained on data from October 1978 to January 2026. The model was validated on data from January 2024 to January 2026.

Figures 1-5 demonstrate forecasting methods evaluation on validation set for North Hemisphere.

Figure 6 and Table 1 show comparison of models' performance metrics.

Due to the lack of long-term observation data, it is only possible to assess the short-term forecast. However, to assess the use of the proposed methods for long-term forecasting, forecast data up to 2100 were analyzed for the presence of attenuation or convergence to a constant value.

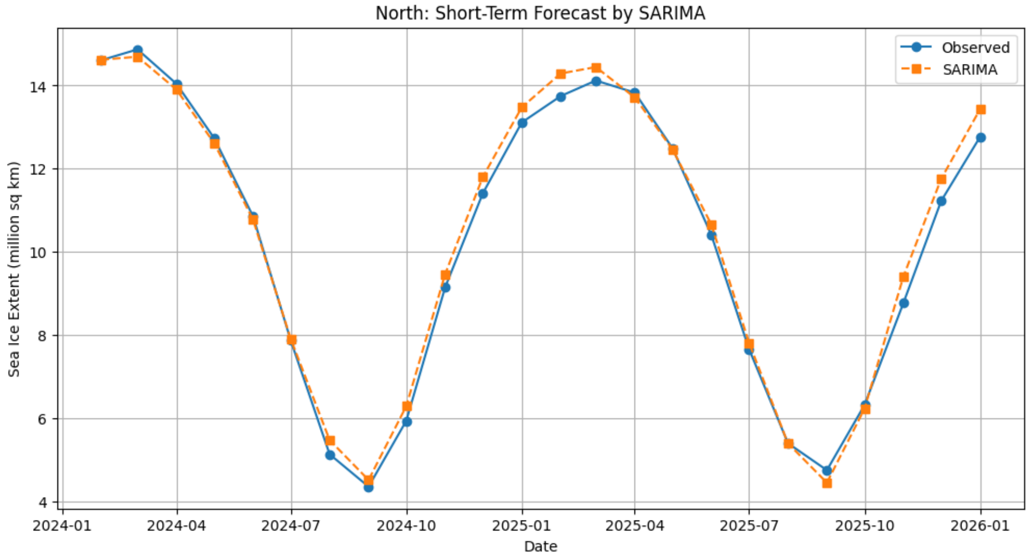

Fig. 1. SARIMA forecast evaluation for North Hemisphere

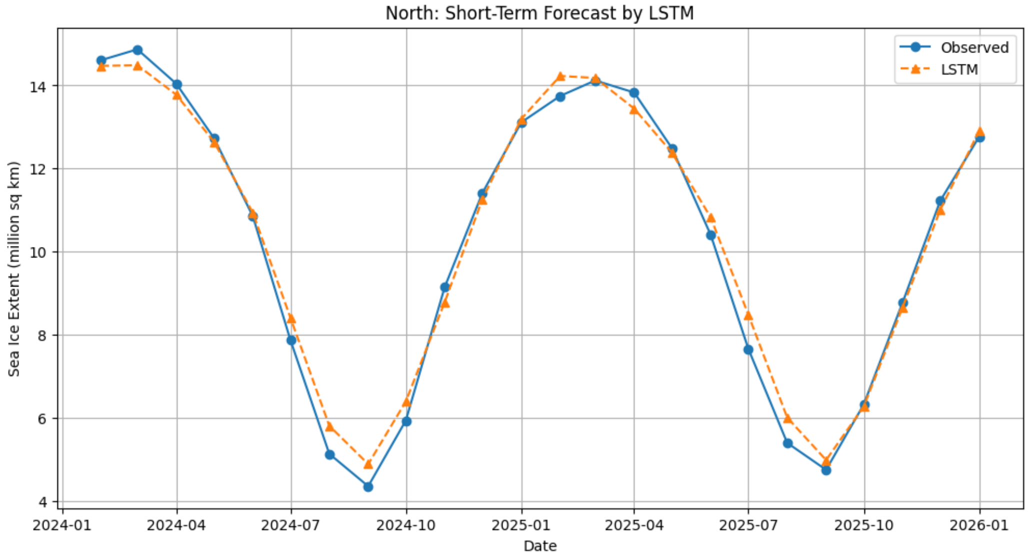

Fig. 2. LSTM forecast evaluation for North Hemisphere

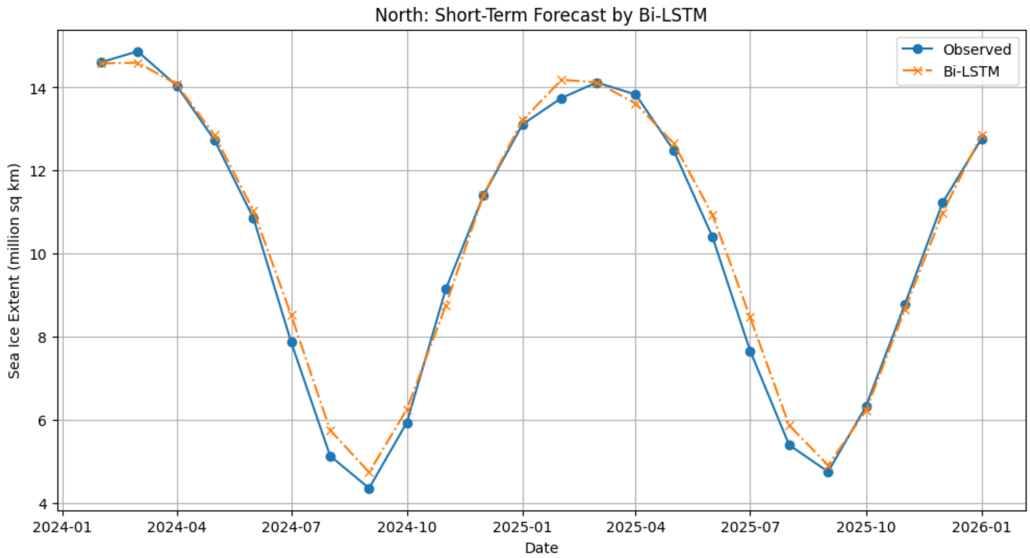

Fig. 3. Bi-LSTM forecast evaluation for North Hemisphere

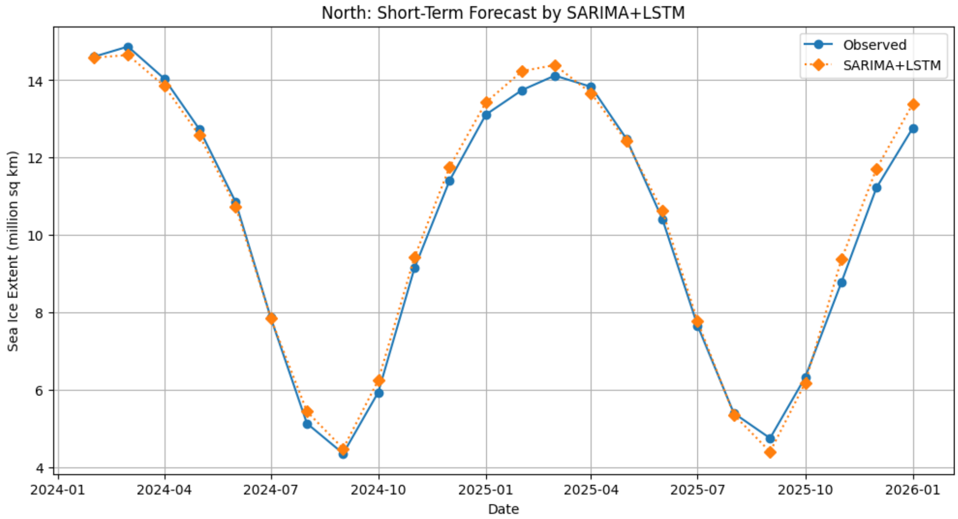

Fig. 4. SARIMA + LSTM forecast evaluation for North Hemisphere

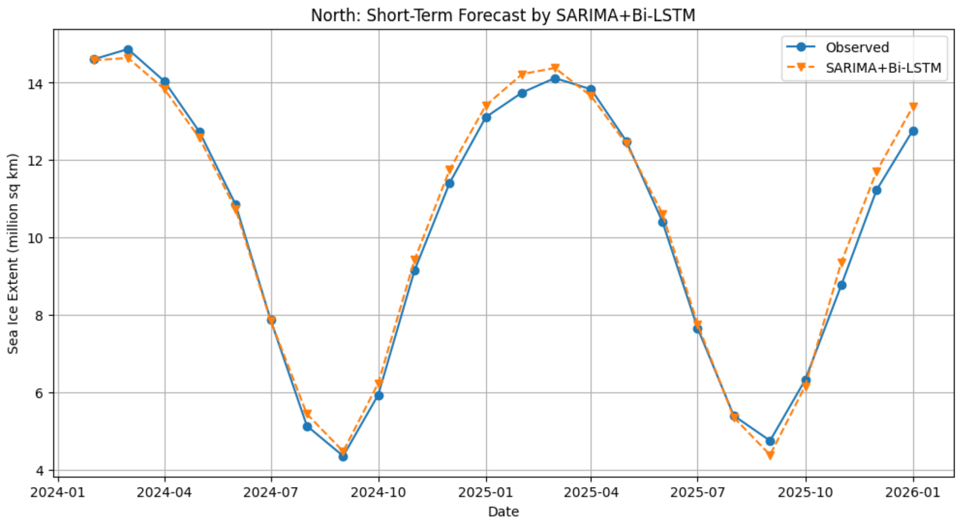

Fig. 5. SARIMA+Bi-LSTM forecast evaluation for North Hemisphere

The experimental results for the Northern Hemisphere demonstrate that the SARIMA model predicts the time series values with high accuracy. The observed deviations are minimal. At the same time, the forecast created by a recurrent neural network with a long short-term memory architecture is less accurate. The deviations, although insignificant in the scale of the predicted values, are larger compared to the SARIMA forecast. The LSTM model also has a smaller amplitude compared to the observational data, which may indicate potential damping when creating a long-term forecast. The model with the Bi-LSTM architecture demonstrates a highly accurate short-term forecast, outperforming the LSTM model, although slightly inferior to SARIMA. Both ensemble models produce a highly accurate short-term forecast. As expected, the SARIMA+Bi-LSTM ensemble model outperforms the SARIMA+LSTM model. Despite the low errors, both ensemble models are slightly inferior to SARIMA.

Overall, all models demonstrate high accuracy in predicting sea ice extent in the short term. Although the error metrics for LSTM are higher than those of other models, they are acceptable. Thus, the proposed models can be used to predict time series of Sea Ice Extent.

The best performance was demonstrated by SARIMA model. The result of the experiment confirmed the first part of the formed hypothesis, namely, that for forecasting the time series of the sea ice extent in the Northern Hemisphere, it is advisable to use classical autoregressors taking into account seasonal patterns.

A visualization of the long-term forecast is shown in Fig. 7. The long-term forecast shows a steady downward trend. Under current climate conditions, starting in 2080, the sea ice extent in the summer months will approach critical values, indicating such dangerous phenomena as the first ice-free day and the first ice-free month in the Arctic. Given that the study used only monthly average data, the first ice-free day may occur somewhat earlier.

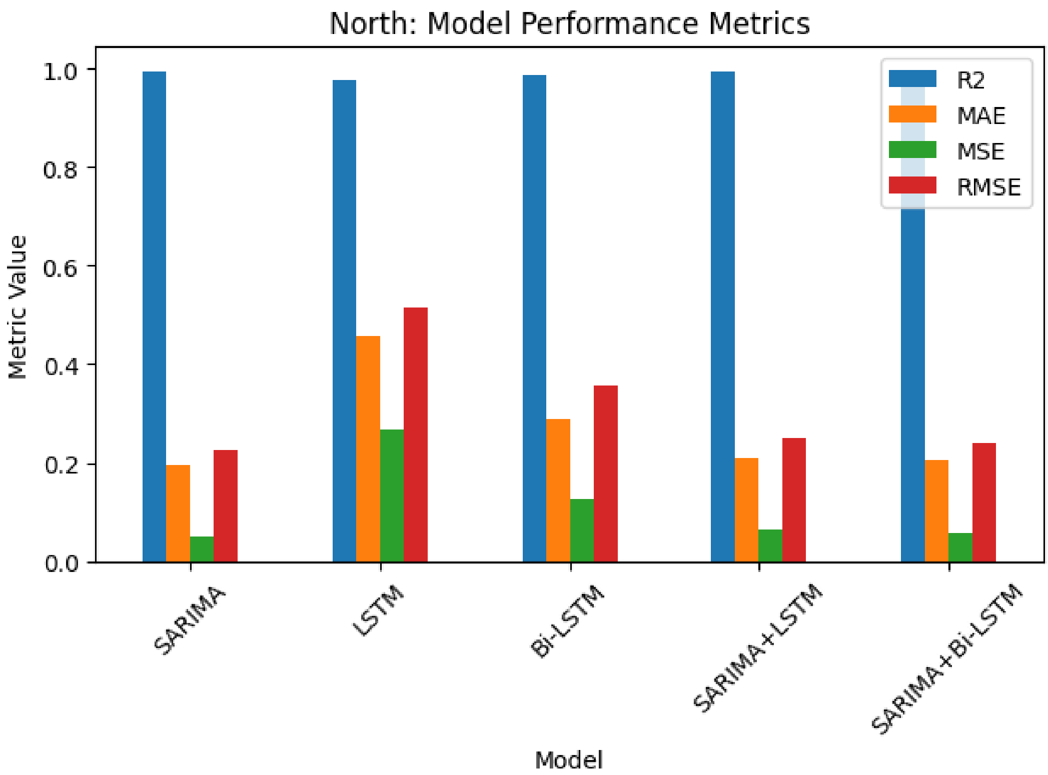

Fig. 6. Performance metrics

Table 1

Model evaluation for North Hemisphere

Model	**Metrics**			
	R^2	**MAE**	**MSE**	**RMSE**
SARIMA	0.9953	0.1932	0.0512	0.2263
LSTM	0.9758	0.4557	0.2658	0.5156
Bi-LSTM	0.9884	0.2887	0.1275	0.3571
SARIMA+LSTM	0.9943	0.2078	0.063	0.251
SARIMA+Bi-LSTM	0.9948	0.205	0.0573	0.2393

The long-term forecast generated by the LSTM and Bi-LSTM models for the Northern Hemisphere is not reliable, since the LSTM model exhibits a gradual decay, which confirms the assumption made during the analysis of the short-term forecast. The Bi-LSTM model decays much faster than the LSTM and converges to a constant value.

Figures 8-12 demonstrate forecasting methods evaluation on validation set for South Hemisphere.

Figure 13 and Table 2 show comparison of models' performance metrics.

The results of the experiment for the Southern Hemisphere differ from those obtained for the Northern Hemisphere. The SARIMA model also predicts the time series values for the Antarctic region with high accuracy, but the error metrics are higher than when predicting for the Arctic region. At the same time, the R^2 metric is also higher. This is due to the fact that the Southern Hemisphere data do not have clearly expressed patterns, compared to the Northern Hemisphere data.

The forecast created by the LSTM model is inferior to the SARIMA model forecast, similar to what is observed in the Northern Hemisphere. The Bi-LSTM model demonstrates high accuracy and is minimally inferior to SARIMA. The use of the SARIMA+LSTM ensemble model allowed to improve the SARIMA metrics. Thus, the use of both methods in the ensemble model allows to take into account both seasonal patterns and hidden patterns, which contributes to the creation of a highly accurate forecast.

The ensemble model SARIMA+Bi-LSTM also performs highly accurate forecasting in the short term,

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but is inferior to both the ensemble model SARIMA+LSTM and the SARIMA model.

The best performance was demonstrated by ensemble SARIMA+LSTM model. The result of the experiment confirmed the second part of the formed hypothesis, namely, that for forecasting the time series of the sea ice extent in the South Hemisphere, it is advisable to use machine learning approach to to reveal hidden patterns.

A visualization of the long-term forecast is shown in Fig. 14. The long-term forecast also has a downward trend, but not as steeply as in the Arctic region. The forecasted values can be divided into two parts. The first is the period from 2020 to 2030, where stability in values is observed.

All deviations are insignificant. After 2030, there is a tendency to a gradual decrease. Although the minimum values approach critical closer to the end of the century, the maximum values remain high. This indicates that the Antarctic region, due to its geographical features, is more resistant to climate change than the Arctic.

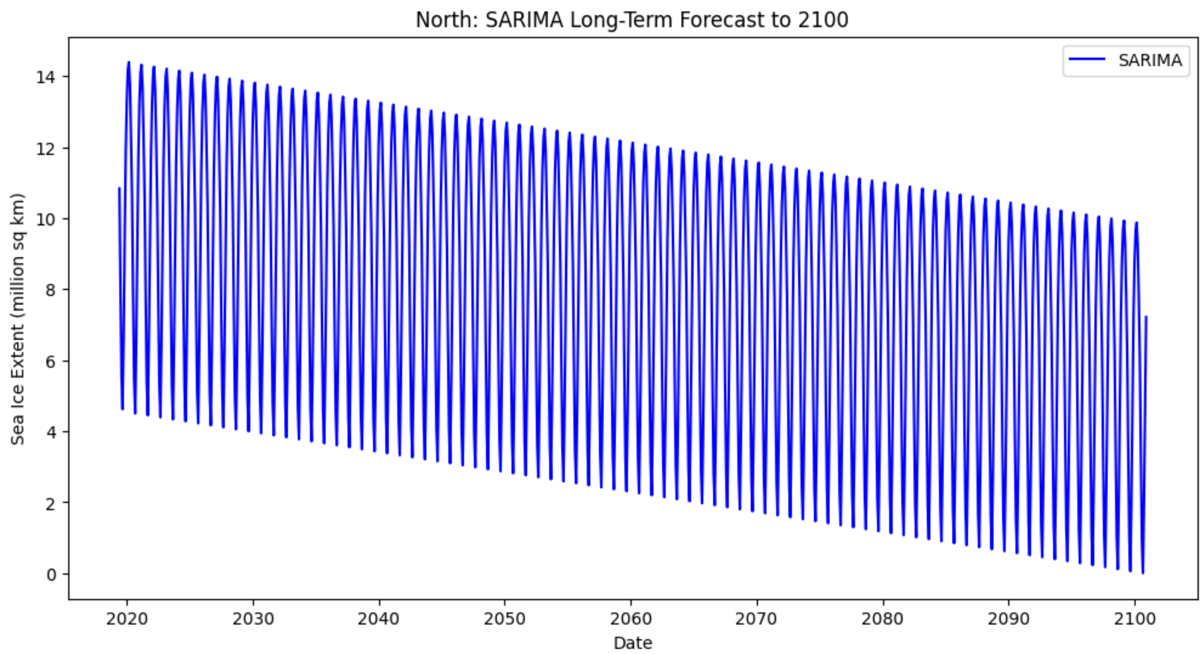

Fig. 7. Long-term forecast by SARIMA

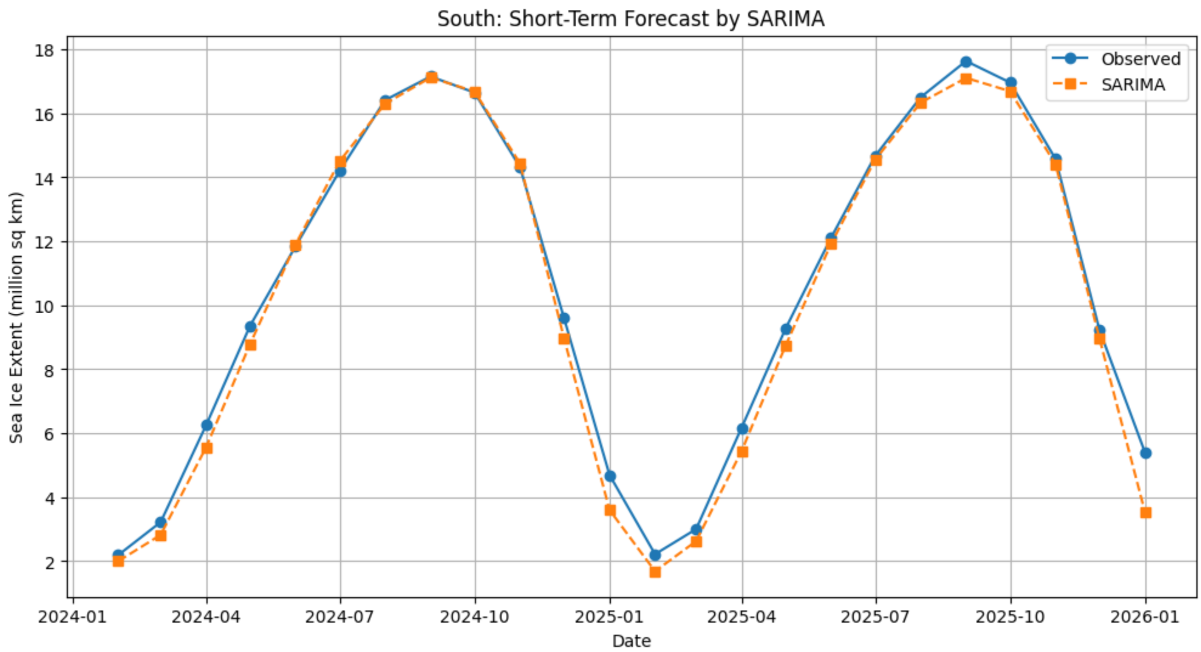

Fig. 8. SARIMA forecast evaluation for South Hemisphere

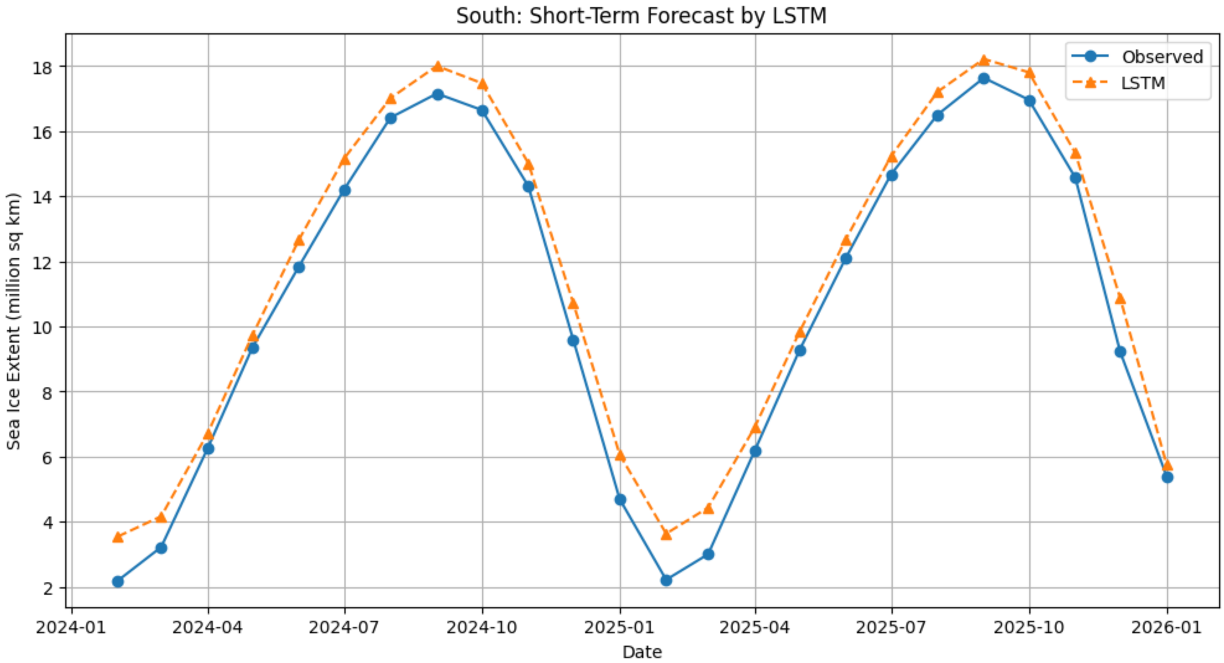

Fig. 9. LSTM forecast evaluation for South Hemisphere

Analysis of the long-term forecast of all methods for the Southern Hemisphere showed similar results to those observed in the Northern Hemisphere. In particular, for the LSTM method, a decay of the forecast was observed with a gradual decrease in amplitude. Bi-LSTM shows a sharp decay, after which the forecast converges to a constant value.

The study confirmed the hypothesis that the time series data of the Sea Ice Extent of the Northern Hemisphere is better predicted by statistical methods, at the same time, for the forecast of the sea ice extent in the Southern Hemisphere, it is advisable to use artificial intelligence technologies and, in particular, deep learning to identify hidden trends and patterns.

Depending on the tasks, the proposed approaches can be implemented in predictive information systems. Short-term forecasting by all models is performed with high accuracy for both hemispheres. Long-term forecasting cannot be fully assessed due to the lack of historical observation data. However, the assessment of the long-term forecast allows to determine the presence of attenuation or approximation of the forecast to a constant value.

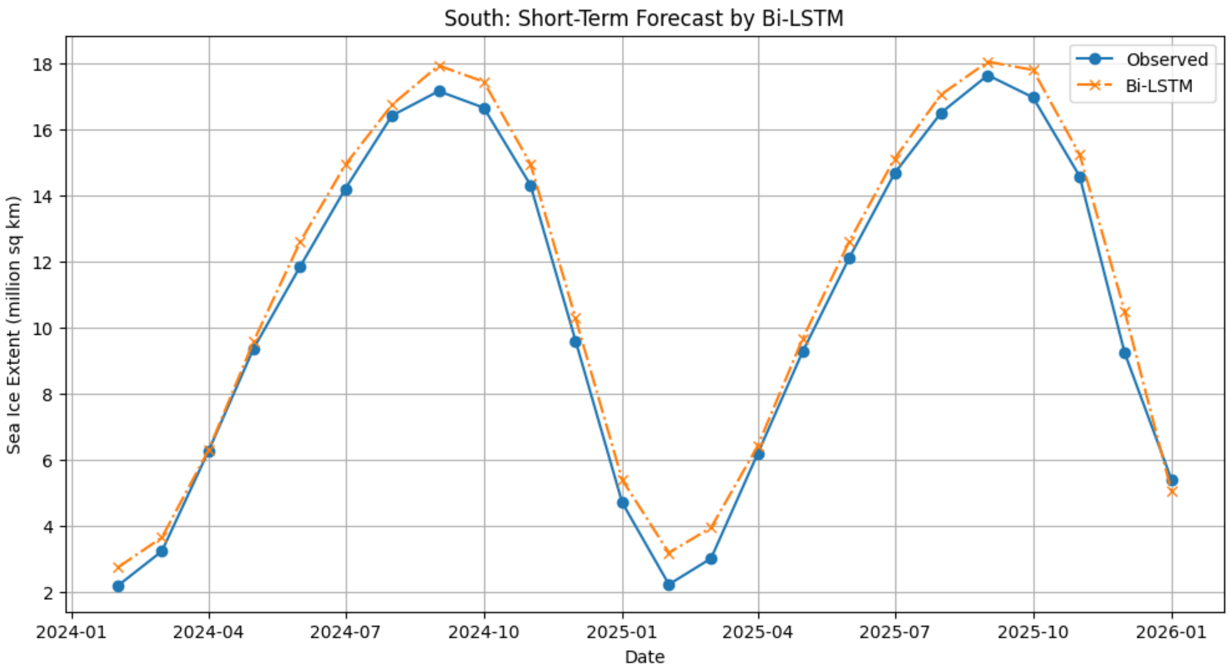

Fig. 10. LSTM forecast evaluation for South Hemisphere

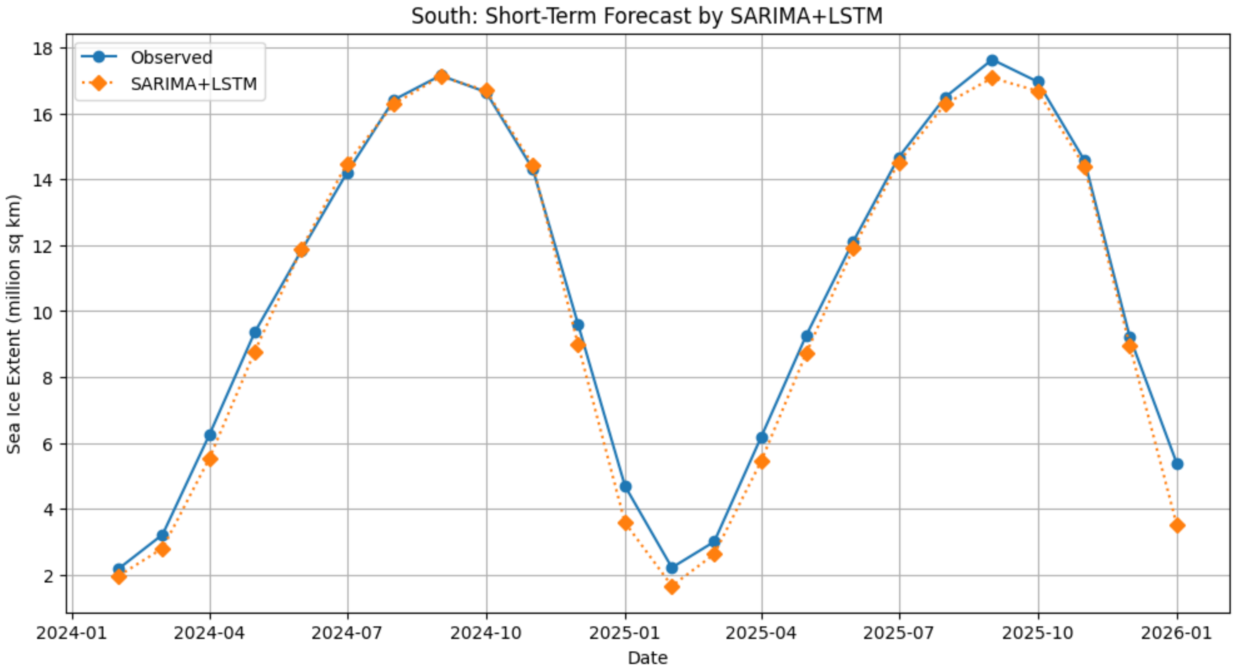

Fig. 11. SARIMA+LSTM forecast evaluation for South Hemisphere

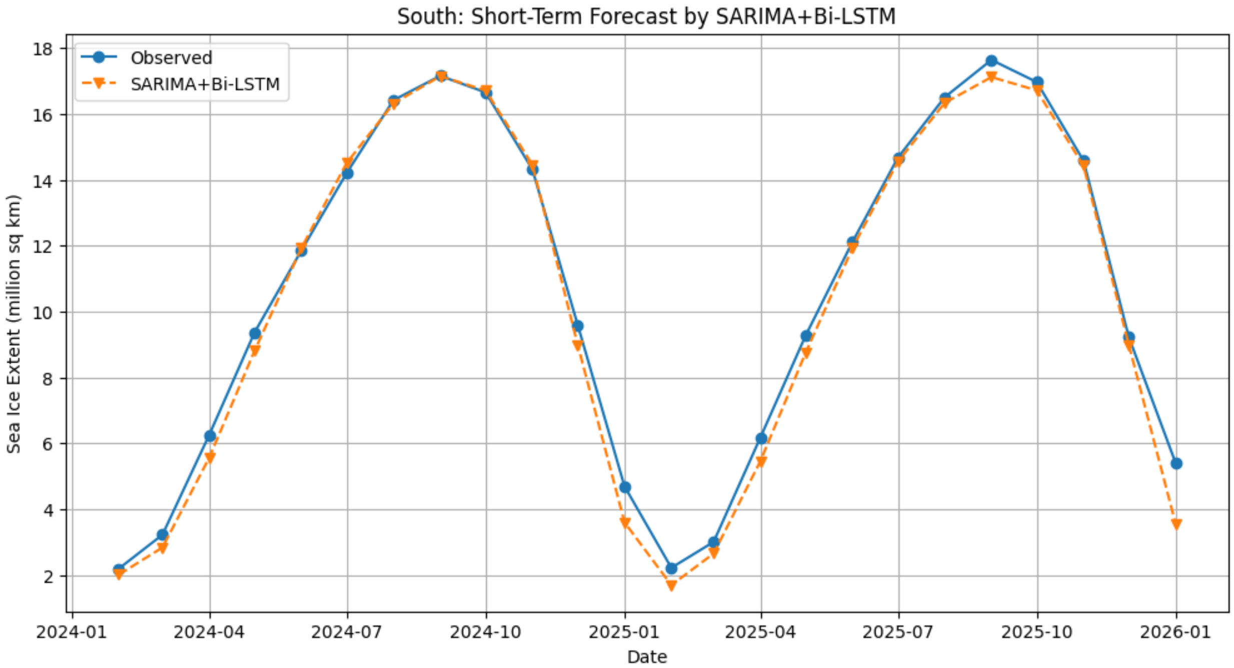

Fig. 12. SARIMA+Bi-LSTM forecast evaluation for South Hemisphere

The study allows us to assess the main climatic trends that have formed in the Arctic and Antarctic regions. Estimating future values of Sea Ice Extent is critically important for implementing the necessary measures to preserve the flora and fauna of the polar regions, as well as for the sustainable development of cities and communities not only in the polar regions, but also in coastal regions around the world, since the melting of glaciers is directly related to the rise in the Sea level.

Thus, the data obtained are critically important for politicians and planners of a number of countries that are vulnerable to climate change in the polar regions.

4. Discussion

Sea Ice Extent forecasting for Arctic and Antarctic regions is crucial for understanding climate change, ecosystems, navigation, and geopolitics. Accurate Sea Ice Extent forecasts are crucial for maritime navigation, infrastructure planning, risk management, ecosystem protection, and policy decision-making on climate change mitigation. Uncertainty in forecasts complicates these processes. Climate models have historically underestimated the rate of Arctic Sea Ice loss. While many models now predict an "ice-free" summer in the Arctic in the coming years, the exact timing and dynamics of this process are still a matter of debate.

The situation with Antarctic sea ice is even more complex. For a long time, there has been little growth or stability in the extent of ice, which contradicts some predictions. However, a sharp decline began in 2016, and record lows were recorded in 2023. This sudden and significant decrease indicates the imperfection of existing forecasting systems.

Recent studies indicate a possible role for increased salinity of the waters around Antarctica in this process, which creates a paradox, since melting ice usually leads to desalination. Thus, the process of sea ice loss is complex and requires a comprehensive analysis. Further research may reveal additional factors that should be taken into account in forecasting models.

Although satellite observations have significantly improved our understanding of sea ice dynamics since 1979, there are still gaps in the data. This is particularly true for ice thickness, as area-based analysis alone does not provide a complete picture of the situation.

The data limitations are due to the fact that collecting data directly in polar regions is difficult and expensive due to the harsh conditions.

Nowadays, there are different approaches to forecasting. Physical models try to simulate the physical processes that drive ice dynamics. They are complex and require significant computing resources. Their accuracy depends on the correct representation of all interactions.

At the same time, statistical models and machine learning use historical data and statistical relationships to make forecasts. They are faster and more efficient for short-term forecasts, but may have limitations in predicting unprecedented events or long-term changes. There are attempts to combine both approaches, in particular, using machine learning to correct errors in dynamic models.

The approach presented in the study allows creating a long-term forecast by combining statistical models and machine learning methods to recognize hidden patterns. Although the models demonstrated high performance indicators, due to the lack of long-term observational data, the models were evaluated only for the short term.

The proposed framework provides a comprehensive analysis and forecasting of time series data of sea ice extent from statistical methods and data mining to forecasting. Methods and approaches for forecasting the sea ice extent of the Arctic and Antarctic regions are proposed.

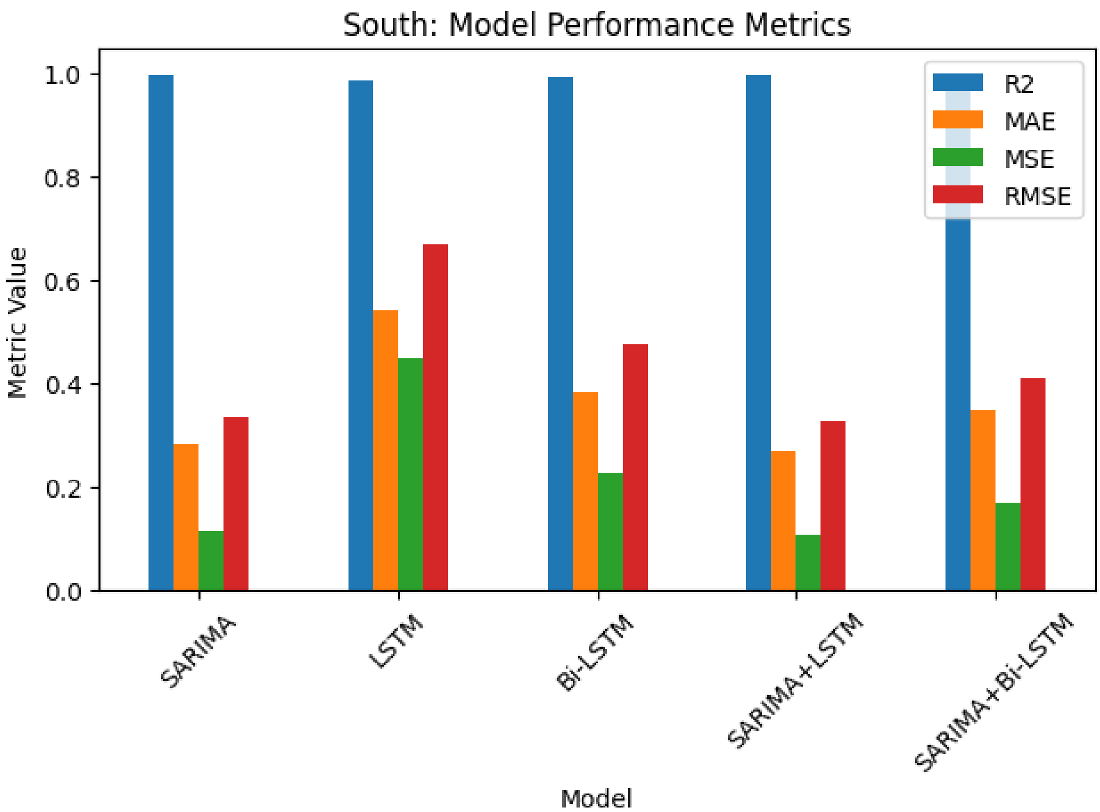

Fig. 13. Performance metrics

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Table 2

Model evaluation for South Hemisphere

Model	Metrics			
	R^2	MAE	MSE	RMSE
SARIMA	0.9965	0.2814	0.1119	0.3345
LSTM	0.986	0.5404	0.447	0.6686
Bi-LSTM	0.993	0.3827	0.2261	0.4755
SARIMA+LSTM	0.9967	0.2685	0.1069	0.327
SARIMA+Bi-LSTM	0.9948	0.3459	0.1674	0.4092

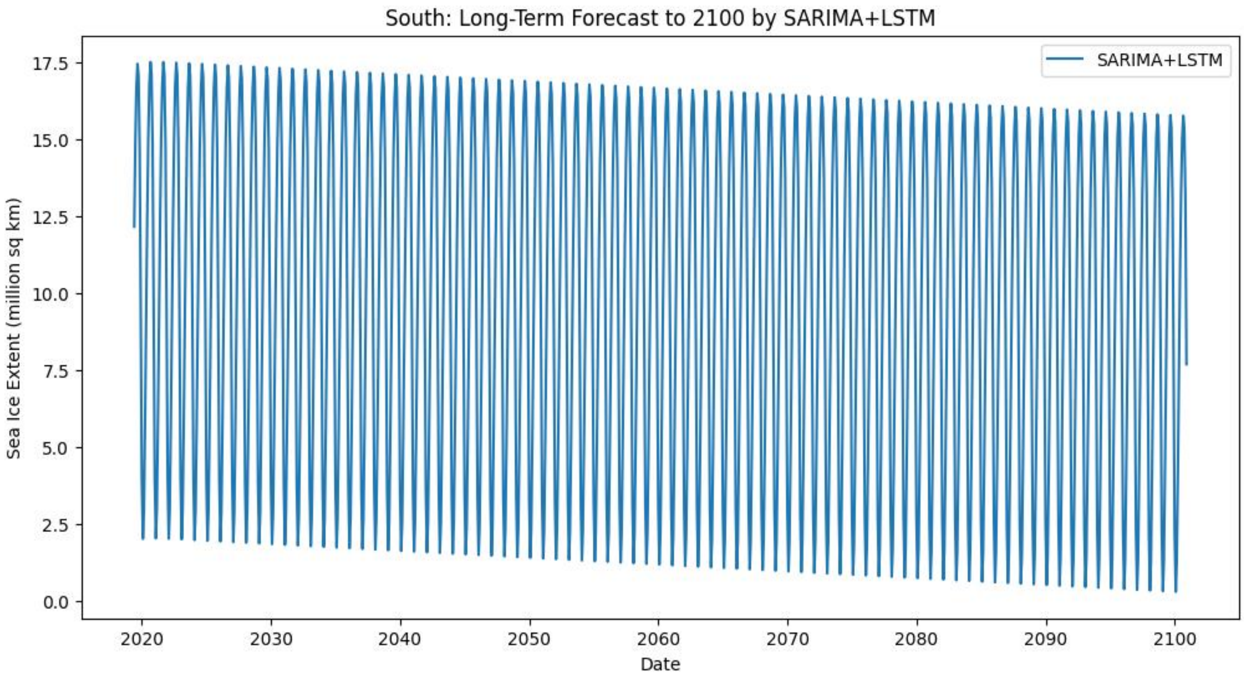

Fig. 14. Long-term forecast by SARIMA+LSTM

To create a highly accurate system, it is advisable to use the principles of dynamic forecasting and the reinforcement learning paradigm, which will allow for prompt correction of the forecast, as well as capture potential model errors or natural anomalies.

Another common approach in such tasks is the use of the federated learning approach. The application of federated learning for the considered task is in principle possible, since sea ice data comes from several observation platforms and agencies.

However, in this problem it is impractical. Federated learning is primarily designed for scenarios involving data confidentiality restrictions, limited data exchange, or decentralized data ownership. Instead, global sea ice records are openly available, centrally curated, and already integrated into unified reanalysis products.

Therefore, predicting sea ice in polar regions remains an active and complex area of research, with new challenges and issues of debate constantly emerging, especially given the unprecedented changes observed in recent years, particularly in Antarctic region.

5. Conclusions

The application of the SARIMA model to long-term forecasting demonstrated its ability to capture persistent trends and generate stable projections based on historical dynamics. In contrast, deep learning models proved effective in identifying hidden nonlinear patterns and exhibited high predictive performance in short-term forecasting. However, for long-term horizons, deep learning models tend to exhibit forecast degradation, with predictions converging toward a limiting value. This behavior can be attributed to overfitting and to the limited capacity of purely data-driven models to extrapolate long-term trends.

To address this limitation, ensemble models were developed that integrate seasonal autoregressive components with deep learning architectures. This combination enables the simultaneous representation of large-scale trend dynamics and hidden nonlinear variability.

The experimental results confirm the hypothesis formulated during exploratory data analysis and demonstrate that the proposed model selection and ensemble construction strategy provides improved robustness and forecasting accuracy across different temporal regimes.

Future research. Based on the experiments conducted, a basis has been formed for further research, in particular:

– Development of an information system for Sea Ice Extent forecasting using the proposed approaches;

– Research into the impact of sea ice extent on other climate indicators and related threats, including sea level rise and the risk of coastal flooding;

– Research into time series of other climate parameters, evaluation of machine learning technologies for their forecasting.

To increase the reliability of the results obtained, it is planned to use the reinforcement learning paradigm for dynamic model adjustment in the future.

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Conflict of Interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, author ship or otherwise, that could affect the research and its results presented in this paper.

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This study was conducted without financial support.

Data Availability

The work has associated data in the data repository.

Use of Artificial Intelligence

During the preparation of this work, the authors used Grammarly in order to: grammar and spelling check; DeepL Translate in order to: some phrases translation into English. After using these tools/services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

All the authors have read and agreed to the published version of the manuscript.

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ПРОГНОЗУВАННЯ ПЛОЩІ ПОШИРЕННЯ МОРСЬКОГО ЛЬОДУ З ВИКОРИСТАННЯМ СТАТИСТИЧНИХ МЕТОДІВ ТА ГЛИБОКОГО НАВЧАННЯ

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Предметом вивчення статті є прогнозування часових рядів площі поширення морського льоду статистичними методами та методами глибокого навчання. Площа морського льоду є одним із найважливіших показників зміни клімату. Сьогодні спостерігаються тенденції до танення льодовиків, що призводить до підвищення рівня моря, і, в свою чергу, створює значну загрозу затоплення прибережних регіонів по всій земній кулі. Крім того, танення льодовиків впливає на флору та фауну арктичного та антарктичного регіонів, а також на економічну стабільність у світі, охоплюючи економічний розвиток та продовольчу безпеку. Сфери сільського господарства, туризму, логістики напряму залежать від кліматичних змін, тому прогнозування майбутніх змін є критично важливим для стабільності та сталого розвитку. У статті проаналізовано основні тенденції зміни площі морського льоду. **Метою** дослідження є аналіз статистичних методів та методів глибокого навчання в контексті створення високоточного довгострокового прогнозу. **Завданнями** статті є проведення порівняльного аналізу статистичних методів та методів глибокого навчання та їх оцінка для задачі прогнозування площі поширення морського льоду. В дослідженні використано **методи** прогнозування на основі статистичних моделей та глибокого навчання. Проведено дослідження, щодо використання різних підходів до прогнозування майбутніх змін часового ряду на основі статистичних методів, методів глибокого навчання та ансамблевих моделей. Одержані **результати** дозволяють оцінити роботу моделей у короткостроковій перспективі та сформовано підхід до довгострокового прогнозування. Запропоновано використання авторегресорів та методів глибокого навчання для створення надійного довгострокового прогнозу. Порівняння роботи методів було проведено для Північної та Південної півкуль. **Висновки.** Наукова новизна одержаних результатів полягає в наступному: набув подальшого розвитку метод прогнозування часових рядів площі поширення морського льоду з використанням статистичних методів та методів глибокого навчання. На основі проведених експериментів визначено найточніші методи. Використання ансамблевих підходів дозволяє забезпечити як врахування основних тенденцій, так і розпізнавання прихованих закономірностей. Отримані результати дають змогу комплексно оцінити часові ряди для Північної та Південної півкуль та вказують на доцільність використання як статистичних методів прогнозування для даних з чітко визначеними закономірностями на прикладі Арктичного регіону, так і методів глибокого навчання задля розпізнавання прихованих закономірностей, що спостерігаються в даних часового ряду Антарктичного регіону.

Ключові слова: площа поширення морського льоду; прогнозування; авторегресори; глибоке навчання; ансамблеві моделі.

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