# Explainable artificial intelligence foundations for web-based sea ice extent forecasting system

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## Abstract

The growing need to regulate AI systems, especially in high-stakes domains like climate science, makes explainability essential for fostering user trust and ensuring transparency. Forecasting climate parameters using opaque models undermines a full understanding of how predictions are made, creating a critical gap in responsible AI application. In this work, we propose the foundations for a web-based information system designed for explainable long-term forecasting of sea ice extent. Our study develops an AI solution that supports environmental sustainability by analyzing and integrating statistical methods, deep learning models, and ensemble techniques. We conduct a detailed comparison of these approaches, outlining their respective advantages and disadvantages in generating reliable long-term forecasts. The proposed system is designed to comply with the principles of Explainable AI (XAI) and the norms of current European Union legislation. By explaining the application of deep learning within ensemble models, this work establishes a framework for developing transparent, accessible, and compliant AI tools to address pressing climate change challenges.

## Keywords

Explainable artificial intelligence (XAI), sea ice extent, forecasting, climate change, web-based information system

## 1. Introduction

Nowadays, there is a sharp growth in artificial intelligence (AI) tools that solve applied problems in various areas of human life. However, quite often, AI models can be imperfect and make incorrect or suboptimal decisions that directly affect the quality of life or cause financial or reputational damage. Thus, users' lack of understanding of the principles of operation of systems with implemented AI models undermines trust in the work of the models. This problem is especially acute for deep learning models.

The concept of Explainable Artificial Intelligence (XAI) is focused on understanding the behavior of an artificial intelligence model, similar to how people do it [1, 2]. When developing XAI systems, it is necessary to ensure four basic principles: Explanation, Meaningful, Explanation Accuracy, and Knowledge Limits [3].

Scientists Ayodeji Olusegun Ibitoye, Makuochi Samuel Nkwo and Rita Orji note: "The discourse on responsible AI has focused on a core set of normative principles: fairness, transparency, accountability, privacy, security and value alignment, which are widely supported as ethical foundations for the development and governance of artificial intelligence" [4].

Thus, the development of XAI systems is extremely relevant. As part of the study, we consider it appropriate to review the concepts and approaches to the development of XAI predictive models,

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identify and describe the main directions of the development of a web-based information system for long-term forecasting of sea ice extent using statistical and deep learning methods, explain the specifics of the application of each of the methods in the context of the use of ensemble models, and determine the compliance of the developed information system with the ethical and legal aspects of responsible AI in the context of existing European Union (EU) legislation.

Web-based sea ice extent forecasting system will be developed taking into account the approaches, principles, and methods already tested by the authors in previous scientific works [5, 6]. The use of proven solutions [7, 8] will ensure methodological continuity, increase the reliability of results, and allow the integration of best practices in explainable artificial intelligence into a new web-based forecasting tool. This approach will contribute to both the scientific validity of the project and the practical effectiveness of the system, which is focused on transparent explanation of forecasts and support for decision-making in the field of ice cover monitoring.

## 2. Related works

Previous works have considered long-term forecasting of the Land Surface Temperature using a recurrent neural network (RNN) with Long Short-Term Memory (LSTM) architecture [9] and the analysis of sea ice extent data using statistical methods and unsupervised learning methods to prepare data for forecasting [10].

A significant problem in the development of XAI is the "black box" on which deep learning models are based. That is, the nature of the algorithm is not transparent, which causes users to distrust certain decisions made by the system. In order to create a counterbalance to the concept of the "black box," scientists have defined the key terms Transparency, Interpretability and Explainability [11]. The study [12] considers the problem of transparency of algorithms used in socially significant and ethically significant contexts. The article [13] discusses XAI approaches in the context of climate change research, in particular model-agnostic distillation or feature attribution methods.

Researchers have shown that hybrid models that combine AI-driven forecasting with climate models demonstrate the potential to improve the forecasting skills of extreme conditions on climatically relevant time scales. However, the use of such approaches leaves numerous challenges in aspects such as data curation, model uncertainty, generalizability, reproducibility of methods and workflows [14]. The research [15] demonstrates the effectiveness of an expert-driven model based on XAI in identifying problem areas for the agricultural sector. [16] describes the importance of explanatory artificial intelligence in climate change research, in order to better understand climate processes and identify factors that cause changes.

The study [17] introduces the assessment of XAI in a climate context and highlights various desirable properties of an explanation, namely: robustness, reliability, randomization, complexity, and localization. The article [18] presents a comprehensive review of the use of XAI technologies for forecasting droughts, floods, and landslides, and describes ways to address gaps in XAI implementation, providing reliable, transparent, and ethical approaches to assessing climate hazards in an era of rapid environmental change. The research [19] evaluates the reliability of XAI methods applied to regression forecasts of Arctic sea ice.

Of particular relevance in the context of explanatory AI is the problem of long-term forecasting. A number of studies are related to this problem. In particular, the article [20] considers long-term forecasting of nutrients at the surface of the Southern Ocean using comprehensible neural networks. The study [21] examines the Transferability and Explainability of deep learning emulators in the context of regional climate model predictions and outlines the prospects for their future applications. The research [22] focuses on the possibility of interpreting the learning process of AI using significance maps.

Scientists W. Li, C.-Y. Hsu and M. Tedesco note that: "In addition to quantifying uncertainty, XAI can play a crucial role in improving scientific understanding of complex Arctic systems" [23]. The study [24] examines the use of explanatory deep learning to predict daily sea ice extent. The article [25] outlines the ethical aspects of developing AI systems for weather forecasting. Researchers pay considerable attention to the legal and ethical issues of applying artificial intelligence and machine learning to analyze and predict climate change [26].

In general, researchers identify the pillars of XAI, such as Transparency, Accountability, and Privacy. The developed information systems should ensure confidentiality, responsibility, and openness as cornerstones that support the moral practice of AI in order to dispel users' fears about AI tools [27, 28]. The analysis allowed us to highlight important aspects that should be paid attention to when developing an information system. The problem of developing XAI for predicting the area of sea ice in the Arctic and Antarctic regions remains relevant and requires further research.

## 3. Methodology

AI-based forecasting relies on robust datasets that capture the dynamics of Time Series Data over time. AI models which can be used for Sea Ice Extent forecasting range from traditional machine learning algorithms to advanced deep learning techniques. It is necessary to evaluate performance across different time horizons and examine model robustness during extreme conditions, such as record-low ice years. Also it is important to promote trust, transparency, and the effective integration of AI technologies into global climate initiatives. Figure 1 presents the research methodology.

To avoid any risks, it is necessary to ensure responsible research. In particular, use only reliable datasets provided by international organizations such as National Aeronautics and Space Administration (NASA), World Meteorological Organization (WMO), National Snow and Ice Data Center (NSIDC). For the accuracy of the forecast, it is advisable to use different approaches, including statistical and data mining, as well as evaluating the performance of machine learning models using known metrics. This will avoid problems of overfitting or underfitting and will help mitigate potential risks in forecasting anomalous values. To avoid legal and ethical risks, it is planned to use open source methodologies and implement a data management policy to comply with ethical and legal standards.

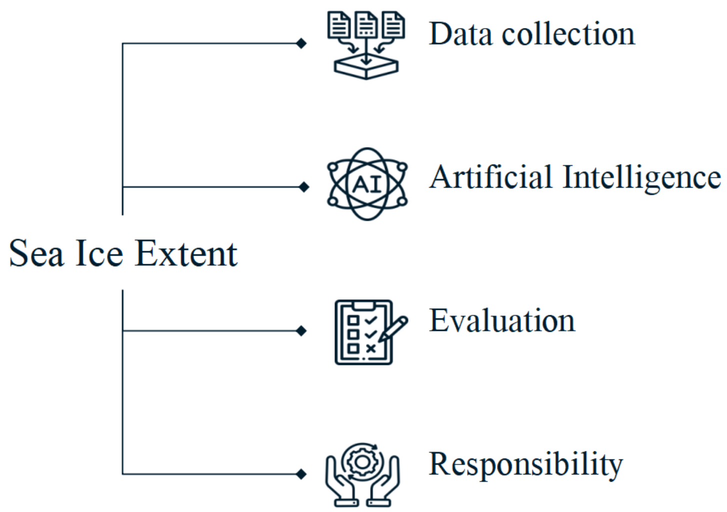


**Figure 1:** A diagram illustrating the core research methodology, which encompasses four key stages: Data collection, application of Artificial Intelligence, Evaluation of the model, and ensuring Responsibility in the overall process for Sea Ice Extent forecasting.

## 4. Results

The study covers a long-term forecast of sea ice extent until 2100. First, let's consider the forecast for the Northern Hemisphere. Figure 2 shows the SARIMA model forecast. The model preserves fluctuations well, but has a clearly linear character, which is also observed in previous observations. This means that the forecast of this model can be considered quite reliable. Figure 3 shows the forecast graph of the LSTM model. Although the forecast for the first year is highly accurate and preserves fluctuations, a rapid attenuation is observed for subsequent years. Thus, this model can only be used for short-term forecasts. The forecast of the recurrent neural network with Bi-LSTM architecture demonstrates similar trends to the LSTM model, but the attenuation in this case is not as rapid (Figure 4). However, this model is also not suitable for long-term forecasting.

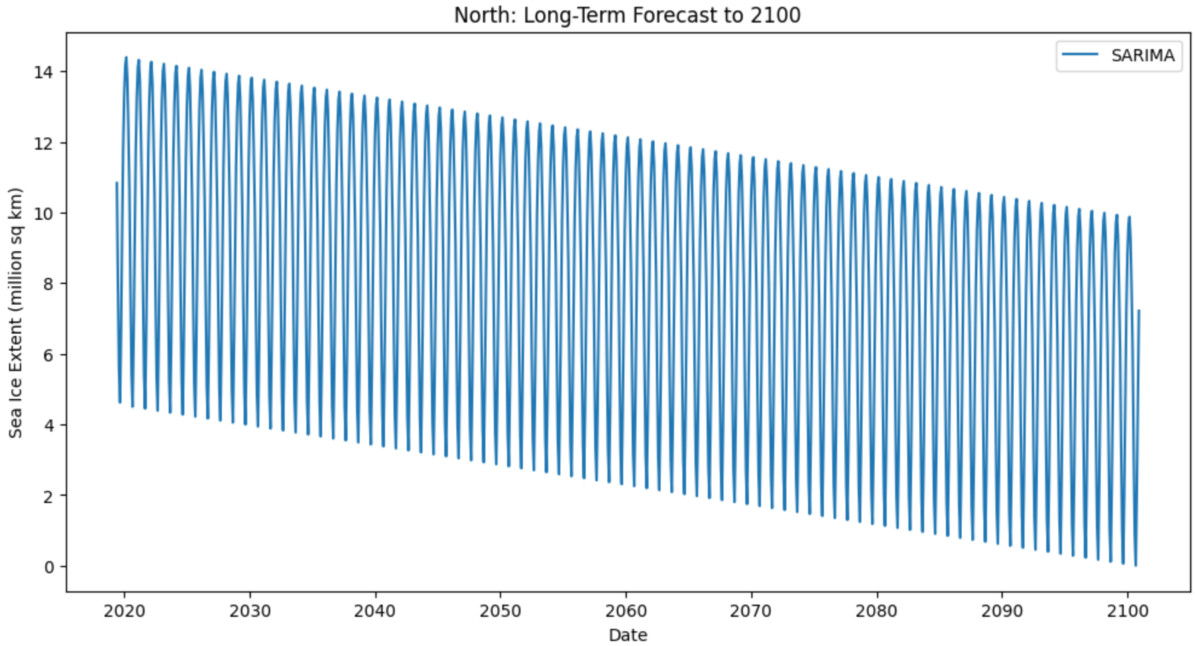


**Figure 2:** Long-term forecast of sea ice extent in the Northern Hemisphere until the year 2100, generated by the SARIMA model. The model effectively preserves seasonal fluctuations but exhibits a clear linear downward trend.

It is obvious that in this case, the use of ensemble models with parallel training will not provide a correct long-term forecast. Therefore, we will perform forecasting using the approach of training deep learning models based on residuals. Figure 5 shows the long-term forecast of the SARIMA + LSTM ensemble model, and Figure 6 shows the SARIMA + Bi-LSTM model. The forecast of both models retains the main trends identified by SARIMA, but adjusts the values according to the hidden patterns identified by recurrent neural networks.

Forecasting the extent of sea ice in the Southern Hemisphere has some differences. The SARIMA model forecast (Figure 7) captures the main patterns well and shows a slight downward trend, which becomes more pronounced for minimum values towards the end of the 21st century.

Figure 8 shows the forecast of the model with LSTM architecture. The forecast shows some amplitude fluctuations, but unlike the forecast for the Northern Hemisphere, there is no signal attenuation over time. The forecast of the Bi-LSTM model is shown in Figure 9. The model shows a gradual signal attenuation. The construction of ensemble models for the Southern Hemisphere was similar to that for the Northern Hemisphere, i.e., residual-based training was used for deep learning models. The forecast of the SARIMA + LSTM model is shown in Figure 10, and that of the SARIMA + Bi-LSTM model is shown in Figure 11.

For implementation in the information system, models were selected that demonstrated high short-term forecast metrics and no long-term forecast deficiencies. Thus, the SARIMA model was selected for the Northern Hemisphere, and the SARIMA + LSTM ensemble model was selected for the Southern Hemisphere.

A web-based information system was developed to implement the model and present it to a wide

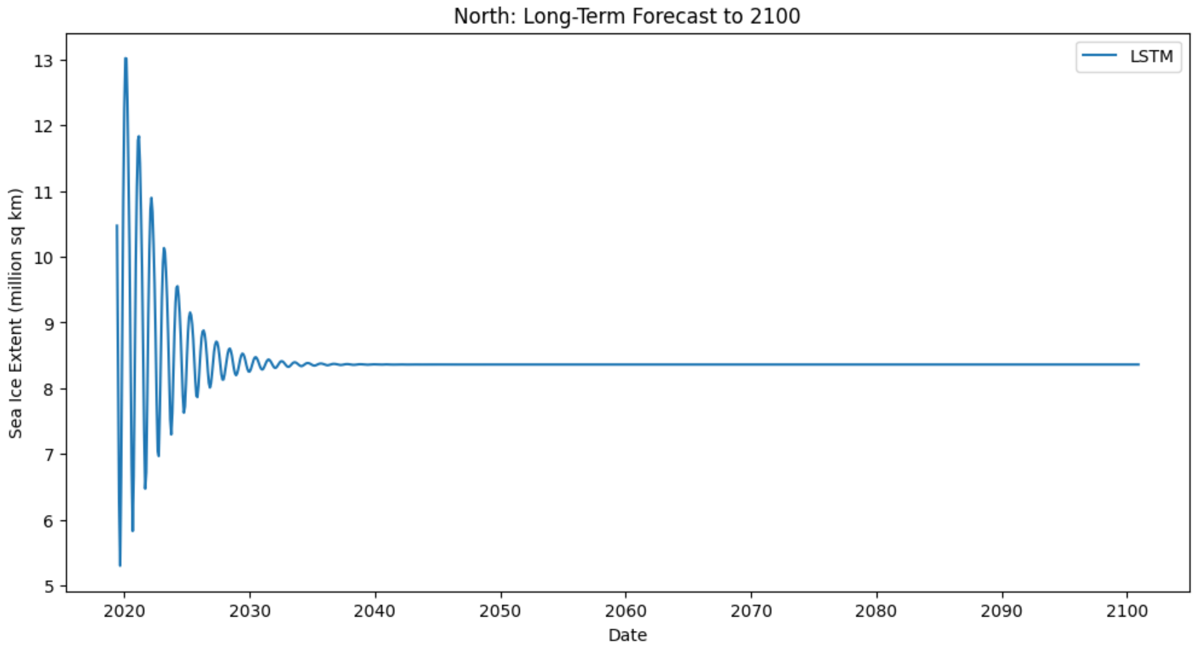


**Figure 3:** Long-term forecast of sea ice extent for the Northern Hemisphere using the LSTM model. The plot shows accurate short-term fluctuations followed by rapid signal attenuation, indicating its unsuitability for long-term predictions.

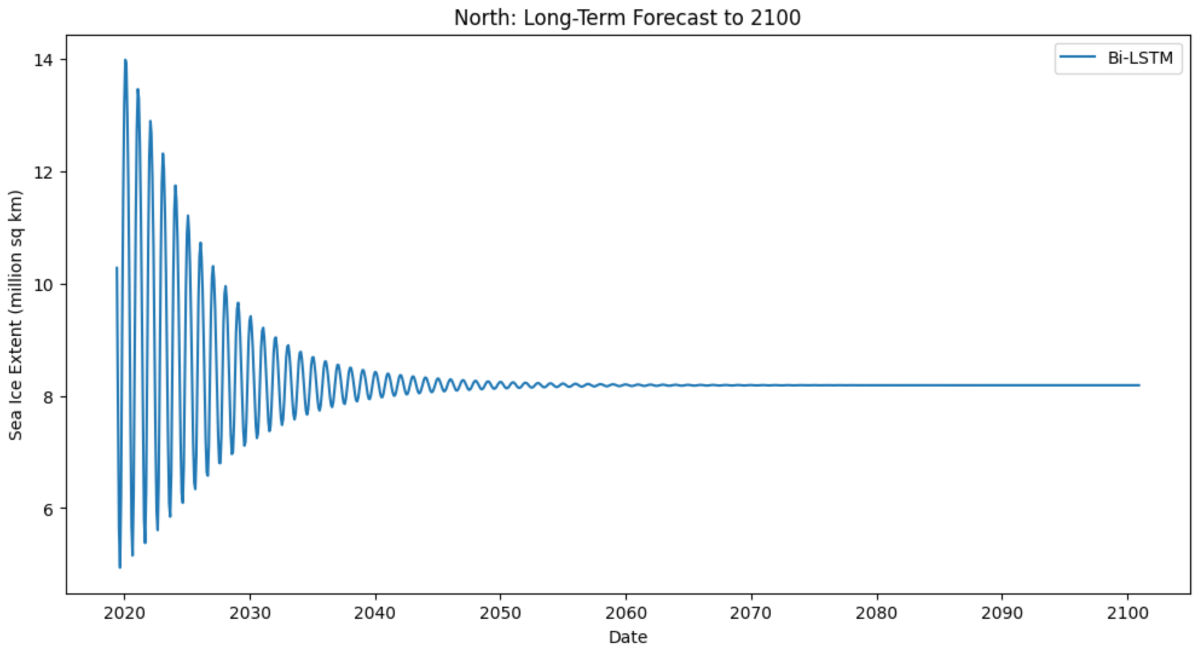


**Figure 4:** Long-term Bi-LSTM forecast for the Northern Hemisphere. Similar to the LSTM model, it shows a gradual attenuation of fluctuations over time, making it unsuitable for reliable long-range forecasting.

range of users. The developed information system displays data from the beginning of sea ice area observations, i.e. from the end of 1978, and provides a forecast until 2100. It also provides the ability to compare data. Figure 1 shows a comparison of data in tabular form, and Figure 12 shows a graphical comparison. For greater clarity, potential changes in coastal areas have been visualised (Figure 13). The service is adaptive, allowing it to be used from different devices. The user interface is convenient, intuitive and complies with all the principles of UI/UX design.

The developed information system can be useful for scientists, researchers of the Arctic and Antarctic

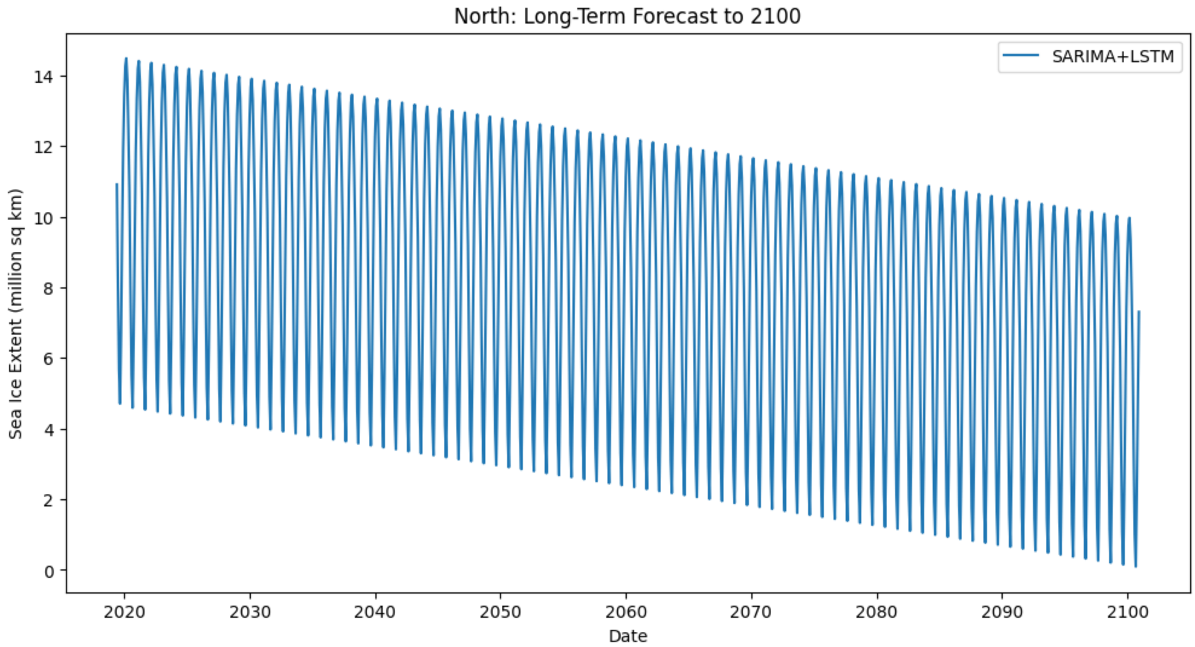


**Figure 5:** Long-term forecast from the SARIMA + LSTM ensemble model for the Northern Hemisphere. This residual-based model maintains the SARIMA trend while incorporating adjustments from the LSTM component.

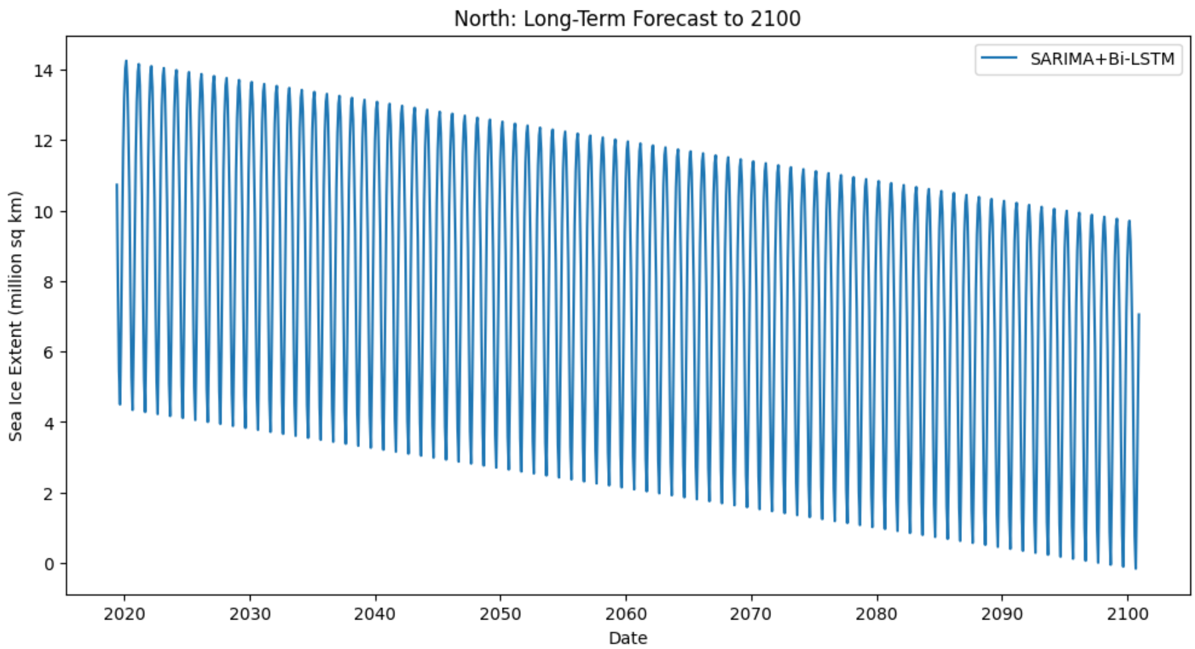


**Figure 6:** Long-term forecast from the SARIMA + Bi-LSTM ensemble model for the Northern Hemisphere. This model also uses a residual-based approach to combine the strengths of both underlying models.

regions, urban planners, to ensure sustainable development of cities and communities in both polar regions and more remote areas, which are nevertheless coastal and therefore vulnerable to fluctuations in the sea level. Also, the information system can be used for educational purposes for a comprehensive understanding of the problem of melting glaciers. The developed tools for visualization of the forecast allow to more clearly demonstrate potential problems that may arise in polar regions. The information system also contributes to a comprehensive understanding of climate change and the key role of the polar regions, whose climate affects the ecosystem of the entire planet.

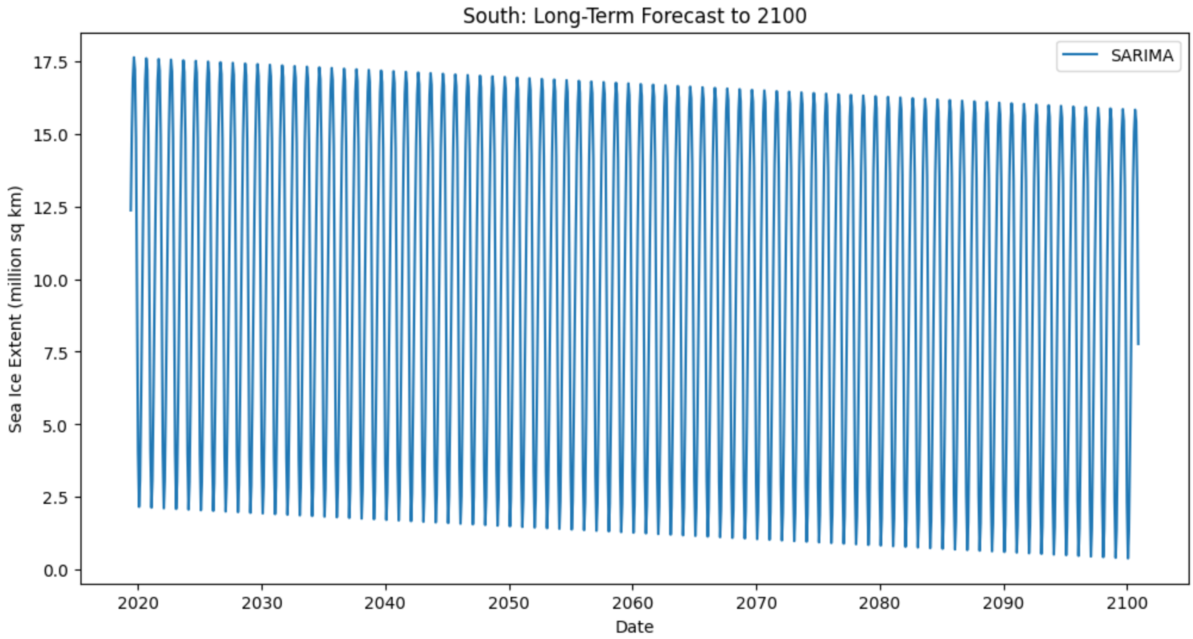


**Figure 7:** Long-term SARIMA forecast for the Southern Hemisphere. The model shows a slight downward trend, with more pronounced decreases in minimum sea ice extent toward the end of the century.

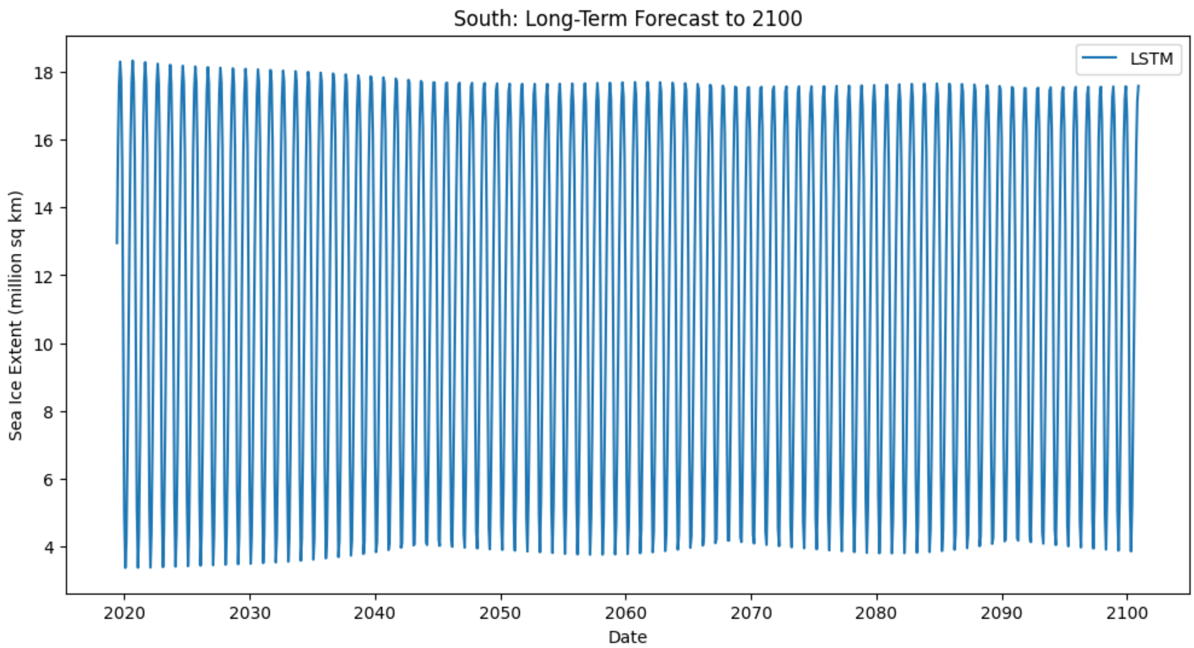


**Figure 8:** Long-term LSTM forecast for the Southern Hemisphere. Unlike its Northern Hemisphere counterpart, this model's forecast does not exhibit significant signal attenuation over the forecast period.

## 5. Discussion

In long-term forecasting, many sequence-to-sequence models, such as LSTM and Bi-LSTM, tend to smooth out fluctuations. As a result, the forecast tends to shrink toward the mean or create flat, i.e., non-dynamic trajectories. This is due to a number of factors, including error buildup, which makes the model cautious, training loss, which increases with deviations, so the network starts to predict average values, and the lack of explicit seasonality, which leads to a loss of model amplitude over time. As a result, forecasts appear to be weakened, with less variance, and flatter forecast curves compared to the

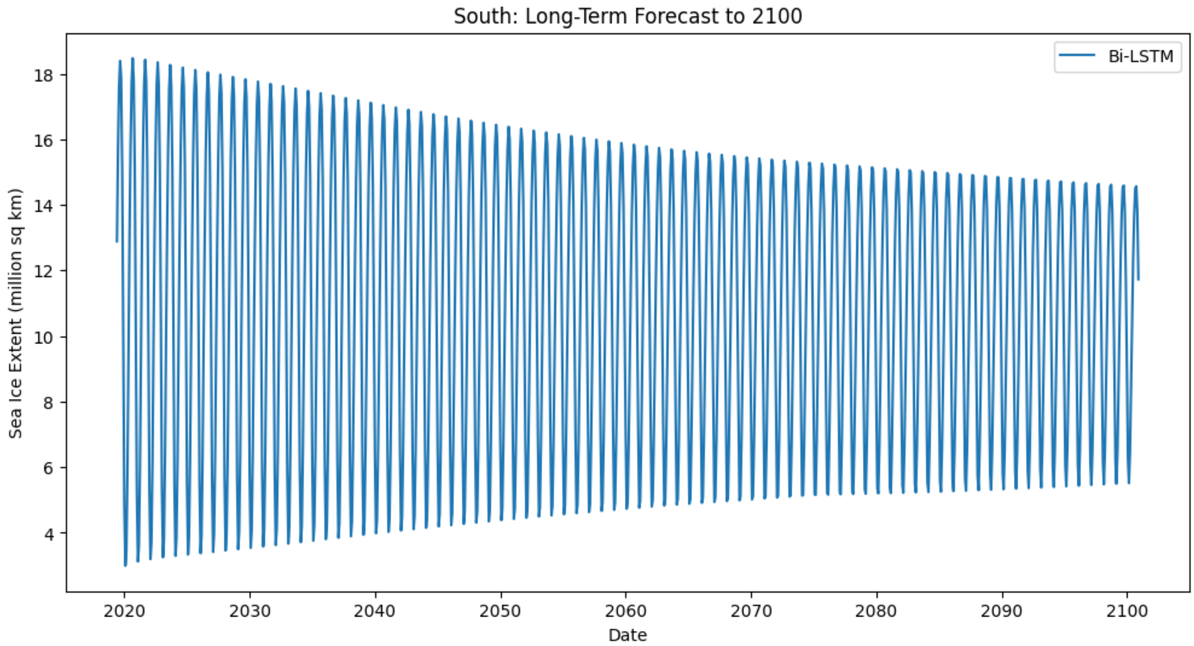


**Figure 9:** Long-term Bi-LSTM forecast for the Southern Hemisphere, which shows a gradual signal attenuation over time, similar to the forecasts for the Northern Hemisphere.

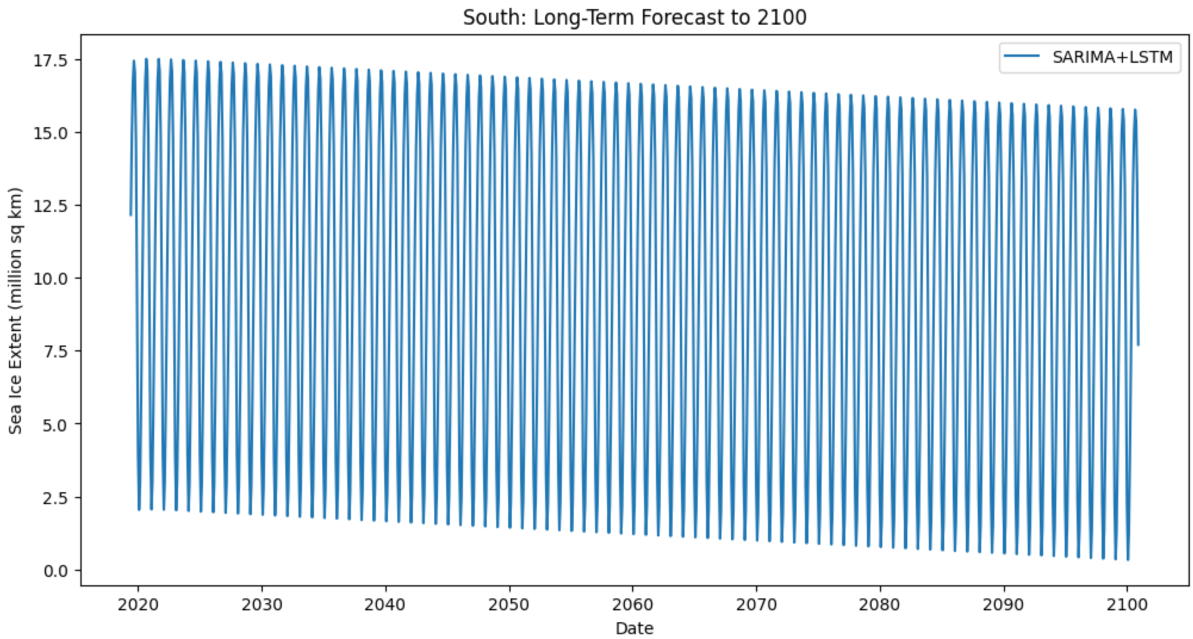


**Figure 10:** Forecast from the SARIMA + LSTM ensemble model for the Southern Hemisphere. This combination provides a stable and adjusted long-term prediction.

real ones.

The SARIMA + DL ensemble can help avoid damping, or at least significantly mitigate it. Since the SARIMA model is specifically designed to maintain seasonal cycles and trend amplitudes, it preserves fluctuations well. Thus, even if DL forecasts fade, SARIMA ensures that the forecast does not flatten out. There are two approaches to building ensemble models: conventional (parallel) training and residual-based (sequential) training.

Conventional or parallel training trains both SARIMA and recurrent neural networks on the same input time series. Thus, both methods produce forecasts independently, and the final forecast is a

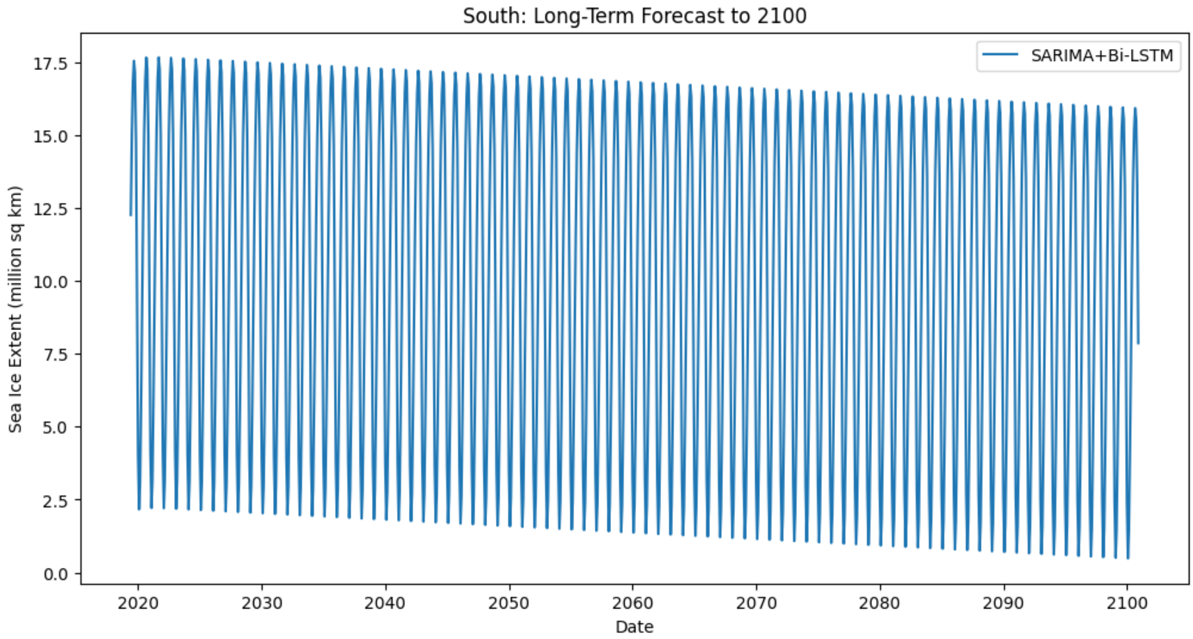


**Figure 11:** Forecast from the SARIMA + Bi-LSTM ensemble model for the Southern Hemisphere, illustrating the result of the residual-based training approach.

**Table 1**
Tabular comparison of observed sea ice extent for the year 2000 against the forecasted extent for the year 2070, showing a significant projected decrease across all months.

| Month | Extent 2000 year | Extent 2070 year |
|---|---|---|
| January | 14.2 | 10.5 |
| February | 15.1 | 11.3 |
| March | 15.2 | 11.6 |
| April | 14.6 | 11.0 |
| May | 13.2 | 9.5 |
| June | 11.7 | 7.8 |
| July | 9.5 | 5.1 |
| August | 7.2 | 2.6 |
| September | 6.2 | 1.7 |
| October | 8.4 | 3.7 |
| November | 10.3 | 6.5 |
| December | 12.6 | 8.9 |

combination of the weighted average forecast of both models. The advantages of this approach are simplicity of implementation and the ability to take into account different aspects, such as linear and nonlinear trends, by each of the models. This helps to avoid the dominance of one model over the structure. However, this approach has a number of disadvantages, including redundancy and a risk of averaging out important dynamics if the weights have not been carefully selected.

Residual-based or sequential training involves using SARIMA to predict explicit patterns, in particular trend, seasonality, and autocorrelation. Then, the residuals are calculated based on the actual values obtained by the SARIMA forecast. The training of a recurrent neural network with an LSTM or Bi-LSTM architecture is performed only on the residuals. That is, the final forecast is the SARIMA forecast and the forecast of the residuals by a deep learning model. The advantages of this approach are a cleaner decomposition, since SARIMA processes linear (seasonal) patterns, and DL processes nonlinear (complex) and hidden patterns. The risk of overtraining is also significantly reduced, since the RNN only needs to model the residual noise, and not the full structure. This approach helps to avoid damping,

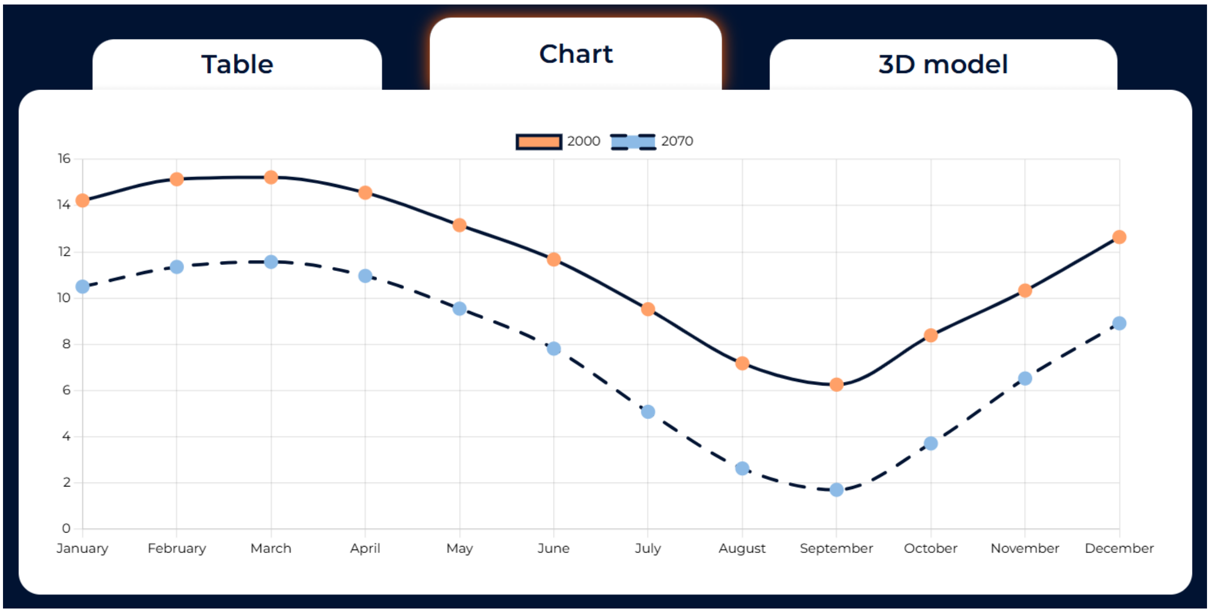


**Figure 12:** Graphical comparison of observed sea ice extent from 2000 (solid line) and the forecasted extent for 2070 (dashed line), visually highlighting the projected seasonal changes and overall reduction.

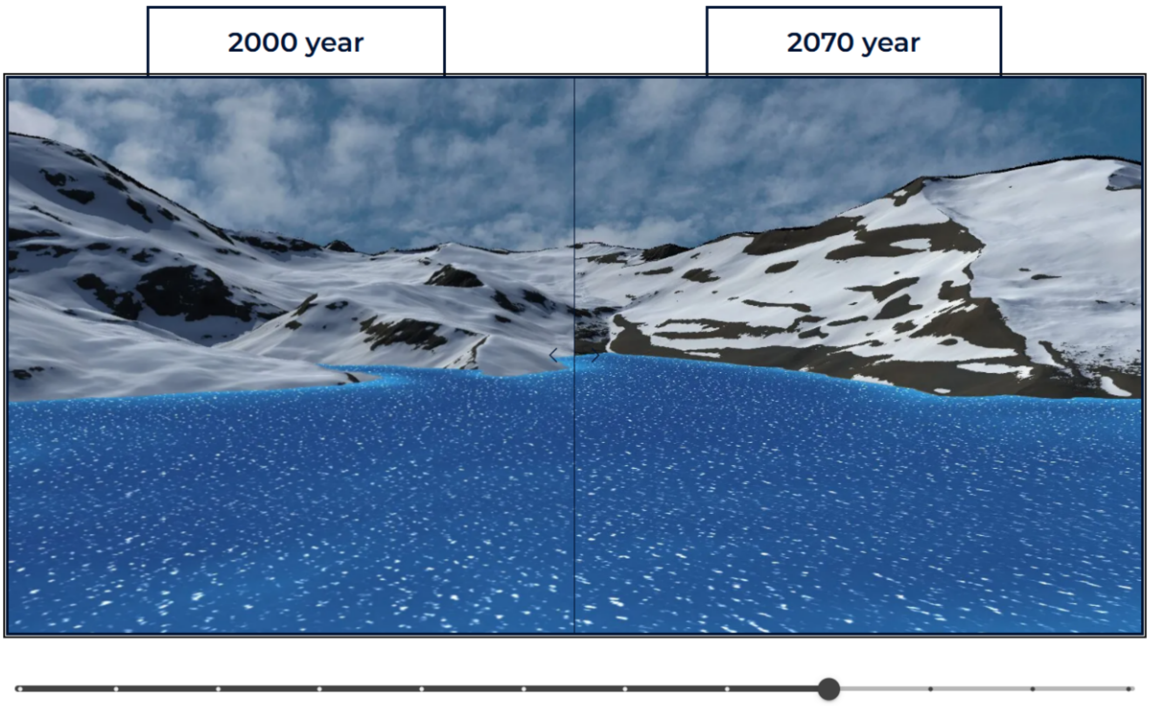


**Figure 13:** Visualization of the forecasted impact of reduced sea ice extent on coastal regions, comparing the observed state in the year 2000 with the projected state for 2070.

since SARIMA preserves amplitude and cyclicity. Some disadvantages of the residual-based training approach are the more complex workflow that involves two-stage training. It is also necessary that SARIMA be quite well-chosen. However, the limitations considered are insignificant, and the effect that can be achieved is significant.

The ensemble model based on residuals is built in such a way that SARIMA captures the trend and seasonality, and the deep learning model models only the remaining nonlinear residuals, and not the entire signal. Thus, since the LSTM is not responsible for generating full cycles, it does not "smooth" them. The use of weighted ensembles allows you to stabilize the variance. That is, SARIMA preserves the amplitude, and deep learning methods focus on hidden patterns and adjust the forecast. This approach prevents the smoothing of the long-term horizon of deep learning models. Compared to autonomous deep learning, ensemble methods help avoid decay, making long-term forecasts less flat and more realistic. As a result of the analysis, a sequential learning approach, i.e., residual-based learning, was chosen for further experiments with ensemble models.

The study analyzed the SARIMA method and deep learning methods: LSTM and Bi-LSTM to create a long-term forecast of sea ice extent. Since the evaluation of the methods in the short term demonstrated low errors and high values of the coefficient of determination for all models, with a slight advantage of the SARIMA method for the Northern Hemisphere and the SARIMA+LSTM ensemble model for the Southern Hemisphere, it is advisable to analyze the forecast in the long term. It should be noted that due to the lack of observational data, it is impossible to conduct a full-fledged forecast analysis. Observational data from NASA and NSDIC, which are freely available, are limited to the end of 1978. Therefore, we consider it advisable to analyze the long-term forecast of the studied methods in the context of their advantages and potential limitations. A comparison of the characteristics of the studied models is given in Table 2.

**Table 2**
A comparative analysis of SARIMA, Deep Learning, and Ensemble (SARIMA+DL) models across various aspects of forecasting performance and characteristics.

| **Aspect** | **SARIMA** | **Deep learning** | **Ensemble (SARIMA+DL)** |
|---|---|---|---|
| Trend and Seasonality | Strong | Weak to moderate | Strong (SARIMA handles it) |
| Nonlinear patterns | Weak | Strong | Strong (LSTM handles it) |
| Overfitting risk | Low (simple parametric model) | High (needs lots of data) | Low (each model focuses on what it does best) |
| Long-term forecasting | Decent for stable seasonality, poor for shocks | Can capture nonlinearities, but unstable long-term | Better stability: SARIMA anchors structure, LSTM adjusts nonlinear dynamics |
| Interpretability | High | Low | Medium |
| Generalization | Good for stationary data | Good for complex, high-volume data | Broader generalization |

## 6. Ethics and responsibility

In the process of developing the web-based information system, the key provisions of ethical and responsible use of artificial intelligence were taken into account in accordance with modern European approaches. Particular attention was paid to the recommendations formulated in the EU Artificial Intelligence Act [29], as well as in the documents of the High Level Group on AI (HLEG AI) [30] at the European Commission.

Developed Information System belongs to the category of low-risk AI systems, as it does not process personal data, does not make decisions that have legal or social consequences for the user, and does not affect the emotional or physical state of a person. The paper implements basic approaches to ensuring transparency. All models used for forecasting (SARIMA, LSTM, Bi-LSTM) are documented and explained within the project. The visualization of trends, seasonality, and residual components allows the user to understand the logic of forecasting. In the future, it is planned to introduce mechanisms for interpreting models (Explainable AI), which will improve the transparency of algorithms.

Several modeling approaches, including ensemble models, are used to improve the accuracy of forecasts. Standardized metrics (MAE, RMSE, $R^2$) are used to evaluate the results. All data comes from open, reputable sources (in particular, NSIDC), which guarantees the quality of the input information. The system has been tested for forecast stability, including residuals and time series stationarity analysis.

Web-based information system does not interact with personal or sensitive data, does not segment users, and does not perform any form of automated human evaluation. Thus, there is no risk of discrimination in the system's operation.

Additionally, when selecting data, priority is given to open sources available to all users on equal terms, which supports the principle of equality in access to technology.

All data used are public, anonymous and obtained from open scientific repositories. No personal information is processed. The project also adheres to an open source policy: the software is available in a public repository under the appropriate license terms. This is in line with the principles of open science and ethical data management.

Information System performs only an auxiliary analytical function. The system does not make decisions automatically, but only provides forecast information for further reflection by the user. All actions that can be taken based on the forecasts remain under the responsibility of the user. Such control ensures compliance with the principle of preserving human autonomy and controllability of the process.

The conducted research allows laying the foundation for further research in the context of developing XAI systems. Further work will be aimed at developing information systems for predicting climate parameters using artificial intelligence. The choice of forecasting methods should be based not only on assessing the quality of the forecast, but also on the clarity of the algorithm, because climate forecasting, especially related to the prediction of natural disasters and climate change, should be transparent to users, explaining why certain decisions were made.

## 7. Conclusion

As a result of the study, an analysis of existing concepts and approaches to the development of XAI predictive models was conducted, because of which the main aspects of the development of a web-based information system for long-term forecasting of the area of Sea Ice extent using statistical methods and deep learning methods were determined. A detailed explanation of the features of the application of each of the methods in the context of the use of ensemble models was provided, and the compliance of the developed information system with the ethical and legal aspects of responsible AI was determined.

The developed information system allows not only to view observation and forecast data, but also to compare indicators from different years, which is especially useful for scientific and educational purposes.

Visualizing the impacts of climate change on coastal regions allows users to model potential scenarios and better understand potential threats and risks, spurring action on climate change and ensuring the achievement of Sustainable Development Goal 13.

## Declaration on Generative AI

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 and services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

## References


[1] A. Dikshit, B. Pradhan, S. S. Matin, G. Beydoun, M. Santosh, H.-J. Park, K. N. A. Maulud, Artificial intelligence: A new era for spatial modelling and interpreting climate-induced hazard assessment, Geoscience Frontiers 15 (2024) 101815. doi:10.1016/j.gsf.2024.101815.

[2] L. Sikora, N. Lysa, O. Fedevych, N. Khyliak, Information and laser technologies for assessing the level of risks from harmful emissions from man-made objects, Computer Systems and Information Technologies 1 (2025) 6–15. doi:10.31891/csit-2025-1-1.

[3] P. J. Phillips, C. A. Hahn, P. C. Fontana, A. N. Yates, K. Greene, D. A. Broniatowski, M. A. Przybocki, Four Principles of Explainable Artificial Intelligence, Technical Report, National Institute of Standards and Technology, 2021. doi:10.6028/NIST.IR.8312.

[4] A. O. Ibitoye, M. S. Nkwo, R. Orji, Rethinking responsible ai from ethical pillars to sociotechnical practice, AI Ethics (2025). doi:10.1007/s43681-025-00809-2.

[5] Y. Hnatchuk, T. Hovorushchenko, O. Pavlova, Methodology for the development and application of clinical decisions support information technologies with consideration of civil-legal grounds, Radioelectronic and Computer Systems (2023) 33–44. doi:10.32620/reks.2023.1.03.

[6] T. Hovorushchenko, Y. Hnatchuk, A. Herts, A. Moskalenko, V. Osyadlyi, Theoretical and applied principles of information technology for supporting medical decision-making taking into account the legal basis, in: Proceedings of the 2nd International Workshop on Modern Machine Learning Technologies and Data Science (MoMLeT+DS 2021), volume 3038 of *CEUR Workshop Proceedings*, 2021, pp. 172–181. URL: http://ceur-ws.org/Vol-3038/paper17.pdf.

[7] T. Hovorushchenko, A. Moskalenko, V. Osyadlyi, Methods of medical data management based on blockchain technologies, Journal of Reliable Intelligent Environments (2022). doi:10.1007/s40860-022-00178-1.

[8] T. Hovorushchenko, A. Herts, Y. Hnatchuk, O. Sachenko, Supporting the decision-making about the possibility of donation and transplantation based on civil law grounds, in: Advances in Intelligent Systems and Computing, Springer International Publishing, 2020, pp. 357–376. doi:10.1007/978-3-030-54215-3_23.

[9] T. Hovorushchenko, O. Pavlova, V. Alekseiko, A. Kuzmin, E. Zaitseva, Long-term land surface temperature forecasting in different climate zones using long short-term memory, International Journal of Computing 24 (2025) 233–242. doi:10.47839/ijc.24.2.4006.

[10] V. Alekseiko, V. Levashenko, Y. Voichur, D. Medzatyi, Sea ice extent data analysis using statistical and unsupervised learning methods, in: Proceedings of the The 6th International Workshop on Intelligent Information Technologies & Systems of Information Security (IntelITSIS 2025), volume 3963 of *CEUR Workshop Proceedings*, 2025, pp. 39–53. URL: http://ceur-ws.org/Vol-3963/paper4.pdf.

[11] P. P. Angelov, E. A. Soares, R. Jiang, N. I. Arnold, P. M. Atkinson, Explainable artificial intelligence: an analytical review, WIREs Data Mining and Knowledge Discovery 11 (2021). doi:10.1002/widm.1424.

[12] J. Walmsley, Artificial intelligence and the value of transparency, AI & SOCIETY (2020). doi:10.1007/s00146-020-01066-z.

[13] G. Camps-Valls, M. Á. Fernández-Torres, K. H. Cohrs, et al., Artificial intelligence for modeling and understanding extreme weather and climate events, Nature Communications 16 (2025) 1919. doi:10.1038/s41467-025-56573-8.

[14] S. Materia, L. P. García, C. van Straaten, S. O, A. Mamalakis, L. Cavicchia, D. Coumou, P. de Luca, M. Kretschmer, M. Donat, Artificial intelligence for climate prediction of extremes: State of the art, challenges, and future perspectives, WIREs Climate Change (2024). doi:10.1002/wcc.914.

[15] A. H. Essenfelder, A. Toreti, L. Seguini, Expert-driven explainable artificial intelligence models can detect multiple climate hazards relevant for agriculture, Communications Earth & Environment 6 (2025). doi:10.1038/s43247-024-01987-3.

[16] H. C. Barutcu, S. Çelik, M. Gezer, Explainable artificial intelligence-based approaches for climate change: a review, International Journal of Global Warming 35 (2025) 244–260. doi:10.1504/ijgw.2025.145102.

[17] P. L. Bommer, M. Kretschmer, A. Hedström, D. Bareeva, M. M. C. Höhne, Finding the right xai method - a guide for the evaluation and ranking of explainable ai methods in climate science, Artificial Intelligence for the Earth Systems (2024). doi:10.1175/aies-d-23-0074.1.

[18] N. R. Chalamalla, Explainable artificial intelligence (xai) for climate hazard assessment: Enhancing predictive accuracy and transparency in drought, flood, and landslide modeling, International Journal of Science and Technology 16 (2025). doi:10.71097/ijsat.v16.i1.1309.

[19] L. Hoffman, M. R. Mazloff, S. T. Gille, D. Giglio, P. Heimbach, Evaluating the trustworthiness of explainable artificial intelligence (xai) methods applied to regression predictions of arctic sea-ice motion, Artificial Intelligence for the Earth Systems (2025). doi:10.1175/aies-d-24-0027.1.

[20] G. G. Navarra, C. Deutsch, A. Mamalakis, A. Margolskee, G. MacGilchrist, Long term predictability of southern ocean surface nutrients using explainable neural networks, Journal of Geophysical Research: Oceans 2 (2025). doi:10.1029/2024jh000268.

[21] J. Baño-Medina, M. Iturbide, J. Fernández, J. M. Gutiérrez, Transferability and explainability of deep learning emulators for regional climate model projections: Perspectives for future applications, Artificial Intelligence for the Earth Systems (2024). doi:10.1175/aies-d-23-0099.1.

[22] C.-Y. Hsu, W. Li, Explainable geoai: can saliency maps help interpret artificial intelligence's learning process? an empirical study on natural feature detection, International Journal of Geographical Information Science (2023) 1–25. doi:10.1080/13658816.2023.2191256.

[23] W. Li, C.-Y. Hsu, M. Tedesco, Advancing arctic sea ice remote sensing with ai and deep learning: Opportunities and challenges, Remote Sensing 16 (2024) 3764. doi:10.3390/rs16203764.

[24] F. Huang, S. Jiang, L. Li, Y. Zhang, Y. Zhang, R. Zhang, Q. Li, D. Li, W. Shangguan, Y. Dai, Applications of explainable artificial intelligence in earth system science, 2024. arXiv:2406.11882.

[25] P. M. Lukacz, Developing ai for weather prediction, Science & Technology Studies (2024). doi:10.23987/sts.125741.

[26] M. N. Joshi, A. K. Dixit, S. Saxena, M. Memoria, T. Choudhury, A. Sar, A study of the application of ai & ml to climate variation, with particular attention to legal & ethical concerns, EAI Endorsed Transactions on Internet of Things 10 (2024). doi:10.4108/eetiot.5468.

[27] R. Ramya, S. Priya, P. Thamizhikkavi, M. Anand, The pillars of ai ethics, in: Advances in Computational Intelligence and Robotics, IGI Global, 2024, pp. 85–110. doi:10.4018/979-8-3693-9173-0.ch004.

[28] N. Yadav, Ethics of artificial intelligence and robotics: Key issues and modern ways to solve them, Journal of Digital Technologies and Law 1 (2023) 955–972. doi:10.21202/jdtl.2023.41.

[29] European Parliament and the Council of the European Union, The EU AI act, Official Journal of the European Union, 2024. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32024R1689, oJ L, 12 July 2024. CELEX: 32024R1689.

[30] High-level expert group on artificial intelligence, Shaping europe's digital future, https://digital-strategy.ec.europa.eu/en/policies/expert-group-ai, 2024. Accessed: 2025-10-15.