ISSN 0027-1349, Moscow University Physics Bulletin, 2024, Vol. 79, Suppl. 2, pp. S739–S749. © Allerton Press, Inc., 2024.

An Overview of Machine Learning and Deep Learning Applications in Earth Sciences in 2024: Achievements and Perspectives

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Received October 1, 2024; revised October 10, 2024; accepted October 20, 2024

Abstract—Machine learning (ML) and deep learning (DL) methods are extensively applied in various fields of Earth sciences, such as oceanography, meteorology, and climatology. These statistical approaches enable efficient processing of large volumes of data, uncovering hidden patterns, reducing or assessing uncertainty in climate and weather forecasts, automating monitoring, and accelerating analytical research. Among most successful examples, one may mention remote sensing data analysis, geophysical processes modeling, approximating unknown physical parameters, and solving statistical weather and climate forecasting problems. However, there are certain challenges, such as the need for large data volumes, computational demands and technical issues of the data science approach, and ensuring the physical plausibility of results. In the future, the development of hybrid models that combine physical and statistical methods is anticipated, as well as improvements in the interpretability of ML and DL models. In this overview, we will examine current achievements in the application of ML and DL in the study of the ocean, atmosphere, and climate, and we will discuss the challenges and prospects for their further development. This overview places particular emphasis on the progress made in the Russian Federation scientific community regarding the application of ML, DL, and AI within Earth sciences, highlighting both its accomplishments and the challenges it faces in the global research landscape.

Keywords: machine learning, deep learning, climate sciences, atmospheric sciences, oceanography

DOI: 10.3103/S0027134924702217

1. INTRODUCTION

In recent years, the domains of machine learning (ML), deep learning (DL), and artificial intelligence (AI) have experienced unprecedented growth and development, particularly within the fields of Earth sciences, climate research, atmospheric sciences, and oceanography. Historically, these technologies were viewed as nascent tools in Earth sciences, primarily confined to computational or theoretical frameworks. However, by 2024, they have evolved into indispensable components of contemporary scientific research methodologies, significantly enhancing the analytical capabilities of researchers across a variety of environmental disciplines.

The integration of ML and DL techniques into Earth sciences enables researchers to analyze complex datasets characterized by high dimensionality, nonlinear relationships, and inherent uncertainties. This has proven particularly valuable in addressing the multifaceted nature of climate systems, where traditional (e.g., linear) methods often fall short. For instance, advanced algorithms allow for the modeling of intricate interactions between atmospheric, oceanic, and terrestrial processes, facilitating a more nuanced understanding of climate dynamics. Furthermore, these technologies have been instrumental in improving predictive accuracy for climate models and weather forecasts, as evidenced by numerous studies highlighting their efficacy in capturing the intricate patterns and trends of environmental phenomena.

The automation of data processing tasks through data-driven algorithms has further transformed the research landscape. By minimizing the reliance on manual analysis, researchers can now focus on interpreting results and deriving insights from their findings. This shift not only enhances the efficiency of research workflows but also accelerates the pace of scientific discovery, particularly in fields where timely

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decision-making is essential, such as disaster response and resource management.

Moreover, the application of ML, DL, and AI has facilitated advancements in remote sensing technologies, enabling the extraction of meaningful information from satellite and aerial imagery. This capability is crucial for monitoring environmental changes, assessing natural resource availability, and understanding the impacts of anthropogenic activities on ecosystems. As highlighted in our previous studies [6–8], the ability to analyze spatial and temporal trends in data has opened new avenues for research and application, bridging gaps between theoretical understanding and practical solutions.

The academic community has responded to this technological revolution with increased publication activity, as seen in the significant rise in peer-reviewed papers integrating ML, DL, and AI methodologies in Earth sciences over the past two decades. This growth underscores a burgeoning recognition of the transformative potential of these approaches in tackling pressing environmental challenges.

An analysis of publication activity sourced from the Scopus database reveals a significant upward trend in the number of peer-reviewed articles that incorporate these advanced computational techniques. This trend is illustrated in Fig. 1, which depicts the annual growth of publications employing ML, DL, and AI methodologies in Earth sciences alongside the total number of published papers in the field. In Figs. 1–4, we use the data collected in aggregated form from Scopus database employing its query language, where NAT_SCI literal refers to the class of studies in Scopus query language, namely natural sciences. The data in Fig. 1 indicates that from 2016 onward, there has been a marked acceleration in the adoption of data-driven methodologies, reflecting a growing recognition of their potential to enhance scientific research.

Globally, the United States and China have emerged as leading contributors to the body of work in Earth sciences that utilize ML and AI, consistently ranking at the top in publication volume. As shown in Fig. 2b, the number of peer-reviewed articles published in these countries substantially outpaces that of other nations, highlighting their robust research infrastructure and investment in advanced computational methods and academic research. In contrast, the Russian Federation has demonstrated a more gradual engagement with these technologies. Despite the country's significant technical expertise and academic resources, its ranking in the global landscape remains relatively low. According to the data presented in Fig. 2, Russia occupied the 19th position in terms of publication activity in Earth sciences incorporating ML and AI from 2000 to 2023. This ranking underscores a critical disparity between Russia's potential and its actual engagement with these emerging methodologies.

Recent data from 2023 indicates a slight improvement in Russia's standing, moving from 19th to 18th place, as depicted in Fig. 3b. This modest advancement suggests a growing interest in machine learning applications within the Russian academic community, albeit at a pace that lags behind leading nations. The progress made by Russia is contextualized in Fig. 3a, which illustrates the rank changes of the top four countries alongside Iran (as an dynamic outlier) and Russia over the years. The data highlights the competitive nature of research in this field at the moment, and the need for enhanced collaboration and investment in ML and AI technologies particularly in Earth and Environmental sciences.

Thus, while the global academic community has made significant strides in integrating ML, DL, and AI within Earth sciences, the progress observed in Russia indicates a path of improvement yet to reach its full potential. The increasing fraction of publications (see Fig. 2a) signifies a burgeoning interest and commitment to leveraging these advanced computational techniques to tackle pressing environmental challenges. Continued efforts to enhance research capabilities, foster collaboration, and support the development of skilled professionals in this domain will be essential for russian scientific community to contribute effectively to the advancement of advanced data-driven statistical approached in Earth and environmental sciences.

2. DATA-DRIVEN TASKS IN EARTH SCIENCES

The integration of ML, DL, and AI into Earth sciences has facilitated the exploration and resolution of a diverse array of data-driven tasks. Commonly, these tasks are systematically categorized based on their mathematical nature and objectives, providing a structured framework for understanding the potential applications of these advanced computational techniques. The classification scheme delineates three primary types of tasks: supervised learning, unsupervised learning, and other types (see Fig. 4), each addressing distinct problem domains and methodological approaches. Further in this overview, we cover the progress of ML, DL, and AI approaches in Earth sciences and environmental sciences with particular focus on the studies landscape of russian scientific society. In Section 3, we overview studies employing supervised learning approach; in Section 4, we overview studies employing Unsupervised learning approach. There is also a distinct Section 5, where we cover the promising topic of self-supervised

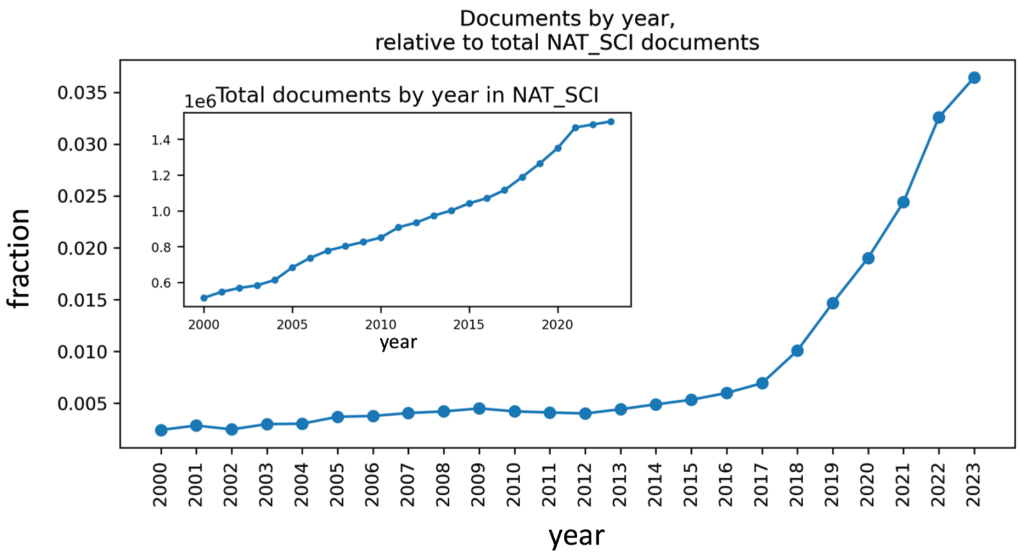

Fig. 1. Annual number of publications employing ML, DL, and AI methodologies in natural sciences alongside the total number of published papers in the field, according to Scopus database.

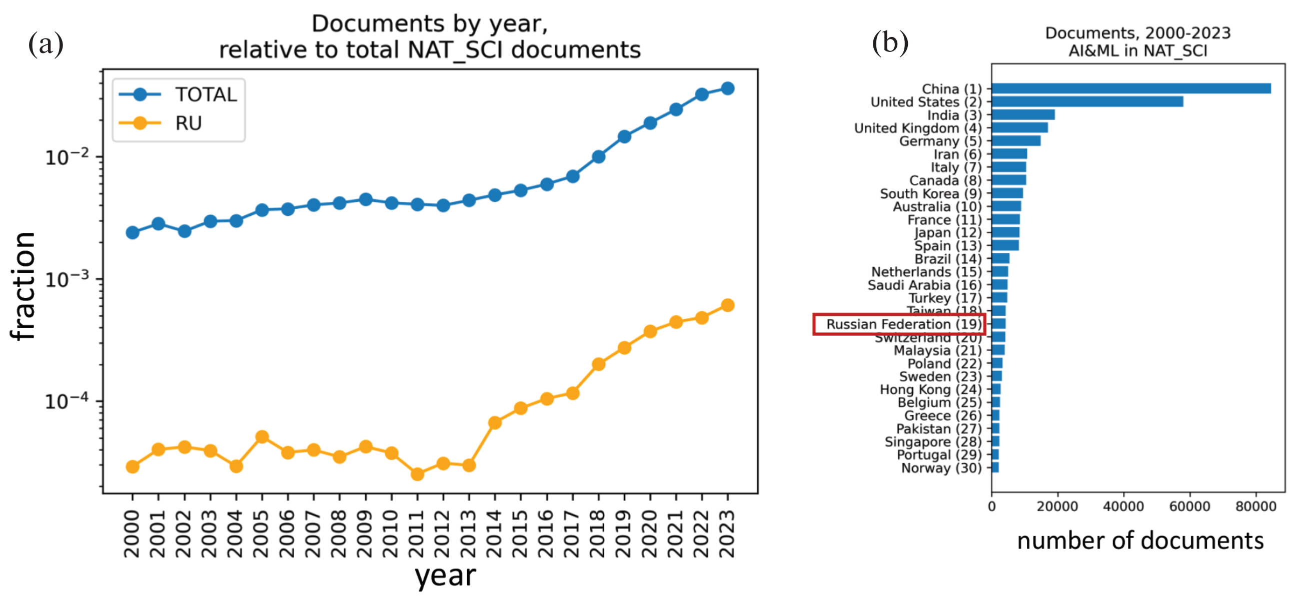

Fig. 2. (a) Annual fractions of publications employing ML, DL, and AI methodologies in natural sciences alongside the fraction of russian studies; (b) ranking of top-30 countries according to Scopus data aggregated from 2000 till 2023. The data is collected in aggregated form from Scopus database using its query language.

generative pretraining which results in foundation models, particularly for climate data. We summarize the overview in conclusion Section 6.

3. SUPERVISED LEARNING

Supervised learning is a prominent category of machine learning that involves training models on labeled datasets, where the input features are paired with corresponding output labels. This approach is particularly valuable in Earth sciences, where researchers seek to predict or classify specific environmental phenomena based on historical data. Common tasks within supervised learning include regression, where the goal is to estimate continuous values [1–3, 5, 7, 8, 14, 15, 19, 22, 23], and classification, which involves categorizing data points into discrete classes [4, 6, 20, 21].

In Earth sciences, supervised learning has been effectively applied to a variety of tasks. For instance,

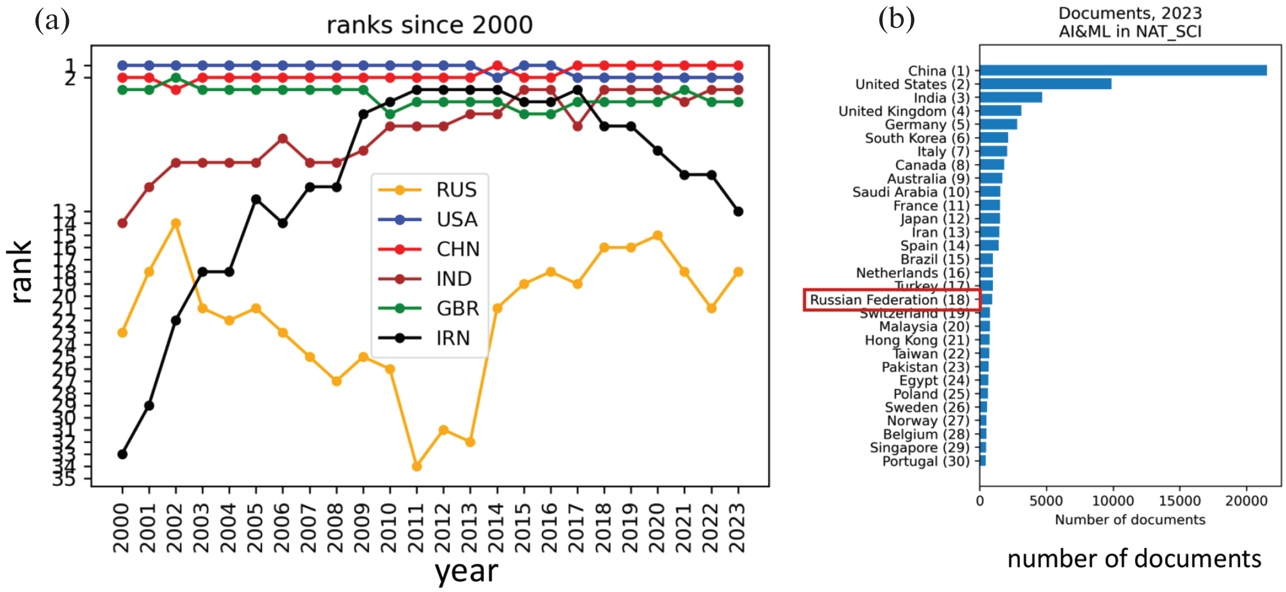

Fig. 3. (a) Annual ranking of top-four nations in publication activity regarding employment of ML, DL, and AI methodologies in natural sciences alongside the ranks of Iran (black line) and Russian Federation (yellow line); (b) ranking of top-30 countries according to 2023 Scopus data. The data is collected in aggregated form from Scopus database using its query language.

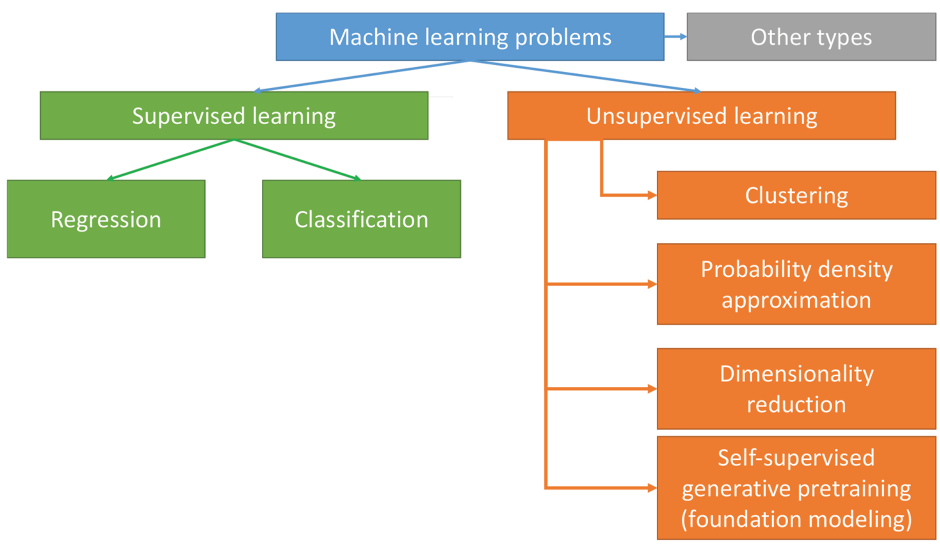

Fig. 4. Classification of ML tasks as a framework of this overview.

models can predict meteorological parameters, such as temperature or precipitation levels [3], based on a range of input variables, including atmospheric pressure, humidity, and wind speed. Another example is the usage of supervised learning techniques in classification of cloud types using remote sensing data [21, 24–26].

One key advantage of supervised learning lies in its ability to leverage vast amounts of historical data, allowing for the development of predictive models that can generalize well to new, unseen data. However, the success of these models is contingent upon the quality and quantity of labeled training data available, which is sometimes a limiting factor in Earth sciences. As researchers continue to explore the potential of supervised learning, the integration of these methods will remain essential for enhancing our understanding of complex environmental systems and improving decision-making processes in climate-related applications.

3.1. Examples of Supervised Learning Tasks

In this section, we present distinct examples of recent studies in Earth Sciences employing ML, DL, or AI methods of Supervised type.

3.1.1. Ocean waves characteristics acquisition with artificial neural networks. The characterization of wind waves is a critical aspect of oceanographic research, as these waves significantly influence the interaction between the ocean and the atmosphere. Accurate estimation of wave parameters, such as significant wave height, wavelength, and wave period, is essential for various applications, including navigation, coastal management, and climate modeling. Traditional methods of wave measurement often rely on buoys or visual observations, which can be limited by their spatial coverage and the expertise of the observers.

In the series of studies presented since 2023 [5, 8], researchers employed artificial neural networks to automate the acquisition of wind wave characteristics from maritime radar data. The data utilized included raw radar images captured by navigation X-band radars aboard research vessels, which provide intrinsic information about wave patterns and surface conditions. The specific ANN architecture employed was a convolutional neural network (CNN), which is particularly well-suited for image processing tasks due to its ability to learn spatial hierarchies of features. The high-level scheme of the study is presented in Fig. 5.

The results of this study demonstrated that the ANN could effectively predict wave characteristics with a high degree of accuracy. The model slightly outperformed traditional statistical methods within the range of its applicability limits, yielding a root mean square error (RMSE) of approximately 0.2 m for significant wave height estimations. This work not only highlights the potential of ANNs in enhancing wave measurement techniques but also underscores the importance of integrating automated systems in oceanographic research.

3.1.2. Detection of mesoscale convective systems from satellite imagery with convolutional neural networks. Mesoscale convective systems (MCSs) are significant weather phenomena that can produce severe weather events, including heavy rainfall, thunderstorms, and tornadoes. Accurate detection and monitoring of MCSs are crucial for weather forecasting and climate studies, as they can have profound impacts on local and regional weather patterns. Traditional methods for identifying MCSs rely heavily on manual analysis of satellite imagery, which can be time-consuming and subjective. Therefore, leveraging machine learning techniques, particularly convolutional neural networks (CNNs), presents an innovative solution to automate and enhance the detection process.

In the study presented in 2023 [6], researchers aimed to develop a CNN-based model to detect MCSs using high-resolution satellite imagery. The dataset used for training the model, namely the DaMesCoS [6] consisted of labeled satellite images, which included various instances of MCSs identified by meteorological experts. This labeled data was complemented by additional meteorological parameters that provided contextual information about the atmospheric state during MCS events.

The results demonstrated a high level of accuracy in detecting MCSs. This performance significantly outpaced traditional detection methods, providing a more efficient means to monitor these weather systems. The study illustrates the power of Dl approach in automating the detection of complex atmospheric phenomena, thereby enhancing capabilities for climatological studies. High-level scheme of the study is presented in Fig. 6.

3.1.3. Statistical downscaling of surface winds with artificial neural networks. Statistical downscaling is a critical technique used in climate science to derive local-scale climate information from coarse-scale global climate models (GCMs) [1]. This approach is essential for capturing the finer details of surface winds, precipitation, and temperature, which are crucial for understanding regional climate impacts and variability. Traditional downscaling methods, often reliant on empirical relationships, can struggle to accurately represent the complex interactions present in localized weather phenomena. Therefore, the application of various ML models [3], DL models [1] and foundation models [49] offers a promising alternative for enhancing the precision of statistical downscaling.

In the series of studies presented since 2021 [1, 60], researchers focused on the statistical downscaling of surface winds using various types of convolutional neural networks. The problem was framed around the need to improve the accuracy of wind forecasts derived from ERA-Interim reanalysis outputs, which often lack the resolution necessary for local applications. The data used for this study included high-resolution dynamical downscaling computed with Weather Research and Forecasting model which provided high-resolution ground truth data. This dataset was paired with larger-scale atmospheric variables produced by ERA-Interim reanalysis, such as pressure and temperature fields, to facilitate the training of the ANN. The results of the study indicated that the CNNs may perform the task of statistical downscaling though the quality needs to be improved. This series of studies demonstrates

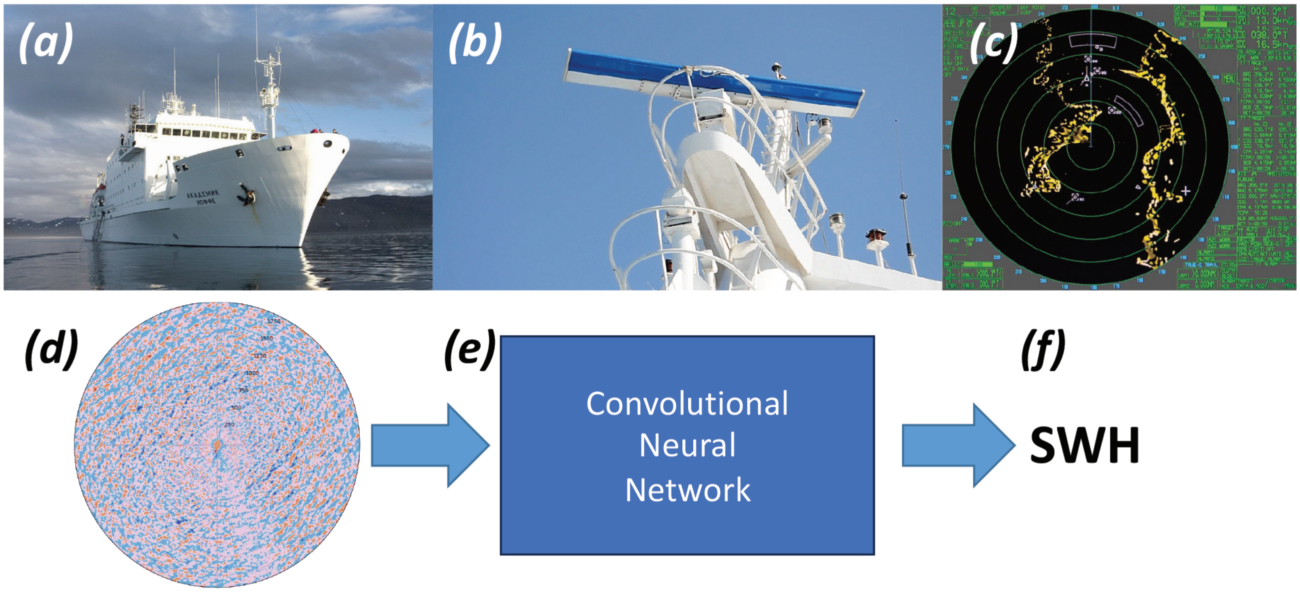

Fig. 5. Components of the task of wind waves characteristics acquisition: (a) a research vessel; (b) X-band maritime radar (particularly, its antenna); (c) filtered radar image prepared for inspection by ship navigator and nonsuitable for acquiring wind wave characteristics; (d) raw radar image without filtering; (e) symbolic annotation of the DL model, convolutional neural network in particular; (f) resulting significant wave height (SWH).

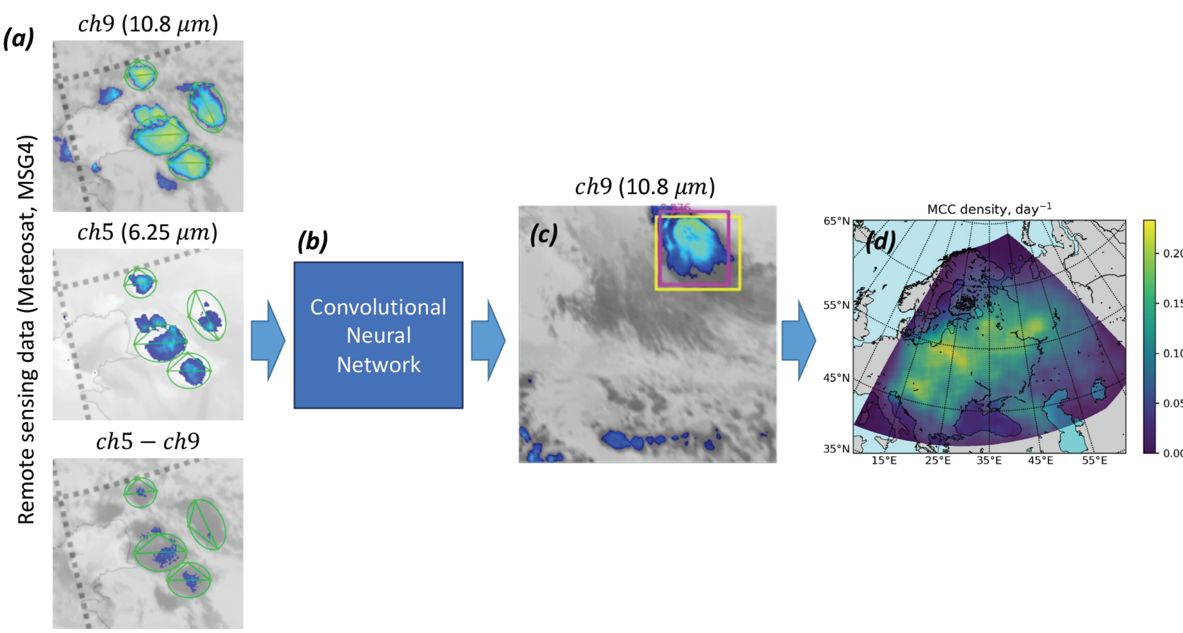

Fig. 6. Components of the task of MCS detection from Meteosat remote sensing imagery: (a) source Meteosat data in three channels colored according to the colormap described in the study [6]; (b) symbolic annotation of the DL model, convolutional neural network in particular; (c) demonstration of one particular result of the network compaing the labels of the model (in magenta) with expert labels (yellow); (d) resulting MCS events density as one of climatological outcomes of the study.

the potential of artificial neural networks in statistical downscaling problem which is yet to be revealed.

4. UNSUPERVISED LEARNING

Unsupervised learning is a critical branch of machine learning that focuses on discovering patterns and structures within unlabeled datasets. Unlike supervised learning, where the model is trained on input-output pairs, unsupervised learning algorithms analyze data without predefined labels, allowing researchers to explore the inherent relationships and organization within the data. This approach is particularly useful in Earth sciences, where datasets may be vast and complex, often lacking explicit labeling.

In Earth sciences, unsupervised learning has been extensively applied to tasks such as clustering [11, 16, 30, 40] and dimensionality reduction [27–29]. Clustering techniques, for instance, can identify groups of similar geographical features or atmospheric patterns based on observed or modeled characteristics [30]. This capability allows researchers to detect emerging phenomena, classify regions based on climate types, or analyze ecological patterns without prior knowledge of group definitions. For example, clustering has been utilized to categorize different ecosystems based on environmental variables, thereby enhancing our understanding of biodiversity and habitat distribution [31].

Dimensionality reduction techniques, such as principal component analysis (PCA), t-distributed stochastic neighbor embedding (t-SNE) [32], or uniform manifold approximation and projection technique (UMAP) [33], help visualize high-dimensional data by compressing it into lower dimensions while preserving essential relationships. This is particularly valuable for exploratory data analysis, enabling researchers to discern trends and anomalies in complex datasets.

4.1. Unsupervised Learning: Anomaly Detection

Anomaly detection, also known as outlier detection, is a specialized task within the realm of unsupervised learning that focuses on identifying data points that deviate significantly from the expected pattern of behavior within a dataset. In Earth sciences, anomaly detection plays a crucial role in monitoring environmental systems, identifying unusual climatic events, detecting rare geological phenomena or identifying unusual behaviour of monitoring equipment [10].

In some cases, the problems of supervised nature may be reformulated as anomaly detection in order to exploit the full potential of vast data amount in case of lacking labeled data. For example, there are studies demonstrating the approach of anomaly detection in problems of marine mammals detection in remote optical sensory data [9].

In the context of climate science, anomaly detection techniques can be employed to identify unusual temperature fluctuations, precipitation extremes, or shifts in atmospheric pressure patterns [34–36]. For instance, researchers can utilize statistical methods and machine learning algorithms to analyze historical climate data and establish baseline conditions. By applying anomaly detection algorithms such as isolation forests [37] or autoencoders [38, 39], scientists can effectively flag instances of extreme weather events, such as heatwaves or heavy rainfall.

Moreover, anomaly detection is instrumental in the analysis of remote sensing data, where it aids in identifying unusual land cover changes, such as deforestation, urban expansion, or the effects of natural disasters. By rapidly detecting these changes, researchers can assess the impact on ecosystems and make informed decisions regarding conservation and land management practices.

Anomaly detection serves as a powerful tool in Earth sciences, enhancing our ability to monitor and respond to environmental challenges by providing insights into rare and significant events that may otherwise be overlooked in large datasets.

4.2. Unsupervised Learning: Generative

Generative models represent a distinct class of machine learning approaches that focus on learning the underlying probability distribution of a dataset. These models aim to approximate the probability density function (PDF) of observed data, mostly implicitly through enabling the generation of new samples that align with the learned distribution. In Earth sciences, generative models, including generative adversarial networks (GANs) [41, 43] including GANs designed for superresolution [42], variational autoencoders (VAEs) [44], and foundation models for climate data [45–54], have gained traction for their ability to synthesize realistic data, enhance predictive modeling, and facilitate uncertainty quantification.

One of the primary advantages of generative models is their capability to capture complex, high-dimensional data distributions without preconceived notions about underlying relationships. This flexibility allows researchers to model intricate environmental phenomena, such as spatial distributions of precipitation or temperature variability across regions. Additionally, by modeling the joint distribution of multiple climate variables, generative models can facilitate the synthesis of synthetic datasets reflecting possible future climate scenarios under varying climatic conditions, which is particularly valuable for climate impact assessments and resource management.

Moreover, generative models address data scarcity issues often faced in Earth sciences. Observational data may be limited due to geographic, temporal, or logistical constraints. By leveraging generative modeling techniques, researchers can augment existing datasets with plausible synthetic data, thereby enhancing the robustness of their analyses. This approach not only improves model training but also contributes to a more comprehensive understanding of environmental processes by filling in gaps where empirical data may be lacking [55]. As the field continues to evolve, the integration of generative modeling techniques, including foundation models, will likely play an increasingly prominent role in tackling the multifaceted challenges posed by climate change and environmental degradation.

5. SELF-SUPERVISED GENERATIVE PRETRAINING (FOUNDATION MODELING)

Foundation modeling in oceanography, atmospheric sciences and climatology represents a transformative approach that leverages self-supervised learning techniques to enhance the prediction and understanding of complex atmospheric, oceanic and climatic phenomena. Recent advancements in deep learning have led to the development of foundation models [45–54], that are pretrained on vast, heterogeneous datasets and can be fine-tuned for various downstream tasks such as weather forecasting, climate projections, and downscaling.

One of the key properties of some of these models, such as ClimaX [51] and Prithvi WxC [54], is their ability to handle diverse data inputs, including those from different sources like CMIP6 and ERA5. By utilizing architectures like vision transformers (ViT), these models can efficiently capture the spatial and temporal dependencies inherent in climate data. They employ innovative tokenization and aggregation methods that allow for effective processing of varying numbers of input variables, thus potentially improving scalability and generalizability.

The training process of foundation models typically involves two phases: a self-supervised pretraining phase that learns representations from unlabeled data, followed by a fine-tuning phase tailored to specific applications. This two-stage method enables the models to capture fundamental atmospheric dynamics and to maintain robust performance across a range of tasks, from short-term weather predictions to long-term climate modeling, statistical downscaling and statistical correction.

The training of foundation models for climate data relies on several key datasets, each with its own strengths and weaknesses. One of the most important datasets is ERA5 [56], which provides a comprehensive reanalysis of atmospheric data at high resolution. Its advantage lies in offering detailed historical records and a wide range of variable coverage. However, it is limited to past observations and does not include future projections. Another significant dataset is CMIP6 [57], which consists of climate simulation data from various models. This dataset allows models to learn from a diverse range of potential future climate scenarios, enhancing their predictive capabilities. However, the simulations can be biased based on the models used, and not all variables may be equally represented. MERRA-2 [58], developed by NASA, offers a long-term climate record with a wide array of atmospheric variables at multiple altitudes. While it enhances model training due to its extensive coverage, the data can be coarser in resolution compared to ERA5. Lastly, CORDEX [59] focuses on regional climate projections and provides high-resolution data useful for downscaling and local climate studies. However, it may lack long-term historical consistency as it emphasizes specific regions. These datasets collectively enhance the robustness of foundation models, but their inherent biases and limitations require careful consideration during the training and evaluation processes.

The incorporation of foundation modeling principles into climate data applications has marked a significant advancement in the field. By harnessing self-supervised learning and adaptable architectures, these models not only outperform traditional numerical methods in some of benchmarks but also offer greater efficiency in inference. The ongoing research and development in this domain promise to further enhance the accuracy and reliability of weather and climate predictions, paving the way for more sophisticated environmental science applications.

6. CONCLUSIONS

Machine learning, deep learning (DL), and artificial intelligence (AI) have emerged as powerful tools for addressing a vast subset of tasks within the realm of Earth sciences. Their application spans various domains, including climate modeling, weather forecasting, and oceanography, where they enhance our ability to analyze complex datasets, improve predictive accuracy, and automate data processing tasks. The studies discussed in this paper exemplify the effectiveness or potential yet to be revealed of these methodologies in acquiring valuable insights and advancing our understanding of intricate environmental processes.

Despite the progress made, there remain significant challenges and research areas within Earth sciences that still lack effective solutions through ML, DL, and AI. Issues such as data scarcity, the lack of labeled datasets, the need for real-time analysis, and the intricacies of modeling nonlinear relationships in complex systems highlight the limitations of current approaches. These gaps present opportunities for further exploration, underscoring the necessity for continued education, research and development in the application of these technologies.

Moreover, the fundamental limitations inherent in data-driven approaches necessitate the incorporation of physical principles into the modeling process. Physics-informed models represent a promising direction for overcoming the shortcomings of traditional ML and DL methods, as they integrate domain knowledge and physical constraints into the learning framework. This synergy can lead to more accurate and reliable predictions. As the field evolves, the integration of physics-informed models with advanced computational techniques will be crucial in unlocking the full potential of ML, DL, and AI in Earth sciences.

The progress in foundation modeling within climate and atmospheric sciences has witnessed explosive development, driven by advancements in self-supervised learning, particularly attention mechanism in artificial neural networks, and the increasing availability of vast and diverse datasets. These foundation models exemplify the potential of leveraging self-supervised learning techniques to capture complex atmospheric dynamics while maintaining generalizability across various downstream tasks. The advantages of foundation modeling include improved accuracy in predictions, enhanced efficiency in training, and the ability to integrate heterogeneous data sources, which can significantly accelerate the development of robust forecasting systems. However, challenges remain, such as potential biases in model outputs due to the training data, and the need for substantial computational resources. Despite these issues, the integration of foundation models into environmental sciences represents a promising frontier. One of the conclusions drawn from the studies presented is that there is currently no oceanic foundation model, which poses a significant challenge in pushing the limits of accurate initial-conditions solutions for mid-term and even seasonal forecasting due to the inherent inertia of ocean systems.

Another surprising conclusion from the examination of ML, DL, and AI applications in Earth Sciences is that these advanced statistical methods have yet to provide significant new insights into the underlying physics of both the atmosphere and the ocean. Furthermore, these approaches appear to struggle with extrapolating beyond the data distribution encountered during training, limiting their capacity to predict the characteristics of climate change or other regime-shifting events and processes.

FUNDING

This research was funded by the program PRIORITY 2030 of the Moscow Institute of Physics and Technology (National Research University). The review of quality metrics applied for climate models was carried out as part of the work under Agreement no. 075-03-2024-117 dated January 17, 2024.

CONFLICT OF INTEREST

The author of this work declares that he has no conflicts of interest.

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