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Machine Learning and Hybrid Approaches in Weather and Climate

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ABSTRACT

Climate change is one of the most significant global challenges that need to be managed Understanding of the natural environment is increasingly important to respond to the climate change negative impacts and anthropogenic pressures on finite natural resources, and their impacts on water, energy and food security, infrastructure, human health, natural hazards. The paper reviewed ML application in weather and acclimate, its further development and activities and achievements of ECMWF in creating and app]lying of ML/AI methods. This is also a major interdisciplinary challenge involving almost all scientific fields Artificial intelligence and machine learning (AI/ML) applications have recently widely expanded in all fields. ML can enhance our computations by adding components or replacing some parts of the process. This is what is called the 'hybrid' approach. Instead, ML can also fully replace the whole model, at a much lower computing cost. In addition, AI/ML opens some avenues in other activities we are involved in, such as flood forecasts, fire danger forecasts, monitoring of observations, managing the supercomputer, or enhancing user experience.

***Key words**: Big Data, Machin Learning, Neural Network, CEMS (Climate and Environmental Monitoring from Space, ECMWF's Artificial Intelligence Forecasting System (AIFS),Hybrid approach*

1. Introduction

Climate change is one of the most significant global challenges that need to be managed. To resolve any of the climate change related challenges, "it is essential to elicit and integrate knowledge across a range of systems, informing the design of solutions that take into account the complex and uncertain nature of the individual systems and their interrelationships" [20]. Many studies and researches are devoted to this problem [1-10]. The trends in data science and information technology supports the integration of various disciplines and research outcomes to represent a socio-environmental system holistically inform policy and decision-making processes, which can be referred as climate computing. Understanding of the natural environment is increasingly important to respond to the climate change negative impacts and anthropogenic pressures on finite natural resources, and their impacts on water, energy and food security, infrastructure, human health, natural hazards. This is also a major interdisciplinary challenge involving almost all scientific fields

In 2013, the UK government announced large-scale investment in Big Data infrastructure for science, particularly in the environmental sector starting funding for a program called CEMS (Climate and Environmental Monitoring from Space) [3,5,20,23]. This allowed for the creation of larger databases to cope with the upcoming Big Data revolution and to allow research partner organizations to work with more data and produce more results. With a specific focus on climate change and planetary monitoring, CEMS storage removed the need to download enormous data sets while reducing the cost of access. Along with Cloud data, this is now the standard globally for some of the world's top research institutes.

Environmental data comes from a wide variety of sources and this is increasingly rapidly with new innovations in data capture:

1. Large volumes of data are collected via remote sensing, typically from satellite sensing or aircraft-borne sensing devices, including an increasing use of drones. This includes passive sensing, such as photography or infrared imagery, and active sensing, e.g., RADAR/LIDAR. The increasing availability of open satellite data is a major trend in earth and environmental sciences. For example, the EU Copernicus program and the associated Sentinel missions, or NASA's Earth Observing System satellites, LandSat archive are regularly mined for data for a variety of applications

2. Other data are collected via earth monitoring systems, which consist of a range of sensor technologies measuring various physical entities. Namely weather stations and monitoring systems
3. Model output is also a significant generator of environmental data with results from previous model runs often stored for subsequent analysis

Machine Learning

Artificial intelligence and machine learning (AI/ML) applications have recently widely expanded in all fields. ML uses a lot of data to produce results, and ECMWF is all about data: to use a lot of data – tens of millions of weather observations per day – and we create a lot of data by producing weather analyses and forecasts at high resolution (Fig.1).

Traditionally, the physics-based methods are used for our computations in the Integrated Forecasting System (IFS). This is the case for numerical weather prediction (NWP), reanalysis of past weather, and atmospheric composition. All computations require large computing power to produce high-quality predictions, based on the accurate description of physical processes.

ML can enhance our computations by adding components or replacing some parts of the process. This is what we call the 'hybrid' approach. Instead, ML can also fully replace the whole model, at a much lower computing cost. In addition, AI/ML opens some avenues in other activities we are involved in, such as flood forecasts, fire danger forecasts, monitoring of observations, managing the supercomputer, or enhancing user experience.

Fig.1. Machine learning is well suited to weather forecasting due to the vast amounts of data that are used to determine the best possible initial conditions and to produce global forecasts [22].

Machine learning (ML) is the use of statistical algorithms that can learn from data and generalize to unseen data without explicit instructions. It is a sub-class of artificial intelligence (AI), which is the capability of computer systems to perform tasks typically associated with human intelligence. Many of the statistical methods that have been used for decades in Earth sciences can be counted into the wider class of ML. Examples are multi-dimensional linear regression, or dimensionality reduction via principal components. Even deep learning – the use of neural networks to perform ML – was already applied at ECMWF for the emulation of the radiation scheme more than two decades ago [1,22]. It may therefore surprise that many claims that we have seen an ML "revolution" during the last couple of years. What happened? Beyond the domain of Earth system science, AI and ML have seen an enormous rise that was mainly fueled by:

• A massive increase in computational power with computer hardware customized towards the needs of deep learning, and deep learning being the ideal application for state-of-the-art supercomputers that excel for simple arithmetic and linear algebra.

• The exponential increase of data in many domains – including weather and climate – and the ability of deep learning to learn systems of arbitrary complexity if enough data and compute capacity are available.

• The availability of software libraries such as TensorFlow and PyTorch that allow a user to create complex deep learning architectures with very minimal Python code.

• The massive amount of experience that was collected on how to design efficient deep learning methods with new neural network architectures and training procedures being invented, including convolutional neural networks, recurrent neural networks, generative adversarial networks, attention and transformers, and diffusion networks

It became more obvious around 2018 that the developments in general machine learning would also impact data assimilation and Earth system modelling. Early success stories across ECMWF's workflow included the use of neural networks for SMOS soil moisture data assimilation for the land surface [21,22] and the use of neural networks for bias correction learned within the 4D-Var data assimilation framework [21. Deep learning has been used successfully for the emulation of the gravity wave drag parametrization schemes [22], and the deep learning emulators could be used to generate tangent linear and adjoint model code for 4D-Var data assimilation. Furthermore, decision trees have been used for the post-processing of ensemble predictions for precipitation, and there have been plenty of links and similarities between data assimilation and deep learning. As ECMWF hosts more than one exabyte of weather and climate data, there were plenty of possible application areas for versatile, scalable tools that allow the extraction of complex information from data – such as deep learning. The potential applications were distributed across all parts of the numerical weather prediction (NWP) pipeline, from observation processing [22 to data assimilation, to the forecast model and the post-processing and dissemination of the forecasts. These included methods to improve our understanding of the Earth system such as unsupervised learning and causal discovery, uncertainty quantification, and AI powered visualization; methods to speed-up conventional models such as emulators for parametrization 3 schemes including with low numerical precision, the optimization of the high performance computing (HPC) and data workflow, and data compression; methods to improve the models such as bias correction tools, tools for quality control of observations, feature detection algorithms, and the learning of model components from observations; and methods that linked different datasets to weather and climate datasets that have interesting applications for health, energy, transport and pollution applications, as well as for extremes such as wildfires or flooding.

Machine learning scientists and Earth Science domain scientists often follow a different philosophy. The former tends to solve data science problems that optimize for specific goal functions (e.g. the reduction of Root Mean Square Error of precipitation at 48-hour lead time), while the latter aim to improve and validate models with physical understanding and checks for physical consistency (e.g. conservation laws or process feedbacks). Domain scientists are sometimes defensive regarding the establishment of machine learning as they consider the new capabilities as a threat rather than as an extension of their toolbox. This makes communication and collaboration difficult, but it also represents a barrier for the uptake of machine learning solutions by domain scientists who do not trust black box approaches that do not offer physical understanding. This is in particular the case as many of the machine learning architectures that are currently applied have been developed for other domains such as image recognition and do not allow for the introduction of domain knowledge into solution design. There is a risk that solutions for specific applications will be developed in parallel with no synergies between domain scientists on the one side and machine learning scientists on the other.

The hybrid approach

Machine learning can be used to better estimate some components of NWP, and to estimate model error. This is true for the process of establishing the best possible starting conditions of forecasts, called data assimilation, but also for forecasts themselves.

Aspects of the Earth system, such as sea ice, snow, soil and vegetation, are hard to model from pure physics, so in practice, the modelling can be quite empirical. In such cases, there is great potential to let the observations increasingly define the models. It is more likely to achieve the best results by carefully combining known physics with empirical and ML components, rather than throwing away physical models entirely.

There are also some predictable model errors which we can estimate and remove from data assimilation and subsequent forecasts using ML. Weather and climate reanalysis can benefit from ML, too. For example [22], for ECMWF's next reanalysis, ERA6, an ML model error correction method developed for the period from 2006 (Fig.2), which is rich in satellite observations, will be applied to earlier, data-sparse periods.

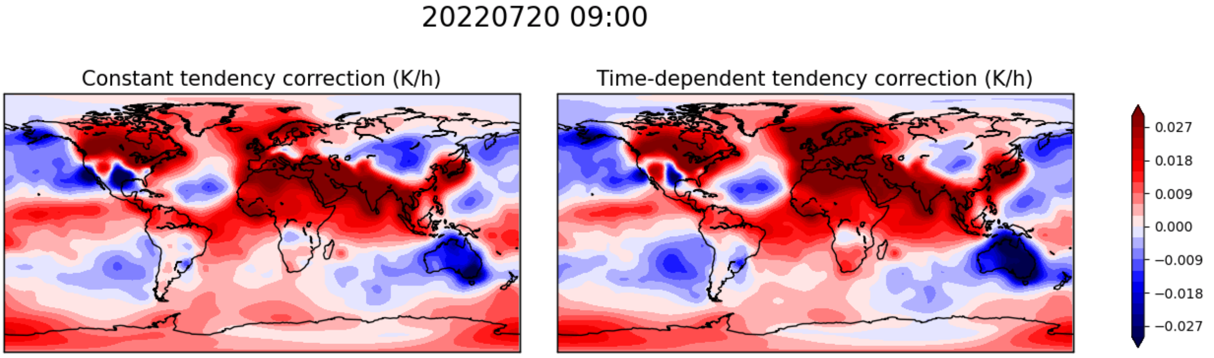

Fig.2. The variable corrections of near-surface temperature tendencies per hour, established by machine learning, that are going to be applied in the data assimilation system from 2025, compared to constant tendency corrections. The constant tendency correction includes small changes for every 12-hour assimilation window. (Time series courtesy of Patrick Laloyaux, ECMWF).

ECMWF made tremendous progress in the last 18 months or so in building such a system, called the Artificial Intelligence Forecasting System (AIFS). This is the result of decisions by our Member States on investments, the motivation and dedication of our staff, and collaborative efforts with partners. The AIFS uses Copernicus climate reanalysis and weather analysis for training, and it relies on IFS initial conditions, so it is not entirely divorced from traditional techniques. But it makes forecasts just on the basis of ML.

This year, *ECMWF* has lowered the grid spacing of the AIFS from 100 to 28 km, and it will go down further. This compares with a grid spacing of currently 9 km for the IFS., *ECMWF* has also built a first AIFS ensemble system, in which a number of slightly different forecasts are made for each time in the future to scan the possible scenarios and thus enable the estimation of uncertainty. These forecasts have been added to our chart's web page, and they are available as open data.

ECMWF is looking at sub-seasonal timescales, up to 46 days ahead, and at the addition of various Earth system components. There are also plans for AIFS forecasts of hydrology and atmospheric composition., *ECMWF* is collaborating in an ECMWF ML pilot project with Member and Co-operating States, taking part in a EUMETNET AI initiative. This will help us to compare different approaches, at different timescales and resolutions. The collaboration with our Member and Co-operating States is also key to the development of a platform called **Anemoi,** which will enable users to build their own ML models (Fig.3).

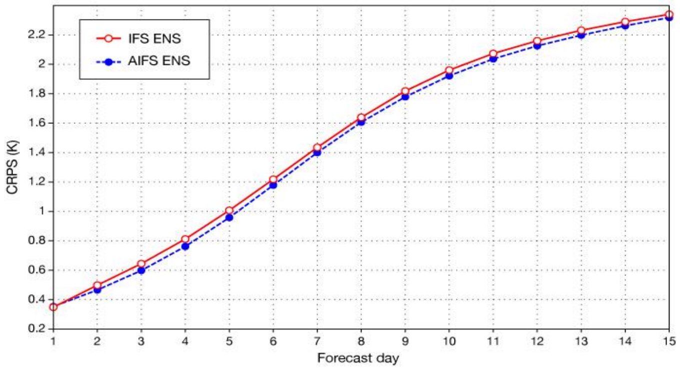

Fig.3. The continuous ranked probability score (CRPS – lower is better) measures the quality of ensemble forecasts. Here we show it for 850 hPa temperature, with results for the IFS ensemble (IFS ENS – red) and for the experimental AIFS ensemble (AIFS ENS – blue). Scores are aggregated over the northern hemisphere extratropics and approximately a five-month period.

Over the last year, *ECMWF* has started a radically new approach to weather prediction: the production of weather forecasts directly from observations. Physics-based data assimilation relies on some assumptions, such as a perfect knowledge of model and observation errors, and of the link between the model and observations. The new approach tries to circumvent these aspects of conventional data assimilation.

It means that observations do not need to be mapped to a fine grid of unmeasured parameters. It also opens up the possibility of exploiting the information content of exciting new observations. This AI-Direct Observation Prediction (AI-DOP) project involves a neural network trained to predict future observations from long historical records of past observations (Fig.4.) [22].

In this new approach, we effectively use observations to forecast future states of the atmosphere learned directly from the observations themselves. First results are very promising, but this approach is still experimental.

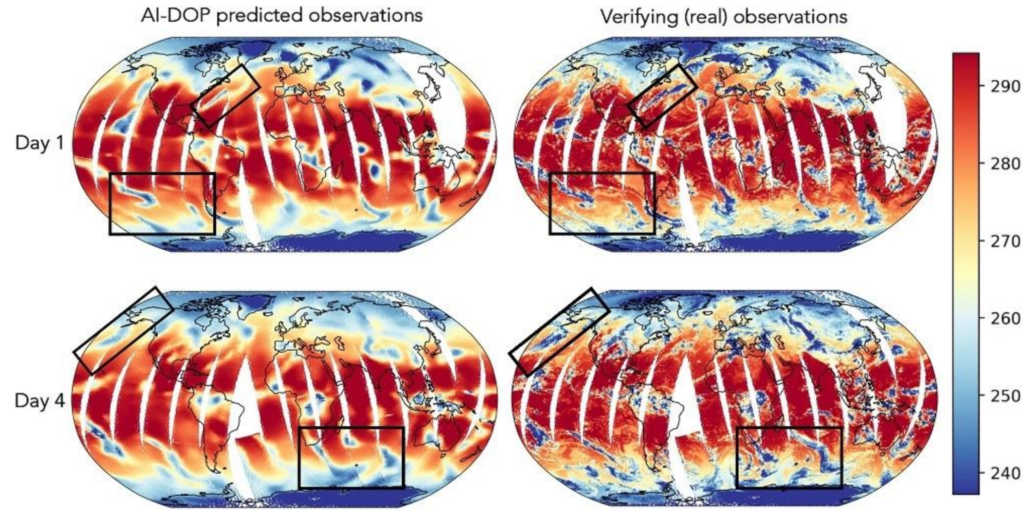

Fig.4. An example of forecasting future observations with AI-DOP. We show infrared window channel brightness temperatures (in Kelvin), measured by the Infrared Atmospheric Sounding Interferometer (IASI), predicted one and four days ahead. The left column shows the predicted values and the right column real radiances measured one and four days later. This channel is very sensitive to atmospheric cloud structures, and we can see that AI-DOP produces very plausible forecasts of the evolution of the large-scale weather patterns, although they are rather smoothed with the current low-resolution experimental system. The rectangles highlight some of the more conspicuous weather patterns that are predicted well.

ML in NWP and climate services

While some of the applications from Machine Learning in Earth system sciences are conceptually close to the use of machine learning methods in other domains (such as the detection of tropical cyclones in model output which can be formulated as an image recognition task), many will require customized machine learning solutions. Physical fields, for example, are often stored on unstructured grids on the sphere which do not allow for a simple application of convolutions in space or time which are a core element of many machine learning approaches. While the vertical dimension of atmosphere models is structured, the physical fields still show very different dynamics close to the surface and at the model top, which will, again, make it difficult to apply standard convolution approaches [1, 23]. Furthermore, physical fields need to follow physical constraints such as conservation laws or a limit to positive values

The training of machine learning tools requires data. As the complexity of machine learning tools can be increased arbitrarily, the only limits for the accuracy of machine learning methods are the amount of data that is available for training and the limits of the computational and data handling infrastructure. More data allow more sophisticated machine learning solutions to be designed. Machine learning users will therefore show a different and more greedy data access pattern when compared to conventional users, towards larger and more selective data access (e.g. retrieving a single field over a specific area of the globe for a long period of time). This generates a significant challenge for data centers such as ECMWF as data production and use is already growing fast for the conventional workflow.

When compared to conventional methods in NWP and climate services, machine learning requires a different set of tools regarding both software and hardware. Most Earth system models are still based on Fortran code and are typically run on CPU-based supercomputing hardware. On the other hand, machine learning tools are typically based on Python code and Python libraries as well as Jupiter notebooks and are trained and used most efficiently on GPU hardware. Most of the computational cost for supervised learning is generated by the training of the machine learning tool, while the application of the tool (the "inference") is typically very cost efficient. As part of the code refactorization to improve portability, models are now being rewritten into domain-specific languages and in some cases also Python or Julia code [22], including the Finite Volume version of the ECMWF Integrated Forecasting System (IFS-FVM). However, it will still take a couple of years until these developments reach a large fraction of domain scientists.

Earthkit

ECMWF has also developed Earthkit, a modular Python ecosystem that provides consistent tools for retrieving, manipulating and analyzing Earth system data. Earthkit builds on the principles used in ECMWF's operations, ensuring that users preparing AI training datasets benefit from the same reliability and transparency that underpin ECMWF's daily forecasts (Fig.5.) [22].

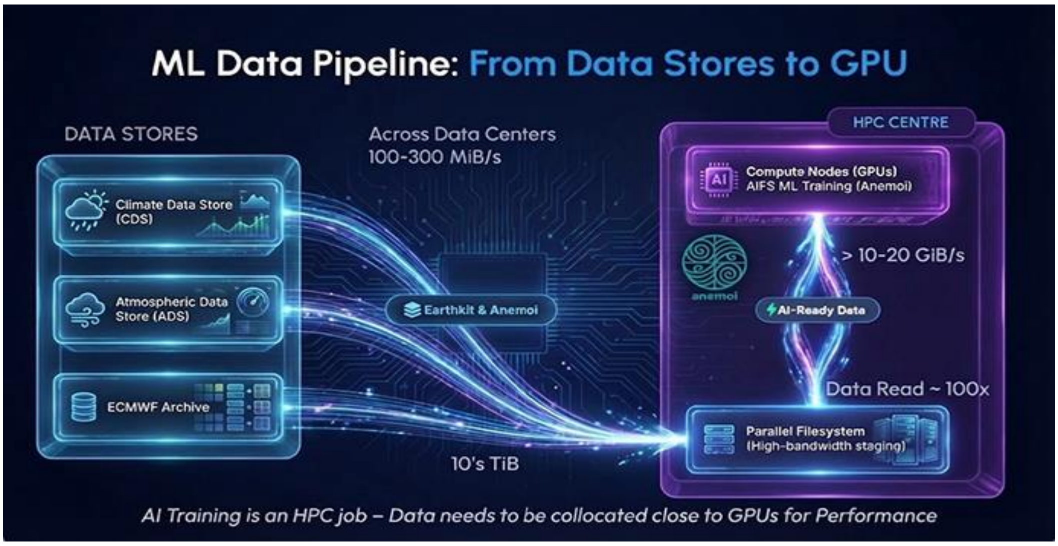

Fig.5. Machine learning pipelines: optimal performance relies on placing large datasets close to Graphics Processing Units (GPUs) within HPC environments, ensuring efficient machine learning workflows.

Anemoi: a shared European framework for AI weather prediction

While datasets and processing tools are essential, the rapid progress in AI weather forecasting across Europe is also due to shared software frameworks that support collaboration.

A major reason Europe has advanced so quickly in AI-based weather and climate prediction is the emergence of Anemoi, a jointly developed, open-source framework created by ECMWF together with several national meteorological services. Anemoi provides a coherent, shared foundation that supports the full lifecycle of developing machine learning models, from data preparation to model training, inference and operational use.

At its core, **Anemoi** offers three essential capabilities (Fig.6):

- AI-ready datasets: production, cataloguing and distribution of more than 150 curated training datasets derived from ERA5, operational ECMWF data, satellite and in situ observations, and Member State archives. These datasets are prepared using domain expertise and deployed across multiple HPC systems across Europe.
- Training and ML operations: tools for large-scale, distributed model training, experiment tracking and workflow reproducibility, enabling consistent development across institutions and HPC environments, including the world-class EuroHPC supercomputers.
- Inference and applications: components that support scalable model execution for weather and climate applications across both timescales and spatial scales. Examples include nowcasting, limited-area ML models, ECMWF's own Artificial Intelligence Forecasting System (AIFS) and the AI Earth system components and climate emulator developed within the Destination Earth initiative of the European Commission.

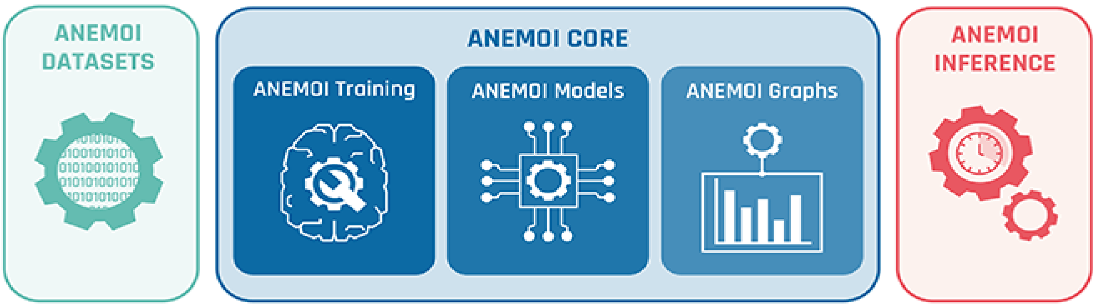

Fig.6. Overview of the Anemoi pipeline, from datasets through core components – training, models, and graphs – to inference [22].

By providing an end-to-end, operationally aligned framework, Anemoi enables ECMWF and its Member States to build, operationalize and improve AI models in a consistent way. This shared framework ensures the rapid progress in AI prediction, while ensuring transparency, scientific robustness and a clear pathway from research to operational implementation."

In 2025, **Anemoi** received two major international recognitions. It was awarded the Technology Achievement Award by the European Meteorological Society (EMS) for its collaborative approach to machine learning, and also the 2025 HPC wire Readers' and Editors' Choice Award for "Best Use of AI Methods for Augmenting HPC Applications".

AIFS: operationalizing AI models

ECMWF's Artificial Intelligence Forecasting System (AIFS), which is operationally run daily since 2025, demonstrates how machine learning models can be integrated into a rigorous operational environment. Running the AIFS alongside the Integrated Forecasting System (IFS) allows ECMWF and its Member States to:

- evaluate AI forecasts with established verification methods,
- analyze strengths and limitations under diverse conditions, and
- explore the complementarity of physics and machine learning forecasting approaches.

This side-by-side exploration ensures that emerging AI methods can be assessed transparently and responsibly, in line with ECMWF's commitment to scientific trust, quality, and reliability (Fig.7).

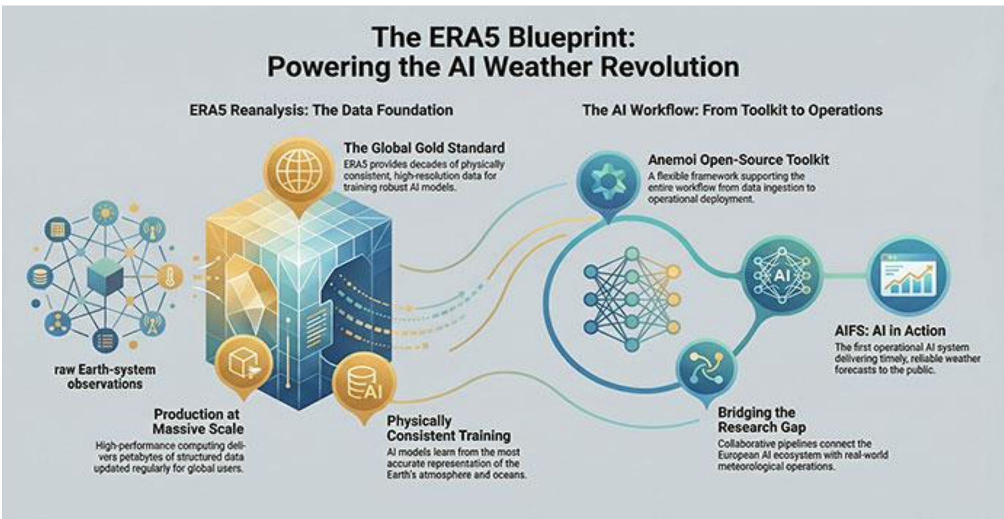

Fig.7. The ERA5 Blueprint illustrates the journey from raw Earth observations to next-generation AI weather forecasts. Credit: generated by Notebook [22].

Interest in AI-enabled forecasting is growing, with ECMWF, national meteorological services, research institutes and private actors exploring applications from post-processing and downscaling to nowcasting and regional and global prediction. One example is the recent operationalization of AICON by the German Meteorological Service (DWD) utilizing **Anemoi.**

Building on shared foundations such as ERA5, Earthkit and Anemoi allows ECMWF and its Member States to develop these methods in a consistent way, supporting joint approaches to model development and evaluation.

This collective momentum is one of Europe's strengths, helping establish a coherent and scientifically robust pathway for AI-enabled weather prediction, strengthening the capacity of the European meteorological infrastructure.

These digital representations combine EO data with advanced modelling frameworks to simulate environmental processes and explore future, "what if", scenarios. Using high-performance computing, machine learning, and satellite data, the digital twins of Destination Earth (DestinE) combine Earth Observation data with numerical models and AI techniques to simulate the behavior of the Earth system and explore possible future scenarios [21].

The **WEkEO** DIAS provides **Earth Observation datasets** coming from many different services (and allows all users to **download data for free**.

Another question about the future of ML for Earth system modelling is whether the domain will follow the developments of large language models (LLMs) towards larger and more generic ML tools that can then be used for multiple application areas – so-called foundation models. LLMs are trained to fill in gaps in huge amounts of text, rather than for a specific task such as the translation from language A to language B. The resulting tools can be used for diverse tasks beyond their training objective, along this line, it may be possible that a foundation model trained from various Earth system datasets and with a huge latent space with many billions of trainable parameters may perform better in certain tasks when compared with a task-specific model. To explore foundation models for weather and climate applications, ECMWF and a number of Member States have started the Weather Generator EU Horizon project that will build such a foundation model and serve as an additional digital twin for **Destination Earth** [21].

The Weather Generator will serve as foundation model for weather and climate applications. It will be able to digest datasets from various sources, including observations, local and global analysis products, and local and global models, and will be useful for many different application domains in weather and climate science. The input and output of the Weather Generator can be local or global, at a resolution between 100 m and 100 km, and can be in the past, present and future. Figure 8: Showing the evolution of 24-hour rainfall forecasts on 16 April 2024 over the grid box including Dubai. The model climate is about zero precipitation, with a maximum of less than 25 mm based on 1,800 forecasts (marked by the black triangle). Experimental versions of AIFS Single (blue dots) and AIFS Ensemble (green box and whisker) models both predicted precipitation values well-outside the model climatology and values in line with the IFS ensemble (blue box and whisker). All systems underestimated the observed value (purple hourglass). Data is obviously a key ingredient in accurate forecasting using physics-based approaches. We view that the role of data will grow even larger with the rise of data-driven forecasting. Curating large, calibrated datasets will be vital to feed these models. Direct incorporation of surface observations into model training and inference will increase the value of sharing these datasets. Novel data sources, e.g. cameras measuring visibility, could be directly included in model pipelines.

Conclusion

Big Data and Artificial Intelligence greatly enhance weather forecast and climate assessment as in spatial-temporal scale as accuracy. The Machine Learning methods are successfully used in prediction of dangerous hydrometeorological events, such as drought [23], flooding, frost, etc. These methods became more and more accurate due to Earth Observing Satellite data and computing facilities. The best way to achieve more accuracy is enhancement of those ML models by learning them physical lows. These includes microphysical processes, thermodynamics and also quantum electrodynamics, due to cosmic weather events [14]. Hybrid approach together with space weather prediction will be able to handle weather forecasting gaps and difficulties.

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მანქანური სწავლება და ჰიბრიდული მიდგომები ამინდსა და კლიმატში

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რეზიუმე

კლიმატის ცვლილება ერთ-ერთი უმნიშვნელოვანესი გლობალური გამოწვევაა, რომლის მართვაც აუცილებელია. ბუნებრივი გარემოს გაგება სულ უფრო მნიშვნელოვანი ხდება კლიმატის ცვლილების ნეგატიურ ზემოქმედებასა და ანთროპოგენურ ზეწოლაზე რეაგირებისთვის, ასევე მათ წყალზე, ენერგეტიკულ და სასურსათო უსაფრთხოებაზე, ინფრასტრუქტურაზე, ადამიანის ჯანმრთელობასა და ბუნებრივ საფრთხეებზე. ნაშრომში განხილულია მანქანური სწავლების გამოყენება ამინდსა და კლიმატში, მისი შემდგომი განვითარება და ECMWF-ის საქმიანობა და მიღწევები მანქანური სწავლების/ხელოვნური ინტელექტის მეთოდების შექმნაში და გამოყენებაში. ეს ასევე მნიშვნელოვანი ინტერდისციპლინარული გამოწვევაა, რომელიც მოიცავს თითქმის ყველა სამეცნიერო სფეროს. ხელოვნური ინტელექტისა და მანქანური სწავლების (AI/ML) აპლიკაციები ბოლო დროს ფართოდ გავრცელდა ყველა სფეროში. მანქანურ სწავლებას შეუძლია გააუმჯობესოს გამოთვლები კომპონენტების დამატებით ან პროცესის ზოგიერთი ნაწილის ჩანაცვლებით. ეს არის ის, რასაც „ჰიბრიდულ“მიდგომას უწოდებენ. სამაგიეროდ, მანქანურ სწავლებას (ML) ასევე შეუძლია მთლიანად ჩაანაცვლოს მთელი მოდელი გაცილებით დაბალი გამოთვლითი ხარჯებით. გარდა ამისა, ხელოვნური ინტელექტი/მანქანური სწავლება (AI/ML) ხსნის გარკვეულ გზებს სხვა პროცესებში, როგორიცაა წყალდიდობის პროგნოზირება, ხანძრის საფრთხის პროგნოზირება, დაკვირვებების მონიტორინგი, სუპერკომპიუტერის მართვა ან მომხმარებლის გამოცდილების გაუმჯობესება.

საკვანძო სიტყვები: დიდი მონაცემები, მანქანური სწავლება, ნეირონული ქსელი, CEMS (კლიმატისა და გარემოს მონიტორინგი კოსმოსიდან), ECMWF-ის ხელოვნური ინტელექტის პროგნოზირების სისტემა (AIFS), ჰიბრიდული მიდგომა.

Машинное обучение и гибридные подходы в погоде и климате

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Резюме

Изменение климата является одной из наиболее значительных глобальных проблем, требующих решения. Понимание природной среды приобретает все большее значение для реагирования на негативные последствия изменения климата и антропогенное давление на ограниченные природные ресурсы, а также на их влияние на водную, энергетическую и продовольственную безопасность, инфраструктуру, здоровье человека и стихийные бедствия. В статье рассмотрено применение машинного обучения в погоде и климате, его дальнейшее развитие, а также деятельность и достижения Европейского центра изучения погоды и климата (ECMWF) в создании и применении методов машинного обучения/искусственного интеллекта (ИИ). Это также важная междисциплинарная задача, затрагивающая почти все научные области. Применение искусственного интеллекта и машинного обучения (ИИ/МО) в последнее время широко распространилось во всех областях. Машинное обучение может улучшить наши вычисления, добавляя компоненты или заменяя некоторые части процесса. Это называется «гибридным» подходом. Кроме того, машинное обучение может полностью заменить всю модель, при этом значительно снизив вычислительные затраты. Помимо этого, ИИ/машинное обучение открывает новые возможности в других областях нашей деятельности, таких как прогнозирование наводнений, прогнозирование пожарной опасности, мониторинг наблюдений, управление суперкомпьютером или улучшение пользовательского опыта.

Ключевые слова: Большие данные, машинное обучение, нейронные сети, CEMS (мониторинг климата и окружающей среды из космоса), система прогнозирования на основе искусственного интеллекта ECMWF (AIFS), гибридный подход.