Artificial intelligence for weather forecasting

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Artificial intelligence (AI), and in particular deep learning methods using neural networks, has been successfully exploited in numerous applications in recent years. Weather forecasting is one of the promising fields of application, with potentially numerous uses of AI that could lead to major methodological advances, associated with significant gains in performance and quality. Through some initial achievements, this article presents the potential of AI for the different stages of weather forecasting, from its calculation to its

practical utilization and communication. The new issues and challenges posed using these techniques are also discussed.

1. What is Artificial Intelligence all about?

Precisely defining artificial intelligence is a first difficulty. In the following, we will consider that it is a vast set of techniques, based on mathematical foundations and computational sciences, whose objective is to reproduce some aspects of human intelligence (reasoning, creativity, for example). Far from being new, AI appeared in the 1950s, first in the form of expert systems: humans establish a set of rules and instructions that the machine executes. The AI methods that are among the most widely used and efficient today follow a completely different approach: humans no longer prescribe rules but develop computer programs capable of learning the best relationships from the data. This is called **machine learning**, whose algorithmic structure is essentially based on **deep neural networks**.

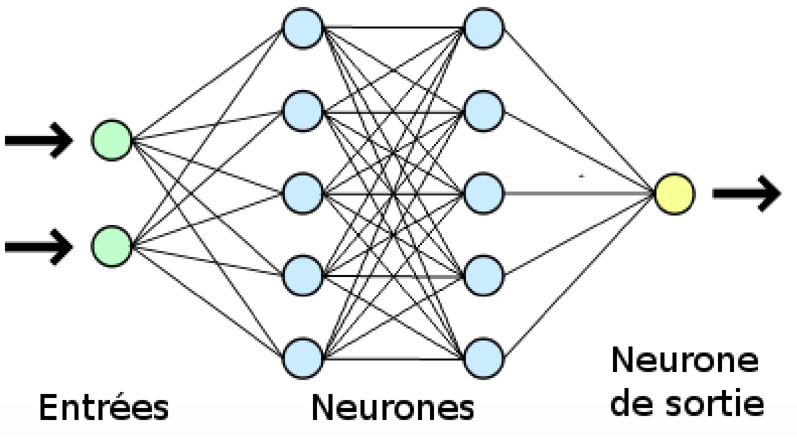

Figure 1. A neural network consisting of a first layer containing the input signal, an output layer (the network forecast), and two so-called 'hidden' layers, each composed of 5 neurons. The more hidden layers there are, the deeper the network. The black lines represent the interactions between the neurons of the successive layers. [source : tpe-ia.lescigales.org/maths.php]

Inspired by the functioning of biological neurons, an artificial neural network is a set of neurons structured in several layers (Figure 1), which transforms an input signal (e.g. the temperature at a time *t*) into an output signal (e.g. the temperature at time *t+1 hour*). It is in the **learning** (or training) phase that a neural network learns from data, in an iterative way, to solve the problem it is facing (in the previous example, predict the temperature an hour later). In practical terms, this step consists of calibrating the connections between the different layers of neurons (also known as the network weights), to provide the most satisfactory possible answer to the problem posed. Training a neural network requires on the one hand sufficiently large input and output datasets representative of all possible situations, and on the other hand significant computing resources. The training phase can indeed be long and expensive, especially when the problem, the neural network and the data are very complex. Once the network is trained, it can be used in inference, i.e. as a predictive model applied to new data. Unlike training, this inference stage is very fast.

Formal neural networks were proposed as early as the 1940s but were relatively little exploited until the 2000s. It is the increase in computing power, and in particular the arrival of graphics processing units (GPUs), as well as the availability of massive datasets, that have enabled these approaches to make a strong comeback since the 2010s.

In the remainder of this article, the term AI will mainly be used to refer to methods using deep neural networks. Convolutional neural networks, introduced by Le Cun *et al.* [1], and specifically designed to process input images, are one of the main techniques applied to weather forecasting.

2. AI for weather forecasting

Weather forecasting is the result of a sequence of complex steps, the central element of which is the **forecasting model** (see Weather forecasting models). Meteorological services regularly propose changes to the model to improve the quality of forecasts. In particular, it is common to increase the resolutions of computing grids and to make the representation of physical processes more complex. However, in both cases, these are costly upgrades, in development and especially in computing resources. AI algorithms, on the other hand, have the advantage of being extremely fast in their inference phase. Thus, the solution of a complex physical problem by AI is generally several orders of magnitude lower than classical approaches, which often require solving several hundred or even thousands of equations. This makes AI a potentially interesting tool for speeding up the calculation of forecasts, among other things.

The use of AI in meteorology is not new. As early as the 1990s, AI techniques enabled innovative developments in the statistical post-processing of weather forecasts. For example, various applications have been developed to reduce systematic errors in forecasts [2]. However, it is only recently that the use of AI has expanded into the core of atmospheric modelling.

2.1 Physical and AI models: what are the differences?

Physical models, of which currently operational weather forecasting models are an example, are built based on expert knowledge of the functioning of the system under study (the atmosphere, in the case of weather), most often translated into equations. These models have the advantage of being physically interpretable, but they remain approximations of the real system, limited by our understanding of the processes at play and by the constraints imposed by the computational resources.

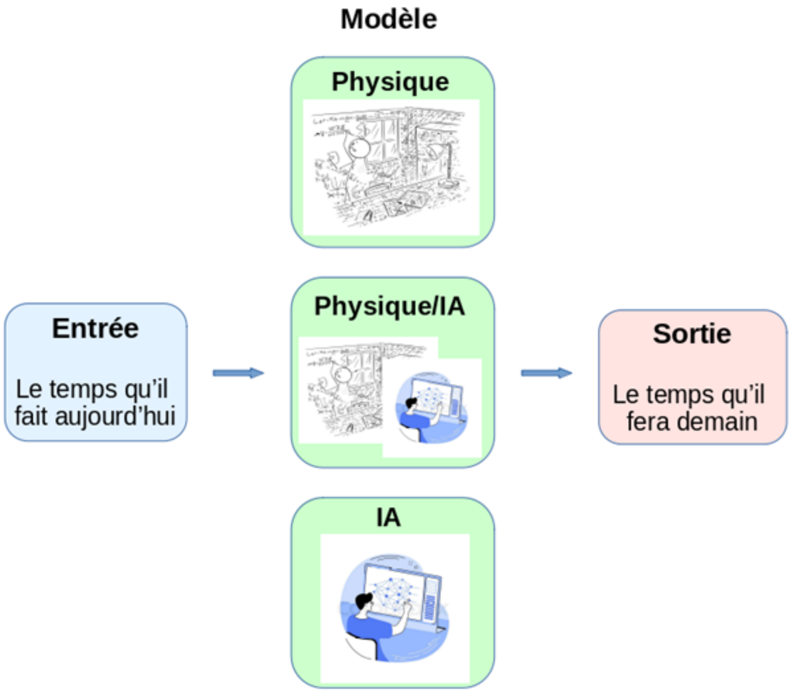

Figure 2. Different modelling approaches for weather forecasting. [Scheme by the author]

AI models work in a very different way since they learn themselves, from very large datasets, the best statistical relationships, allowing them to move from the input data to the output data. Compared to physical models, AI models are less interpretable (often referred to as a "black box") and do not offer a guarantee that physical laws will be respected, but they can make it possible to discover complex relationships that have not yet been understood or identified by scientists.

Let's take the example of the temperature forecast at a due time. Its calculation with a physical model amounts to solving well-known equations prescribed by humans, while its calculation with an AI model consists of applying a sequence of statistical relationships learned by a neural network from the data during the training phase. Physical modelling and 'AI' modelling are therefore two very different approaches in their foundation, but also complementary, to solve a given problem (Figure 2).

2.2 Towards a hybridization of physical and AI approaches for atmospheric modelling

As illustrated in Figure 2, AI can be integrated into the forecasting process in various ways. The complementary nature of the physical and AI approaches initially motivated the development of **'hybrid' forecasting systems**, combining physical modelling and AI. This involves, for example, replacing the most expensive or least well-represented elements of a physical model with an AI algorithm. Other work has explored the possibility of using AI to improve certain characteristics of forecasts (e.g. the accuracy of spatial sampling), and ultimately their quality, at lower cost. Several examples of hybrid forecasts are presented below.

Physical parameterizations, which simulate the effects of fine-scale processes such as radiation, convection, or turbulence, are currently among the most expensive components of a model, as well as one of the main sources of uncertainty in weather (and climate) forecasts. Several studies have begun to examine the possibility of replacing all or part of these parameterizations with AI algorithms, with promising initial results [3]. The example in Figure 3 shows a very good consistency between the precipitation forecast by a physical model and by a hybrid model, in which the processes associated with deep convection are learned by a neural network.

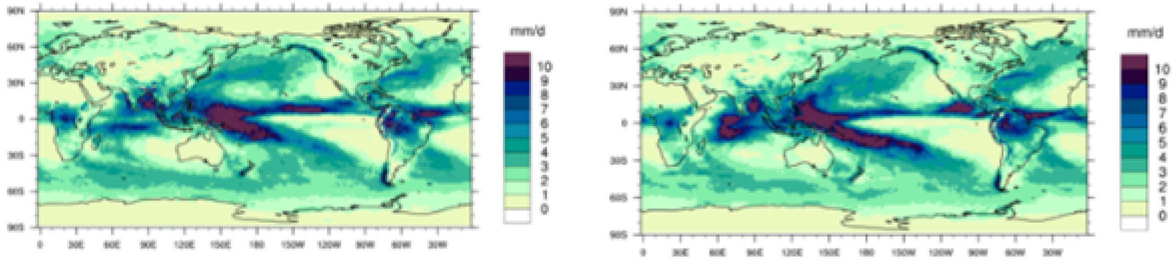

Figure 3. Annual averages of precipitation (in millimeters per day) calculated with (left) a physical prediction model and (right) a hybrid physical-AI model. [Source Blanka Balogh, reproduced with permission]

Increasing the spatial resolution of the forecasting model allows for better description of small-scale weather events. This is particularly important for the prediction of high-impact events such as thunderstorms, fog, urban heat islands, but at the cost of a significant, even prohibitive, increase of computing cost. **Statistical downscaling** is an alternative to increasing model resolution, which involves learning a statistical relationship between low-resolution and higher-resolution forecasts. It is thus possible to simulate forecasts at the local scale by directly applying this relationship to the forecasts of a lower-resolution physical model. Several studies have demonstrated the ability of neural networks to effectively solve this problem [4]. An example of AI downscaling of a temperature forecast is shown in Figure 4.

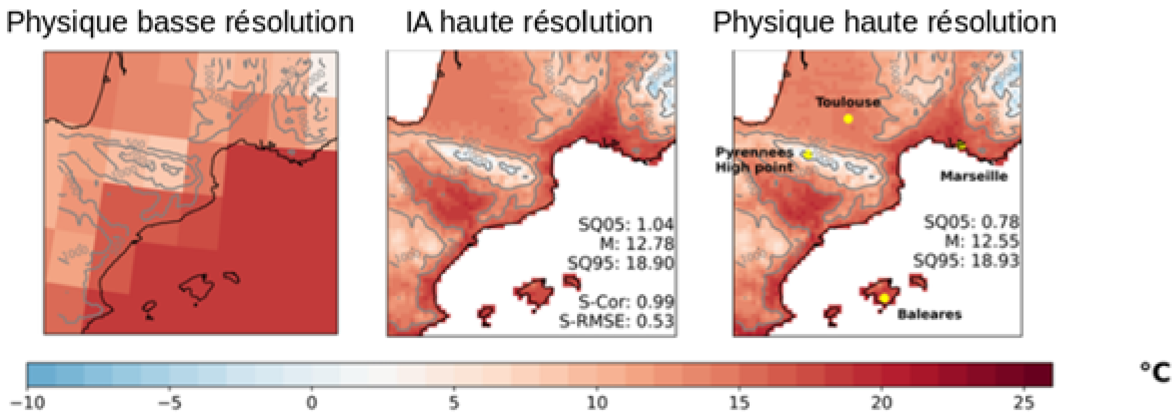

Figure 4. Temperature forecast calculated by (left) a low-resolution physical model, (middle) an AI downscaling of the low-resolution forecast, and (right) a high-resolution physical model. [Source: Antoine Doury, reproduced with permission]

The last example concerns ensemble forecasting systems, used to characterise the different possible weather scenarios thanks to the parallel production of several forecasts (see The ensemble forecasting). Ensemble forecasting is now at the heart of the strategy of many forecasting services, but its characteristics, and particularly the number of realizations (also known as "members"), remain highly constrained by the available computing resources. Operationally used ensemble forecasts use no more than 50 members, whereas an accurate estimate of probability distributions of the future state of the atmosphere requires several hundred or thousands. Could AI be leveraged to generate additional ~~achievements~~ members by replacing the forecasting model? Recent studies [5] provide ~~the~~ first encouraging answers. Relying on generative AI algorithms (a category of AI used to create new content and popularized by applications such as ChatGPT or DALL.E), they show that it is possible to produce realistic weather fields guided by physical simulations, and thus pave the way for hybrid ensemble forecasts of several dozens or even hundreds of members.

2.3 Towards atmospheric models entirely based on AI

Previous examples have shown how AI can complement physical weather forecasting systems to improve computational performance and quality. A new step has recently been ~~taken~~ passed by several research teams, who have proposed to completely replace the physical prediction model with an AI model. In 2022 and 2023, a succession of studies tackles the problem of global medium-range weather forecasting by AI [6]. Against all expectation, AI models such as Pangu-Weather or GraphCast, trained on more than 40 years of historical data, now compete in some aspects with the physical model of the *European Centre for Medium-Range Weather Forecasting* (ECMWF), considered to be the best operational forecasting model at the moment. The daily forecasts of these new models were soon released publicly, and interested readers can view them at https://www.meteociel.fr/modeles/ecmwf_aifs.php and https://charts.ecmwf.int/.

Although these AI models still provide a very partial representation of the atmosphere, far from that produced by physical models, and with well-identified weaknesses, it has been demonstrated that it is possible to predict some of the meteorological parameters, with a certain quality (Figure 5). These new models are also capable of anticipating high-impact events such as storms [7] or tropical cyclones several days in advance.

An undeniable advantage of AI models is their efficiency in terms of computing cost when used for inference. Forecasts can be produced several days ahead in a matter of seconds or minutes, much faster than physical forecasting models, which take tens of minutes or more. These first AI models thus open a new field of research with a long list of scientific and technical questions, and new opportunities for operational forecasting.

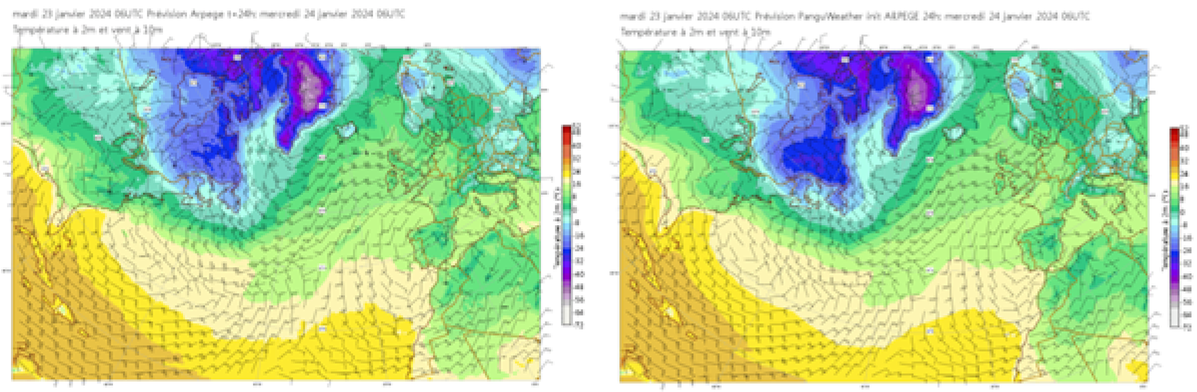

Figure 5. Temperature (colour range) and wind (barbulae) forecast, calculated by the Arpège physical model of Météo-France (left) and the IA model PanguWeather (right) for the Europe-Atlantic domain. [Source: Météo-France]

For these AI models to become exploitable new tools for operational weather forecasting, and more generally for all applications requiring meteorological data, there are still many obstacles to be overcome. The first challenge is to develop **models tailored to the needs of users**, trained on very high spatial resolution data, and capable of predicting the meteorological variables of interest and the associated uncertainties. This raises the question of the availability and accessibility of these datasets, and the ability to mobilize significant computing resources for training that can last up to several weeks. The second challenge is the **development of methods and diagnostics for the interpretability and explainability of these models**. Like physical models, it is legitimate to be able to determine whether AI has produced a good prediction for the right reasons, or, in the case of poor forecasts, to identify which components of neural networks are to blame. An underlying perspective is the development of **physics-informed neural networks**, to force models to produce physically coherent solutions.

3. AI for expertise and prediction communication

3.1 AI and forecasters

Weather forecasts, whether produced by a physical model or an AI model, require human expertise to produce bulletins, warnings, or assistance to different sectors of activity (see The role of the forecaster). Operational production tends to evolve towards an increase in the information made available to users, with forecasts refreshed more frequently and carried out in the form of ensembles. As a result, the amount of data to be assessed is constantly increasing, often within very tight timescales.

AI offers new opportunities to facilitate human expertise in operational forecasting. Its capabilities for pattern recognition and automatic classification can be leveraged to extract and summarize relevant information from large volumes of forecast or observation data. Two examples of application are presented below.

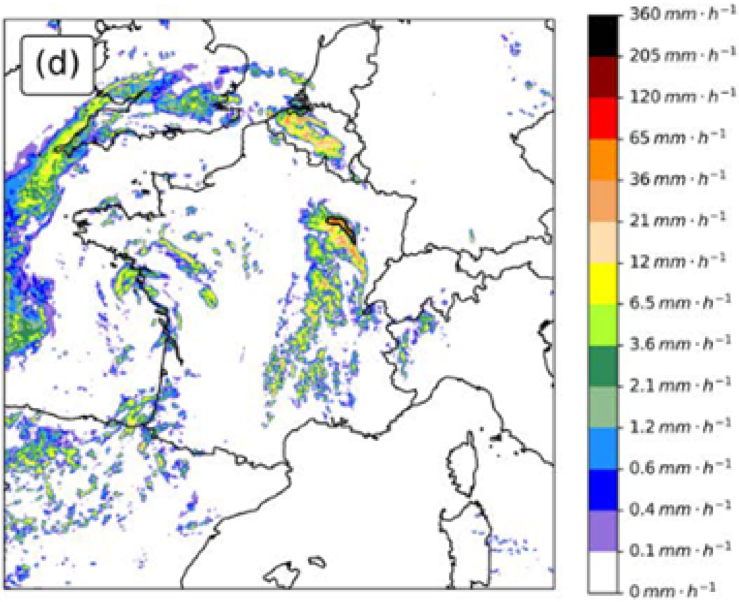

Figure 6. Rain forecast (in color range, unit: millimeters per hour). The 'arcuate echo' thunderstorm detected over the North-East of France by an AI algorithm is delimited by the black outline. [Source: Arnaud Mounier, reproduced with permission]

For decades, human expertise has been based on the **recognition of meteorological structures and conceptual schemes**. In model outputs, for example, this involves identifying the presence, location and characteristics of events such as depressions, tropical cyclones and thunderstorm structures. For a long time, this tedious work was carried out 'by hand' by forecasters. In many areas, AI has shown very good performance in object detection, excelling, for example, in recognising dogs and cats in images. The transposition to the detection of meteorological objects is straightforward. Using rain, wind or pressure maps as input data, a neural network can be trained to recognise structures of interest. Figure 6 shows the result of an AI trained to detect a particularly violent type of thunderstorm known as a~~n~~ 'bow echo' (for its bow shaped structure). Synthesising detections made in many forecasts can then provide useful products for quantifying the risk of such an event occurring, and more generally for decision-making [8].

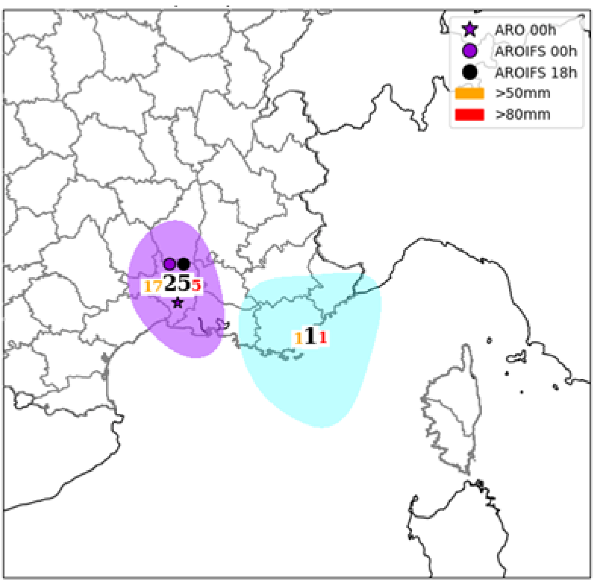

Figure 7. The classification of several valid forecasts for the same event reveals two preferred locations for the heaviest rainfall, represented by the areas in purple and blue. [Source: Arnaud Mounier, reproduced with permission]

Another use of AI involves synthesising the information from several dozen forecasts into a limited number of representative scenarios, such as the majority scenario (the one that emerges preferentially from the analysis of the various forecasts) and a few alternative scenarios (less likely but not to be ruled out, because of the forecast uncertainties or risks associated with these scenarios). **Automatic classification methods**, aimed at grouping similar information within the same class, are particularly well-suited to dealing with this problem. This approach can be used, for example, to identify the main precipitation scenarios emerging from a set of several dozen forecasts (Figure 7).

3.2 AI and weather forecast communication

While AI is a tool that can be integrated throughout the forecasting chain, from modelling to expertise, both human and automatic, it could also change the way in which forecasts are communicated or accessed by users. AI, in more or less sophisticated forms, is already used in certain automatic productions that power mobile applications, for example. The new conversational AI tools also offer a new means of accessing weather information, enabling the user's request to be formulated explicitly (Figure 8). Could AI go so far as to replace weather presenters? A first response was recently provided by Switzerland (Figure 9). These technologies are still in their infancy, but they could well be the beginnings of a new standard of communication and interaction with users.

Figure 8. Excerpt from an exchange with the conversational AI tool Copilot. [Scheme by the author]

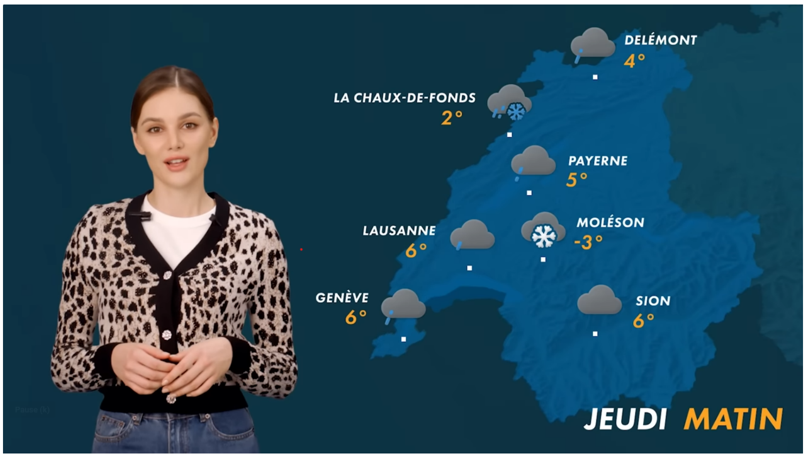

Figure 9. Jade, an AI-generated avatar, presents the weather in Switzerland. [Screen copy of the web page "Météo de Jade" - 20 avril 2023 - M le Média. Link to the video]

4. Messages to remember

AI methods have been used in various sectors of activity, and weather forecasting is no exception. The availability of large datasets and the increase in computing resources have made it possible to develop high-performance AI algorithms that can be applied to the various stages of the operational weather forecasting chain. While most of these developments are still at the research stage, their operational use now seems conceivable in the short to medium term.

The most unexpected and potentially most impactful element is the advent of weather forecasting models based entirely on AI. While the incremental development of numerical weather prediction since the 1950s is often described as a ‘quiet revolution’, it is a much faster revolution that seems to be taking place with AI. It also opens a new area of research for meteorological services, with new scientific and technical challenges.

These advances in AI should not, however, hamper improvement of physics-based forecasting models, which are still of vital importance. At this stage, the aim is not to replace one by the other, but rather to exploit the complementary nature of these two approaches.

Notes and references

Cover image. Image created by the author and generated by DALL. E, a generative AI, based on the text description 'Neural networks for weather forecasting'.

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