Opportunities and limits of AI in climate modeling

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Earth system models are the most important tools for quantitatively describing the physical state of Earth, and—for example, in the context of climate models—predicting how it might change in the future under the influence of human activities. How the increasingly used methods of artificial intelligence (AI) can help to improve these forecasts and where the limits of the two approaches lie has now been investigated by an international team led by Christopher Irrgang from the German Research Centre for Geosciences Potsdam (GFZ) in a Perspectives article for the journal *Nature Machine Intelligence*. One key proposal: To merge both approaches into a self-learning "neural Earth system modeling."

The earth as a system—a challenge

The development of Earth is a complex interplay of many factors, including the land surface with flora and fauna, the oceans with their ecosystem, the polar regions, the atmosphere, the carbon cycle and other biogeochemical cycles, and radiation processes. Researchers therefore speak of the Earth system.

With so many interconnected spheres and factors of influence, it is a great challenge to predict future scenarios, as is required, for example, in the context of research on climate change. "Enormous progress has been made here in recent years," says Christopher Irrgang, lead author of the study and postdoctoral researcher in the section "Earth System Modelling" at the GFZ. For example, the recently published sixth Assessment Report of the IPCC summarizes our current knowledge of the future impacts of various greenhouse gas emission scenarios in greater detail than ever before.

The report relies, on the one hand, on increasingly comprehensive and detailed findings from observations and measurements of the Earth system to assess past warming and its impacts, for example in the form of increasing extreme events, and on the other hand on a large number of simulations carried out with state-of-the-art Earth system models (ESMs).

Classical Earth system modeling with major progress

Classical Earth system models are based on both well- and lesser-known physical laws. With the help of mathematical and numerical methods, the state of a system at a future time is calculated from what is known about the state of the system at a present or past time.

The underlying models have improved continuously in recent decades: An unprecedented number of subsystems and processes of Earth can be taken into account, including—to some extent—such complex key processes as the effects of clouds. Their performance is demonstrated, for example, by the fact that they can accurately trace the development of global mean temperatures since the beginning of data collection. Today, it is also possible to derive conclusions about the effects of climate change on a regional level.

Limitations

The price, however, is that the increasingly complex ESMs require immense computational resources. Despite this development, even the predictions of the latest models contain uncertainties. For example, they tend to underestimate the strength and frequency of extreme events. Researchers fear that abrupt changes could occur in certain subsystems of Earth, so-called tipping elements in the climate system, which the classical modeling approaches cannot predict accurately. And many key processes, such as the type of land use or the availability of water and nutrients, cannot (yet) be represented well.

Machine learning approaches are making inroads

The challenges of classical ESM approaches, but also the ever-increasing amounts of available Earth observations, open up the field for the use of artificial intelligence. This includes, for example, machine learning (ML) methods such as neural networks, random forests or support vector machines. Their advantage is that they are self-learning systems that do not require knowledge of the—possibly very complex or not even fully known—physical laws and relationships. Instead, they are trained on large data sets for specific tasks and learn the underlying systematics themselves. This flexible and powerful concept can be extended to almost any desired complexity.

For example, a neural network can be trained to recognize and classify patterns in satellite images, such as cloud structures, ocean eddies or crop quality. Or it learns to make a weather forecast based on previous records, models and physical balance equations.

"Although first studies showed that machine learning concepts can be used for image analysis already in the early 1990s, the "Cambrian explosion' of AI in Earth and climate sciences has only been taking place for about five years," Irrgang notes. Not least because the pools of measurement and model data are growing daily and more and more ready-to-use ML libraries are available.

Can one trust in the results of artificial intelligence?

However, the extent to which this self-learning approach can actually extend or even replace classical modeling approaches remains to be seen. Because machine learning also—still—has its pitfalls: "Many of today's ML applications for climate science are proof-of-concept studies that work in a simplified environment. Further research will tell how well this is suited for operational and reliable use," Irrgang sums up.

Another decisive aspect: As in a black box, input and output are known, but the processes behind them for gaining knowledge are not. This causes problems in validating the results for physical consistency, even if they seem plausible. "Interpretability and explainability are important issues in the context of machine learning that need to be improved in the future to strengthen transparency and trust in the method. Especially when the results of the predictions are an important basis for political decisions, as is the case in climate research," emphasize the authors of the study.

A new and rapidly evolving third way: Hybrids of ESM and AI

In the present publication, the team around the mathematician proposes a third way: The fusion of the two approaches discussed above into a "neural Earth system modeling." In this way, the respective strengths could be combined and their limits extended. The first promising steps on this path have already been taken. For example, ML is no longer only used for pure data analysis, but also to take over or accelerate certain process steps within the framework of classical ESMs. This would then free up computing capacities that could flow into further model refinements.

In the future, novel interfaces can establish a dynamic exchange of information between the two approaches so that they continuously improve each other. This deep extension of classical process-based Earth and climate research lifts Neural Earth System Modeling to a new and rapidly emerging research branch. At its core are hybrid system that can test, correct, and improve their physical consistency and, thus, allow for more accurate predictions of geophysical and climate-relevant processes.

At present, Irrgang and his colleagues conclude that AI and the hybrid approach still contain high risks and pitfalls, and it is far from clear that the current hype surrounding the use of artificial intelligence will—at least on its own—solve the open problems of Earth and climate research.

In any case, however, it is worth pursuing this path. For this to happen, however, close cooperation between climate and Earth research on the one hand and AI experts on the other hand will become more and more important.

More information: Christopher Irrgang et al, Towards neural Earth system modelling by integrating artificial intelligence in Earth system science, *Nature Machine Intelligence* (2021). DOI: 10.1038/s42256-021-00374-3

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