IA et environnement : une (r)évolution ?

Exemple de la prévision météo-climatique

10 ans d'AERIS, 28 janvier 2025

Laure Raynaud, Météo-France

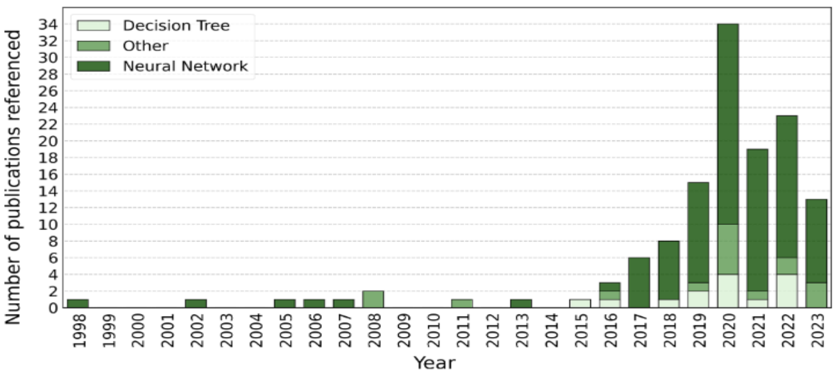
2019-2024 : Essor de l’IA en environnement

L’IA : un outil bien connu des sciences environnementales (ES)

- Utilisé depuis plusieurs décennies

24th Conference on Artificial Intelligence for Environmental Science

- Forte accélération depuis ~ 5 ans, en particulier des approches de ‘deep learning’



(From O. de Burgh-Day and Leeuwenburg, 2023)

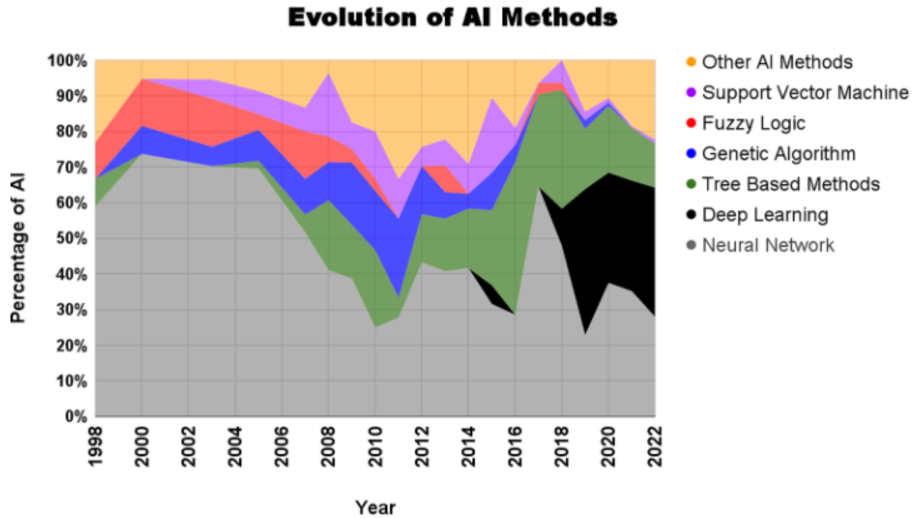


Fig. 3. Evolution of the AI methods used for works presented at the AMS AI conferences through the years.

(From Haupt et al., 2022)

ES : une application naturelle de l’IA ?

- Des grandes archives de données, structurées et contrôlées, en accès libre
- Des tâches pour lesquelles l’IA est performante : prévision, traitement de données (détection de structures, reconstruction d’image, ...), etc

2019-2024 : Essor de l'IA en environnement

(Quelques) Leçons apprises

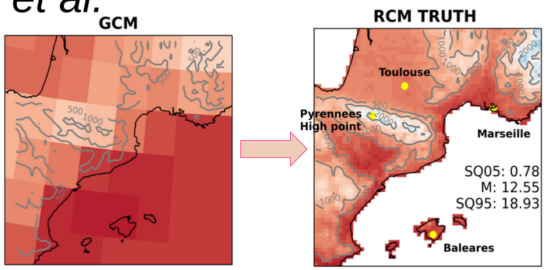
- L'IA est là pour rester : il s'agit d'un **nouvel outil** dans la panoplie utilisée en ES
- Des **premières réalisations** convaincantes, à consolider : une majorité de travaux encore à l'état de recherche
- Des **nouvelles opportunités** pour améliorer et accélérer les systèmes de prévision, traiter efficacement des gros volumes de données, extraire l'information utile, …
- Mais aussi de **nouveaux challenges**
  - Disponibilité et accessibilité des données d'entraînement
  - Interprétabilité/explicabilité des algorithmes
  - Généralisation des modèles sur les événements extrêmes, en climat changeant
  - Des changements à mettre en oeuvre : de nouveaux outils, de nouvelles compétences et méthodes de travail requises
  - Flexibilité face aux évolutions rapides
  - ...

2019-2024 : an overview of AI applications in ES

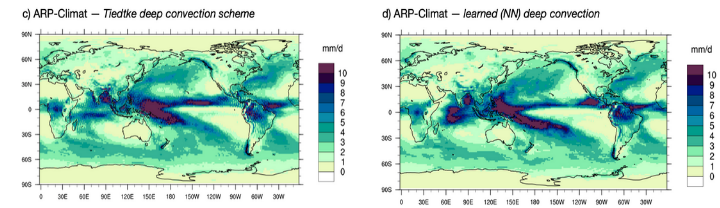
Descente d'échelle statistique et super-résolution

Emulation de paramétrisations physiques

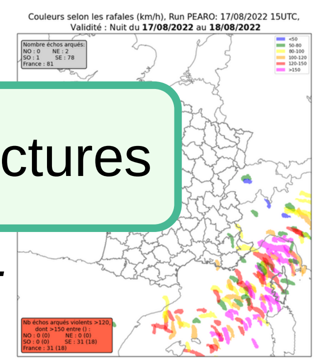
Doury et al.



Prévision immédiate



Balogh et al.

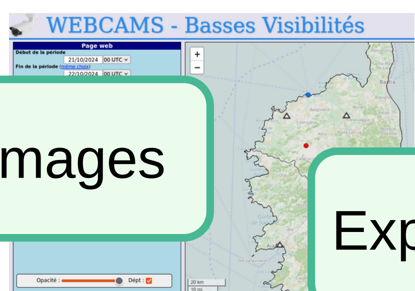


Calibration statistique des prévisions

Détection de structures

Emulation complète de modèles de prévision

Mounier et al.



Traitement d'images

Exploitation d'observations

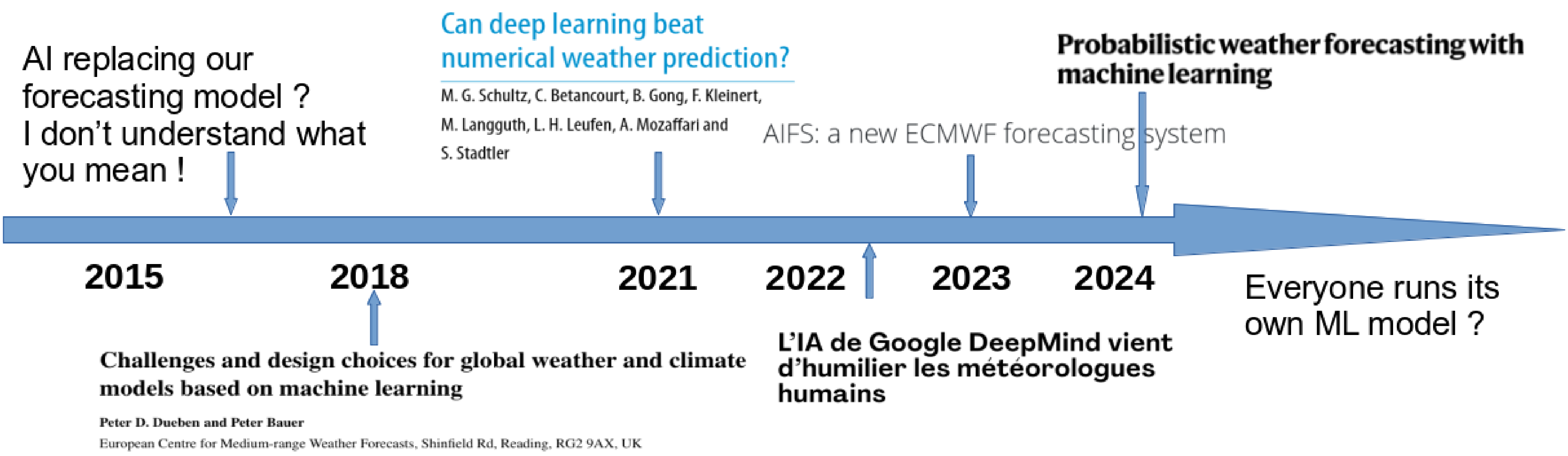
Prévision hybride

Lepetit et al.

- **Certains travaux permettent de réaliser des tâches mieux et plus vite**
- **D'autres annoncent un vrai changement de paradigme**

Focus : l’IA, une nouvelle voie pour la modélisation de l’atmosphère ?

- **Peut-on remplacer tout ou partie des modèles physiques par de l’IA ?**
  - Certainement l’application de l’IA la plus inattendue, rapide, et disruptive des 2 dernières années

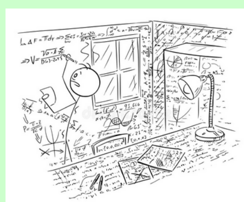


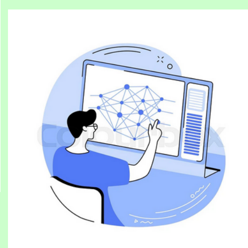
From physics-based models to data-driven models : a range of possible solutions

Initial conditions → **Physics model** → **Forecast**

Well established models, but performances limited by
- understanding of physics
- computing resources

Initial conditions → **Hybrid Physics/AI** → **Forecast**

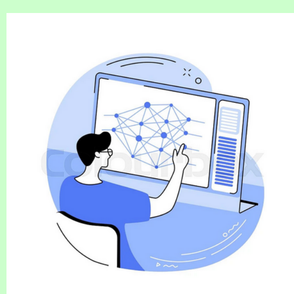




The 'in-between', ML could help
- uncover physical relationships
- reduce computational burden

while preserving the physical consistency of classical modeling

Initial conditions → **AI model** → **Forecast**



A change of paradigm, with very rapid predictions, and challenges
- costly training
- reliance on availability of high quality datasets
- black box, physical consistency ?
- generalization to out of distrib ?

Pure AI models : the neverending story

GenCast: Diffusion-based ensemble forecasting for medium-range weather

Ilan Price[*,1], Alvaro Sanchez-Gonzalez[*,1], Ferran Alet[1], Timo Ewalds[1], Andrew El-Kadi[2], Jacklynn Stott[1], Shakir Mohamed[1], Peter Battaglia[1], Remi Lam[1] and Matthew Willson[1]
[*]Equal contributions, [1]Google DeepMind, [2]Imperial College, London

Google, Huawei, NVIDIA, Microsoft, ECMWF

GraphCast: Learning skillful medium-range global weather forecasting

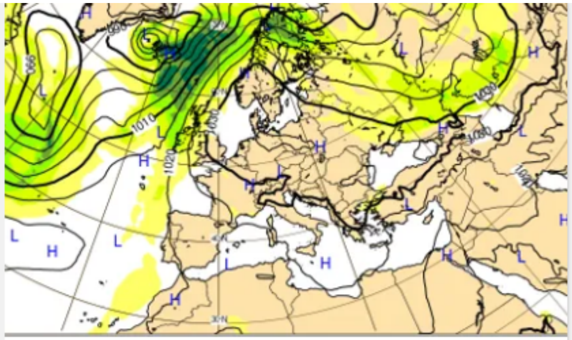
Remi Lam[*,1], Alvaro Sanchez-Gonzalez[*,1], Matthew Willson[*,1], Peter Wirnsberger[*,1], Meire Fortunato[*,1],
...aton-Rosen[1], Weihua Hu[1], Alexander Merose[2],
...lynn Stott[1], Alexander Pritzel[1], Shakir Mohamed[1] and

Pangu-Weather: A 3D High-Resolution System for Fast and Accurate Global Weather Forecast

Kaifeng Bi, Lingxi Xie, Hengheng Zhang, Xin Chen, Xiaotao Gu, and Qi Tian, *Fellow, IEEE*

Plusieurs nouveaux modèles chaque mois
https://github.com/jaychempan/Awesome-LWMs

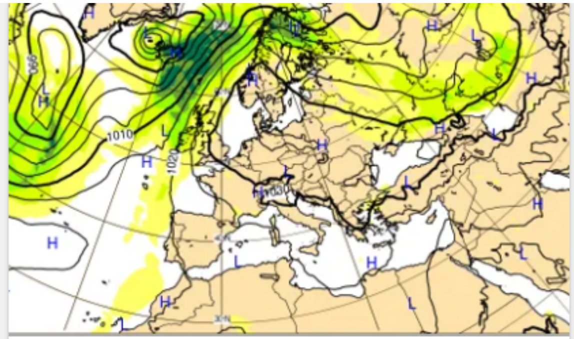
Pure AI models : the neverending story



Latest forecast

Experimental: AIFS (ECMWF) ML model: Mean sea level pressure and 850 hPa wind speed

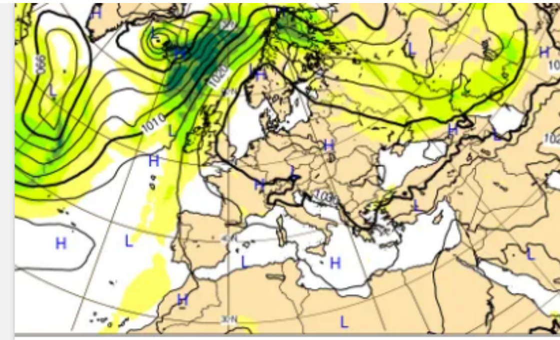
AIFS (ECMWF): a deep learning-based system developed by ECMWF. It is initialised with ECMWF HRES analysis. AIFS operates at 0.25° resolution



Latest forecast

Experimental: Aurora ML model: Mean sea level pressure and 850 hPa wind speed

Aurora: a deep learning-based system developed by Microsoft. It is initialised with ECMWF HRES analysis. Aurora operates at 0.1° resolution.

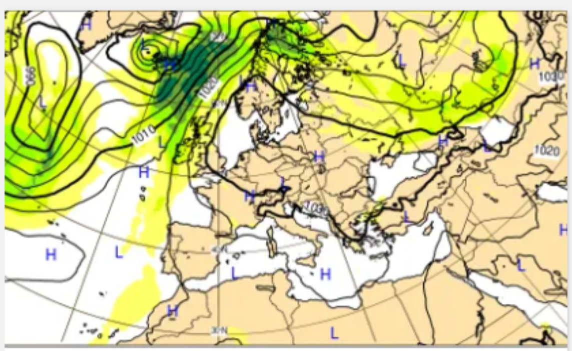


Latest forecast

Experimental: FourCastNet ML model: Mean sea level pressure and 850 hPa wind speed

FourCastNet v2-small:a deep learning-based system developed by NVIDIA in collaboration with researchers at several US universities.It is initialised with ECMWF HRES analysis. FourCastNet operates at 0.25° resolution.

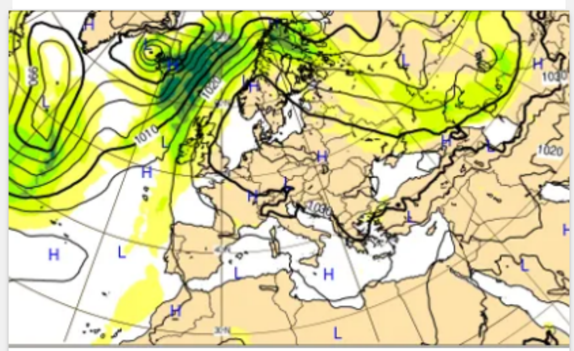
https://charts.ecmwf.int/



Latest forecast

Experimental: FuXi ML model: Mean sea level pressure and 850 hPa wind speed

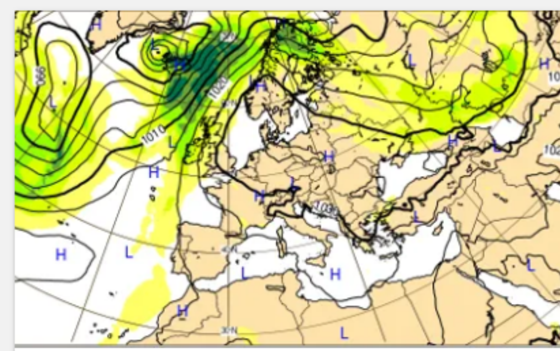
FuXi: a deep learning-based system developed by researchers at Fudan University. It is initialised with ECMWF HRES analysis. FuXi operates at 0.25deg resolution.



Latest forecast

Experimental: GraphCast ML model: Mean sea level pressure and 850 hPa wind speed

GraphCast (Google DeepMind): a deep learning-based system developed by Google DeepMind.It is initialised with ECMWF HRES analysis. GraphCast operates at 0.25° resolution.



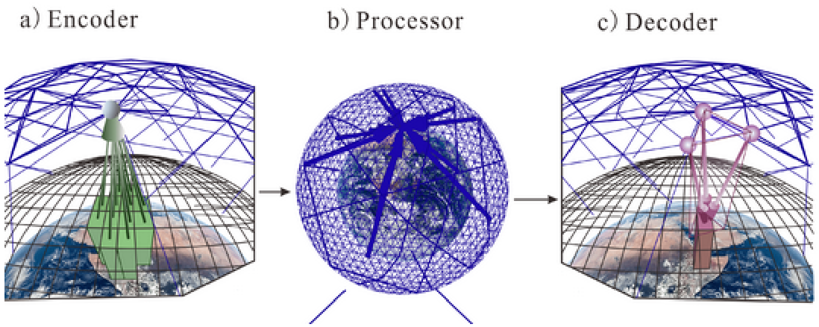
Latest forecast

Experimental: Pangu-Weather ML model: Mean sea level pressure and 850 hPa wind speed

Pangu-Weather: a deep learning-based system developed by Huawei. It is initialised with ECMWF HRES analysis. Pangu-Weather operates at 0.25° resolution.

Pure AI models : what's behind ?

A common training dataset : ERA5 data, ~30km global mesh, available from 1940s



A diversity of DL architectures
- CNN
- Vision Transformers
- Graph Neural Networks
- Neural operators

Mostly deterministic but ensembles are coming

Performances close to those of physical models for the medium range, with some known weaknesses https://docs.google.com/spreadsheets/d/1n30zDDjEzlXl5nAGF8uD_dbZWJAamqImQGCZjfOMuDg/edit?gid=0#gid=0

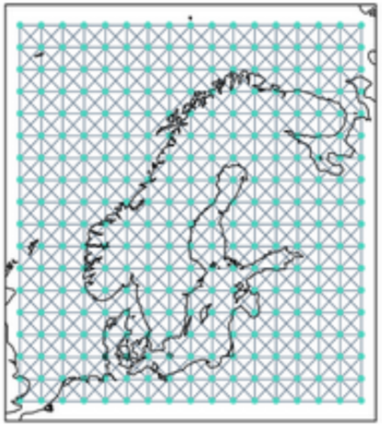
Capacity to predict extreme weather events such as mid-latitude thunderstorms, tropical cyclones, extra-tropical depressions, heatwave

A very rapid inference time : a few sec to min (compared to ~ hour with physical models)

A black box
- Need for interpretability and explainability tools

Ongoing challenge : km-scale AI models

- **Adapt network architectures** to the problem of regional high-resolution modeling
- Identify or produce **relevant datasets**
- **A European collaboration** has been set up



Neural-LAM

Neural Weather Prediction
for Limited Area Modeling

REGIONAL DATA-DRIVEN WEATHER MODELING WITH A GLOBAL STRETCHED-GRID

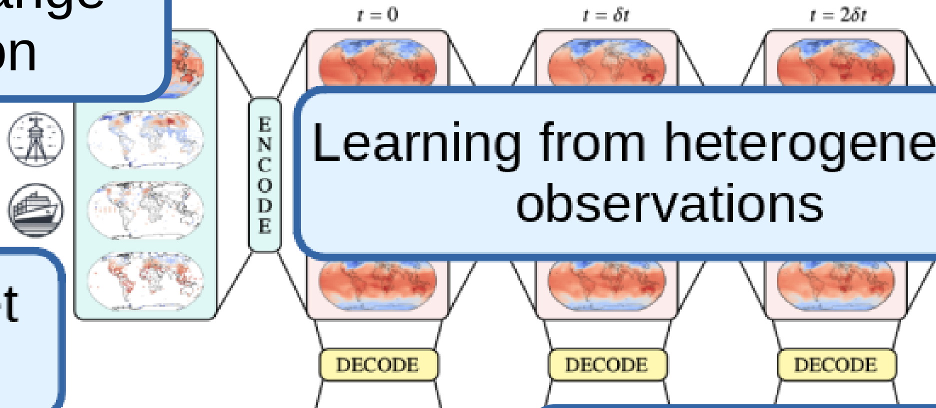
Kilometer-Scale Convection Allowing Model
Emulation using Generative Diffusion Modeling

Jaideep Pathak[*1], Yair Cohen[*1], Piyush Garg[*1], Peter Harrington[*2], Noah Brenowitz[1], Dale Durran[1,3], Morteza Mardani[1], Arash Vahdat[1], Shaoming Xu[†4], Karthik Kashinath[1], Michael Pritchard[1]

2025-2035 : extending the capabilities, a new paradigm shift for Earth system prediction ?

The forthcoming 'hot topics'

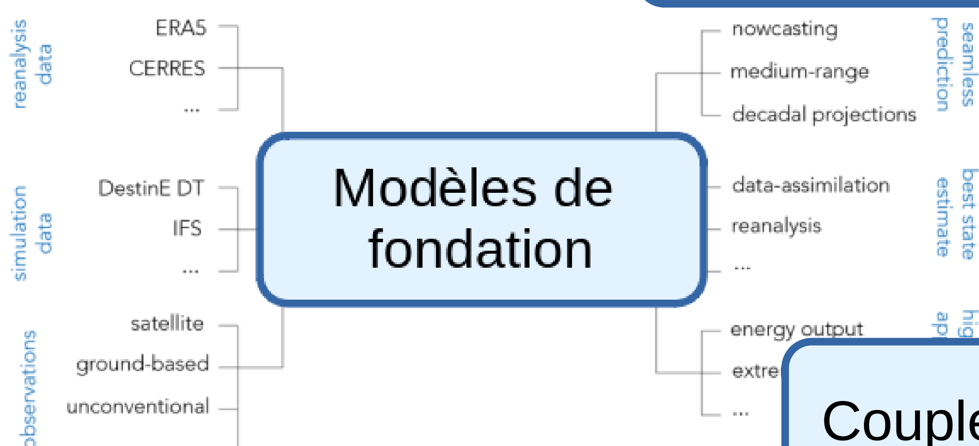
Extended range prediction



Learning from heterogeneous observations

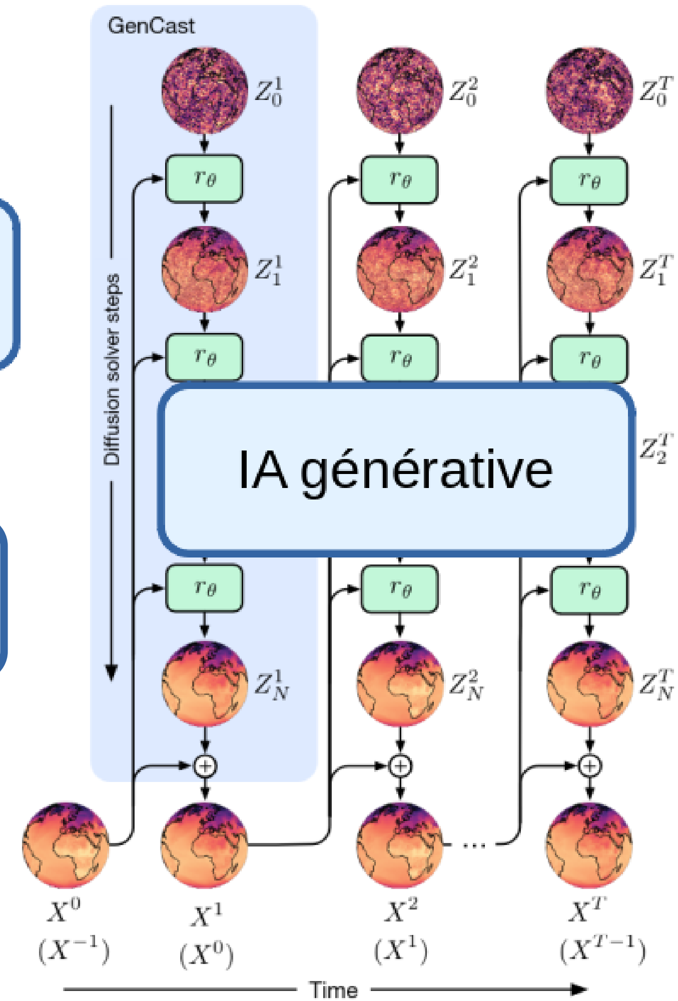
IA certifiable et de confiance

Interpretable Machine Learning for Weather and Climate Prediction: A Survey



Extreme events

Modèles de fondation

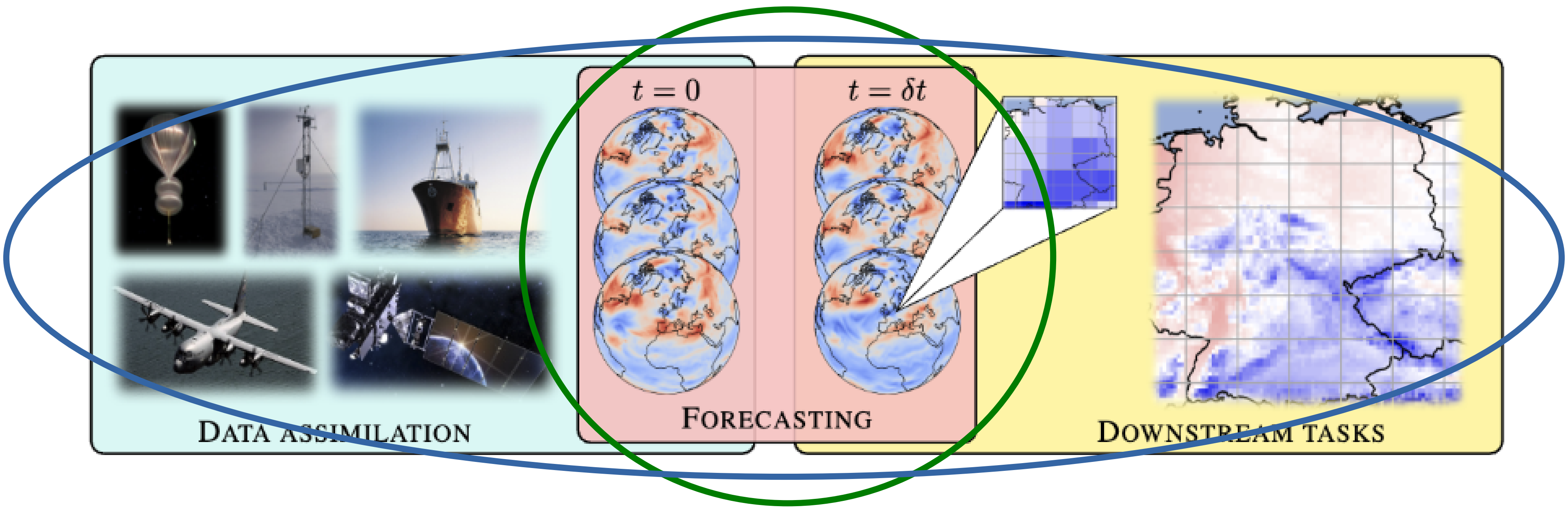


IA générative

Coupled systems

End-to-end approaches

- In current approaches the initial state remains estimated by traditional approaches : **the next challenge is to design systems that directly learn from heterogeneous, sparse and non-static observations**, in order to emulate the entire pipeline.



Current AI models

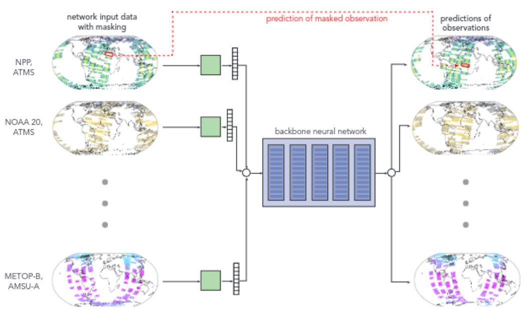
Next generation AI models : an end-to-end approach

Learning from observations : can we produce a weather forecast from observations ?

Assessing the Feasibility of an NWP Satellite Data Assimilation System Entirely Based on AI Techniques

Eric S. Maddy, Sid A. Boukabara, and Flavio Iturbide-Sanchez, *Senior Member, IEEE*

Deep Learning for Day Forecasts from Sparse Observations

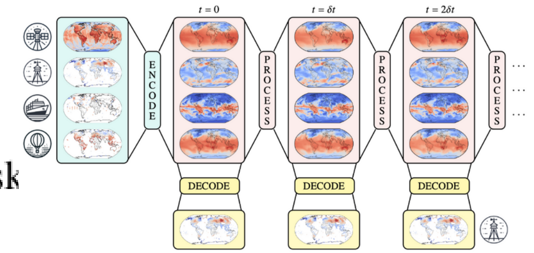


DATA DRIVEN WEATHER FORECASTS TRAINED AND INITIALISED DIRECTLY FROM OBSERVATIONS

ECMWF

End-to-end data-driven weather prediction

Anna Vaughan[*†1], Stratis Markou[*†2], Will Tebbutt[2], James Requeima[3], Wessel P. Bruinsma[4], Tom R. Andersson[‡9], Michael Herzog[6], Nicholas D. Lane[1], Matthew Chantry[8], J. Scott Hosk and Richard E. Turner[*2,4]



JACOBIAN-ENFORCED NEURAL NETWORKS (JENN) FOR IMPROVED DATA ASSIMILATION CONSISTENCY IN DYNAMICAL MODELS

Earth system AI models

A Hybrid Physics–AI Model to Improve Hydrological Forecasts

COUPLED OCEAN-ATMOSPHERE DYNAMICS IN A MACHINE LEARNING EARTH SYSTEM MODEL

Chenggong Wang *† Princeton University
Michael S. Pritchard * NVIDIA
Noah Brenowitz NVIDIA
Yair Cohen NVIDIA
Boris Bonev NVIDIA
Thorsten Kurth NVIDIA
Dale Durran University of Washington NVIDIA
Jaideep Pathak * NVIDIA

Superfast Microsoft AI is first to predict air pollution for the whole world

Data-driven rolling model for global wave height

Xinxin Wang [3], Jiuke Wang [4], Wenfang Lu [5], Changming Dong [6], Hao Qin [3], Haoyu Jiang *[1,2,3]

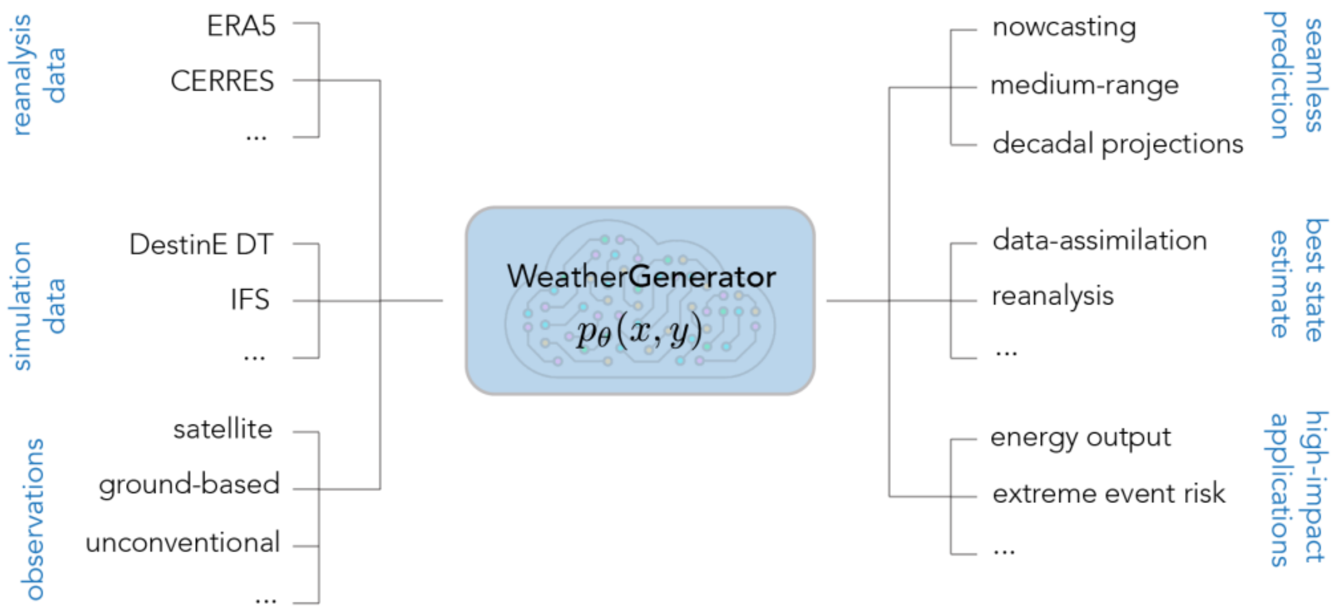
LandBench 1.0: A benchmark dataset and evaluation metrics for data-driven land surface variables prediction

Data-driven surrogate modeling of high-resolution sea-ice thickness in the Arctic

Charlotte Durand[1], Tobias Sebastian Finn[1], Alban Farchi[1], Marc Bocquet[1], and Einar Òlason[2]
[1]CEREA, École des Ponts and EDF R&D, Île-de-France, France
[2]Nansen Environmental and Remote Sensing Center, 5007 Bergen, Norway

Task-specific models vs a foundation model ?

- Coming soon : **Weather Generator** (Horizon 2025-2029, PI ECMWF)
- From heterogeneous data to a wide range of applications



Imagine if … there are off-the-shelf tools for a wide range of applications, including (1) data assimilation, (2) global and limited area ensemble predictions, (3) downscaling, (4) local vegetation, urban, flood, health, and energy models, (5) visualisation, (6) data compression and many more. (From P. Dueben, ECMWF)

Cross-cutting challenges

- **Physical consistency** (custom loss, architectures constraints, verification methods)
- **Generalization** on out-of-distribution samples (representation of extreme events)

ROBUSTNESS OF AI-BASED WEATHER FORECASTS IN A CHANGING CLIMATE

- **Uncertainty quantification** : probabilistic deep learning approaches

Experimental: AIFS ENS (ECMWF) ML model

Probabilistic weather forecasting with machine learning

Ilan Price, Alvaro Sanchez-Gonzalez, Ferran Alet, Tom R. Andersson, Andrew El-Kadi, Dominic Masters, Timo Ewalds, Jacklynn Stott, Shakir Mohamed, Peter Battaglia, Remi Lam & Matthew Willson

Nature (2024) | Cite this article

- Opening the black box with **eXplainable AI (XAI)**

Finding the Right XAI Method—A Guide for the Evaluation and Ranking of Explainable AI Methods in Climate Science

Interpretable Machine Learning for Weather and Climate Prediction: A Survey

Concluding remarks

- AI has changed the landscape of ES research and will continue to reshape the future of ES
- **Data-driven emulators of the atmosphere** are an example of disruptive achievement over the 2022-2024 period, made possible thanks to open-access datasets such as ERA5
- In the short to medium range, it is expected that more and more **emulators will coexist with physics-based models** for the different Earth compartments (ocean, land and more)
- Next challenge is **multi-modal AI systems** that exploit the large corpus of Earth system observations, in addition to model data
- This evolution also comes with a number of challenges :
  - **Gain more insight into the black box**, integrate more physical constraints and further refine the evaluation framework
  - Fully exploiting the potential of AI requires a **pluri-disciplinary approach** : different communities need to work together
  - How to tackle the **cost of training** and organize the **production and access to high-quality large datasets** ?

"I think that you will all agree that we are living in most interesting times. I never remember myself a time in which our history was so full, in which day by day brought new objects of interest, and, let me say also, new objects for anxiety."

British statesman Joseph Chamberlain, 1898