AI-baserade väderprognosmodeller

Tomas Landelius med kollegor

Hur görs en väderprognos?

10^8

10^5

$$\frac{d\rho}{dt} = -\rho d\mathrm{iv}\, c$$

$$\frac{du}{dt} = \frac{\tan\phi}{R}uv - \frac{uw}{R} + fv - f'w - \frac{1}{\rho}\frac{\partial p}{R\cos\phi\,\partial\lambda} + F_\lambda$$

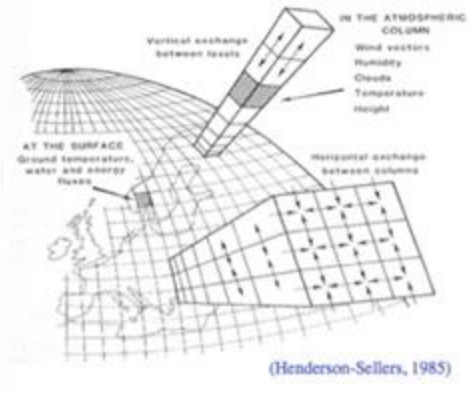
$$\frac{dv}{dt} = -\frac{\tan\phi}{R}u^2 - \frac{vw}{R} - fu - \frac{1}{\rho}\frac{\partial p}{R\,\partial\phi} + F_\phi$$

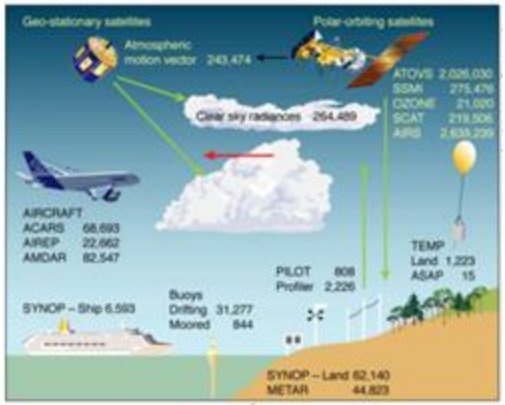
$$\frac{dw}{dt} = \frac{u^2}{R} + \frac{v^2}{R} + f'u - \frac{1}{\rho}\frac{\partial p}{\partial z} - g + F_z$$

$$c_p\frac{dT}{dt} = Q + \alpha\frac{dp}{dt}$$

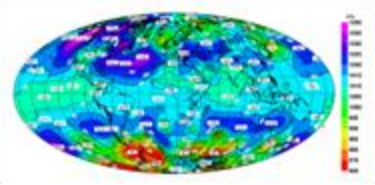
$$\frac{dq}{dt} = s(q) + D$$

$$p = qrT(1 + 0.61q)$$





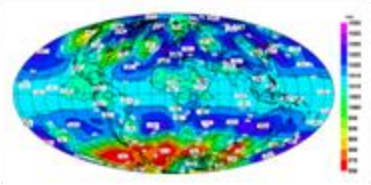
Initial state



$T,u,v,w,q,p_s,\mathrm{cloud},..$

up to 10-15 days

Forecast

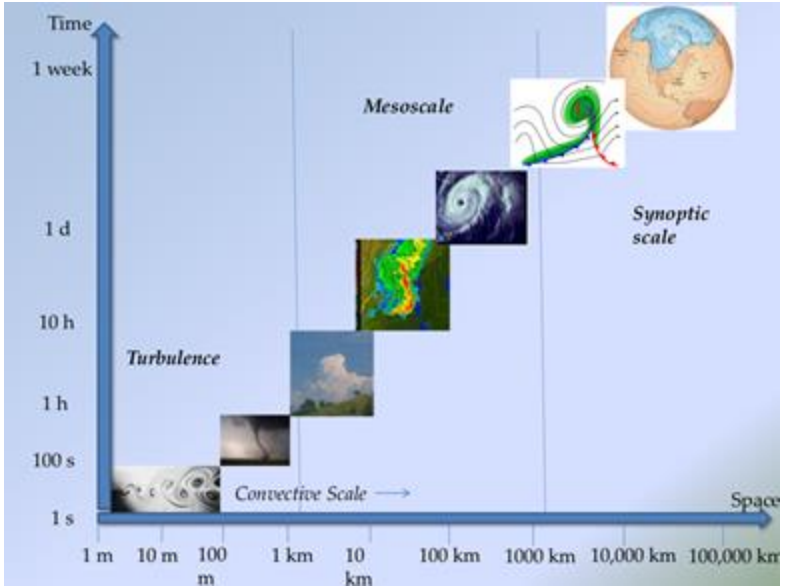


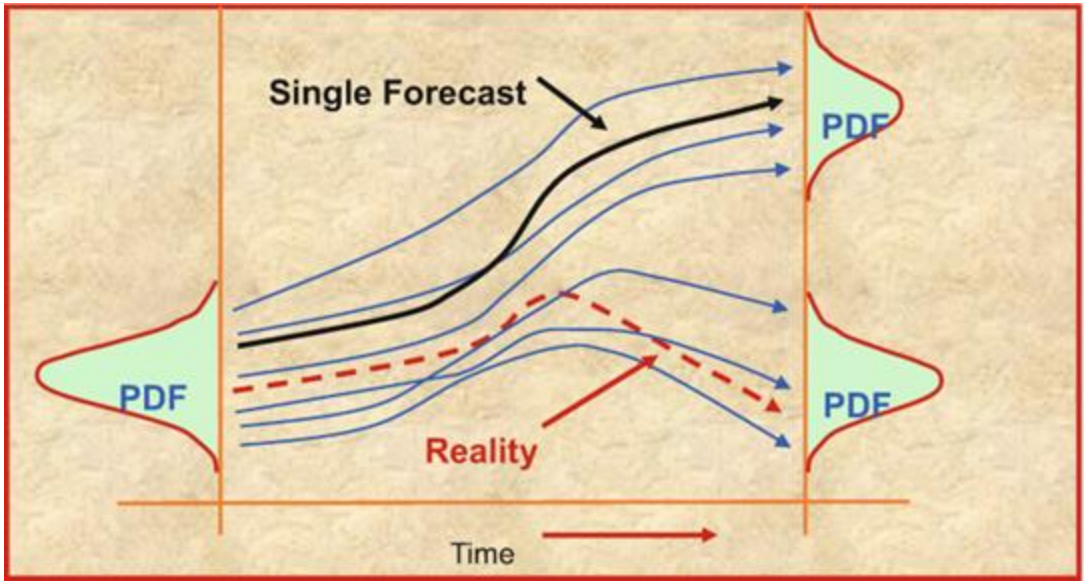
up to 1-3 days

ECMWF

MetCoOp: Sve, Nor, Fin, Est, Let, Lit

Vädret är kaotiskt - behov av sannolikhetsprognoser





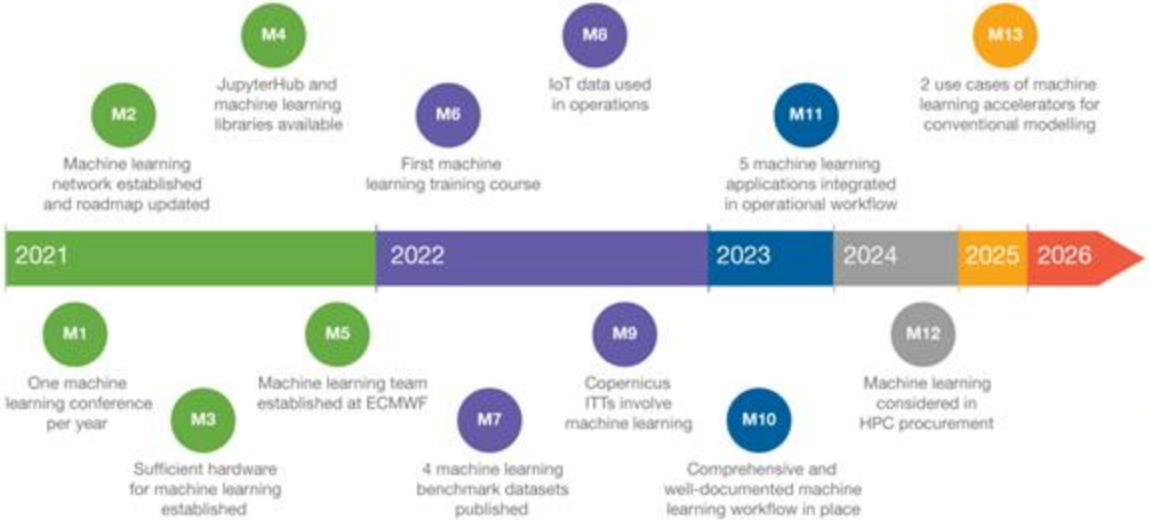
N_{ens} = ca 50

ML-utvecklingen inom NWP - en revolution

Machine learning at ECMWF: A roadmap for the next 10 years

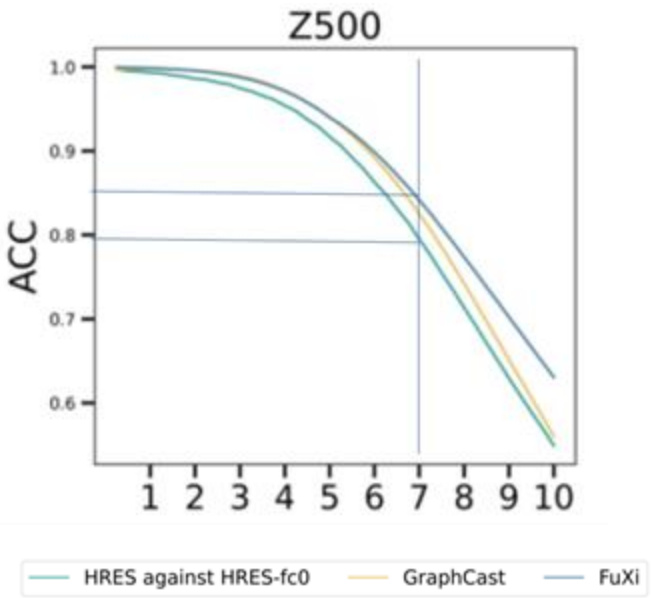
Peter Dueben, Umberto Modigliani, Alan Geer, Stephan Siemen, Florian Pappenberger, Peter Bauer, Andy Brown, Martin Palković, Baudouin Raoult, Nils Wedi, Vasileios Baousis

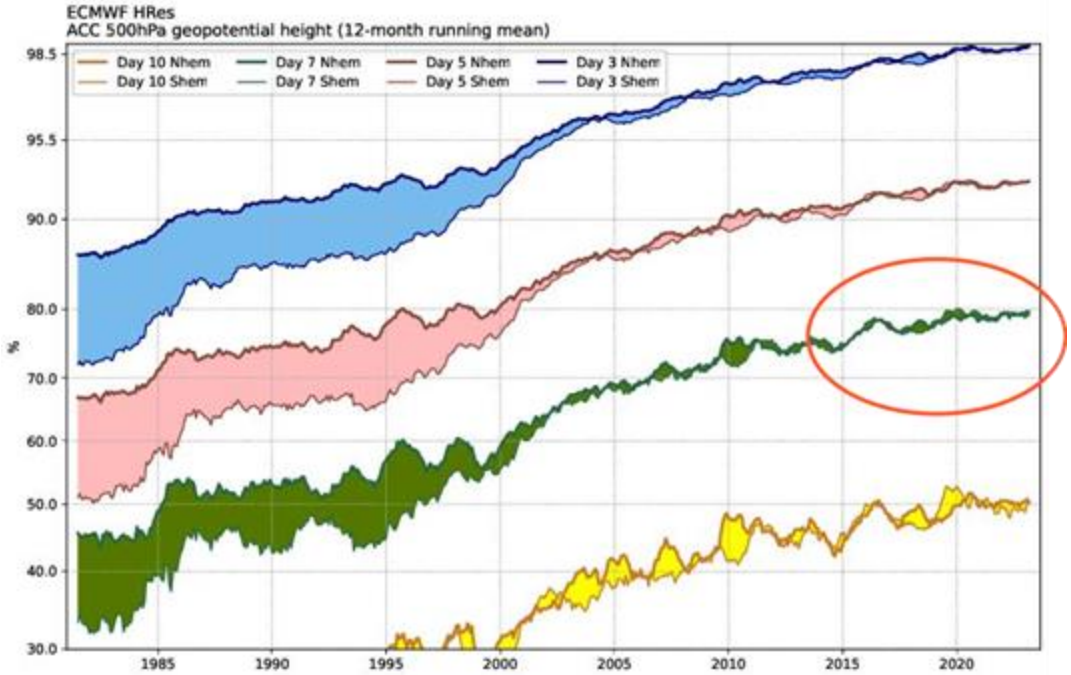
January 2021



FourcastNet
Pangu-Weather
GraphCast

Förbättringen med ML motsvarar 10 års utveckling





Progression

Globala modeller

Regionala modeller

Deterministisk (återanalys)

Sannolikhetsbaserad (återanalys)

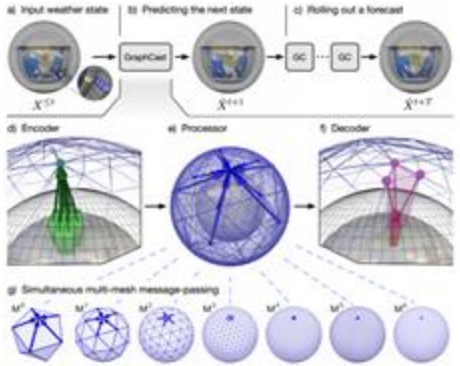
Neural ODEs

Data-assimilation

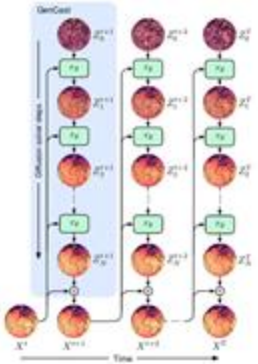
Foundation models

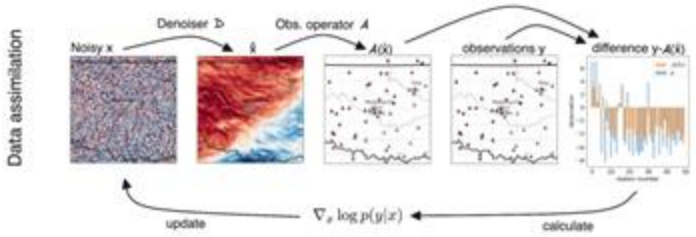
Observations-baserat

GraphCast

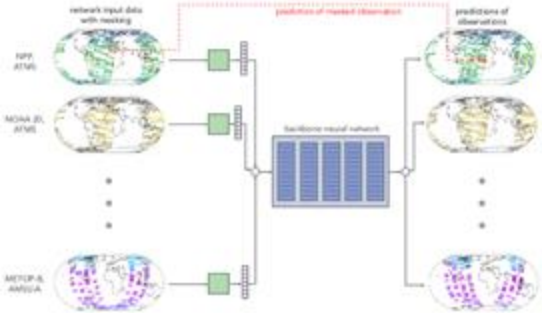


GenCast





Generative data-assimilation



Atmorep OBS

Två olika ansatser för regionala modeller

Graph-based Neural Weather Prediction for Limited Area Modeling

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Probabilistic Weather Forecasting with Hierarchical Graph Neural Networks

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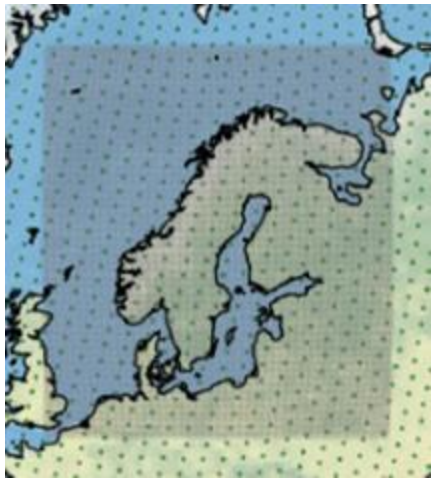

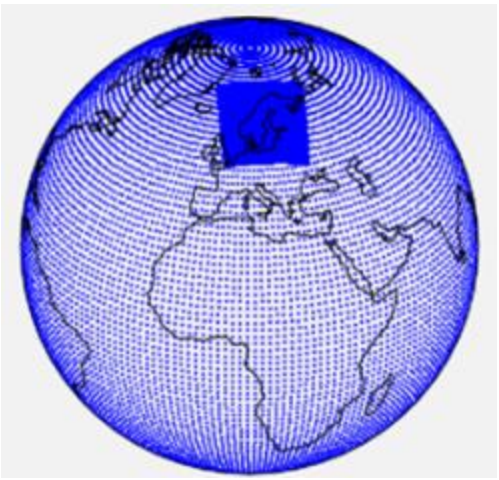

REGIONAL DATA-DRIVEN WEATHER MODELING WITH A GLOBAL STRETCHED-GRID

Thomas Nils Nipen
Håvard Homleid Haugen
Magnus Sikora Ingstad
Even Marius Nordhagen
Aram Farhad Shafiq Salihi
Paulina Tedesco
Ivar Ambjørn Seierstad
Jørn Kristiansen
Simon Lang
Mihai Alexe
Jesper Dramsch
Baudouin Raoult
Gert Mertes
Matthew Chantry

+ Behöver bara träna en regional modell
+ Kan ha olika modeller på randen
- Olika “fysik” utanför än innanför

+ Samma “fysik” utanför som innanför
- Måste träna global & regional modell

ML-arkitekturer för väderprognosmodeller

Exploring the design space of deep-learning-based weather forecasting systems

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Model Name	# of Parameters
FNO (Li et al., 2020a)	233,039,081
FourCastNet (Pathak et al., 2022)	79,900,416
SFNO (Bonev et al., 2023)	289,392,337
UNO (Ashiqur Rahman et al., 2022)	145,418,729
ISNet (Qin et al., 2022)	45,114,917
ResNet-50 + Fully Convolutional Decoder (Long et al., 2015)	47,202,505
Segformer (Xie et al., 2021)	82,208,137
Segmentation Transformer (SETR) (Zheng et al., 2021)	343,751,497
Swin Transformer (Liu et al., 2021)	59,086,083
Efficient ViT L2 (Cai et al., 2022)	51,403,689
PanguWeather (Bi et al., 2022)	64,247,821
UNet (4 Layers) (Ronneberger et al., 2015)	47,152,969
UNet (5 Blocks) (Ronneberger et al., 2015)	399,563,977
UNet (4 Layers - 128-dim initial projection) (Ronneberger et al., 2015)	188,520,649
UNet (5 Blocks - 128-dim initial projection) (Ronneberger et al., 2015)	1,598,034,889
GraphCast (Lam et al., 2022)	8,866,377
Point Transformer v3 (Wu et al., 2023)	46,439,017
Octformer (Wang, 2023)	40,497,325
Graph UNet (4 Blocks) (Ronneberger et al., 2015)	47,377,417
Graph UNet (5 Blocks) (Ronneberger et al., 2015)	399,788,425

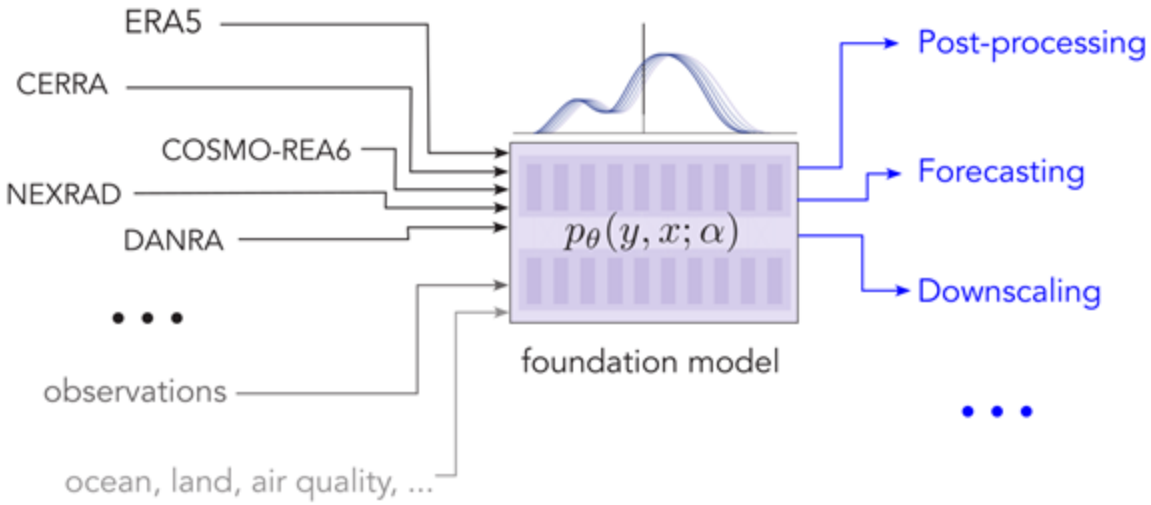
Nästa steg - foundation models

IBM and NASA (Prithvi WxC)

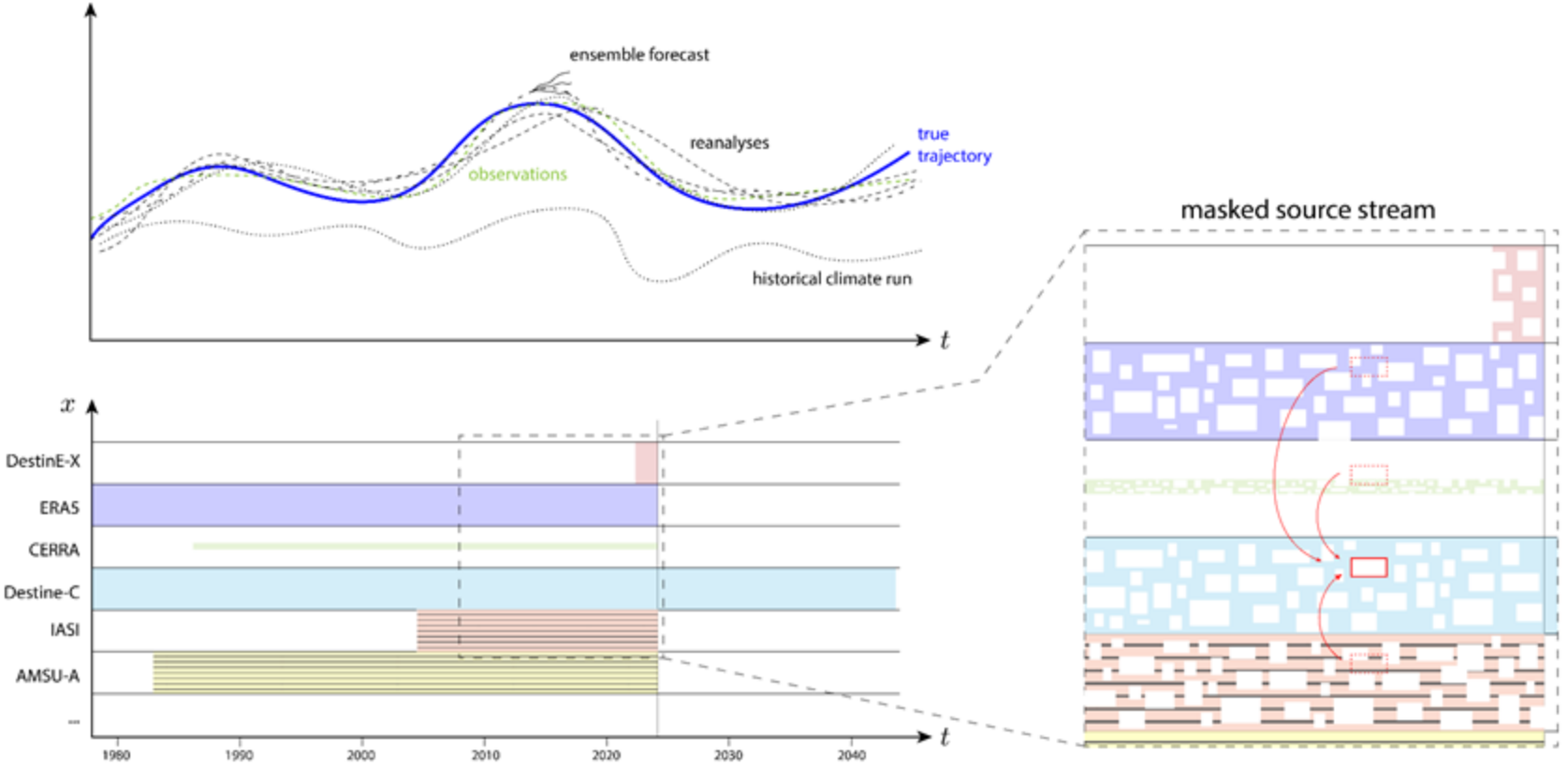
Microsoft (ClimaX and Aurora)

Google (TimesFM)

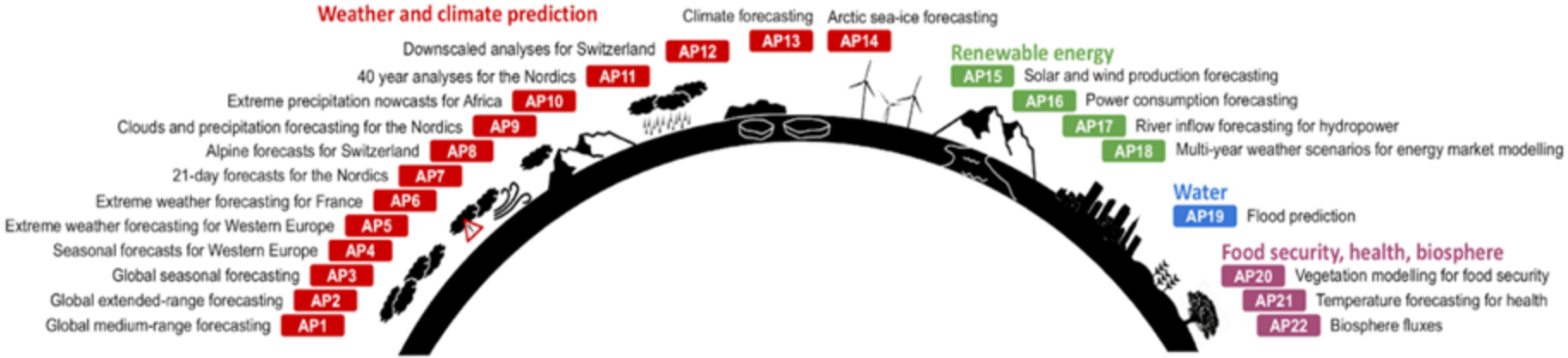
EU project WeatherGenerator



Foundation models - Self supervised learning



WeatherGenerator applications



ML-baserade väderprognoser: för- och nackdelar

+ Snabba att köra (x10,000)
+ Stora ensemble-prognoser
+ Kortare tidsglapp - aktuellare prognos
+ Bättre än NWP för många parametrar
+ 10^3 rader kod istället för 10^6

- Långa prognoser blir utsmetade (det)
- Viktiga parametrar saknas - t ex moln
- Kräver NWP-analyser för träning
- Längre tidssteg än för NWP

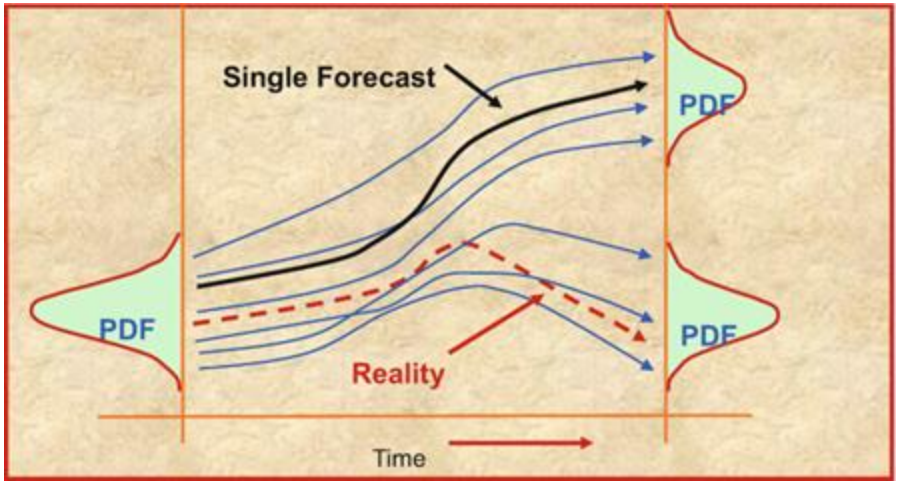
Lösningar på gång…

Nytta inom energisektorn?

Bättre och snabbare sannolikhetsprognoser för “cost-loss” kalkyler som beslutsstöd vid:

- Produktion, konsumtion och lagring
- Balansering och överföringskapacitet
- Riskhantering (extremer) och underhåll
- Handel på elmarknaden

“Foundation models” för atmosfären kan vara grund för väderberoende energi-modeller.



Funding Partners

Smart Energy Systems ERA-Net

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Optimized Weather-related GReen Energy production and consumption
Project No 110206