The Rise of Machine Learning in Weather Prediction

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November 13th, 2024

Do we see a(nother) revolution in weather forecasting?

A revolution is a fundamental and lasting structural change in one or more systems, usually occurring abruptly or within a relatively short period.

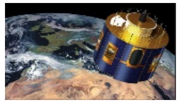
......	1980s – early 1990s	late 1990s - 2000s	2010s	2020er
Innovationens	• Statistical post-processing (regression & neural networks) • 3D-Var Data Assimilation • Perturbation of initial conditions	• 4D-Var Data Assimilation • Perturbation of initial conditions & model physics	• Hybrid Data Assimilation (DA): AI for integrating various data • 4D Ensemble-Var DA • AI-based nowcasting • Deep Learning for post-processing	• Large Ensembles (50–100 members) • AI-enhanced DA (e.g., variational autoencoder) • Introduction of purely data-driven models
Resolutio	**Spatial**: 150-200 km **Temporal**: 6-12 hours **Vertical**: 10-20 levels **Ensemble**: introduced	**Spatial** : 100 km **Temporal** : 6 hours **Vertical** : 20-40 levels	**Spatial** : 10-25 km **Temporal** : 3-6 hours **Vertical** : 40-60 levels	**Spatial** : 10-25 km (global), 1-3 km(regional) **Temporal** : 1-6 hours, sub-hourly **Vertical** : 120+ levels

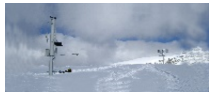
Adapted after A. Ahmadalipour, https://geoaiunpacked.substack.com/p/geoai-unpacked-2-ai-for-weather-forecasting

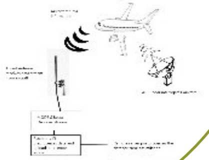
How does a classical weather model work?

… complicated … but worth it!

Observations







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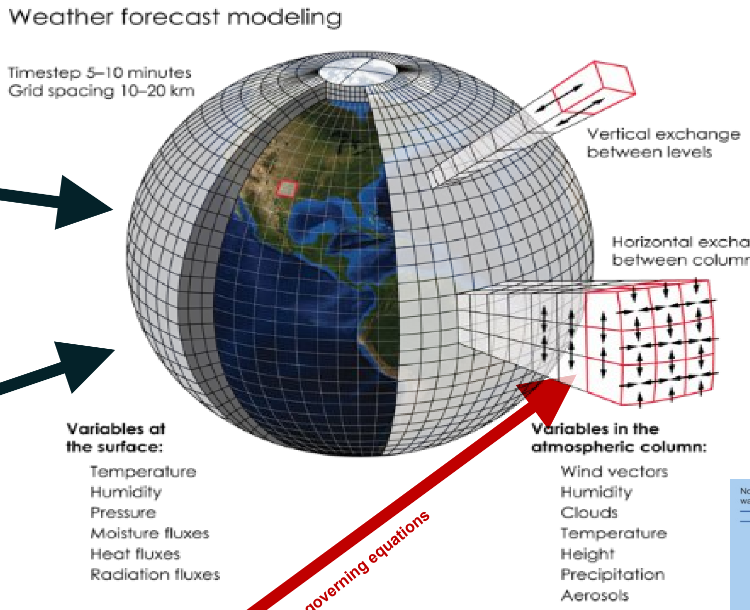
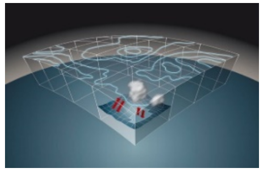
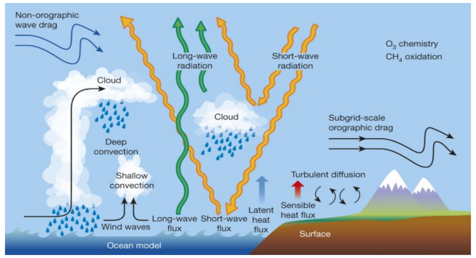
data assimilation

9 x 9 km / 11 x 11 km grid resolution ECMWF global model

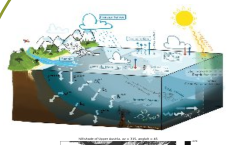


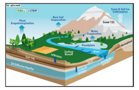


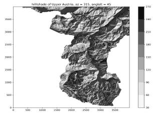
subgrid scale Processes (also equations / parametrizations)



governing equations







Ocean and surface model
Static fields

"Primitive" Weather Forecasting Equations

$p = \rho R T$ *Ideal Gas Law* (Equation of State)

$$\vec{a}_h = \sum\left(\vec{F}_h / m\right)$$ *Newton's Second Law of Motion*

$$\vec{a}_v = \sum\left(\vec{F}_v / m\right) = (\vec{P}\vec{G}\vec{A})_v - \vec{g}$$

$\Delta p = -\rho g \Delta z$

$(PGA)_v = g$

Hydrostatic Law (Obtained from the Equation of Vertical Motion)

$\Delta T = \Delta q / c_p + (1/\rho)\Delta p$ *First Law of Thermodynamics*

$(1/\rho)\Delta\rho/\Delta t = -DIV$

Conservation of Mass Applied to the Atmosphere (Equation of Continuity)

Zonal wind:

$$\frac{\partial u}{\partial t} = \eta v - \frac{\partial \Phi}{\partial x} - c_p\theta\frac{\partial \pi}{\partial x} - z\frac{\partial u}{\partial \sigma} - \frac{\partial(\frac{u^2+v^2}{2})}{\partial x}$$

Meridional wind:

$$\frac{\partial v}{\partial t} = -\eta\frac{u}{v} - \frac{\partial \Phi}{\partial y} - c_p\theta\frac{\partial \pi}{\partial y} - z\frac{\partial v}{\partial \sigma} - \frac{\partial(\frac{u^2+v^2}{2})}{\partial y}$$

Temperature:

$$\frac{\delta T}{\partial t} = \frac{\partial T}{\partial t} + u\frac{\partial T}{\partial x} + v\frac{\partial T}{\partial y} + w\frac{\partial T}{\partial z}$$

Precipitable water:

$$\frac{\delta W}{\partial t} = u\frac{\partial W}{\partial x} + v\frac{\partial W}{\partial y} + w\frac{\partial W}{\partial z}$$

Pressure thickness:

$$\frac{\partial}{\partial t}\frac{\partial p}{\partial \sigma} = u\frac{\partial}{\partial x}x\frac{\partial p}{\partial \sigma} + v\frac{\partial}{\partial y}y\frac{\partial p}{\partial \sigma} + w\frac{\partial}{\partial z}z\frac{\partial p}{\partial \sigma}$$

$$\frac{\partial T}{\partial t} + u\frac{\partial T}{\partial x} + v\frac{\partial T}{\partial y} + \omega\left(\frac{\partial T}{\partial p} + \frac{RT}{pc_p}\right) = \frac{J}{c_p} \qquad \frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial \omega}{\partial p} = 0 \qquad 0 = -\frac{\partial \phi}{\partial p} - \frac{RT}{p}$$

Do we see a(nother) revolution in weather forecasting?

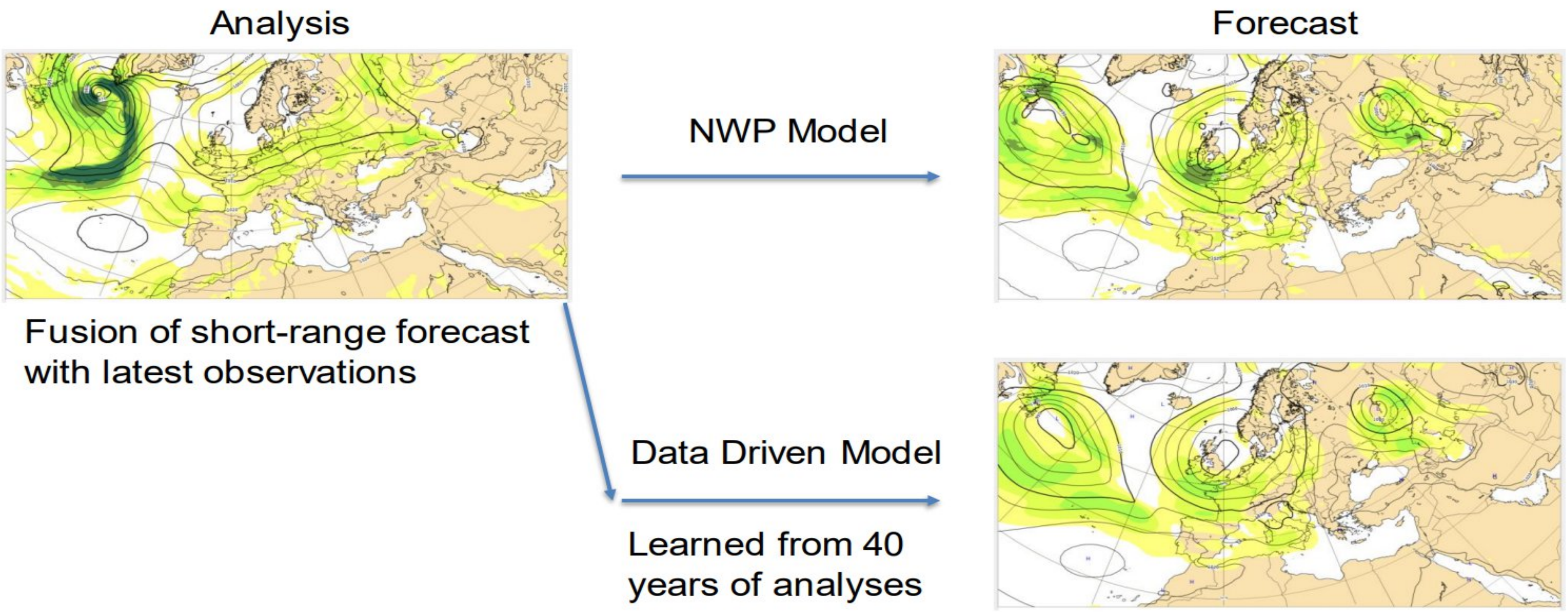
GeoSphere Austria

......	1980s – early 1990s	late 1990s - 2000s	2010s	2020er	2022 – today
Innovationens	• Statistical post-processing (regression & neural networks) • 3D-Var Data Assimilation • Perturbation of initial conditions	• 4D-Var Data Assimilation • Perturbation of initial conditions & model physics	• Hybrid Data Assimilation (DA): AI for integrating various data • 4D Ensemble-Var DA • AI-based nowcasting • Deep Learning for post-processing	• Large Ensembles (50–100 members) • AI-enhanced DA (e.g., variational autoencoder) • Introduction of purely data-driven models	**The rise of AI** Several companies (NVIDIA, HUAWEI, GOOGLE) are discovering meteorological data and starting to develop data-driven prediction models. ECMWF follows suit, along with others.
Resolutio	**Spatial**: 150-200 km **Temporal**: 6-12 hours **Vertical**: 10-20 levels **Ensemble**: introduced	**Spatial** : 100 km **Temporal** : 6 hours **Vertical**: 20-40 levels	**Spatial** : 10-25 km **Temporal** : 3-6 hours **Vertical** : 40-60 levels	**Spatial** : 10-25 km (global), 1-3 km(regional) **Temporal** : 1-6 hours, sub-hourly **Vertical** : 120+ levels	**Spatial**: ca. 25 km (global), 1-3 km(regional), not all parameters **Temporal**: 1-6 hours **Vertical**: reduced **Ensemble**: next step

Adapted after A. Ahmadalipour, https://geoaiunpacked.substack.com/p/geoai-unpacked-2-ai-for-weather-forecasting

Differences in classical and ML models in forecasting

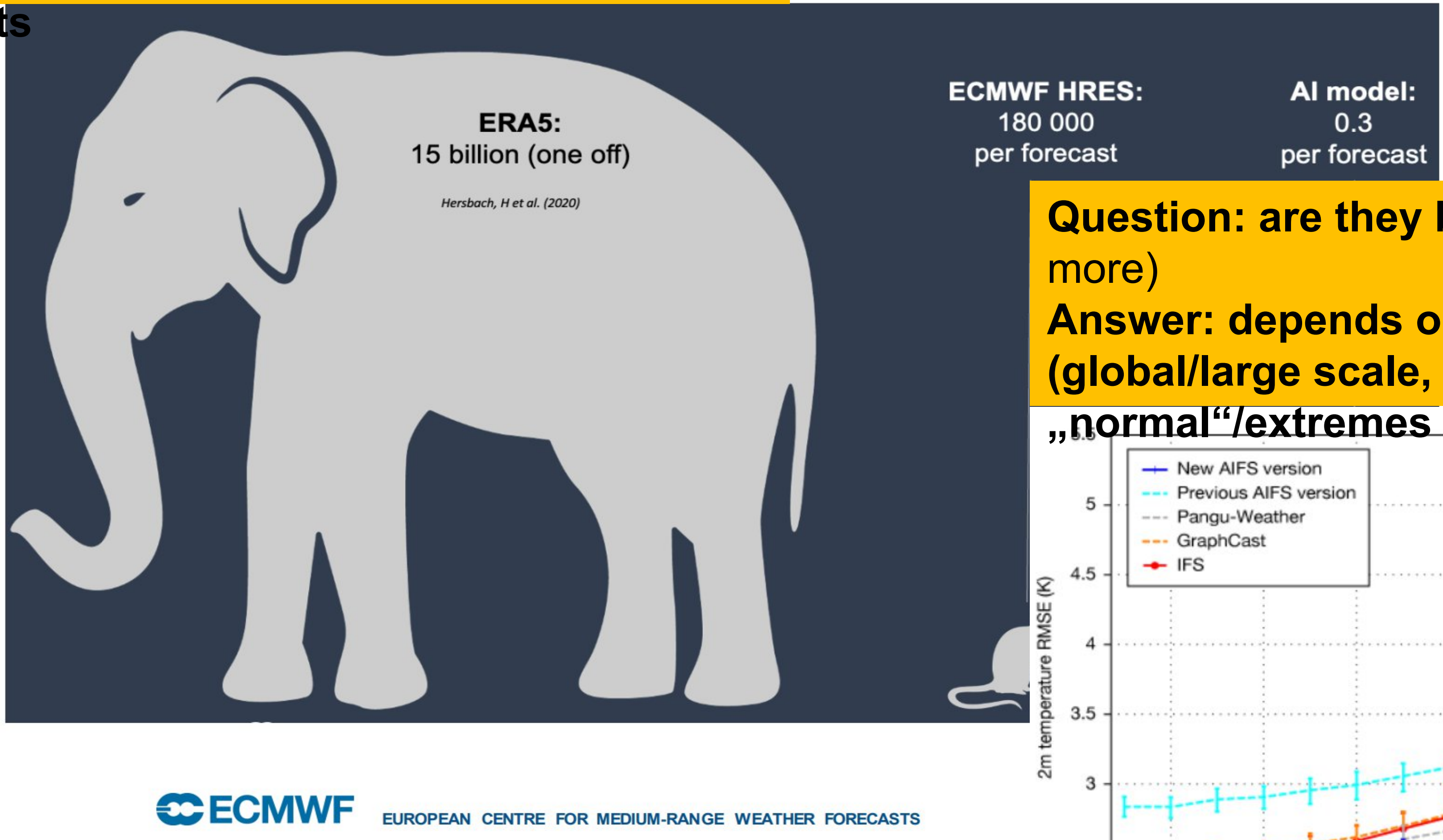
Traditionally weather forecasts are generated by running NWP model – computer code that has been designed to represent the physical processes governing the evolution of the atmosphere. But can you produce a forecast without a NWP model?



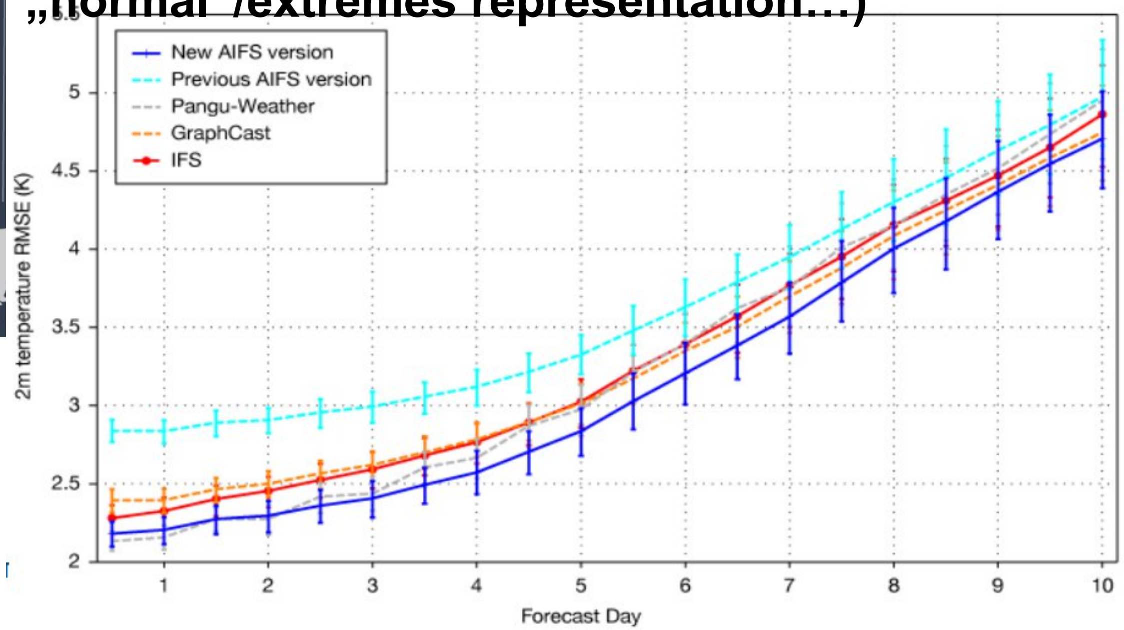
ECMWF EUROPEAN CENTRE FOR MEDIUM-RANGE WEATHER FORECASTS

Differences in classical and ML models in forecasting

Advantage: operational computational costs



Question: are they better? (Mariana will show more)
Answer: depends on what your scrope is (global/large scale, local/regional, „normal“/extremes representation…)



Are there differences in classical and ML forecasts?

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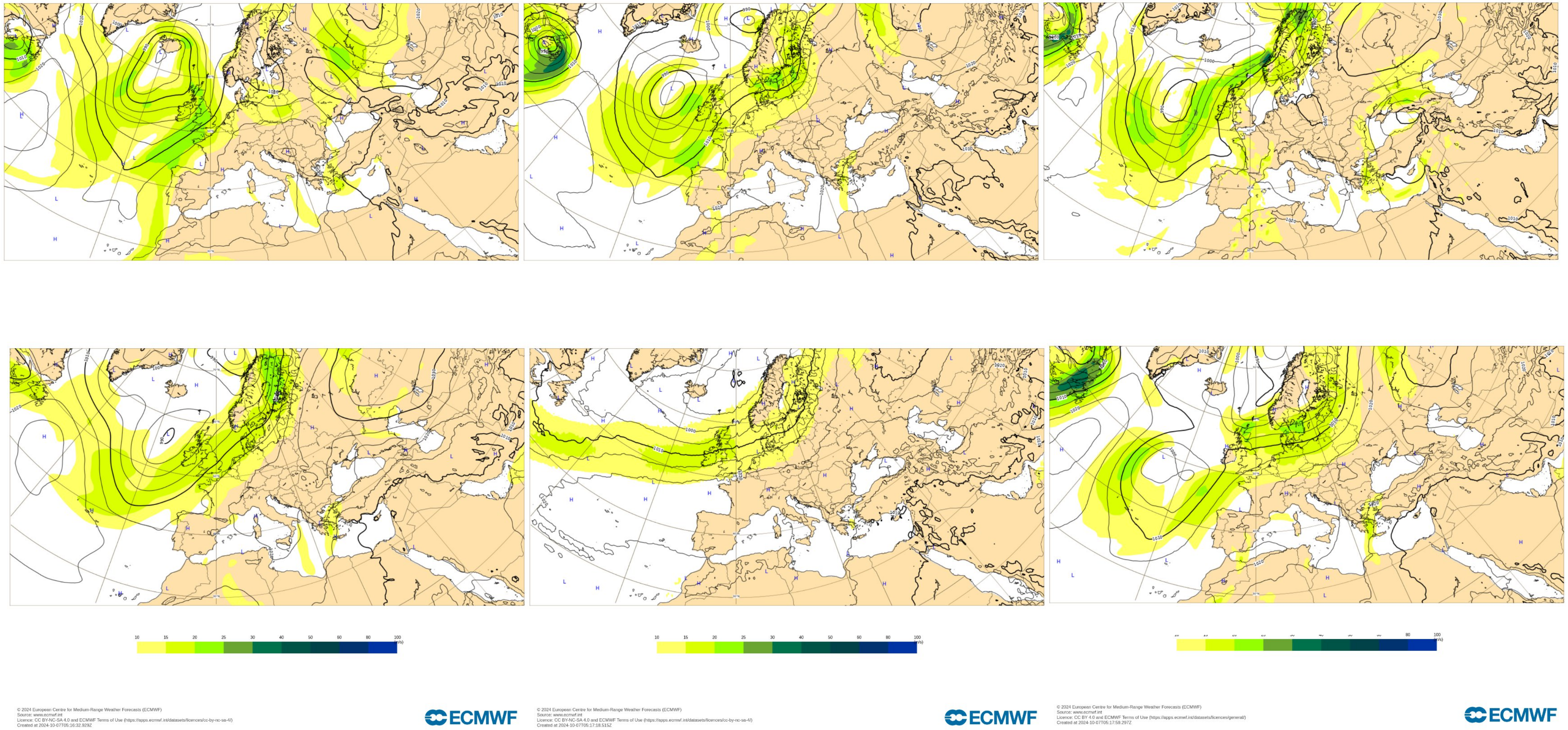
Who finds the physical model?



But… that was global, what about regional, comparable to LAMs?

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Problem:
Global models (physical and esp. ML) are coarse, we need higher spatial

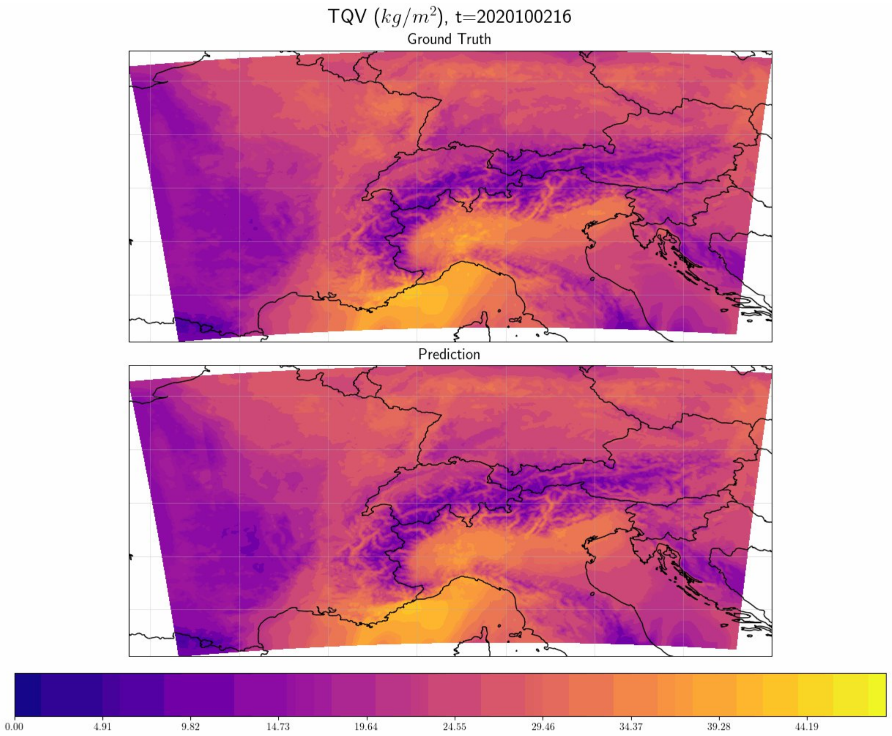
Solutions (there are more):
Neural-LAM und Bris

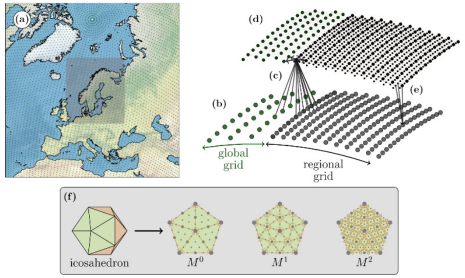
Neural-LAM
An emulator of limited area models

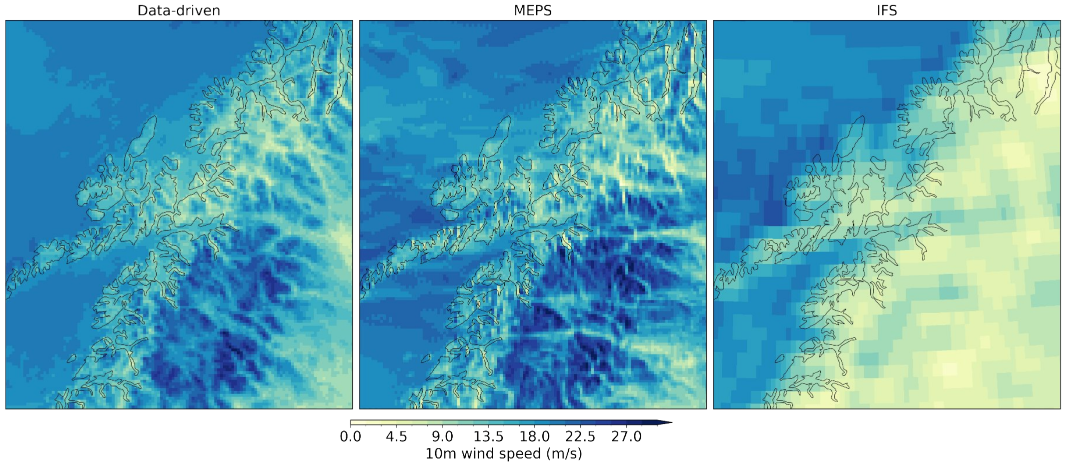
Advantage: not a lot of training data needed, “relatively” easy to implement

Bris
A stretched grid/zoomed AIFS version

Advantage: lots of different types of training data can be included (global, local)

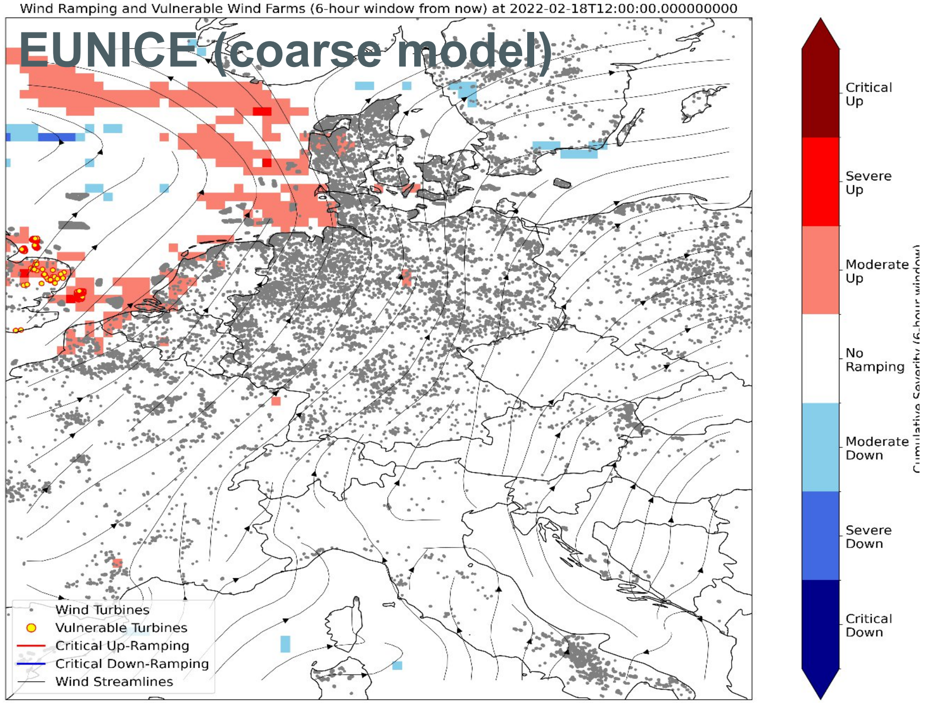




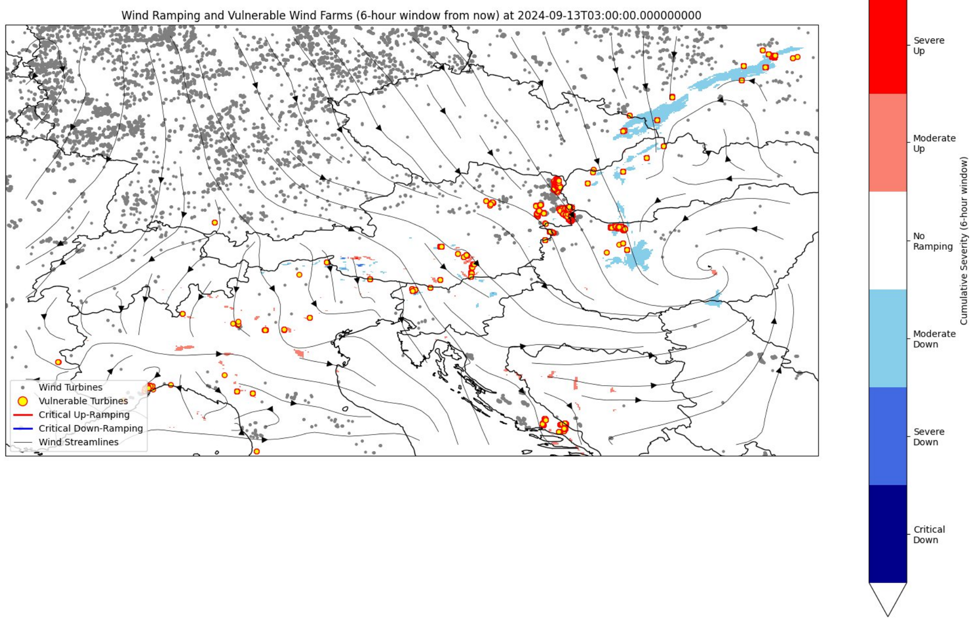


Support: how can we use ML (and the new models) for applications?

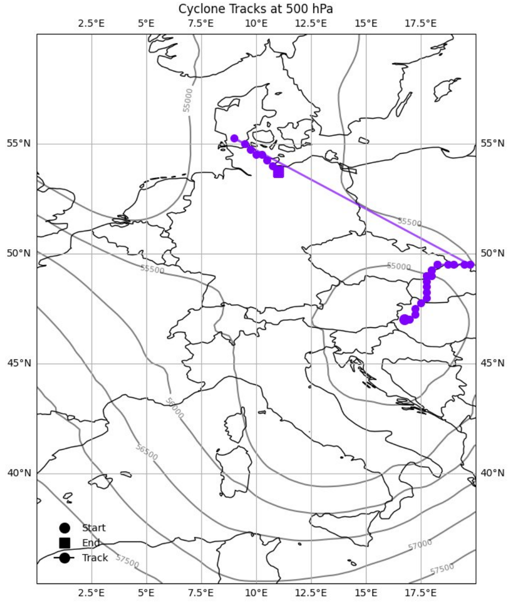
Detection of extreme events for weather extremes and application extremes (e.g. „Dunkelflaute“)



BORIS (AROME regional model)



Cut-off low detection

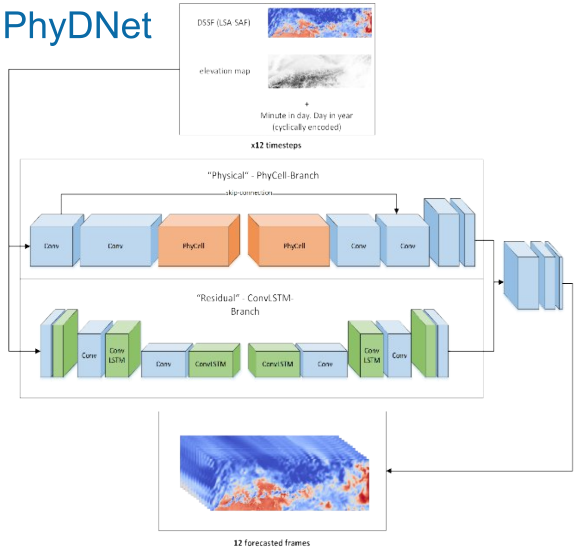


… allowing us to issue severity predictions of events and supporting mitigation measures early onwards

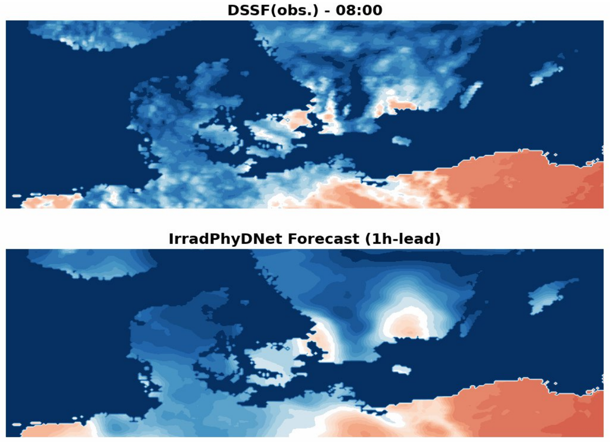
Renewable energy – how can we support the transition with targeted ML-models?

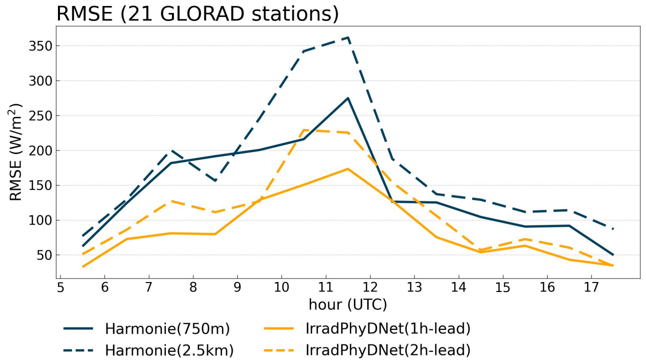
Data-driven nowcasting and intra-day forecasts for wind, PV, and hydropower – meteorological support (traders, TSO, etc.)

IrradPhyDNet

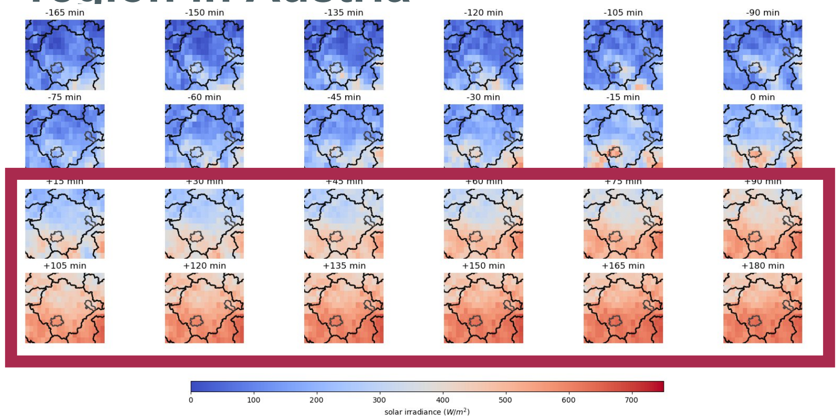


Thunderstorm in Denmark





nowcasting of global irradiation for a region in Austria



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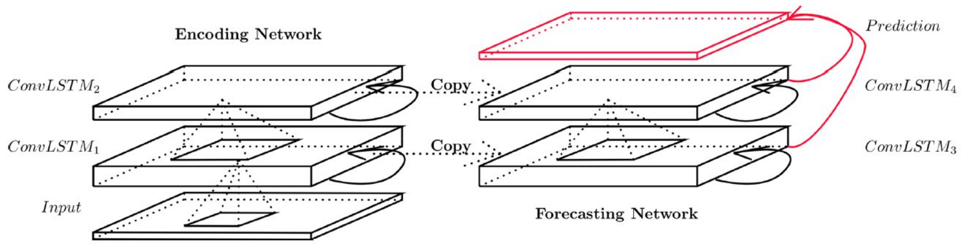
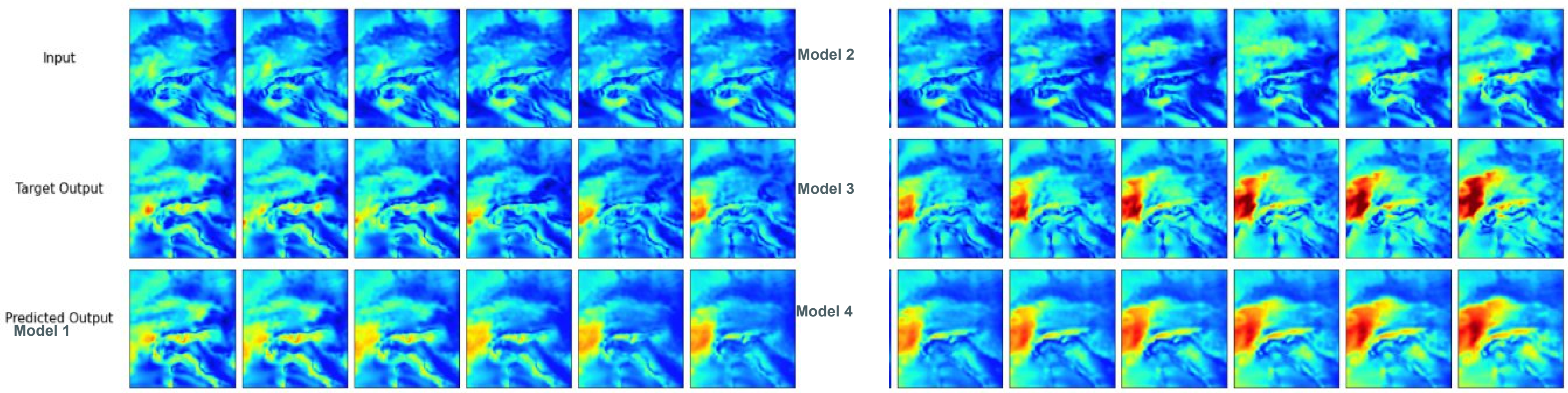


+ loss functions fit for imbalanced regressions

+ per gridpoint- wise transformations and normalisations

Intra-day windspeed prediction ensemble optimized for extremes



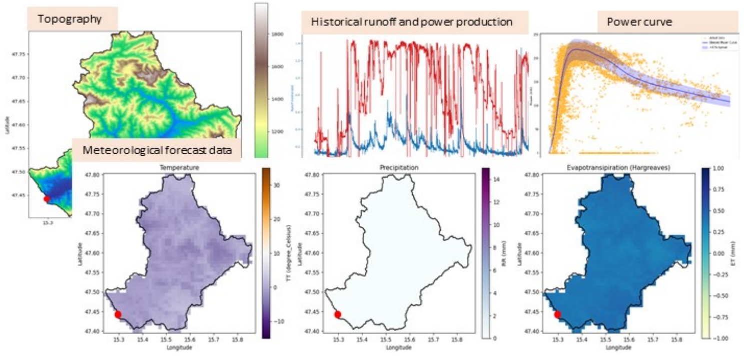
Not shown: temperature and precipitation nowcasting

Renewable energy – how can we support the transition with targeted ML-models?

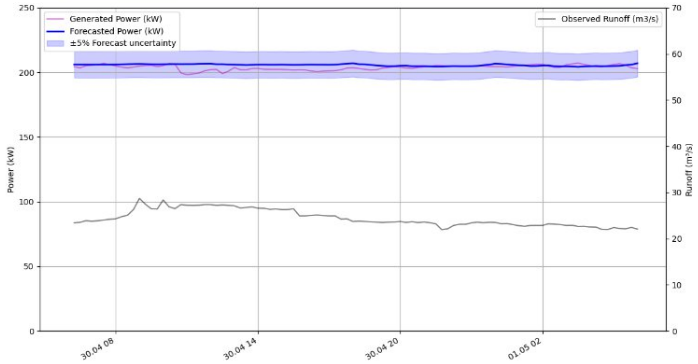
GeoSphere Austria

Location post-processing – what the users need

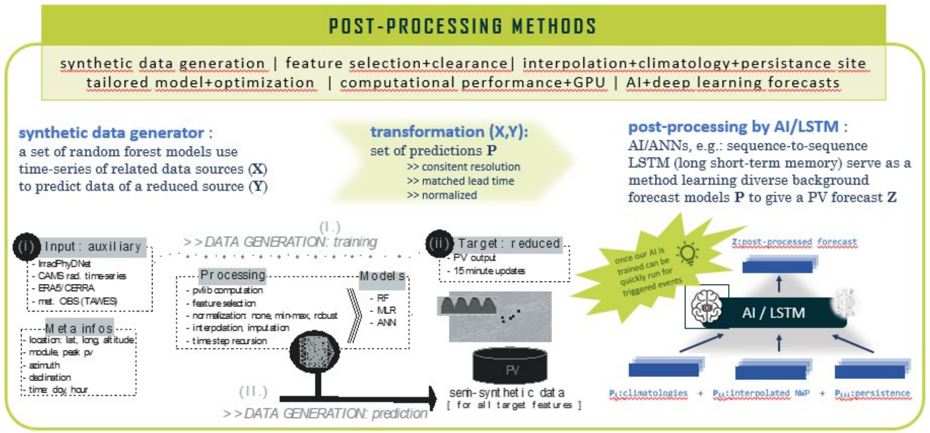
Hydropower predictions



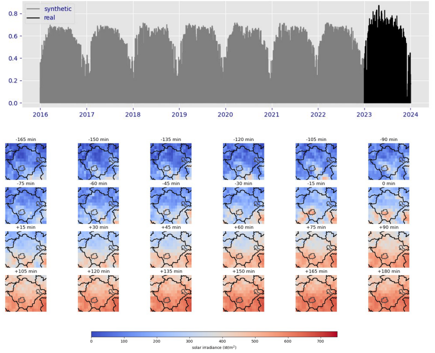
Foundation time series model



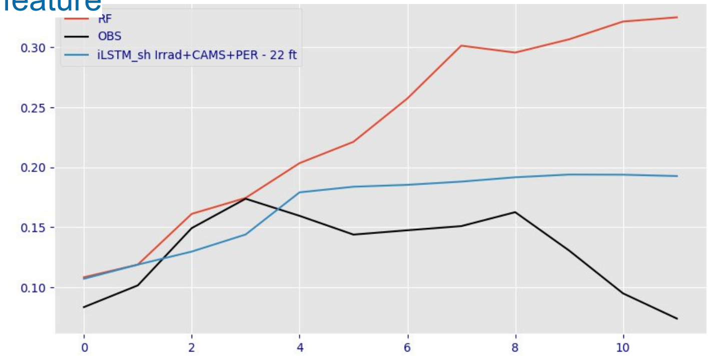
PV, global irradiation, and (semi-)synthetic data



NWP/ML weather prediction model



Use case Austria using IrradPhyDNet as extra feature

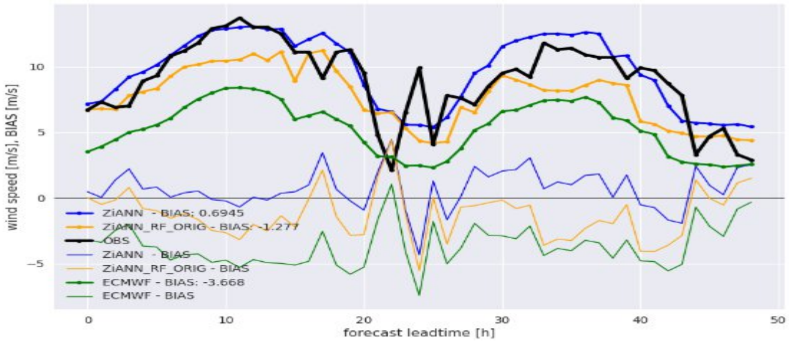


Renewable energy – how can we support the transition with targeted ML-models?

GeoSphere Austria

Location post-processing – what the users need

Windspeed predictions/post-processing and aggregated per country



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Turbine Model	Rated Power (MW)	Rotor Diameter (m)	Hub Height (m)	Specific Power (W/m²)	Est. Annual Energy Production (GWh)*	IEC Wind Class
Turbine Model	Rated Power (MW)	Rotor Diameter (m)	Hub Height (m)	Specific Power (W/m²)	Est. Annual Energy Production (GWh)*	IEC Wind Class
Vestas V90	2.00	90	80-105	314	5.5 - 7.0	IA/IIA
Vestas V150	4.20	150	166	238	14.0 - 17.0	IIIB
Vestas V162	7.20	162	119-166	350	21.0 - 28.0	S
Vestas V172	7.20	172	112-148	311	22.0 - 30.0	S
Senvion 3.2M114	3.17	114	93-143	310	9.5 - 11.5	IIA
Senvion 3.2M122 NES	3.20	122	89-139	273	10.0 - 12.5	IIIA
Enercon E-101	3.05	101	99-159	380	8.0 - 10.0	IA
Enercon E-138 EP3 E2	3.50	138	81-160	234	12.0 - 15.0	IIA
Nordex N163	7.00	163	118-164	335	20.0 - 26.0	S
Vestas V126	3.45	126	87-166	276	11.0 - 14.0	IIB

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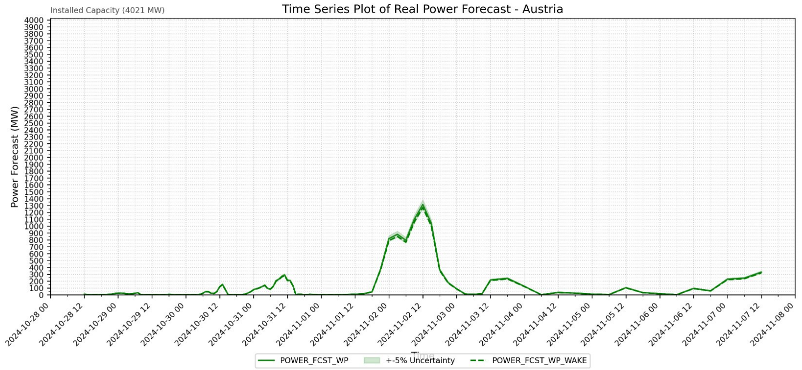
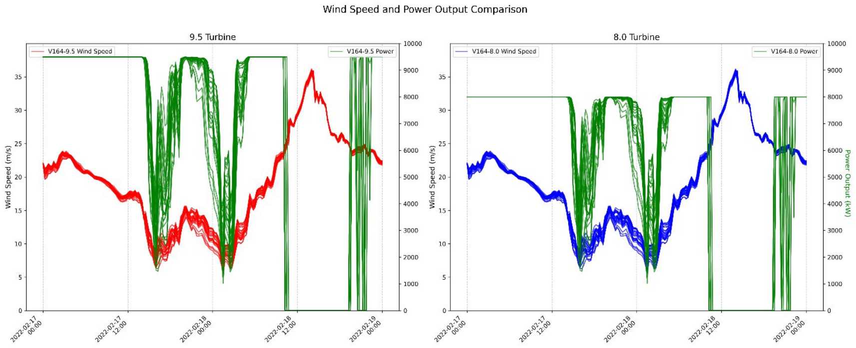


and for every turbine in a wind farm/region



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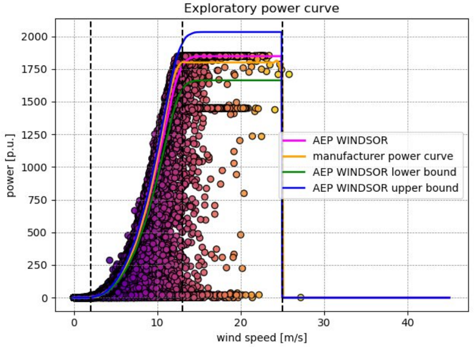
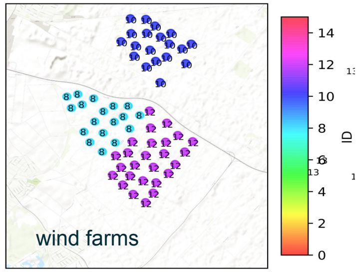
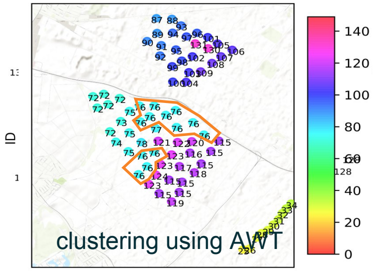
Quality control of data and missing value replacement us clustering of similar turbines

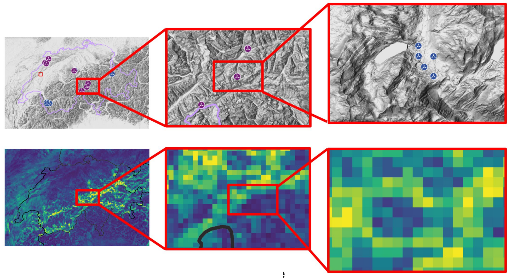


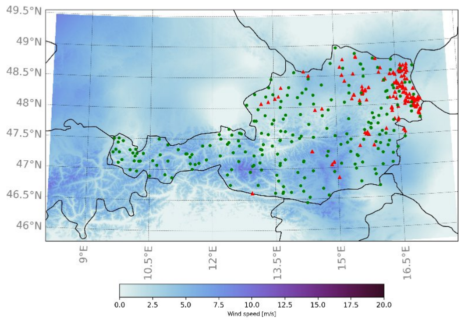


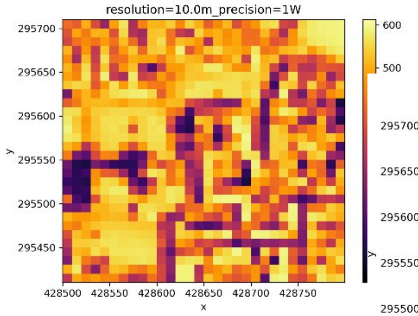


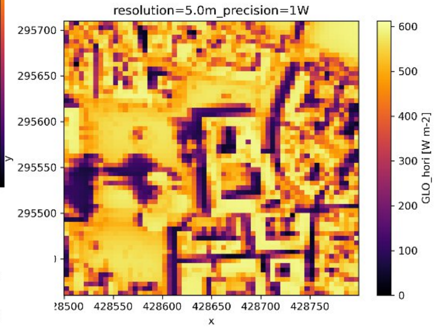
Supporting weather, subsaisonal/saisonal, and climate

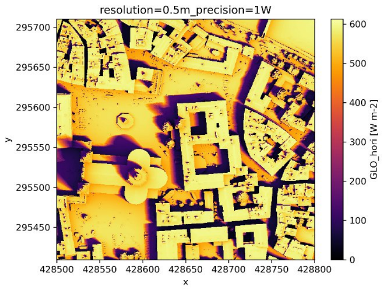
Building a base for climate/coarse prediction downscaling – generating „training“ data/wind and solar altases using ML (interpolation/downscaling)



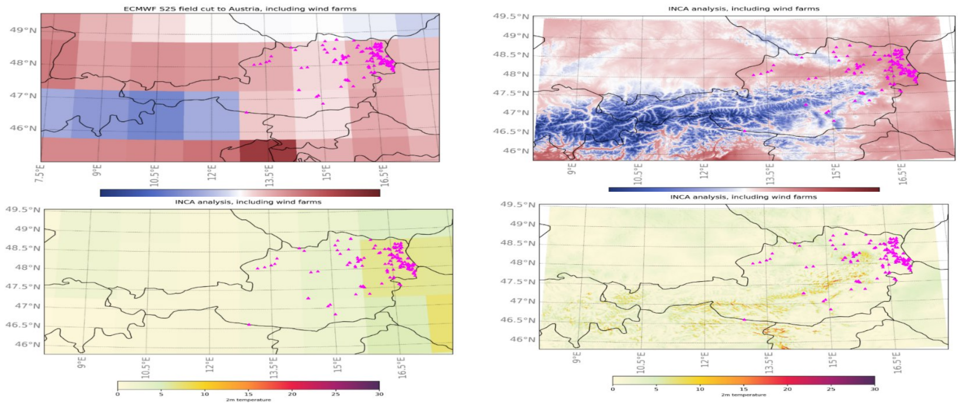




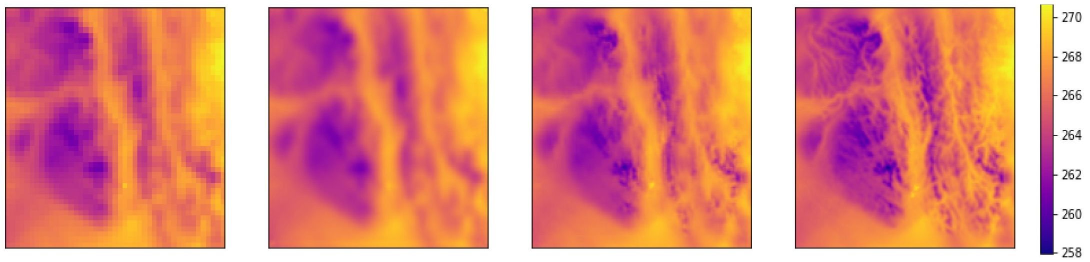




Downscaling S2S prediction and climate scenarios



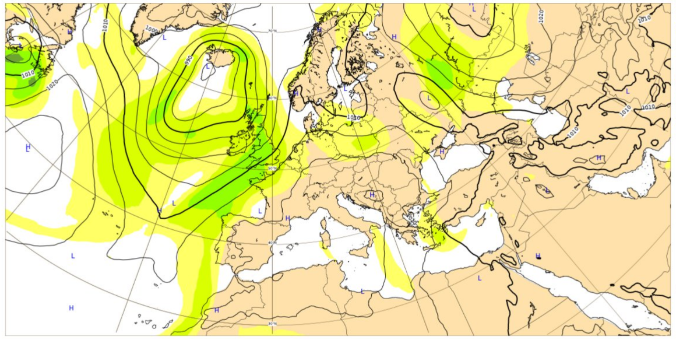
Coarse AI-model1 AI-model2 target



Solution – where is the physical model?

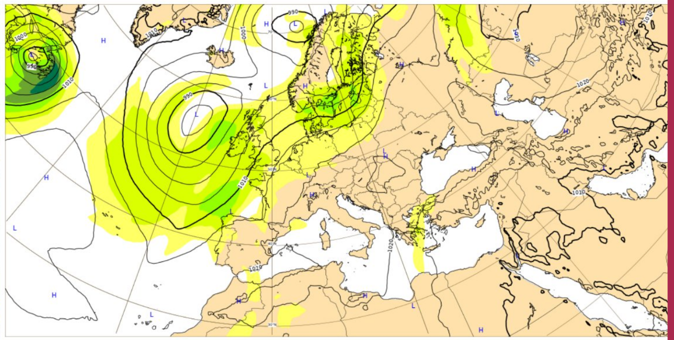
Experimental: Pangu-Weather ML model: Mean sea level pressure and 850 hPa wind speed

Base time: Sun 06 Oct 2024 12 UTC Valid time: Tue 15 Oct 2024 12 UTC (+216h) Area : Europe



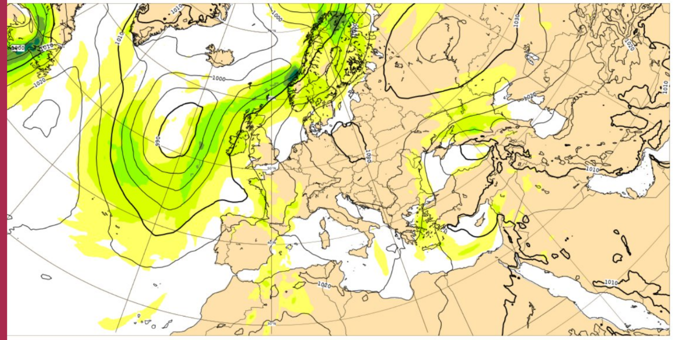
Experimental: GraphCast ML model: Mean sea level pressure and 850 hPa wind speed

Base time: Sun 06 Oct 2024 12 UTC Valid time: Tue 15 Oct 2024 12 UTC (+216h) Area : Europe



Mean sea level pressure and 850 hPa wind speed

Base time: Sun 06 Oct 2024 12 UTC Valid time: Tue 15 Oct 2024 12 UTC (+216h) Area : Europe



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

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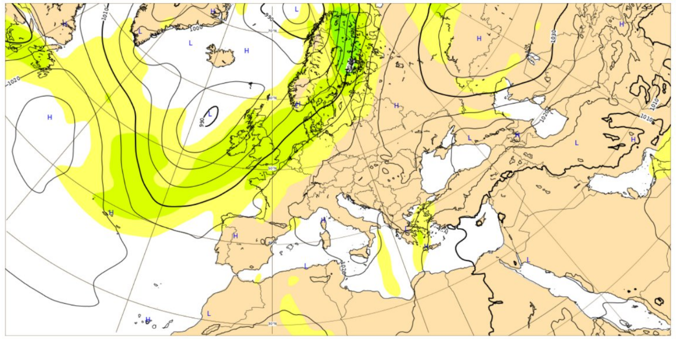


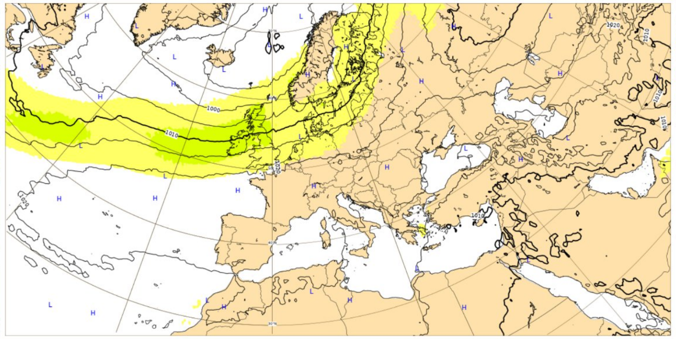
Experimental: FourCastNetv2-small ML model: 850 hPa wind speed (m/s)

10 15 20 25 30 40 50 60 80 100 (m/s)

Experimental: FourCastNetv2-small ML model: Mean sea level pressure (hPa)

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

Base time: Sun 06 Oct 2024 12 UTC Valid time: Tue 15 Oct 2024 12 UTC (+216h) Area : Europe



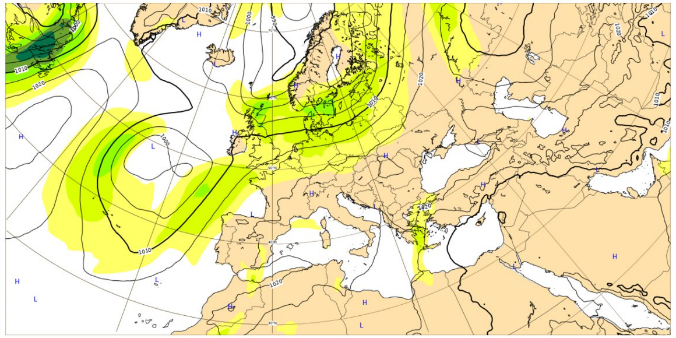
Experimental: FuXi ML model: 850 hPa wind speed (m/s)

10 15 20 25 30 40 50 60 80 100 (m/s)

Experimental: FuXi ML model: Mean sea level pressure (hPa)

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

Base time: Sun 06 Oct 2024 12 UTC Valid time: Tue 15 Oct 2024 12 UTC (+216h) Area : Europe



Experimental: AIFS (ECMWF) ML model: 850 hPa wind speed (m/s)

10 15 20 25 30 40 50 60 80 100 (m/s)

Experimental: AIFS (ECMWF) ML model: Mean sea level pressure (hPa)

THANK YOU!

Irene.schicker@geosphere.at

Projects @GeoSphere

- **Atmol4REN-4Cast**
- MEDEA
- AI4Wind and Wind4Future
- Destination Earth Extremes
- EnergyProtect
- PV4Community
- AI4Grids
- ReduceData
- EnergAIze
- AI-Prometheus
- HectoRenew
- MTGreen
- …