MAELSTROM

Empowering weather & climate forecast:

ML Apps & Datasets

ML Workflow Tools

Hardware Systems

Bing Gong
Jülich Supercomputing Centre

EuroHPC
Joint Undertaking

"The MAELSTROM project has received funding from the European High-Performance Computing Joint Undertaking (JU) under grant agreement No 955513. The JU receives support from the European Union's Horizon 2020 research and innovation programme and United Kingdom, Germany, Italy, Luxembourg, Switzerland, Norway".

Co-ordinated by
ECMWF

Agenda

ML Apps & Datasets

ML Workflow Tools

Hardware Systems

- Motivation, objectives & tasks
- Scientific solutions & achievements
- Delivered products
- Outlook

EuroHPC Joint Undertaking

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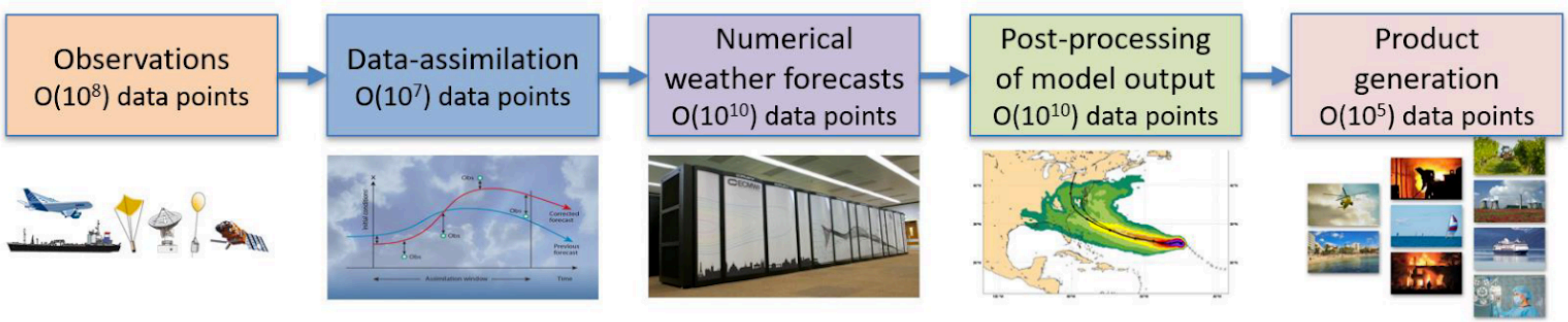
Motivation: ML for weather forecasts?



- Numerical atmospheric models: backbone of operational weather prediction

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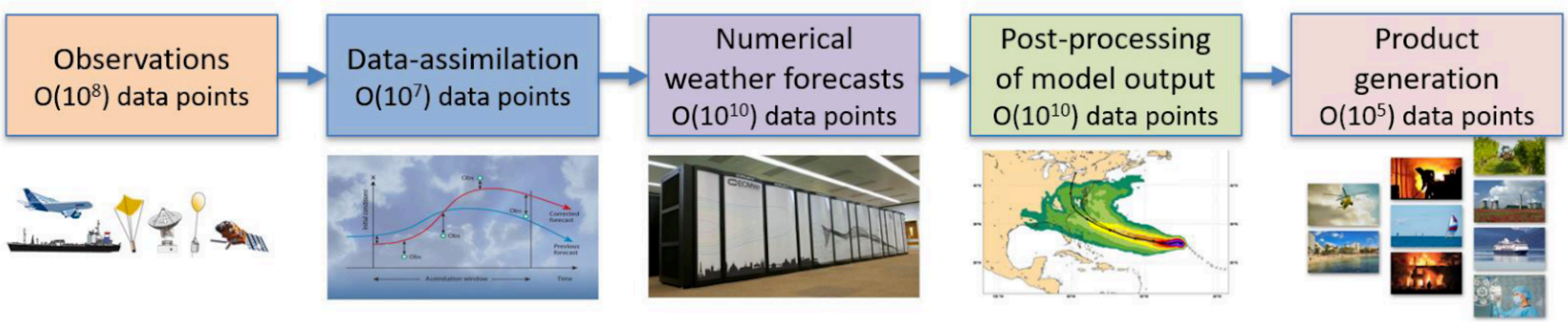

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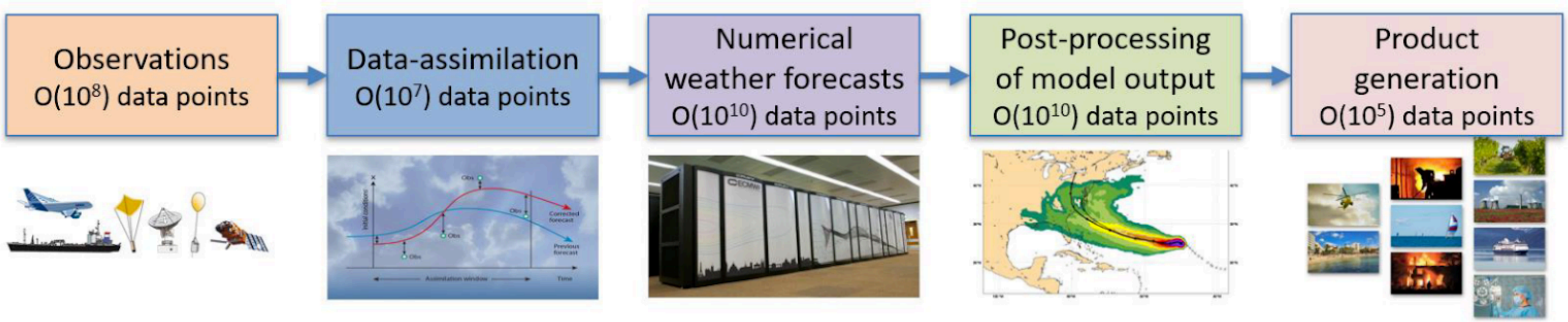
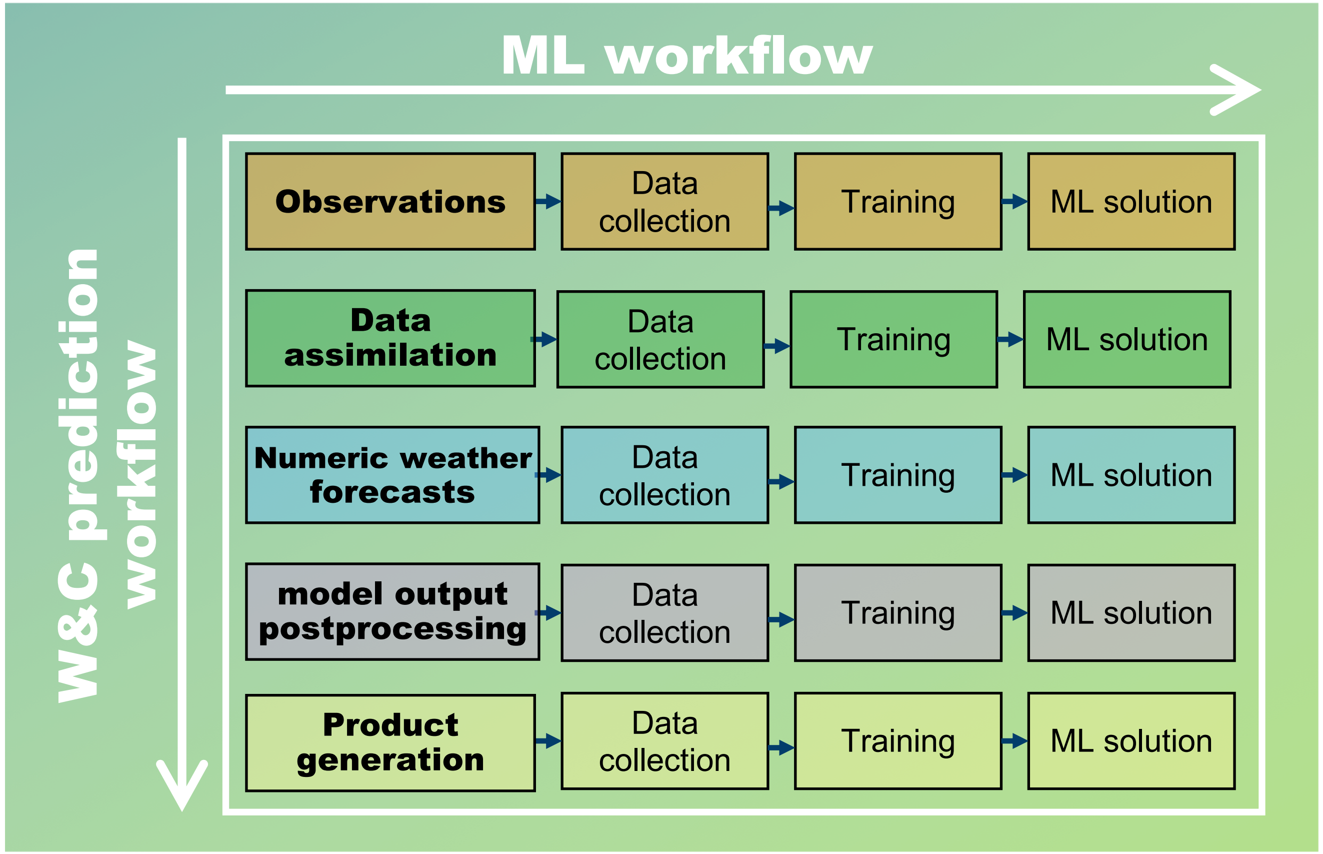


- Numerical atmospheric models: backbone of operational weather prediction
- Increasing success of machine learning (ML) in various applications
- ML for new applications in the weather prediction workflow

Objective: open W&C prediction as new usage domain for ML application that exploit exaflop performance



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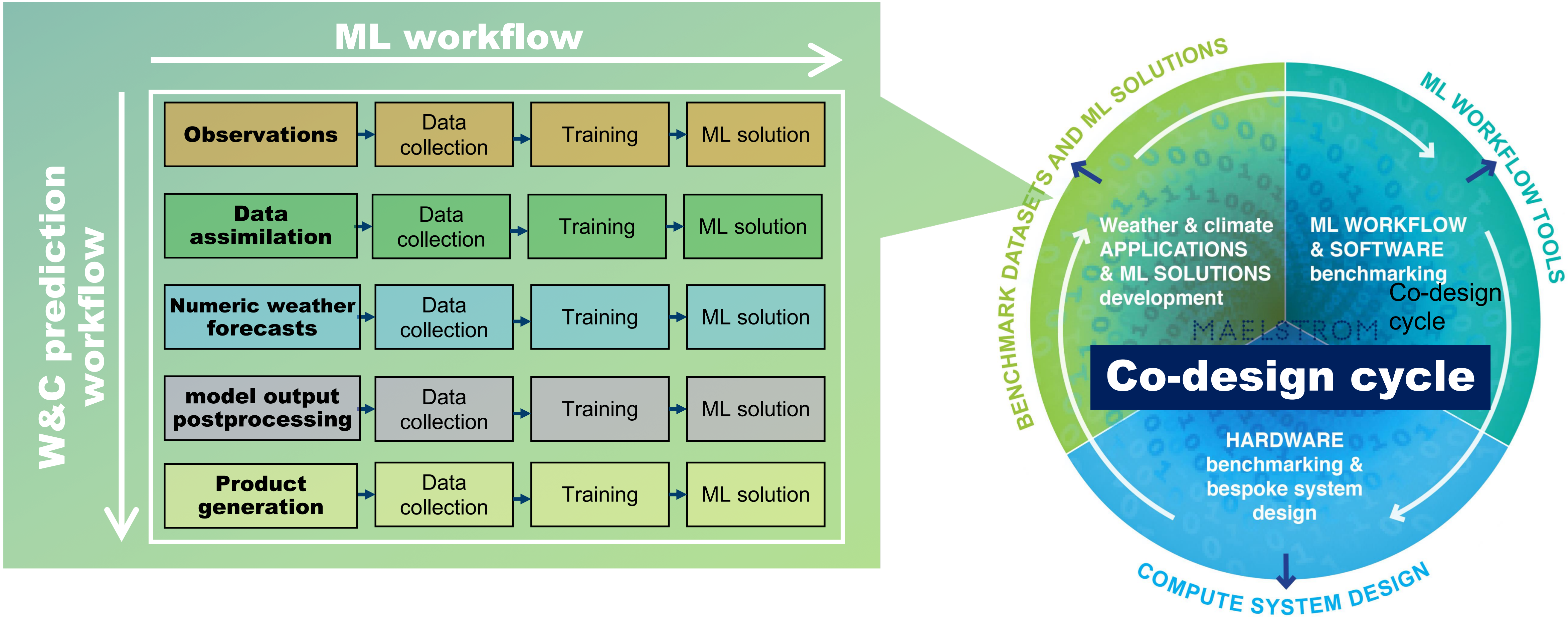

ECMWF 4cast E4 COMPUTER ENGINEERING ETH zürich JÜLICH Forschungszentrum Norwegian Meteorological Institute uni.lu UNIVERSITÉ DU LUXEMBOURG

ML apps & datasets: deliverables

month 5

ML benchmark datasets

month 6

Requirements documentation for ML solutions and tools in applications areas A1-6

Check the deliverable reports:
https://www.maelstrom-eurohpc.eu/deliverables

ML apps & datasets: deliverables

month 5
ML benchmark datasets

month 6
Requirements documentation for ML solutions and tools in applications areas A1-6

month 18
Apply ML tools to benchmark datasets to develop ML solutions

month 30

month 36
Test ML tools within the W&C workflow

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Scientific questions

- **Q1**: Can we use machine learning method to provide **accurate and high-resolution weather forecasts**? → Application 1, 2 and 5

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- **Q2:** Can we rely on weather forecasts by machine learning for **renewable energy generation?** → Application 6
- **Q3:** Can we use machine learning to create a sufficient accurate, yet **fast emulator?** → Application 3

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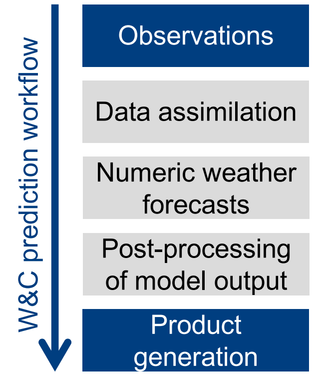
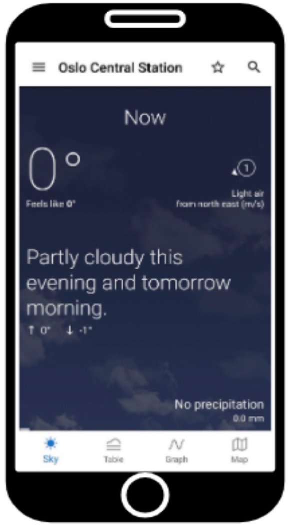
- **Q2:** Can we rely on weather forecasts by machine learning for **renewable energy generation?** → Application 6
- **Q3:** Can we use machine learning to create a sufficient accurate, yet **fast emulator?** → Application 3
- **Q4:** Can we use machine learning to quantify **uncertainty** and correct weather forecast **biases**? → Application 1 and 4.

App 1: Blend citizen observations and numerical weather forecasts



Why citizen observations for weather forecasts?

- Strong demand for accurate local weather forecasts
- NWP models may not be able to forecast local (extreme) weather
- Citizen observations can be applied for high-resolution analyses
- NWP post-processing can significantly improve operational weather forecasts on weather apps like yr.no



Thomas Nipen, Ivar Seierstad, John Bjørnar Bremnes

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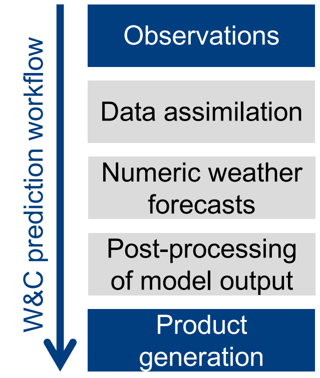

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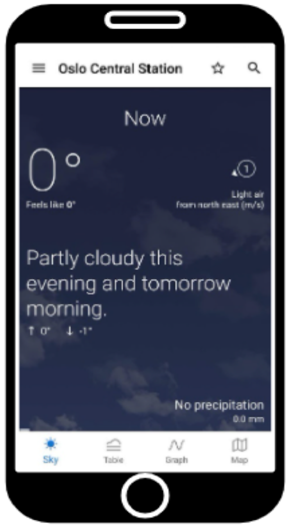
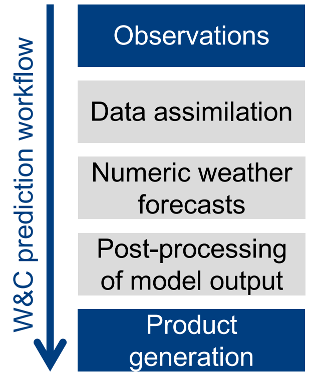
ML solution & achievement:

- Goal: hourly probabilistic temperature and/or precipitation forecasts in terms of 10th, 50th and 90th percentiles on a 1×1 km grid for the Nordic area
- Approach: convolutional networks with filters grouped by lead time
- Results: MAE (50th percentile) about 0.76 K vs 1.04 K for raw NWP



Norwegian Meteorological Institute
Thomas Nipen, Ivar Seierstad, John Bjørnar Bremnes

App 2: Incorporate social media data into prediction framework

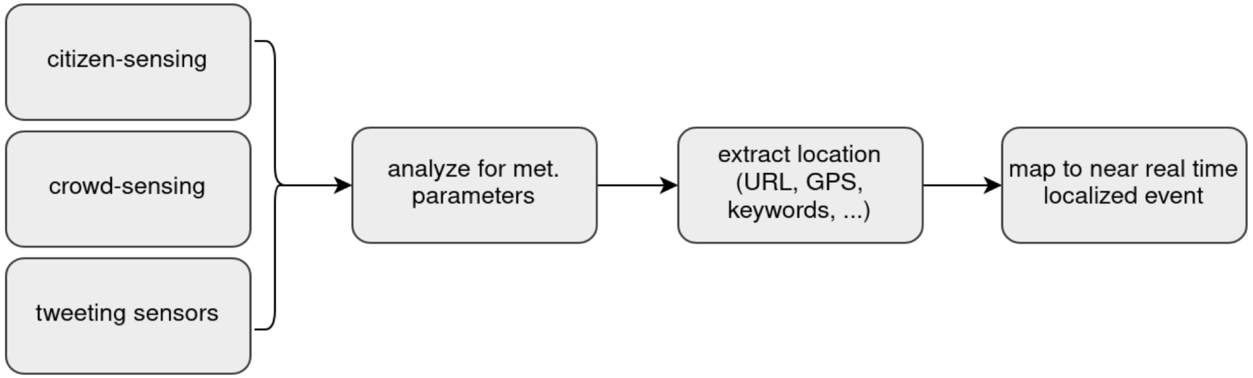


Why social media for weather forecasts?

- Weather-related information from social networks could enhance local weather predictions for most dominant infrastructures in Europe (e.g. airports) in near real-time
- Tweets: a new sensor

ML solution:

- Adopt weather and unstructured text data with meta data (e.g. time, geolocation) for weather forecasts



Dr. Markus Abel, Greta Denisenko, Fabian Emmerich

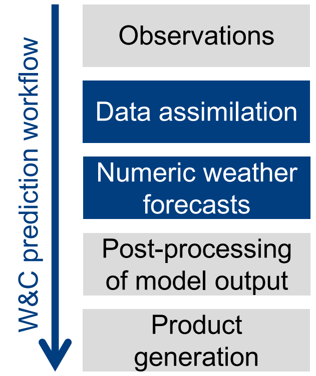
App 3: neural network emulators for faster weather forecast models & data assimilation

W&C prediction workflow

- Observations
- Data assimilation
- Numeric weather forecasts
- Post-processing of model output
- Product generation

Why neural network as emulator for radiative heating?

- Radiative heating is a vital component of atmospheric models.
- Significant cost → lower resolution and larger timestep
- More physics (e.g. 3D cloud effects) → we can’t afford in the weather forecasting model



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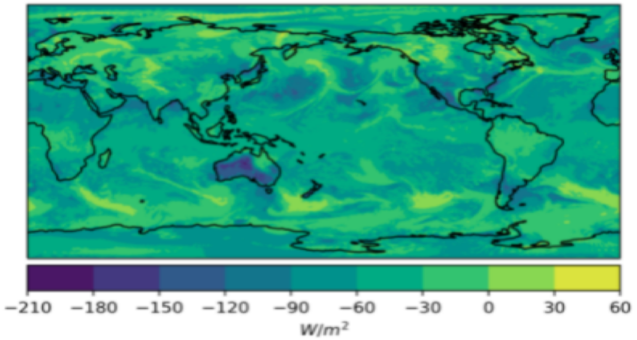
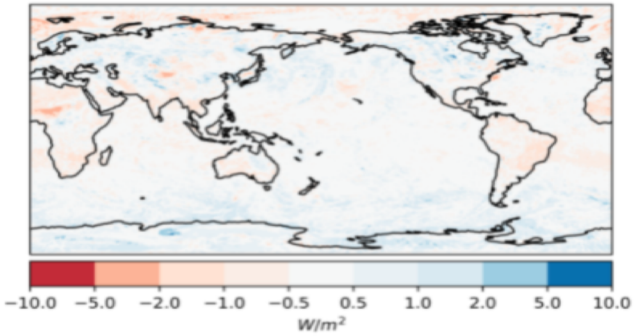
ML solution and achievement:

- Approach: MLP, CNN & RNN.
- Results: Offline metrics very promising (RMSE ~0.5W/m^2)





ECMWF Matthew Chantry & Peter Dueben

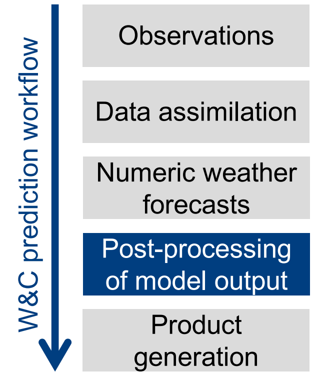
App 4: Improved ensemble predictions in forecast post-processing

W&C prediction workflow

- Observations
- Data assimilation
- Numeric weather forecasts
- **Post-processing of model output**
- Product generation

Why improve ensemble prediction by ML?

- Weather is a chaotic system. Minor perturbations affect the further outcome we predict
- Ensemble prediction predicts weather as a probability distribution.
- ML solution should be applied to **uncertainty quantification** and **bias corrections**.



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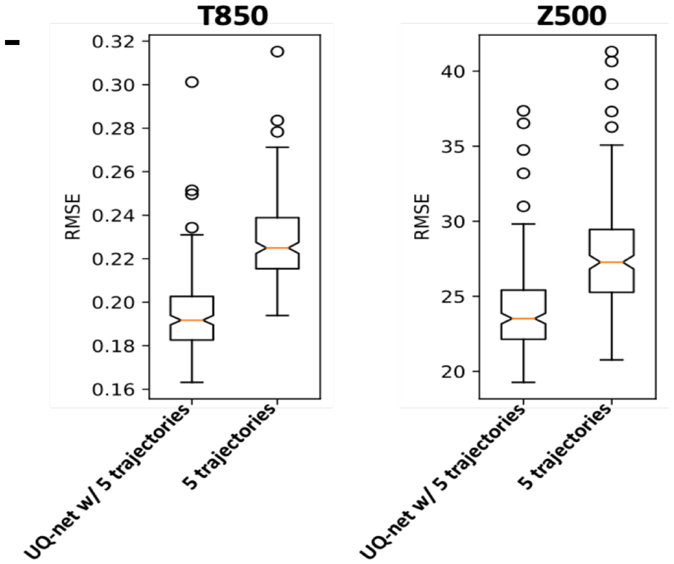
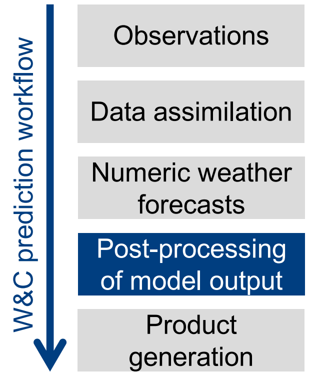
ML solution and achievement:

- Goal: Predict T850, Z500 as a probability distribution
- Approach: inception-style network for Uncertainty Quantification



App 5: Improved local weather predictions in forecast post-processing



Why ML for downscaling 2m temperature?

- High spatial variability of T2m in complex terrain
- Local variations in T2m with adverse effects (e.g. Loss in agriculture)
- Increase in spatial resolution
  → Computational cost
  → Challenges across gray-zone resolutions

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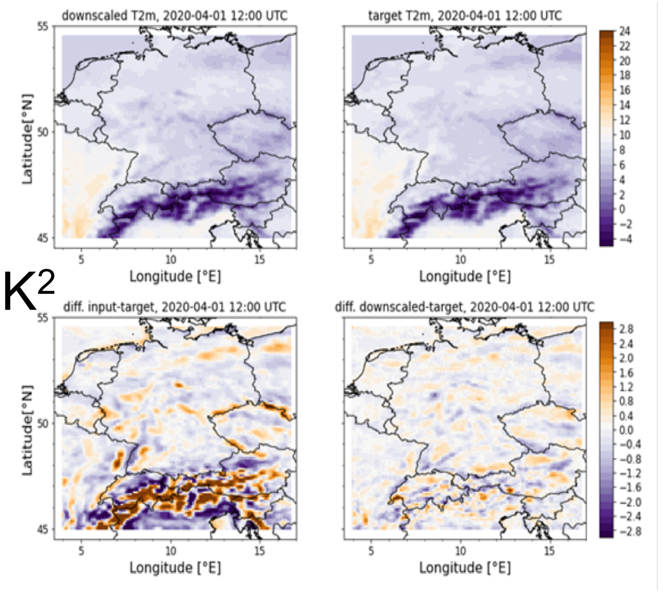
ML solution and achievement:

- Goal: Mapping from (coarsened) 0.8° to 0.1° grid
- Approach: U-Net
- Results: MSE ~ 0.2 K^2



JÜLICH Forschungszentrum Michael Langguth & Bing Gong

W&C prediction workflow

Observations

Data assimilation

Numeric weather forecasts

Post-processing of model output

Product generation

App 6: Bespoke weather forecasts to support energy production in Europe

Why ML for energy generation forecast?

- Allow large market share of renewable energies by optimal efficiency throughout all providers (solar, wind, biogas, storage capacities, ...)
  → requirement for accurate forecasts for energy generation
- Increase of renewable energy generation important for mitigation to climate change
- Accurate predictions for the exact location of wind/solar parks by ML algorithms

4cast Dr. Markus Abel, Greta Denisenko, Fabian Emmerich

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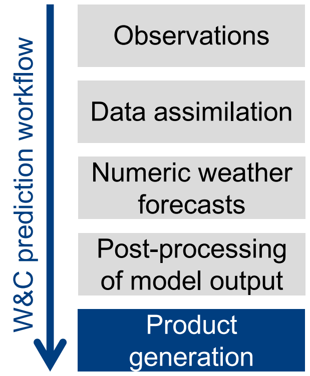

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ML solution and achievement:

- Goal: Power production forecasts
- Approach: Gradient boosting (intraday/day ahead), Neural Networks (intraday)
- Results: NMAE approximately: Wind 12%; Solar 7%

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Delivered: Benchmark datasets

Application	Res.	Grid size	Data size	Data format	Pip package name	CML dataset name
A1: Postprocessing	1 km	1796×2321	~ 5 TB	NetCDF	climetlab-maelstrom-yr	'maelstrom-yr'
A3: Radiation	40 km	137 vertical levels	~ 2 TB	NetCDF/TFRecords	climetlab-maelstrom-radiation	'maelstrom-radiation'
A4: ENS10	0.5°	720x361x11x11	~ 2.6 TB	GRIB/NetCDF	climetlab-maelstrom-ens10	'maelstrom-ens10'
A5: Downscaling	0.1°	128x96	~ 7.5 GB	NetCDF	climetlab-maelstrom-downscaling	'maelstrom-downscaling'
A6: Power production	0.1°	351x551 10 vertical levels	~ O (TB)	NetCDF	climetlab-maelstrom-power-production	'maelstrom-constants-a-b' 'maelstrom-power-production' 'maelstrom-weather-model-level' 'maelstrom-weather-pressure-level' 'maelstrom-weather-surface-level'

Delivered: Benchmark datasets

CliMetLab manages the downloading and loading of data, for a variety of datasets, dubbed plugins.

```
!pip install climetlab climetlab-maelstrom-radiation
import climetlab as cml
cmlds = cml.load_dataset('maelstrom-radiation')
ds = cmlds.to_xarray()
```

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Delivered: ML with customized loss function for weather forecasts applications

Quantile Scores: $S_{\tau}(u) = \begin{cases} u(\tau - 1), & u < 0 \\ u\,\tau\,, & u \geq 0 \end{cases}$ → **AP1**

The Ranked Probability Score (CRPS): CRPS$(F, y) = \int_{-\infty}^{\infty} \left[F(x) - 1_{x>y}\right]^2 dx$ → **AP4**

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Adversarial loss : $\min_{G} \max_{D}\,(D, G) = \mathrm{E}_{x\sim p_{data}(x)}\left[\log\left(D(x)\right)\right] + E_{z\sim p_z(z)}\left[\log\left(1 - D(G_Z)\right)\right].$ → **AP1, AP5**

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Jupyter notebooks have been created to explore the datasets and demonstrate simple machine learning solutions to act as first benchmarks → https://www.maelstrom-eurohpc.eu/deliverables

Outlook to the next two years

Towards Tier 2 Datasets → Large data

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Use ML tools → Integrate ML solutions with workflow tools

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Scientific aspects → Further ML solution developments for all applications

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Hardware Testing → Parallelizing ML solutions on HPC www.maelstrom-eurohpc.eu

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