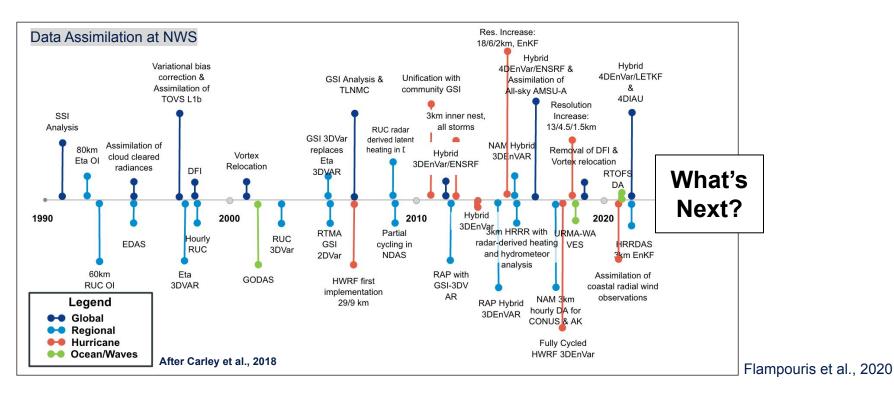




Introduction

Looking for the Next Breakthrough in Modeling and Model initialization...



Proprietary and Confidential



Upgrading the NWP forecast and analysis systems

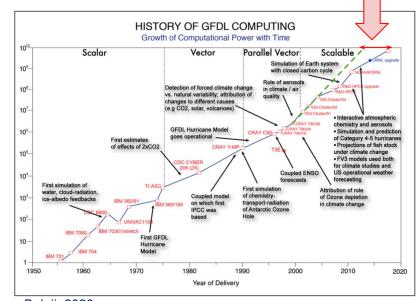
Constraints and Challenges

Innovating within the Modus Operandi

- Incremental scientific advancements
- Investment in the infrastructure
- Well-defined development path
- Operational Stability
- Optimization of cost

Overcoming ongoing Challenges to Innovation:

- Significant increase of data, model and observations (e.g., Tomorrow.io and others)
- Unresolved (coupled) physical processes
- Complexity of the models
- Prohibitive computational cost for the required resolution (Tolmann et al., 2022)



Balaji, 2020

Is Data Science (ML/AI) an Alternative/Supplemental Development Path?



Machine Learning and Earth Modeling

Machine learning: The study of computer algorithms that improve automatically through learning from data by using mathematics and the scientific process.

Why Now:

- 1. Unprecedented data volume
 - Our current analytical capabilities restrict the discovery
- 2. Daily maturation of the AI/ML capabilities/algorithms
 - Hundreds of applications are published daily
- 3. Evolution of hardware allows efficient ML models training
 - NVIDIA, AMD, Graphcore, Atmo, and more
- 4. Availability of open-source, well-documented, extensively tested software frameworks
 - TensorFlow, PyTorch, Keras, Scikit-Learn and more
- 5. The cost of running ML models is orders of magnitude lower than for NWP models

Driven by the (Weather) Industry, the ML solutions have been adopted!

Adoption of ML/AI from Governmental Institutions

NOAA / NWS (Boukabara et al., 2020)

Earth observations	 Data ingest Calibration Bias correction 	Boukabara e al., 2020
and remote sensing	Data selection Pre-processing Inverse problems QC Forward models Data fusion	Data assimilation
	Observation operators DA emulation	
Environmental	• NWP	
numerical modeling	Parameterization emulation Enhanced parameterizations Empirical parameterizations Dynamics emulation Whole model emulation	
	Short-range forecasts	Extreme
	• Nowcasting • Hail • Hurricanes	weather monitoring and prediction
	 Probabilistic guidance Analog forecasting Nonlinear ensemble averaging 	•
Post-processi	ing	

ESA/ECMWF (Schneider et al., 2022)

Stand	dardization of ML applications within the NWP:	
1.	Enhancing Satellite Observation with ML	
	a. Earth monitoring, biomass and volcanic plumes	
	b. Radar backscatter and optical images	
2.	Hybrid Data Assimilation - ML approaches	
	a. Approximation of nonlinear systems and extracting meaning	gful
	features from high-dimensional data	
	b. Replacement of physically based model	
	c. Application error corrections	
3.	Geophysical Forecasting with ML and Hybrid Models	
	 Speed up complex and time-consuming processing 	
	b. Diagnostics	
	c. Model improvements	
4.	ML for Post-Processing and Dissemination	
	 Post-processing and optimization forecast outputs 	
	b. Downscaling	

Intention: Integration of ML in the current forecast paradigm.

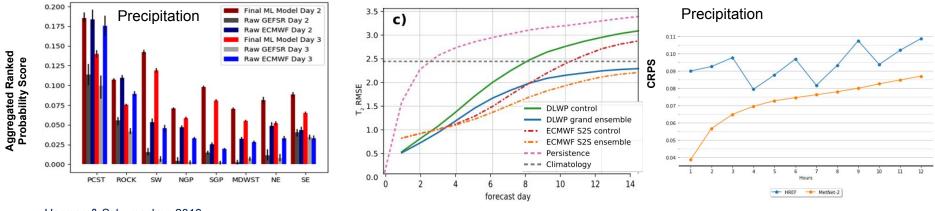


ML-Based Innovation in the Weather Industry

Broad spectrum of ML applications

Schneider et al., 2022: ESA-ECMWF Report on recent progress and research directions in machine learning for Earth System observation and prediction.

- *Herman & Schumacher, 2018 Extreme precipitation forecasts with Random Forests
- Rasp & Lerch, 2018 Neural network post processing of temperature
- Brey & Eckel, 2020, Dai and Hemri 2021- Ensemble ML-Prediction for Cloud Cover
- *Weyn et al., 2021- NWP-free ML-based weather forecast
- *Sønderby et al., 2020 Neural-net based precipitation nowcasting



Herman & Schumacher, 2018 Proprietary and Confidential

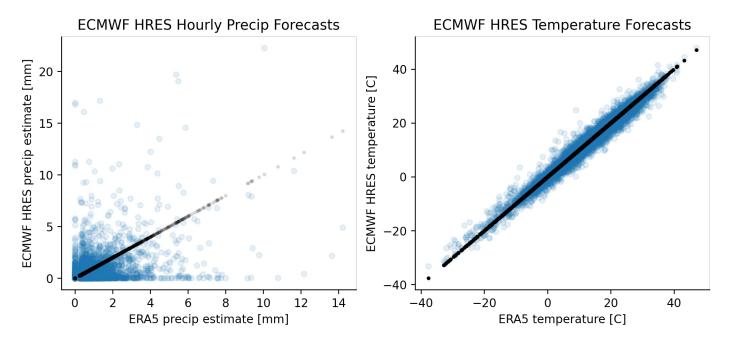
Weyn et al., 2021

Sønderby et al., 2020



ML in post-processing at Tomorrow.io

Seamlessly merging multiple weather models into one intelligent and accurate forecast



Focusing on the grand challenges of forecast, e.g., Precipitation Prediction

7



ML in Action at Tomorrow.io

ML is used to learn and correct the errors of traditional physics-driven forecasts

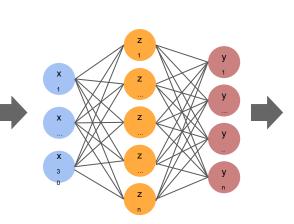
Input Predictors







Any physically relevant observation



The exact model, configuration, features, training strategy, *etc.*, vary prediction-to-prediction.

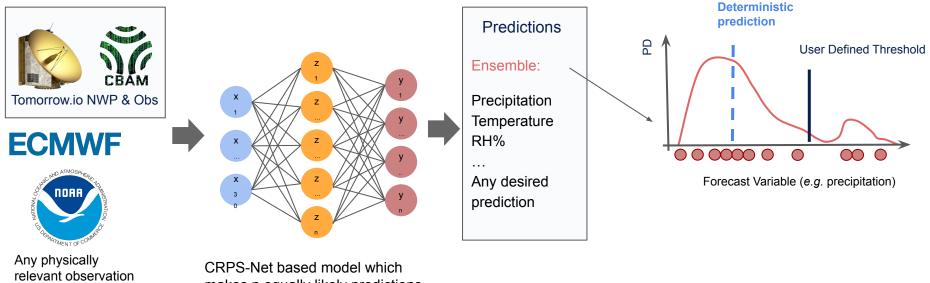
Predictions
Deterministic or
Ensemble:
Precipitation
Temperature
RH%
...
Any desired
prediction



ML in Action at Tomorrow.io

ML is used to learn and correct the errors of traditional physics-driven forecasts and can provide uncertainty

Input Predictors



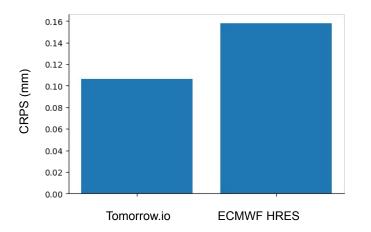
CRPS-Net based model which makes n equally likely predictions and the CRPS as its loss function.

$$CRPS(\hat{Y}, y) = E_F |\hat{Y} - y| - 1/2 \times E_F |\hat{Y} - \hat{Y}'|$$

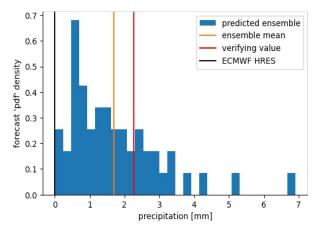


Forecasting Precipitation

CONUS Precipitation Verification 1yr



51-Member Ensemble





Summary

- Data driven models have numerous applications in Weather Industry, for instanc Tomorrow.io has a suite of applications (DA, Nowcasting, Postprocessing)
- ML models are not the solution to all the problems
- The adoption of the ML approaches is changing the NWP: From modeling physical processes and initialization to data driven models and their training
- The typical development cycle, R2O2R, for NWP is extremely long for the Machine Learning common practices → Operational Innovation
- Considering the increasing number of observations and preliminary results, if and when purely ML weather predictions based on observations will be possible?



Thank you!