CGMS WG-II: AI/ML Use Cases Report

Presented to CGMS-53 Plenary
Évian-les-Baines, France, 3-5 June 2025

F. Joseph Turk (JPL/Caltech), IPWG rapporteur to CGMS

All contributions acknowledged within

Background

During the April 2025 CGMS WG-II meeting (Xi'an, China), presentations highlighted several examples of AI/ML techniques in use or development, applied to a variety of meteorological satellite & forecasting applications

The WG-II Rapporteurs solicited additional materials from CGMS members and the science working groups. This presentation summarizes materials received.

The purpose of this presentation is two-fold:

- To examine how these AI uses are distributed amongst different satellite-based instruments and data products
- To assess potential ways to promote cross-agency and cross science working group synergies

All contributions acknowledged within

OFFICE OF THE CHIEF SCIENCE DATA OFFICER

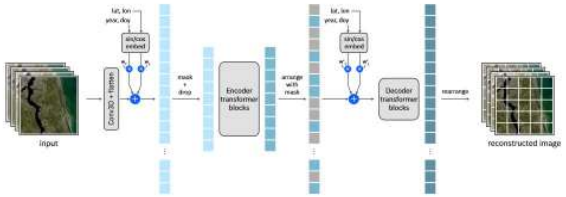
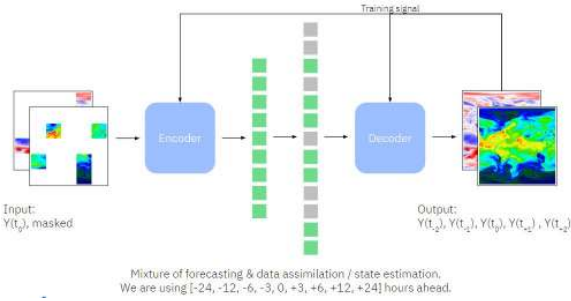


Fig. 4: Prithvi architecture and general pretraining framework.



Mixture of forecasting & data assimilation / state estimation.
We are using [-24, -12, -6, -3, 0, +3, +6, +12, +24] hours ahead.

Full presentation from March 2025 WG-II

AI foundation models (large machine learning models trained on extensive, generic corpora of atmospheric training data), are emerging as powerful tools for tackling complex challenges in atmospheric science. The AI Foundation Models for the Atmosphere workshop will bring together atmospheric scientists and model developers to assess the current state of the art of AI FMs and related validation frameworks, explore their applications, and identify remaining data, technology, and knowledge gaps hindering their adoption.

[More information]

AI Foundation Models for the Atmosphere

Date: August 18 - August 21, 2025

Location: Colorado State University, Fort Collins, USA

A workshop bringing together atmospheric scientists and model developers to discuss and develop emerging applications of AI foundation models for atmospheric science.

ATMOSPHERIC SCIENCE
COLORADO STATE UNIVERSITY

NASA Grantee*

IBM

SLALOM: First PMW snowfall retrieval algorithm based on ML

Goal: achieve snowfall global coverage (including polar regions) exploiting all current and future *passive microwave imagers and sounders* (ATMS, MWI/ICI, MWS, AMSR3, and AWS (EPS-Sterna))

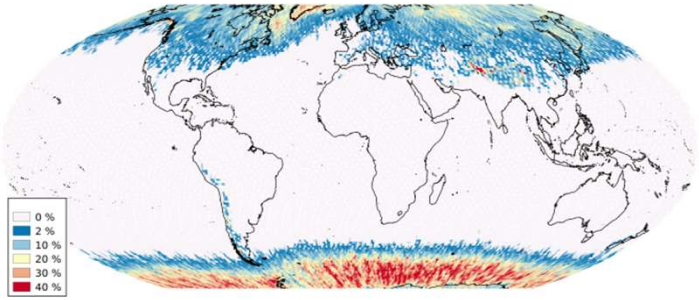
SLALOM for GMI *(Rysman et al., 2018, 2019, 10.1029/2019GL084576)*
SLALOM-CT for ATMS *(Sanò et al., 2022, 10.3390/rs14061467)*
HANDEL for high latitudes *(Camplani et al., 2024 10.5194/amt-17-2195-2024)*

CloudSat CPR/Calipso-based training datasets

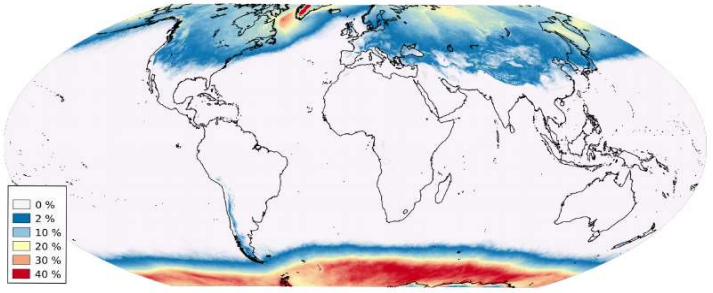
- ***No auxiliary info on background surface conditions but exploitation of all channels (frozen surface classification at the time of the overpass)***
- **Separate ML modules** for snowfall detection and supercooled liquid water detection
- **Separate ML modules for Snow Water Path (SWP) and surface snowfall rate (SSR) estimate**

SLALOM: Snowfall Occurrence 05/2014 - 05/2016

CloudSat CPR



SLALOM for GMI

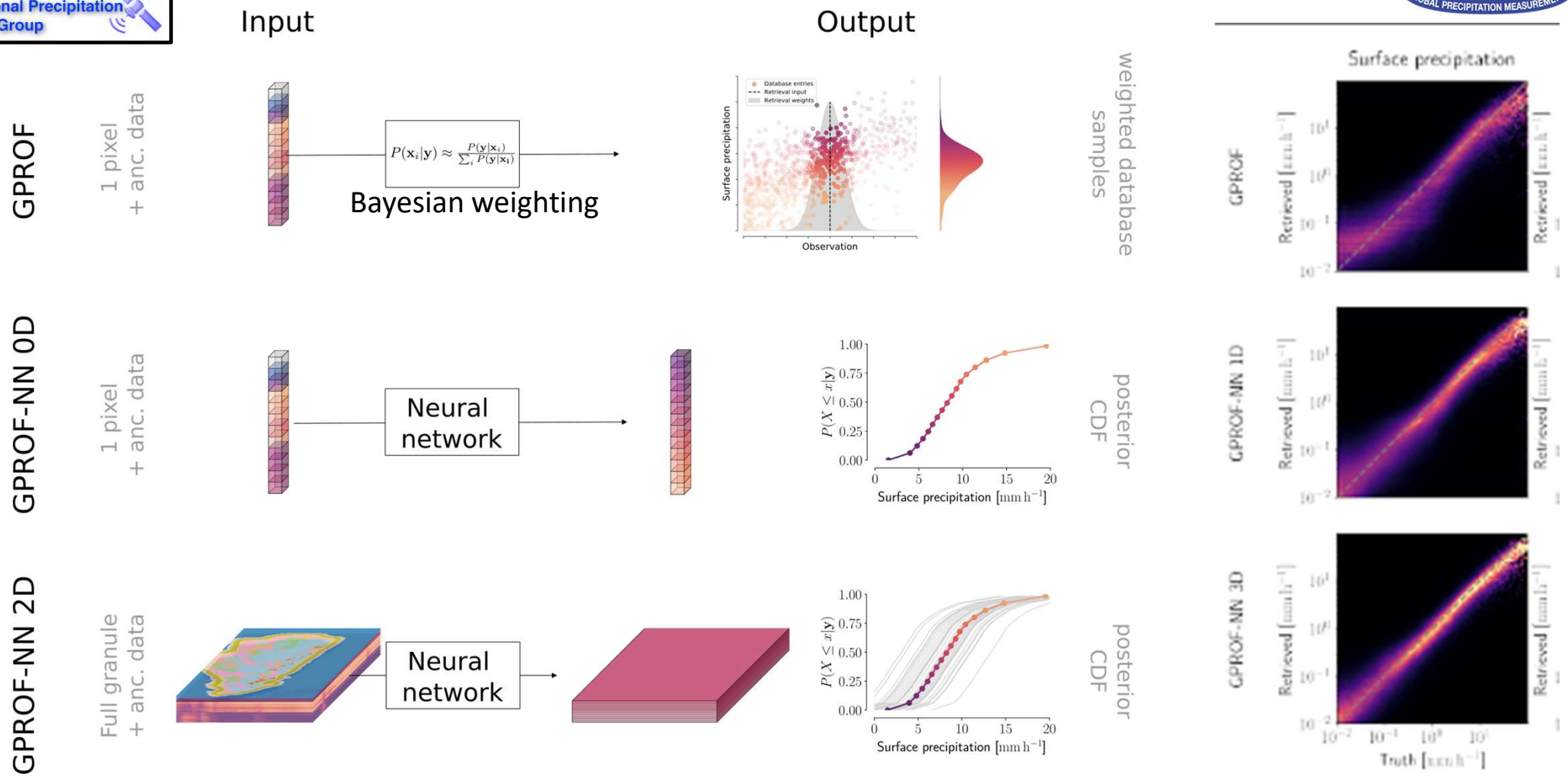


SLALOM approach is used for the upcoming H SAF global precipitation products including EPS-SG MWI and MWS day-1 to be released after launch

EarthCARE continues W-band radar observations

Rysman et al., 2018, 2019, 10.1029/2019GL084576

GPM Operational Radiometer Precipitation Scheme



Pfreundschuh et al, 2022: [GPROF-NN: a neural-network-based implementation of the Goddard Profiling Algorithm]

Direct Observation Prediction

(c) Chris Burrows & the AI-DOP team @ ECMWF

Goal: to train and run weather forecasts based on observations alone

i.e., not using NWP fields or physical equations in

- Observation pre-processing
- Quality control
- Training
- Running the forecast

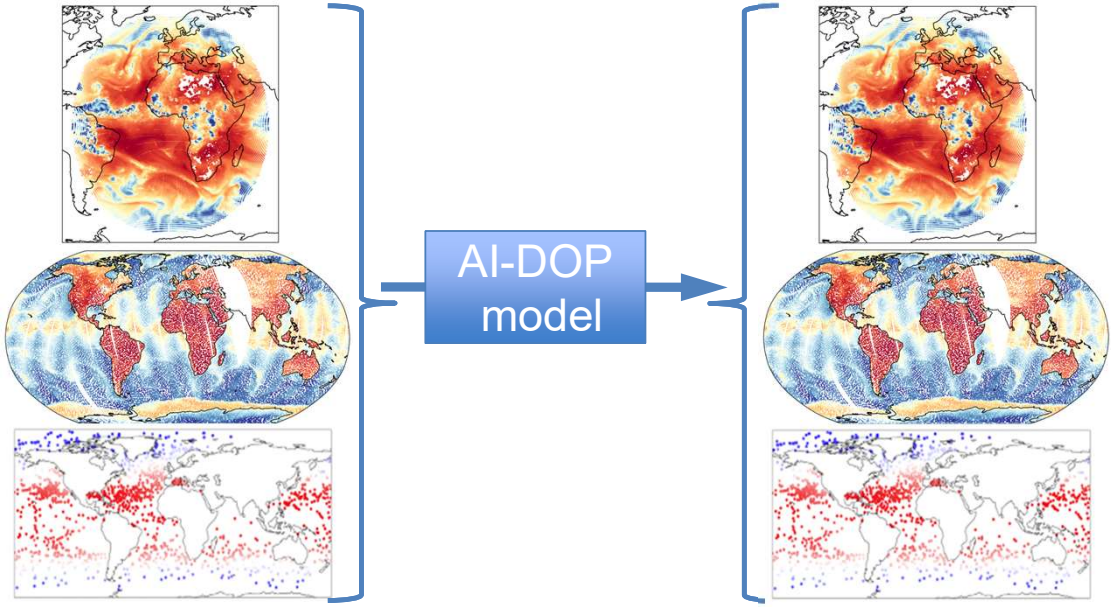
The concept is proven to produce skillful forecasts

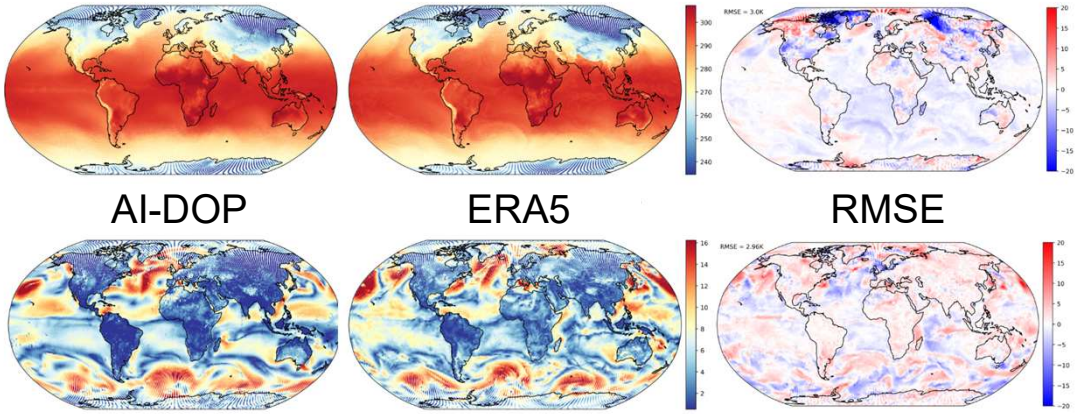
- Upper-air scores currently 1-2 days worse than IFS (but improving rapidly)
- Surface results competitive with IFS

Weather forecasts produced directly from observations

Inputs: All observations in a 12-h window

Outputs: All observations in the **next** 12-h window





Gridded 5-day forecasts of

- 2-m temperature (top)
- 10-m wind speed (bottom)

INTERNATIONAL ATOVS WORKING GROUP

All-sky AI-RTM

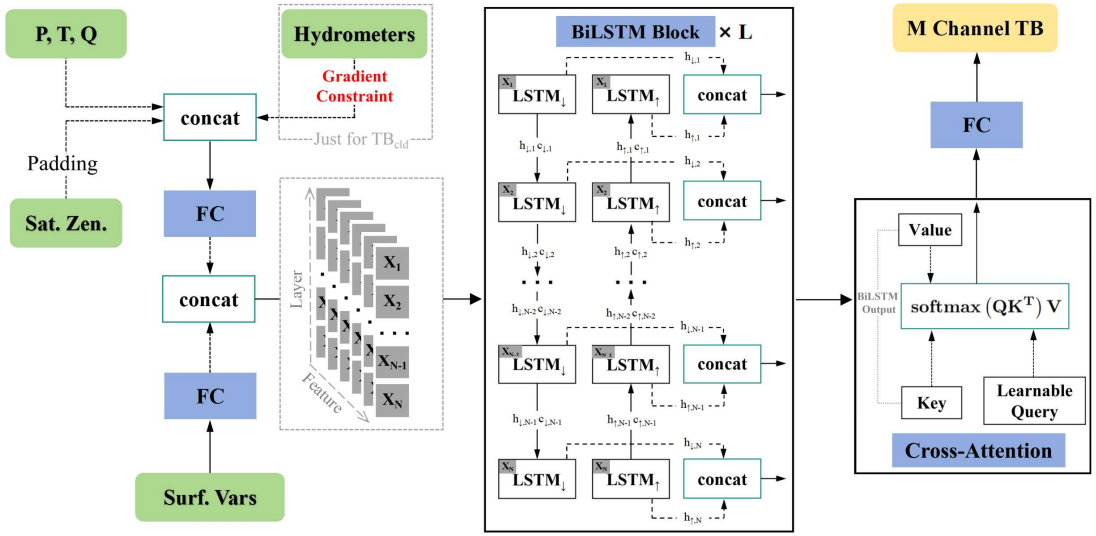
(c) Wei Han and his team @ CMA

INTERNATIONAL ATOVS WORKING GROUP

All-sky microwave radiance observation operator based on deep learning with physical constraints
→Significant improvement in computational efficiency still maintaining high accuracy in forward and Jacobian calculations

[All-Sky Microwave Radiance Observation Operator Based on Deep Learning With Physical Constraints]

Architecture of AI-RTM

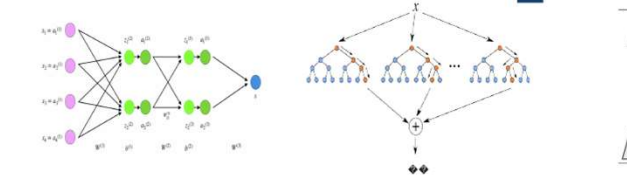


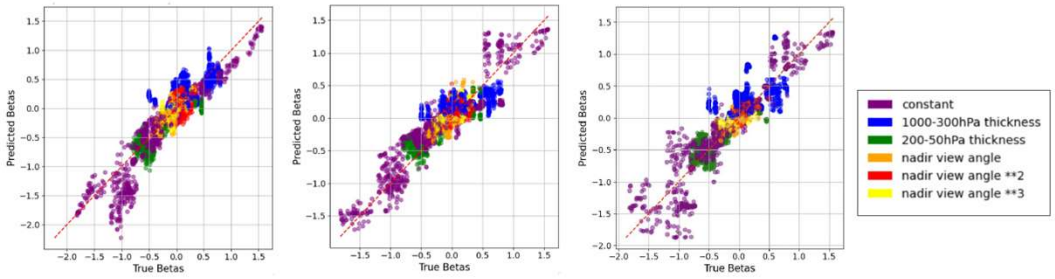
Bias correction using ML methods

(c) Alice Abramowicz et al. @ KNMI

Emulating coefficients of Variational Bias Correction – traditionally estimated within 4D-Var – for better robustness and applicability to use radiance data in high- and very-high-resolution regional NWP systems

Results of ML models





Scoring metrics/Models	MSE	R^2
NN	0.0250	0.757
RF	0.0252	0.754
AB	0.0267	0.740

	Training time
NN	3min
RF	9min
AB	2min

Data-driven AI models

Acknowledgements: CMA

FENGLEI(风雷)

CMA AI Nowcasting System

A nonlinear nowcasting model for extreme precipitation that unifies physical-evolution schemes and conditional-learning methods into a neural-network framework with end-to-end forecast error optimization

FENGQING(风清)

CMA AI Global Short-Medium Range Forecast System

FENGSHUN(风顺)

CMA AI Global Subseasonal-Seasonal Range Forecast System

S2S data-driven model based flow-dependent perturbation in latent space

Hour

Daily or Weekly

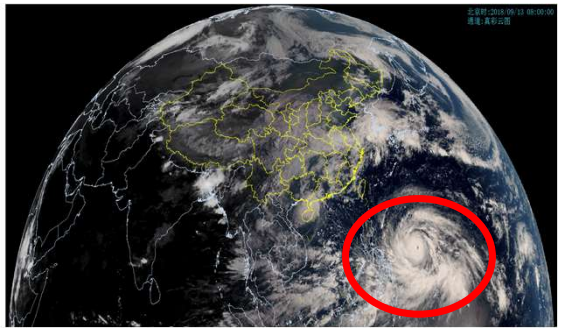
Weekly or monthly

Forecast Range

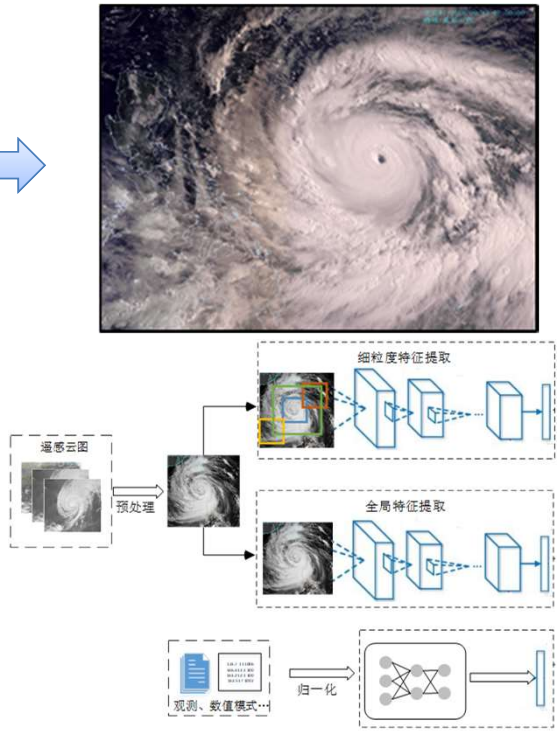
AI's application in tropical cyclone prediction

Acknowledgements: CMA

- For instance, AI technology is now employed in the monitoring and early warning of typhoons throughout their entire lifecycle.

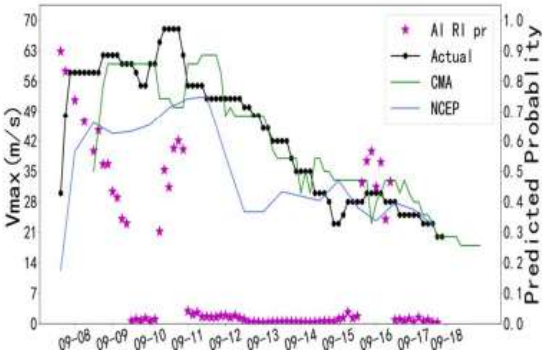


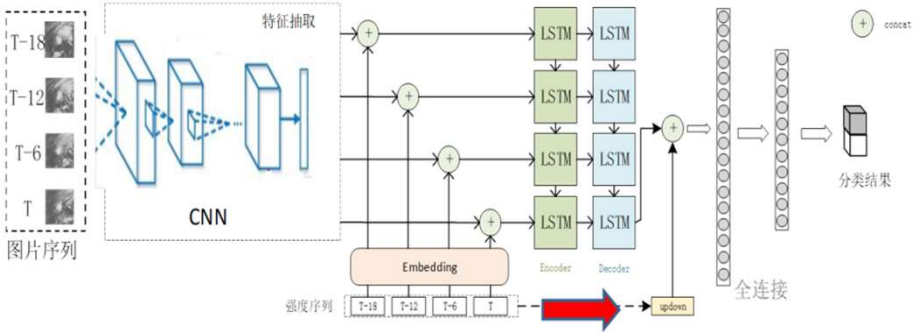
Based on SSD object detection method, the TC vortices are positioned automatically.



With a CNN model, the intensity of TC is determined.

强度	概率	相似云图
23	41%	
25	32%	
21	21%	
…	…	

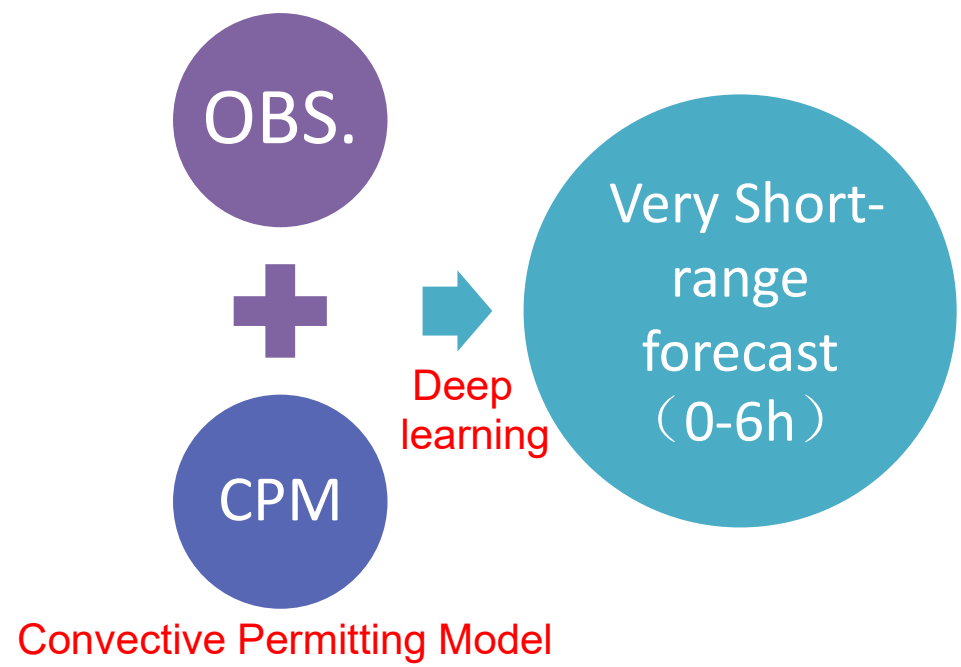


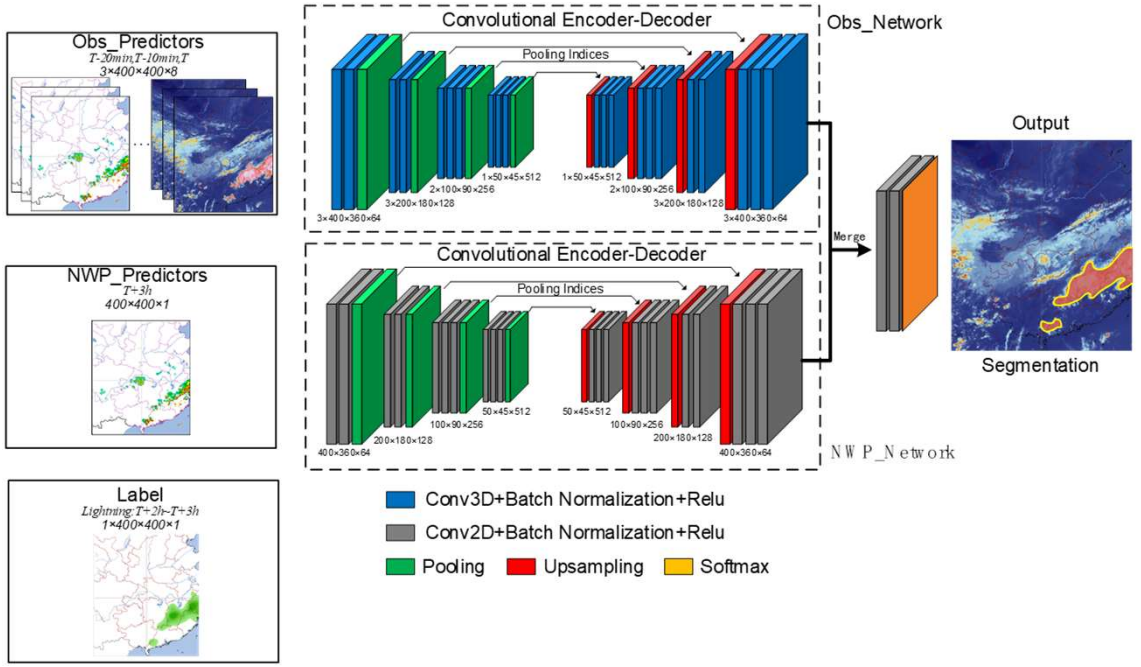


Discriminating Model of double-layer LSTM network was developed for rapid intensification of typhoon.

AI-based Convective Weather Very Short-range forecast

Acknowledgements: CMA





☐DL network merge the OBS and CPM

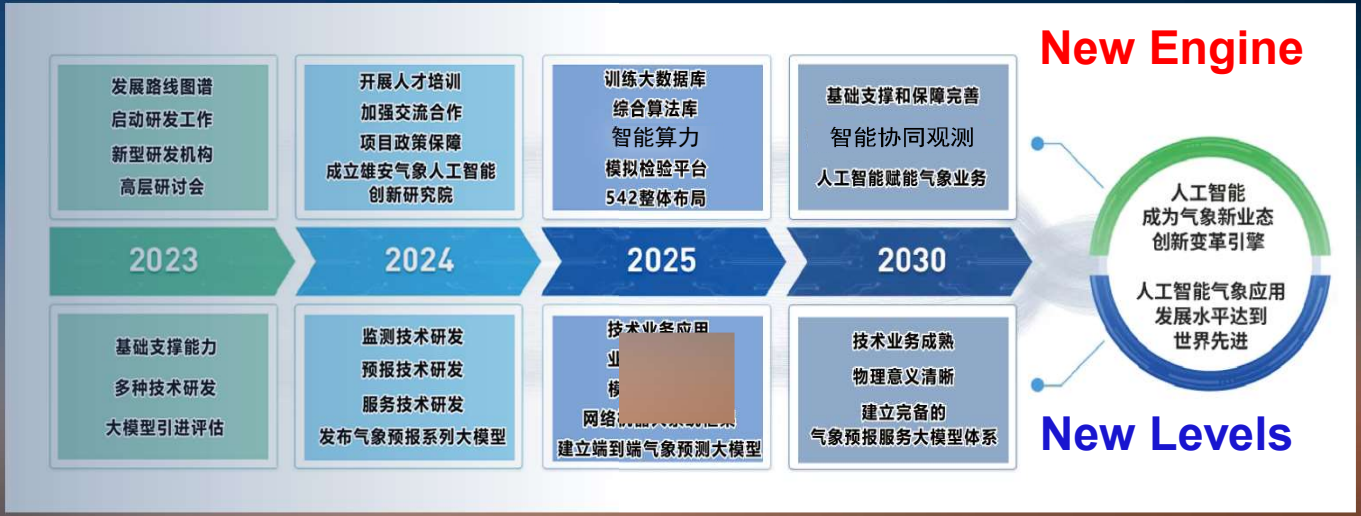
- ☐ Obs. provides the evaluation and structure features of the current convective system
- ☐ CPM provides the convective environmental condition
- ☐ Deep learning could extract the valuable features both from obs. and CPM.
- ☐ **Deep learning +Obs.+CPM**

CMA's AI Roadmap 2023-2030

Acknowledgements: CMA

- Establishing robust foundational supports
- Building intelligent and synergistic observation system
- Integrating AI deeply into the Earth system forecasting
- Providing intelligent meterological service for end users.

Roadmap 2030



By 2030, AI will emerge as a critical force driving innovation in China's meteorological development, with AI-powered meteorological applications within the CMA achieving global.

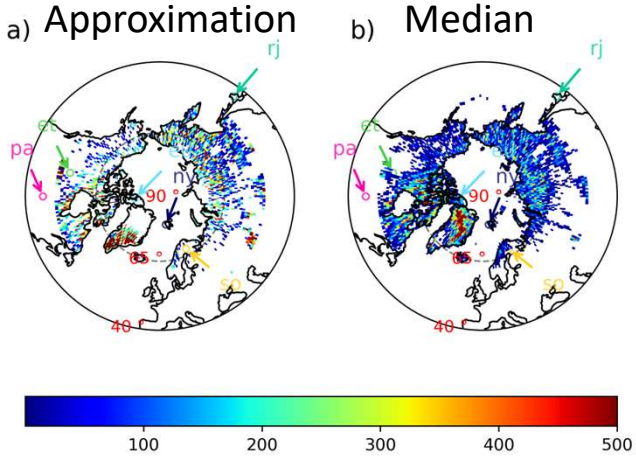
Courtesy Joseph Mendonca
Joe.Mendonca@ec.gc.ca

Environment and Climate Change Canada
Environnement et Changement climatique Canada

Neural Network Filter for OCO-2 XCO_2 Snow Scene Retrievals

Truth Proxies

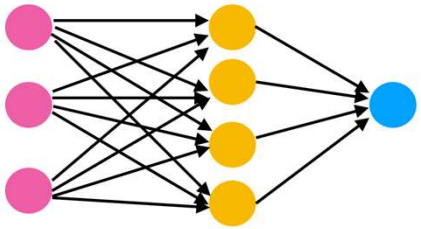
Small Area Approximation



Multi-Model Median

- Truth proxies are used to determine the retrieval bias.
- Small area approximation assumes changes in XCO_2 for a small area (<100km) is varying due to measurement noise and bias.
- Multi-model Median based on the median of 5 models

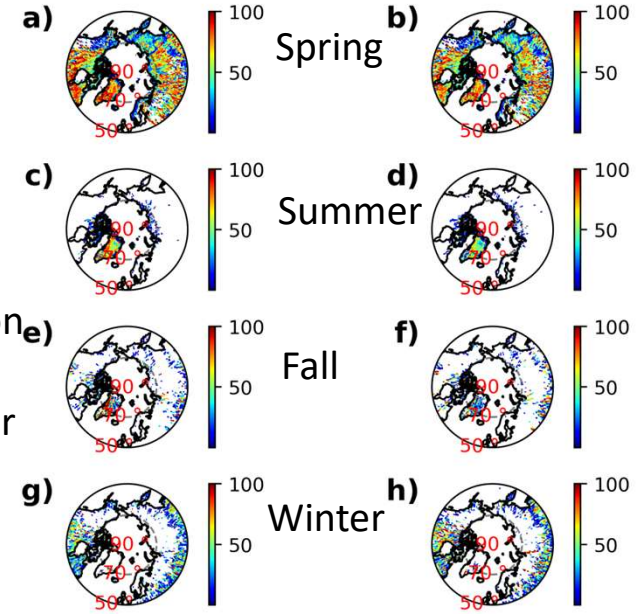
Neural Network



- Input: Features found in the lite files like albedo, aerosol optical depth etc.
- One hidden layer.
- Output layer is a value between 0 an 1. Where 0 is "good and 1 is "bad".
- Each truth proxy is used to train a NN filter.

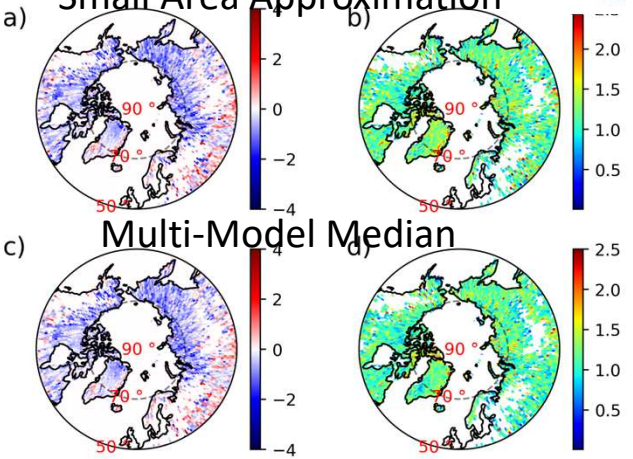
Throughput

- Most of the throughput is in spring.
- Most of throughput in summer and fall on Greenland.
- Throughput in winter limited in the Arctic due to no sun light



Bias and Precision

Small Area Approximation



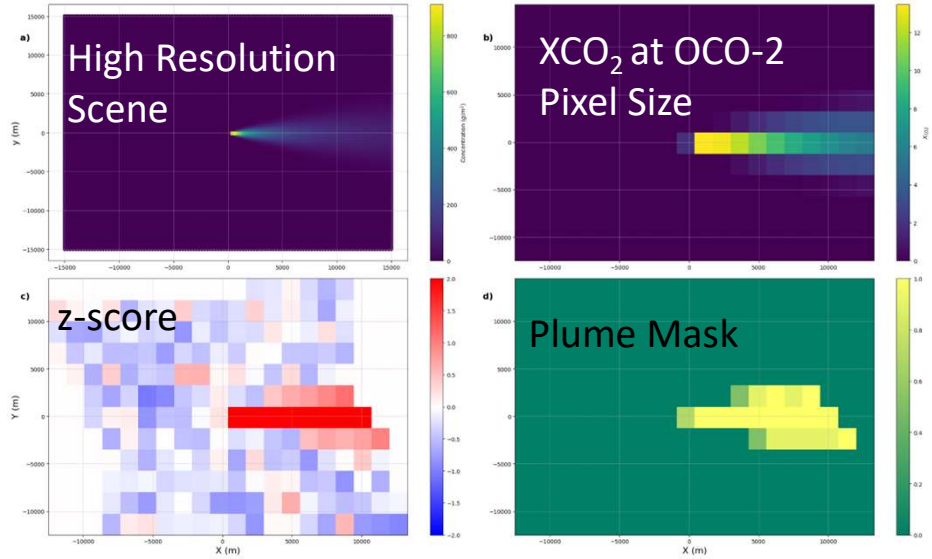
- One model left for independent evaluation.
- Bias is -0.38 ± 1.38 ppm and -0.40 ± 1.30 ppm SAA-NN and MMM-NN
- Recovered some snow scenes!
- Manuscript in prep.

Environment and Climate Change Canada
Environnement et Changement climatique Canada

Machine Learning for Power Plant Emission Quantification From OCO-2 Target Mode XCO_2

Courtesy Joseph Mendonca
Joe.Mendonca@ec.gc.ca

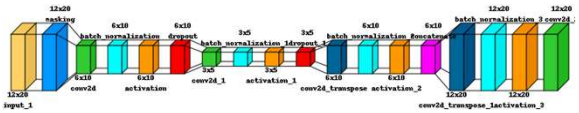
Simulated Data



- Generated high resolution scenes using a gaussian plume model for different emissions (F), wind speed (u), and wind direction.
- Average and convert to XCO_2 at OCO-2 pixel size.
- Added gaussian noise and converted to z-score as input to Convolution Neural Network (CNN).
- Define plume mask to train CNN.

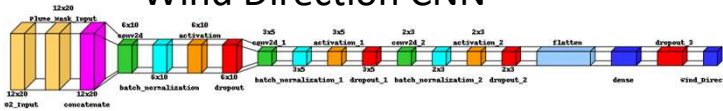
Models

Plume Mask CNN



- Used U-net style architecture for plume Mask.

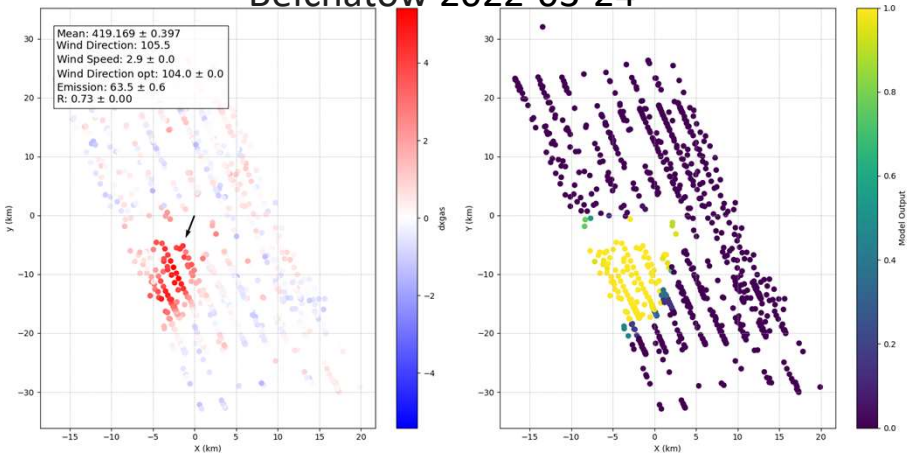
Wind Direction CNN



- Input both z-score and plume mask.
- Output wind direction

Emission Quantification

Bełchatów 2022-03-24



- Can quantify emissions from target scene in automated way.
- Manuscript in prep.

- Used plume mask to determine background XCO_2. Predicted wind direction from data.
- Wind speed from MERRA2.
- Fitted Gaussian plume model to determine emission .

National Environmental Satellite, Data, and Information Service
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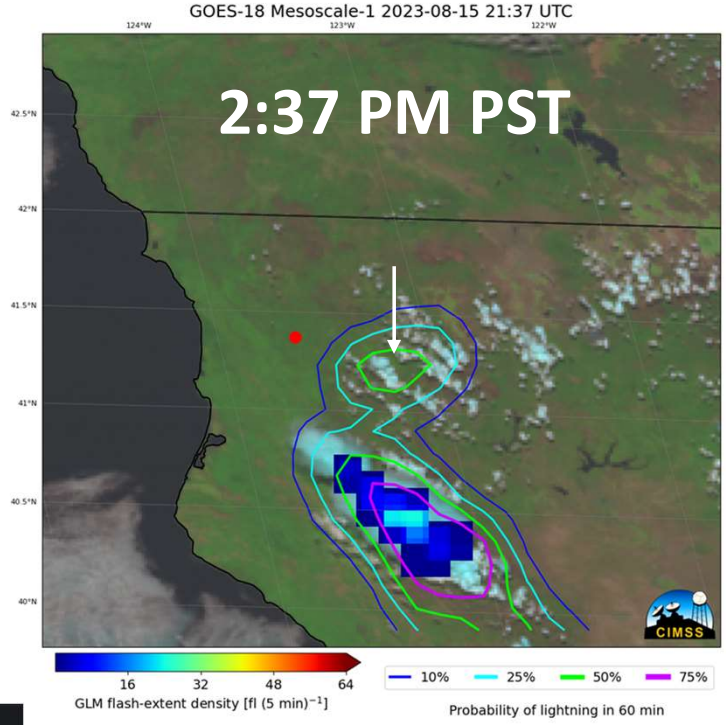
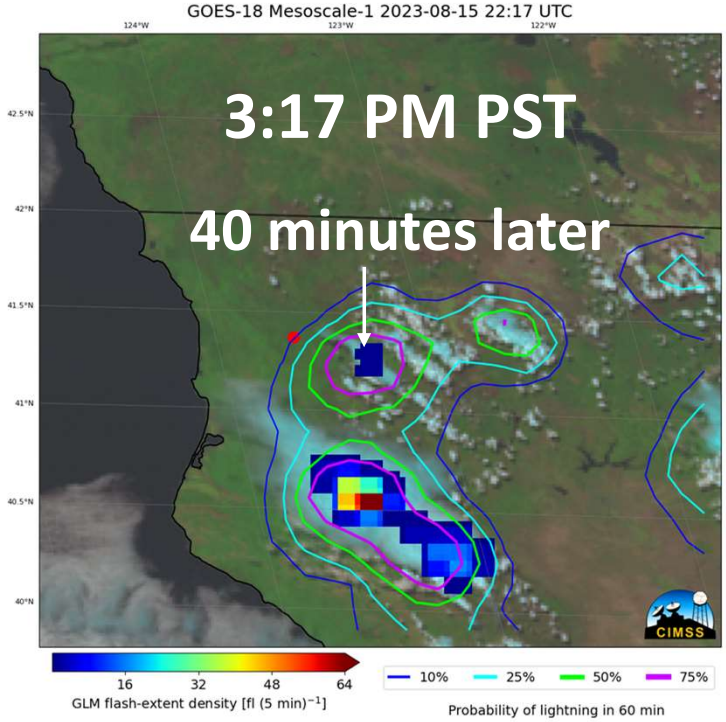
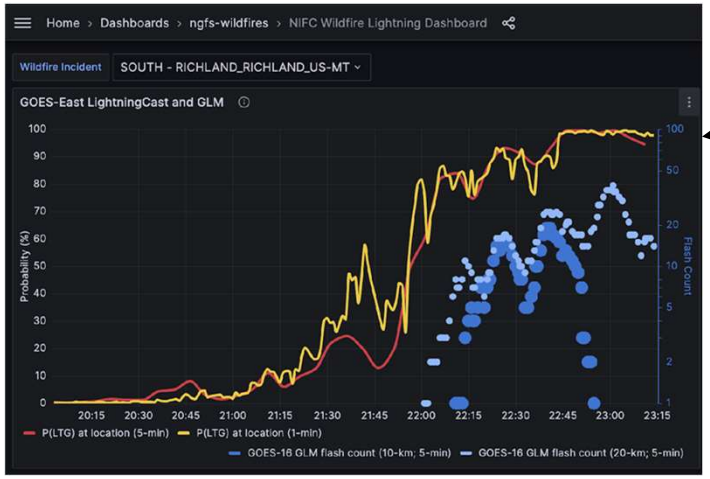
LightningCast Model

AI that transforms GOES-R satellite imagery into lightning predictions







Predicted flash probability (red/orange)
GOES-16 flash count (blue)

Custom LightningCast forecasts are available for active wildland fire incidents (used by NWS IMETs*)

***Incident Meteorologist**

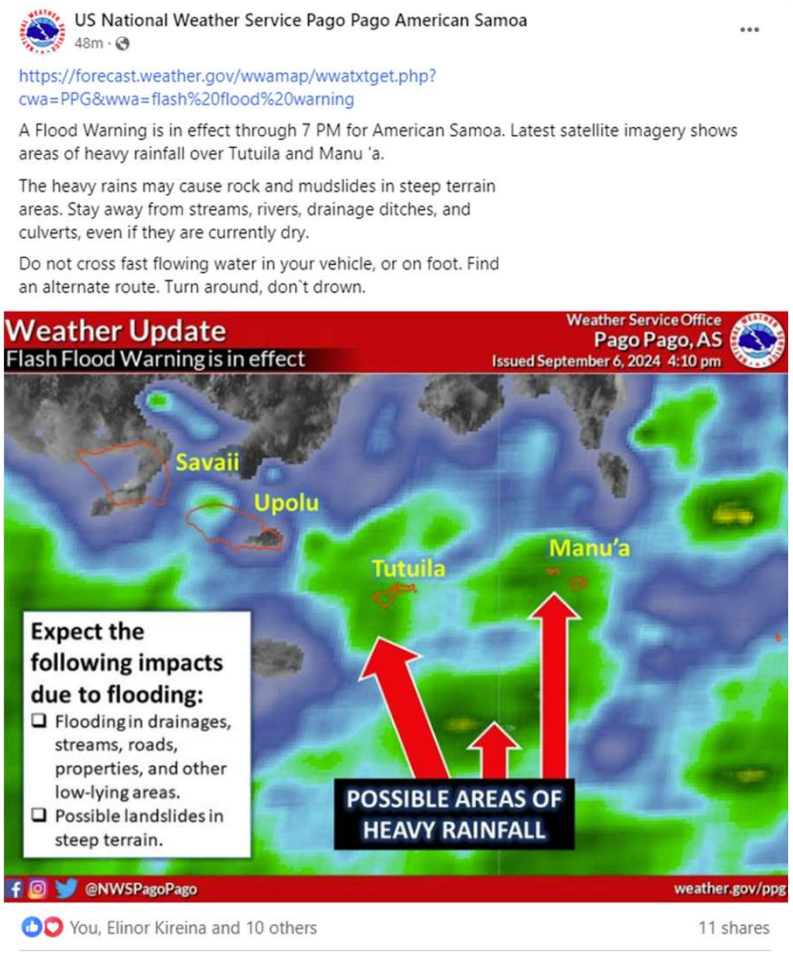
Realtime access

National Environmental Satellite, Data, and Information Service
DEPARTMENT OF COMMERCE

GREMLIN: GOES Radar Estimation via Machine Learning to Inform NWP

- Uses GOES-R ABI and GLM to predict weather radar reflectivity using a CNN.
- Real-time processing running on NOAA GeoCloud and available on AWS
- GREMLIN on AWIPS in the Cloud
- GREMLIN validation paper
  - https://doi.org/10.1175/JAMC-D-23-0103.1
- Demonstration at 2024 HWT
- Usage at Pago Pago (American Samoa) WSO
- GREMLIN at CIRA-SLIDER*:
  - https://rammb-slider.cira.colostate.edu

***Satellite Loop Interactive Data Explorer in Real-time**
***Hazardous Weather Testbed**
***Advanced Weather Interactive Processing System**



An example of GREMLIN being used for providing a weather update to the public. The intuitive display makes it a useful social media tool.

国土交通省 気象庁 Japan Meteorological Agency

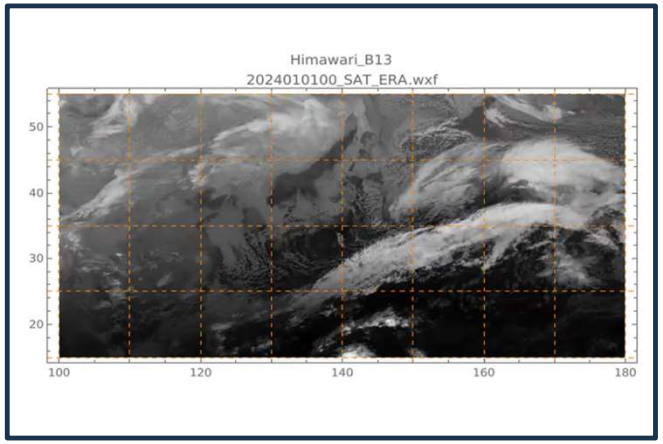
Direct retrieval from satellite data to products using AI/ML methods

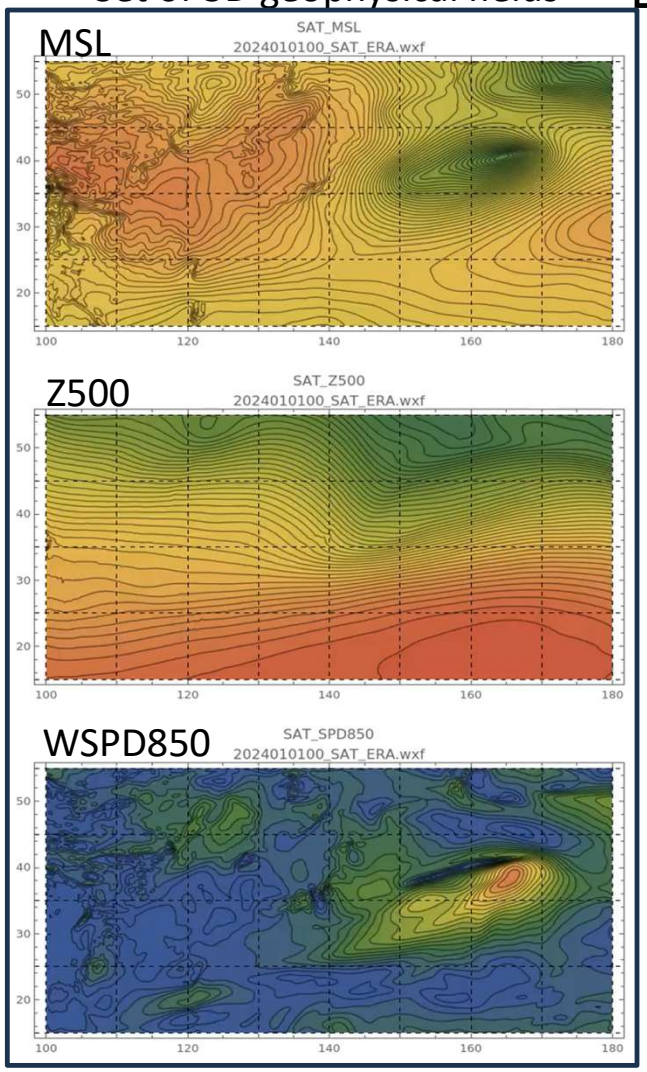
Input
Multi-channel satellite data

Output
Set of 3D geophysical fields

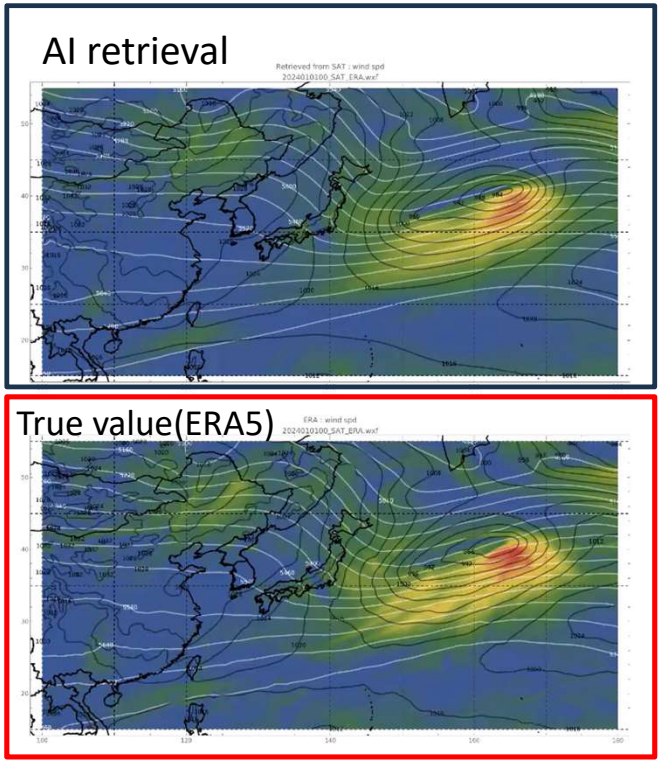
Products for forecasters

Uses time-continuous multi-channel data from imagers and sounders as input





Generate the Level-3 products forecasters need from the retrieved basic geophysical fields

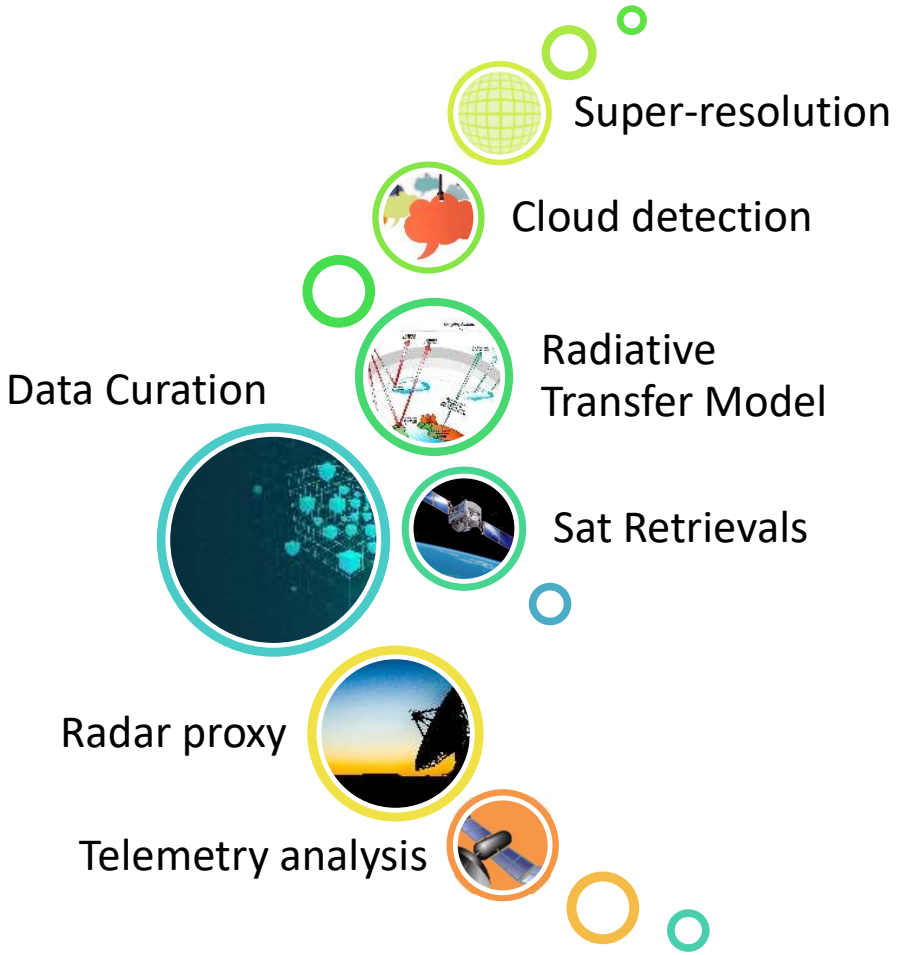


Visualization of retrieval results of wind speed field at 850hPa, geopotential height at 500hPa, and mean sea level pressure from Himawari-8/9 data in the region around Japan from January to February 2024.

AI EUMETSAT landscape

This cascade of use cases shows the main ML applications to satellite data in EUMETSAT.

Other key areas not considered in this figure, feature MLOps, using AI in operations and data query/exploration.



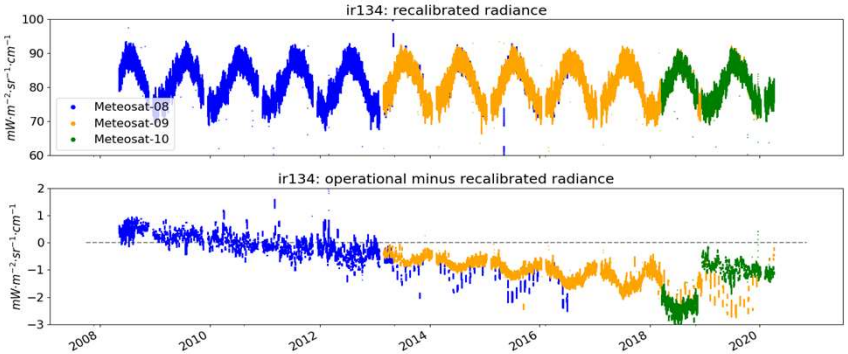
EUMETSAT

AI related products - examples

Climate data records provides excellent basis for training ML-models

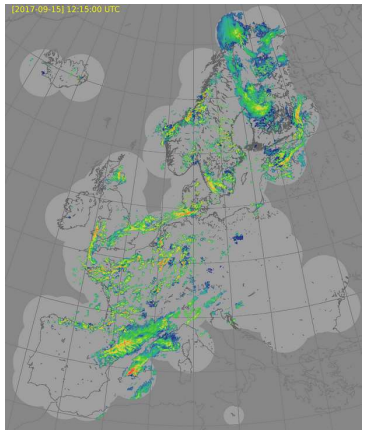
Machine learning models are at best as good as their training data
Training data must be 1) good quality 2) long-enough to contain sufficient variation 3) consistent and respective to the data used in interference phase
CDRs provide consistent long timeseries (40 years) with known quality

Consult info page and EUMETSAT Data Catalogue for more information

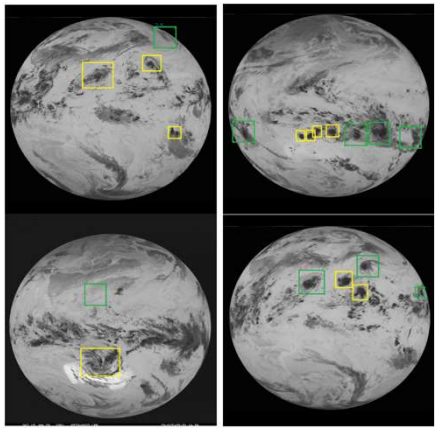


Time series of recalibrated radiance for IR channel 13.4 mm and MSG satellites 8-10. The upper plot shows recalibrated radiance, the lower plot operational minus recalibrated radiance.

EUMETSAT produced a combined dataset of SEVIRI, weather radar data, and lightning weather radar data for training ML-based nowcasting models



Systematic Earth system feature identification activity supports downstream applications and model development



EUMETSAT

Brief Summary of Uses

Address complex satellite forward and inverse problems; improve processing efficiency

Scene masking and identification from multispectral data

Customized products, short-term predictions of hazardous weather

Foundation models (e.g., Aurora) already used for medium range weather forecasts and advancing rapidly

Data-driven forecasts based on observations alone

Continued rapprochement & consultation between science WG's is encouraged