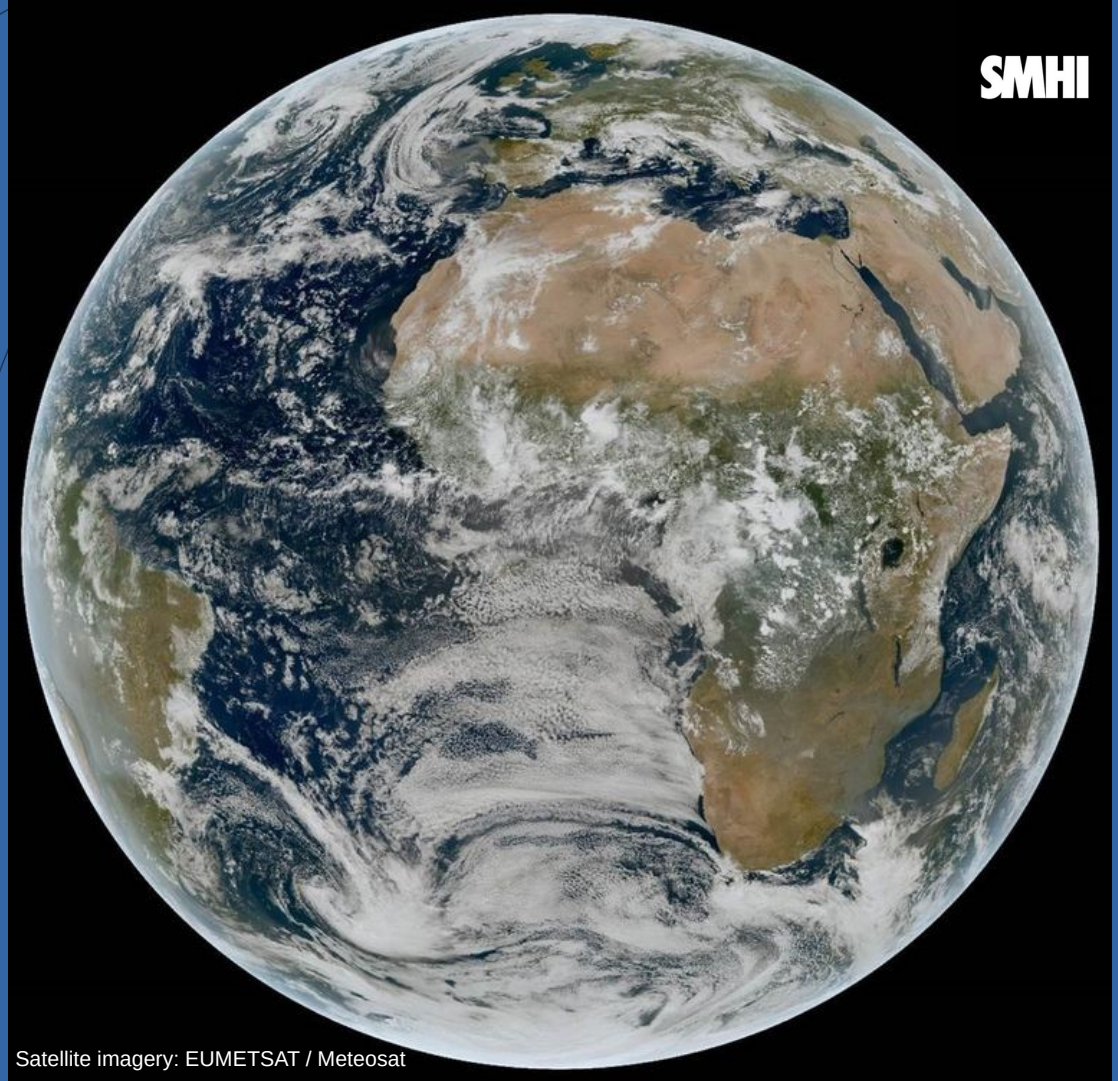
Opportunities, Limitations and Responsible AI use in the African Context

From Advances in AI weather prediction to Trustworthy Weather and Climate Services

Dwaipayan Chatterjee
Swedish Meteorological and Hydrological Institute



Satellite imagery: EUMETSAT / Meteosat

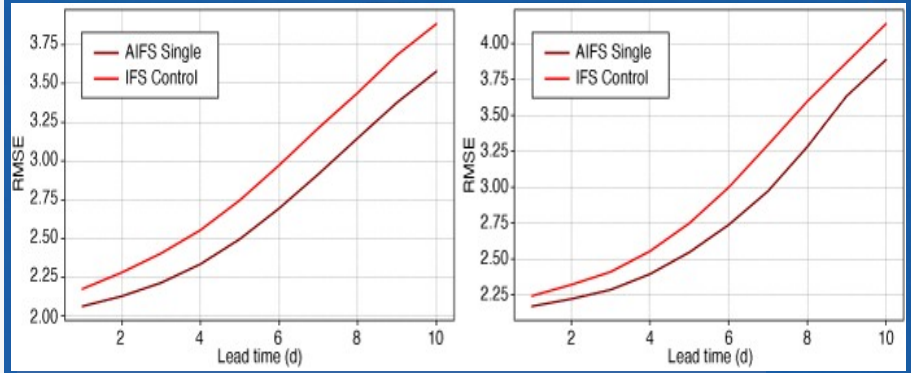
Can an AI model be globally skilful but locally unreliable?

Global performance

Strong average skill across many variables and regions

Regional reliability

Uncertain skill for local rainfall, convection and extremes



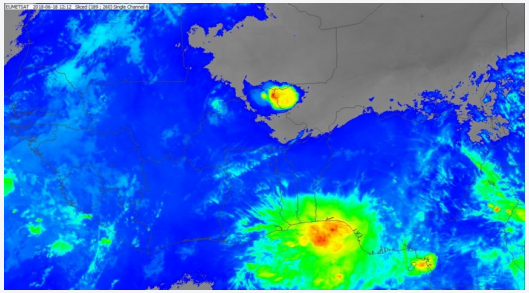
Ben Bouallègue, Janoušek & Olivetti, ECMWF (2025), Figure 1.

Global improvement ≠ guaranteed local improvement

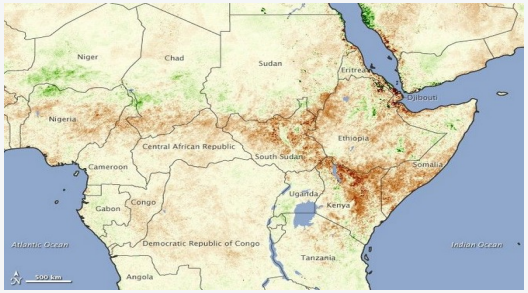
Satellite imagery: EUMETSAT / Meteosat

Africa is not one forecasting problem

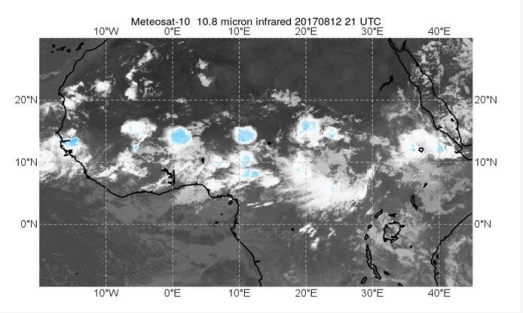
Different meteorological regimes demand different definitions of forecast skill



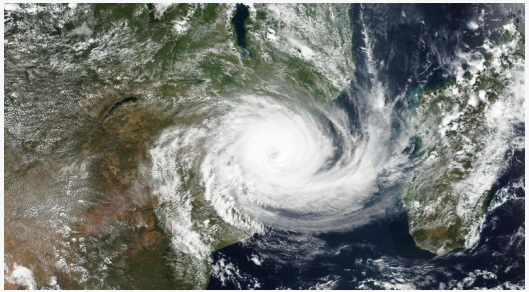
West Africa: Monsoon · Organized convection



East Africa: Seasonal rainfall · Drought



Central Africa: Deep convection · Cloud organization

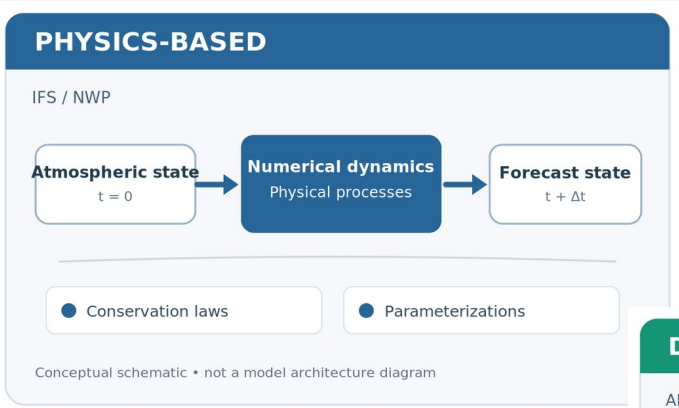


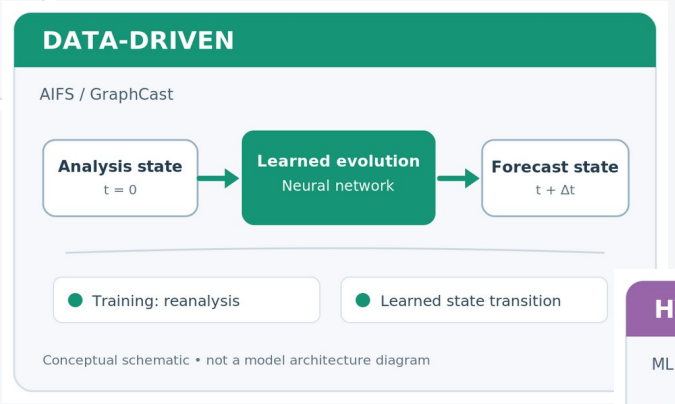
Southeast Africa: Tropical cyclones · Extreme rainfall

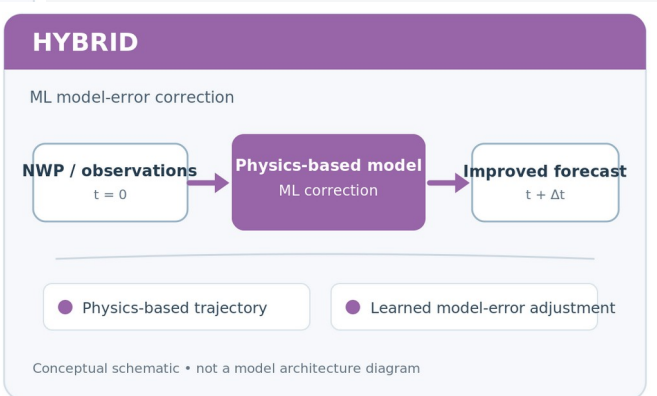
Different weather regimes → Different forecasting challenges → Different evaluation requirements

Image sources (TL → TR → BL → BR): EUMETSAT; NASA; ECMWF; EUMETSAT

A new prediction landscape



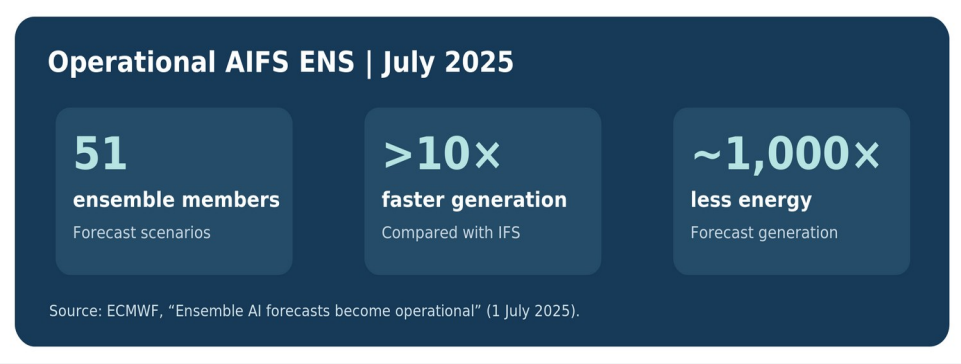




Opportunity 1: Fast and accessible weather prediction

AI inference can reduce the computational cost of weather prediction, enabling new forecasting applications.





What the comparison does NOT include

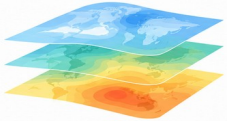
Training cost • Production of initial conditions • Data delivery
Operational maintenance • Local verification • Technical expertise

Lower inference cost ≠ zero operational cost

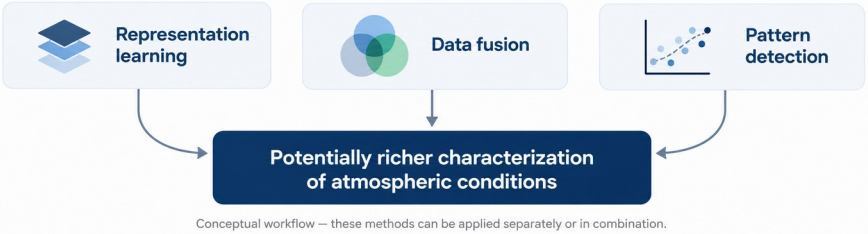
Opportunity 2: Extracting information from observations

AI can help make greater use of existing Earth observations

Complementary sources of atmospheric information

SATELLITES	GROUND STATIONS	REANALYSIS
		
Radiances and cloud patterns	**Rainfall, temperature, wind**	**Model + observations**
Broad spatial coverage	Local direct measurements	Spatially complete estimate

AI can extract, combine and interpret complementary signals



Conceptual workflow — these methods can be applied separately or in combination.

Opportunity — not a substitute for observations

AI can extract more information from observations, but cannot replace independent measurements.

Independent local measurements remain essential for evaluation.

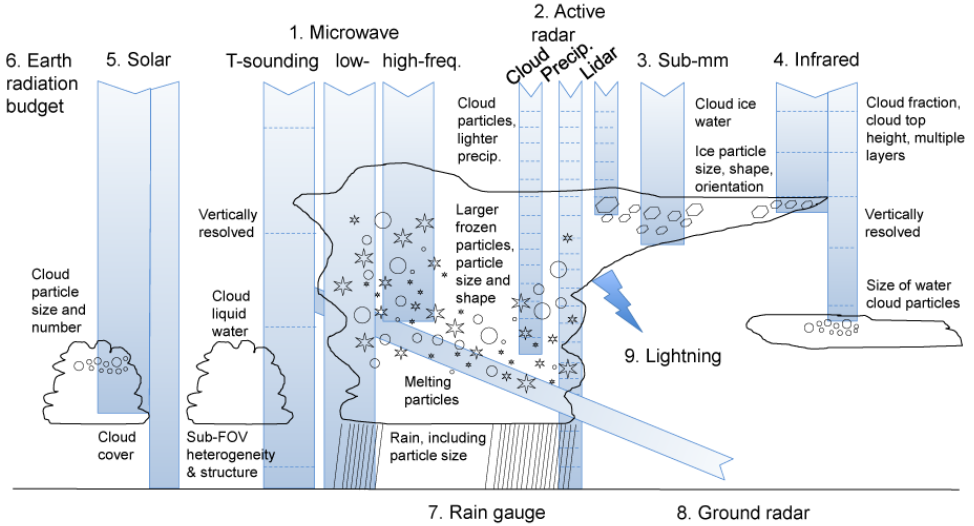
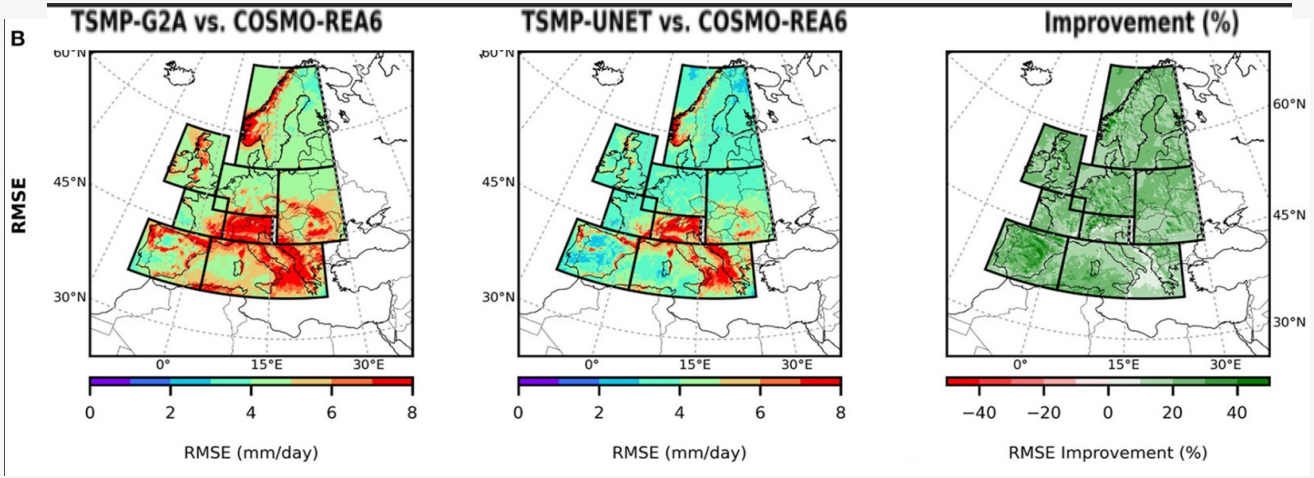


Image source: Geer 2017, ECMWF

Opportunity 3: Local adaptation of global information

A global forecast is often the starting point, not the final product.



01 **Bias correction**
Reduce systematic forecast errors

02 **Downscaling**
Estimate local-scale fields

03 **Calibration**
Improve probabilistic reliability

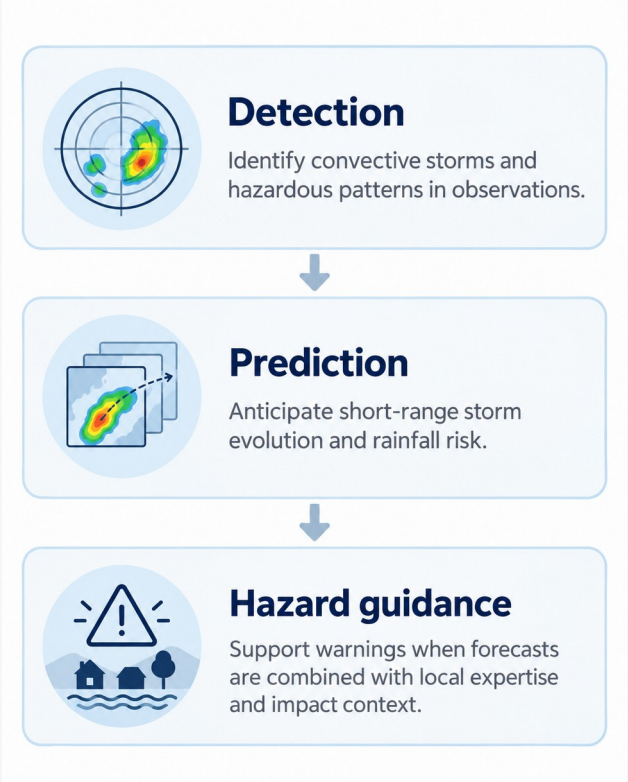
AI can improve regional precipitation estimates, but the gains must be evaluated locally.

Source: Fig 12, Yousefi et al 2023, panels B, E and H

Opportunity 4: High-impact weather and extremes

From identifying developing storms to anticipating hazardous weather

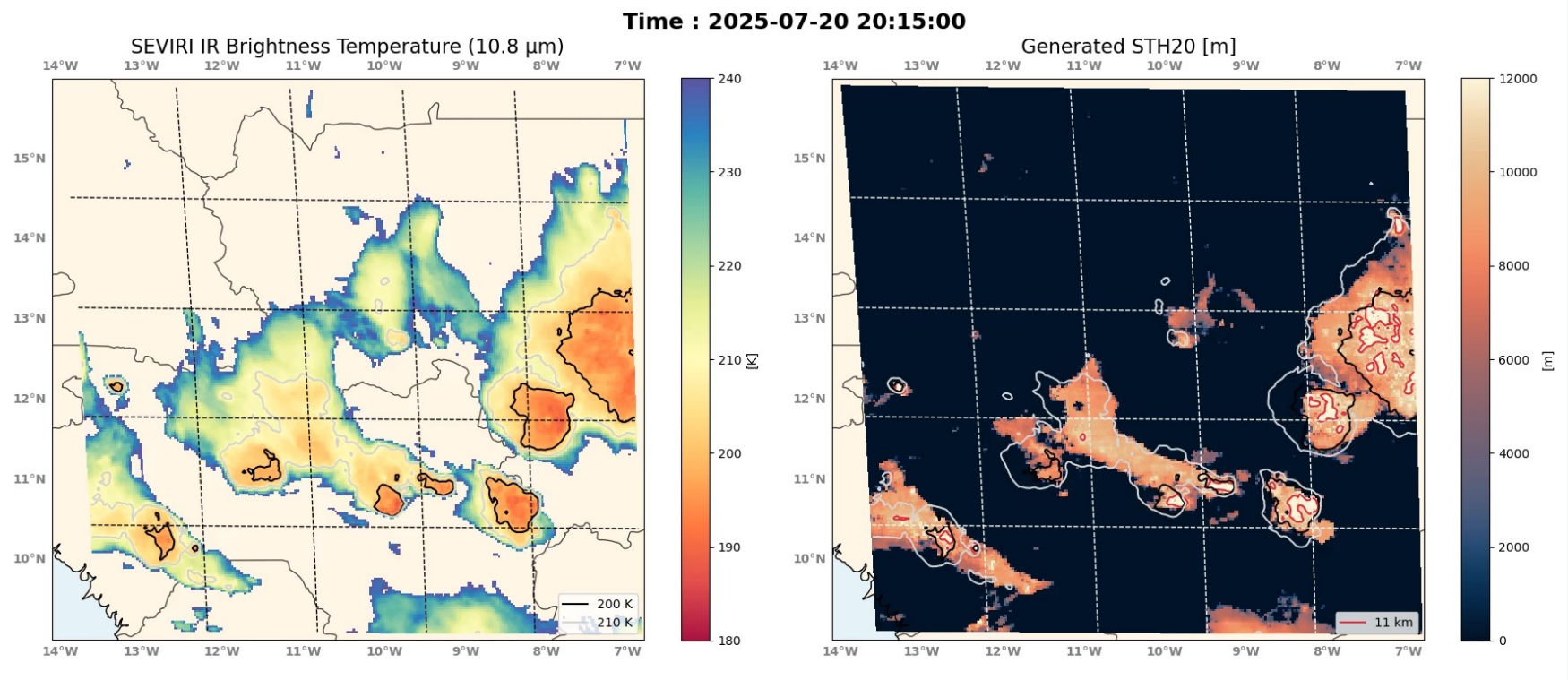




Detecting a storm is not the same as predicting its evolution or its impacts.

From geostationary imagery to continuous monitoring of deep convection

A generative deep-learning framework for estimating a radar-derived proxy of vertical storm extent



Netz et al 2026, under revision, AIES

Opportunity 5: From weather prediction to climate services

The value of AI is realised when predictions support decisions.

From forecast to agricultural decision support

Rainfall outlook
Weather / subseasonal / seasonal forecast

Local context
Observations, soil moisture, crop stage

AI / translation layer
Bias correction, downscaling, calibration

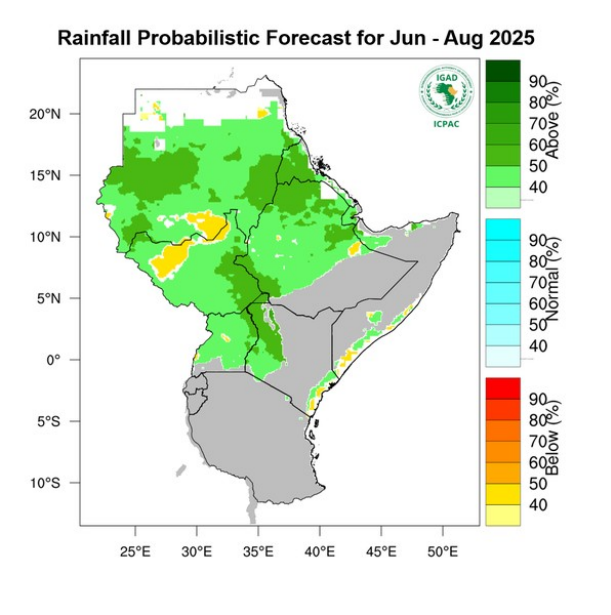
Decision-relevant information
Planting window, dry-spell risk, irrigation need

Action
Farmer advice and local planning

Prediction timescales and decision horizons

Weather	Subseasonal	Seasonal	Climate
Hours to days	Weeks	Months	Years to decades
Warnings, operations	Preparedness, planning	Agriculture, water resources	Adaptation, infrastructure

Different horizons involve different sources of predictability and different user decisions.



Better forecasts create value only when they become timely, understandable and actionable information.

Image source: ICPAC

Limitation 1: AI is only as informative as its training evidence

Data availability, data representativeness, and data quality are different problems.

Training-data challenges

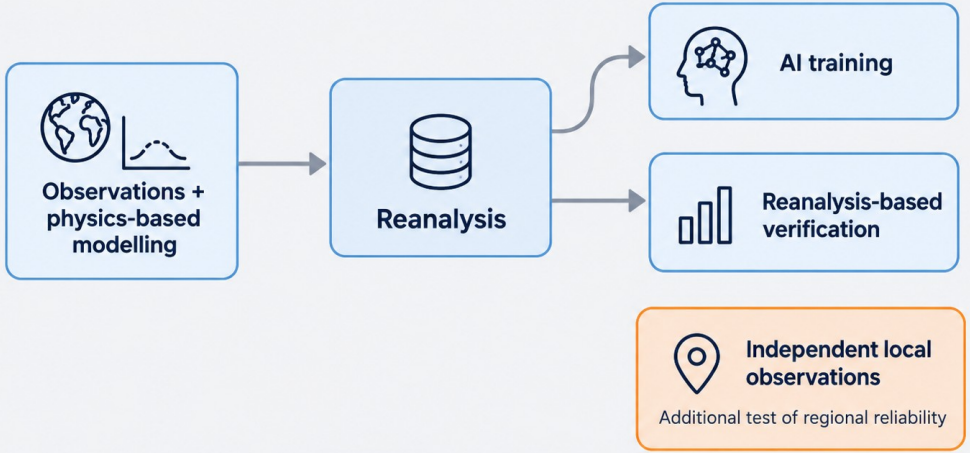
Sparse observations
Uneven station coverage limits local evidence.

Reanalysis uncertainty
Training data combine observations with model assumptions.

Rare events
Extremes are underrepresented in historical samples.

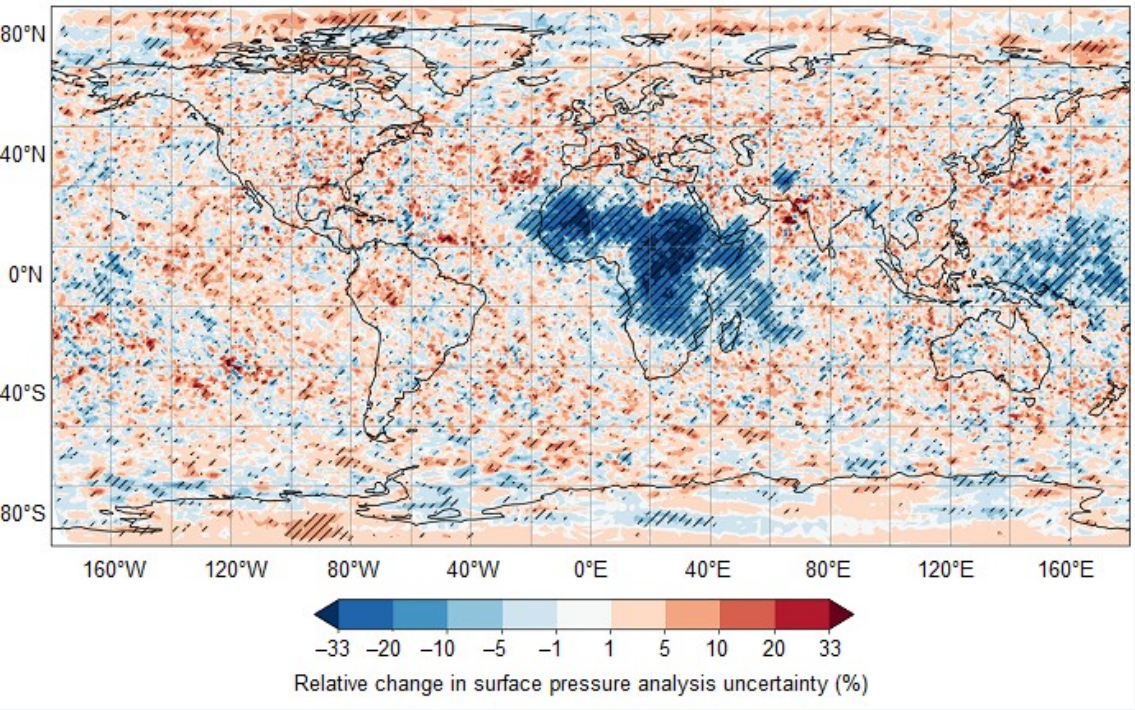
Changing observing systems
Sensors and reporting practices evolve over time.

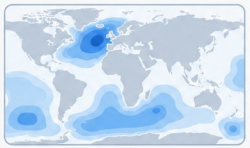
Training and verification are not always independent



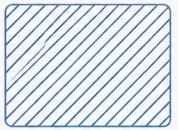
A model can perform well against reanalysis while still needing independent local evaluation.

Observational gaps have measurable consequences for forecast quality





Blue shading
Reduced surface-pressure analysis uncertainty



Hatching
Statistically significant improvement

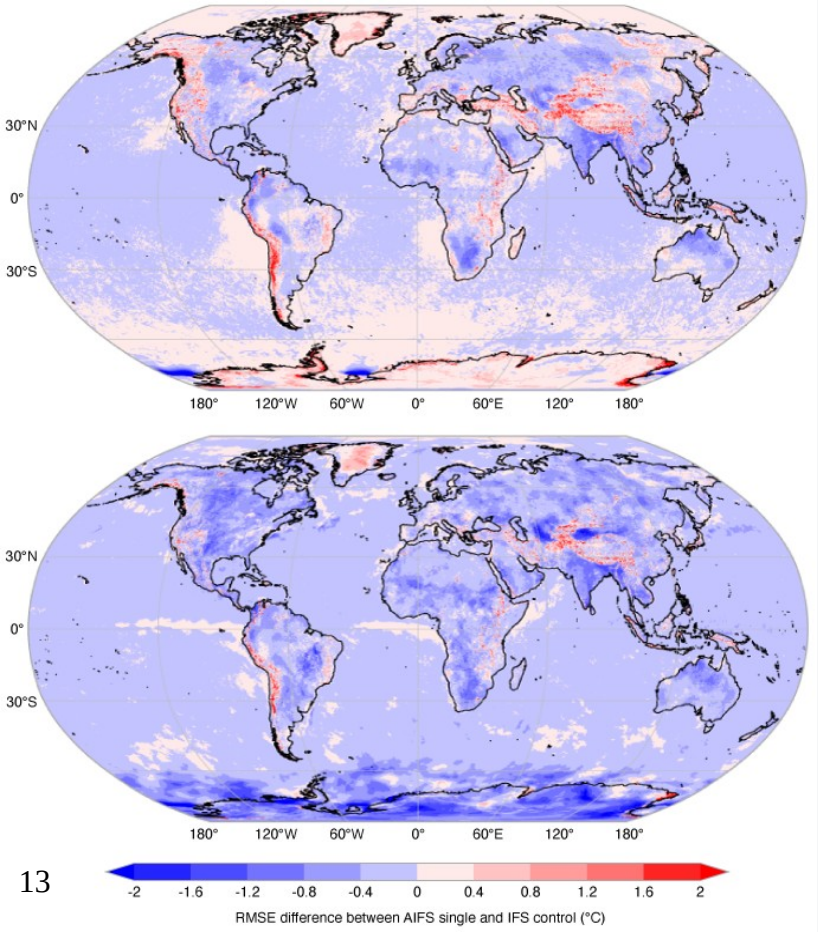
More observations can substantially reduce forecast uncertainty in Africa.

In WMO / ECMWF observing-system experiments, some high-impact African regions showed more than 30% reduction in forecast uncertainty.

Source WMO

Limitation 2: Global skill is not local skill

Improvements in average forecast performance may conceal substantial regional differences



Three questions for regional evaluation

WHERE? Region, terrain, coast, city

WHAT? Variable, process, event

WHEN? Season, lead time, weather regime

Regional skill depends on location, phenomenon and timescale.

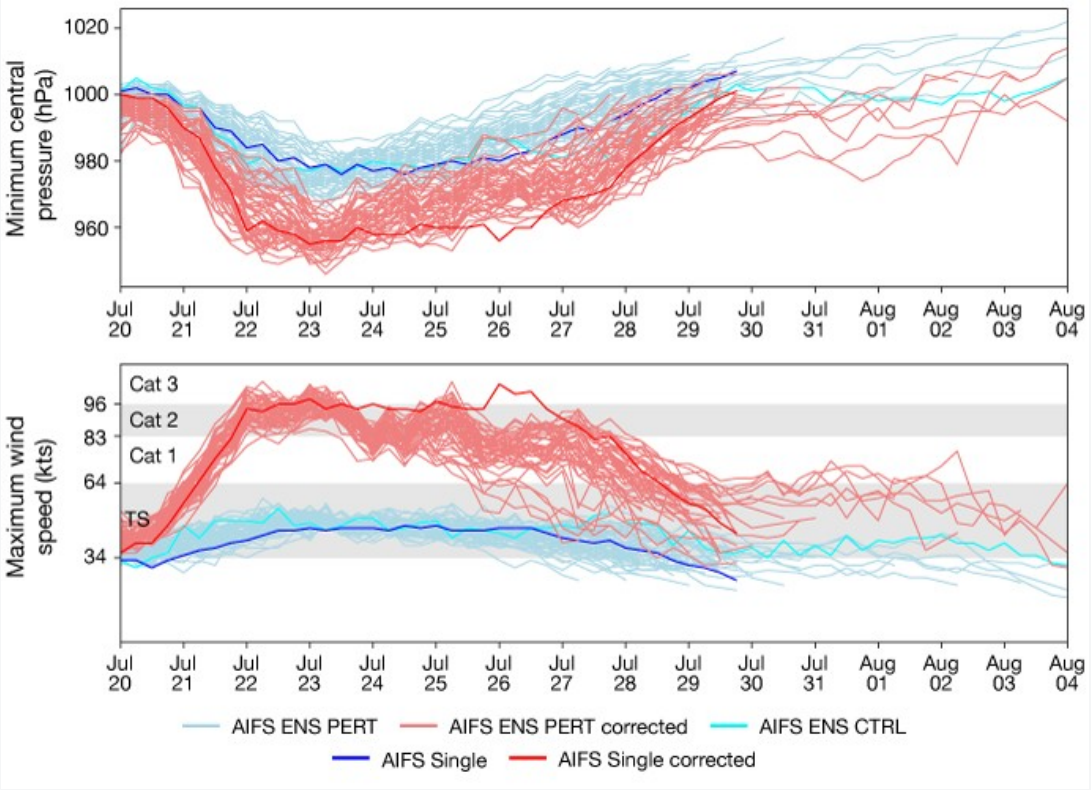
A globally better model is not necessarily the best model for every region, variable or event.

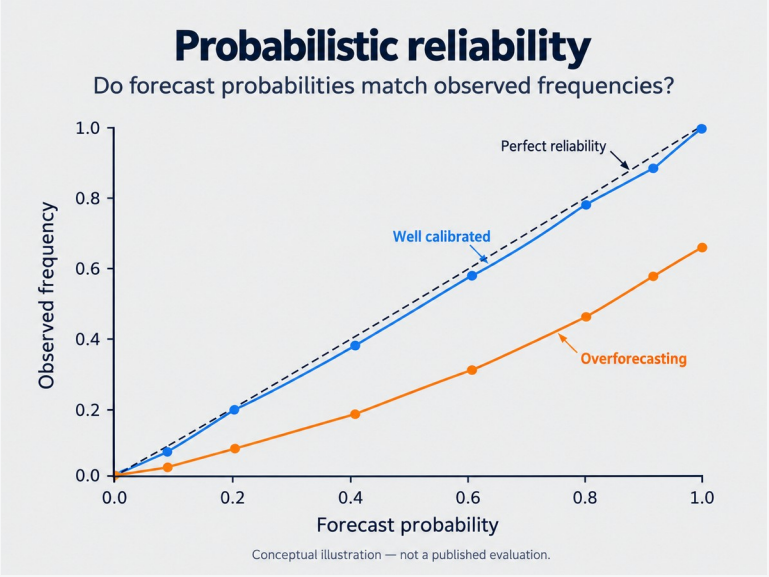
Image source: Ben Bouallègue, Janoušek & Olivetti, ECMWF (2025), Figure 2.

Limitation 3: Rare events and uncertainty

A small mean error does not guarantee a reliable extreme-event forecast.

SMHI





ML correction reduces mean tropical-cyclone wind-speed bias from approximately −29 to −2 kt.

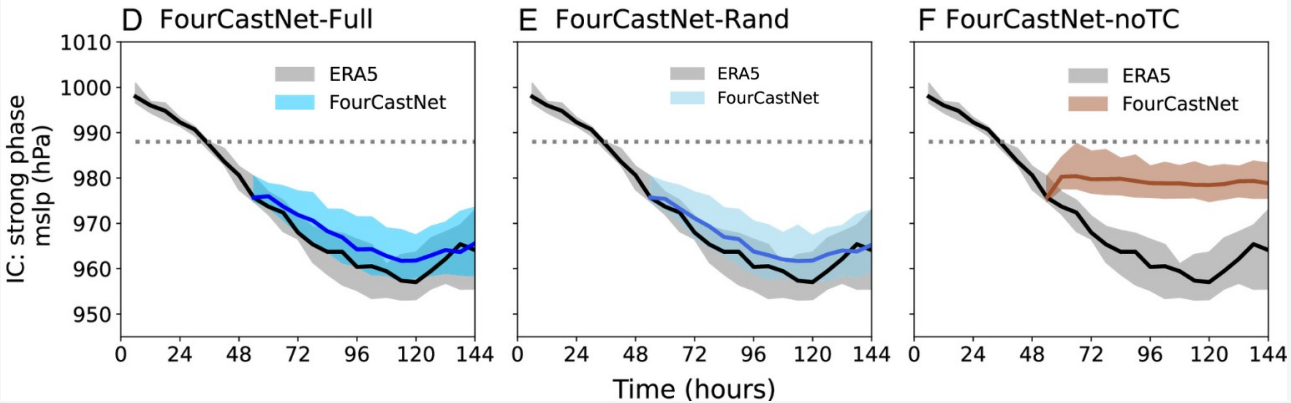
Image source: ECMWF

Skill for common weather does not establish reliability for rare, high-impact events

Limitation 4: Physical consistency and changing climate conditions

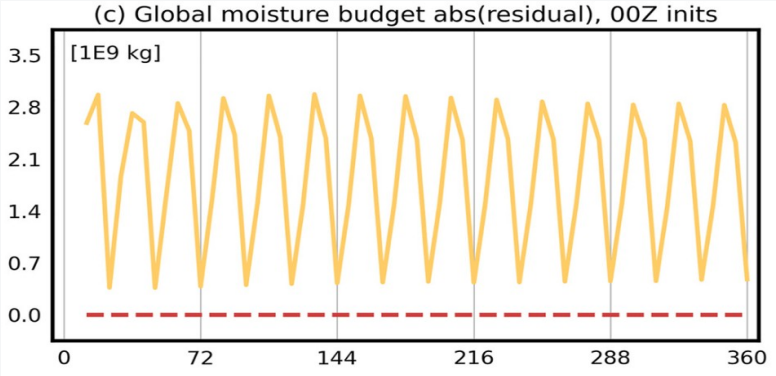
SMHI

Accurate predictions do not automatically imply physical consistency or reliable extrapolation



Can the model predict unseen extremes?

Generalization beyond training examples



Does the model obey the moisture budget?

Physical consistency

Forecast skill alone does not establish physical consistency or reliable extrapolation.

Source top, bottom: Sun et al, 2025, Sha etal, 2025

Limitation 5: Operational readiness is a different test

Scientific performance is necessary, but operational reliability requires much more

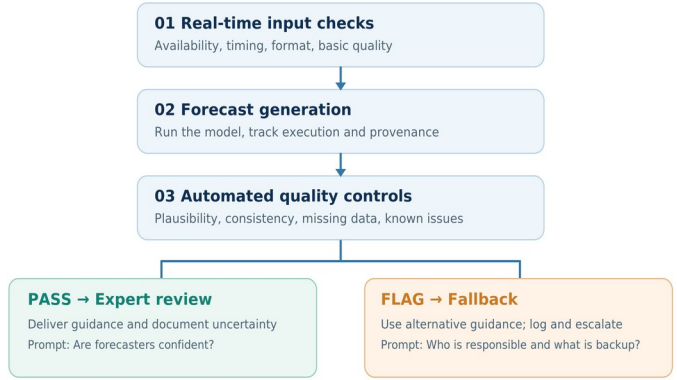
SMHI

From a successful prototype to a reliable service

RESEARCH PROTOTYPE	OPERATIONAL SERVICE
Curated historical data Offline and reproducible	**Real-time data and deadlines** Will inputs arrive on time?
Retrospective performance Fixed evaluation period	**Continuous skill monitoring** Does skill hold across seasons?
Experimental model version Research code and checkpoints	**Controlled updates and checks** What changes after an update?
Successful demonstration Selected test situations	**Fallback and staff responsibilities** Who acts if the system fails?

Talking point: Skill on a test set is only one condition for operational readiness.

Operational quality control and fallback



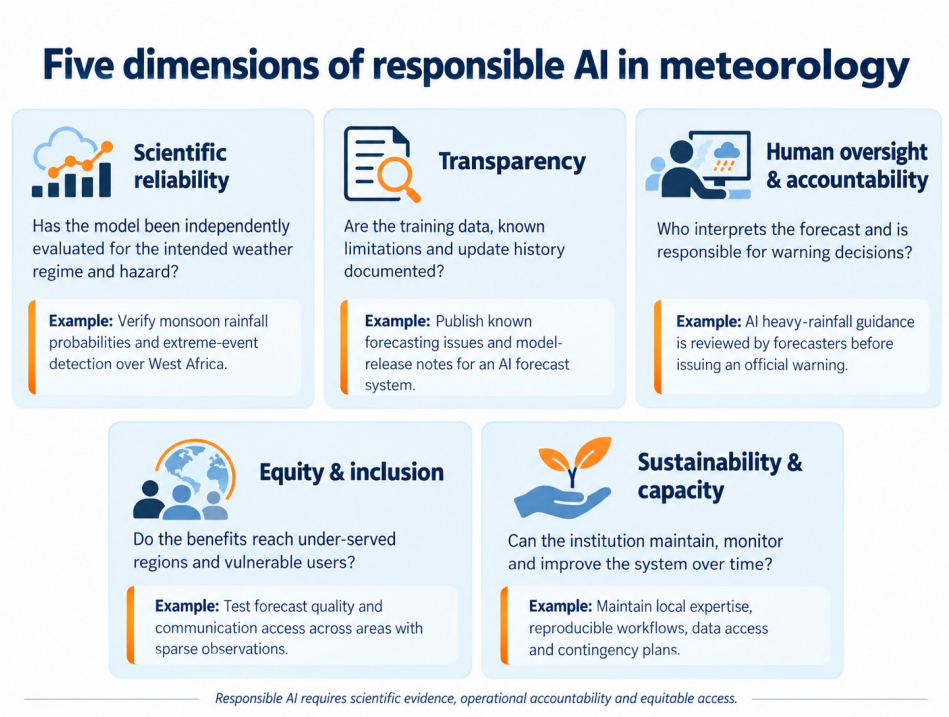
Conceptual workflow — exact controls depend on the forecasting institution.

Operational trust is more than the forecast skill

Further resources: ECMWF AIFS Single issues · AIFS ENS issues · Forecast-in-a-Box training

What does responsible AI mean in meteorology?

Trustworthy AI requires scientific evidence, operational accountability and equitable access



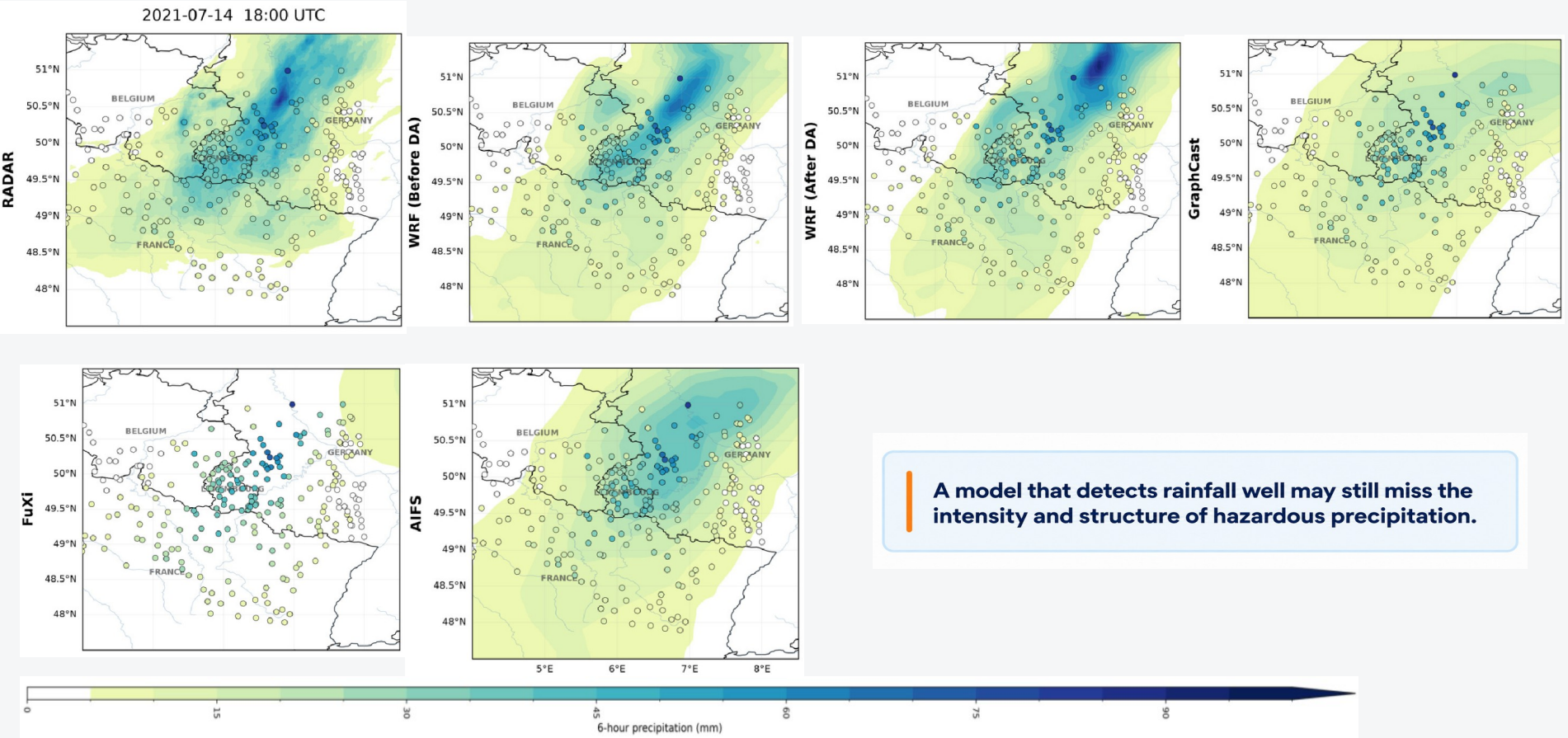
Responsible AI is not just about building better models — it is about building trustworthy forecasting services.

Scientific reliability • transparency • oversight • inclusion • sustainability

Source: WMO AI Conference Statement (2025)

How should we evaluate AI before using it?

AI weather prediction during the July 2021 European floods — Luxembourg and the Greater Region.



A model that detects rainfall well may still miss the intensity and structure of hazardous precipitation.

Rehman and Teferle (2026), Fig 12

Three messages to take away

SMHI



AI creates new opportunities

Faster prediction, greater use of observations, local adaptation, and improved weather and climate information.



Predictive skill is conditional

Performance depends on regional weather regimes, observational evidence, extreme events, physical consistency, and changing conditions.



Trust must be established through evidence

Independent evaluation, transparent limitations, human oversight, and sustainable local scientific capacity are essential.

? How do we move from **globally impressive AI models** to **locally trustworthy weather and climate services**?

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