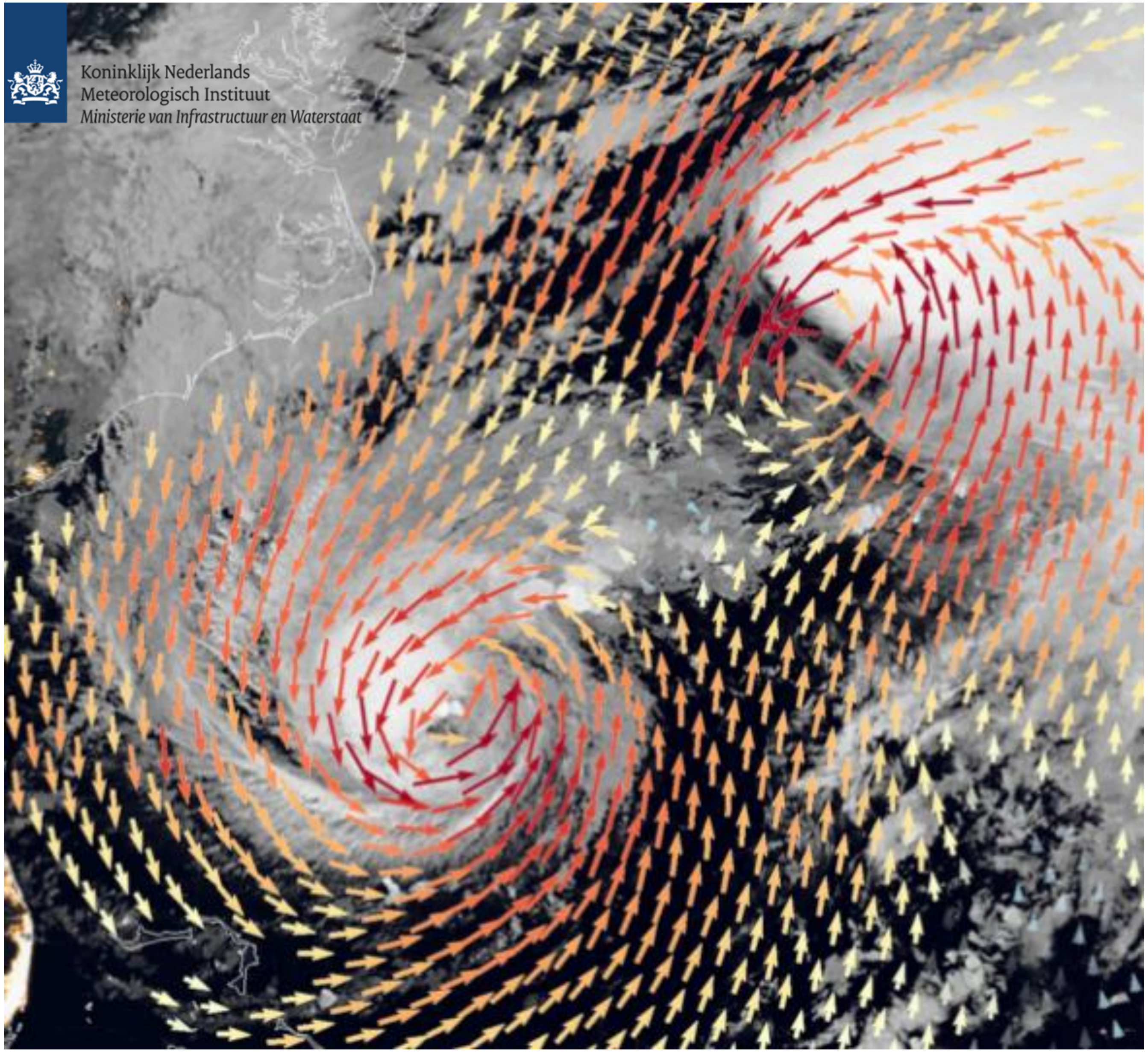
Ocean surface vector winds

Copernicus
Marine Service

EUMETSAT
OSI SAF

osi-saf.eumetsat.int



Climate Reanalyses
ERA5 -> ERA6 -> ERA7

Ad Stoffelen

- Head Active Remote Sensing Cluster -
R&D Satellite Obs. (RDSW)

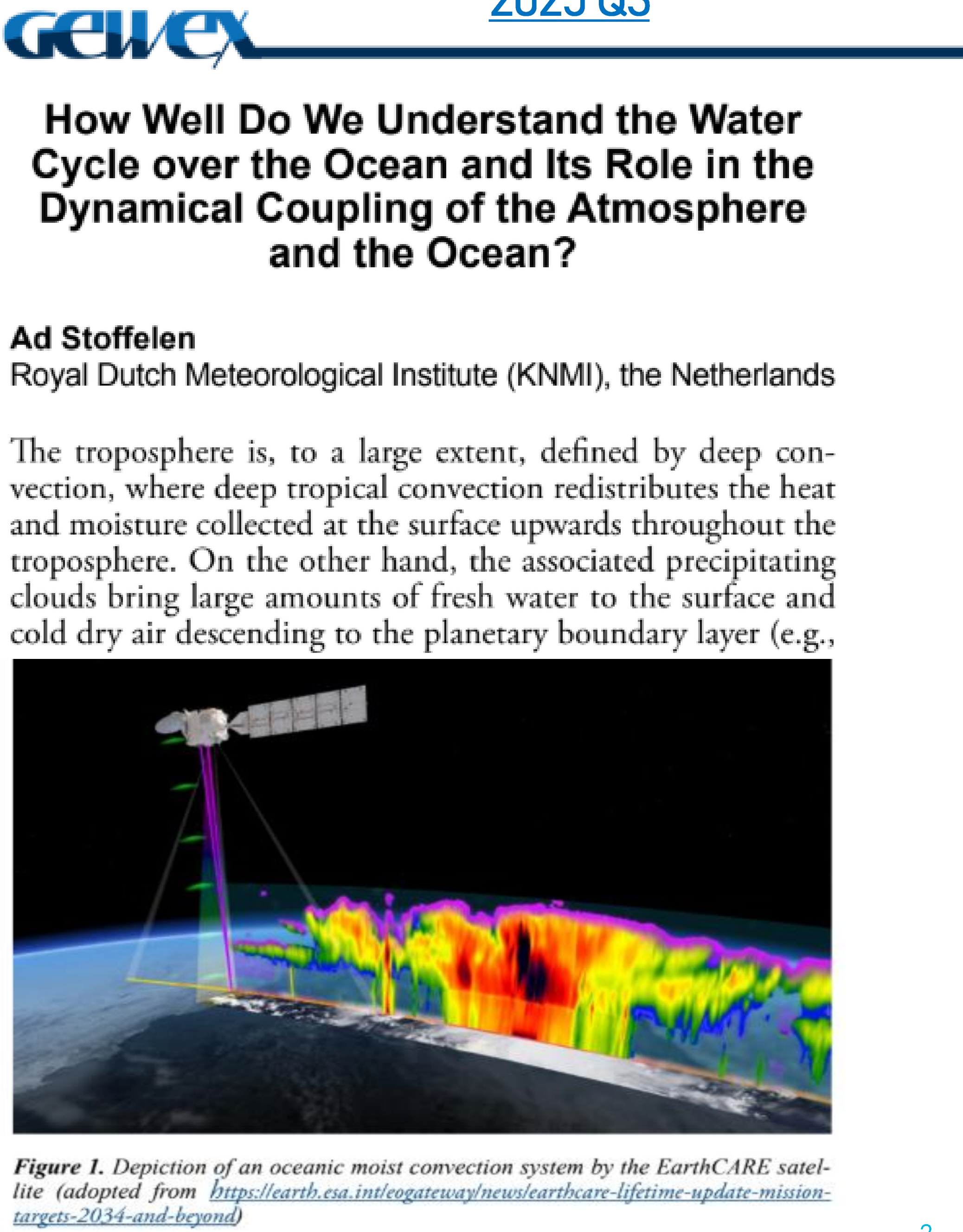
- ✓ Global ocean winds, 24/7 & Climate Data Records
- ✓ Hurricanes
- ✓ Wind profiles with Aeolus
- ✓ Radiation, aerosol and clouds with ESA EarthCare and Harmony
- ✓ Coupling the ocean and the atmosphere determines to a large extent climate dynamics

Climate questions we observe

- Are hurricanes getting stronger?
- Do global winds change?
- Is moist convection deepening, enhancing updrafts/downdrafts/rain?
- Do we understand basic cloud properties, cloud dynamics?
- Do we understand climate dynamics? How do El Nino, MJO, QBO, NAO, etc. change in a changing climate and how do climate models capture this?
- Do the substantial heat and carbon exchanges with the ocean change over time and in the future?
- How much can we trust climate reanalyses?
- Can AI/ML help reanalyses?

Aeolus, scatterometers, EarthCare, Harmony, . . .

2025 Q3



GEWEX

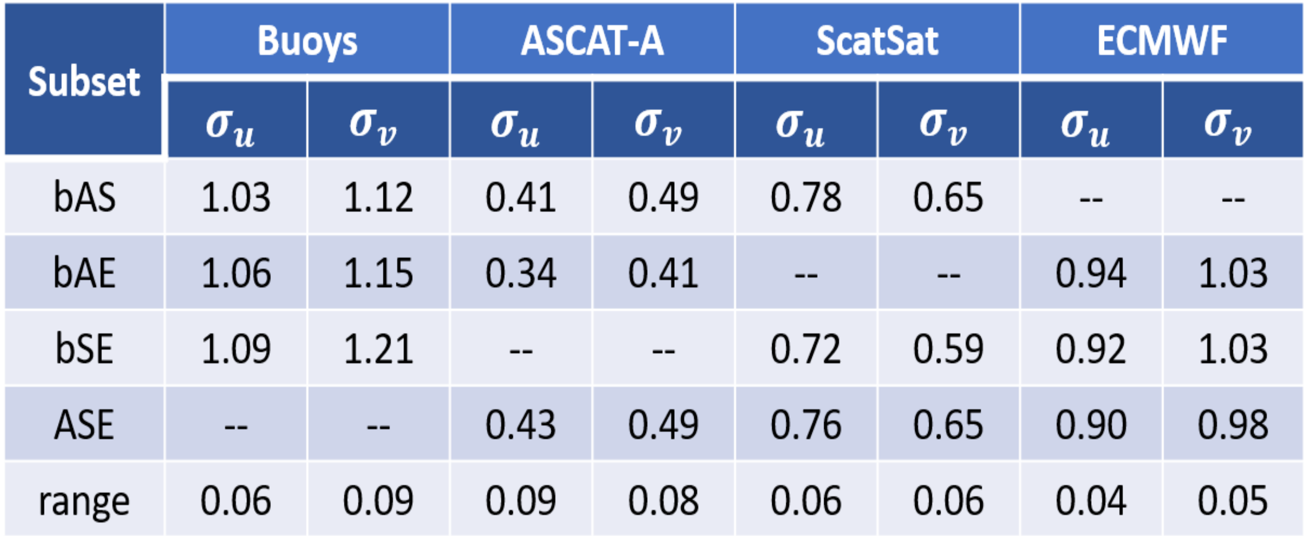
How Well Do We Understand the Water Cycle over the Ocean and Its Role in the Dynamical Coupling of the Atmosphere and the Ocean?

Ad Stoffelen
Royal Dutch Meteorological Institute (KNMI), the Netherlands

The troposphere is, to a large extent, defined by deep convection, where deep tropical convection redistributes the heat and moisture collected at the surface upwards throughout the troposphere. On the other hand, the associated precipitating clouds bring large amounts of fresh water to the surface and cold dry air descending to the planetary boundary layer (e.g.,

Figure 1. Depiction of an oceanic moist convection system by the EarthCARE satellite (adopted from https://earth.esa.int/eogateway/news/earthcare-lifetime-update-mission-targets-2034-and-beyond)

Scatterometer winds are excellent quality

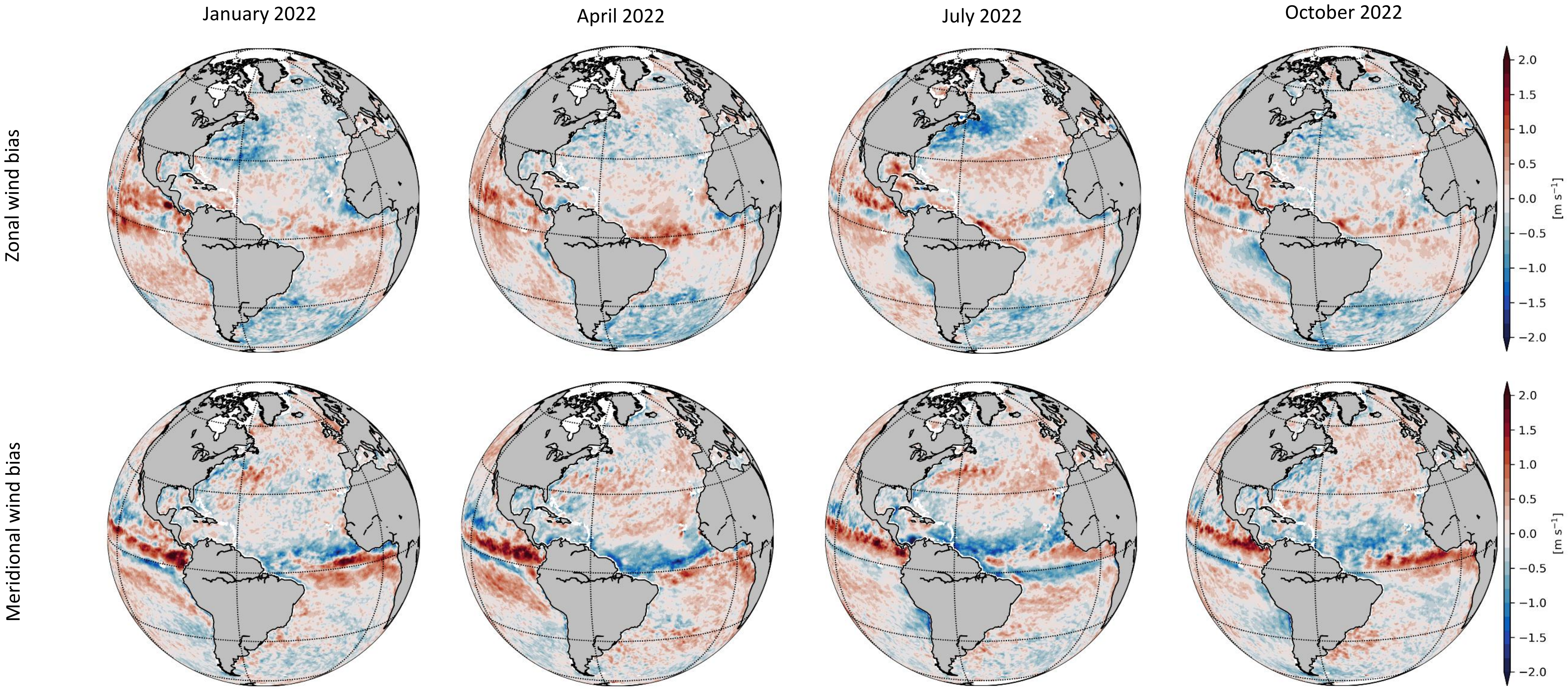


Subset	Buoys		ASCAT-A		ScatSat		ECMWF	
	σ_u	σ_v	σ_u	σ_v	σ_u	σ_v	σ_u	σ_v
bAS	1.03	1.12	0.41	0.49	0.78	0.65	--	--
bAE	1.06	1.15	0.34	0.41	--	--	0.94	1.03
bSE	1.09	1.21	--	--	0.72	0.59	0.92	1.03
ASE	--	--	0.43	0.49	0.76	0.65	0.90	0.98
range	0.06	0.09	0.09	0.08	0.06	0.06	0.04	0.05

Jur Vogelzang and Ad Stoffelen, 2022a, 2022b, 2021

- Scatterometers winds and stresses are unbiased with respect to moored buoys and have the smallest random error among in-situ and NWP winds
- Added better ability to approximate the errors of the errors in triple collocation
- ASCAT has only 10% speed error in hurricane conditions (no saturation; Ni et al., 2022)
- Confirms the excellent accuracy of scatterometer winds
- Stress-equivalent 10-m buoy and ECMWF winds, taking out air stability and mass properties
- KNMI processes all scatterometer winds globally to L2, L3 and L4 products in the EUMETSAT OSI SAF and the EU Copernicus Marine Services for NRT and CDR

SC: Metop-B/C
ASCAT
ECMWF ERA5



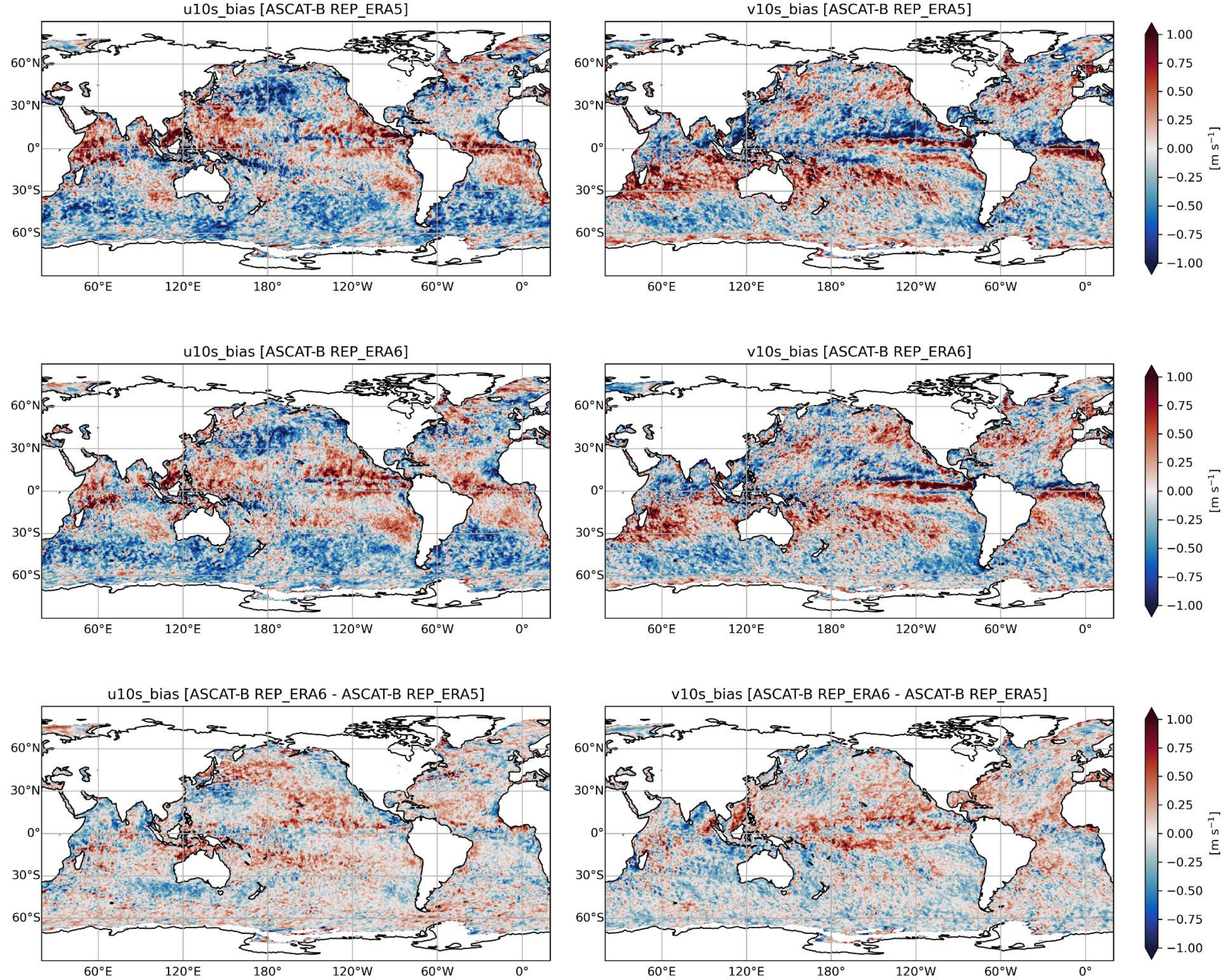
- The operational global ECMWF model and ERA5 renalyses are superior!
- Large model biases much beyond scatterometer uncertainty in ERAi, ERA5, OPS and ERA6 (prototype)
- Also substantial ECMWF model biases in wind variances on <100km scales and in time/space gradients

Giesen & Stoffelen, Quality Information Document on (corrected) hourly winds/stresses ; Steenge et al. (2024) on Divergence and curl biases

L3 scatterometer-model biases:

- u10s and v10s
- ERA6 vs ERA5
- ERA6 is coupled with waves and ocean

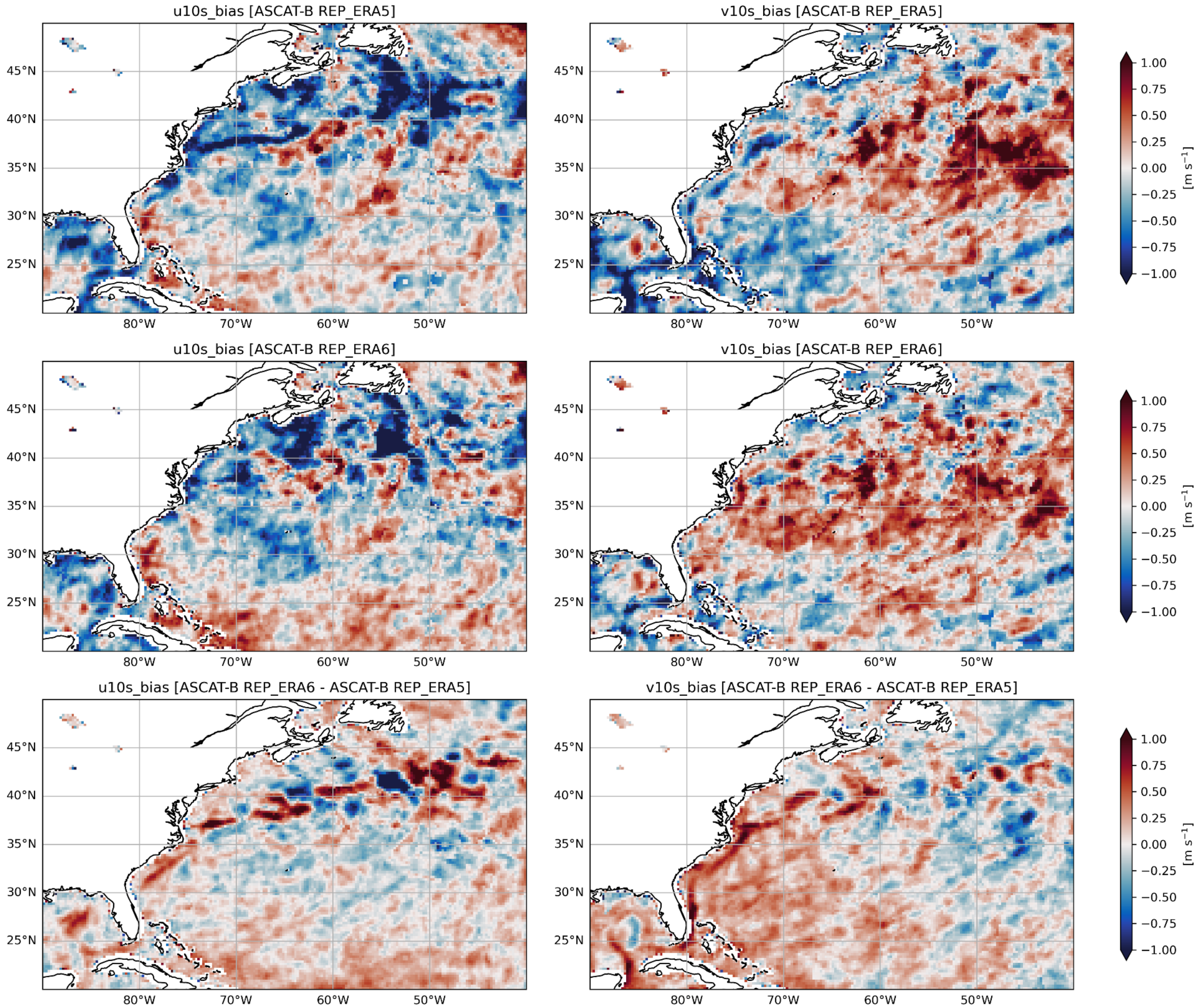
> Some changes
> Little statistical improvement
> More physically plausible errors



20 day average:
1-20 January 2020

L3 scatterometer-model biases:
- u10s and v10s
- ERA6 vs ERA5
- Gulfstream

> Note that ERA6 eddies can be misplaced
> Errors remain complex



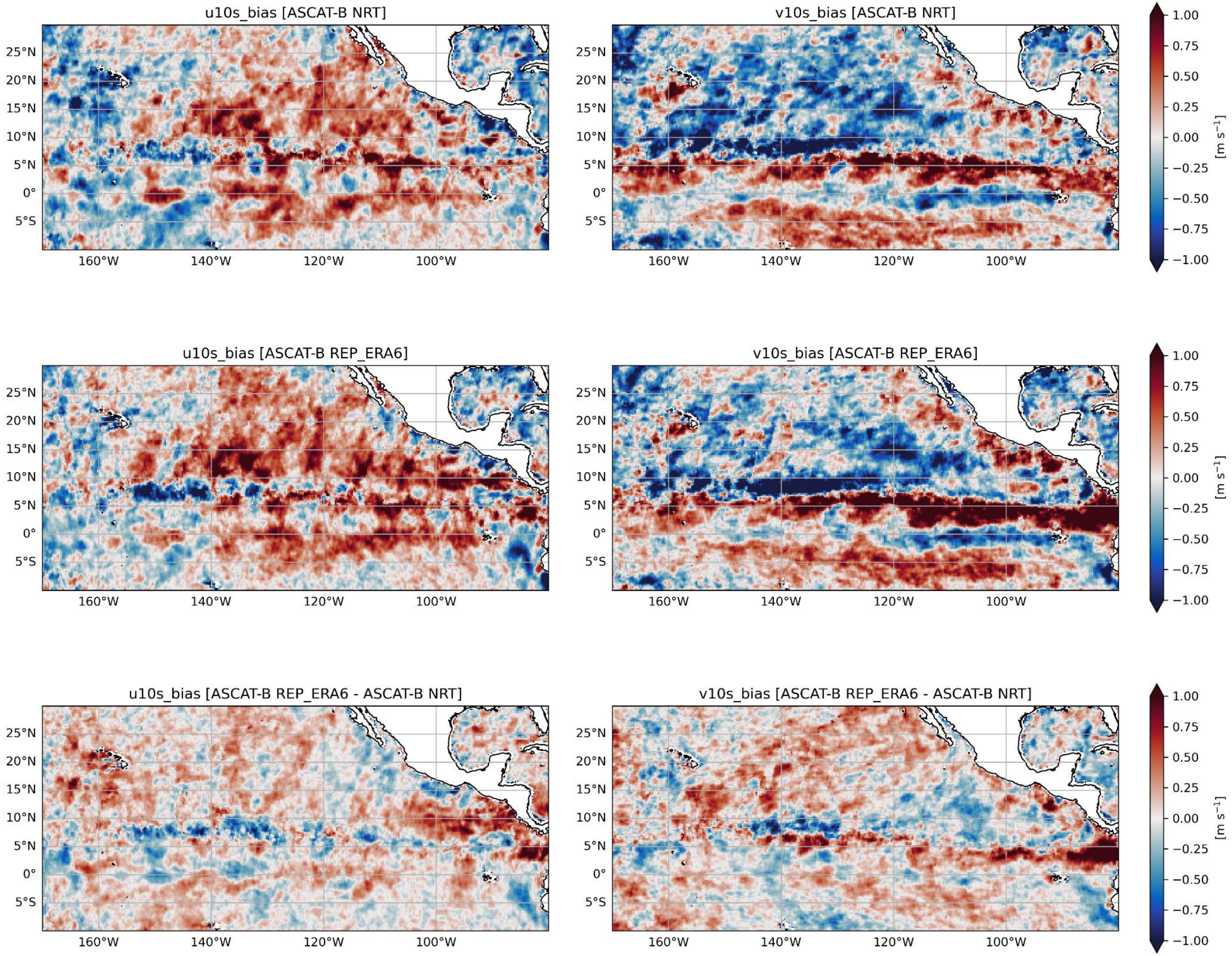
20 day average:
1-20 January 2020

L3 scatterometer-model biases:

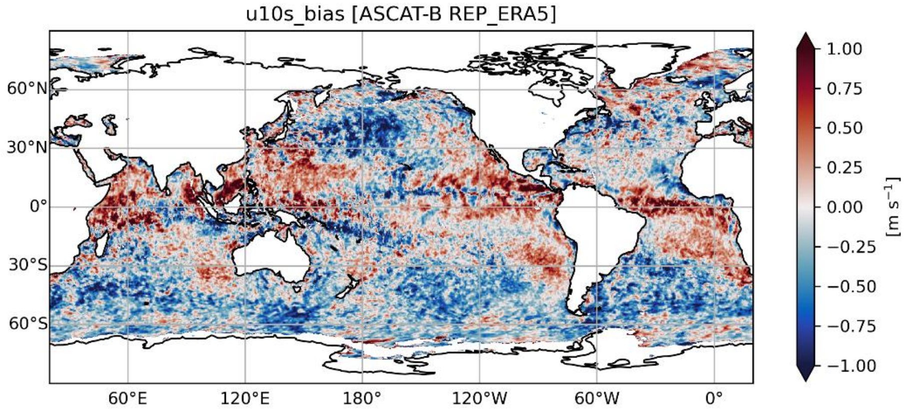
- u10s and v10s
- ERA6 vs OPS
- Similar model
- tropical Pacific

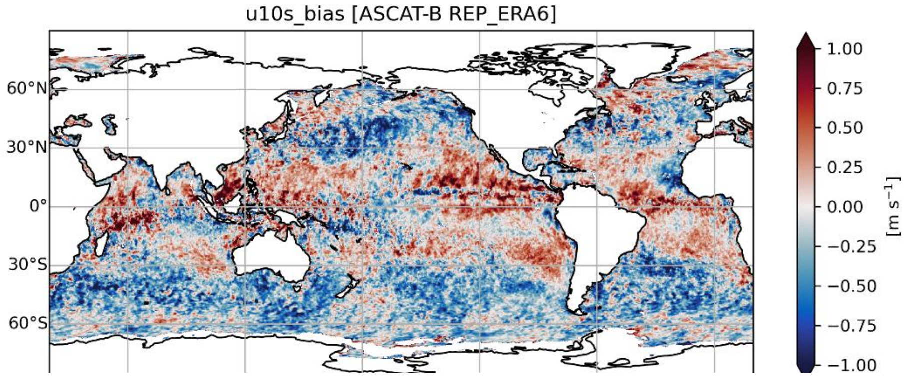
> ITCZ OPS errors smaller
> NH extra-tropical errors larger

20 day average:
1-20 January 2020

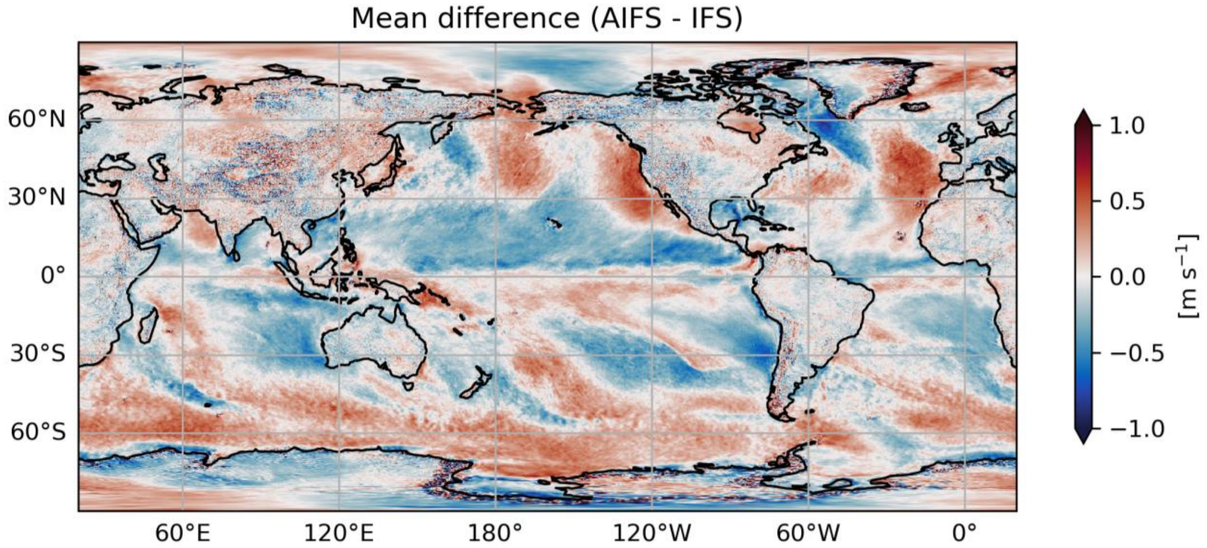


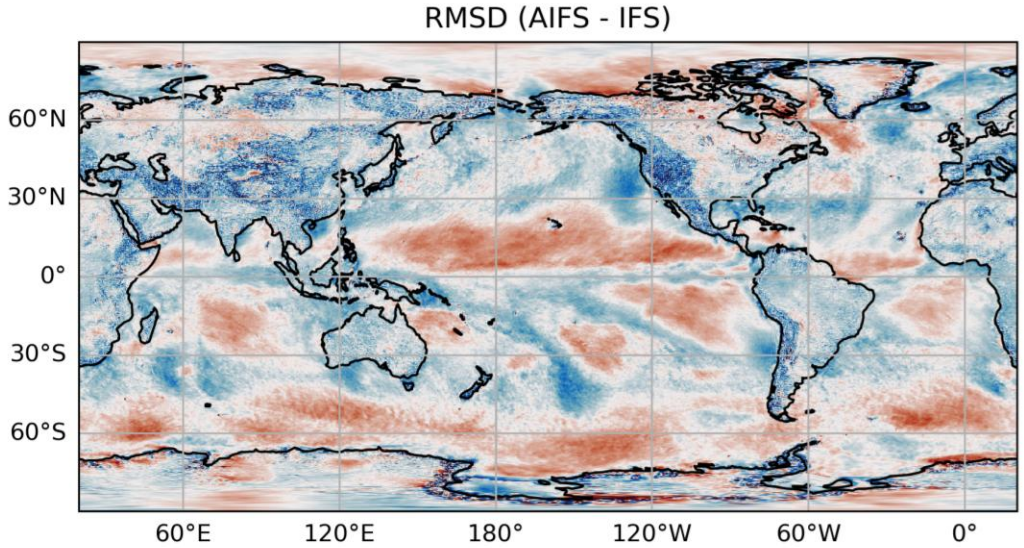
L3 scatterometer-model biases:
- u10s and v10s
- ERA6 vs ERA5
- global


u10s_bias [ASCAT-B REP_ERA5]


u10s_bias [ASCAT-B REP_ERA6]

- AIFS is learned on IFS, not informed using observations or using model output statistics
- AIFS – IFS differences are smaller than IFS-ASCAT differences
- Mean errors (left) added to top plots to approximate ASCAT – AIFS, but does not obviously clear (NH) biases


Mean difference (AIFS - IFS)


RMSD (AIFS - IFS)

Royal

CHERRI: Climate Hazards Enhanced Reanalyses & Reasoning with AI

(HORIZON-CL4-2025-02-SPACE-41)

23/09/2025

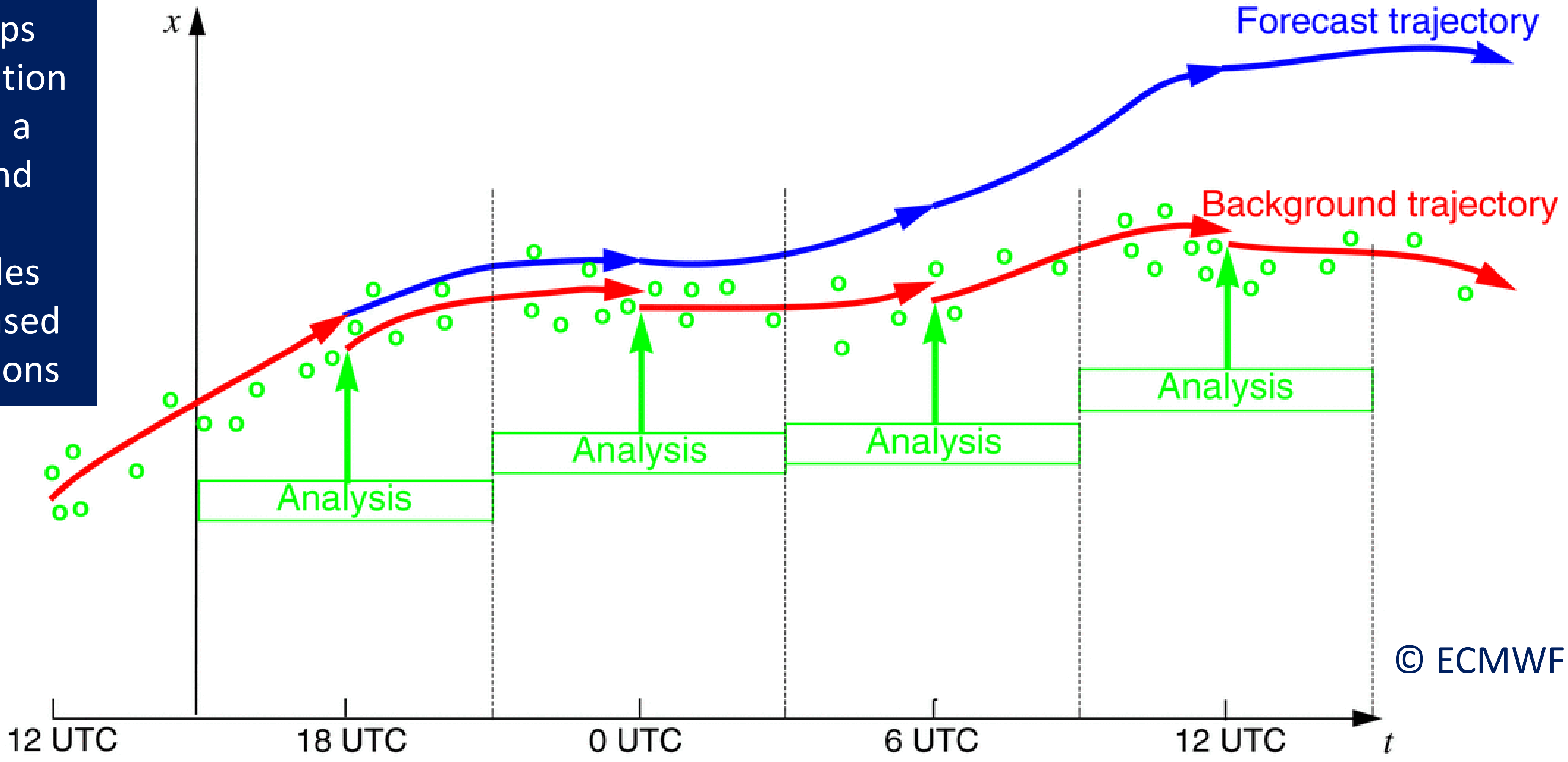
Pete Weston, PI

- ✓ **NWP – Numerical Weather Prediction**
- ✓ **AIWP – AI Weather Prediction**
- ✓ **DOP – Direct Observation Prediction**

Prototypes to prepare for ERA7

Observations steer weather models (NWP)
- Data Assimilation -

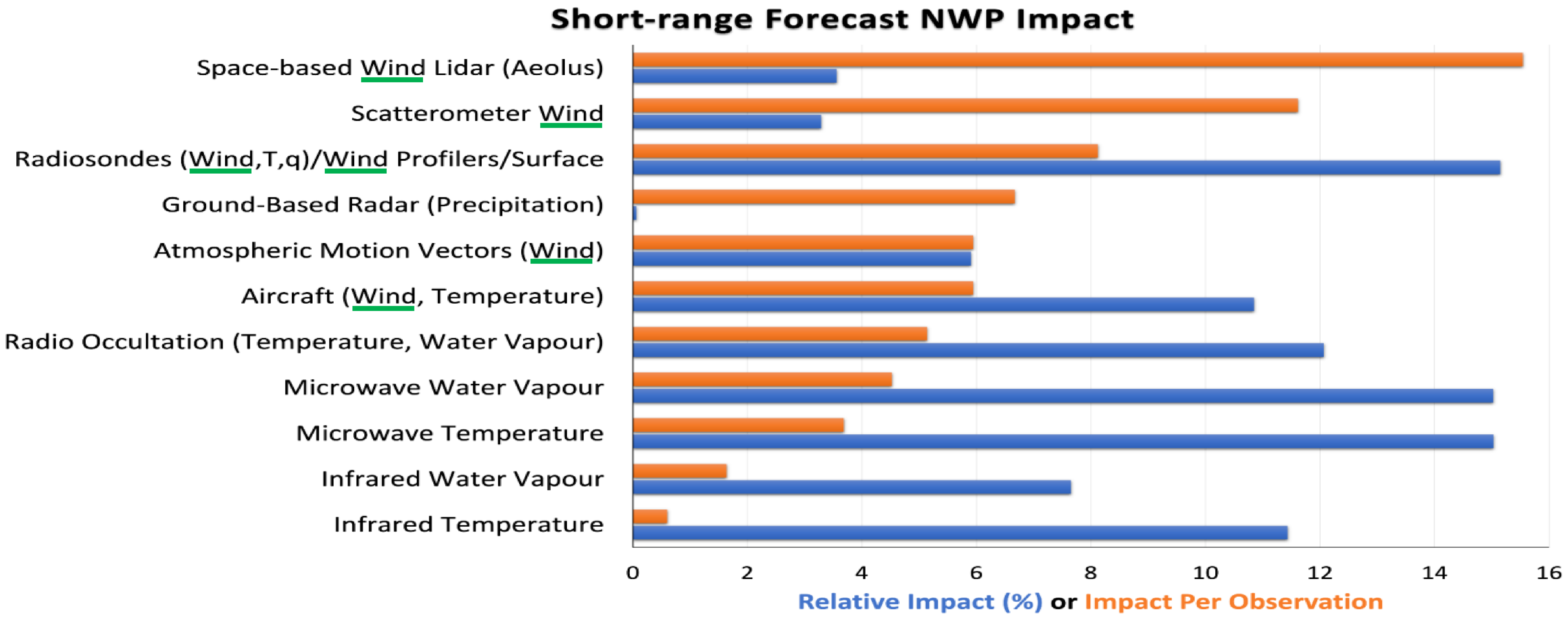
- AIFS changes the red and blue arrows
- AIFS may skip steps
- In Direct Observation Prediction (DOP), a future location and time is targeted (lead) and variables are forecasted based on past observations



© ECMWF

- Series of weather analyses determine climatology

What does IFS say contributes most today?



Short-range Forecast NWP Impact

- ➢ Wind obs. contribute the most based on projected IFS impact, in line with dispersion relationships

Can ML help low TRL?

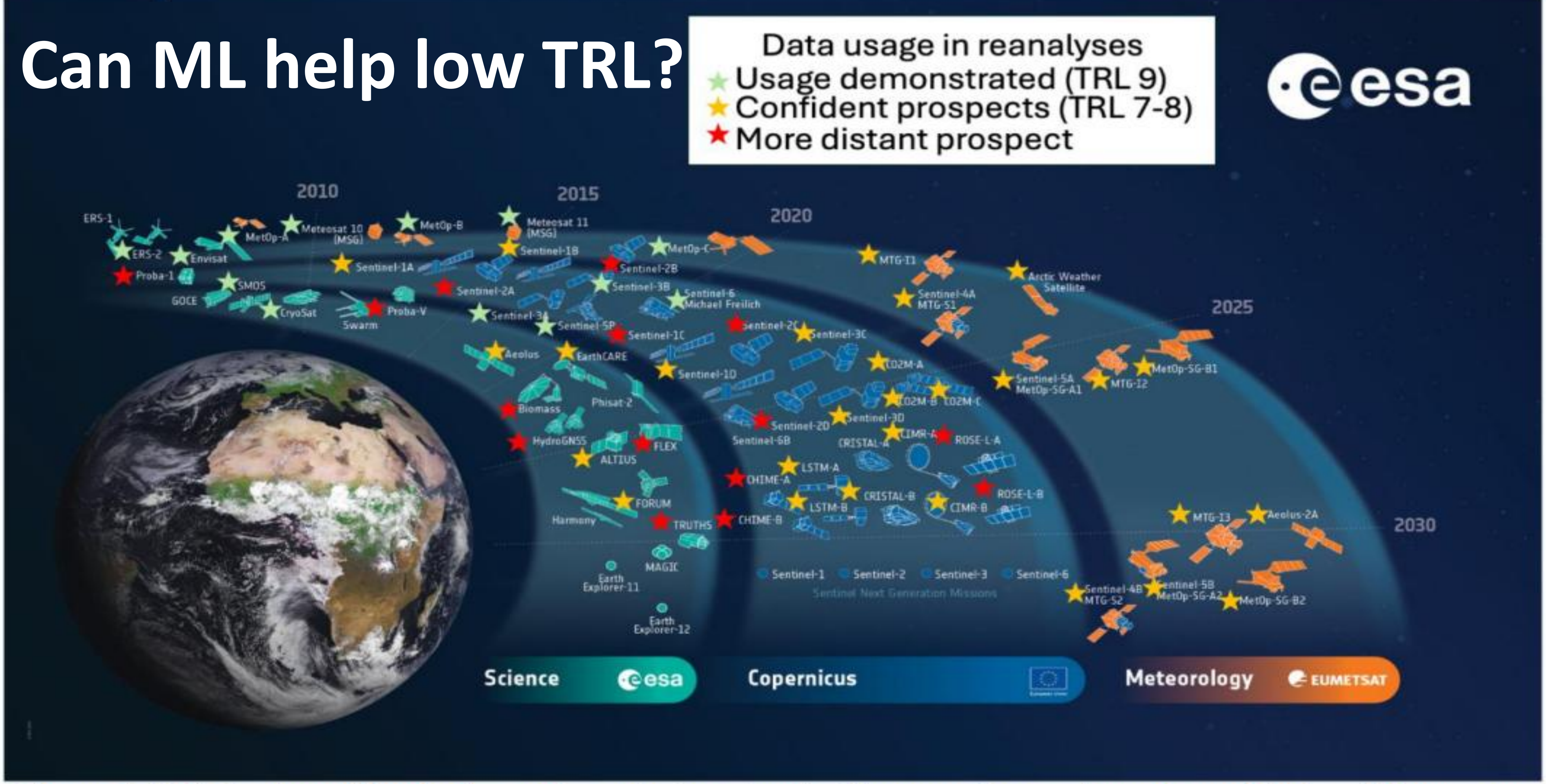


***Figure 1**. ESA-developed Earth observation missions (credit: European Space Agency), modified as follows: stars (and legend) indicate the usage of observations in climate reanalyses, and the corresponding Technical Readiness Level (TRL) that this represents for this application, given the TRL referential in Table A.1.*

ERA7 / Can ML help in observation void areas ?

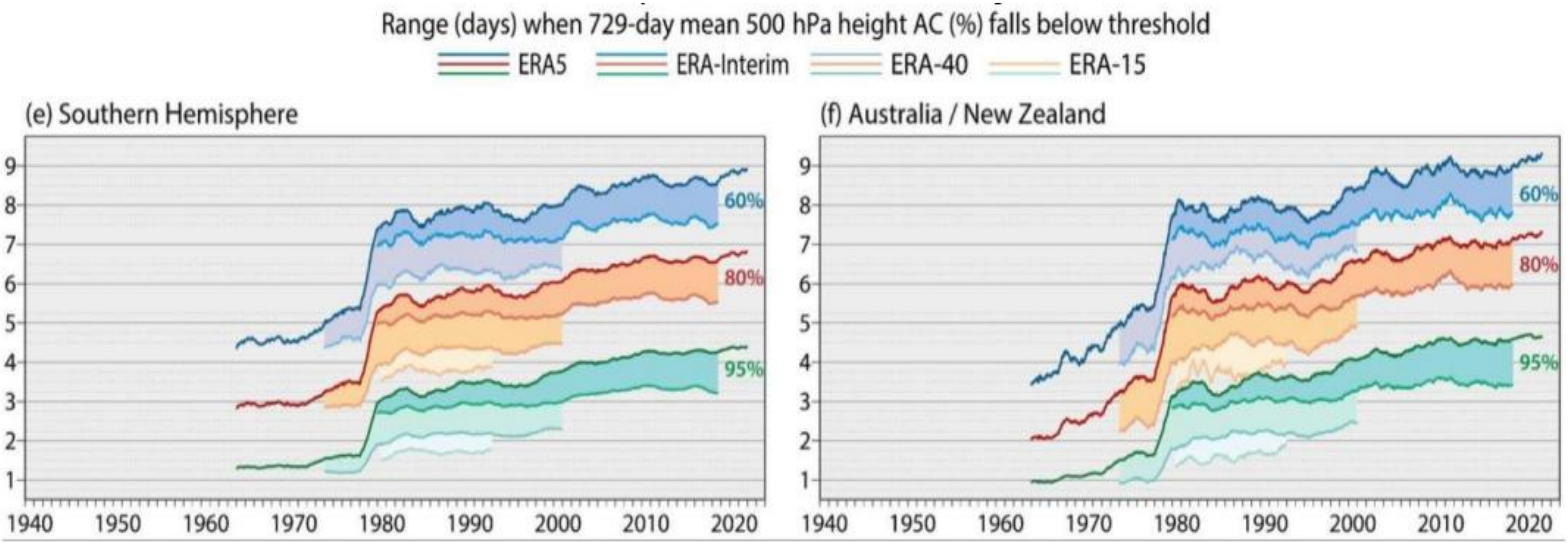
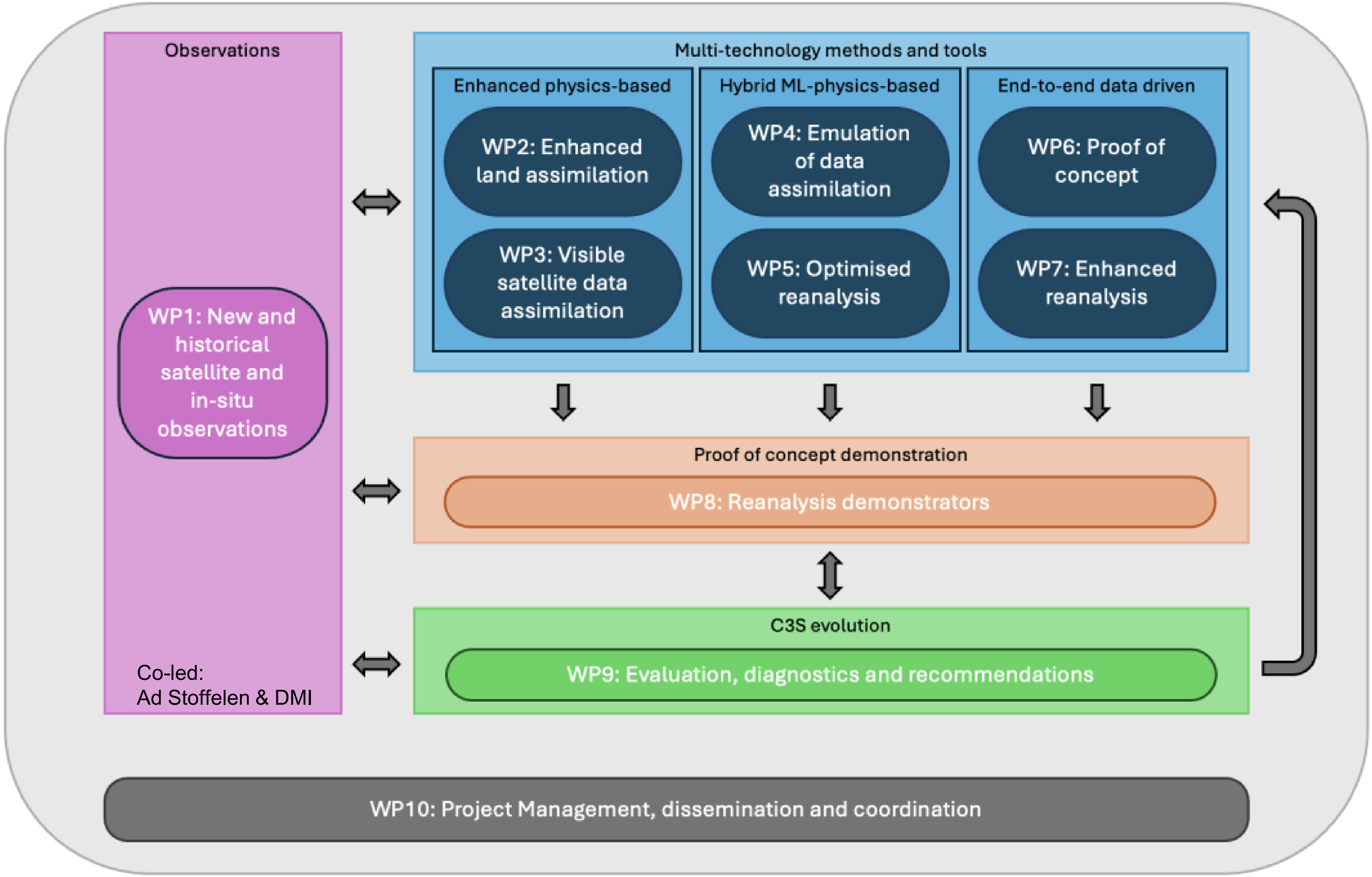


***Figure 3**: Range (days) at which running 729-day mean anomaly correlations of 500 hPa height forecasts at 0000 and 1200 UTC from 1940 to 2022 reach 95% (green), 80% (orange), and 60% (blue) for (e) Southern Hemisphere, and (f) Australia/New Zealand. The heavy lines denote ERA5, and the thin lines denote ERA-Interim, ERA-40, and ERA-15. Shading denotes the difference between ERA5 and other reanalysis products during the period for which both are available. ERA: European Centre of Medium-range Weather Forecasts Reanalysis (-5: v.5; -Interim: January 1979–August 2019; -40: September 1957–August 2002; -15: 1979–1993). Credit: Soci et al. (2022)*

Work package structure multi-technology approach towards ERA7



Observations

WP1: New and historical satellite and in-situ observations

Co-led:
Ad Stoffelen & DMI

Multi-technology methods and tools

Enhanced physics-based
- WP2: Enhanced land assimilation
- WP3: Visible satellite data assimilation

Hybrid ML-physics-based
- WP4: Emulation of data assimilation
- WP5: Optimised reanalysis

End-to-end data driven
- WP6: Proof of concept
- WP7: Enhanced reanalysis

Proof of concept demonstration

WP8: Reanalysis demonstrators

C3S evolution

WP9: Evaluation, diagnostics and recommendations

WP10: Project Management, dissemination and coordination

***Figure 4**: CHERRI work package structure*

(ERA6 = cycle 50r1)

Timeline

- Call issued on 22nd May 2025

- Sep 2025
  - Finalize proposal text, administrative part and submit

- Jan 2026
  - Accepted

- April 2026
  - Vacancy out

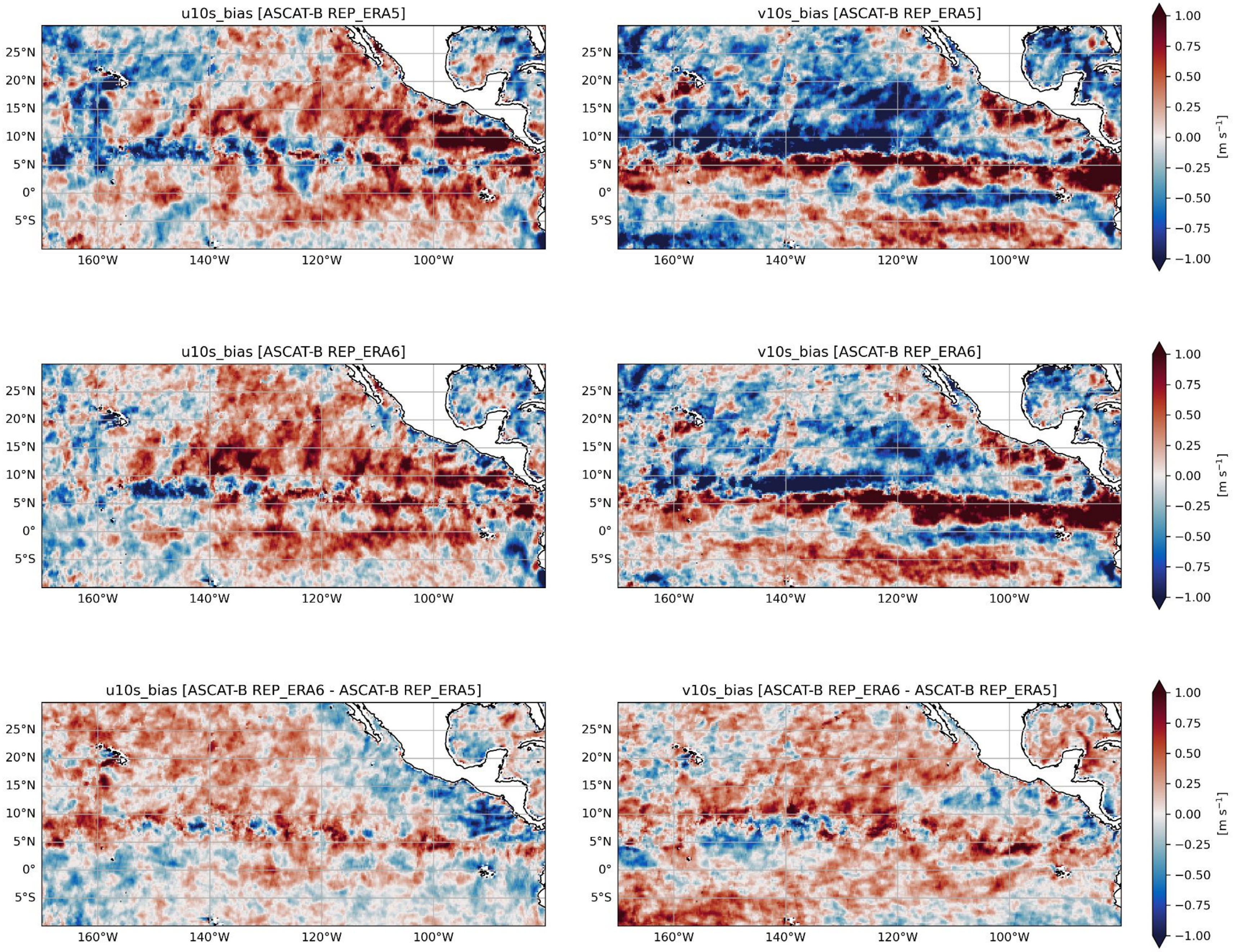
- Sep 2026
  - Expected start

Final word

- ➢ Happy to discuss suggestions to collaborate and contribute to CHERRI
- ➢ Thanks for your attention

L3 scatterometer-model biases:

- u10s and v10s
- ERA6 vs ERA5
- tropical Pacific



20 day average:
1-20 January 2020

Introduction to the call

- Call is available here
- Innovative methods to prepare and pre-process observational input for Earth-system reanalysis datasets, including the **Copernicus Sentinel missions,** including observation operators and error characterization
- Enhanced **sparse data assimilation** and initialisation methods of climate sub-component in Copernicus products
- Comprehensive and better information about the climate records to be extracted from the available observations
- Expanded range of reanalyses products towards **centennial reanalyses**, and enhanced climate counterfactuals data sets to support data-driven predictions
- Improve the ability of Copernicus' and other models to assimilate new and existing satellite observations that are sensitive to surface parameters and fluxes, **coupled across different Earth system components**
- Exploit **innovative methods (including AI/ML)** for data rescue for in situ and remote sensing observations, and on error analysis, quality control and **bias adjustment**
- Explore innovative methods (e.g. AI/ML) to **accelerate the production** and updates of reanalyses, to capture reanalyses uncertainties efficiently, and to reduce overall computing energy/carbon footprint.

- ECMWF
- DMI
- DWD
- ICM
- KNMI
- Met.No
- Meteo France

***Figure 6**: Geographical representation of the partners involved on the project.*

Partner WP contributions

Work package	ECMWF	Met Norway	Meteo France	DWD	KNMI & ICM	DMI
1 & 2 Observations	✅			✅	✅	✅
3 & 4 Enhancing classical methods	✅	✅	✅	✅	✅	
5 & 6 Hybrid classical/ML methods	✅	✅	✅	✅	✅	
7 & 8 End-to-end data driven methods	✅	✅			✅	
9 Reanalysis demonstrators	✅	✅		✅		
10 Diagnostics	✅				✅	✅

Work package 1 & 2 - Observations

- Key aim of this work package is to produce a database of observations for use in the other work packages, e.g., scatterometer data
  - This will build on existing efforts to create the database in Zarr format for direct observation prediction at ECMWF
  - The database will be made available to partners and member states via the Anemoi framework
- One of the key themes of the call is to make better use of existing observations, e.g. from the Sentinel missions or from the early days
  - Develop assimilation of visible reflectances from Sentinel-3 OLCI
  - Develop coupled assimilation of thermal IR radiances from Sentinel-3 SLSTR
- Apply assimilation methodologies developed for recent data to historical data
  - E.g. AVHRR and older research instruments for visible
  - E.g. ATSR, AATSR and older research instruments for thermal IR

WP 1.3 (KNMI, M0-M30)

- Contribute high-quality wind observations by preparing an “analysis-ready” stable observation database of backscatter and stress-equivalent wind vectors, stresses and spatial derivatives and variances and share this across all partners;
- Employ “cone metrics” to achieve backscatter stability from 1991 until today to within ~0.02 dB (0.5%; cf. Belmonte Rivas et al., 2017) over sea, land and ice.

We know how to do this, but a state-of-the-art ocean wind vector CDR does not yet exist (no ESA CCI, not in C3S portal, . .).

All KNMI scatterometer wind products contain first-guess ECMWF stress-equivalent wind vectors, stresses and spatial derivatives and variances in every sea WVC. This may be from any ECMWF experiment. Some scatterometers are any time of day and collocate well with other satellite sensors. We can offer triple collocation and spatiotemporal analyses (to understand model, in-situ and satellite accuracies in context).

To be done:

- Format in Zarr
- What ECMWF experiments? Temporal range and number?

Work package 3 & 4 – Enhancing physical methods

- Land data assimilation generally doesn't use variational methods due to the land-surface models being notoriously difficult to differentiate/linearize:
  - The use of ML emulated land-surface models opens the door for variational methods e.g. 3- or 4D-Var for the land-surface
- Improved use of observations from WP1 in the physical DA systems:
  - Visible data for clouds, snow, vegetation
  - Thermal IR data for land and sea surface temperature
- Systematic biases are a big issue for reanalysis products, affecting trends
  - Plan to address these by ML training corrections on well-observed periods and applying in less well observed periods (cf. EMETSAT OSI SAF VS study by ICM)
- Improved and more automated quality control, especially important for historic data when the quality of the background is lower
- Improve DA in sparse observing periods e.g. by extending the DA window

WP 3.4 (KNMI, ECMWF, ICM; M6-30)

1) Enhancing existing physically-based SCAT assimilation systems for reanalysis

- Remove persistent local model wind vector biases during data assimilation; Exploit Copernicus Marine Service L3/L4 production chain; exploit full resolution

2) Improving air-sea interaction

- Remove persistent local model wind vector / stress curl / variability biases in ocean forcing;
- At least test sensitivity of physical atmosphere, wave and ocean model state to these biases; plan with ECMWF/DWD (e.g., avoid double counting effects)
- Test improvements by parameterization updates or ML approach (for ERA7) KNMI/ICM/ECMWF/DWD (ML Ocean slab model?)

Work package 5 & 6 – Hybrid physical-ML methods

- ML-based forecast models such as AIFS can now outperform physical models in most forecast metrics
  - However, the AIFS just produces a forecast and still relies on physical-based DA systems to produce the initial conditions (with model biases)
- An analysis with AIFS could be produced by combining previous AIFS short-range forecasts with observations in a hybrid ML-DA system
- This could enable us to explore a methodology similar to Greg Hakim’s work using very long DA windows and a combination of forward and back propagation of AIFS to produce the most optimal analysis
- Note that long DA windows are made more feasible by faster ML forecasts/adjoints

Work package 7 & 8 – End-to-end data driven methods

- This will build on the current “direct observation prediction” (DOP) approach
  - Existing system exclusively uses observations to predict future observations
  - Scatterometer OSVW and derivatives without biases
- One feature of the existing system is the ability to decode the latent space representation of the forecast onto any observation location
  - This can be exploited to produce a gridded reanalysis product at any chosen time
  - Possibility to investigate a product with varying resolution e.g. high resolution near the surface, lower resolution higher in the atmosphere
- The existing DOP system has exploited some observations which have been difficult to exploit using physical methods
  - This system is a good candidate for experimenting with the visible and thermal IR data from WP1
- The existing DOP system still relies on a “curated” set of observations using QC from physical system
  - Plan to develop ML-based QC to remove this dependency

Pathways for KNMI contribution to the EU call WP3-8

2) Enhancing existing physically-based data assimilation systems for reanalysis

- Elaborate SCA science plan (2017):
  - Remove persistent local model wind vector biases during data assimilation;
  - Remove persistent local model wind vector biases in ocean forcing;
  - At least test sensitivity of physical atmosphere, wave and ocean model state to these biases.

3) Hybrid ML and physical data assimilation for reanalysis (See ICM proposal)

- Use ML for learning local model OSVW biases in mean, variance, spatial gradients, as observed by scatterometers, from model parameters
  - Apply these ML biases in data assimilation and evaluate effect;
  - Apply these biases in ocean forcing and evaluate effect of these.

4) End-to-end data driven approaches such as “direct observation prediction” for reanalysis (needs DOP co-worker)

- Improve model capability to predict scatterometer OSVWs in terms of biases in mean, variance, spatial gradients

WP7.2 (ICM, KNMI; M12-M30)

4) End-to-end data driven approaches such as “direct observation prediction” for reanalysis (needs DOP co-worker)

- Improve model capability to predict scatterometer OSVWs in terms of biases in mean, variance, spatial gradients
- Generates DOP
- KNMI evaluates ERA7 performance using our well-established tools in WP9-10

Work packages 9 & 10: Demonstrators and evaluation

- The scientific developments (prototypes) in WP1-8 will be tested in various reanalysis demonstrators using different periods:
    - A recent well-observed period
    - An older less well-observed period
- Each of WPs 3-8 would have demonstrators (prototypes) based on the most advanced version of the corresponding DA system (in 2 rounds)
    - These could then be systematically compared for both quality and speed of production
- Evaluation and novel diagnostics will be key to understanding the relative strengths and weaknesses of the different approaches
    - KNMI will further investigate the biases of ERA6 (cf. Belmonte Rivas) to understand what needs initial improvement for ERA7
    - The findings will then be fed back to WPs 3-8 to improve and refine the methodologies (in a 2nd round)

Work package leaders

Work package	Lead	Co-lead
1 & 2 Observations	Ad Stoffelen	Suman Singha (DMI)
3 & 4 Enhancing classical methods	Jean-Christoph Calvet	Christoph Herbert
5 & 6 Hybrid classical/ML methods	Jostein Blyverket	Ewan Pinnington
7 & 8 End-to-end data driven methods	Jan Keller	?
9 Reanalysis demonstrators	Met Norway	Paul Poli
10 Diagnostics	Jacob Hoyer	Jonny Day

Current consortium

Partner	Partner contacts
Met Norway	Harald Schyberg Jostein Blyverket Jørn Kristiansen
DWD	Olaf Stiller Leonhard Scheck Jan Keller
Meteo-France	Jean-Christophe Calvet Camille Birman Sophie Marimbordes
KNMI	Ad Stoffelen Vacancy Anton Verhoef Rianne Giesen Gert-Jan Marseille
DMI	Pia Englyst Suman Singha Jacob Hoyer
ICM	Marcos Portabella Evgeniia Marakova Federico Cossu
University of Reading	Chris Merchant Owen Embury
TRACASA	Pablo Vega Ezquieta

Budget

- Total budget is 10 million euros for a 3 year project, starting summer 2026

- Draft budget allocation:
  - ECMWF ~3.5 million euros
  - Rest ~6.5 million euros between ~8 partners
  - KNMI 700 k euros
  - ICM 400 k euros
  - KNMI proposes to organize 2027 GA for ~30-40 CHERRI colleagues

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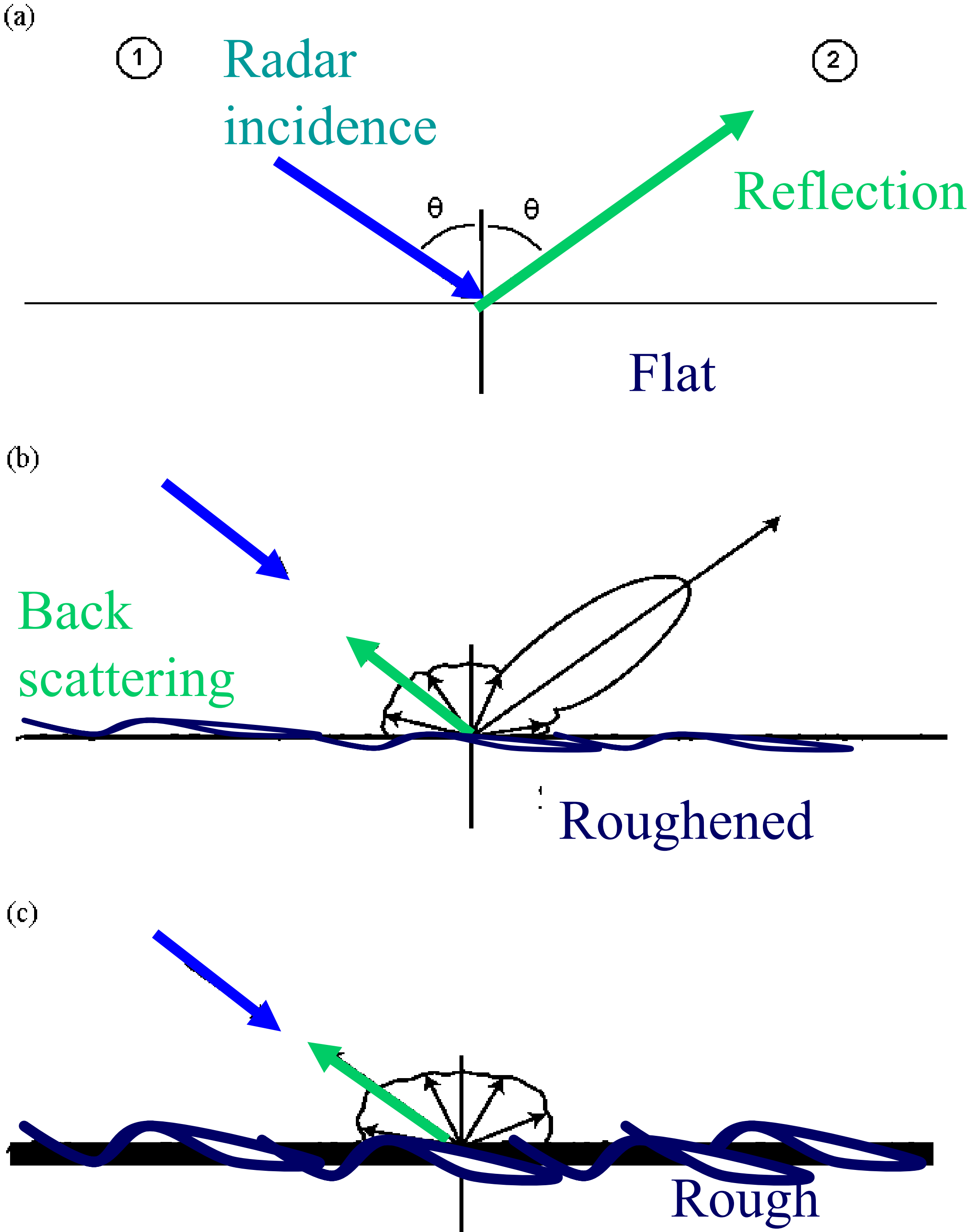
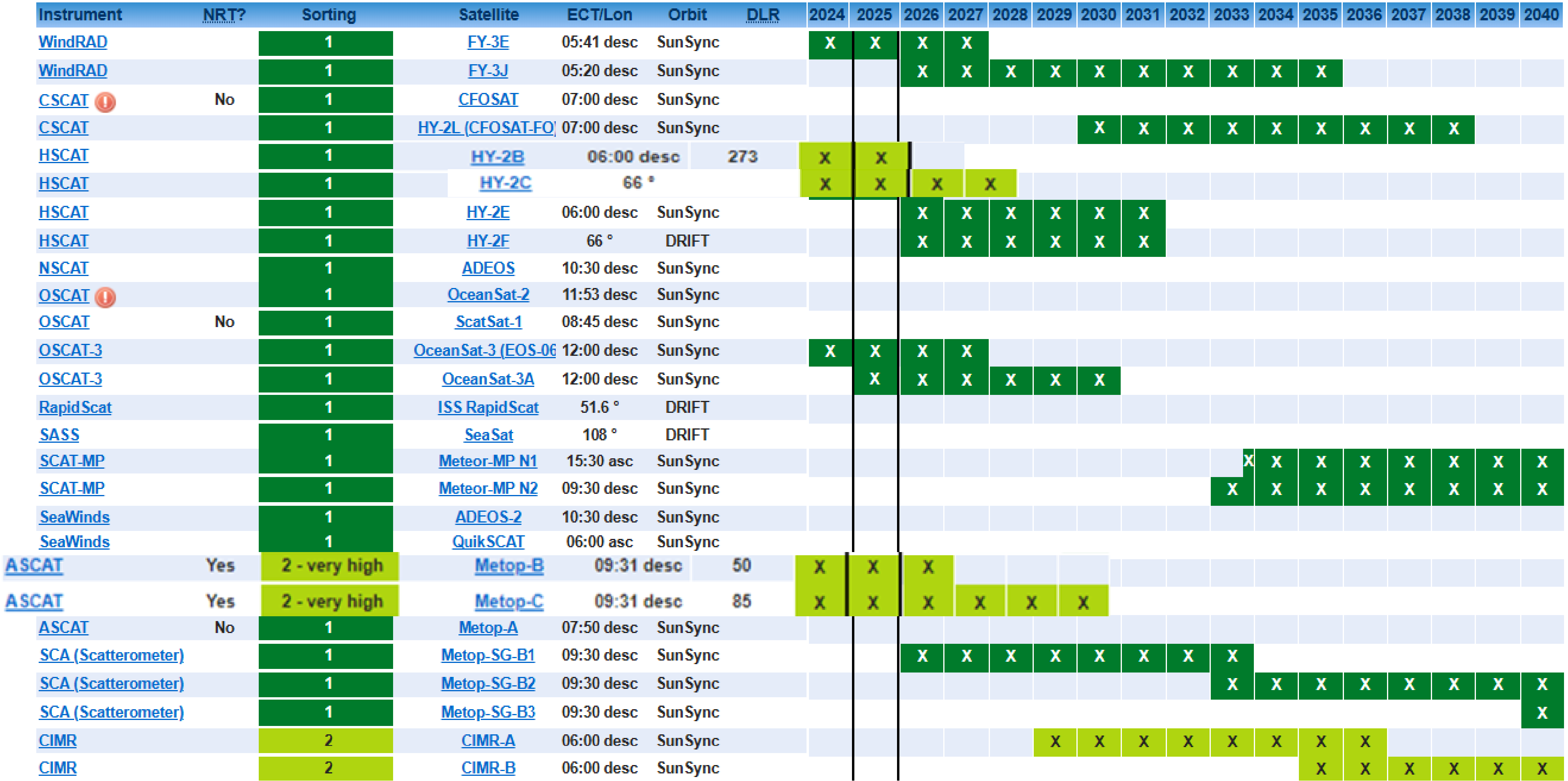


- Interference with ocean cm-size waves
- The more wind, the more μ-wave scattering
- Depends on direction
- Also under cloud, rain
- Data science approach
- Closed problem, cone metrics for relative calibration
- Wind vector solution is informed by local scatterometer measurements and by scatterometer measurements in the neighbourhood
- ~ independent of model background

Golden age of wind scatterometry, CGMS IWWg17



Instrument	NRT?	Sorting	Satellite	ECT/Lon	Orbit	DLR	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	2036	2037	2038	2039	2040
WindRAD		1	FY-3E	05:41 desc	SunSync		X	X	X	X													
WindRAD		1	FY-3J	05:20 desc	SunSync				X	X	X	X	X	X	X	X	X	X					
CSCAT ❗	No	1	CFOSAT	07:00 desc	SunSync																		
CSCAT		1	HY-2L (CFOSAT-FO	07:00 desc	SunSync								X	X	X	X	X	X	X	X	X		
HSCAT		1	HY-2B	06:00 desc		273	X	X															
HSCAT		1	HY-2C	66 °			X	X	X	X													
HSCAT		1	HY-2E	06:00 desc	SunSync				X	X	X	X	X	X									
HSCAT		1	HY-2F	66 °	DRIFT				X	X	X	X	X	X									
NSCAT		1	ADEOS	10:30 desc	SunSync																		
OSCAT ❗		1	OceanSat-2	11:53 desc	SunSync																		
OSCAT	No	1	ScatSat-1	08:45 desc	SunSync																		
OSCAT-3		1	OceanSat-3 (EOS-06	12:00 desc	SunSync		X	X	X	X													
OSCAT-3		1	OceanSat-3A	12:00 desc	SunSync			X	X	X	X	X	X										
RapidScat		1	ISS RapidScat	51.6 °	DRIFT																		
SASS		1	SeaSat	108 °	DRIFT																		
SCAT-MP		1	Meteor-MP N1	15:30 asc	SunSync											X	X	X	X	X	X	X	X
SCAT-MP		1	Meteor-MP N2	09:30 desc	SunSync											X	X	X	X	X	X	X	X
SeaWinds		1	ADEOS-2	10:30 desc	SunSync																		
SeaWinds		1	QuikSCAT	06:00 asc	SunSync																		
ASCAT	Yes	2 - very high	Metop-B	09:31 desc		50	X	X	X														
ASCAT	Yes	2 - very high	Metop-C	09:31 desc		85	X	X	X	X	X	X											
ASCAT	No	1	Metop-A	07:50 desc	SunSync																		
SCA (Scatterometer)		1	Metop-SG-B1	09:30 desc	SunSync				X	X	X	X	X	X	X	X							
SCA (Scatterometer)		1	Metop-SG-B2	09:30 desc	SunSync											X	X	X	X	X	X	X	X
SCA (Scatterometer)		1	Metop-SG-B3	09:30 desc	SunSync																		X
CIMR		2	CIMR-A	06:00 desc	SunSync							X	X	X	X	X	X	X	X				
CIMR		2	CIMR-B	06:00 desc	SunSync													X	X	X	X	X	X

Source: https://space.oscar.wmo.int/gapanalyses?mission=12

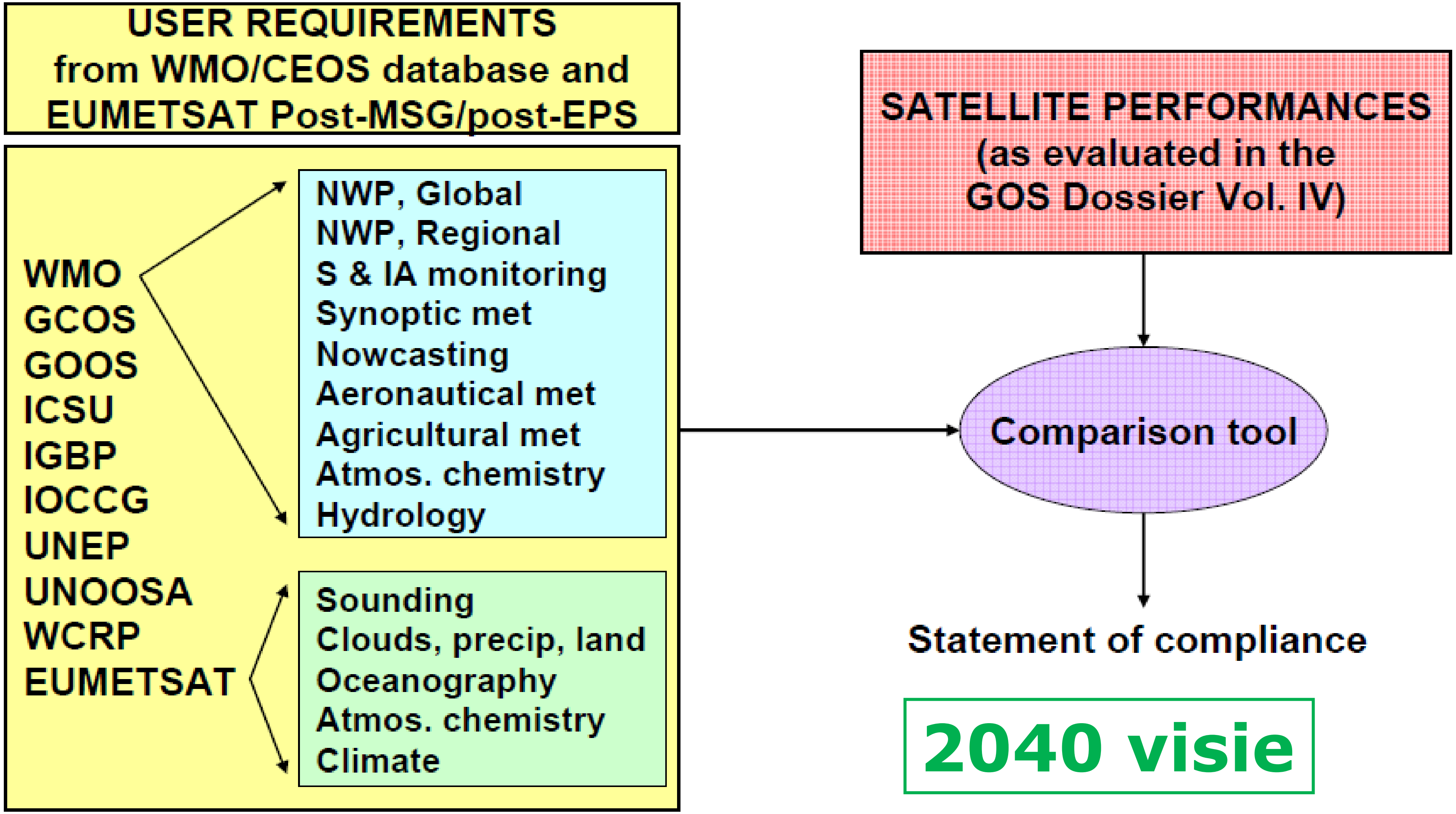
Past C-band missions :

ESCAT/ERS-1,2	10:30 desc.	1992-1996, 1995-2000
MetOp-A/ASCAT	9:30 desc.	2007-2021

Past Ku-band missions :

SeaWinds/QuikScat	6:00 desc.	1999-2009
RapidScat/ISS	52 *	2014-2016
OceanSat-2/OSCAT	0:00 desc.	2009-2014
ScatSat-1/OSCAT	8:45 desc.	2016-2021

WMO G(C)OS gap analysis



USER REQUIREMENTS
from WMO/CEOS database and
EUMETSAT Post-MSG/post-EPS

WMO
GCOS
GOOS
ICSU
IGBP
IOCCG
UNEP
UNOOSA
WCRP
EUMETSAT

- NWP, Global
- NWP, Regional
- S & IA monitoring
- Synoptic met
- Nowcasting
- Aeronautical met
- Agricultural met
- Atmos. chemistry
- Hydrology

- Sounding
- Clouds, precip, land
- Oceanography
- Atmos. chemistry
- Climate

SATELLITE PERFORMANCES
(as evaluated in the
GOS Dossier Vol. IV)

Comparison tool

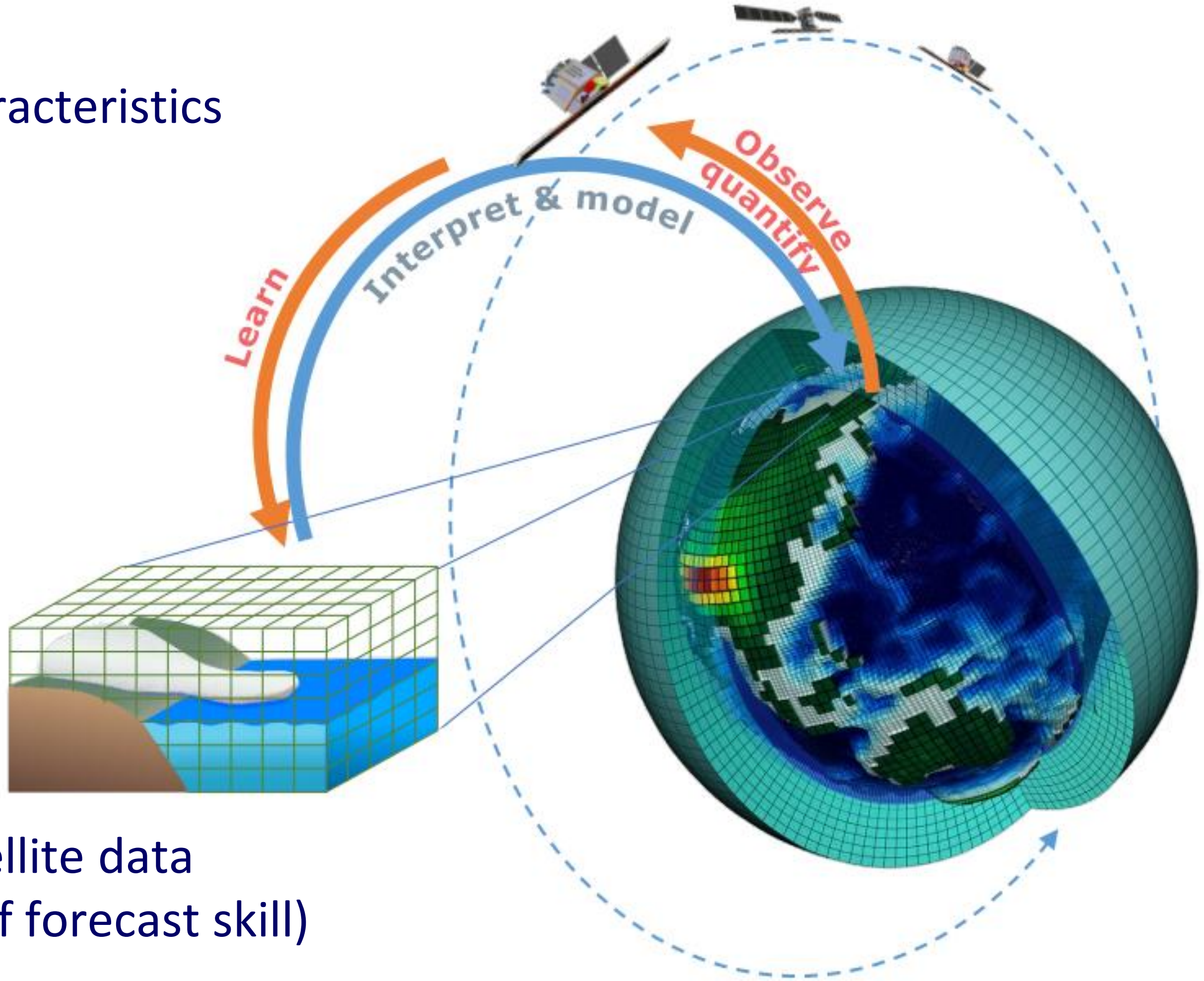
Statement of compliance

2040 visie

http://www.wmo-sat.info/oscar/

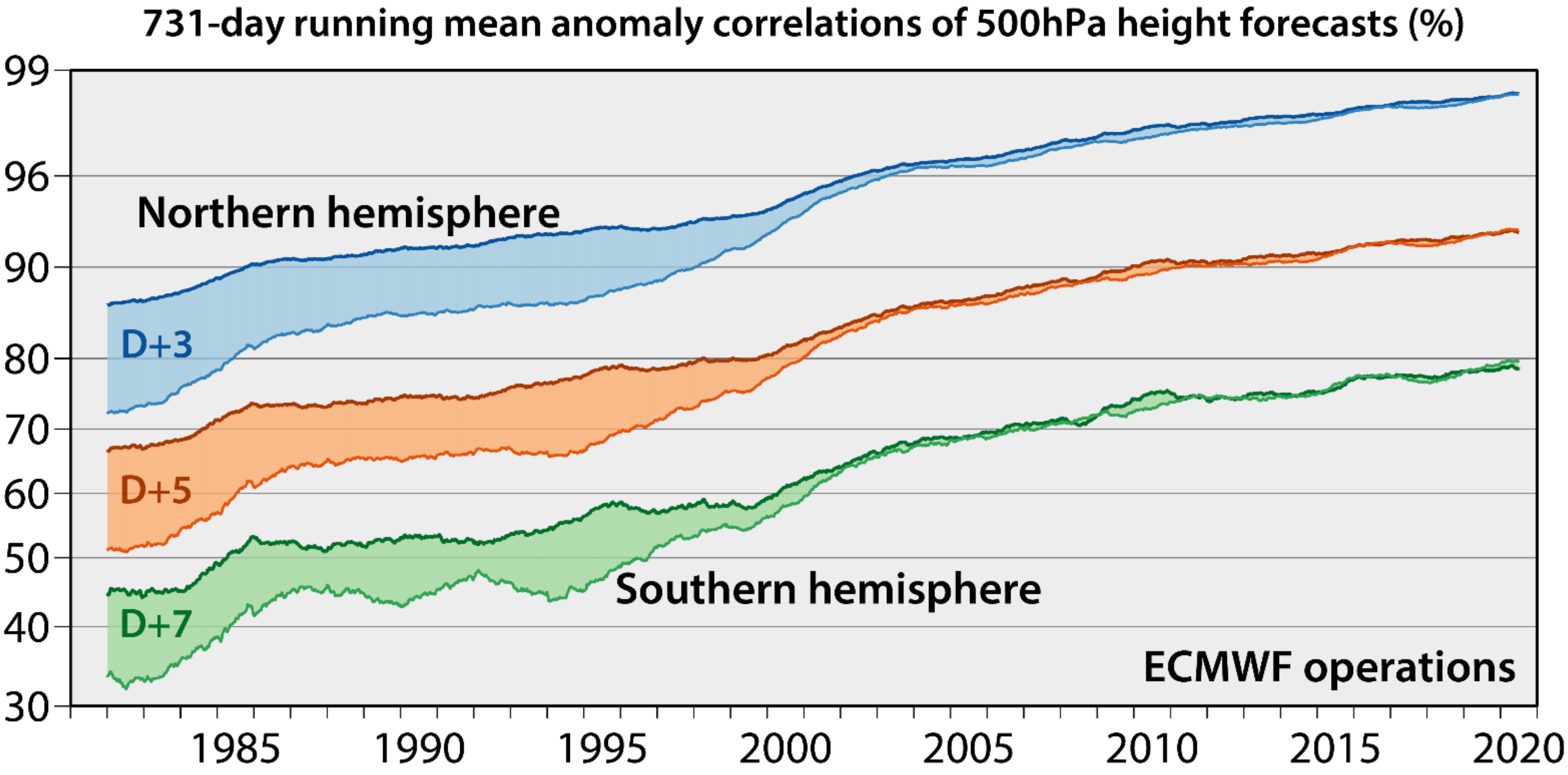
System earth and classical models

- Digital model of Earth's dynamics, in which all available knowledge and information are integrated
- The earth is divided in small cells, in where key characteristics are tracked (millions of variables)
- Forecasts need evolution equations, Navier Stokes flow equations for atmosphere and ocean
- Measurements for initialization and for learning all detailed Earth processes
- The coupling of the ocean and the atmosphere is complex due to processes on different time and spatial scales
- To be able to make increasingly better predictions, we must integrate more and more satellite data into these models (Satellites today provide > 80% of forecast skill)



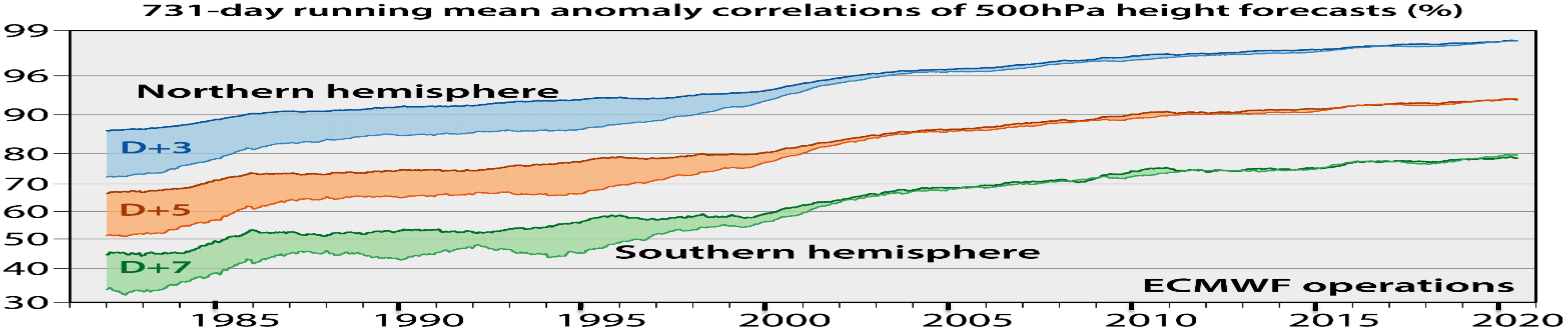
Silent revolution in NWP

- Improved use of observations, in particular from satellites (> 80% of skill today)
- Bigger computers
- Better weather models



- Skill score for predicting day-to-day weather variations
- The skill deteriorates with forecast day due to chaos, which is fundamental to atmospheric flow
- Over the years skill improves at all forecast ranges, due to improved initialization of model state variables
- The observing system defines the achievable model state initialization and forecast skill (low SH skill 20th century)

Career in NWP (with a CHERRI bias)



KNMI research director advises **not** to work on NWP satellite data assimilation

v/d Dool, Cascaded forecasting with degraded models improves weather forecasts (not used)

Stoffelen&Cats, Scatterometer winds make no beneficial impact on QEII storm in KNMI LAM

Move to ECMWF to work on global NWP and the new ERS scatterometer

Isaksen&Stoffelen, 4Dvar and scatterometers allow TC prediction at ECMWF

Crepon et al. ML efforts for scatterometer wind retrieval, GMF

Stoffelen et al., OSSE shows DWL impact on NWP

Cornford et al. ML wind retrieval and GMF (not used)

Marseille et al., SOSE, EDA, DWL & extremes

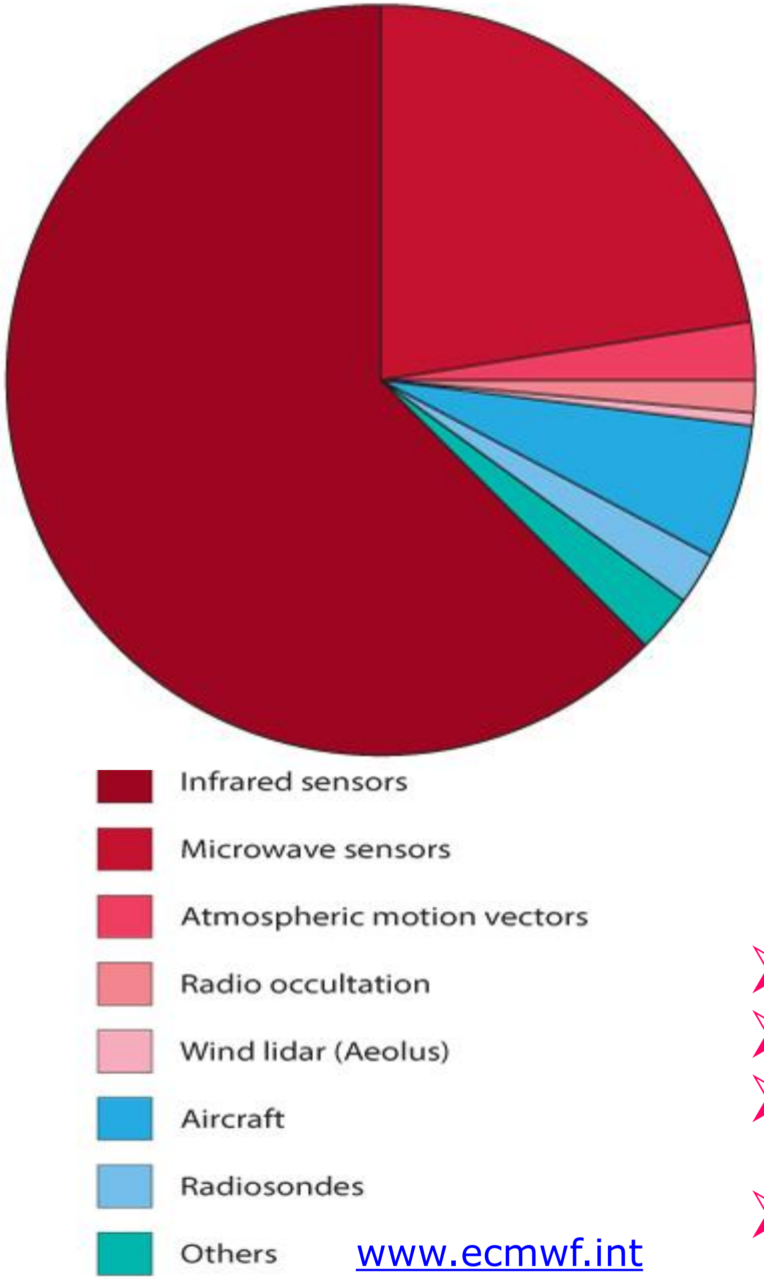
Aeolus DWL

ERA5 biases

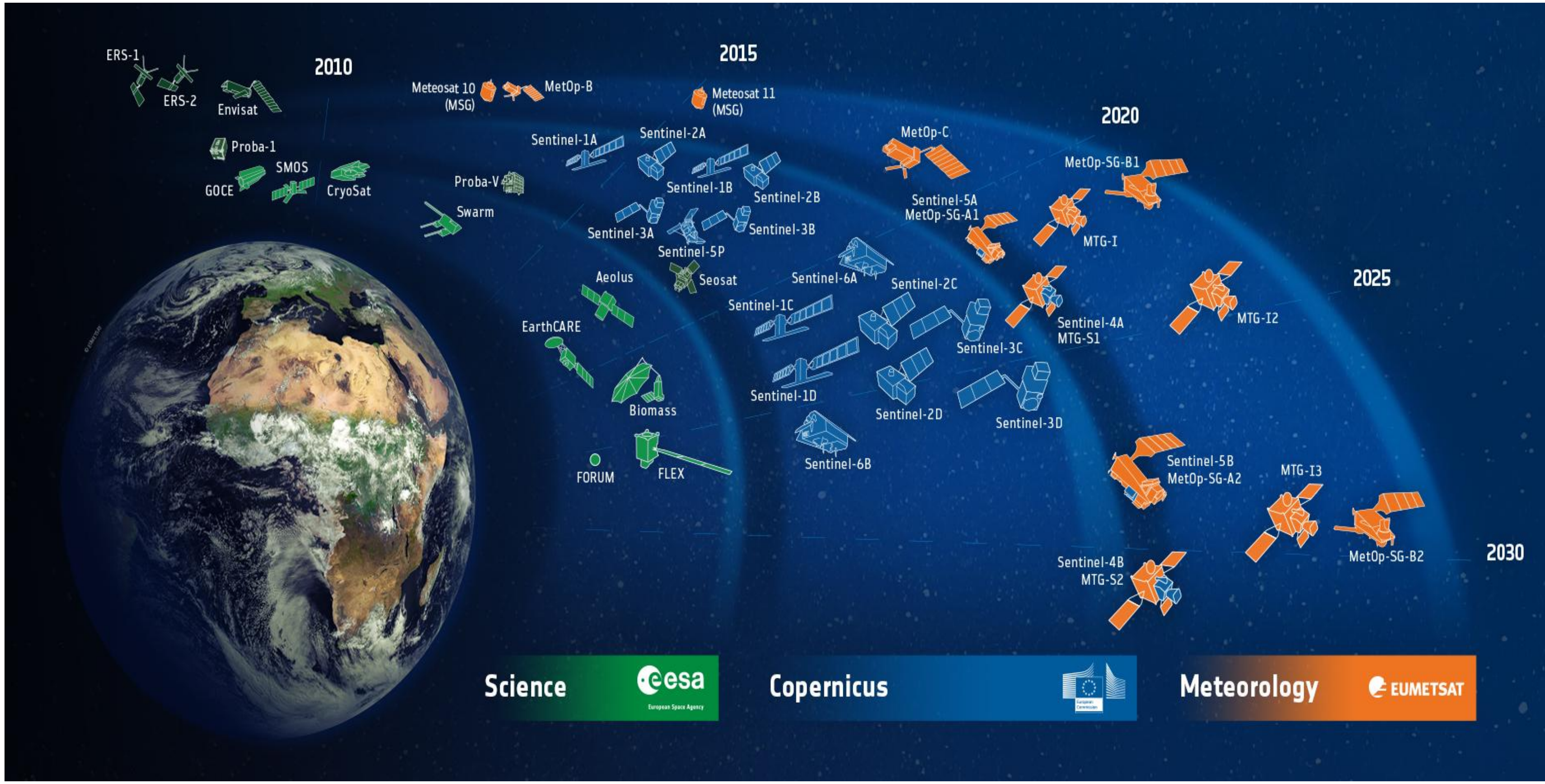
- Bayesian estimation, atmospheric dynamics and ML knowledge has been well explored over the past 40 years in NWP

ECMWF IFS data use 2020

Actively assimilated observations

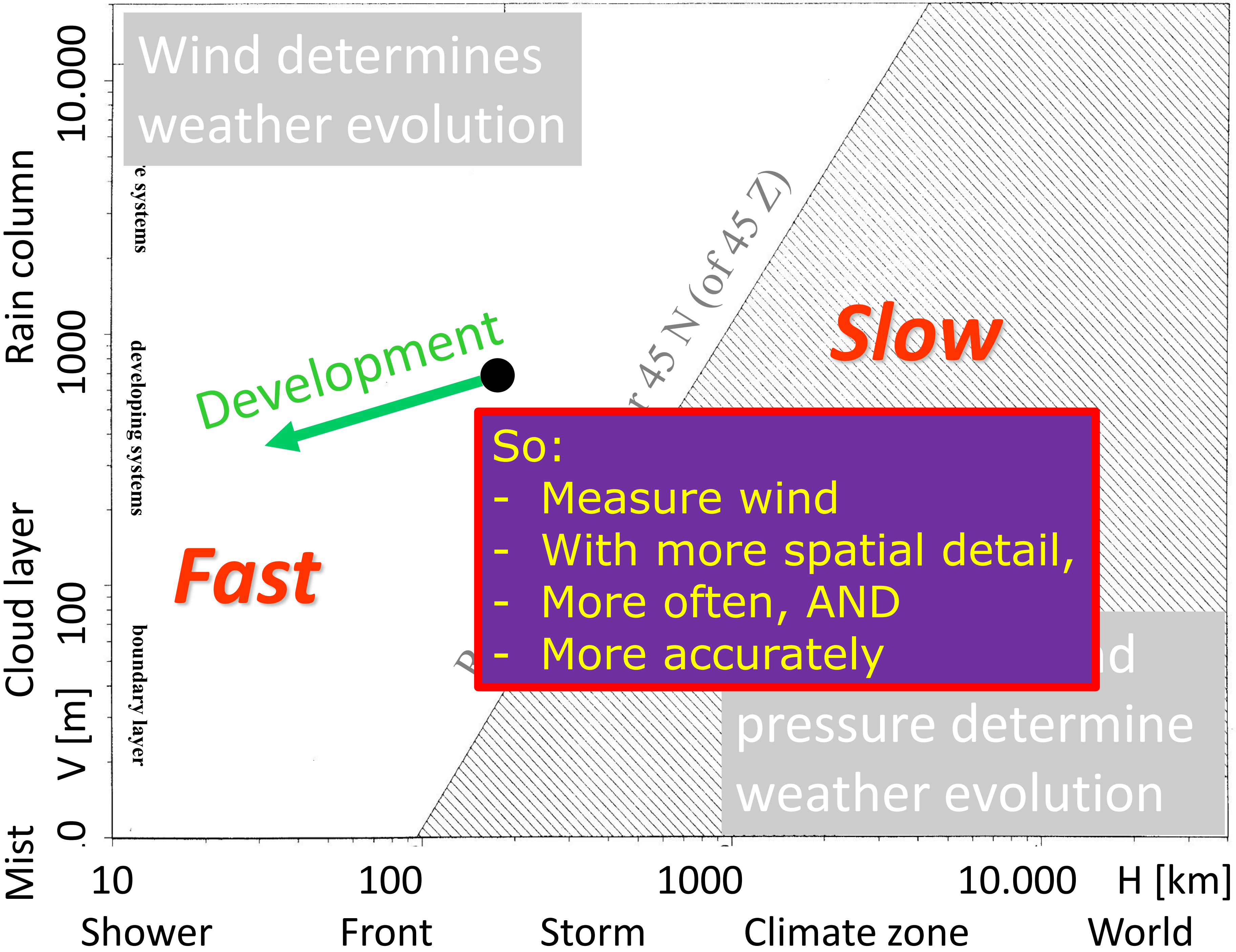


www.ecmwf.int



- About 100 instruments
- Novel instruments keep coming and require substantial work
- New observation operators might inform the assimilation of old observations
- What new observations are needed?

Atmospheric flow properties determine how best to initialize for weather prediction, irrespective of forecasting model



Wind determines weather evolution

So:

- Measure wind
- With more spatial detail,
- More often, AND
- More accurately

d pressure determine weather evolution

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