ECMWF ANNUAL SEMINAR 2026, READING

EXPLOITING CLOUD AND MOISTURE INFORMATION FROM SOLAR SATELLITE CHANNELS

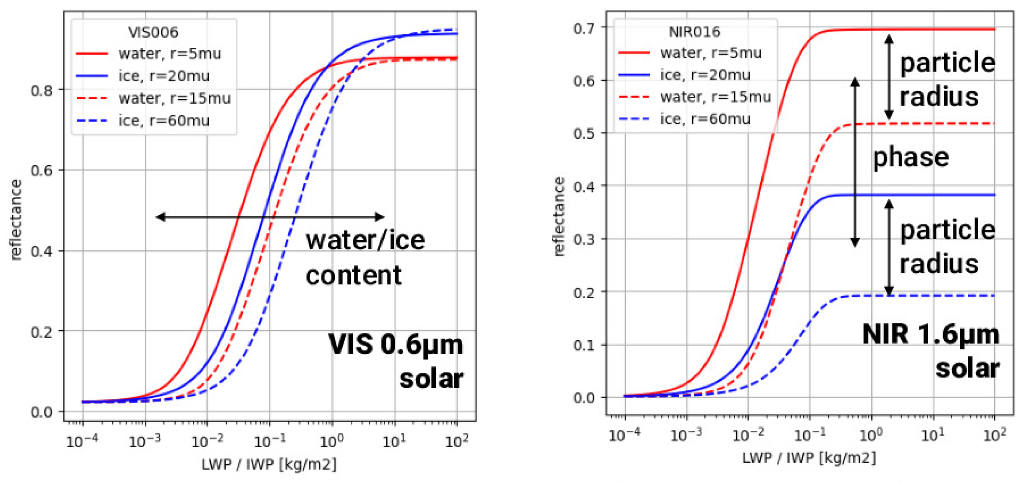
Leonhard Scheck[1,2], Stefano Franzoni[1], Christopher Bülte[1], Phillip Gregor[1], Bernhard Mayer[1], Christian Keil[1], George Craig[1], Christina Stumpf[2], Olaf Stiller[2], Pascal Raisig[2], Christina Köpken-Watts[2]
1) Hans Ertel Centre for Weather Research / LMU Munich 2) German Weather Service

MOTIVATION

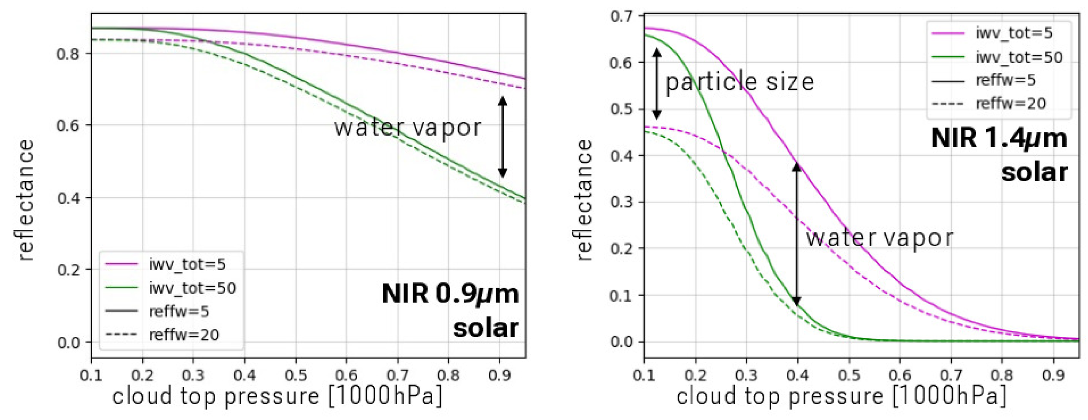
- **Solar satellite channels contain a wealth of information on clouds, aerosols and humidity,** which is complementary to the information in the widely used thermal infrared channels
- **Exploiting this information for data assimilation and model evaluation / improvement requires forward operators** to compute synthetic observation from the numerical weather prediction / earth system model state
- Doing this with standard radiative transfer methods requires **high computational effort**, but **machine learning approaches** can be used to reduce the effort strongly
- Here we report on **MFASIS-NN**, a **neural network-based forward operator for solar satellite channels** that has been **integrated in NWP SAFs RTTOV** package and supports now nearly all solar channels on the current generation of imagers, including water vapor sensitive channels on MTG / MetOpSG.
- We tried also to quantify the **joint information content of multiple solar channels** using a distributional regression network, which provides a full uncertainty covariance matrix.

SOLAR CHANNELS

Standard visible and near-infrared channels: Reflectance for water / ice clouds (fixed height) with varying water / ice paths.



Water vapour sensitive solar channels (e.g. on MTG FCI): Reflectance for thick water clouds (optical depth 100) with varying cloud top pressure and two different droplet sizes in a moist atmosphere (water vapor content 50mm) and a dry atmosphere (water vapor content 5mm)

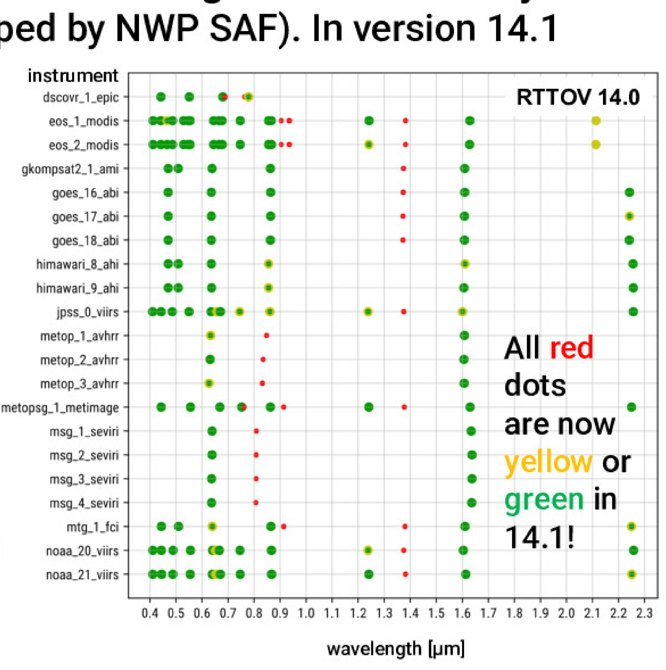


- **0.9µm:** significant wv absorption → sensitive to (mostly low-level) WV
- **1.4µm:** Stronger effective radius sensitivity + very strong absorption by water vapor → sensitive to moisture and clouds in upper part of troposphere only

RTTOV INTEGRATION

MFASIS-NN for clouds has been **integrated in the widely used RTTOV package** (developed by NWP SAF). In version 14.1 (released in February) nearly all channels with λ < 2.5µm are now supported.

Since version 14.1 also an aerosol version is included (supporting only a few channels at the moment).



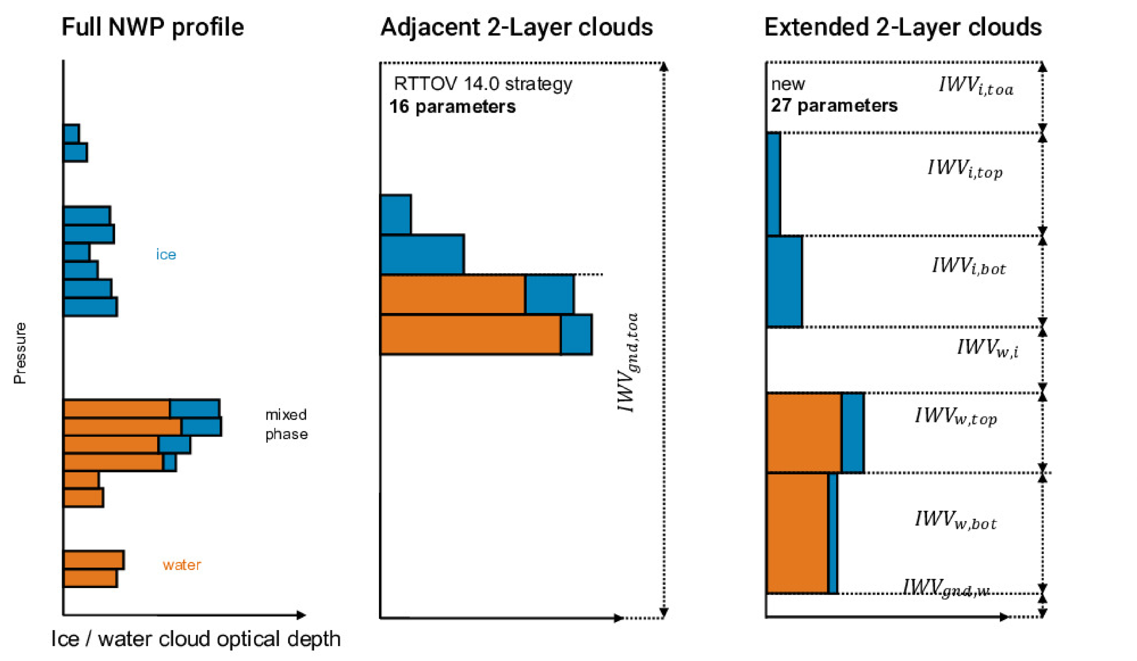
Green = small errors (like 0.6µm)
Yellow = acceptable errors
Red = errors too high

MFASIS-NN WITH NEW WATER VAPOUR INPUT VARIABLES

Basic approach for MFASIS-NN:
(1) Replace complex NWP model profiles by idealised profiles, which can be described by few parameters (features)
(2) Compute reflectances (using RTTOV DOM) for these idealised profiles for random parameter combinations
(3) Train a deep neural network that estimates the reflectances from the idealised profile parameters / features

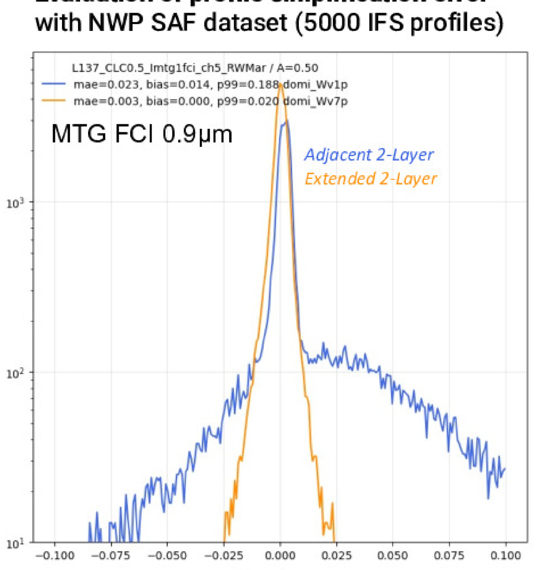
Constructing suitable idealised profiles (which lead to nearly the same reflectances as the original profiles) = **"feature engineering"**. "Harmless" channels (e.g. 0.6µm visible, see Scheck, 2021) only four cloud parameters (optical depths and effective particle radii) are sufficient. For channels with more complicated dependencies (e.g. 1.6µm NIR, see Baur et al. 2023) additional parameters are required.

NEW: Idealised profiles with additional parameters for **strongly water-vapor sensitive channels** (e.g. MTG FCI 0.9µm and 1.38µm)

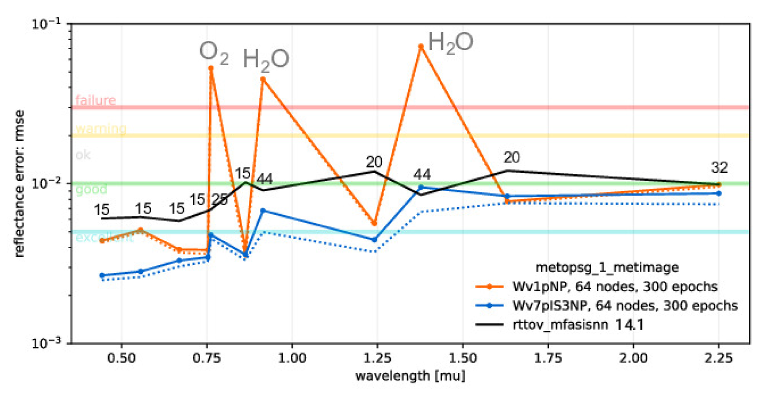


Left: Profile simplification/idealization strategies. For strongly WV-sensitive channels not only the optical but also the geometric thickness of the clouds must be taken into account and the WV contents of all layers in and between the clouds are required as input parameters.

Evaluation of profile simplification error with NWP SAF dataset (5000 IFS profiles)



The profile simplification error (reflectance computed for idealized profile minus reflectance computed for original profile) distribution for the strongly WV-sensitive MTG FCI 0.9µm channel is significantly improved with the new approach



Left: Total errors for all channels of the Metimage instrument on MetOpSG using the old adjacent layers (orange) approach and the new extended layers approach (blue) and a NN with 64 nodes per layer. For the black line NNs with the indicated number of nodes per layer were used to balance accuracy & effort.

Networks: Training & Inference

- Small (=fast) deep feed forward NNs are trained with synthetic training data using Tensorflow
- Typically, 8 hidden layers and 15 – 50 nodes per layer are used (depending on channel)
- A vectorized Fortran code (Including an adjoint version) requires less than 1µsec per sample for most channels on standard CPUs
- The total reflectance error (simplification and imperfect training) is typically < 0.01

Next steps:

- Automatic feature detection
- 3D radiative effects
- Improved aerosol version

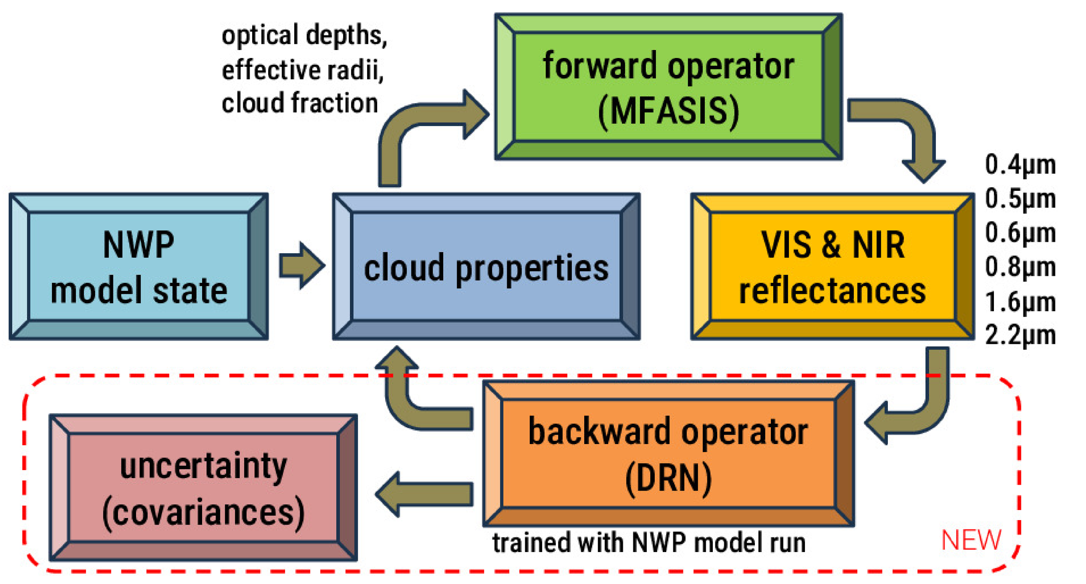
JOINT INFORMATION CONTENT OF MULTIPLE SOLAR CHANNELS

Many solar channels are now supported by MFASIS-NN. What is the best way to assimilate them and what can we potentially gain?

Two important problems: Observation impact of reflectances is limited by **nonlinear dependence on model state** (→ less effective error reduction in LETKF) and **ambiguity** (different model states lead to same reflectance → one may improve reflectance, but not state). Using multiple channels should reduce ambiguity (but which improvements can we expect?) and retrievals are more linearly related to model state (but often characterizing their errors is problematic)…

Can we quantify the potential joint impact of multiple solar channels (independent of a specific DA system and its deficiencies)?
Can we design a cloud property retrieval that provides uncertainty information suitable for DA?

→ Two address both questions we developed a **"backward operator"** based on **distributional regression network**



cloudiness	fully cloudy									partially cloudy								
thickness	thick			inter			thin			thick			inter			thin		
phase	water	w+i	ice	water	w+i	ice	water	w+i	ice	water	w+i	ice	water	w+i	ice	water	w+i	ice
Percentage [%]	4.95	15.0	0.0201	0.104	7.47	0.519	0.00547	4.90	2.92	12.1	5.21	0.00490	12.9	4.79	0.338	13.7	8.25	6.89
rel. err. τ [%]	34.8	37.9	29.0	44.7	44.1	24.2	57.0	55.0	43.9	46.1	42.9	25.1	58.2	53.3	22.1	76.9	72.4	49.0
$log(\tau)$	0.336	0.363	0.280	0.419	0.411	0.234	0.519	0.492	0.399	0.430	0.402	0.244	0.523	0.482	0.215	0.660	0.624	0.442
γ	0.0476	0.0312	0.0362	0.120	0.0579	0.0590	0.171	0.128	0.161	0.104	0.0696	0.0556	0.150	0.129	0.109	0.115	0.191	0.207
f_{ice}	0.00931	0.0659	0.187	0.0216	0.141	0.160	0.0365	0.215	0.167	0.0149	0.0479	0.164	0.0293	0.0823	0.132	0.0527	0.193	0.144
r_{effw} [μm]	1.23	1.35	-	1.38	1.37	-	1.32	1.18	-	1.50	1.39	-	1.35	1.34	-	0.769	1.00	-
r_{effi} [μm]	-	3.57	2.57	-	3.80	2.33	-	4.13	3.01	-	7.23	2.46	-	7.23	2.28	-	5.62	3.02

Predicted uncertainties of the retrieved cloud properties for different situations.

	OnlyNIRs	NIR16-VIS6	NIRs-VIS4	NIRs-VIS5	NIRs-VIS6	NIRs-VIS8	NIRs-VIS4-VIS5	NIRs-VIS4-VIS5-VIS6	All
$log(\tau)$	0.5435	0.4674	0.4392	0.4390	0.4415	0.4396	0.4159	0.4051	0.3965
γ	0.1259	0.1226	0.1198	0.1174	0.1181	0.1173	0.1054	0.1022	0.09968
f_{ice}	0.1200	0.1147	0.1119	0.1106	0.1109	0.1046	0.09925	0.09740	0.09347
r_{effw} [μm]	1.372	1.249	1.109	1.105	1.116	1.135	1.068	1.021	0.9929
r_{effi} [μm]	7.510	7.169	7.088	7.012	7.056	6.856	6.754	6.640	6.490
ES	3.230	3.012	2.947	2.900	2.926	2.818	2.708	2.616	2.521

RMSE of the output variables and Energy Score for different channel combinations.

- **NN structure:** MLP, 4-8 hidden layers with 256 neurons
- **Inputs:** MTG FCI reflectances for six solar channels (0.4µm, 0.5µm, 0.6µm, 0.8µm, 1.6µm, 2.2µm), corresponding albedos, sun and satellite angles
- **Outputs:** 6 variables (cloud optical thickness τ, cloud fraction γ, ice fraction f_{ice}, effective radii for water and ice clouds, $r_{eff,w}$ and $r_{eff,i}$) assumed to follow multivariate gaussian distribution and the associated 6 x 6 error covariance matrix
- **Cost function:** Energy Score ("strictly proper" score, multivariate generalization of CRPS, see Gneiting and Raftery (2007) "Strictly Proper Scoring Rules, Prediction, and Estimation") yielded best results
- **Training data:** One month of ICON-D2 forecasts and synthetic images generated for them for six solar MTG FCI channels

Results:

- Backward operator produces reliable (good coverage), situation-dependent uncertainty estimates
- Covariance structure in training data is well reproduced
- Adding more (strongly correlated) channels still improves results

Next step: Comparison of retrieval vs. reflectance assimilation in OSSEs (R = covariance matrix from DRN + representivity term)

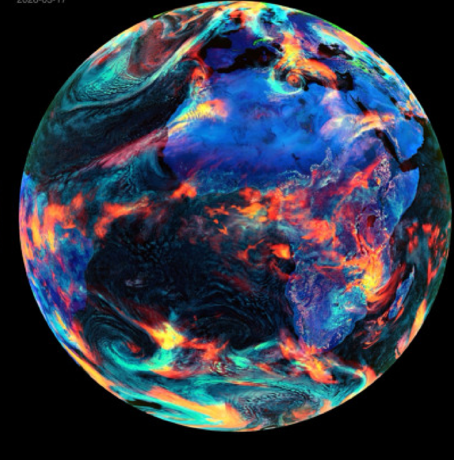
See Franzoni et al. 2026, „Using Distributional Regression Networks to Retrieve Cloud Properties from Solar Satellite Channels for Data Assimilation

MODEL EVALUATION / METEOSAT FCI RGB COMPOSITES

- Solar satellite channels provide high-resolution information on clouds, aerosols and humidity
- MFASIS for clouds supports now all of these channels → they can be used for model evaluation
- Comparing observed and synthetic RGB composites (see full disk FCI examples to the right) is often the first step in the evaluation
- The "cloud phase" composite can already be generated with RTTOV 14.0 and contains also information on effective radii
- The "cloud type" composite uses the 1.38µm now available in 14.1

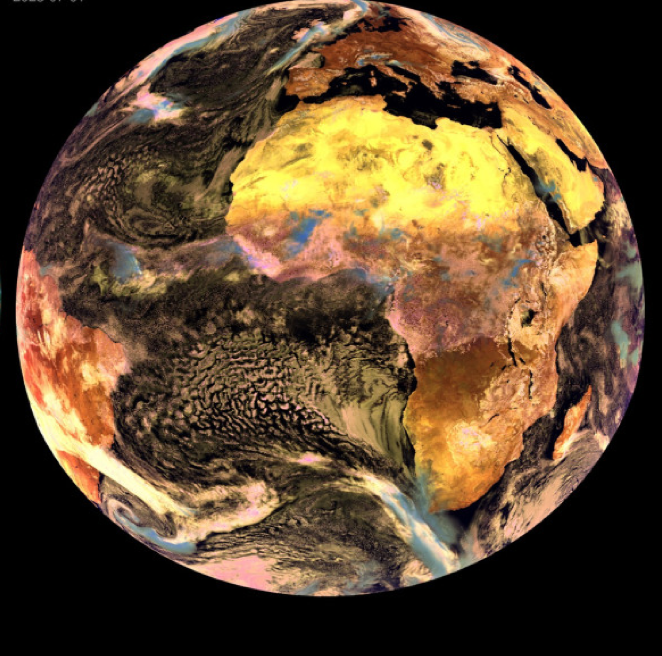
FCI observation

"True colour" RGB composite (R=0.6µm, G=85% 0.5µm + 15% 0.8µm, B=0.4µm)

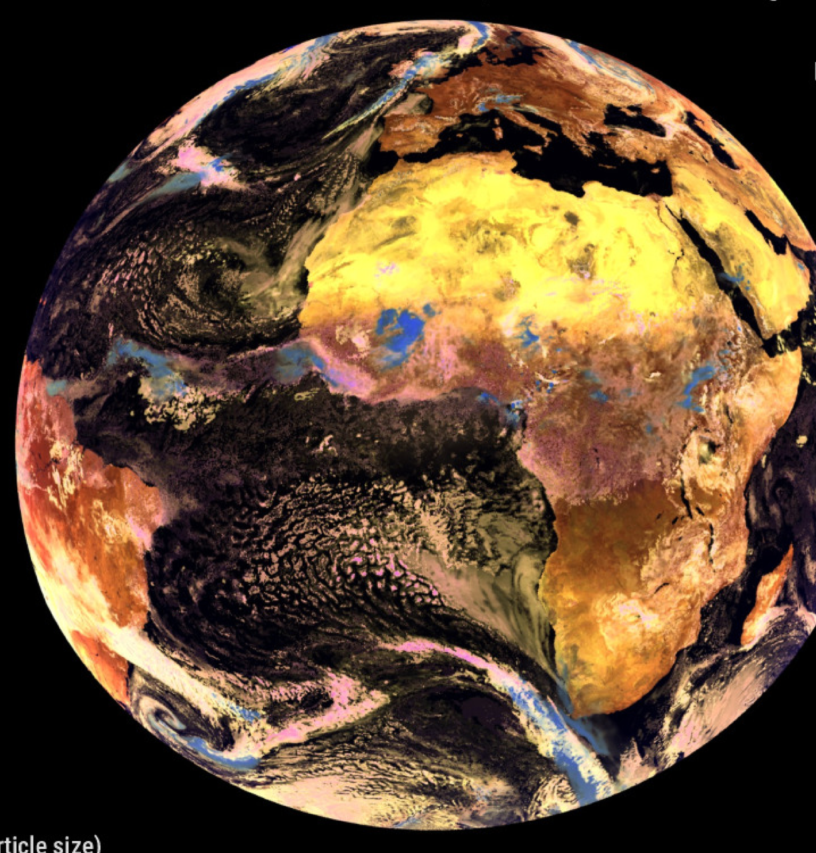


EUMETSAT cloud type RGB composite (R=1.3µm, G=0.6µm, B=1.6µm) High clouds are red to yellow

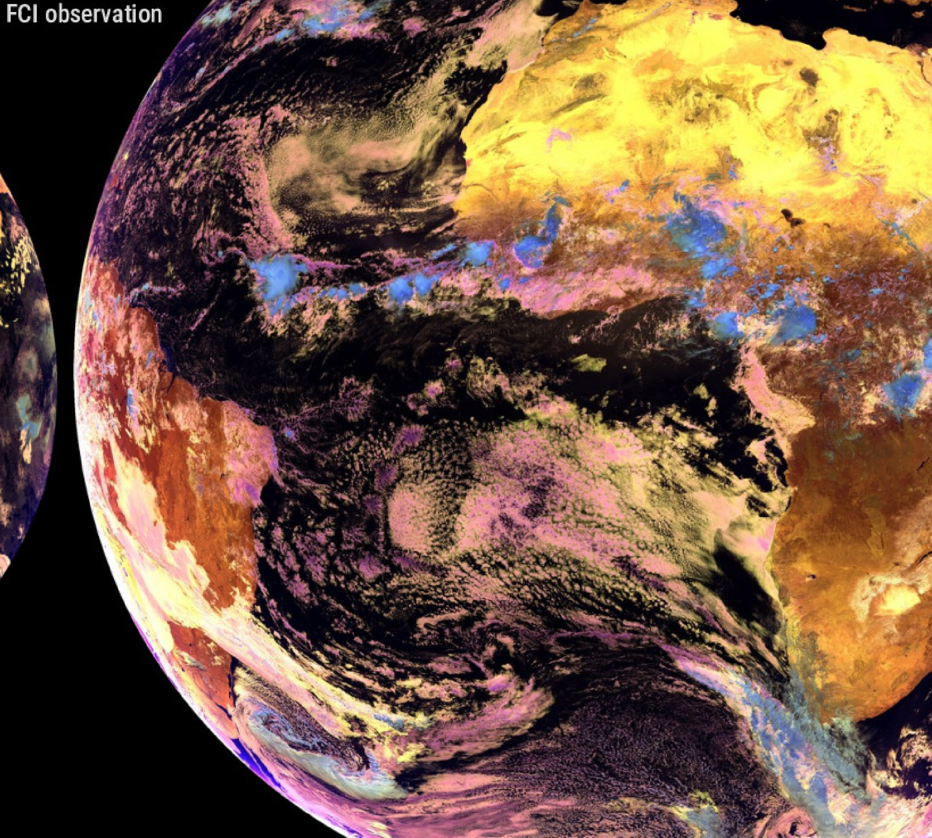
Operational 13km ICON forecast (1-moment scheme)



13km ICON forecast with 2-moment scheme, modified cloud cover settings



FCI observation



EUMETSAT cloud phase RGB composite (R=1.6µm, G=2.2µm, B=0.6µm)
Water clouds are pink to yellow, ice clouds are blue to turquoise (depending on particle size)