Advancing Cloud Prediction: Integrating Hyperspectral Satellite Insights and Deep Learning to improve Operational Forecast Accuracy and Model Validation

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DoD Cloud Post-Processing and Verification Workshop

Outline

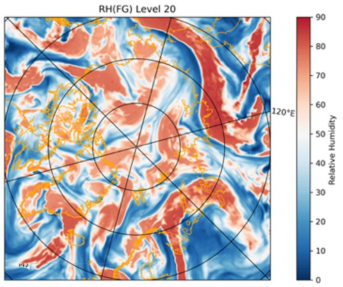
Presentation focuses on:

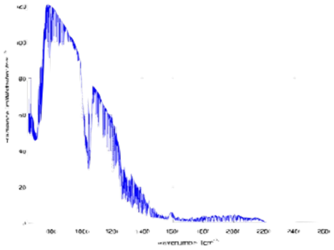
- the prediction of cloud cover through the assimilation of satellite data and products (Transformed Retrievals derived from hyperspectral IR data and MW) into a Rapid Update Cycle NWP model.
- the advantages and challenges of employing satellite data and products in cloud forecasting.
- the enhancement of validation of cloud forecasts through the use of the cloud mask products derived from VIIRS/AVHRR data.
- the potential of integrating algorithms based on deep learning to effectively harness the extensive data volume from current and future satellite sensors.

Forecasting Clouds with NWP models

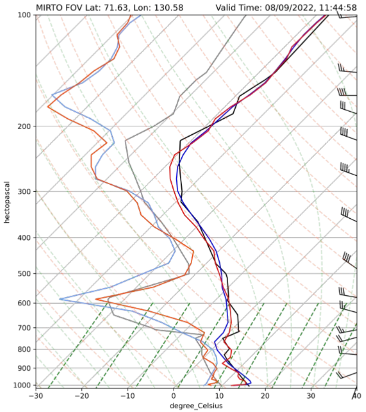
- NWP models require accurate initial conditions to make forecasts. Proper water vapor characterization is a vital part of these initial conditions. Inaccurate information about water vapor levels can lead to errors in subsequent cloud forecasting.
- The forecasting system developed at the University of Hawaii Mauna Kea Weather Center (MKWC) is based on the WRF model run in Rapid Update Cycle mode with direct assimilation of Transformed Retrievals (TRs) from hyperspectral IR data.
- TRs are compressed forms of hyperspectral IR observations obtained through a bayesian inversion and a linear transformation known as the Migliorini Transformation (Migliorini 2008, 2012, Rodgers 2000).
- The system developed at MKWC as been tested on both the Central Pacific area (Antonelli 2018, 2020 and Cherubini 2023) and over the Arctic Region within the THINICE experiment.
- In both cases the assimilation of hyperspectral and MW data has proved to increase the accuracy of the forecasts for water vapor fields laying the foundations for improved cloud forecasts.

Forecasting with NWP models and TRs





A-priori (model) knowledge regarding the atmospheric state + hyperspectral space-borne observations (Antonelli et al. 2016, 2020)

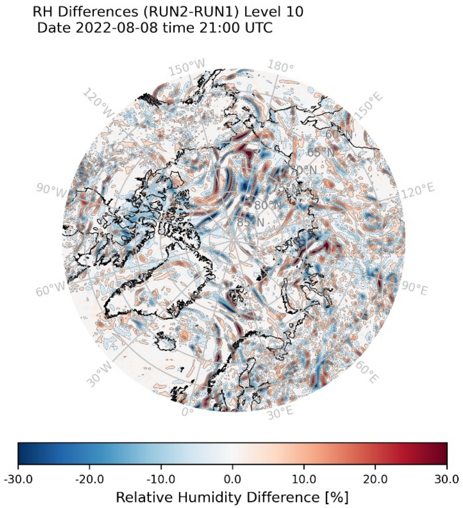


Physical Retrievals provide updated knowledge of the atmospheric state

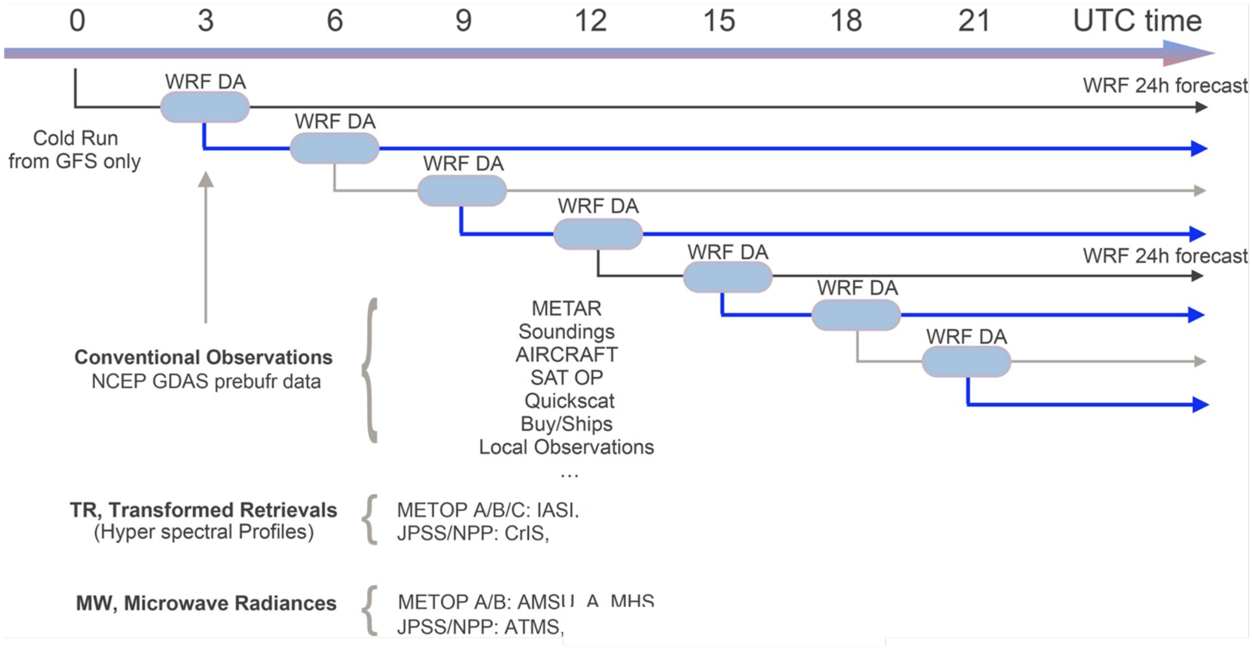
Physical Retrievals
in cloudy scenes
(with a priori)

Transformed Retrievals
in clear scenes
(without a priori)

RH Innovations at 800 mb due to Physical Retrievals (above clouds) + Transformed Retrievals (clear sky) assimilation in rapid update cycle (Migliorini 2008, 2012 – Rodger 2000)



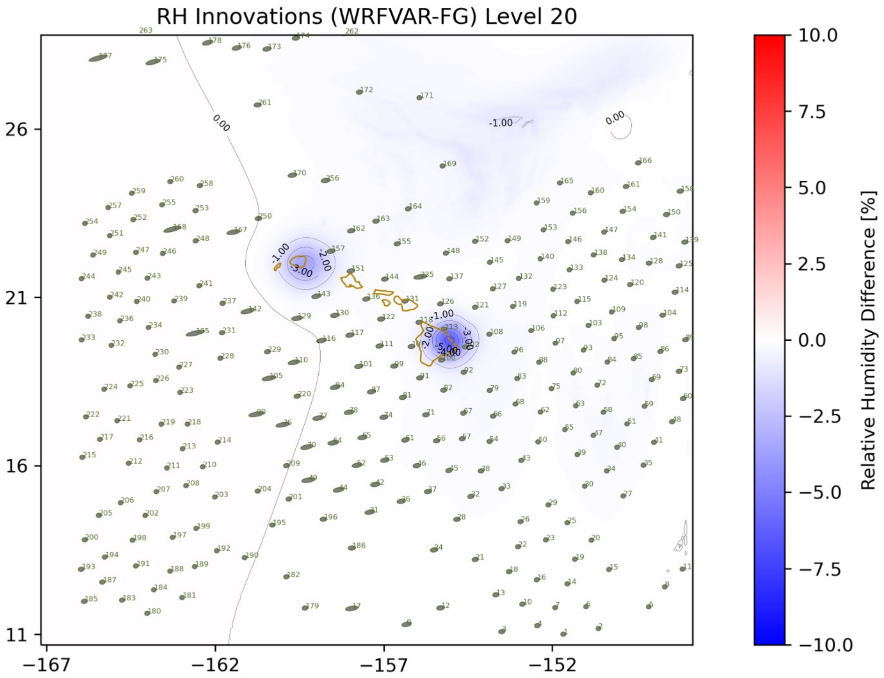
Forecasting in Rapid Update Cycling Mode

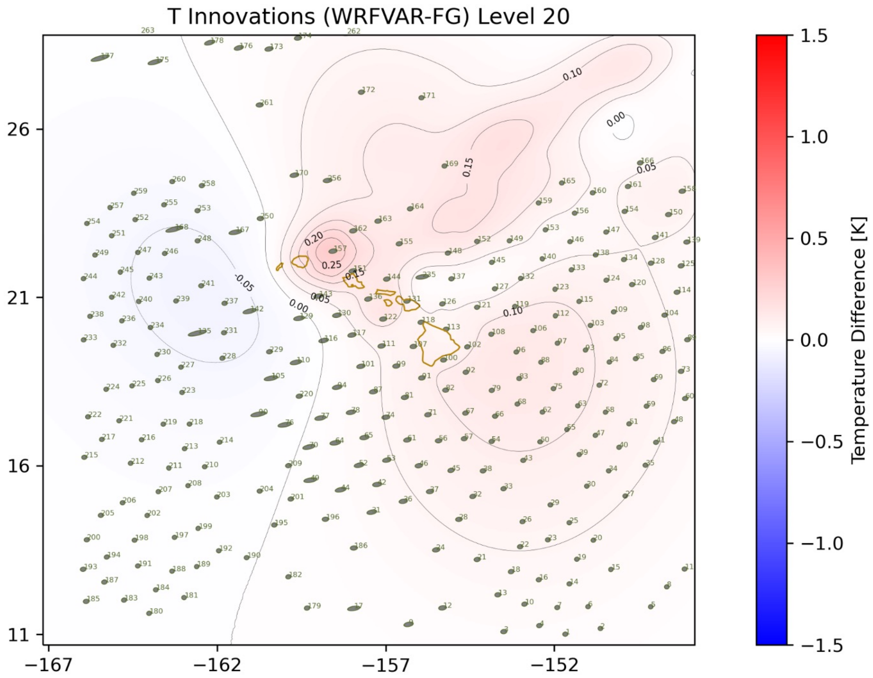


Pro: no need to wait for analysis availability;
ingestion of local observations;
optimal use of hyperspectral IR Data

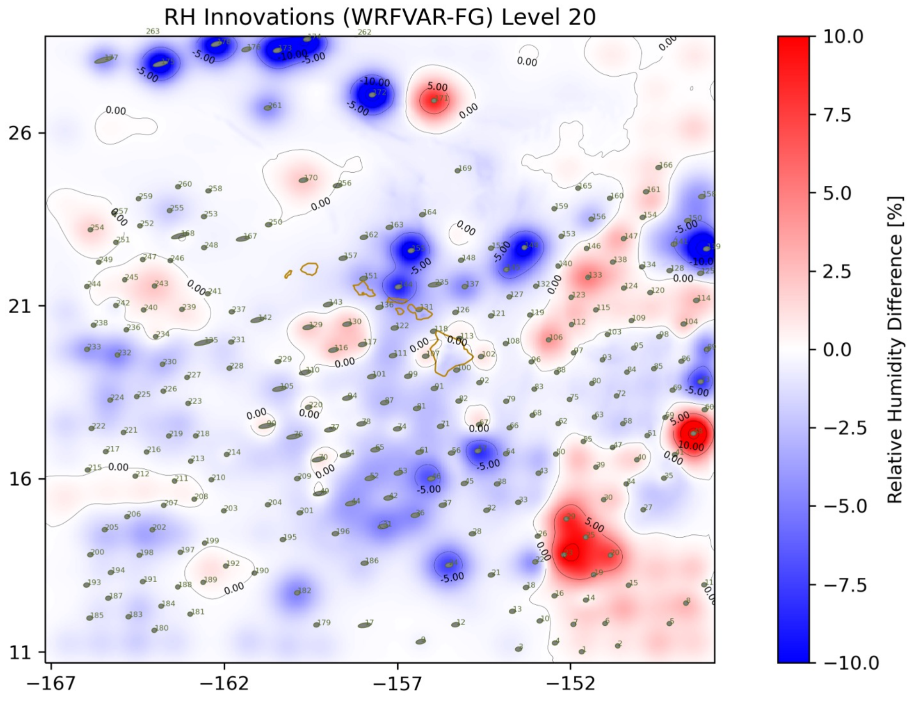
Current Limitations:
Cloud and aerosols handling.

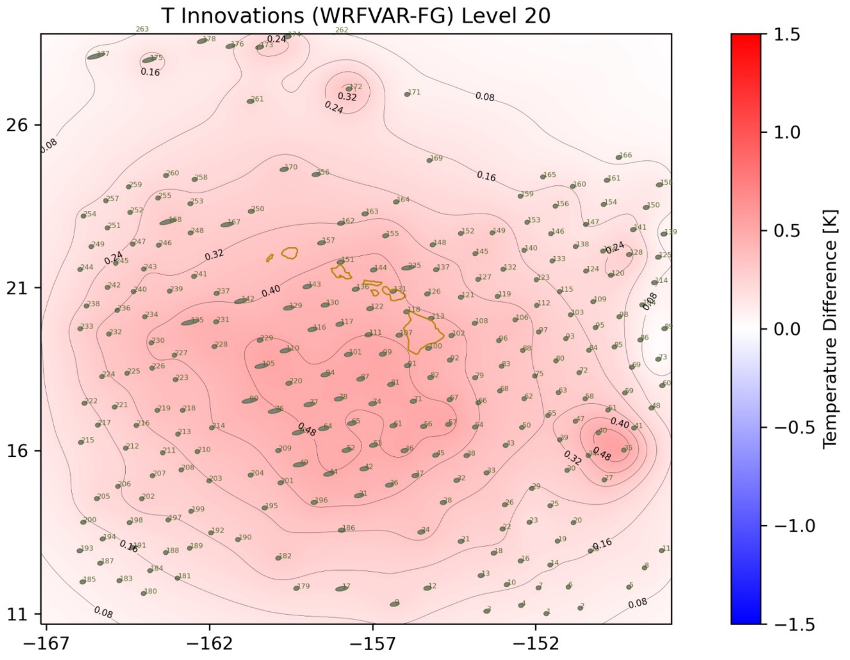
Innovations for CNTRL run



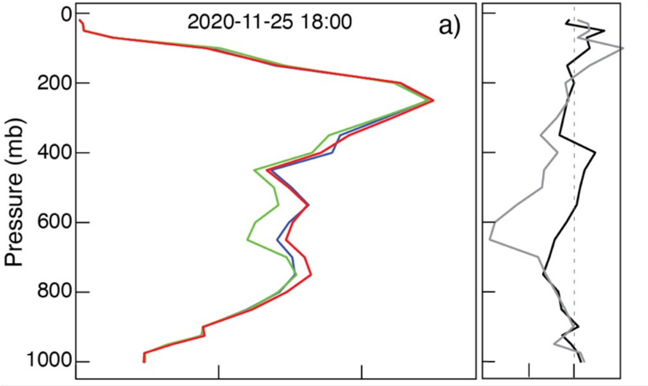


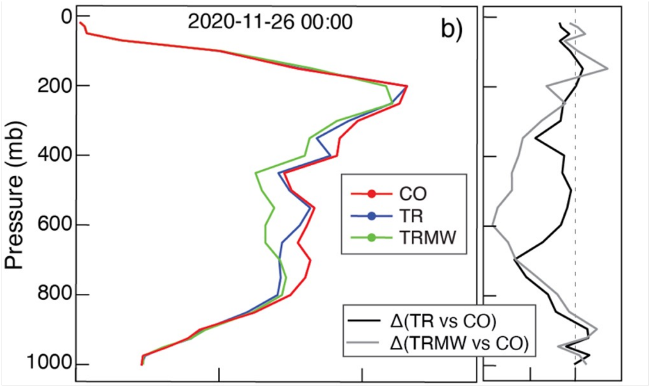
Innovations for FULL run



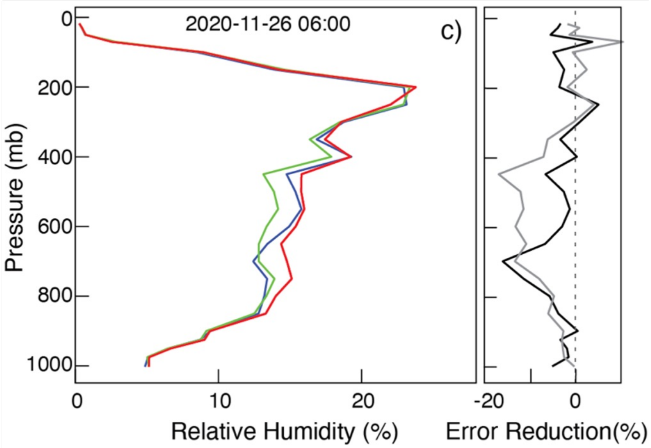


Improvements in RH forecasting

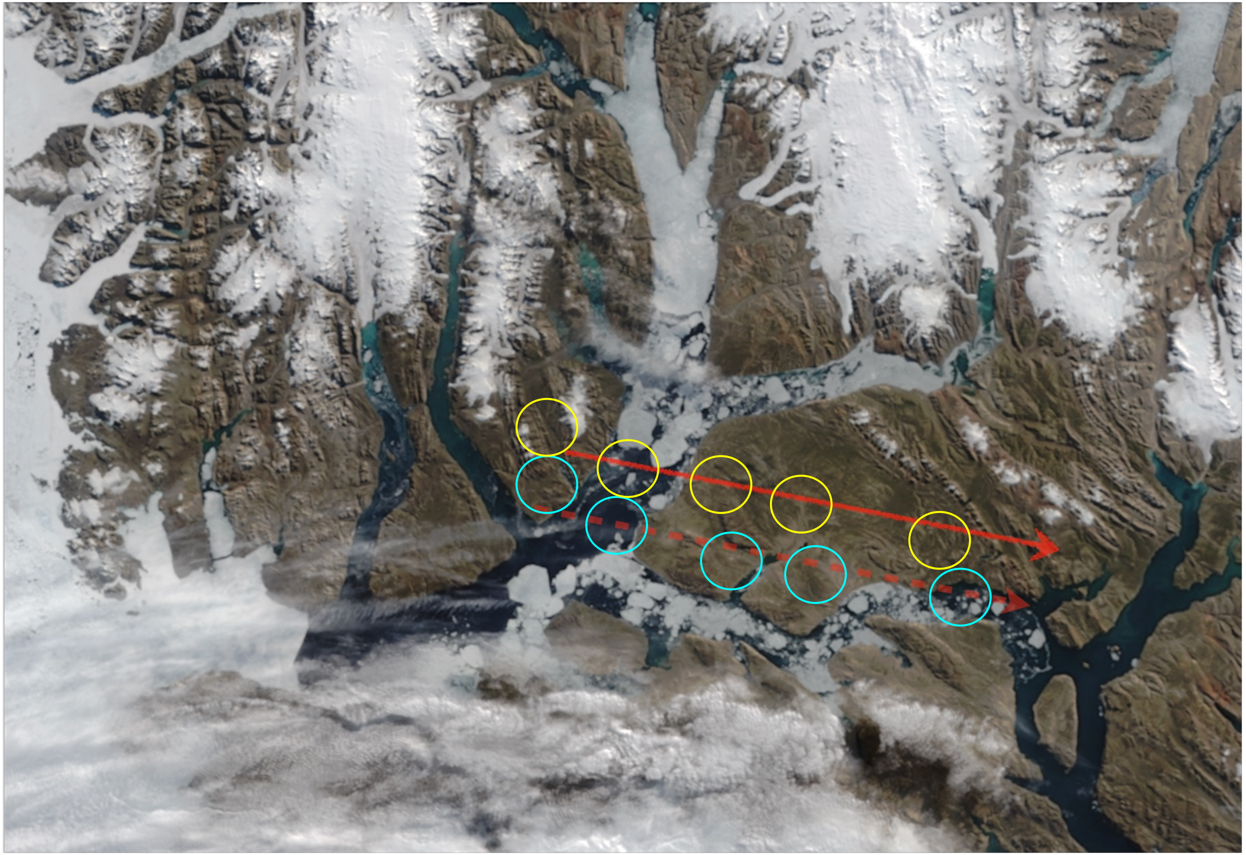


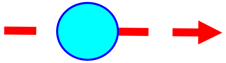


Vertical profiles of RH RMSEb for: (a) the 6h forecast started on Nov. 25 at 12:00 UTC; (b) the 3h forecast started on the Nov. 25 at 21:00 UTC, and c) the 6h forecast started on Nov. 26 at 00:00 UTC. The GFS is used as the reference field in the statistics. Each profile is obtained by averaging throughout the model domain (Cherubini et al. 2023).



Observing Cirrus with Hyperspectral IR data

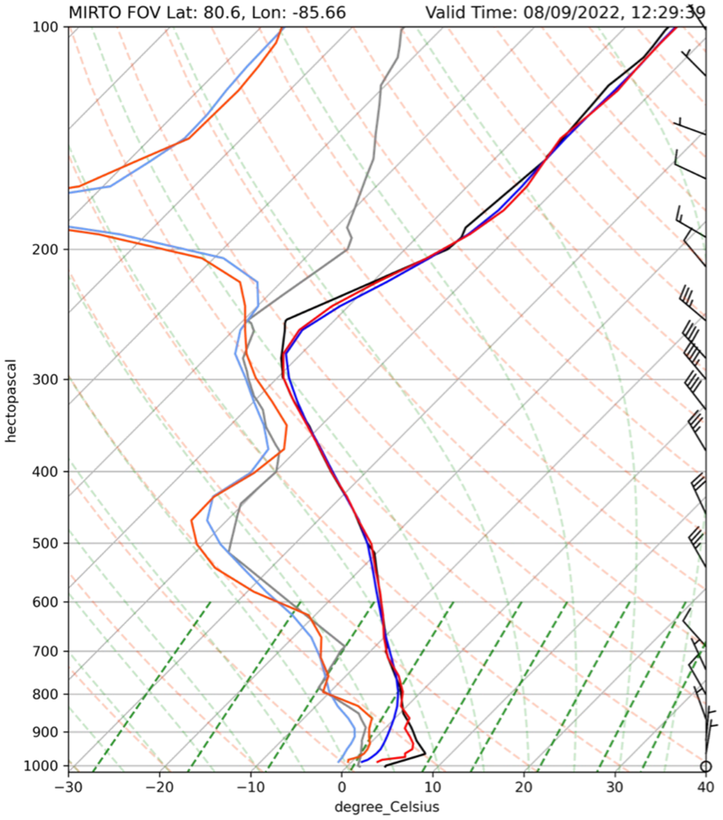


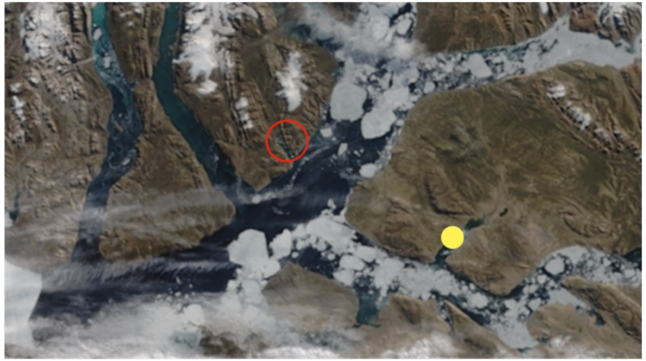


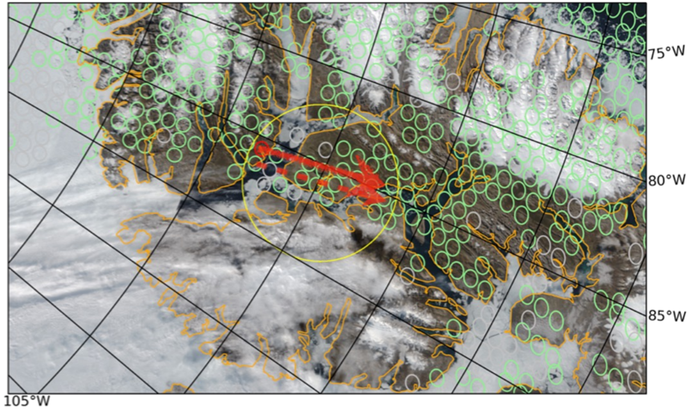
CrIS Fields of View On Cirrus Cloud

CrIS Fields of View Off Cirrus Cloud

Observing Clear Sky with Hyperspectral IR data

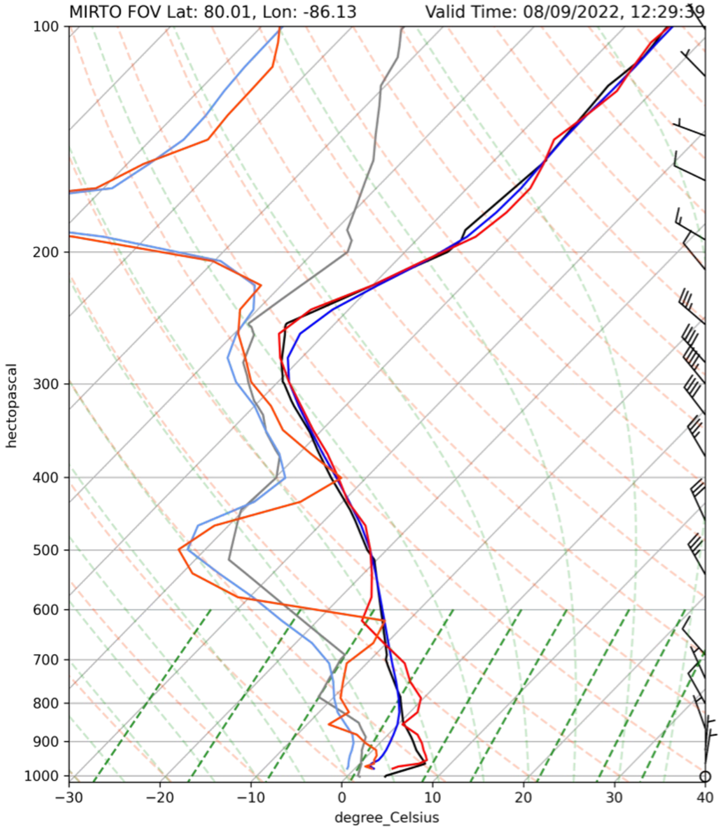


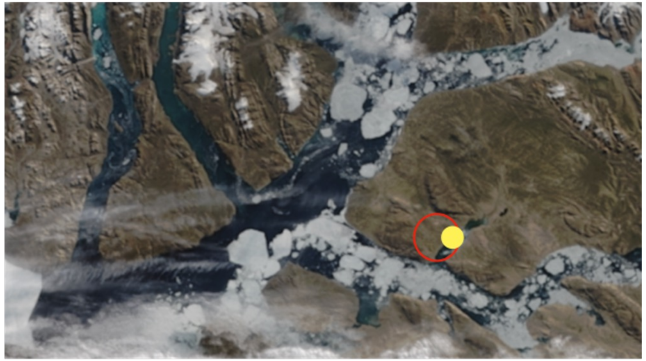


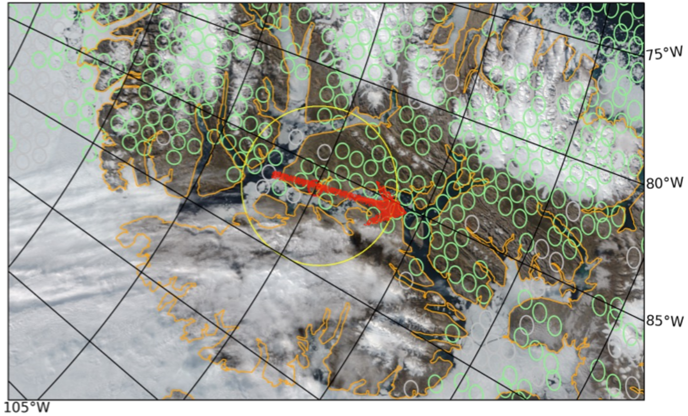


Moving to 85°W cleaner retrievals

Observing Cirrus with Hyperspectral IR data

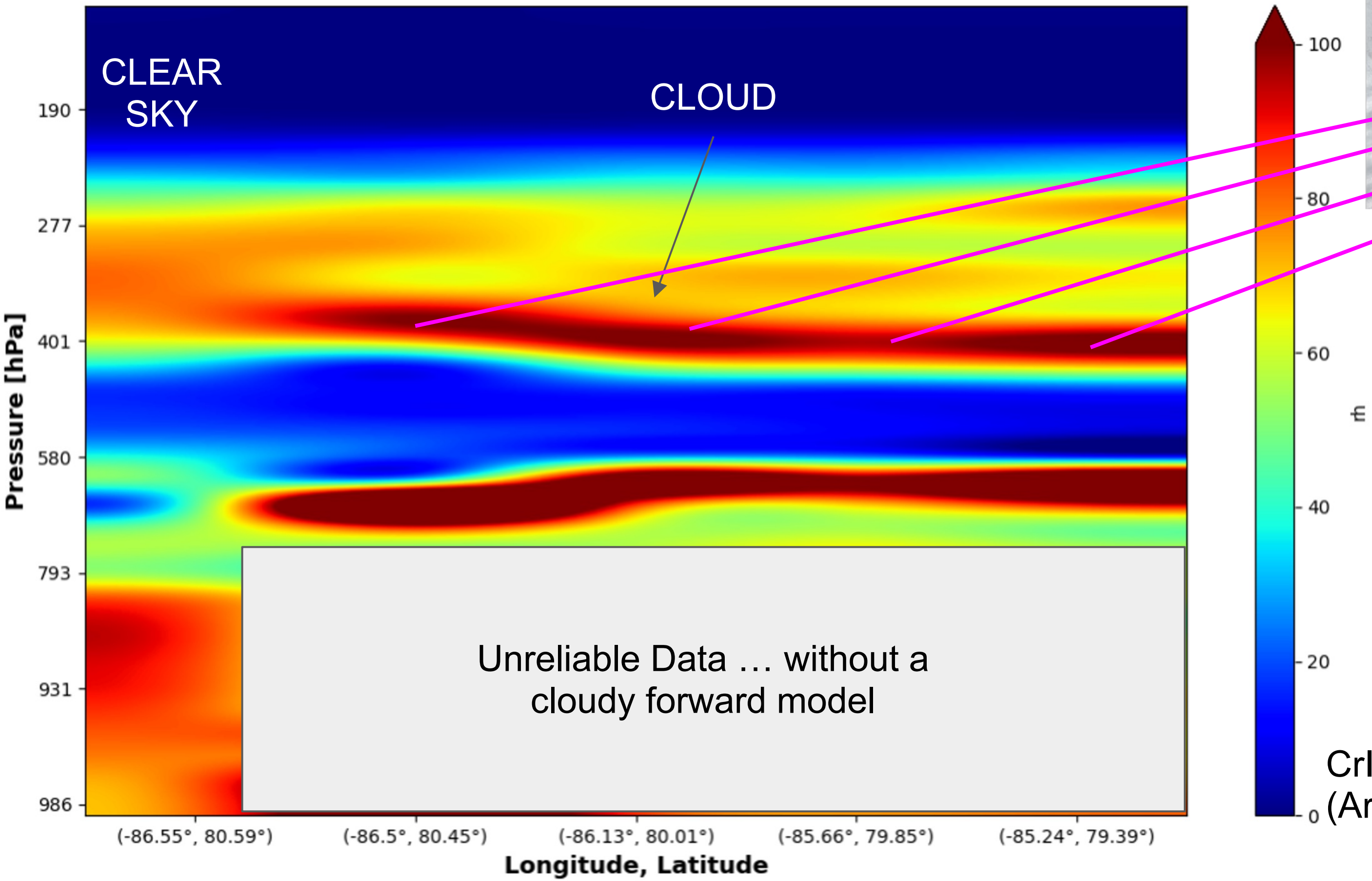


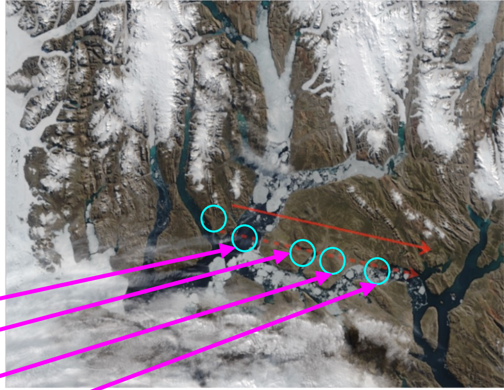




Edge of cirrus clouds around 87°W

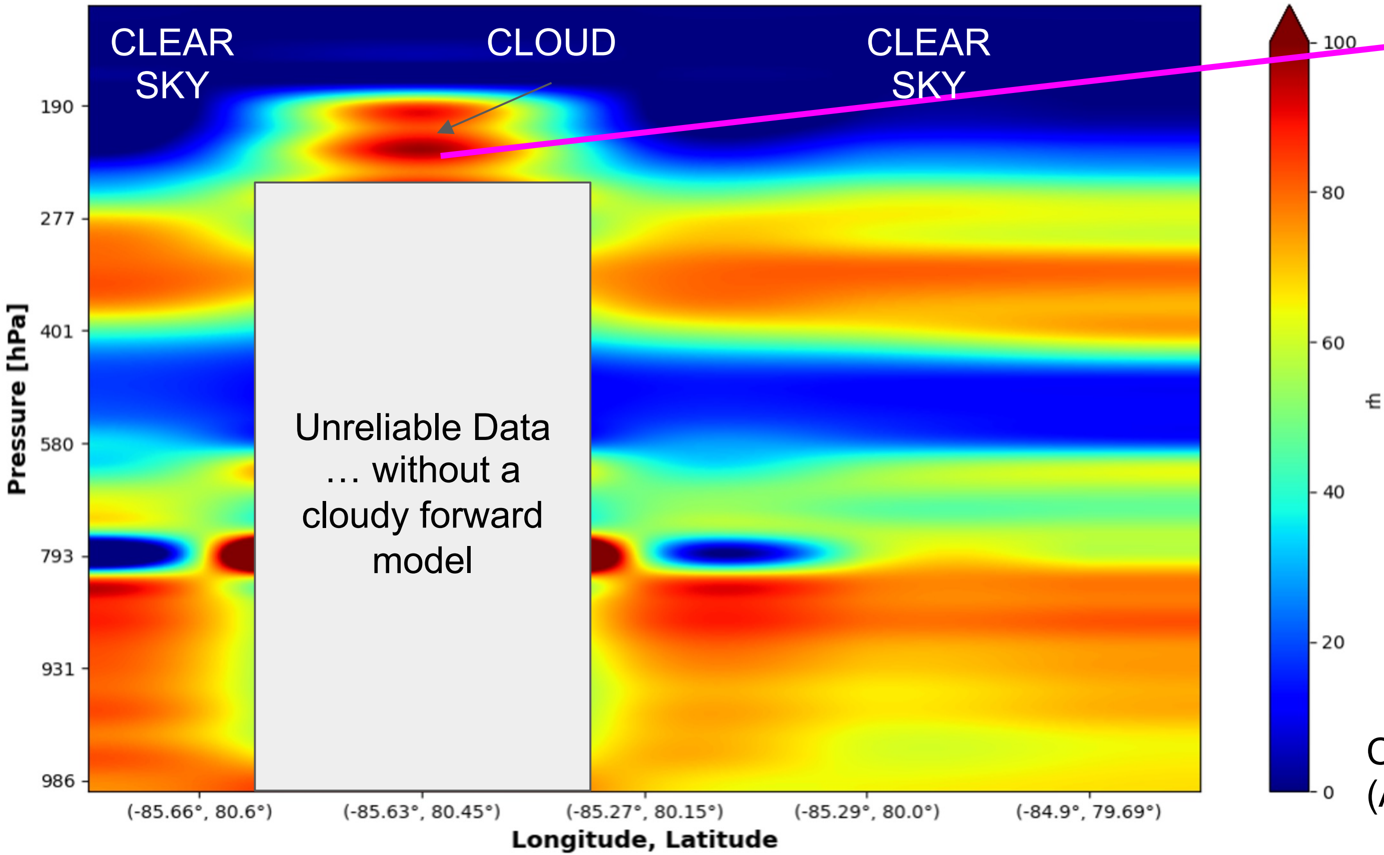
CrIS retrieved RH vertical X section

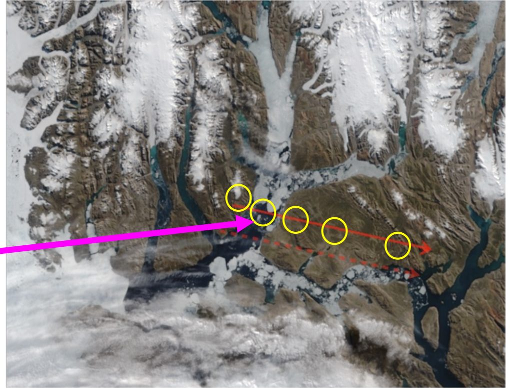




CrIS - VIIRS THINICE 2023
(Arctic Region)

CrIS retrieved RH vertical X section

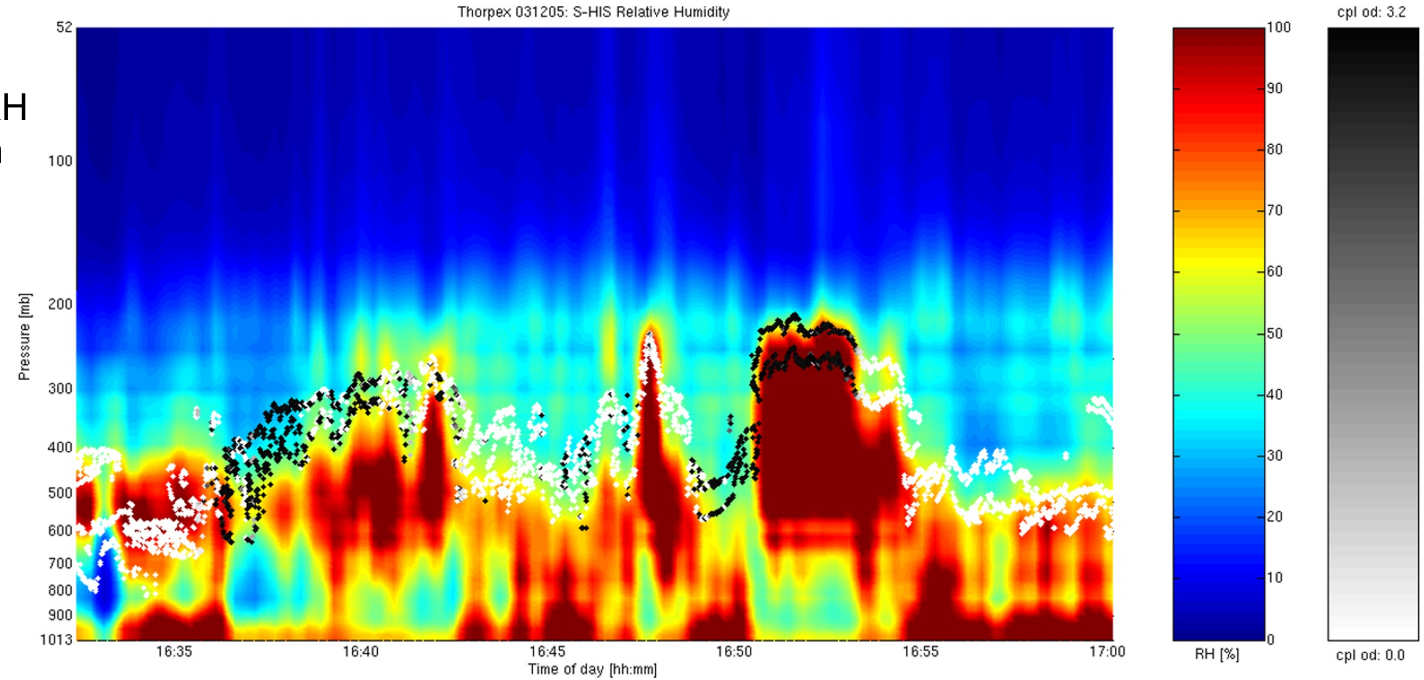


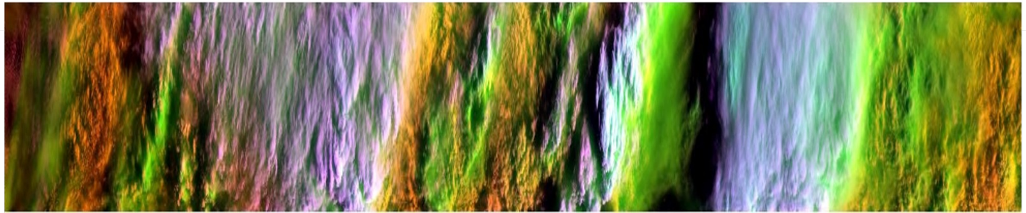


CrIS - VIIRS THINICE 2023
(Arctic Region)

Well known since before satellite hyperspectral IR era

SHIS retrieved RH
vertical X section





S-HIS, MAS, CPL
ATReC 2003 (Bangore, Maine)

Predicting Clouds with Hyperspectral IR data

- **Hyperspectral IR observation carry valuable information about the vertical and horizontal structure of the relative humidity field (and of the clouds).**
- With adequate time resolution (geostationary at low and middle latitude, and polar orbiting at higher resolution) it would be possible to monitor cloud formation and dissipation.
- At this stage hyperspectral data, in form of Quality Controlled Transformed Retrievals, are ingested into the WRF model operated in Rapid Update Cycle to exploit their information content but are limited by use of only clear sky observations.
- **Moving to a system capable of handling explicitly cloud contamination (CRTM) would greatly improve the accuracy of the forecasted fields.**
- **Future applications, currently under development, foresee the use of deep learning to derive cloud properties and dynamic directly from the combination of sounders, imagers and microwave sensors.**

Validating WRF Cloud Fraction

WRF and WRF-DA outputs can be validated by comparing the CLOUD COVER (Cloud Fraction) generated by the model with the CLOUD COVER effectively observed from SATELLITE (using VIIRS Cloud Mask co-located with the WRF grid).

CLOUD COVER is not a prognostic variable for the WRF model. It can been derived through different approaches. One common approach is based on a parametric algorithm which derives the cloud cover within 3 broad atmospheric layers by applying a linear transformation to the maximum layer RH values.

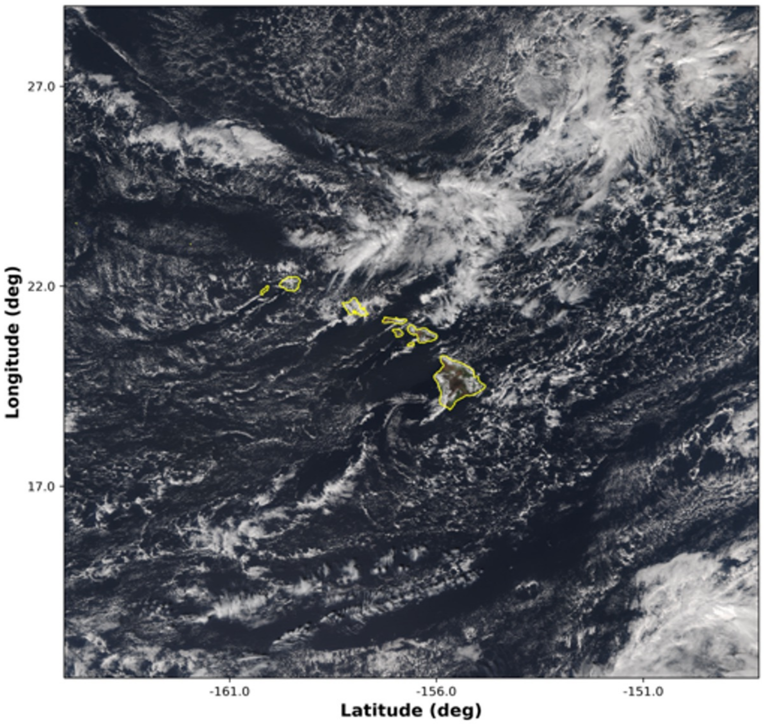
BASELINE approach has been to compare the CLOUD COVER generated from the WRF immediately before and after the assimilation with the CLOUD COVER observed by the closest VIIRS overpass. Unfortunately this approach showed the severe limitations due to inaccurate static parameterization used to estimate the CLOUD COVER from the model.

An ENHANCED approach has been defined to enable the WRF CLOUD COVER based validation. The new approach uses dynamic parameters optimised through a genetic algorithm. A further enhancement is foreseen in the near future moving toward an Artificial Neural Network approach.

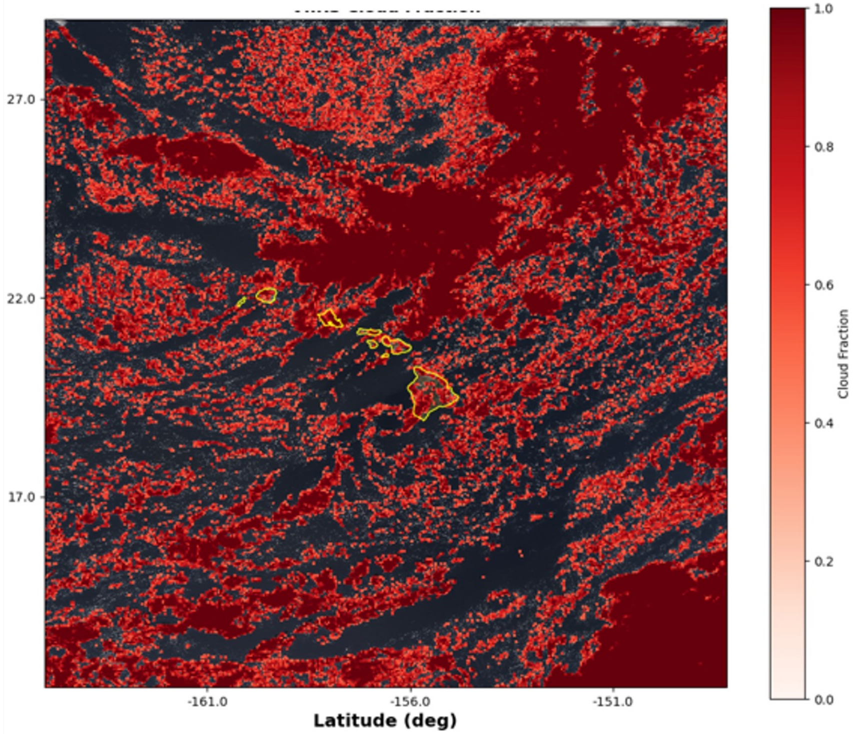
The WRF CLOUD COVER validation is expected to assess both the relative merits of different kind of observations in the assimilation and the overall forecast accuracy, it is therefore considered a crucial elements of the system under development in support of the THINICE EXPERIMENT.

Colocation of VIIRS CF on WRF grid cells

REAL CLOUD MASK VIS IMAGE

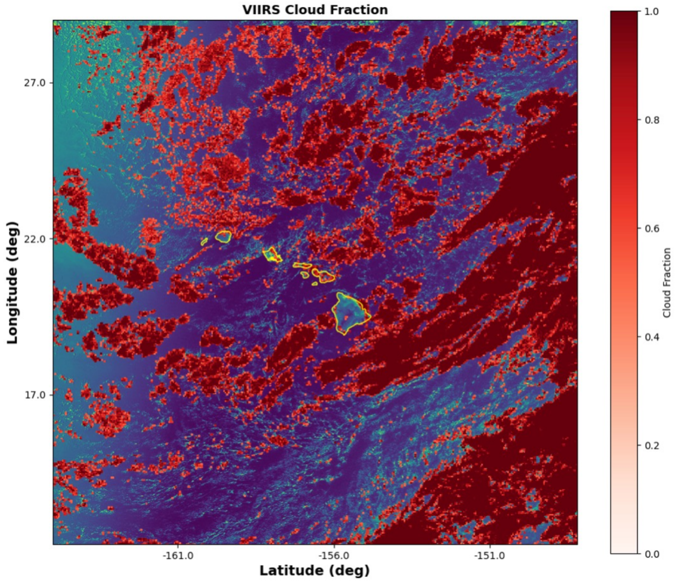


SATELLITE DERIVED CLOUD MASK

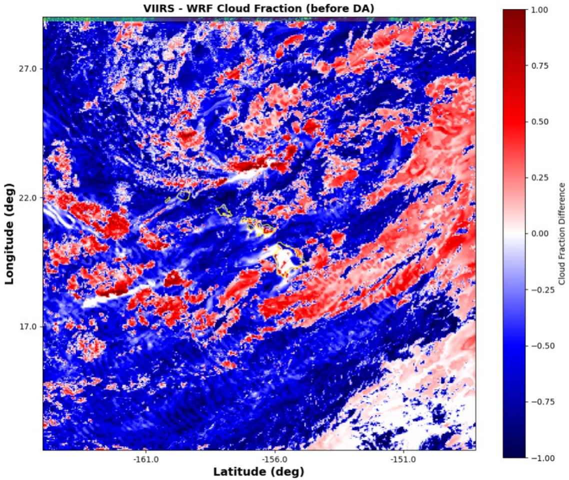


WRF Cloud Fraction Comparison

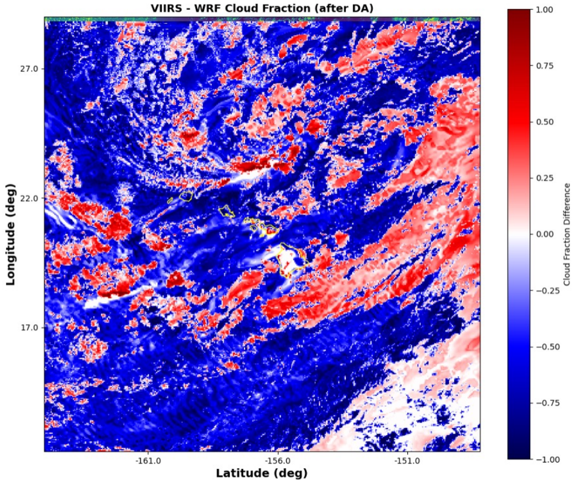
Assimilation time:
2020 Nov 28 at 12:00 UTC



"True" (VIIRS) CLOUD FRACTION



WRF BASELINE CF BEFORE ASSIMILATION

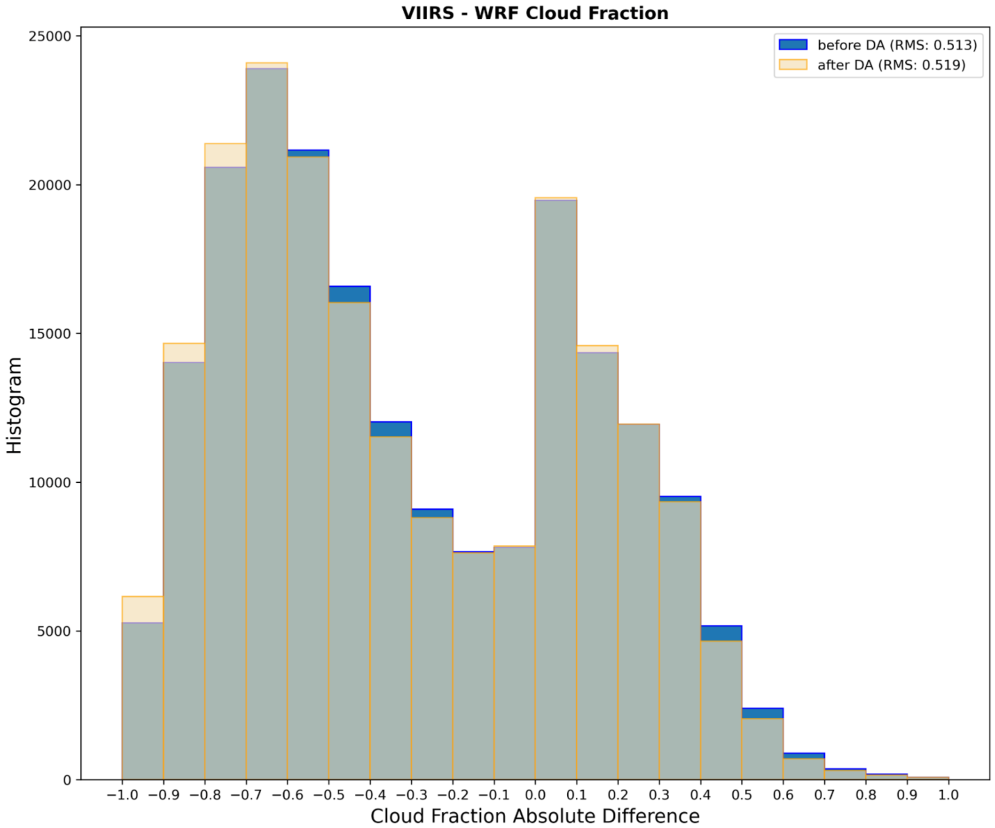


WRF BASELINE CF AFTER ASSIMILATION

WRF Cloud Fraction Comparison

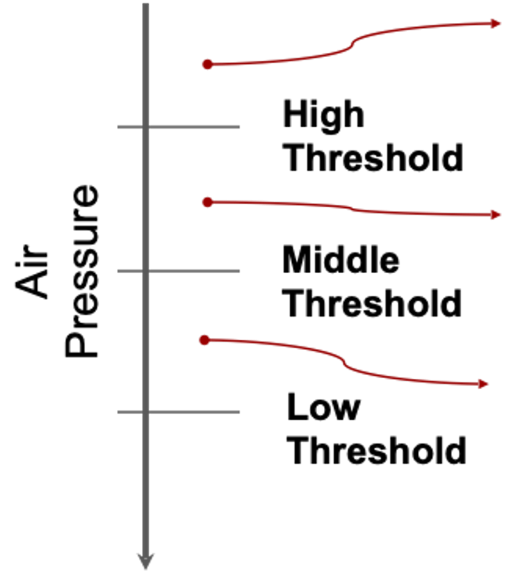
Assimilation time:

2020 Nov 28 at 12:00 UTC



RMSE of CLOUD FRACTION differences seems to slightly increase after assimilation. This might be due to the crudeness of BASELINE WRF CLOUD FRACTION estimation algorithm. For this reason an ENHANCED scheme for WRF CLOUD FRACTION estimation has been derived by using GENETIC algorithms

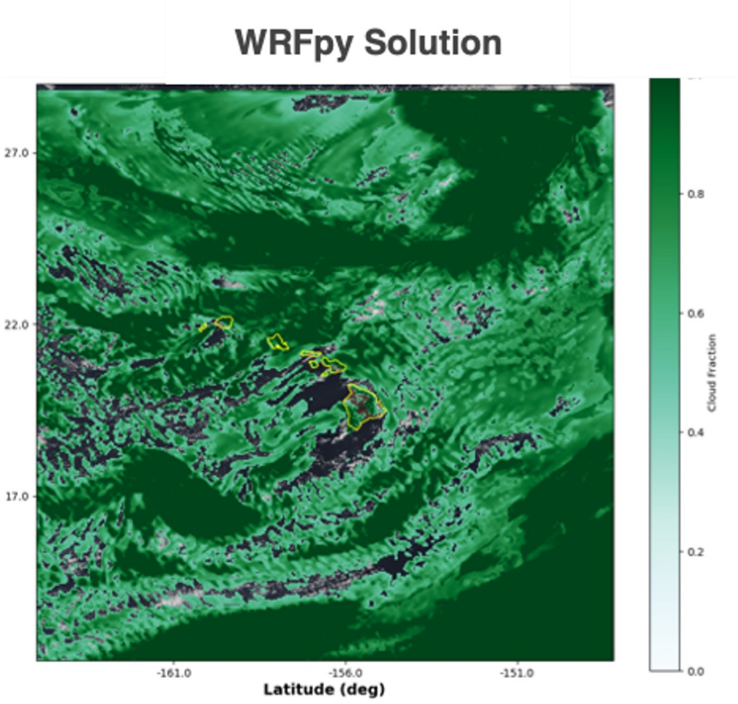
WRFpy solution for Cloud Fraction



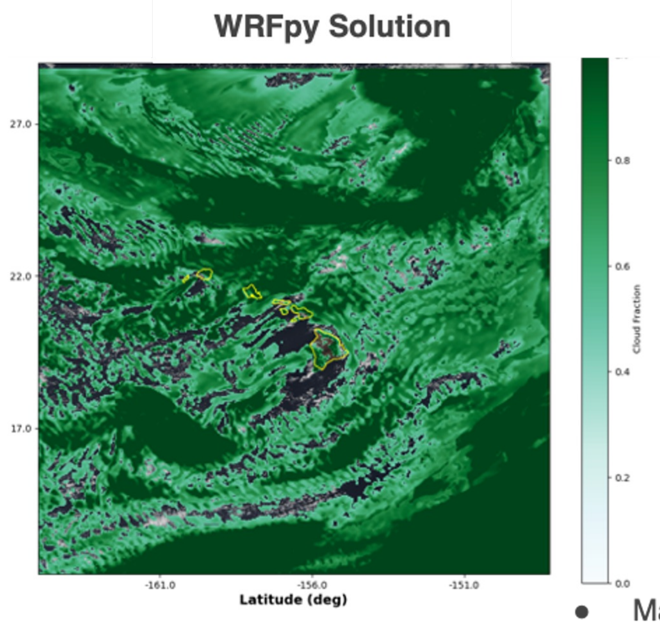
$$CF_{High} = E \times RH_{HighMax} / 100 - F$$

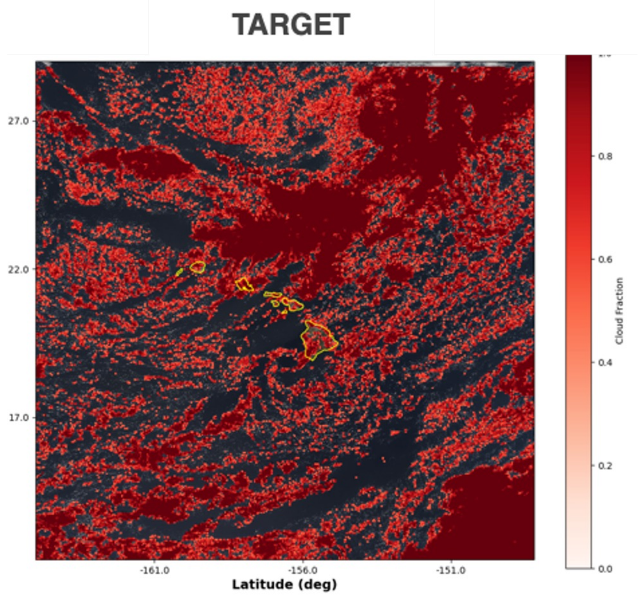
$$CF_{Middle} = C \times RH_{MiddleMax} / 100 - D$$

$$CF_{Low} = A \times RH_{LowMax} / 100 - B$$



Development of an Adaptive System for WRF Cloud Fraction Estimation





A genetic algorithm selects the best fitting parameters minimizing:

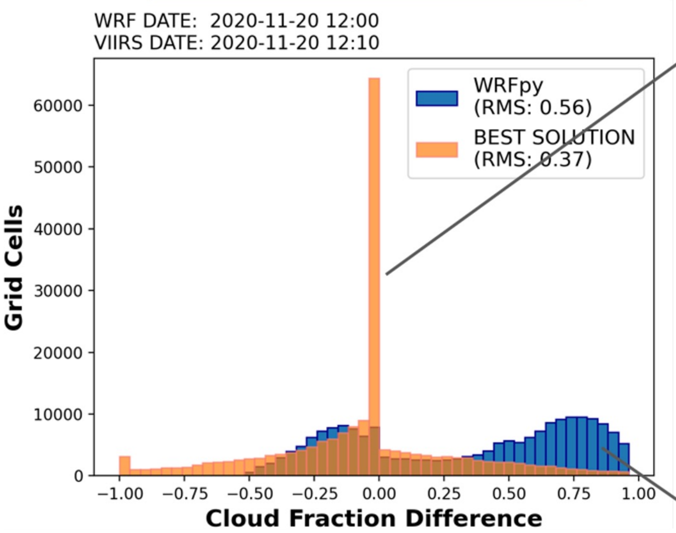
- Maximum distance between the cloud fraction cumulative functions

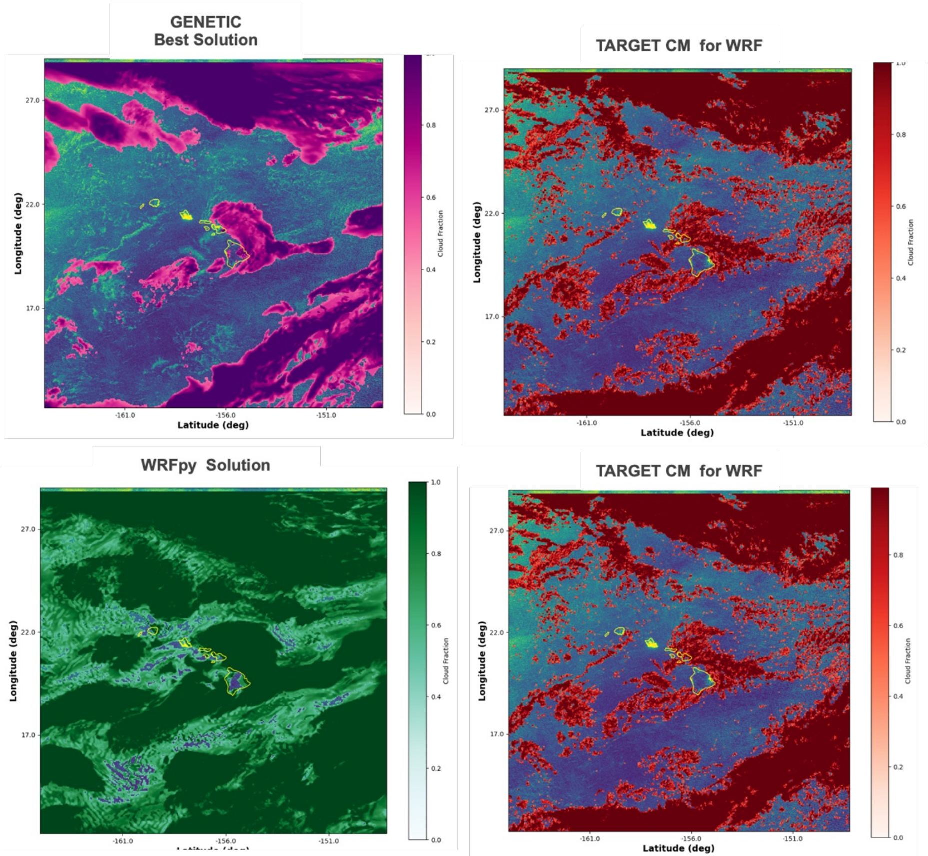
$$\max(\,|\,CDF_{Model}(x) - CDF_{Real}(x)\,|\,)$$

- Root Mean Square Error $\sqrt{\frac{1}{N_{cells}}\sum(CF_i - CF_i^{VIIRS})^2}$

Development of an Adaptive System for WRF Cloud Fraction Estimation

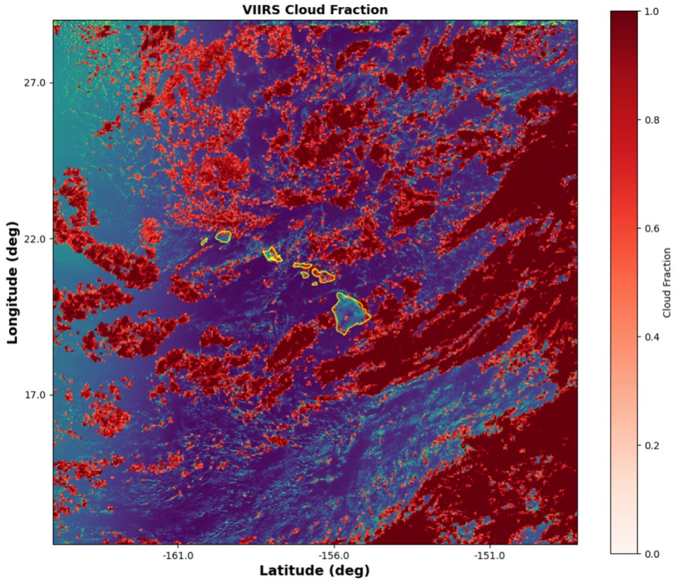
HISTOGRAM OF CM DIFFERENCES WITH THE TARGET



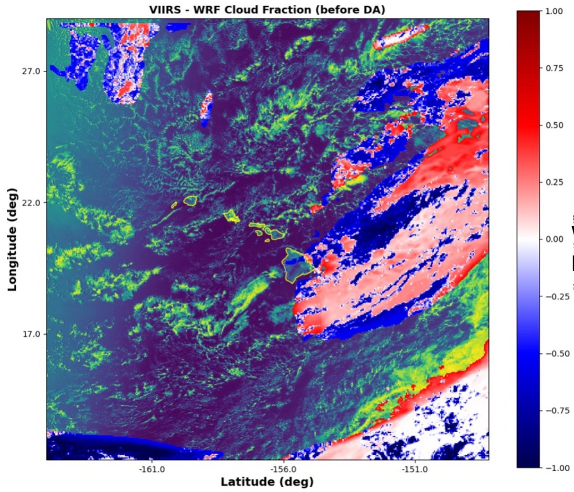


AS WRF Cloud Fraction Comparison

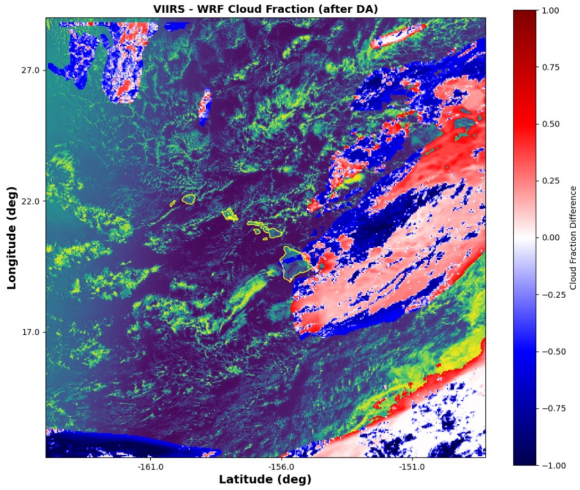
Assimilation time:
2020 Nov 28 at 12:00 UTC



“True” (VIIRS) CLOUD FRACTION



WRF BASELINE CF
BEFORE ASSIMILATION

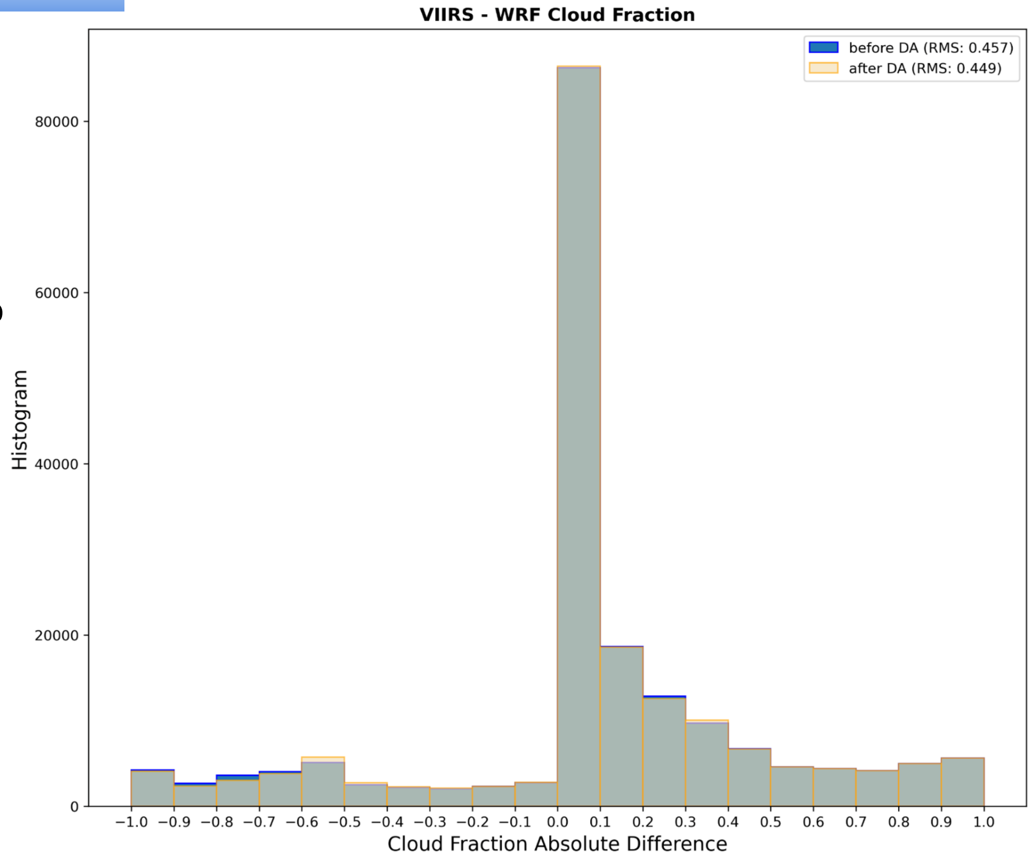


WRF BASELINE CF
AFTER ASSIMILATION

NOTE: CF < 0.5 have been masked-out

WRF Cloud Fraction Comparison

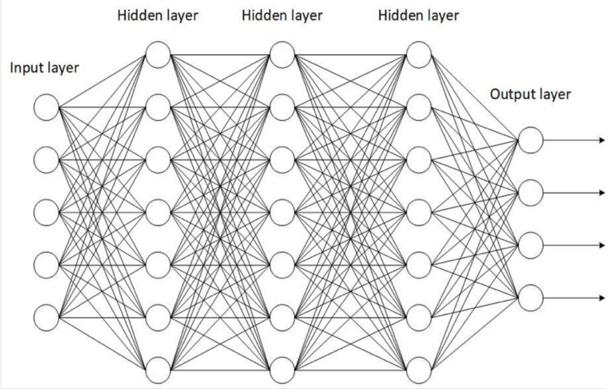
Assimilation time:
2020 Nov 28 at 12:00 UTC



RMSE of CLOUD FRACTION differences seems to slightly decrease after assimilation. More important the differences are now centred in the ZERO bin. This might be due to the improvement of the GENETIC WRF CLOUD FRACTION estimation algorithm.

Foreseen ENHANCEMENT scheme for WRF CLOUD FRACTION estimation

WRF Input Parameters



Convolutional Neural Network

Output Cloud Fraction

Microphysics, Temperature, Water Vapor, Wind, ...

Fang, Wei, et al. "Survey on the application of deep learning in extreme weather prediction." *Atmosphere* 12.6 (2021): 661.

Conclusions

- The presented study focuses on the operational prediction and evaluation of cloud cover, coupled with the subsequent enhancement and validation of cloud forecasts.

- Prediction of cloud cover and other atmospheric state variables is achieved through the assimilation of Transformed Retrievals derived from hyperspectral IR data into a Rapid Update Cycle NWP model.

- Enhancement and validation of cloud forecasts involve the use of the cloud mask products derived from VIIRS/AVHRR data.

- Advantages and limitations of employing satellite data and products in cloud forecasting are strictly related to the capacity of explicitly accounting for cloud contamination in hyperspectral data inversion (Cloudy Radiative Transfer Model such as CRTM).

- Algorithms based on deep learning are showing potential to effectively harness the extensive data volume from current and future satellite sensors.

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An assessment using sky camera and ceilometer data."
Journal of Geophysical Research: Atmospheres 120.19 (2015): 10-297

WRF Cloud Coverage Prediction Skills validated by means of sky camera imagery

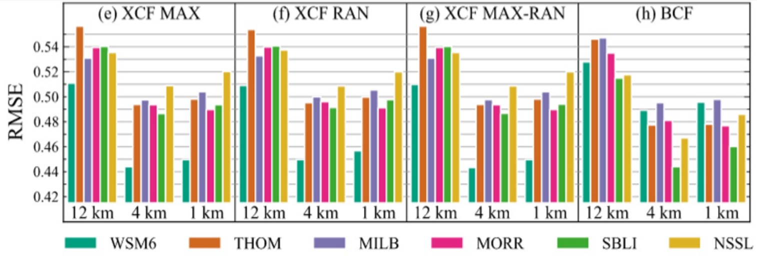

Figure 6. Performance scores of the WRF cloud cover prediction skill. (a–c), (e–g) RMSE using the XCF cloud fraction and different cloud fraction overlapping schemes, and (h) RMSE using the BCF cloud fraction. Scores are separately shown for the domains with 12, 4, and 1.3 km grid cell spacing and each microphysics parameterization (see Table 1). BIAS and RMSE are in cloud cover unit. The scores have been computed over 2268 simulation-observation pairs for each CF method, overlapping model, spatial resolution, and microphysics parameterization choice.