Real-Time MLP Neural Network Atmospheric Retrievals via Direct Broadcast: CSPP-Compatible Packages for ATMS-Only and Combined CrIS/ATMS/VIIRS

(plus, IASI and AWS)

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EUMETSAT

The City College of New York

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SCIENCE & TECHNOLOGY TO SUSTAIN THE EARTH

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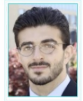

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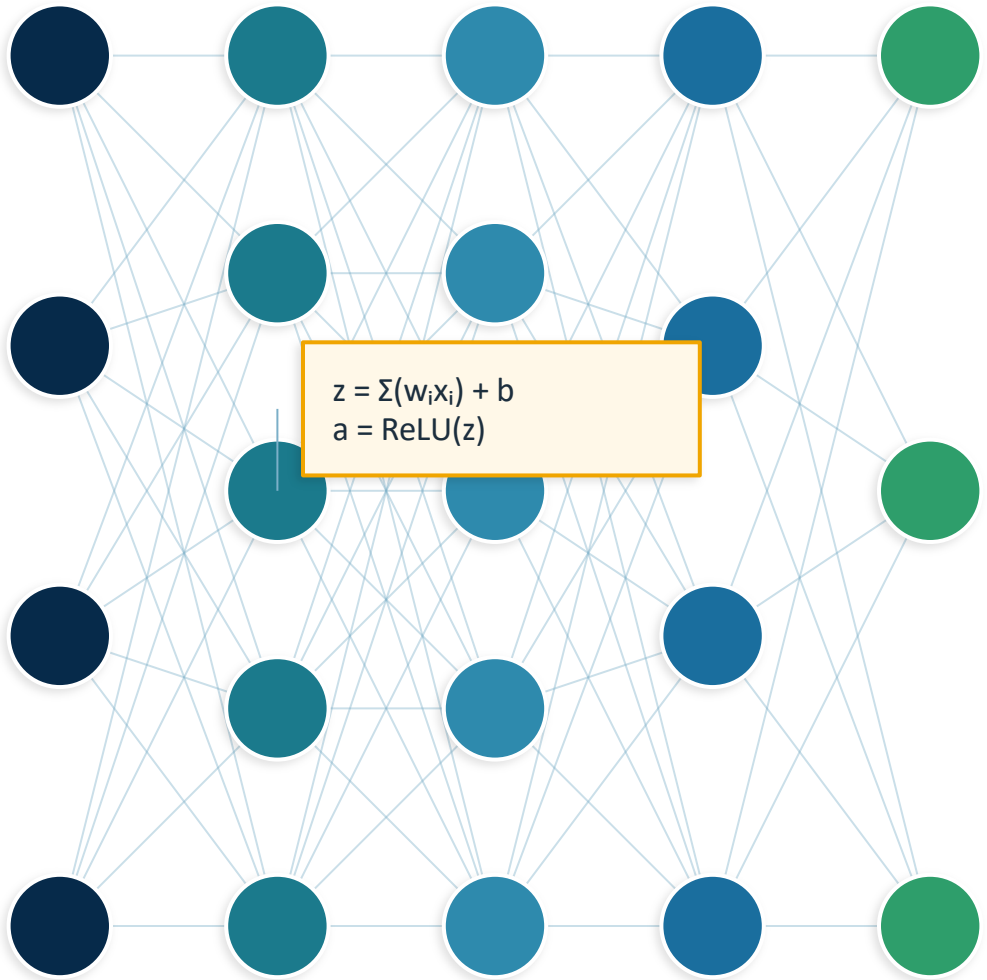
Ciara Dorsay (ChE PhD Candidate)

What is a Multi-Layer Perceptron (MLP)?

A feed-forward neural network that maps inputs to outputs through learned transformations



Neuron

Each neuron computes a weighted sum of its inputs plus a bias, then applies a non-linear activation function.

Weights & Biases

Free parameters adjusted during training. Weights scale each input; biases shift the activation threshold.

ReLU Activation

Rectified Linear Unit: a = max(0, z). Adds non-linearity so the network can learn complex patterns beyond linear mappings.

Depth = Capacity

Each hidden layer learns progressively more abstract features. More layers → more expressive model, higher capacity.

MLPs are universal approximators — given enough neurons, they can approximate any continuous function

Single Multi-Output Model Design

One MLP predicts all 37 pressure levels simultaneously

Why a Single Multi-Output Model?

Vertical Consistency

Shared hidden layers enforce physically consistent profiles

Smoother Bias Profiles

Adjacent level predictions are naturally correlated

Inter-level Learning

Network learns thermal structure relationships

Efficiency

One training pass vs. 37 separate models

Fewer Artifacts

Reduces level-to-level discontinuities

```
from sklearn.neural_network import MLPRegressor
from sklearn.preprocessing import StandardScaler
import numpy as np
import time
import joblib
import psutil
hidden_layers = (64, 128, 64)
max_iter = 70
alpha = 0.0005
learning_rate_init = 0.0005
n_iter_no_change = 12
validation_fraction = 0.10
batch_size = 1024

mlp_model = MLPRegressor(
    hidden_layer_sizes=hidden_layers,
    activation='relu',
    solver='adam',
    alpha=alpha,
    batch_size='auto',
    learning_rate='adaptive',
    learning_rate_init=learning_rate_init,
    max_iter=max_iter,
    early_stopping=True,
    validation_fraction=0.1,
    n_iter_no_change=n_iter_no_change,
    tol=1e-4,
    random_state=42,
    verbose=True  # Show iteration progress
)

# Train on ALL levels simultaneously
mlp_model.fit(X_train, y_train)

model_filename = 'AWS_single_TP_single_mlp_model_FINAL.pkl'
scaler_filename = 'AWS_single_TP_single_mlp_scaler_FINAL.pkl'
joblib.dump(mlp_model, model_filename)
joblib.dump(scaler, scaler_filename)
```

Temperature Retrieval: Input Features

Four sensor configurations — architecture noted for each

CrIS + ATMS Temperature	
CrIS PCA Scores	78
ATMS Tbs (22 ch)	22
sec(θ) − 1	1
Land/Sea Mask	1
Surface Pressure	1
TOTAL	**103**
Arch: 256–256–128–64	

CrIS Only Temperature	
CrIS PCA Scores	78
sec(θ) − 1	1
Land/Sea Mask	1
Surface Pressure	1
TOTAL	**81**
Arch: 256–256–128–64	

ATMS (AWS) Only Temperature	
ATMS Tbs (22 ch) AWS Tbs (19 ch)	22 (19)
sec(θ) − 1	1
Land/Sea Mask	1
Surface Pressure	1
TOTAL	**25 (22)**
Arch: 64–128–64	

IASI Only Temperature	
IASI LW PCs	90
IASI SW PCs	60
sec(θ) − 1	1
Land/Sea Mask	1
Surface Pressure	1
TOTAL	**153**
Arch: 256–256–128–64	

All features standardized to zero mean, unit variance via StandardScaler before input to the MLP

Water Vapor Retrieval: Input Features

Four sensor configurations — all use 64–128–64 architecture

CrIS Only Water Vapor	
CrIS PCA Scores	78
sec(θ) − 1	1
Land/Sea Mask	1
Surface Pressure	1
TOTAL	**81**
Arch: 64–128–64	

CrIS + ATMS Water Vapor	
CrIS PCA Scores	78
ATMS Tbs (22 ch)	22
sec(θ) − 1	1
Land/Sea Mask	1
Surface Pressure	1
TOTAL	**103**
Arch: 64–128–64	

ATMS Only Water Vapor	
ATMS Tbs (22 ch) AWS Tbs (19 ch)	22 (19)
sec(θ) − 1	1
Land/Sea Mask	1
Surface Pressure	1
TOTAL	**25 (22)**
Arch: 64–128–64	

IASI Only Water Vapor	
IASI LW PCs	90
IASI SW PCs	60
sec(θ) − 1	1
Land/Sea Mask	1
Surface Pressure	1
TOTAL	**153**
Arch: 64–128–64	

All features standardized to zero mean, unit variance via StandardScaler before input to the MLP

Surface & Column Parameters : Input Features

Four sensor configurations — all use 64–128–64 architecture | Output: 4 scalars simultaneously

Skin Temperature | TPW | CLW | TCRW

CrIS + ATMS		CrIS Only		ATMS (AWS) Only		IASI Only	
CrIS PCA Scores	78	CrIS PCA Scores	78	ATMS Tbs (22 ch) AWS Tbs (19 ch)	22 (19)	IASI LW PCs	90
ATMS Tbs (22 ch)	22	sec(θ) − 1	1	sec(θ) − 1	1	IASI SW PCs	60
sec(θ) − 1	1	Land/Sea Mask	1	Land/Sea Mask	1	sec(θ) − 1	1
Land/Sea Mask	1	Surface Pressure	1	Surface Pressure	1	Land/Sea Mask	1
Surface Pressure	1					Surface Pressure	1
TOTAL	103	TOTAL	81	TOTAL	25 (22)	TOTAL	153
Arch: 64–128–64		Arch: 64–128–64		Arch: 64–128–64		Arch: 64–128–64	

Training Dataset Construction Pipeline – CrIS/ATMS

1 CrIS Eigenvector Generation

Input: CrIS L1B radiances — every day 2019, every 12th 6-min granule → SVD / EOF analysis → 150 global eigenvectors

CrIS L1B

Every 4th day, 2019
~53 M FOVs

Step 2
PC Projection
Apply eigenvectors from Step 1 → 150 PC scores per FOV

CrIS 150 PCs

VIIRS Imagery

Cloud Mask

Step 3
Spatial Aggregation (UW)
Aggregate VIIRS pixels within each CrIS FOV footprint → cloud fraction

Cloud Fraction @ CrIS FOV

ATMS L1B

22-channel microwave brightness temps

Step 4
Backus-Gilbert Interpolation
Optimal linear combination of nearby ATMS FOVs → averaged Tb

ATMS 22 Tbs @ CrIS FOV

ERA5 Reanalysis

0.25° × 1-hr ECMWF model-level output

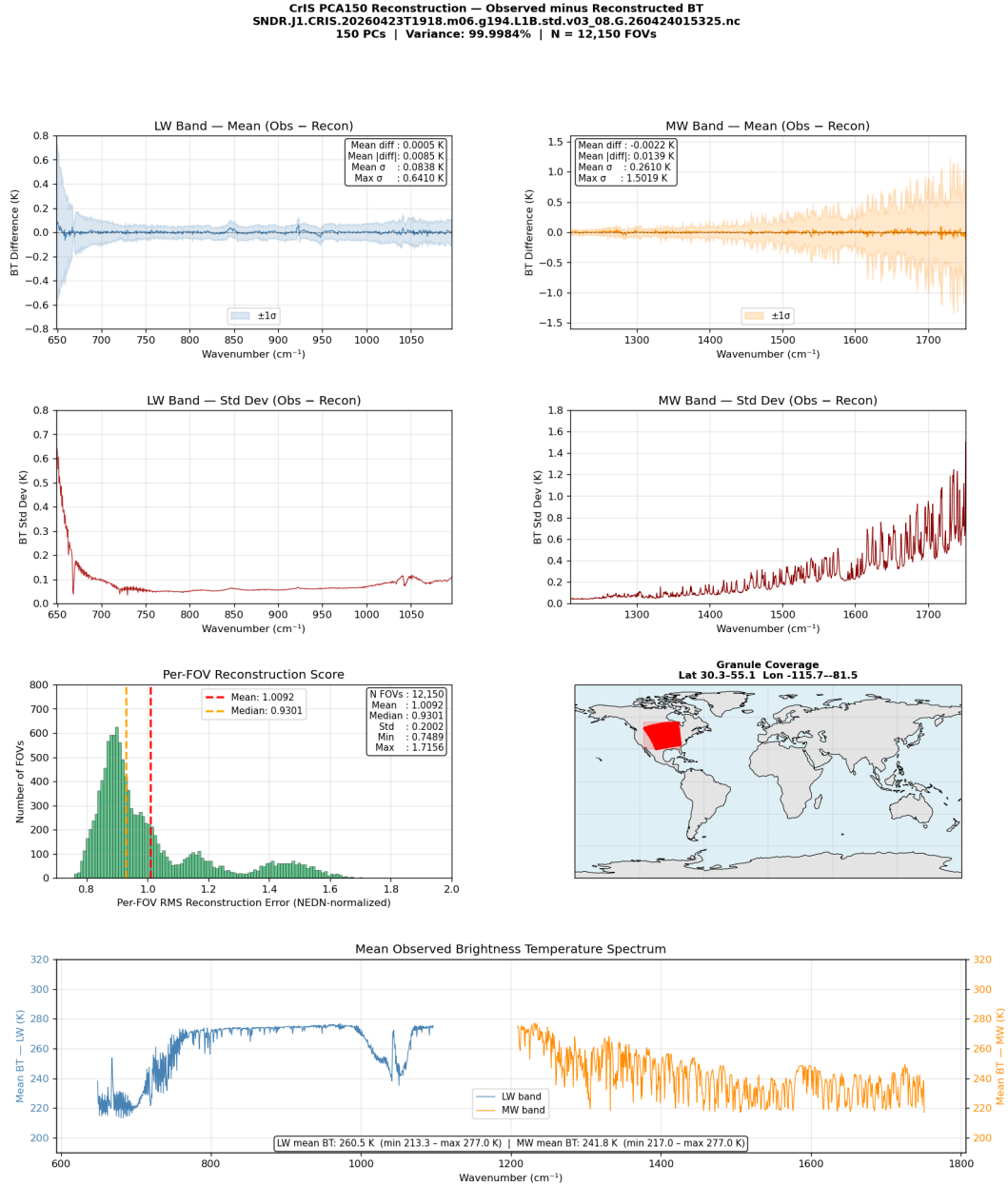
Step 5
Temporal + Spatial Interpolation
Bilinear spatial + linear temporal interp to each CrIS FOV & time

T, q, Skin, TPW CLW, TCRW @ FOV

⊕ **COLLOCATION & MERGE — All four streams matched to common CrIS FOV index, timestamp, and geolocation**

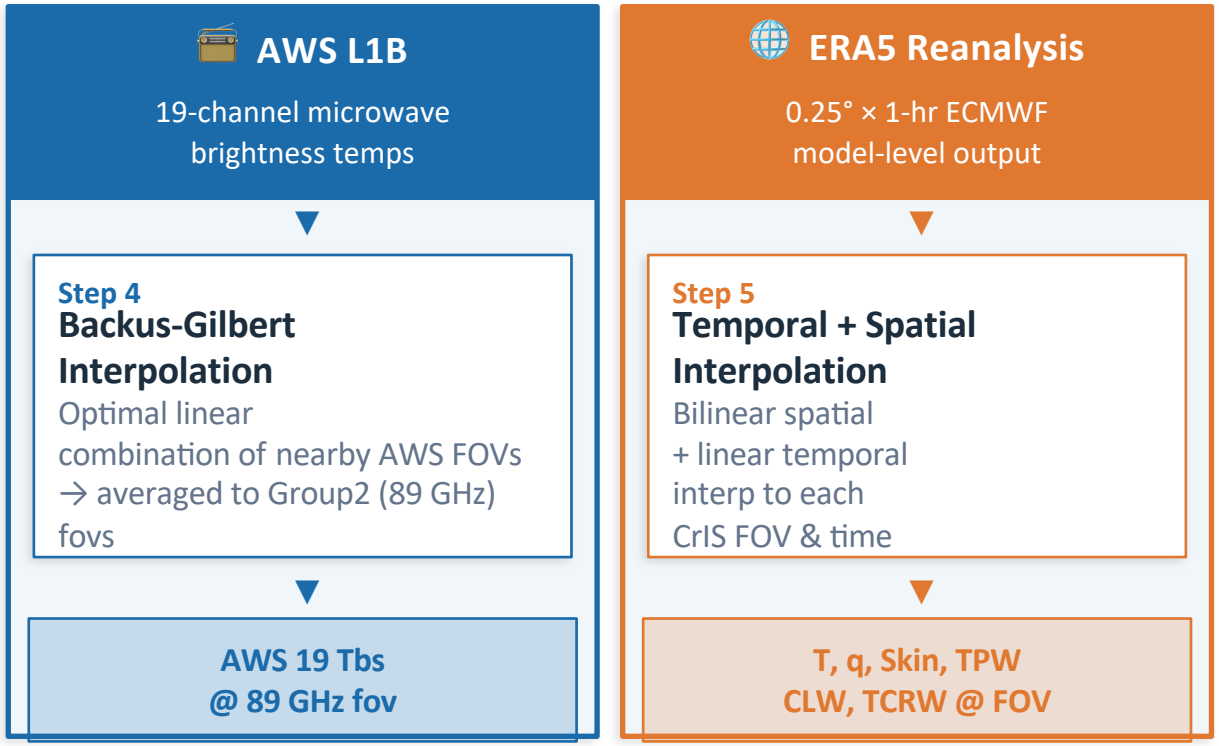
✓ **Training Dataset: ~53 M samples | CrIS 150 PCs + VIIRS cloud fraction + ATMS 22 Tbs + ERA5 T, q, surface/column truth**

Diagnostic Plots when converting CrIS spectra to PC



Training Dataset Construction Pipeline for AWS

1



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Simple Code

```
# ============================================================================
# SECTION 1: CONFIGURATION
# ============================================================================
NPZ_FILE  = '/Volumes/Crucial II 4TB/ERA5 Apr 2026/NOAA20_CrIS_PC150_ATMS_ERA5_Apr23_2026.npz'
OUTPUT_NC = 'gridded_025deg_CRISPC78ATMS_April232026_full.nc'

MODEL_PATHS = {
    'T': {
        'model':  '/Users/macpro/Box Sync/Default Sync/Latest CRIS and ATMS and CRISplusATMS MLP/TP/
CRISPC78ATMS_53M_BG_Every4thDay_2019_LWMW_NOVIIRS_TP_25625612864_single_mlp_model_FINAL.pkl',
        'scaler': '/Users/macpro/Box Sync/Default Sync/Latest CRIS and ATMS and CRISplusATMS MLP/TP/
CRISPC78ATMS_53M_BG_Every4thDay_2019_LWMW_NOVIIRS_TP_25625612864_single_mlp_scaler_FINAL.pkl',
    },
    'WV': {
        'model':  '/Users/macpro/Box Sync/Default Sync/Latest CRIS and ATMS and CRISplusATMS MLP/WV/
CRISPC78_ATMS_BG_01953Mevery4thday_WV_alpha001learn0001_single_mlp_model_FINAL.pkl',
        'scaler': '/Users/macpro/Box Sync/Default Sync/Latest CRIS and ATMS and CRISplusATMS MLP/WV/
CRISPC78_ATMS_BG_201953Mevery4thday_WV_alpha001learn0001_single_mlp_scaler_FINAL.pkl',
    },
    'SURF': {
        'model':  '/Users/macpro/Box Sync/Default Sync/Latest CRIS and ATMS and CRISplusATMS MLP/TSTPWTCRWCLW/
CRISPC78_ATMS_BG_53M_AllSky_2019every4th26M_TSTPWTCRWCLW_all_mlp_models_FINAL.pkl',
        'scaler': '/Users/macpro/Box Sync/Default Sync/Latest CRIS and ATMS and CRISplusATMS MLP/TSTPWTCRWCLW/
CRISPC78_ATMS_BG_53M_AllSky_2019every4th26M_TSTPWTCRWCLW_scaler_FINAL.pkl',
    },
}
```

```
# ============================================================================
# SECTION 6: MLP RETRIEVALS
# ============================================================================
def apply_single_model(BT, model_path, scaler_path, truth, label):
    print(f"\n  Loading {label} …")
    model  = joblib.load(model_path)
    scaler = joblib.load(scaler_path)
    print(f"    Architecture : {model.hidden_layer_sizes}  "
          f"Outputs: {model.n_outputs_}")
    t0        = time.time()
    retrieval = model.predict(scaler.transform(BT)).astype(np.float64)
    retrieval[np.isnan(truth)] = np.nan
    print(f"    Shape: {retrieval.shape}  in {time.time()-t0:.1f}s")
    return retrieval


def apply_multi_model(BT, model_path, scaler_path, truth, label):
    print(f"\n  Loading {label} …")
    models = joblib.load(model_path)
    scaler = joblib.load(scaler_path)
    t0     = time.time()
    X_sc   = scaler.transform(BT)
    if isinstance(models, list):
        retrieval = np.column_stack(
            [m.predict(X_sc) for m in models]
        ).astype(np.float64)
    else:
        retrieval = models.predict(X_sc).astype(np.float64)
    retrieval[np.isnan(truth)] = np.nan
    print(f"    Shape: {retrieval.shape}  in {time.time()-t0:.1f}s")
    return retrieval


print("\n" + "=" * 80)
print("SECTION 6: RUNNING RETRIEVALS")
print("=" * 80)

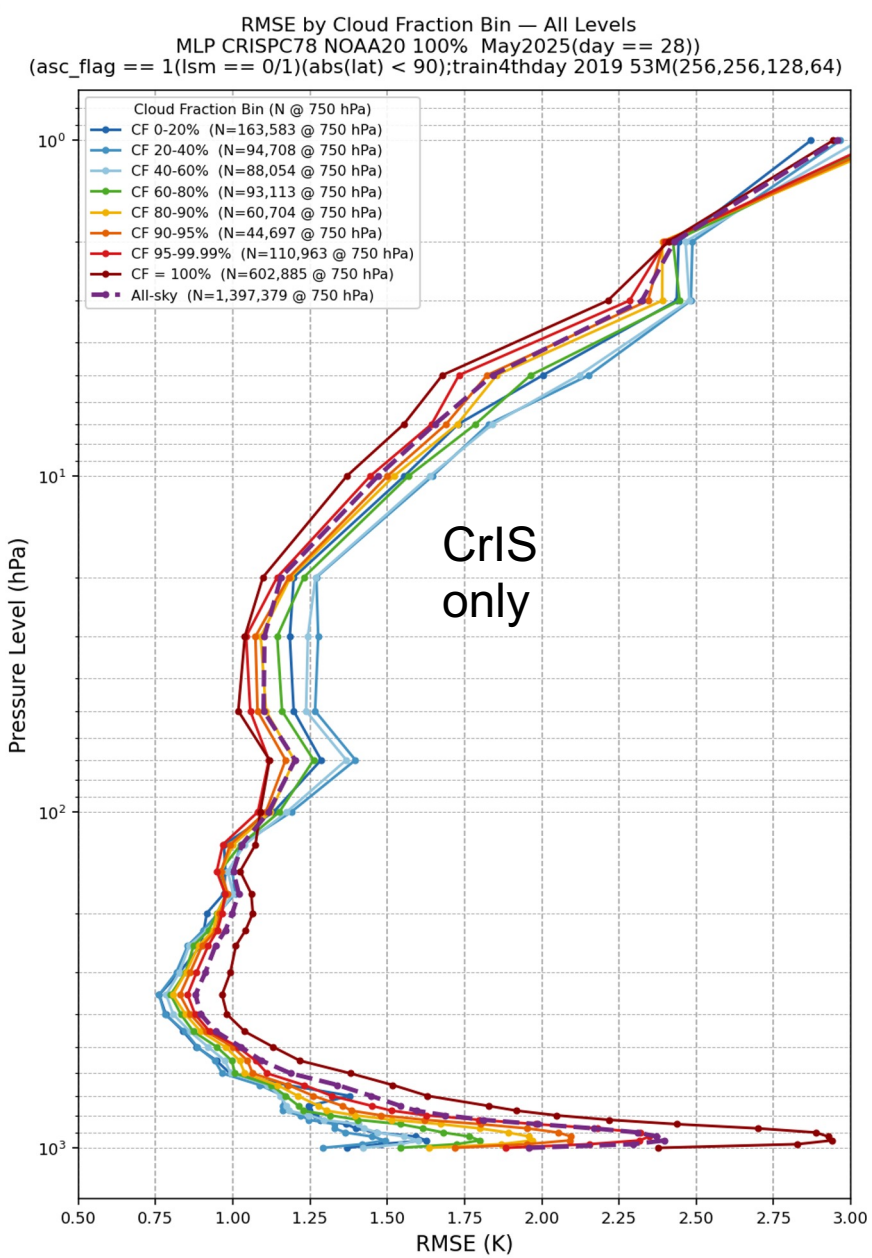
T_retr  = apply_single_model(
    BT, MODEL_PATHS['T']['model'],  MODEL_PATHS['T']['scaler'],
    T_truth_full, "Temperature (37 levels)")

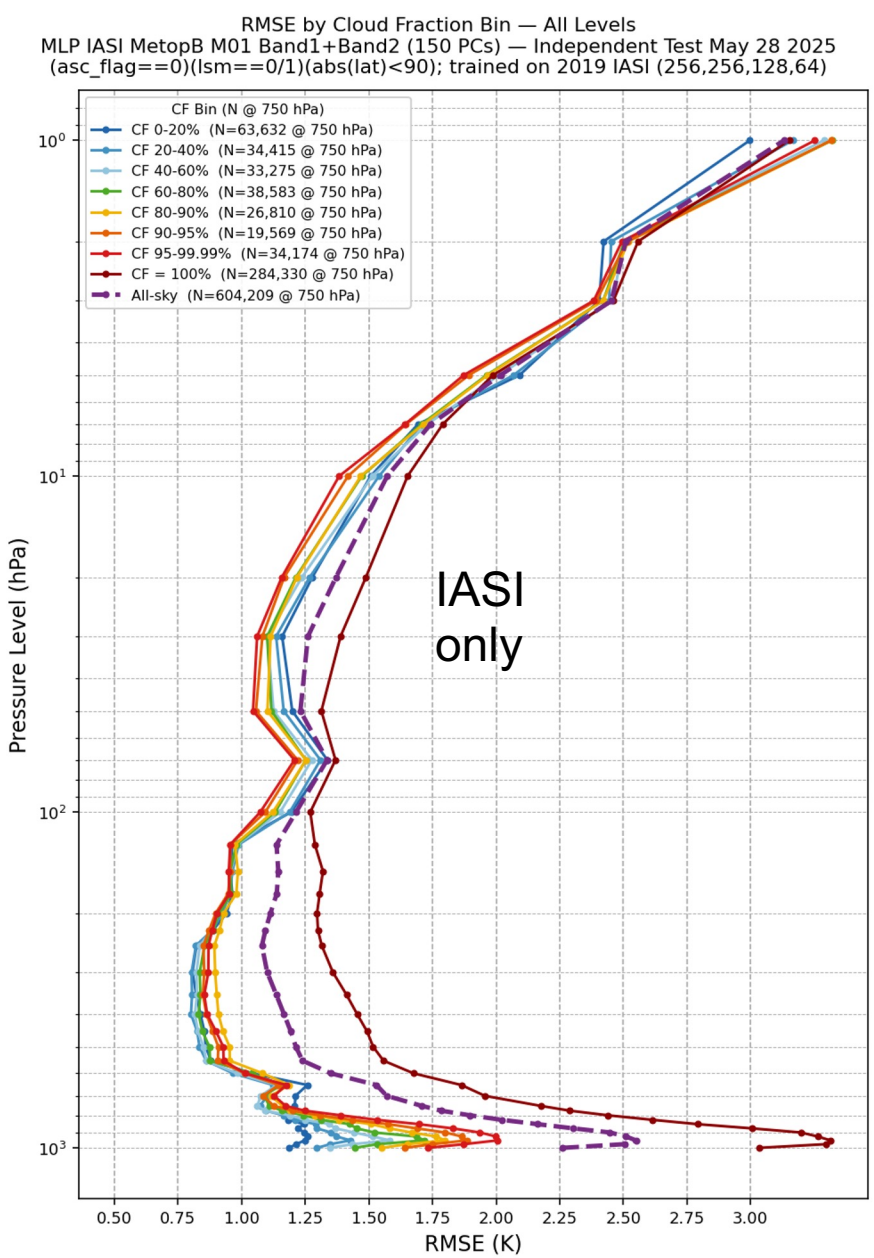
WV_retr = apply_single_model(
    BT, MODEL_PATHS['WV']['model'], MODEL_PATHS['WV']['scaler'],
    WV_truth_full, "Water vapour mixing ratio (27 levels)")

surf_truth_matrix = np.column_stack([SURF_truth[v] for v in SURF_VARS])
surf_retr_matrix  = apply_multi_model(
    BT, MODEL_PATHS['SURF']['model'], MODEL_PATHS['SURF']['scaler'],
    surf_truth_matrix, "Surface params (SKIN, TPW, CLW, TCRW)")

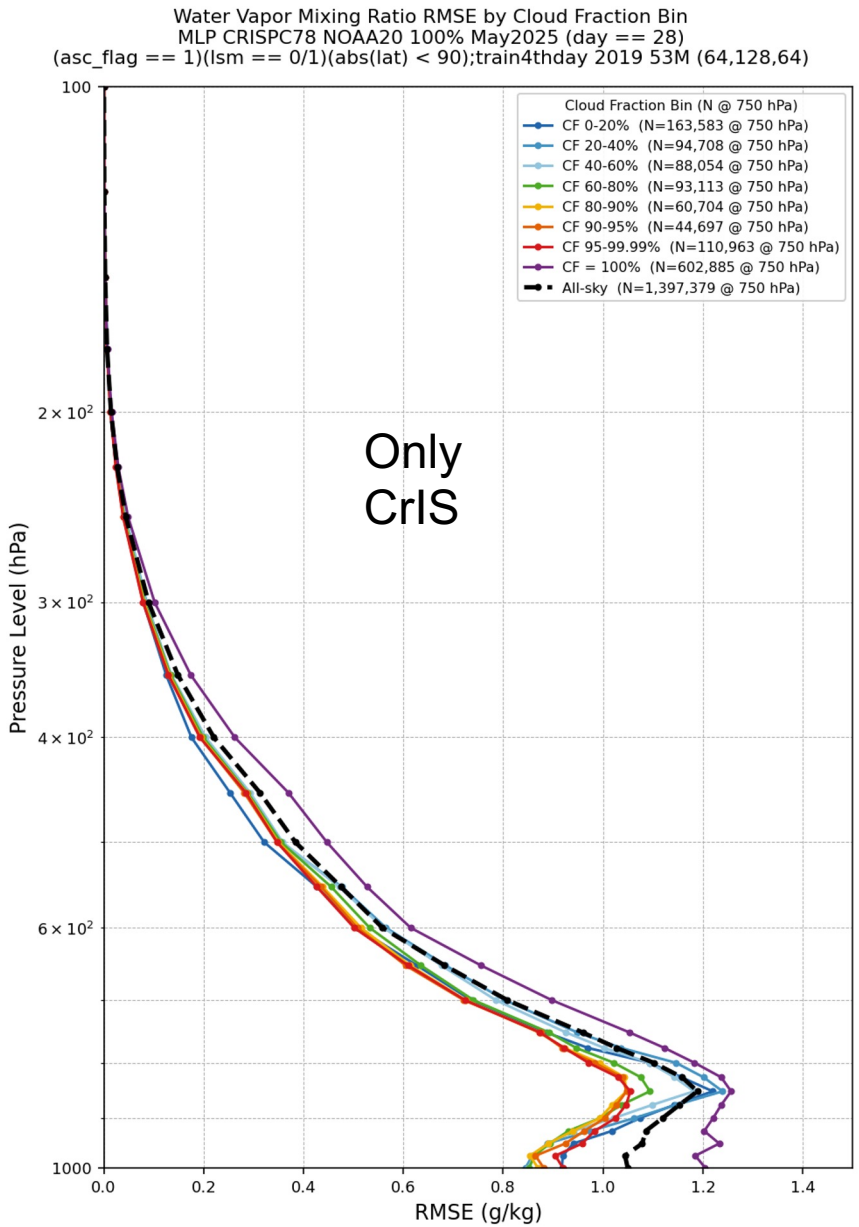
SURF_retr = {v: surf_retr_matrix[:, i] for i, v in enumerate(SURF_VARS)}
```

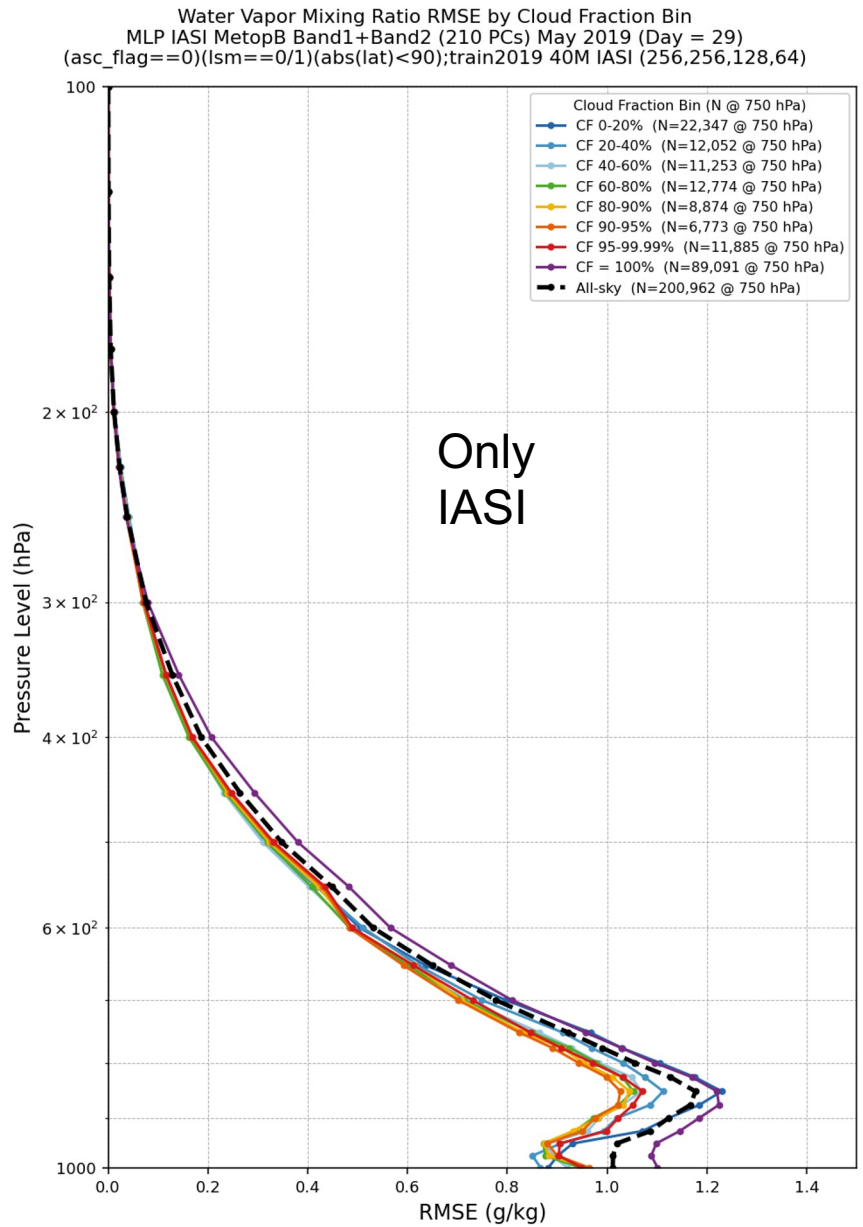
Temperature Retrieval Performance



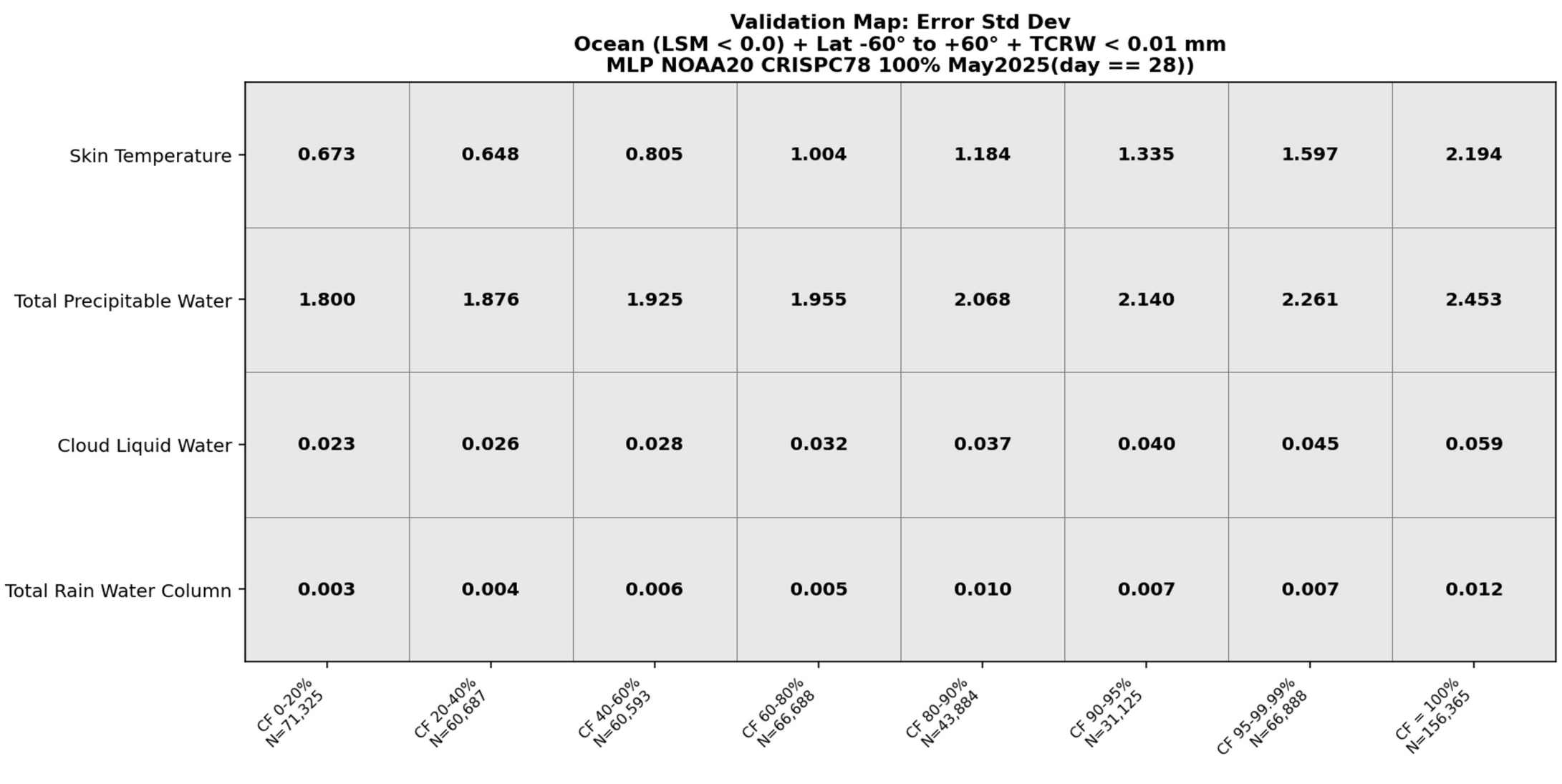


Water Vapor Mixing Ratio Retrieval Performance



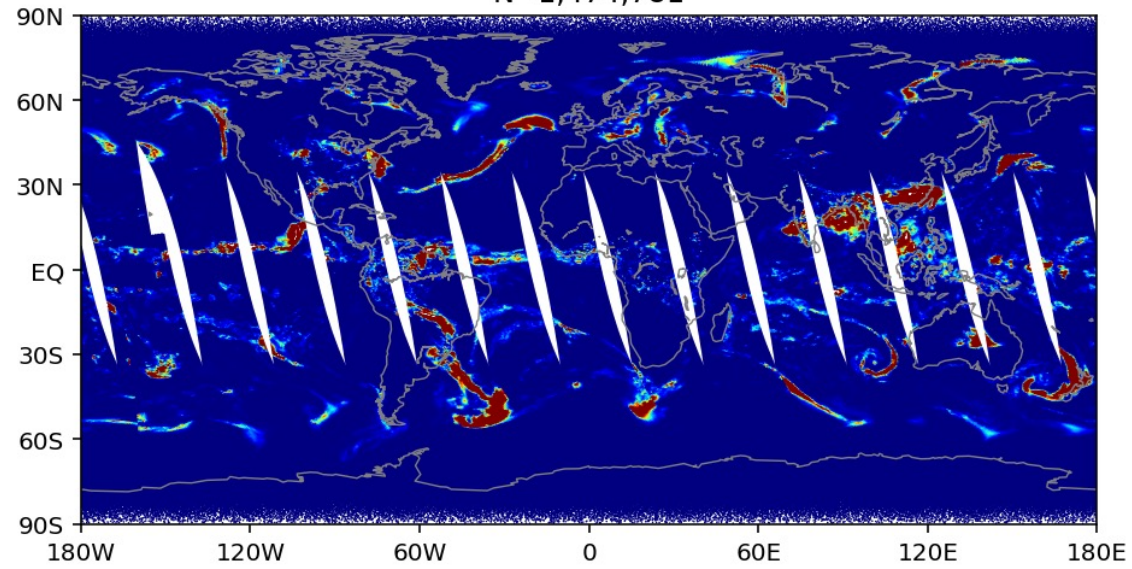


CrIS only

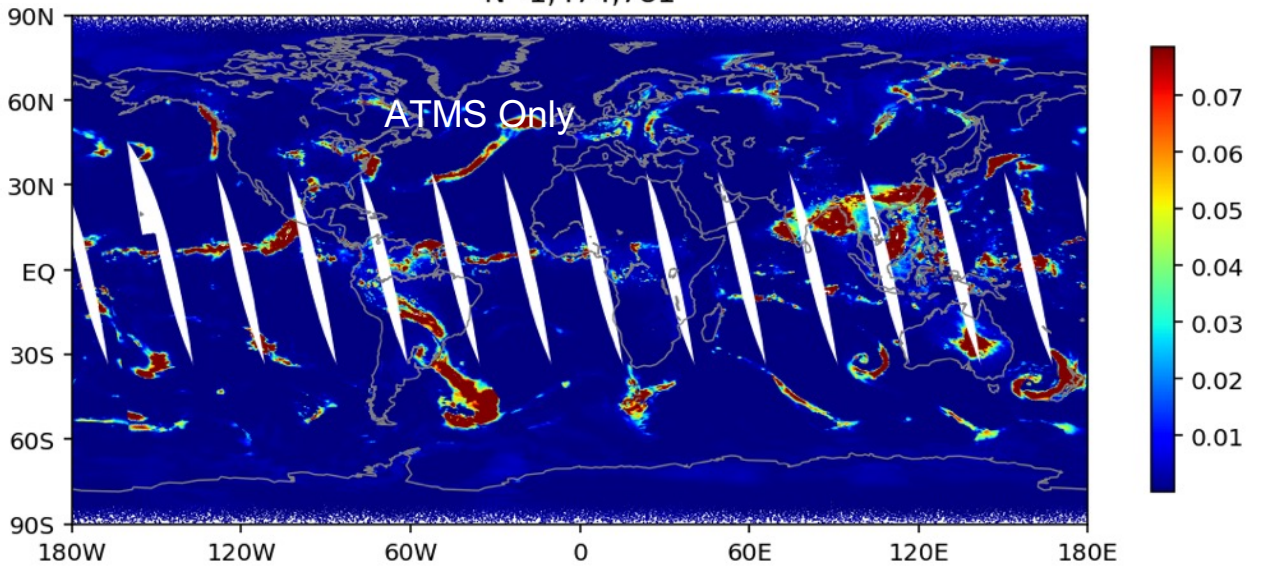

Validation Map: Error Std Dev
Ocean (LSM < 0.0) + Lat -60° to +60° + TCRW < 0.01 mm
MLP NOAA20 CRISPC78 100% May2025(day == 28))
Skin Temperature
Total Precipitable Water
Cloud Liquid Water
Total Rain Water Column
0.673
0.648
0.805
1.004
1.184
1.335
1.597
2.194
1.800
1.876
1.925
1.955
2.068
2.140
2.261
2.453
0.023
0.026
0.028
0.032
0.037
0.040
0.045
0.059
0.003
0.004
0.006
0.005
0.010
0.007
0.007
0.012
CF 0-20% N=71,325
CF 20-40% N=60,687
CF 40-60% N=60,593
CF 60-80% N=66,688
CF 80-90% N=43,884
CF 90-95% N=31,125
CF 95-99.99% N=66,888
CF = 100% N=156,365

TCRW

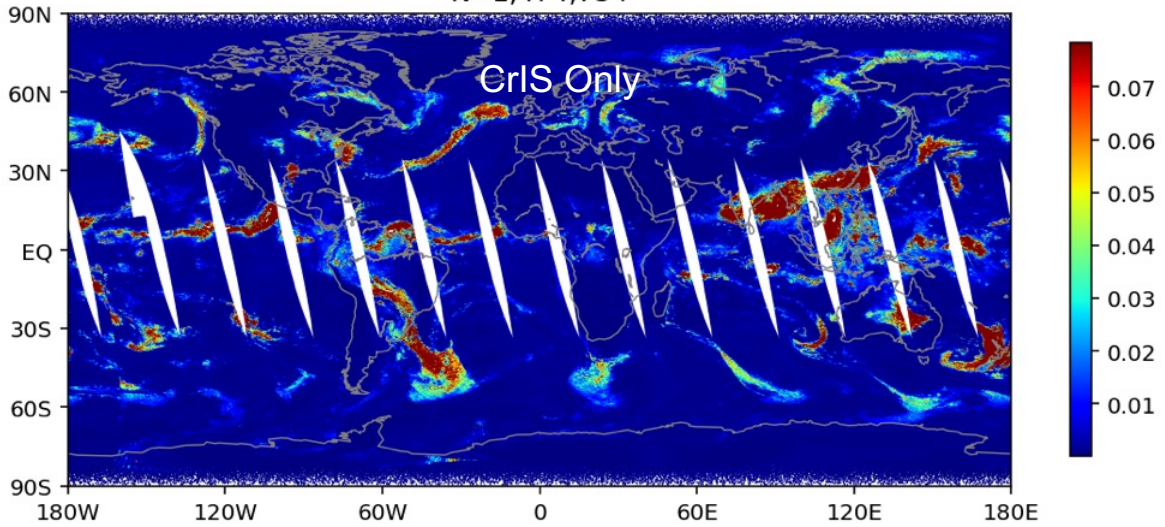
ERA5
MLP NOAA20 ATMS-BG 100% May2025(day == 28))
(asc_flag == 1)(lsm == 0/1)(abs(lat) < 90);train 2019 53M
N=1,474,781



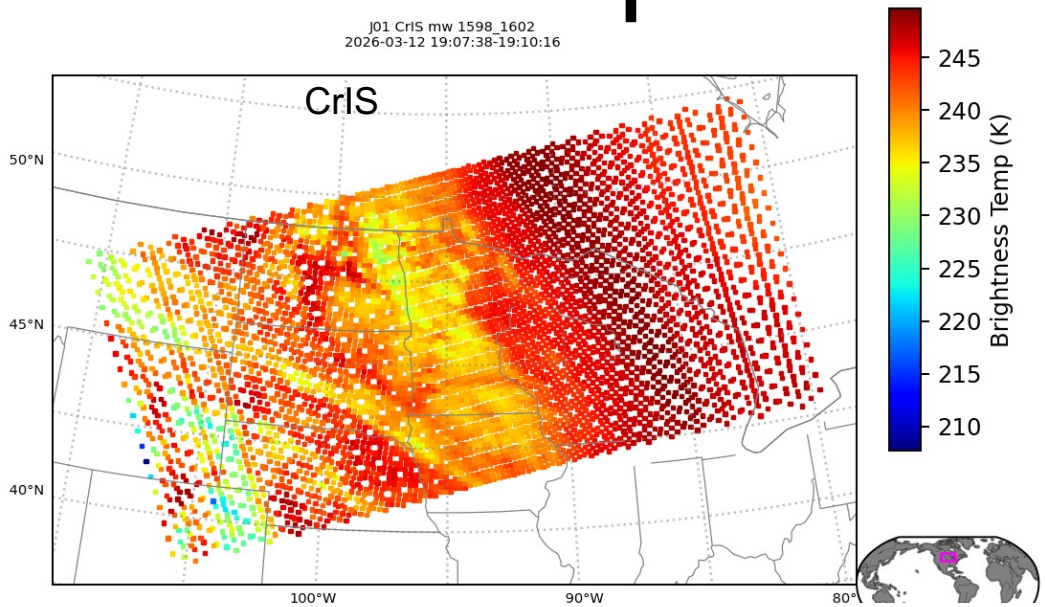
Retrieval
MLP NOAA20 ATMS-BG 100% May2025(day == 28))
(asc_flag == 1)(lsm == 0/1)(abs(lat) < 90);train 2019 53M
N=1,474,781

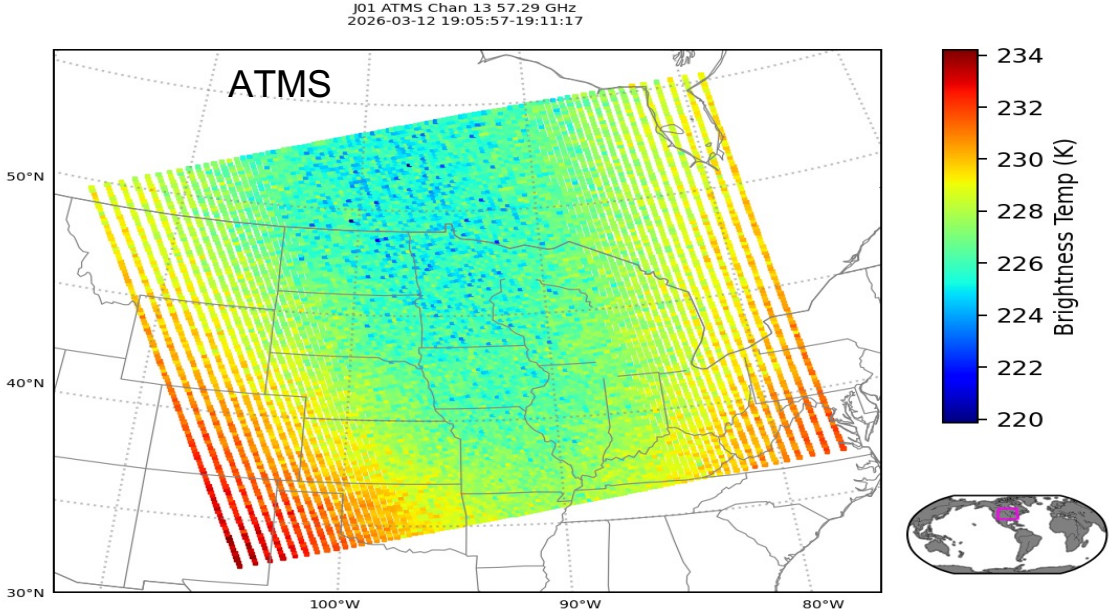


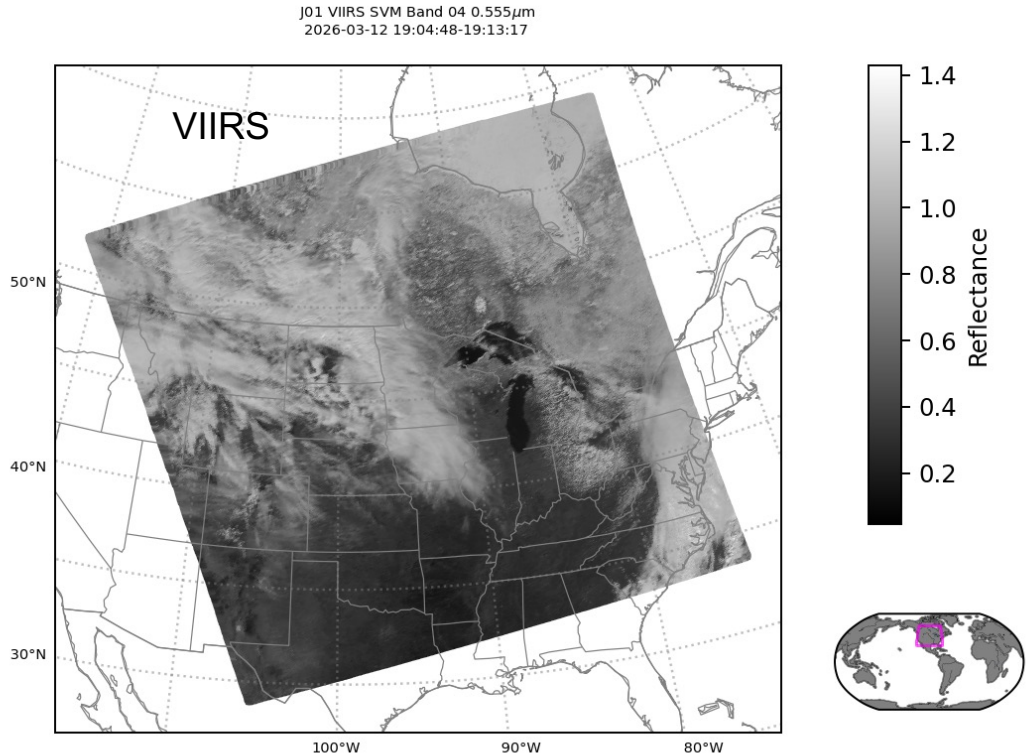
Retrieval
MLP NOAA20 CRISPC78 100% May2025(day == 28))
(asc_flag == 1)(lsm == 0/1)(abs(lat) < 90);train 2019 53M
N=1,474,734



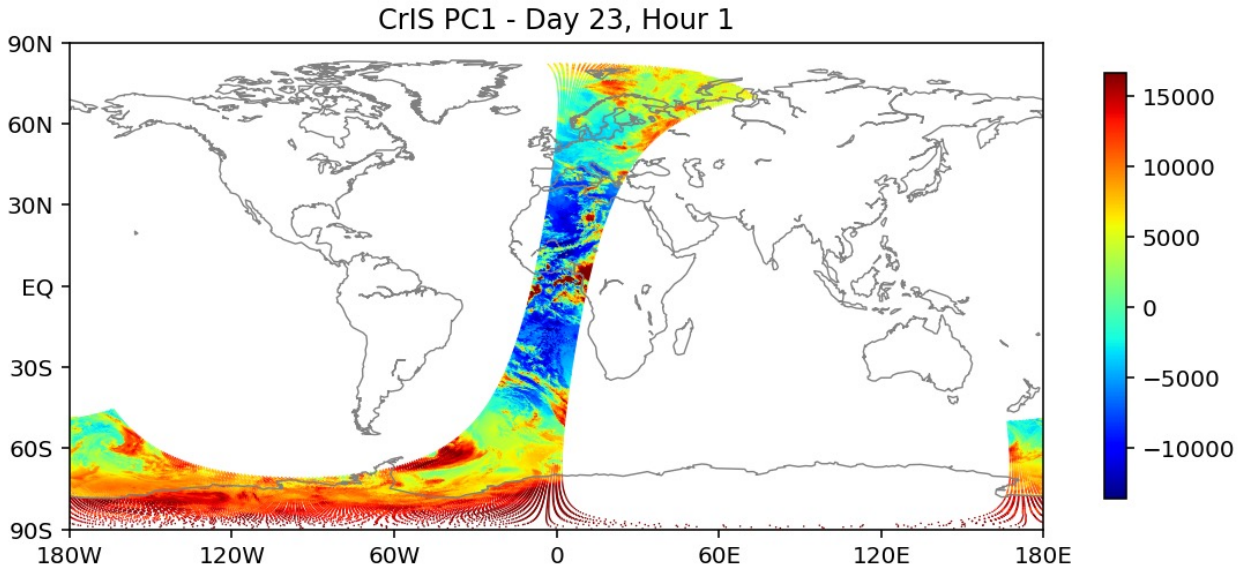
Request - Please extend CrIS

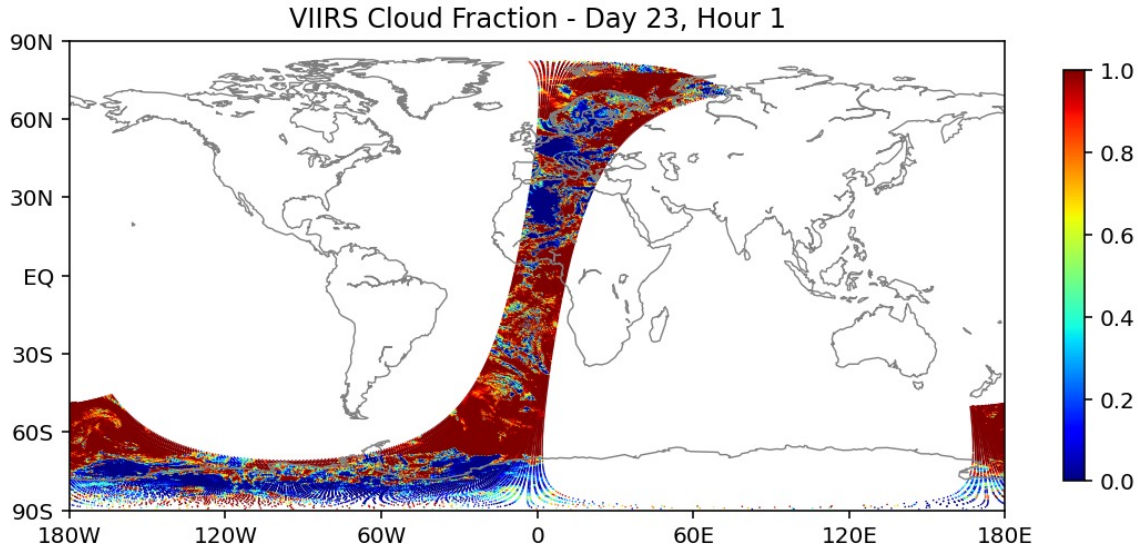


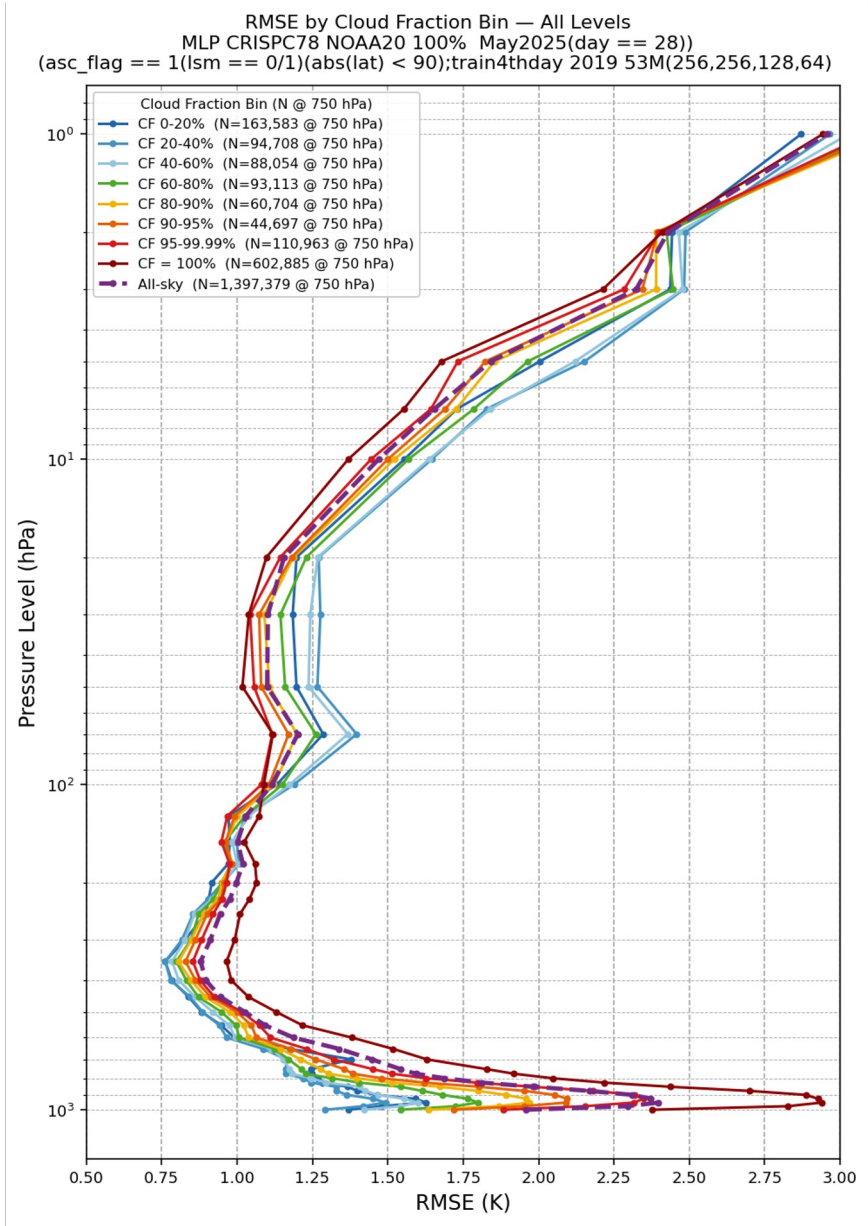


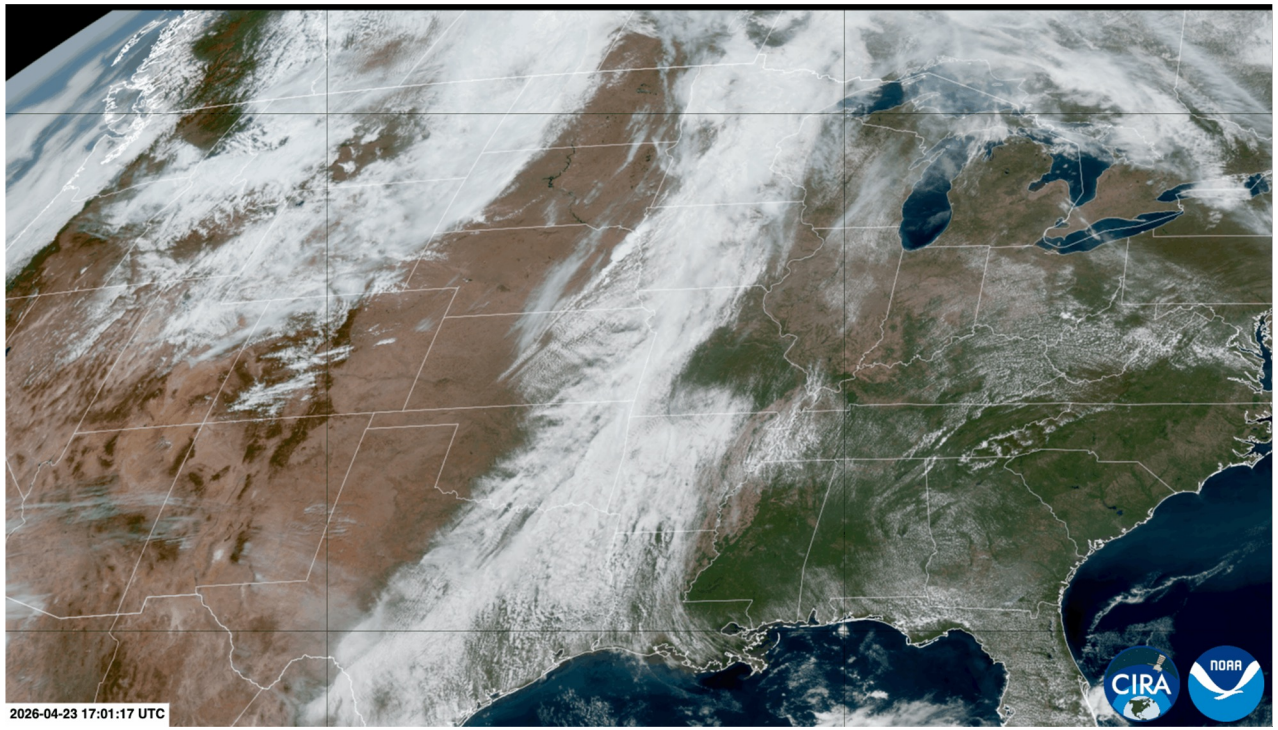


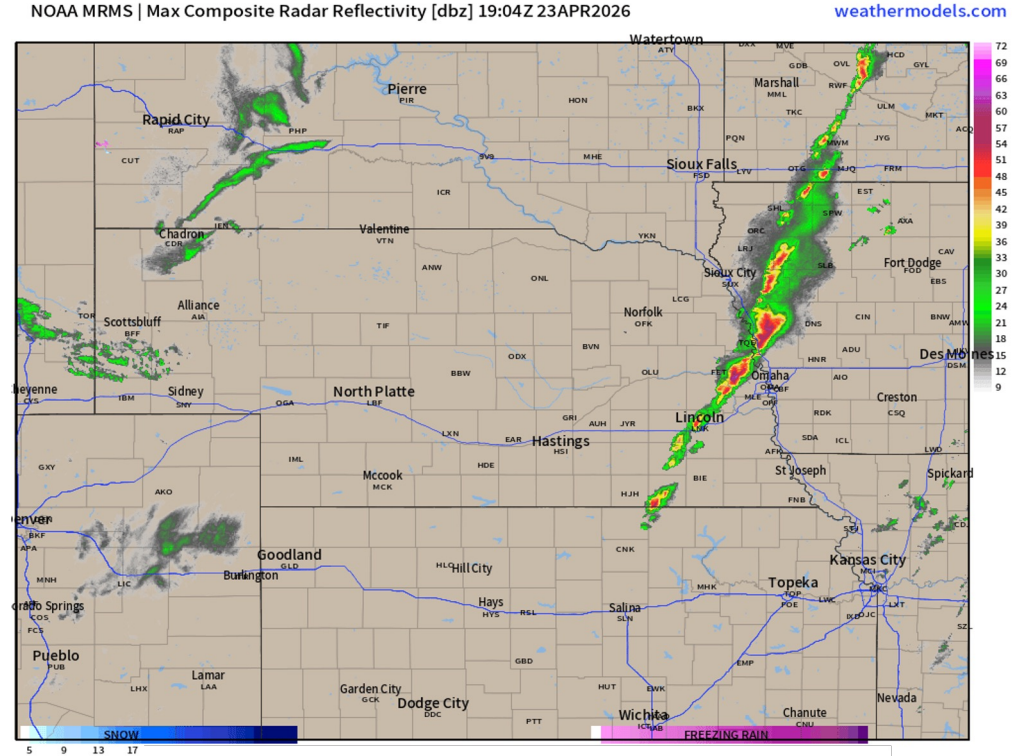
Please add VIIRS Cloud Fraction @ CrIS resolution to CrIS as an environmental control (EC) indicator for MLP – all sky retrievals

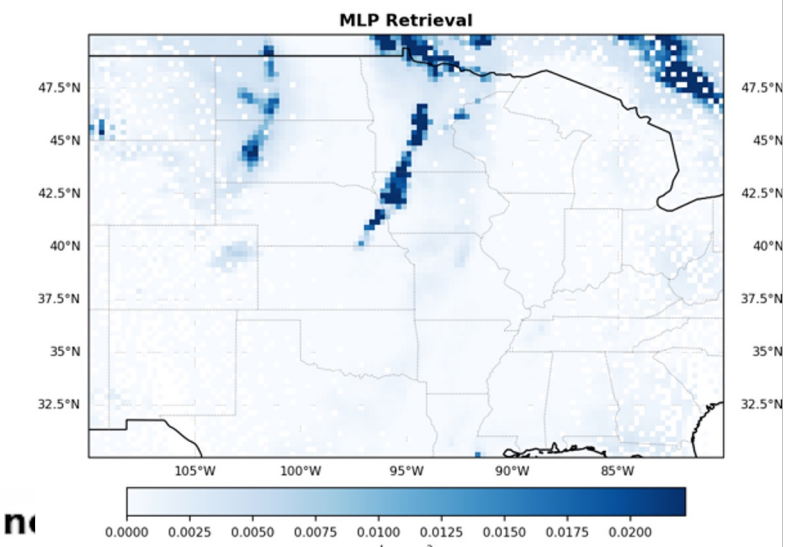








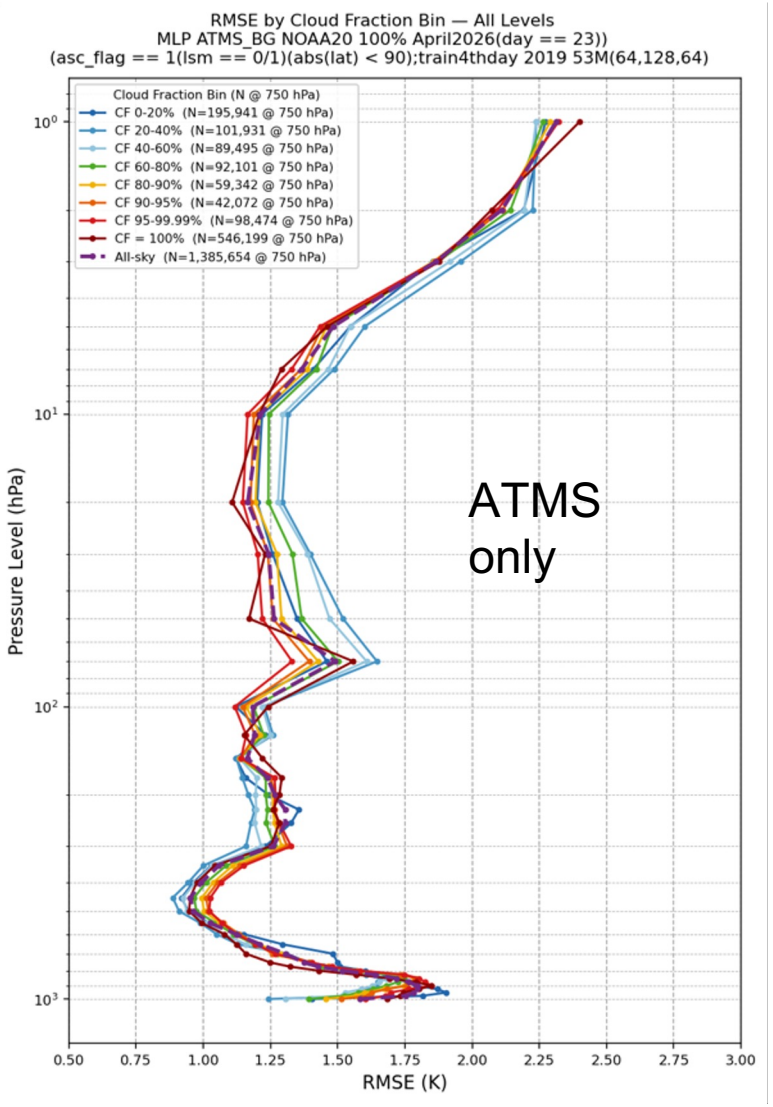


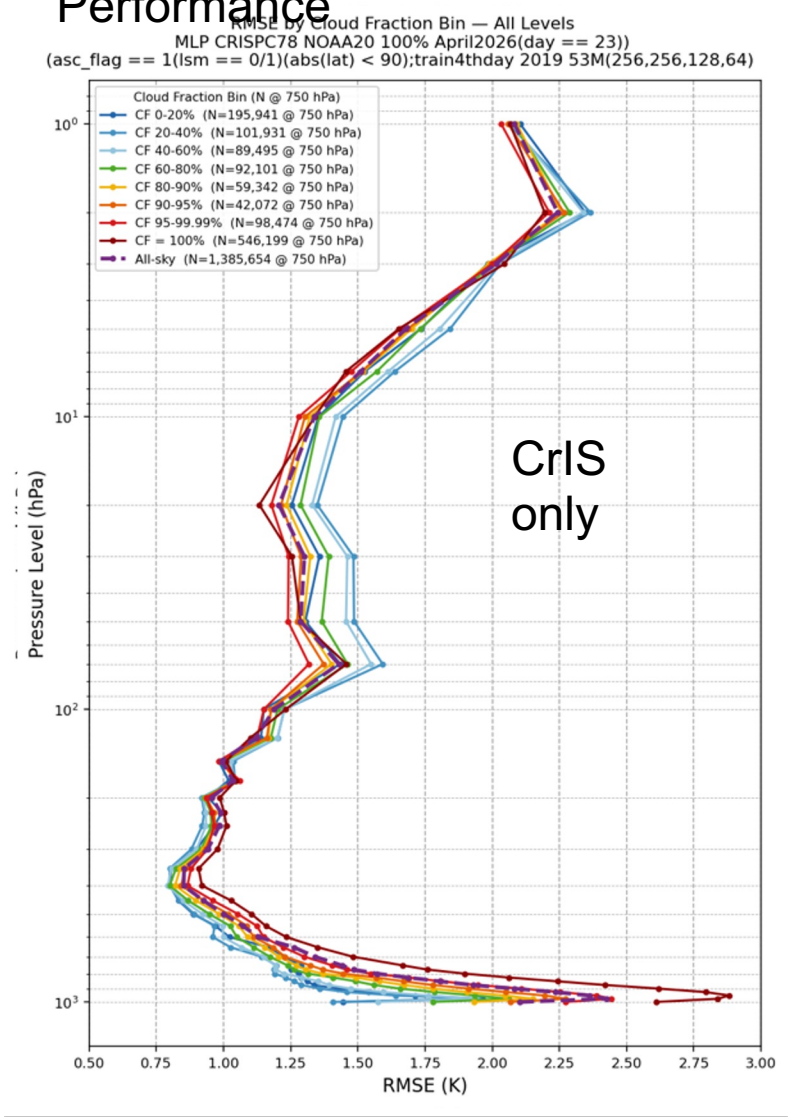


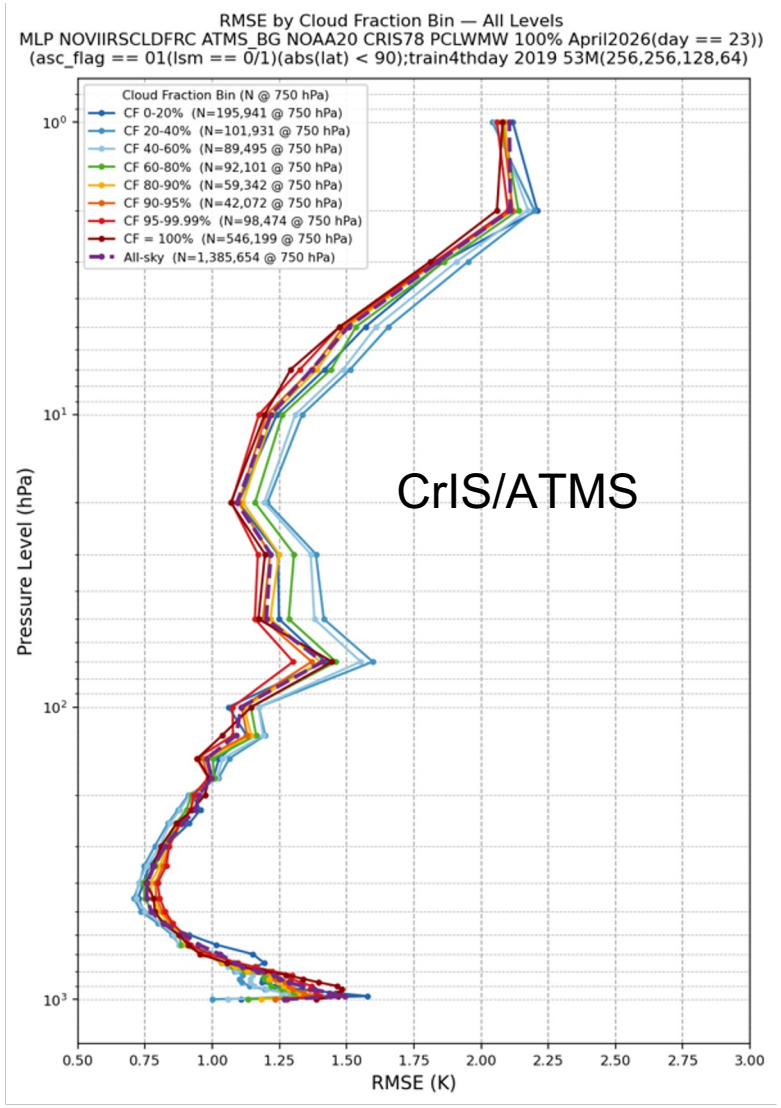
SNDR.J1.CRIS.20260423T1918.m06.g194.L1B.std.v03_08.G.260424015325.n

April 23, 2026 – Global Statistics – All Sky

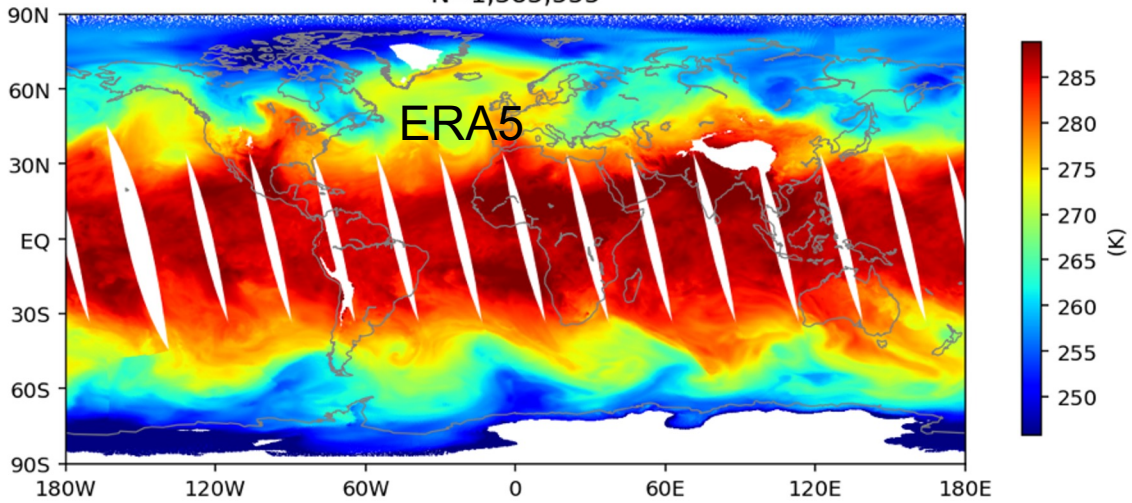
Temperature Retrieval Performance



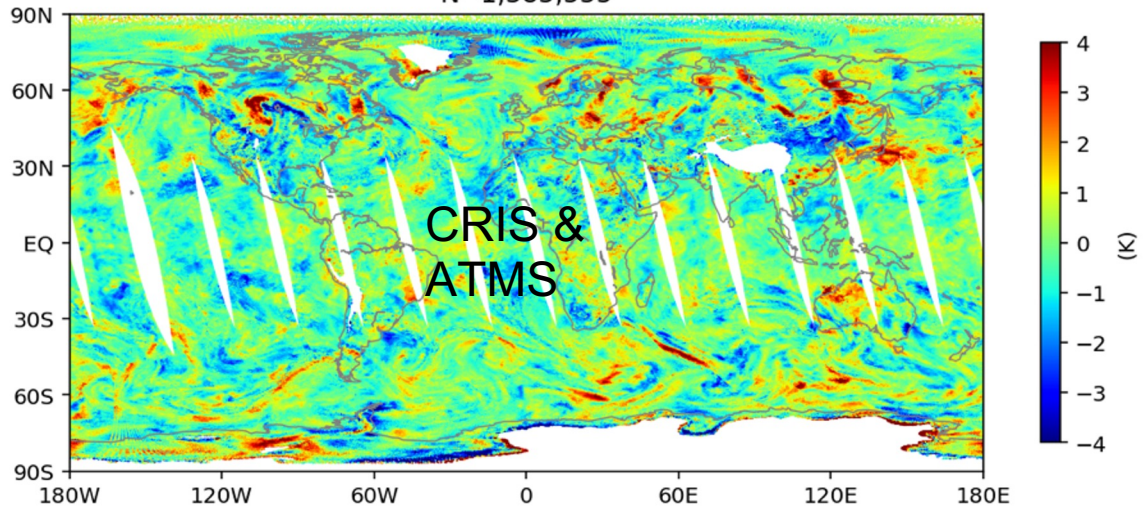




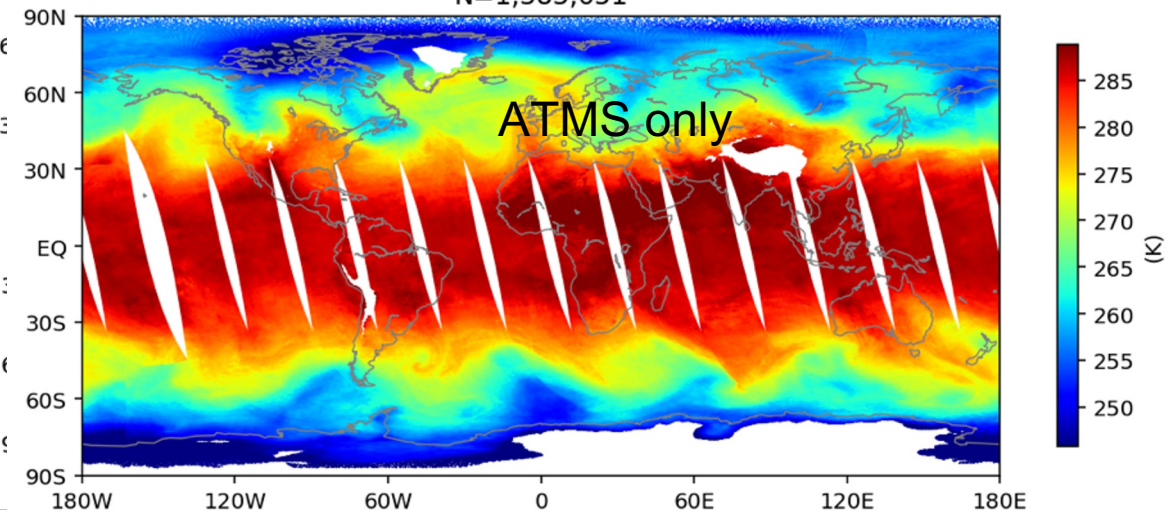
ERA5 Level 11, 750.0 hPa
MLP NOVIIRSCLDFRC ATMS_BG NOAA20 CRIS78 PCLWMW 100% April2026(day == 23))
(asc_flag == 01(lsm == 0/1)(abs(lat) < 90);train4thday 2019 53M(256,256,128,64)
N=1,385,555



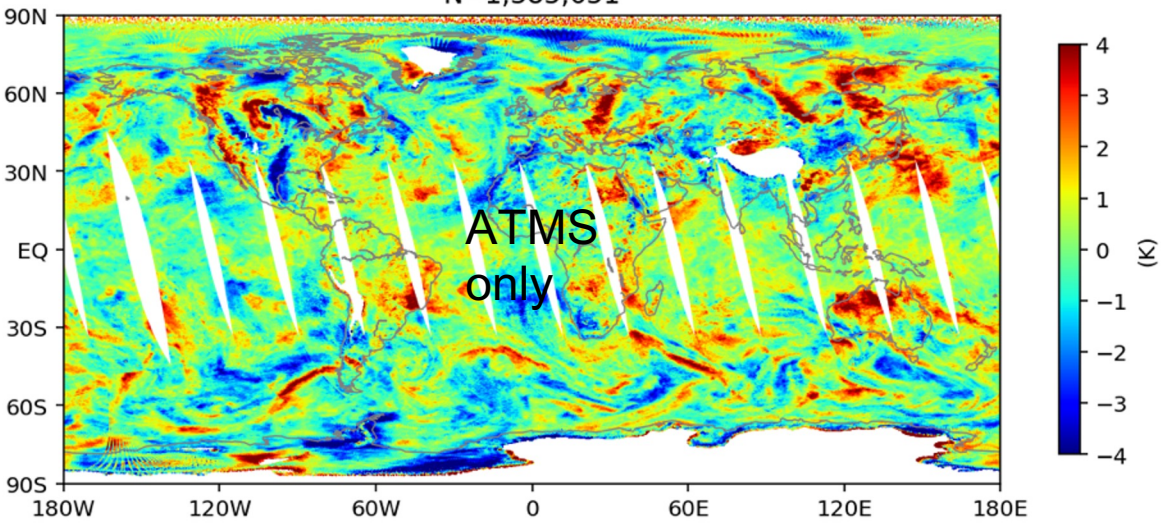
Retrieval minus ERA5 at Level 11, 750.0 hPa
Min: -10.15072, Max: 10.62810, Bias: -0.11701, Std Dev: 1.07122
MLP NOVIIRSCLDFRC ATMS_BG NOAA20 CRIS78 PCLWMW 100% April2026(day == 23))
(asc_flag == 01(lsm == 0/1)(abs(lat) < 90);train4thday 2019 53M(256,256,128,64)
N=1,385,555



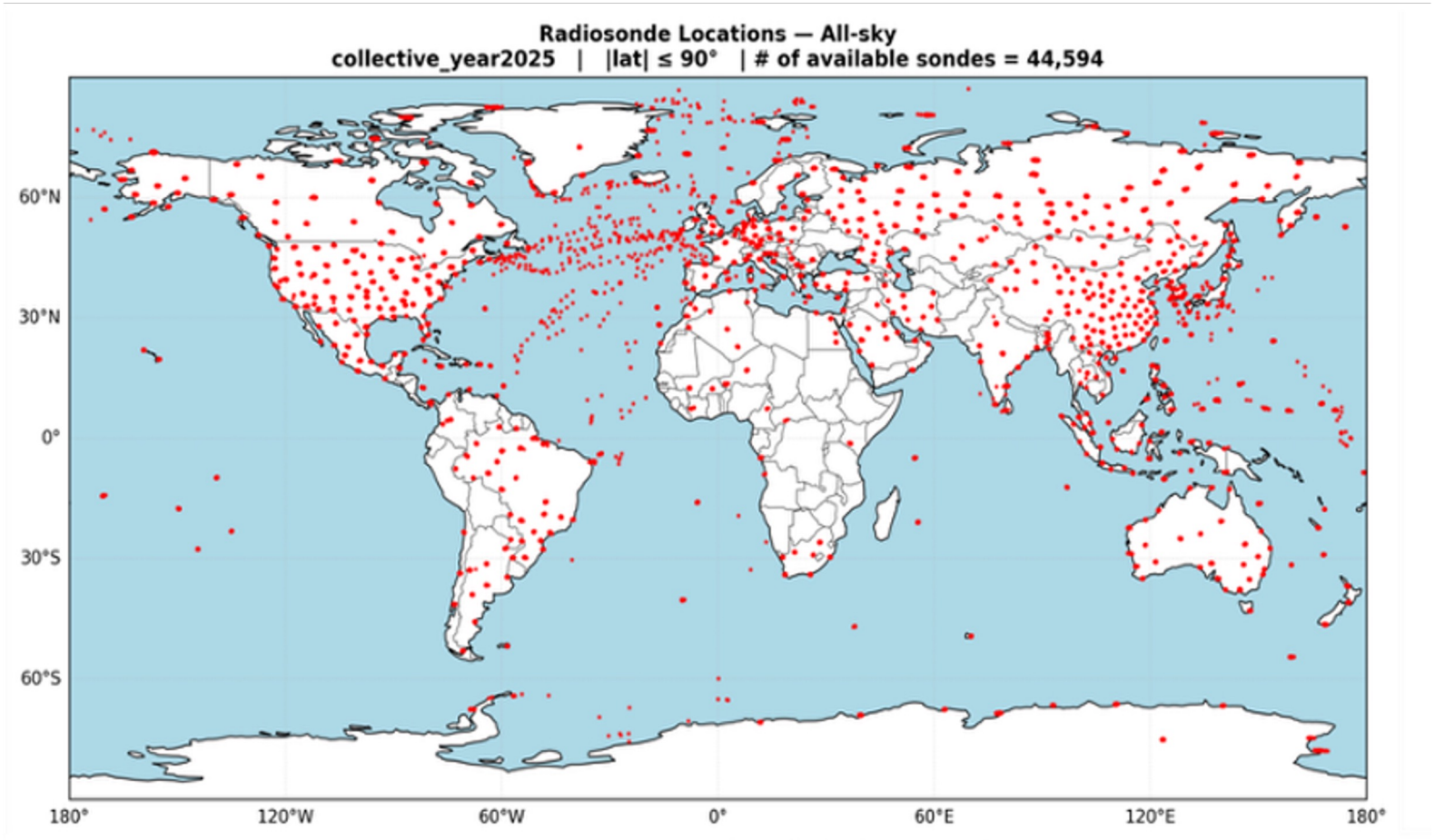
Retrieval Level 11, 750.0 hPa
MLP ATMS_BG NOAA20 100% April2026(day == 23))
(asc_flag == 1(lsm == 0/1)(abs(lat) < 90);train4thday 2019 53M(64,128,64)
N=1,385,651

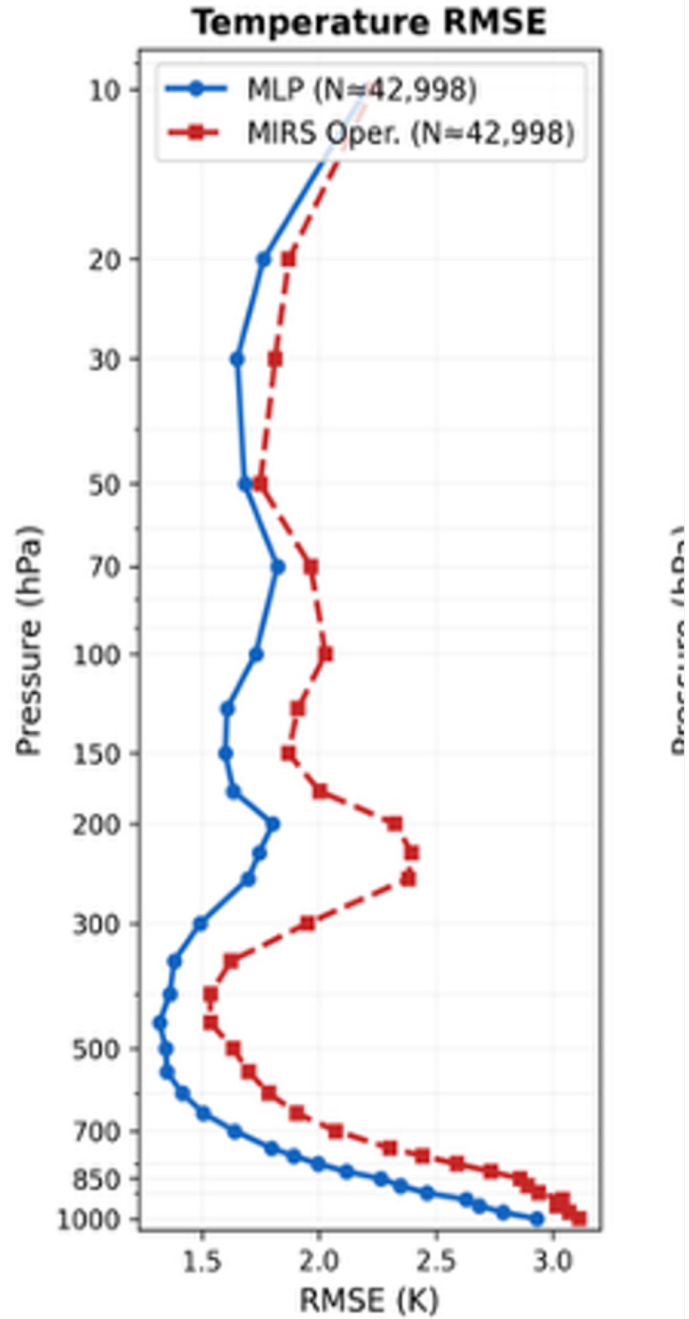


Retrieval minus ERA5 at Level 11, 750.0 hPa
Min: -11.24361, Max: 13.70394, Bias: 0.08602, Std Dev: 1.37274
MLP ATMS_BG NOAA20 100% April2026(day == 23))
(asc_flag == 1(lsm == 0/1)(abs(lat) < 90);train4thday 2019 53M(64,128,64)
N=1,385,651

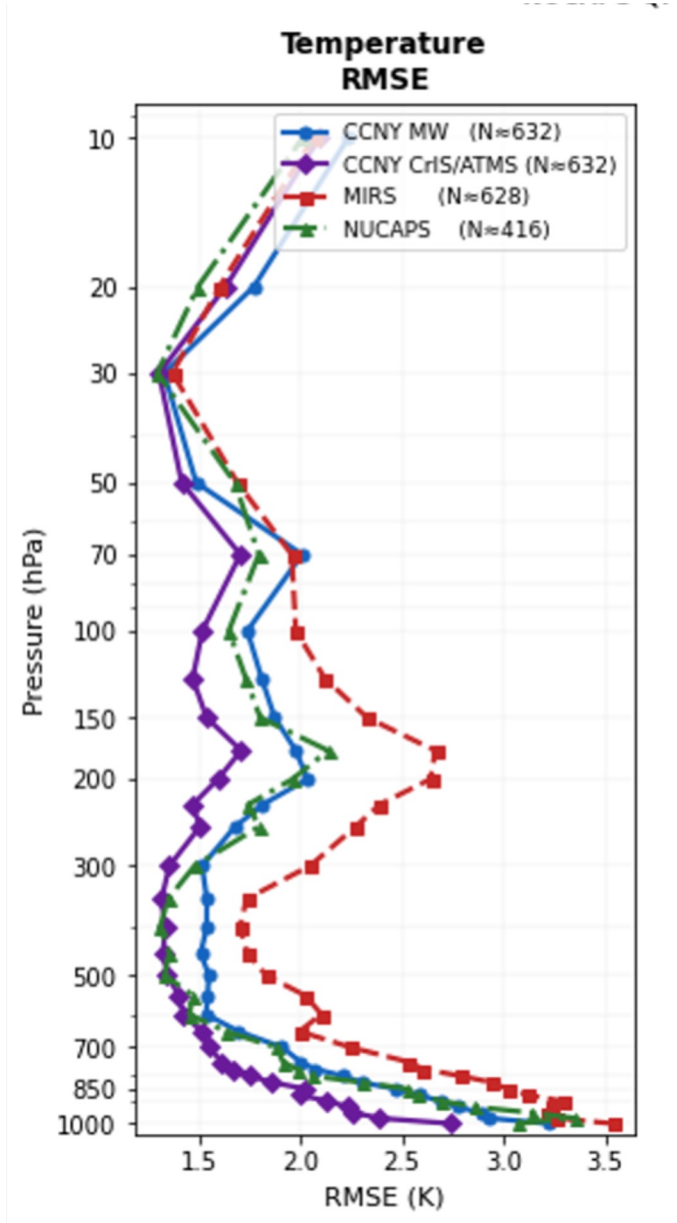


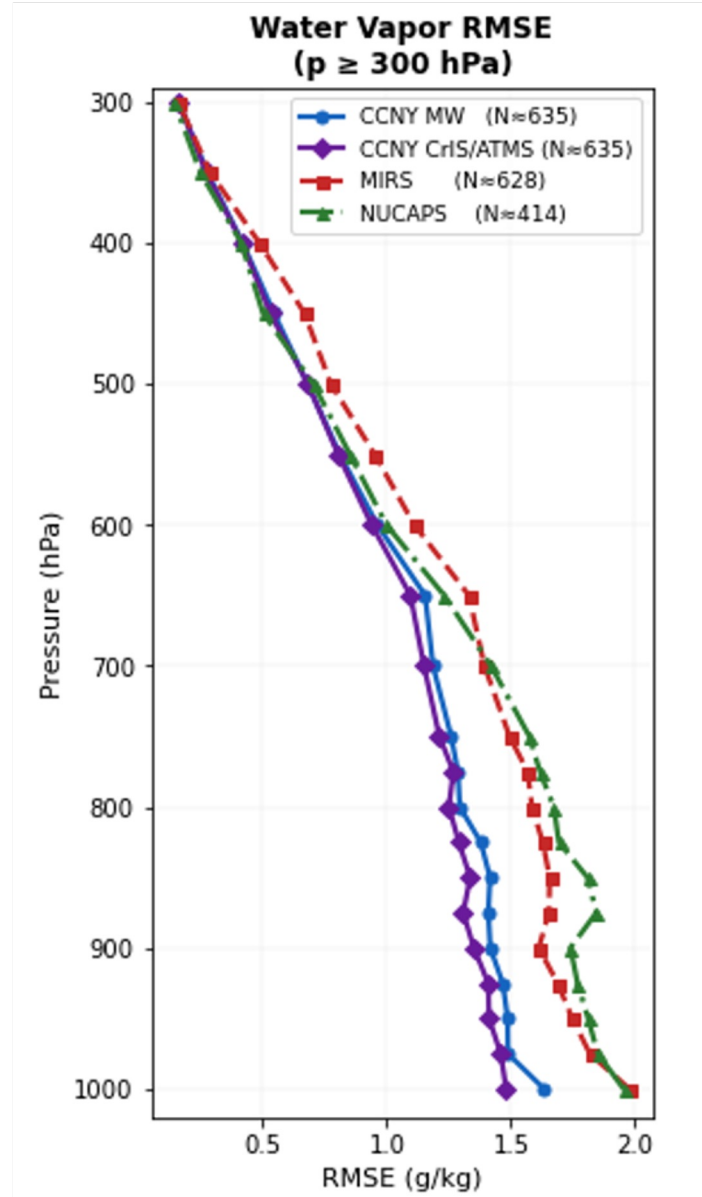
CCNY MLP Retrieval Performance vs NESDIS Operational MIRS Algorithm Using Collocated Radiosondes from 2025





CCNY MLP Retrieval Performance vs NESDIS Operational MIRS and NUCAPS Algorithm



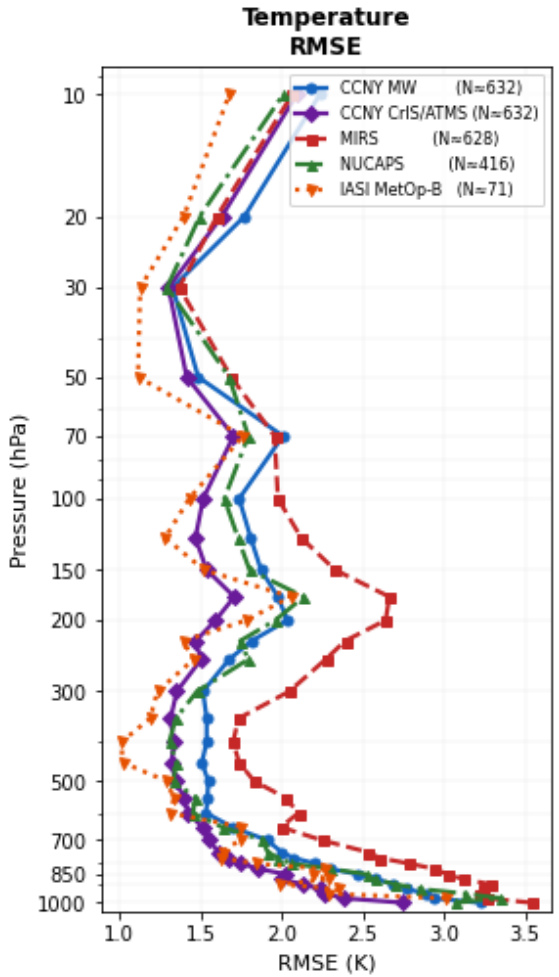


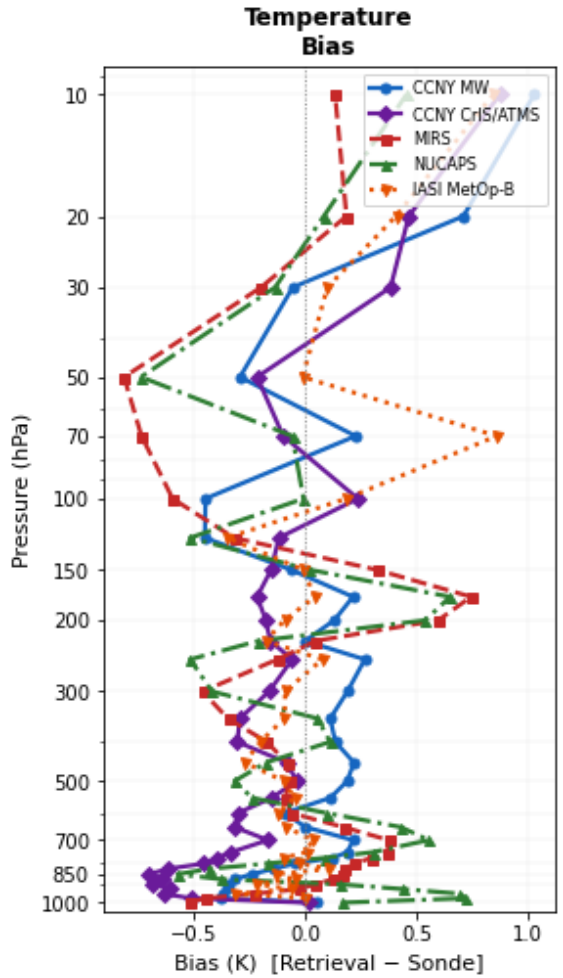
NOAA-CESSRST

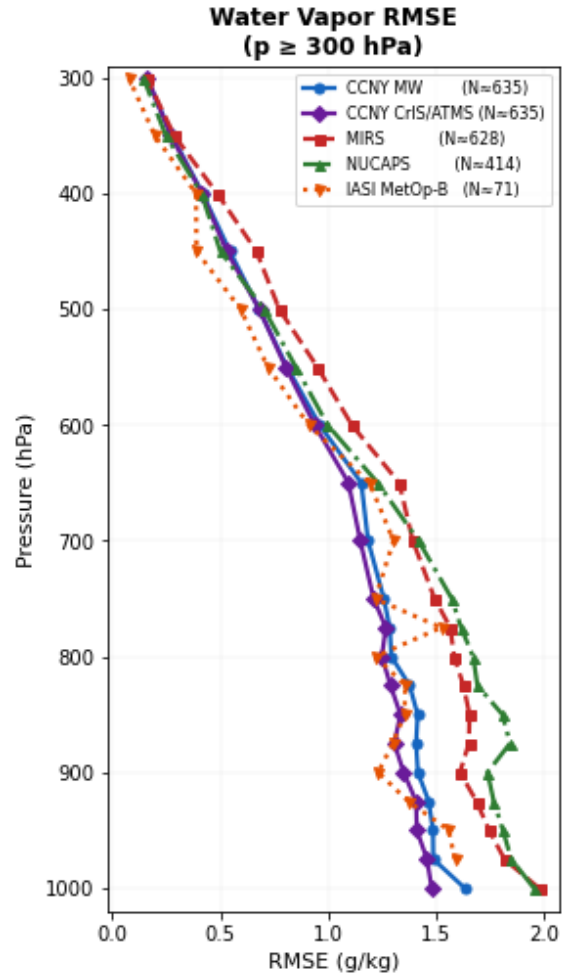
CENTER FOR EARTH SYSTEM SCIENCES
AND REMOTE SENSING TECHNOLOGIES

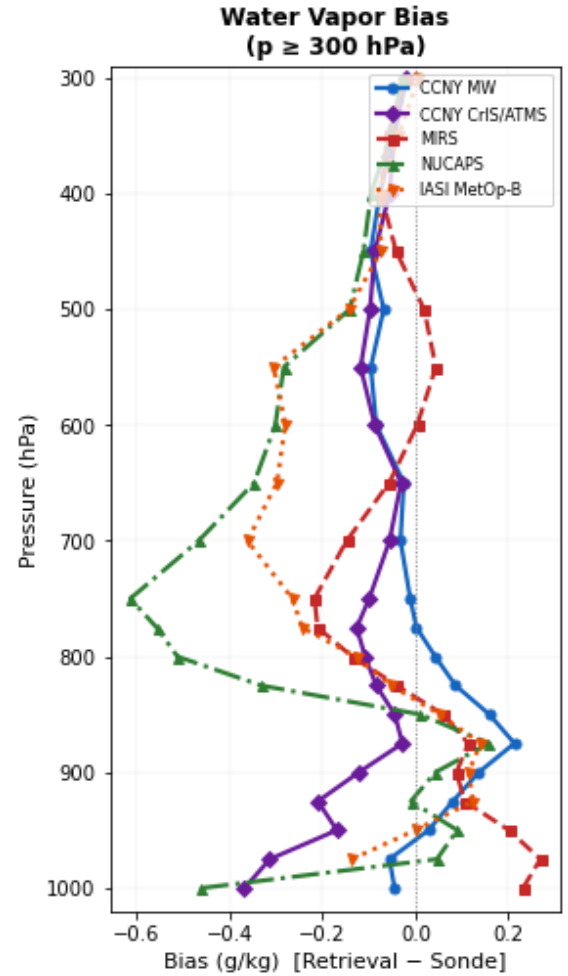
CUNY CREST
SCIENCE & TECHNOLOGY TO SUSTAIN THE EARTH

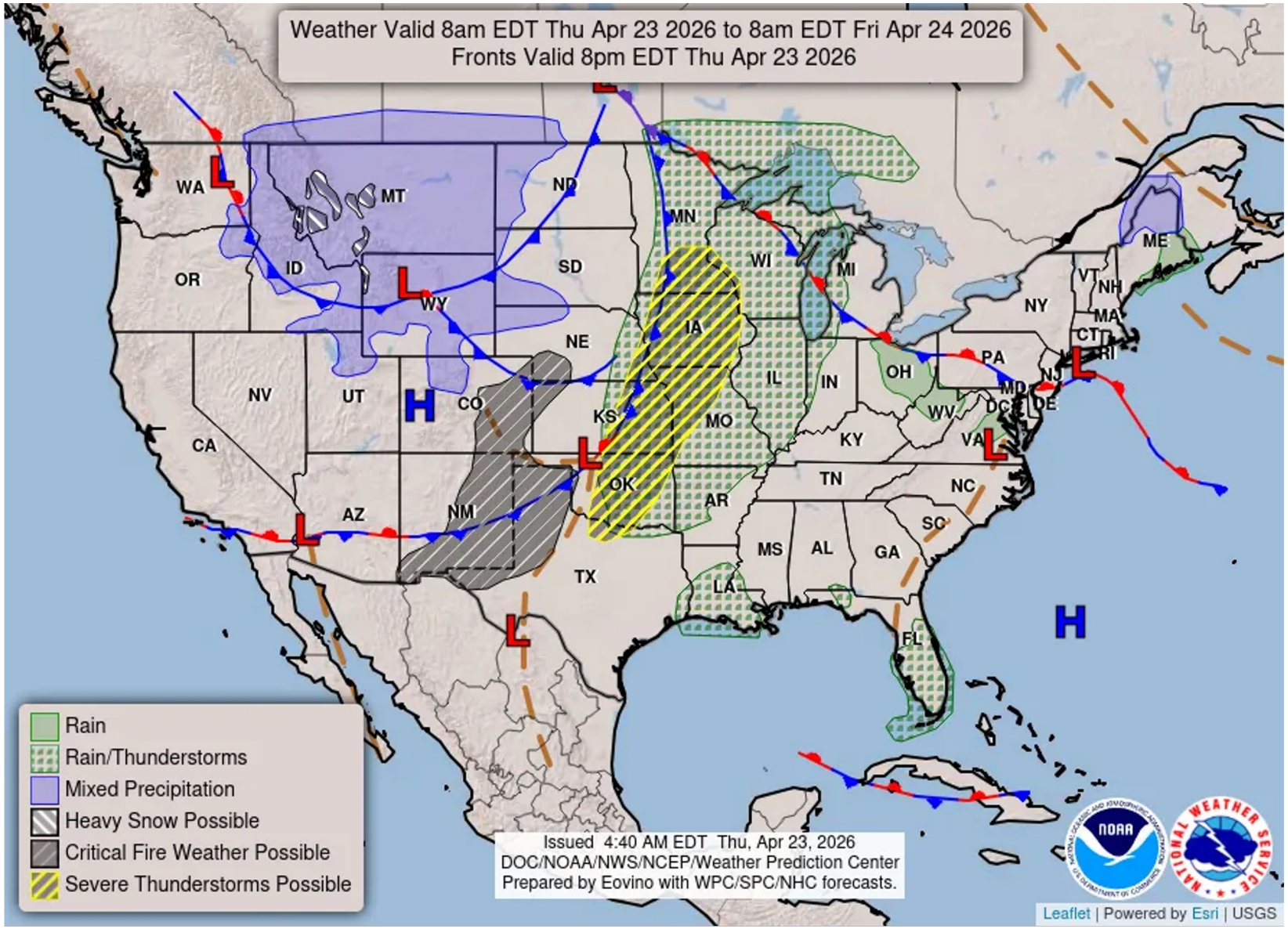
CCNY MW vs CCNY CrIS/ATMS vs MIRS (MIRS_NOAA20_317) vs NUCAPS (NUCAPS_NOAA20_605) vs IASI (EUMETSAT_IASI_MetOpB_703) — Land [QC ON]
NOAA-20 (1:30PM): CCNY/MIRS/NUCAPS restricted to CrIS-matched sondes (N=661) | MetOp-B (9:30AM): IASI uses all May-28 sondes (N=701) | Truth: RadCorr Sonde
NUCAPS QF=[0] | MIRS QC=ON | IASI QC=ON | CrIS search ≤500 km, accept ≤150 km, ≤3 hr (N_cris_pairs=661) | IASI min-N threshold=10



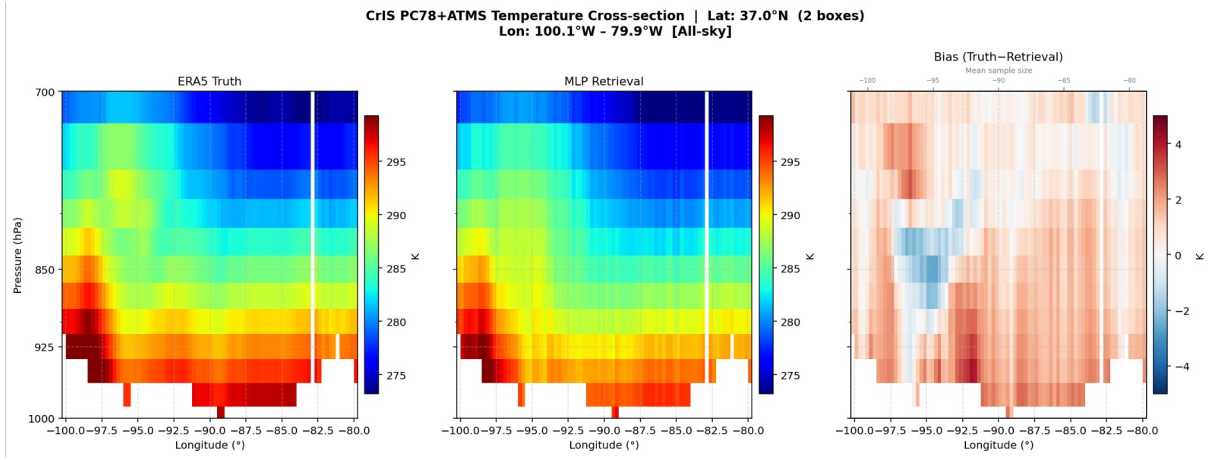


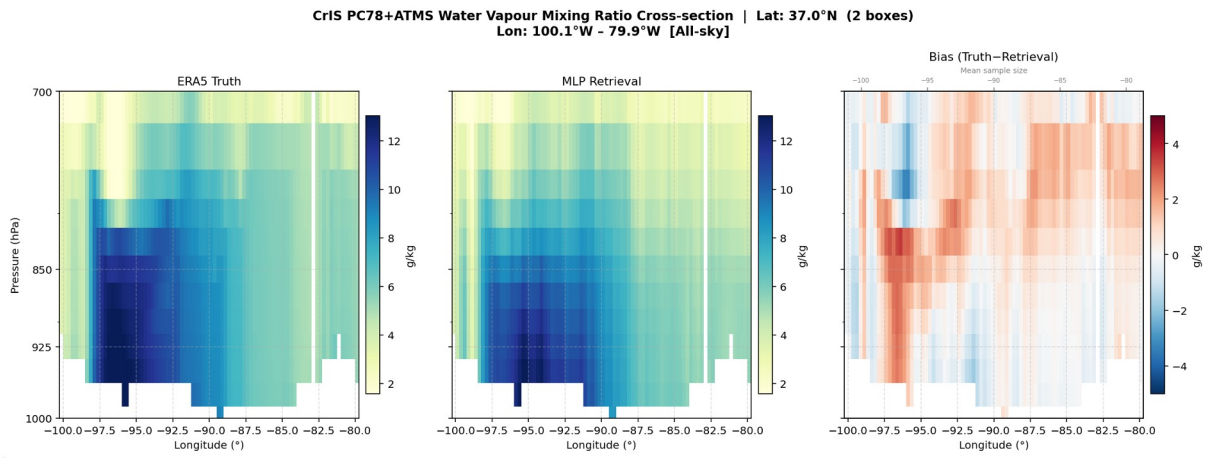


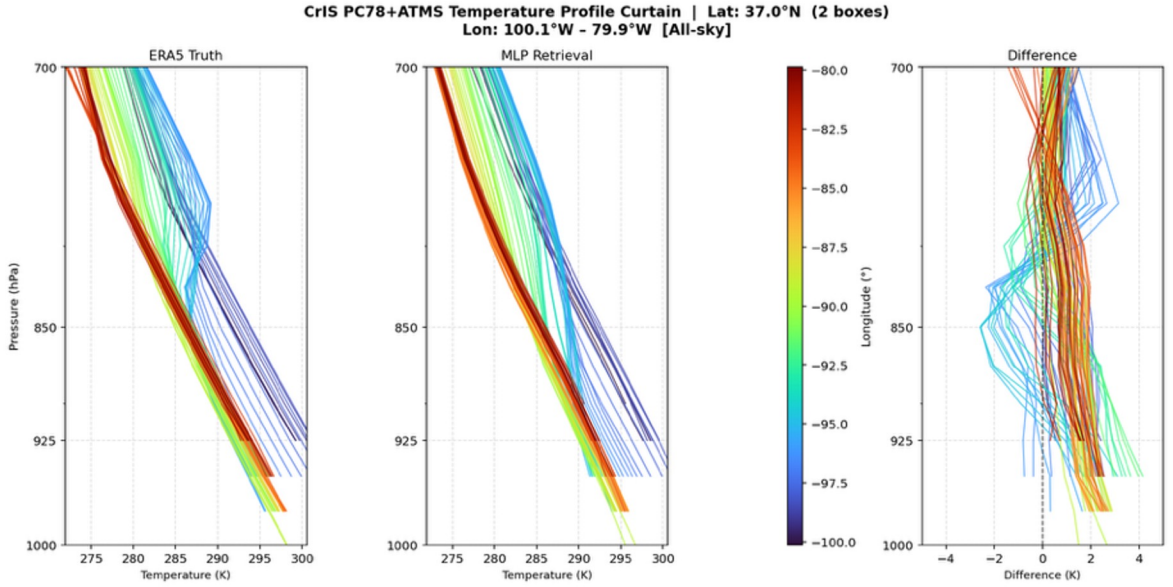


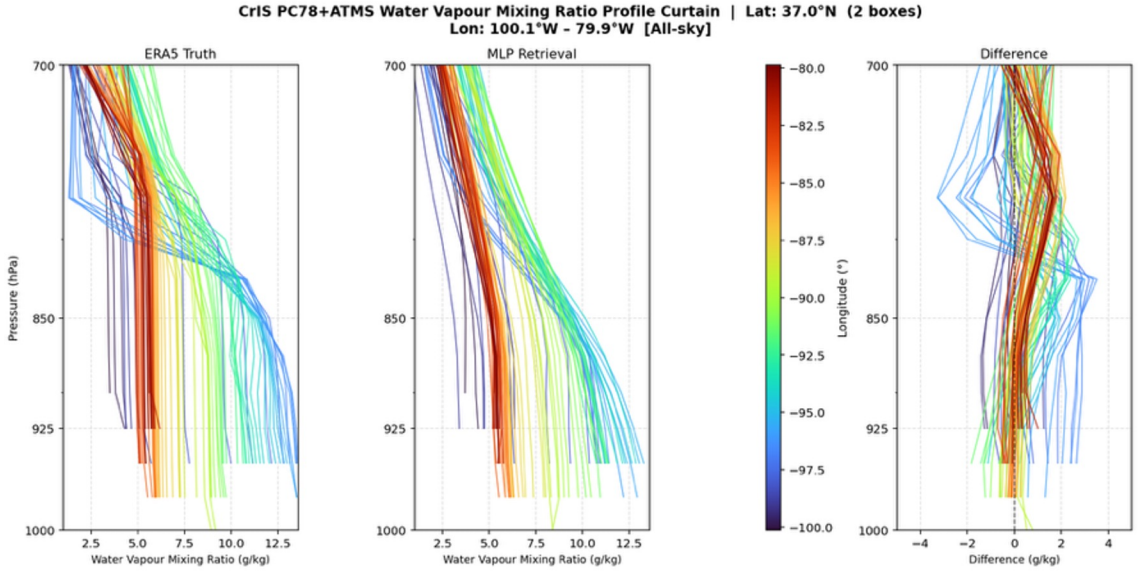

Weather Valid 8am EDT Thu Apr 23 2026 to 8am EDT Fri Apr 24 2026
Fronts Valid 8pm EDT Thu Apr 23 2026
WA
OR
CA
ID
NV
MT
WY
UT
AZ
CO
NM
ND
SD
NE
KS
OK
TX
MN
IA
MO
AR
LA
WI
IL
MS
MI
IN
KY
TN
AL
OH
WV
GA
FL
SC
NC
VA
PA
NY
MD
DC
DE
NJ
CT
RI
MA
VT
NH
ME
Rain
Rain/Thunderstorms
Mixed Precipitation
Heavy Snow Possible
Critical Fire Weather Possible
Severe Thunderstorms Possible
Issued 4:40 AM EDT Thu, Apr 23, 2026
DOC/NOAA/NWS/NCEP/Weather Prediction Center
Prepared by Eovino with WPC/SPC/NHC forecasts.
Leaflet | Powered by Esri | USGS

Temperature and Water Vapor CRIS and ATMS – All Sky

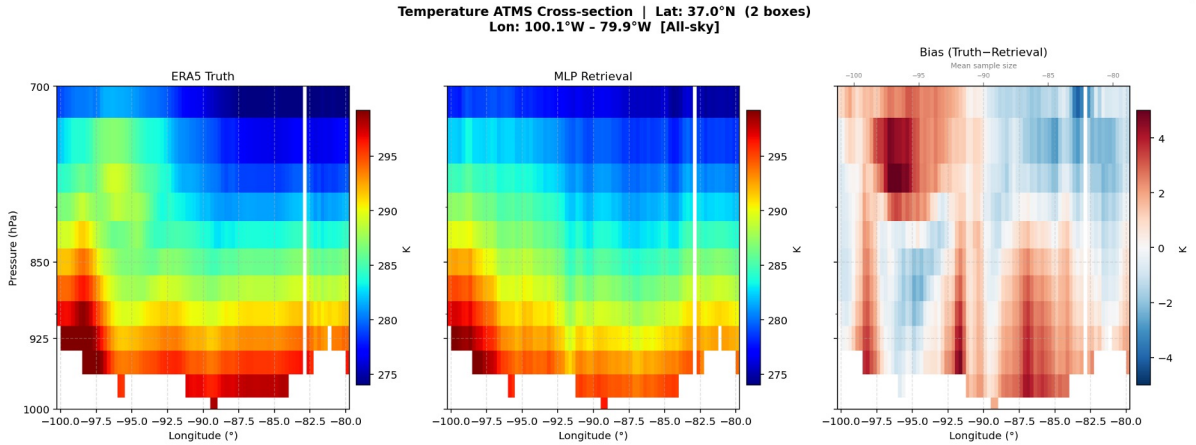


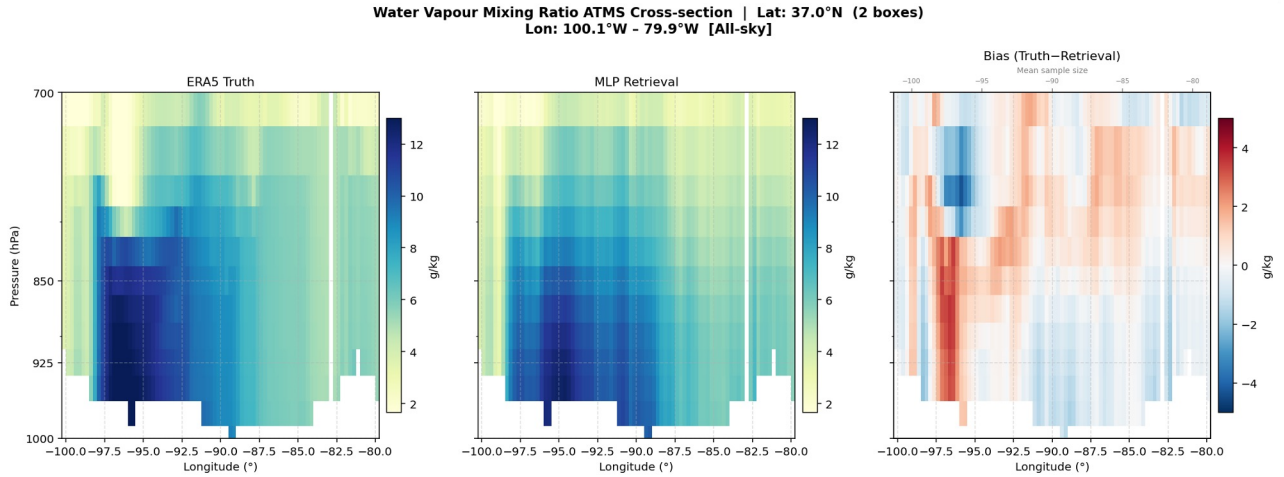


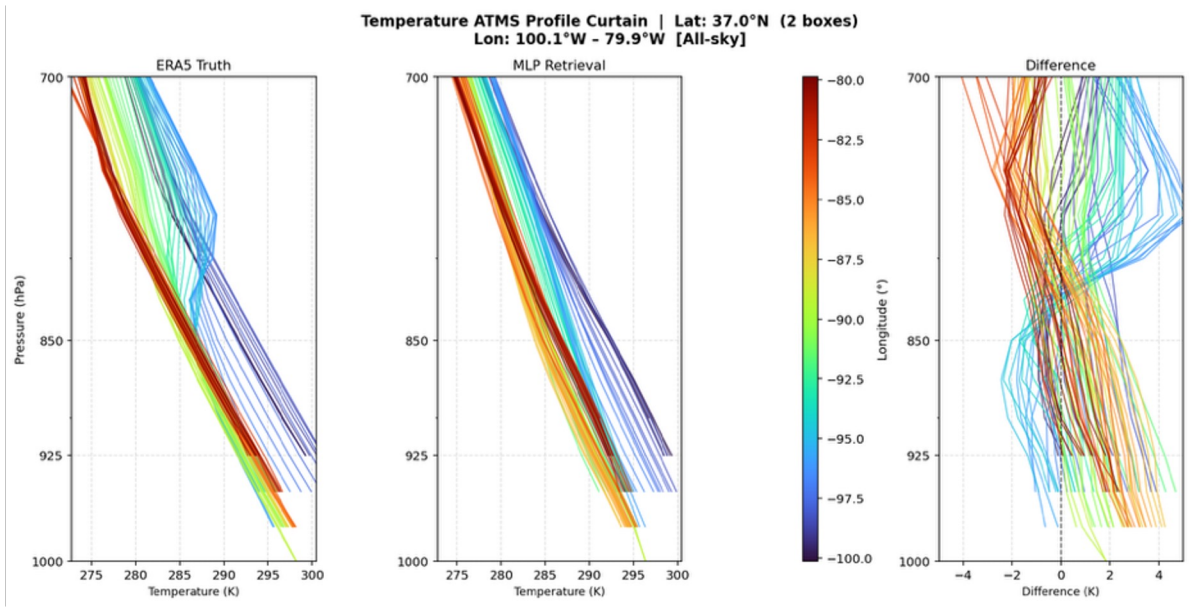


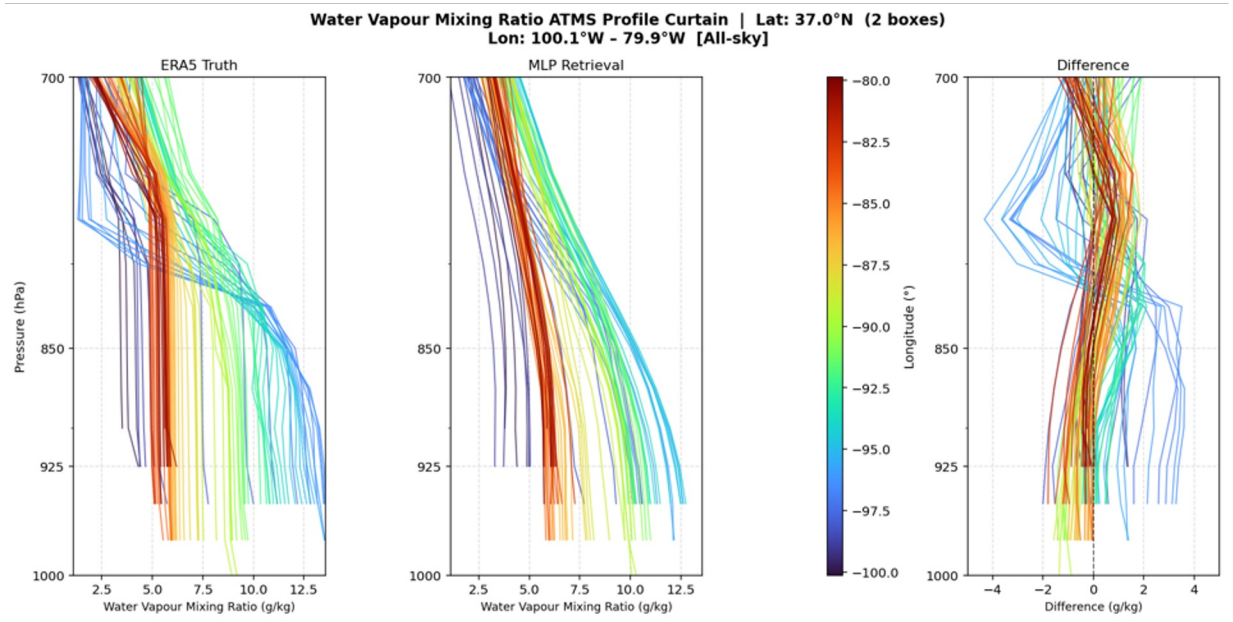


Temperature and Water Vapor ATMS only – All Sky

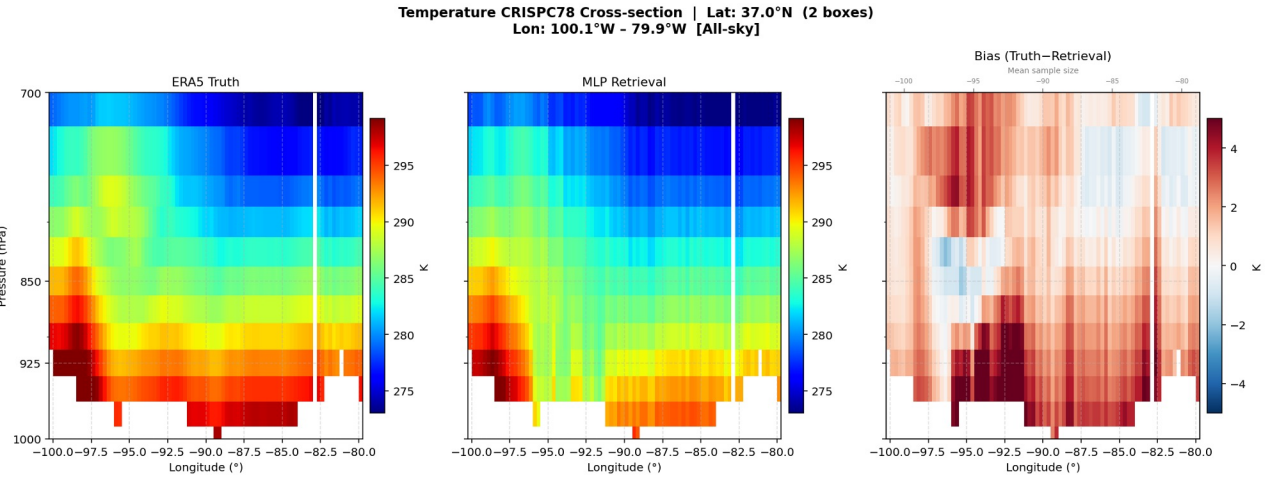


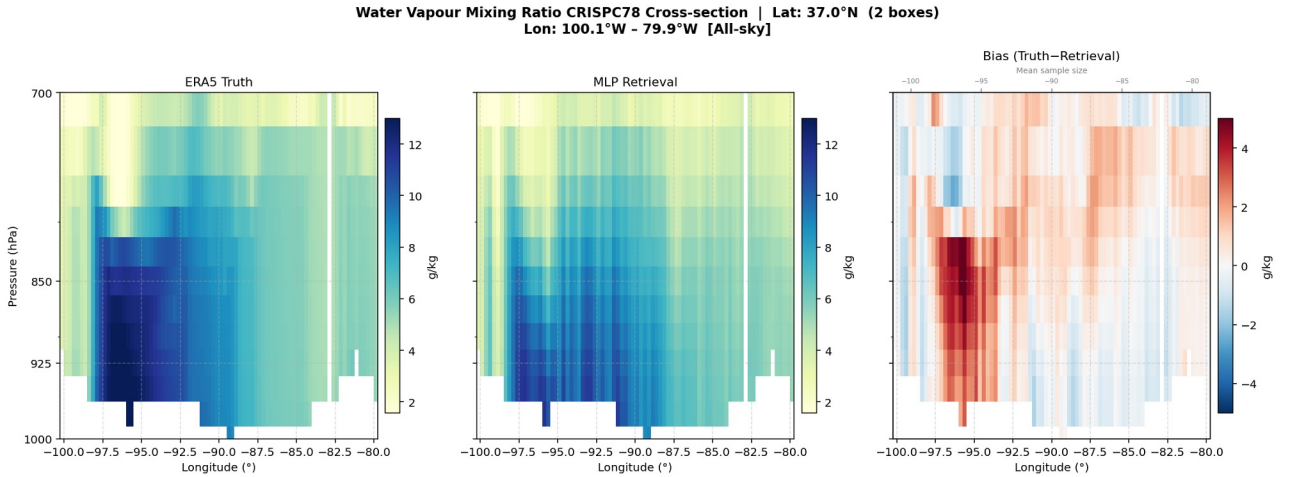


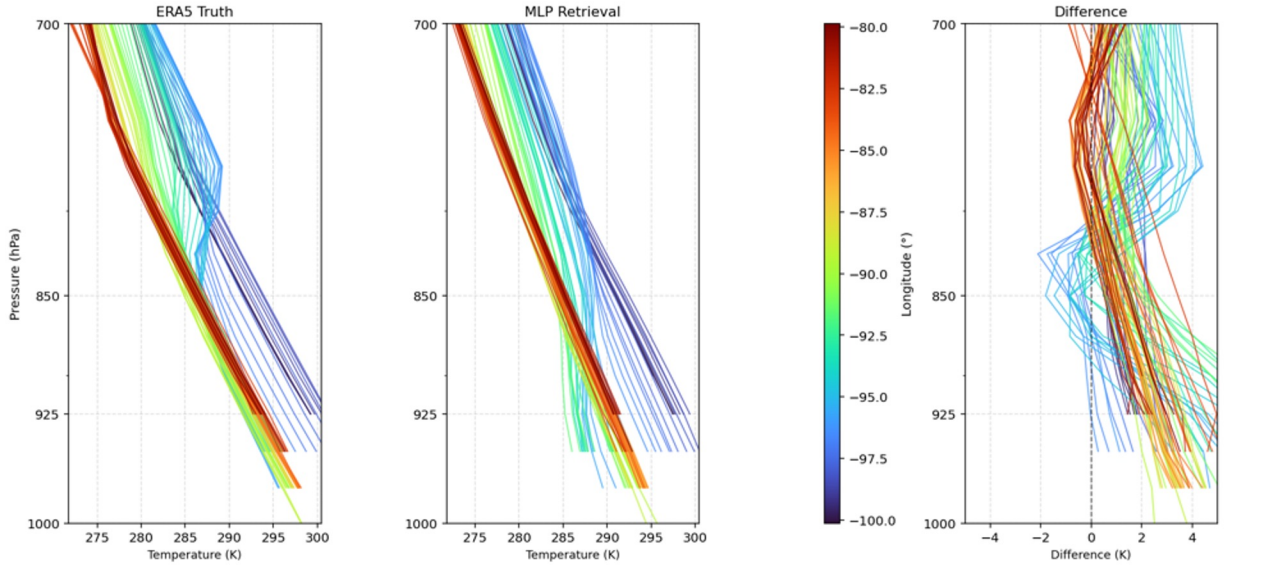


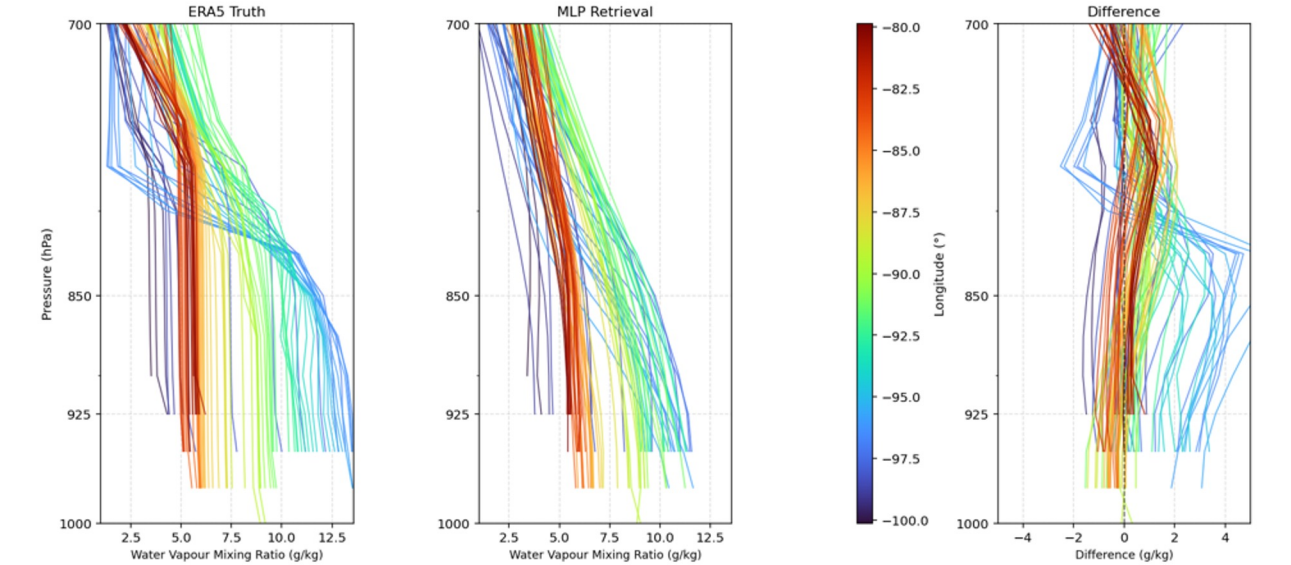


Temperature and Water Vapor CRIS only – All Sky

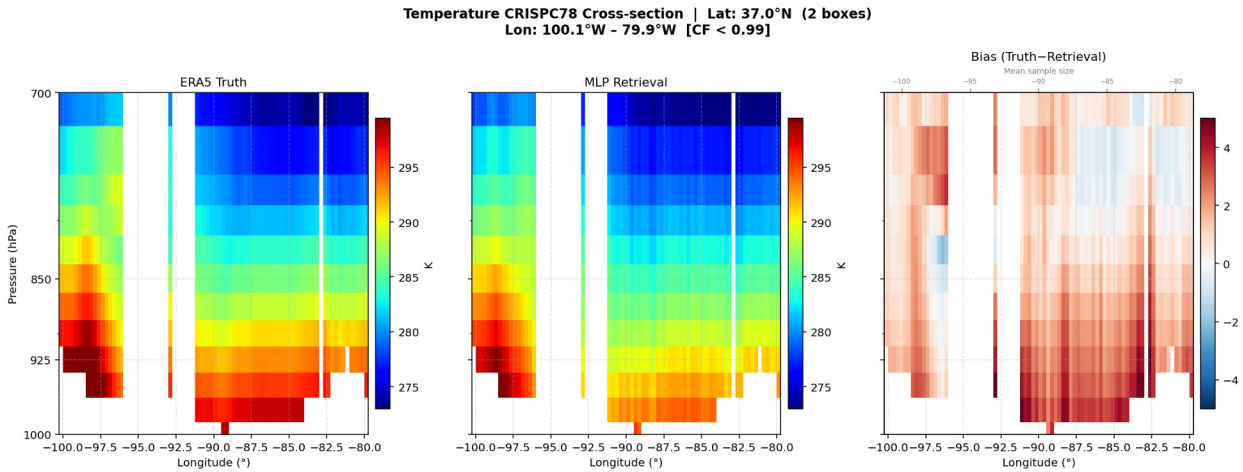


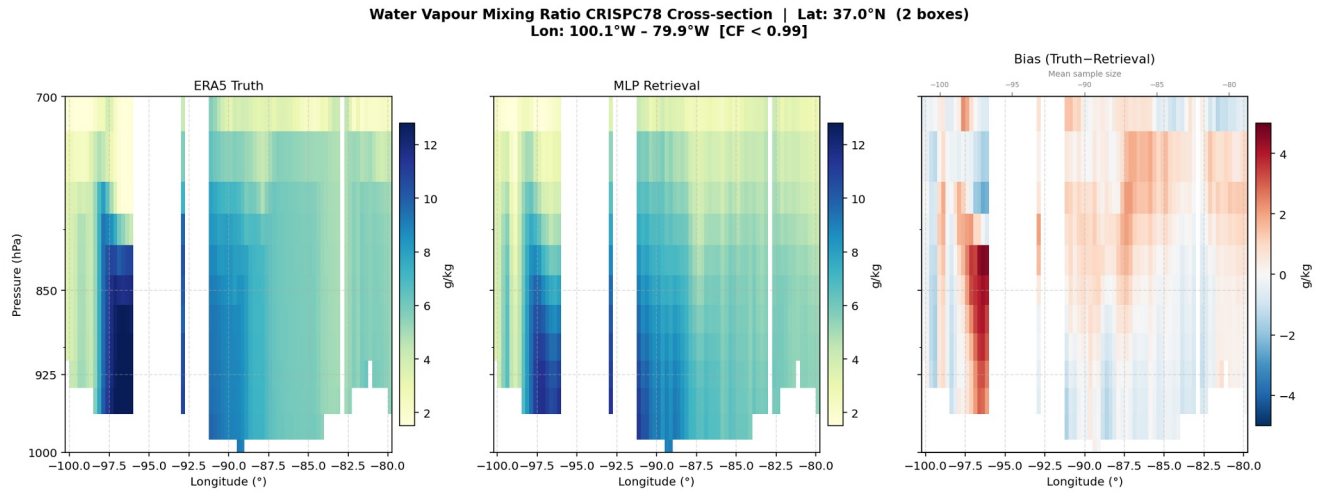


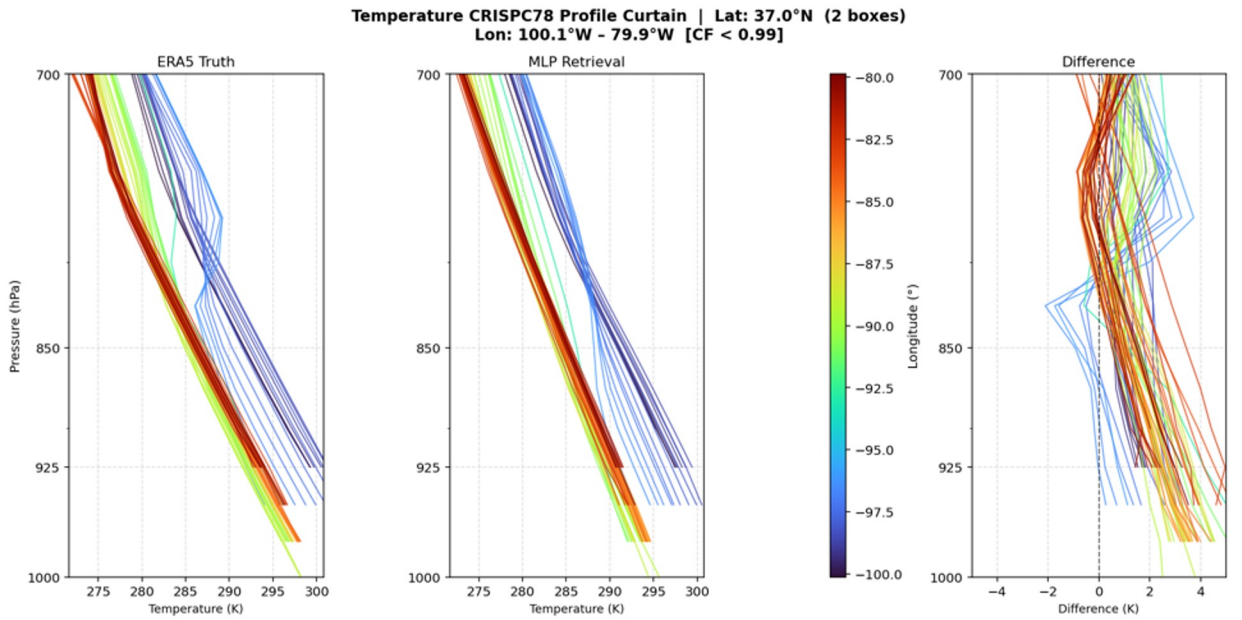


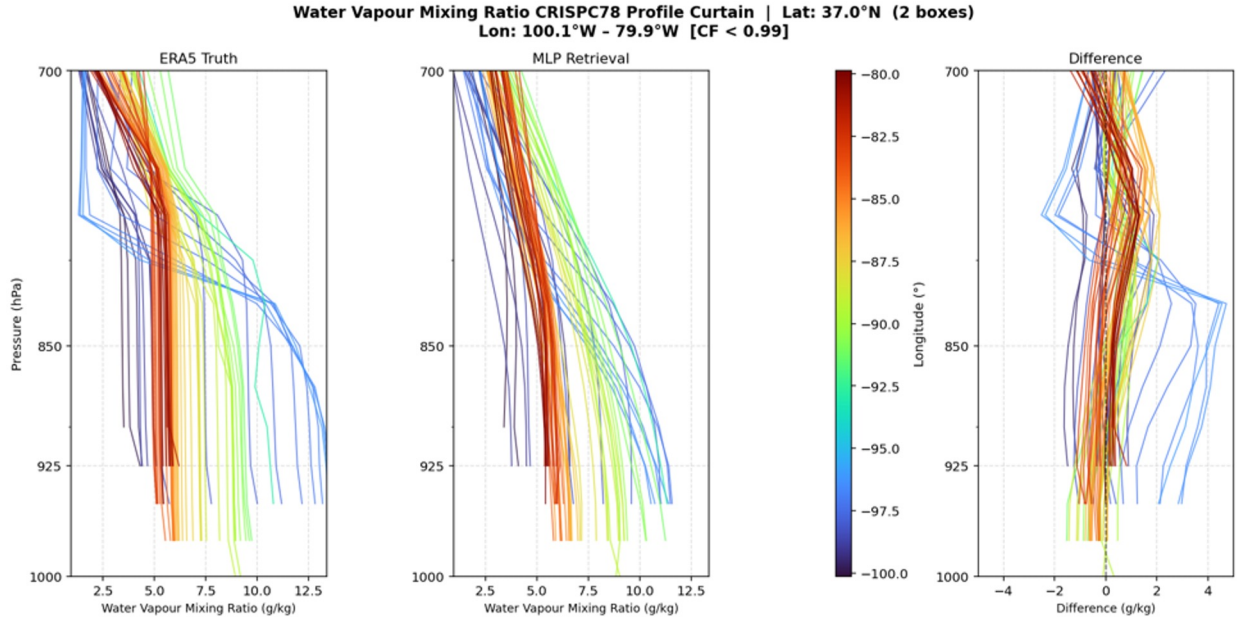


Temperature and Water Vapor CRIS only and Cloud Fraction < 0.991





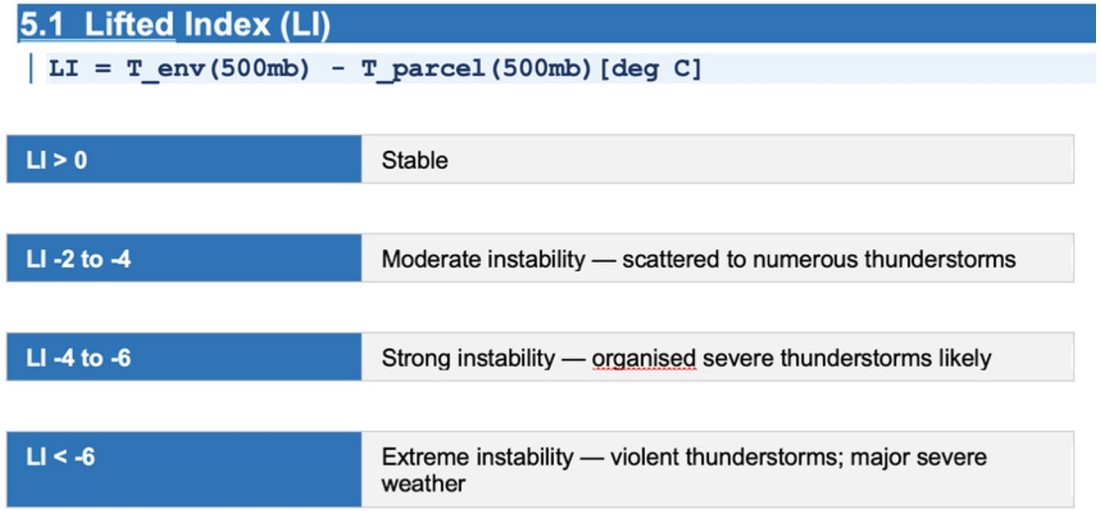




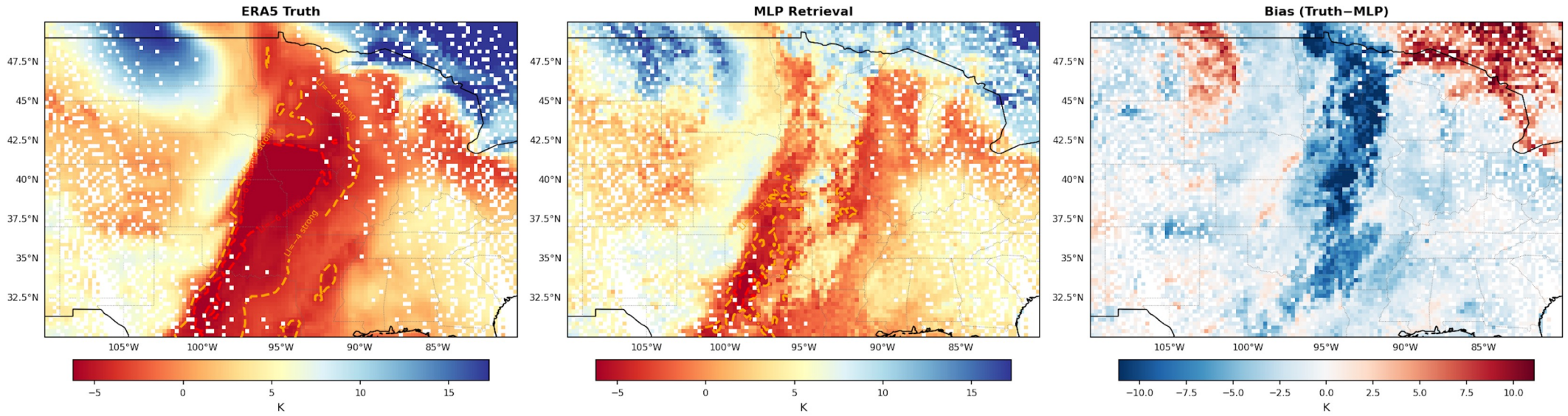
The **Lifted Index (LI)** is a measure of atmospheric instability used in convective weather forecasting. It is defined as the difference between the environmental temperature at 500 hPa and the temperature a parcel of surface air would have if lifted dry-adiabatically to its Lifting Condensation Level (LCL) and then moist-adiabatically to 500 hPa:

LI = T_env(500 hPa) − T_parcel(500 hPa)

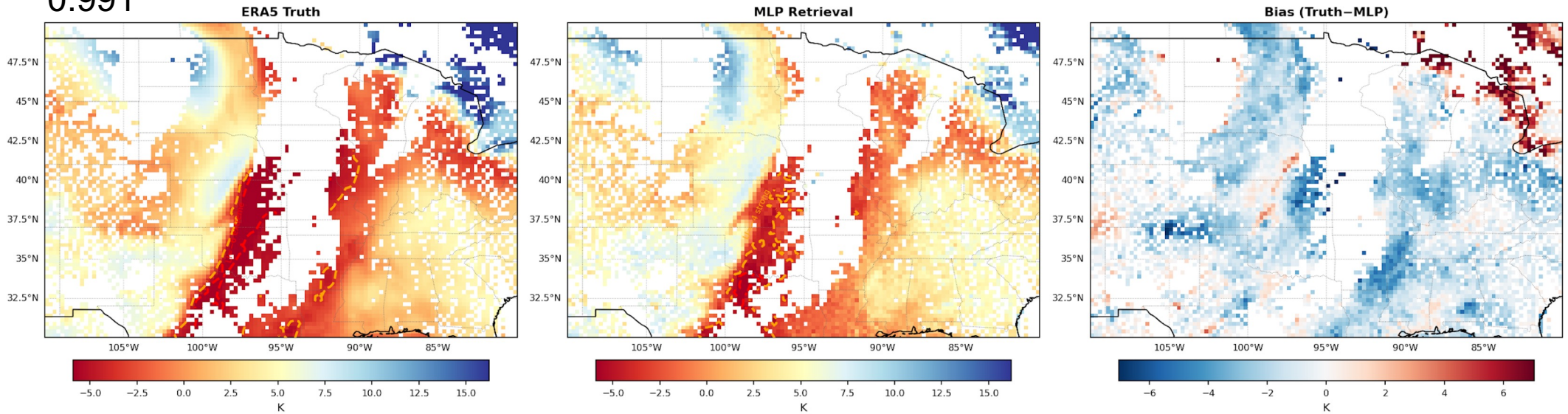
A **negative LI** means the lifted parcel is warmer than its environment at 500 hPa — the atmosphere is unstable and the parcel will continue to rise, potentially producing deep convection. The more negative the value, the greater the instability: values between −2 and −6 K indicate moderate to severe thunderstorm potential, and values below −6 K suggest extreme convective instability. A **positive LI** indicates a stable atmosphere where the parcel is cooler than its surroundings and convective development is suppressed



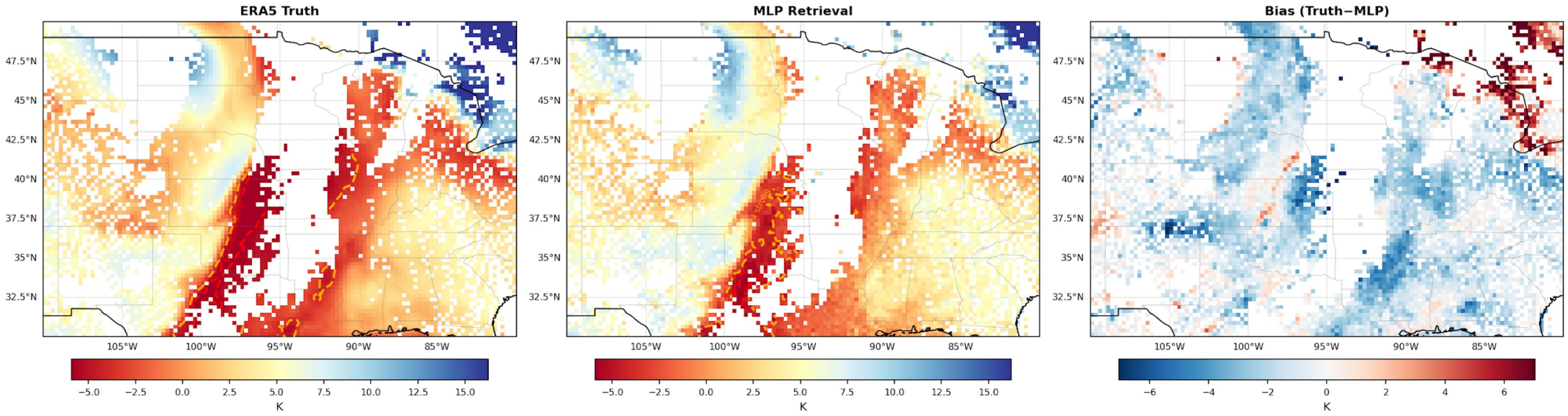
CRIS only



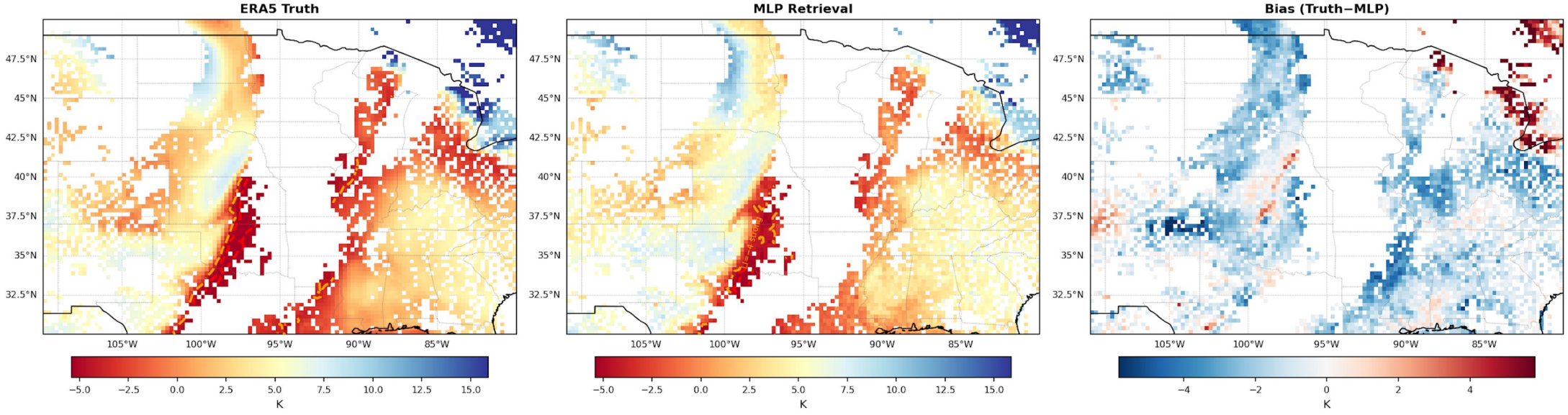
CrIS only , CF < 0.991



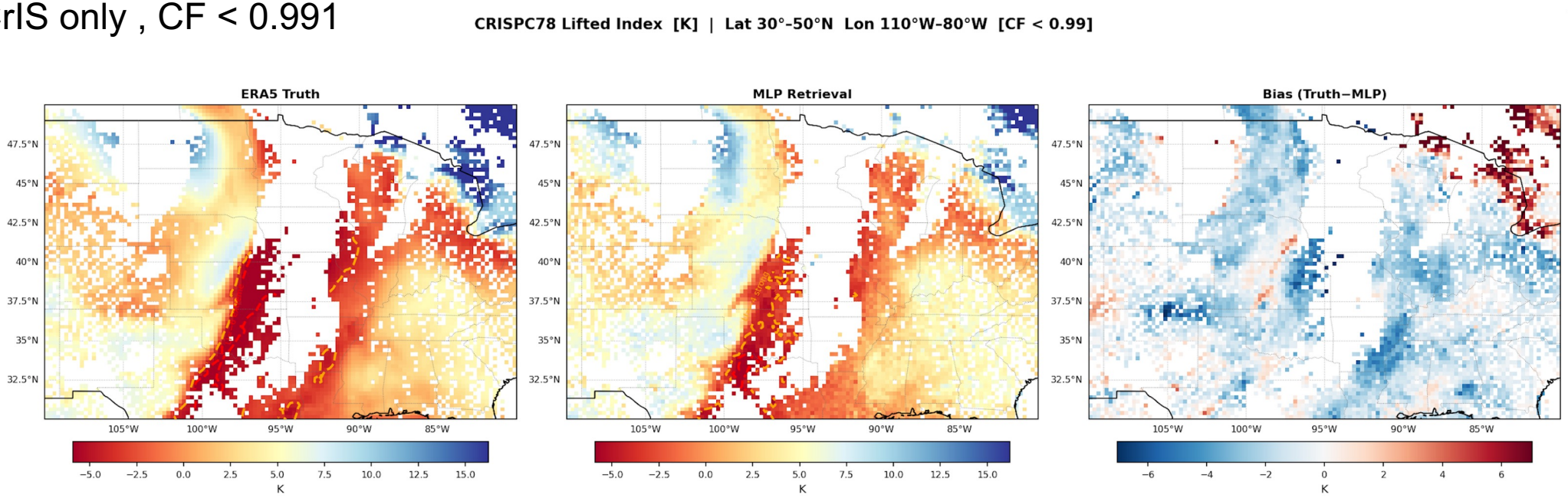
CrIS only , CF < 0.991



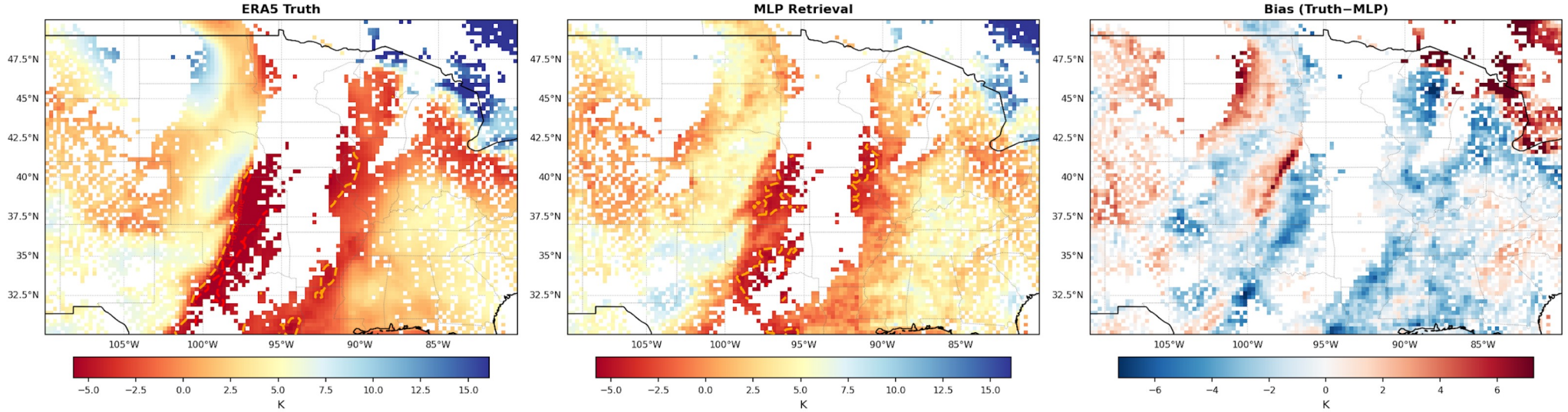
CrIS only , CF < 0.80



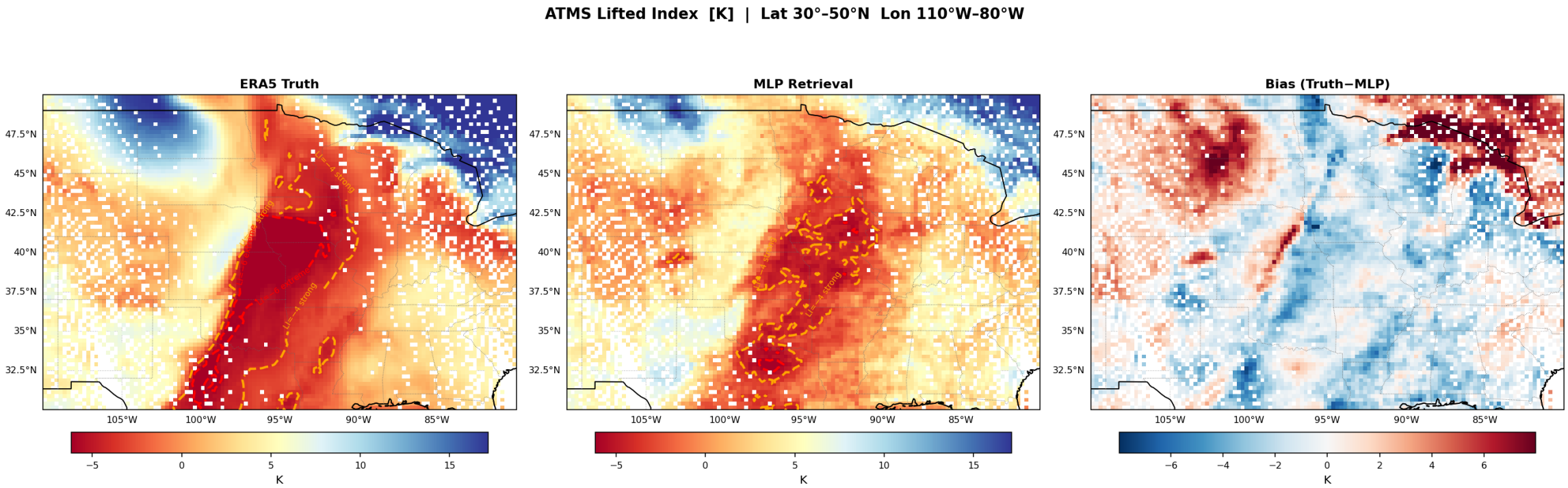
CrIS only , CF < 0.991



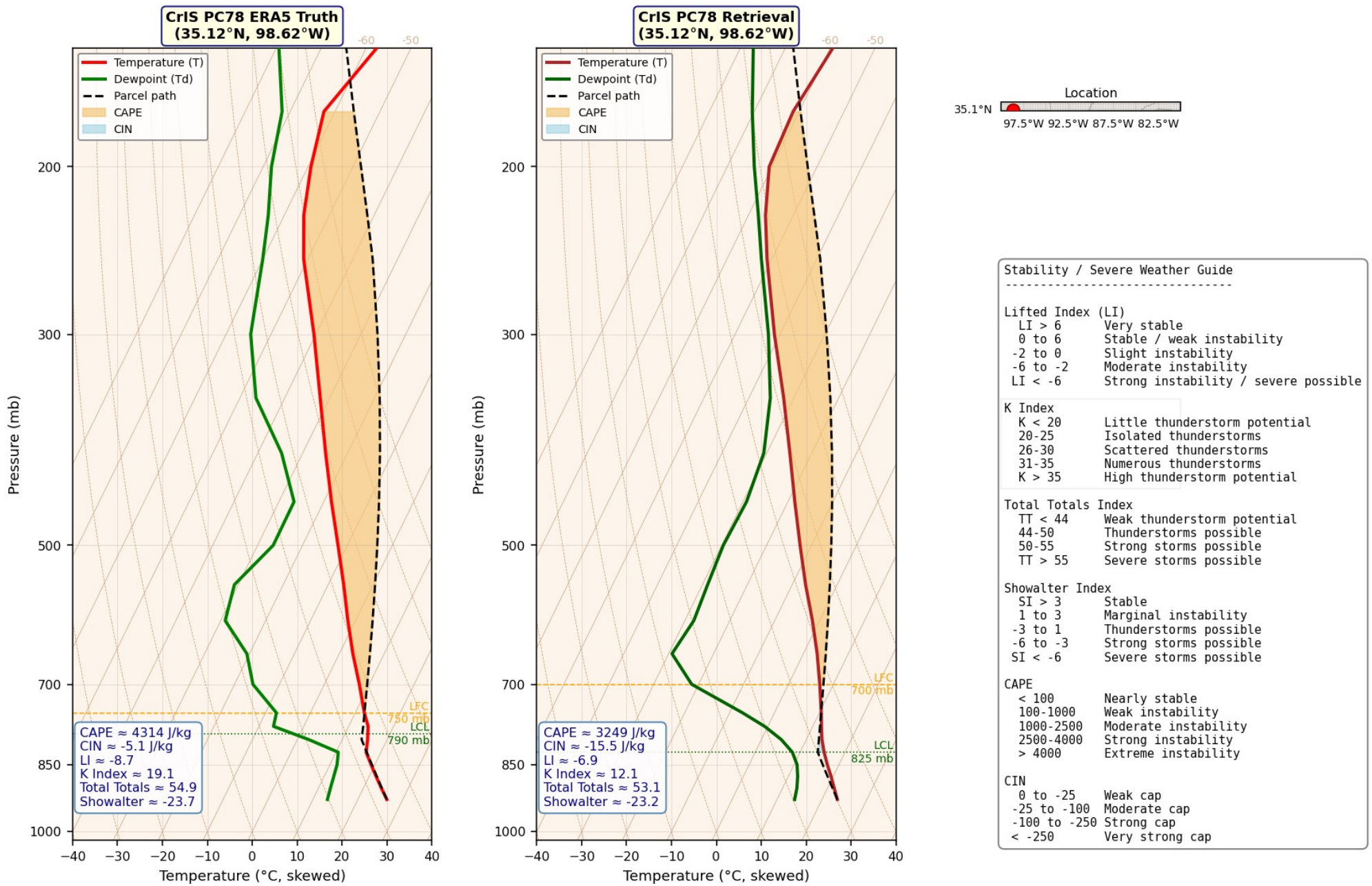
ATMS only , CF < 0.991



ATMS only


ATMS Lifted Index [K] | Lat 30°–50°N Lon 110°W–80°W
ERA5 Truth
MLP Retrieval
Bias (Truth−MLP)
47.5°N
45°N
42.5°N
40°N
37.5°N
35°N
32.5°N
105°W
100°W
95°W
90°W
85°W
−5
0
5
10
15
−6
−4
−2
2
4
6
K

CRIS Only




```
Stability / Severe Weather Guide
--------------------------------

Lifted Index (LI)
  LI > 6      Very stable
  0 to 6      Stable / weak instability
 -2 to 0      Slight instability
 -6 to -2     Moderate instability
 LI < -6      Strong instability / severe possible

K Index
  K < 20      Little thunderstorm potential
  20-25       Isolated thunderstorms
  26-30       Scattered thunderstorms
  31-35       Numerous thunderstorms
  K > 35      High thunderstorm potential

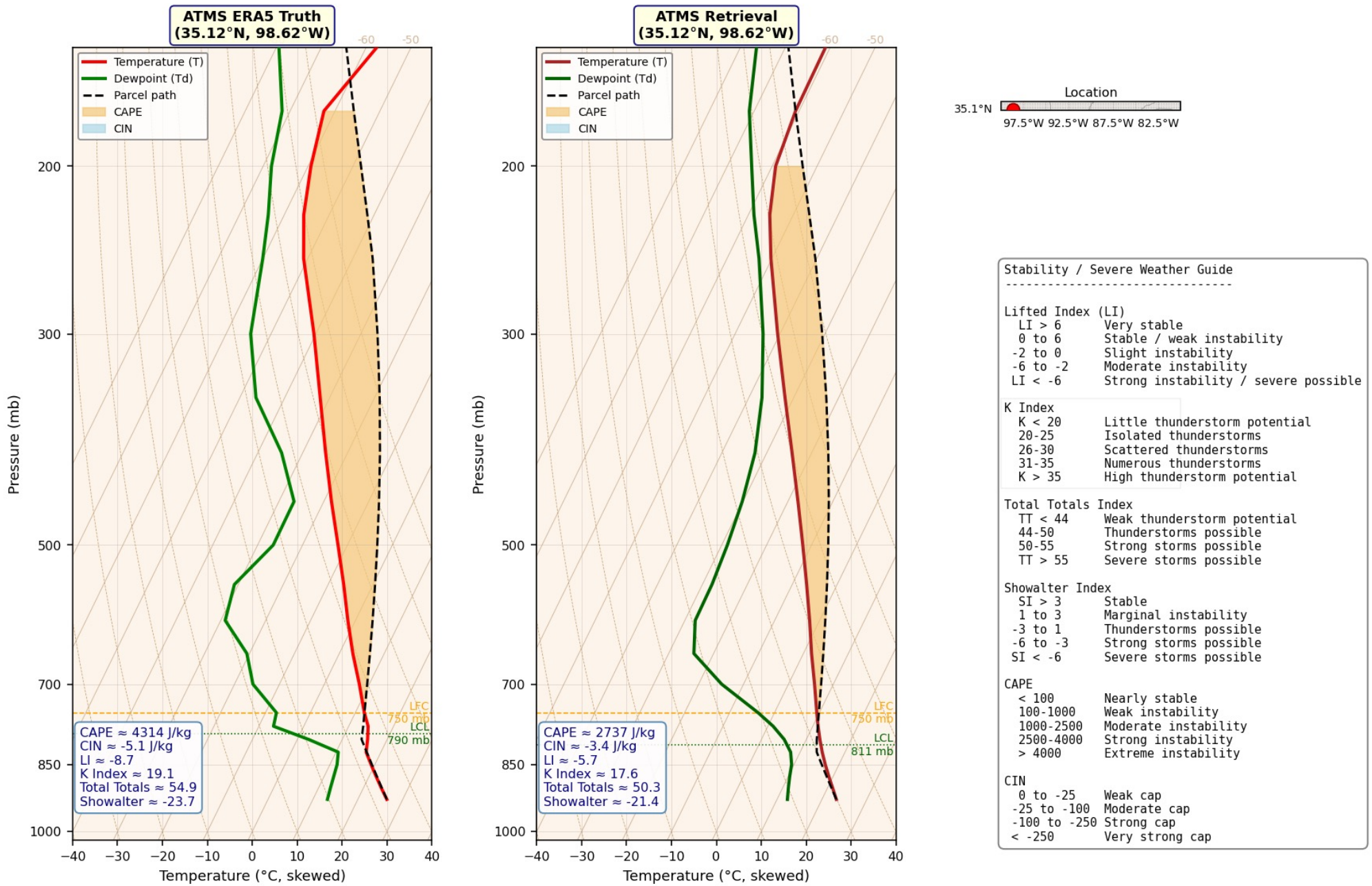
Total Totals Index
  TT < 44     Weak thunderstorm potential
  44-50       Thunderstorms possible
  50-55       Strong storms possible
  TT > 55     Severe storms possible

Showalter Index
  SI > 3      Stable
  1 to 3      Marginal instability
 -3 to 1      Thunderstorms possible
 -6 to -3     Strong storms possible
 SI < -6      Severe storms possible

CAPE
  < 100       Nearly stable
  100-1000    Weak instability
  1000-2500   Moderate instability
  2500-4000   Strong instability
  > 4000      Extreme instability

CIN
  0 to -25    Weak cap
 -25 to -100  Moderate cap
 -100 to -250 Strong cap
 < -250       Very strong cap
```

ATMS only

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Stability / Severe Weather Guide
--------------------------------

Lifted Index (LI)
  LI > 6       Very stable
  0 to 6       Stable / weak instability
 -2 to 0       Slight instability
 -6 to -2      Moderate instability
 LI < -6       Strong instability / severe possible

K Index
  K < 20       Little thunderstorm potential
  20-25        Isolated thunderstorms
  26-30        Scattered thunderstorms
  31-35        Numerous thunderstorms
  K > 35       High thunderstorm potential

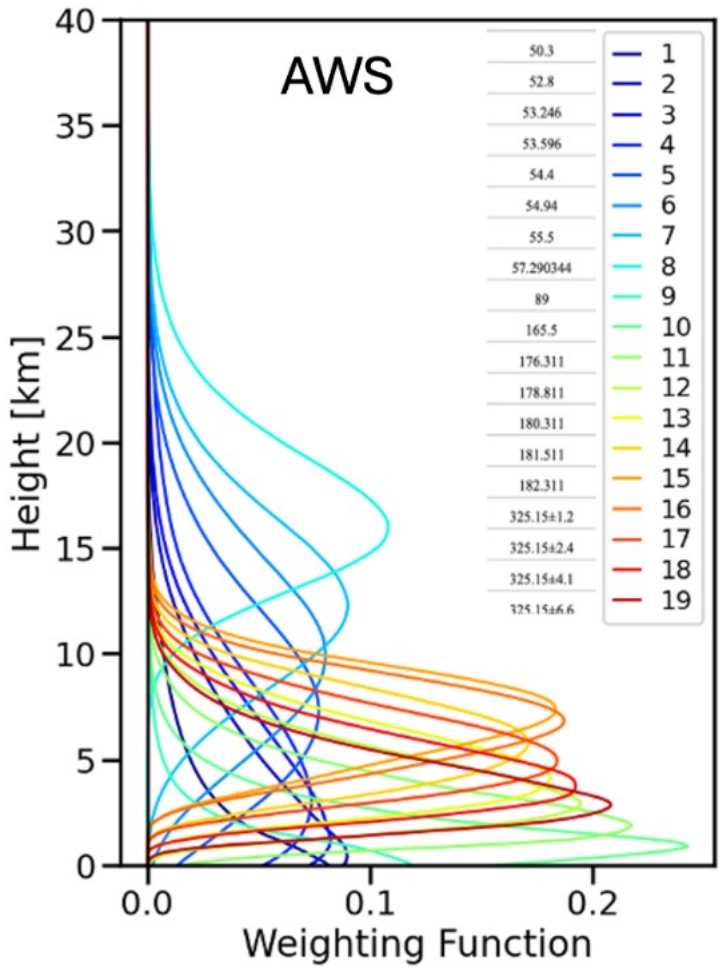
Total Totals Index
  TT < 44      Weak thunderstorm potential
  44-50        Thunderstorms possible
  50-55        Strong storms possible
  TT > 55      Severe storms possible

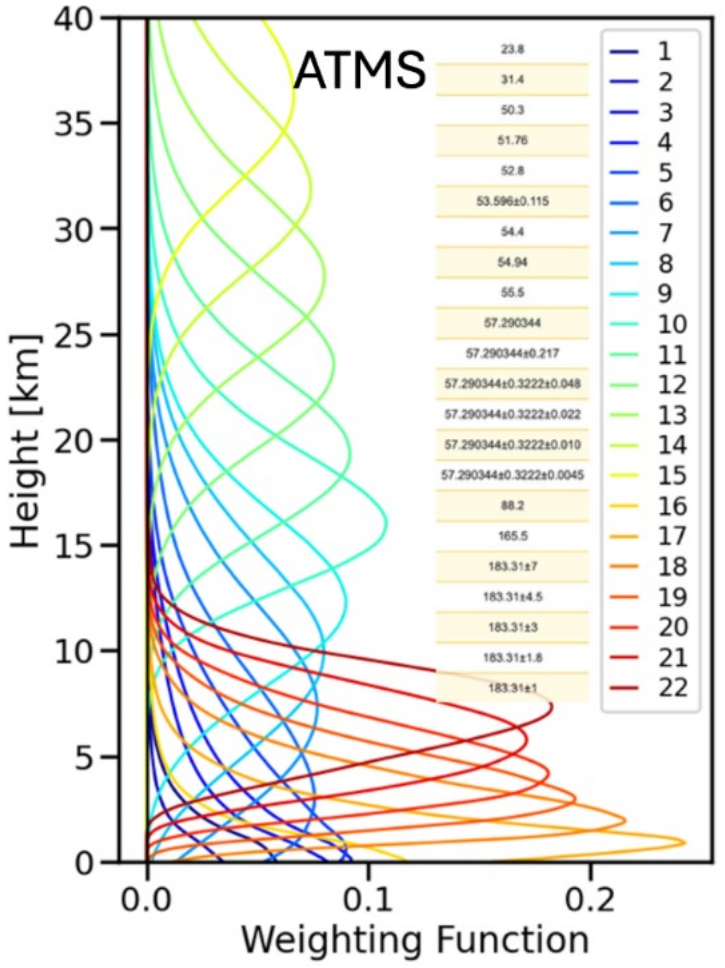
Showalter Index
  SI > 3       Stable
  1 to 3       Marginal instability
 -3 to 1       Thunderstorms possible
 -6 to -3      Strong storms possible
 SI < -6       Severe storms possible

CAPE
  < 100        Nearly stable
  100-1000     Weak instability
  1000-2500    Moderate instability
  2500-4000    Strong instability
  > 4000       Extreme instability

CIN
  0 to -25     Weak cap
 -25 to -100   Moderate cap
 -100 to -250  Strong cap
 < -250        Very strong cap
```

Arctic Weather Satellite





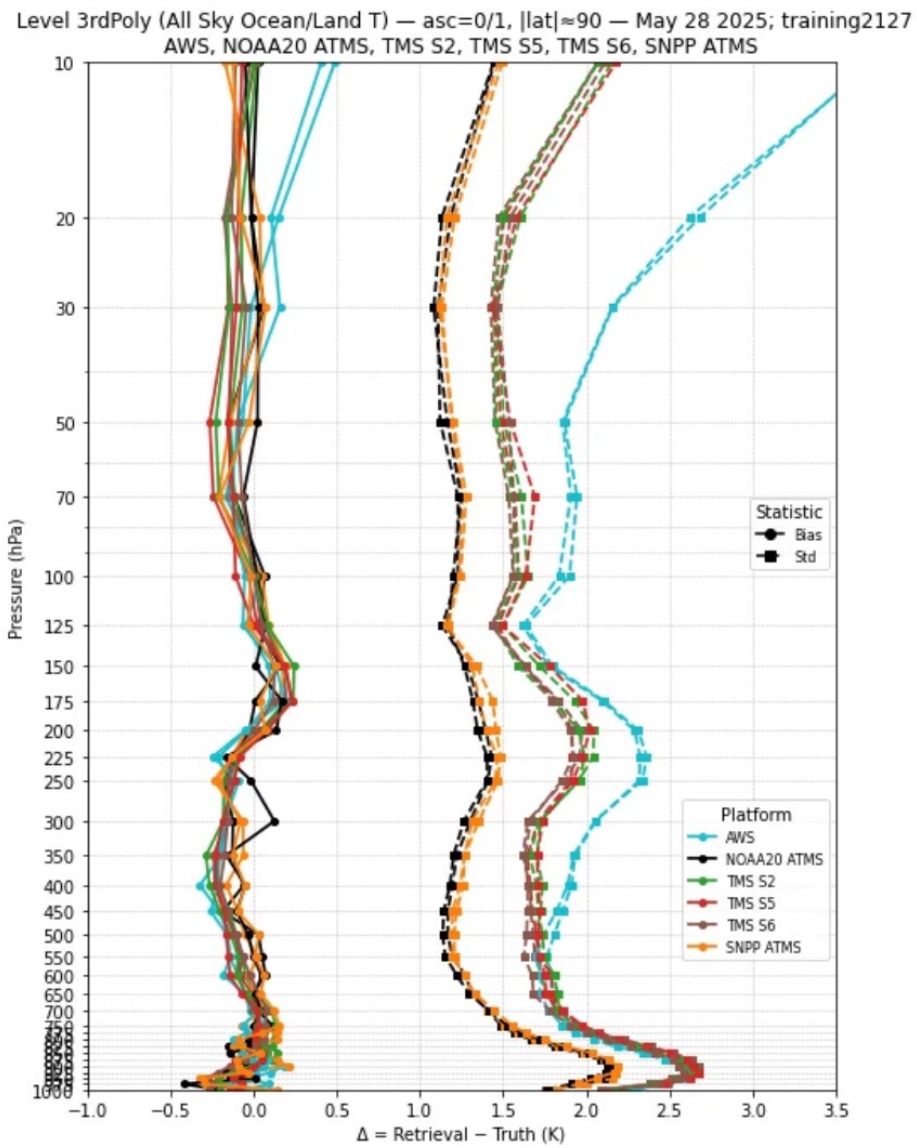
Noise Comparison. (Used adjacent fovs under clear skies in tropics over ocean)

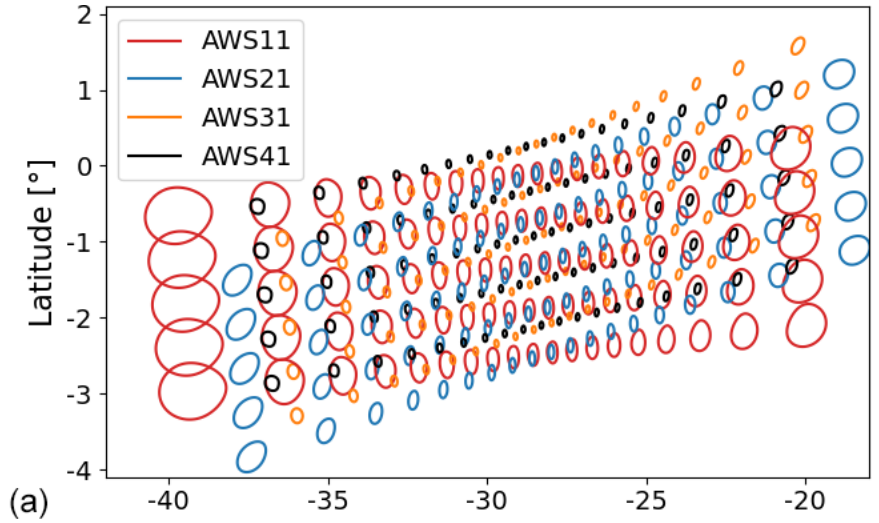
ESA AWS near-nadir estimated instrument noise (Goldberg)

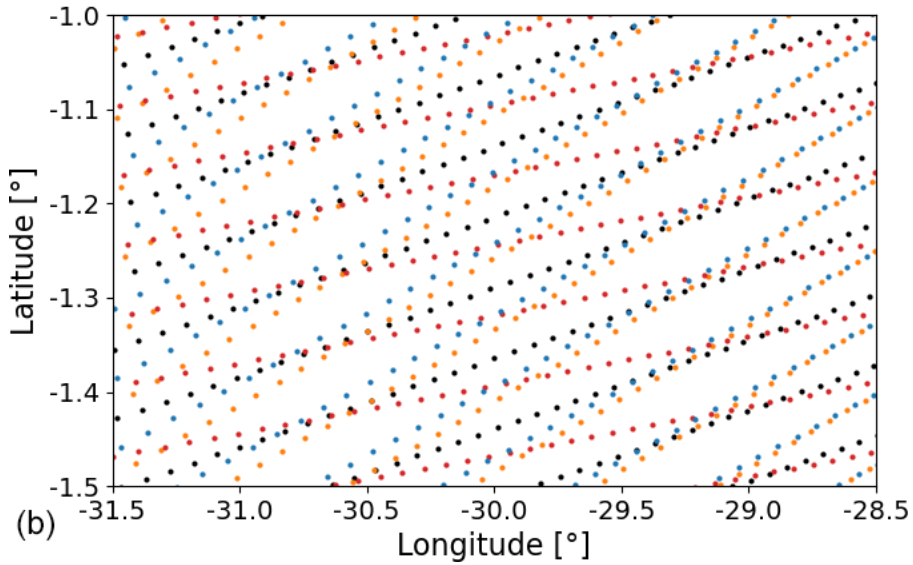
Ch.	Center frequency (GHz)	Band / purpose	Near-nadir noise (K)
1	50.300	50–58 GHz temp.	0.84
2	52.800	50–58 GHz temp.	0.52
3	53.246	50–58 GHz temp.	0.58
4	53.596	50–58 GHz temp.	0.49
5	54.400	50–58 GHz temp.	0.49
6	54.940	50–58 GHz temp.	0.61
7	55.500	50–58 GHz temp.	0.82
8	57.290334	50–58 GHz temp.	2.03
9	89.000	89 GHz window	0.84
10	165.500	165.5 GHz window	0.50
11	176.311	183 GHz humidity	0.54
12	178.811	183 GHz humidity	0.58
13	180.311	183 GHz humidity	0.76
14	181.511	183 GHz humidity	0.84
15	182.311	183 GHz humidity	1.04
16	325.15 ± 1.2	325 GHz sub-mm	1.53
17	325.15 ± 2.4	325 GHz sub-mm	1.64
18	325.15 ± 4.1	325 GHz sub-mm	0.99
19	325.15 ± 6.6	325 GHz sub-mm	0.80

NOAA-20 ATMS near-nadir estimated instrument noise (Goldberg)

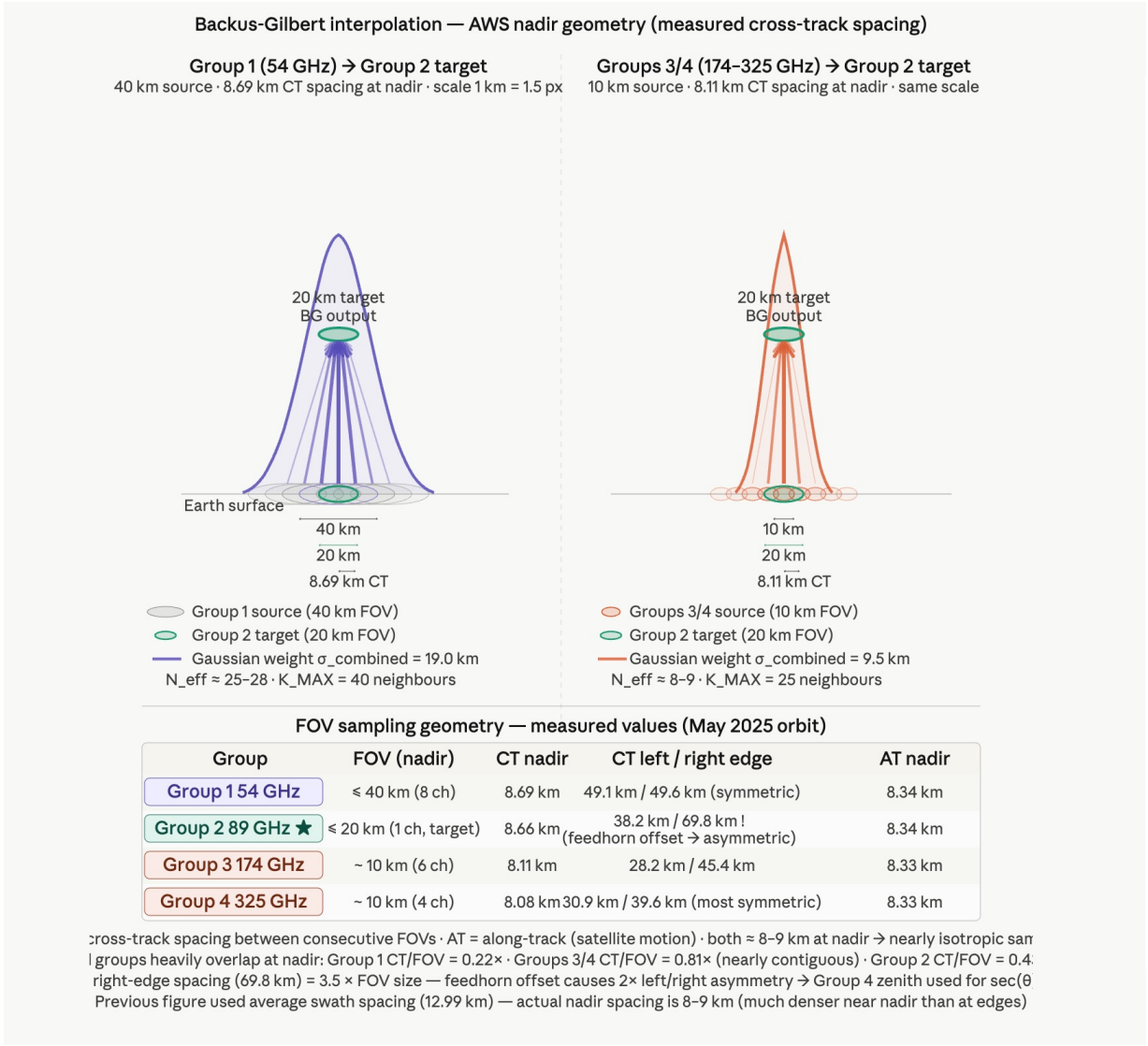
Ch.	Center frequency (GHz)	Band / purpose	Near-nadir noise (K)
1	23.800	23 GHz window	1.500
2	31.400	31 GHz window	1.600
3	50.300	50–58 GHz temp.	0.780
4	51.760	50–58 GHz temp.	0.500
5	52.800	50–58 GHz temp.	0.290
6	53.596 ± 0.115	50–58 GHz temp.	0.235
7	54.400	50–58 GHz temp.	0.198
8	54.940	50–58 GHz temp.	0.192
9	55.500	50–58 GHz temp.	0.203
10	57.290344 (f_0)	57 GHz temp.	0.284
11	f_0 ± 0.217	57 GHz temp.	0.410
12	f_0 ± 0.3222 ± 0.048	57 GHz temp.	0.430
13	f_0 ± 0.3222 ± 0.022	57 GHz temp.	0.650
14	f_0 ± 0.3222 ± 0.010	57 GHz temp.	0.930
15	f_0 ± 0.3222 ± 0.0045	57 GHz temp.	1.550
16	88.200	88 GHz window	1.100
17	165.500	165 GHz window	0.570
18	183.31 ± 7.0	183 GHz humidity	0.430
19	183.31 ± 4.5	183 GHz humidity	0.450
20	183.31 ± 3.0	183 GHz humidity	0.510
21	183.31 ± 1.8	183 GHz humidity	0.530
22	183.31 ± 1.0	183 GHz humidity	0.690


Level 3rdPoly (All Sky Ocean/Land T) — asc=0/1, |lat|≈90 — May 28 2025; training2127
AWS, NOAA20 ATMS, TMS S2, TMS S5, TMS S6, SNPP ATMS
Pressure (hPa)
Δ = Retrieval − Truth (K)
Statistic
Bias
Std
Platform
AWS
NOAA20 ATMS
TMS S2
TMS S5
TMS S6
SNPP ATMS


AWS11
AWS21
AWS31
AWS41
Latitude [°]
(a)


Latitude [°]
Longitude [°]
(b)

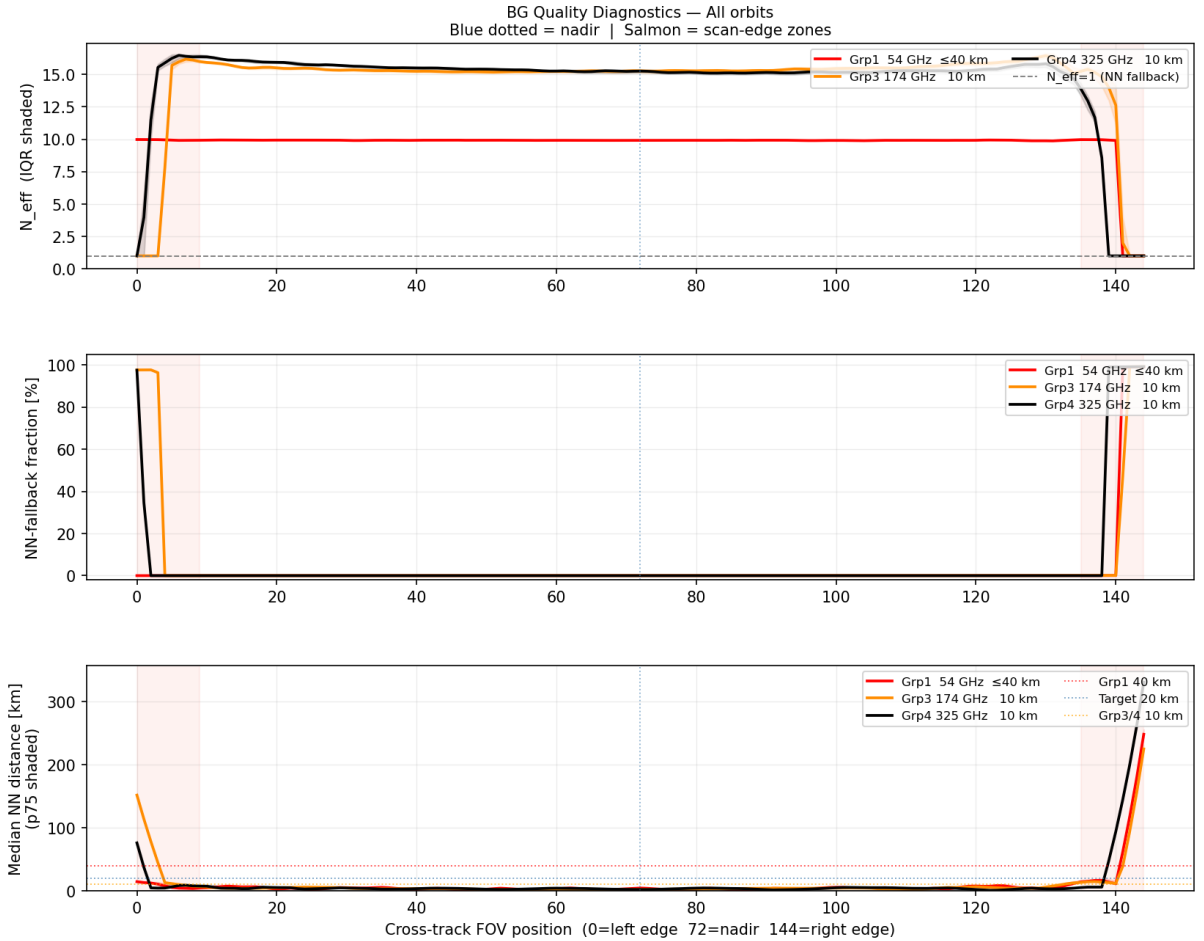
Exclude scan-edge FOVs — keep only positions 3-136 (134 FOVs)



FOV sampling geometry — measured values (May 2025 orbit)

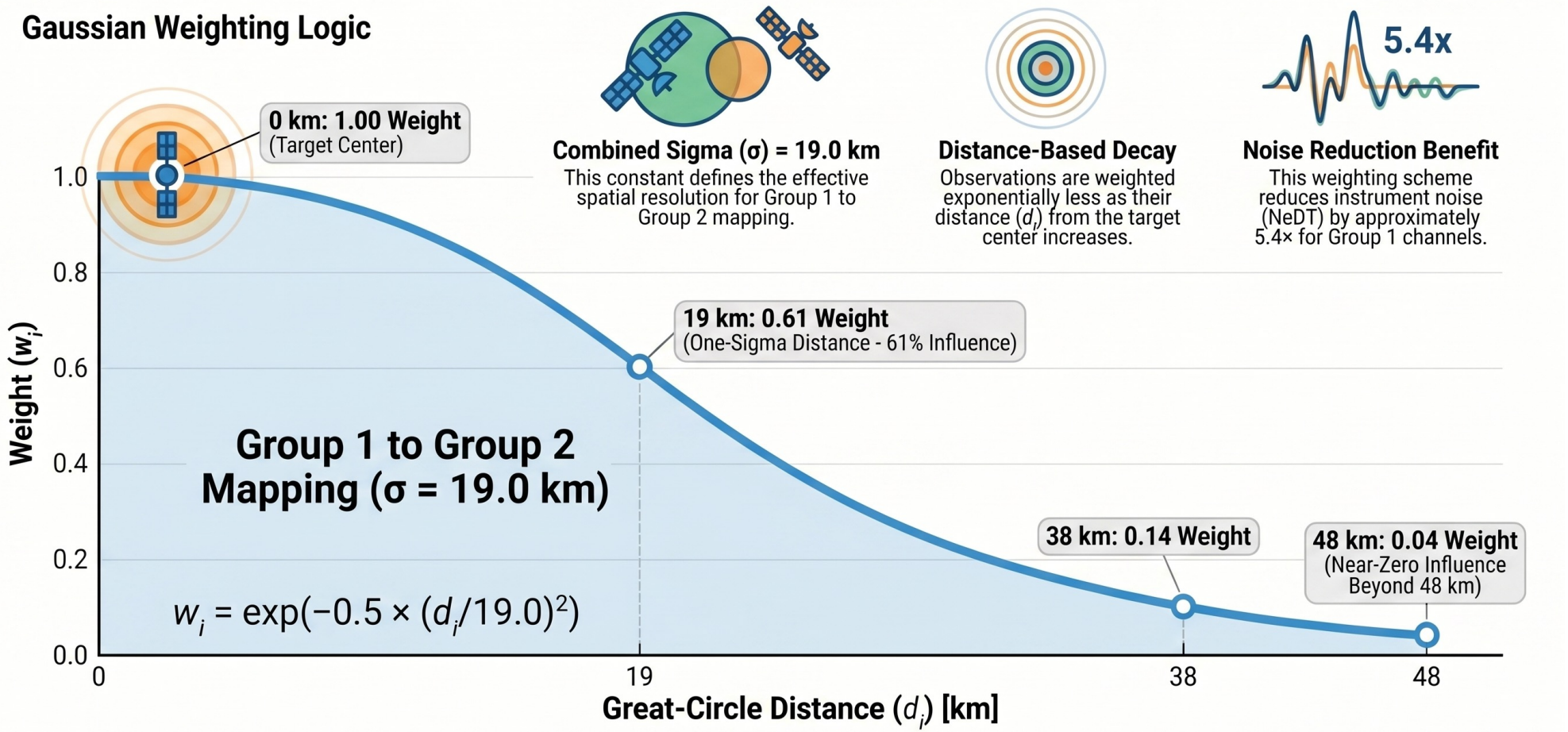
Group	FOV (nadir)	CT nadir	CT left / right edge	AT nadir
Group 1 54 GHz	⩽ 40 km (8 ch)	8.69 km	49.1 km / 49.6 km (symmetric)	8.34 km
Group 2 89 GHz ★	⩽ 20 km (1 ch, target)	8.66 km	38.2 km / 69.8 km ! (feedhorn offset → asymmetric)	8.34 km
Group 3 174 GHz	~ 10 km (6 ch)	8.11 km	28.2 km / 45.4 km	8.33 km
Group 4 325 GHz	~ 10 km (4 ch)	8.08 km	30.9 km / 39.6 km (most symmetric)	8.33 km

cross-track spacing between consecutive FOVs · AT = along-track (satellite motion) · both ≈ 8–9 km at nadir → nearly isotropic sam
l groups heavily overlap at nadir: Group 1 CT/FOV = 0.22× · Groups 3/4 CT/FOV = 0.81× (nearly contiguous) · Group 2 CT/FOV = 0.4
right-edge spacing (69.8 km) = 3.5 × FOV size — feedhorn offset causes 2× left/right asymmetry → Group 4 zenith used for sec(θ
Previous figure used average swath spacing (12.99 km) — actual nadir spacing is 8–9 km (much denser near nadir than at edges)

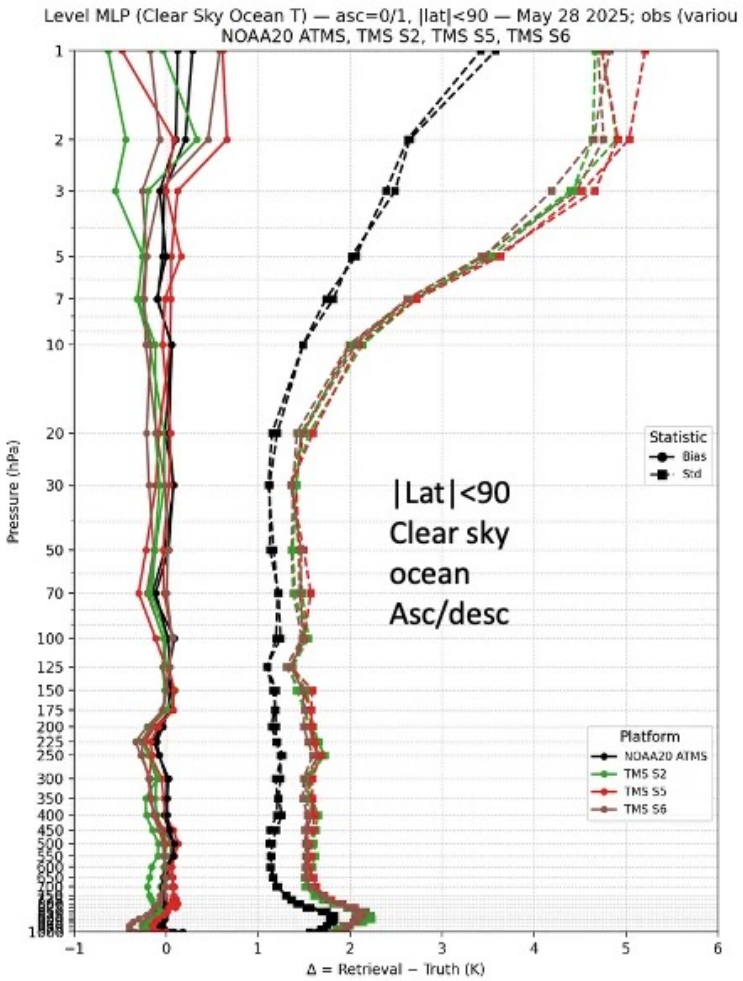


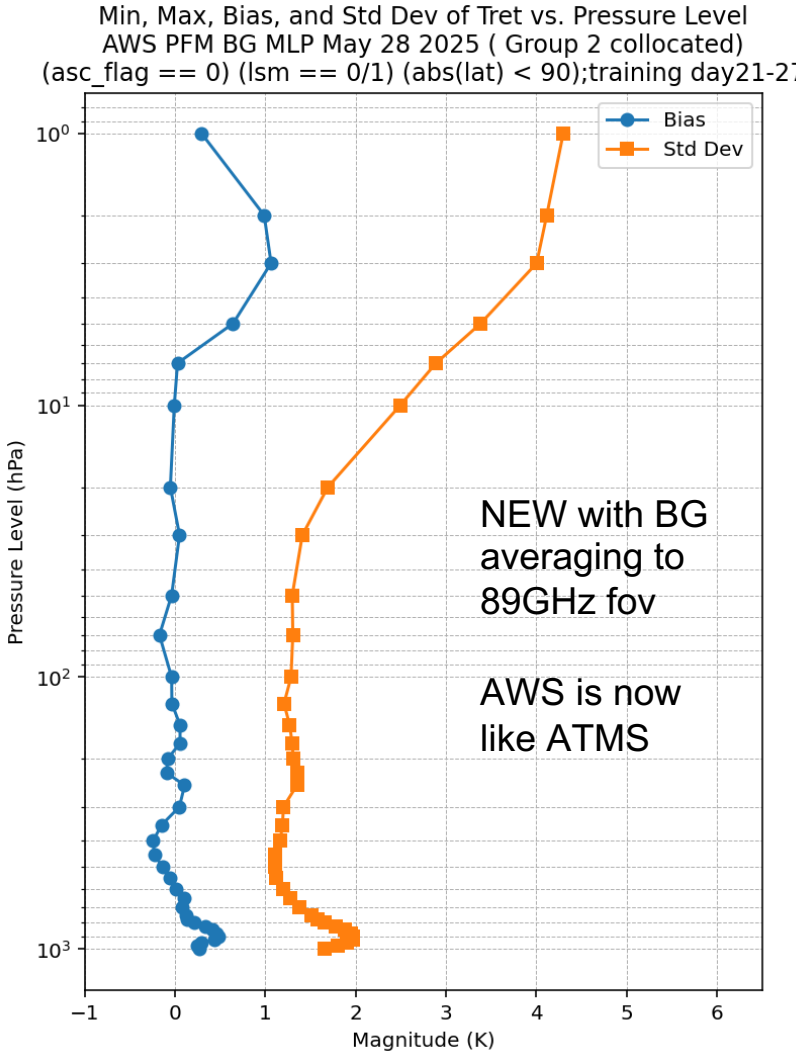
FWHM 40 km fov , 20 km fov

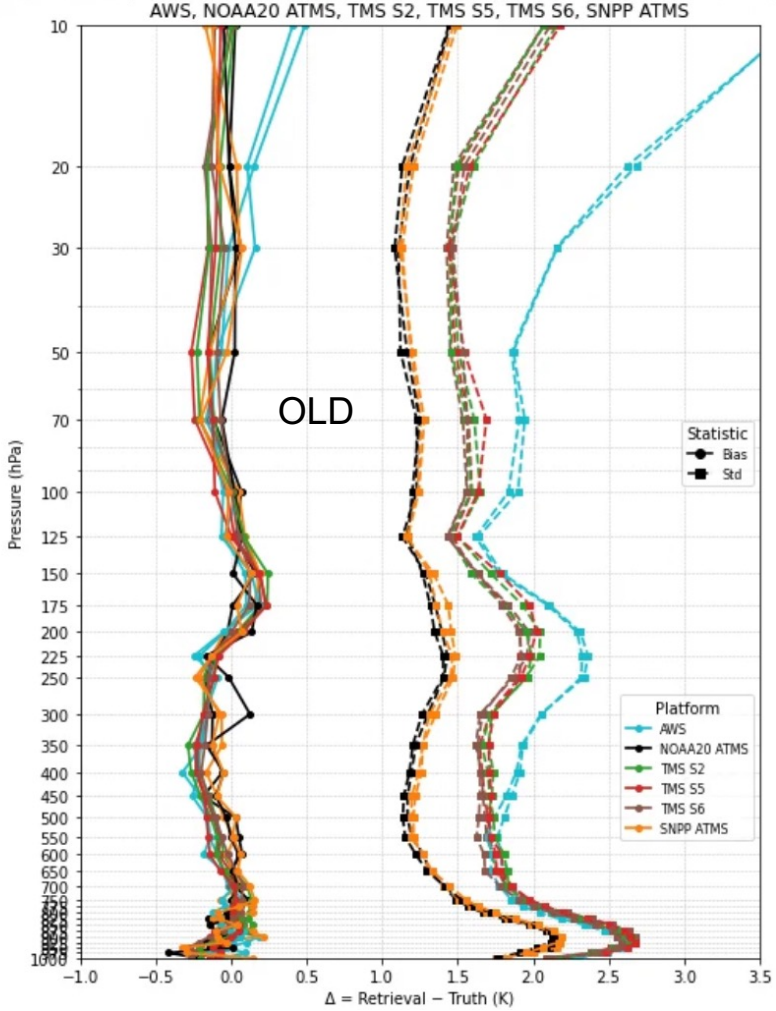
$$\sigma_{combined} = \sqrt{(\sigma_1^2 + \sigma_2^2)} = \sqrt{(16.99^2 + 8.49^2)} = 19.0 \text{ km}$$

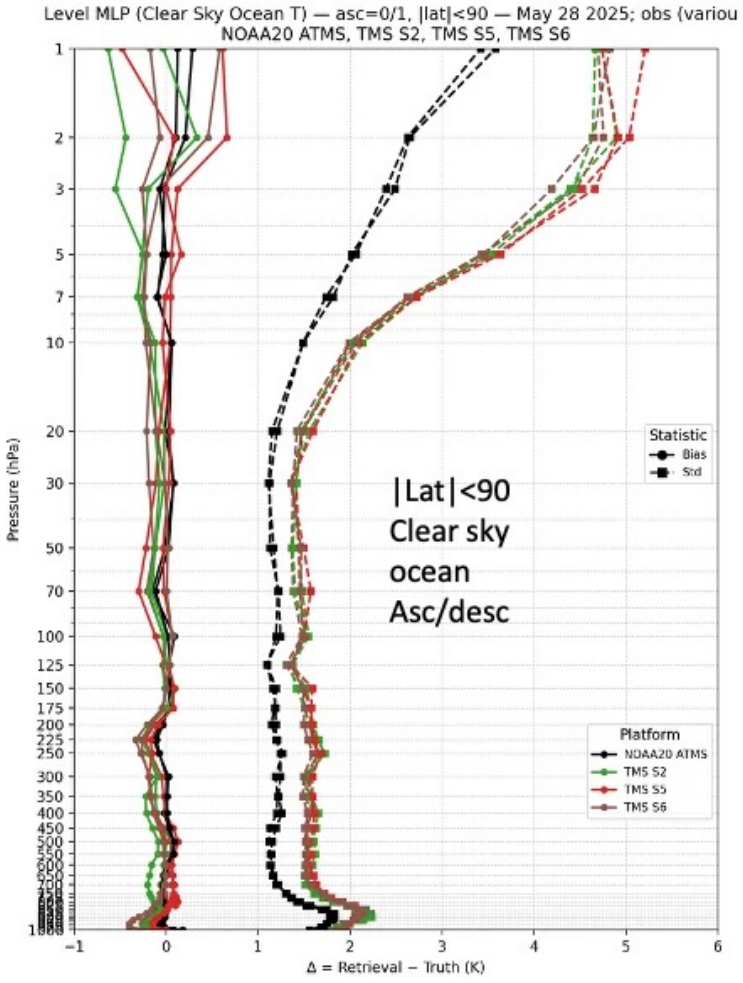


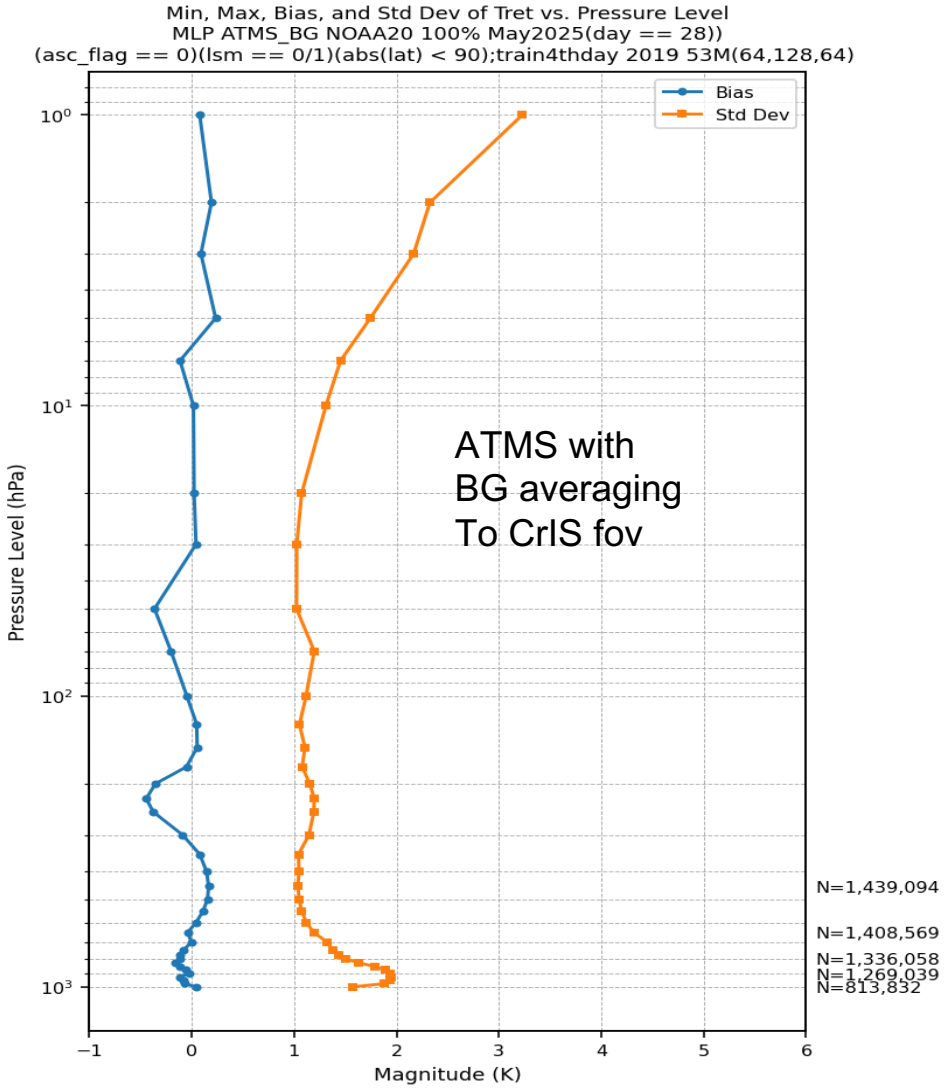
The Arctic Weather Satellite uses Backus-Gilbert interpolation with this weighting to align coarse Group 1 observations to the Group 2 reference for machine learning.

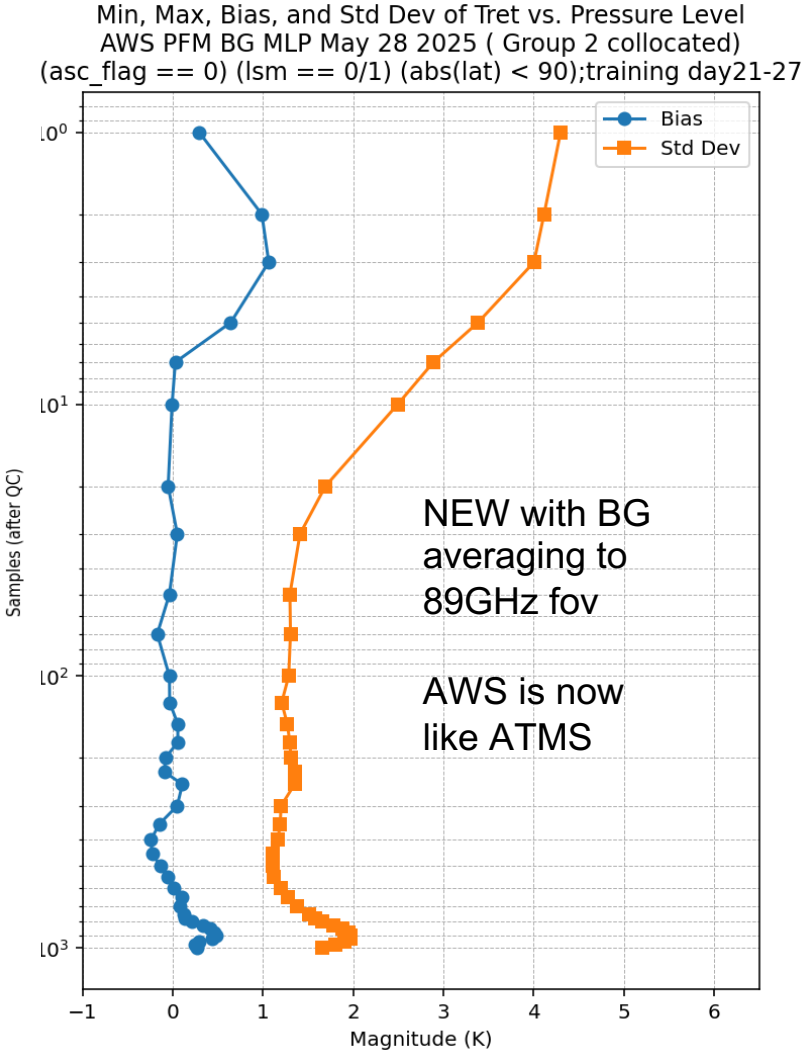

Level MLP (Clear Sky Ocean T) — asc=0/1, |lat|<90 — May 28 2025; obs (variou
NOAA20 ATMS, TMS S2, TMS S5, TMS S6
Pressure (hPa)
Δ = Retrieval − Truth (K)
Statistic
Bias
Std
Platform
NOAA20 ATMS
TMS S2
TMS S5
TMS S6
|Lat|<90
Clear sky
ocean
Asc/desc


Min, Max, Bias, and Std Dev of Tret vs. Pressure Level
AWS PFM BG MLP May 28 2025 (Group 2 collocated)
(asc_flag == 0) (lsm == 0/1) (abs(lat) < 90);training day21-27
Pressure Level (hPa)
Magnitude (K)
Bias
Std Dev
NEW with BG
averaging to
89GHz fov
AWS is now
like ATMS

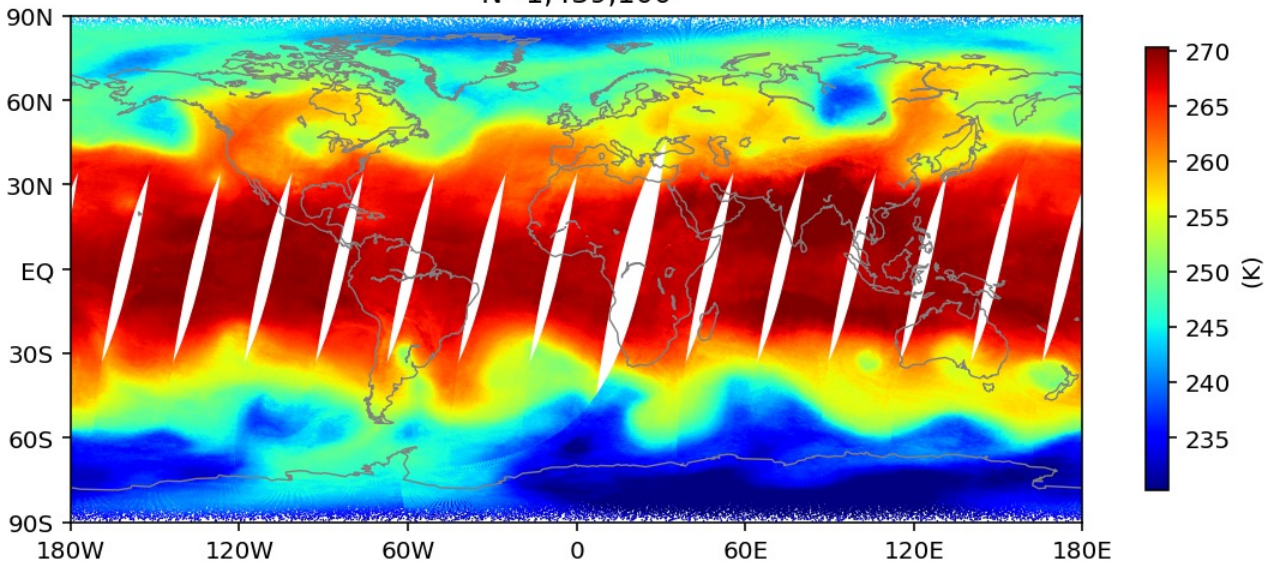

Level 3rdPoly (All Sky Ocean/Land T) — asc=0/1, |lat|≈90 — May 28 2025; training2127
AWS, NOAA20 ATMS, TMS S2, TMS S5, TMS S6, SNPP ATMS
Pressure (hPa)
Δ = Retrieval − Truth (K)
OLD
Statistic
Bias
Std
Platform
AWS
NOAA20 ATMS
TMS S2
TMS S5
TMS S6
SNPP ATMS


Level MLP (Clear Sky Ocean T) — asc=0/1, |lat|<90 — May 28 2025; obs (variou
NOAA20 ATMS, TMS S2, TMS S5, TMS S6
Pressure (hPa)
Δ = Retrieval − Truth (K)
Statistic
Bias
Std
Platform
NOAA20 ATMS
TMS S2
TMS S5
TMS S6
|Lat|<90
Clear sky
ocean
Asc/desc

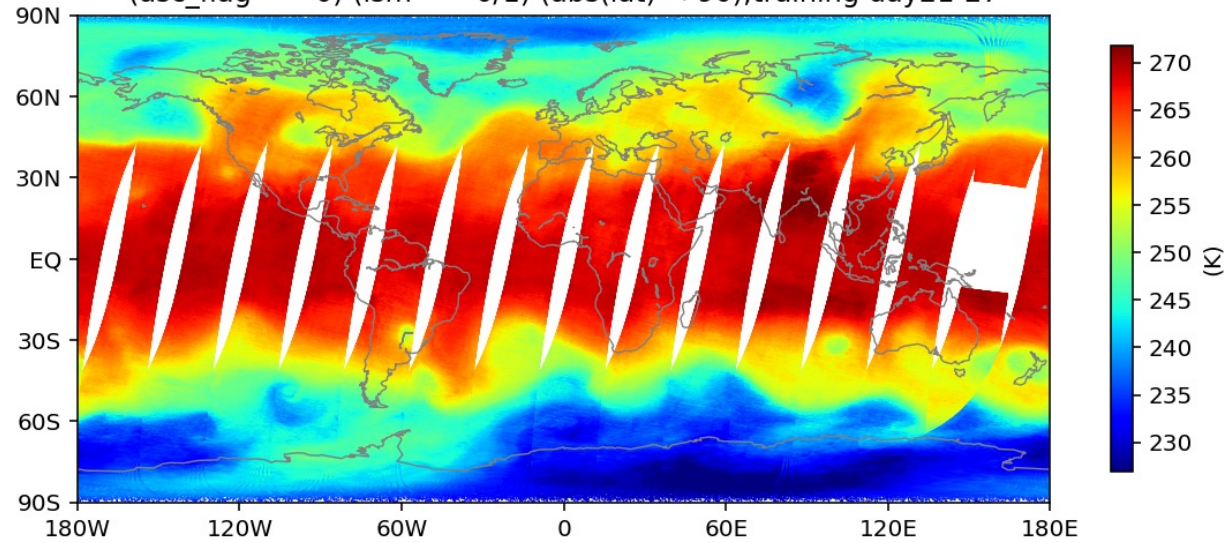

Min, Max, Bias, and Std Dev of Tret vs. Pressure Level
MLP ATMS_BG NOAA20 100% May2025(day == 28))
(asc_flag == 0)(lsm == 0/1)(abs(lat) < 90);train4thday 2019 53M(64,128,64)
Pressure Level (hPa)
Magnitude (K)
Bias
Std Dev
ATMS with
BG averaging
To CrIS fov
N=1,439,094
N=1,408,569
N=1,336,058
N=1,269,039
N=813,832


Min, Max, Bias, and Std Dev of Tret vs. Pressure Level
AWS PFM BG MLP May 28 2025 (Group 2 collocated)
(asc_flag == 0) (lsm == 0/1) (abs(lat) < 90);training day21-27
Samples (after QC)
Magnitude (K)
Bias
Std Dev
NEW with BG
averaging to
89GHz fov
AWS is now
like ATMS

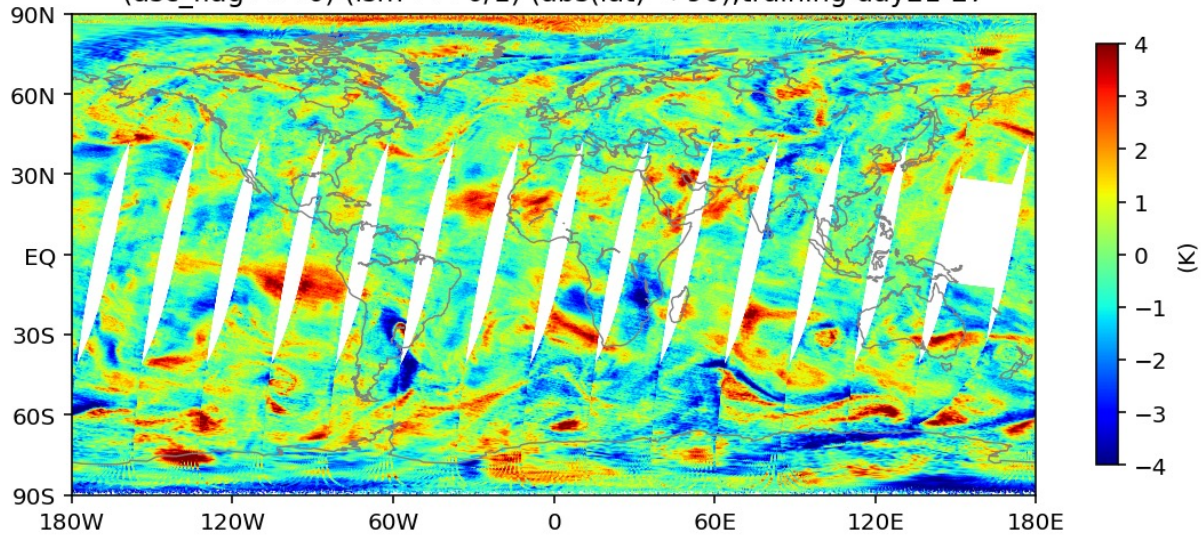
Retrieval Level 16, 500.0 hPa
MLP ATMS_BG NOAA20 100% May2025(day == 28))
(asc_flag == 0)(lsm == 0/1)(abs(lat) < 90);train4thday 2019 53M(64,128,64)
N=1,439,100



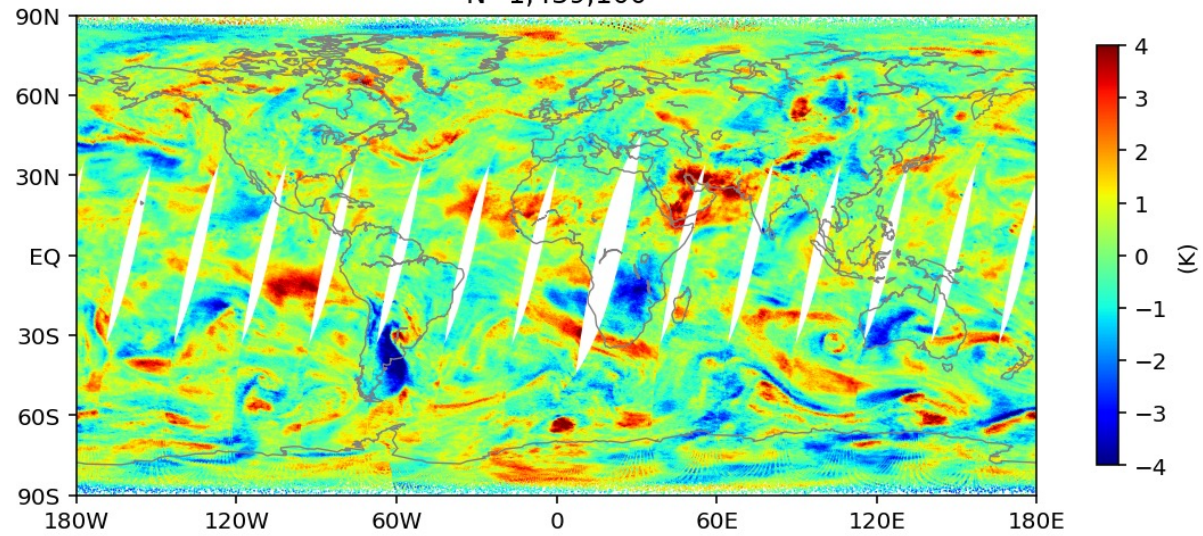
Retrieval Level 16, 500.0 hPa
AWS PFM BG MLP May 28 2025 (Group 2 collocated)
(asc_flag == 0) (lsm == 0/1) (abs(lat) < 90);training day21-27



Retrieval minus ERA5 at Level 16, 500.0 hPa
Min: -8.73381, Max: 6.78747, Bias: -0.05114, Std Dev: 1.18256
AWS PFM BG May 28 2025 (Group 2 collocated)
(asc_flag == 0) (lsm == 0/1) (abs(lat) < 90);training day21-27



Retrieval minus ERA5 at Level 16, 500.0 hPa
Min: -6.12361, Max: 6.38845, Bias: 0.15526, Std Dev: 1.04970
MLP ATMS_BG NOAA20 100% May2025(day == 28))
(asc_flag == 0)(lsm == 0/1)(abs(lat) < 90);train4thday 2019 53M(64,128,64)
N=1,439,100



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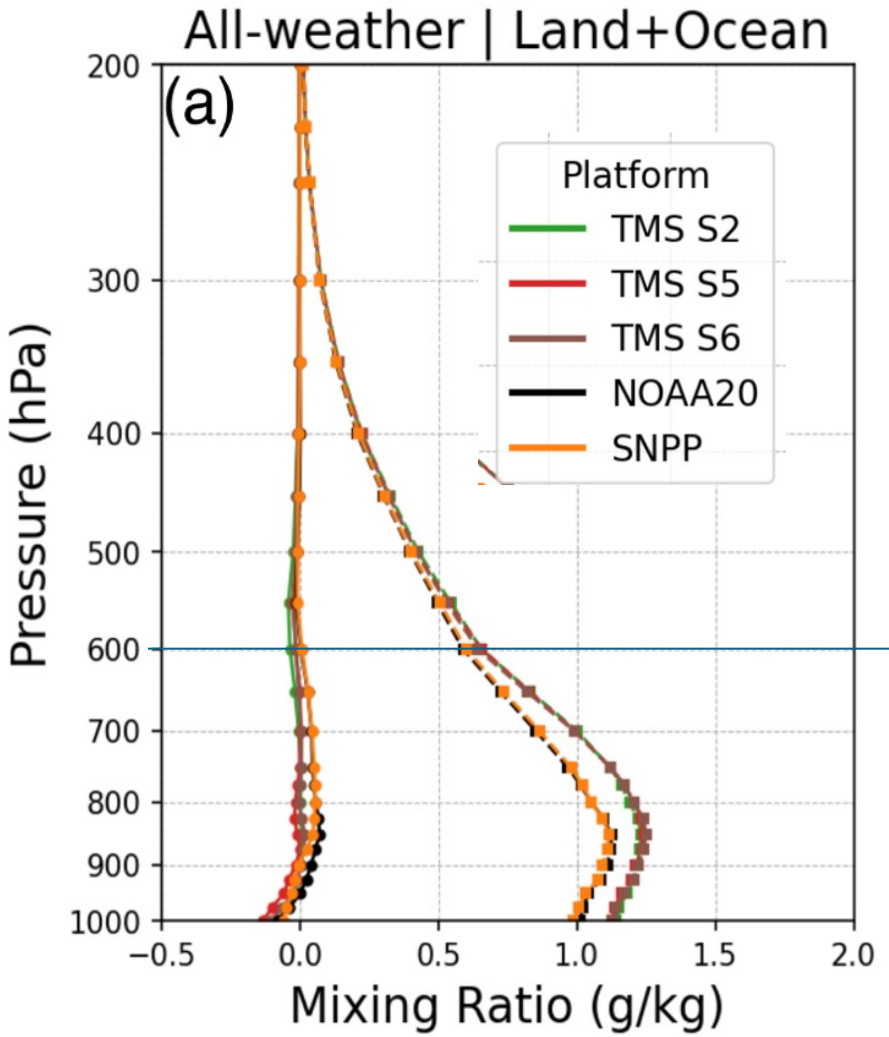
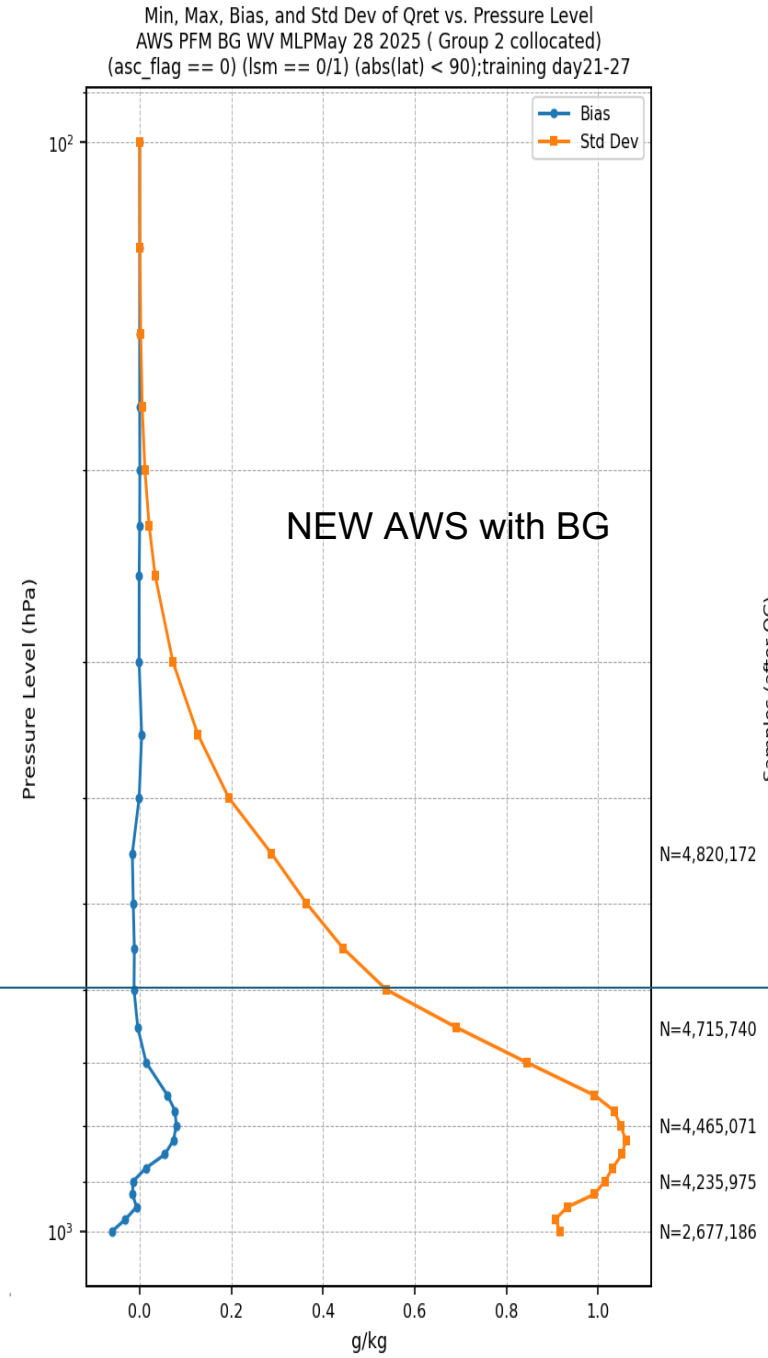
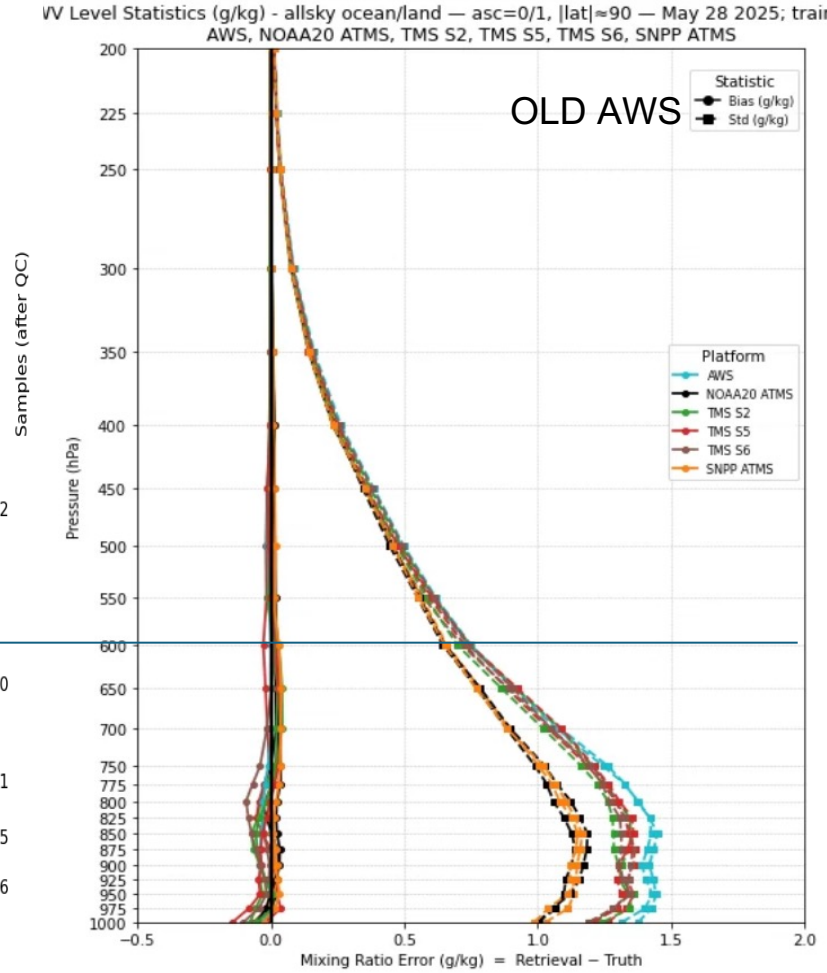
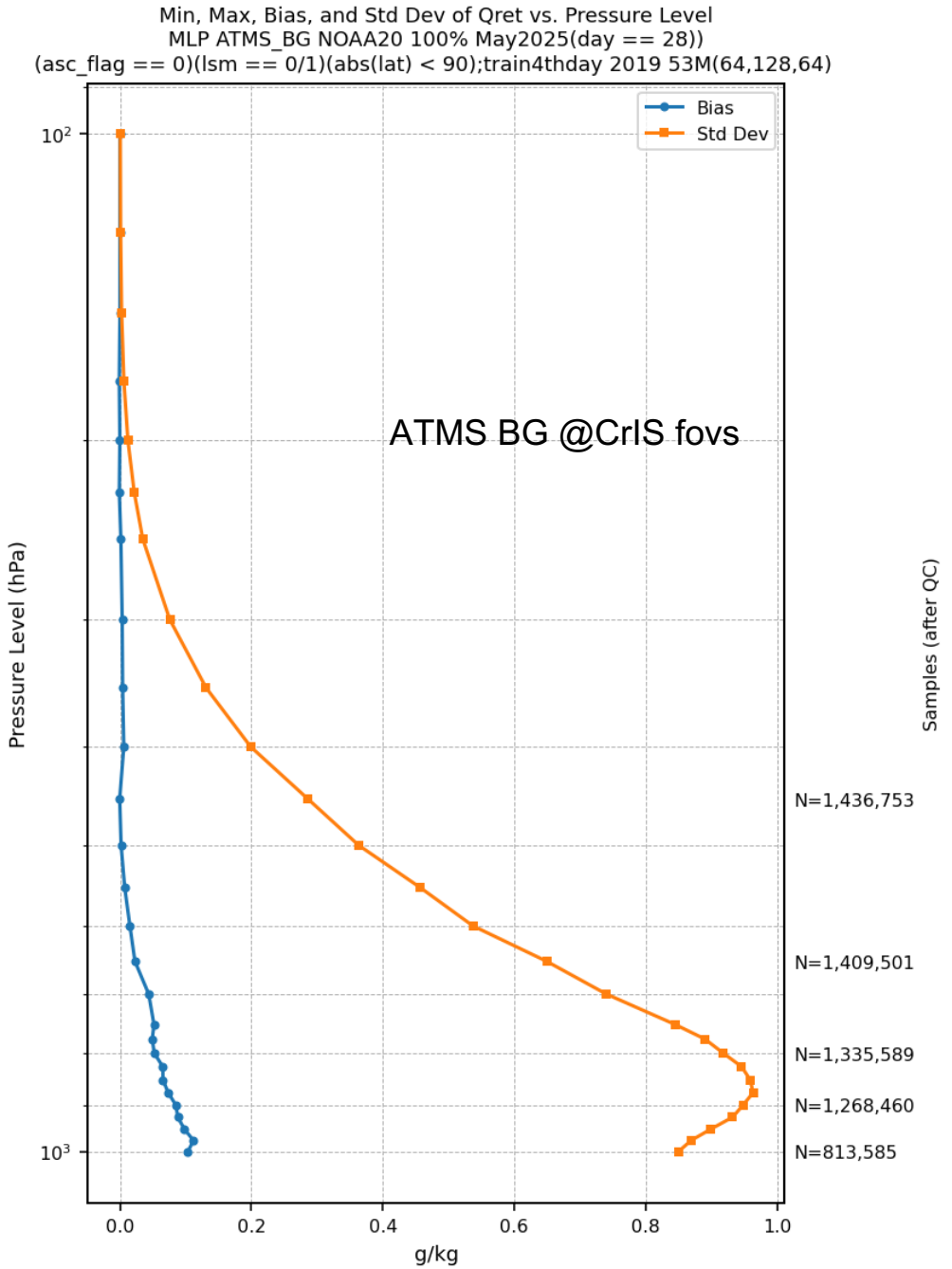
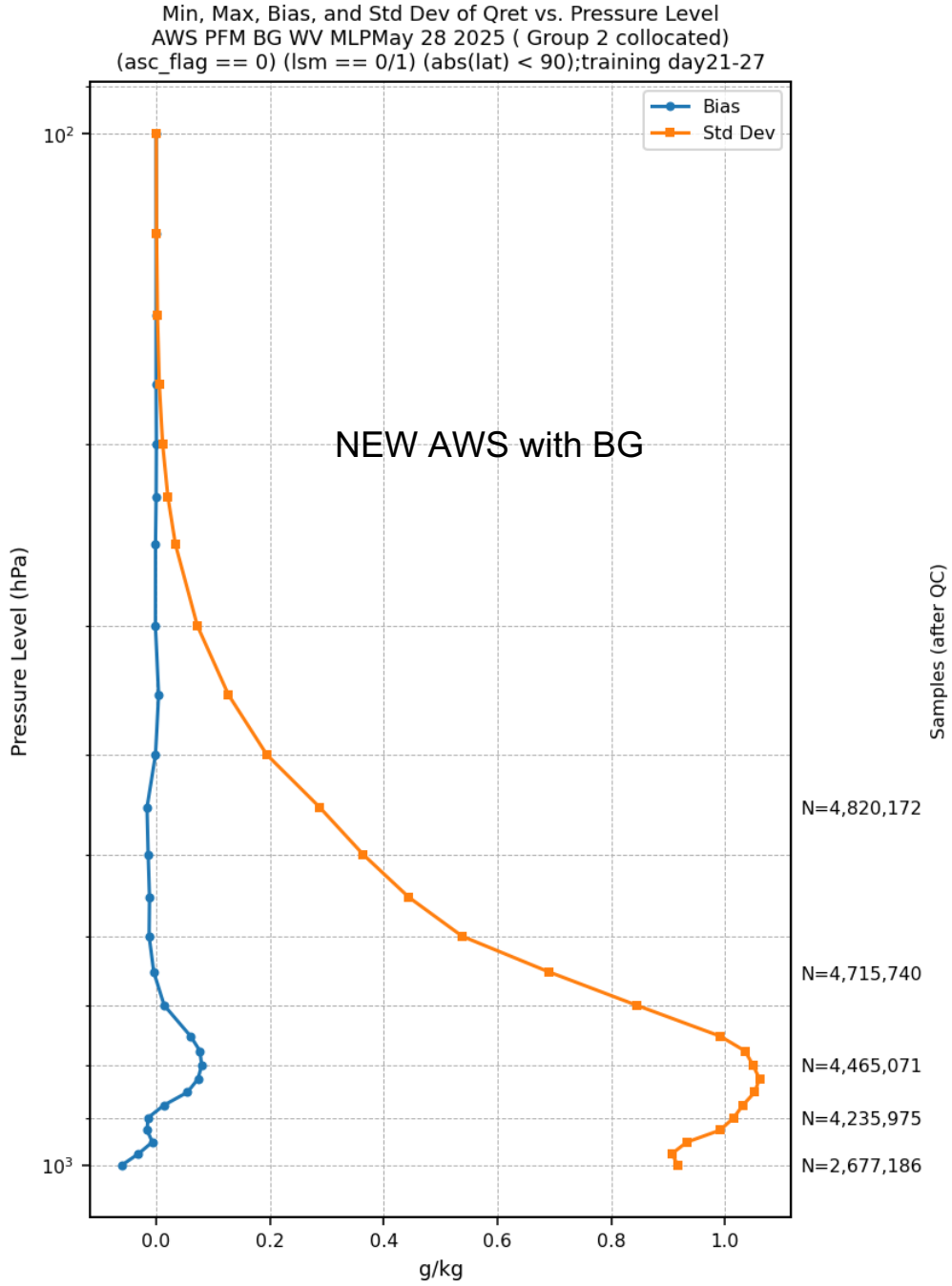


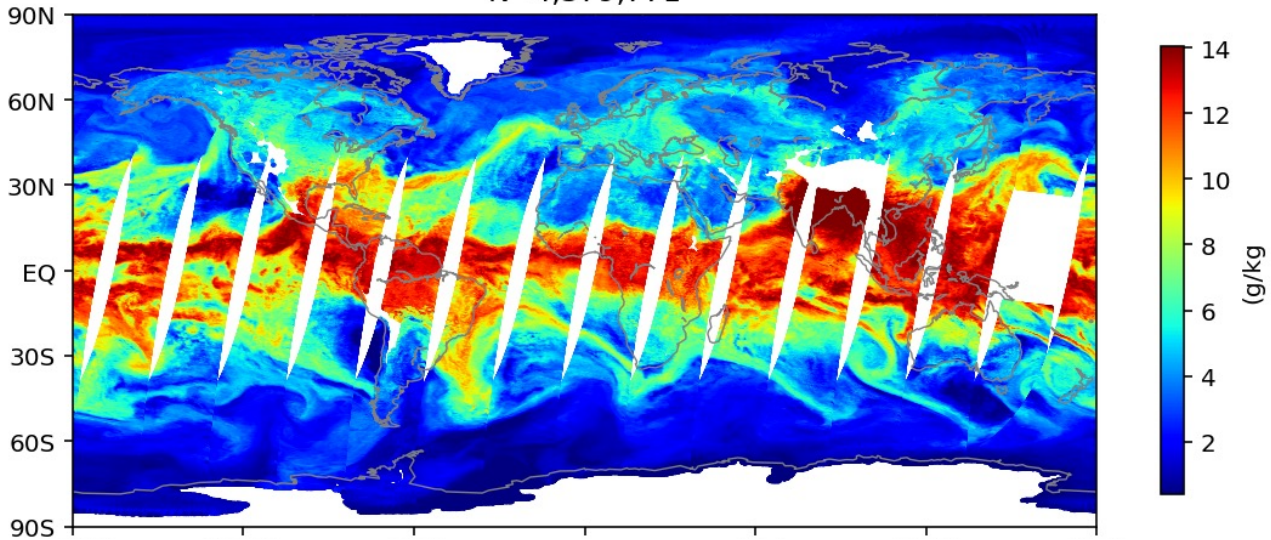




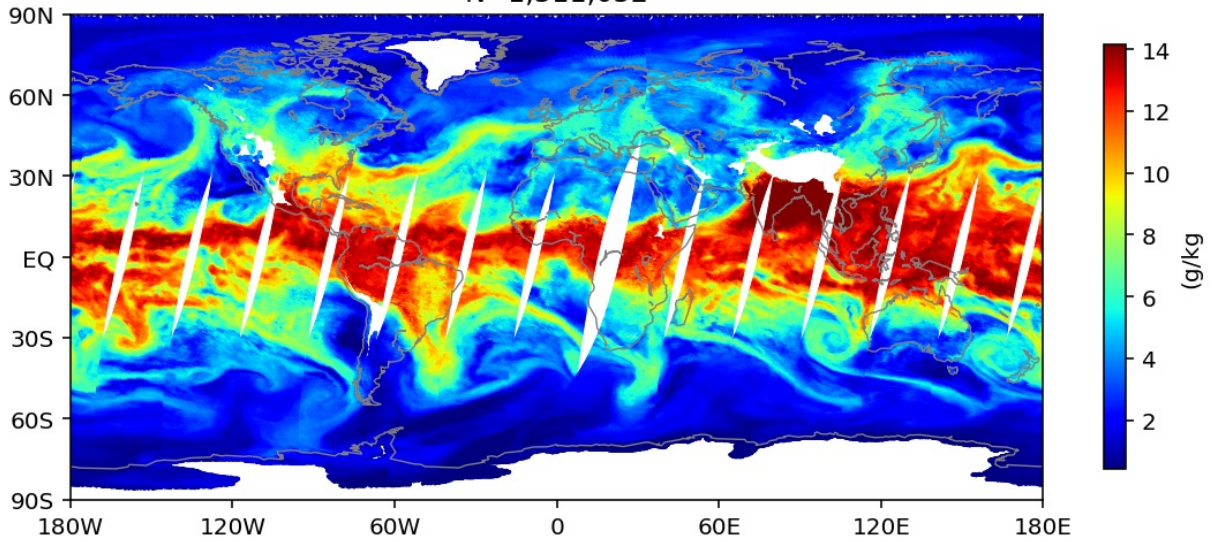

Min, Max, Bias, and Std Dev of Qret vs. Pressure Level
MLP ATMS_BG NOAA20 100% May2025(day == 28))
(asc_flag == 0)(lsm == 0/1)(abs(lat) < 90);train4thday 2019 53M(64,128,64)
Bias
Std Dev
ATMS BG @CrIS fovs
Pressure Level (hPa)
10^2
10^3
0.0
0.2
0.4
0.6
0.8
1.0
g/kg
Samples (after QC)
N=1,436,753
N=1,409,501
N=1,335,589
N=1,268,460
N=813,585


Min, Max, Bias, and Std Dev of Qret vs. Pressure Level
AWS PFM BG WV MLPMay 28 2025 (Group 2 collocated)
(asc_flag == 0) (lsm == 0/1) (abs(lat) < 90);training day21-27
Bias
Std Dev
NEW AWS with BG
Pressure Level (hPa)
10^2
10^3
0.0
0.2
0.4
0.6
0.8
1.0
g/kg
Samples (after QC)
N=4,820,172
N=4,715,740
N=4,465,071
N=4,235,975
N=2,677,186

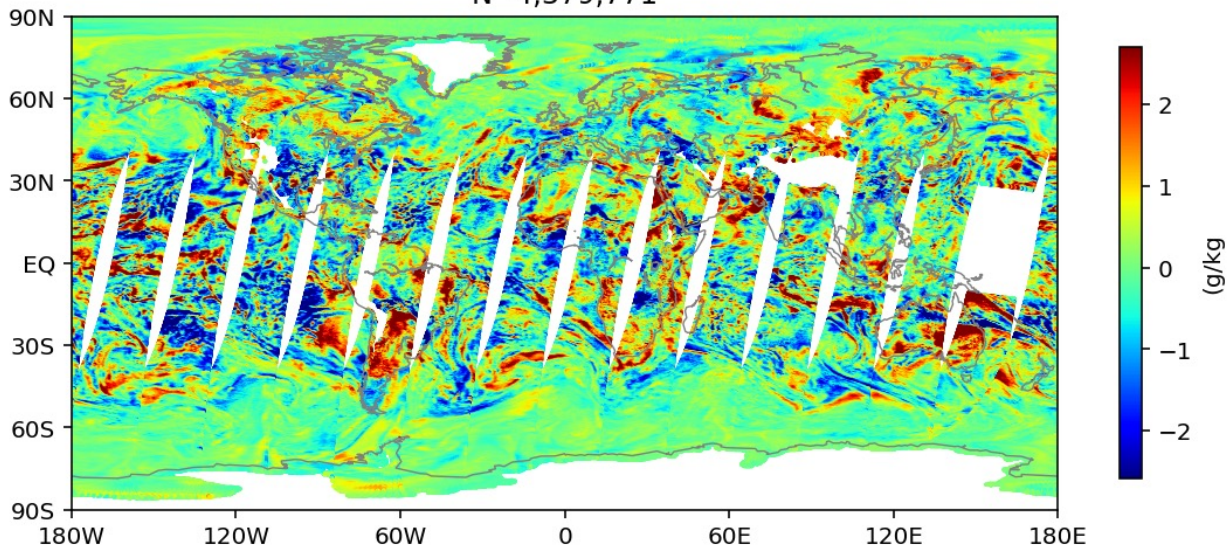
Retrieval Level 7, 850.0 hPa
AWS PFM BG WV MLPMay 28 2025 (Group 2 collocated)
(asc_flag == 0) (lsm == 0/1) (abs(lat) < 90);training day21-27
N=4,379,771



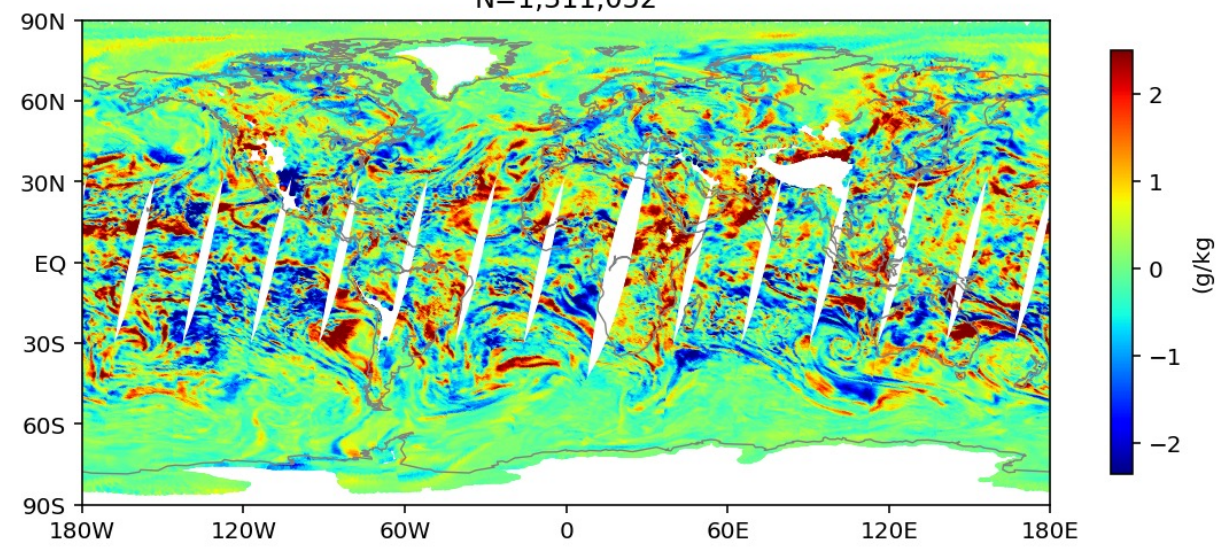
Retrieval Level 7, 850.0 hPa
MLP ATMS_BG NOAA20 100% May2025(day == 28))
(asc_flag == 0)(lsm == 0/1)(abs(lat) < 90);train4thday 2019 53M(64,128,64)
N=1,311,052



Retrieval minus ERA5 at Level 7, 850.0 hPa
Min: -8.58034, Max: 9.05567, Bias: 0.05598, Std Dev: 1.05925
AWS PFM BG WV MLPMay 28 2025 (Group 2 collocated)
(asc_flag == 0) (lsm == 0/1) (abs(lat) < 90);training day21-27
N=4,379,771



Retrieval minus ERA5 at Level 7, 850.0 hPa
Min: -9.22011, Max: 9.64829, Bias: 0.06859, Std Dev: 0.97271
MLP ATMS_BG NOAA20 100% May2025(day == 28))
(asc_flag == 0)(lsm == 0/1)(abs(lat) < 90);train4thday 2019 53M(64,128,64)
N=1,311,052



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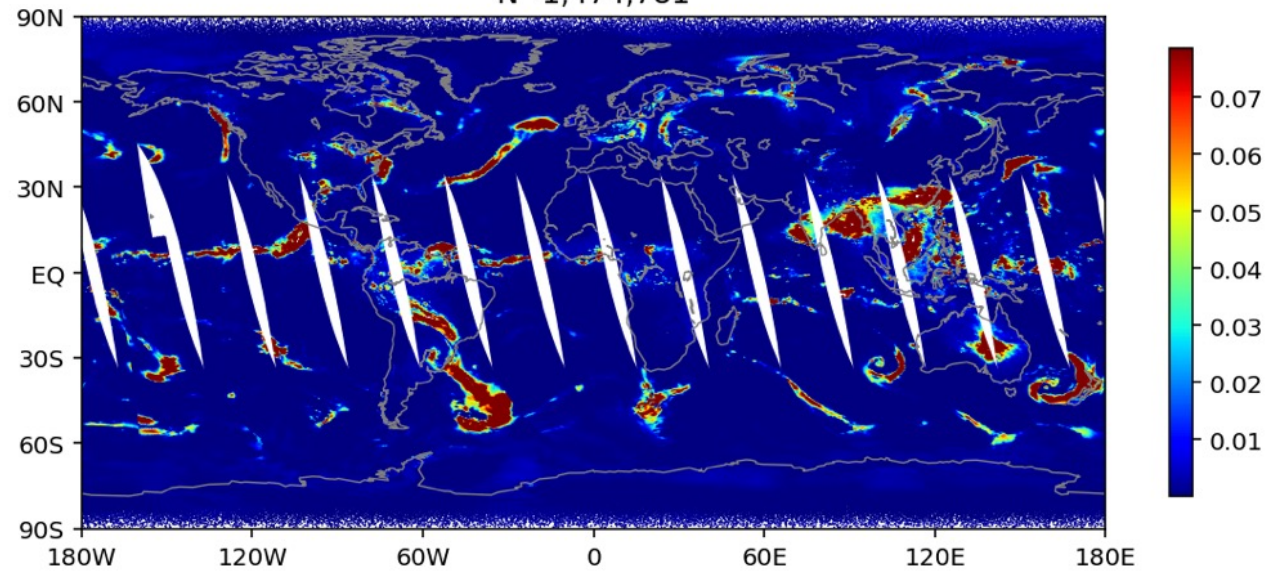
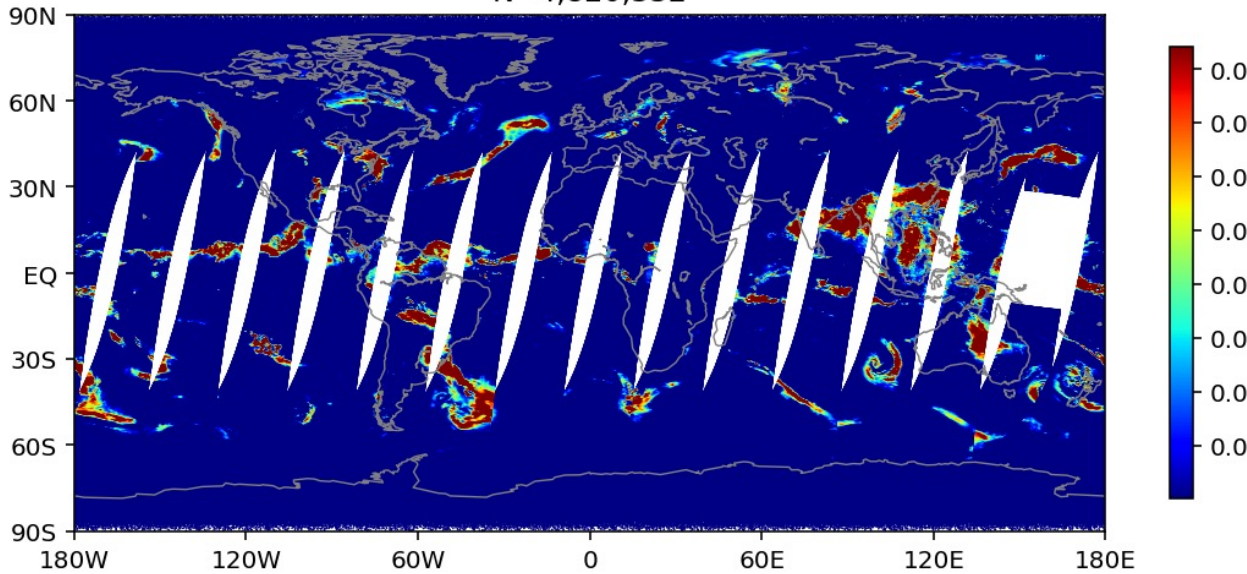
Validation Map: Std by Variable and CLW Percentile Bin
AWS PFM BG SKIN TPW CLW TCRW MLP May 28 2025 (Group 2 collocated)

	CLW 0-20% N=965,363	CLW 20-40% N=965,363	CLW 40-60% N=965,362	CLW 60-80% N=965,363	CLW 80-90% N=482,681	CLW 90-95% N=241,341	CLW 95-100% N=241,341	All Cases N=4,826,814
Skin Temperature	**3.7938**	**2.3816**	**2.1754**	**2.3253**	**2.3080**	**2.4044**	**2.7008**	**2.6947**
Total Precipitable Water	**1.4023**	**1.7617**	**1.9394**	**2.1152**	**2.2924**	**2.5997**	**2.9948**	**1.9963**
Cloud Liquid Water	**0.0090**	**0.0218**	**0.0317**	**0.0499**	**0.0775**	**0.1173**	**0.1865**	**0.0620**
Total Rain Water Column	**0.0010**	**0.0021**	**0.0111**	**0.0472**	**0.0868**	**0.1566**	**0.2554**	**0.0756**

Retrieval
MLP NOAA20 ATMS-BG 100% May2025(day == 28))
(asc_flag == 1)(lsm == 0/1)(abs(lat) < 90);train 2019 53M
N=1,474,781



Retrieval
AWS PFM BG SKIN TPW CLW TCRW MLP May 28 2025 (Group 2 collocated)
(asc_flag == 0) (lsm == 0/1) (abs(lat) < 90);training day21-27
N=4,820,332



Students developing CSPP Visualizations

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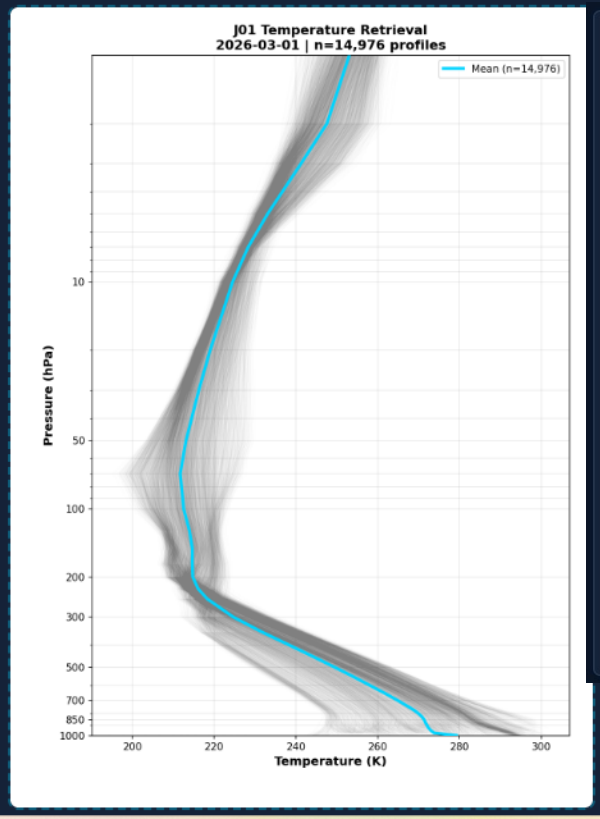
SATELLITE: NOAA-20 (j01) | REFERENCE: ERA5 | MODEL: MLP SNPP 2018 (Current) | ORBIT MODE: All

MONTH: March | DAY: 01 | Load Profiles

TEMPERATURE PROFILE (RETRIEVAL)

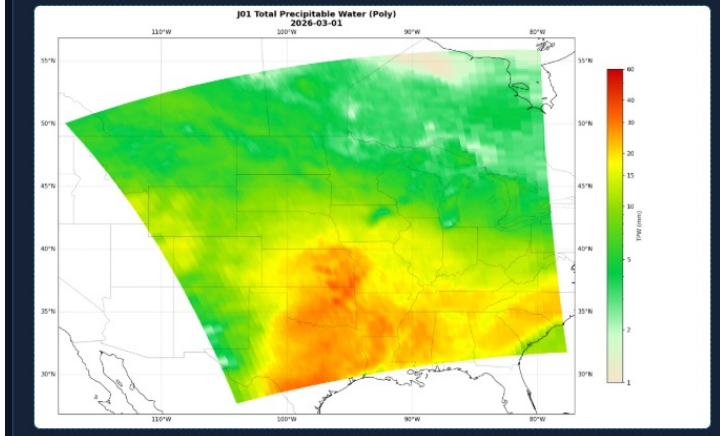


WATER VAPOR PROFILE (RETRIEVAL)

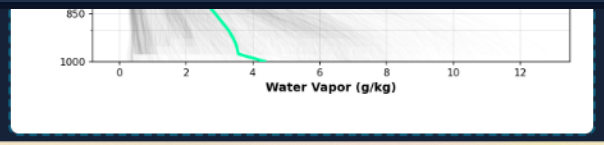
SURFACE PARAMETERS (POLYNOMIAL MODELS)

PARAMETER: TPW — Total Precipitable Water | Load Map

Derived from polynomial regression on limb-corrected ATMS BTs



J01 | 2026-03-01 | TPW (Poly) | Polynomial regression model



VERTICAL CROSS-SECTION (RETRIEVAL)

PARAMETER: TEMPERATURE | WATER VAPOR

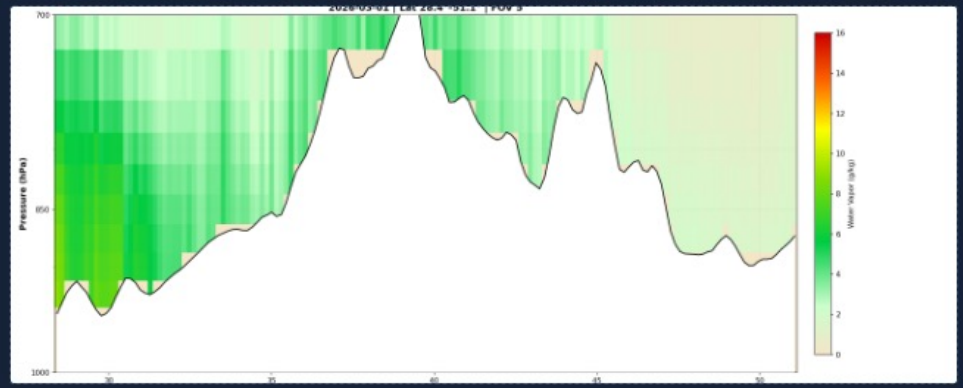
VIEW MODE: FOV (ALONG-TRACK) | ROW (ACROSS-TRACK)

DISPLAY: RETRIEVAL | BIAS VS ERA5

PRESSURE RANGE: FULL (1000 HPA) | LOWER ATM (700 HPA)

FOV COLUMN: 5 / 96

FOV 1 (left edge) | FOV 48 (nadir) | FOV 96 (right edge) | Load Cross-Section



J01 | 2026-03-01 | water vapor | FOV 5 along-track cross-section | Black line = surface pressure

Summary

- Developed MLP Weights for CrIS only, CrIS/ATMS, ATMS IASI ,and AWS
- Retrieval performance are very good!! Outperforms NUCAPS and MIRS.
- We plan to add to CSPP, along with some applications tools - e.g. Skew-T plots, Stability Maps, and more
- We are working closely with partners (NWS offices, University of Alaska, GINA).
- Working with EUMETSAT on comparisons with IASI

Looking how to integrate ground-based observations for certain areas

Network	# CONUS Stations	Temporal Res	Approx Spacing	Free Access
ASOS	~900	1 min	50–150 km	Yes (IEM, NCEI)
AWOS	~1,500	1 min	30–100 km	Yes
State Mesonets (combined)	~2,000	5 min	20–50 km	Yes (most)
CWOP/MADIS personal wx	~20,000+	5–60 min	1–30 km	Yes (MADIS)
MesoWest/Synoptic	100,000+	1–60 min	< 1 km urban	Free academic
DOT RWIS	~2,000	1–10 min	10–50 km	Yes (state DOTs)
NOAA CRN	114	5 min	~200 km	Yes