Assilimation results for AIRS at METEO FRANCE

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Florence Rabier

ECMWF Workshop on Assimilation of high spectral resolution sounders in NWP
28^{th} June - 1^{st} July 2004

INTRODUCTION

EOS AQUA

NESDIS

Met Office

Météo-France D.B.

324 Tbs (1/18 pixels)

4D-Var Data Assimilation

Screening (obs-fg)

Minimisation

First Guess

ARPEGE NWP operational model

ARPEGE : global spectral model

T358, C2.4, 41 vertical levels

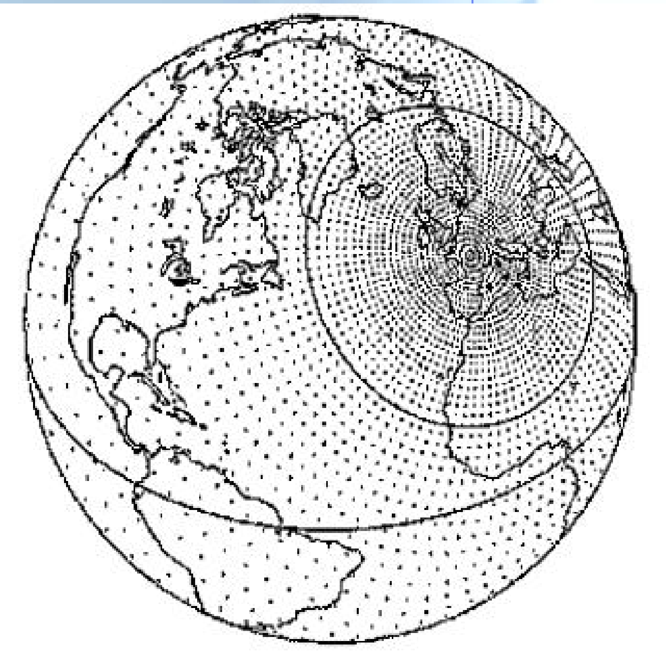
Associated grid: 25km (France) to 150km

6-hour assimilation:

00, 06, 12, 18 UTC

Multi-incremental

T107 & T161, 41 L



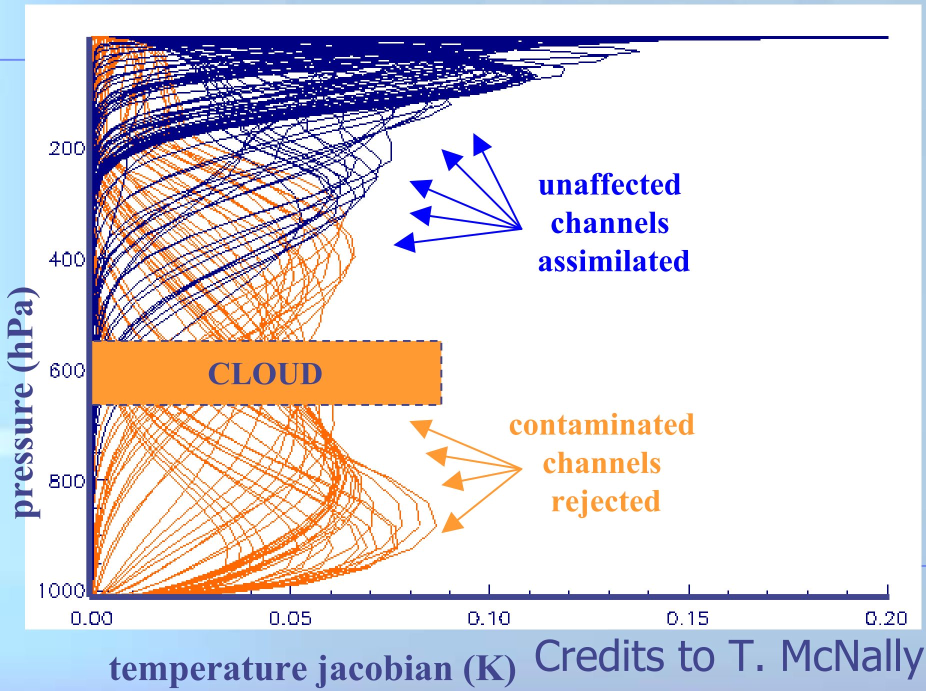
INTRODUCTION

- ✓Recent developments to assimilate AIRS into ARPEGE NWP model
- ✓AIRS in parallel suite this summer.
- ✓Further studies (cloudy radiances, CO2-slicing, …)
  →cf. Lydie Lavanant presentation

CLOUD DETECTION

Information on a channel basis:

ECMWF scheme (McNally & Watts, 2001)



Credits to T. McNally

→Data volume too big (for an operational start)

Arpège model is biased in stratosphere + 4DVar constraint on iterations

→ Focuses assimilation on stratosphere and not troposphere

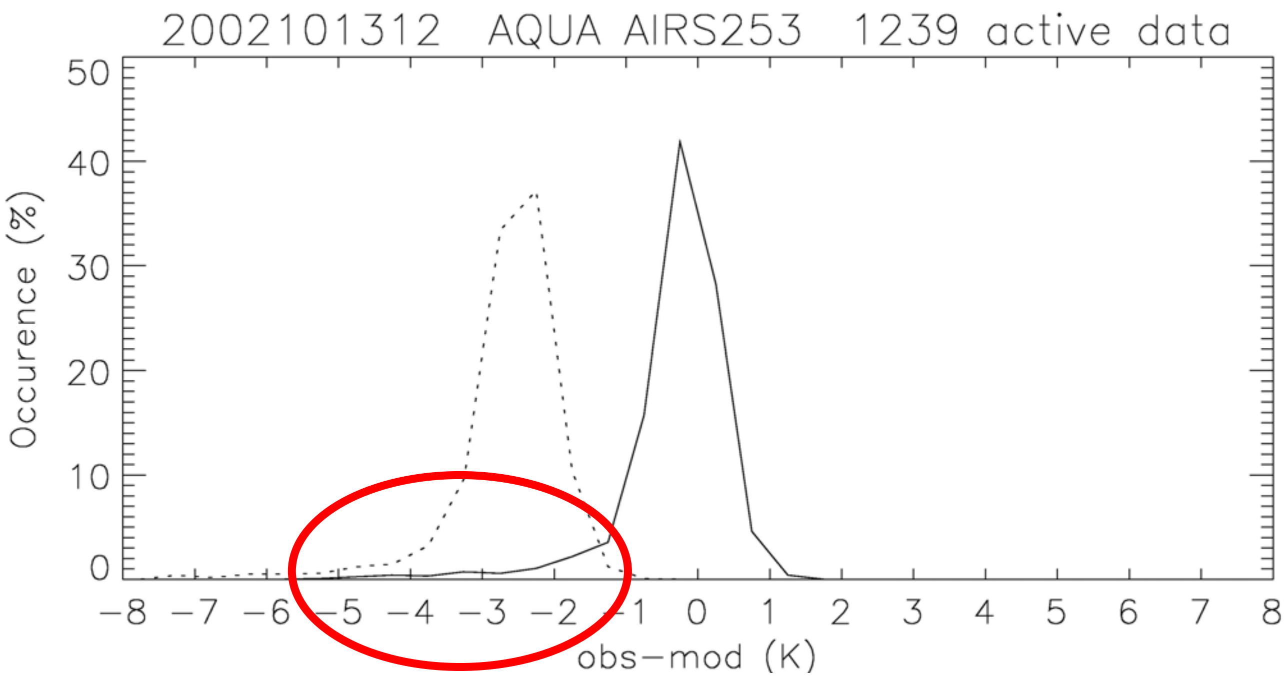
CLOUD DETECTION

Information on a channel basis:
ECMWF scheme (McNally & Watts, 2001)

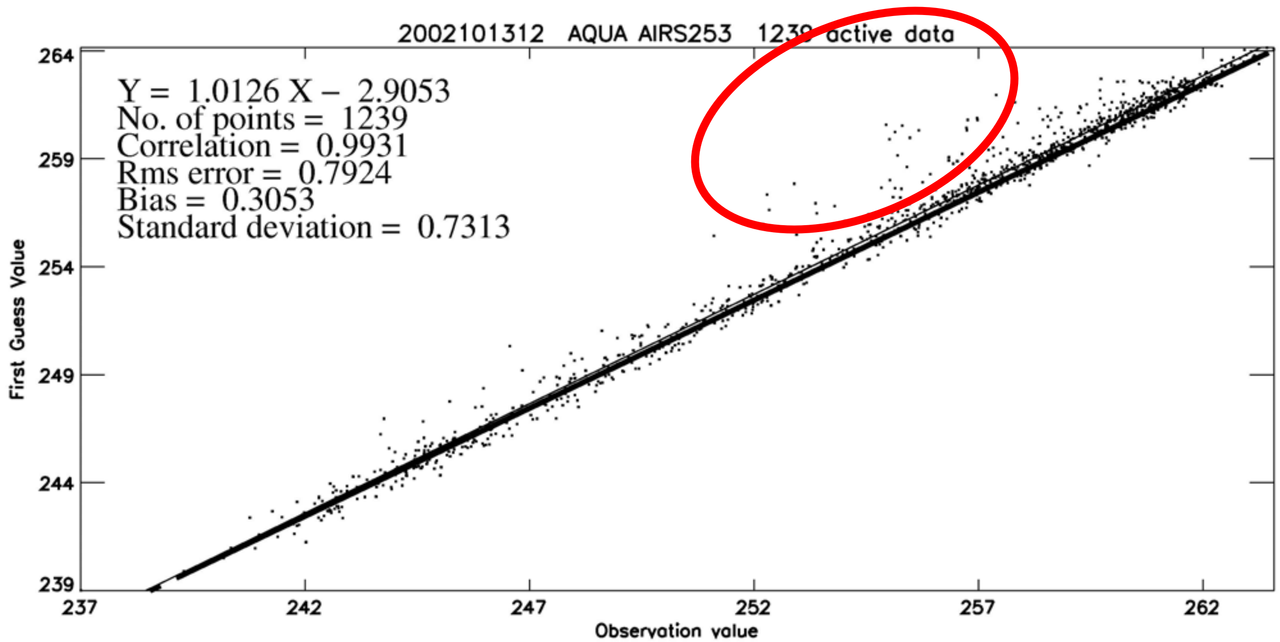
Information on a pixel basis:

✓NESDIS scheme (Goldberg et al.) based on thresholds recomputed for ARPEGE model

✓VIS/NIR image (day-time only) : less than 10% of clouds in pixel

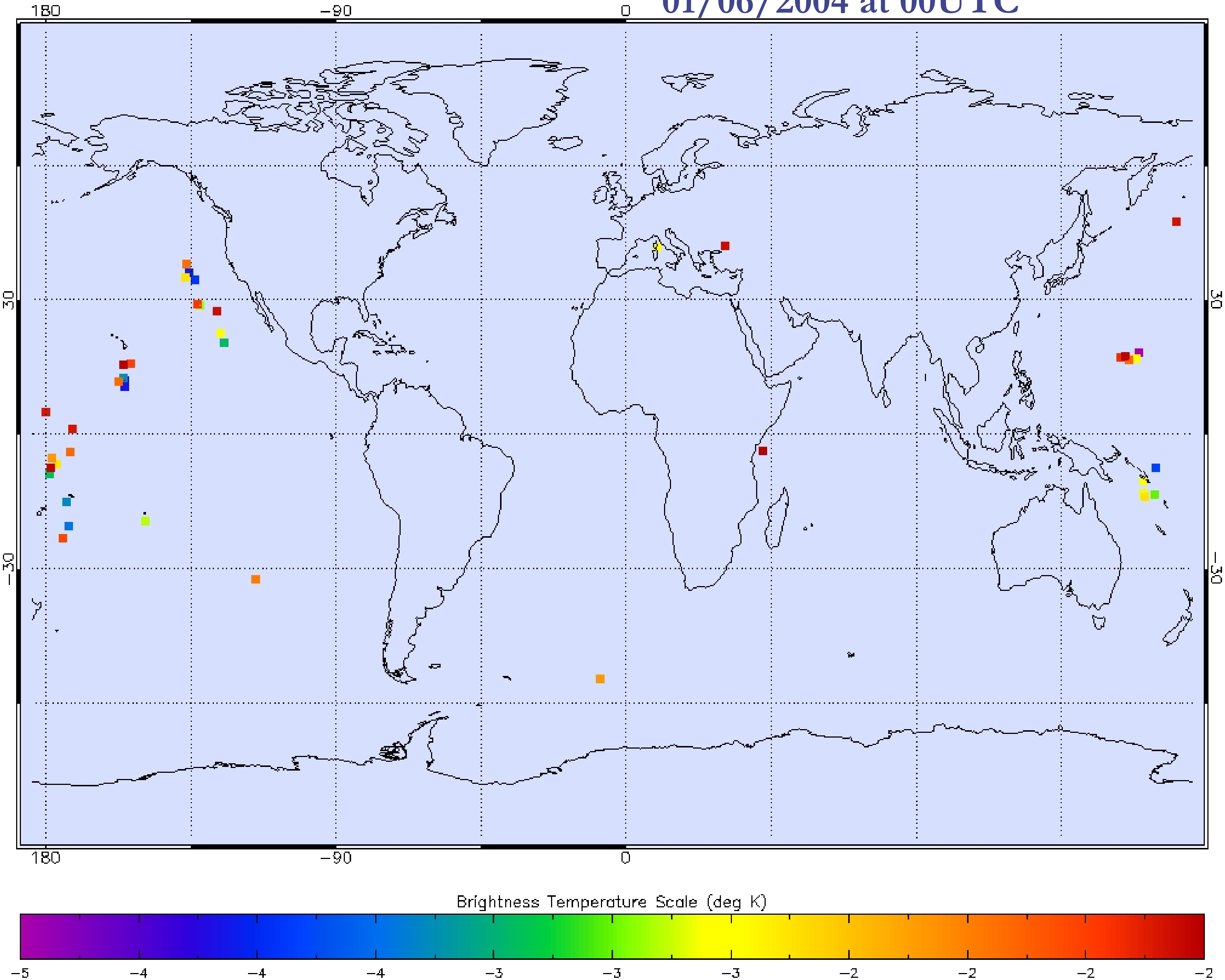


ON



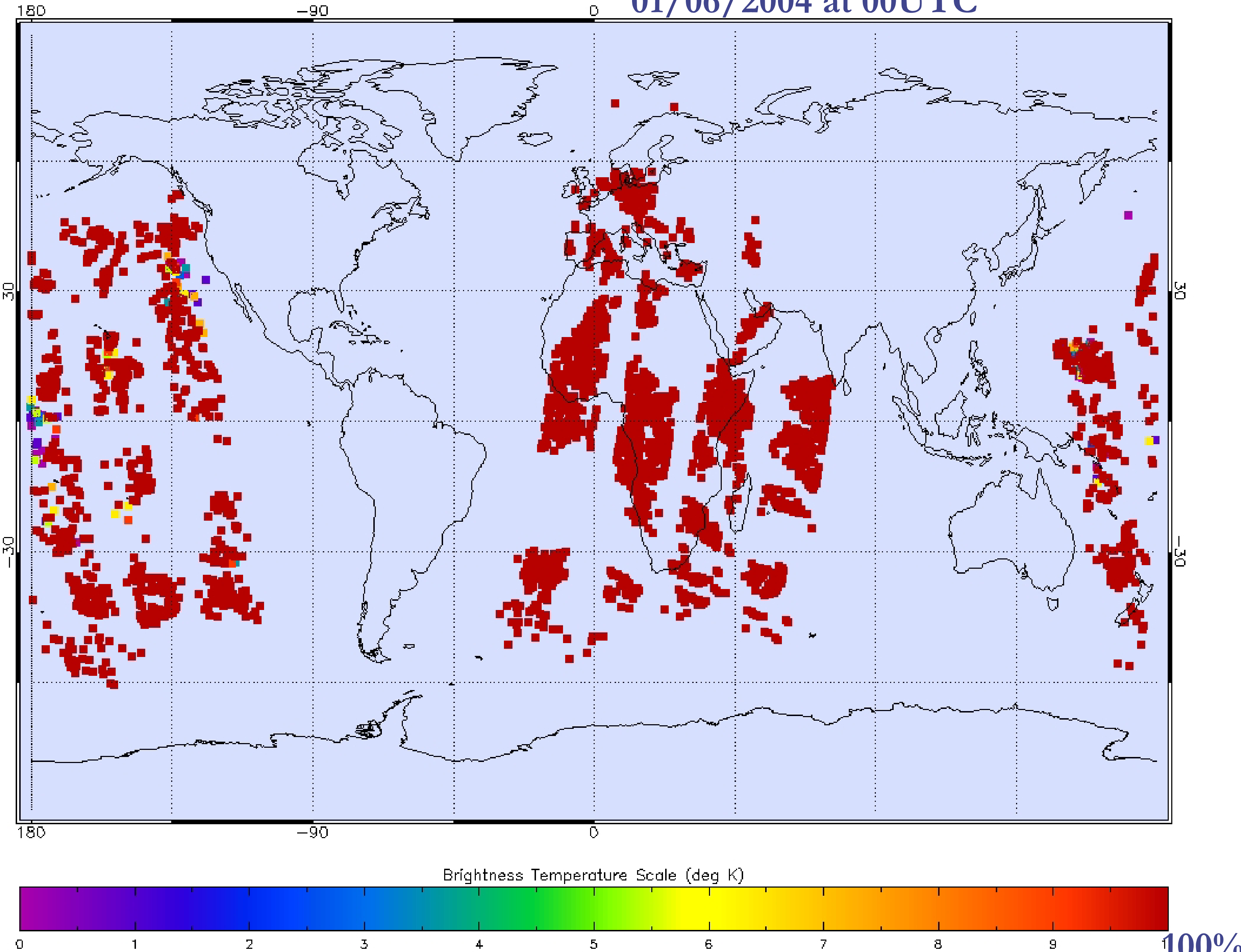
ECMWF Workshop on
high spectral resolutio

01/06/2004 at 00UTC



Observation - Guess

01/06/2004 at 00UTC



VIS/NIR percentage of clouds in AIRS pixel

CLOUD DETECTION

✓VIS/NIR image (day-time only) : less than 5% of clouds in pixel

CHANNEL SELECTION

Channels in O_3 and SW bands, peaking above/near model cloud top (1hPa), at edges of scan, tropospheric channels over land are blacklisted

Data quality control:

✓Gross check: $150 < Tb < 350$

& $(obs\text{-}guess) < 20$

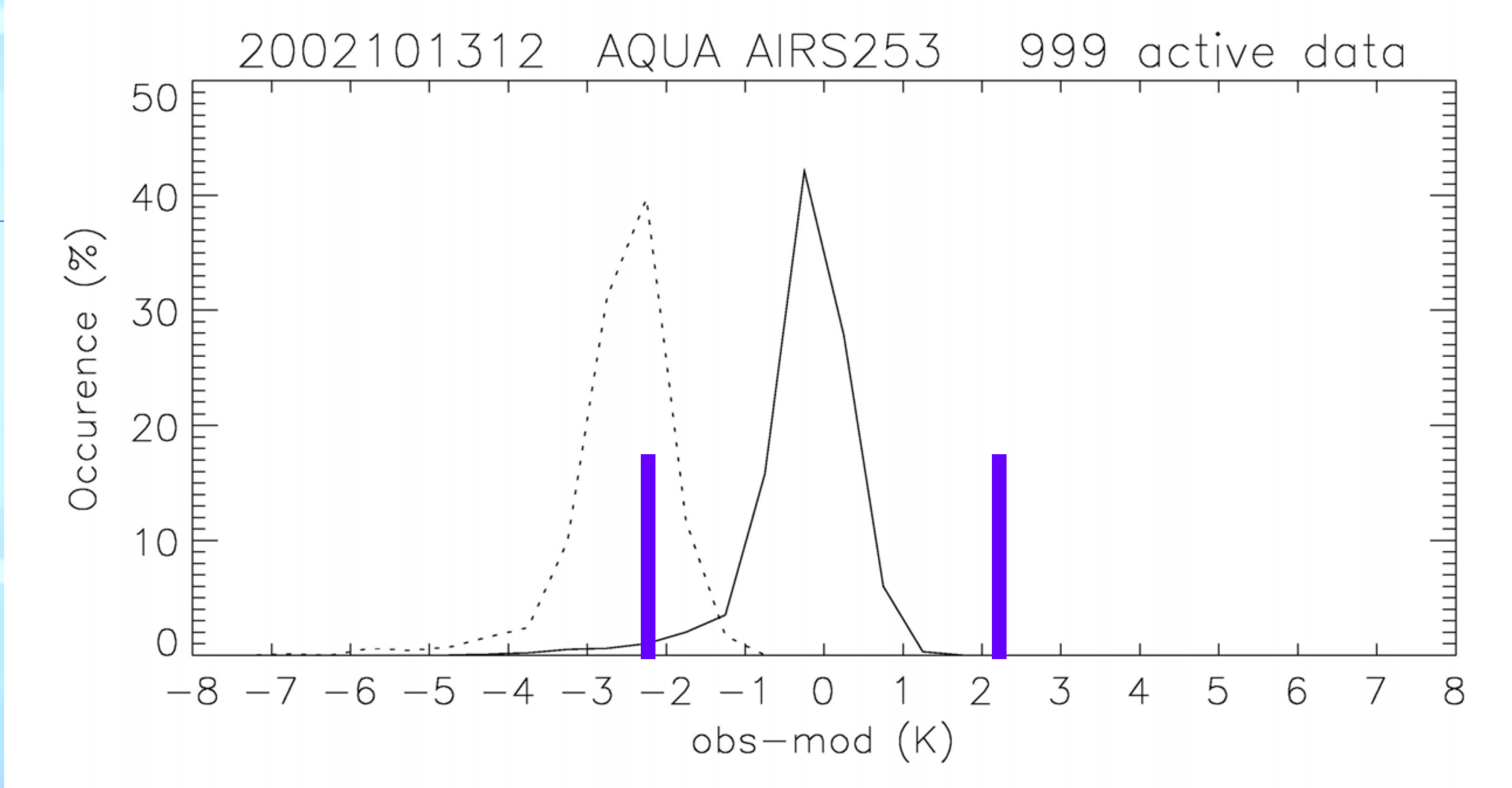
✓First-guess check: $(obs\_guess)^2 < \alpha\ (\sigma_o^2 + \sigma_b^2)$

ERROR STATISTICS TUNING (σ_o & σ_b)

- ✓Observation error statistics:
  σ_o tuned for 12 bands of channels.

- ✓Background error statistics:
  σ_b tuned for each channel to remove residual "cold tail" (cloud contamination) in first-guess check.

ERROR STATISTICS TUNING
(σ_o & σ_b)



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BIAS CORRECTION
Motivation

✓Systematic errors in instrument + forward model (interpolation, representativness, radiative transfert model) and adjoint (jacobian)

✓Errors in NWP model

→Bias in (Obs-Guess) departures in 4DVar assimilation system. Non constant in time & space (dependence to scan, air-mass). Channel dependent.

Need for bias correction scheme.

BIAS CORRECTION
Implementation

✓Flat bias correction for each channel calculated over all active data.

✓Harris & Kelly bias correction adapted for AIRS

→ non optimal results

BIAS CORRECTION
Implementation

✓Harris & Kelly philosophy:
use predictors from model guess to "correct" the observations. Separate bias correction for each channel.

✓Non-linear regression.
✓Learning process performed on dataset declared "active" in former screenings (full coherence with assimilation QC & cloud detection).

BIAS CORRECTION
Implementation

92 PREDICTORS:

- ✓Ps
- ✓Ts
- ✓Land/Sea mask
- ✓Sat zenith angle
- ✓Latitude
- ✓Guess → Tb
- ✓T profile
- ✓Q profile

(43 RTTOV levels)

LEARNING PROCESS

NEURAL NETWORK

Bias correction

OBSERVED BIAS :

Obs-Guess

BIAS CORRECTION
Neural Network

- ✓Multi-layer perceptron for each channel.

(92 inputs, 1 hidden layer, 1 output)

- ✓Preconditioning: normalization (+PCA) of inputs
- ✓Learning process = minimize a cost function to calculate the weights defining the Network

(RMS error between observed and calculated bias)
→Use M1QN3 minimizer to reach better convergence & faster.

- ✓Regularization:

trade between bias & variance performance
"Weight smoothing" to stabilize Jacobians

BIAS CORRECTION
Neural Network

92 PREDICTORS:

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(43 RTTOV levels)

LEARNING PROCESS

NEURAL NETWORK

Multi-layer perceptron

OBSERVED BIAS :

Obs-Guess

BIAS CORRECTION
Neural Network

92 PREDICTORS:

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(43 RTTOV levels)

BIAS PREDICTION

NEURAL NETWORK

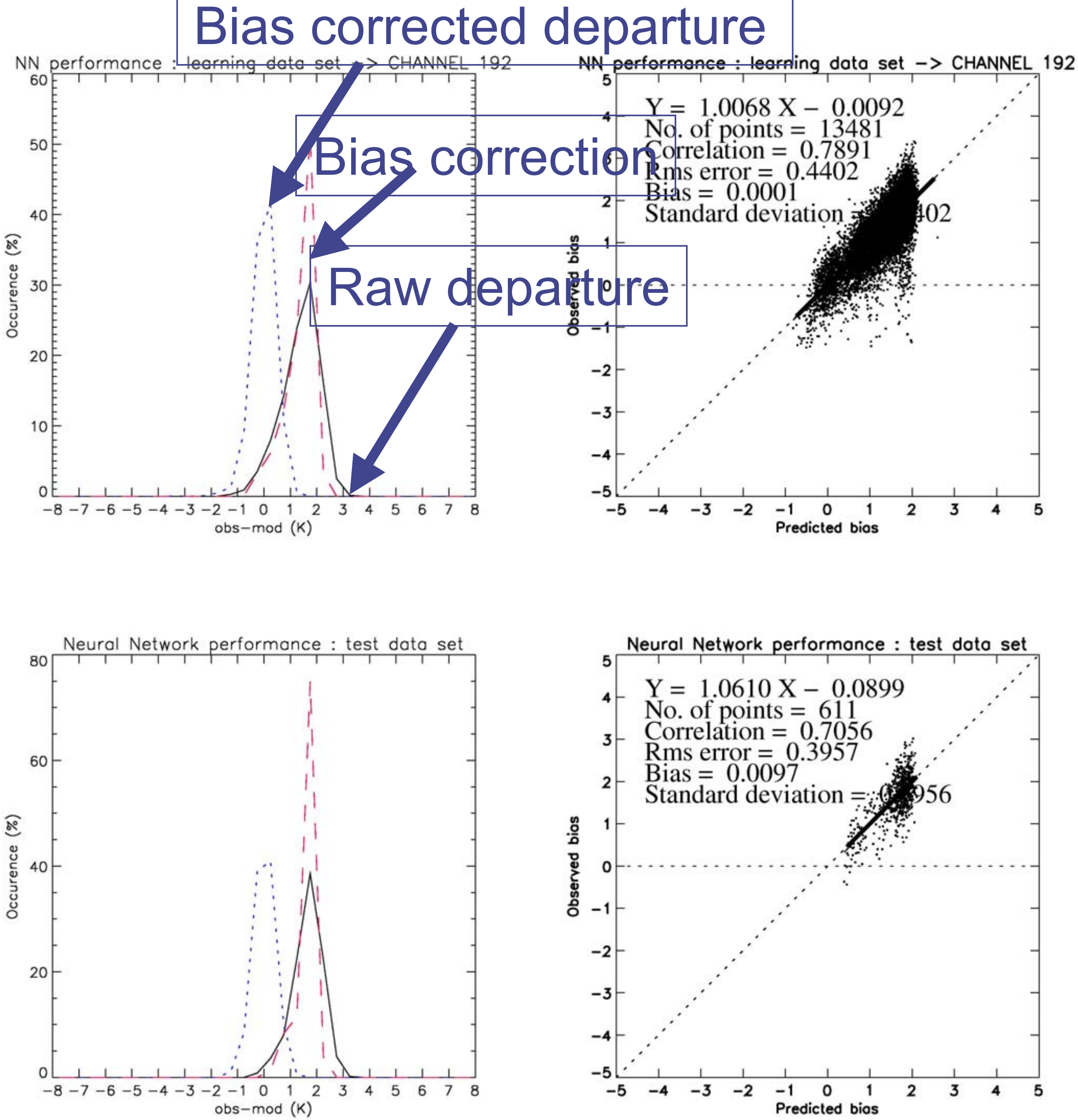
Multi-layer perceptron

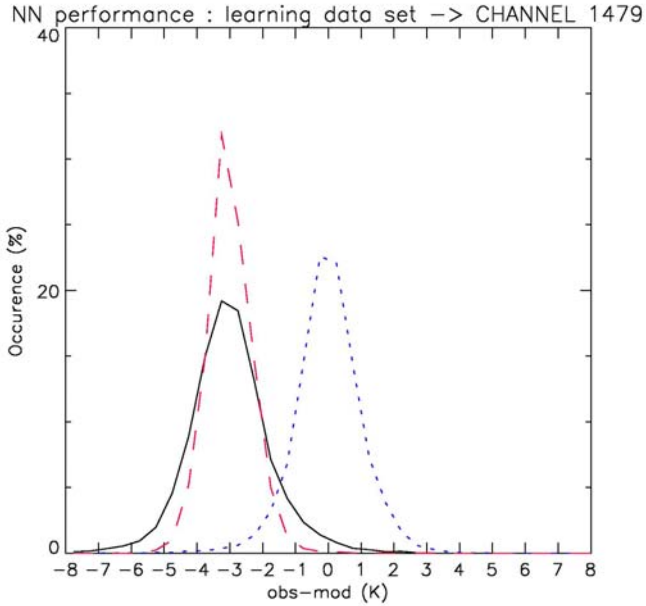
PREDICTED BIAS :

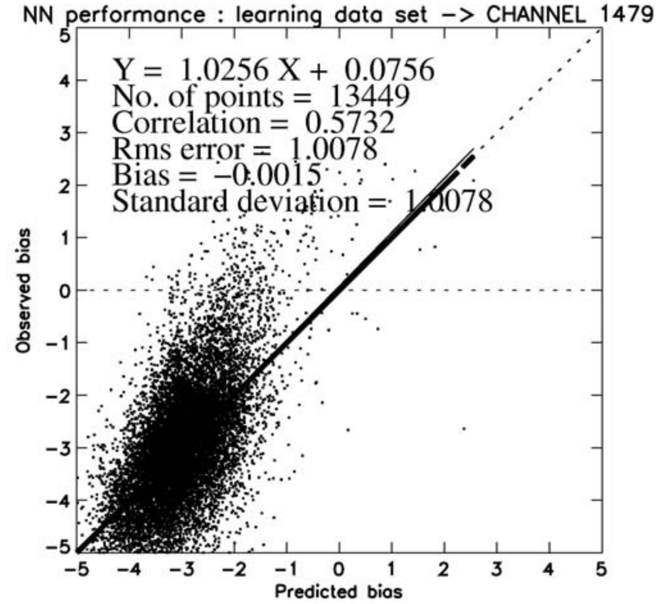
Obs-Guess

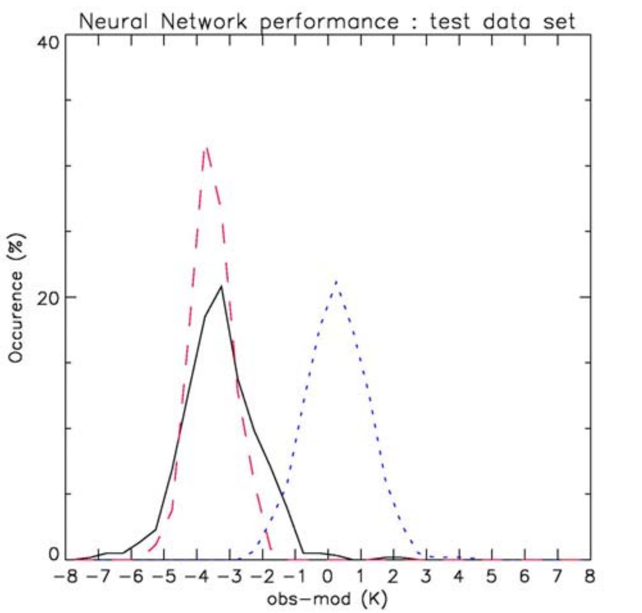
SENSITIVITY :

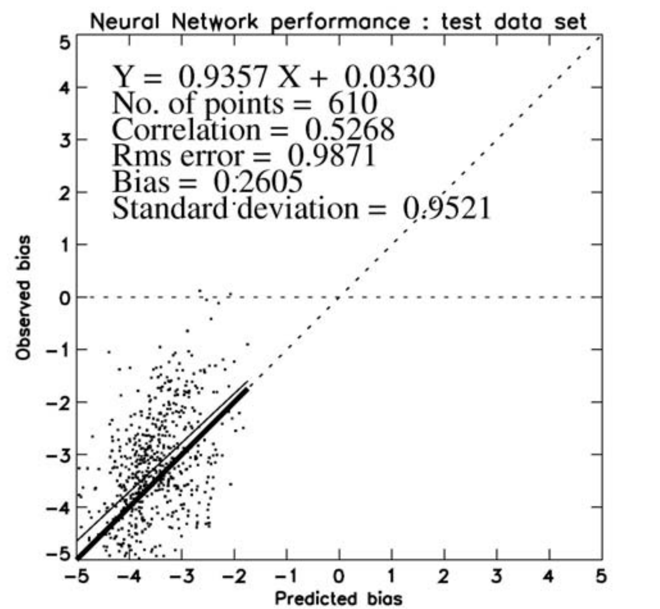
Of the channel bias for each predictor

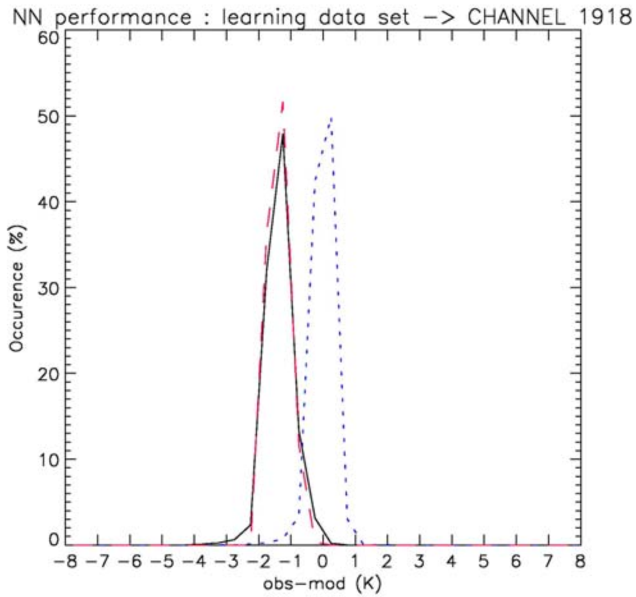

Bias corrected departure
Bias correction
Raw departure
NN performance : learning data set -> CHANNEL 192
Occurence (%)
obs-mod (K)
NN performance : learning data set -> CHANNEL 192
Y = 1.0068 X – 0.0092
No. of points = 13481
Correlation = 0.7891
Rms error = 0.4402
Bias = 0.0001
Observed bias
Predicted bias
Neural Network performance : test data set
Occurence (%)
obs-mod (K)
Neural Network performance : test data set
Y = 1.0610 X – 0.0899
No. of points = 611
Correlation = 0.7056
Rms error = 0.3957
Bias = 0.0097
Observed bias
Predicted bias

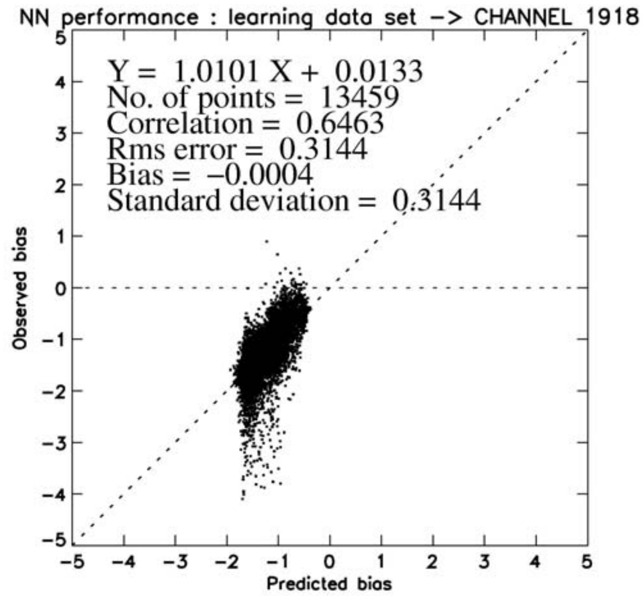

NN performance : learning data set -> CHANNEL 1479
Occurence (%)
obs-mod (K)

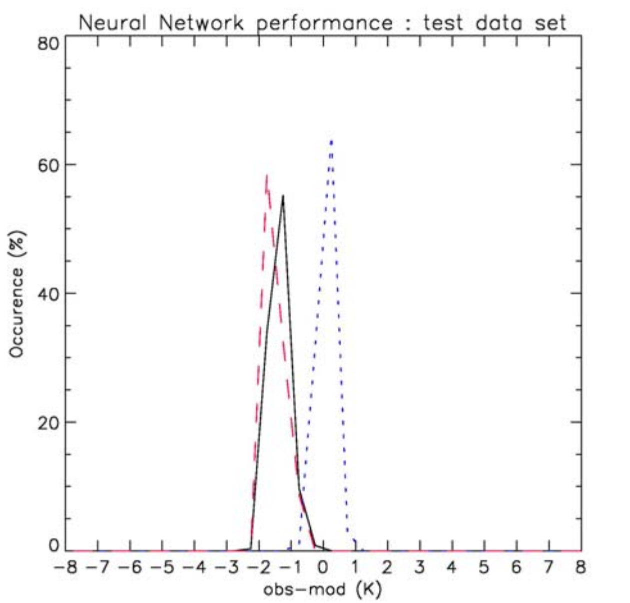

NN performance : learning data set -> CHANNEL 1479
Y = 1.0256 X + 0.0756
No. of points = 13449
Correlation = 0.5732
Rms error = 1.0078
Bias = -0.0015
Standard deviation = 1.0078
Observed bias
Predicted bias

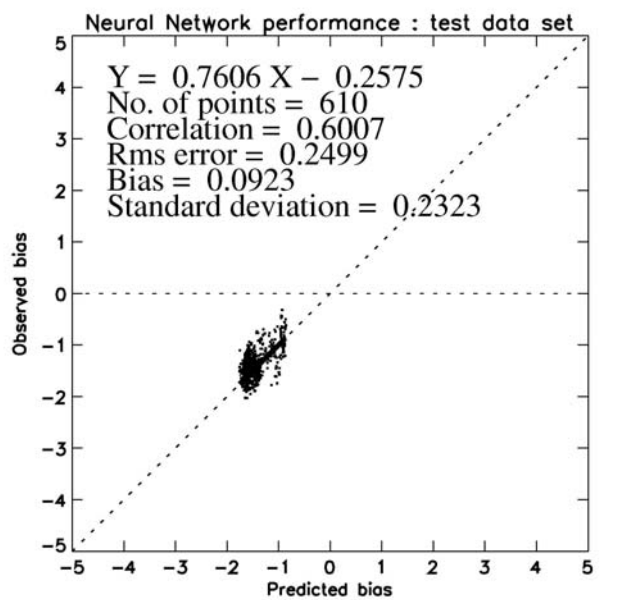

Neural Network performance : test data set
Occurence (%)
obs-mod (K)


Neural Network performance : test data set
Y = 0.9357 X + 0.0330
No. of points = 610
Correlation = 0.5268
Rms error = 0.9871
Bias = 0.2605
Standard deviation = 0.9521
Observed bias
Predicted bias

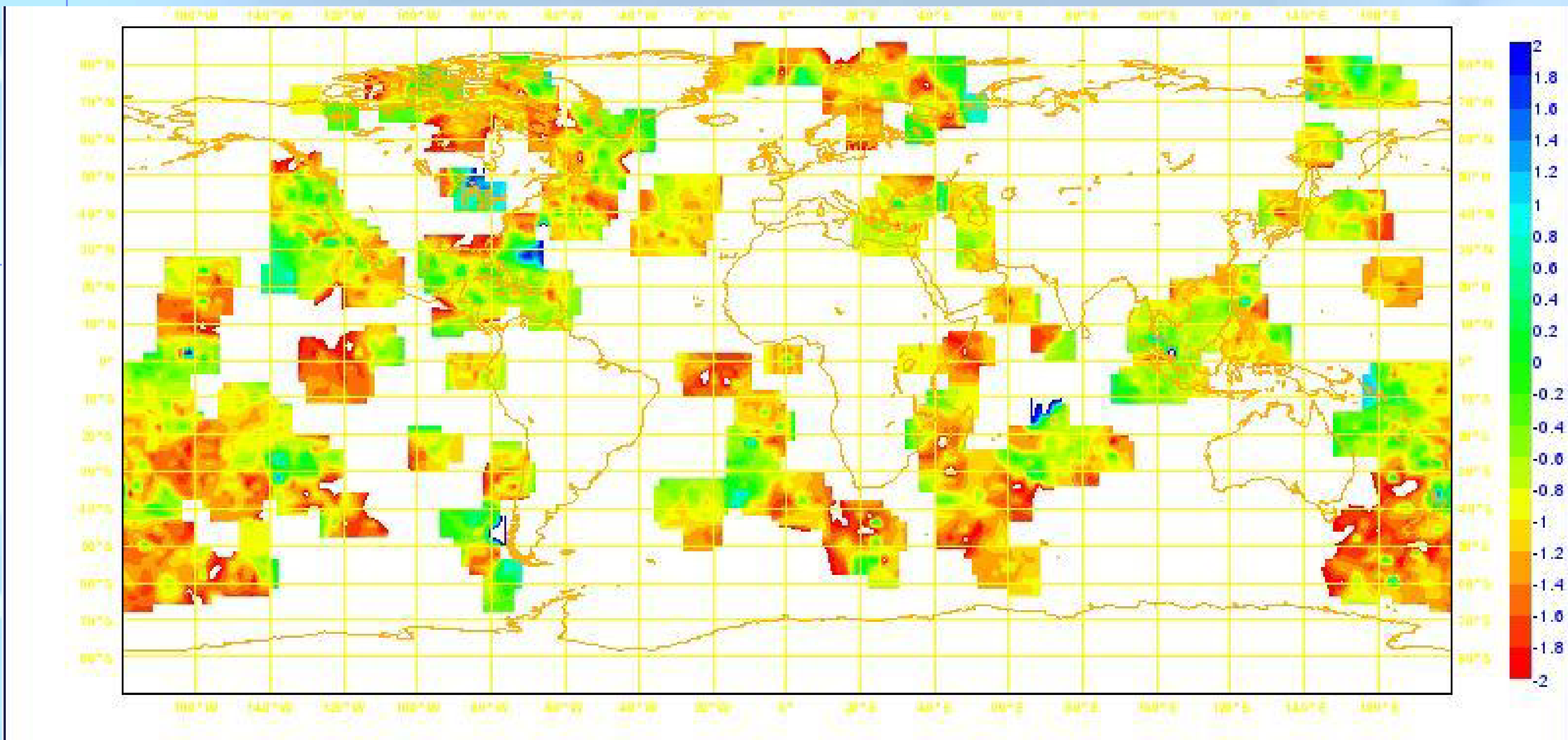

NN performance : learning data set -> CHANNEL 1918
Occurence (%)
obs-mod (K)


NN performance : learning data set -> CHANNEL 1918
Y = 1.0101 X + 0.0133
No. of points = 13459
Correlation = 0.6463
Rms error = 0.3144
Bias = -0.0004
Standard deviation = 0.3144
Observed bias
Predicted bias


Neural Network performance : test data set
Occurence (%)
obs-mod (K)


Neural Network performance : test data set
Y = 0.7606 X - 0.2575
No. of points = 610
Correlation = 0.6007
Rms error = 0.2499
Bias = 0.0923
Standard deviation = 0.2323
Observed bias
Predicted bias

BIAS CORRECTION
NN fit to Obs-Guess



Initial Obs-Guess

Window channel 787

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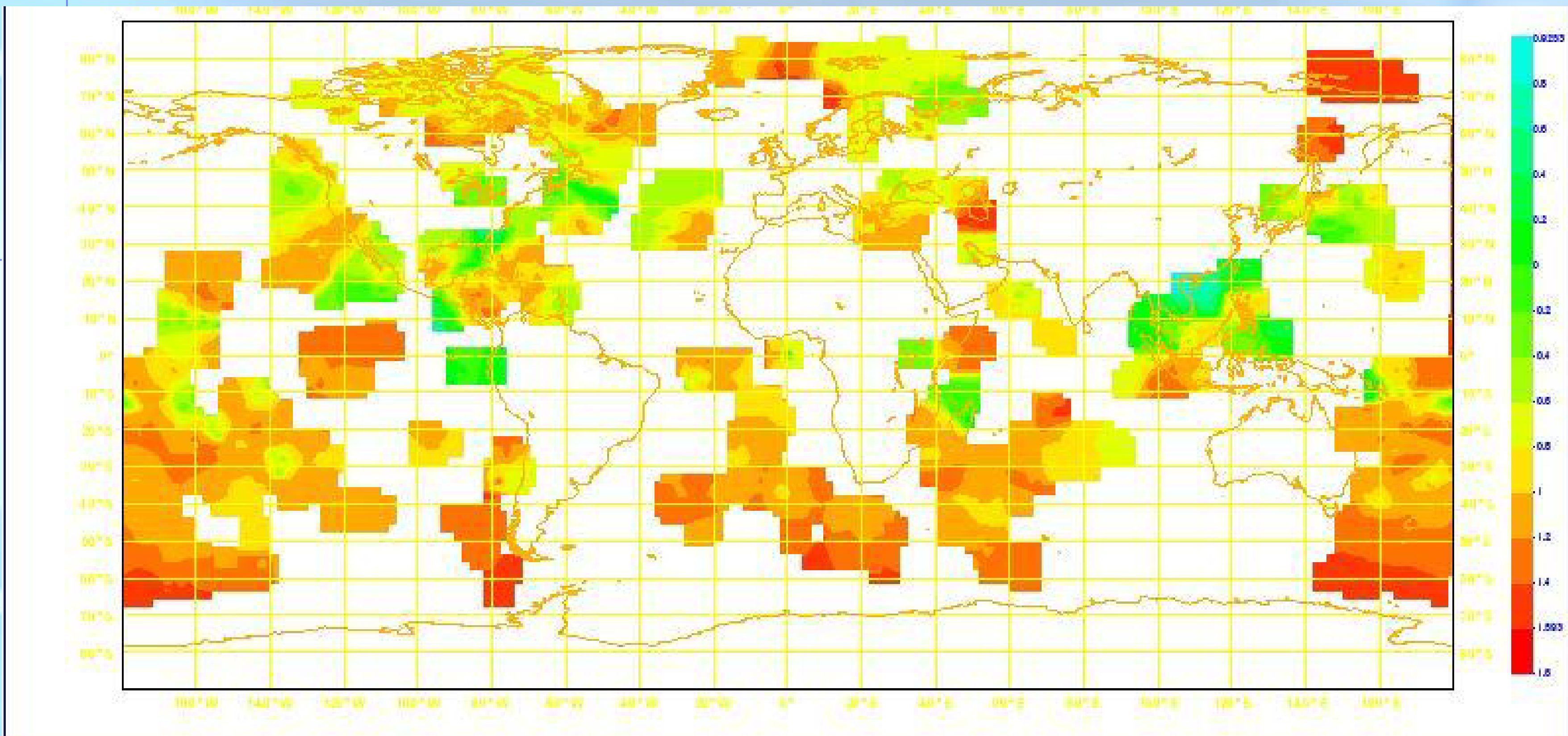
BIAS CORRECTION
NN fit to Obs-Guess



Neural Network Bias Correction

Window channel 787

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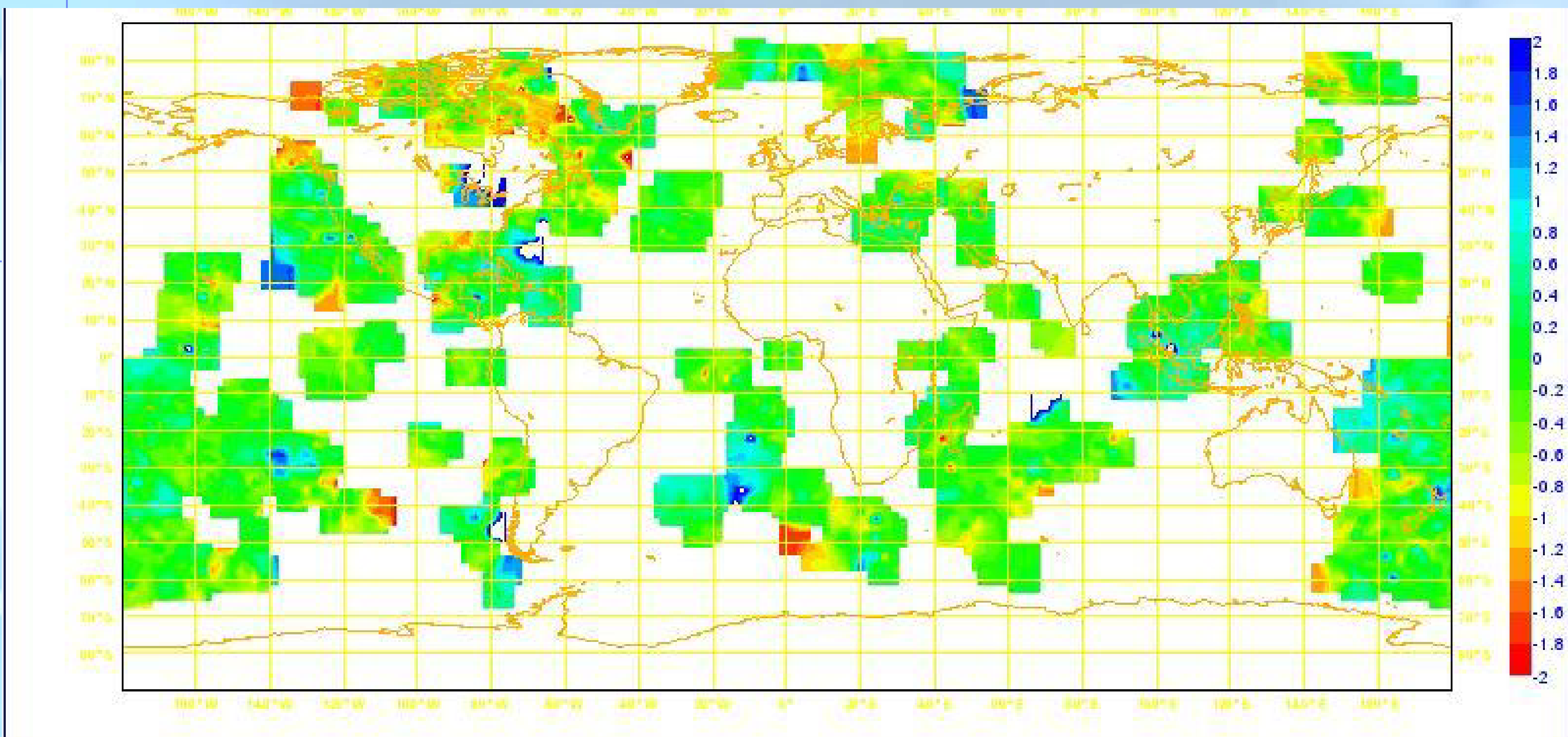
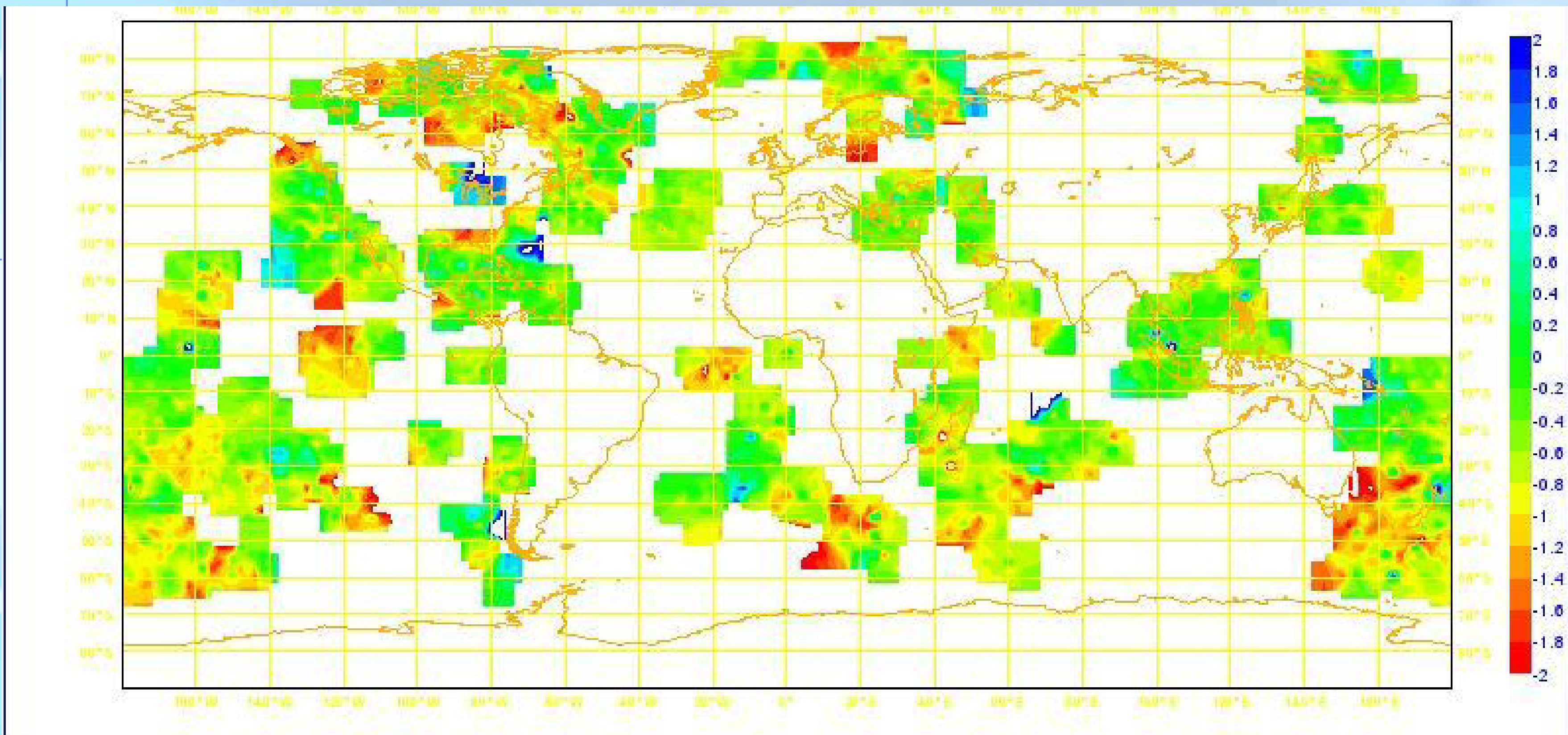
BIAS CORRECTION
NN fit to Obs-Guess



Residual Bias

Window channel 787

BIAS CORRECTION NN fit to Obs-Guess



Residual Bias after Flat Bias Correction

Window channel 787

BIAS CORRECTION
NN fit to Obs-Guess

✓Learning process using Obs-Guess for "active" data: very good ability of NN to predict Obs-Guess (even after learning over only one assimilation cycle) & good generalisation on independent datasets.
(nearly Gaussian, low biased inputs to 4DVar)

BUT
✓Correction of observation bias AND model bias.
→ kills most of the information useful for NWP
(observations do not correct the model any more...)

→ Bad results in NWP trials ☹

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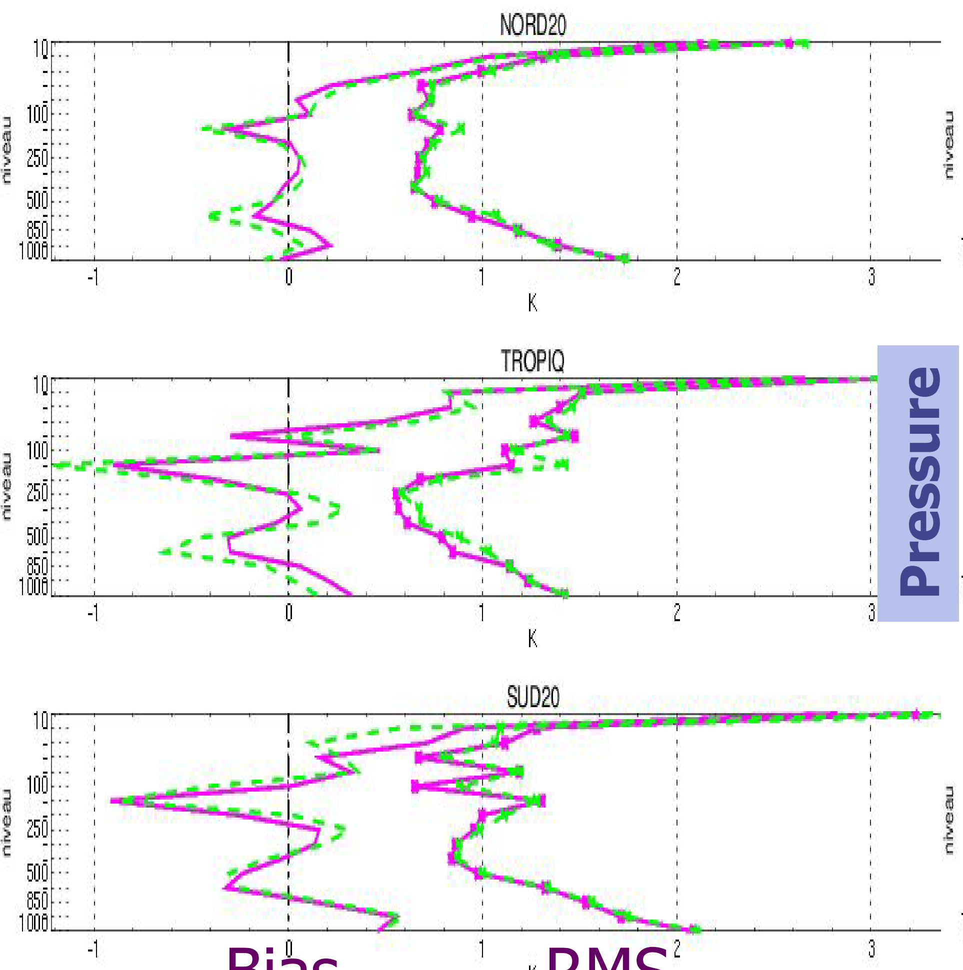
BIAS CORRECTION
NN fit to Obs-Analysis

- ✓Learning process using Obs-Ana for "active" data, predictors generated from analysis state vector.

- ✓Advantages:
Analysis closer to "true" state. NN scheme will predict less model bias (e.q. systematic error).

- ✓Unfortunately...
Analysis is also biased.

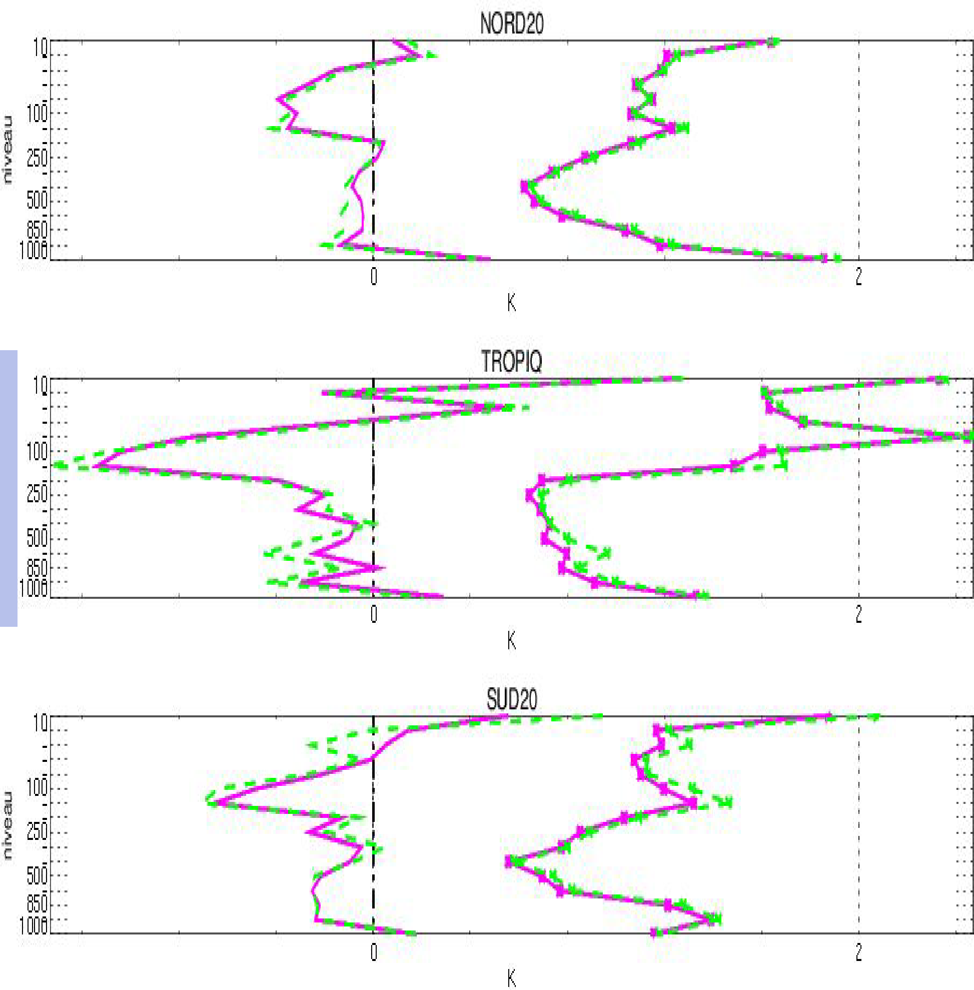
BIAS CORRECTION
NN fit to Obs-Analysis



Bias RMS

Temperature Analysis - ECMWF

Pressure



Temperature Analysis - RS

BIAS CORRECTION NN fit to Obs-Analysis

✓NN bias correction creates a dataset homogeneous with NWP analysis
→ AIRS observations confort the analysis in its own bias.

→ Bias amplification. ☹

What is the best estimate for NN bias correction learning ?

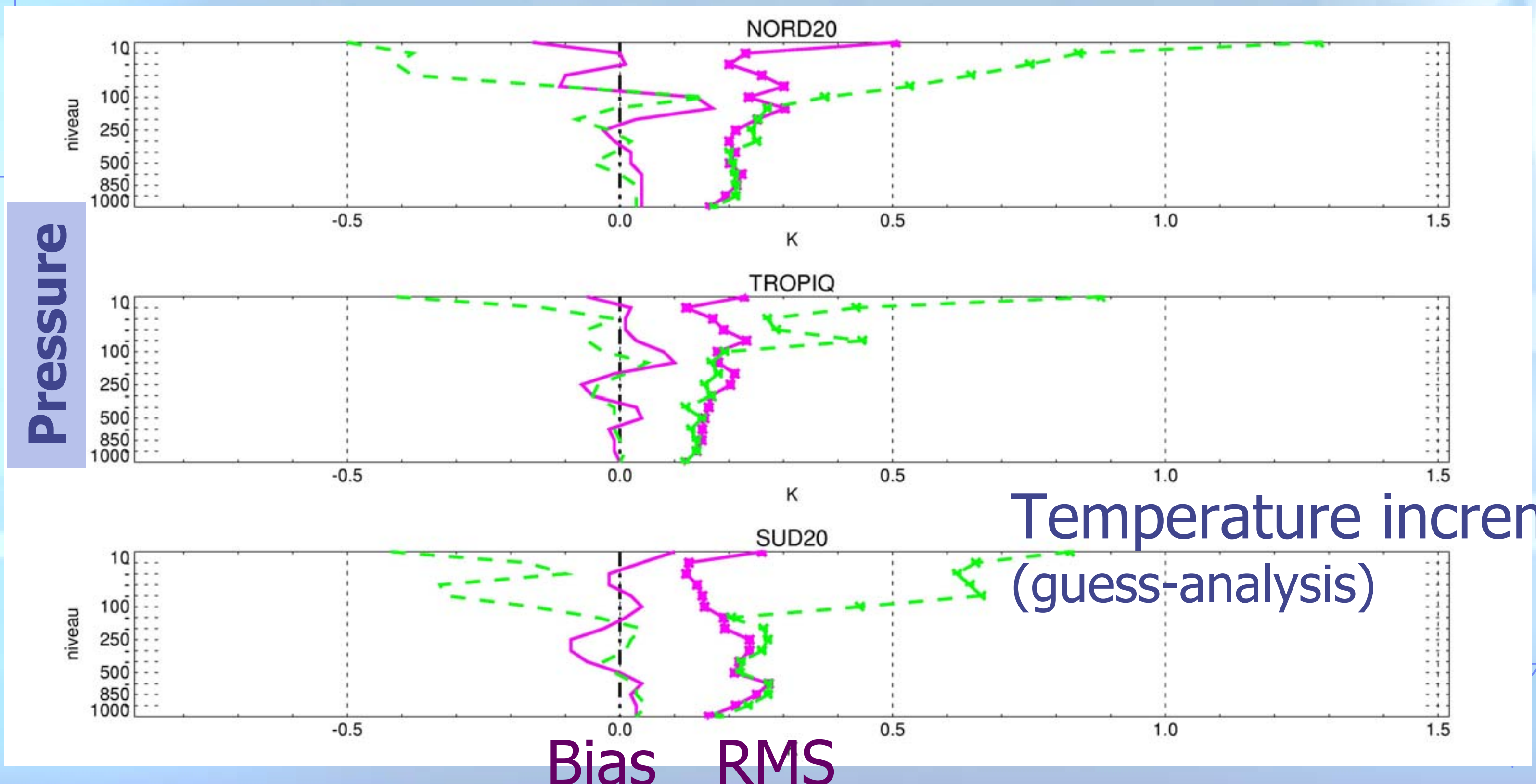
ECMWF analysis ?!!! Same observation operator → close obs bias
IFS analysis is less biased than ARPEGE

✓Learning process using Obs-Ana(ECMWF) for "active" data, predictors generated from ECMWF analysis state vector interpolated to ARPEGE grid (vertical&horiz).

✓Unfortunately...
Meteo-France does not correct RadioSondes bias yet.
→biased above 100hPa

BIAS CORRECTION
NN fit to Obs-Analysis(ECMWF)

- ✓Very big increments in stratosphere



Reference:Arpege (AMSU-A&B,HIRS,EARS,QuikSCAT, VarQC)

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BIAS CORRECTION

NN fit to Obs-Analysis(ECMWF)

✓Very big increments in stratosphere

→ AIRS versus RS, AMSU-A,AMSU-B,HIRS

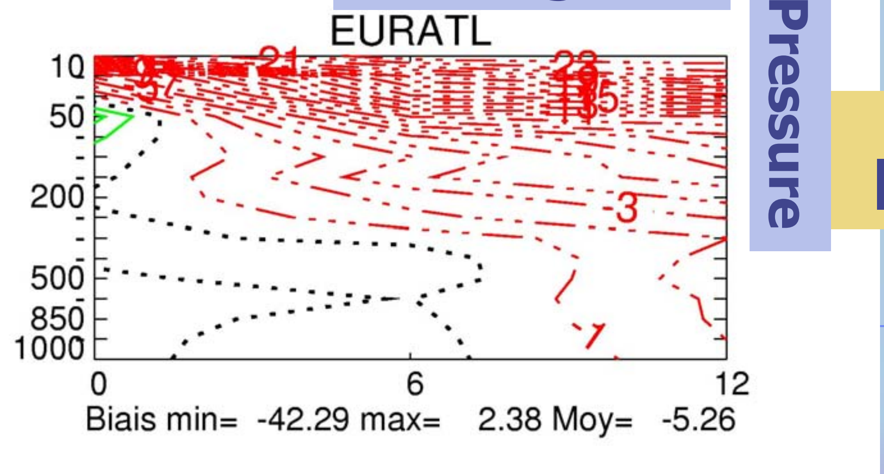
→ focuses 4DVar to upper levels, less minimization in troposphere

→ structure fonctions (B matrix) bring unphysical increments downwards into the troposphere

Forecast range

Pressure

1 case…



|BIAS$_{REF}$| - |BIAS$_{EXP}$|

VERIF = own analysis

Geopotential bias difference in increments

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How to make analysis increments "digestable" to the assimilation system ?

✓Need for observation dataset compatible with ARPEGE analysis

✓Observations must drag the assimilation towards the "true" state.

→For each channel:

NN bias correction (learning w/r Obs-Analysis(ARPEGE))

+ α * Constant bias(Arpege - ECMWF)

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BIAS CORRECTION

NN fit Obs-Analysis+α*B(Arpege -ECMWF)

Quick & dirty experiment:

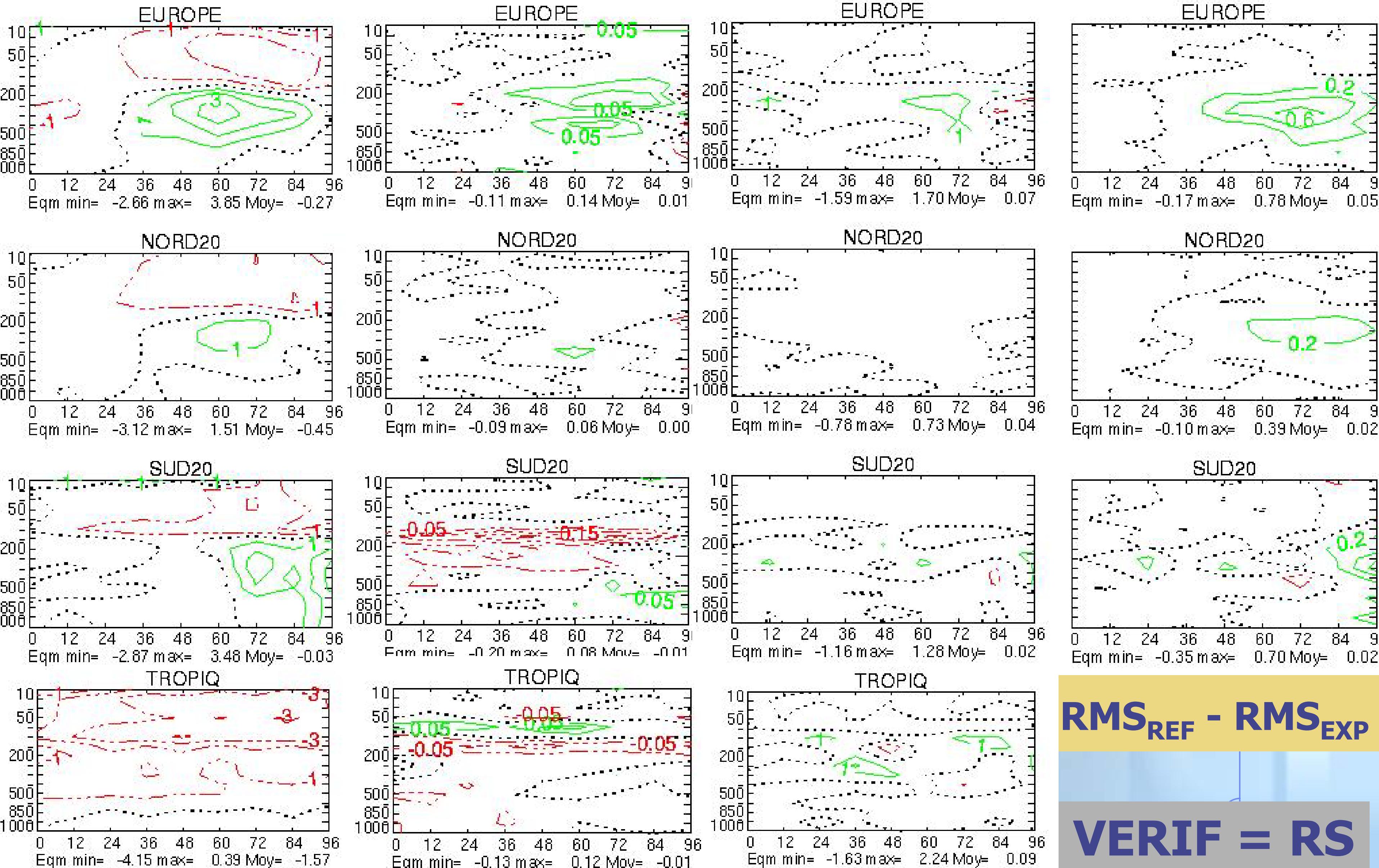
✓α=0.4

✓NN learning over one assimilation cycle, then set constant.

✓ σ_o drastically increased for upper-level channels

✓Assimilation period :12 days

✓Reference:Arpege (AMSU-A&B, HIRS, EARS, QuikSCAT, VarQC)



RMS_{REF} - RMS_{EXP}

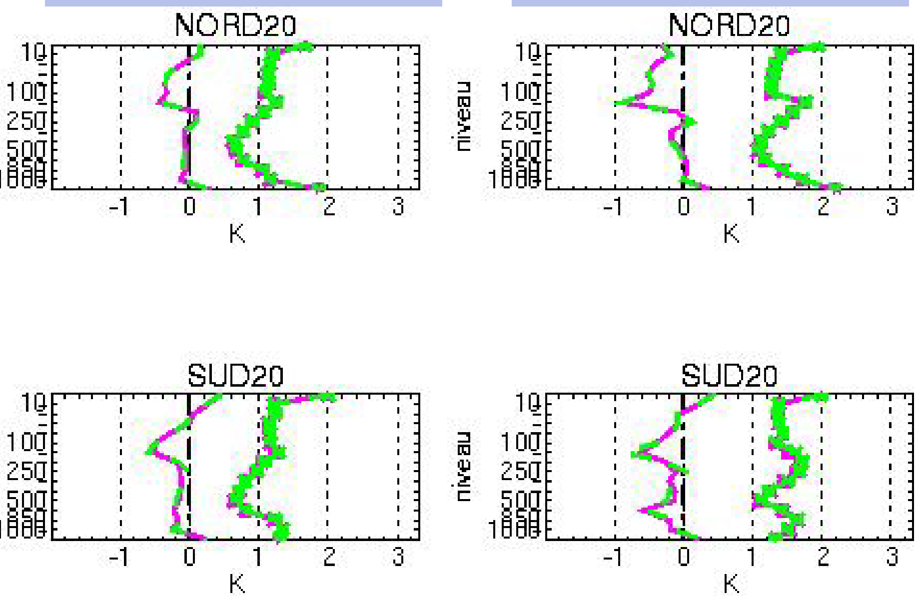
VERIF = RS

Geopotential Temperature Humidity Wind

Can we distinguish model bias from observation/forward model bias ?

✓Analysis bias seems to spread with forecast range

Analysis	24h Forecast	48h Forecast	72h Forecast



Temperature Bias & RMS w/r to Radiosondes

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BIAS CORRECTION

NN fit Obs-Analysis+β*(OMA-OMF)

→modelize analysis bias by: β * Bias Growth

Quick & dirty experiment:

Ana_bias= β * (Guess_bias – Ana_bias)

→Ana_bias= β * (OMA – OMF)

✓β = 0.5

✓Assimilation period :9 days

✓Reference:Arpege (AMSU-A&B, HIRS, EARS, QuikSCAT, VarQC)

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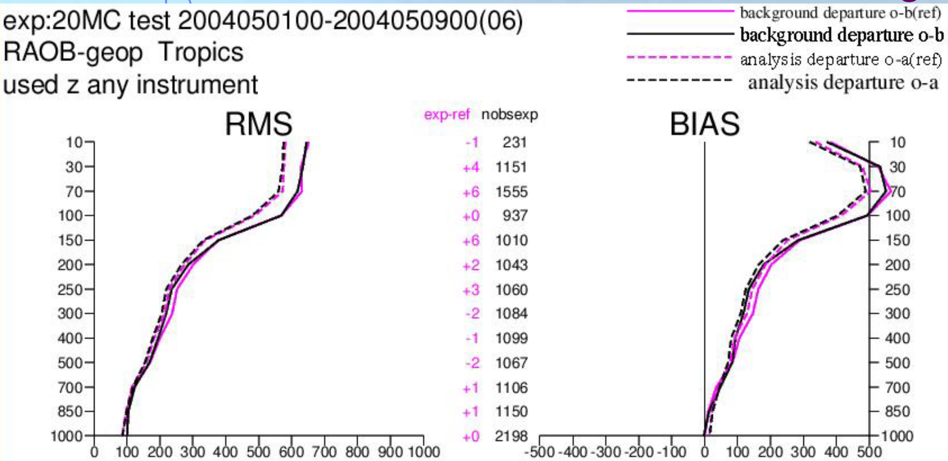
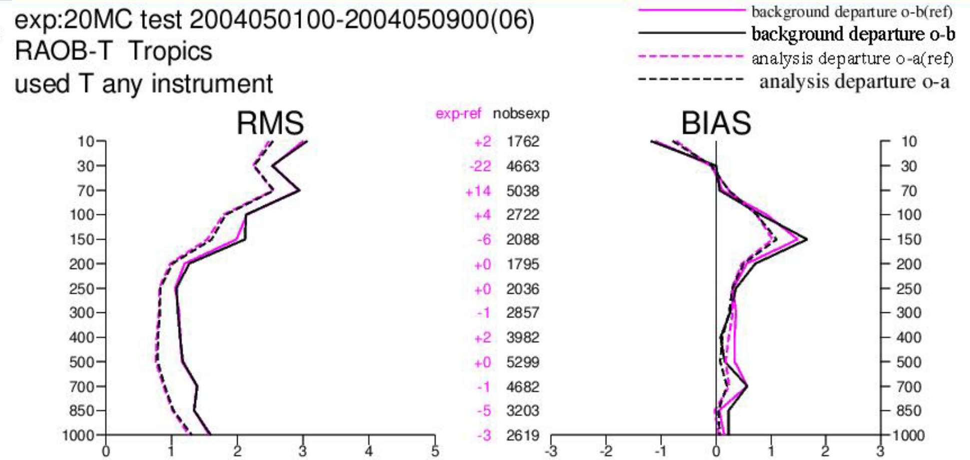
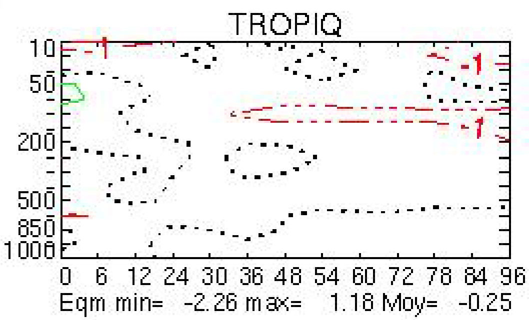
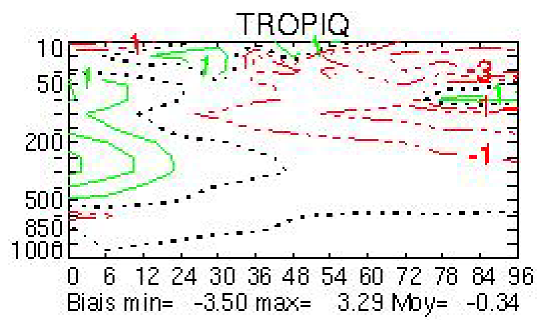
BIAS CORRECTION

NN fit Obs-Analysis+β*(OMA-OMF)

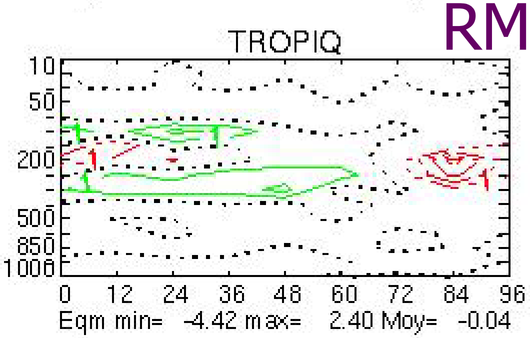


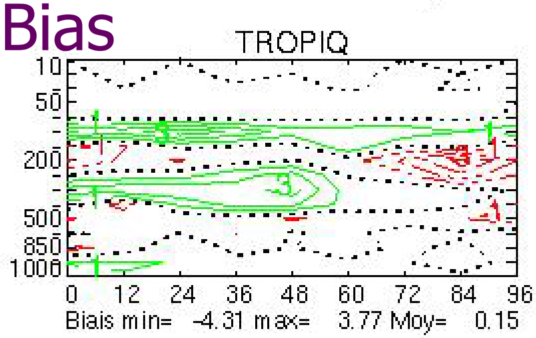






RMS Bias





Geopotential

RMS_{REF} - RMS_{EXP}

VERIF = RS

Humidity

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CONCLUSION & PERSPECTIVES

Neural Network bias correction scheme needs more tuning (α & β).
Good start to separate observation bias from model/analysis bias.

NN bias correction should be more robust with learning process over a longer period for total bias & updated learning model/analysis bias.

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CONCLUSION & PERSPECTIVES

Need for RadioSondes bias correction in upper levels
(and updated bias corrections for AMSU & HIRS)

Extra thinning might be necessary for AIRS to be consistent with other observations&model.
AIRS σ_o shall be increased in order to reduce analysis increment variability due to AIRS.

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