Developments with a Modular Algorithm for Atmospheric Profiling Earth System Data Records

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Outline

- AER Earth system science profiling algorithm
- Modular software for collaboration and experimentation
- Radiance-based pre-classification of fields of regard
  - Pre-classification method
  - Class definition method
  - Pre-classification performance
  - Implementation in profiling algorithm
  - Impact on retrieval performance
  - Impact on climate change signal detection

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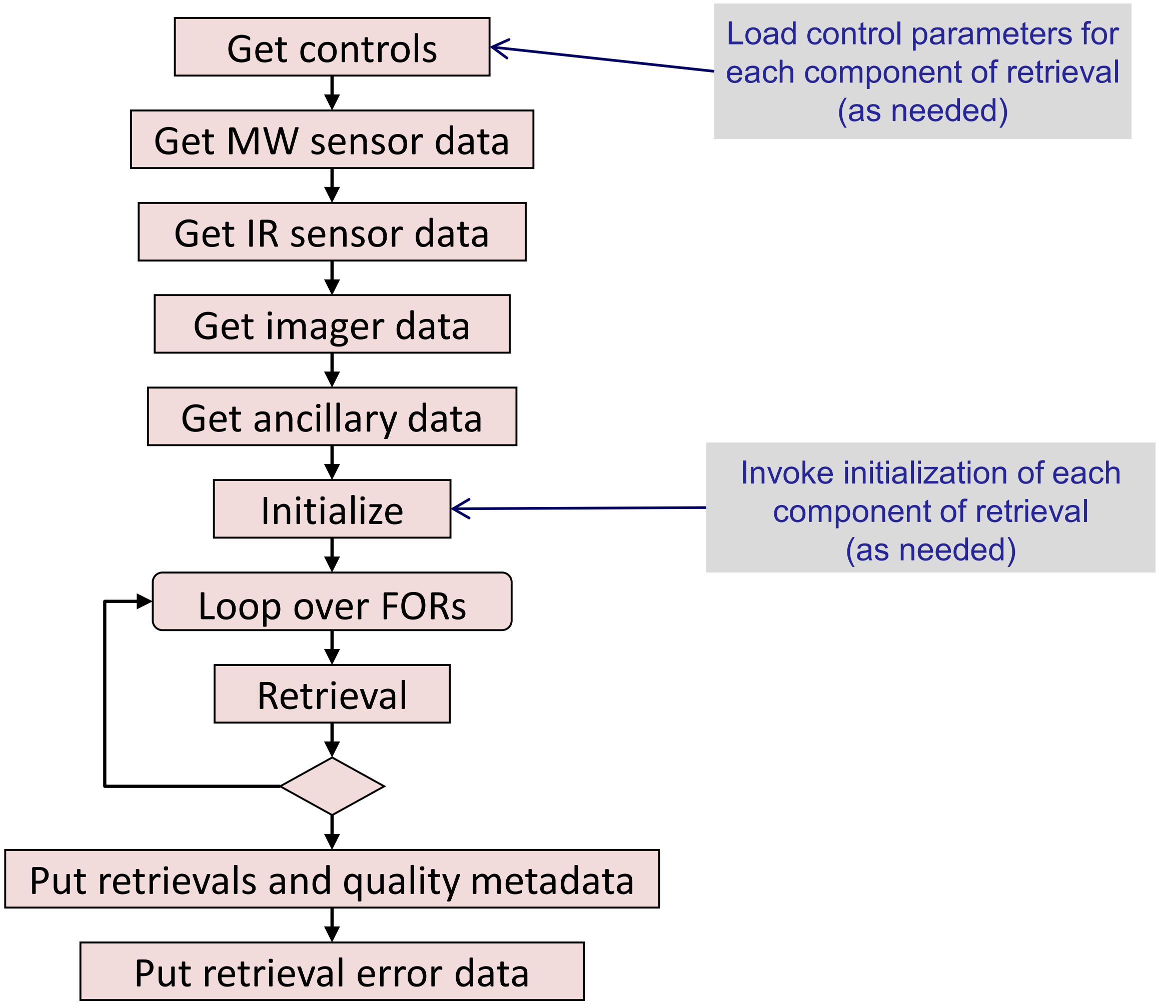
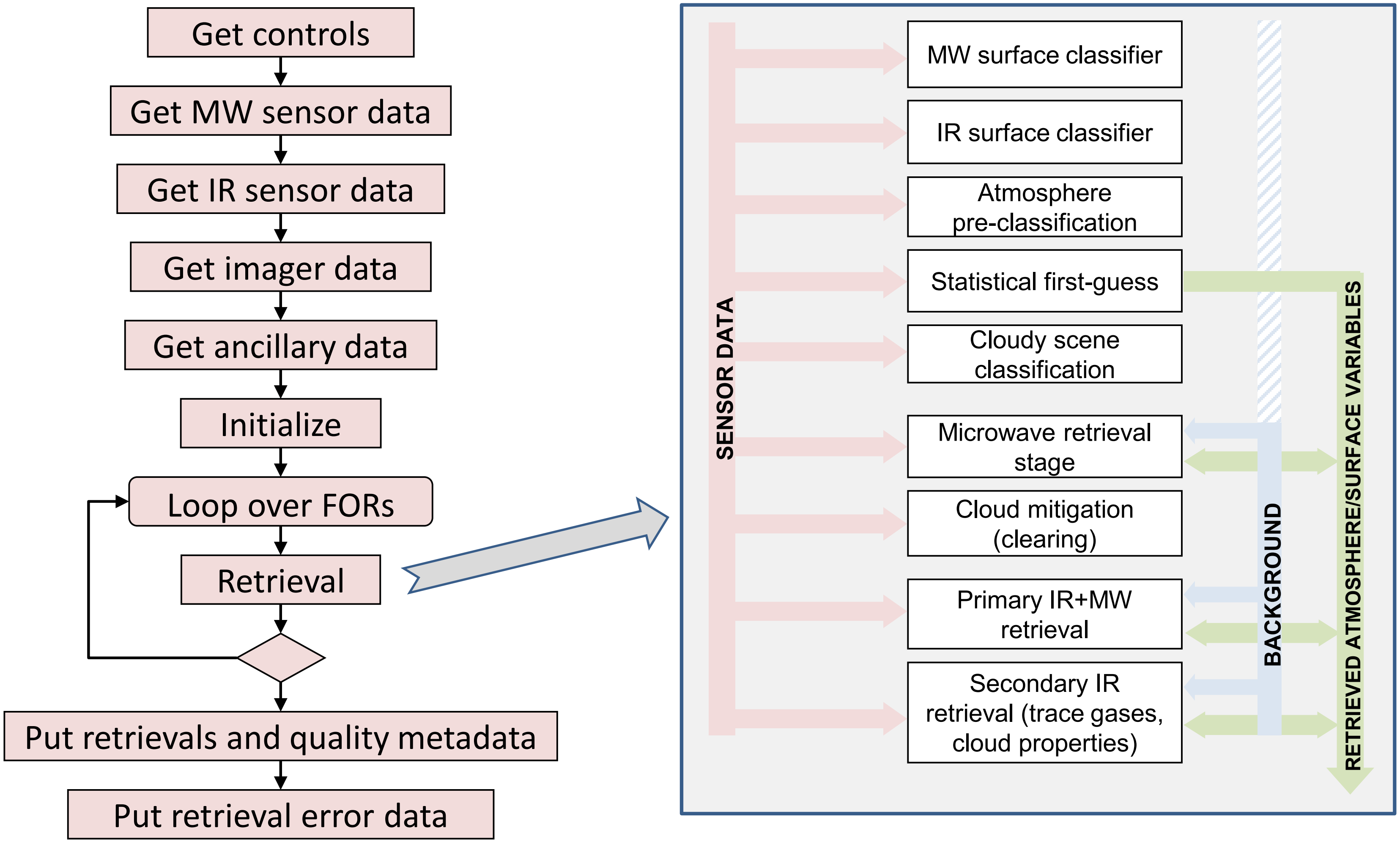
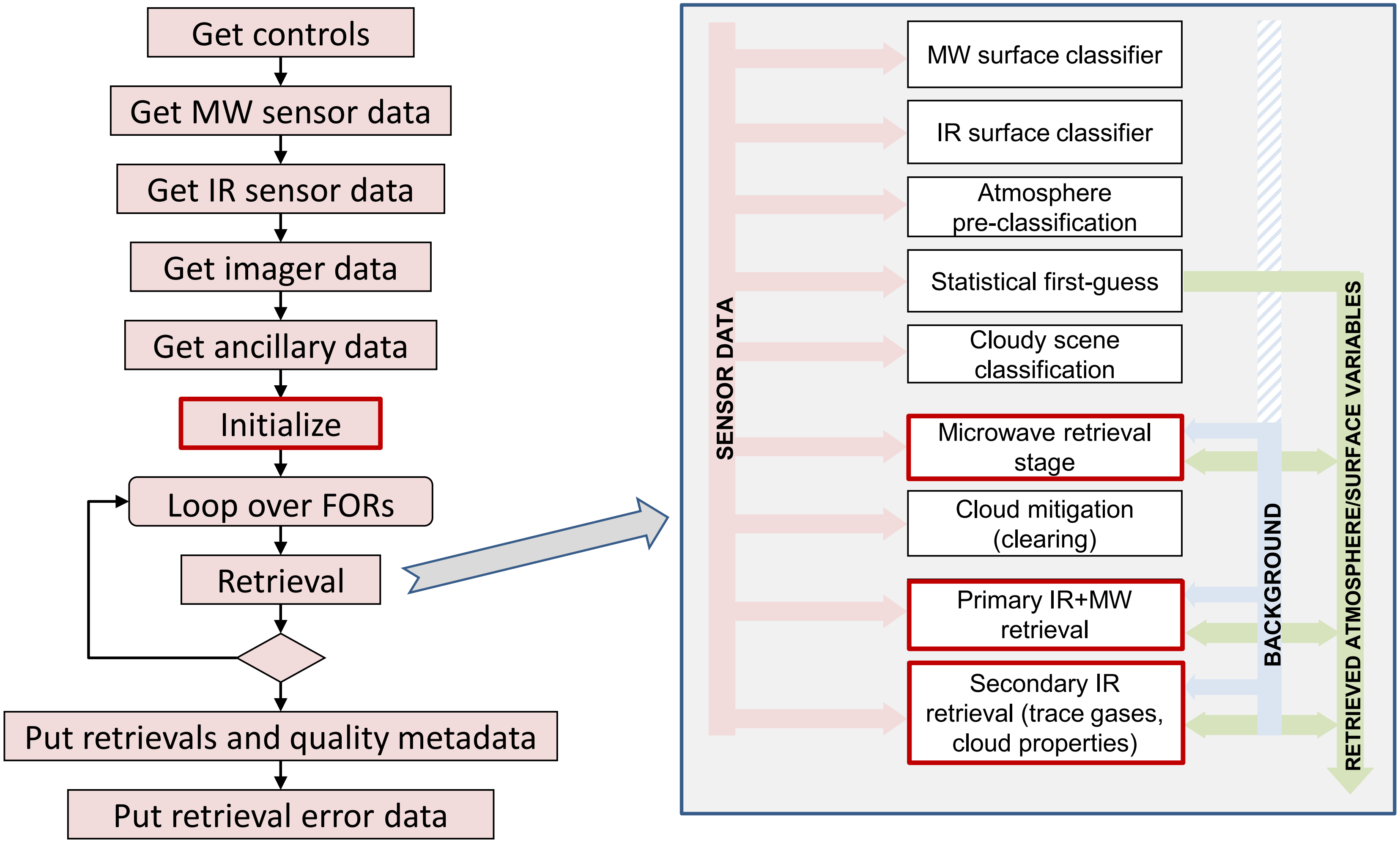
Top-level modular organization



Top-level modular organization



Top-level modular organization



Generic physical retrieval stage operations: Initialization

- Load and initialize atmospheric background (*a priori*)
  - Defines the vertical grid used in retrieval (e.g., hybrid pressure-σ)
  - Basis functions (e.g., EOF, trapezoid) and pseudo-inverse are loaded with background data
- Load and initialize surface MW background
- Load and initialize surface IR background
- Configure retrieved variables
  - Number of variables for temperature, cloud variables retrieved, etc.

Background handler is object-oriented
Each retrieval stage has its own instance of background controls and data

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Generic physical retrieval stage operations: Execution

- Get atmosphere background (e.g., climo) ← Atmosphere class
- Get surface MW background (e.g., climo) ← Surface MW class
- Get surface IR background (e.g., climo) ← Surface IR class
- Get FOR-specific atmosphere background (e.g., T,q_{H2O}, for trace gases)
- Get FOR-specific surface background (e.g., gridded database)
- Combine backgrounds (e.g., weighted average)
- Apply basis function transformation to background
- Fill first guess with result of prior retrieval stage
- Iterate:
  - Radiative transfer (e.g., OSS)
  - Transform to retrieval space
  - Inversion
  - Test for convergence
  - Transform to geophysical space

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Radiance-based pre-classification concept

- Optimal estimation (OE) algorithm uses global background, by default
  - Loose constraint allows solution to have strong dependence on the satellite measurements
- Pre-classification selects background that represents a subset of the global conditions
  - Background errors better comply with Gaussian assumption of OE
- Pre-classification is based on the satellite measurements only
  - Does not introduce influences of ancillary data sources
  - No explicit geographic or seasonal associations
  - Use only microwave channels sensitive to upper troposphere and stratosphere and infrared channels sensitive to stratosphere
    - Avoid effects of surface and clouds that could cause misclassification

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Pre-classification method

- Probabilistic neural network
- Objective is to select an atmosphere class based on measurements
- Inputs are radiances (or brightness temperatures) for ATMS channels 9 to 14 and secant of zenith angle
  - Each input variable is normalized to the maximum of the variable among all training cases
- PNN training uses the same global profile database as used to compose the background
- Radiances computed for each profile
  - Sensor noise added to be consistent with application
- Training involves finding the optimal value of a tuning parameter
  - Based on % correct classification with an independent dataset

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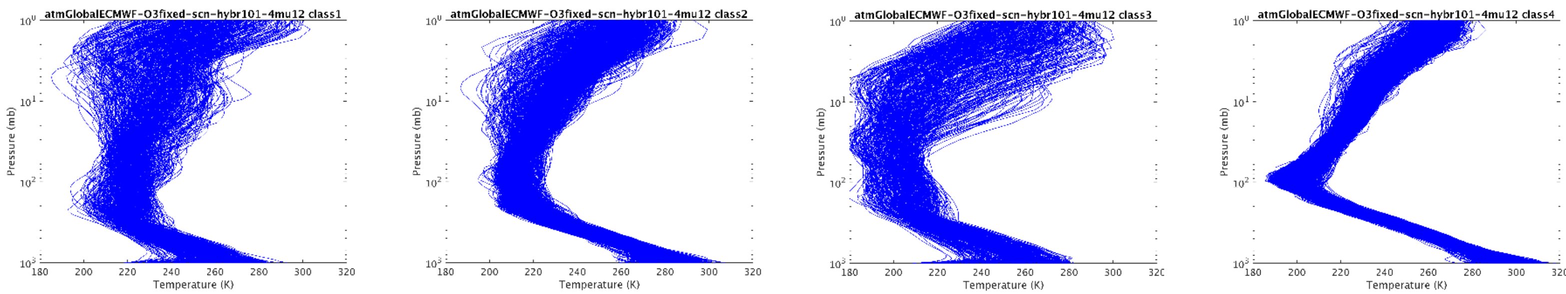
Definition of atmospheric profile types

- Clustering of the same global profile database as is used to compose the global background
  - 3000 profiles from a database collated by ECMWF
- Unsupervised k-means clustering method
  - Applied to combined temperature (p>1 mb) and water vapor profiles (p>300 mb) on hybrid pressure-σ coordinate
    - Profiles represented as departures from the mean, normalized by the standard deviation*
    - Relative influences of temperature and water vapor levels is regulated by a weight factor*
      - 0.12 selected subjectively, with relatively high influence of temperature, consistent with intent to use temperature channels for classification
- Number of clusters is specified
  - Sets with 4 clusters to 8 clusters were tested
  - With such low numbers of clusters, the background constraint is still loose

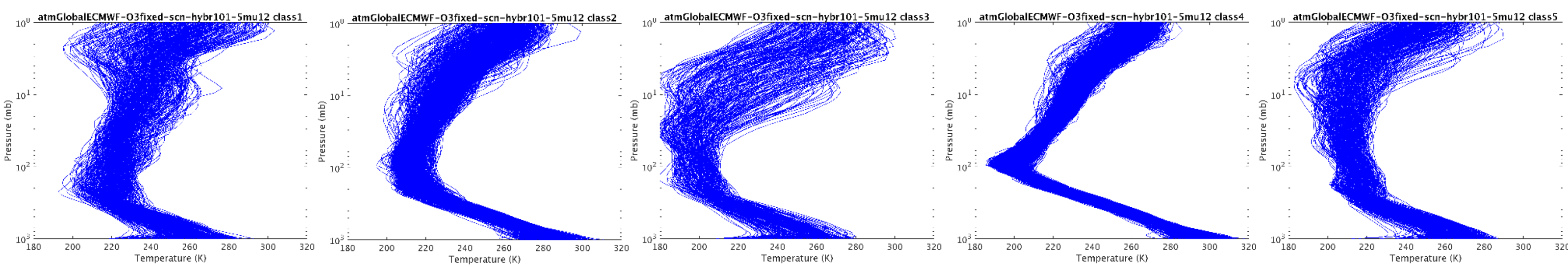
*Following Chevallier et al., 2000, QJRMS

Clustering results

4-cluster set temperature profiles



5-cluster set temperature profiles



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Definition of atmosphere classes

- The classes are not defined directly by the profile data clustering results
- Classes are defined by the same radiance-based classification method as is used in the retrieval
  - Addition of noise means that class boundaries overlap, within the range of uncertainty of the set of measurements that are input to the classifier
    - "fuzzy" classification

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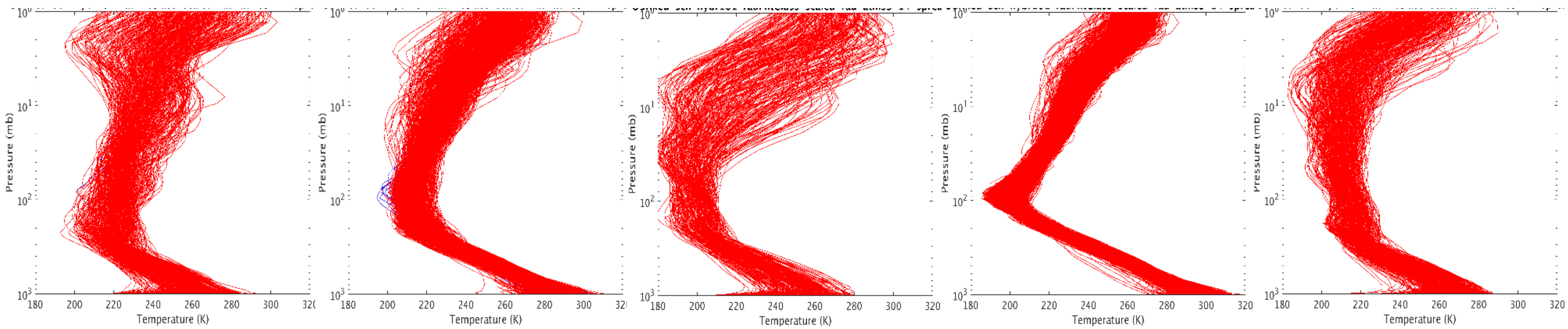
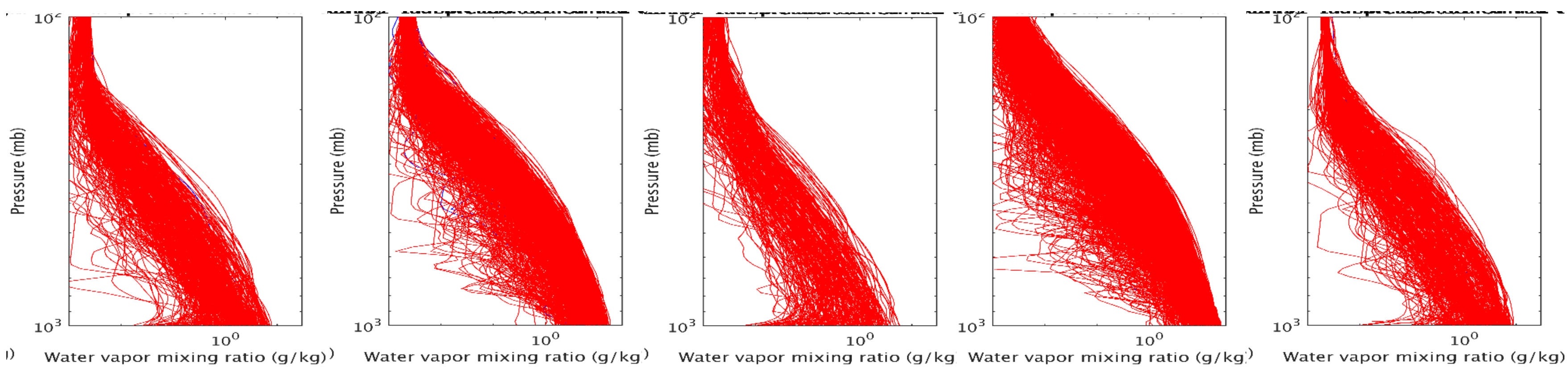
Atmospheric classes

Classifier results (red) plotted over cluster results (blue)

5-cluster/class set temperature profiles

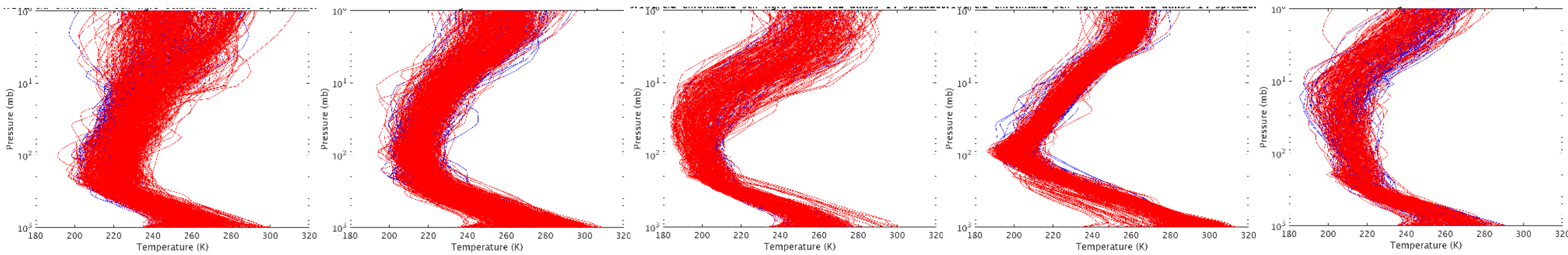


5-cluster/class set water vapor profiles



Classification performance with independent dataset

- Independent data are from TIGR3 dataset
- True class determined from profile data, using result of clustering defined with the background dataset
- Radiance-based classification trained from the background dataset



Classifier results (red) plotted over cluster results (blue)

Performance on TIGR3 set:
4 classes 22% misclassification
5 classes 22% misclassification
6 classes 29% misclassification

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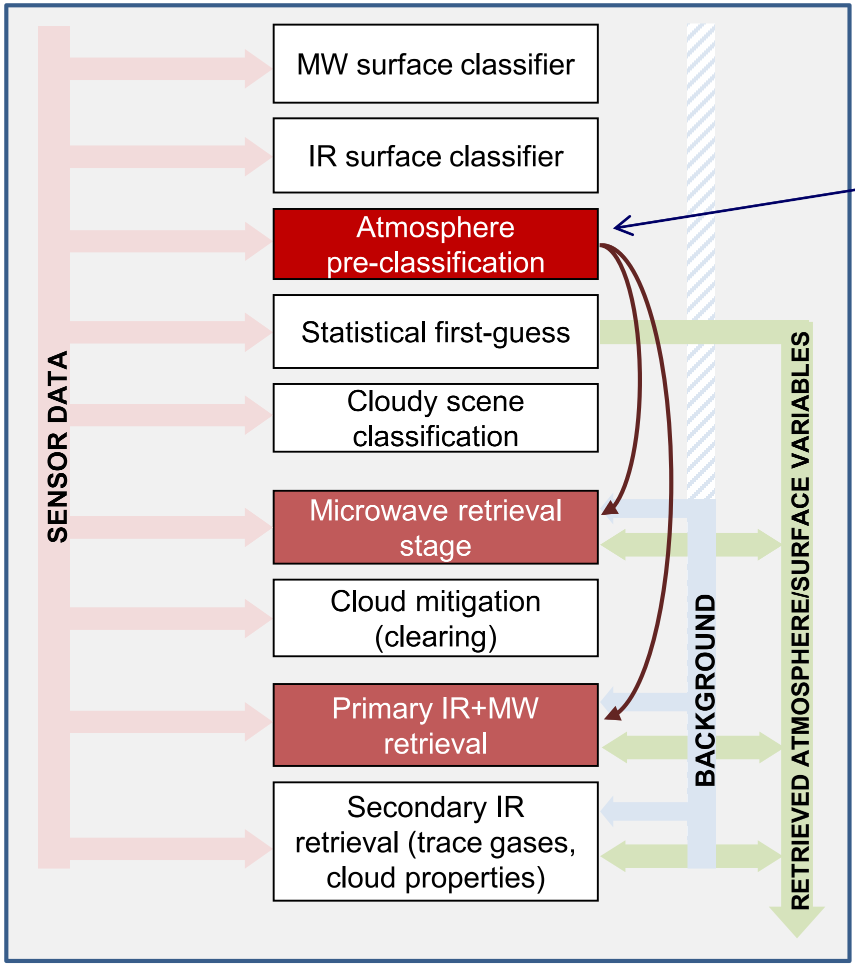
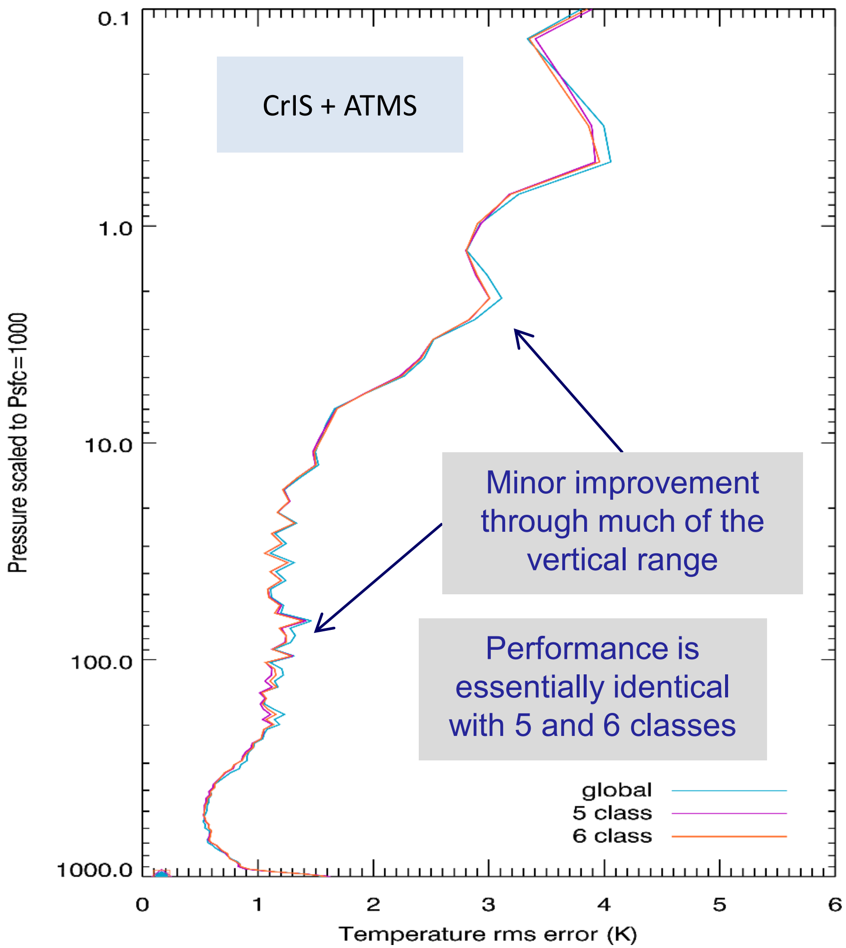
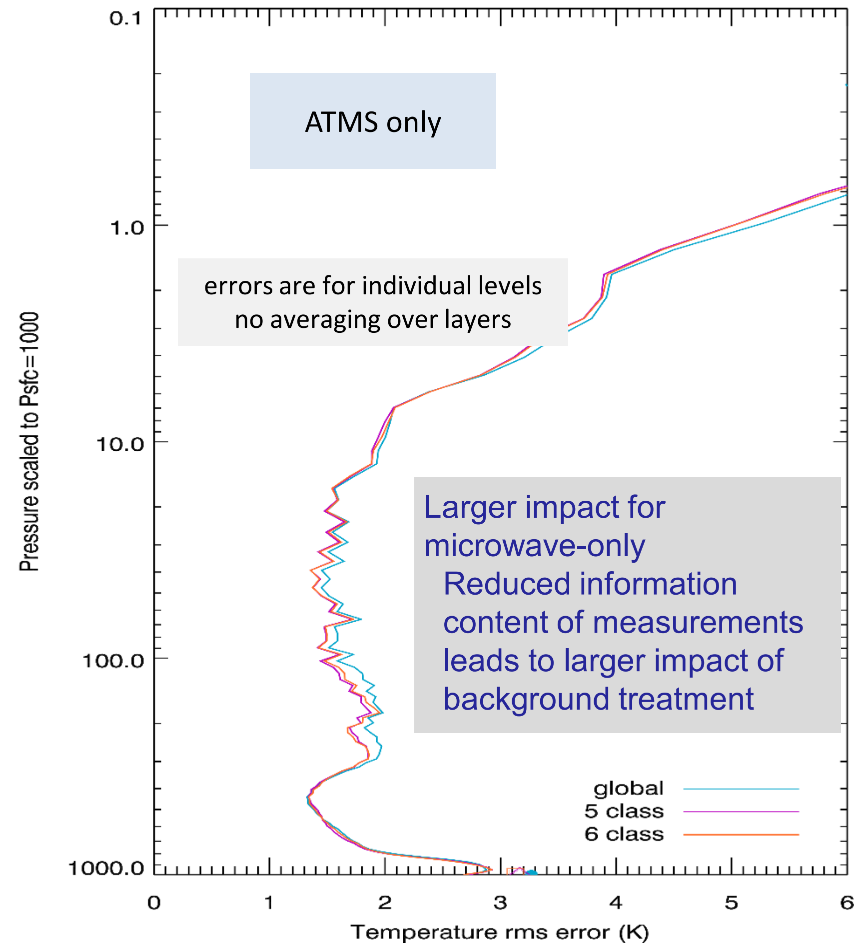
Implementation in profiling algorithm



Executes probabilistic neural network

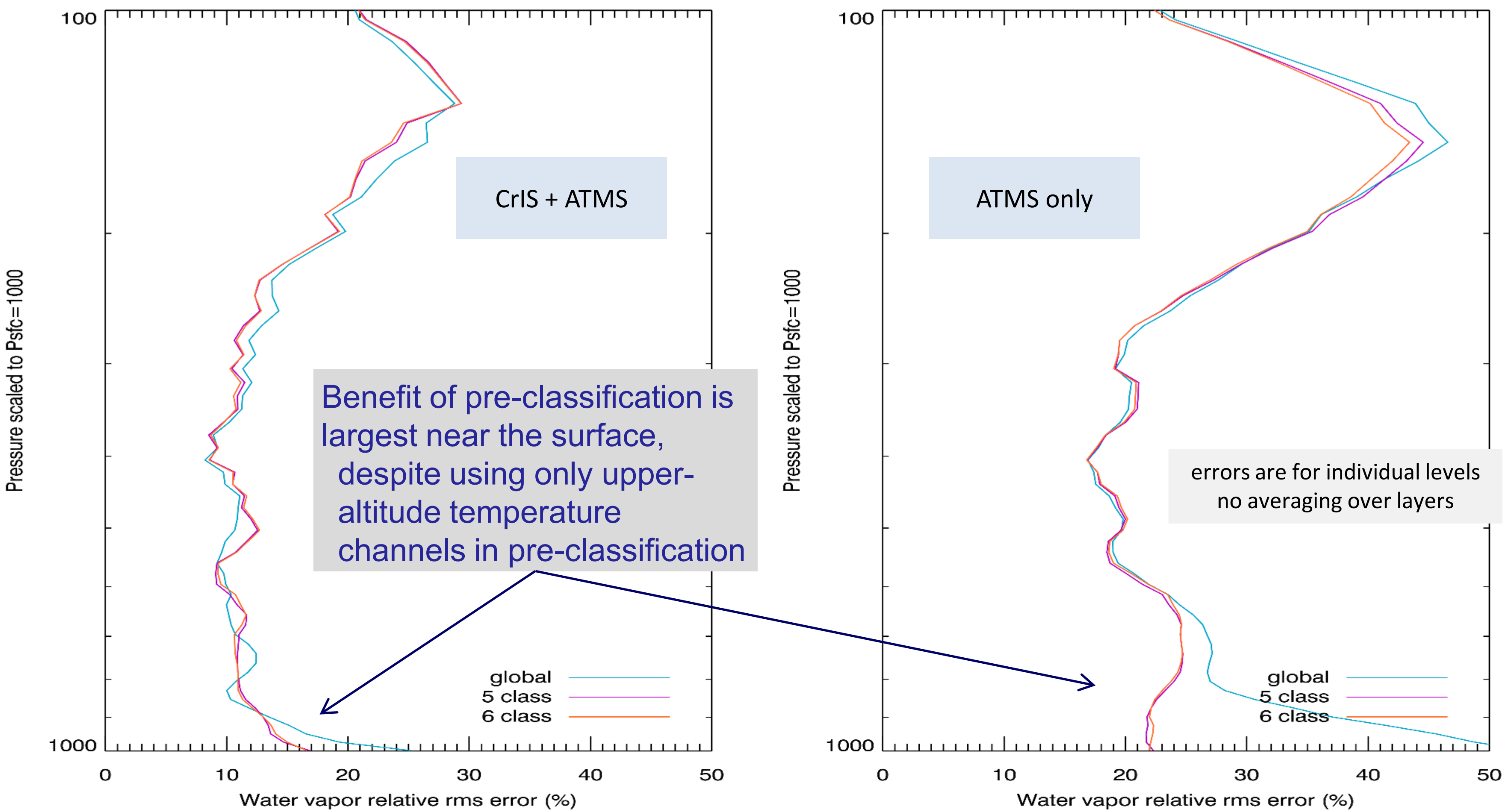
Impact on temperature retrieval results





500 profiles from simulated measurements

Impact on water vapor retrieval results



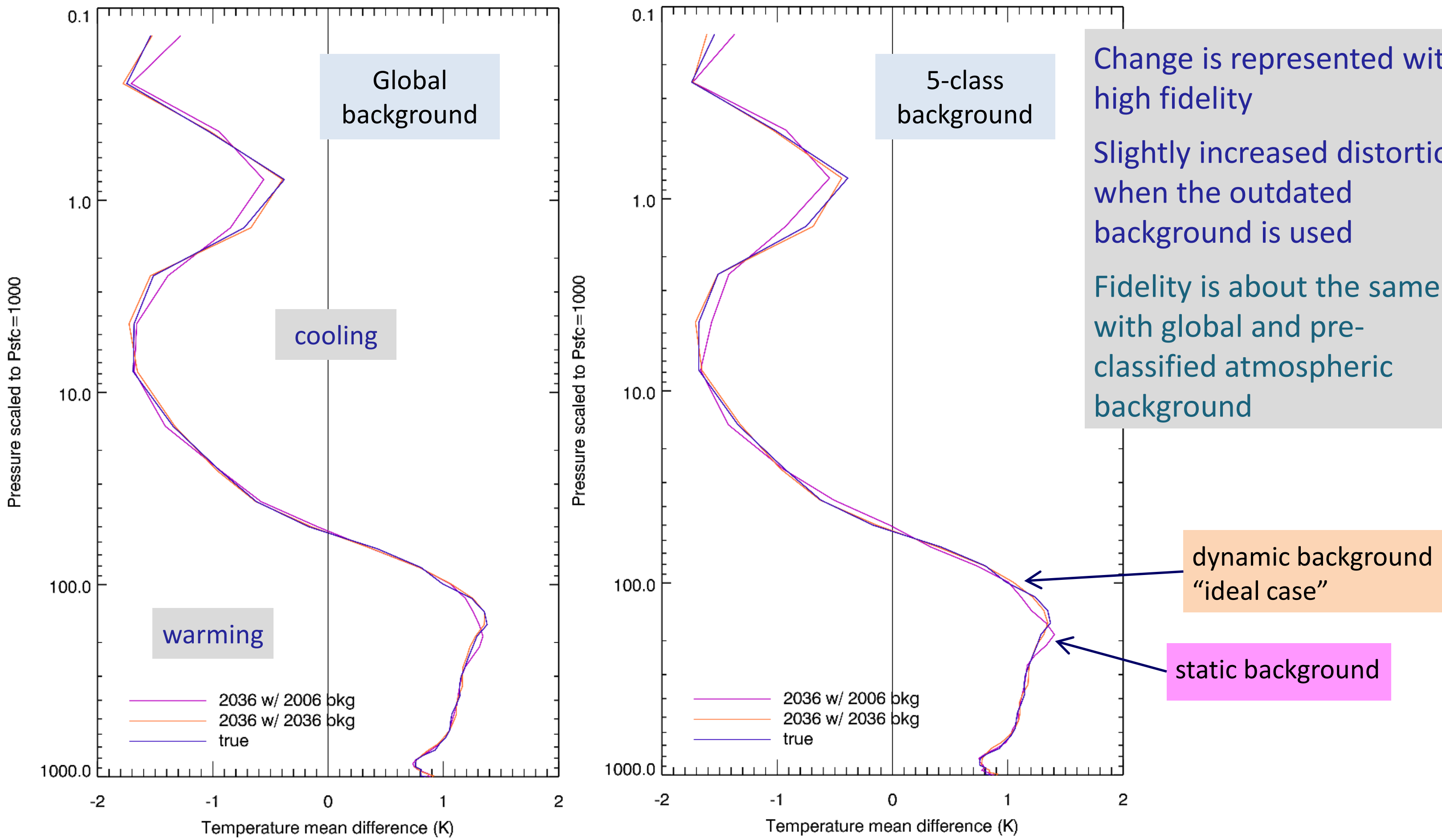
500 profiles from simulated measurements

Response of retrievals to climate change

- Would atmosphere pre-classification affect the response to change?
- When algorithm products are used to monitor climate change, would response to change be muted or biased by using a static background, composed from past profiles?
- Experimental approach:
  - 30-year climate change (2006 to 2036) simulated by GISS-E2-R for CMIP5 RCP4.5
  - Take one sample of profiles from 2006 and another from 2036 and use data from each sample to make separate background estimates and error covariances
  - Take independent samples from each to use in retrieval experiments
  - Simulated CrIS and ATMS measurements

Fidelity of 30-year climate change in retrievals: temperature

CrIS + ATMS



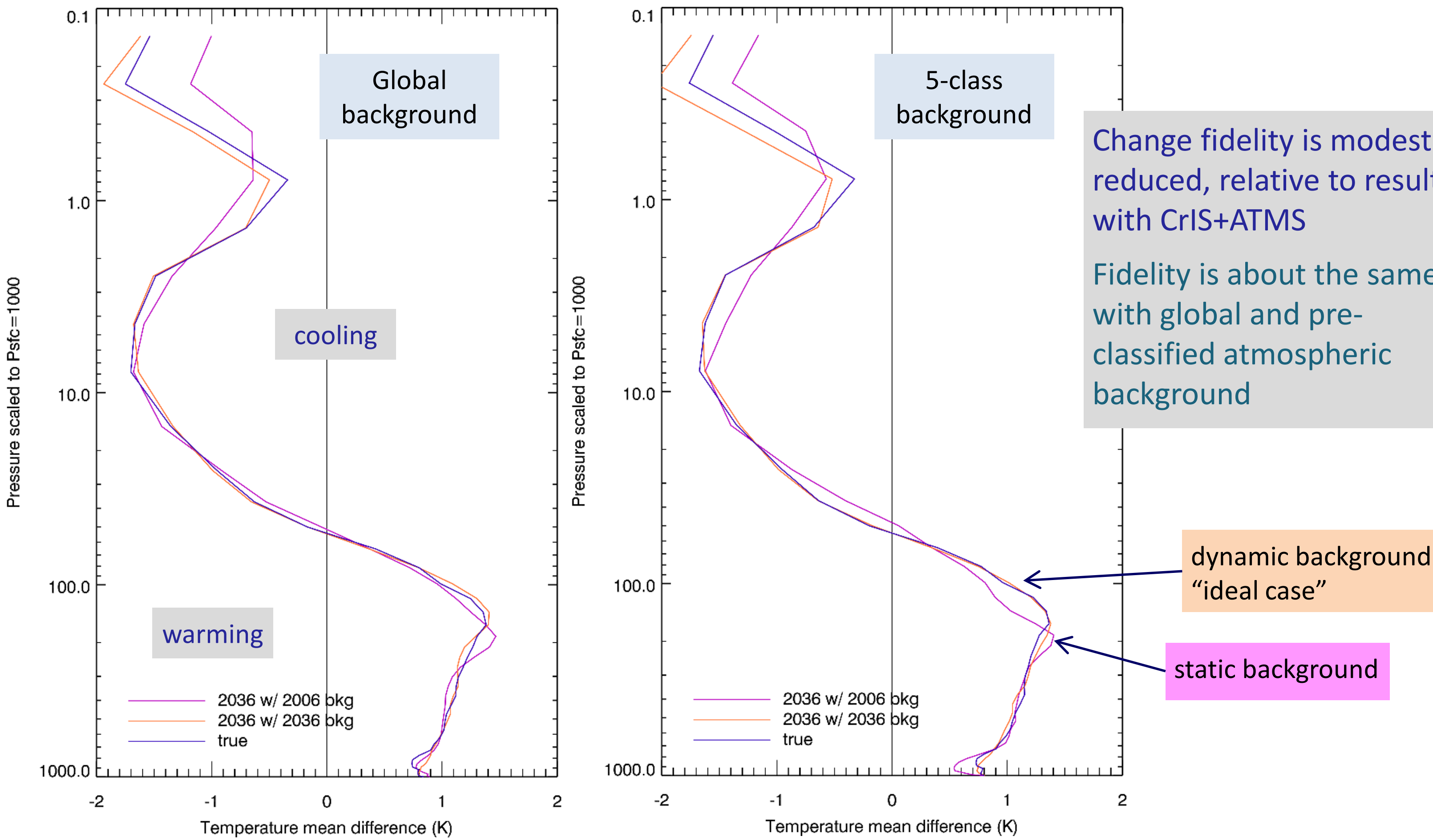
Change is represented with high fidelity

Slightly increased distortion when the outdated background is used

Fidelity is about the same with global and pre-classified atmospheric background

Fidelity of 30-year climate change in retrievals: temperature

ATMS only

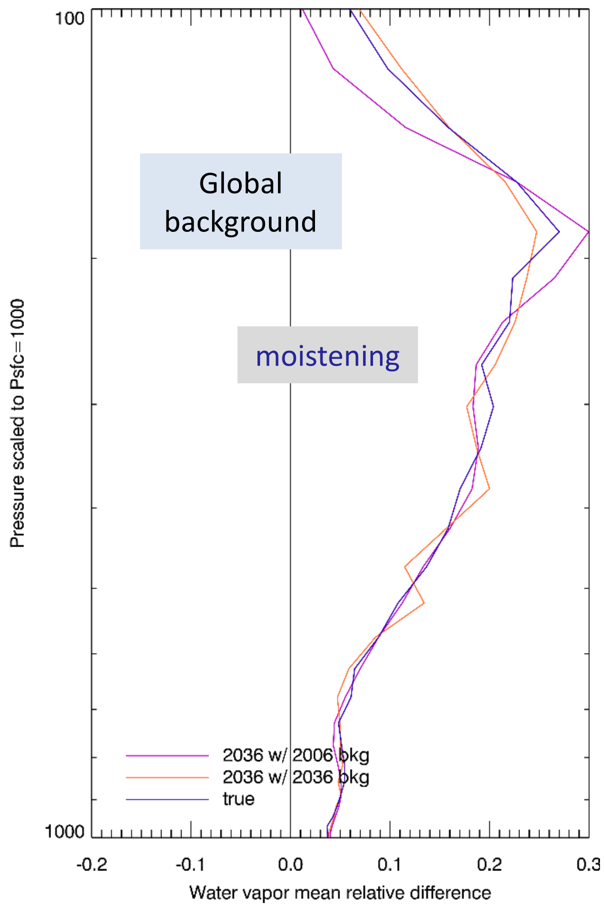


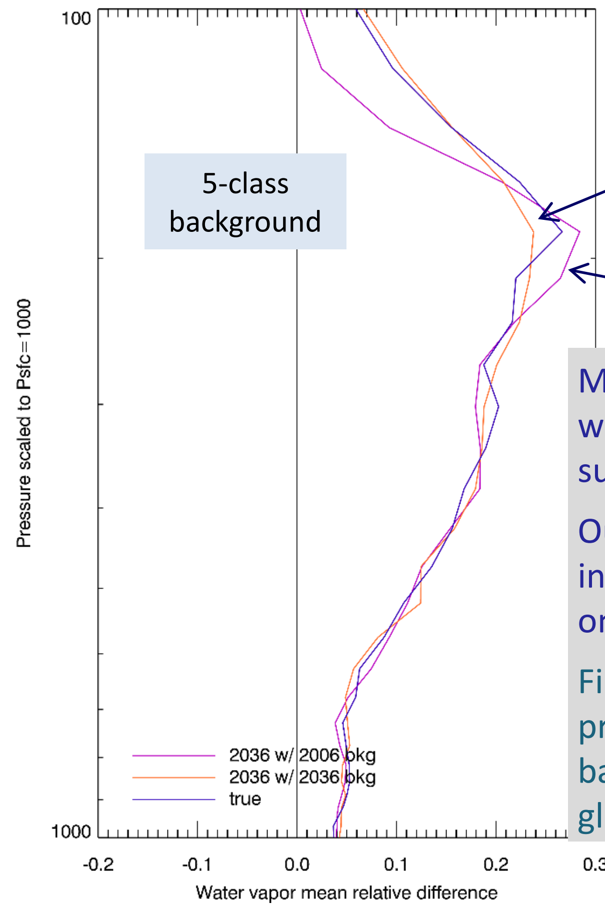
Change fidelity is modestly reduced, relative to results with CrIS+ATMS

Fidelity is about the same with global and pre-classified atmospheric background

Fidelity of 30-year climate change in retrievals: water vapor

CrIS + ATMS





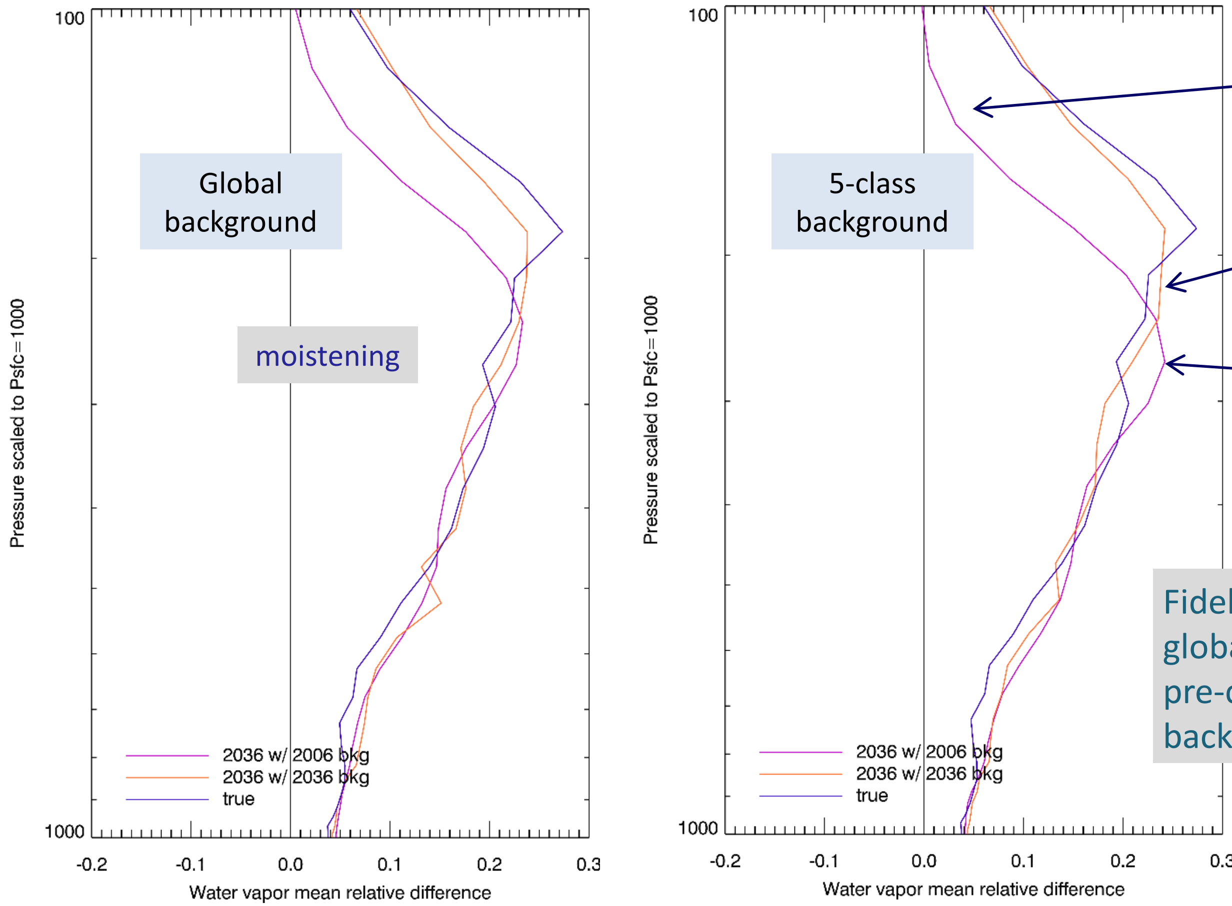
Moistening is represented with high fidelity from surface to about 250 mb

Outdated background increases the distortion only ~100–250 mb

Fidelity is a little better with pre-classified atmospheric background than with global background

Fidelity of 30-year climate change in retrievals: water vapor

ATMS only



Above ~200 mb the outdated background mostly eliminates the moistening MW data have little water vapor signal

dynamic background "ideal case"

static background

Fidelity is a little better with global background than with pre-classified atmospheric background

ATMS-only results simulate what would happen if it were necessary to rely on ATMS-only retrievals *globally*, but global change assessment would rely on CrIS+ATMS retrievals substantially

Current developments and next steps

- Preliminary version of AER ESDR algorithm software was delivered and is being integrated at Sounder SIPS (JPL)
- Parameterization of non-LTE effects for the optimal spectral sampling (OSS) radiative transfer model
  - Using updated datasets
- Developing empirical model of ocean surface emissivity dependence on wind speed for ATMS
  - To improve forward model and background
- Integrating alternatives for cloud mitigation
- Tests and performance analysis with S-NPP measurements