Numerical Weather Prediction

Parametrization of Subgrid Physical Processes

Clouds (4)

Model evaluation: Clouds

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Outline

Today's lecture - two parts:

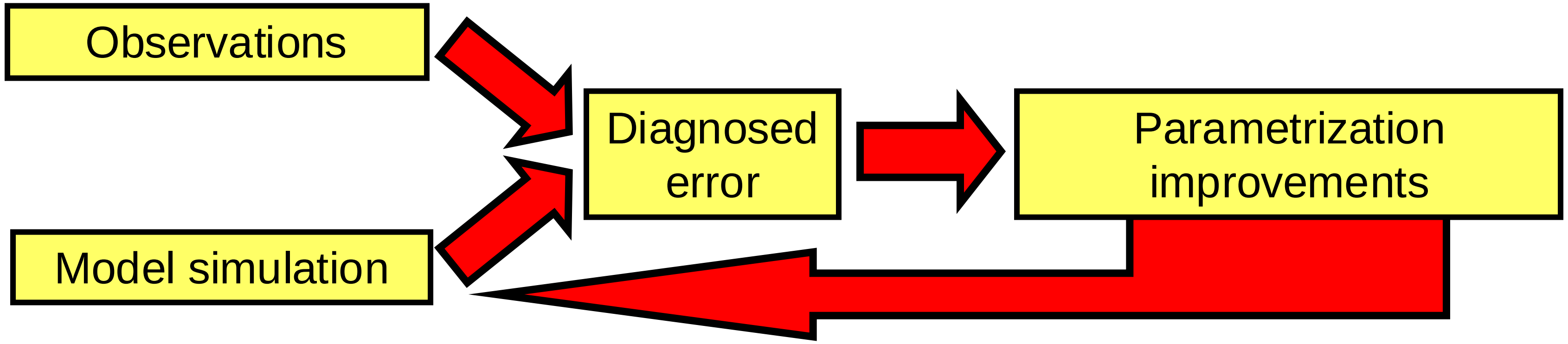
1. Methodologies for diagnosing model errors

2. Evaluation uncertainties and limitations

Model Evaluation

APPROACH:

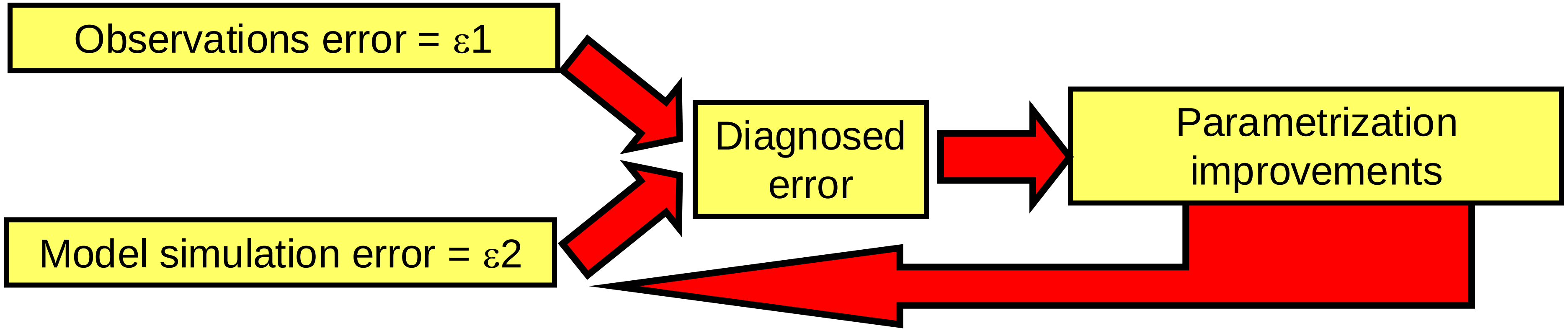
- Evaluate the model against observations
- Use the information concerning apparent errors to improve the model physics, and subsequently the forecasts.



Sounds easy?

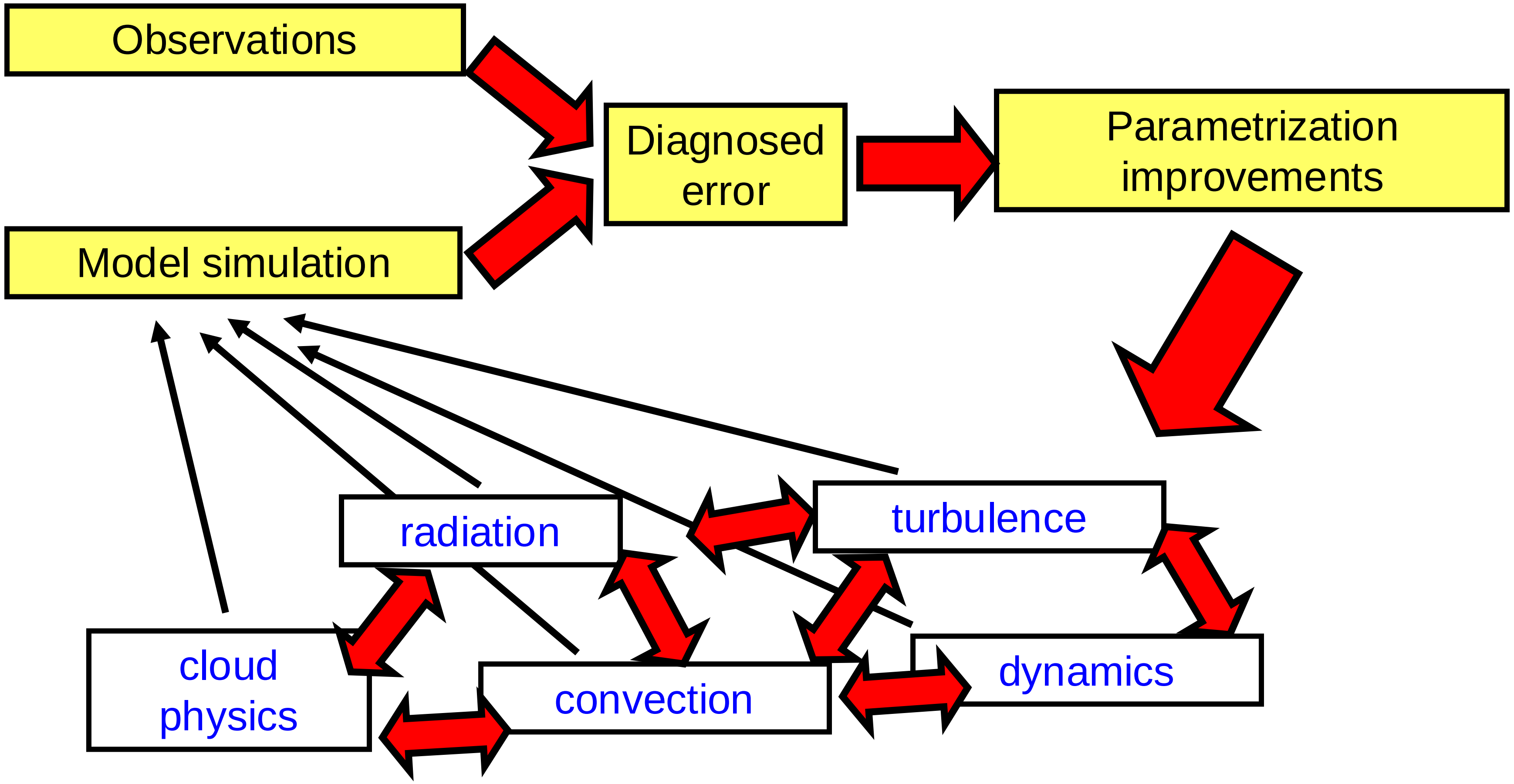
Model Evaluation: The problems

- How much of the ‘error’ derives from observations and how much from the model?

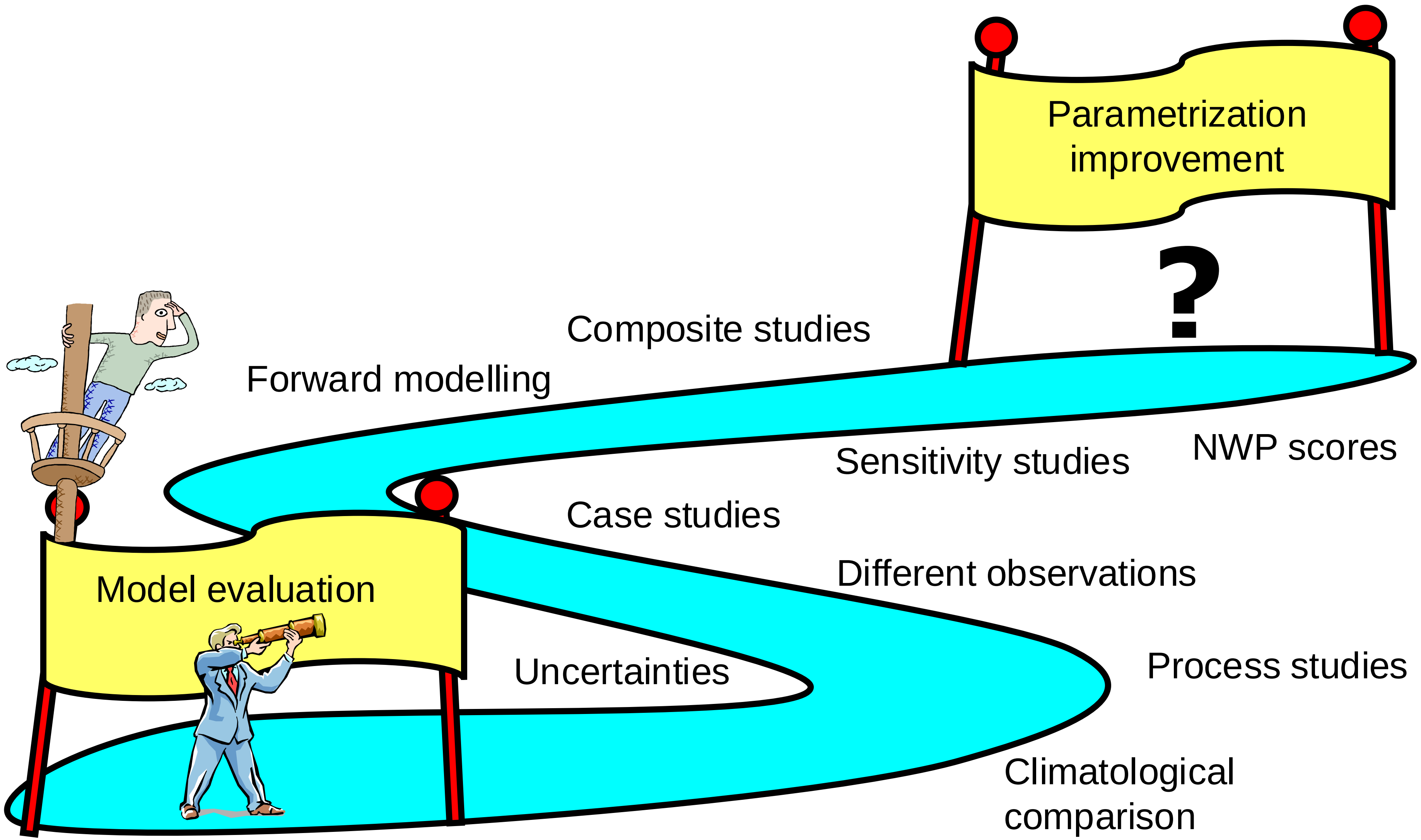


Model Evaluation: The problems

- Which physics is responsible for the error?

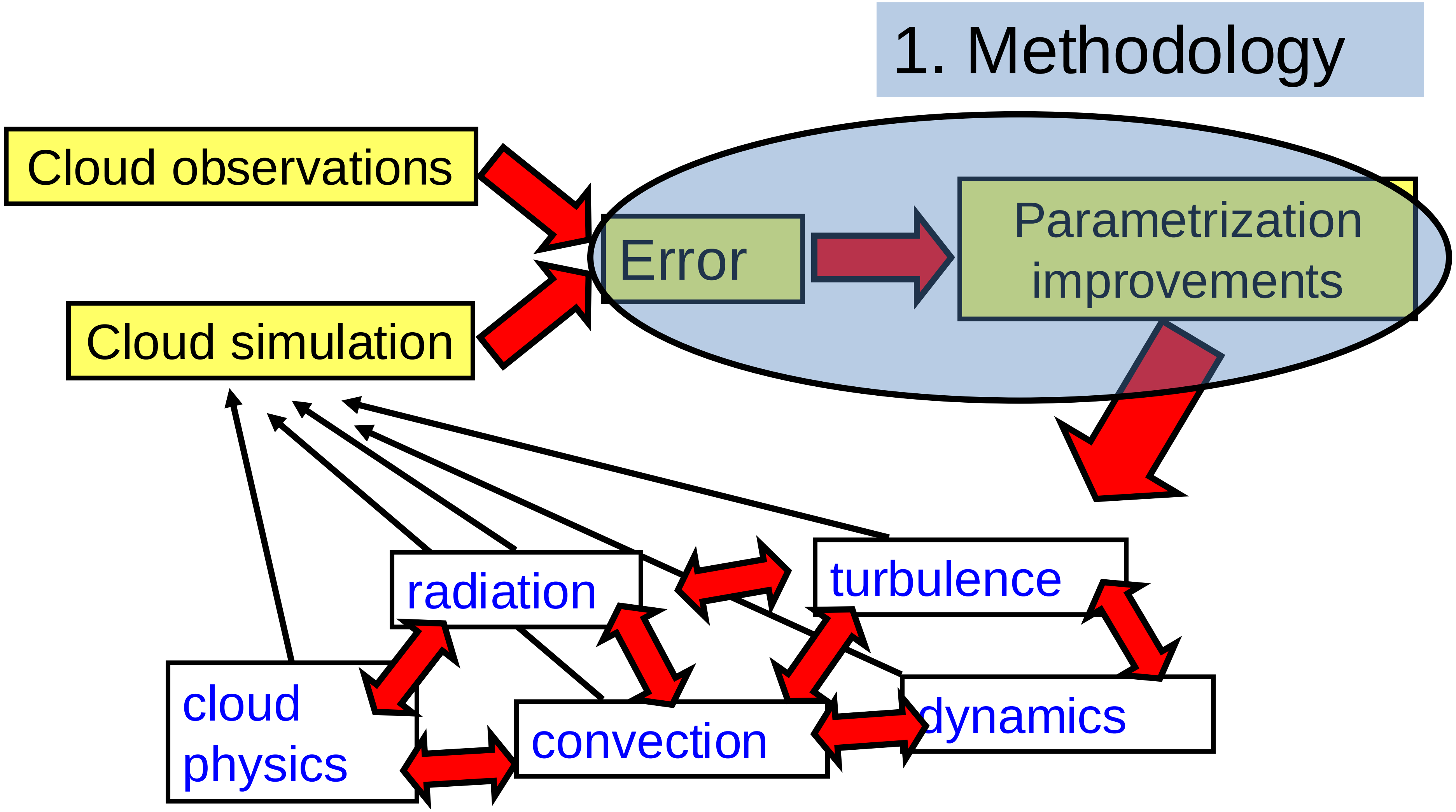


The path to improved parametrization…

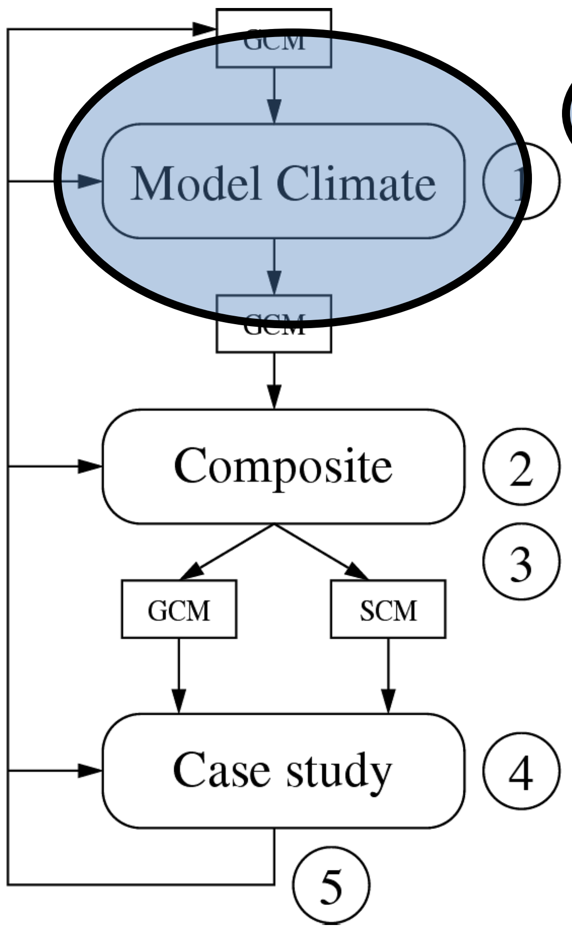


1. **Methodologies for diagnosing errors and improving parametrizations**

Cloud validation: The problems



A strategy for parametrization evaluation



Step 1 : identify major problem areas

Step 2 : identify major problem regimes

Step 3 : identify typical case

Step 4 : identify detailed problems

Step 5 : improve parametrization

From C.Jakob

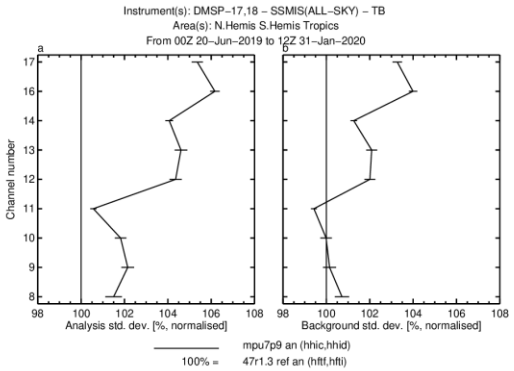
”Model Climate” in this case meaning systematic errors in short, medium or long forecasts:

- Statistical evaluation (e.g. mean, PDFs) aggregated over many forecasts (months to years)
- 12 hour assimilation window, medium-range forecasts, seasonal or multi-year simulations…
- Use wide variety of observational data and NWP(re-)analyses
- E.g. NWP scores, maps of mean errors versus analyses or observations, supersite profiles etc.

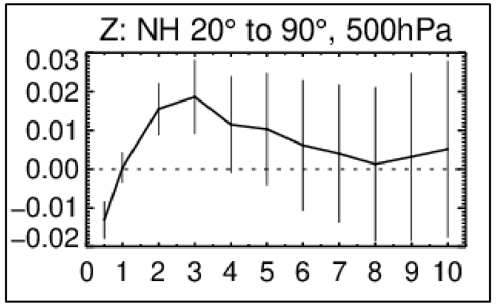
NWP skill scores: assimilation departures and medium-range forecasts

Run the IFS 10 day forecasts over a period of a few months and compare forecasts with analyses or observations to get statistics of systematic errors (bias, variability etc.)

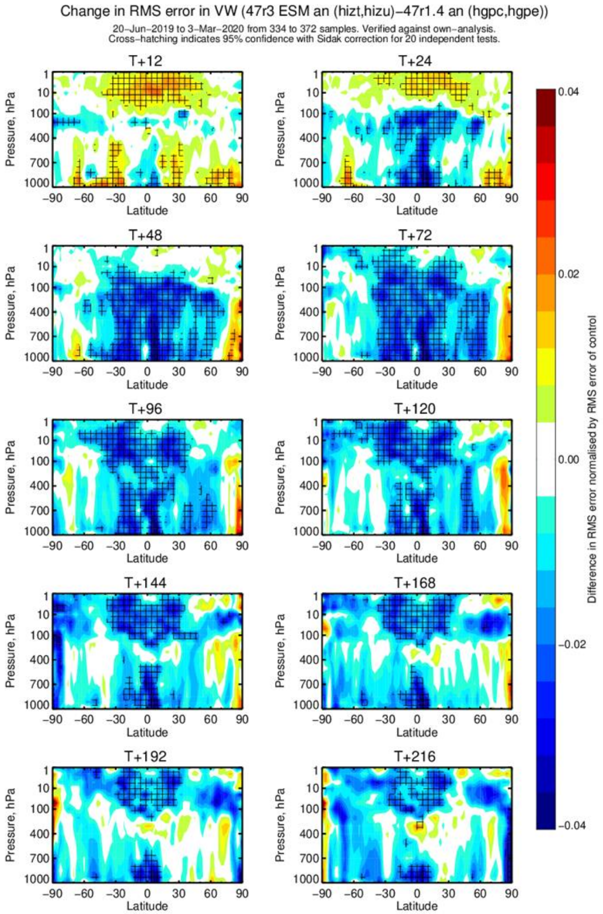
Analysis and first guess departures (12hr assimilation window)
e.g. SSMIS (microwave channels sensitive to moisture, cloud liquid water)



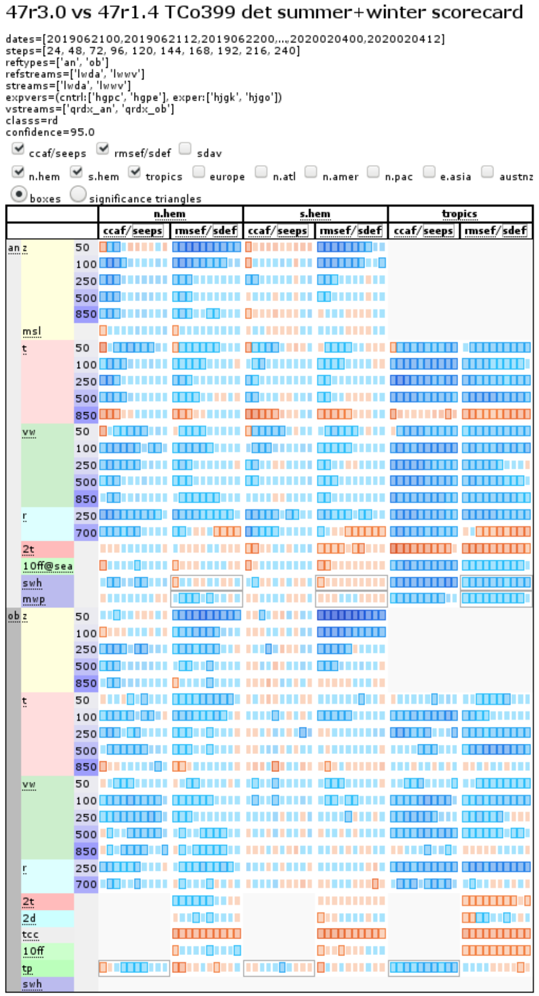
Regional average skill changes with lead time for different quantities and pressure levels



Zonal mean or spatial map of skill changes with lead time for different quantities

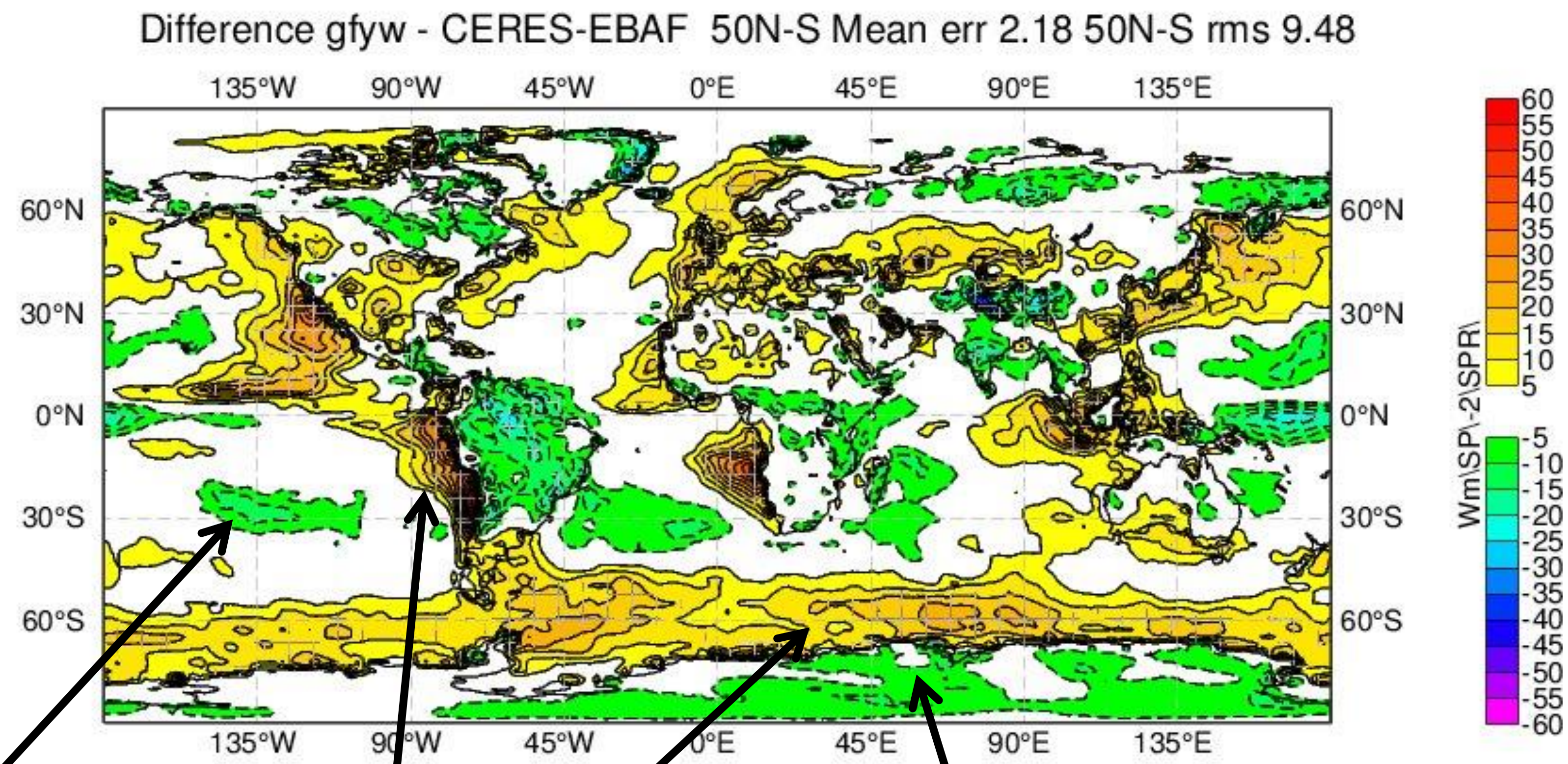


"Scorecard" summary of changes in various skill scores for different regions and parameters



Example: systematic radiation errors in the model (older Cycle of the IFS)

TOA broadband SW radiation shows pattern of systematic error



Too bright,
cloud too reflective

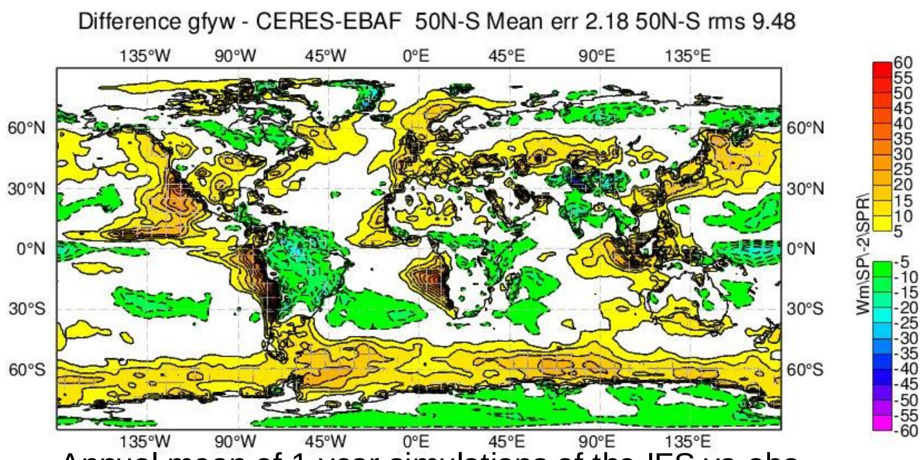
Or maybe surface albedo?

What is causing these errors?

Too dark, clouds don't reflect enough

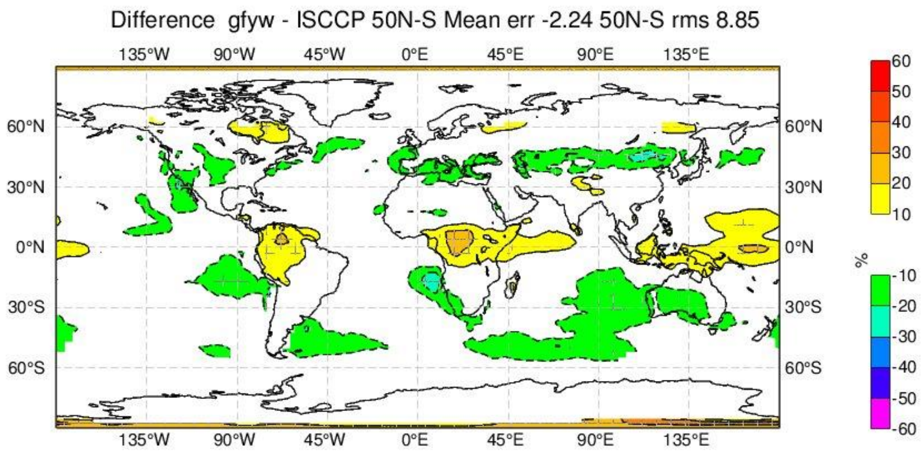
Is cloud bias the reason for the SW radiation bias? Different observation products

SW radiation – CERES-EBAF

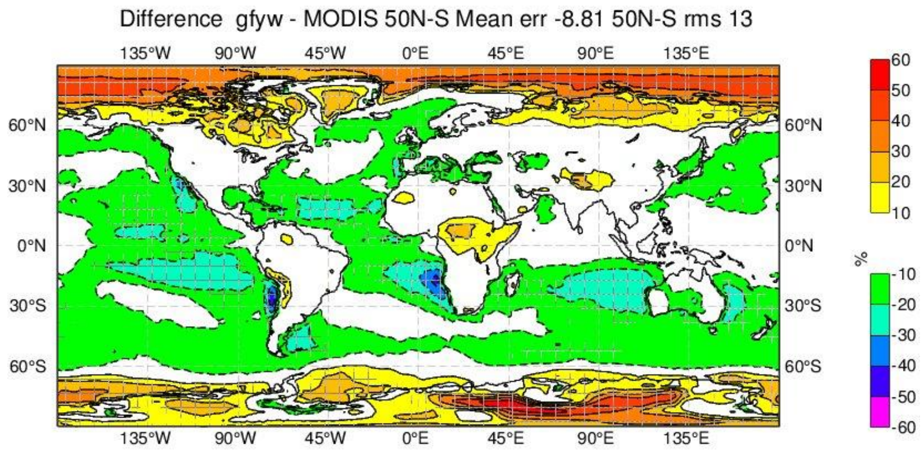


Annual mean of 1 year simulations of the IFS vs obs

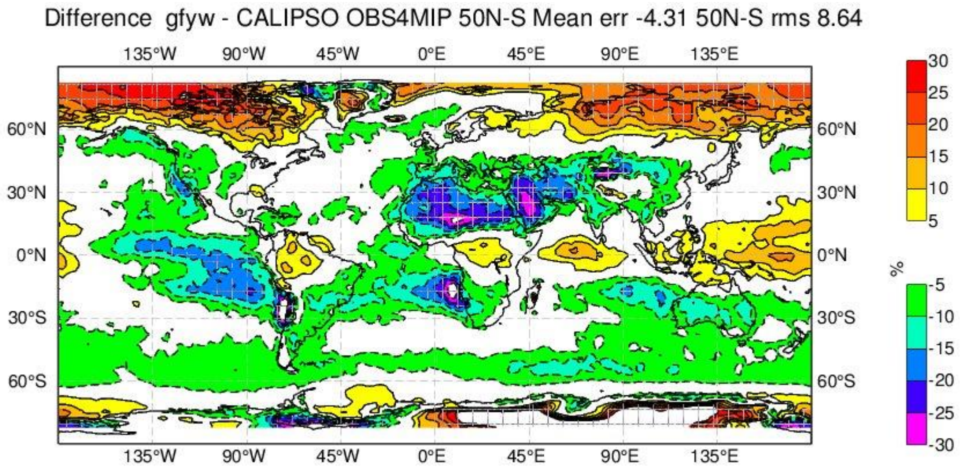
TCC - ISCCP from brightness temperatures



TCC - MODIS

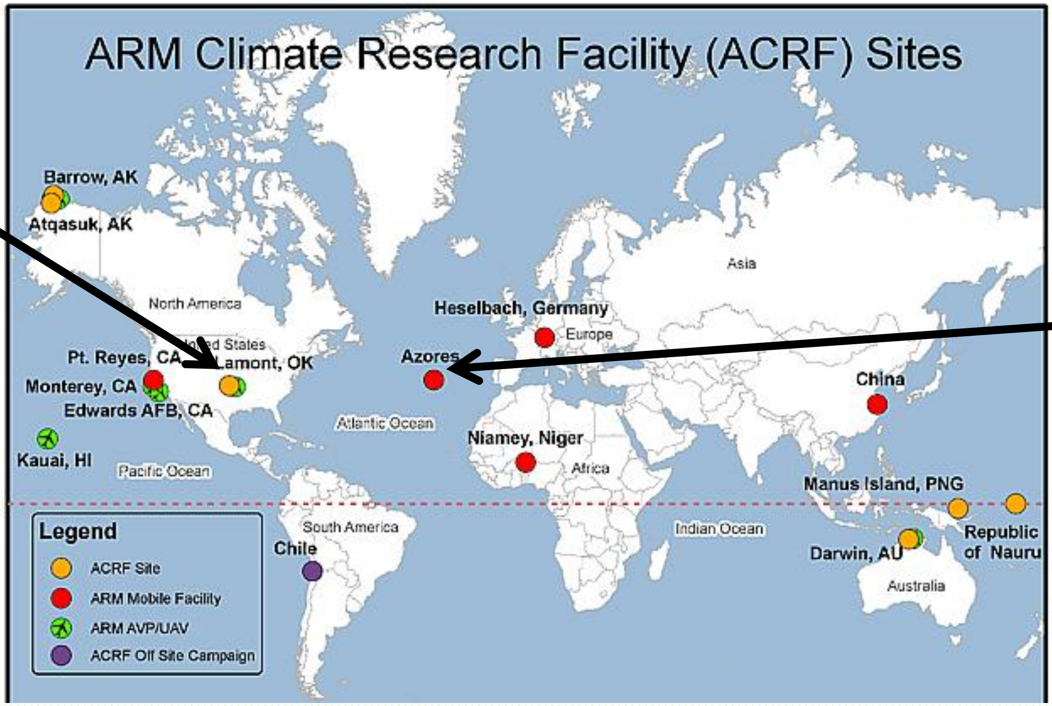


TCC - CALIPSO from lidar backscatter



Different observational datasets can have different uncertainties (their own systematic "errors")

Compositing of long-term data records



Global ARM and Cloudnet observation sites

cloudnet.fmi.fi
www.arm.gov

Chilbolton, UK
51.1445 North 1.4370 West
Operated by RCRU, RAL.

SIRTA, Palaiseau (Paris), France
48.713 North 2.204 Est
Operated by CNRS/IPSL

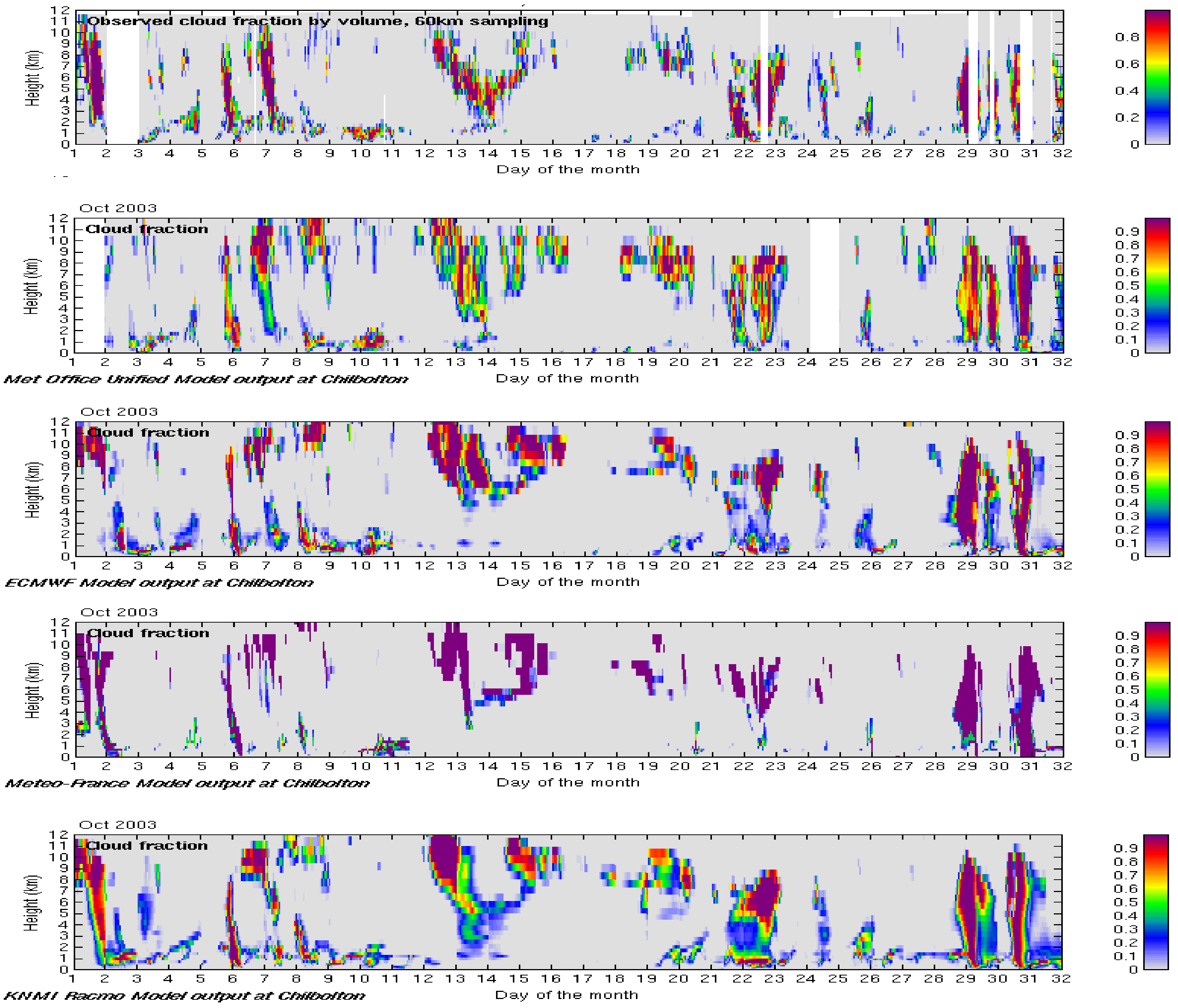
Cabauw, The Netherlands
51.971 North 4.927 Est
Operated by KNMI

Cloud fraction

Chilbolton Observations

Example from a comparison performed with models in 2003

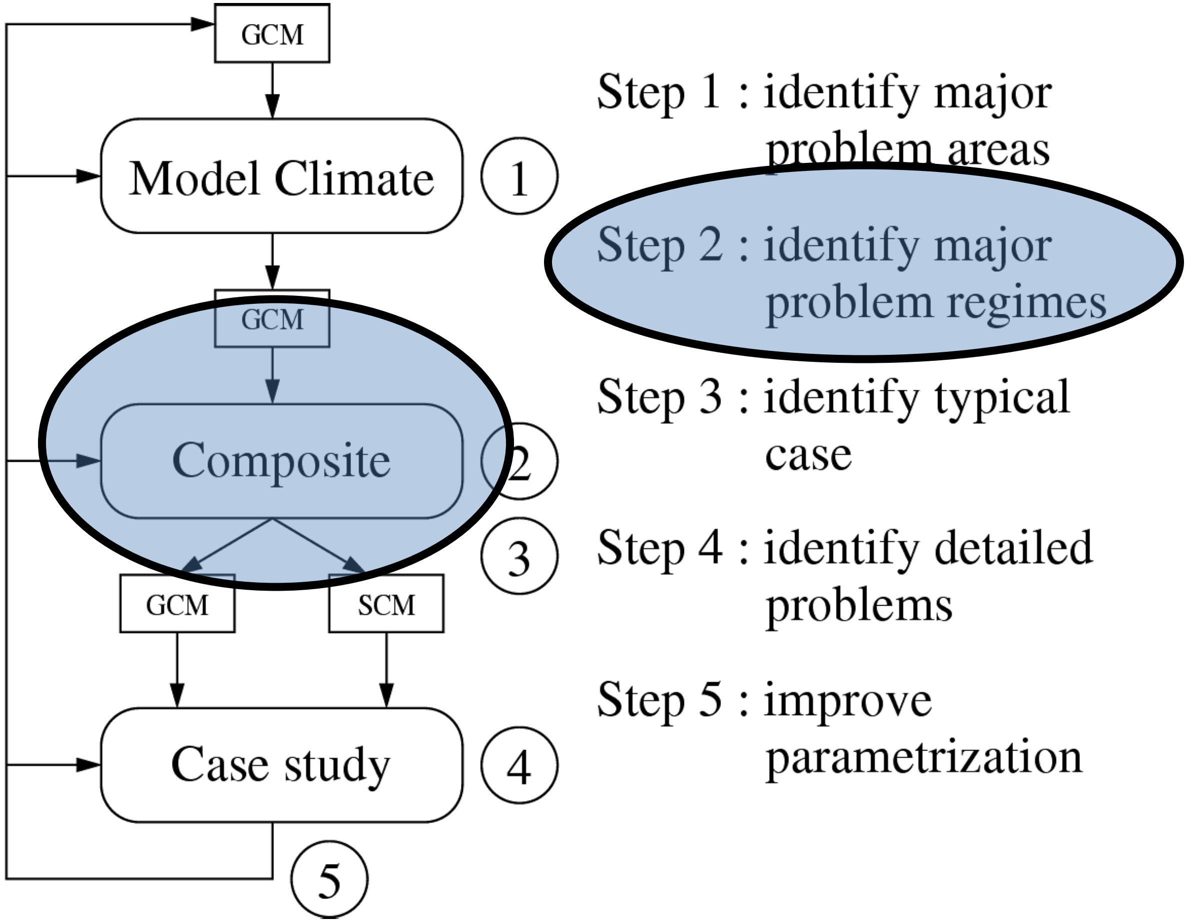
Same timeseries from short-range forecasts (12-36hr)
 from various NWP models



Identifying major problem areas

- Need to evaluate the model from many different view points to identify which problems are associated with cloud.
- Evaluate the statistics of the model (mean, pdf,…) - long timeseries of data.
- Use of long forecasts (climate) and short forecasts (to avoid climate interactions and feedbacks).
- Use of data assimilation increments, initial tendencies.

A strategy for cloud parametrization evaluation



C.Jakob

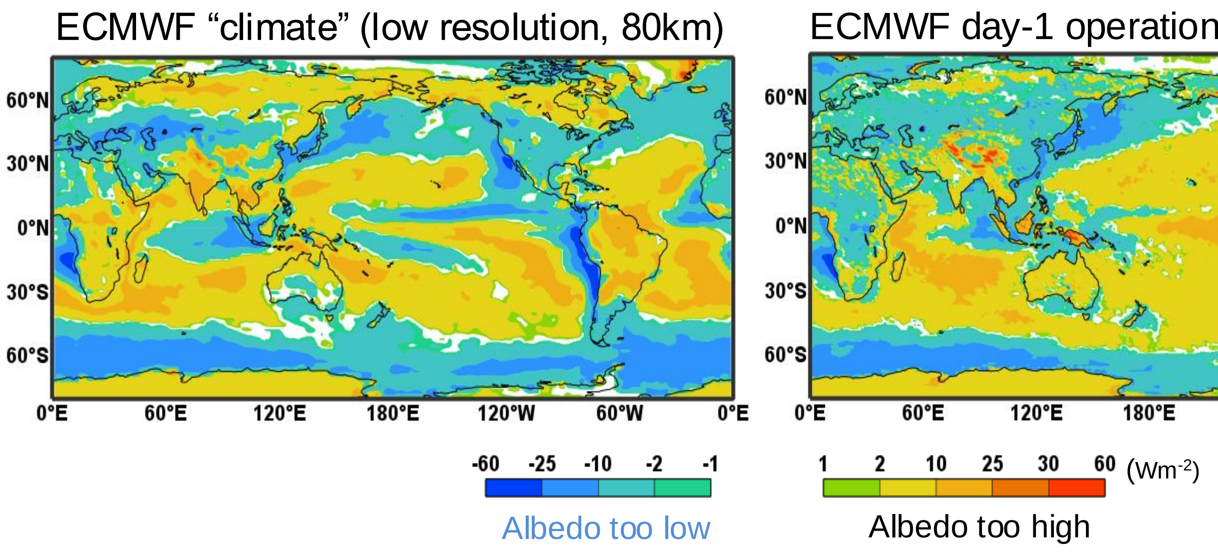
Geographical compositing - shortwave radiation bias

Similar systematic errors found across models, in climate and in short-range forecasts

Global model outgoing shortwave radiation systematic errors

Similarities across models, across resolutions, across timescales

Annual mean top-of-atmosphere SW radiation difference from CERES-EBAF



We can use observations and short-range NWP forecasts/DA system

…to understand and reduce regime-dependent systematic errors

…to improve global models across time and space scales

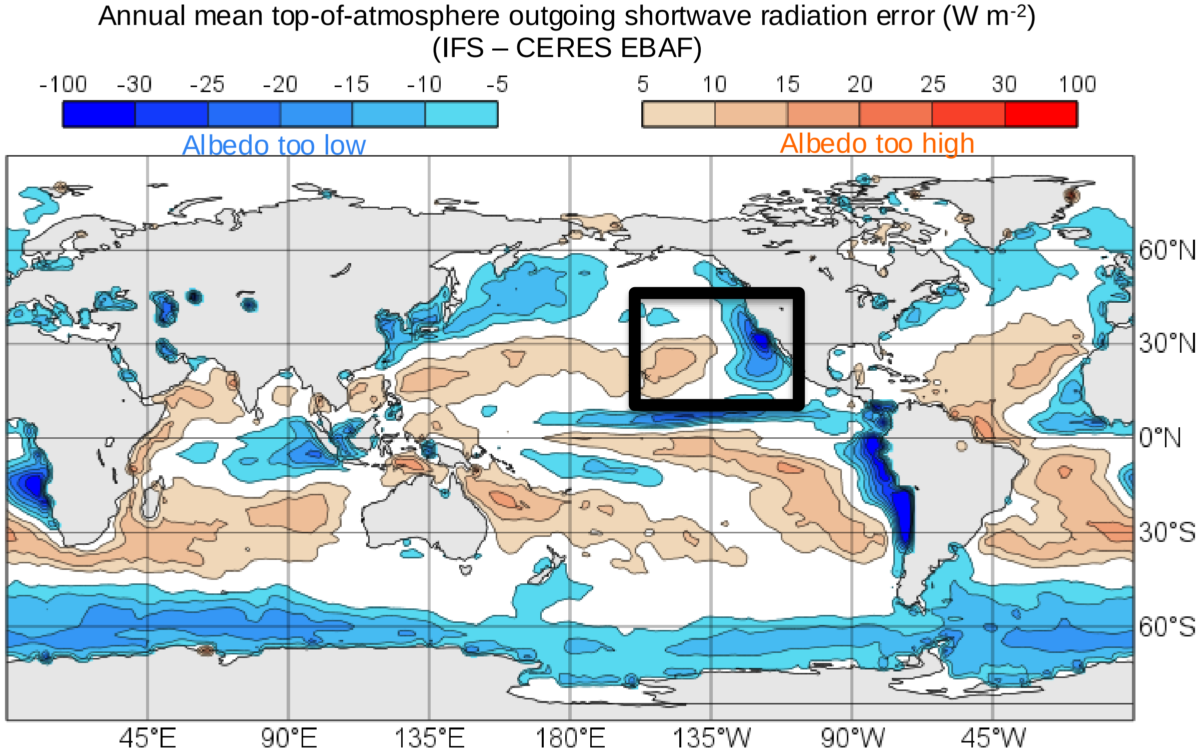
Forbes et al. 2016

Shortwave radiation bias

Top-of-atmosphere SW radiation bias focus on boundary layer cloud – marine cumulus-stratocumulus

Annual mean outgoing shortwave radiation bias (IFS minus CERES-EBAF)

Subtropical marine stratocumulus to cumulus



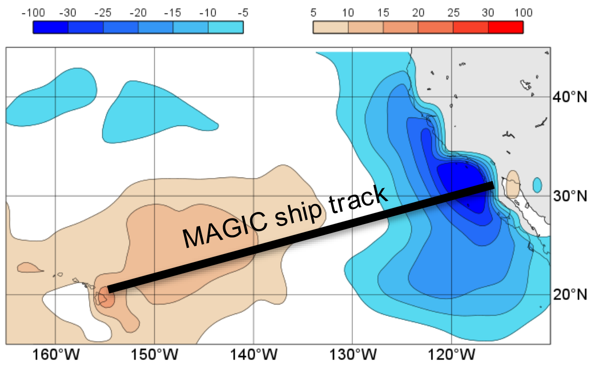
Geographical compositing - shortwave radiation bias

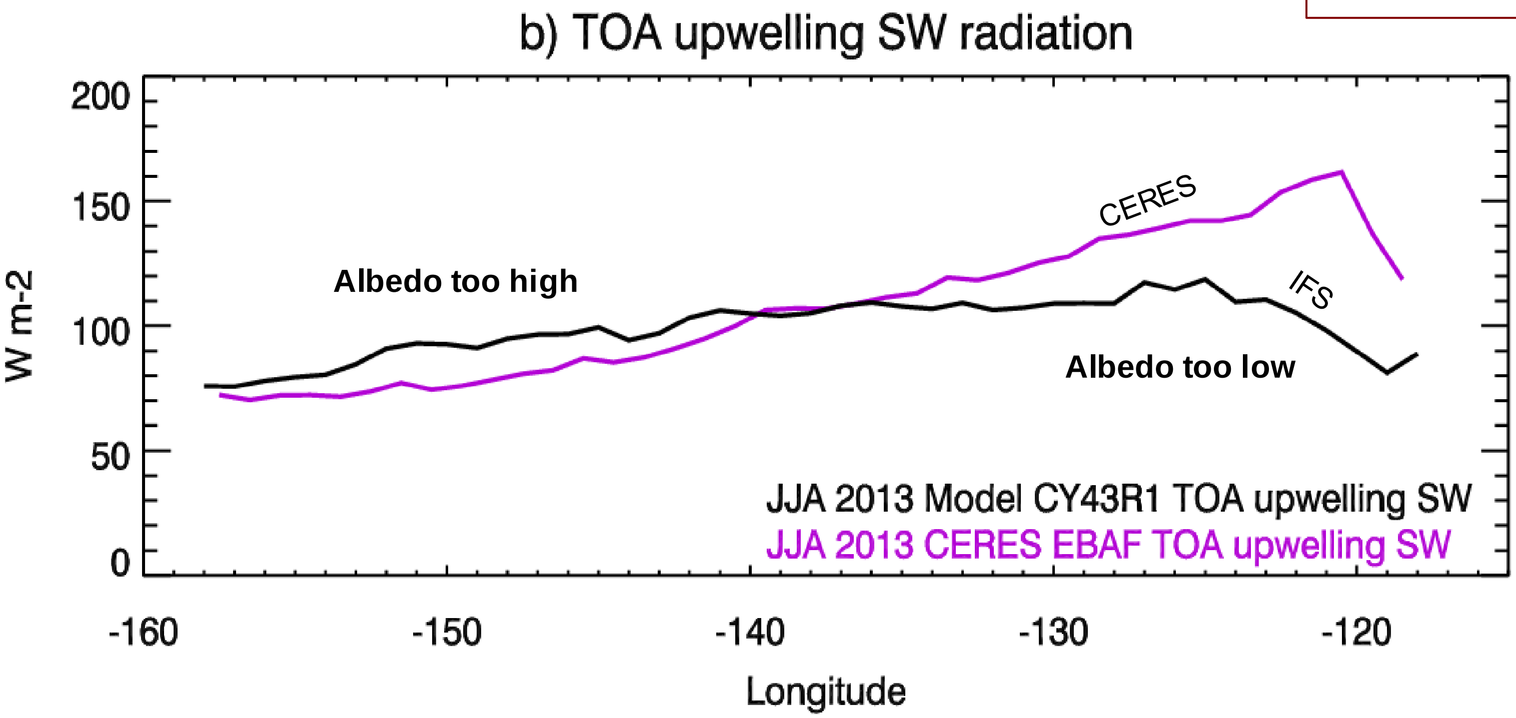
Understanding the subtropical marine cloud/shortwave radiation bias

MAGIC – ASR/ARM observational ship campaign

IFS albedo too high in trades

IFS albedo too low in stratocumulus



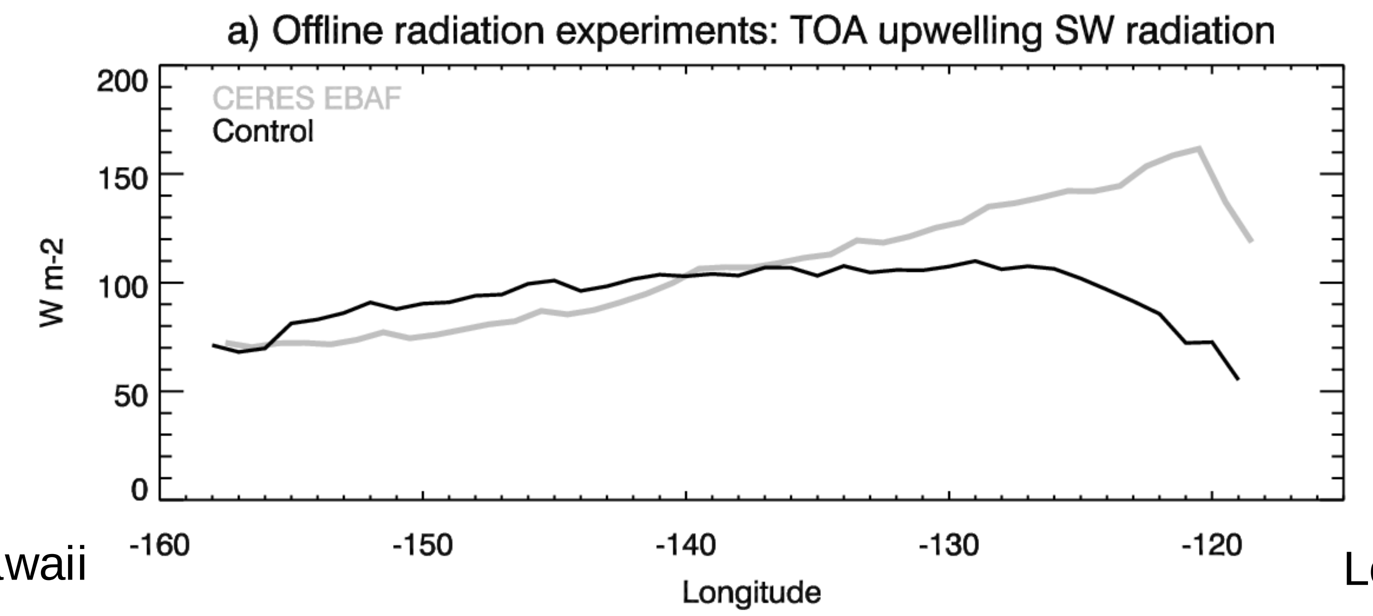


Ahlgrimm et al. (2018, JAMES)

Understanding the shortwave radiation bias

Ahlgrimm et al. (2018, JAMES)

Hawaii



Los Angeles

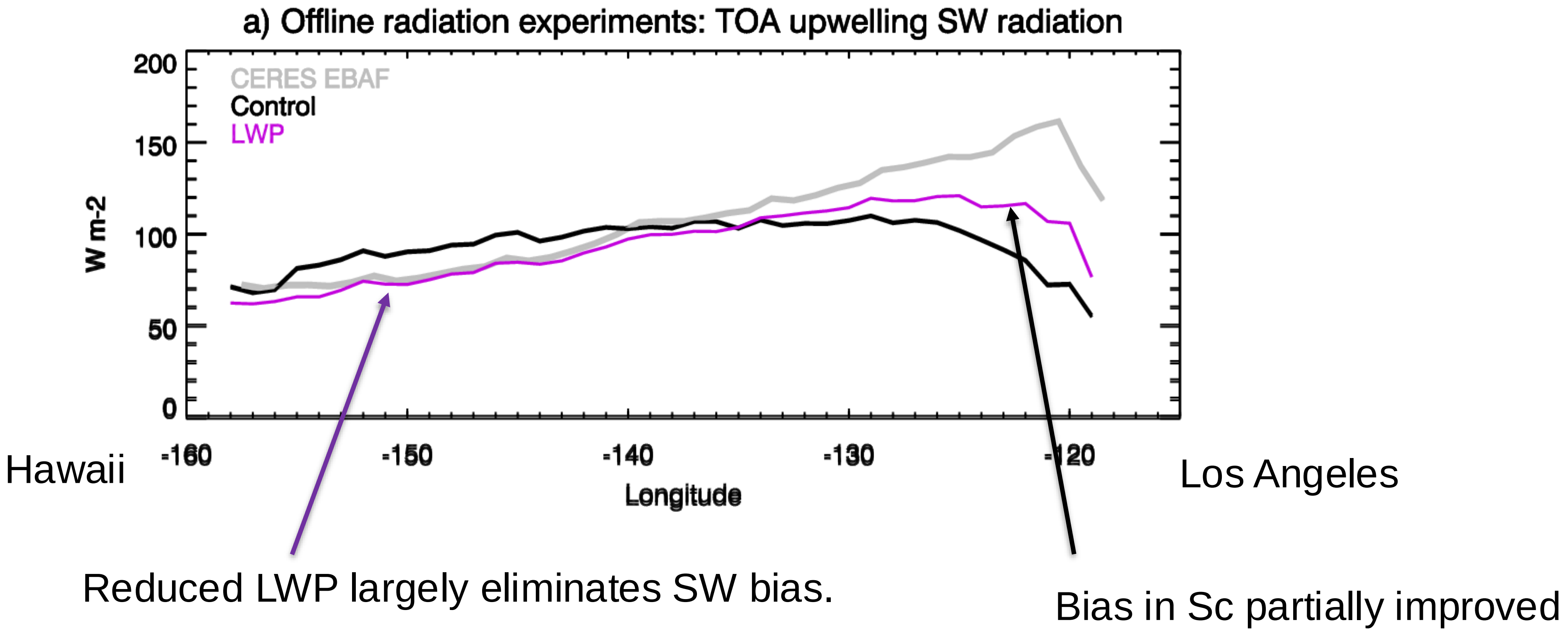
→ use the ship observations and satellite data along the track to constrain different aspects of the cloud field in an offline radiation calculation

Understanding the shortwave radiation bias

i) LWP bias primary cause of SW error in Trades

Ahlgrimm et al. (2018, JAMES)

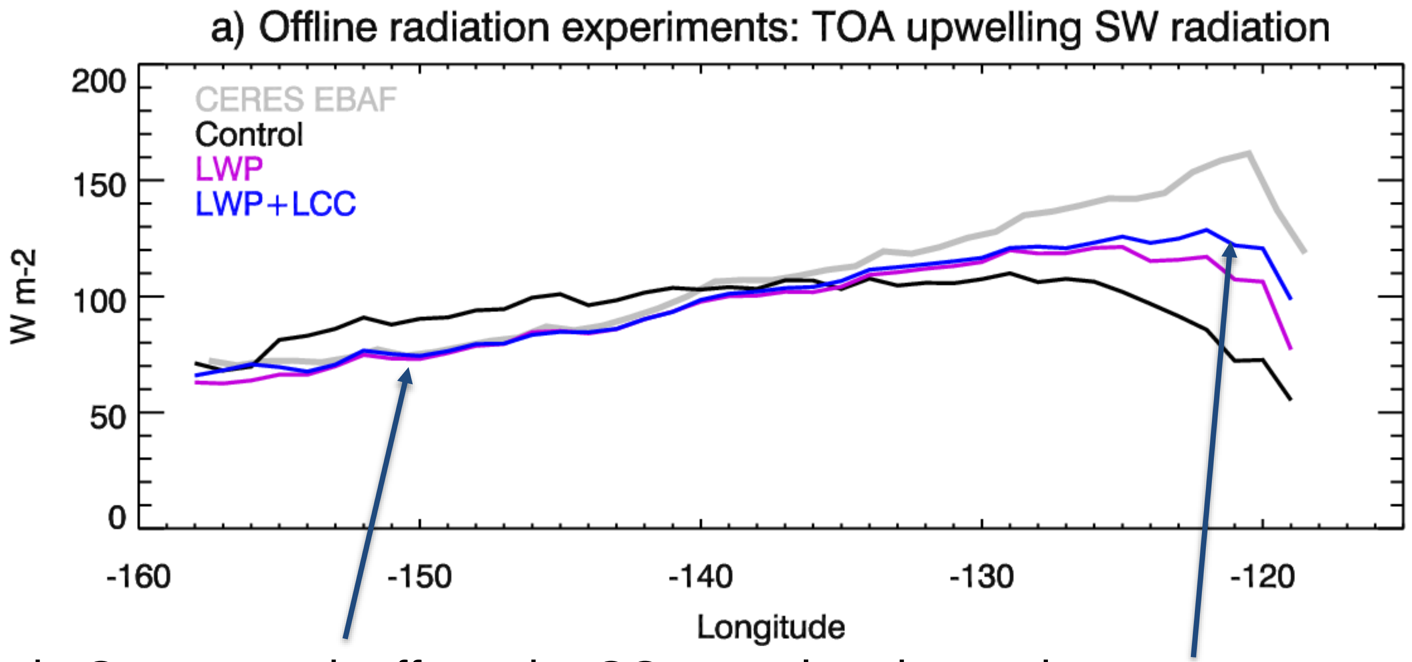
Experiment: force LWP to be consistent with observed values



Understanding the shortwave radiation bias

ii) Cloud cover and LWP both contribute to bias in stratocumulus albedo

Experiment: force total cloud cover towards observed values (in addition to LWP)



Trade Cu not much affected – CC was already good.

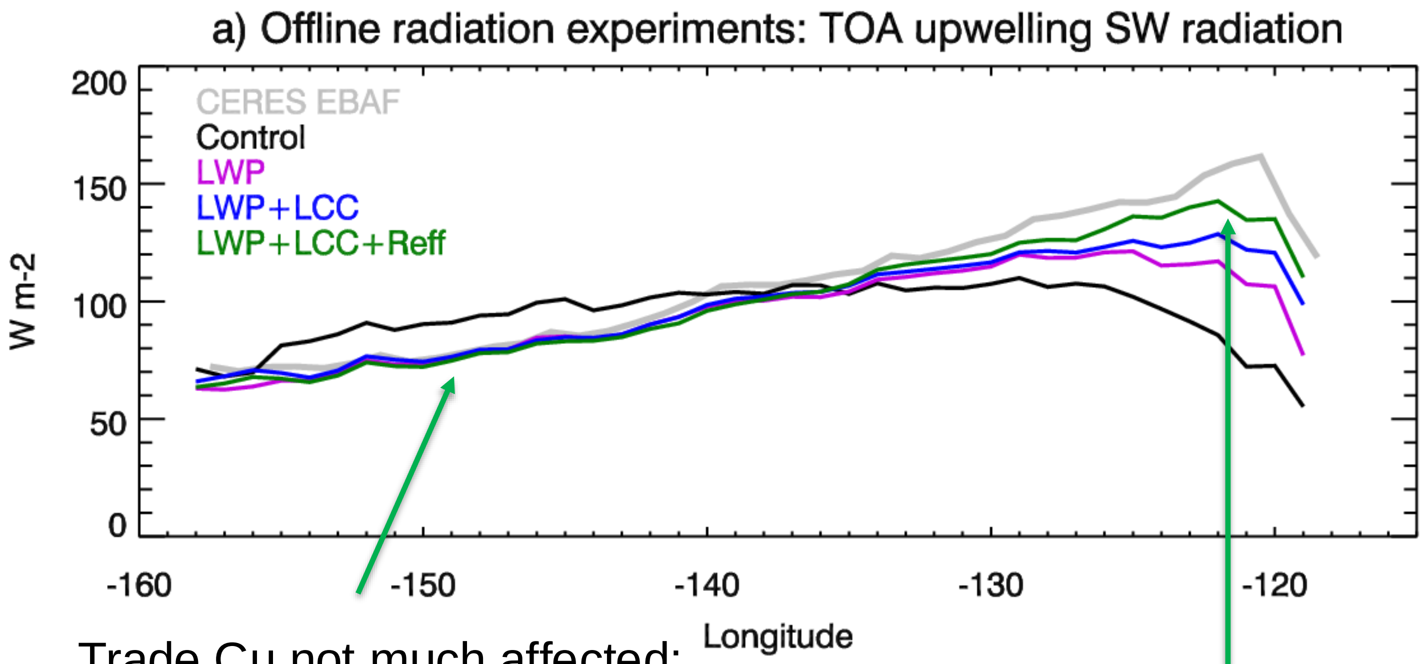
Additional improvement in Sc region!

Ahlgrimm et al. (2018, JAMES)

Understanding the shortwave radiation bias

iii) Effective radius gradient along track enhances albedo in Sc

Experiment: use CDNC derived from ship-based observations in model calculation of effective radius



Trade Cu not much affected:

- new and old R_{eff} differ less
- smaller cloud fraction means less impact

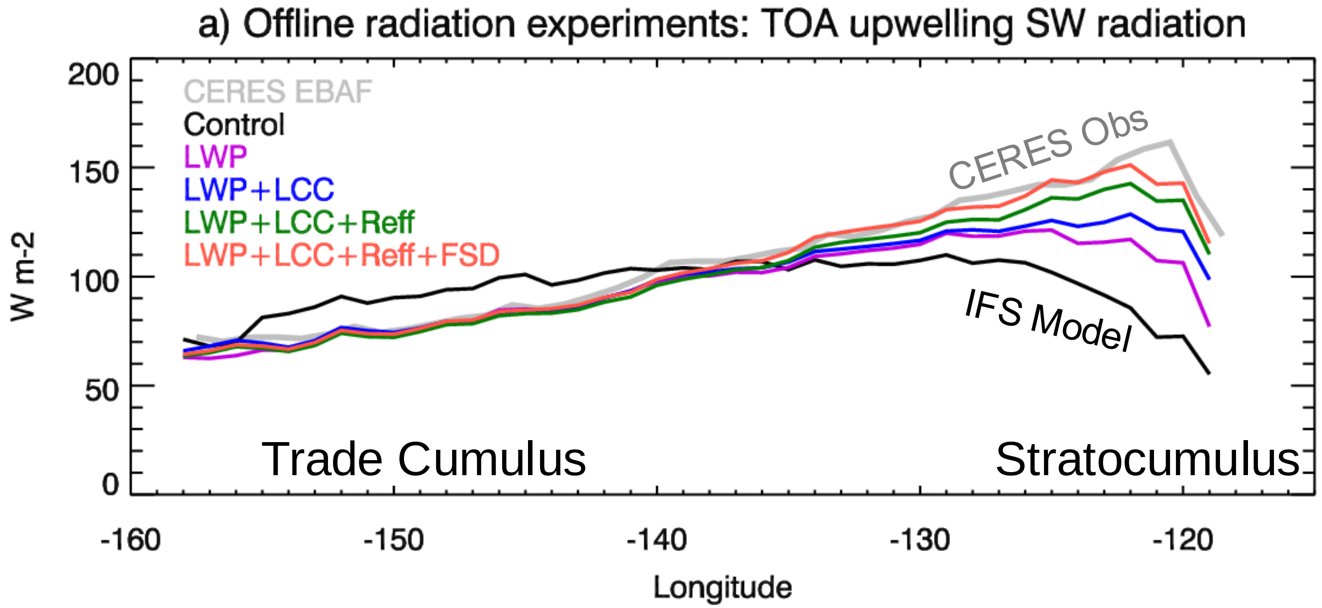
Additional improvement in Sc region!

Ahlgrimm et al. (2018, JAMES)

Understanding the shortwave radiation bias

iv) Subgrid variability of liquid water content enhances stratocumulus albedo

Experiment: use in-cloud LWC variability fractional standard deviation (FSD) from satellite study



Carefully matched observation evaluation using many different satellite and ground-based instruments can disentangle the multiple sources of cloud error and explain the observed subtropical marine shortwave radiation systematic errors in the IFS!

Helps to focus and prioritise where further developments should go to improve the model,
….but still need to improve the parametrizations!

Ahlgrimm et al. (2018, JAMES)

Cloud evaluation methodologies summary

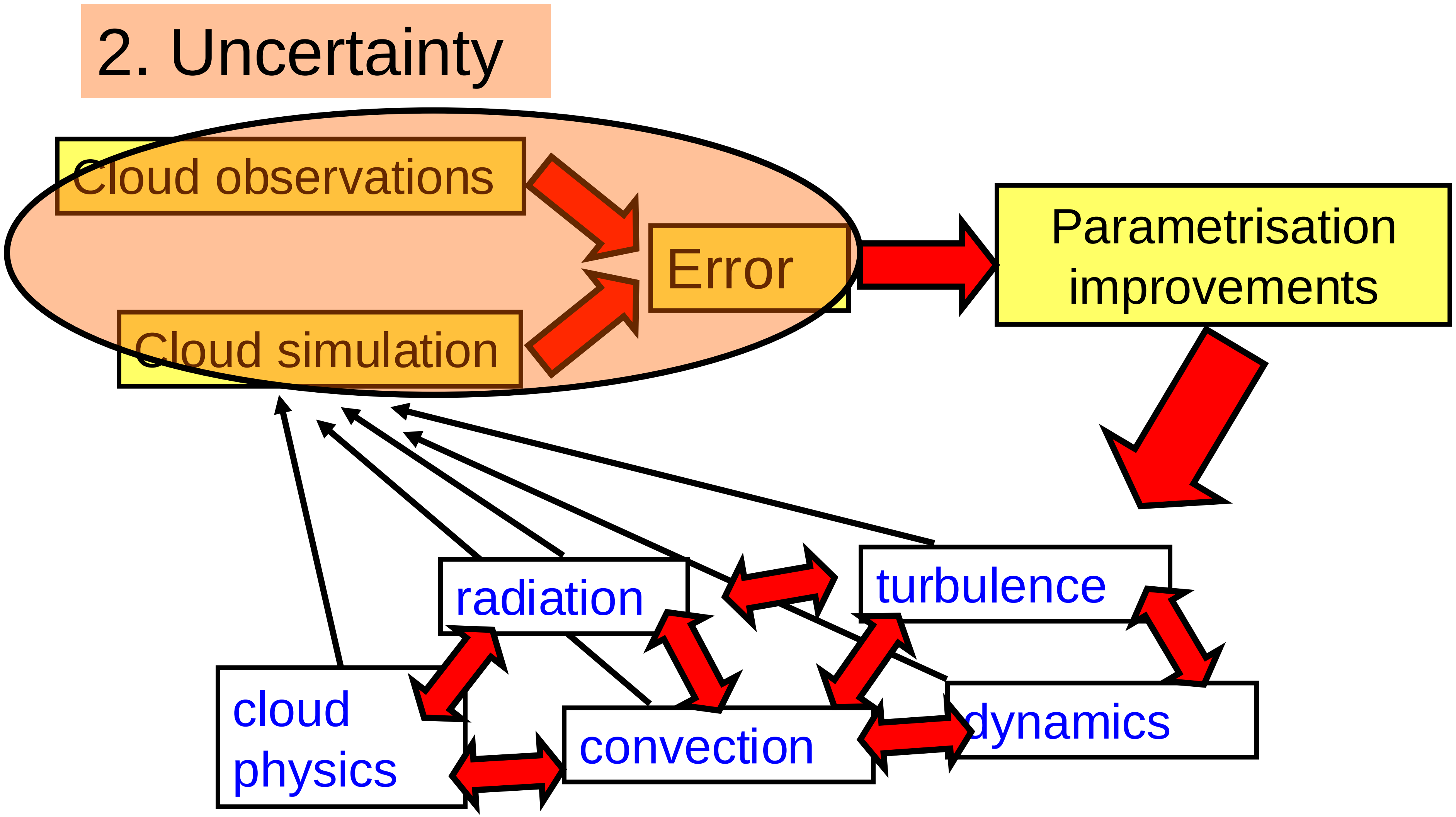
- Statistical evaluation:
  - Systematic regime-dependent errors
  - But which physics is responsible for the errors? Non-linear interactions.
  - Long term response vs. transient response. Look at different forecast lead times.

- Isolating regimes:
  - Composites and focus on geographical regions.

- Case studies
  - Detailed studies with Single Column Models, Cloud Resolving Models, NWP models
  - Easier to explore parameter space.
  - Are they representative? Do changes translate into global skill?

2. Comparing model and obs of cloud and precipitation: Uncertainty and limitations

Cloud validation: The problems



Defining a cloud

- What is a cloud? It's all (or mostly) electromagnetic radiation…
  - sky-view cloud cover (observer)
  - brightness temperature (passive satellite, different frequencies)
  - reflectivity (radar)
  - backscatter (lidar)
- How accurately can we measure this quantity?
  - observation error/uncertainty
  - conditional sampling (e.g. viewing geometry, instrument shut off)
  - sensitivity thresholds, signal attenuation, "noise" from other sources (insects, aerosol)
- How well does this quantity compare to variables predicted by the model?
  - retrieval of the model quantity from the observations, errors?
  - forward model the observed quantity, errors?

Space-borne active remote sensing: A-Train

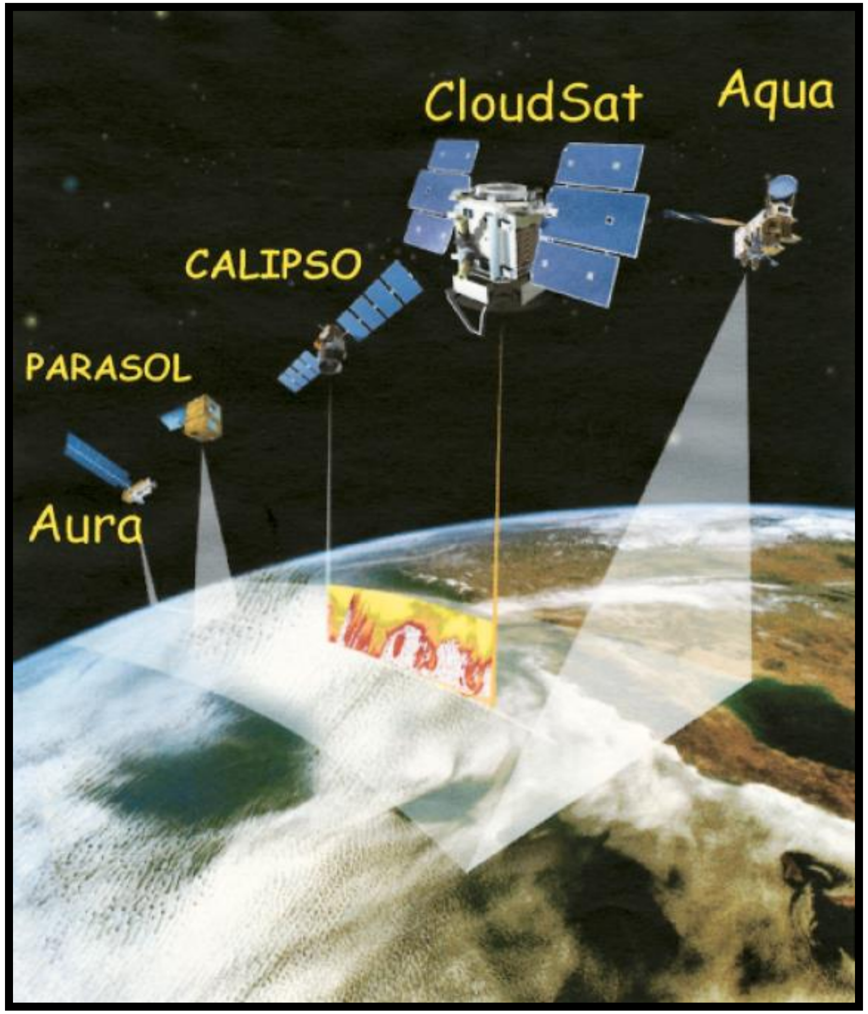
- CloudSat and CALIPSO have active radar and lidar to provide information on the vertical profile of clouds and precipitation. (Launched April 2006)

- Approaches to model validation:

  Model → Obs parameters (forward operator/model)

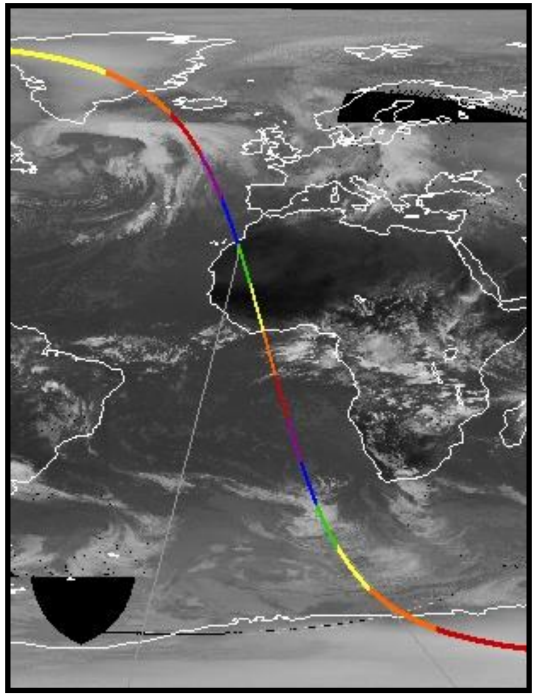
  Obs → Model parameters (retrieval)

- Spatial/temporal mismatch



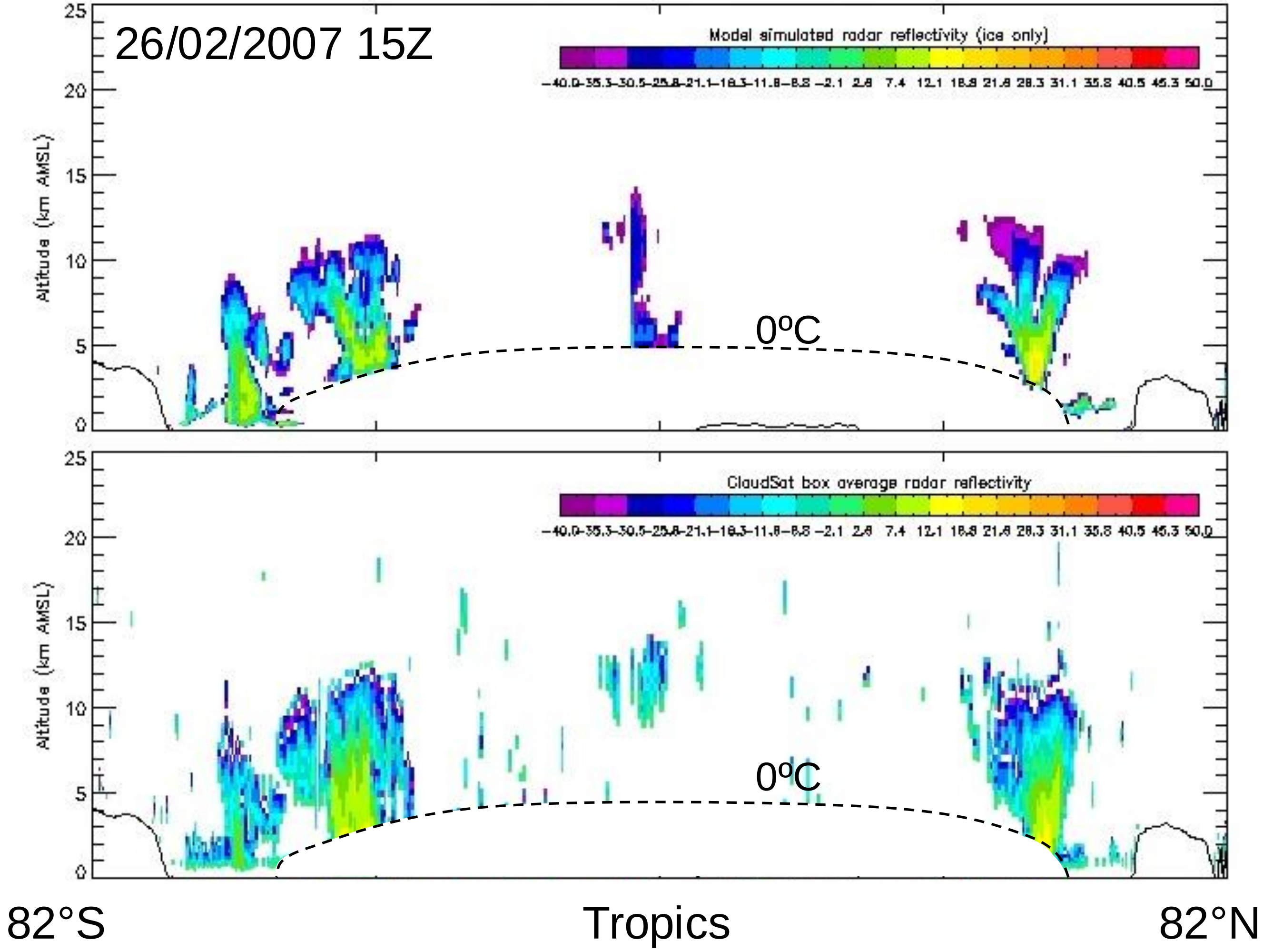
Compare model with observed parameters: Radar reflectivity

Example section of a CloudSat orbit
26th February 2007 15 UTC



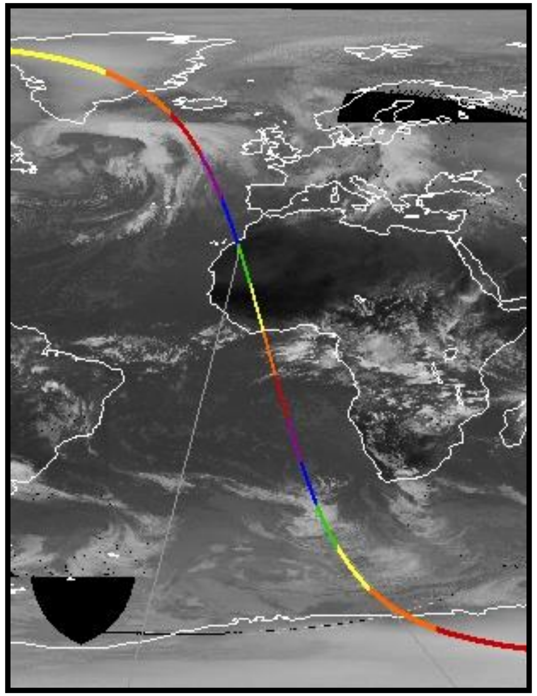
Simulated radar reflectivity from the model for ice only (< 0°C)

Observed radar reflectivity from CloudSat (ice + rain)



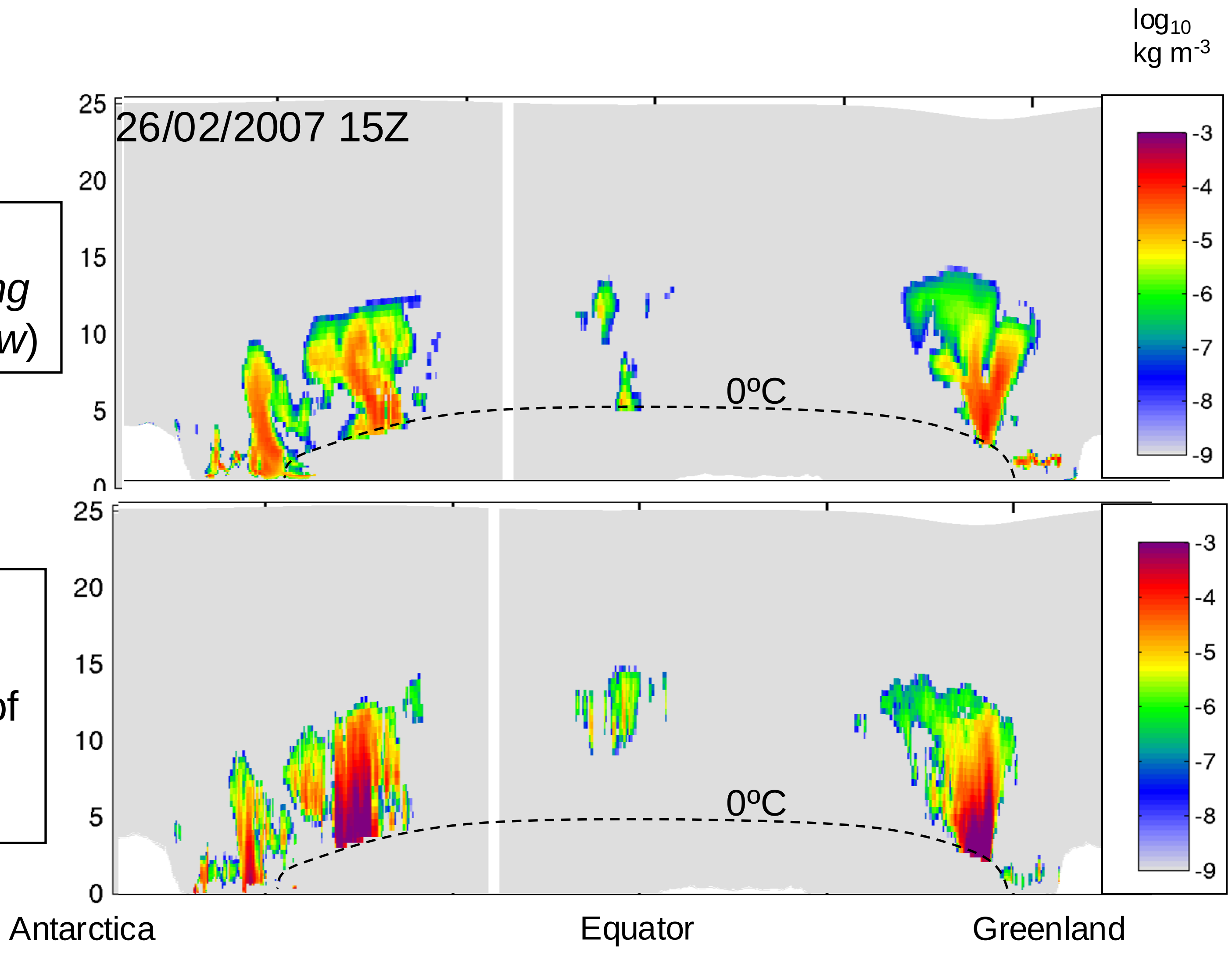
Compare model parameters with equivalent derived from observations: Ice Amount

Example section of a CloudSat orbit
26th February 2007 15 UTC



Model ice water content (*excluding precipitating snow*)

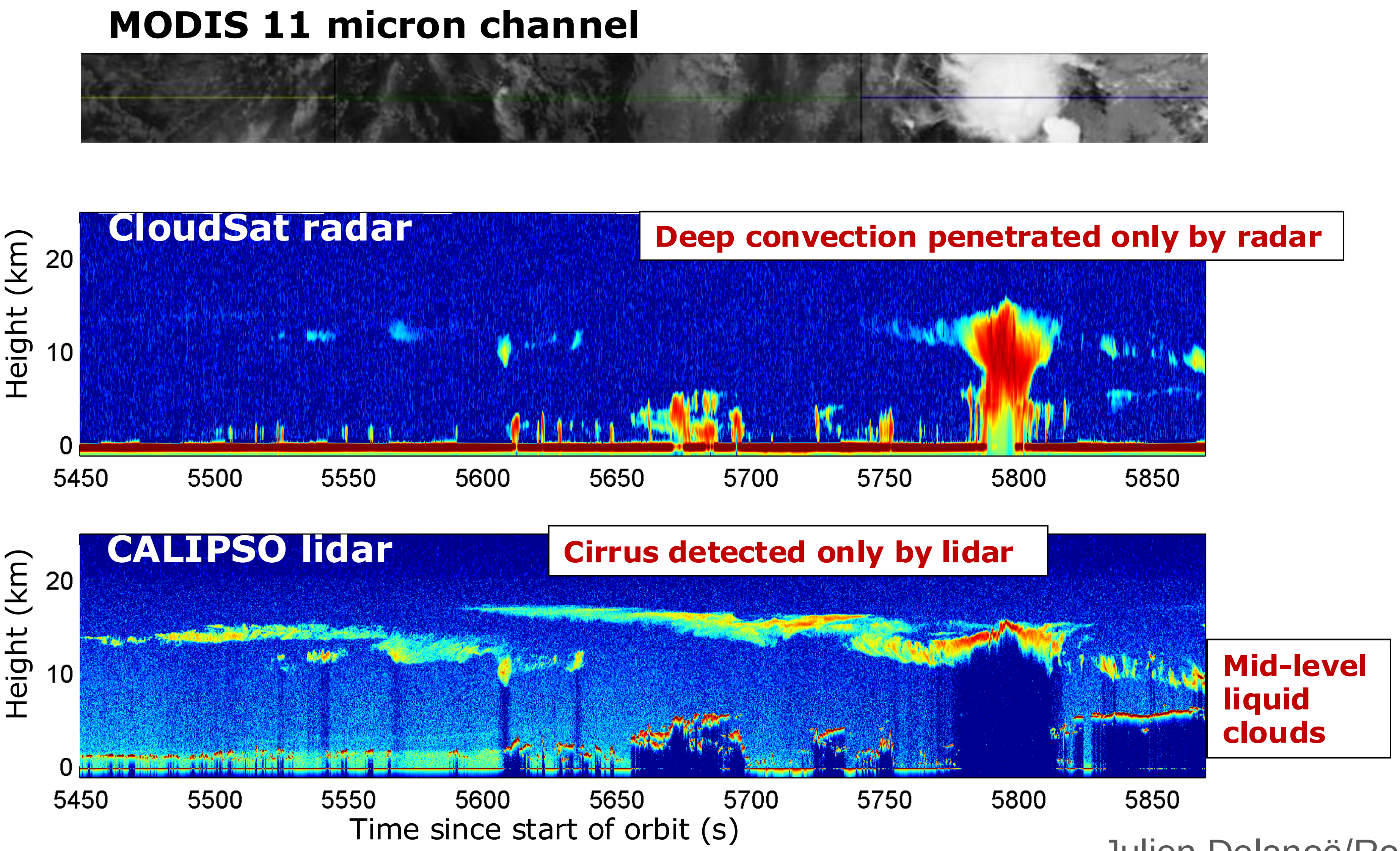
Ice water content derived from a 1DVAR retrieval of CloudSat/ CALIPSO/Aqua



(Delanöe and Hogan (2007), Reading Univ., UK)

Complementary observations – radar and lidar

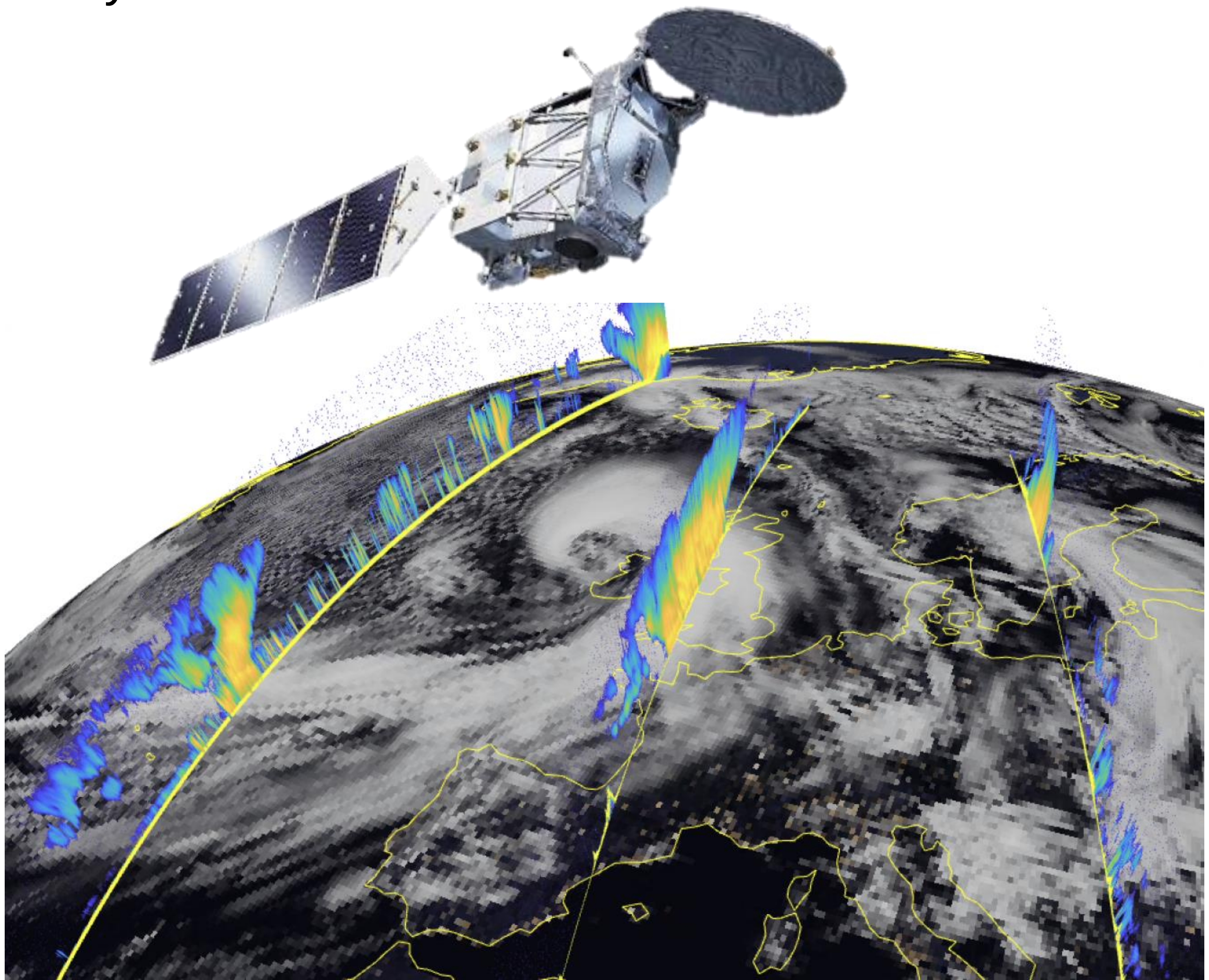
Example of mid-Pacific convection



Julien Delanoë/Robin Hogan

EarthCARE

- satellite with radar, lidar, radiometers
- aerosols, clouds and precipitation
- launched in May 2024



Summary

- **Different approaches** to verification (climate statistics, case studies, composites), different techniques (model-to-obs, obs-to-model) and a **range of observations** are required to validate and improve cloud parametrizations.

- Need to **understand the limitations** of observational data. Ensure we are **comparing like with like**. Use complementary observations - **synergy.**

- The model developer **needs to understand physical processes** to improve the model. Requires, theory and modelling and novel techniques for extracting **process-oriented information** from observations.

The path to improved cloud parametrization…