Assimilating clouds in perfect global models (or trying to - a work in slow progress)

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Assimilating observations of clouds in global models

Current observations of clouds and rain don't affect cloud or convection variables directly
(Clouds aren't part of the "control vector")

Could direct constraints on clouds improve analyses? forecasts?

How would that work?

Clouds are represented by *prognostic* variables that co-vary with other state variables (esp. temperature and humidity)

The link is the "cloud scheme;" balance between
Turbulence, convection, large-scale uplift vs.
Mixing, microphysics, large-scale descent

Some physics is sub-grid and/or diagnostic, others resolved

Data assimilation formally merges models and observations

An assimilation system produces the *most likely* state of the atmosphere given some prior knowledge ("background") and a current set of observations

This is a kind of model evaluation

Practical systems (e.g. Kalman filter) assume

- linear relationships among variables
- Gaussian distributions of background and observational errors

Models are mapped to observations via "observation operator" (retrievals/products are not always necessary)

Knowledge of error characteristics is *crucial*

Ensemble data assimilation

A Monte Carlo technique to solve the Kalman filter equations

An ensemble of model runs provides time-evolving, spatially-dependent estimates of background error and analysis uncertainty

Computationally on a par with 4D-Var but
easy to code: no adjoint or tangent-linear model

Compared to variational methods:

Less mature
Competitive in performance
Just moving into operations in some centers

Diversion - Data assimilation and climate model evaluation (i)

Weather prediction and climate models are structurally very similar

Resolved physics (dynamics) + un-resolved physics (convection, clouds, microphysics, radiation...)

Two key differences

Climate models might include physics acting on longer time scales (interactive land surface, sea ice)...

NWP models are linked to data assimilation systems

Diversion - Data assimilation and climate model evaluation (ii)

Evaluation methods for NWP and GCMs are very different

- Routine, time-specific evaluation against observations vs. statistical comparison on many time- and space-scales

Many GCM errors should be detectable in short forecasts

- See DOE CAPT project, Rodwell & Palmer (2007), ...

In one case (Met Office) the NWP and climate models are essentially the same (and very good)

Ensemble Kalman filters can bring data assimilation to those climate models without access to NWP infrastructure

Assimilation for clouds: the observational problem is very hard

Observations are indirect measures of cloud state

e.g. cloud optical depth is a loose constraint on a profile of cloud water content

Observational errors are non-Gaussian

Satellite data is very dense (many per model grid cell)

How can many observations be related to a single instance of the state? How should observations be aggregated?

Perfect model experiments

Skip the hard part for now and assimilate "observations" of cloud variables (e.g. cloud water, ice contents) directly

The "observations" come directly from a free run of the model. Observational error (10% of the observed value) is added

This tells us how much analysis skill we could possibly hope to gain (we plan to see how this translates into forecast skill)

Technical details

Two GCMs with different cloud schemes

AM2: prognostic cloud ice, water, fraction

CAM3: prognostic cloud water and ice

coupled to NCAR's Data Assimilation Research Testbed (DART)

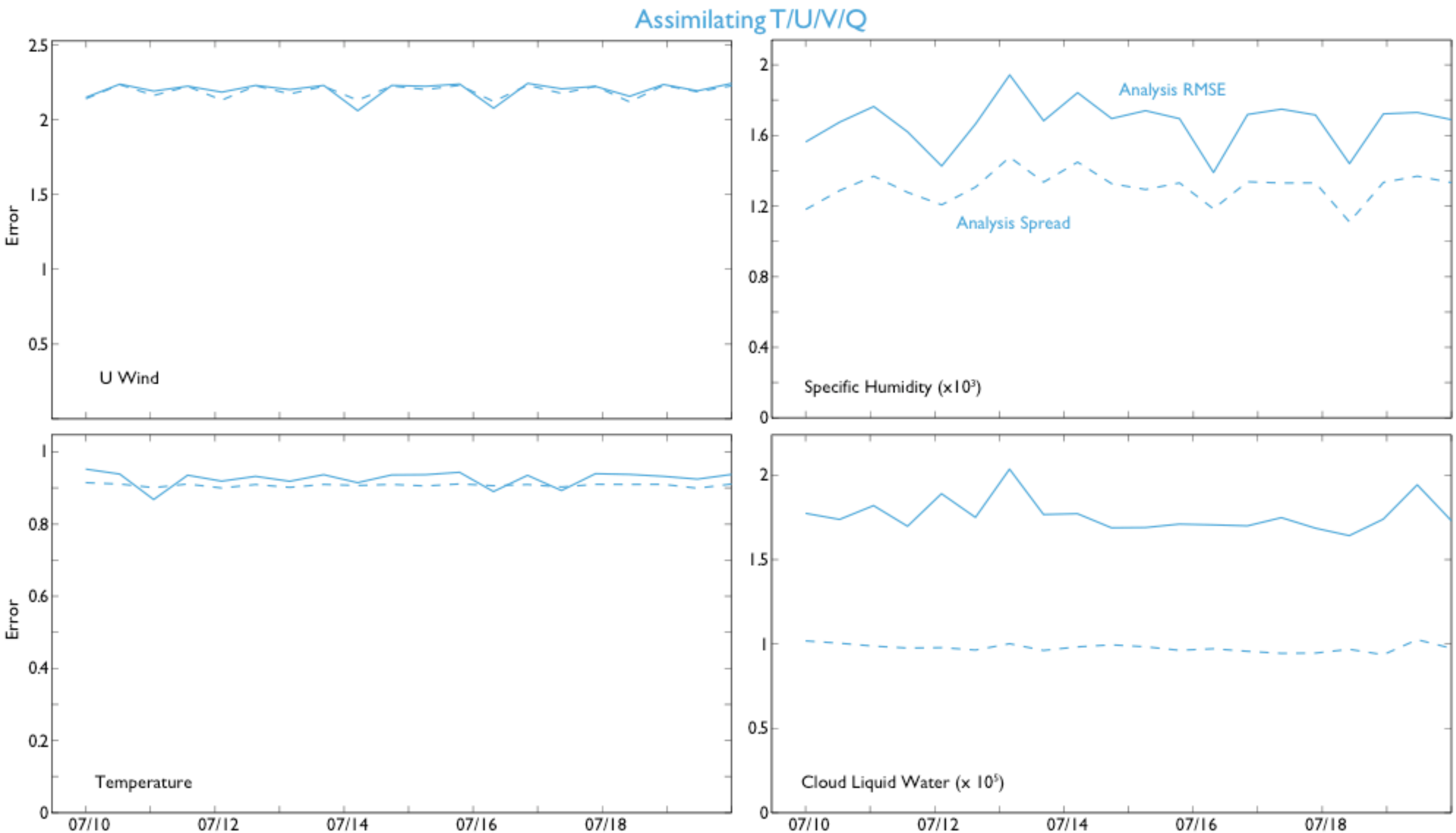
80-member ensembles, assimilating T/U/V/Q for ten days

assimilating conventional obs + O(1000) uniformly-distributed observations of clouds every 6 hours (greatest possible impact)

Covariance localization and adaptive inflation

We impose a floor on cloud water of 10^{-10} kg/kg;
about 1/3 of all cloud observations are rejected

Cloud observations help constrain the state (i)



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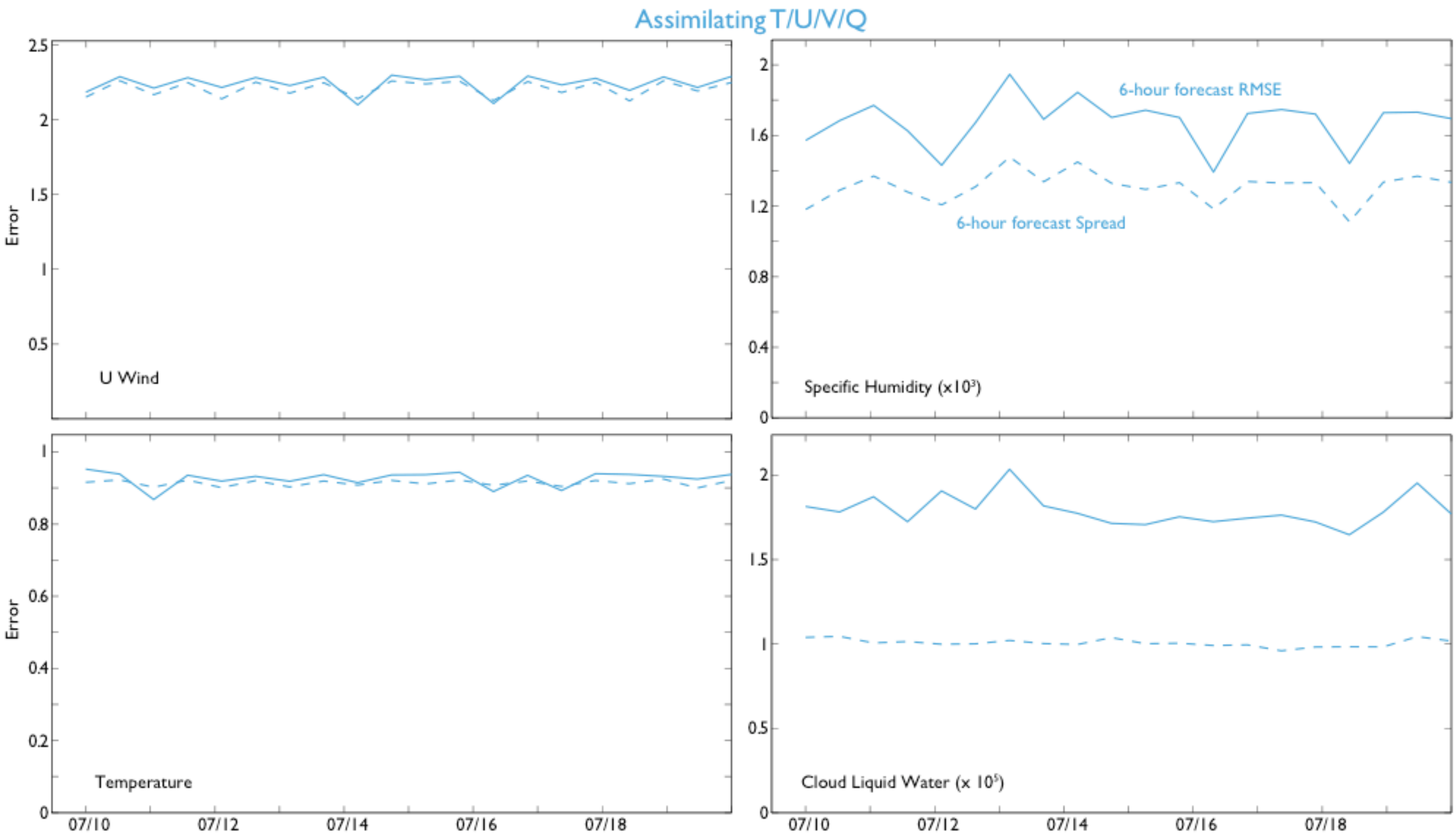

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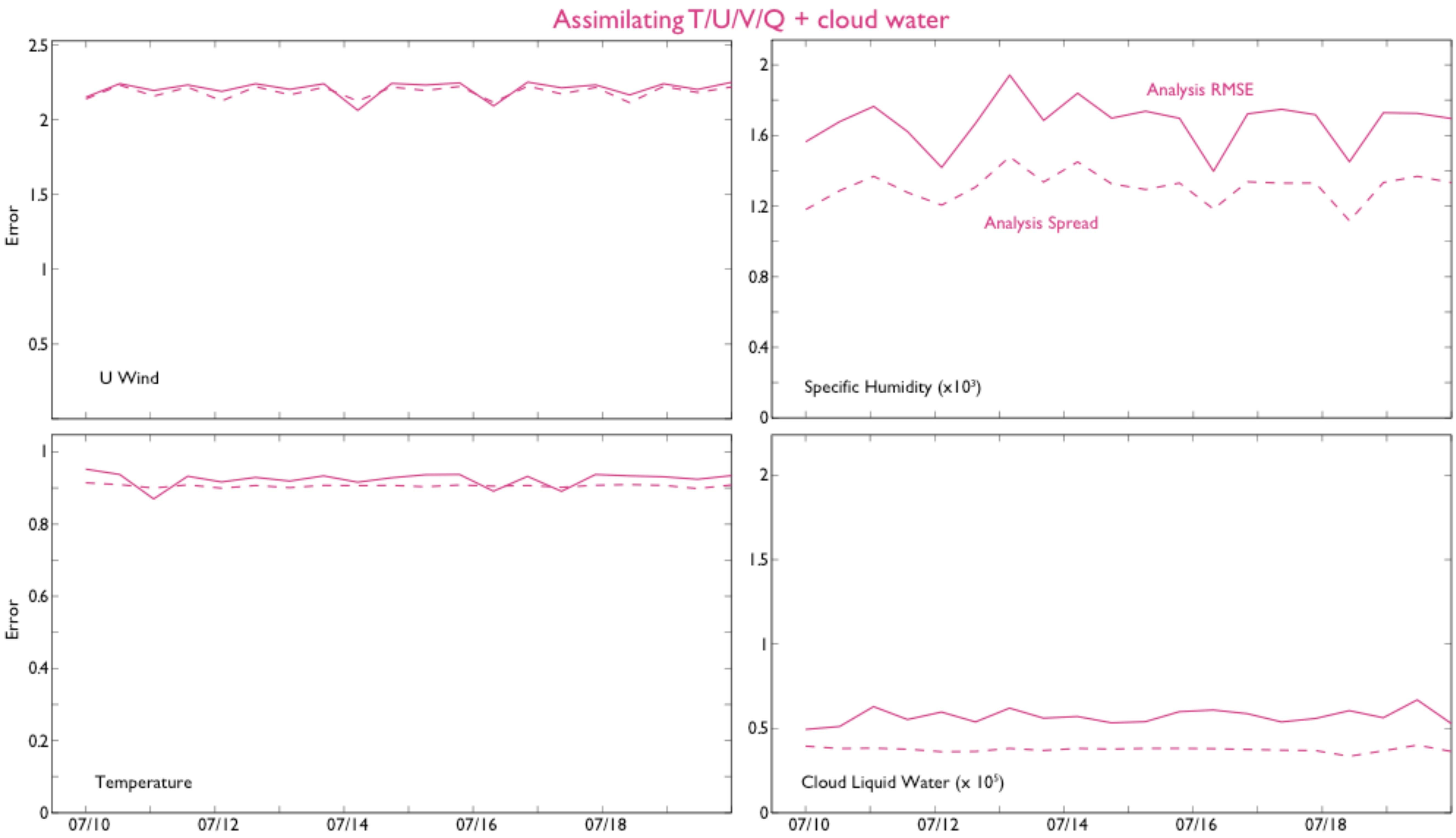

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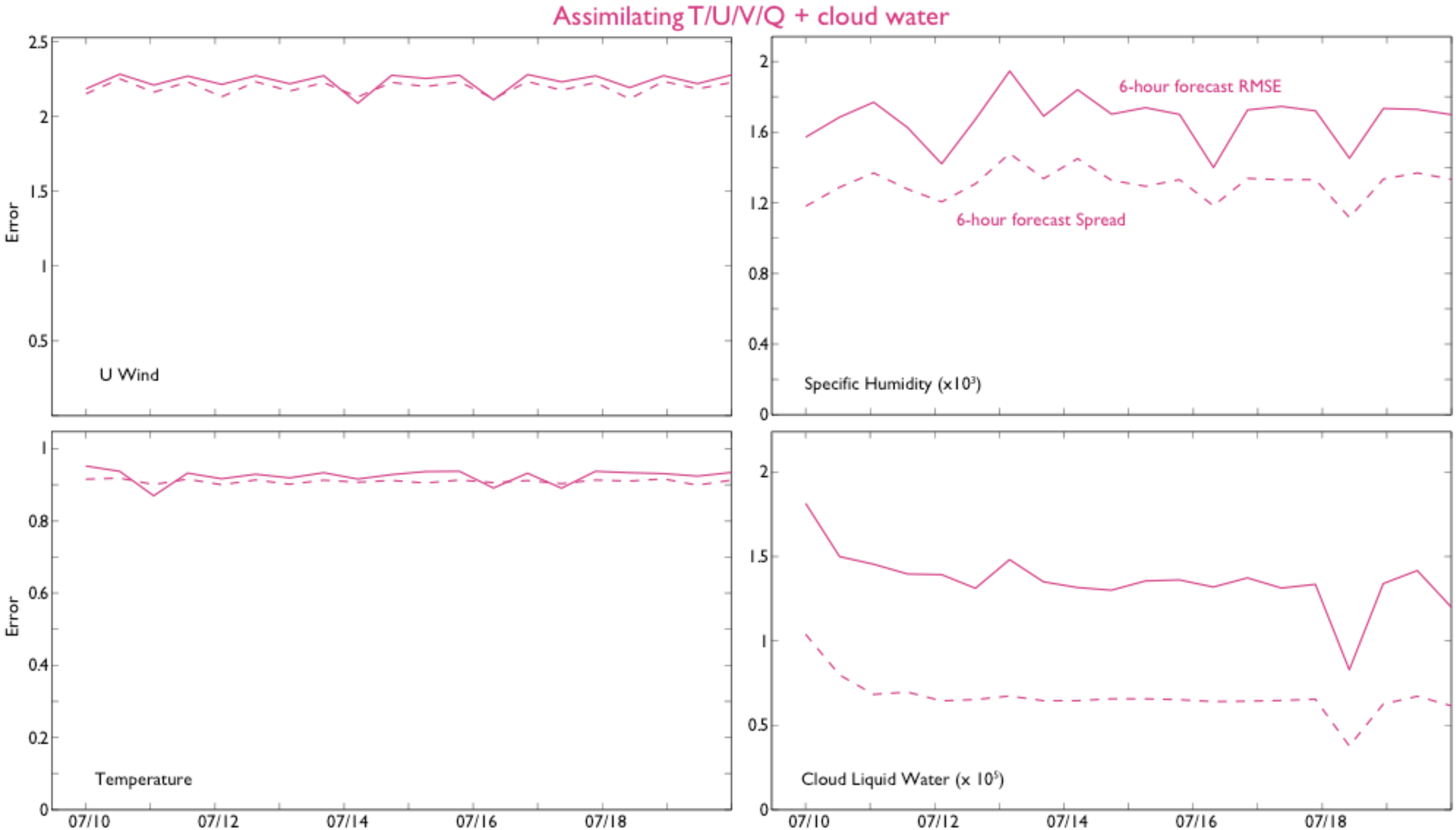
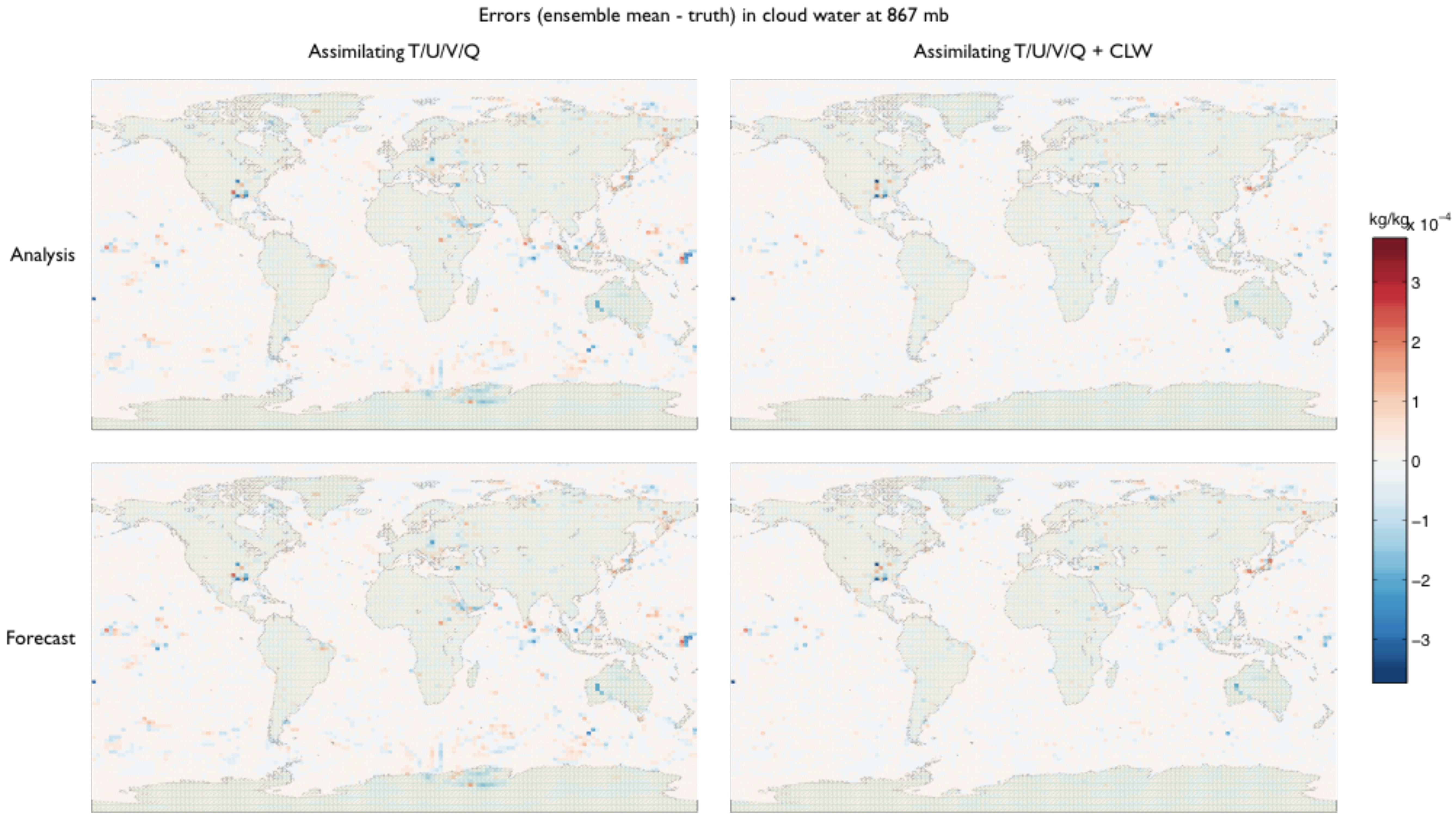
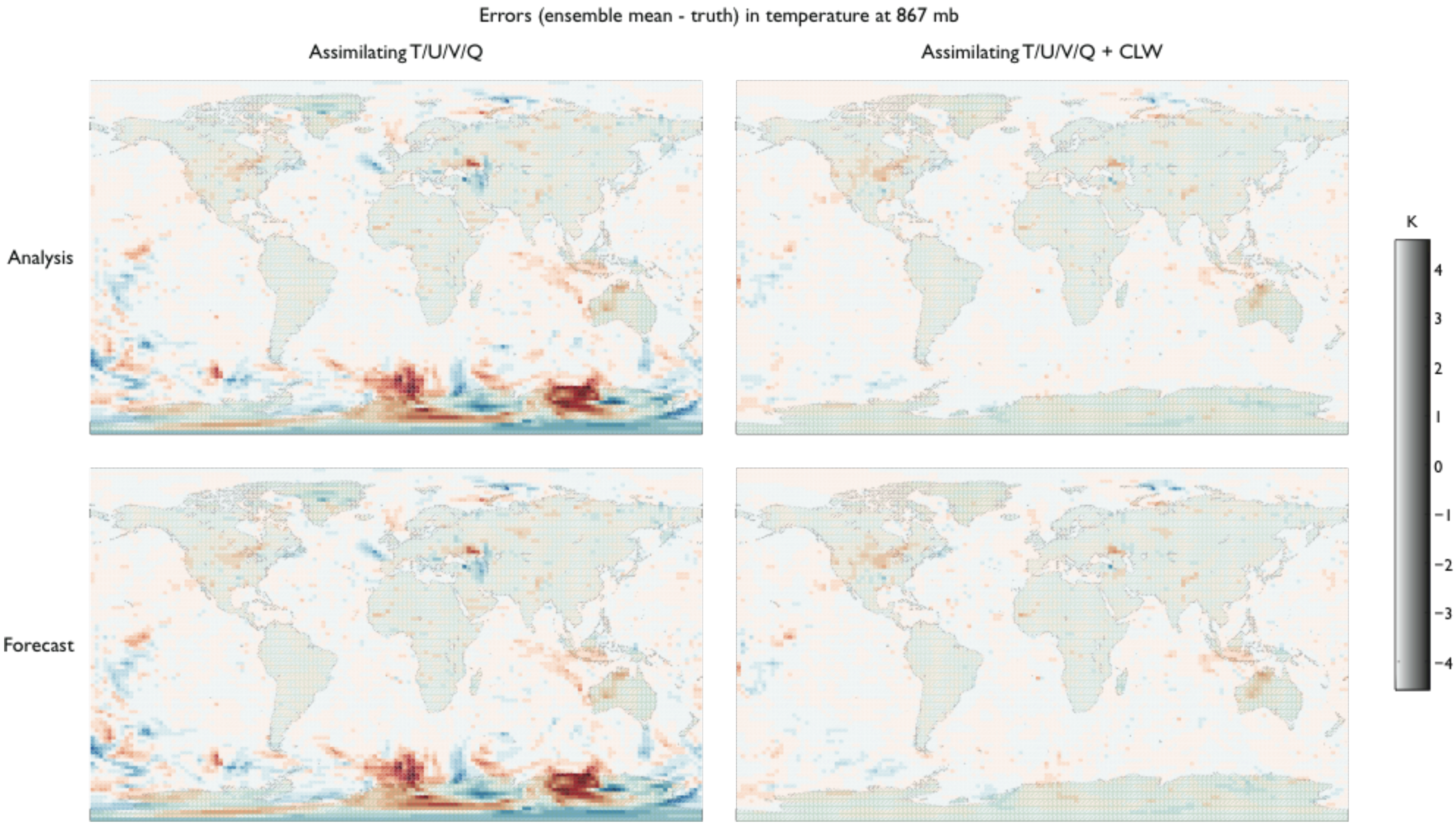


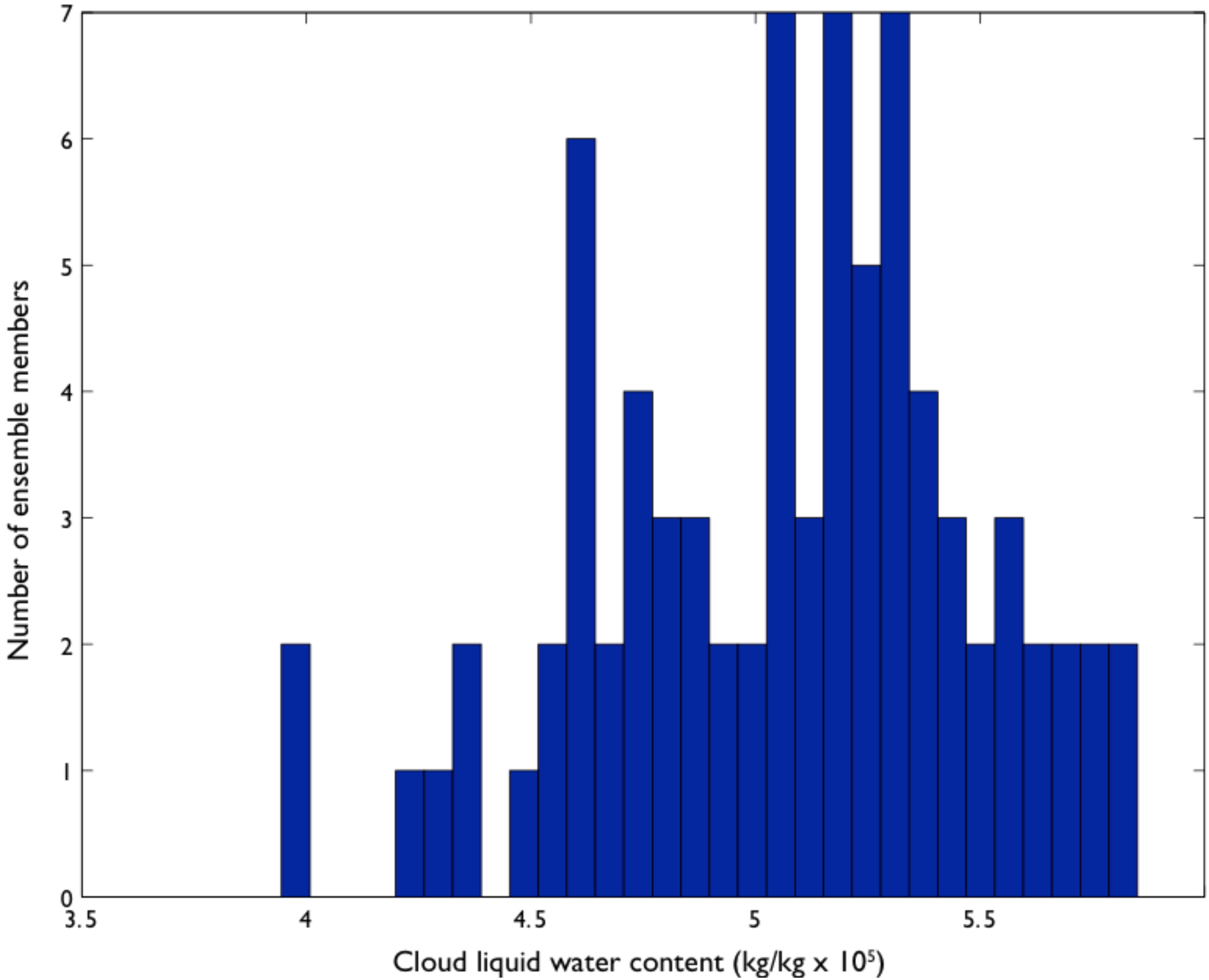
Cloud observations help constrain the state (ii)



Cloud observations help constrain the state (ii)



But clouds don't always behave well in the ensemble



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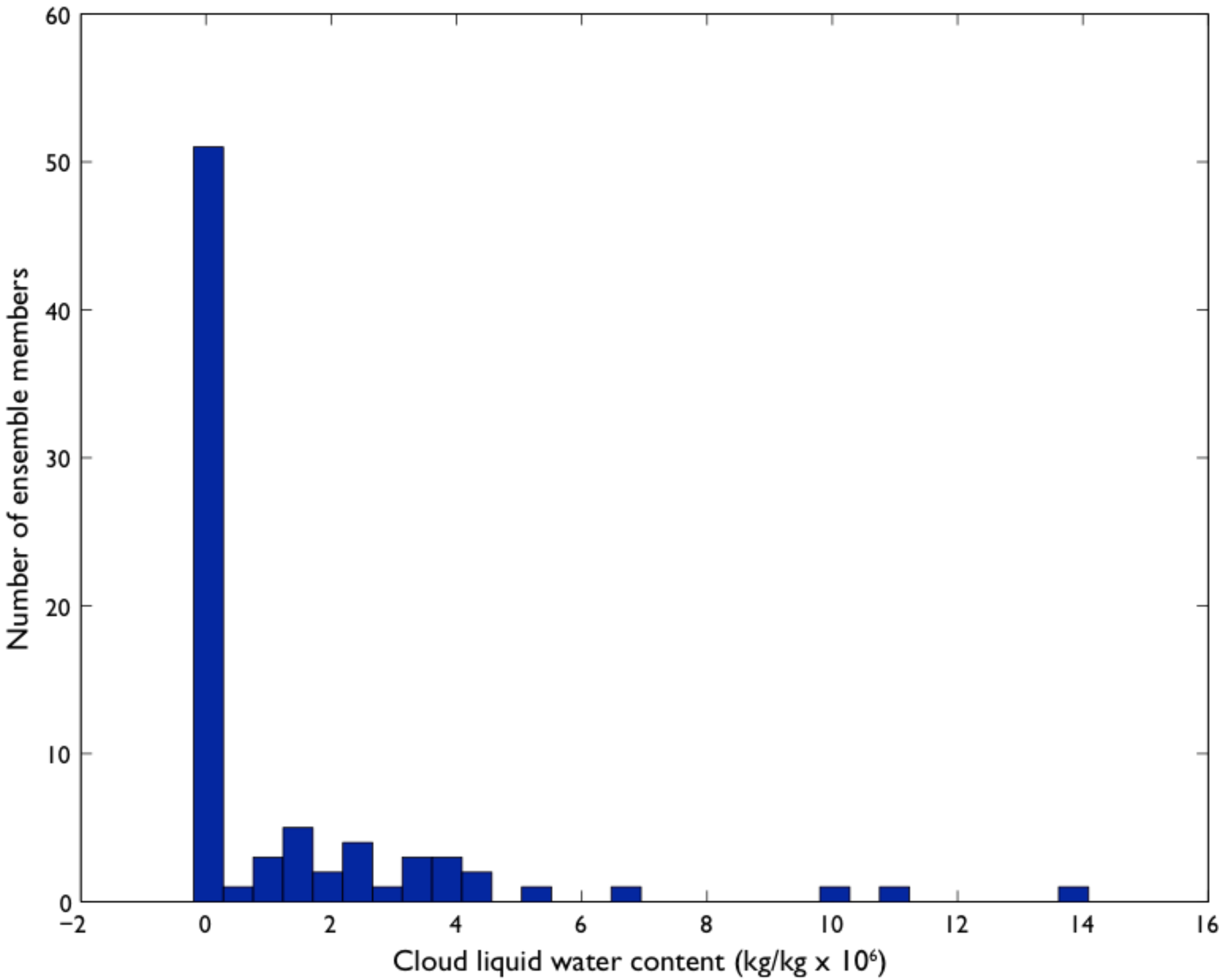
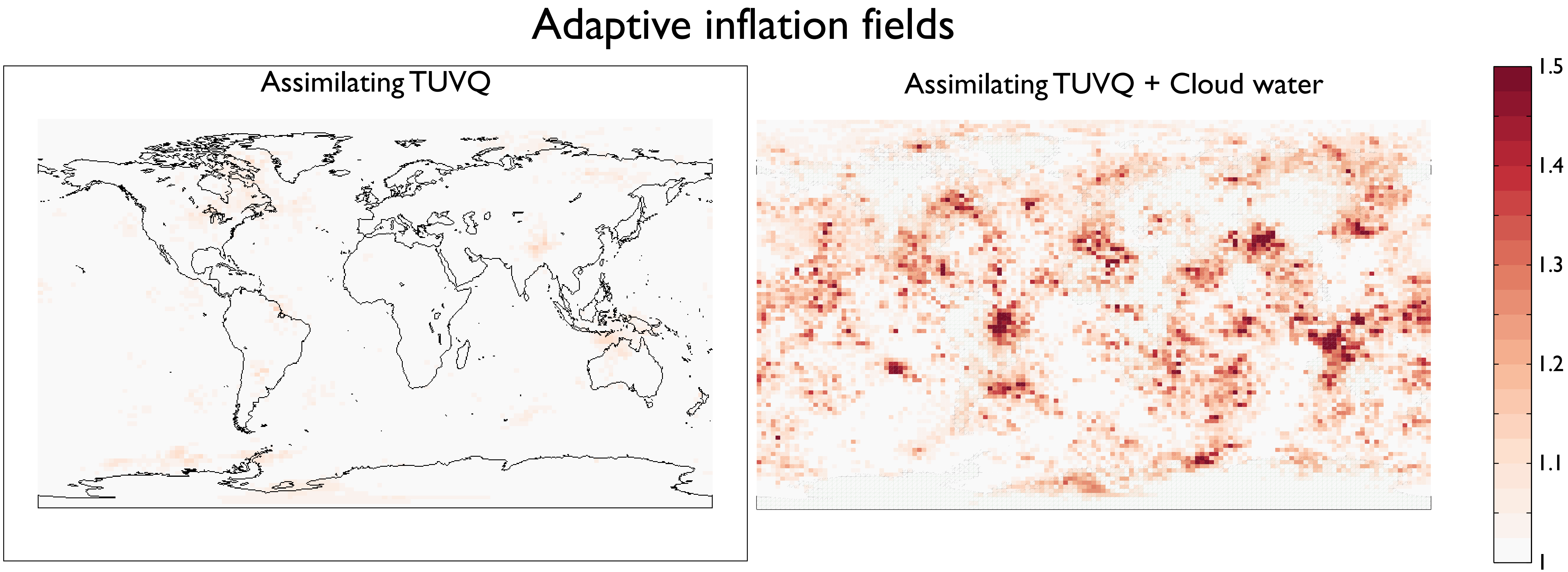


Poorly-behaved clouds look like model error



Preliminary lessons from CAM experiments

Observations of clouds can indeed be assimilated in global models

- given no model error, no observational bias, sparse observations, stringent rejection criteria

Observations of cloud water/ice improve analyses and forecasts

- Cloud water certainly improves, but this skill increase is quickly lost
- Other fields are improved; this may be less dramatic in more realistic observational scenarios

Prospects for using satellite observations of clouds in DA

In a perfect world, observations of cloud state can improve the overall analysis

But don't smile too much: there are large hurdles to practical applications

a) clouds are not the problem for which assimilation is optimal

b) it's not clear how much extra information cloud observations bring

c) it's not clear how well practical observations constrain cloud state

d) it's not clear how to resolve representativeness issues