

Observing System Simulation Experiments for Convective Clouds

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(and the A+CCP Science Impacts Team)

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Modern Satellite Mission Design

- Technological advances (especially cube-sat and small-sat) have greatly expanded the trade space for satellite mission design
- There are increasing demands to demonstrate (quantitatively) the value of a new set of measurements in advance
- Especially important to evaluate constellations of small satellites
- There is room for innovation in the design of experiments and evaluation of measurement impact.



Aerosols, Clouds, Convection, and Precipitation (A+CCP)

- Designated observables from 2017 Decadal Survey
- Dynamic cloud systems are important and not as well observed as we would like
 - Produce all of the Earth's fresh water (support of human society, input to surface hydro)
 - Source of largest atmospheric climate uncertainties
- Aerosol distribution and properties and interactions with clouds are highly uncertain
- Science foci (specific to CCP)
 - Relate cloud properties to precipitation processes and radiative forcing
 - Understand how convective dynamics and vertical transport are connected to cloud and precipitation properties
- Prior to KDP-A, conduct extensive architecture studies
- These take the form of a spectrum of observing system simulation experiments
- **Program of record will be part of the mission**



Quantifying Observational Requirements

Observing System Simulation Experiments (OSSEs)

- Traditionally: evaluation of potential impact of new observations on a NWP forecast (Errico et al. 2013 (QJRMS); Hoffman and Atlas, 2016 (BAMS))
- **Data assimilation at cloud scales is challenging.**
- Fundamentally: OSSEs quantify information in a future observing system
- Consider a *spectrum* of OSSEs:
 - **Sampling:** What are the sampling requirements for observing a given feature?
 - **Retrieval:** Do measurements provide enough information to estimate geophysical quantities of interest? What are the uncertainties?
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OSSEs for CCP: Specific Considerations

- **Goal: assess the degree to which specific measurements:**
 - Achieve the observing system desired capability
 - Address the science goals and objectives
- **Forecast OSSEs for convective processes and at convective scales have limitations**
 - Data assimilation for clouds, convection and precipitation is challenging (nonlinearity, representativeness, rapid temporal evolution)
 - Addressing a science objective may not lead to forecast improvement (and vice versa)
 - Forecast OSSEs would not leverage the existing field campaign data archive
- ***However*, forecast OSSEs consider the program of record (assuming PoR is simulated accurately...)**



OSSEs for CCP: Key Objectives

1. Assess **sampling**
 1. Is a single observatory sufficient, or is a train / convoy needed?
 2. What are the tradeoffs among swath width, footprint size, and sensitivity/SNR?
2. Trace observables to science objectives
 1. Is uncertainty in **retrieved** geophysical quantities small enough to identify signals of interest?
 2. Do measurements reduce uncertainty in a **process** or outcome of a process (**analysis/forecast**)?
3. Connect measurables to value (science outcomes, risk, cost)



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Quantifying Observational Requirements

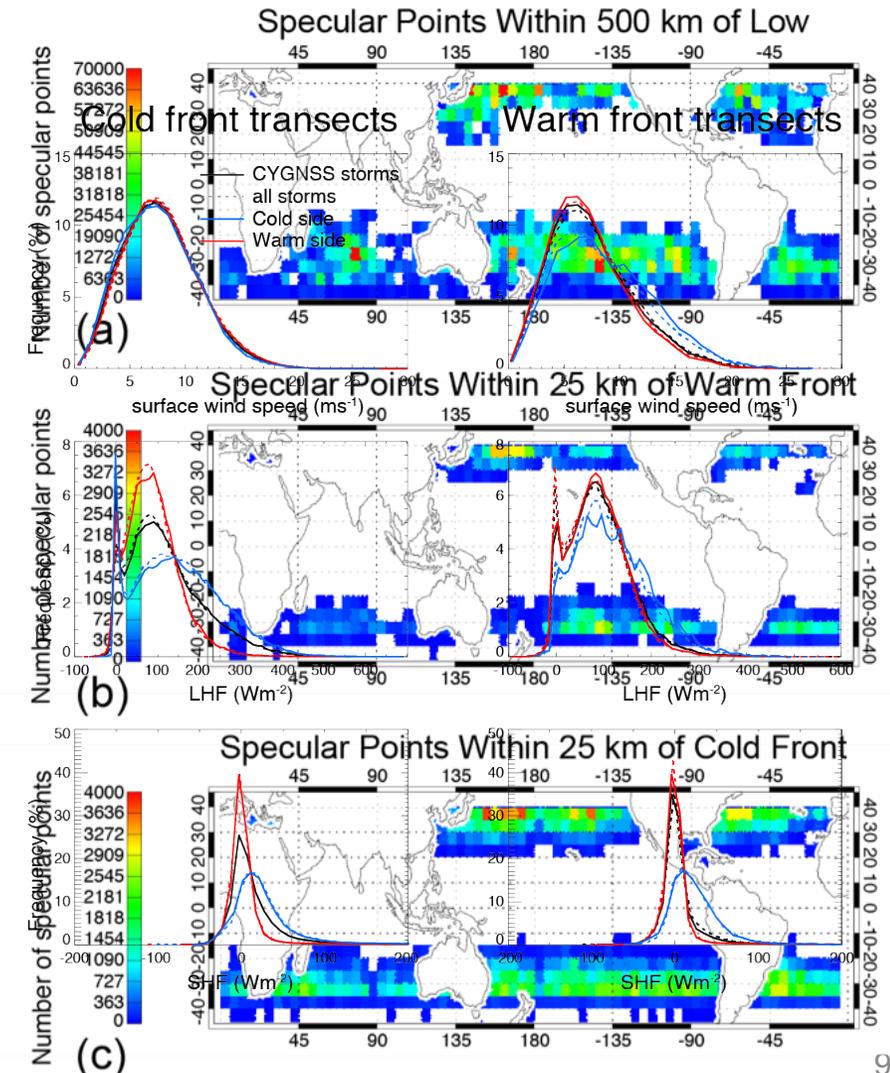
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Sampling OSSE

- Determine orbital and/or swath characteristics
- Given a dataset that includes the feature(s) of interest, this is fast and simple
- Fundamental question: can the characteristics of a distribution be reproduced from a particular sub-sample?
- Compute statistics from a large dataset (e.g., a global nature run)
 - Full dataset
 - Sub-sample consistent with particular swath, resolution, and orbit
- Compare the distributions



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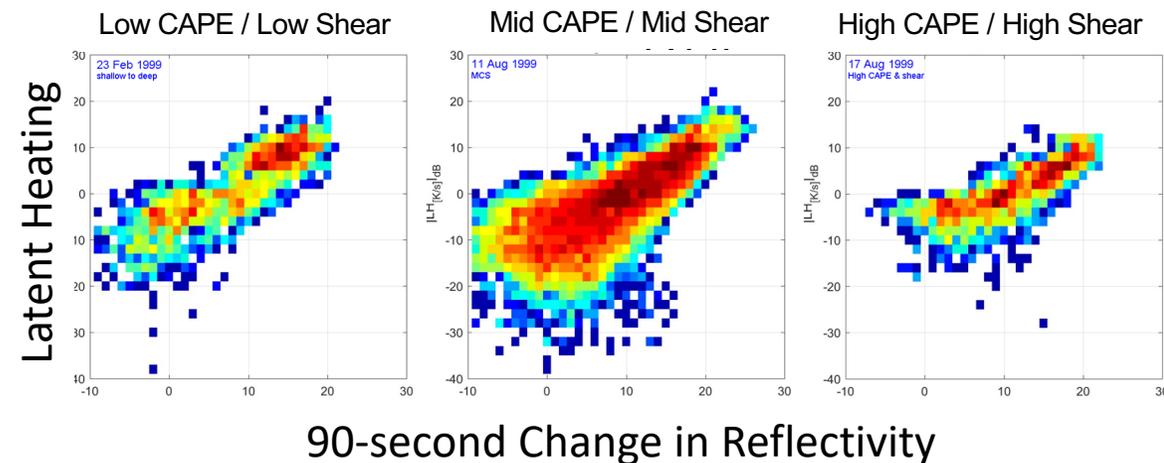
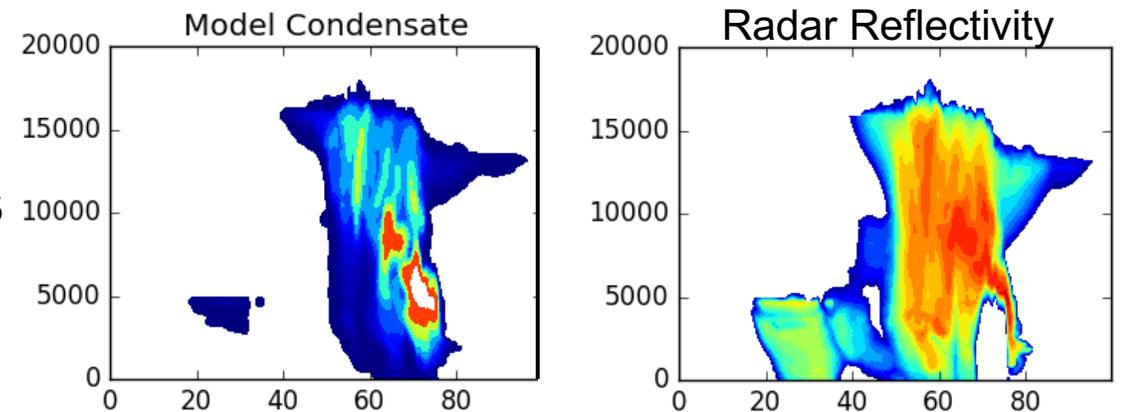
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Retrieval OSSE

Use simulated atmospheric states + instrument simulators + retrieval algorithms to assess observability and uncertainty

- Step 1: use model + simulator
 - Rapidly assess relationships among geophysical quantities and measurements
 - Fast and simple, but does not place error bars on the retrieval
- Step 2: add a retrieval algorithm
 - Simulate measurements from specified state, then conduct retrieval
 - Vary obs types and uncertainties



Retrieval Uncertainty Assessment

- **Recall** components of an OSSE:
 - Representation of nature
 - Simulation of observations
 - Quantitative measure of impact / effectiveness of measurements
- Observing system uncertainty experiment for cloud observables
 1. Define geophysical parameters of interest
 2. Set desired uncertainty bounds*
 3. Collect a list of candidate measurements**
 4. Perform simulated retrievals***
 5. Compare uncertainty in retrieval with desired uncertainty

* Quantifying this is a challenge

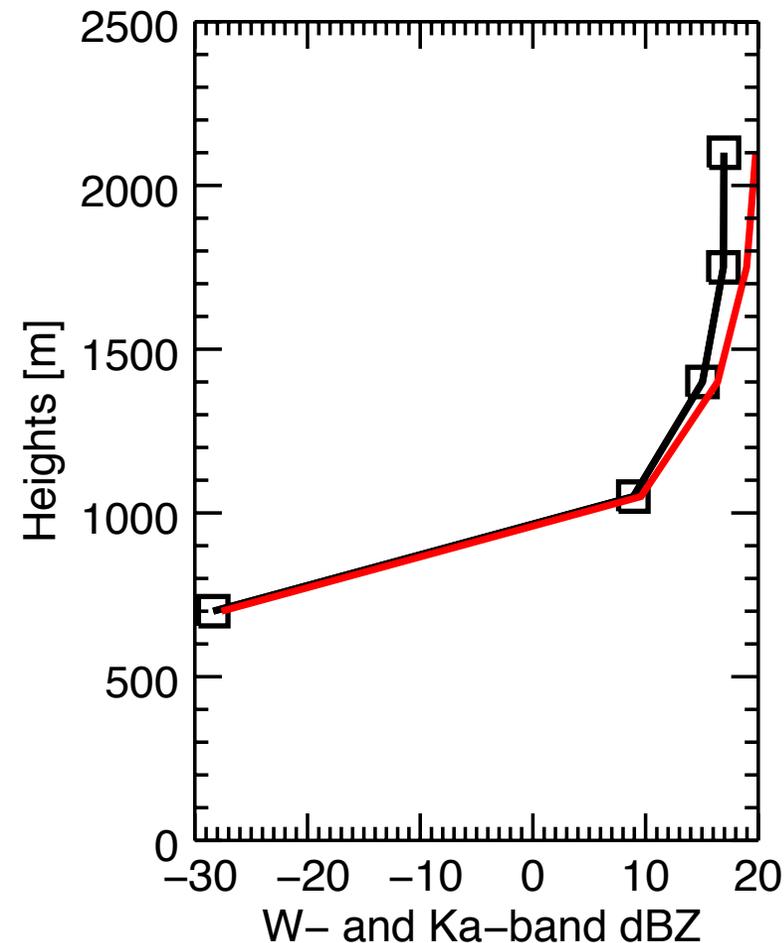
** Presumes the existence of accurate measurement simulators

*** Presumes the existence of a retrieval algorithm that produces estimates of uncertainty



Drizzle Processes in Liquid Clouds

- Rain initiation in shallow clouds is crucial for climate feedbacks and remains poorly understood
- Depends on the size distribution of cloud and rain drops
- Conduct a retrieval OSSE to understand which observations are needed to inform cloud and rain droplet population
- Nature: in-situ (aircraft) obs of clouds
- Candidate measurements: active (radar) and passive (microwave and visible/near-IR)
- Measurement simulators readily available



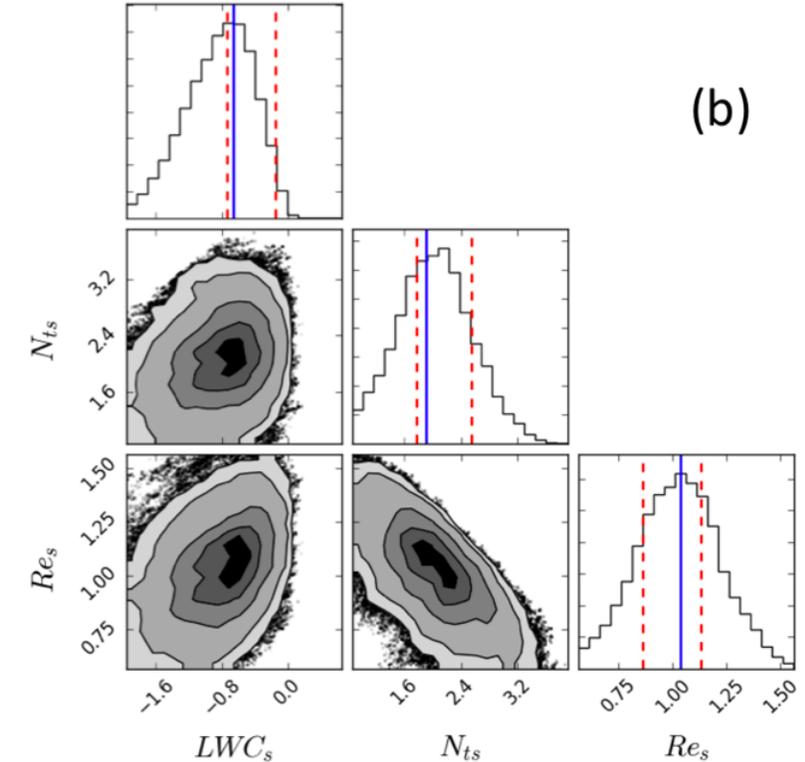
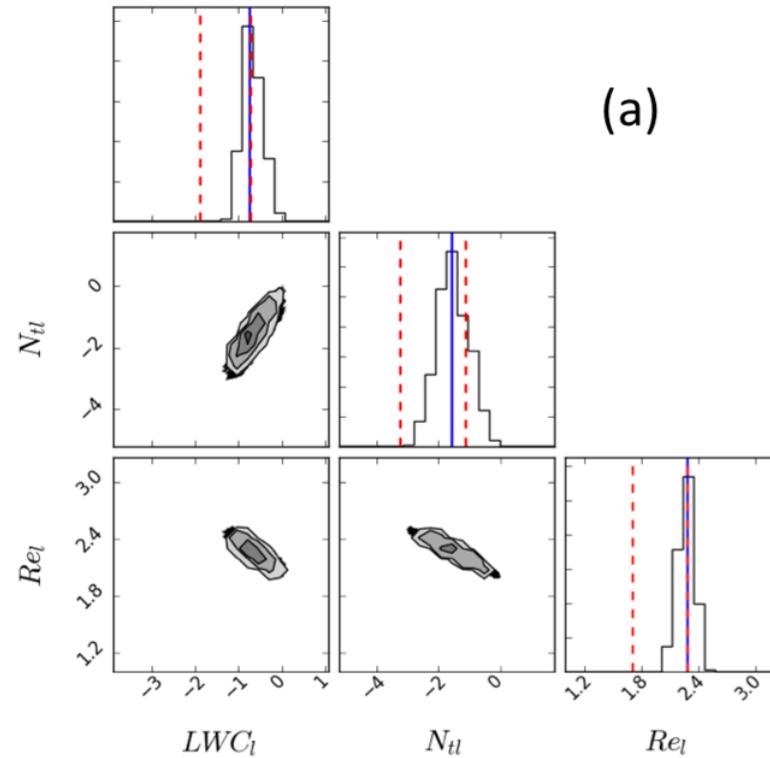
Retrieval

- In practice: optimal estimation
- Characterize information space using a Markov chain Monte Carlo (MCMC) algorithm
 - Sample of the probability distribution of retrieved states
 - Understand Gaussianity of solution
 - Flexible computation of error statistics
- Assess current observing system (CloudSat + MODIS)
- Test future observing system (dual frequency radar + microwave + reflectances)



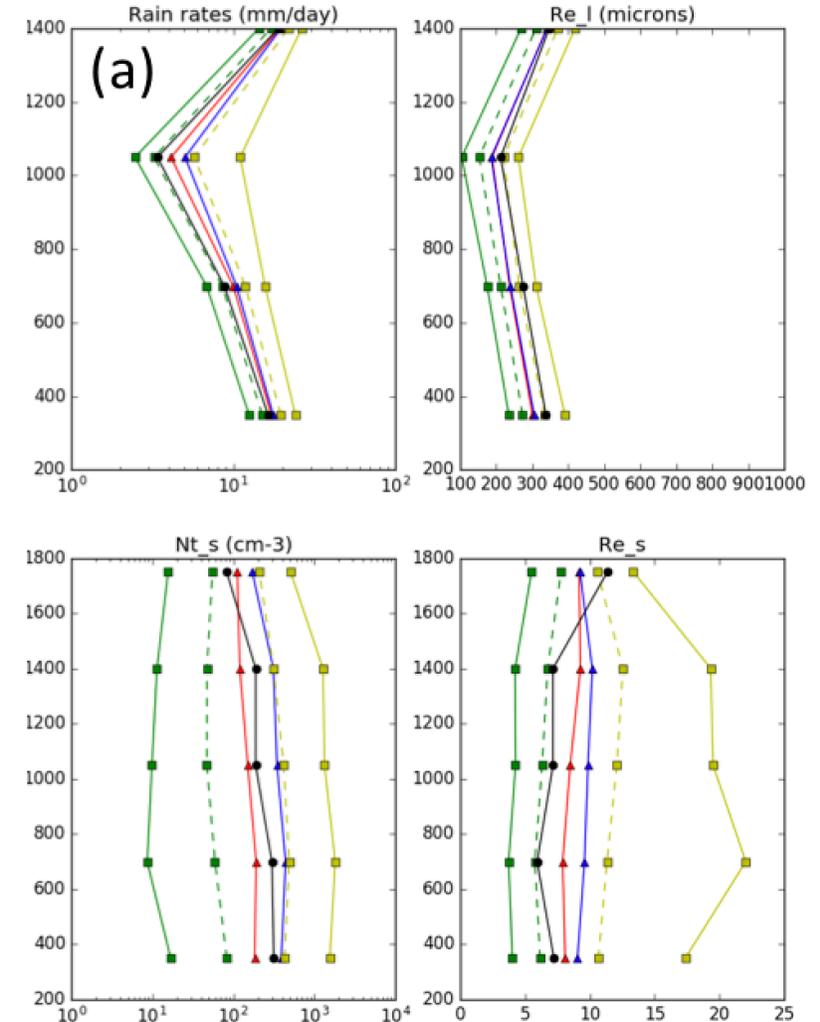
Posterior Densities from MCMC

- Run MCMC for several candidate observing configurations
- Evaluate CloudSat vs notional CCP measurements



Statistics of Profiles

- Compare profiles
- Uncertainty represented in quantiles
- Addition of radar frequency provides significant constraint on the profile
- What is the role of the program of record?
- How much uncertainty is too much?

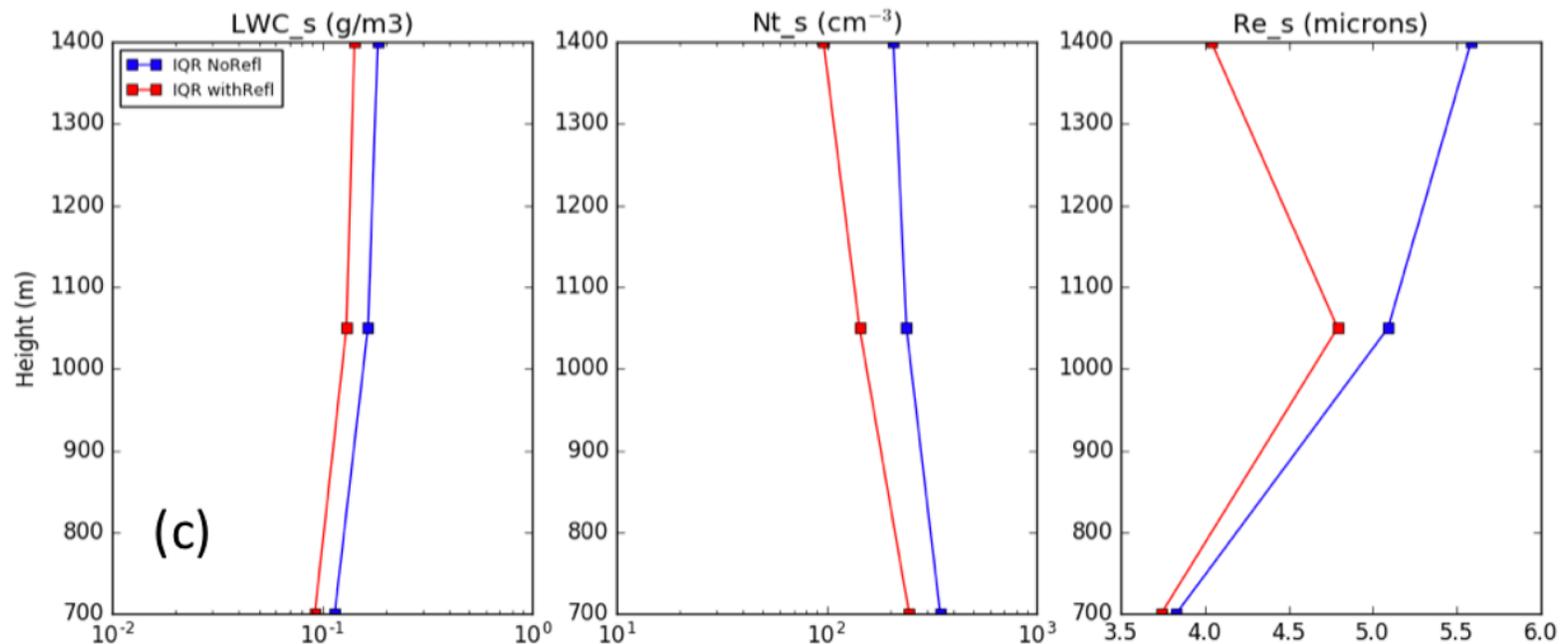


Assess Measurement Uncertainty

- Degrade radar and passive microwave measurements
- Ultimately, most information is provided by program of record (visible and near infrared reflectance)

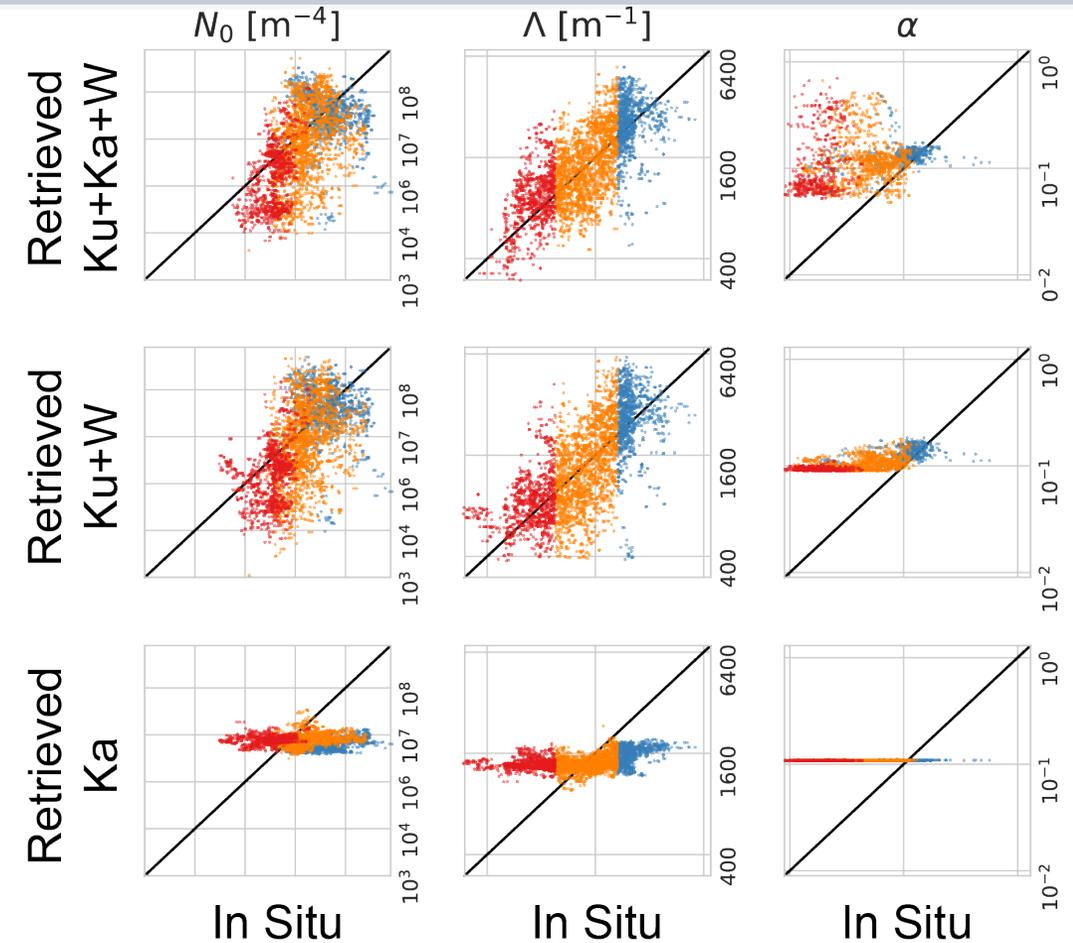
Uncertainty:

- a) 3 dB radar + 2 K Tb
- b) 3 dB radar + 4 K Tb
- c) 6 dB radar + 8 K Tb



Use of Field Campaign Data in Retrieval OSSEs

- A key component of the DS study is the use of existing field campaign data
- When combined with a Bayesian retrieval framework, field measurements can be used in an OSSE context
- Example: “data denial” retrieval study from OLYMPEX (Leinonen et al. 2018; JAOT)
- Retrieve parameters of snow PSD using 1, 2, or 3 radar frequencies (APR-3: W, Ka, Ku)
- Compare vs. in situ data (2D-S Probe, UND Citation)



In situ vs retrieved snow PSD parameters from 3, 2, and 1 radar frequencies. Adapted from Fig. 3, Leinonen et al. 2018 (JAOT)

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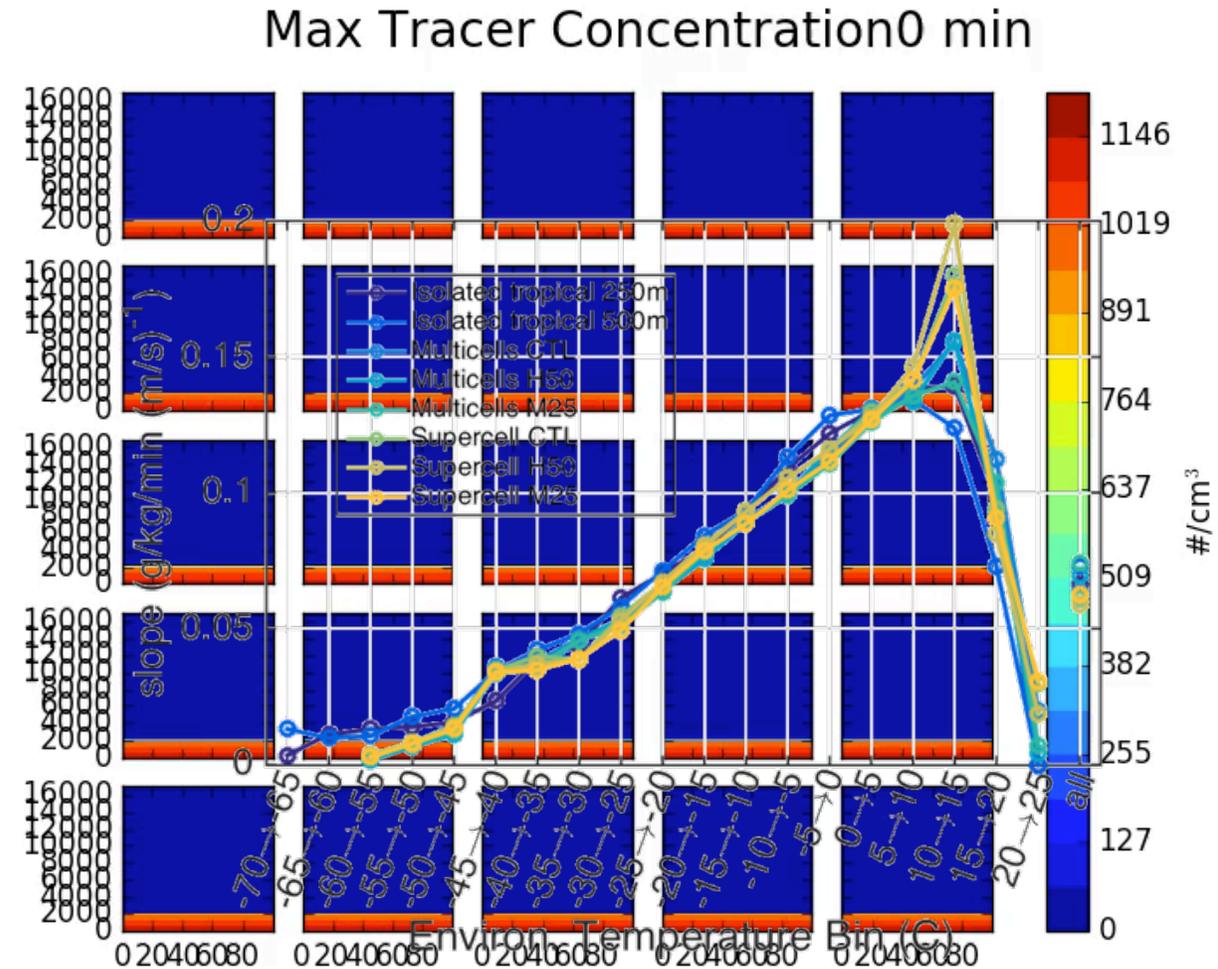
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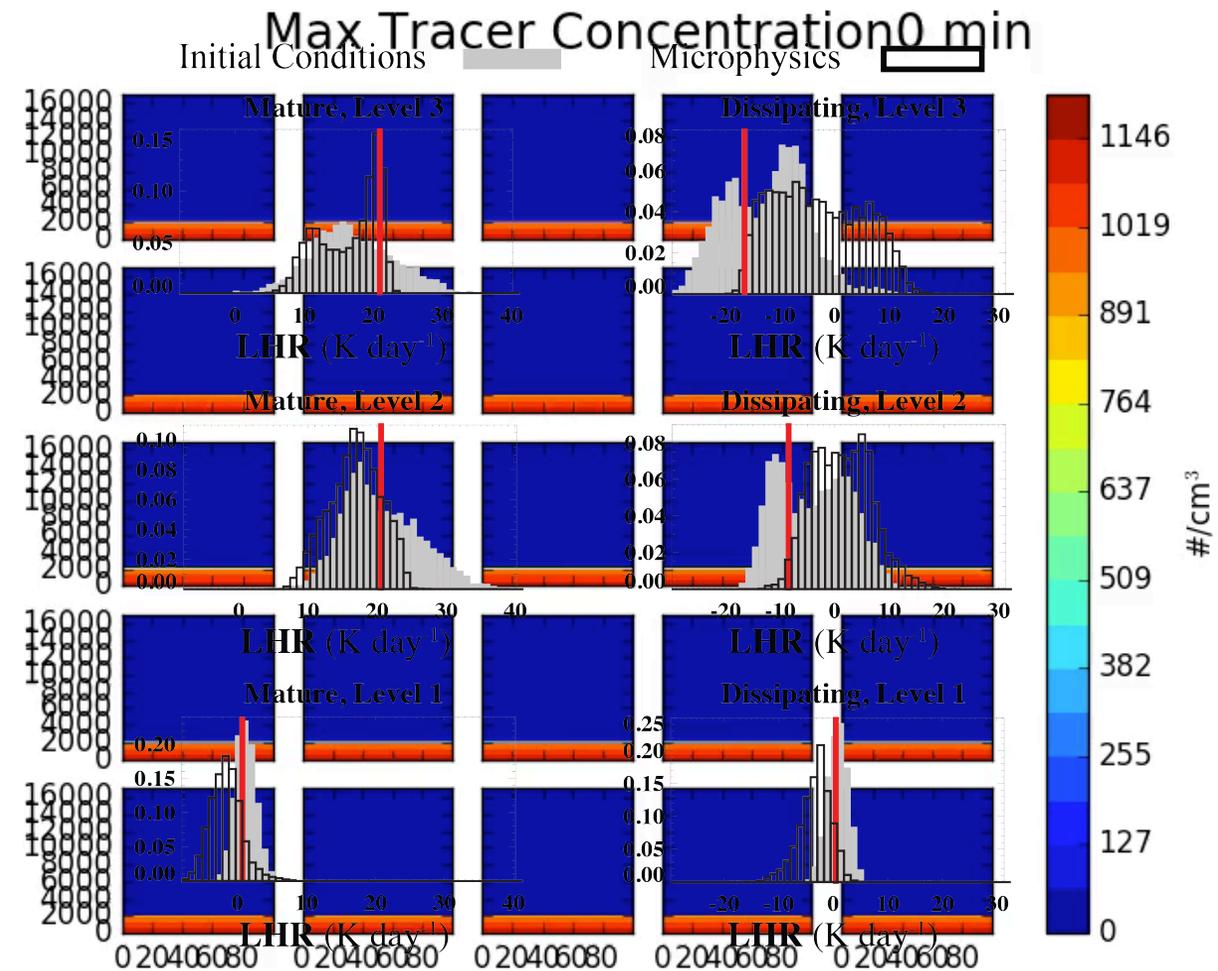
Process OSSE

- Assessment of whether a measurement captures a *process* is challenging
- E.g.: "determine convective transport and redistribution of mass, moisture, momentum, and chemical species"
- Requires:
 - Identify process of interest
 - Establish uncertainty bounds on the process
 - Connect (quantitatively) measurement with process
- This is an area of research, but early results indicate ensembles of simulations can be used to quantify capability



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Cloud-Scale All-Sky Data Assimilation

(Courtesy Masashi Minamide, masashi.minamide@jpl.nasa.gov)

- Cloud-scale all-sky DA is challenging due to *representativeness*

If... Observation Forecast or Observation Forecast
  or   then obs increment can be very large

- Consider an update to sea level pressure given obs of brightness temp

SLP update will be
$$\left(\frac{\sigma_{f,y} \sigma_{f,x} \text{corr}(x,y)}{\sigma_{f,y}^2 + \sigma_o^2} \right) \Delta y = \frac{5 \times 5 \times 0.5}{5^2 + 3^2} \times 40K \sim \mathbf{15hPa}$$

- Need to deal with obs-forecast mismatch

Inflate Background Error (ABEI)

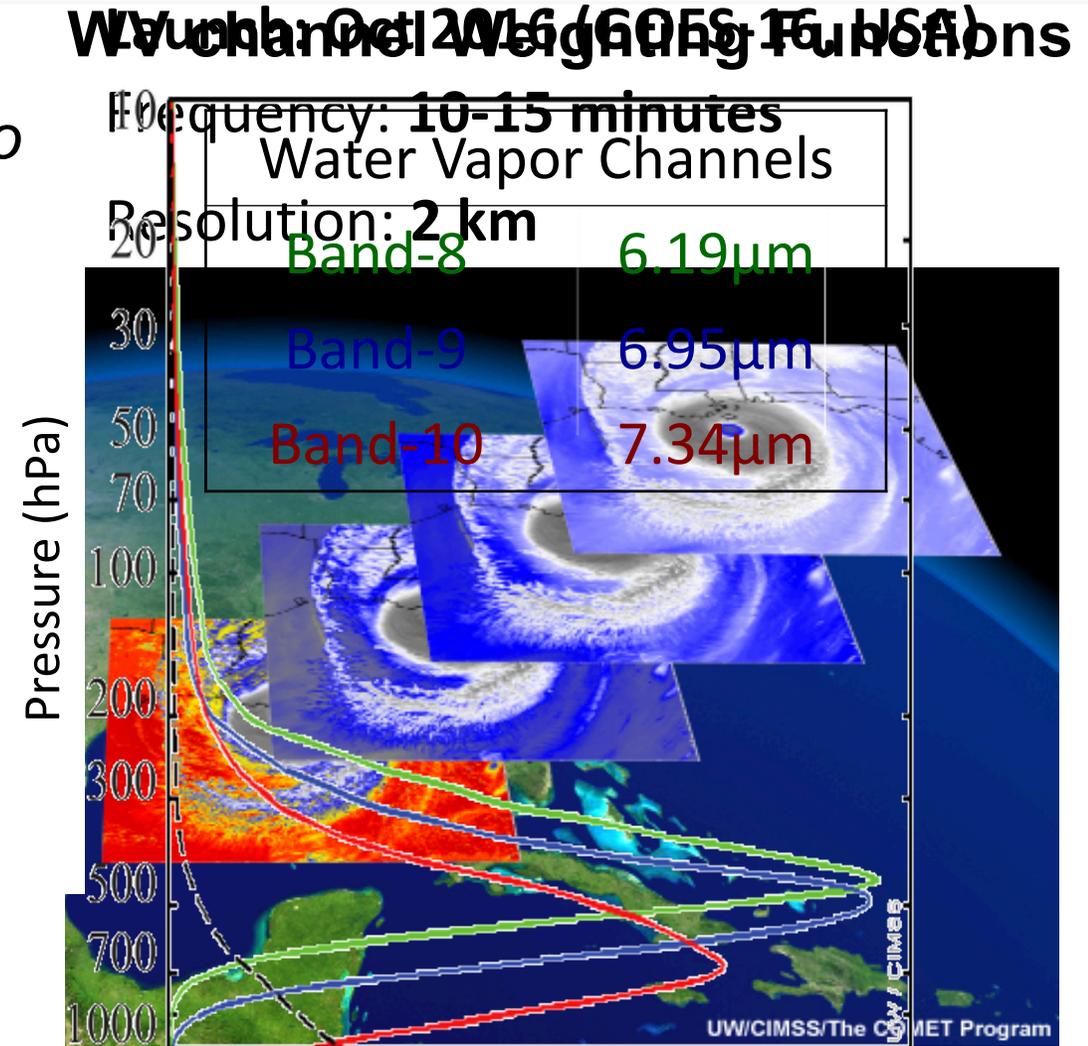
Inflate Observation Error (AOEI)



Forecast/Analysis OSSE

(Results courtesy Masashi Minamide, masashi.minamide@jpl.nasa.gov)

- Applications may or may not explicitly include forecasting, but *data assimilation can be used to assess measurement information*
- Measurement effect on the *analysis* – the state estimate produced by data assimilation
- Assimilate new data alongside current data - allows assessment of information *in context*
- Example: assimilation of GOES-16 brightness temperatures
 - WRF model with 3 km grid spacing on inner domain
 - Use Ensemble Kalman Filter DA with 60 members
 - Account for representativeness using AOEI and ABEI

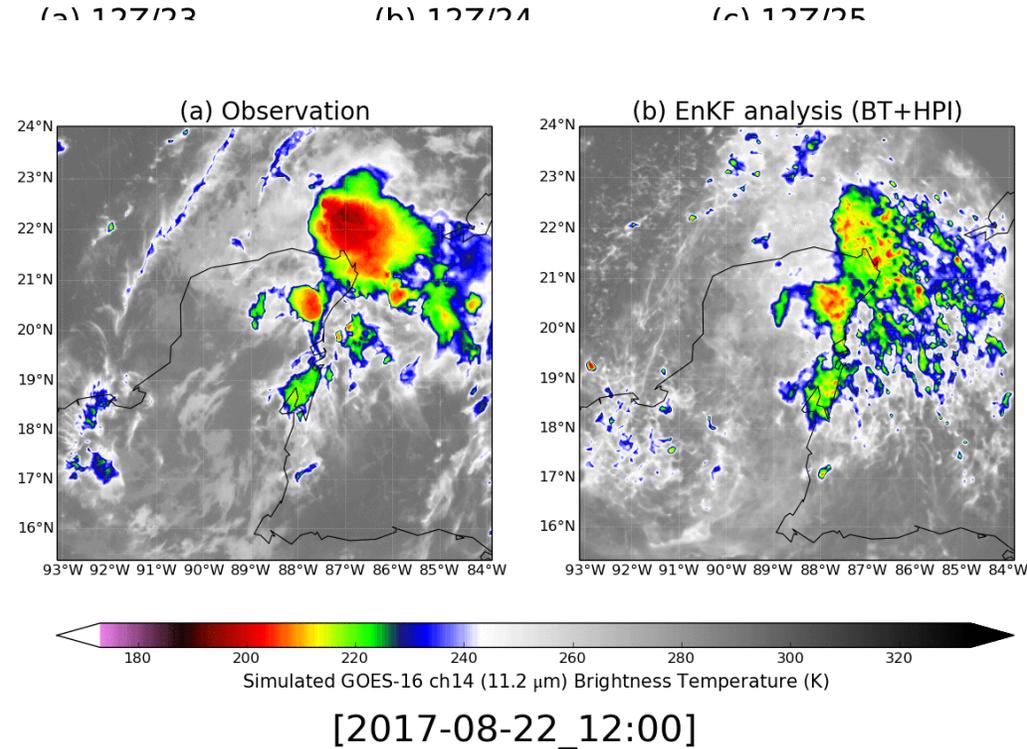


(Otkin 2012)

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(Results courtesy Masashi Minamide, masashi.minamide@jpl.nasa.gov)

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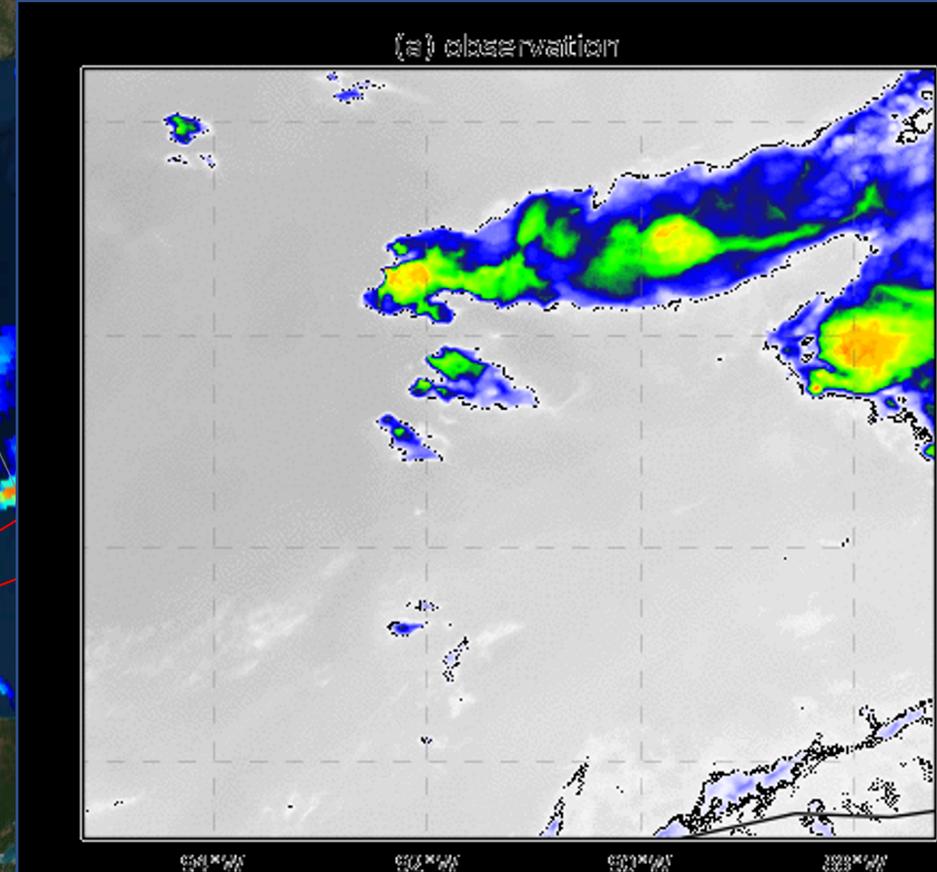
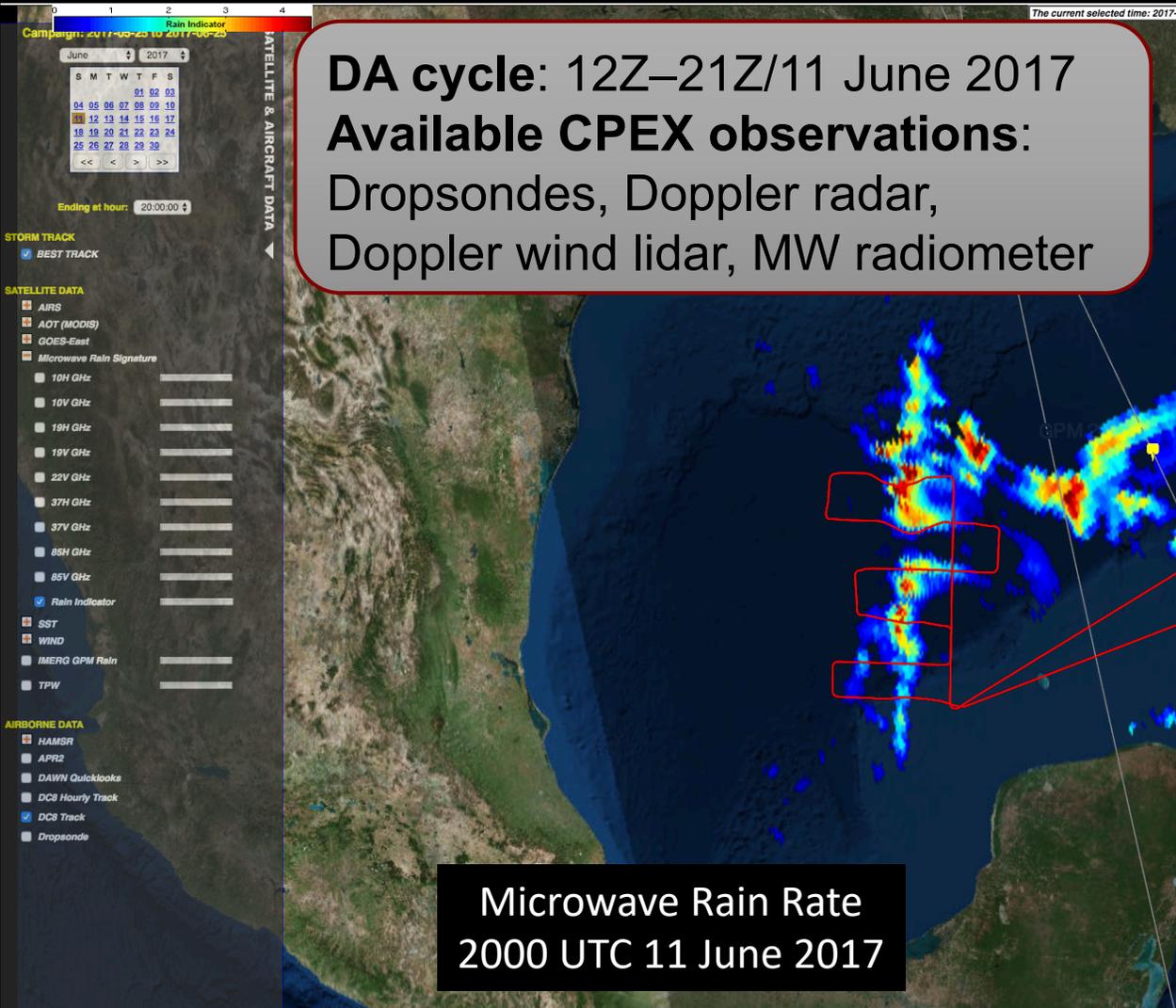


Unorganized Convection: 06/11/2017 during CPEX

NASA Jet Propulsion Laboratory
California Institute of Technology

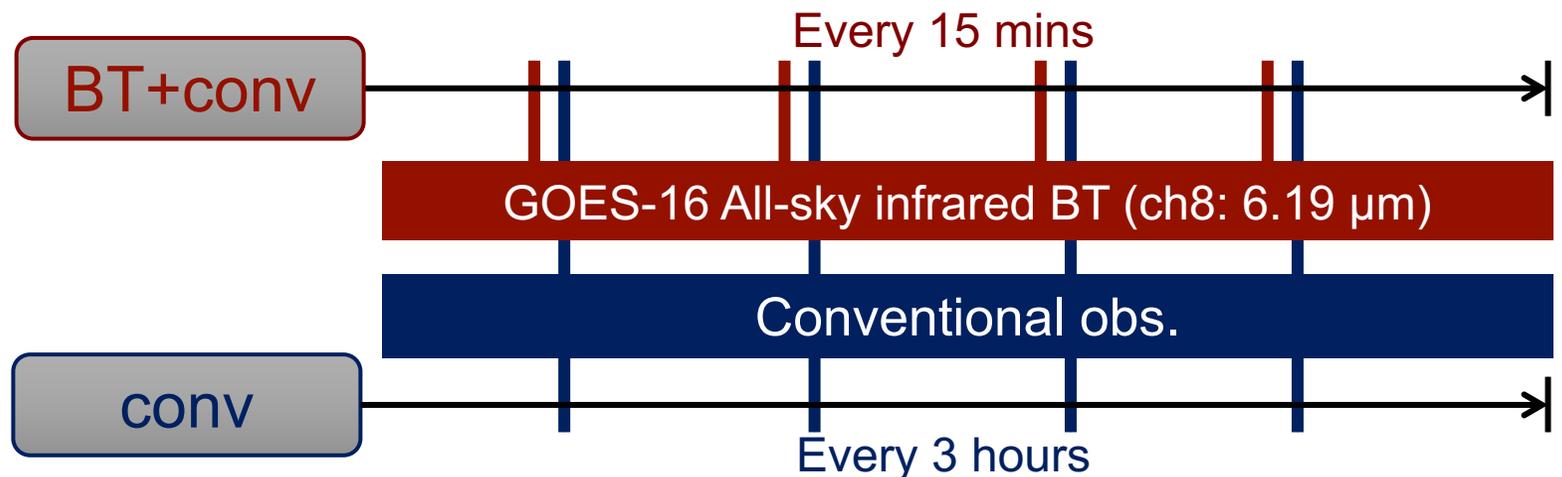
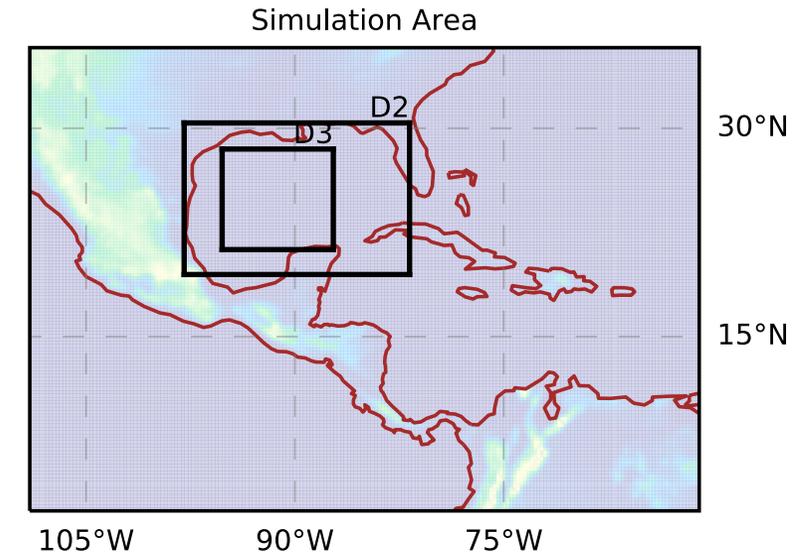
NASA CONVECTIVE PROCESS EXPERIMENT [CPEX]

CPEX Data Portal, JPL: <https://cpexportal.jpl.nasa.gov>



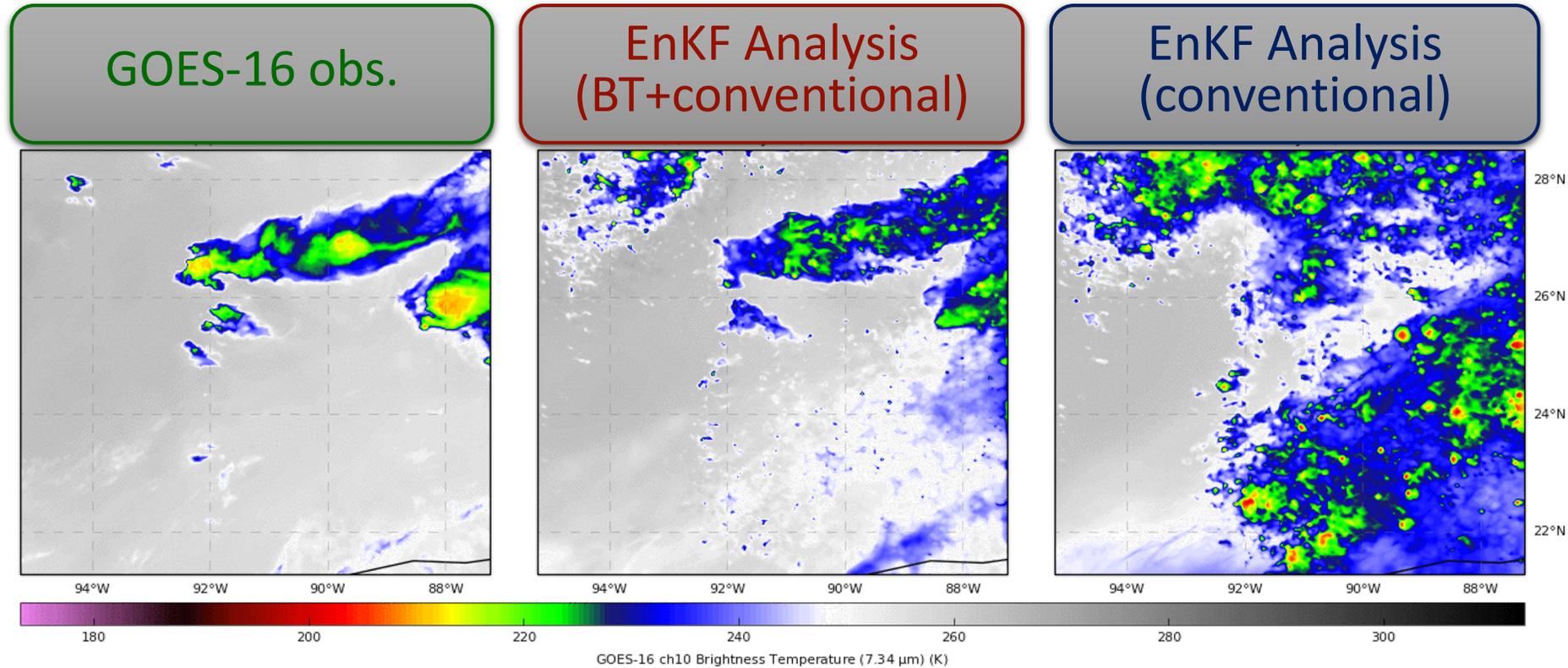
Model Configuration and Experiment Settings

- WRF ver.3.6.1, CRTM, PSU WRF-EnKF (APSU) DA
- 27/9/3 km grid, 60 member ensemble (EnKF on domain 3)
- Assimilate conventional obs every 3 hours, GOES-16 channel 8 every 15 min
- Error modeling, inflation, and localization
 - Adaptive Observation Error Inflation (AOEI) (Minamide & Zhang, 2017, MWR)
 - Adaptive Background Error Inflation (ABEI) (Minamide & Zhang, 2019, QJRMS)
 - Successive covariance localization:
 - 18 km thinning with 200 km localization radius
 - 12 km thinning with 30 km localization radius
 - 3K brightness T errors



EnKF Performance (Analysis)

(Results courtesy Masashi Minamide, masashi.minamide@jpl.nasa.gov)



[2017-06-11_12:00]

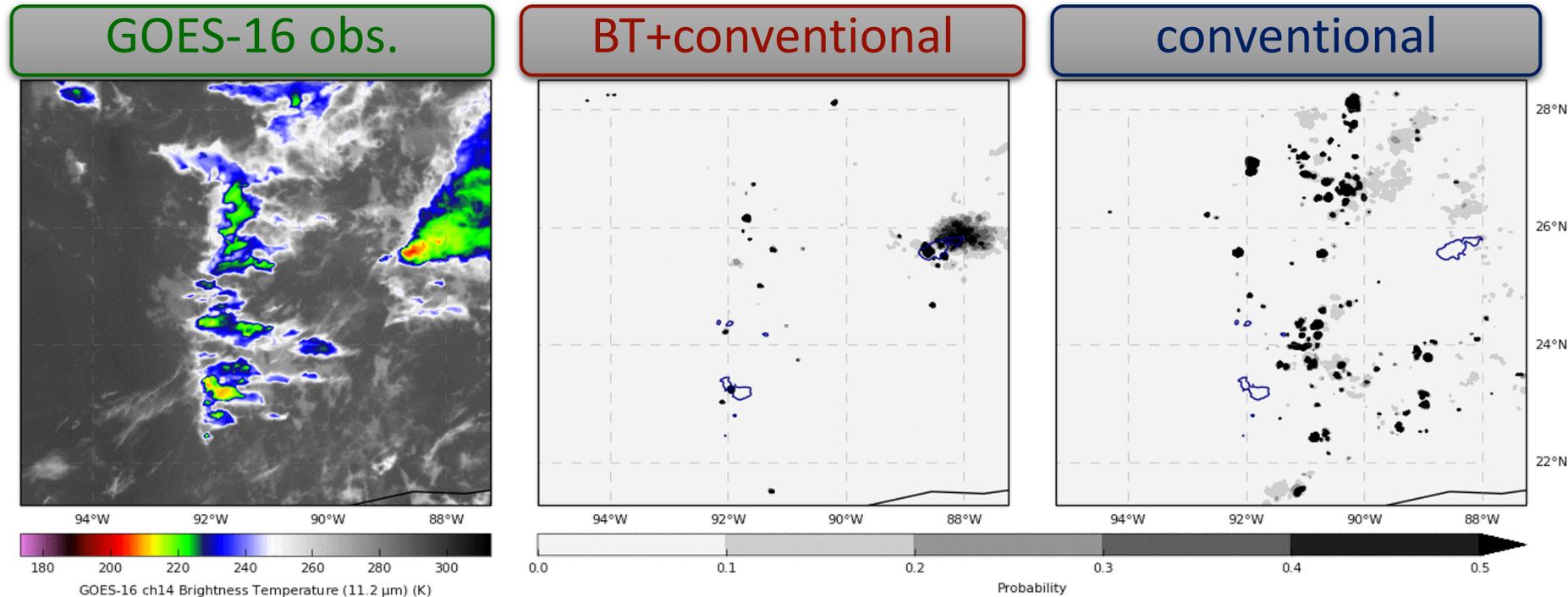
Assimilation of GOES-16 brightness temperature (with Adaptive Observation & Background Error Inflation (AOEI and ABEI) methods) worked well in constraining the convective activity during CPEX



EnKF Performance (Probabilistic Forecast)

(Results courtesy Masashi Minamide, masashi.minamide@jpl.nasa.gov)

20 Ensemble probabilistic forecast of $T_b < 215$ K
Initialized at 15Z/11 June 2017 (after 3-hours of assimilation)



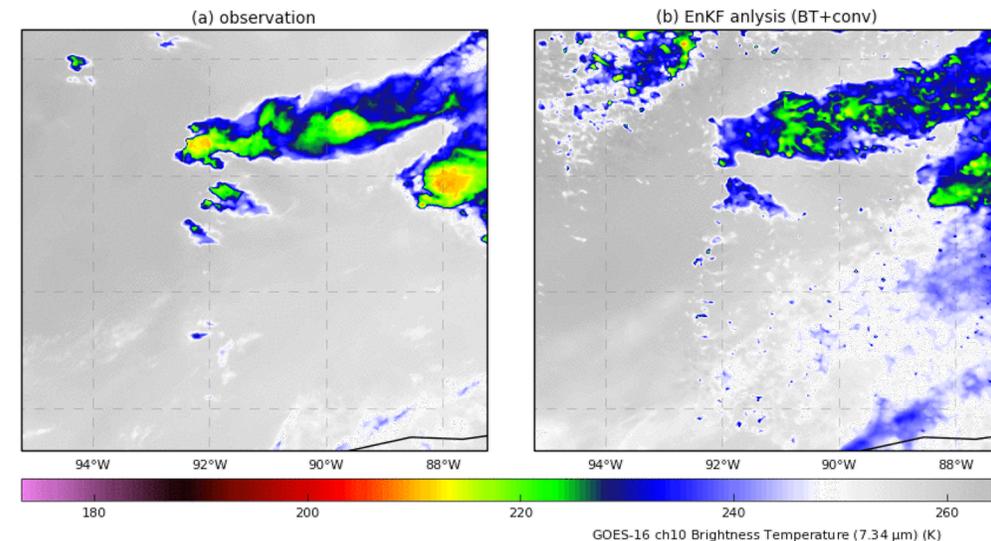
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Although shifted eastward, assimilation of all-sky BTs helped to better constrain the occurrence of newly developing convection.



Next Step: Convective Dynamics

- CPEX and Harvey DA results look very realistic, but... are they?
- Cloud top brightness temperatures are connected to unorganized deep convective updrafts, but only indirectly.
- Questions:
 - What constraint did the GOES-16 observations place on convective dynamics?
 - Which additional observations may be necessary to constrain convective vertical mass flux?
- Next steps:
 - Mine ensemble to explore constraint of GOES-16
 - Simulate other observations and assess their impact (probabilistically)



[2017-06-11_12:00]

OSSE Spectrum: Summary and Caveats

- Adequate sampling and resolution is the low bar
- Next step is geophysical parameter uncertainty assessment
- Both are pre-requisites for process and/or forecast OSSEs
- Uncertainty can be quantified, but results should be qualified...
 - Outcomes of any OSSE depend on
 - Representation of “nature”
 - Representation of uncertainty in measurements and forward models
 - Caution - by the time of launch/data acquisition:
 - Retrieval framework may (will) be different
 - Program of record may (will) be different
 - Forecast/DA systems may (will) be different



Putting it all together: A Notional End to End OSSE for Convective Dynamics

Targeted Observable: Convection and Cloud Dynamics (DS TO-5)

Science Objective: measure vertical motion in deep convective cloud systems

- **Sampling:**
 - GMAO nature run + convective system feature identification: determine orbit period, swath, single vs multiple observatory, etc
 - Use database of high resolution CRM simulations to explore effect of changes in footprint size, instrument sensitivity, and swath width (consequences of partial observation of updrafts)
- **Retrieval:**
 - Apply instrument simulator to CRM database
 - Retrieve vertical motion, compare uncertainty vs desired capability
- **Process:**
 - Vary controls on convective dynamics in a CRM ensemble
 - Use synthetic dynamics retrieval to assess information on convective processes
- **Analysis:**
 - Use a convective scale ensemble as a baseline
 - Assimilate GOES-16 (and other PoR data)
 - Simulate measurements from one member, and assimilate them in the EnKF system to assess addition of information relative to PoR



Backup Slides



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OSSEs for CCP: Tools and Algorithms

Leverage available resources

1. Instrument simulators with (nonlinear) Bayesian retrieval algorithms
 - Allow robust estimates of information content and observability
 - Produce quantitative assessments of retrieval uncertainty
 - Accommodate multiple possible instrument types (including program of record)
2. High resolution simulations of clouds, convection, and precipitation coupled with instrument simulators
 - Large ensembles (100s of members) have already been generated for convection of multiple types and in multiple regions at 250 m grid spacing
 - Ensembles (10s of members) also generated for extratropical cyclones at 1.33 km grid spacing
 - The GEOS-5 Nature Run, while not convection resolving, can be used for coarse-grained sampling studies
3. Ensemble-based data assimilation systems at convection resolving scales
 - Ensembles naturally accommodate process nonlinearity and representativeness
 - Recent work has demonstrated effective assimilation of PoR – experiments can be expanded to include potential future observations



OSSEs for CCP: Study Team

- Science Impacts Team
 - Univ. Utah (J. Mace, Z Xu)
 - GSFC (J. Munchak, M. Grecu, I. Adams)
 - JPL (D. Posselt, M. Lebsock, M. Minamide, E. Nelson, R. Storer)
 - MSFC (W. Peterson, D. Cecil, P. Gatlin, T. Lang)
- Conduct OSSEs for CCP, which involve any of the elements of the spectrum deemed necessary to provide information to the architecture study
- Note that many studies have already been conducted and “expert elicitation” is a valid source of information



All-sky satellite radiance DA

New assimilation techniques for all-sky DA

Adaptive observation error inflation (AOEI)

- **Minamide, M.**, and F. Zhang, 2017: Adaptive Observation Error Inflation for Assimilating All-sky Satellite Radiance, *MWR*, 145,1063-1081

Adaptive background error inflation (ABEI)

- **Minamide, M.**, F. Zhang, 2019: An Adaptive Background Error Inflation Method for Assimilating All-sky Radiances, *QJRMS*, doi:10.1002/qj.3466.

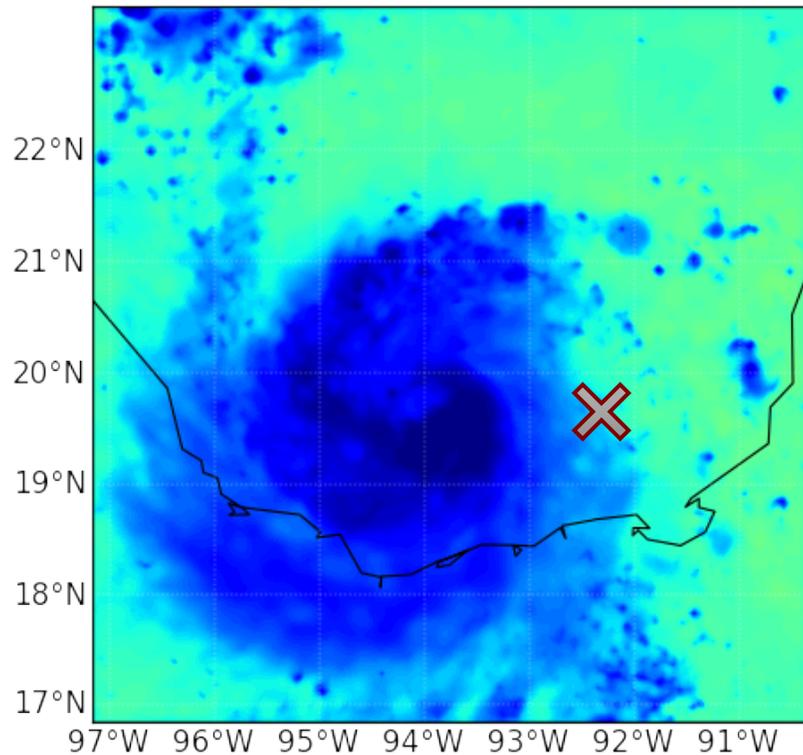
Application to TC prediction

Real-data application on GOES-16 ABI:

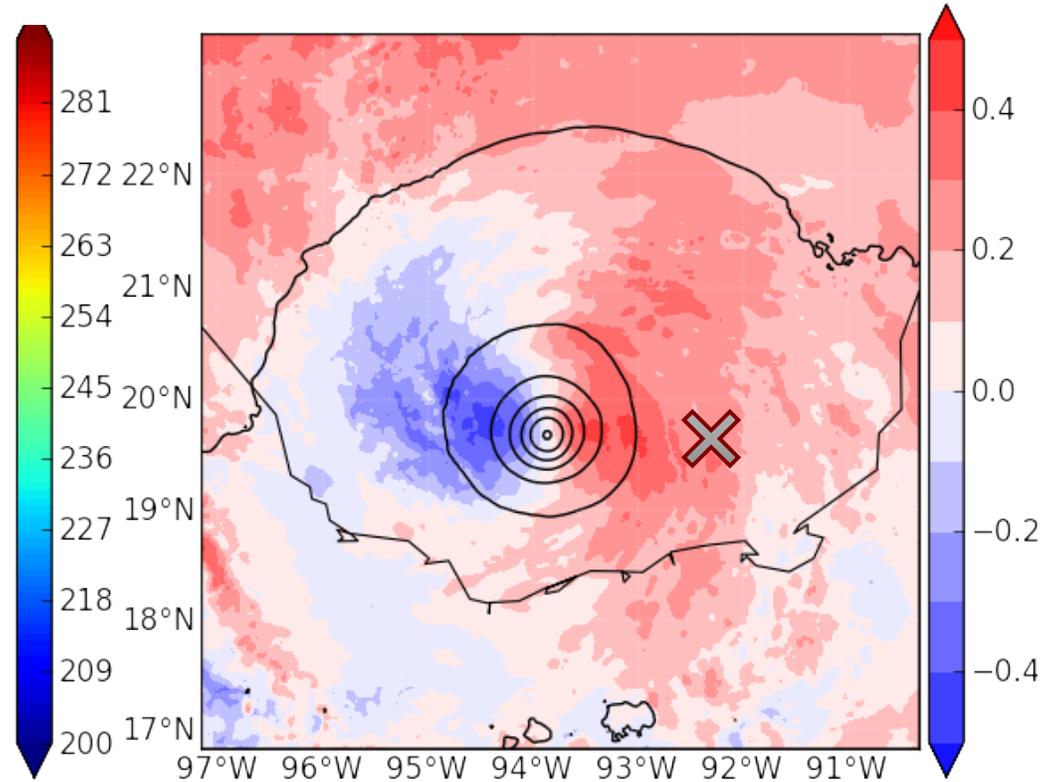
- **Minamide, M.**, F. Zhang, E.E. Clothiaux, 2018: Dynamics and Predictability of Hurricane Harvey (2017) Examined through Convection-permitting Ensemble Assimilation of All-sky GOES-16 Radiances, in prep for the submission
- Zhang, F., **M. Minamide**, X. Chen, R. G. Nystrom, S.-J. Lin and L. M. Harris, 2018: Improving Harvey forecasts with next-generation weather satellites, *BAMS IN-BOX*



Potential impacts of assimilating BTs



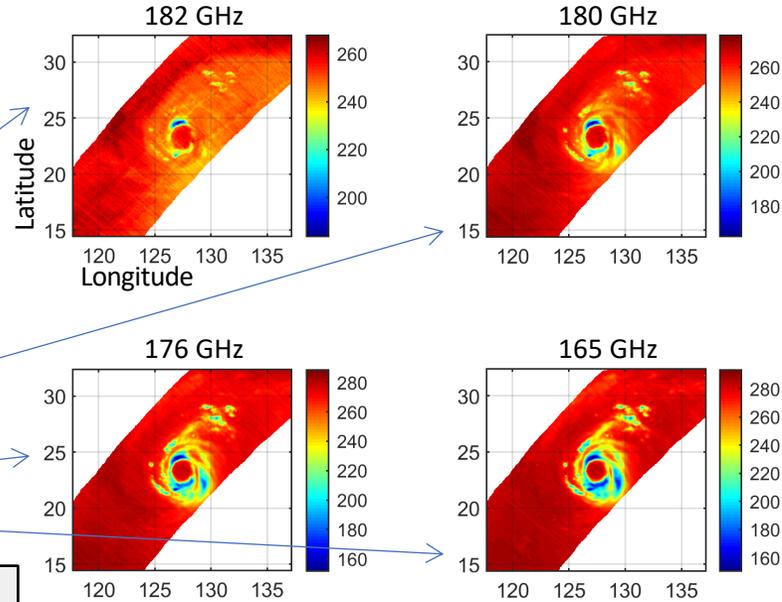
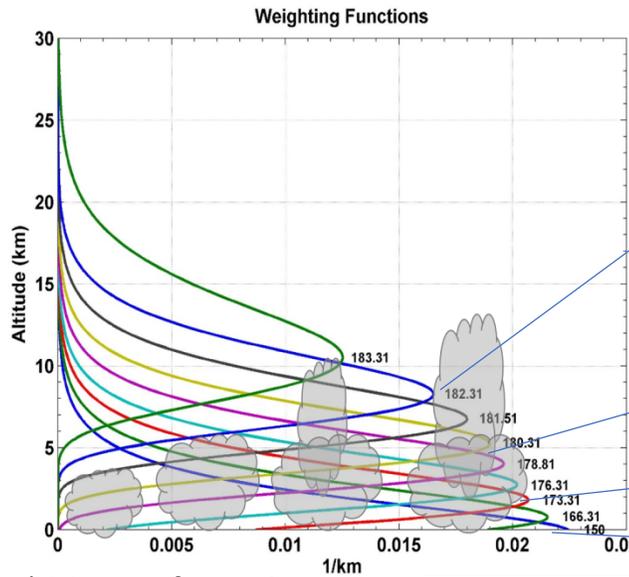
Simulated GOES-R ABI
Ch8 (6.19 μm)
brightness temperature



Colors: ensemble correlation of
SLP to brightness temp. at 'X'
Contours: ensemble mean SLP

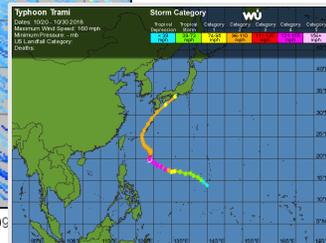
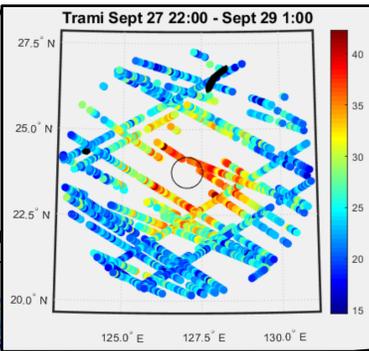
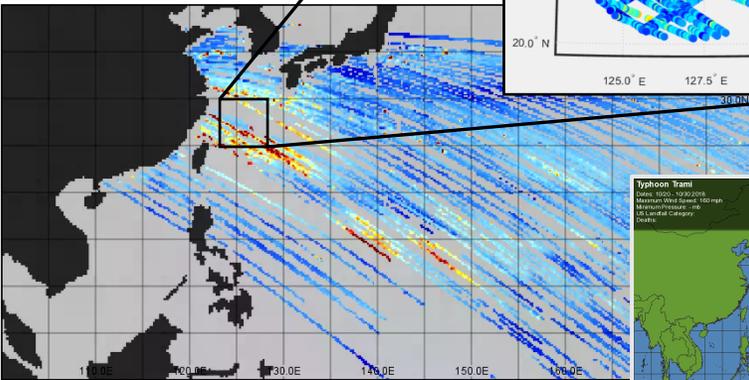


Exploring Synergy Among Small-Sats: Typhoon Trami



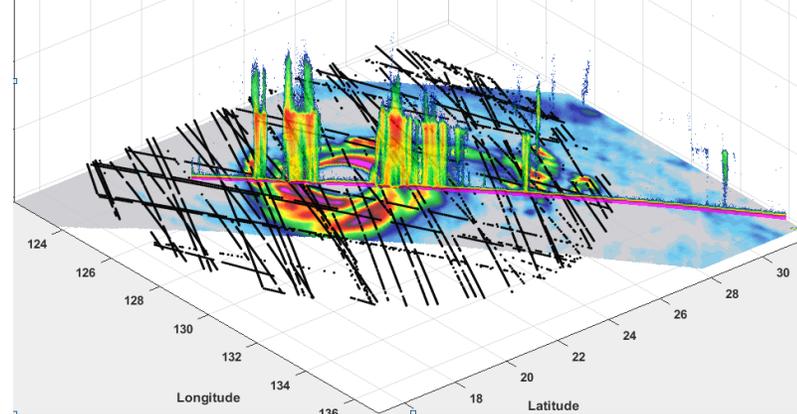
(below) Max surface wind throughout Trami lifecycle;
(insert) Storm-centric composite wind tracks latent heat flux

CYGNSS L3 Max Hold Young Sea Limited Fetch Wind Speed - H.T



NHC Storm Track

Similar asymmetry observed in depth of eyewall convection between TEMPEST-D and RainCube (strongest on west side and to the south). CYGNSS winds in inner core provide estimate of latent heat flux.



Future: exploit synergy among measurements to capture process-level interactions in TCs

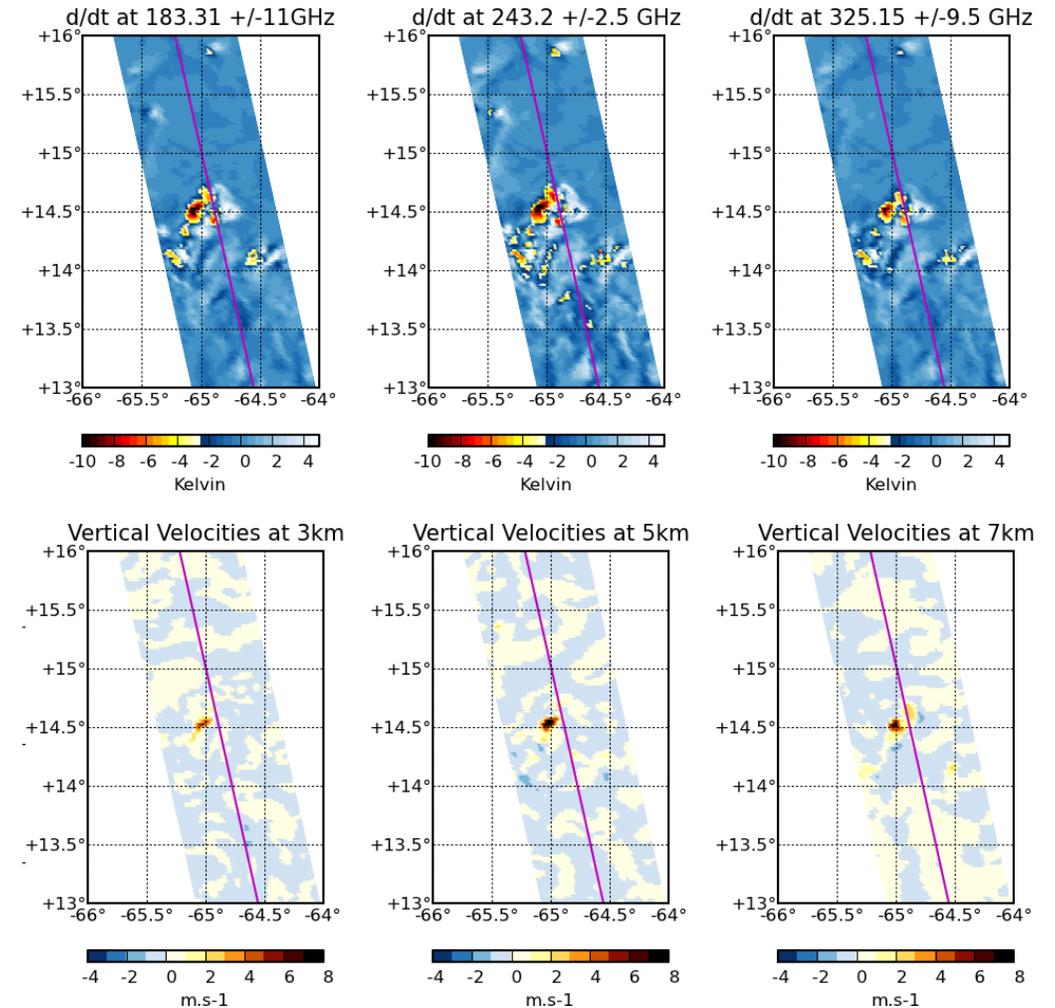
Combination of CYGNSS, TEMPEST-D, and RainCube for Typhoon Trami

- Surface Latent Heat Flux (CYGNSS)
- Spatial Cloud/Precip Context (TEMPEST-D)
- Cloud Vertical Structure (RainCube)

Future advance: rapid revisit?

Retrieval OSSE: Temporal Sampling

- Recent simulation results using a cloud resolving model and microwave brightness temperature simulator
- Close correspondence between brightness temperature difference and vertical velocity
- Results courtesy Philippe Chambon (MeteoFrance) via Ziad Haddad



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