National Aeronautics and Space Administration

Trusted Data Analytics: Uncertainty Quantification

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Program: Strategic

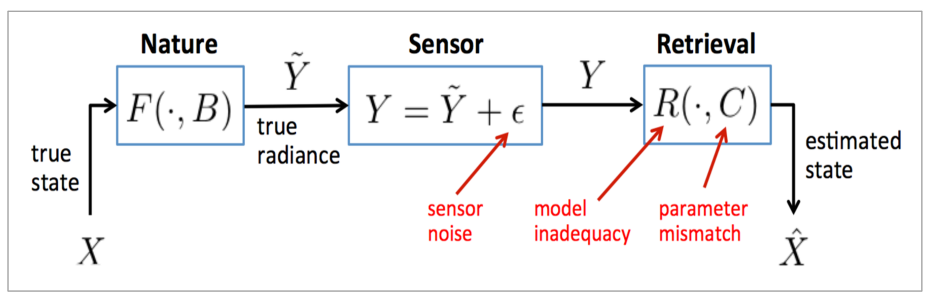
Project Objective

We focus on Uncertainty Quantification (UQ) for error assessment for Earth science retrievals. Ultimate goal is to improve science outcomes & enable decision support.

We do not target data assimilation, OSSEs, or formulation.

Technical focus areas:
- Groundwater UQ (*below right*)
- Surface water UQ (*below*)
- Relevant to GRACE and SWOT
- Atmospheric retrievals like AirMSPI/MAIA (*right*)

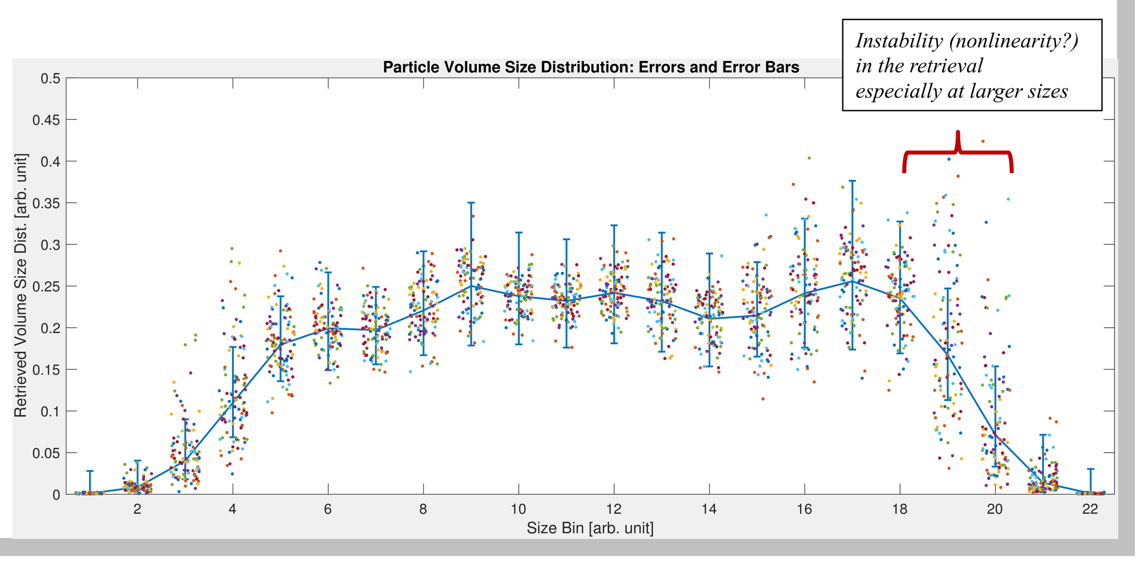
UQ for Atmospheric Retrievals



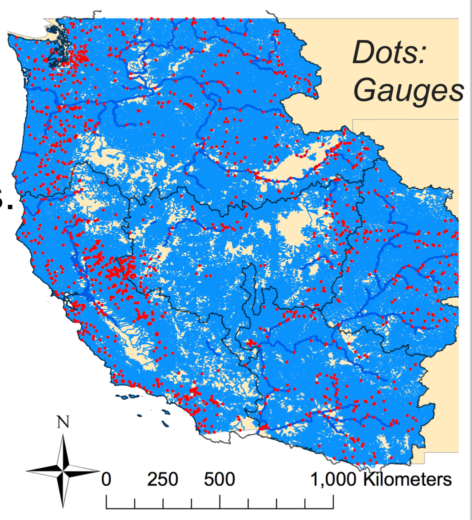
Many Earth Science retrievals (MLS, AIRS, EcoStress, OCO-2) follow the same framework (right).

Retrieval finds a state estimate from radiances arising from a true state-of-nature, like CO_2 abundance.
One core UQ problem here is quantifying the uncertainty injected when the forward model is not exactly known.

A Monte Carlo framework (Observing System Uncertainty Experiment, or OSUE) can estimate actual uncertainty for such complex forward models.
A multi-angle retrieval related to the MAIA AOD retrieval is plotted. The actual errors for the particle size distribution are much larger than those predicted by linear analysis.



Streamflow Uncertainty Propagation



Objective: Propagate uncertainty from runoff to surface flows.

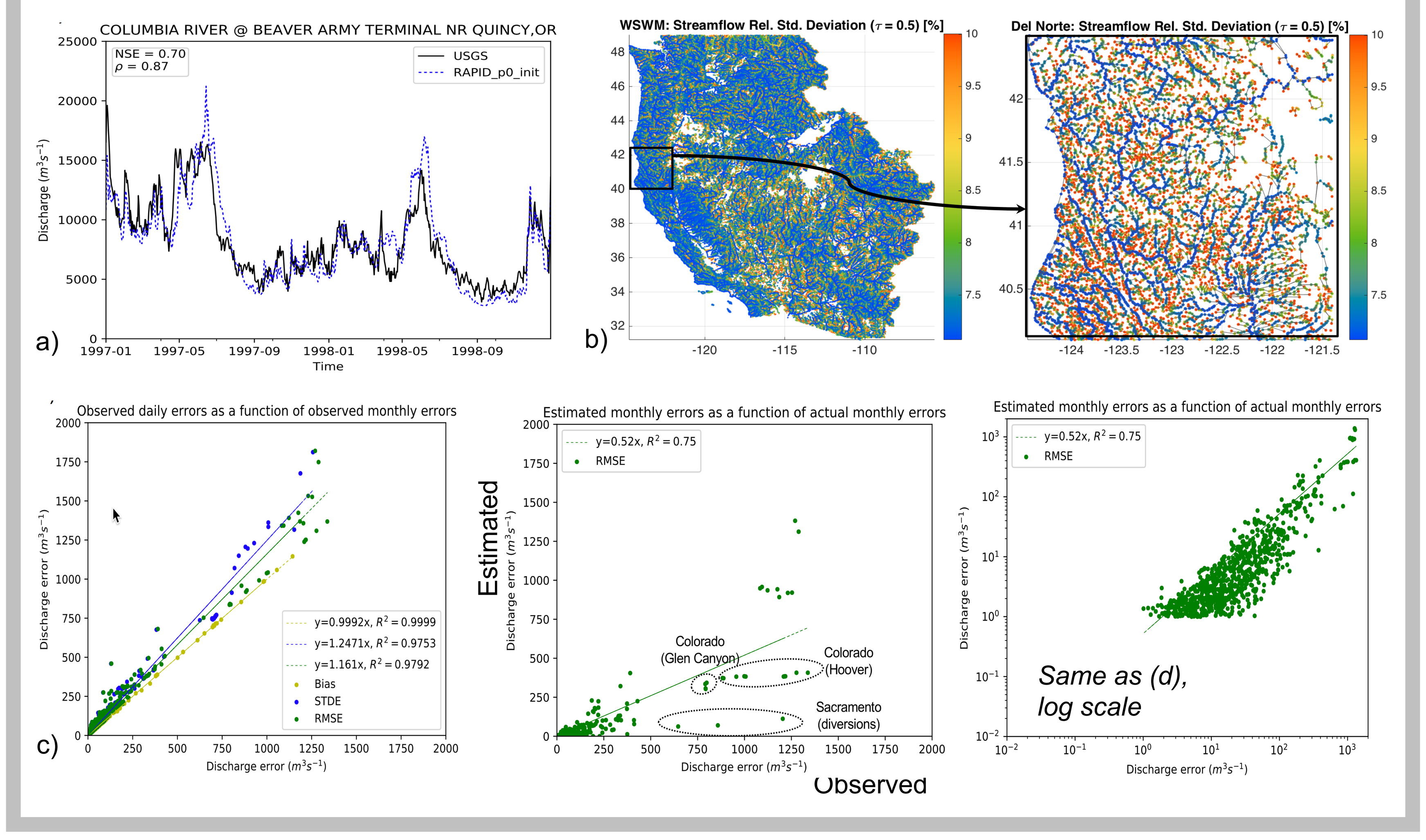
Check agreement of model + uncertainty with the 1562 USGS gauges in the Western U.S. (domain, at right; hydrograph, panel (a)).

Runs cover years-to-decades over ~10^6 river reaches. Problem scale (panel (b)) means no full covariances.

Errors from a monthly block length *can be extrapolated to daily* (panel (c)).

A local/regional spatial error decomposition allows error propagation in time similar to the flow computation itself. Capturing spatial co-variation is *critical*.

Propagated errors (panel (d)) show order-of-magnitude agreement, but also indicate significant unquantified error in runoff. More: David et al., *GRL*, 2019.



Groundwater UQ

Objective: Develop methodology for high-resolution estimates, with uncertainty, for groundwater and total water storage for the Western U.S.

Method combines virtues of remote sensing data and process models.
- GRACE: spatially-coarse but unbiased observation of water storage anomalies.
- Land surface model (VIC, with deep groundwater layer) provides realistic fine-spatial-resolution simulation but is subject to model bias.
- Infer high-resolution total water storage (TWS) through Bayesian statistical model that combines the two data sources.
- Uncertainty estimate is a key benefit of the Bayesian approach.

Statistical Model is overlaid upon:
- GRACE = True low-resolution TWS + Random error
- VIC = True high-resolution TWS + Model error + Random error

Work this year focused on sensitivity of results to model/error assumptions.

Available Data **Estimate** **Uncertainty**

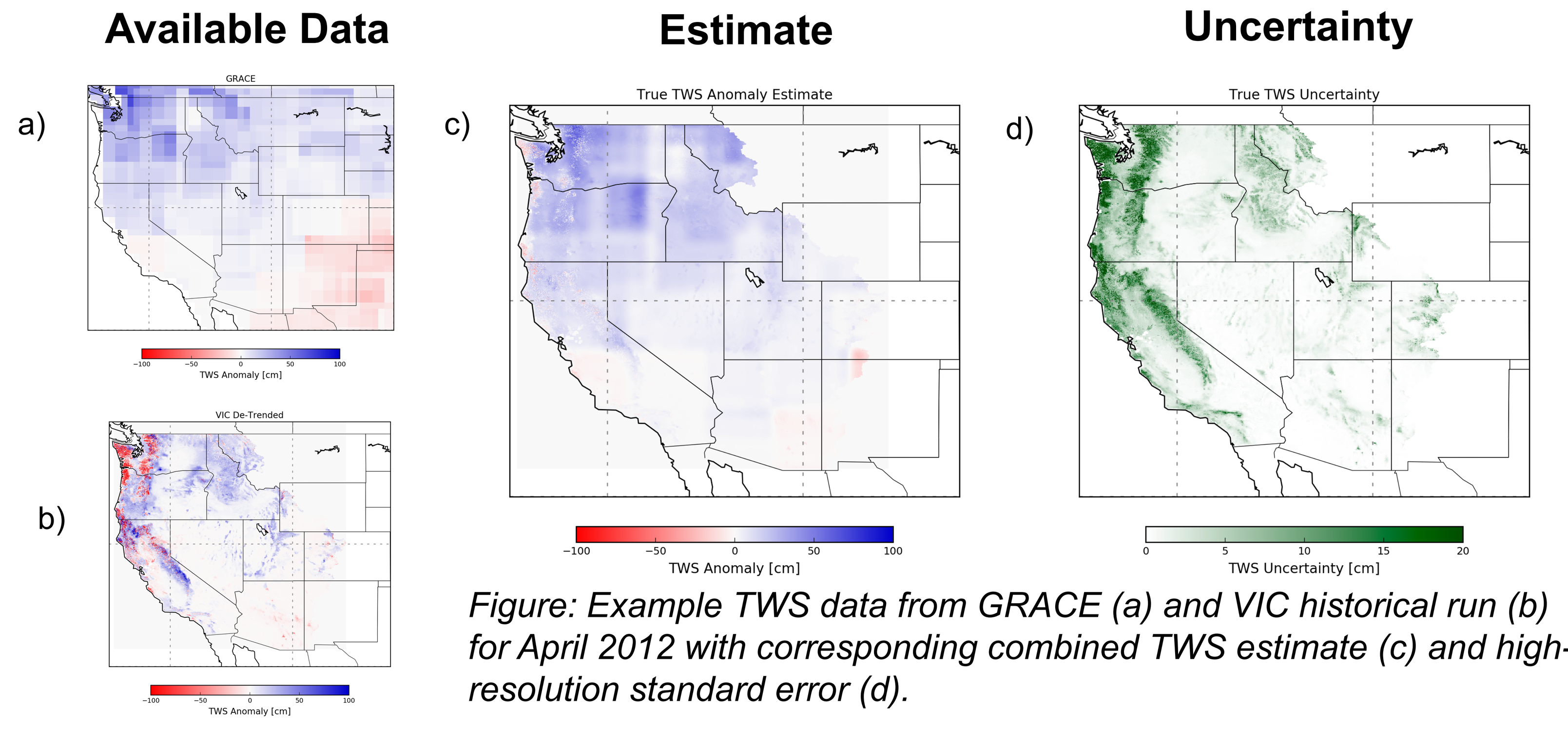


Figure: Example TWS data from GRACE (a) and VIC historical run (b) for April 2012 with corresponding combined TWS estimate (c) and high-resolution standard error (d).

Significance of Results

Conventional uncertainty propagation is insufficient to correctly assess errors of JPL data products. FY17 workshop identified these UQ needs: a written UQ best-practice methodology (addressed partly by OSUE methodology); derivation of spatial covariances as well as point-by-point standard errors; methods to verify retrieval standard errors. Results in streamflow uncertainty underline the importance of quantifying spatial covariances.

Streamflow uncertainties are crucial for assimilation of coming SWOT surface water measurements, and three publications from this work have addressed this problem. Similarly, uncertainties for high-resolution groundwater are important for water management applications to realize the potential of GRACE measurements.

Publications and Documents

Xu, F., et al., "Coupled retrieval of liquid water cloud and aerosol above cloud properties using AirMSPI," *J. Geophys. Res. Atmos., 2018.*

C. H. David, J. M. Hobbs, M. Turmon, C. M. Emery, J. T. Reager, and J. S. Famiglietti, "Analytical Propagation of Runoff Uncertainty into Discharge Uncertainty through a Large River Network," *Geophys. Res. Lett.*, May 2019.

C. Emery, C. H. David, K. Andreadis, M. Turmon, J. T. Reager, J. Hobbs, M. Pan, J. Famiglietti, R. E. Beighley, and M. Rodell, "Underlying Fundamentals of Kalman Filtering for River Network Modeling," *J. Hydromet.*, re-submitted 9/2019.

Y. Yang, P. Lin, C. K. Fisher, M. Turmon, J. Hobbs, C. M. Emery, J. T. Reager, C. H. David, … and M. Pan, "Enhancing SWOT Discharge Assimilation through Spatiotemporal Correlations," *Remote Sensing of Environment*, 2019.

Elias Massoud, M. Turmon, J. T. Reager, J. Hobbs, Zhen Liu, and C. David, "Characterizing trends of Total Water Storage and its uncertainty using satellite and hydrologic information", in preparation for *Hydrological Processes*, 2019.

J. Hobbs, "Downscaling GRACE Total Water Storage Estimates With a High-Resolution Land Surface Model Simulation," tech report, 2019.

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