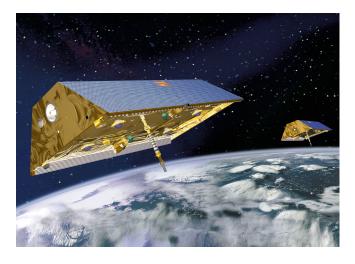
# **Towards Improved Snow Water Equivalent Estimation Via GRACE Assimilation** Bart Forman<sup>1,2</sup> (Barton.A.Forman@nasa.gov), Rolf Reichle<sup>1</sup>, Matt Rodell<sup>3</sup>

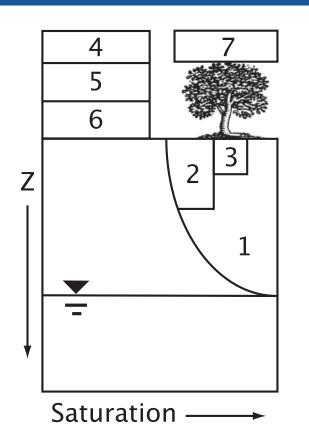


### Motivation

Improve snowpack characterization via assimilation of Gravity Recovery and Climate Experiment (GRACE) measurements into a distributed land surface model.

# **Prognostic Model and EnKS**

Figure 1. The prognostic Catchment Land Surface Model (CLSM) [1] estimates terrestrial water storage (TWS) as a function of groundwater, soil moisture, surface water, snow water equivalent, and canopy interception. CLSM utilizes meteorological forcings to propagate model states forward in time as expressed in Equation (1).



$$\mathbf{x}_t^{i-} = \mathbf{f}_t \left( \mathbf{x}_{t-1}^{i+} \right) + \mathbf{w}_t^i \text{ for } i \in N.$$
 (1)

CLSM-derived TWS is conditioned on GRACE TWS measurements using an ensemble Kalman smoother (EnKS) similar to that in [2]. The Bayesian framework is posed as:

$$\mathbf{x}_{\tau}^{i+} = \mathbf{x}_{\tau}^{i-} + \mathbf{K}_{\tau} \left[ \mathbf{y}_{\tau} + \mathbf{v}^{i} - \mathbf{H}\mathbf{x}_{\tau}^{i-} \right], \qquad (2)$$

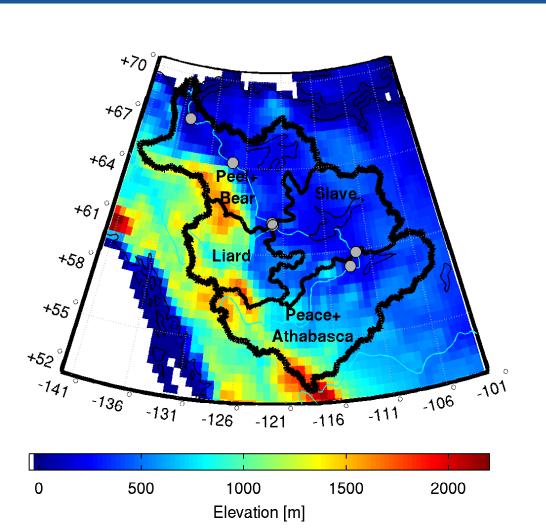
where  $\mathbf{x}_{\tau}^{i+}$  is the posterior state vector,  $\mathbf{K}_{\tau}$  is the Kalman gain,  $\mathbf{y}_{\tau}$  is the observation vector,  $\mathbf{H}$  is the observation operator that maps the model states into measurement space, and  $\tau$  is the temporal assimilation window such that  $\tau \in [t_o \ t_f]$  where  $t_o$ and  $t_f$  are the first and last day of a given month, respectively. Measurement and model uncertainties are accounted for as

$$\mathbf{K}_{\tau} = \mathbf{P}_{\tau}^{-} \mathbf{H}_{\tau}^{T} \left( \mathbf{H}_{\tau} \mathbf{P}_{\tau}^{-} \mathbf{H}_{\tau}^{T} + \mathbf{R}_{\tau} \right)^{-1}, \qquad (3)$$

where  $\mathbf{P}_{\tau}^{-}$  is the background error covariance computed from  $\mathbf{x}_{\tau}^{i-}$  and  $\mathbf{R}_{\tau}$  is the specified measurement error covariance.

#### **Experimental Setup**

GEOS-5 Figure 2. elevation map of the Mackenzie River Basin (MRB) in northwest Canada including subbasin delineation (black lines). Runoff measurement stations shown as gray points.



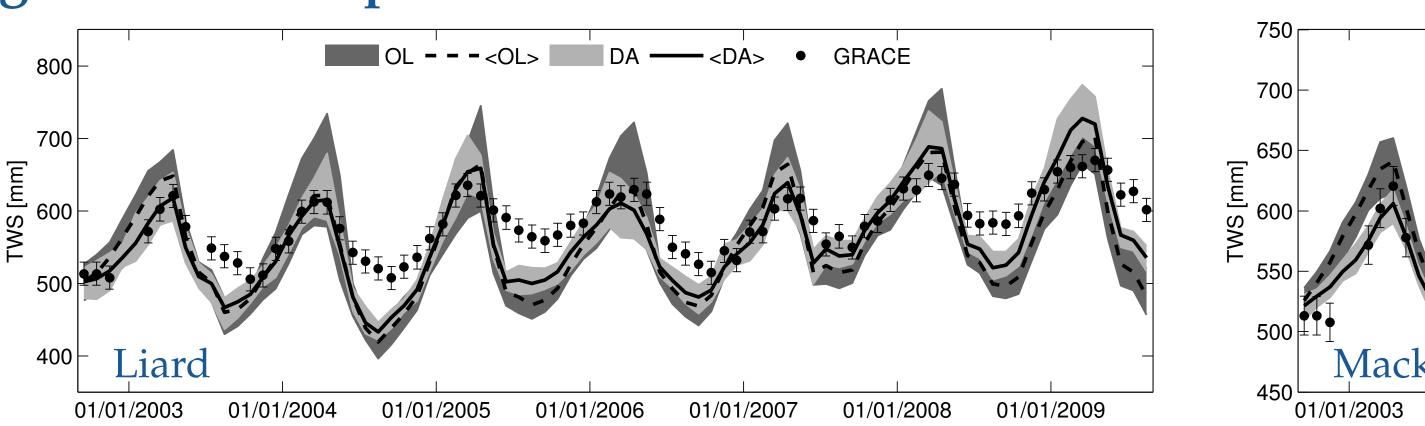
- Modern Era Retrospective-analysis for Research Applications (MERRA) meteorological forcing [3]
- Monthly-averaged, basin-averaged GRACE TWS assimilation
- Simulation from September 2002 to September 2009

<sup>1</sup> NASA Goddard, Global Modeling and Assimilation Office <sup>2</sup> Oak Ridge Associated Universities <sup>3</sup> NASA Goddard, Hydrologic Sciences Branch

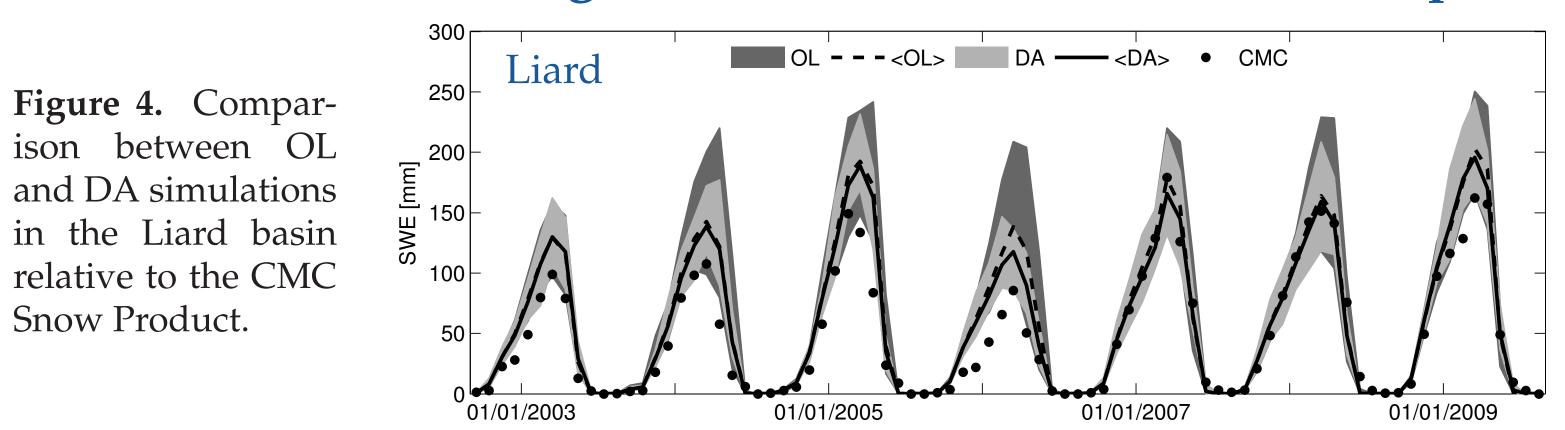
#### Results

### I. GRACE Terrestrial Water Storage (TWS) Comparison

Figure 3. Comparison between open-loop (OL) and data assimilation (DA) simulations for the Liard basin (left) and the entire Mackenzie basin (right). The assimilated GRACE observations and corresponding observation error standard deviation from the Space Geodesy Research Group (GRGS) are included for reference. Note the obvious bias in variability between the OL and GRACE observations.

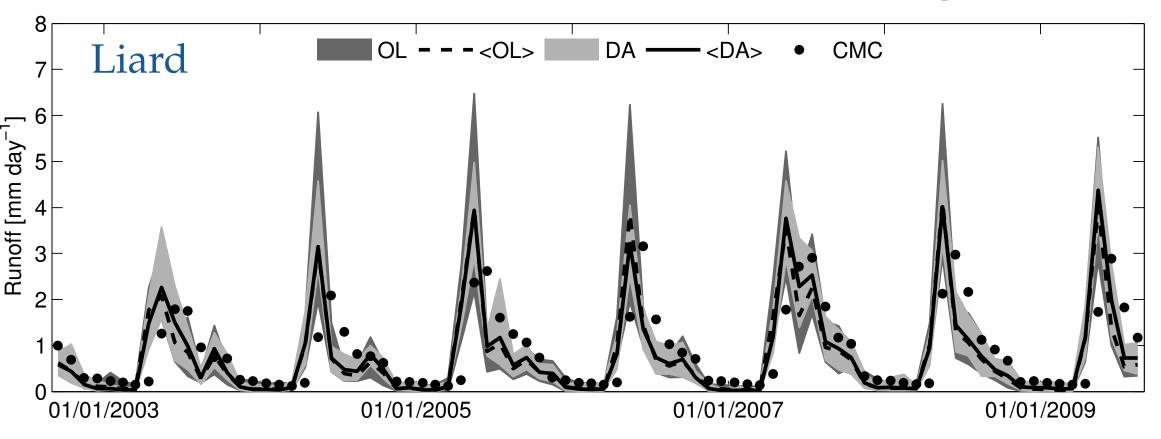


#### II. Canadian Meteorological Centre (CMC) Snow Water Equivalent (SWE) Comparison



### **III. Global Runoff Data Centre (GRDC) River Discharge Estimates**

Figure 6. Similar to Figure 4 except comparisons that are made relative to GRDC observations.



#### **Conclusions and Future Work**

#### **Key Findings:**

- Modest reduction in MD and RMSD in SWE estimates in most sub-basins
- Modest improvement in anomaly correlation in SWE estimates in most sub-basins (not statistically significant)
- Modest reduction in MD and RMSD in runoff estimates at most locations
- Modest improvement in anomaly correlation in runoff estimates at most locations (not statistically significant)
- GRACE assimilation offers some beneficial information exchange, but more work is needed, particularly in appropriate processing of GRACE observations and accurate accounting of GRACE observation errors (see Figure 8)

#### **Future Items to Address:**

- Optimal basin kernel?
- Lake level storage?
- GRACE signal leakage?

Figure 5. Computed statistics for OL and DA simulations for all sub-basins relative to the CMC Snow Product. Anomaly R calculations include removal of monthlyaveraged climatology. Differences in anomaly R are not significant within a 95% confidence interval.

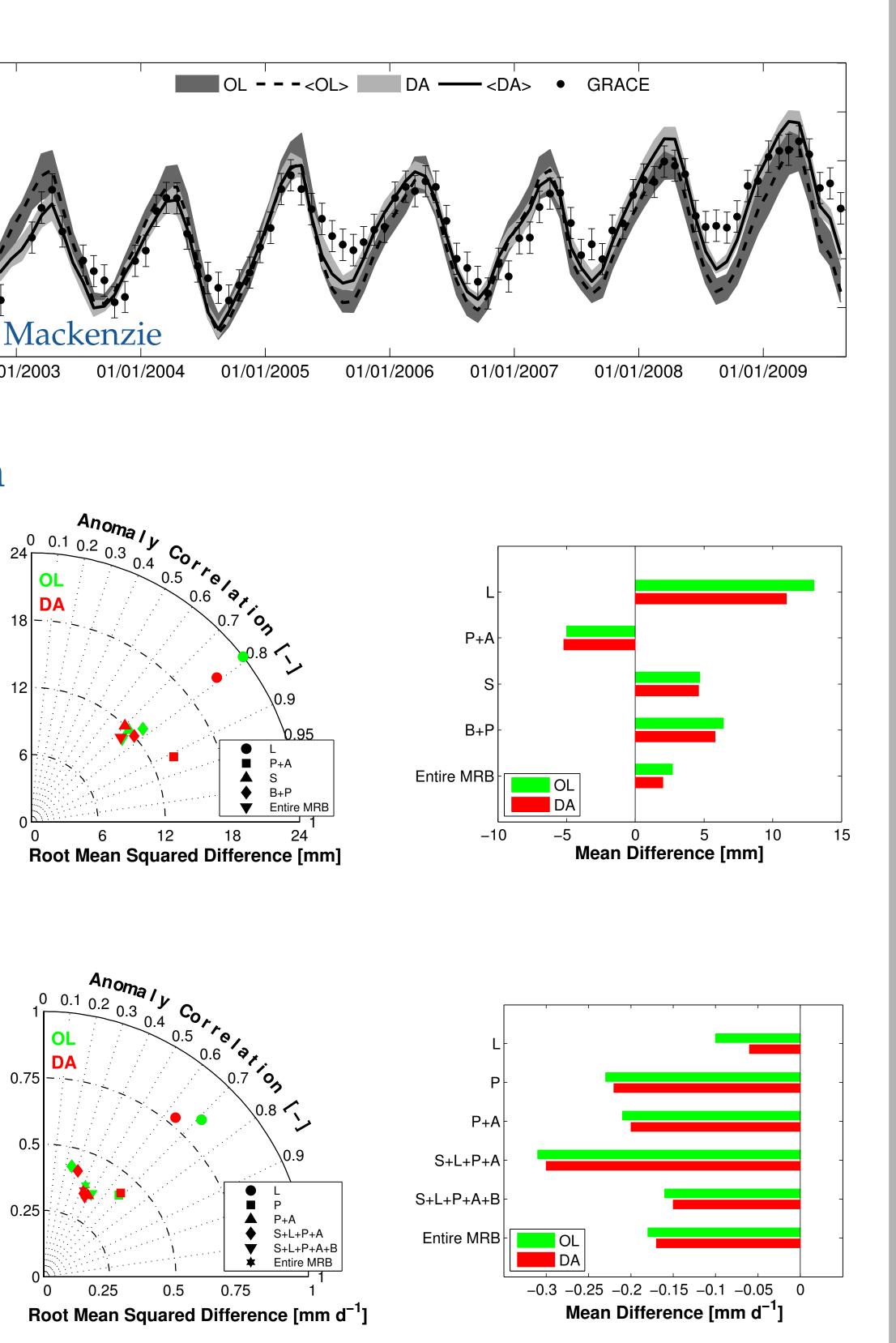
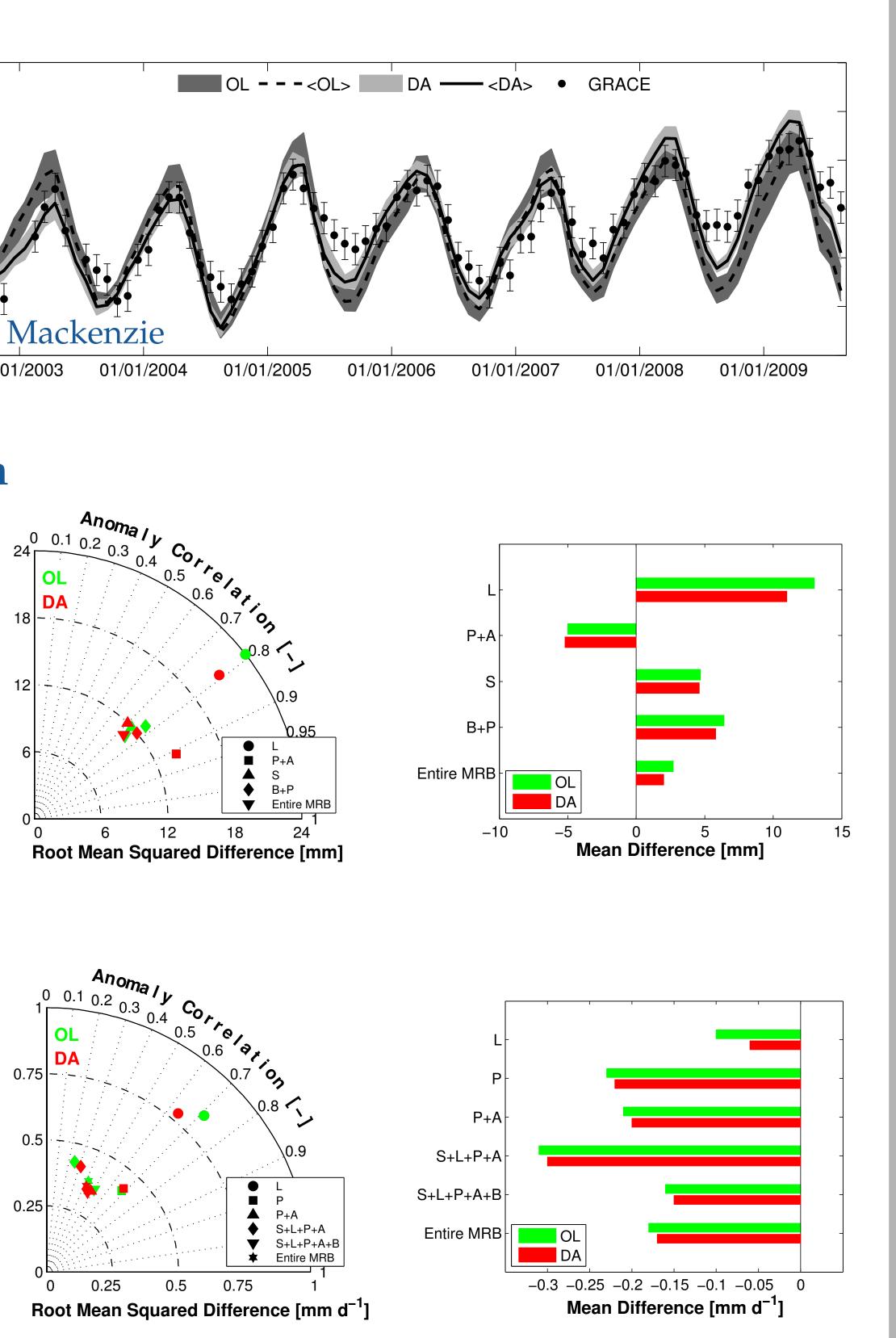
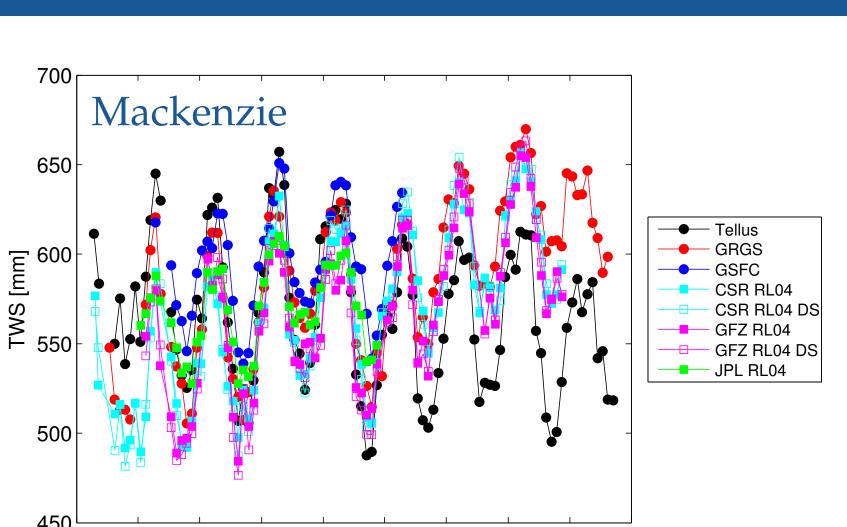


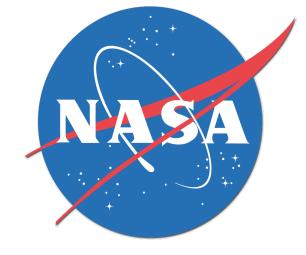
Figure 7. Similar to Figure 5 except that comparisons are made relative to GRDC runoff observations. Again, differences in anomaly R are **not** significant within a 95% confidence interval.





2002 2003 2004 2005 2006 2007 2008 2009 2010 2011

Figure 8. GRACE TWS estimates based on different retrieval algorithms yield significantly different TWS estimates within the MRB. The most efficient assimilation of GRACE into a land surface model will likely depend on the use of an optimal smoothing kernel.



#### References

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[2] B.F. Zaitchik, M. Rodell, and R.H. Reichle. Assimilation of GRACE terrestrial water storage data into a land surface model: Results for the Mississippi river basin. J. Hydromete*orol.*, 9:doi:10.1175/2007JHM951.1, 2008.

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## Funding

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