Overview of (Global-Continental) Land Data Assimilation

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Motivation/outline

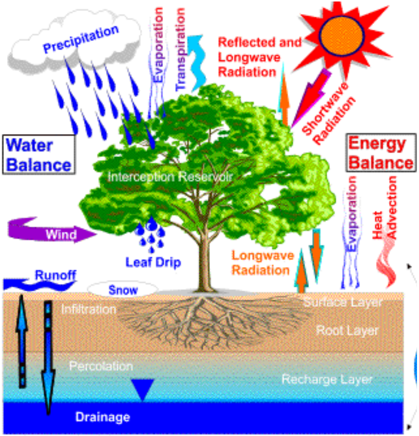
Motivation for land data assimilation:

- Improve land surface state estimates for use in weather prediction, seasonal prediction, run-off to ocean, flood forecasts, agriculture, drought monitoring, water/energy/carbon accounting, ...

Presentation outline:

- Land surface models and remotely sensed observations
- Examples of land data assimilation from NASA GMAO (near-surface soil moisture, terrestrial water storage, land skin temperature)
- Challenges / opportunities

Global land surface models



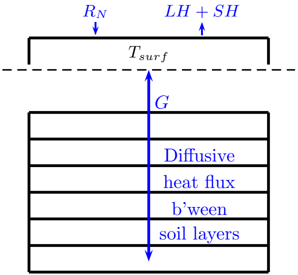
c/o NASA Hydrological Sciences Branch

- Land surface models are strongly non-linear, and non-differentiable (no adjoint for variational assimilation)
- Ensemble methods are well suited to solving land data assimilation

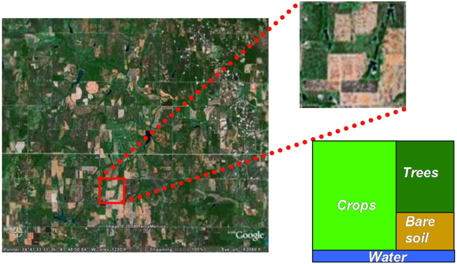
Global land surface models

Vertical resolution: 1cm - 1m

$$\frac{dT_{surf}}{dt} = \frac{1}{shc}(R_N - LH - SH - G)$$



Spatial resolution: O(10km) for global models



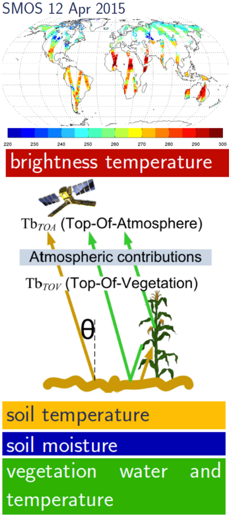
- Each grid cell is modeled independently (no sub-surface horizontal flow)

Assimilated remotely sensed land observations

- Near-surface soil moisture
  passive microwave: AMSR-E, SMOS, SMAP
  active microwave: ERS, ASCAT, SMAP
- Land surface temperature
  TIR/Vis: Geostat., MODIS
- Snow cover fraction
  Vis.: MODIS, VIIRS
- Snow water equivalent
  passive microwave: AMSR-E
- Vegetation
  Vis: MODIS, AVHRR
- Terrestrial water storage
  change in gravity: GRACE
- ...

Assimilated remotely sensed land observations

- Usually assimilate retrieved geophysical variables
- Vertical support: often a shallow surface layer
- Temporal resolution: polar-orbiters: 1-3 days, geostationary: sub-daily
- Spatial resolution: microwave O(10's km), Vis O(1 km)

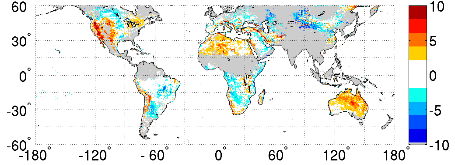


c/o G. De Lannoy

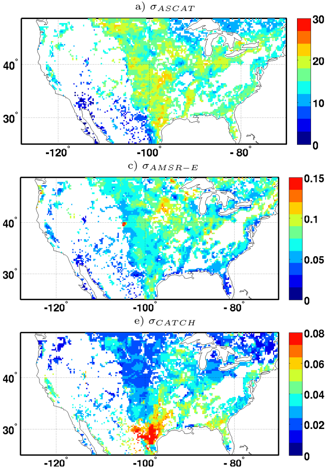
Comparing observed and forecast estimates

- Large systematic differences in mean and variance of observations and forecasts
- For many variables, the true values are unknown
- Differences due to:
  - Errors in obs. and/or forecast
  - Differences in the variable defined by each (representativity differences)

Difference in means: Geostat.- GEOS-5 monthly mean T_{skin} [K]



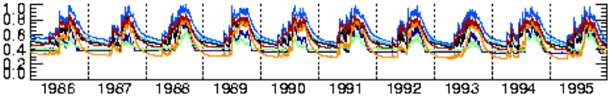
Difference in variance: 3 soil moisture estimates



Model-specific nature of soil moisture

- The mean and variance of can soil moisture varies dramatically between different models, but temporal behavior is often in better agreement

Soil wetness index for 7 GSWP-2 models [-]



Koster et al, 2009 (J. Clim)

In terms of assimilation:

- Forcing a model away from it's preferred climatology toward the observed climatology can cause inconsistencies, seriously degrade forecasts
- The usable information in remotely sensed observations is the temporal behavior

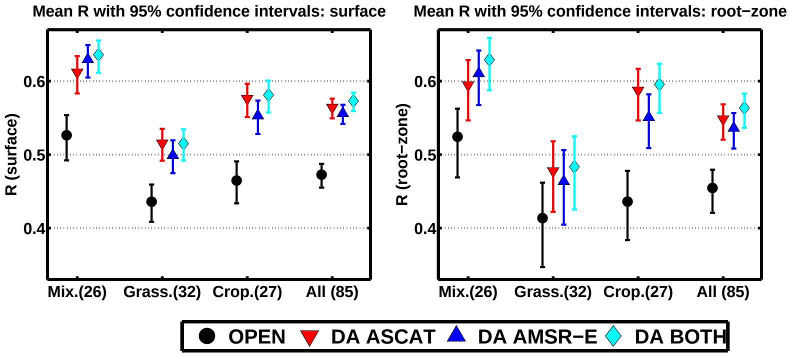
Assimilation of near-surface soil moisture observations

- Passive microwave: AMSR-E, LPRM X-band retrievals (38 km resolution, depth < 1cm)
- Active microwave: ASCAT C-band retrievals (25 km resolution, $\sim$ 1cm depth)
- Assimilate into Catchment model at 0.25°, from Jan. 2007 - May 2010
- Use GMAO offline 1-D EnKF, update near-surface and root-zone soil moisture
- Remove systematic differences between observations and f'casts by rescaling the obs. to match the CDF of the f'casts (Reichle and Koster, 2004 (GRL))
  - Bias-blind assimilation of temporal anomalies

Draper et al, 2012 (GRL)

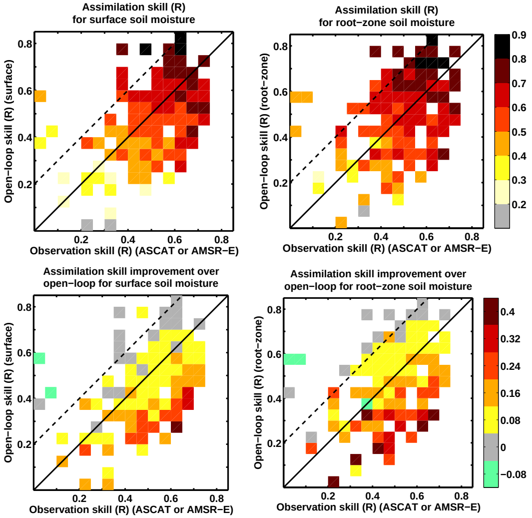
Assimilation skill by land cover class

- Evaluate against in situ observations from SCAN/SNOTEL (US) and Murrumbidgee Soil Moisture Monitoring Networks (Aus), using correlation of anomalies from the seasonal cycle (R)



Draper et al, 2012 (GRL). See also Reichle et al, 2007 (JGR), Crow et al, 2011 (WRR), Liu et al, 2011, (J. Hydromet), ...

Contribution of observation skill to assimilation skill



- Based on assimilation of ASCAT or AMSR-E
- If (obs skill − open-loop skill) > -0.2, assimilation improved the model skill

Draper et al, 2012 (GRL)

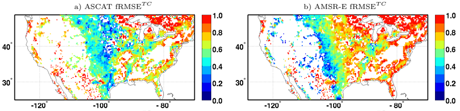
Specifying obs. error variance at continental scales

Triple colocation

1.Solve simple error model:

$\theta_A = \alpha(\theta + \epsilon_A)$
$\theta_L = \lambda(\theta + \epsilon_L)$
$\theta_C = \gamma(\theta + \epsilon_C)$

fRMSE = Root Mean Square Errors, normalized by stdev.

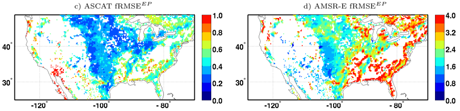


+ve: gives relative errors between estimates

-ve: assumptions frequently violated, needs large sample of 3 ind. estimates

Error Propagation

fRMSE = Root Mean Square Errors, normalized by stdev.

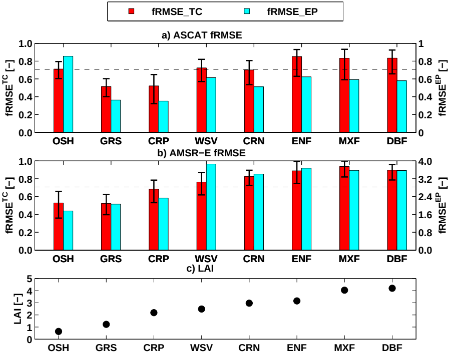


2. Propagate expected measurement & parameter errors through retrieval model

+ve: temporally varying error estimates

-ve: assumes retrieval model structure is correct, little confidence in absolute values

Specifying obs. error variance at continental scales

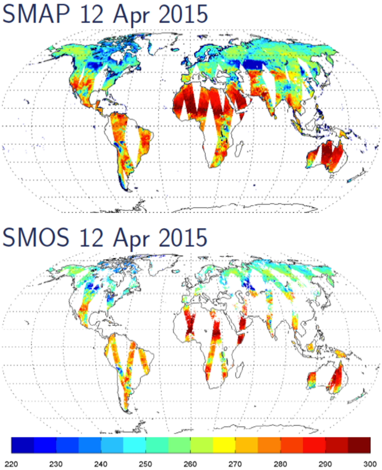


- Using triple colocation errors in observation error covariance matrix for assimilation of ASCAT and AMSR-E soil moisture gives small improvements in assim. output
- Both methods perhaps most valuable for identifying regions with very large errors
- Neither accounts for representativity error (can be substantial for land DA)

Draper et al, 2013 (RSE)

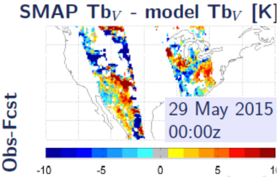
L-band soil moisture from SMOS and SMAP

- NASA's SMAP, launched Jan. 2015, 3-40 km, passive radiometer + active radar*
- ESA's SMOS, launched Nov. 2009, 40 km resolution, passive radiometer
- Both observe at L-band (1.4 GHz)
- Ideal for soil moisture sensing, observed 5 cm layer

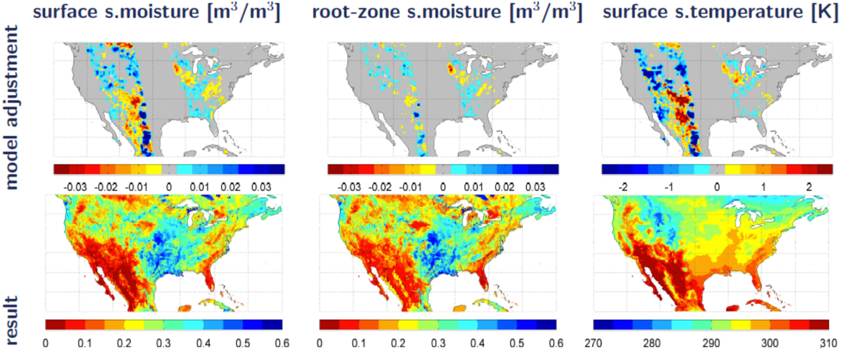


c/o Gabrielle De Lannoy, Rolf Reichle

Level 4 SMAP root-zone soil moisture (G. De Lannoy)

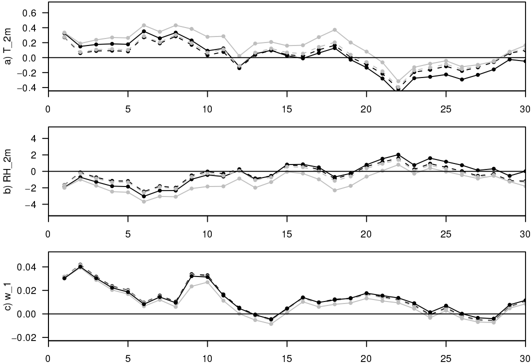


- EnKF direct assimilation of brightness temperature
- RTM calibrated to remove systematic differences between obs. and f'casts



Improving flux forecasts with soil moisture assimilation

- Near-surface soil moisture assimilation has been shown to improve root-zone soil moisture
- Improvements to subsequent flux forecasts (run-off, LH, SH) has been more elusive



July 2006 mean daily O-F: open loop (black), assim. of 2m vars. (black, dashed), AMSR-E SM (gray), and both (gray, dashed).
Draper et al, 2010 (JGR)

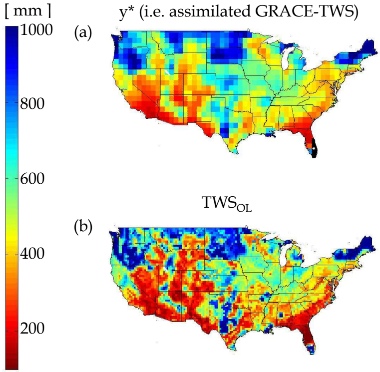
See also Seuffert et al, 2004 (J. Hydromet), Dharssi et al, 2011 (HESS) , de Rosnay et al, 2012 (QJRMS)

Assimilation of GRACE TWS (M. Girotto)

- GRACE measures the c between twin satellites gravity anomalies
- Terrestrial Water Stora (TWS) anomalies then from the gravity anoma
- Observation is change monthly mean TWS, a ~basin-scale horizontal resolution (330 km at e

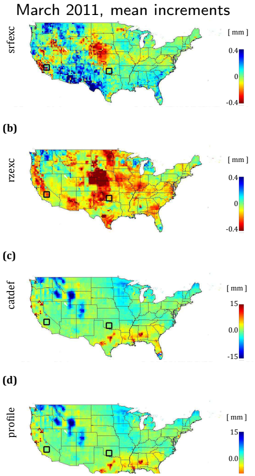
+ve: observation over full p

-ve: temporally and spatially coarse



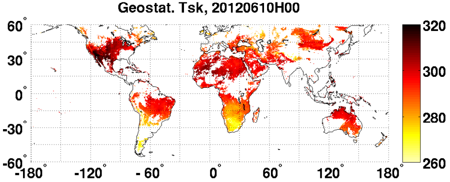
Assimilation of GRACE TWS (M. Girotto)

- Assimilate (JPL 1°) GRACE observations into Catchment LSM at 36 km resolution, with an EnKF filter (localization radius 3°)
- Linearly rescale ΔTWS obs. into Catchment-specific TWS using the Catchment climatology
- GRACE assimilation improves model groundwater, but not root-zone or near-surface soil moisture
- Assimilate together with near-surface soil moisture observations



Assimilation of geostationary land T_{skin}

- Near-real time geostationary T_{skin} data set from NASA Langley Research Center



- Reported hourly (clear-sky) at 0.25° resolution
  - GOES-E, GOES-W, Meteosat-9, MTSAT-2, FengYun-2E
- Observation of the TIR clear-sky effective radiative temperature of the land surface
- Catchment equivalent, T_{surf}, is the average temperature of the canopy and soil surface for an arbitrarily thin layer with minimal heat capacity

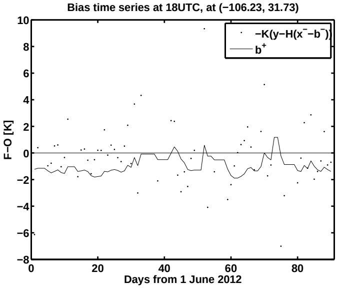
Assimilation of geostationary land T_{skin}

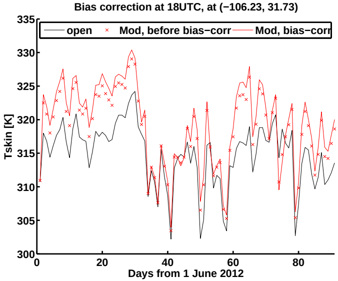
- Use a bias-aware assimilation with model bias correction
  - Update model T_{surf} towards mean geostationary observed T_{skin} (assuming latter is unbiased!)
  - Use a two-stage EnKF to estimate forecast biases from the O-F
- Assimilate the geostationary T_{skin} into the GEOS-5 atmospheric assimilation and modeling system
  - Use weakly coupled LDAS and ADAS system, GEOS-5 LA-DAS
- Motivation:
  - Improve modeled low level atmosphere
  - Improve background T_{skin} for assimilation of land-sensitive atmospheric observation

LDAS with forecast bias correction

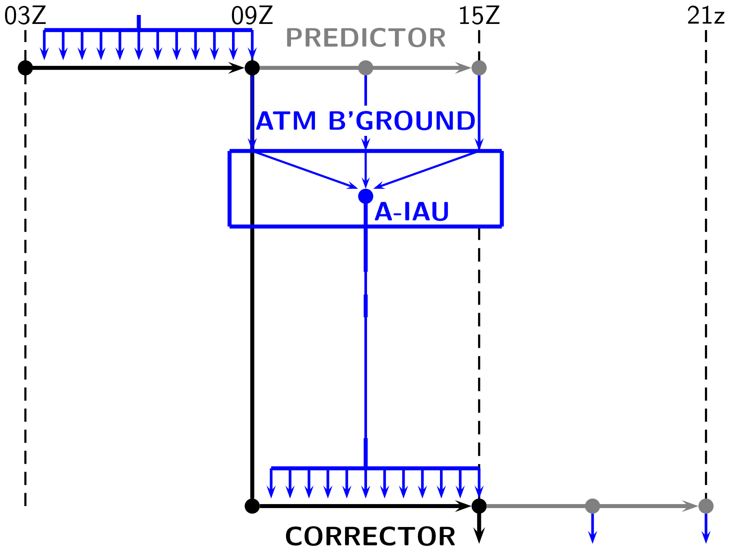
- Bias update
  $b^-_{t+1} = (1 - \Delta t_{mod}/\tau) b^+_t$
  $b^+_t = b^-_t - L_t(< y_t - H[x^-_t - b^-_t] >)$
  Assume $P^x \sim P^b$ gives $L_t = \alpha K_t$

- State update
  $x^-_{t,i} = f(x^+_{t-1,i}, q_{t,i})$
  $x^+_{t,i} = x^-_{t,i} - b^-_t + K_t(y_{t,i} - H[x^-_{t,i} - b^-_t])$





See also Reichle et al, 2010 (J. Hydromet.), Bosilovich et al, 2007 (J. Met. Soc. Japan)



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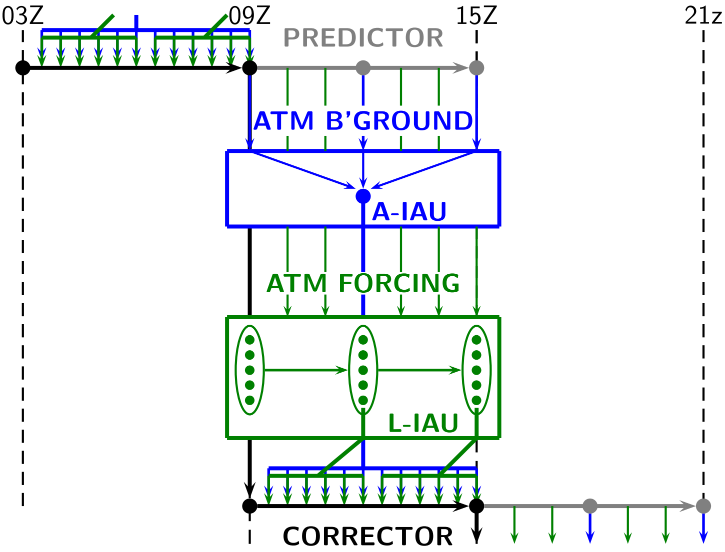
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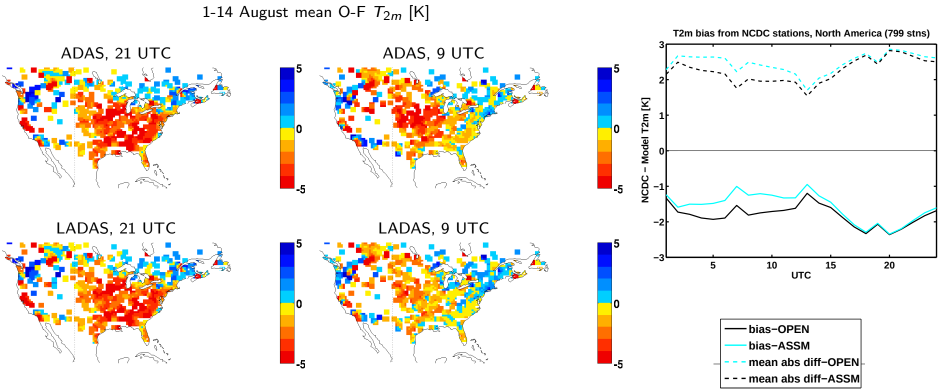
Evaluation against NCDC T_{2m} station observations



- Improvements in nighttime T_{2m} biases
- V. little impact during the day (and possible negative consequences)
- Currently testing changes to GEOS-5 T_{skin} formulation

Summary

- Land assimilation is v. different to atmospheric assimilation (no adjoint, models have no horizontal flow, damped physics, often no recognized 'truth' for anchoring observed and forecast biases)
- Global to continental-scale assimilation has often been uni-variate in offline (land only) systems, strong focus on soil moisture (also land surface temperature, TWS, snow cover, snow depth)
- Can improve unobserved variables (root-zone soil moisture from near-surface soil moisture), downscale information from coarse observations (TWS components at finer resolution from GRACE)

Future challenges

- Multi-variate assimilation
- Assimilation in coupled systems
- Consistent improvements to dependent flux forecasts (LH, SH, runoff)
- Direct assimilation of satellite radiance and backscatter
- Specification of error variances, evaluation of assimilation output
- Handling of systematic differences in observation and forecasts (within assimilation, diagnosing causes)
- Assimilation of new observations (SMAP freeze-thaw), with new models (global dynamic vegetation)

Thank you for listening