What is Model Soil Moisture and How Do We Improve it?

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CABLE Workshop 2012

Contents

1) Why is Soil Moisture important for Numerical Weather Prediction?
2) The Nature of Model Soil Moisture
3) Comparison of ACCESS NWP soil moisture against observations
4) Land Data Assimilation
   - How do NWP centres initialise Soil Moisture in their models?
   - Development of an Extended Kalman Filter Land DA scheme
   - Satellite derived surface soil moisture
5) Conclusions

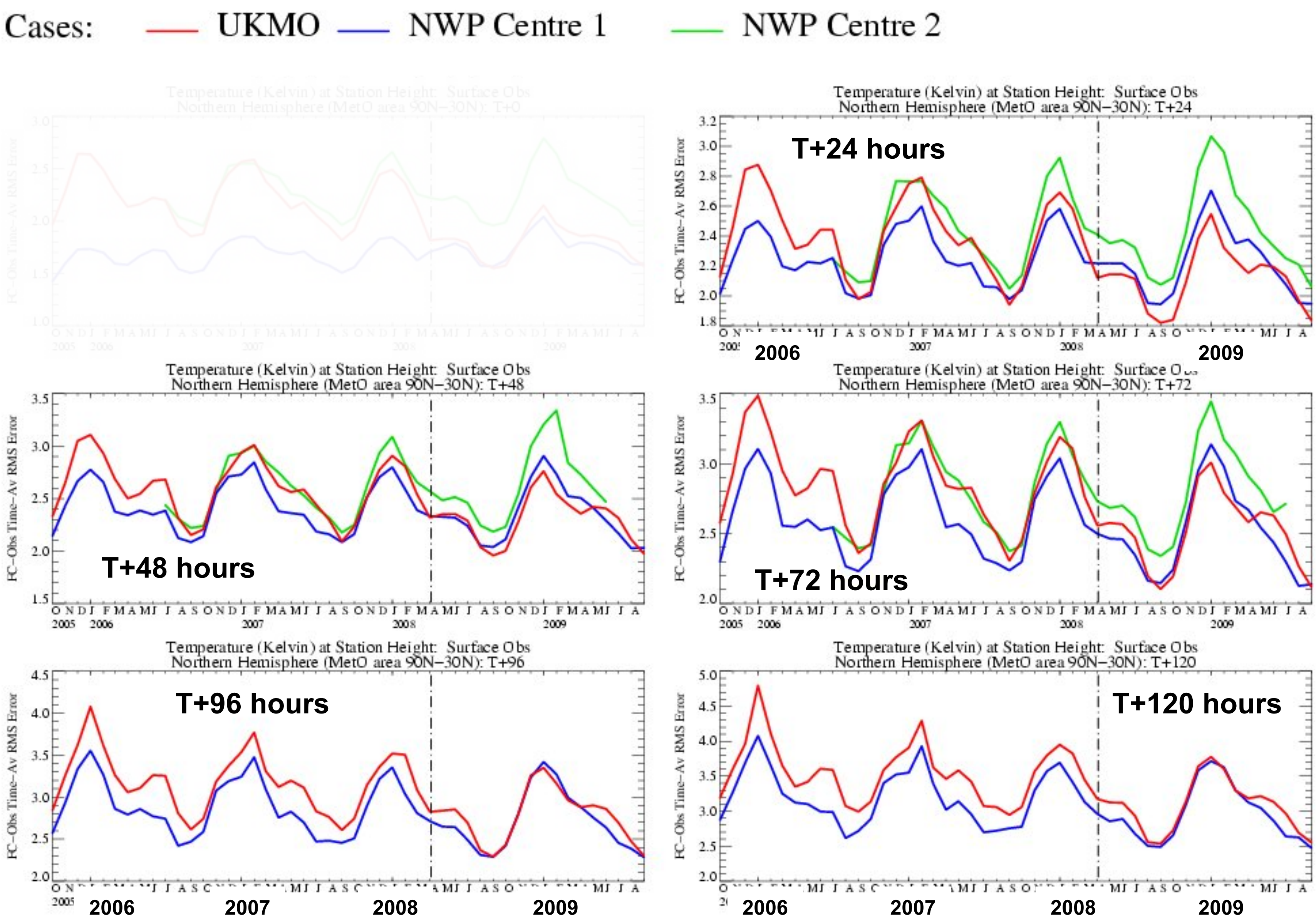
Why do we care about soil moisture?

- Soil moisture influences the exchange of heat and moisture between the atmosphere and land surface.
  - Soil moisture affects evaporation from plants and bare soil.
  - Soil moisture affects the soil heat capacity and soil thermal conductivity and thus the ground heat flux.

- Soil moisture is potentially very important for forecasts of precipitation and clouds.

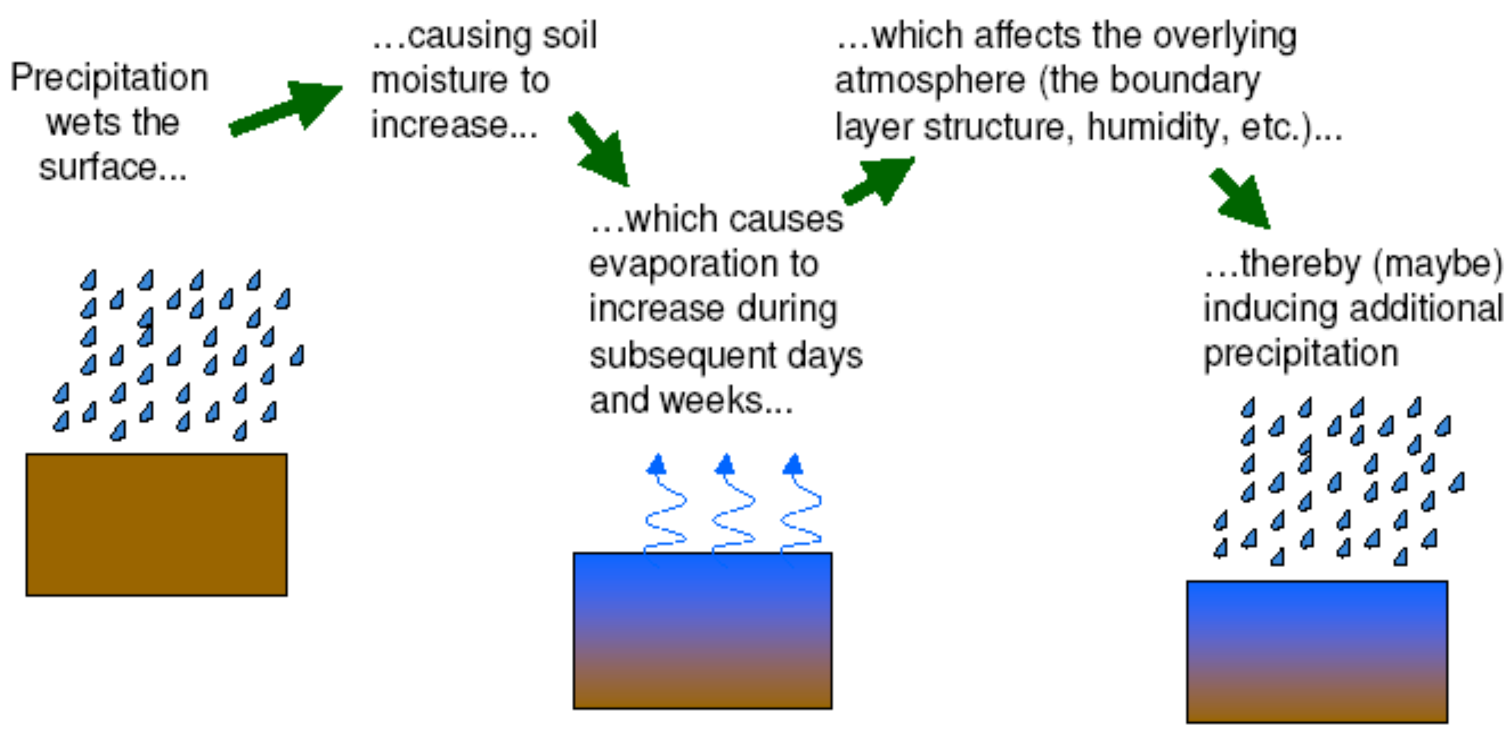
- Soil moisture, together with other land properties, has a significant impact on forecasts of near surface temperature and humidity.

Improvement in Operational forecasts of Screen Temperature due to better parameterisation of soil properties, Dharssi et al (2009)

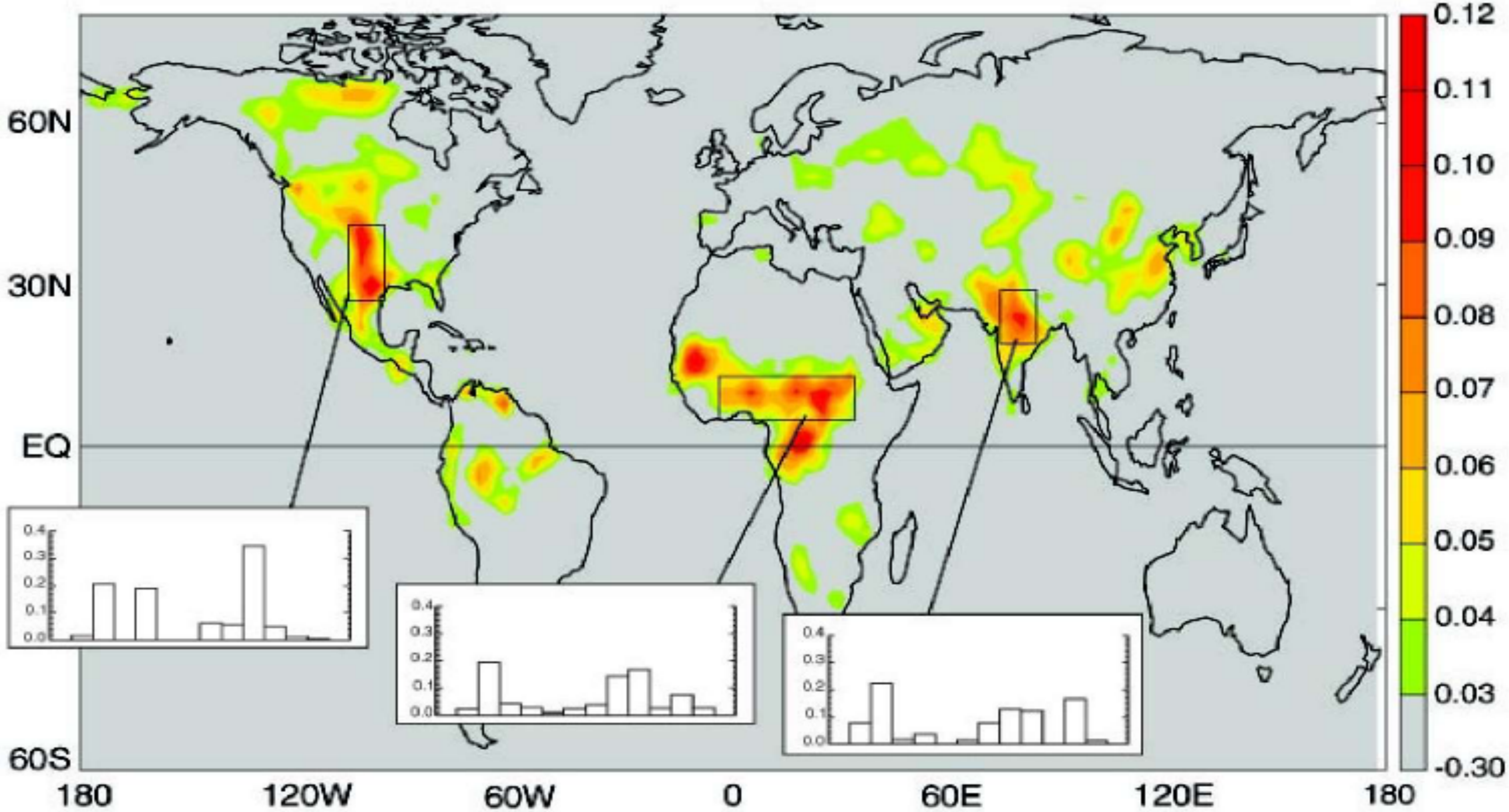


From Reichle and Koster:
Land data assimilation and sub-seasonal climate prediction

A simple view of land-atmosphere feedback



GLACE: Global Land-Atmosphere Coupling Experiment (a GEWEX initiative)



Multi-Model Estimation of Regions of Strong Coupling Between Soil Moisture and Precipitation for **June/July/August**, (Koster et al. 2004).

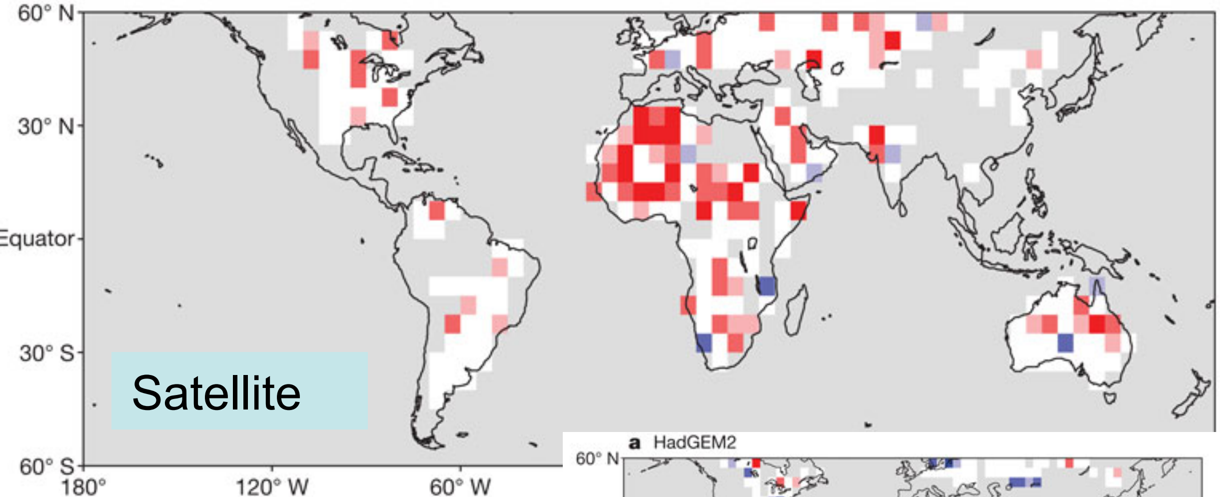
Do GCMs Correctly Represent the Soil moisture/ Precipitation Feedback?

- **Preference for afternoon precipitation over soil moisture anomalies. Taylor et al (2012) Nature 489, 423–426 (September 2012) doi:10.1038/nature11377**
  - "The cross-model signal favouring precipitation over wet soil, particularly across the tropics, **demonstrates a fundamental failing in the ability of convective parameterizations to represent land feedbacks on daytime precipitation**."
  - "the erroneous sensitivity of convection schemes demonstrated here is **likely to contribute to a tendency for large-scale models to 'lock-in' dry conditions, extending droughts unrealistically**, and potentially exaggerating the role of soil moisture feedbacks in the climate system"

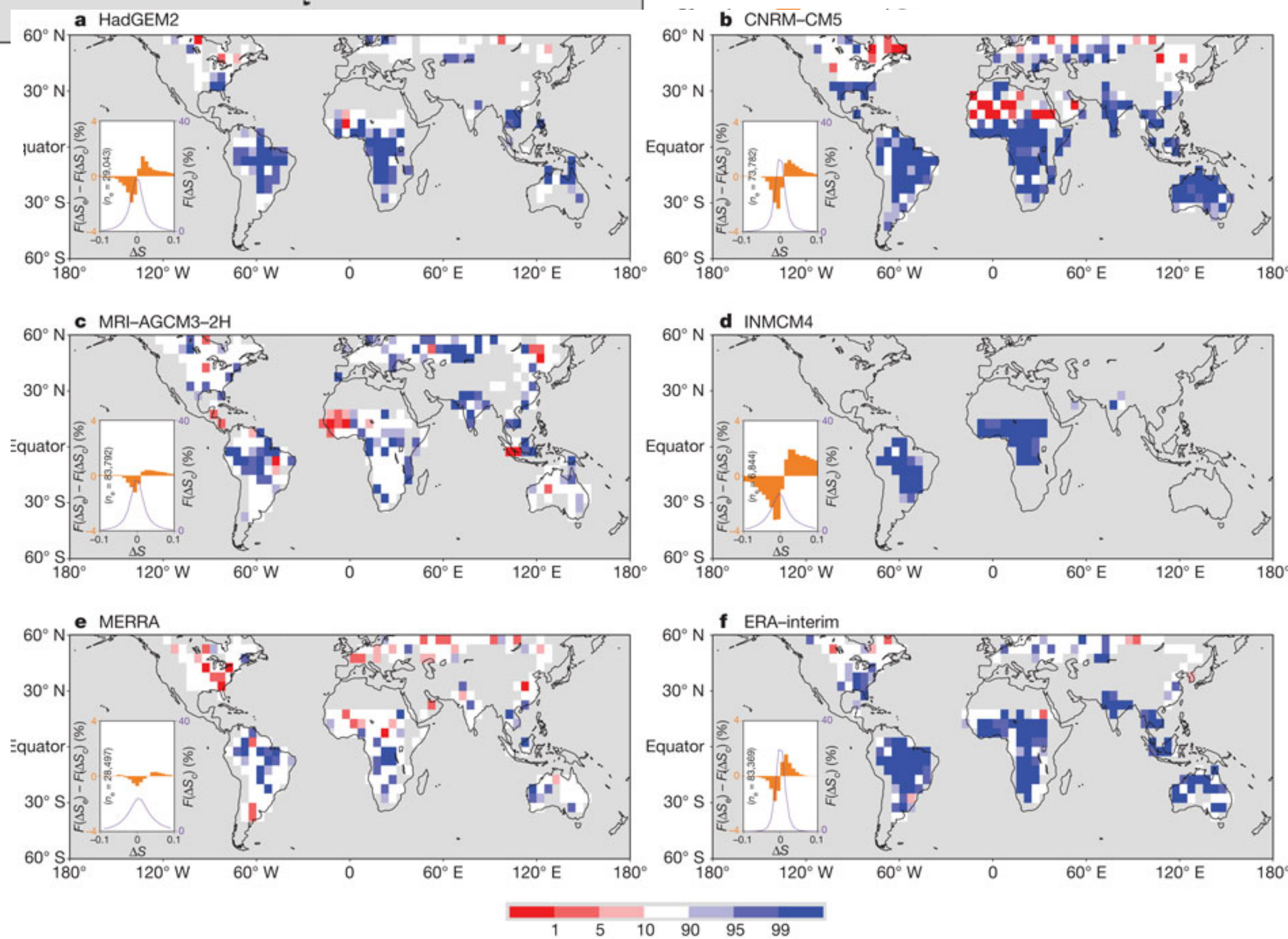
Preference for afternoon precipitation over soil moisture anomalies.

Taylor et al (2012)

Nature 489, 423–426 (September 2012) doi:10.1038/nature11377



Do GCMs correctly use the soil moisture information?



Model Simulated

Nature of Model Soil Moisture

- The true information in model soil moisture estimates is in the temporal variations and not the absolute magnitudes (Koster et al, 2009)
  - The true soil moisture climatology is unknown
  - Different models have very different soil moisture climatologies
    - Even when driving the land models with identical precipitation and other meteorological data (e.g. GSWP2)
    - Model soil moisture is model specific
  - Models tend to agree on the temporal variations of soil moisture
  - For NWP, the priority is to correctly model the surface fluxes of heat and moisture

On the Nature of Soil Moisture in Land Surface Models

Koster et al (2009)

"**Simulated ''soil moisture'' does not have an unambiguous meaning. It is a strongly model-specific quantity, essentially an ''index'' of the moisture state, with a dynamic range defined by the specific evaporation and runoff formulations utilized by the given model** (Koster and Milly 1997), in addition to model-specific soil parameters such as porosity, hydraulic conductivity, wilting point, and layer depth. Large differences are seen in the soil moisture products generated by different land models, even when the models are driven with precisely the same meteorological forcing (Dirmeyer et al. 2006)."

"once the climatological statistics of each model's soil moisture variable are accounted for (here, through a simple scaling using the first two moments), **the different land models tend to produce very similar information on temporal soil moisture variability**"

How does the model use soil moisture?

- Evaporation from plants

$$E = \rho \frac{\Delta q}{r_a + r_{s,veg}}$$

Like Ohm's Law; I=V/R

E	Evaporation
ρ	Density of Air
Δq	Difference in Specific Humidity between the surface and model level 1
r_a	Aerodynamic Resistance between the surface and model level 1

$$r_{s,veg} = \frac{r_s^{\min}}{\beta_{veg}}$$

Calculated by a photosynthesis model and depends on vegetation type, temperature, humidity and incident solar radiation.

The soil moisture availability depends on soil moisture, plant root fraction and soil texture.

Soil Moisture Availability

$$\beta_{veg} = \sum_{k=1}^{4} f_k \beta_{veg,k} \qquad \sum_{k=1}^{4} f_k = 1$$

$$\beta_{veg,k} = \begin{cases} 0 & \theta_k < \theta_w \\ \dfrac{\theta_k - \theta_w}{\theta_c - \theta_w} & \theta_w < \theta_k < \theta_c \\ 1 & \theta_k > \theta_c \end{cases}$$

θ_k Soil Moisture in soil level k

f_k Fraction of plant roots in soil level k

θ_w Wilting Point

θ_c Critical Point (Field Capacity)

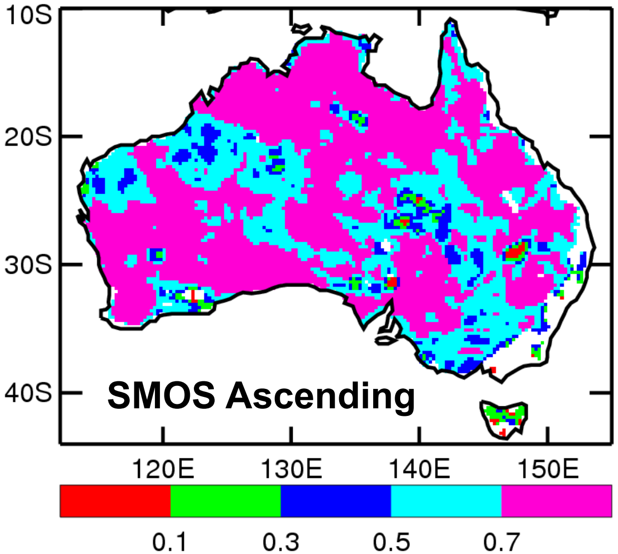
Comparison against OZnet in situ Soil Moisture, Temporal Correlation (Nov 2010 to May 2011)

Generally, the model is most accurate. SMOS soil moisture retrieved from the ascending pass is more accurate than from the descending pass and more accurate than ASCAT

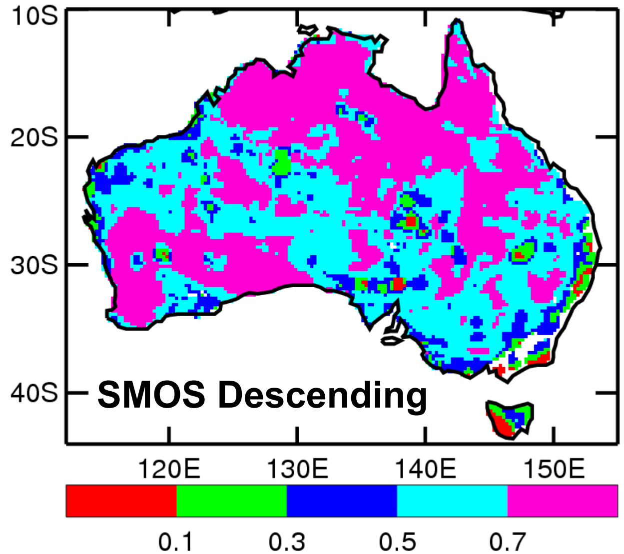
Oznet site	ACCESS NWP	ASCAT	SMOS Ascending	SMOS Descending
M1	0.599	0.546	**0.740**	0.613
M2	**0.850**	0.702	0.308	0.496
M3	**0.847**	0.498	0.714	0.613
M4	0.763	0.720	**0.849**	0.773
M5	**0.899**	0.813	0.869	0.863
M7	**0.777**	0.704	0.647	0.594

Temporal Correlation between model surface soil moisture and remotely sensed products (Nov 2010 to Aug 2011)

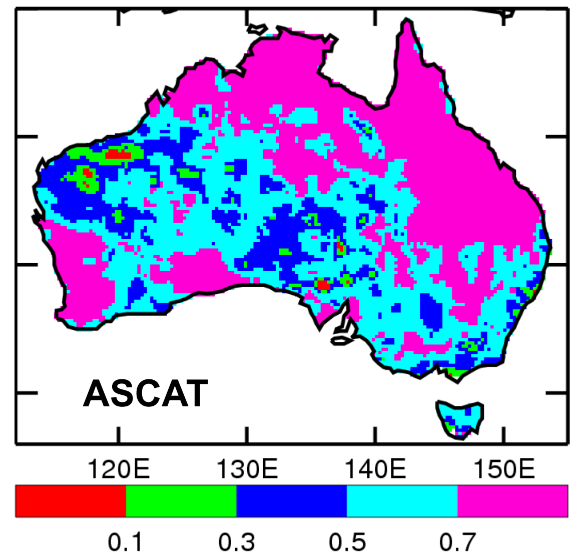
Pearson Correlation
SMOS Ascending vs ACCESS NWP Mo



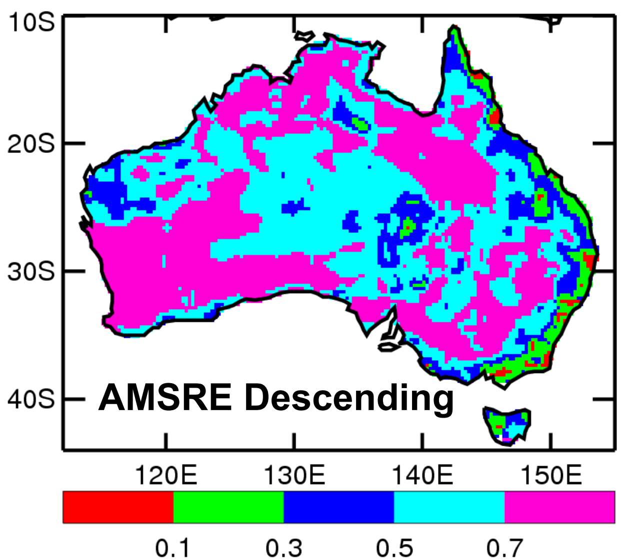
Pearson Correlation
SMOS D vs ACCESS NWP Model



Pearson Correlation
ASCAT vs ACCESS NWP Model



Pearson Correlation
AMSRE LPRM DC vs ACCESS NWP Model



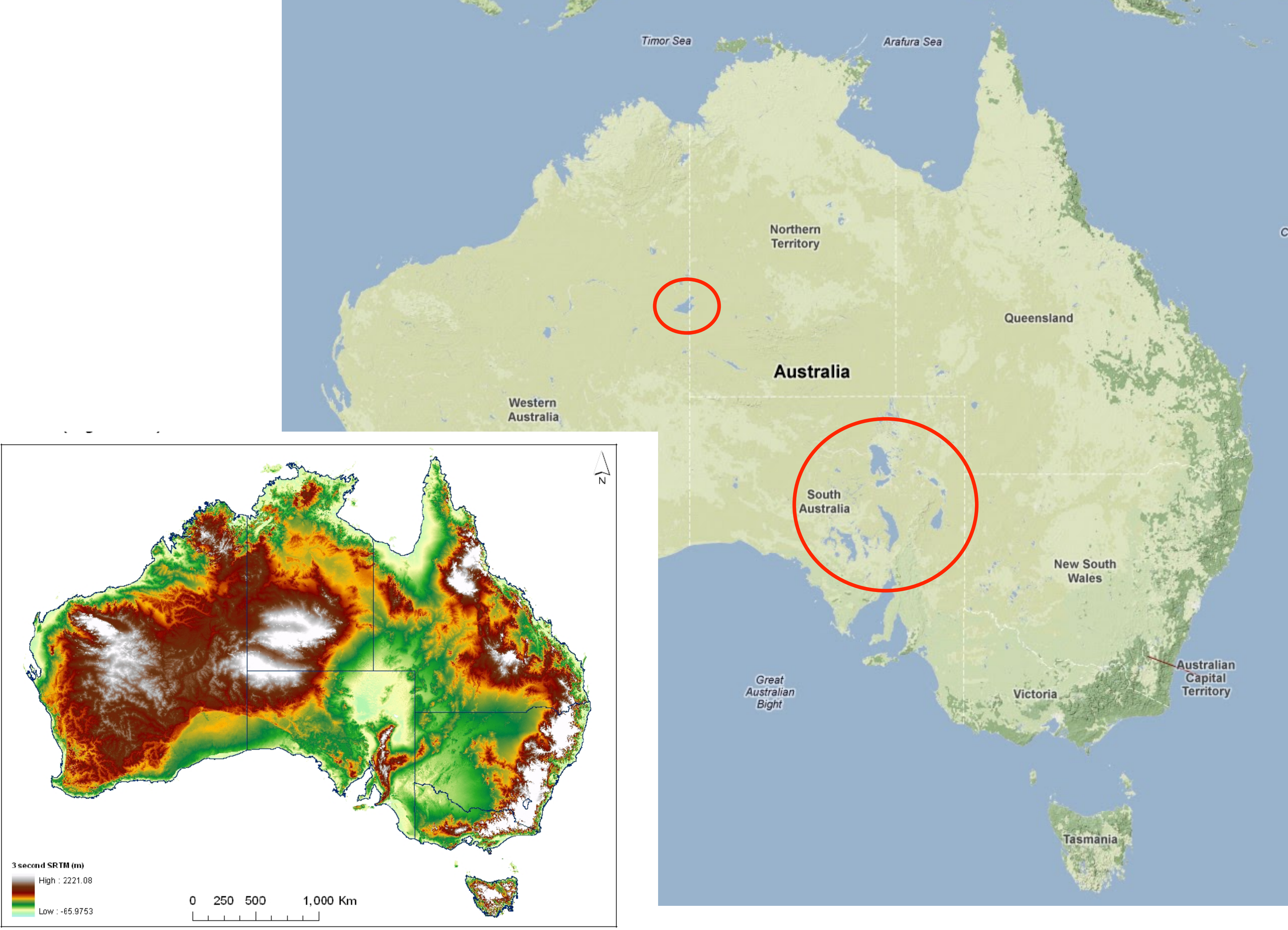


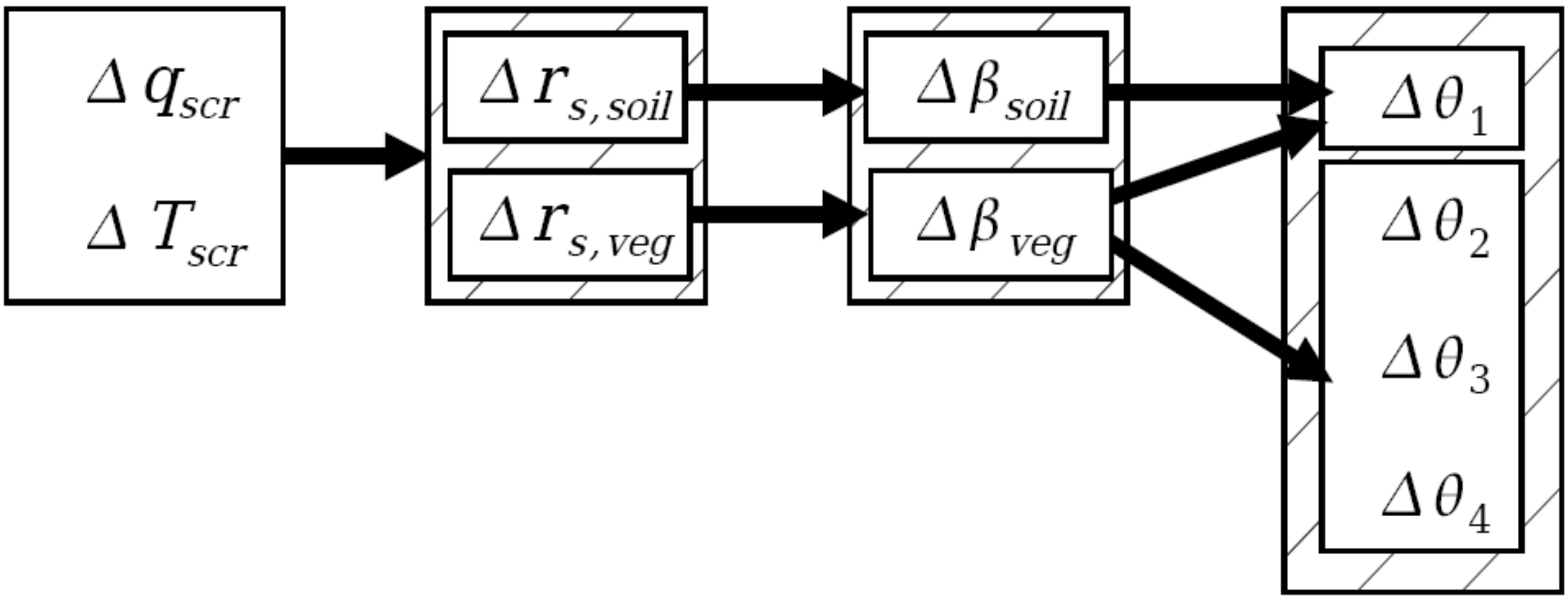
Figure 53. 3 second National DEM coverage.

Current Operational Soil moisture DA Schemes

Bureau	2m T and q	Physically Based Nudging	Best and Maisey (2002)
UKMO	2m T and q ASCAT* soil wetness	Nudging	Dharssi et al (2011)
ECMWF	2m T and RH	Extended Kalman Filter	de Rosnay et al (2012)
Meto France	2m T and RH	OI Nudging	Giard and Bazile (2000)
Canadian Met Service	2m T and RH	OI Nudging	Belair et al (2003)
German Weather Service	2m T	2D Var	Hess et al (2008)

*Advanced Scatterometer on the MetOP satellite

Physically Based Soil Moisture Nudging Scheme



Development of a Extended Kalman Filter based land DA scheme

- Dharssi et al (2012), CAWCR Tech Report 54
- Assimilate many sources of data
  - 2m T and q,
  - Satellite derived surface soil moisture
  - Satellite derived skin temperature
  - Leaf Area Index (LAI) and Fraction of photosynthetically active radiation (FPAR)
    - Long term aim
- Analyse Soil Moisture and Soil Temperature
  - In principle, any model land variable can be analysed

Satellite based measurements of surface soil moisture

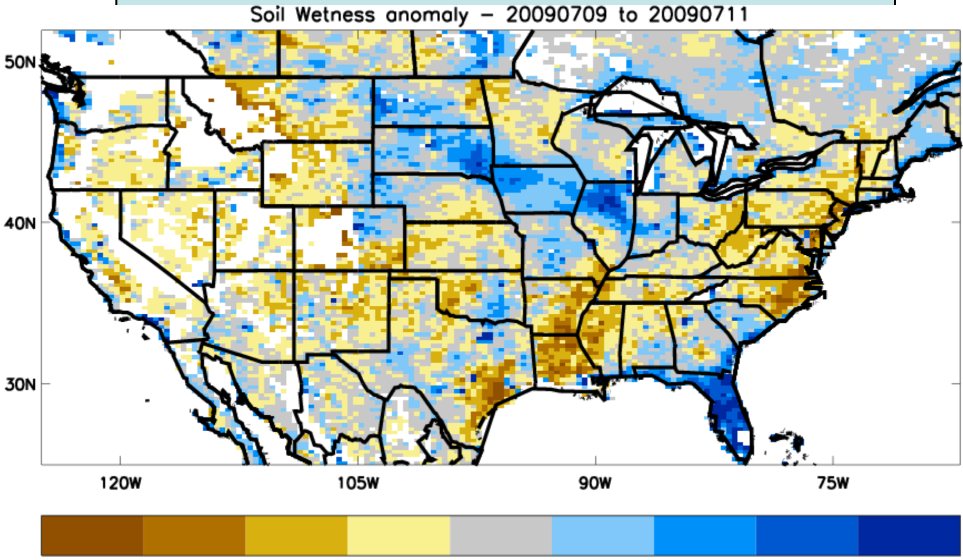
- Remote sensing by satellites is attractive since satellites offer **global data coverage.**

- At microwave frequencies the dielectric constant of liquid water (~70) is much higher than that of the soil mineral particles (< 5) or ice.
  - An increase in soil moisture leads to an increase in the dielectric constant of the soil which leads to a decrease in soil emissivity and an increase in soil reflectivity.

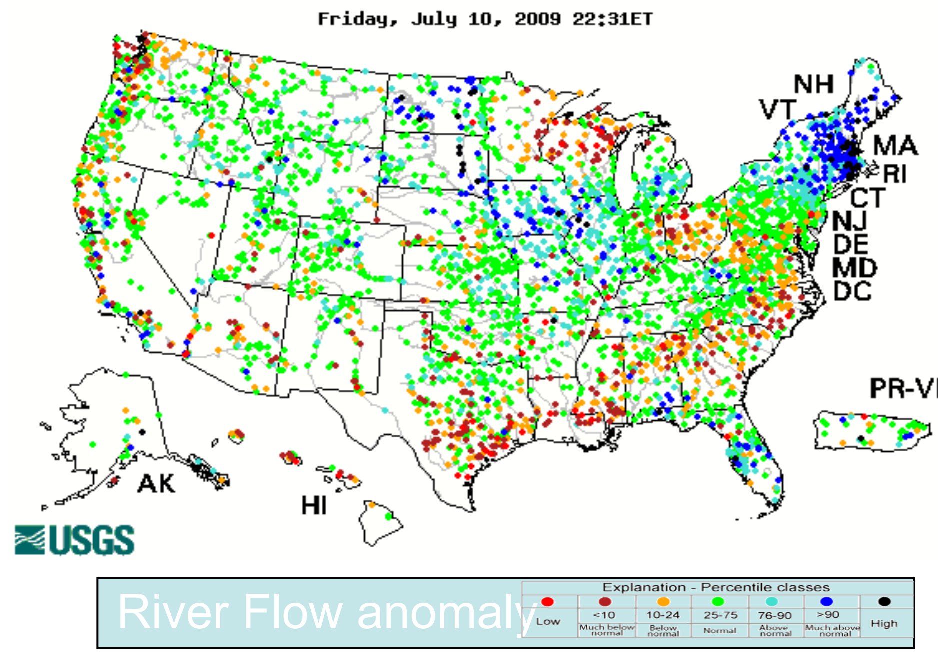
- Microwave backscatter/brightness temperature is affected by many factors, including:
  - Vegetation water content
  - Soil roughness, soil salinity, soil texture, soil temperature
  - Lower frequencies are less affected so **SMOS and SMAP should be more accurate than ASCAT and AMSR-E**.

Water anomalies: 9 to 11 July 2009

ASCAT surface soil wetness anomaly



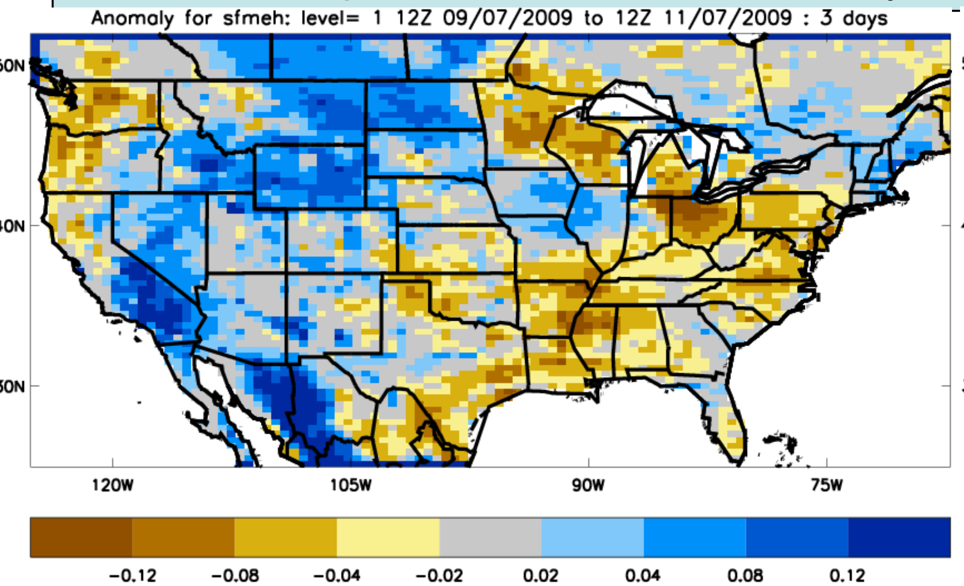
Good qualitative agreement between the two data.



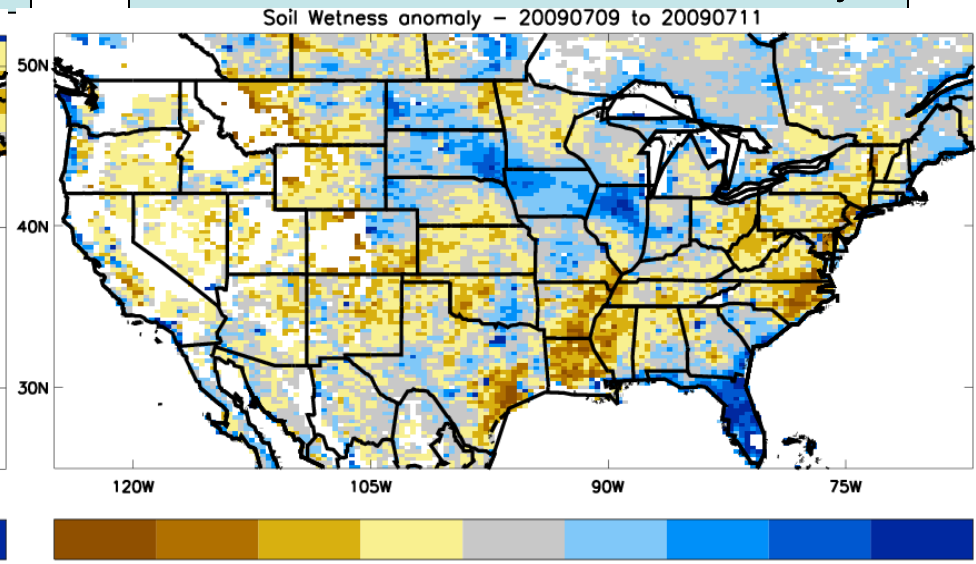
River Flow anomaly

Water anomalies: 9 to 11 July 2009

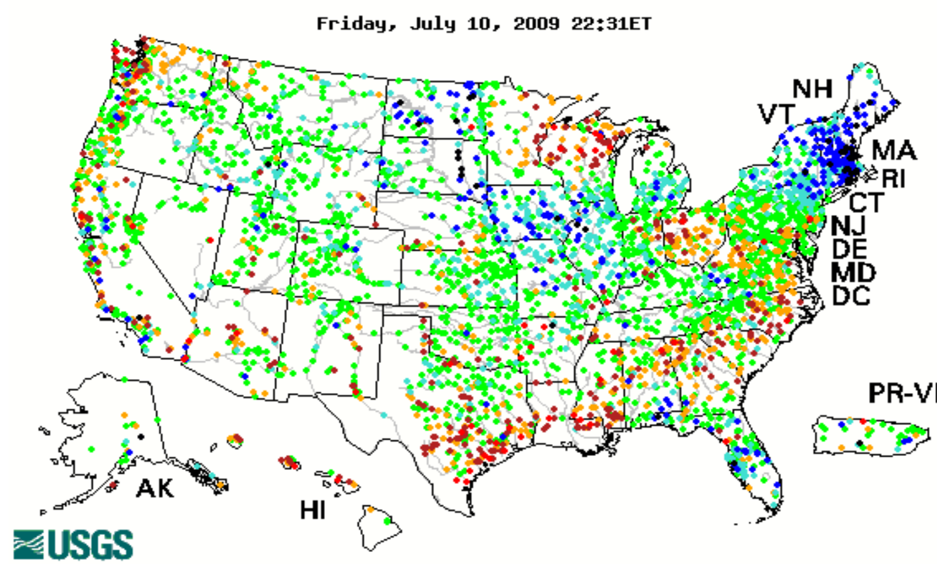
Control run: top 10cm soil moisture anomaly



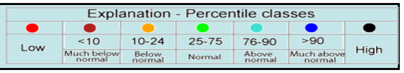
ASCAT surface soil wetness anomaly



Model soil too wet in the west and possibly too dry in the east (e.g. Florida).

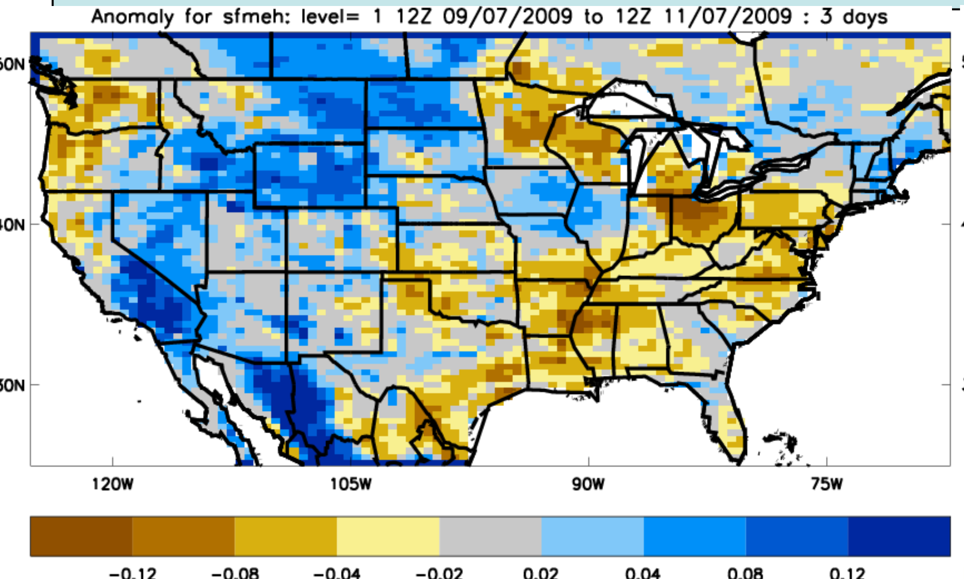


River Flow anomaly

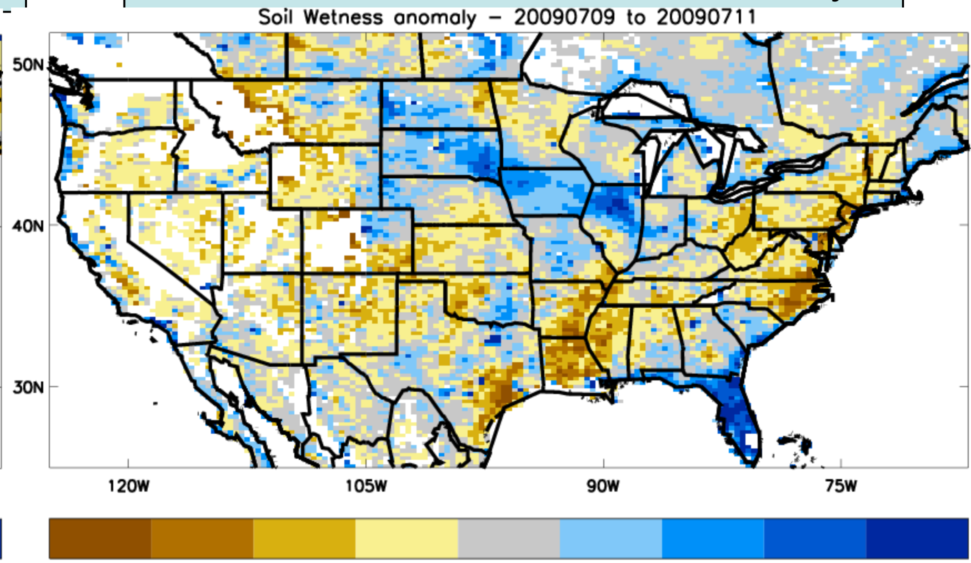


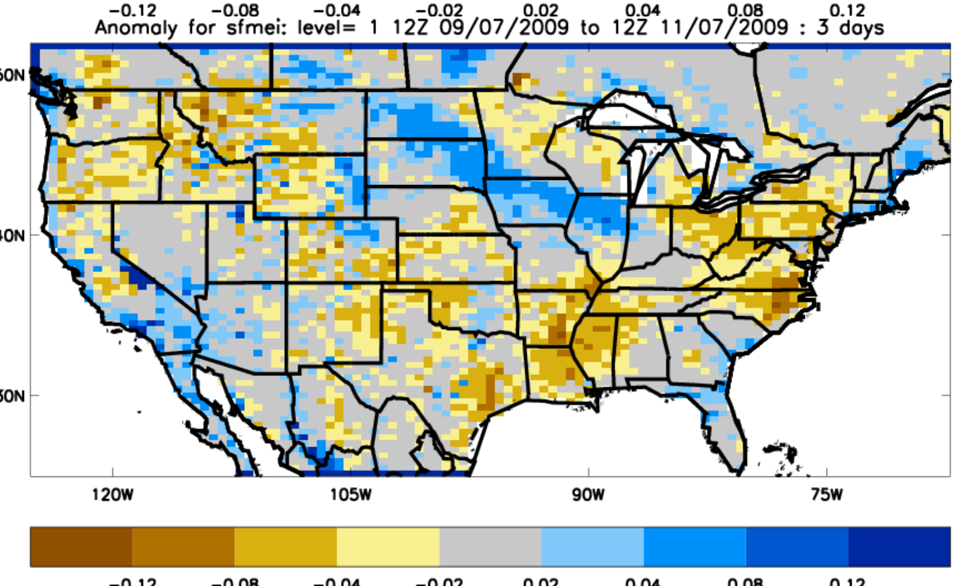
Water anomalies: 9 to 11 July 2009

Control run: top 10cm soil moisture anomaly

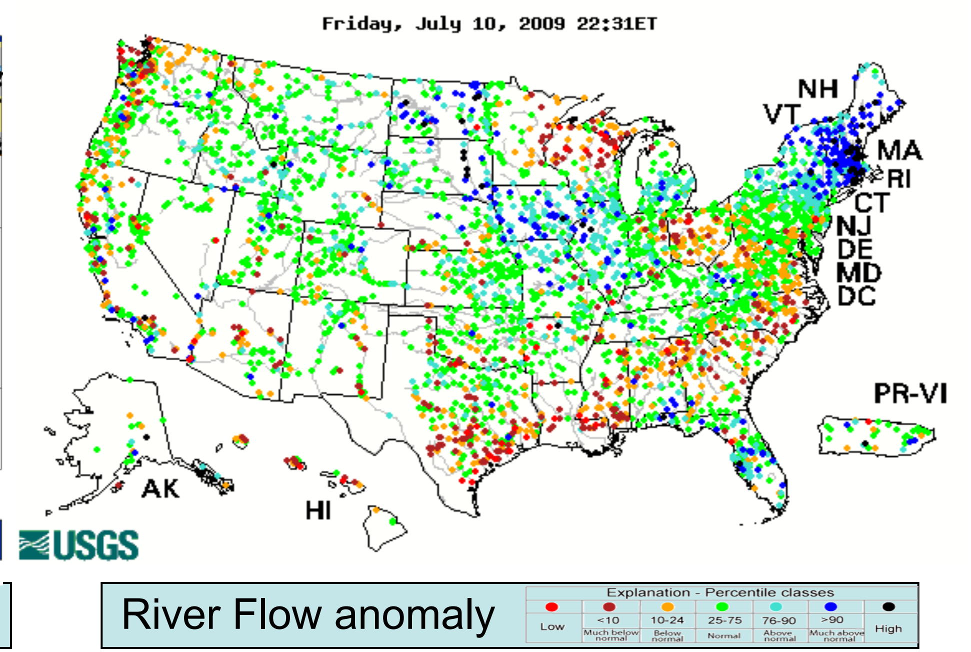


ASCAT surface soil wetness anomaly





Test run: top 10cm soil moisture anomaly



River Flow anomaly

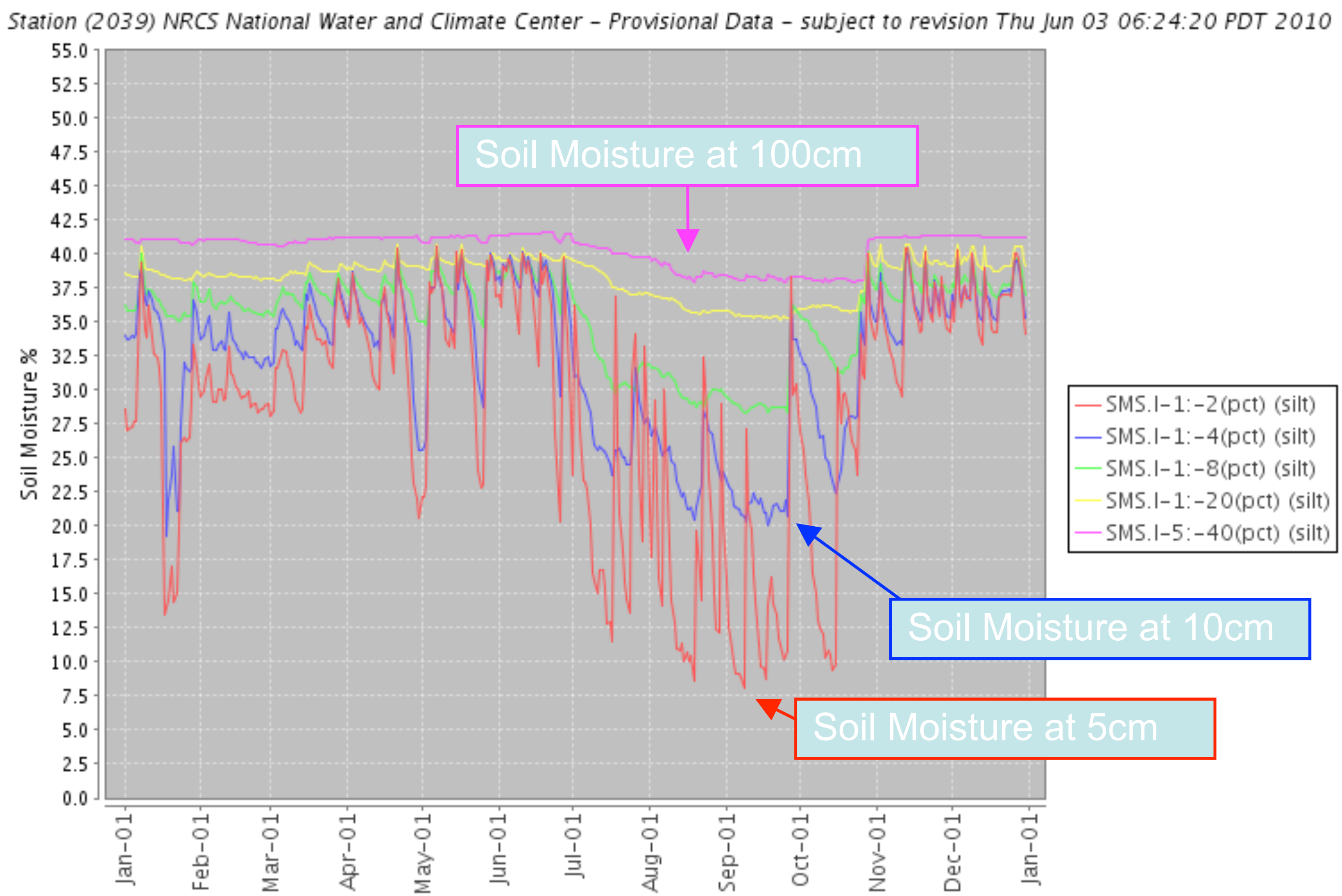
Conclusions

- The primary information content of model and remotely sensed soil moisture is in the temporal variations
- There is potential to improve NWP precipitation forecasts by improving land DA
  - But only if the model uses the soil moisture information correctly
- Comparison of ACCESS NWP model soil moisture with satellite derived and in situ observations shows good agreement (high temporal correlation)
- Satellite derived soil moisture such as from ASCAT and SMOS contain useful information
  - The SMOS ascending pass appears to be best
- A new land DA scheme is in development at the Bureau and UKMO

Challenges to using Satellite derived soil moisture for weather forecasting (1)

1. Satellites microwave sensors only sense a thin top layer of soil; ~1cm.
   i. Weather forecasting requires knowledge of soil moisture in the plant root-zone (~ top 1m of soil) since plants extract soil water through the roots which then evaporates from their leaves.
   ii. There are often significant vertical gradients in the soil moisture.
      - In the summer the surface soil can become very dry while the deep soil layers are close to saturation.

Variation of soil moisture with depth: measurements from in-situ sensors at a station in Virginia state, US.



Challenges to using Satellite derived soil moisture for weather forecasting (2)

1. Satellites microwave sensors only sense a thin top layer of soil.

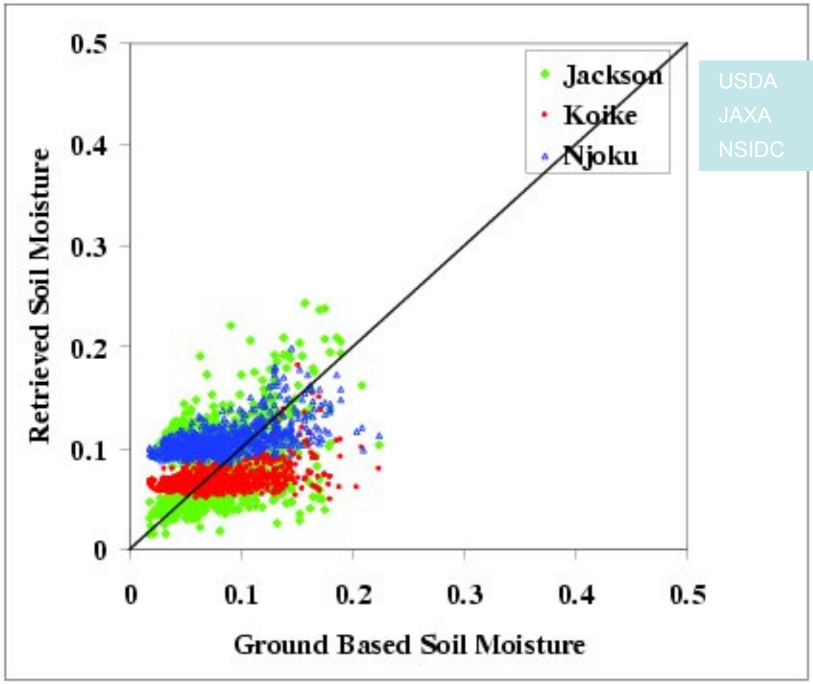
2. Retrieval algorithms are needed to convert satellite measurements of backscatter/brightness temperature into soil moisture. These **retrieval algorithms often produce very biased estimates of soil moisture.**

3. **Land surface and atmosphere models contain biases** and approximations so assimilating more accurate soil moisture may make the model's surface fluxes of heat and moisture worse and therefore make weather forecasts worse.
    i. Improving the models and parameters is as important as improving the soil moisture analysis.

from Jackson et al (2006)

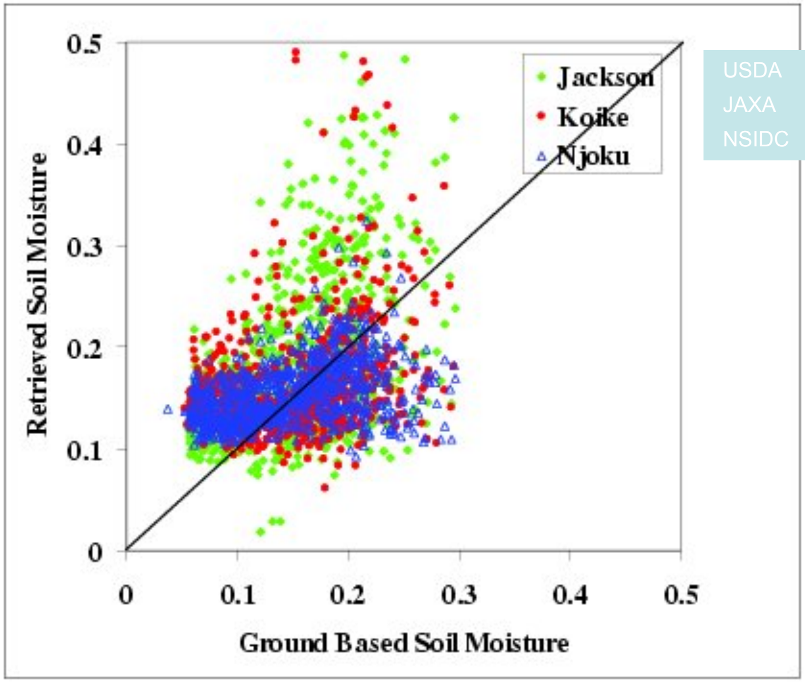
AMSR-E Soil Moisture Algorithm Validation Exercise Using Data from Walnut Gulch, AZ (WG) and Little Washita, OK (LW) June 18, 2002-Dec. 31, 2005

WG Arizona



USDA
JAXA
NSIDC

LW Oklahoma

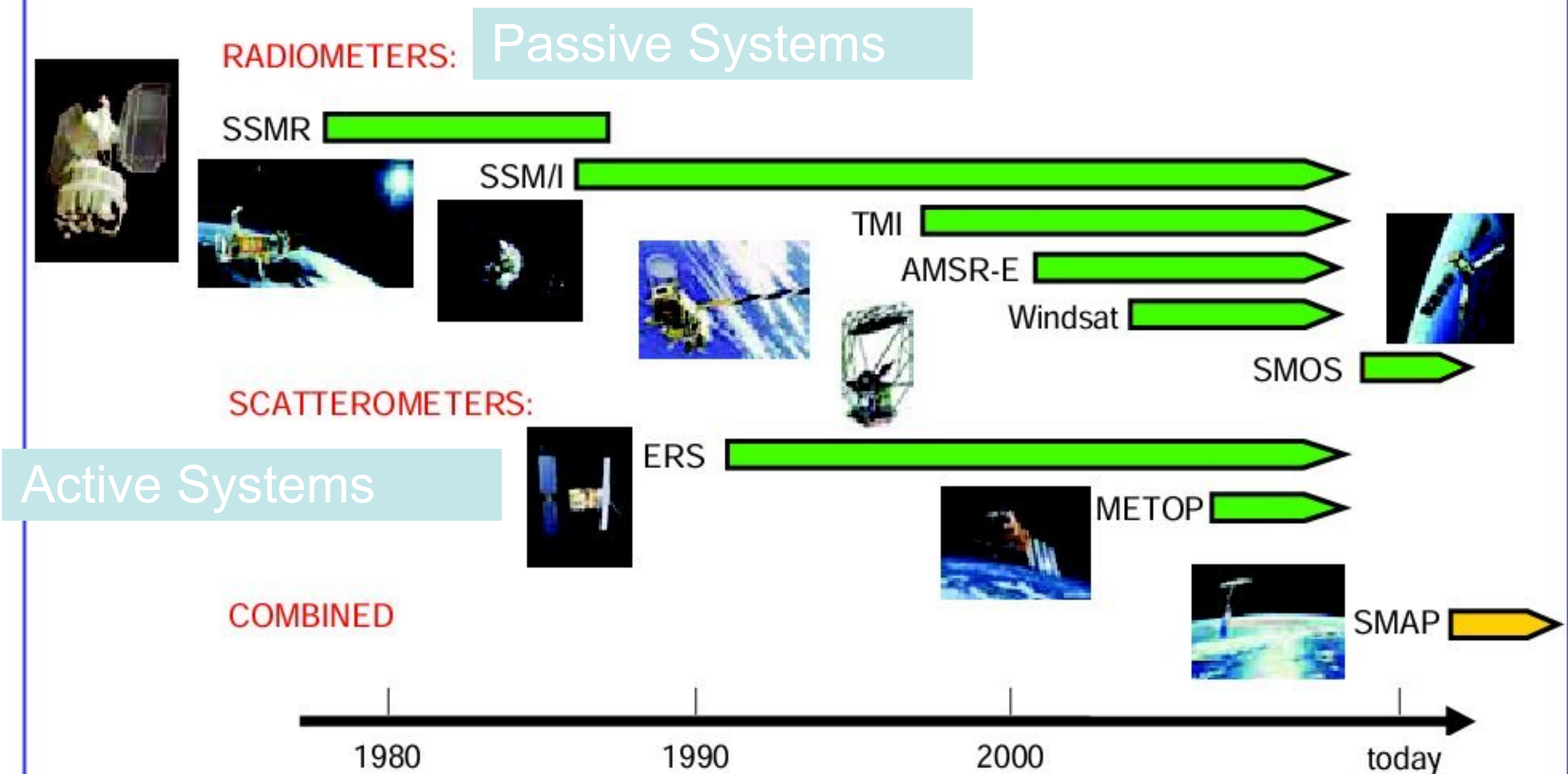


USDA
JAXA
NSIDC

Bias Correction of the satellite data

- The model soil moisture climatology is used to bias correct (rescale) the retrieved satellite soil moisture.
  - The available observation data is insufficient to determine the true soil moisture climatology.
- The climatology of the bias corrected satellite soil moisture will agree quite closely with the climatology of the model soil moisture.
  - This has the advantage that the bias corrected satellite soil moisture will be consistent with the assumptions made by the land surface model.
- Consequently, data assimilation of the bias corrected satellite soil moisture is more likely to improve model surface fluxes and lead to better weather forecasts.
  - Consistent with the assertion that the true information content of model soil moisture is in the temporal variations

Microwave Sensors



Long time-series of data from ERS1/2 and also time overlap with MetOP/ASCAT.

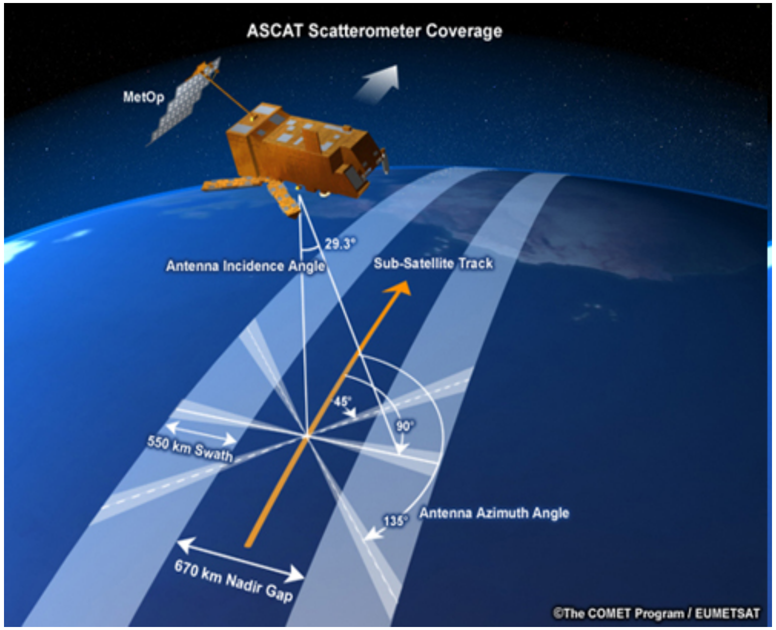
Vienna University of Technology
Institute of Photogrammetry and Remote Sensing

SMOS surface soil moisture product

- Soil Moisture and Ocean Salinity (launched 2009)
- Multi-angular measurements of Brightness Temperature at L-band (1.4 GHz)
  - Passive microwave
- SMOS senses top ~5 cm of surface
- Sun-synchronous orbit with the Ascending pass at 06:00 Local Solar Time (LST) and Descending pass at 18:00 LST

These data were obtained from the "Centre Aval de Traitement des Données SMOS" (CATDS), operated for the "Centre National d'Etudes Spatiales" (CNES, France) by IFREMER (Brest, France)"

ASCAT surface soil wetness product



- Advances Scatterometer on MetOP (launched 2006)
- Measurements of Backscatter at C-band (5.3 GHz)
  - Active Microwave
- ASCAT senses top ~1 cm of surface
- Surface soil wetness index based on TUWien (Vienna University of Technology) retrieval scheme
- Sun-synchronous orbit with the Descending pass at 09:30 LST and the Ascending pass at 21:30 LST

ASCAT operational Soil Wetness product disseminated to Numerical Weather Prediction community via EUMETCAST in BUFR format

AMSRE surface soil moisture product

- Advanced Microwave Scanning Radiometer-EOS (Launched 2002)
- Measurements of Brightness Temperature at C-band (6.9 GHz) and X-band (10.7 GHz)
  - Passive Microwave
- AMSRE senses top ~1 cm of surface
- VUA-NASA Land Parameter Retrieval Model (LPRM) used to retrieve surface soil moisture
- Sun-synchronous orbit with the Descending pass at 01:30 LST and Ascending pass at 13:30 LST

Data downloaded from ftp://hydro1.sci.gsfc.nasa.gov/data/s4pa/WAOB/

Error Characterisation of Model and Satellite Derived Soil Moisture

Comparison of AMSRE soil moisture with in situ observations, Jackson et al (2010)

For the LPRM Algorithm, the soil moisture derived from the descending (night-time) pass is significantly more accurate than from the ascending pass (day-time). The JAXA algorithm is generally less accurate than LPRM.

	LPRM Retrieval Algorithm Temporal Correlation		**JAXA Retrieval Algorithm Temporal Correlation**	
Watershed	***Descending***	***Ascending***	***Descending***	***Ascending***
Walnut Gulch, AZ	0.717	0.361	0.717	0.534
Little Washita, OK	0.567	0.508	0.343	0.429
Little River, GA	0.608	0.515	0.231	0.332
Reynolds Creek, ID	0.571	0.363	0.219	-0.033

Triple Collocation – Theory

Stoffelen (1998), Scipal et al (2008), Miralles et al (2010), Hain et al (2011), Vogelzang and Stoffelen (2012);

Suppose, we have three separate sources of data that each provides a long timeseries at a given location of soil moisture. Each timeseries contains both biases and random errors.

1) Starting Equations

$$
\begin{aligned}
X(t) &= a_x + b_x T(t) + \epsilon_x(t) \quad , \\
Y(t) &= a_y + b_y T(t) + \epsilon_y(t) \quad , \\
Z(t) &= a_z + b_z T(t) + \epsilon_z(t) \quad .
\end{aligned}
$$

a and *b* parameters describe the bias and are unknown.

ε describe the random errors

T(t) is the unknown truth

2) Rescaling Equations

$$
\begin{aligned}
Y^* &= \langle X \rangle + \frac{b_x}{b_y}(Y - \langle Y \rangle) \quad , \\
Z^* &= \langle X \rangle + \frac{b_x}{b_z}(Z - \langle Z \rangle) \quad .
\end{aligned}
$$

There are different methods to estimate b_x/b_y and b_x/b_z. Alternatively, replace steps 2 and 3 with Cumulative Distribution Function (CDF) matching.

3) Rescaled Time Series

$$
\begin{aligned}
X(t) &= a_x + b_x T(t) + \epsilon_x(t) \quad , \\
Y^*(t) &= a_x + b_x T(t) + \epsilon_y^*(t) \quad , \\
Z^*(t) &= a_x + b_x T(t) + \epsilon_z^*(t) \quad .
\end{aligned}
$$

4) Estimated Error Variances

$$
\begin{aligned}
\langle (\epsilon_x)^2 \rangle_{TC} &= \langle (X - Y^*)(X - Z^*) \rangle \quad , \\
\langle (\epsilon_y^*)^2 \rangle_{TC} &= \langle (Y^* - X)(Y^* - Z^*) \rangle \quad , \\
\langle (\epsilon_z^*)^2 \rangle_{TC} &= \langle (Z^* - X)(Z^* - Y^*) \rangle \quad , \\
\langle (\epsilon_y)^2 \rangle_{TC} &= (b_y/b_x)^2 \langle (\epsilon_y^*)^2 \rangle_{TC} \quad , \\
\langle (\epsilon_z)^2 \rangle_{TC} &= (b_z/b_x)^2 \langle (\epsilon_z^*)^2 \rangle_{TC} \quad .
\end{aligned}
$$

Assumptions in TC

- The random errors have zero mean
- The random errors have constant variance

$$\langle(\epsilon_i)^2\rangle = \text{constant}$$

- Random errors have no cross correlation

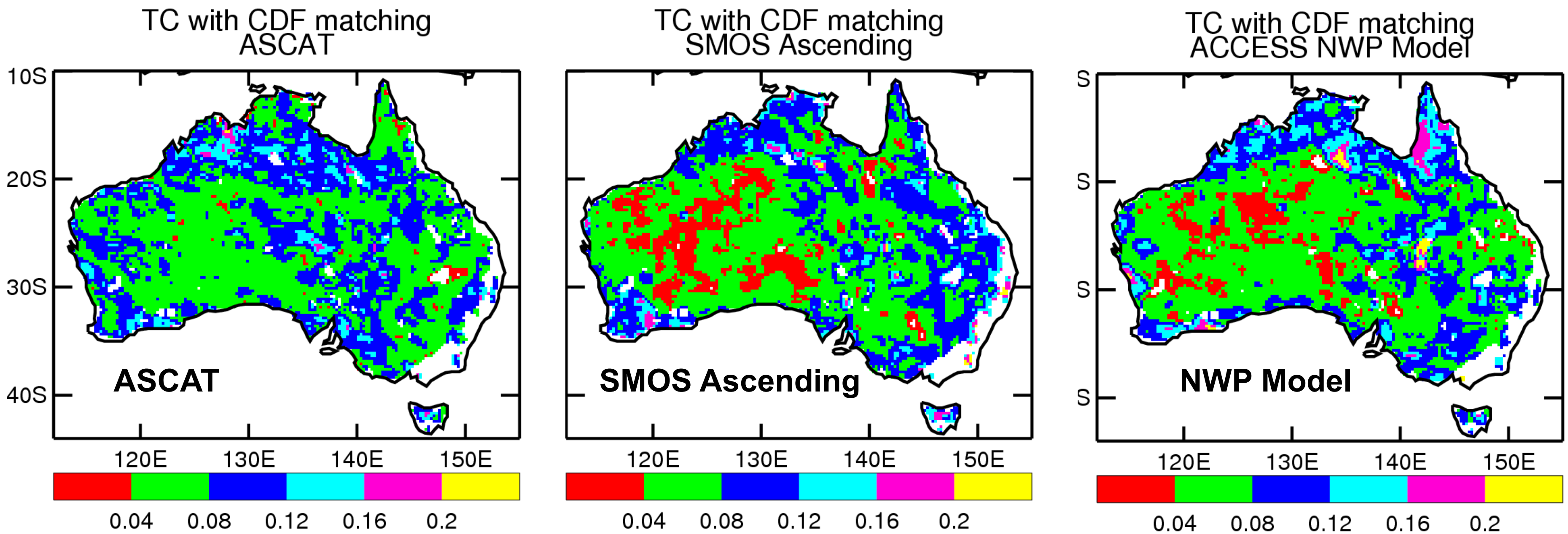
$$\langle\epsilon_i\epsilon_j\rangle = 0 \quad \text{if} \quad i \neq j$$

- Random errors are uncorrelated with the Truth

$$\langle\epsilon_i T\rangle = 0$$

Estimated Standard Deviation of the Error

in units of ASCAT surface soil wetness



Triple Collocation: X=ASCAT, Y=SMOS, Z=Model

Rescaling using CDF matching

Questions about Triple Collocation (TC)

- Can the TC equations be written in terms of temporal correlation?
- How do the different rescaling methods affect the TC error estimates?
- How Accurate is TC?
- Is the rescaling in TC consistent with the bias correction (rescaling) used by the land DA?
- Which Time Series should be used as the Reference (the X time series)?
  - For DA?
  - For Verification?
  - Does it matter?
- Which estimated error variances should be compared/ used for DA?

$$\langle(\epsilon_x)^2\rangle_{TC},\ \langle(\epsilon_y^*)^2\rangle_{TC} \text{ and } \langle(\epsilon_z^*)^2\rangle_{TC}\ \mathbf{OR}\ \langle(\epsilon_x)^2\rangle_{TC},\ \langle(\epsilon_y)^2\rangle_{TC} \text{ and } \langle(\epsilon_z)^2\rangle_{TC}$$

- Can TC be used for Quality Control?

TC with Linear CDF matching

$$\boxed{\begin{aligned}\left(\frac{b_x}{b_y}\right)_{LCDF} &= \frac{\sigma_x}{\sigma_y} \quad ,\\ \left(\frac{b_x}{b_z}\right)_{LCDF} &= \frac{\sigma_x}{\sigma_z} \quad .\end{aligned}}$$

$$\sigma_x^2 = \langle (X - \langle X \rangle)^2 \rangle,\ \sigma_y^2 = \langle (Y - \langle Y \rangle)^2 \rangle \text{ and } \sigma_z^2 = \langle (Z - \langle Z \rangle)^2 \rangle$$

$$\boxed{\begin{aligned}\langle (\epsilon_x)^2 \rangle_{TC,LCDF} &= \sigma_x^2 (1 - C_{X,Y} - C_{X,Z} + C_{Y,Z}) \quad ,\\ \langle (\epsilon_y^*)^2 \rangle_{TC,LCDF} &= \sigma_x^2 (1 - C_{X,Y} - C_{Y,Z} + C_{X,Z}) \quad ,\\ \langle (\epsilon_z^*)^2 \rangle_{TC,LCDF} &= \sigma_x^2 (1 - C_{X,Z} - C_{Y,Z} + C_{X,Y}) \quad ,\\ \langle (\epsilon_y)^2 \rangle_{TC,LCDF} &= \sigma_y^2 (1 - C_{X,Y} - C_{Y,Z} + C_{X,Z}) \quad ,\\ \langle (\epsilon_z)^2 \rangle_{TC,LCDF} &= \sigma_z^2 (1 - C_{X,Z} - C_{Y,Z} + C_{X,Y}) \quad .\end{aligned}}$$

$C_{i,j}$ is the temporal correlation between time series i and j

Vanilla TC

Vogelzang and Stoffelen (2012);

$$\boxed{\begin{aligned} \left(\frac{b_x}{b_y}\right)_{VTC} &= \frac{\langle (X-\langle X\rangle)(Z-\langle Z\rangle)\rangle}{\langle (Y-\langle Y\rangle)(Z-\langle Z\rangle)\rangle} \quad , \\ \left(\frac{b_x}{b_z}\right)_{VTC} &= \frac{\langle (X-\langle X\rangle)(Y-\langle Y\rangle)\rangle}{\langle (Z-\langle Z\rangle)(Y-\langle Y\rangle)\rangle} \quad . \end{aligned}}$$

$$\begin{aligned} \left(\frac{b_x}{b_y}\right)_{VTC} &= \left(\frac{\sigma_x}{\sigma_y}\right)\left(\frac{C_{X,Z}}{C_{Y,Z}}\right) \quad , \\ \left(\frac{b_x}{b_z}\right)_{VTC} &= \left(\frac{\sigma_x}{\sigma_z}\right)\left(\frac{C_{X,Y}}{C_{Y,Z}}\right) \quad . \end{aligned}$$

$$\boxed{\begin{aligned} \langle (\epsilon_x)^2\rangle_{TC,VTC} &= \sigma_x^2\left(1-\frac{C_{X,Y}C_{X,Z}}{C_{Y,Z}}\right) \quad , \\ \langle (\epsilon_y^*)^2\rangle_{TC,VTC} &= \sigma_x^2\frac{C_{X,Z}^2}{C_{Y,Z}^2}\left(1-\frac{C_{X,Y}C_{Y,Z}}{C_{X,Z}}\right) \quad , \\ \langle (\epsilon_z^*)^2\rangle_{TC,VTC} &= \sigma_x^2\frac{C_{X,Y}^2}{C_{Y,Z}^2}\left(1-\frac{C_{X,Z}C_{Y,Z}}{C_{X,Y}}\right) \quad , \\ \langle (\epsilon_y)^2\rangle_{TC,VTC} &= \sigma_y^2\left(1-\frac{C_{X,Y}C_{Y,Z}}{C_{X,Z}}\right) \quad , \\ \langle (\epsilon_z)^2\rangle_{TC,VTC} &= \sigma_z^2\left(1-\frac{C_{X,Z}C_{Y,Z}}{C_{X,Y}}\right) \quad . \end{aligned}}$$

Accuracy of Triple Collocation

- Monte Carlo Simulations
  - Generate Synthetic Data (X,Y, Z time series) with biases and random errors with zero mean and constant variance

$$
\begin{aligned}
X(t) &= a_x + b_x T(t) + \epsilon_x(t) \quad , \\
Y(t) &= a_y + b_y T(t) + \epsilon_y(t) \quad , \\
Z(t) &= a_z + b_z T(t) + \epsilon_z(t) \quad .
\end{aligned}
$$

    - The random errors may contain cross correlation and auto-correlation
  - Use TC to estimate the variances
    - Examine the errors in the TC estimates

Main Conclusions From Monte Carlo Simulations

- Need 500 triplets to estimate the error variance with an accuracy of 10%. Assuming no cross correlation or auto correlation.
  - Zwieback et al (2012) come to the same conclusion using an analytically derived formula
  - 500 triplets is equivalent to about two years of satellite data

- The affect of auto-correlation is to reduce the sample size
  - Need more than 500 triplets to estimate the error variances with an accuracy of 10%
- The presence of cross correlation causes a low bias in the TC estimates
- No significant difference in accuracy between the TC with Linear CDF matching and the Vanilla TC
  - This result is still provisional and needs more testing

Is the rescaling in TC consistent with the bias correction (rescaling) used by the land DA?

- Most land DA schemes use CDF matching to rescale the satellite derived soil moisture
  - CDF matching is a non-linear scaling method
- In my opinion the DA and TC should use the same rescaling method
  - Which rescaling method is best is still an open question
  - A very recent paper, Yilmaz and Crow (2012) suggests that the VTC rescaling should be used for DA
    - Based on identical twin experiments with synthetic observations

Which Time Series should be used as the Reference (the X time series)?

- The choice of Reference will affect the estimated error variances
- For DA the Reference time series must be the model soil moisture
- For verification it might be better to use a remotely sensed time series (e.g. ASCAT) as the Reference
  - This allows an inter-comparison of different models
  - Otherwise the model with the smallest dynamic range will gain an unfair advantage

Which estimated error variances should be compared/ used for DA?

$$\langle(\epsilon_x)^2\rangle_{TC},\ \langle(\epsilon_y^*)^2\rangle_{TC} \text{ and } \langle(\epsilon_z^*)^2\rangle_{TC} \textbf{ OR } \langle(\epsilon_x)^2\rangle_{TC},\ \langle(\epsilon_y)^2\rangle_{TC} \text{ and } \langle(\epsilon_z)^2\rangle_{TC}$$

- Is 12km/hour bigger than 5 m/s?
  - No, because 12km/hour=3.3m/s
  - To make a proper comparison, all values should be scaled to have the same units.
- Even when different model soil moisture products claim to have identical units (e.g. m^3/m^3), they often have very different dynamic ranges
  - So it is better to think of every model soil moisture product as having its own unique units

Can TC be used for Quality Control?

- Consider a case where a new satellite has been launched and produces a time series Z(t). Suppose that due to processing error, Z(t) contains only random numbers. What output will TC produce?
  - The correlations $C_{X,Z} \rightarrow 0$; $C_{Y,Z} \rightarrow 0$
  - Inserting the above into the equations for Vanilla TC and TC with Linear CDF matching shows that Triple Collocation can't be used for Quality Control!