Development of Data Assimilation Techniques for Hydrological Applications

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◆Advances in hydrological modeling

- Growth in computational power
- Availability of distributed hydrological Obs.
- Improved understanding of physics and dynamics of hydrologic system

Complex hydrological models

Need of concrete methods to deal with increasing uncertainty in models and obs.

✧ **Address uncertainty:**
- Understand
- quantify
- reduce

✧ Address uncertainty

Understand

Various sources of uncertainty:

- **Model structure**
- **Parameters**
- **Initial conditions**
- **Observational data**

Quantify

Present the predictions in terms of probability distribution

[performing probabilistic instead of deterministic prediction/modeling]

Reduce

(1) Acquisition of more informative and higher quality data

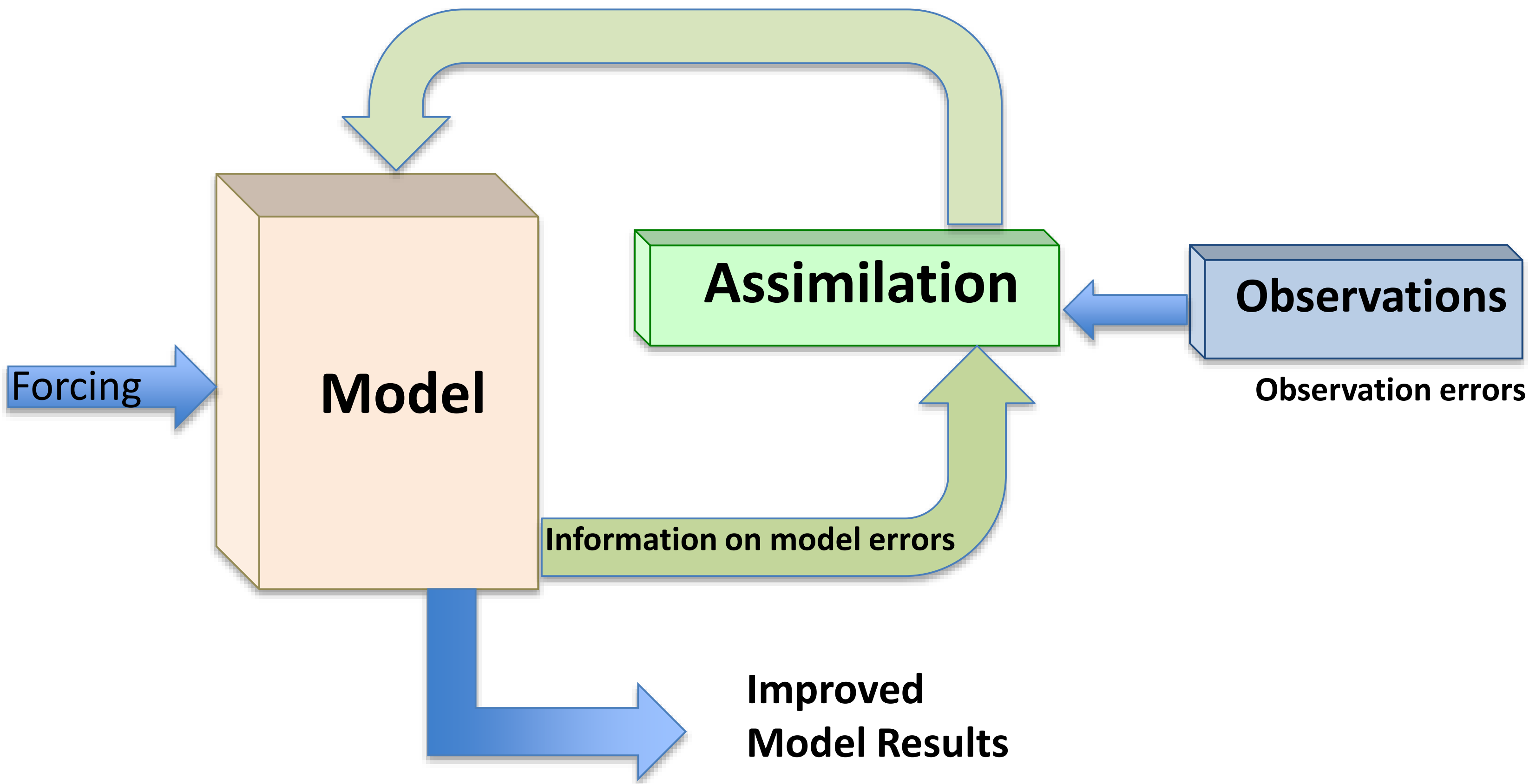
(2) Developing improved hydrological models

(better representation of physical processes and mathematical techniques)

(3) Development of techniques that can better extract and assimilate information from the available data via model identification and prediction

Data Assimilation (DA) methods

Data Assimilation: Procedures that aim to produce physically consistent representations/ estimates of the dynamical behavior of a system by <u>merging the information present in imperfect models and uncertain data</u> in an optimal way to achieve <u>uncertainty quantification and reduction.</u>



◆ Different types of DA problems:

❑ **Parameter Estimation**

- **Deterministic approaches** (calibration method)
- **Stochastic approaches**
  (e.g. Generalized Likelihood Uncertainty Estimation(GLUE), Bayesian Recursive Estimation(BaRE))

❑ **State Estimation**

- **Kalman filtering** [e.g. Ensemble Kalman Filter]
- **Particle filtering**
  (e.g. bootstrap filtering, sequential Monte carlo(SMC),...)
- **Variational Data Assimilation (VDA)**
- **.....**

❑ **System(structure) Identification**

- Generalized likelihood uncertainty estimation (GLUE)
- Bayesian model averaging (BMA)
- ......

◆ Simultaneous State and Parameter Estimation

-*Vruget et al*.[2005] Simultaneous Optimization and Data Assimilation(SODA)

- *Moradkhani et al*.[2005a,2005b] dual state-parameter estimation based on EnKF

- Joint state-parameter estimation-State augmentation [e.g. *Gelb*, 1974; *Drecourt et al*., 2005]

- Different DA problems may require different techniques/algorithms that best fit into the specific problem setting.

- **State Estimation**

Assimilation of Freeze/Thaw Observations into the NASA Catchment Land Surface Model

[Farhadi, L., Reichle, R., De Lannoy, G. J. M., Kimball, J. (2014). Assimilation of Freeze/Thaw Observations into the NASA Catchment Land Surface Model, submitted to *journal of hydrometeorology*]

- **Parameter Estimation**

Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

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Assimilation of F/T Observations into the NASA Catchment Land Surface Model

Introduction:

- ❑ The land surface (F/T) state is a critical threshold that controls **hydrological** and **carbon cycling** and effects.

✓ water and energy exchanges
✓ net primary productivity

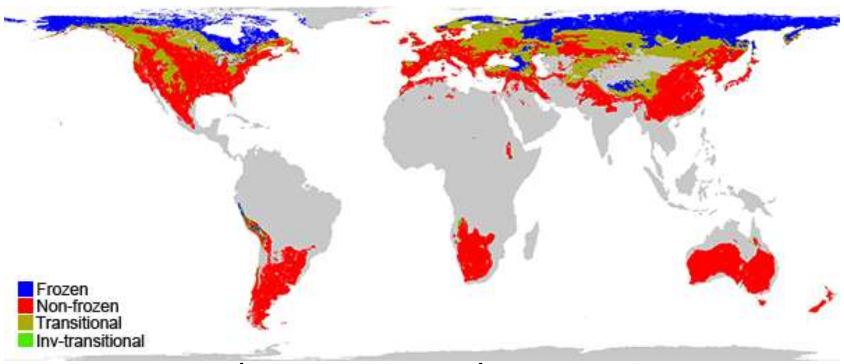


Figure: shows the SMMR-SSM/I daily combined AM/PM FT status for 9 April 2004. Areas colored in gray lie outside of the FT data set domain

- ❑ **Growing season**, **Net Primary Productivity (NPP)**, **Land- Atmosphere CO_2 exchange patterns** shift as a result of Global warming , **consistent** with the patterns and changes in **seasonal F/T dynamics**.

Thus:

✓ Improved representation of the landscape F/T state in land surface schemes is needed.
✓ Assimilation of F/T index should improve the simulation of carbon and hydrological processes.

Assimilation of F/T Observations into the NASA Catchment Land Surface Model

Objective:

- To update the GEOS-5 land data assimilation system with a newly designed F/T assimilation module.

- To provide a framework for the assimilation of SMAP (Soil Moisture Active Passive) F/T observations.

The New F/T Algorithm:

- ❑ the observed F/T variable is essentially a binary observation (not continuous)
- ❑ A rule based assimilation approach is proposed:

✧ If model forecast and observation disagree on F/T variable, model prognostic variables are adjusted to match the observed F/T more closely.

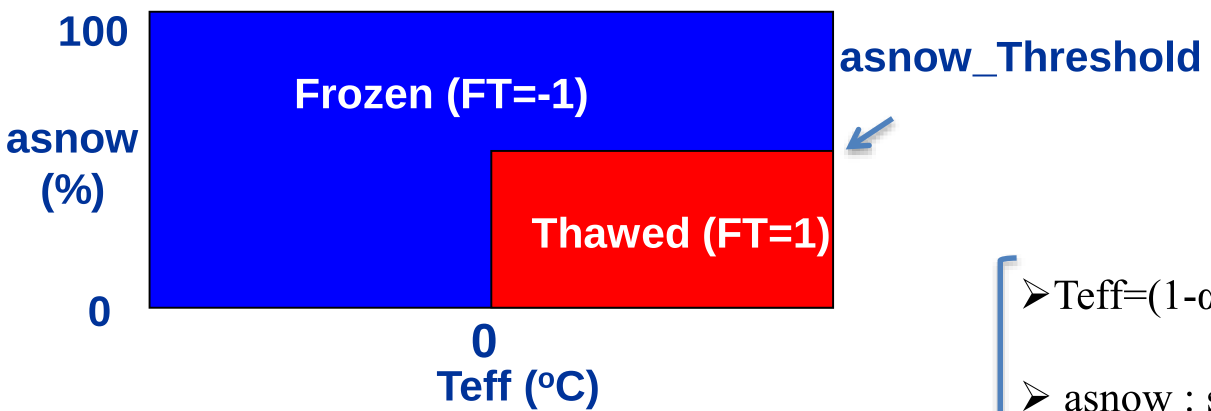
✧ To account for model and observation errors, the delineation between frozen and thawed regimes is defined with some uncertainty in the assimilation algorithm

Assimilation of F/T Observations into the NASA Catchment Land Surface Model

F/T Detection Algorithm :

- **F/T =f (Tsurf_nosnow, Tsnow, Tsoil)**

  = g(Teff (effective temperature); asnow (snow cover fraction))



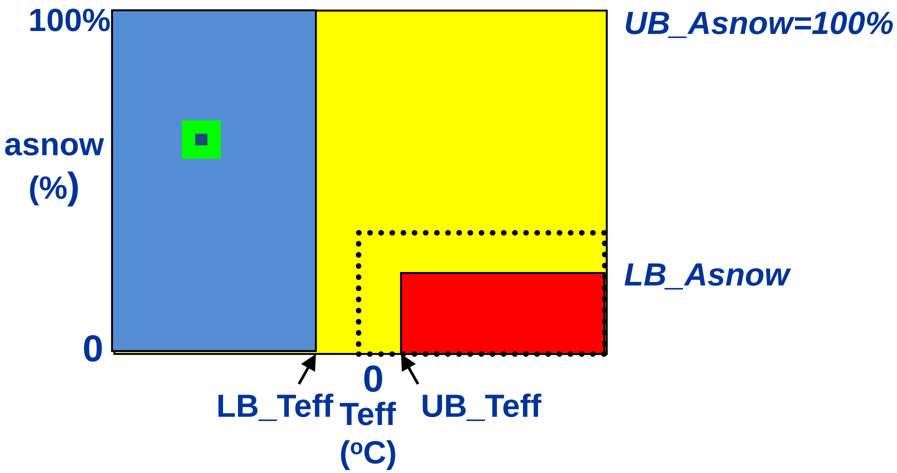
- Teff=(1-α)Tsoil+ α Tsurf_nosnow
- asnow : snow cover fraction(%)
- asnow_threshold: depends on the microwave frequency of backscatter/Tb.

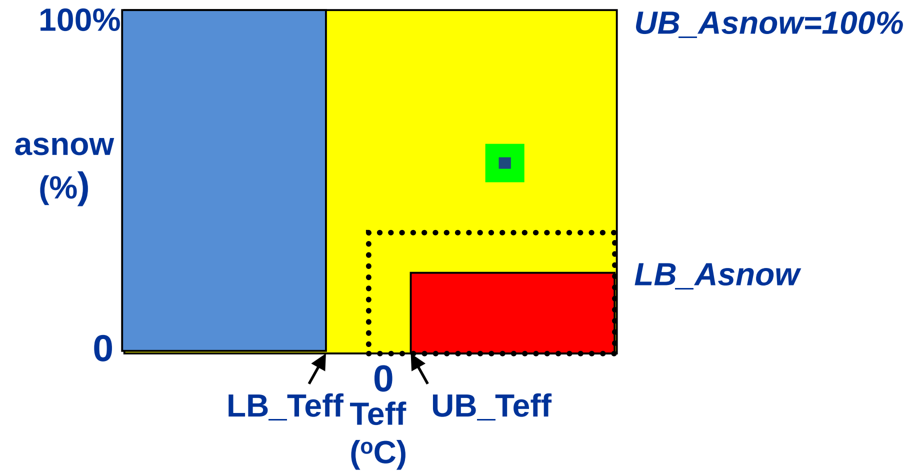
  [Higher frequency-> lower threshold and vice versa];

Assimilation of F/T Observations into the NASA Catchment Land Surface Model

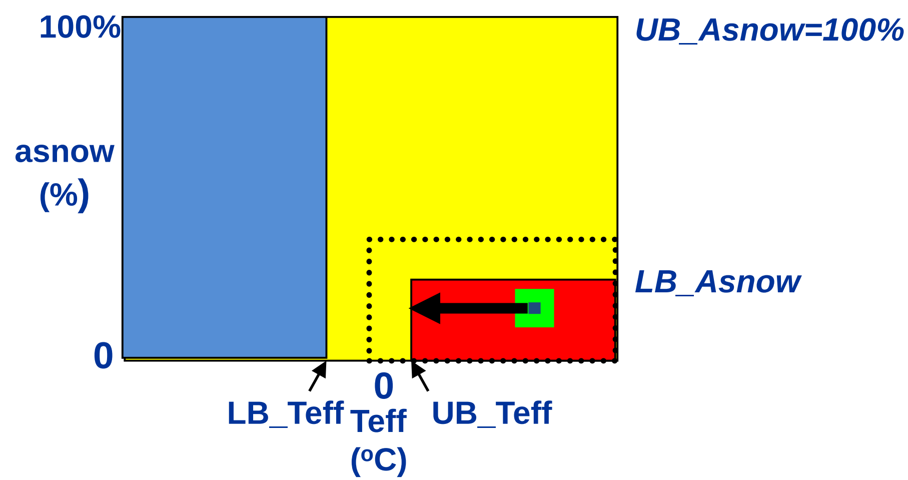
F/T Analysis Algorithm :

Observed F/T=-1 (freeze)





Analysis happens

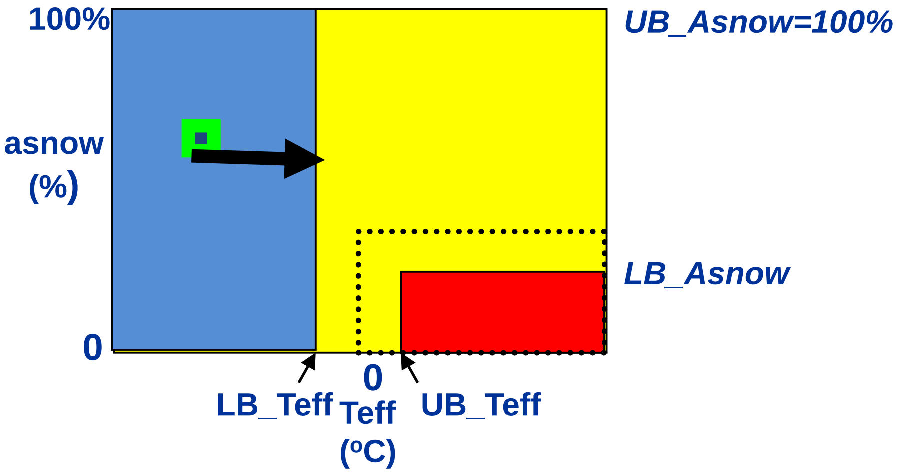


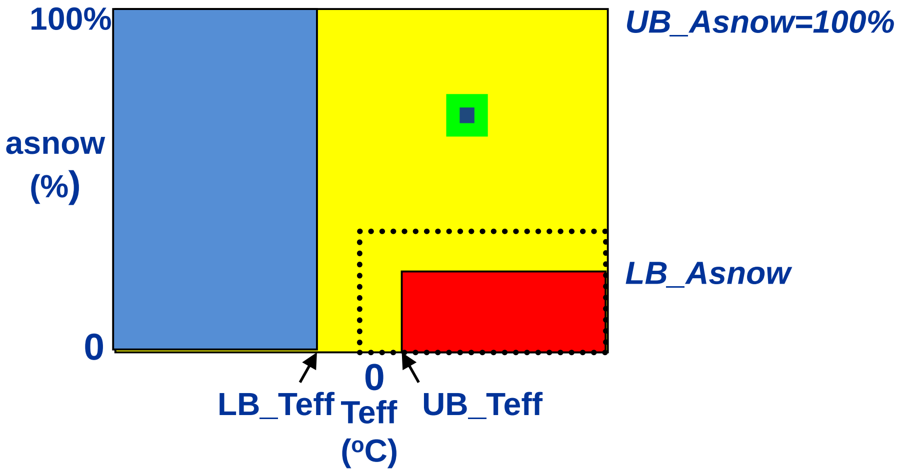
- **Red region:** Completely thawed
- **Blue region:** Completely frozen
- **Yellow region:** Undetermined

Assimilation of F/T Observations into the NASA Catchment Land Surface Model

F/T Analysis Algorithm :

Observed F/T=1 (Thaw)





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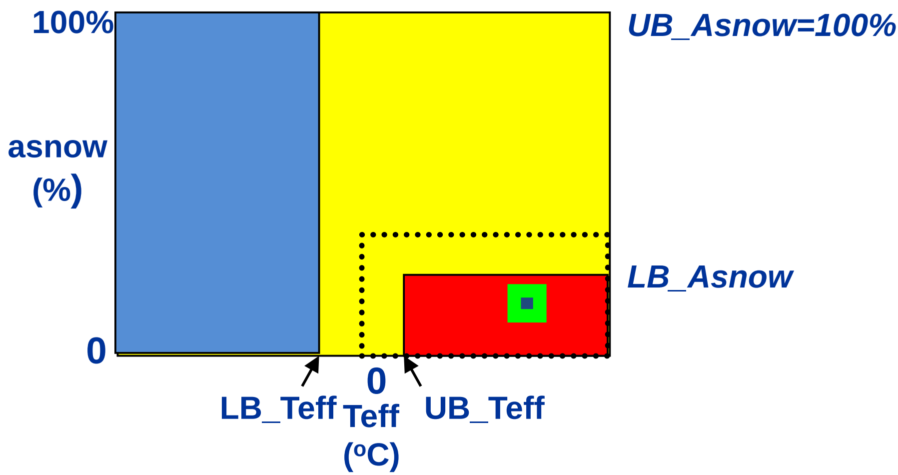

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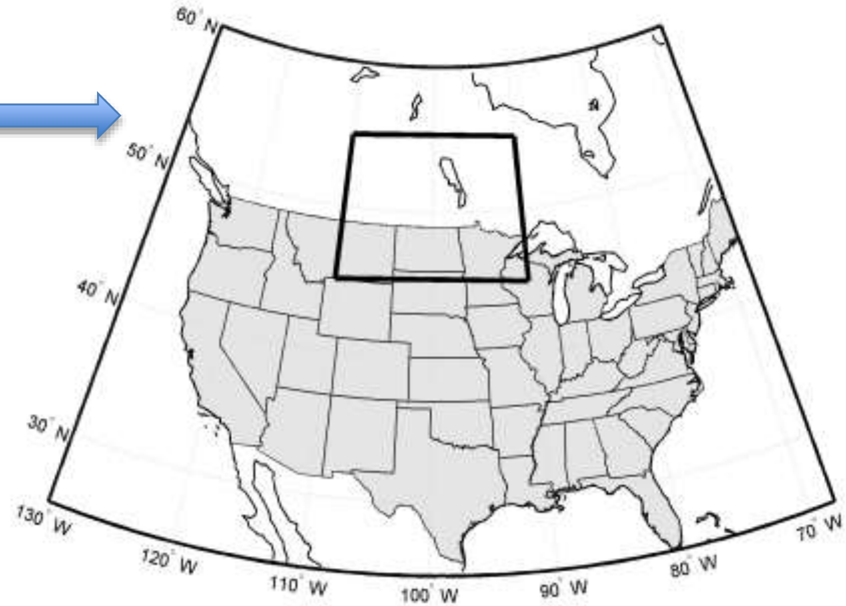
Assimilation of F/T Observations into the NASA Catchment Land Surface Model

Experimental Setup:

- Area under investigation
  45-55° N and 90-110° W



- Time period :
  8 year (2002-2010)

- Grid:
  36 km EASE grid (1137 grid cells)

- Design Setting:

asnow	Teff
asnow_threshold=10%	Teff_threshold=0°C
UB_asnow=100%	UB_Teff=1°C
LB_asnow=5%	LB_Teff=-1°C

Assimilation of F/T Observations into the NASA Catchment Land Surface Model

Simulations:

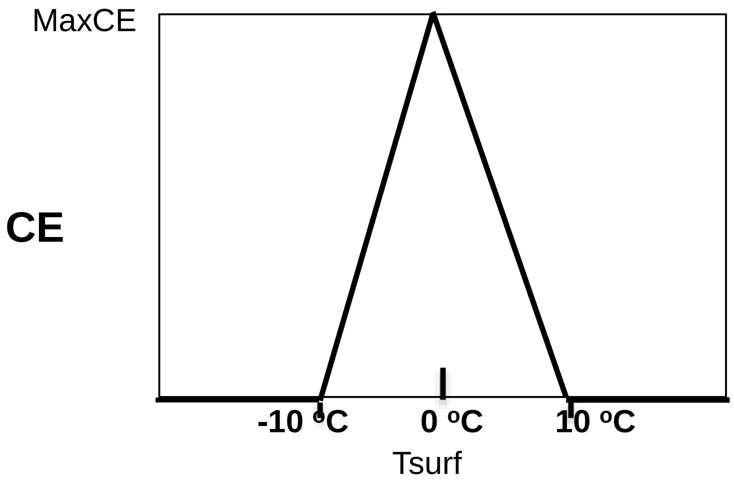
✧ Synthetic true F/T index:

Produced by running the Catchment model using MERRA forcing

✧ Synthetic observed F/T index:

Produced by applying classification error (CE)* to synthetic true data set.

* We assume classification error as a function of Tsurf



✧ Open Loop (No assimilation):

Produced by running the Catchment model with GLDAS forcing.

✧ FT Analysis (Data Assimilation):

Produced by performing FT analysis, using synthetic observation and running the Catchment model with GLDAS forcing.

Assimilation of F/T Observations into the NASA Catchment Land Surface Model

Results:

Open Loop (OL) F/T classification error= 4.87%

RMSE (Open loop vs. true; 2002-2010; 6am/pm local time)

Variables	RMSE (K)
Tsurf (K)	3.08
Tsoil (K)	1.97

RMSE(OL. vs. true)- RMSE(FT analysis. vs. true)

Max(CE) / Variables	0%	5%	10%	20%
Tsurf(K)	0.206*	0.192	0.178	0.149
Tsoil(K)	0.061**	0.049	0.036	0.006

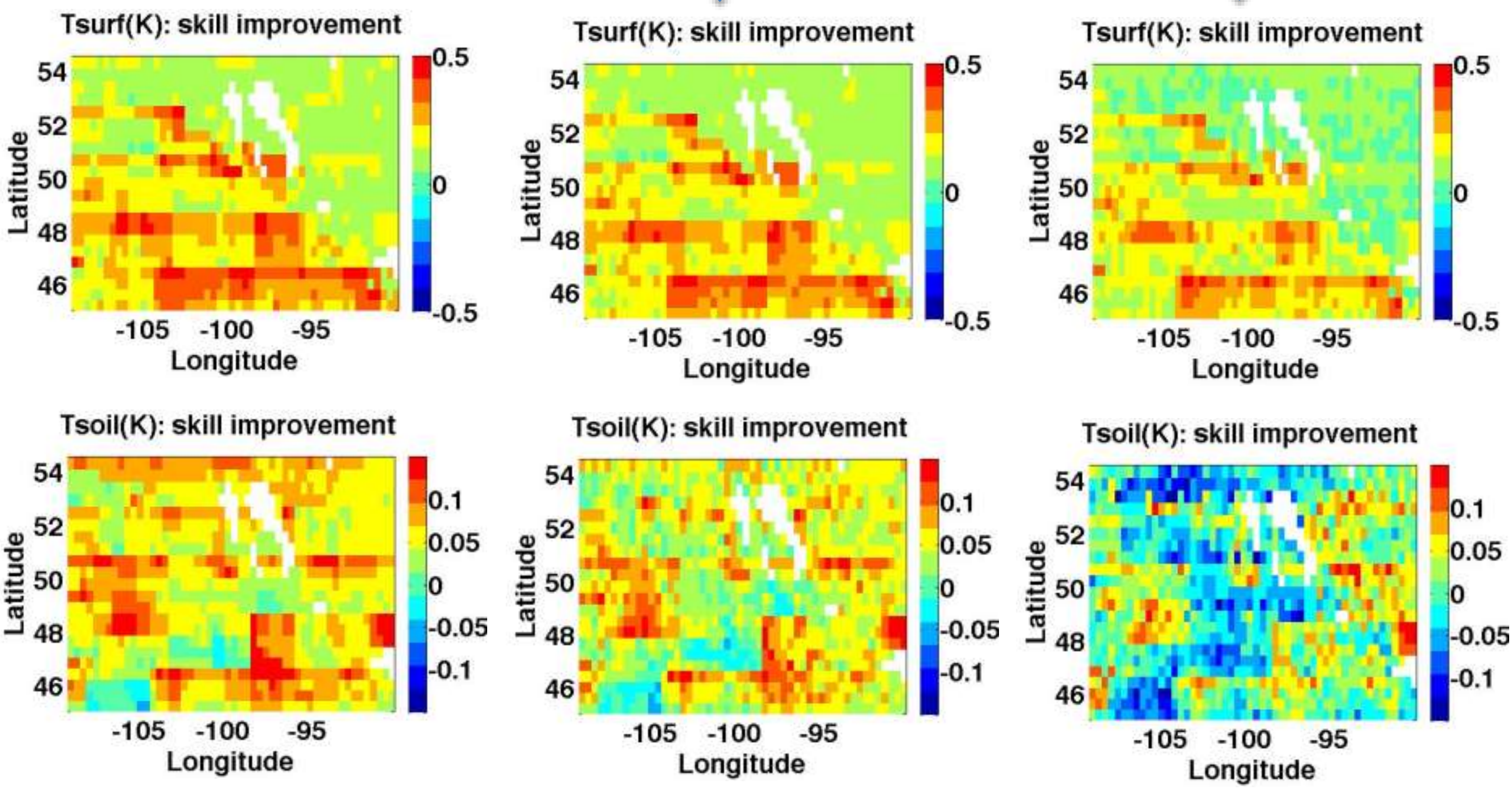
*6.7% RMSE reduction

** 3.1% RMSE reduction

Assimilation of F/T Observations into the NASA Catchment Land Surface Model

Results:

No classification error | max(CE)=5% | max(CE)=20%



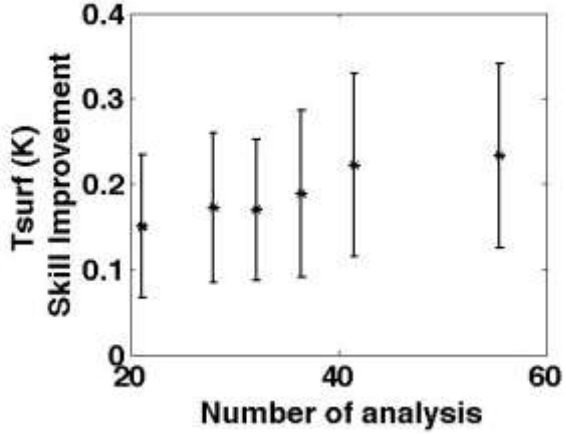
Assimilation of F/T Observations into the NASA Catchment Land Surface Model

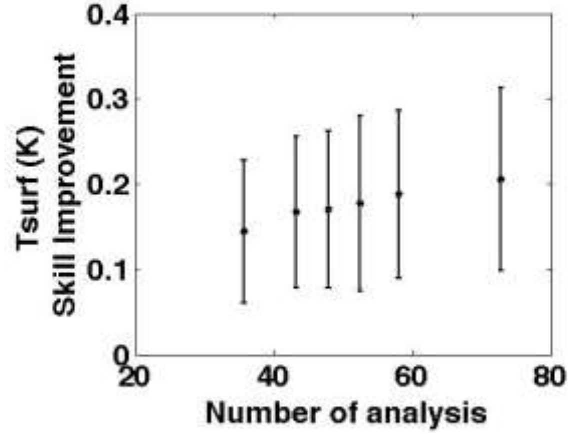
Results:

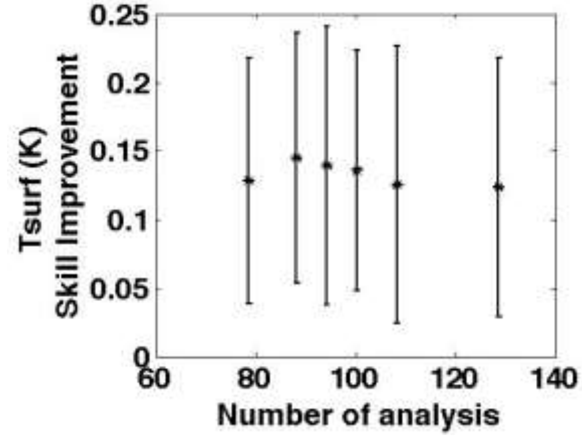
No classification error

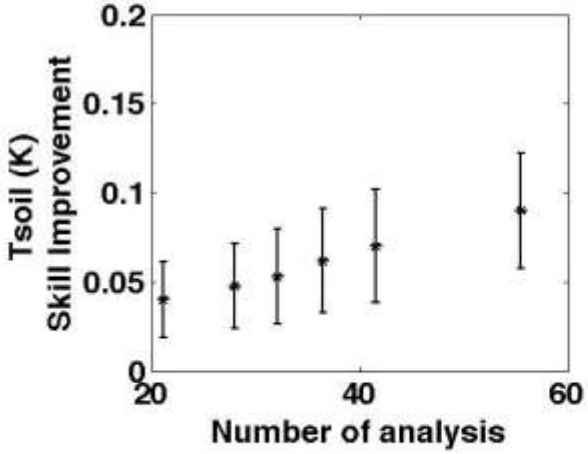
max(CE)=5%

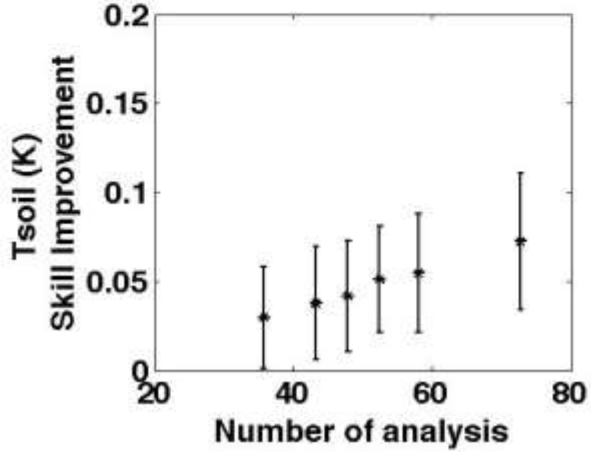
max(CE)=20%

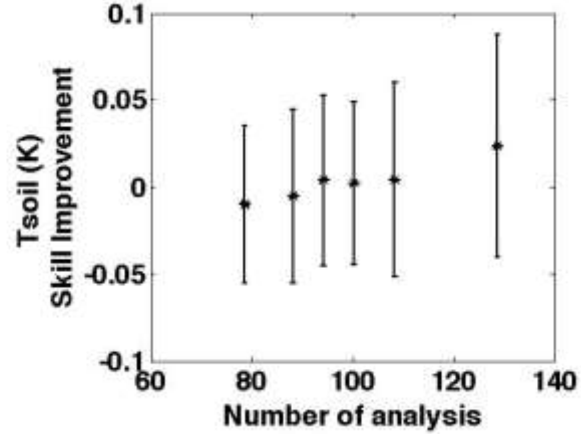






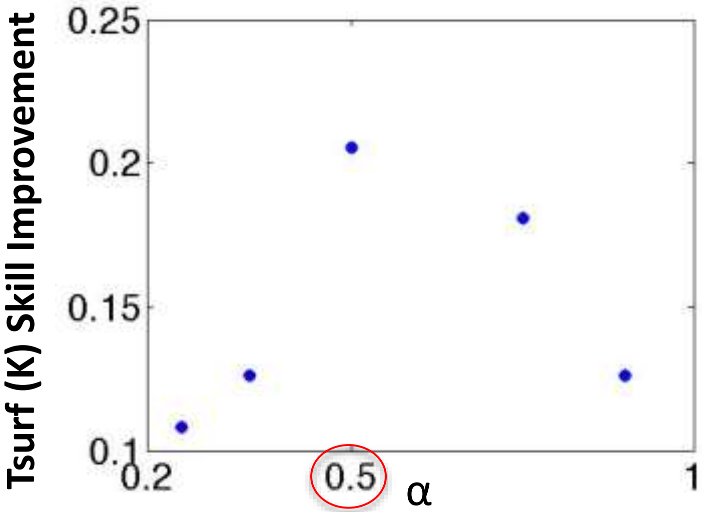






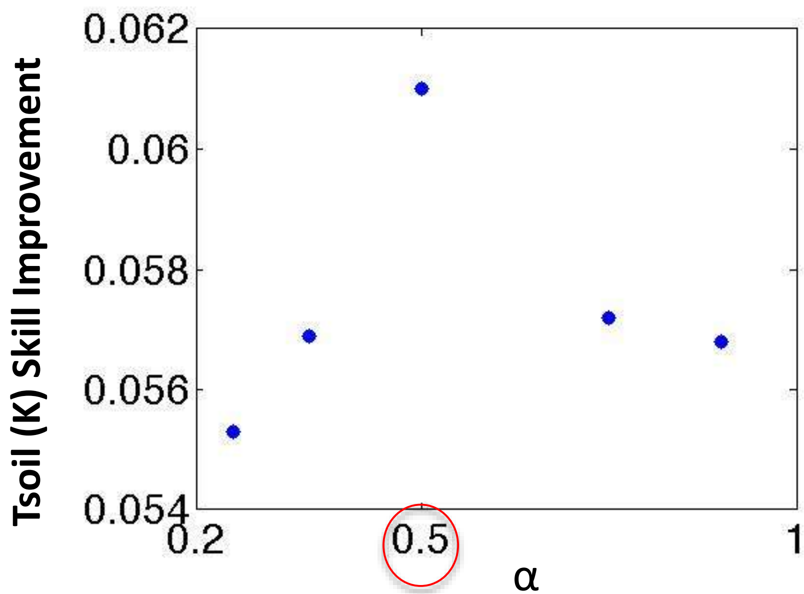
Assimilation of F/T Observations into the NASA Catchment Land Surface Model

Results:



Sensitivity of assimilation results to α

$$Teff = (1 - a) * Tsoil + a * T_{Surf}^{no-snow}$$



Conclusion:

- An algorithm was developed for diagnosis of F/T state of soil in the NASA Catchment land surface model.

- The Global Modeling and Assimilation Office (GMAO)'s land data assimilation system in offline mode was updated with the newly designed F/T assimilation module.

- The performance of the method for a synthetic experiment showed encouraging improvements in skill of Tsoil and Tsurf.

- The average skill improvement reduces with increasing classification error on the observed F/T index.

- Data Assimilation (DA) performance is sensitive to the α parameter.

(A realistic value for this parameter which is compatible with the effect of Tsurf and Tsoil in determining remotely sensed soil F/T state, can improve the performance of DA method)

- This Freeze/Thaw assimilation module will be tested with satellite retrievals of F/T from AMSR-E to test its performance at large scale.

Ultimate goal: **Provide a framework for the assimilation of Soil Moisture Active Passive (SMAP) F/T observations into the NASA Catchment land surface model.**

- Different DA problems may require different techniques/algorithms that best fit into the specific problem setting.

- **State Estimation**

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- **Parameter Estimation**

✓ Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

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Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Motivation:

- Links (and closure) for surface water and energy balance

Surface water & energy balance linked through **latent Heat** flux

The need for consistency requires a **closure function**

Over bare soil this closure often can take the form of soil moisture (s) dependent empirical functions:

1. $\beta(s) = \dfrac{\text{Actual Evaporation}}{\text{Potential Evaporation}}$
2. $h(s) = \text{Humidity at soil-atmosphere interface}$

In plant continuum, it often takes the form of :

1. Soil moisture-dependent root water extraction resistance r_g
2. Stomatal resistance r_s due to plant water stress

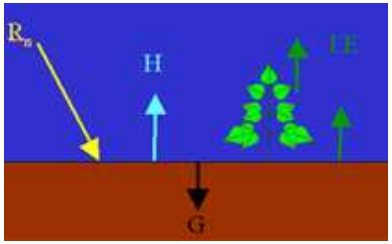
Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Motivation:

- All Land Surface Models – LSMs include (**explicitly or implicitly**) a form of this closure.

- No matter how complex the closure function is, LSM's still tend to produce an Evaporative fraction function which increases with Soil moisture or is insensitive to it

- Land response to radiative forcing and partitioning of available energy are **critically dependent on the functional form (<u>shape</u>)** of the closure relationship.



- The function affects the **surface fluxes**, the influence reaches through the boundary layer and manifests itself in the lower atmosphere weather

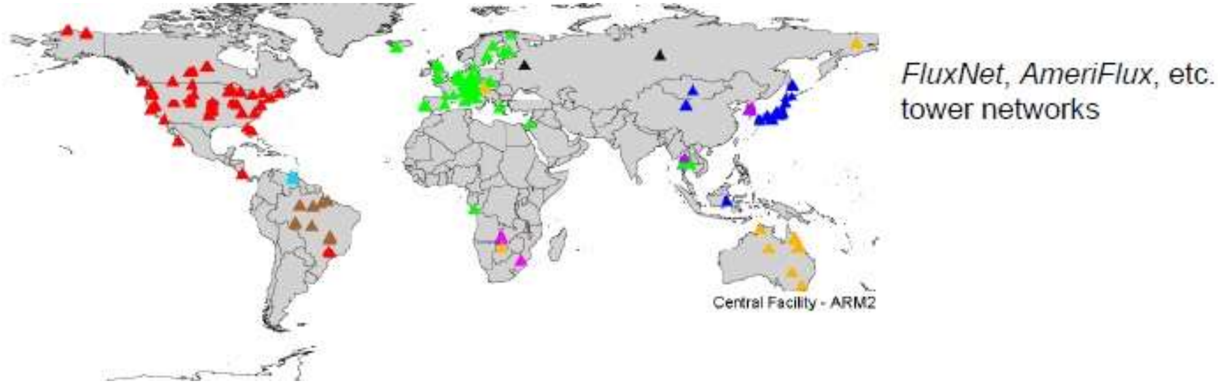
- **Important as these closure functions are, they still remain essentially empirical and untested across diverse soil and vegetation conditions.**

Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Motivation:

- The overarching goal of this project is to develop a **scale free**, **calibration free** **technique** to better estimate the unknown parameters (e.g. the flux components) of water and energy balance equation (and the closure relation between the two) using **discrete observation**.

✓Estimation procedure is distinct from **"calibration"** since only forcing (P, $R_{in}^{\downarrow}$) and state (s, T_s) observations are used. No information about fluxes (e.g. flux towers) is needed.

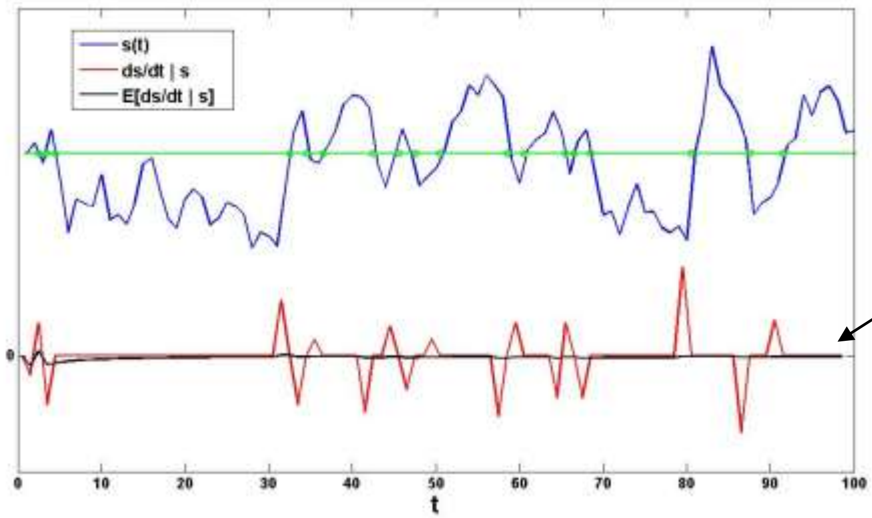


✓The method is scale- free, i.e. it can be applied to diverse scales of states and forcing (remote sensing applications)

✓The method can be applied to diverse climates and land surface conditions using remotely sensed measurements.

Methodology:

✓The approach is based on the conditional sampling method of Salvucci (2001) which exploits the fact that the expected value of increments of seasonally detrended soil moisture (s) conditioned on moisture is zero (E[ds/dt|s]=0) for stationary systems.



Result of stationarity
E[ds/dt|s]=0

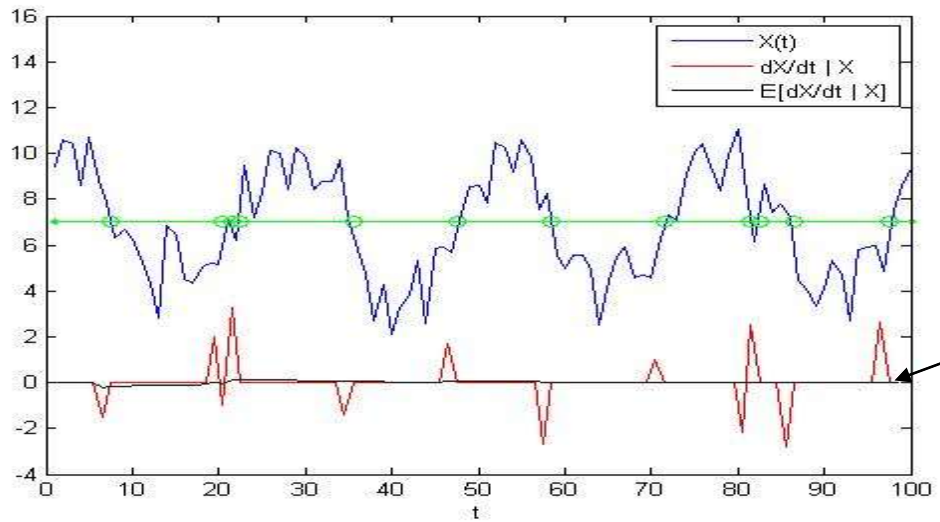
- [Mathematical proof: conditional expectation minimizes least squared loss function]

✓Model parameters (sum of evaporation and drainage) are estimated by matching the soil moisture conditional expectation of modeled fluxes to soil moisture conditional expectation of precipitation. (E[Sum of fluxes|s]=E[P|s])

- Problem in distinguishing evaporation from drainage

Methodology:

✓ It can be proved that for seasonally (periodically) stationary process (X_t), The relation $E[dX_t/dt|X_t]=0$ holds



Result of Stationarity $E[dX_t/dt|X_t]=0$

Soil moisture (S) and soil surface temperature(Ts) are seasonally stationary, Thus: $E[dS/dt|S]=0$ and $E[dT_s/dt|T_s]=0$

Thus by applying to the two balance equations we can separate out drainage from evaporation(Note: both hydrologic fluxes important but not measured widely)

Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Methodology:

Example Moisture Diffusion Eq :

$$l\frac{ds}{dt} = P - ET - D + CR$$

$E[ds/dt|s]=0$

$$0 = E[P|s] - E[ET|s] + E[D|s] - E[CR|s]$$

Example Heat Diffusion Eq :

$$\frac{dT_S}{dt} = \left(\frac{2\sqrt{\pi\omega}}{P_i}\right)\left[\underbrace{R_n}_{R_{in}^{\downarrow} - R_{out}^{\uparrow}} - LE - H\right] - 2\pi\omega(T_S - T_D)$$

$E[dT_s/dt|T_s]=0$

$$0 = E\left[\bar{R}_{in}|T_s\right] - E[LE|T_s] - E[H|T_s] - E[P_i.\frac{pw}{\sqrt{pw}}(T_s - T_D)\,|T_s] - E[\varepsilon\sigma T_s^4\,|\,T_s]$$

Process	**Unknown Par's**	**Form**
Drainage	K_s, c	$D(s)=K_s.s^c$
Capillary rise	w, n	$CR(s)=w.s^n$
Thermal Inertia	P_i	f(soil type, soil moisture)
Neutral turbulent heat coefficient (C_{HN})	α, β	$C_{HN}= \exp(\alpha LAI+\beta)$
Evaporative Fraction (EF=LH/(LH+H))	a,θ_s,θ_w	$EF=1-\exp(-a(\theta/ \theta_s- \theta_w/ \theta_s)$

Methodology:

- S and T_s are discretized to n and m ranges respectively

$$\begin{cases} E\left[\rho LP \middle| \bar{s}_i\right] = M_w(i) + \xi_1 \\ E\left[R_{in}^{\downarrow} \middle| \overline{T}_{sj}\right] = M_e(j) + \xi_2 \end{cases}$$

Units:W/m^2

Where:

Forcing uncertainty:

$$\begin{cases} \xi_1 \sim N(0,(\rho L)^2 \sigma_P^2); \\ \xi_2 \sim N(0,\sigma_{R_{in}^{\downarrow}}^2)); \end{cases} \qquad Cov(\xi_1,\xi_2) = 0$$

- **The cost function:**

$$\mathrm{J} = \frac{1}{2}(\mathrm{d}-\mathrm{m})^{\mathrm{T}}.\mathrm{A}.(\mathrm{d}-\mathrm{m})$$

d : Vector of data (n+m x1)

M: Vector of Model Counterparts (n+m x1)

A=σ^{-2}I (n+m x n+m)

$$\mathrm{d}: \left[\mathrm{E}\left[\rho \mathrm{LP}\middle|s_1\right], E\left[\rho LP\middle|s_2\right], \ldots.. E\left[R_{in}^{\downarrow} \mid T_{s1}\right], E\left[R_{in}^{\downarrow} \mid T_{s2}\right], \ldots.\right]$$

⇨ Unknown parameters: $[\theta_s, \theta_w, a, C_{HN}, P_i, K_s, c, w, n]$

- **Note:** Estimation procedure is distinct from " calibration" since only forcing data (P,$R_{in}^{\downarrow}$) and state observation (s, T_s) are used. No information on fluxes (e.g. Problematic evaporation and drainage) is needed.

Methodology:

- **Minimize nonlinear Cost Function J**

- **Estimation of Uncertainty Bounds**

- Inverse of Hessian of Cost function is an approximation for the Covariance matrix.

- Covariance matrix is used to estimate the uncertainty of any model output and thus determine which aspects of the model are poorly determined by the data

- First Order Second Moment propagation of uncertainty (FOSM) analysis, or Monte Carlo method is used to define the uncertainty around different flux components.

Methodology:

- **Determining the sufficiency of a particular data set to determine the model parameters**

1- Uncertainty of each individual parameter should be reasonable in physical sense.

2-Uncertainty of the least well-determined combination of variables given by the eigenvectors of Hessian should be reasonable.

3- Correlation matrix between unknown variables should be reasonable.

-Linear dependency between variables is a sign of discrepancy between data and model

-Best scenario: The correlation between all the parameters is small,

-The next best scenario: High correlation is only between parameters representing one flux type and suggests the model is robust with regard to flux components

-The worse scenario: The correlation between parameters representing different flux types is high and/ or physically not meaningful.

Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Synthetic test

- 30 year of hourly meteorological data for humid climate of Charlotte North Carolina obtained from "Solar and Meteorological Surface Observational Network" (SAMSON) [National Climate Data Center];

- Simultaneous Heat and Water(SHAW) model was used to derive consistent hourly time series of state and fluxes

- Assume 20% precipitation and radiation error.

- 8 unknown parameters

$$\boxed{a = \left[K_s, c, w, n, C_{HN}, a, S_w, q_s \right]}$$

Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Synthetic test

$$\alpha = [K_s, c, w, n, C_{HN}, a, S_w, \theta_s]$$

Estimated model variables for the system with 8 unknown variables

Par	Dimension	Opt solution ± std	Relative error (%)
K_s	m/hr	0.0021±0.0003	14.3%
w	m/hr	0±1.257	$\rightarrow \infty$
C_{HN}	[ ]	0.0032±0.0002	6.25
a	[ ]	6.44±0.14	2.15
n	[ ]	146.11±152.1	104.09
S_w	cm^3/cm^3	0.46±0.0014	0.3
C	[ ]	9.41±0.2544	2.7
θ_s	cm^3/cm^3	0.474±0.0000	0.00

Uncertainty of combination of variables determined by eigen vectors

Eigen Values	Relative error (%) $\frac{\sigma_{e_i^T X}}{E[e_i^T X]} \times 100$
4.3225e-005	104.1
0.6147	1920.5
17.6851	2.72
54.6745	1.82
7.7479e+005	0.27
5.5736e+007	0.89
1.6690e+008	1.41
2.6540e+017	0.00

❑ **Data is insufficient to determine the model states with acceptable accuracy- linear dependency is generated as seen in the correlation matrix**

Correlation Matrix between variables of the system

	K_s	w	C_{HN}	a	n	S_w	C	θ_s
K_s	1.00							
w	-0.124	1.00						
C_{HN}	-0.78	0.13	1.00					
a	0.89	-0.15	-0.89	1.00				
n	-0.00	0	0.00	-0.00	1.00			
S_w	0.55	-0.09	-0.33	0.58	-0.00	1.00		
C	-0.11	0.02	0.097	-0.12	-0.36	-0.10	1.00	
θ_s	-0.94	0.19	0.82	-0.97	0.00	-0.62	0.12	1.00

- w~0; its variation is high; in addition, n is large, S^n is very small (0<S<1) Thus, ***WS***

- Due to high linearity btw " Ks ,θ_s" and " a, θs" Taking θs out of the parameter space will improve the condition number of Hessian ;

(**replace : θs ~ max(recorded θ)**)

- This is not a sample correlation but derived from Hessian and related to shape of J around minimum. Used for diagnosing collinearity and has no statistical significance.

Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Synthetic test

$$\alpha = [K_s, C, C_{HN}, a, S_w]$$

Estimated model variables for the system with 5 unknown variables

Par	Dimension	Opt solution ± std	Relative error (%)
K_s	m/hr	0.0020±0.0003	15%
C_{HN}	[]	0.0028±0.0004	14.28%
a	[]	6.55±0.49	7.52%
S_w	cm^3/cm^3	0.416±0.011	2.6%
C	[]	9.05±0.3	3.31%

Uncertainty of combination of variables determined by eigen vectors

Eigen Values	Relative error (%) $\frac{\sigma_{e_i^T X}}{E[e_i^T X]} \times 100$
3.89	13.43
13.22	2.61
9888.5	1.77
1.2277e+007	19.34
2.5527e+007	8.7
3.89	13.43

Correlation Matrix between variables

	K_s	C_{HN}	a	S_w	C
K_s	1.00				
C_{HN}	0.18	1.00			
a	-0.45	-0.64	1.00		
Sw	-0.11	0.40	-0.18	1.00	
C	0.7	0.13	-0.32	-0.23	1.00

-Parameters are estimated reasonably well

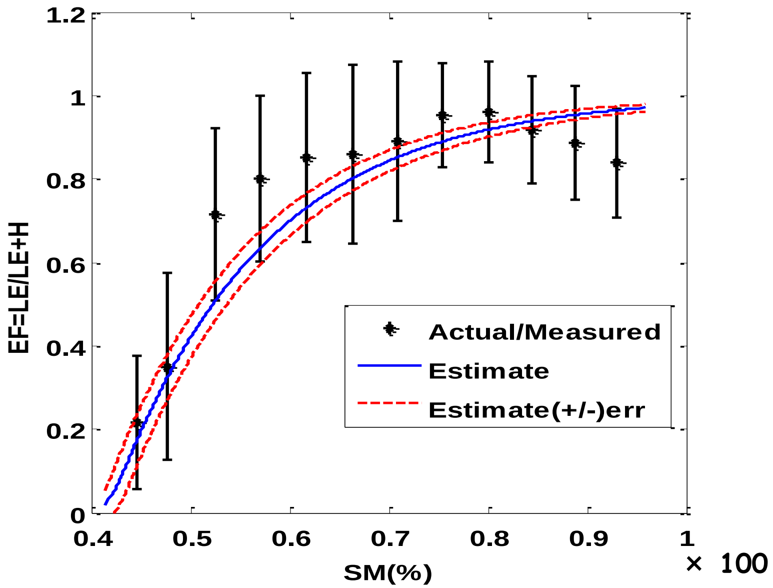
-High correlation between Ks and C is the sign of robust estimation of Drainage.
Ks increases→ $Ks.S^c$ increases
C increases→ $Ks.S^c$ Decreases

-"C_{HN} and a" parameters have negative Correlation;
Increase in parameter "C_{HN}" → Increase in estimated sensible heat flux
Decrease in parameter " a" → Decrease in estimated Latent heat flux

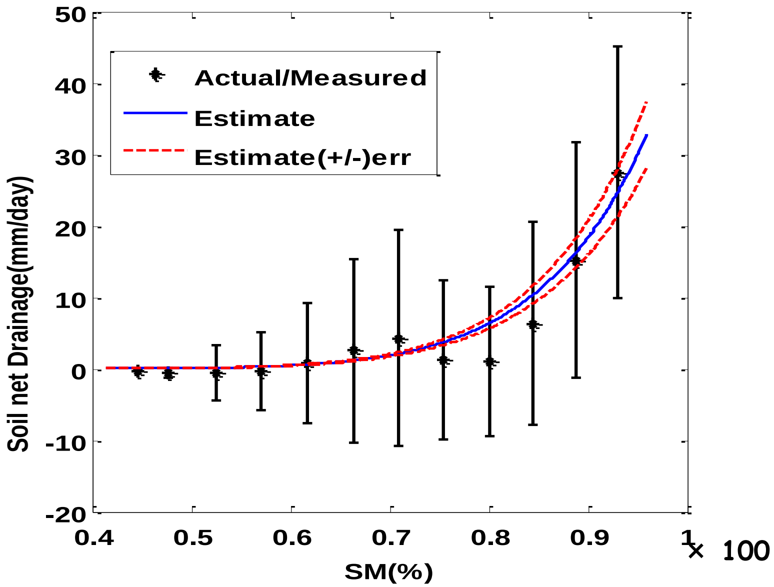
This result is physically meaningful, since the sum of sensible heat flux(H) and Latent heat flux (LE) represent the available energy to the system (Rn-G) and when the available energy to the system is constant, an increase in H results in a decrease in LE and vice versa.

Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Synthetic test



Comparing Actual EF and model estimate of EF



Comparing Actual /measured net soil water flux and its model counterpart

- ✓ The closure function EF(s)=LE/LE+H is well estimated in this synthetic data set
- ✓ This approach is robust at point scale

Field site test

3 Field sites were investigated:

- ✓ Vaira Ranch, grassland, CA, Mediteranation climate
- ✓ Audubon Research ranch, grassland, AZ, Arid/semi arid climate

- ✓ Santa Rita Mesquite , woody savanna, AZ, Arid/semi arid climate

Field site test

Source of Data (estimation and validation)

- **AMERIFLUX (Tower data)**

  Soil water content θ ; Wind speed(u), Air temperature (T_a), Soil surface Temperature (T_s), Precipitation (P), Net radiation (R_n)

- **MODIS (Satellite data)**

  LAI

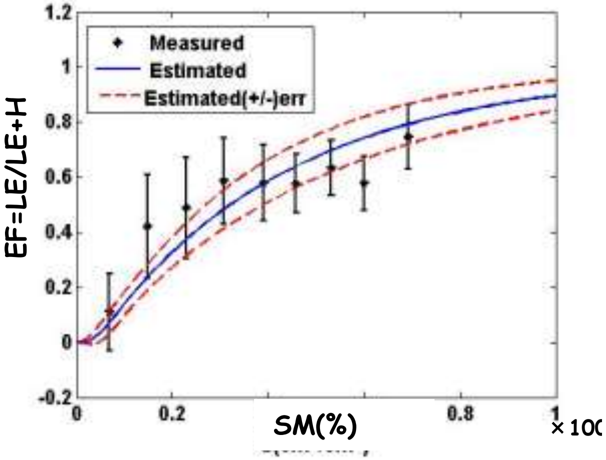
❑ Error of data

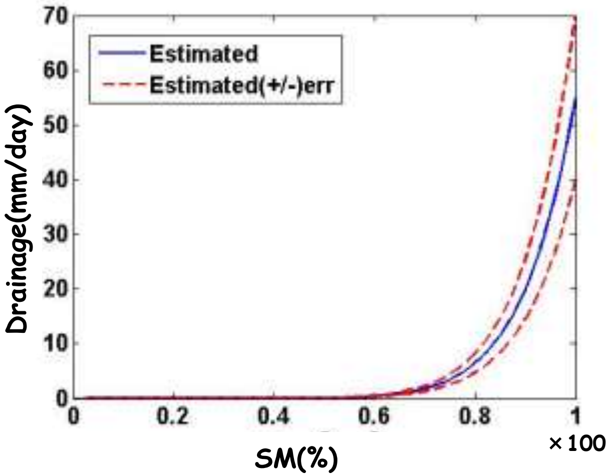
$\varepsilon_{E[\ P|s]} \sim N(0, (6\%\ E[\ P|S])^2)$; $\varepsilon_{E[\ Rin|s]} \sim N(0, (8\%\ E[\ R_{in}|T_s])^2)$;

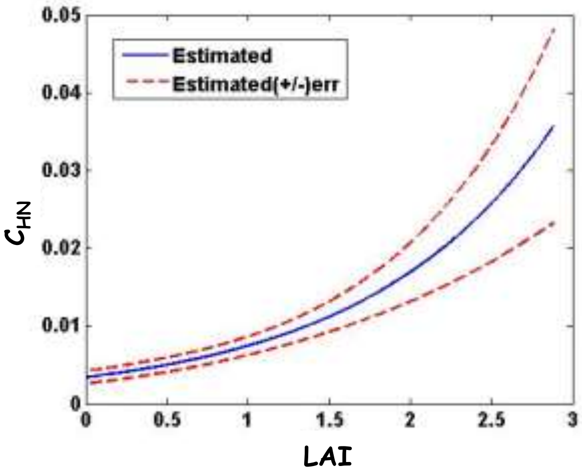
Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

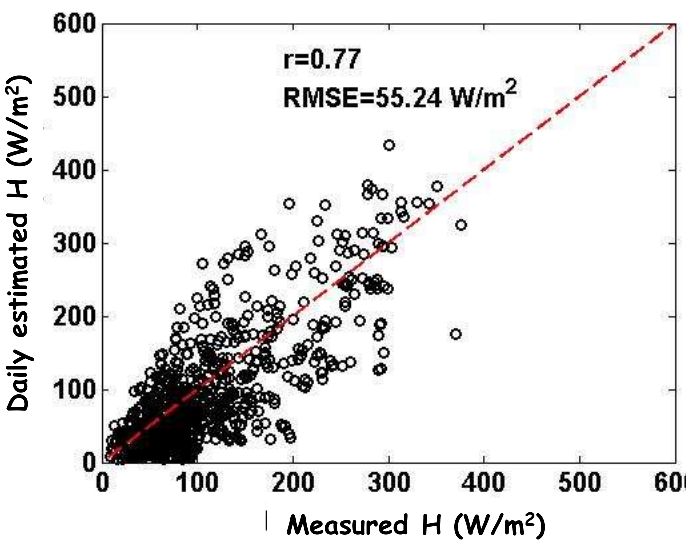
Field site test

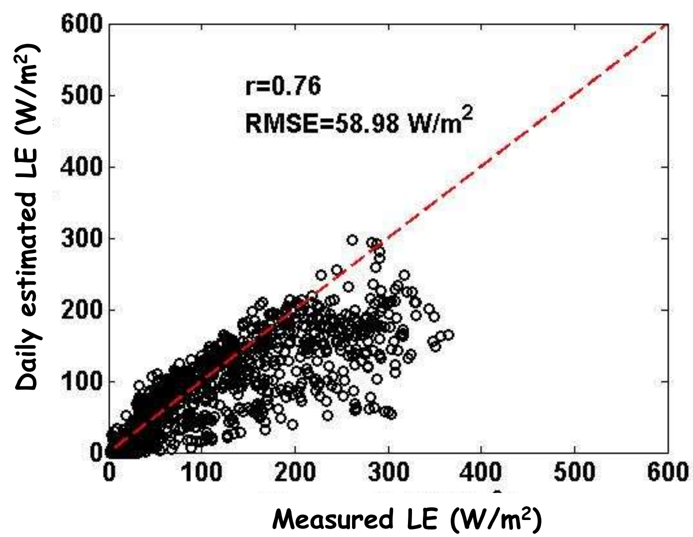
✓ Vaira Ranch, grassland, CA





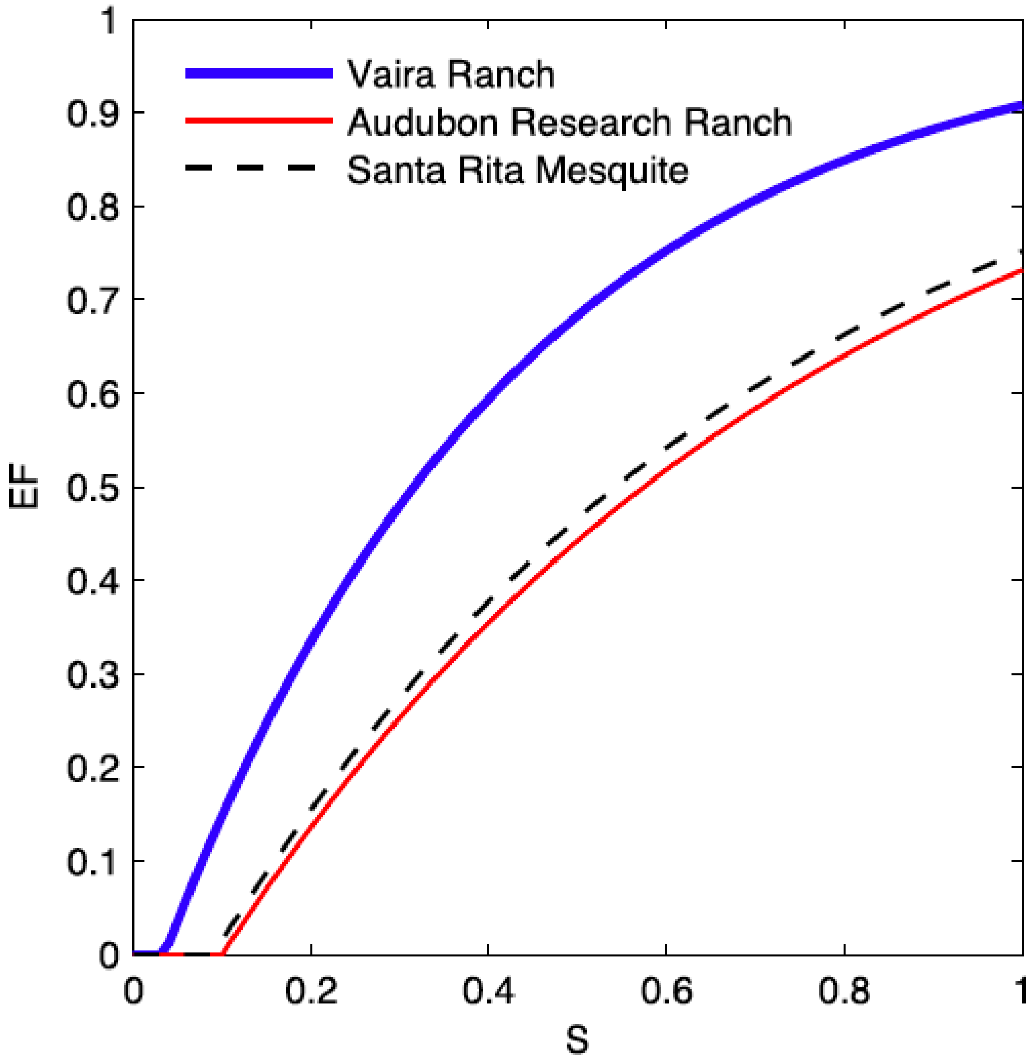






- 30 published validations of remote sensing based estimated flux against ground based measurements of evapotranspiration shows an average RMSE value of about 50 W/m2 (Kalma et al., 2008).

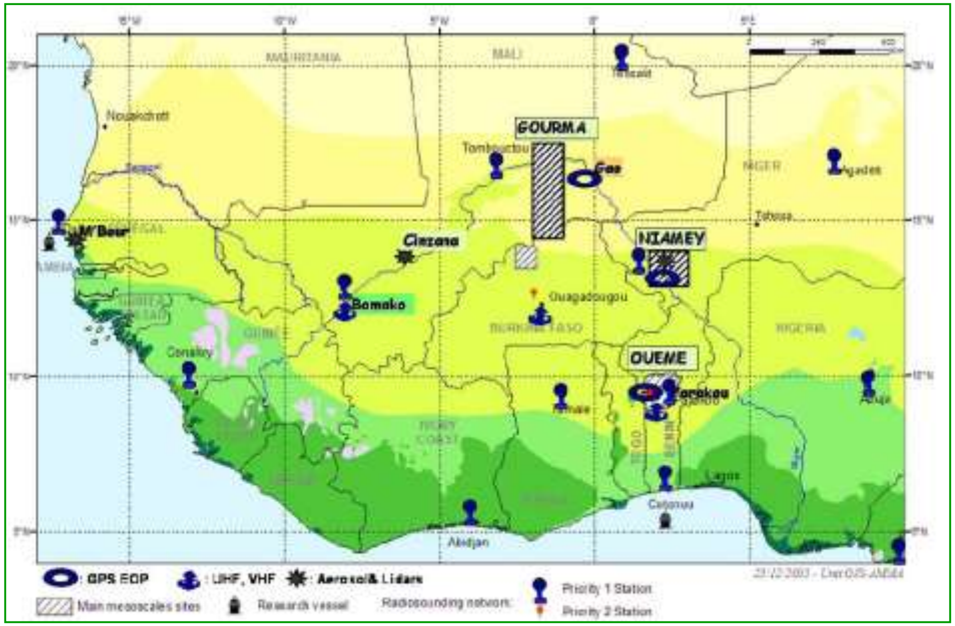
Field site test



- Distinct Closure function

Remote sensing

- The Gourma meso scale site in Mali of West Africa is an area located in the Gourma region. (14.5-17.5 ^{O}N, 1-2 ^{O}W), 40,000 km^2 area.



Reference [AMMA Documentation]

- **Why this region**

1- vast spatial and temporal coverage, remote sensing data which give access to surface variables in this area;

2- Gourma region is located in Sahara & Sahelian-Sahara climate; Evaporation is generally water limited (EF=EF(S)) ;

3- Runoff can be considered negligible in most areas;

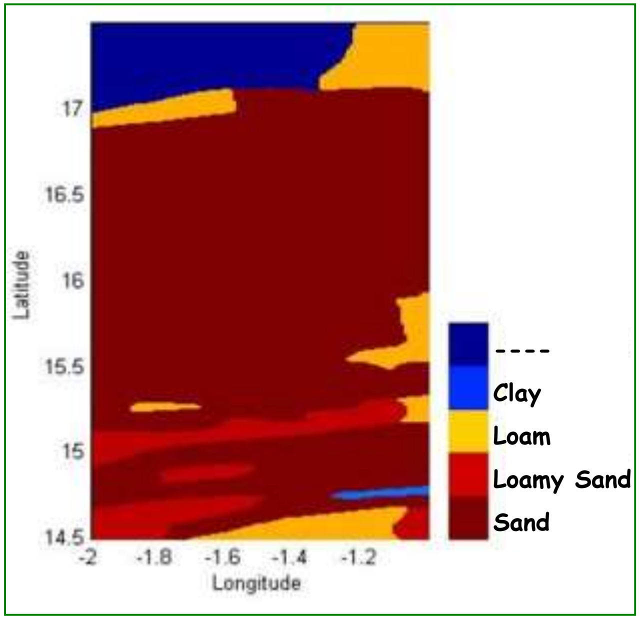
Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Var	Definition	Source of Data	Spatial Resolution	Temporal Resolution
u	Wind speed	AMMA-ECMWF	50km	6hr
T_a	Air Temp	AMMA-ECMWF	50km	6hr
Rs	Down Welling short wave	SEVIRI	3km	15 min
α	albedo	SEVIRI	3km	Daily
LAI	Leaf Area Index	SEVIRI	3km	Daily
P	Precipitation	PERSIANN	4km	hrly , daily
S	Soil Moisture	AMSR-E	25km	1:30 pm;1:30 am
T_s	Surface Temperature	SEVIRI	3km	15 min
T_D	Soil Deep Temperature	Filtering Ts	3km	15 min

- 2008 data sets were selected.
- Data were aggregated to present daily time step
- Data are interpolated on a 3km*3km grid

Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

- In order to reduce dimensionality, USGS categorical soil maps are used to find common soil hydraulic parameters in similar regions (alternative dimensionality reduction approaches can be applied)



Sand
Loamy Sand
Clay
Loam

Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Sand region….

Sand pixels ~ 81% of the pixels corresponding to the 4 different soil categories)

$$\boxed{\alpha = [K_s, \alpha, \beta, a, S_w)]}$$

Estimated model variables for the system

Par	Dimension	Opt solution± σ	Relative error (%)
K_s	m/hr	0.755±0.0999	13.3%
α	[ ]	-5.69±0.076	1.4%
a	[ ]	4.029±0.452	11.2%
S_w	cm^3/cm^3	0.07±0.02	29.4%
β	[ ]	1.165±0.397	34%

Uncertainty of combination of variables determined by eigen vectors

Eigen values	Relative error (%) $\frac{\sigma_{e_i^T X}}{E[e_i^T X]} \times 100$
4.5338	12.8%
6.6974	13.4%
206.57	4%
358.98	1.1%
3732	14.4%

Correlation Matrix

	K_s	α	a	S_w	β
K_s	1.00				
α	0.49	1.00			
a	-0.61	-0.66	1.00		
S_w	-0.03	0.025	0.23	1.00	
β	-0.26	-0.16	-0.15	0.58	1.00

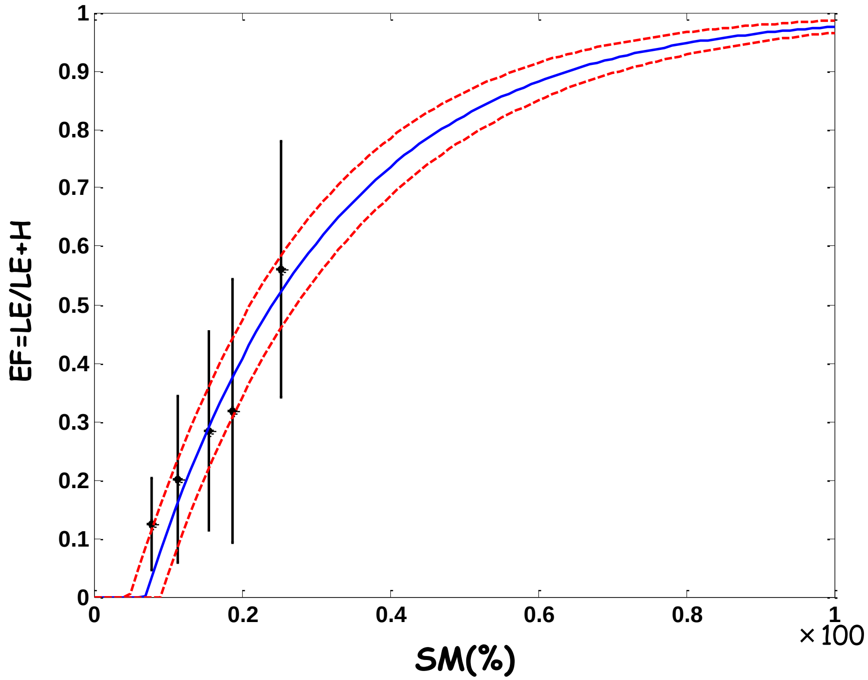
- ✓ Parameters are estimated robustly
- ✓ Correlation btwn different parameters is reasonable & physically meaningful

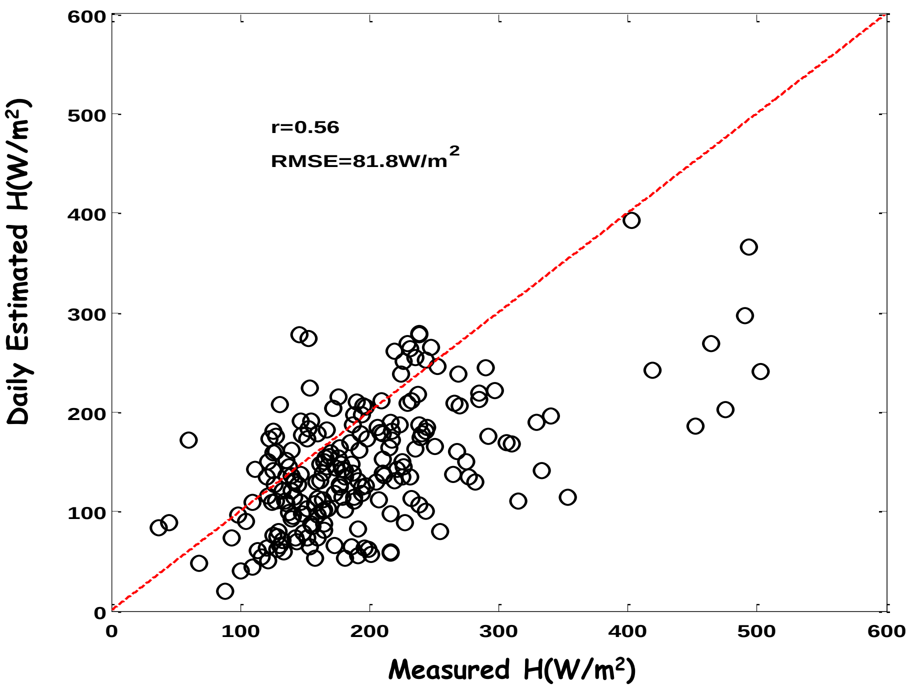
Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Validating The results ….

- **Agoufa flux tower site**

- hourly H, LE, LE/(LE+H)
- Soil type: Sand
- Vegetation type: Grassland
- Soil water content: AMSR-E data interpolation

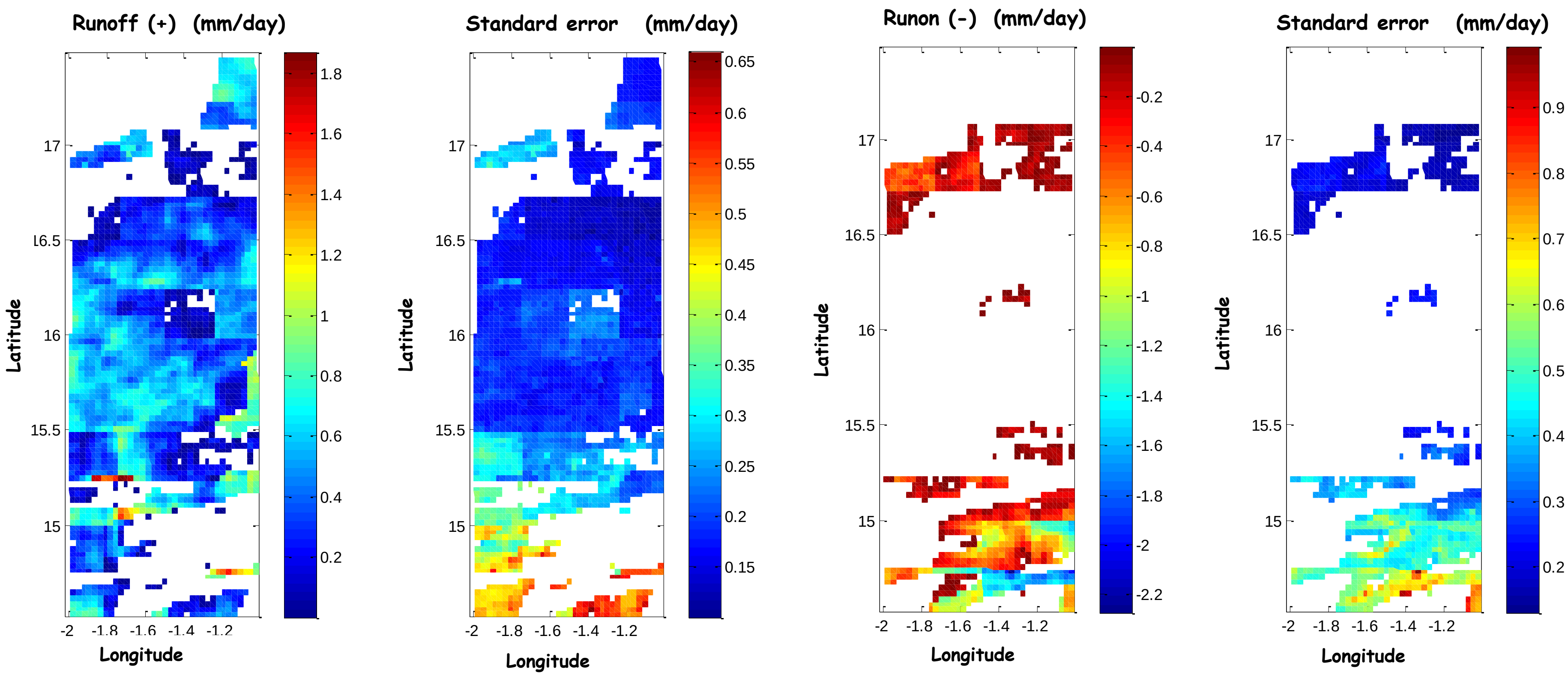




Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Validating the results …

- Map of water balance residual (runoff/runon) over the Gourma region

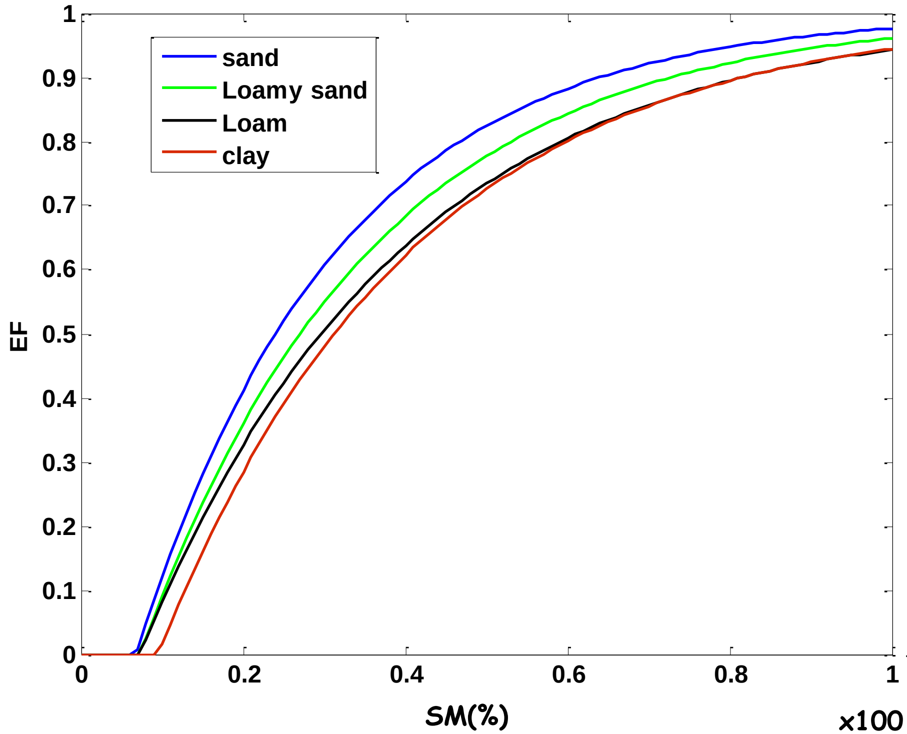


- **Yearly average water balance equation over all the pixels results in the map of runoff/ runon (+/-)**
- **The errors in this estimation methodology manifests itself in the form of runoff/ run residuals**
- **The map of runoff/ runon corresponds well with the characteristics of Gourma region**

Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

Validating the results …

- **EF-SM relationship for different soils**



- Soil water potential increases between coarser to finer soils.

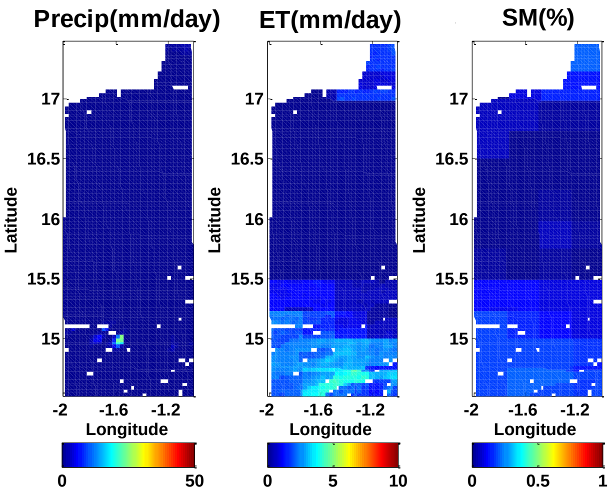
- Higher water potential is a barrier to water extraction, thus the rate of Evaporation from soils with coarser texture is higher than from soils with finer texture.

Estimation of Land Surface Water and Energy Balance Parameters Using Conditional Sampling of Surface States

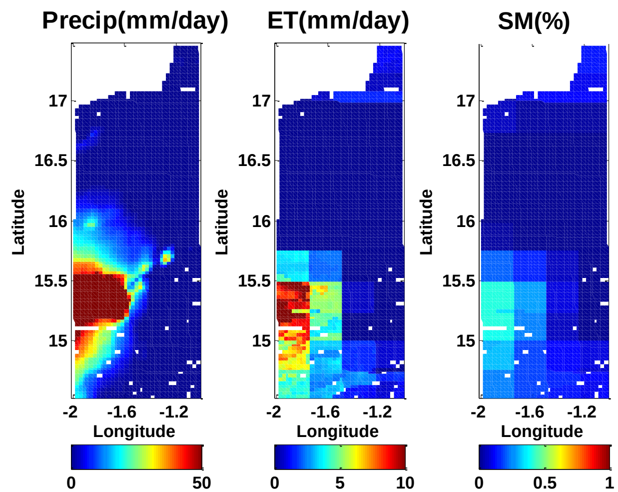
Evaluating the results …

- **Precipitation- Evaporation patterns**

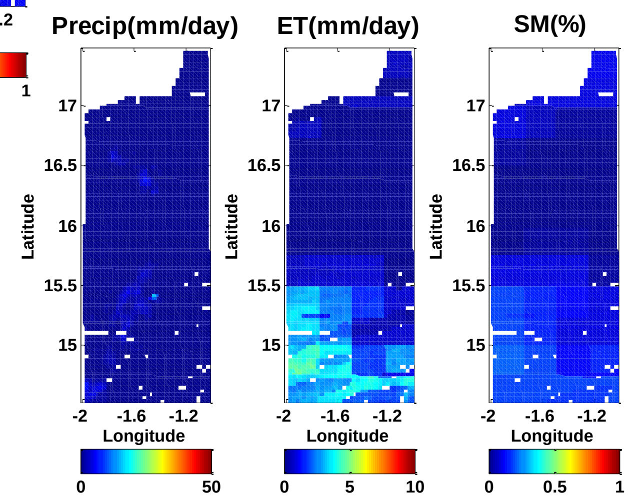
Note: No water balance or soil moisture accounting used



Day 190



Day 191



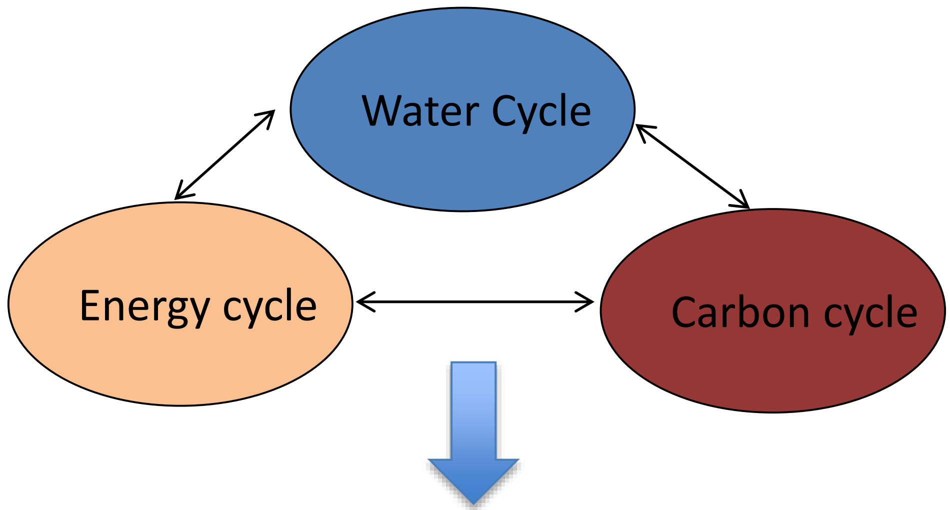
Day 192

Conclusion:

- Methodology developed to use both water and energy balance to constrain parameter estimation of surface energy and water balance
- Method is distinct from traditional calibration because it does not need flux information (eg. problomatic drainage and evaporation data) to estimate parameters
- Only forcing ($P, R_{in}^{\downarrow}$) and states (s, T_s) used; hence scalable for remote sensing and mapping applications
- Feasibility demonstrated at point-scale with synthetic data (true parameters known for evaluation) and Ameriflux field site data
- Application over West Africa using remote sensing shows feasibility of using satellite data to estimate effective values of important land surface model parameters

Current & future work

- ✓ Coupling water, energy and carbon cycle (improve climate predictions models)



Coupled through flux of Transpiration

Thank you for your attention