Assimilation of Satellite Derived Soil Moisture Profiles Into a Crop Modeling System for Robust Yield Estimates

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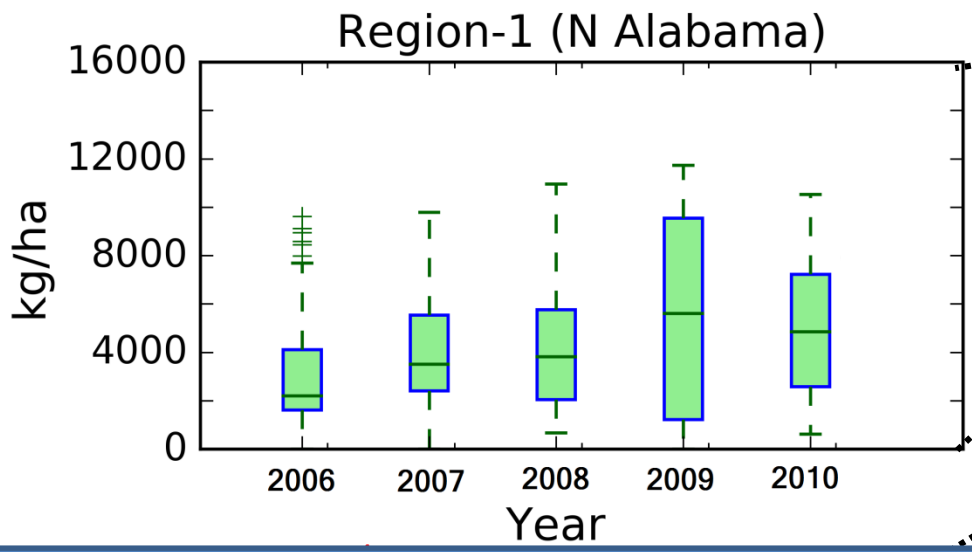
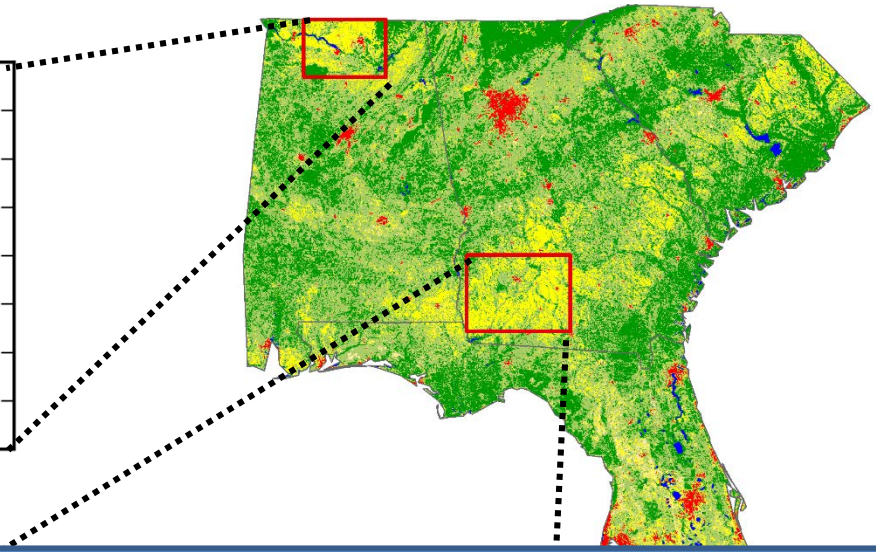
Drought Forum
2018

Introduction





- *Despite being well calibrated and populated with good high resolution weather inputs, why rainfed yields are not able to match NASS yields?*
- *What can be done to improve the performance of crop model at regional scale?*

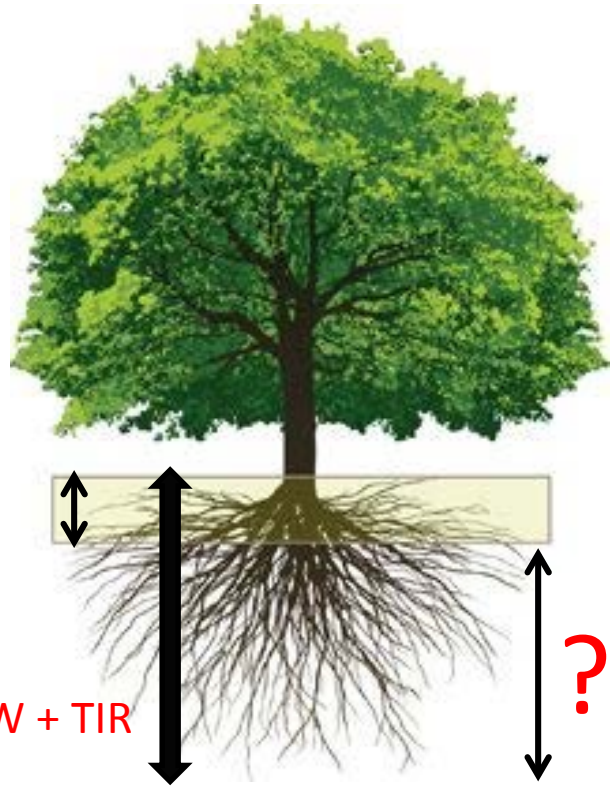
One potential solution is the use of remotely sensed (RS) observations into crop model – particularly soil moisture (SM)

Soil Moisture Measurement – *Remote Sensing*

Microwave (MW) Remote Sensing

- Physically based and quantitative in nature
- Based on difference in dielectric constant
- Coarse spatial resolution 25-40 km
- Shallow SM estimation depth 0-5 cm (approx.)
- All weather capabilities

e.g. – Advanced Microwave Scanning Radiometer – Earth Observing System(AMSR-E), Soil Moisture and Ocean Salinity (SMOS), Soil Moisture Active Passive (SMAP) etc.



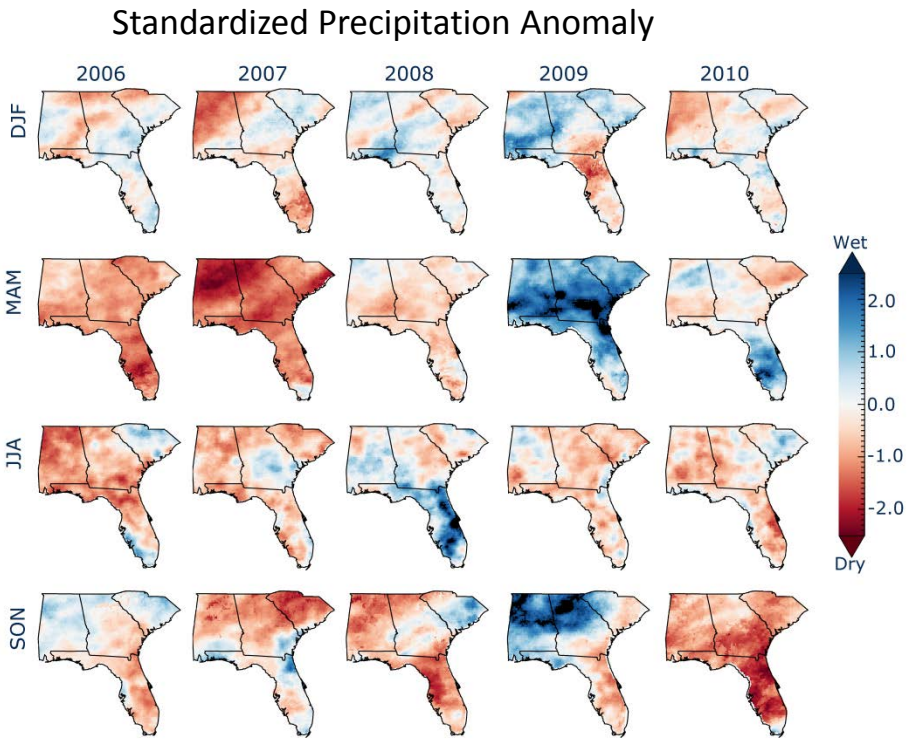
Thermal Infrared (TIR)

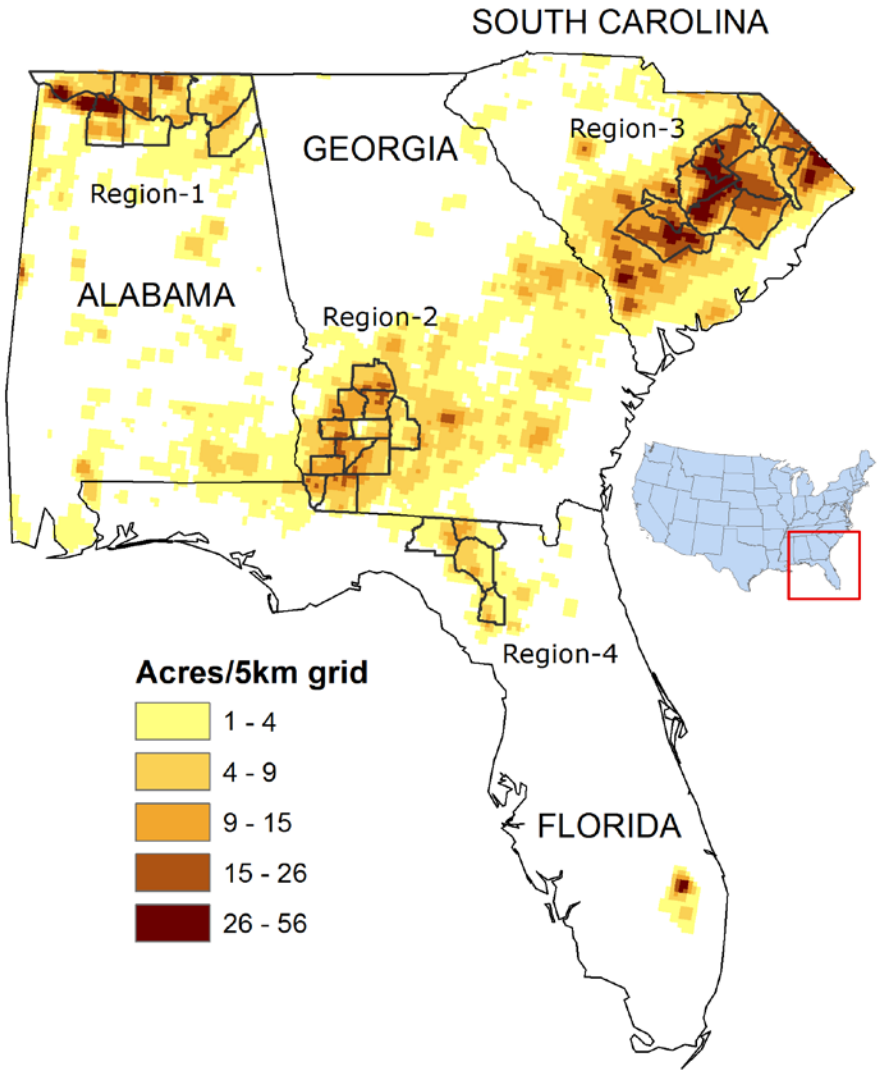
- Indirect SM retrieval through energy flux estimations
- Relatively better spatial resolution 1-10 km
- Root-zone moisture retrieval capability
- Can not penetrate through clouds, hence data gaps.

e.g. – Surface Energy Balance Algorithm for Land (SEBAL), Atmospheric Land Exchange Inverse (ALEXI) etc.

Study Area

- Total 32 counties from 4 states
- Maize is one of the top three crops of these counties
- Region 2 and 4 were highly irrigated 30-50%
- Regions 1 and 3 are 0-6% irrigated
- 2006-2010 were used for analysis
  - 2006 and 2007 was abnormally dry year
  - 2009 was relatively wet year





Satellite Derived Soil Moisture Profile

25-40 km

1-10 km

MW (AMSR-E, SMAP etc.) – Surface SM

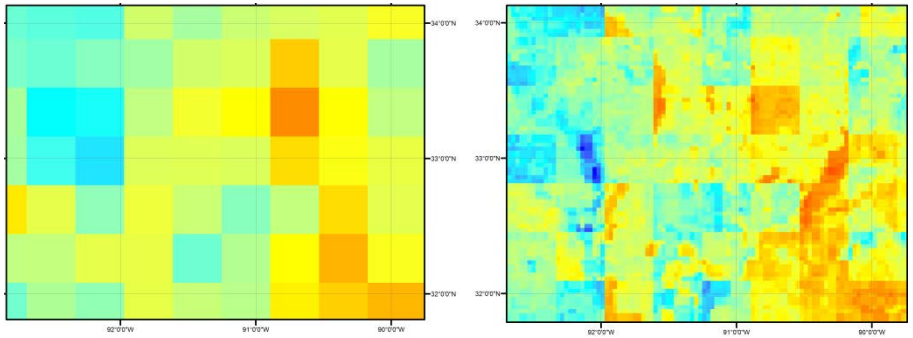
TIR (ALEXI, TSEB etc.) Surface + root zone SM

Disaggregation (Surface SM)

Crop Model (DSSAT)

Profile Development Model (POME)

Kalman Filter (EnKF)

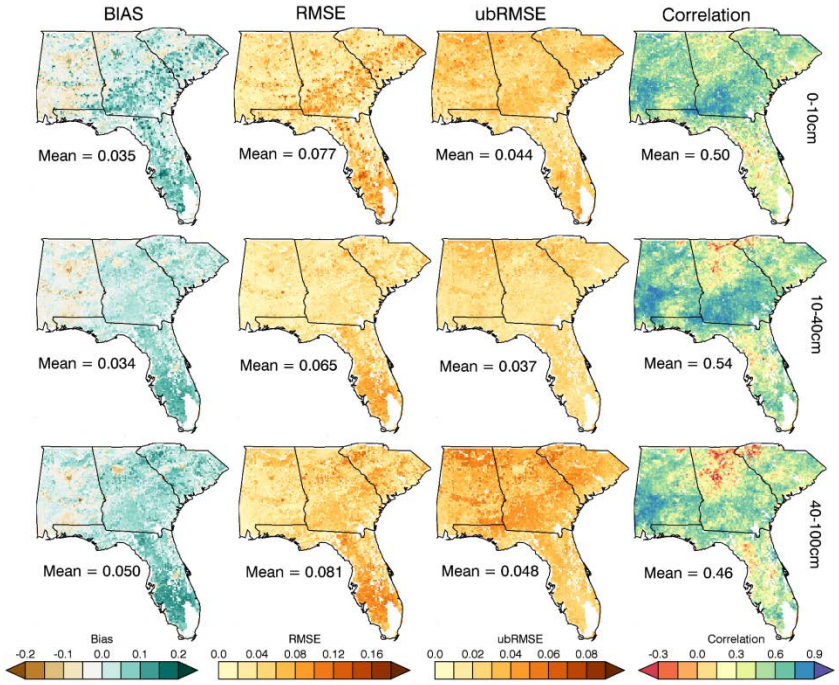


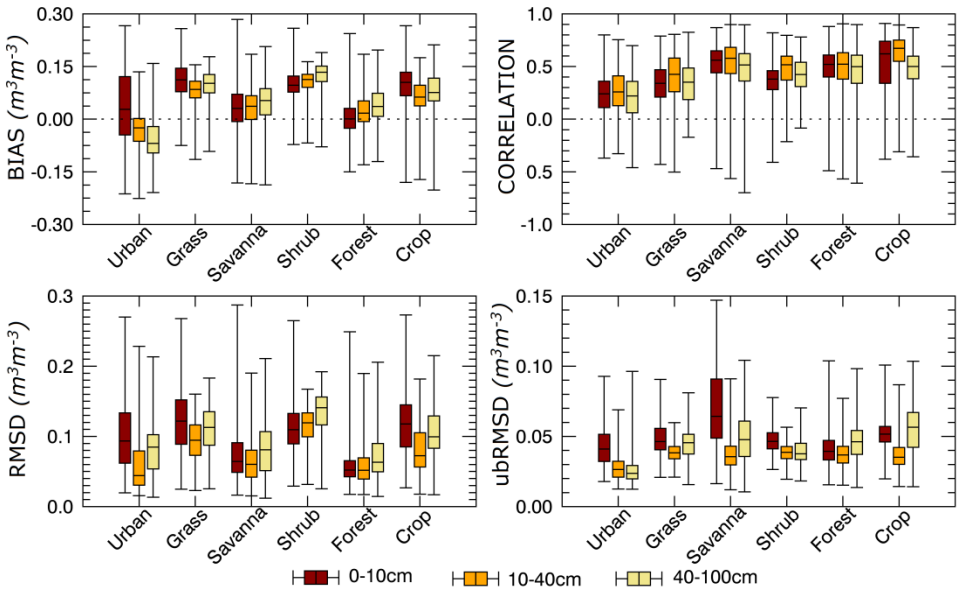
36-km SMAP

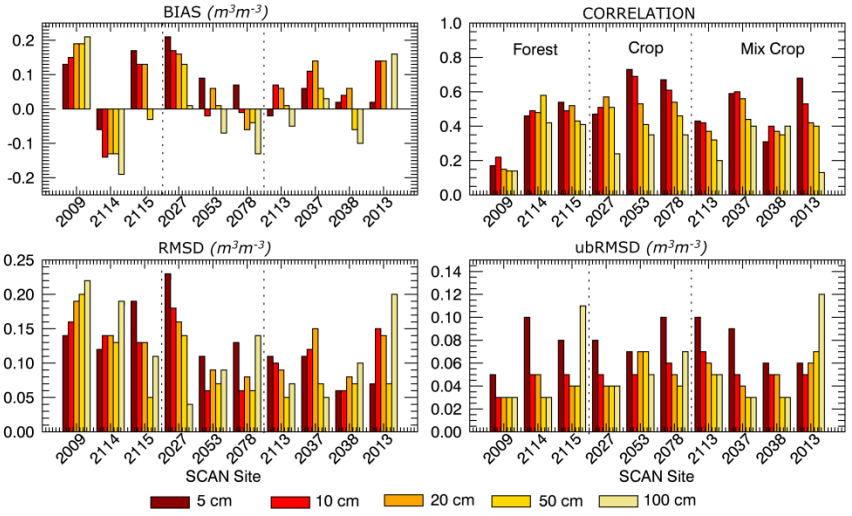
5-km disaggregated SMAP

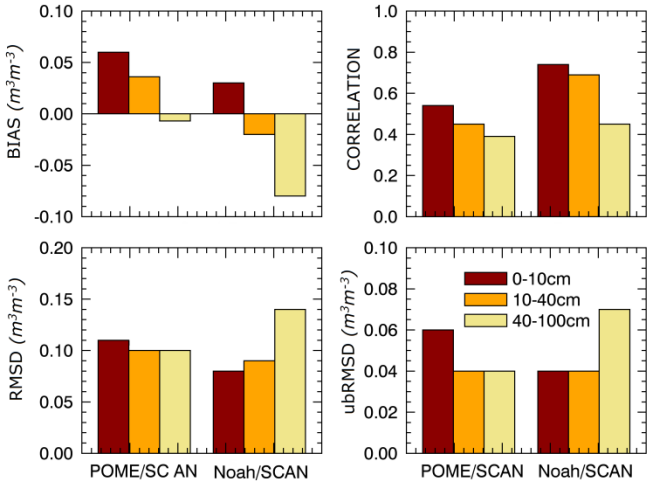
Simplified block diagram

Profile Results









Crop Model Assimilation

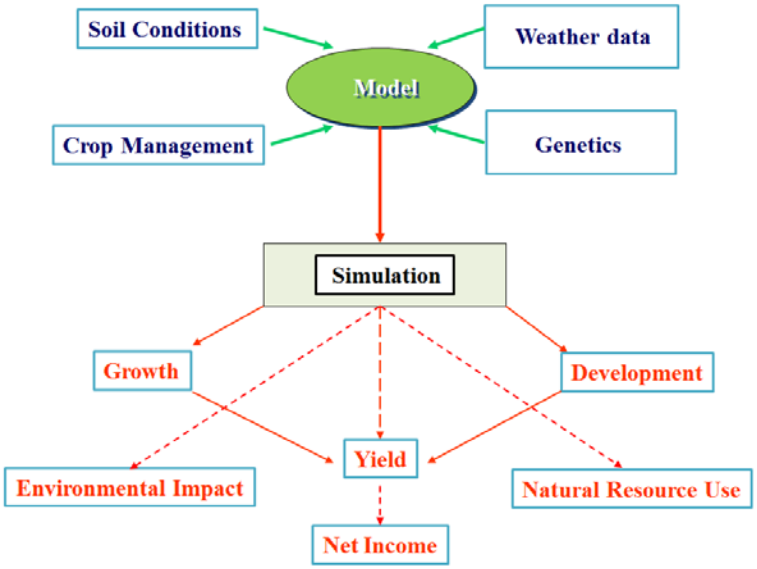
- Decision Support System for Agro-Technology Transfer - **DSSAT**
- Computer simulation model of the soil-plant-atmosphere system
- Widely accepted crop model – nearly 30 years with 28+ crops

Inputs:

- Min/Max Temperature
- Precipitation
- Insolation (sunshine)
- Soil

Outputs:

- Yield
- Drought Stress
- Irrigation Demand etc.



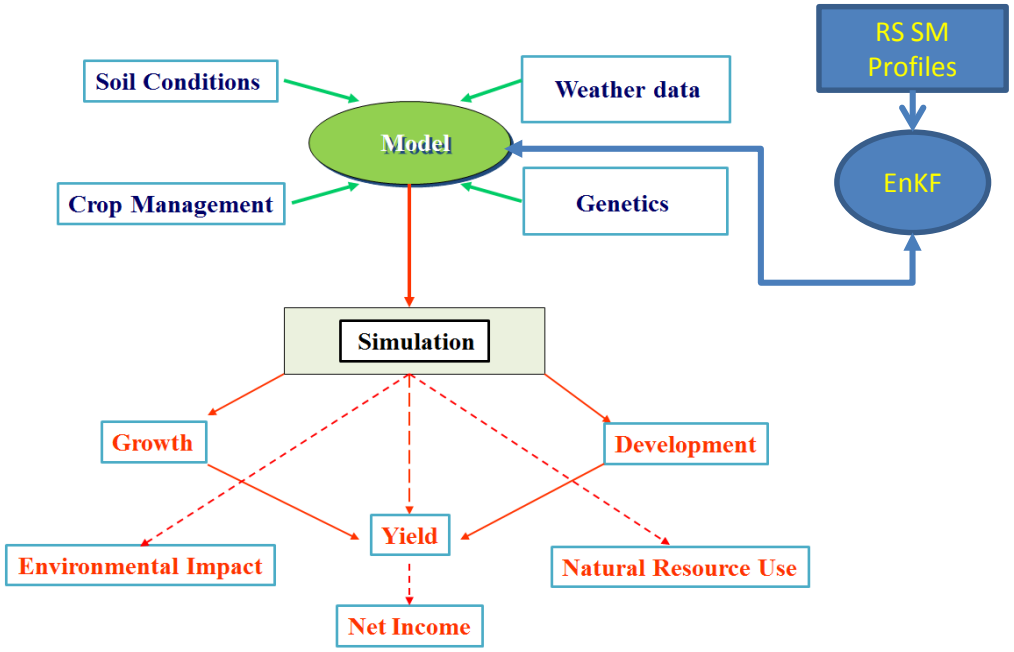
- A gridded version of DSSAT (GriDSSAT: *McNider et al.,* [2011]) is being used in this study
- The original code was modified to read in external SM profiles and a wrapper script was developed for data assimilations (DA) computations.

GriDSSAT Simulations

Multiple GriDSSAT simulations will be made to assess the sensitivity of the satellite assisted model runs.

a) Model run with all the **known** inputs (the current official form of GriDSSAT from UAH) as test case - **<u>True Case</u>** (with optimal fertilization)
b) Simulations with rainfed and DA.

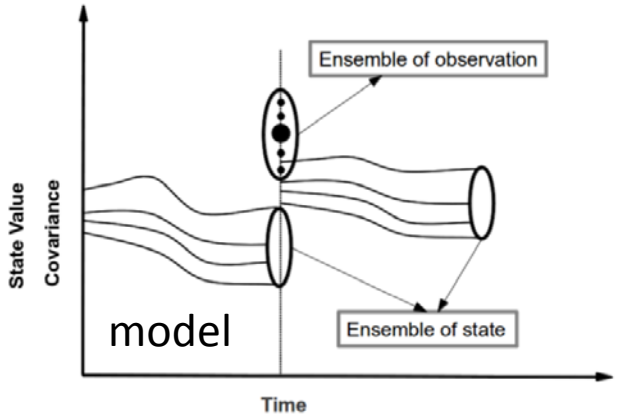
The yields will also be compared at the county level with National Agricultural Statistics services (NASS) reported yields.



Data Assimilation - Ensemble Kalman Filter (EnKF)

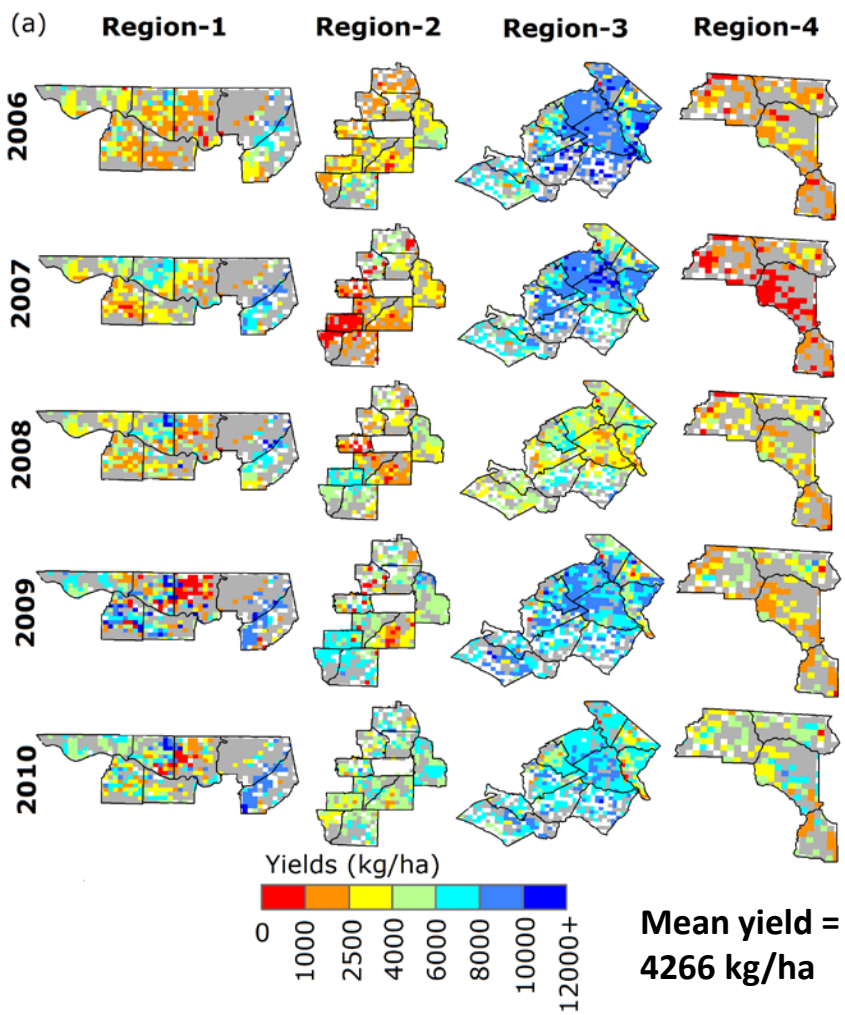
- Data assimilation allows for optimal merging of model and observations by statistically taking into account their respective errors.
- The representation of model and observation error covariance is crucial for the optimal performance of the filter.
- Following *Yin et al., [2015],* this study uses 12 ensemble members.
- Model ensembles were generated by randomly drawing data from 100 year historical weather information.
- Average triple collocation errors from 10 SCAN sites of remotely sensed profiles (between SCAN, NOAH and POME profiles) was used as observation error at each layer depth.

EnKF flow



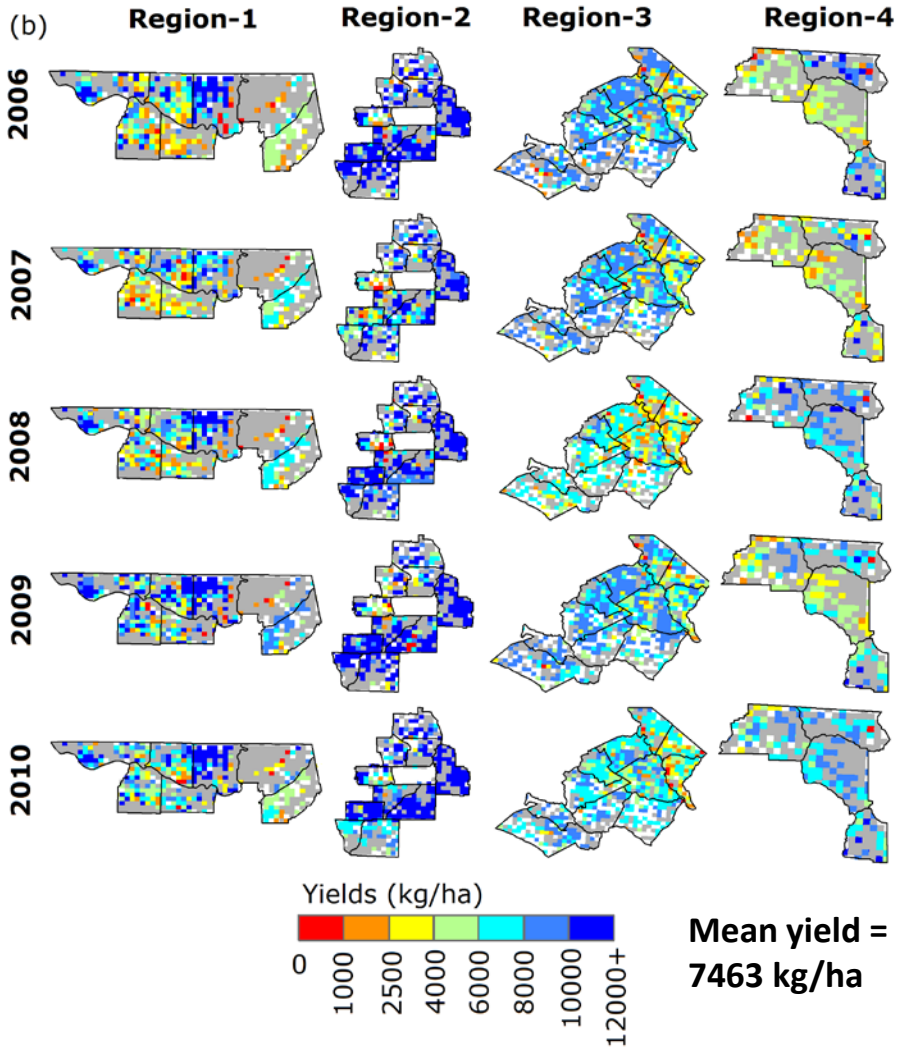
DA Results

Open-loop DSSAT Simulation (Rainfed only)



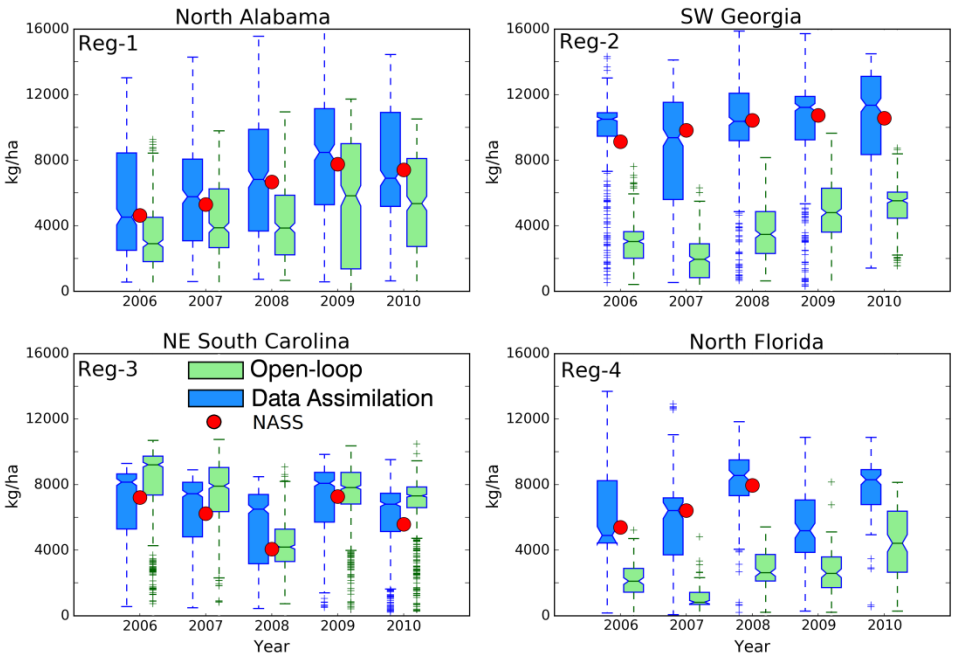
Mean yield = 4266 kg/ha

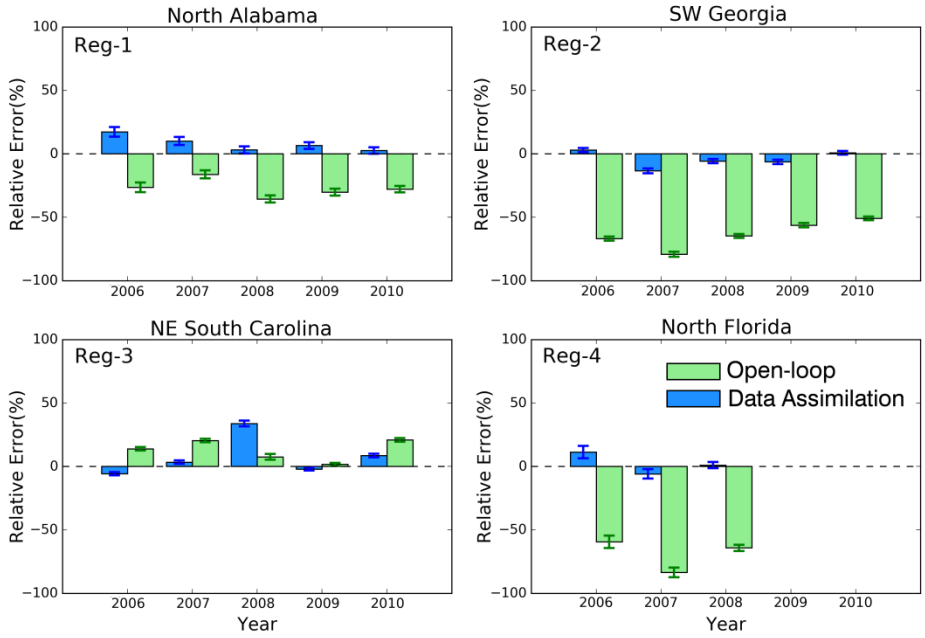
DA DSSAT Simulation (Rainfed+ Satellite SM Profile)



Mean yield = 7463 kg/ha

DA Results



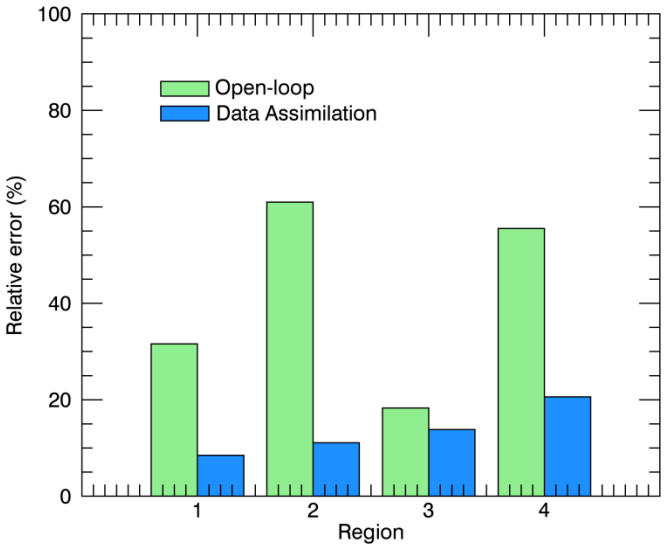


NASS = 7152
Rainfed = 4266
DA = 7463

NASS
Rainfed without DA
Rainfed with DA

- Compared to NASS reports, open-loop had nearly 39.2% errors
- While DA model simulation had only 12.6% errors
- There is a significant difference in yields for Region 2 and 4 between open-loop and NASS

Overall result



- Our results show that the assimilation of RS profile improved the yield estimates in regions dominated with irrigated cropland (Regions 1,2 & 4) 30-60% to 10-20%
- Non-irrigated (region 3) –model forced with gridded precipitation showed some improvement with DA 18% to 14.4%
- In non-irrigated regions, the assimilation of noisy RS profiles added to the overall model error.

Highest improvements were observed for irrigated regions where rainfed model simulation failed to register additional water supply but remotely sensed profiles were able to detect such supplements.

Conclusion

- The open-loop simulation yields in comparison with the reported NASS yields showed an overall absolute relative error of nearly 39.2% whereas the data assimilation mode yields on the other hand had an absolute relative error of 12.6%.

- Assimilating satellite SM profiles into the crop model improved the yield estimation most in irrigated regions (2 and 4) with average relative errors (< 2%) whereas for the relatively non-irrigated regions (1 and 3) the mean relative error was nearly 8%.

- Overall, taking all regions together, the data assimilation yield errors were less than $1/4^{th}$ of the open-loop yield errors.

- The results indicate that the assimilation of RDSMP data into the crop model was effective in improving yield estimates compared to open-loop (rain-fed only) simulations. The results also highlight the effectiveness of TIR-based SM estimates in sensing irrigation applications on a reginal scale.

- Further improvements can be made through modifying the application of the EnKF, where a variable error term can be applied to the remote sensing SM profiles taking into account the error in the sensors related to vegetation coverage.

Thank you

Questions ??

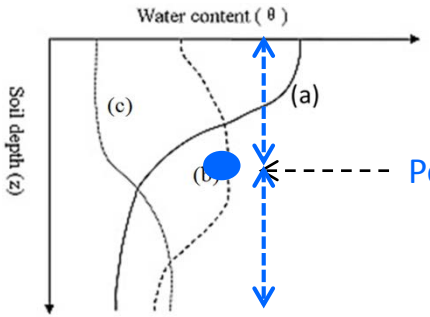
Extra Slides

POME Profiles

The POME based SM profiles were compared with SCAN site (2078) observations under various conditions:

Inputs for POME model-

- Surface Soil Moisture
- Bottom Soil Moisture
- Mean Moisture content

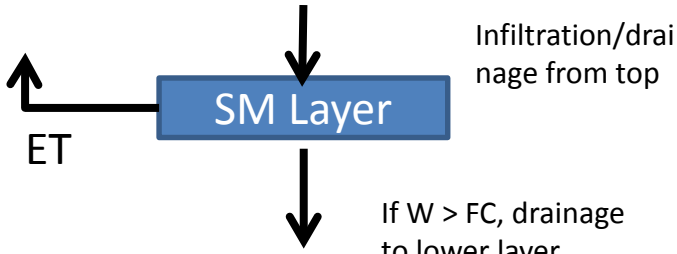


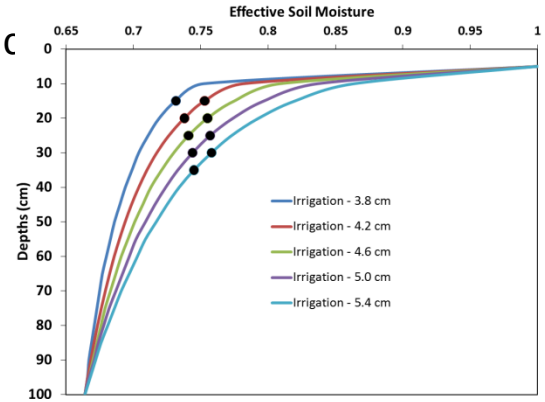
Additional Inputs

- Location of inflection point
- Soil moisture at inflection point

Derivation of Inflection Point

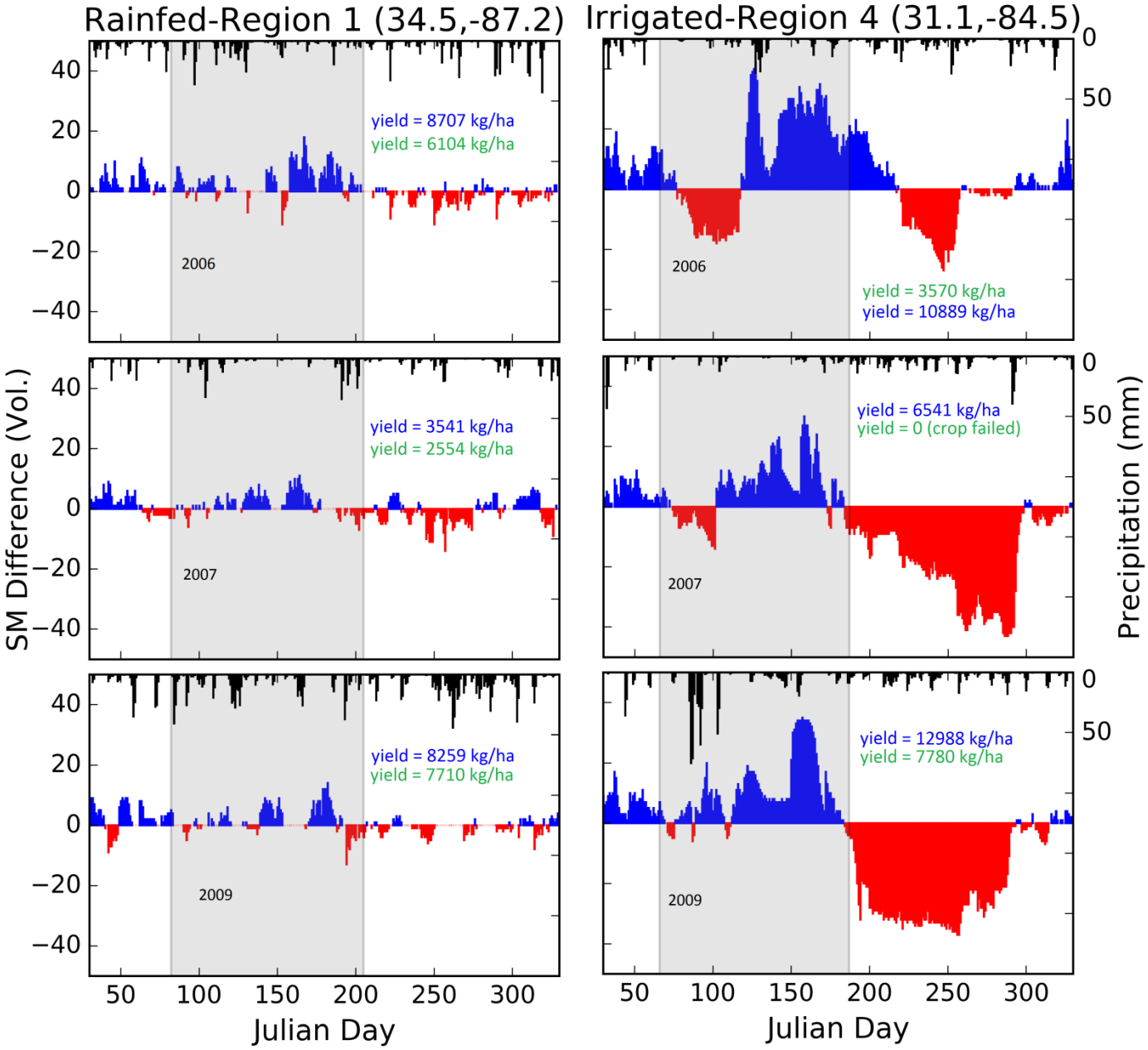
- By redistribution of moisture above field capacity (tipping bucket)
- Uses information such as: irrigation/precipitation amount, ET, drainage etc. to redistribute moisture content
- First layer to reach field capacity is usually the location of inflection point
- Initial SM content at inflection point was assumed to be as field capac



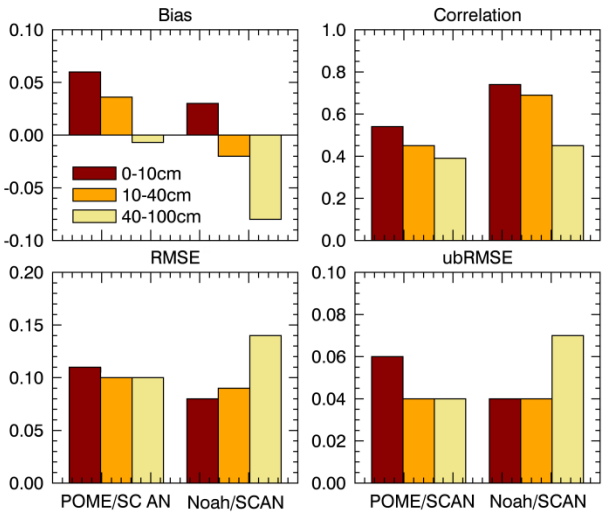


EnKF

- $A^a = A^f + K\left(D_i - HA^f\right)$
- $K = \frac{P_e}{HP_eH^T + R_e}$
- H – measurement operator, here = unity
- $P_e \; and \; R_e \; are \; model \; and \; observation \; error \; covariances, respectively$
- $P_e = \frac{1}{H^T(N-1)} \sum_{n=1}^{N} (A^f - \overline{A^f})(HA^f - H\overline{A^f})^T$
- $\overline{A^f}$ is ensemble mean


Rainfed-Region 1 (34.5,-87.2)
Irrigated-Region 4 (31.1,-84.5)
SM Difference (Vol.)
Precipitation (mm)
Julian Day
Julian Day
yield = 8707 kg/ha
yield = 6104 kg/ha
2006
yield = 3570 kg/ha
yield = 10889 kg/ha
2006
yield = 3541 kg/ha
yield = 2554 kg/ha
2007
yield = 6541 kg/ha
yield = 0 (crop failed)
2007
yield = 8259 kg/ha
yield = 7710 kg/ha
2009
yield = 12988 kg/ha
yield = 7780 kg/ha
2009

Profile Results



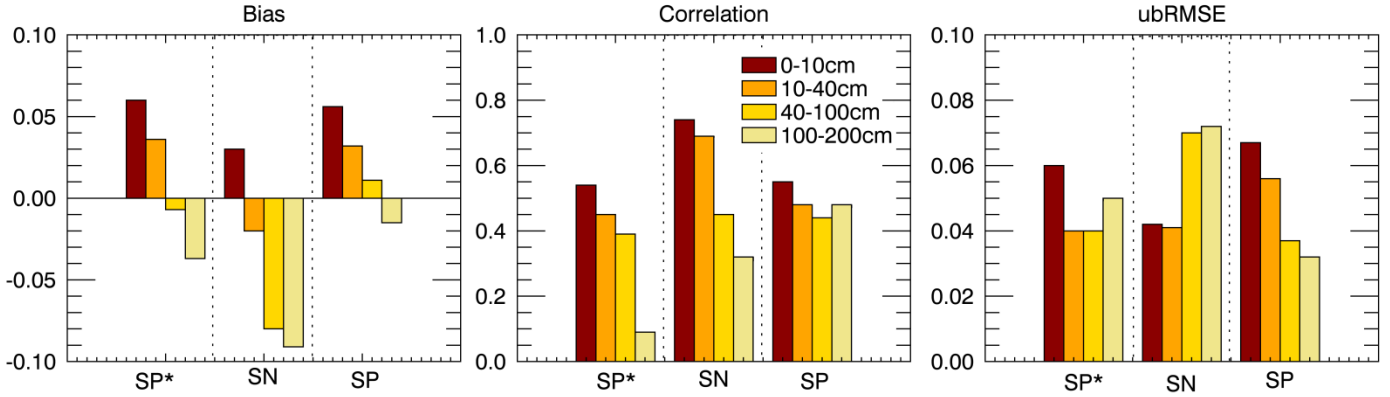
Constant (50% AWC) lower boundary condition

With increase in layer depths, the POME profile error statistics tend to improve in terms of bias and RMSE.

Whereas, Noah LSM tends to show reverse trend with increase in errors with depth.

Effect of bottom layer calibration

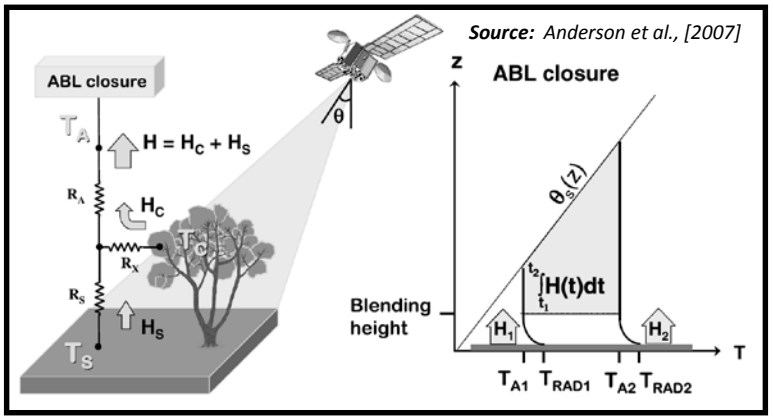
Calibrating bottom boundary condition with rainfed GriDSSAT SM data, a further improvement in profile results were observed.



P - uncalibrated POME profiles*
P – Calibrated POME profiles
S – SCAN Profiles

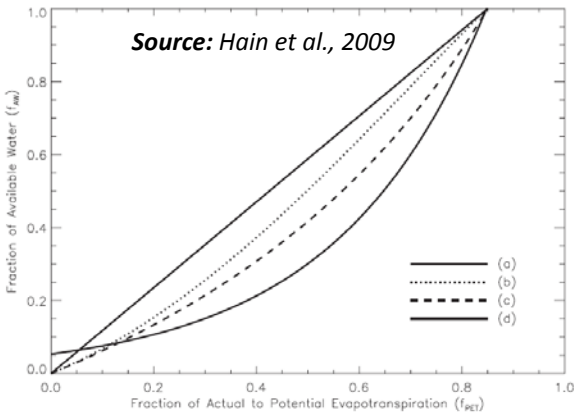
ALEXI

- Atmospheric Land EXchange Inverse model *(Anderson et al.,* [1997]*)*
- Based on 'Two Source Energy Balance' model.
- The rate of temperature increase of either a soil or canopy component is related to an increase or decrease in evapotranspiration (ET), which in turn is related to soil moisture. In general, dry soil or stressed vegetation heats up more rapidly than wet soil or unstressed vegetation.
- Cloud-free constraint limits data availability.
- Grid size : 0.04 degrees
- Fractional PET is functionally related to fraction of available water content



$$f_{PET} = \frac{AET}{PET}$$

$$f_{AW} = \frac{(\theta_{ALEXI} - \theta_{wp})}{(\theta_{fc} - \theta_{wp})}$$

Relation between f_{PET} and f_{AW}:

- **Linear**
- Piece-wise
- Non-Linear