TEXAS Geosciences
The University of Texas at Austin
Jackson School of Geosciences
Bureau of Economic Geology

Jet Propulsion Laboratory
California Institute of Technology

The Texas Soil Observation Network – one year in

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MOISST: The Growing Science of Soil Moisture Sensing, 17-18 May 2016

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We Know You Hate ‘Moist.’ What Other Words Repel You?

By JONAH BROMWICH MAY 6, 2016, New York Times.

Moist. Luggage. Crevice. Stroke. Slacks. Phlegm. One word appears to rise above all others: “moist”

“…associations with disgusting bodily functions”

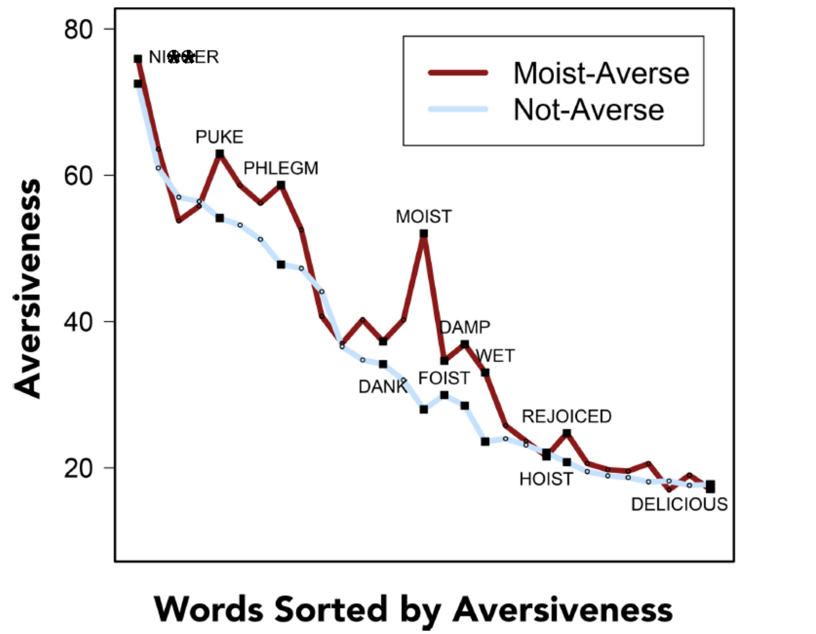

Fig 3. Rated words sorted from most to least aversive. Separate means of word *aversiveness* are presented for participants who reported an aversion to moist (dark red) and for participants who did not (light blue). A subset of words are identified in the plot as reference points.

http://www.nytimes.com/2016/05/07/science/moist-word-aversion.html

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RESEARCH ARTICLE

A Moist Crevice for Word Aversion: In Semantics Not Sounds

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Abstract

Why do people self-report an aversion to words like “moist”? The present studies represent an initial scientific exploration into the phenomenon of word aversion by investigating its prevalence and cause. Results of five experiments indicate that about 10–20% of the population is averse to the word “moist.” This population often speculates that phonological properties of the word are the cause of their displeasure. However, data from the current studies point to semantic features of the word–namely, associations with disgusting bodily functions–as a more prominent source of peoples’ unpleasant experience. “Moist,” for averse participants, was notable for its *valence* and *personal use*, rather than *imagery* or *arousal*–a finding that was confirmed by an experiment designed to induce an aversion to the word. Analyses of individual difference measures suggest that word aversion is more prevalent among younger, more educated, and more neurotic people, and is more commonly reported by females than males.

Introduction

Many people report that they find words like “moist,” “crevice,” “slacks,” and “luggage” acutely aversive. For instance, *People Magazine* [1] recently coined “moist” the “most cringeworthy word” in American English and invited their “sexiest men alive” to try to make it sound “hot.” One writer, in response, described the video as “. . .pure sadism. It’s torture, it’s rude, and it’s awful. . .” and claimed that the only way to overcome the experience was to “go Oedipal and

Soil moisture at multiple scales (a look back)

I. What is soil moisture? And why should we care?

- ✓ LE/H, floods, and validation of RS/LSM …

II. Do we need a some kind of Mesonet in Texas?

- ✓ Yes! And TxSON is a solid model

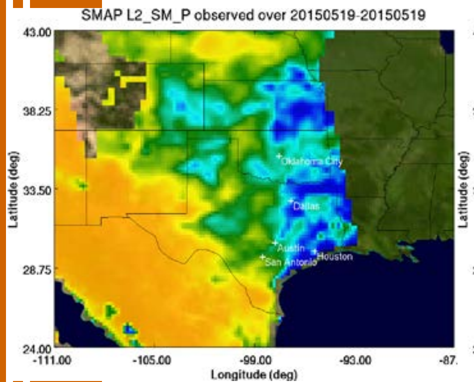
III. Can we validate products like SMAP and land surface models?

- ✓ Yes! That's what TxSON is for.

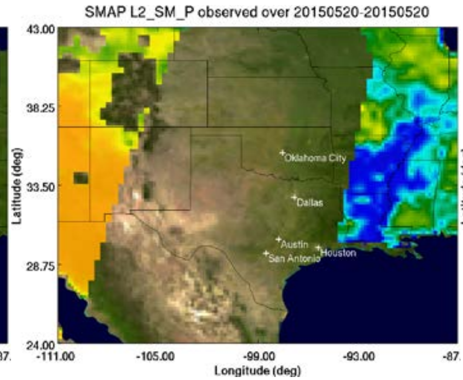
"Soil moisture is of modest value to everyone but critical value to none"

- State (withheld) Climatologist

Flood and tornadoes across Oklahoma and Texas



May 19, 2015



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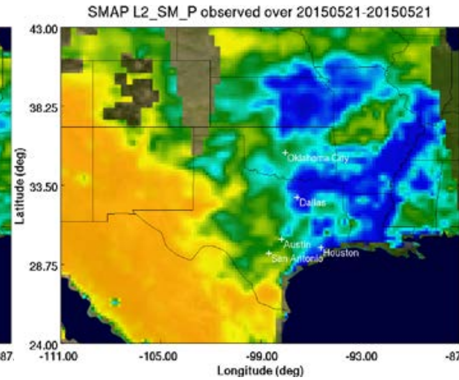
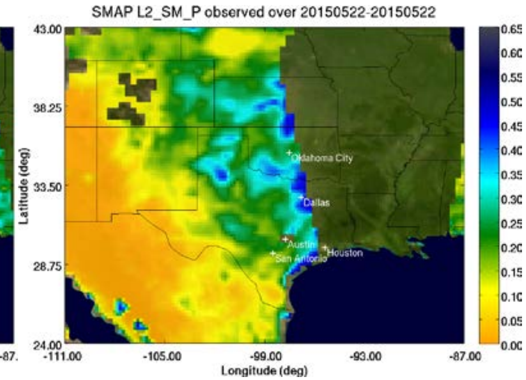
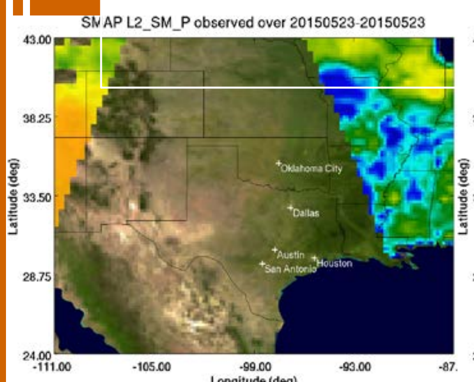


May 21, 2015



May 22, 2015

At least 31 people are presumed dead from storm related events



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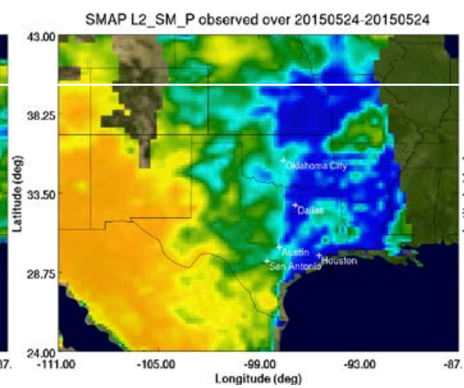
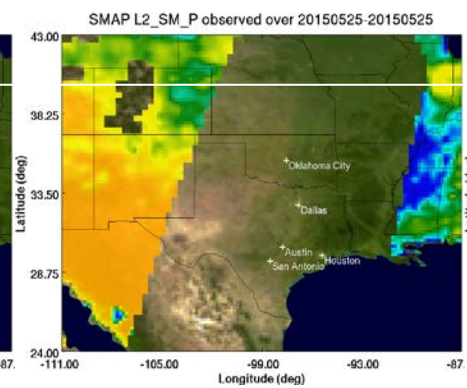
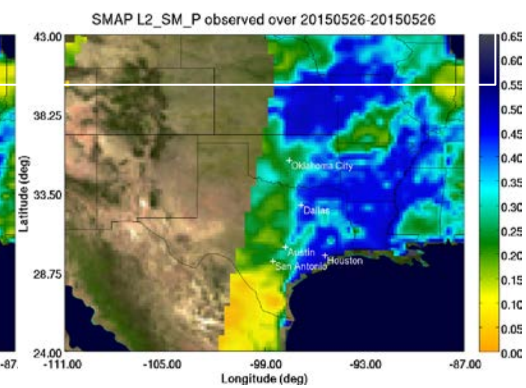


May 24, 2015



May 25, 2015

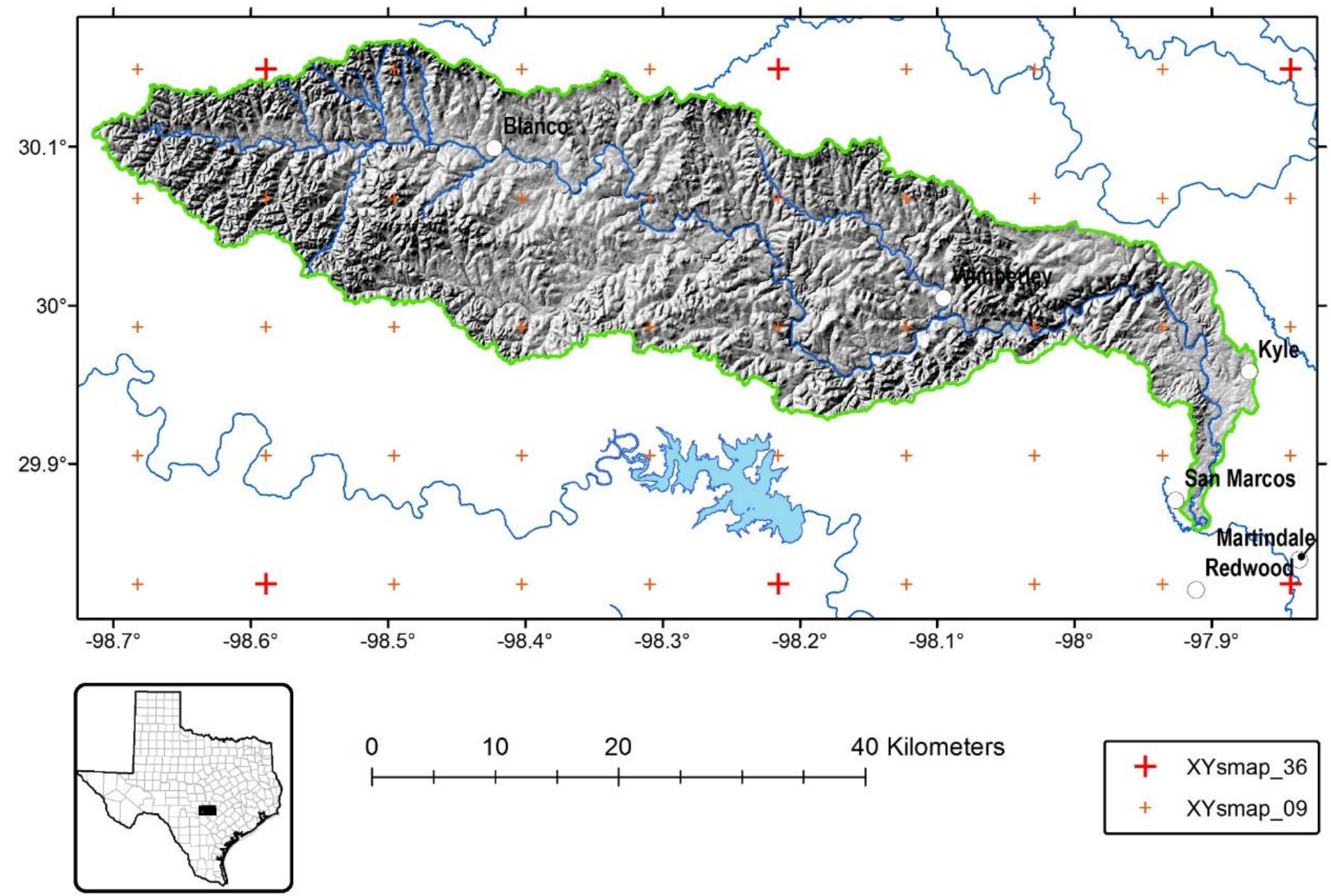
Austin underwater



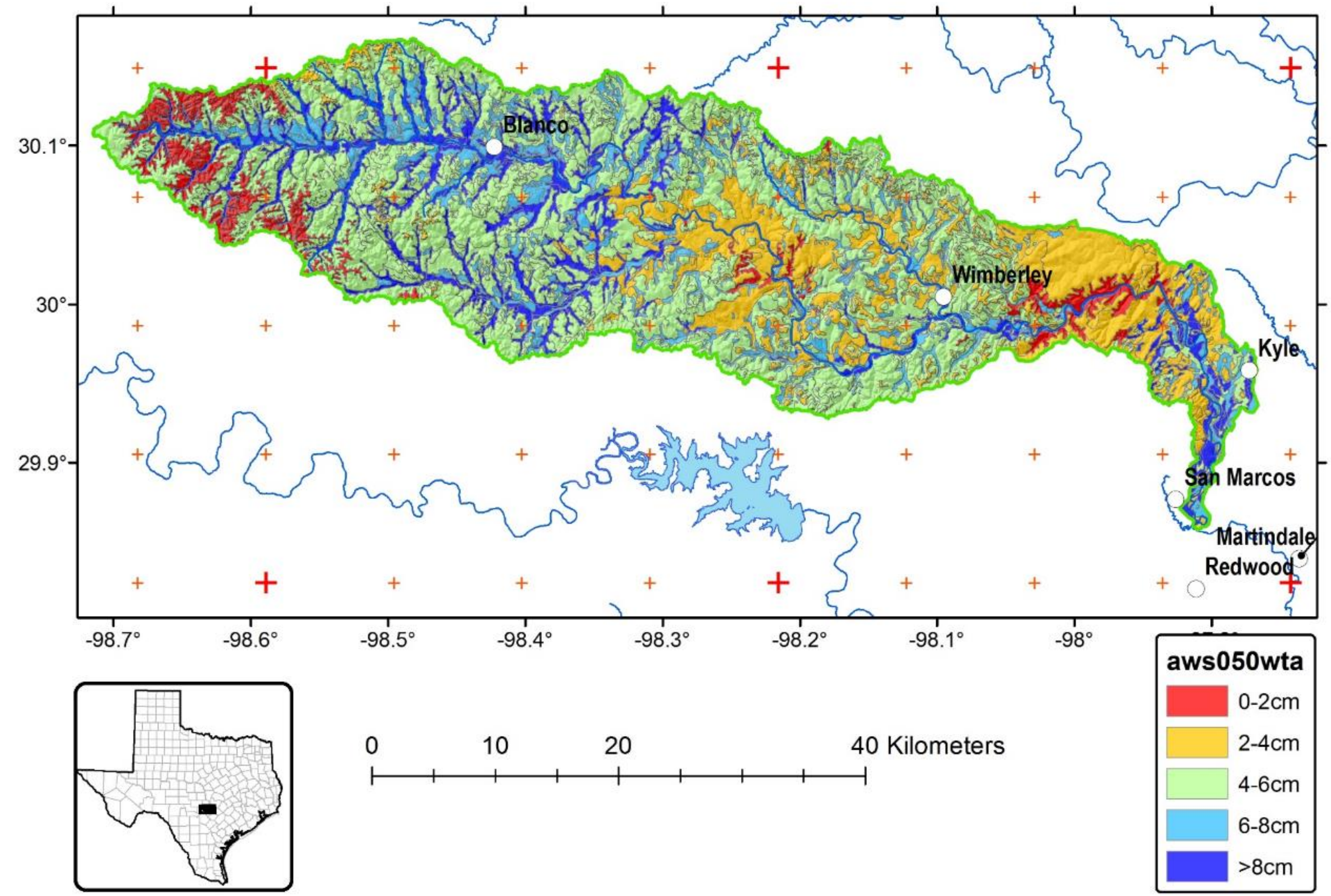
May 26, 2015

Flash floods across Houston

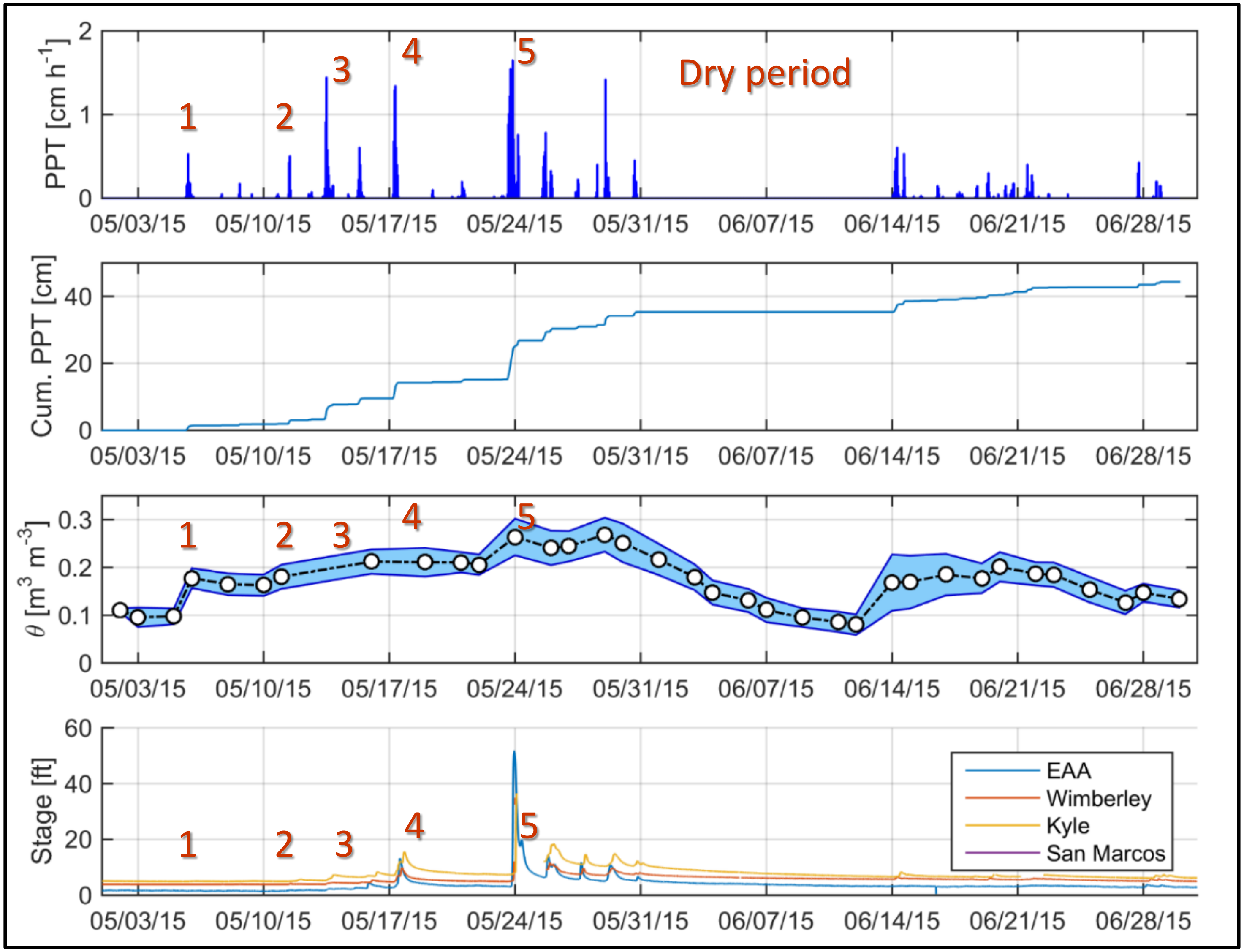
Scale: Wimberley Flood and SMAP



Scale: Wimberley Flood and SMAP



Wimberley Flood and (SMAP) soil moisture

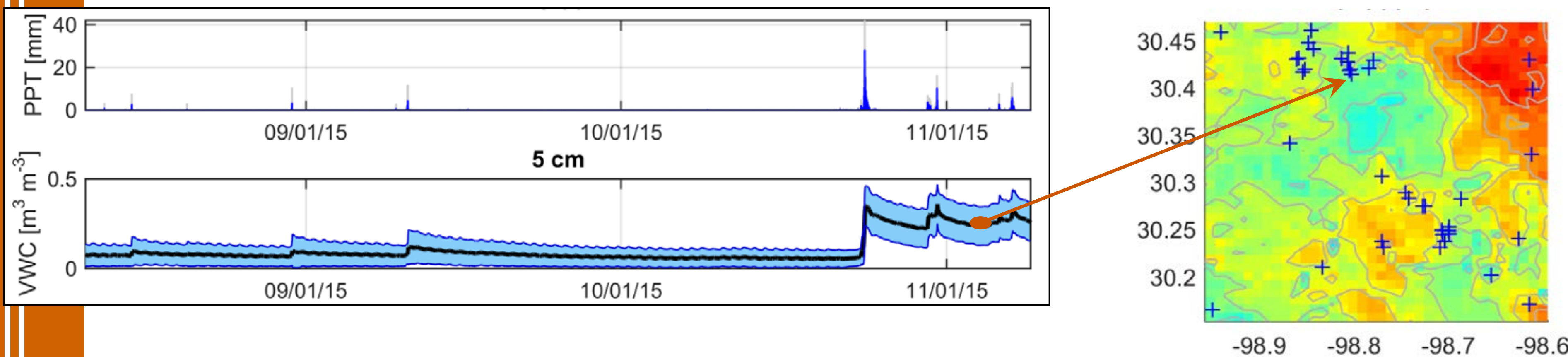


Continuous soil moisture fields

HOW DO WE VALIDATE SATELLITE OR MODEL DATA?

WHAT CAN WE DO 0-5CM SOIL MOISTURE?

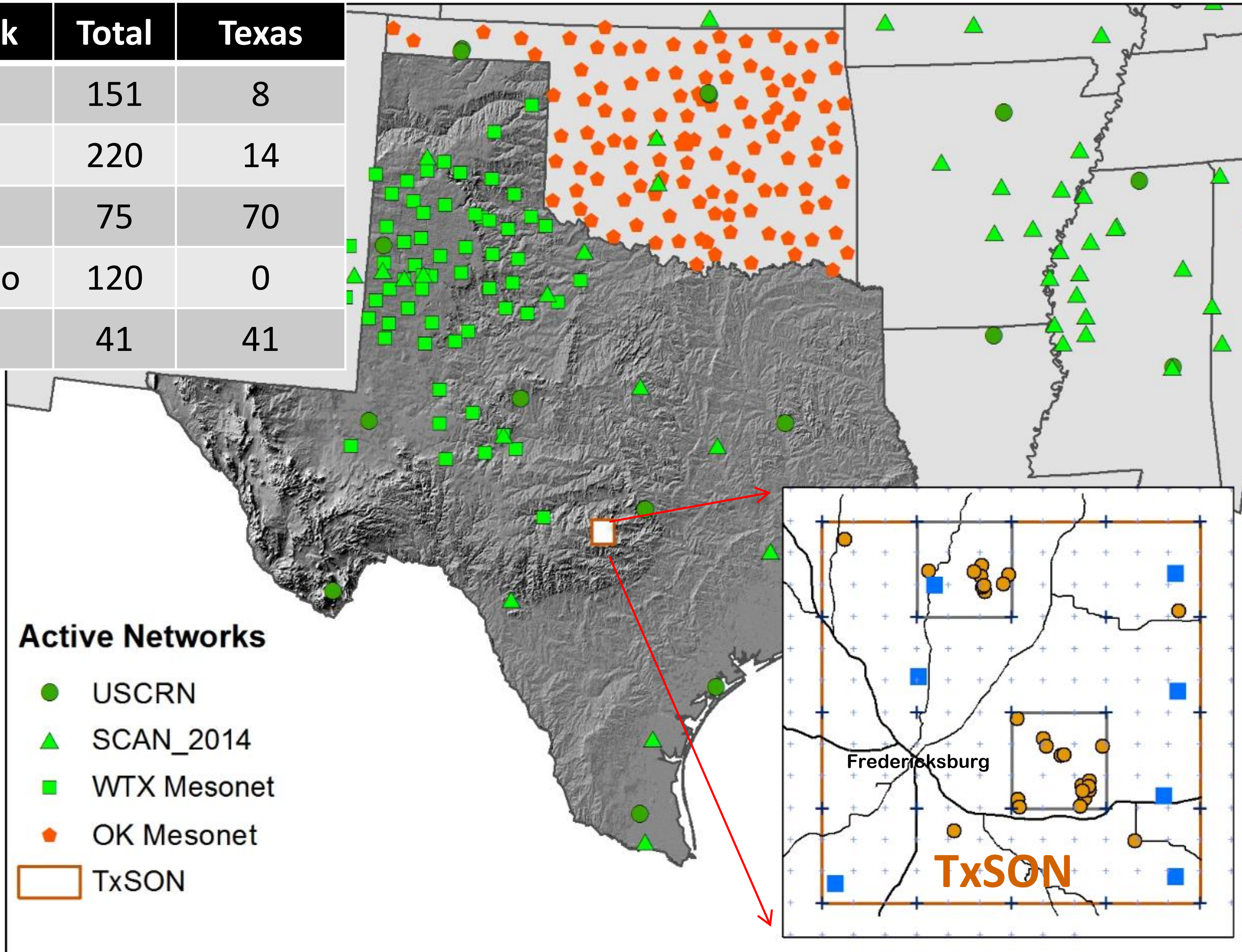
HOW CAN WE UTILIZE THIS DATA REGIONALLY?



- Soil moisture variability depends on climate, topography, vegetation, land use and soil
  - All can change a lot of 3, 9, or 36km!

Dense networks and the general lack of monitoring data

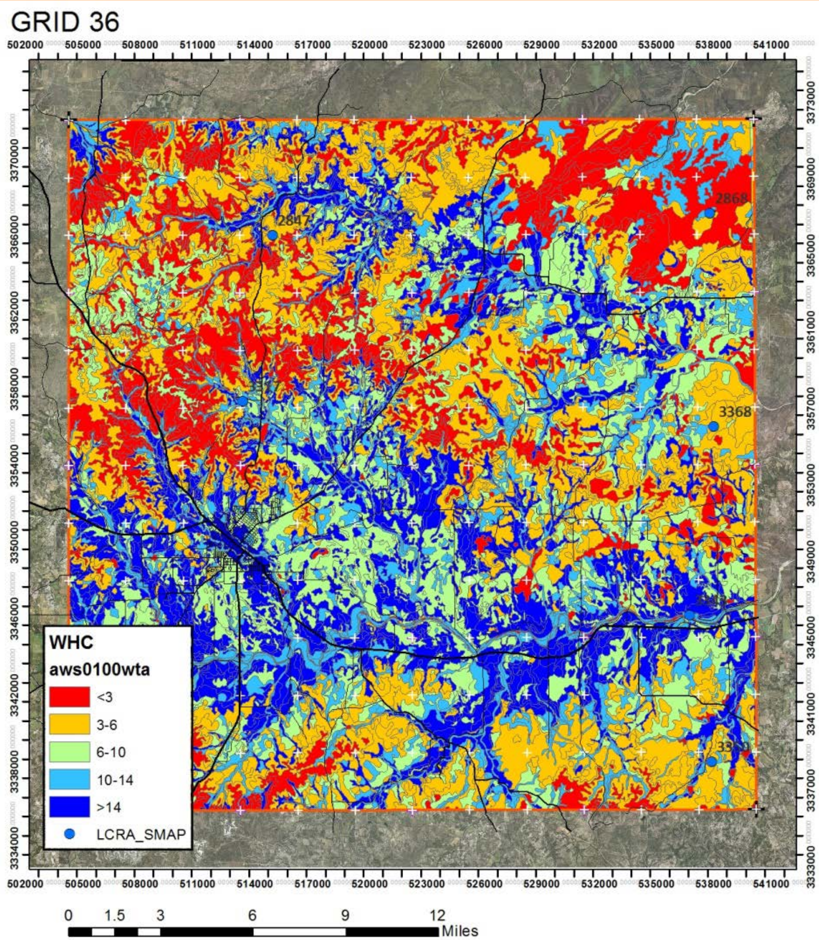
Network	Total	Texas
USCRN	151	8
SCAN	220	14
WTX	75	70
OK Meso	120	0
TxSON	41	41

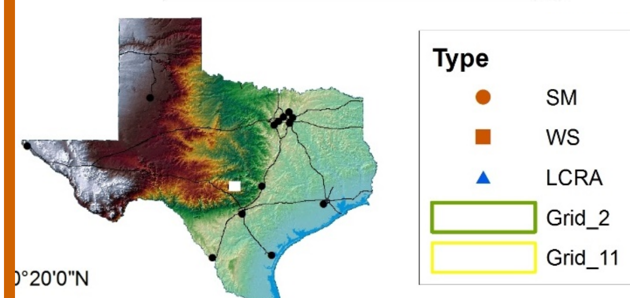


Texas Soil Observation Network (TxSON)

- Began August 2014
- Operational December 15, 2014
- 41 stations, 20 land owners
- 36km footprint (1)
- 9 km cells (2)
- 3 km cells (3)
- Calibration – field and lab
- NASA Airborne campaigns: PALScan (4 flights)
- UT-Lidar for both 9 km cells
- Network expansion
  - Brady, Texas (23 stations)
  - Edwards Aquifer (26 stations, 3 EC)

SMAP CORE Cal/Val site – Fredericksburg, TX





TxSON:

- 41 soil moisture stations (expanding throughout Texas)
- 6 meteorological stations
- 7 Participating LCRA stations

- 36 km footprint, n = 1
- 9 km footprint, n = 2
- 3 km footprint, n = 3

Soil moisture at 5, 10, 20, and 50 cm

http://www.beg.utexas.edu/txson/

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Site installation – soil micrologger

- 12” diameter auger to ~3’
- CS655 Sensor (12-cm rods)
  - High EC (<8 dS/m)
  - θ, EC, and T (SDI-12)
  - 5, 10, 20, and 50 cm
- Precipitation (TE525)
- Cellular modems – hourly

CS655 Laboratory calibrations

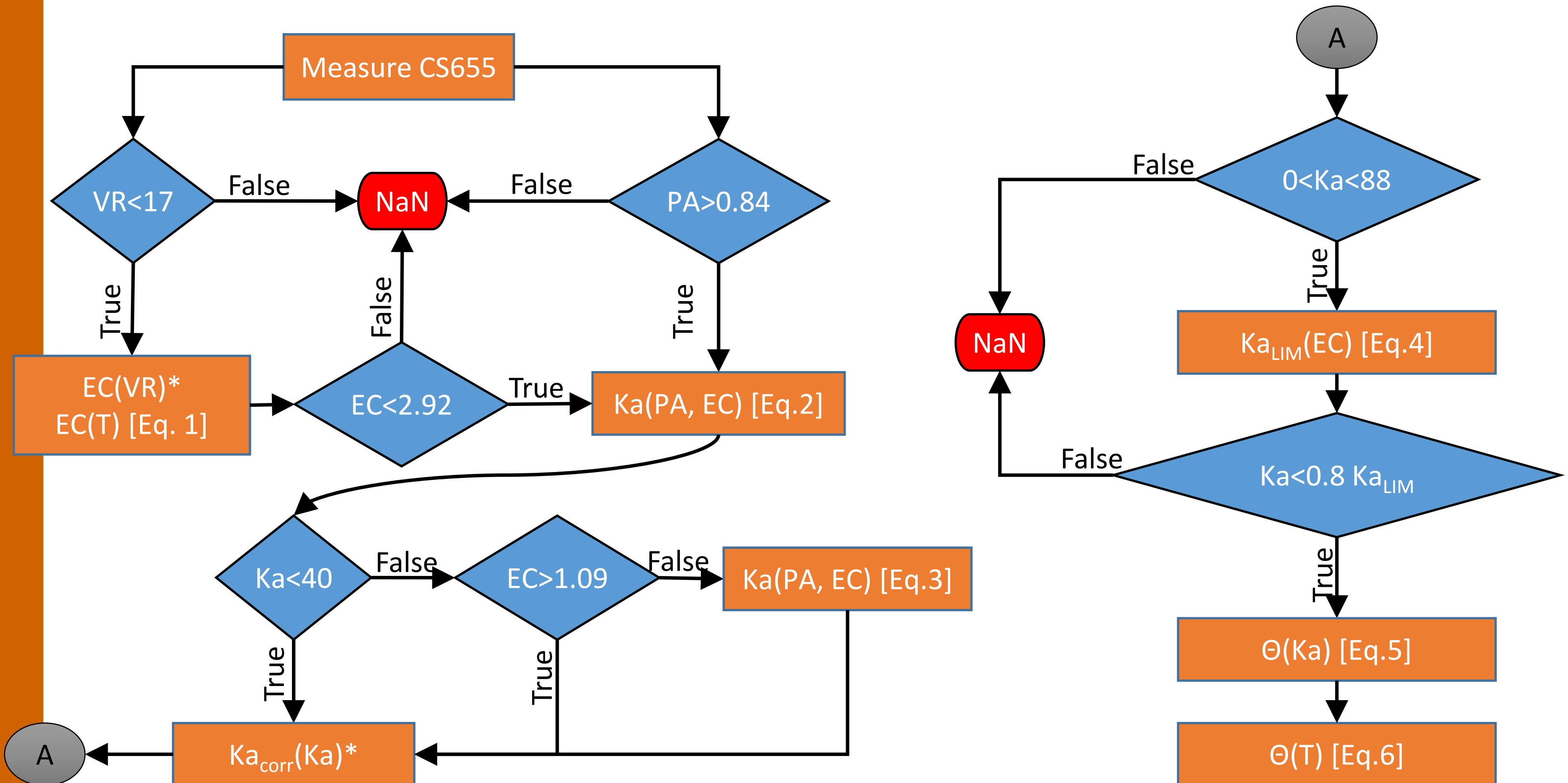
- Five soils based on 1 year in situ MRD
  - Ranked low (BaC/HnD) to high (LuB)
- Three methods: batch, upward and downward infiltration
- All soils show a significant deviation from standard Topp Eq.

CS65x and Hydrosense Sensors from CSI

- Differential emitter-coupled logic oscillator
  - Updated CS616 with EC/T correction
- Two probe lengths (we use 12cm)
  - 12cm: solution 8 dS/m, bulk 2.7 dS/m
  - 30-cm: solution 3 dS/m, bulk 0.8 dS/m
- Measures voltage ratio (VR), period average (PA), temperature (T)
- Calculates T and EC correct permittivity (Ka) and Topp SWC

Soil	MRD	Sand	Silt	Clay	ρ_b	EC	pH
	~18	-------------	%	-------------	g cm^{-3}	dS m^{-1}	--
BaC	3	79.0	16.9	4.9	1.26	0.10	6.97
HnD	12	79.3	17.6	3.1	1.26	0.10	6.81
Fr	26	54.0	35.1	10.9	1.29	0.13	7.50
PuC	24	33.7	49.5	16.8	1.11	0.14	7.58
LuB	29	52.5	33.7	13.8	1.50	0.13	6.90

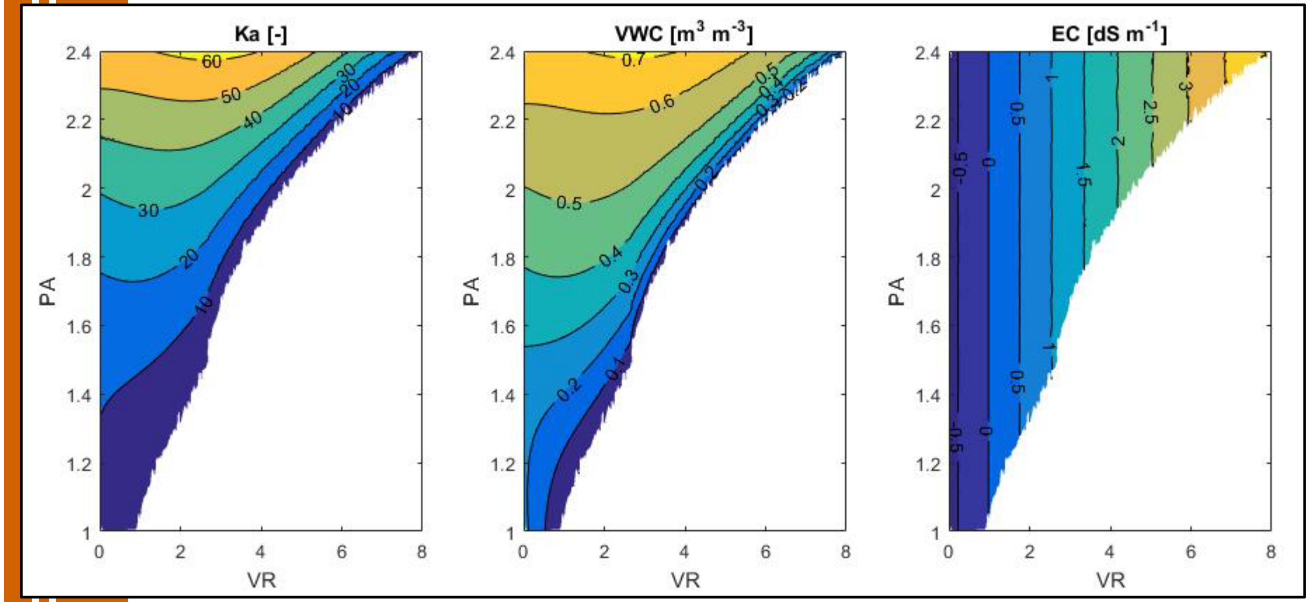
CS655 Algorithm and Logic Checks



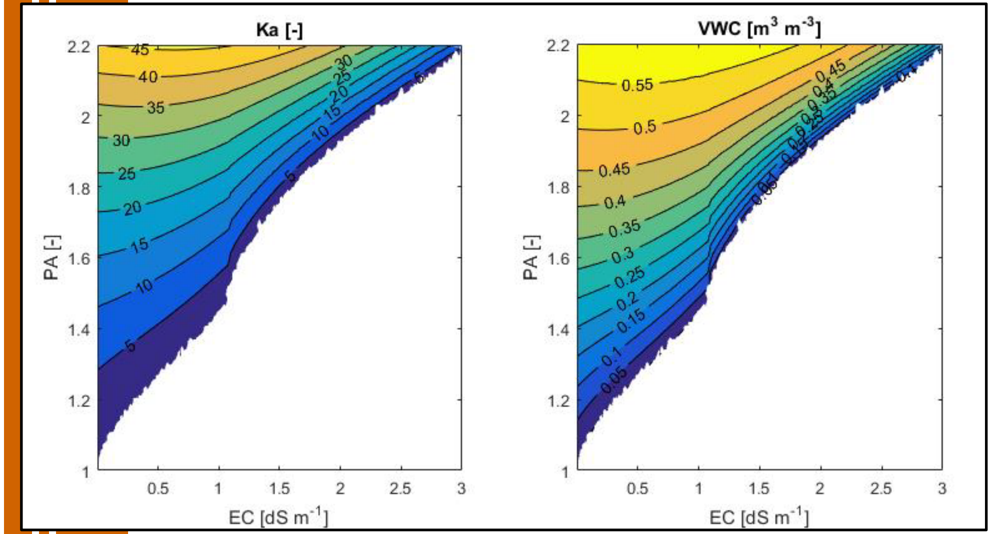
$$Ka = C_0EC^3PA^2+C_1EC^2PA^2+C_2ECPA^2+C_3PA^2+C_4EC^3PA+ C_5EC^2PA+$$
$$C_6ECPA+C_7PA+C_8EC^3+ C_9EC^2+C_{10}EC+ C_{11}$$

*Probe-specific

CS-655 Algorithm Assessment



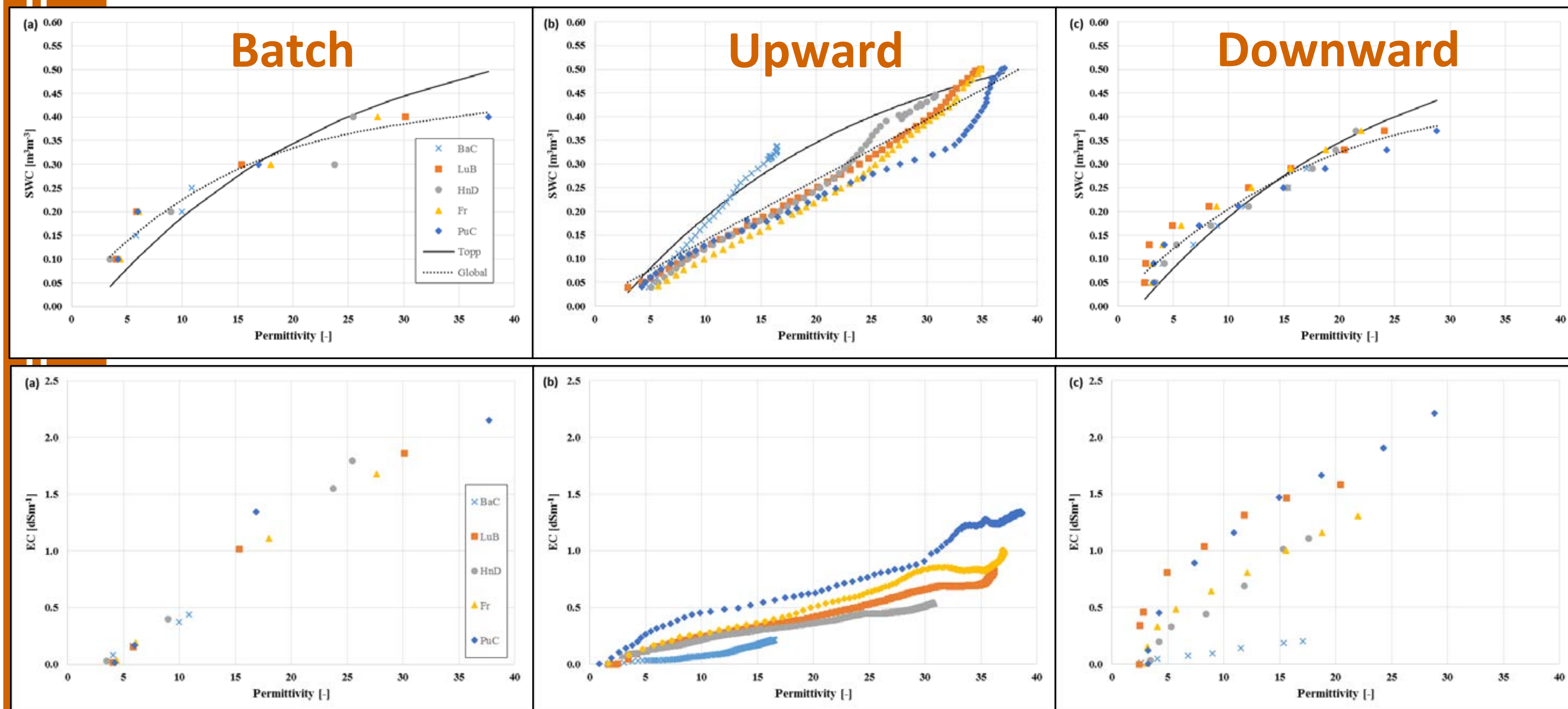
- Decreasing Sensitivity to PA at higher EC
- High sensitivity (Ka and VWC) to VR < 3
- EC(VR) is linear – not much else is



- Underestimated EC from upward data would produce higher Ka and much higher VWC
- Ka from CS65x sensor is very sensitive to EC. (We did not evaluate T)
- Vertical installation is not recommended

CS-655 Lab calibrations – Standard/downward

- Batch and downward produced correct Ka(θ) response
- VR is a function of 'wetting direction'
  - EC from upward infiltration too low
  - EC from downward infiltration too high



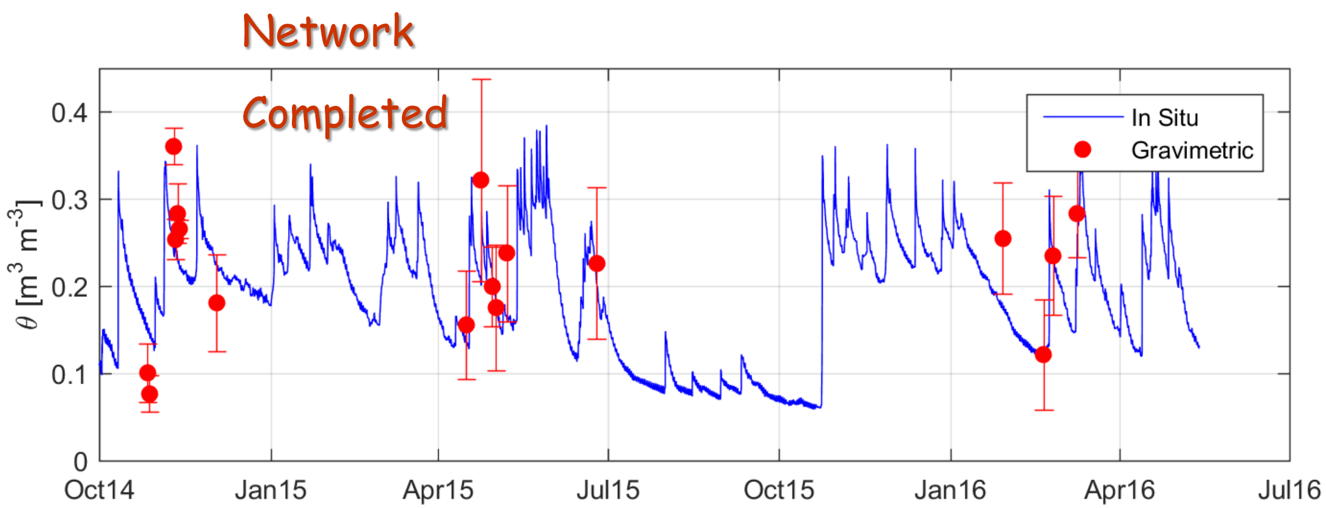
CS655 Laboratory calibrations

- Site Specific Calibration dependent on methodology
- Upward and downward infiltration produced different VR
- All soils show a improvement from standard Topp Equation

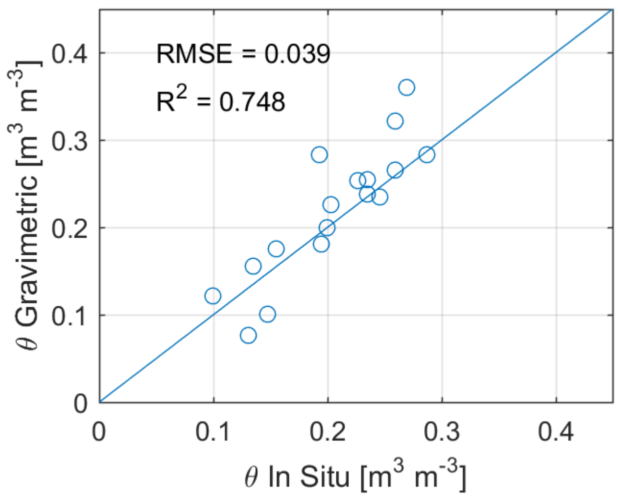
Site Specific	c0	c1	c2	c3	r^2	RMSE
						$m^3\ m^{-3}$
Batch	6.77E-02	1.72E-02	-2.32E-04	0	0.929	0.026
Downward Infiltration	2.3E-05	-1.74E-03	5.13E-02	1.69E-01	0.924	0.033
Upward Infiltration	1.23E-02	1.27E-02	0	0	0.881	0.045
Standard & Downward	3.37E-02	2.05E-02	-2.98E-04	0	0.933	0.026
Topp Equation	-5.30E-02	2.92E-02	-5.50E-04	4.30E-06	0.930	0.050

Soil Specific Calibration using Batch and Downward Infiltration						
Soil	c0	c1	c2	c3	r^2	RMSE
BaC	4.61E-05	-1.94E-03	3.84E-02	-3.41E-02	0.943	0.030
LuB	2.11E-05	-1.34E-03	3.43E-02	1.07E-02	0.957	0.059
HnD	1.60E-05	-9.35E-04	2.87E-02	-1.06E-02	0.948	0.036
Fr	3.36E-05	-1.89E-03	4.26E-02	3.30E-02	0.958	0.046
PuC	9.72E-06	-8.17E-04	2.75E-02	8.57E-03	0.955	0.055

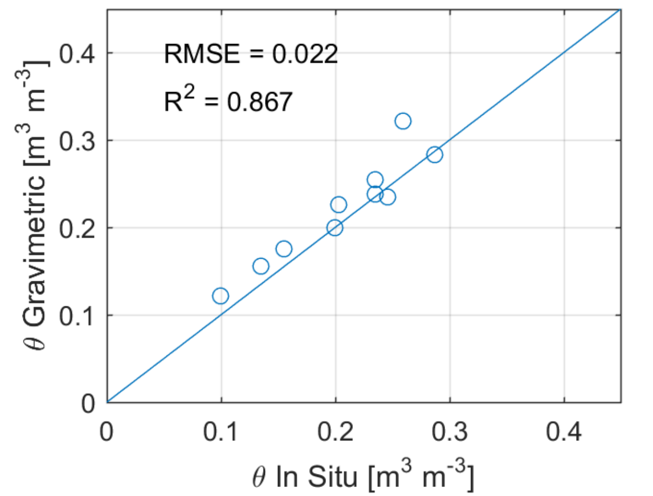
Field calibration – looks awesome



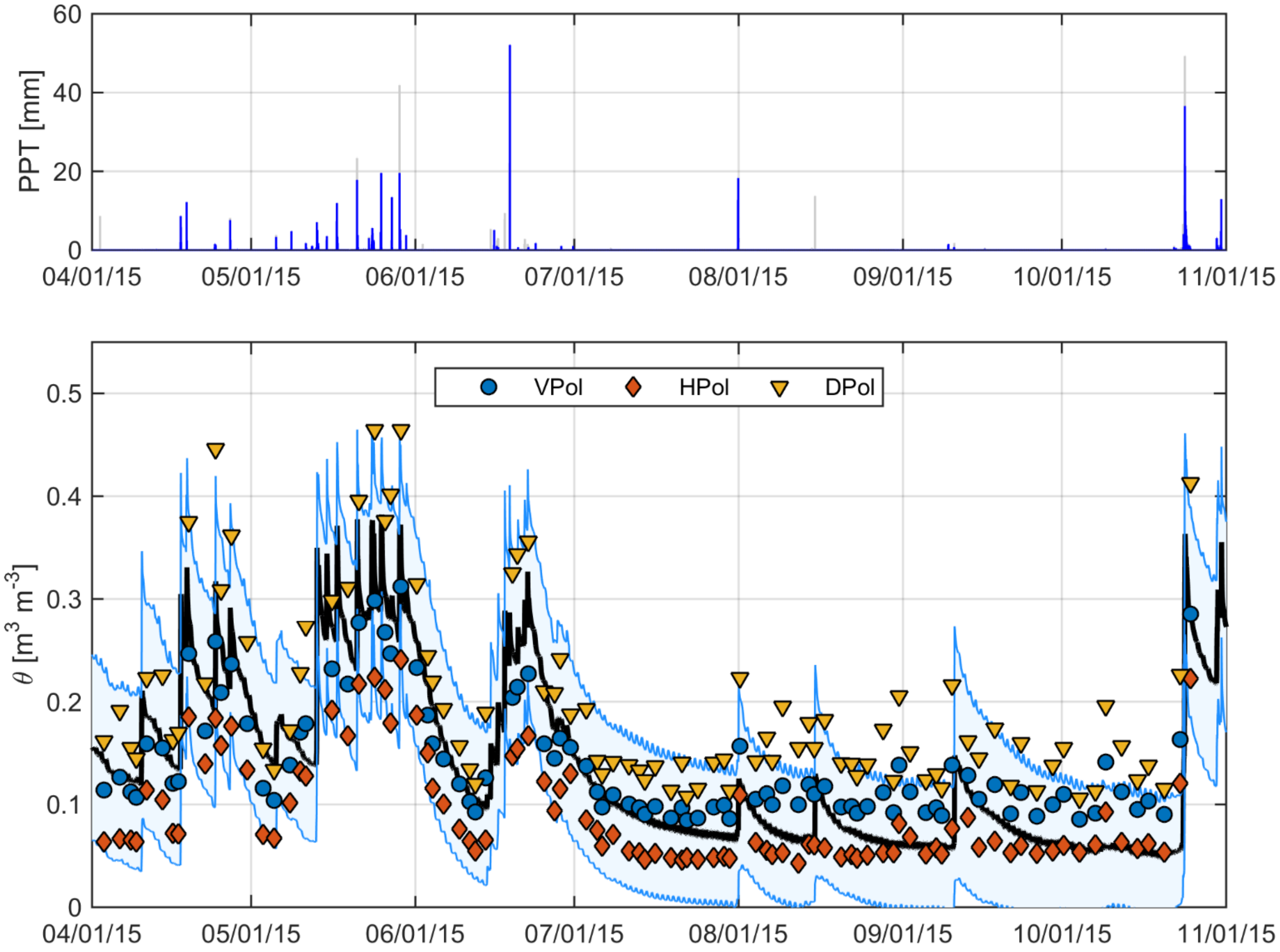
All data



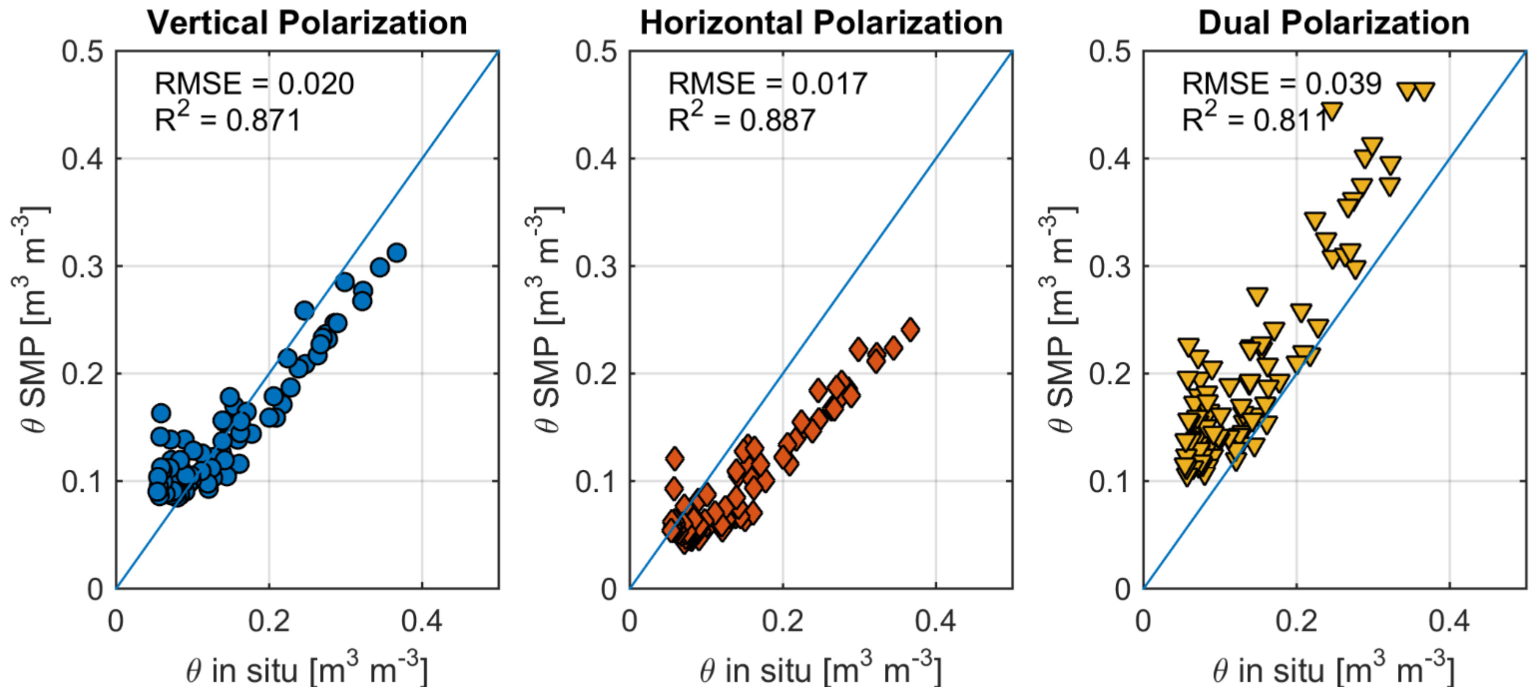
Post January 1, 2015



SMAP SMP_L2: Passive radiometer (36km)

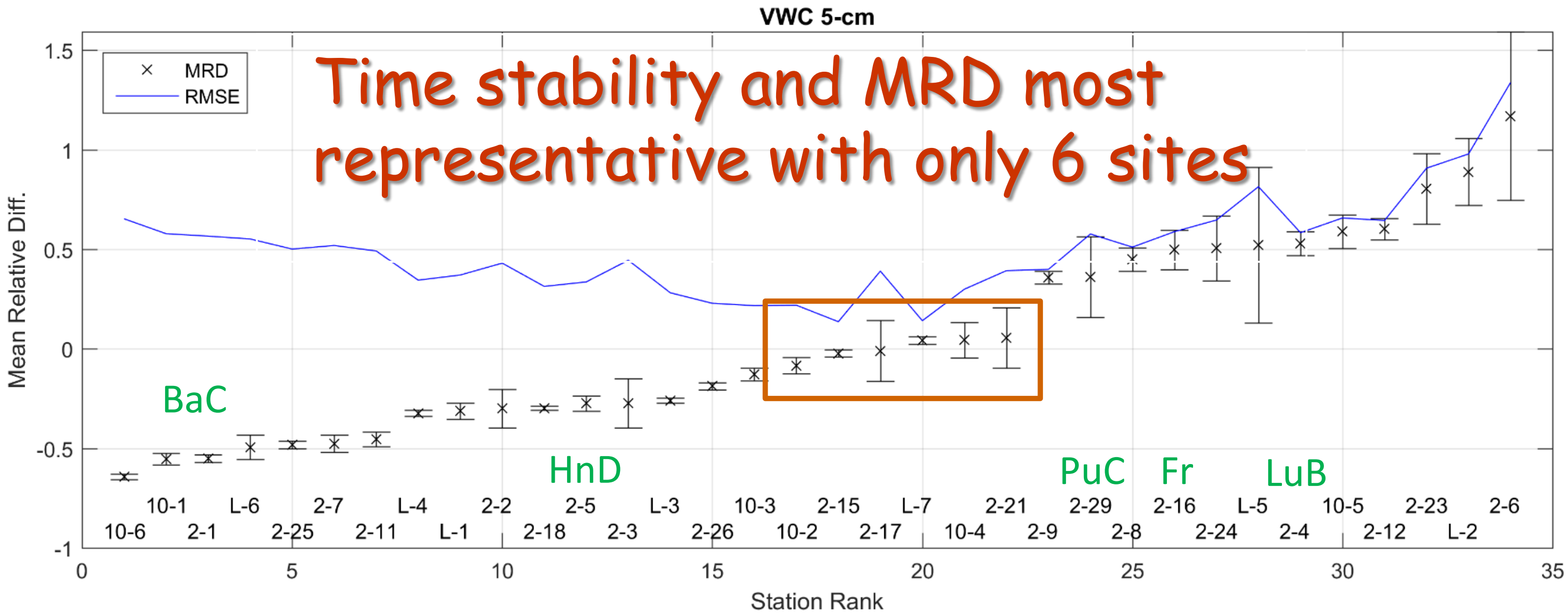


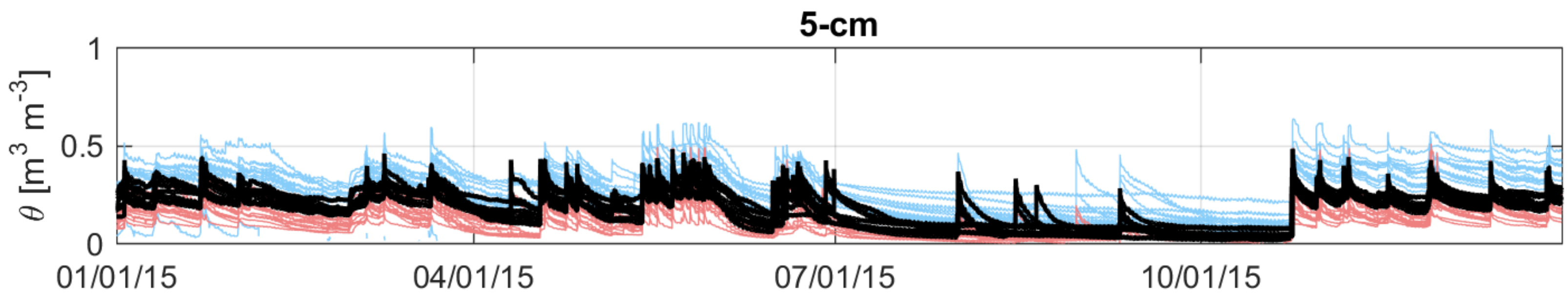
SMAP SMP_L2: Passive radiometer (36km)



- All 3 retrieval algorithms meet objectives over TxSON (RMSE <0.04)
  - SCA-V was chose for SMAP beta-release (L2_SM_P)
  - Universal factory calibrations for in situ sensors
  - Simply arithmetic averaging or IDW upscaling
  - TxSON has a "Textbook response" for soil moisture retrieval from passive microwave

TxSON upscaling: mean relative difference (2015)





Climate class: Temperate (Cfa)

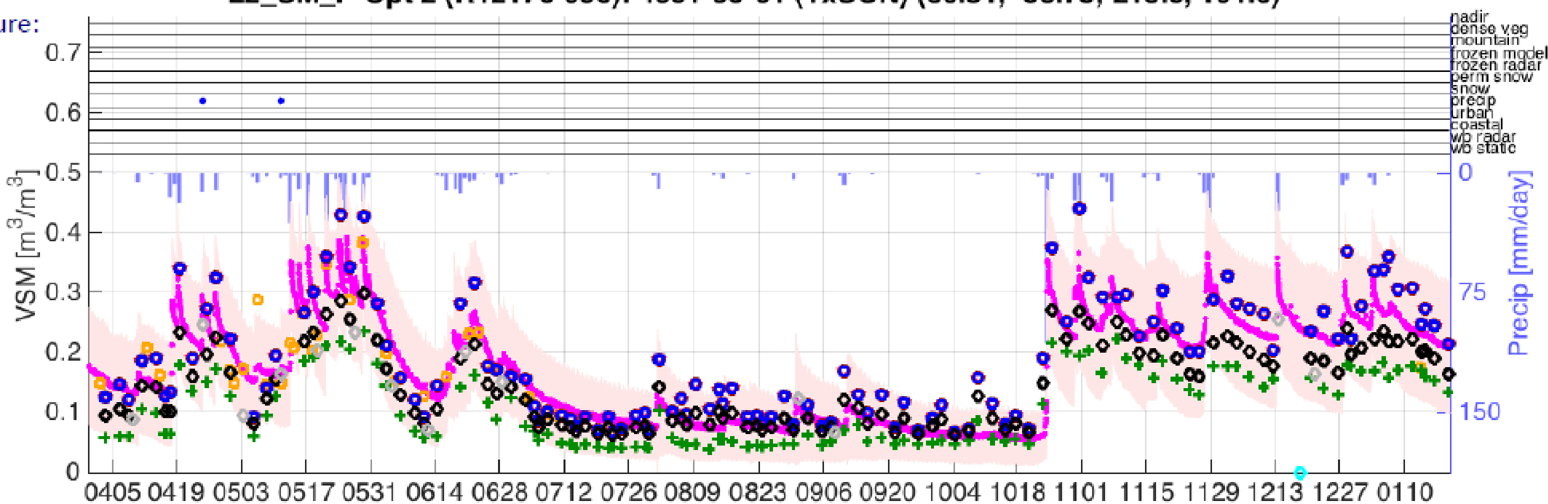
Landcover: Grasslands

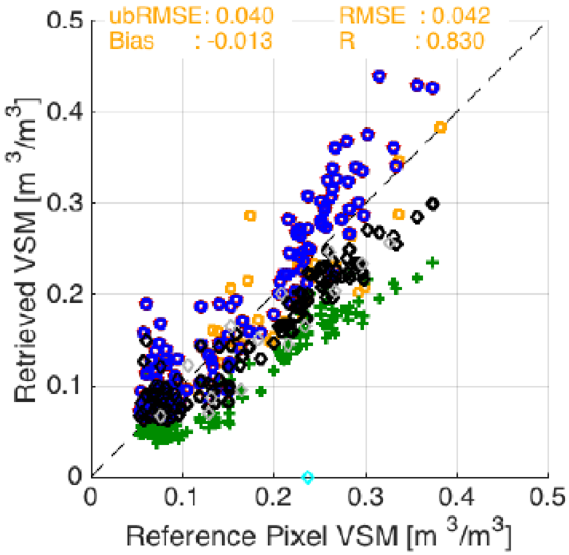
TxSON (Core Pixel)

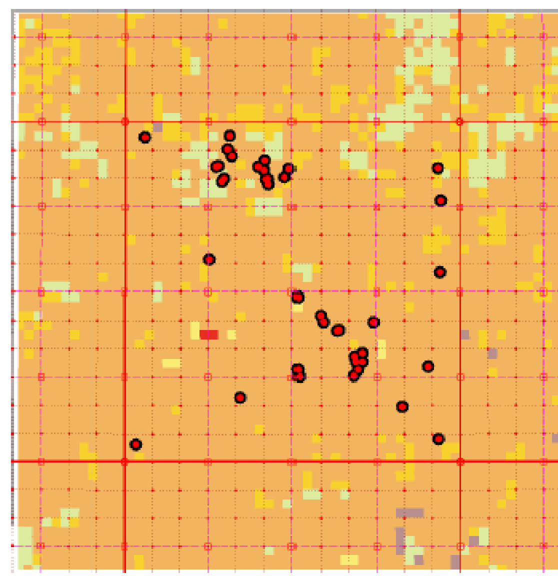
Jet Propulsion Laboratory
California Institute of Technology

Soil texture:
S-%: 33
C-%: 33
BD: 1.42

L2_SM_P-Opt 2 (R12170-999): 4801-36-01 (TxSON) (30.31, -98.78; 218.0, 101.0)







Alg	ubRMSE	Bias	RMSE	R
SCA-H	0.035	-0.059	0.069	0.953
SCA-V	0.031	-0.023	0.039	0.954
DCA	0.035	0.021	0.041	0.934
MPRA	0.035	0.021	0.041	0.934
E-DCA	0.035	0.021	0.041	0.934

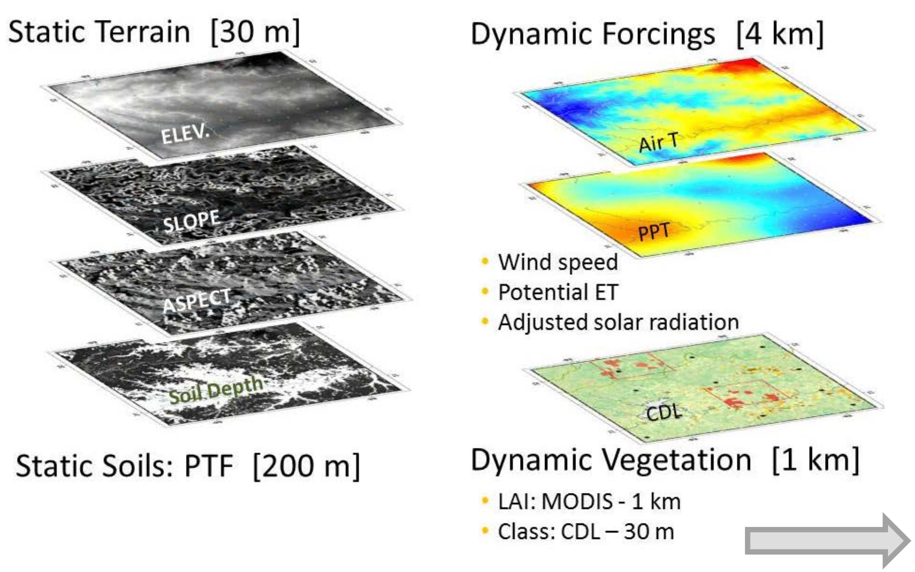
Black: Use recommended [Retrieval Quality Flag bit(0)=0]
Gray: Retrieval attempted and succeeded but use not recommended [bit(0)=1, bit(1)=0, bit(2)=0]
Green: Retrieval attempted but failed [bit(0)=1, bit(1)=0, bit(2)=1]
Cyan: Retrieval not attempted [bit(0)=1, bit(1)=1]

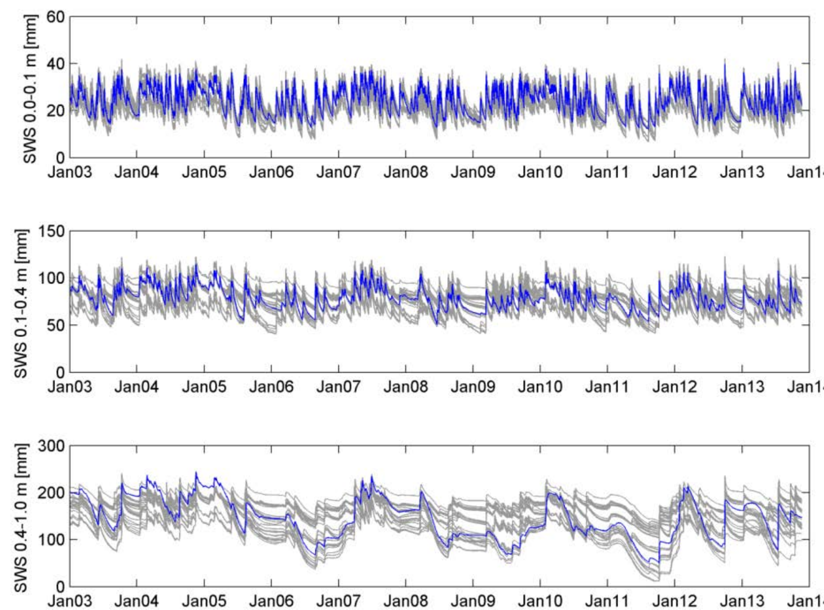
SMAP performance metrics 3/31/15 – 1/20/16

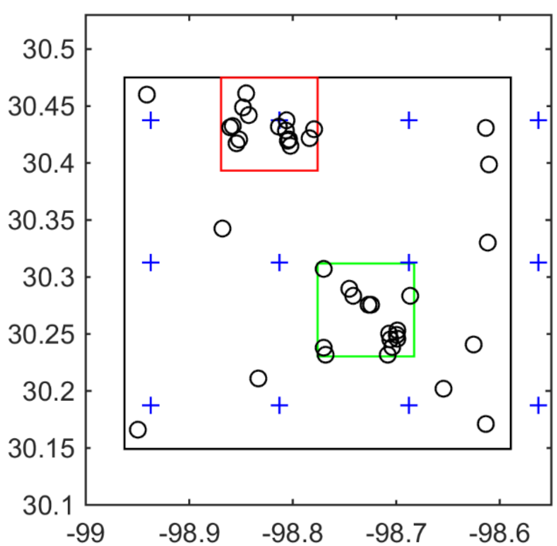
Ref Pixel	ubRMSE	Bias	RMSE	R
Reynolds Creek (0401-36-01)	0.044	-0.055	0.070	0.641
Walnut Gulch (1601-36-01)	0.031	-0.018	0.036	0.601
TxSON (4801-36-01)	0.031	-0.023	0.039	0.954
Fort Cobb (1603-36-01)	0.032	-0.063	0.070	0.881
Little Washita (1602-36-01)	0.024	-0.042	0.049	0.937
South Fork (1607-36-01)	0.056	-0.094	0.109	0.510
Little River (1604-36-01)	0.025	0.057	0.062	0.914
Kenaston (2701-36-01)	0.031	-0.060	0.067	0.723
Carman (0901-36-01)	0.059	-0.114	0.128	0.640
Monte Buey (1902-36-01)	0.052	-0.015	0.054	0.811
REMEDHUS (0301-36-02)	0.041	-0.052	0.066	0.689
Twente (1204-36-06)	0.066	-0.030	0.073	0.549
Yanco (0701-36-01)	0.047	0.013	0.048	0.954
Kyeamba (0702-36-01)	0.056	0.037	0.067	0.965
MEAN:	**0.042**	**-0.033**	**0.067**	**0.769**

- Replication helps
- Low vegetation water content probably helps
- Despite TxSON being ‘hill country’, it is mostly flat
- Irrigated agriculture is minimal, mostly rangeland

Land surface model validation using TxSON



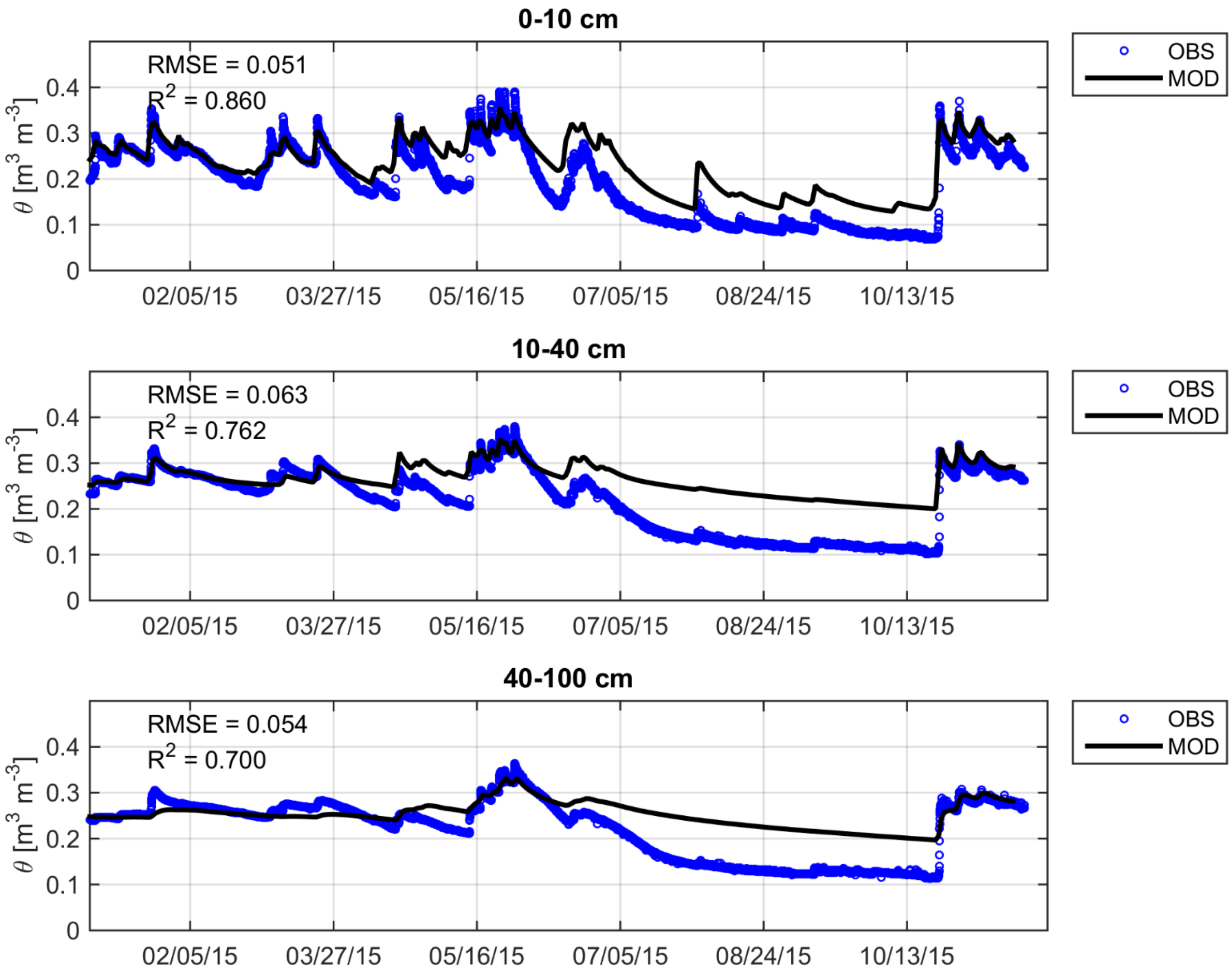




- We can parameterize and force LSM at any resolution.
  - Hyper-resolution ~1km
  - Need for HPC

- EASE-2 and NLDAS grid are not aligned
- Nine NLDAS nodes within TxSON 36km cell

LSM validation using TxSON: NLDAS-2 Noah SWS

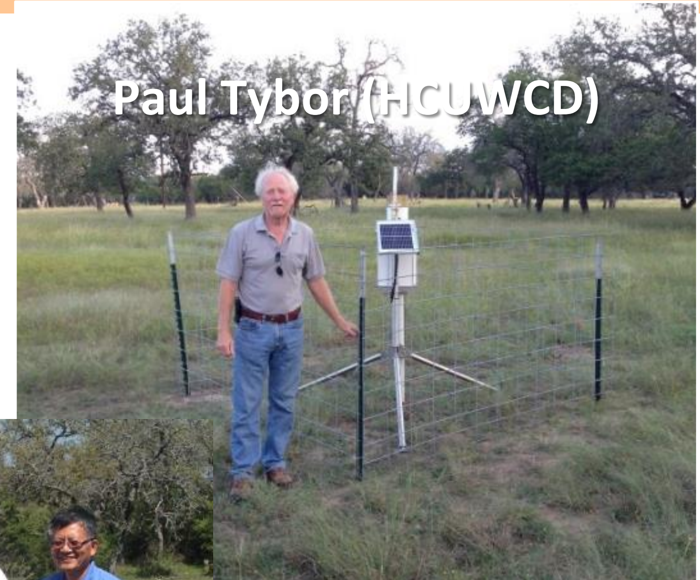


Conclusions, on the importance of soil moisture

- Soil moisture remains a big 'challenge' in hydrology
- The scale of interest is not the scale of observation
- Dense in situ networks offer insight but require significant effort

- TxSON fills a unique gap in our understanding
  - Spatial variability of soil moisture
  - SMAP/SMOS validation
  - LSM validation

http://www.beg.utexas.edu/txson



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