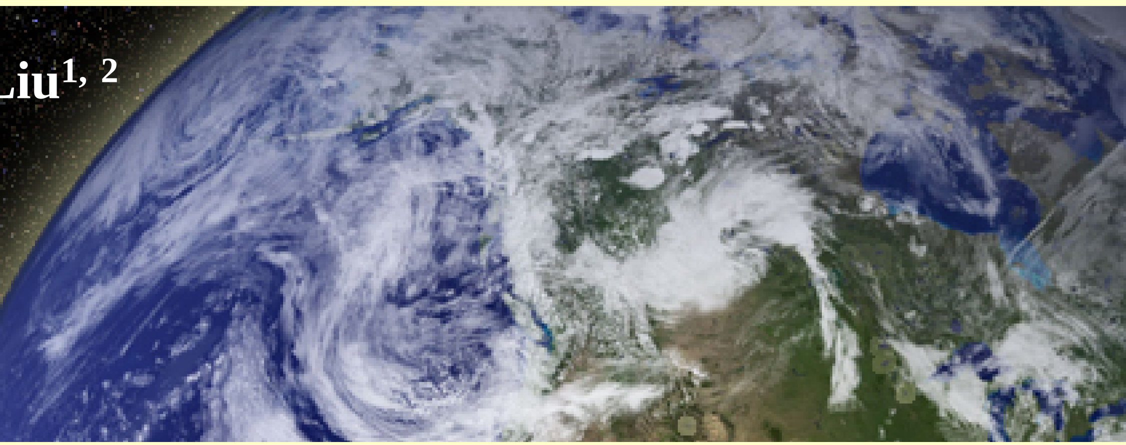
CICS Science Meeting, ESSIC, UMD, 2017

Merging Microwave and Optical Satellite Observations for High Resolution Soil Moisture Products



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Outline

Background

- SMAP lost the capability to directly generate high resolution SM after the loss of L-band radar
- July 7, 2015

Objectives

- Which one or type of downscaling algorithms would produce the most reliable high resolution soil moisture product?
- Can they be implemented for operational generation?
- Operationalization criteria
  - Reliable high resolution observations (e. g. MODIS/VIIRS VI/LST products)
  - Simple to implement
  - Computational efficiency requirement (latency less than 6 hours)
  - Satisfactory accuracy

Downscaling Algorithms

Data Source	Type	Input	Examples	Reference
	Active microwave	Radar backscatters	SMAP L2-SM-A/P product	Entekhabi et al (2014, ATBD) Wagner et al, 2007; Sabel et al, 2007
	Optical	Vegetation Index, albedo	VIIRS SM product	Zhan et al., 2002
	Thermal Infrared	LST	R LST changes and SM; "universal triangle"	Fang et al. 2013; Carlson, 2007; Petropoulos et al., 2009; Zhan et al., 2002
	Microwave BT	Ka-band BT	AMSR-E or AMSR2	

Down-Scaling Approach	Type	Examples	Reference
	Liner Regression	1. Relationship between backscatter and SM 2. linear regression relationships between daily LST changes and SM	Entekhabi et al (2014, ATBD) Fang et al. 2013
	Change detection	Relationship between changes in radar backscatter and SM	Njoku et al., 2002; Narayan et al., 2006; Das et al., 2011
	Regression Tree (RT)	RT, a data mining technique, is used to sharpen coarse resolution satellite imageries using fine resolution optical products	F. Gao, et al. 2012
	Neural network (NN)	NN is trained with samples of AMSR-E BT matched to SMOS L3m which is then applied retrospectively or future observations	Rodriguez-Fernandez et al., 2015, 2016
	Bayesian merging	Using the tau-omega equation and a radar backscatter model from the Observing System Simulation Experiment (OSSE) of the SMAP mission (formerly called Hydros), Zhan et al (2006) implemented a Bayesian merging method to combine the observations of 36km radiometer and 3km radar	Zhan et al (2006, TGARS)
	Combined modeling and RS	Models are used in the downscaling DISPATCH method	Merlin et al. 2005,2006,2008 Fang et al. 2013
	Deterministic	Using fine-scale SM obtained from a hydrologic model	Ines et al. 2013 Merlin et al (2008, RSE)

Downscaling Algorithms

NASA SMAP Enhanced 9km (L3_SM_P_E)

- Enhanced SMAP radiometer-based SM retrievals at 9 km resolution
- Enhancement of spatial resolution is based on oversampled observations in the across-track direction

  Jeffrey Piepmeier, Steven Chan, at al., 2016

SMAP L2-SM-A/P Product Algorithm

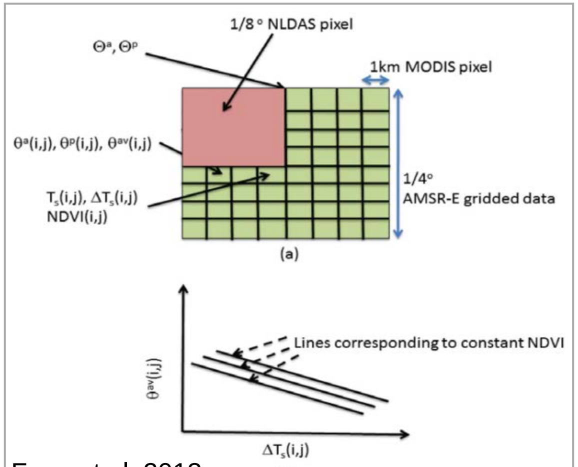
- Linear relationship between the radar backscatter (3 km) and radiometer brightness temperature (36 km)
- Linear coefficient being vegetation-dependent and spatially homogeneous across the SMAP radiometer pixel
- Available for only 84 days before July 7^{th}, 2015

  D. Entekhabi, et al., 2014

Downscaling Algorithms

Thermal Inertial Linear Regression

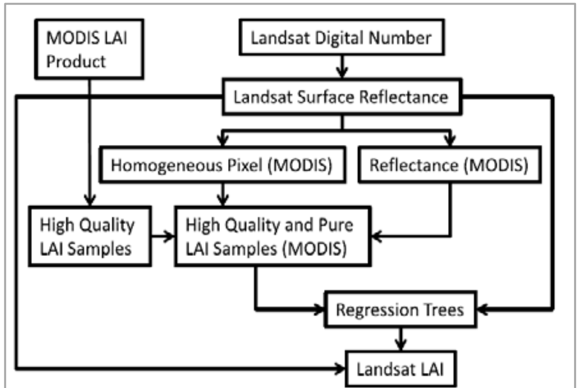
- Linear regression relationships between daily land surface temperature (LST) changes and average soil moisture under different vegetation conditions
- In our study, Evaporative Stress Index (ESI) from the Atmosphere-Land Exchange Inversion (ALEXI) model was treated as a soil moisture proxy



Fang at al.,2013

Regression Tree Algorithm

- Data mining technique developed to sharpen coarse resolution thermal satellite imageries using fine resolution optical products
- MODIS LAI and LST (daytime and nighttime)

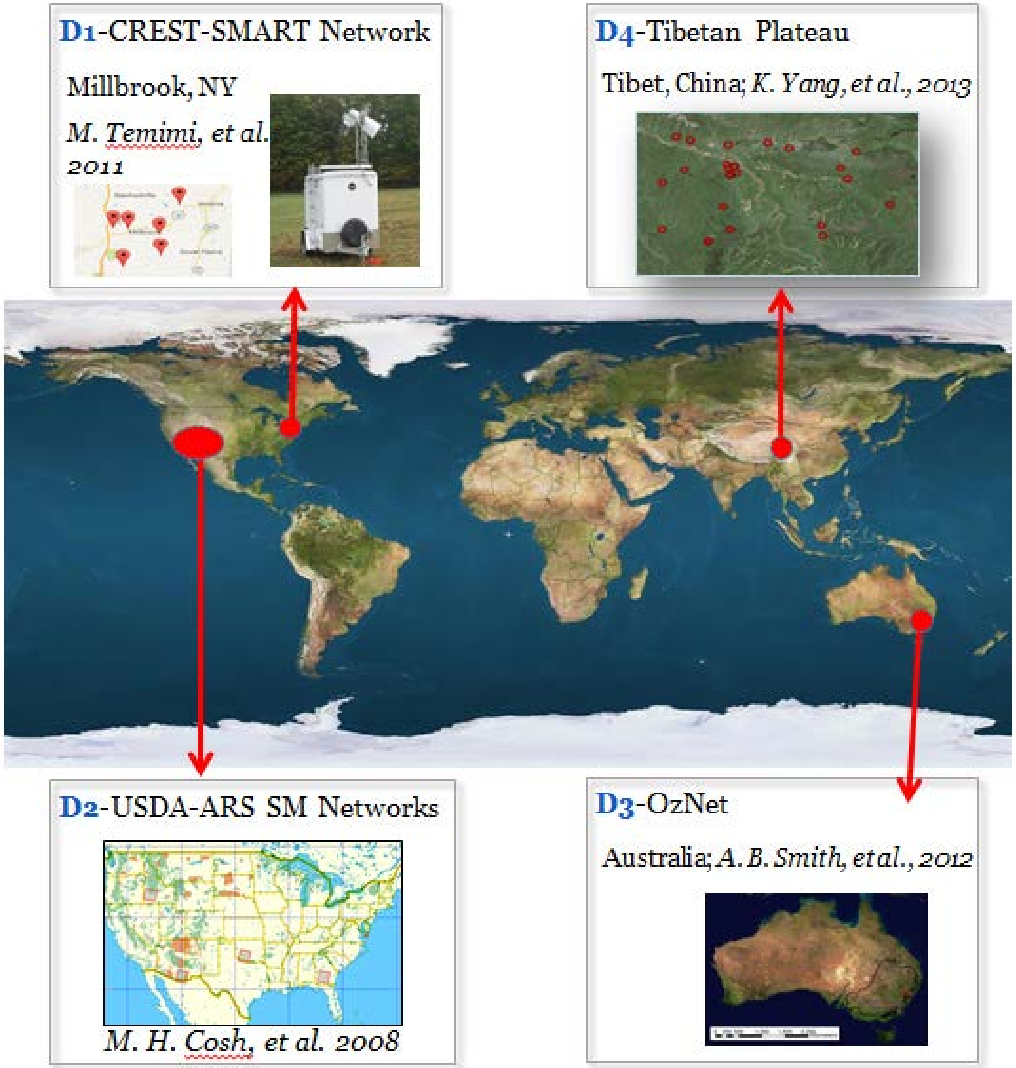


Gao at al., 2012, 2017

SMAP SM products to be validated

ID	Satellite SM Products	Resolution	Spatial coverage	Temporal coverage
A0-SMAP36km	SMAP 36km (L3_SM_P)	36 km	Global	April 2015, Oct., 2016
A1-SMAP9km	NASA SMAP Enhanced 9km (L3_SM_P_E)	9 km	Global	April 2015, Oct., 2016
A2-LR_ESI	Downscaled SMAP SM based on Thermal Inertial Linear Regression Algorithm	9 km	CONUS	April-Oct. 2015, April-July, 2016
A3-RT9km	Downscaled SMAP SM based on Data Mining method, using MODIS LST/LAI	9 km	Global	April 2015 – Oct. 2016
A4-RT1km	Downscaled SMAP SM based on Data Mining method, using MODIS LST/LAI	1 km	Global	April 2015 – Oct. 2016

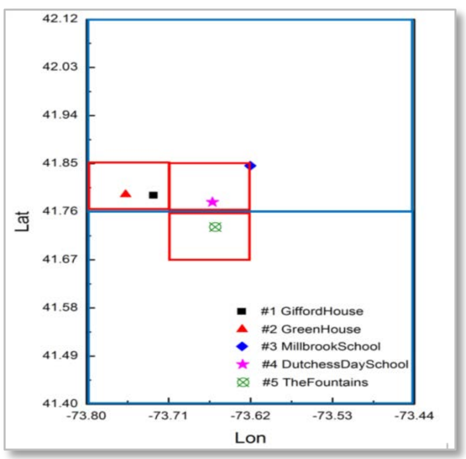
SM in-situ measurements



SM in-situ measurements

D1 -- CREST-SMART Network

- NOAA Cooperative Remote Sensing Science and Technology (CREST) Center of City University of New York
- Soil moisture advanced radiometric testbed (SMART)
- Composite of open field (40%) and forested (60%) terrains and a small urban fraction (the Village of Millbrook)
- **Millbrook, New York**



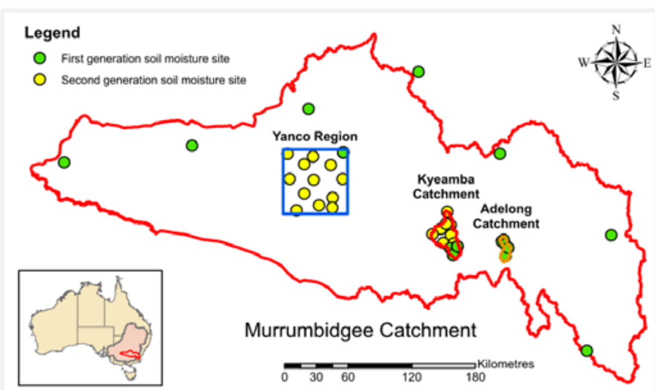
D2 -- USDA-ARS

- **Walnut Gulch Watershed** -- Arizona; semiarid climate region; rangeland(83%), forest(12%), and miscellaneous(5%)
- **Little Washita Watershed** -- Oklahoma; sub-humid region; mixed agricultural land; grassland/rangeland (68%), cropland (20%), forests (8%), and miscellaneous uses (4%)
- **Fort Cobb Watershed** -- Oklahoma; semiarid; agricultural land
- **Little River Watershed** -- Georgia; woodland (40%), row crops (36%) , pasture (18%), and 4% water

SM in-situ measurements

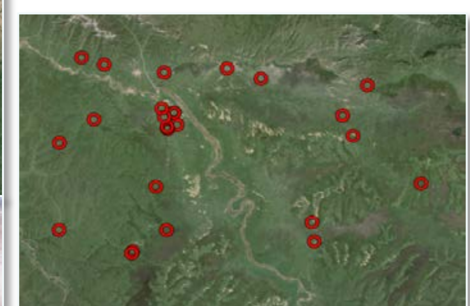
D3 -- OzNet Hydrological Monitoring

- An Australian monitoring network for soil moisture and micrometeorology developed by Monash University and the University of Melbourne
- More than 30 sites distributed across the Yanco study area and 14 for Kyeamba
- Predominantly agricultural with the exception of steeper parts of the catchment, which are a mixture of native eucalypt forests and exotic forest plantations



D4 -- Tibetan Plateau SM Networks

- Maqu soil moisture measurement networks developed in the Tibetan Plateau by Chinese Academy of Sciences
- About 25 sites in the east TP covers about 100km×60km area with sensors at 5, 10, 20, 40, 80cm depths
- A uniform land cover of short grassland used for grazing by sheep and yaks



From Jun Wen of CAS

SMAP SM at coarse and fine scales

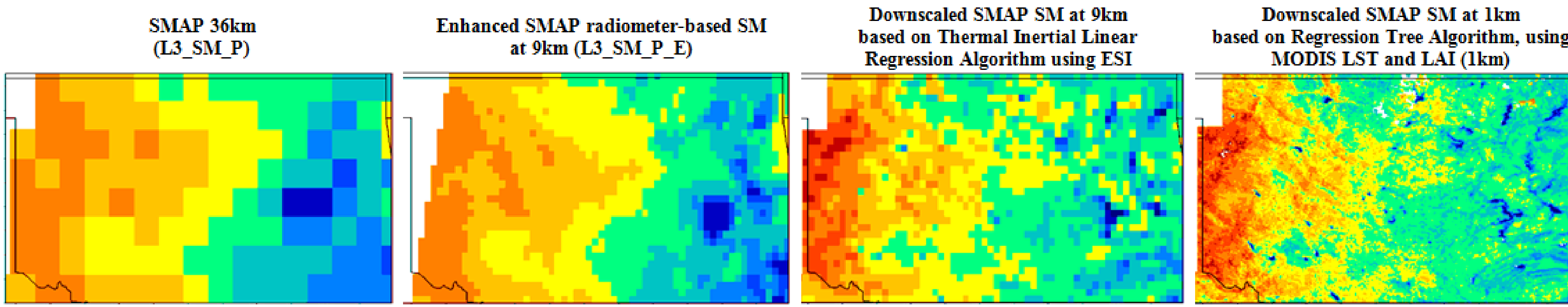


Figure 1. Comparison of SMAP SM data sets to be validated, over Oklahoma region (100.15W~ 94.53W, 34.2N~37.06N), on April 30th, 2015, including 1) SMAP SM product at 36km (L3_SM_P); 2) Enhanced SMAP radiometer-based SM at 9km (L3_SM_P_E); 3) Downscaled SMAP SM at 9km based on ESI; 4) Downscaled SMAP SM at 1km based on Regression Tree Algorithm, using MODIS LST and LAI (1km)

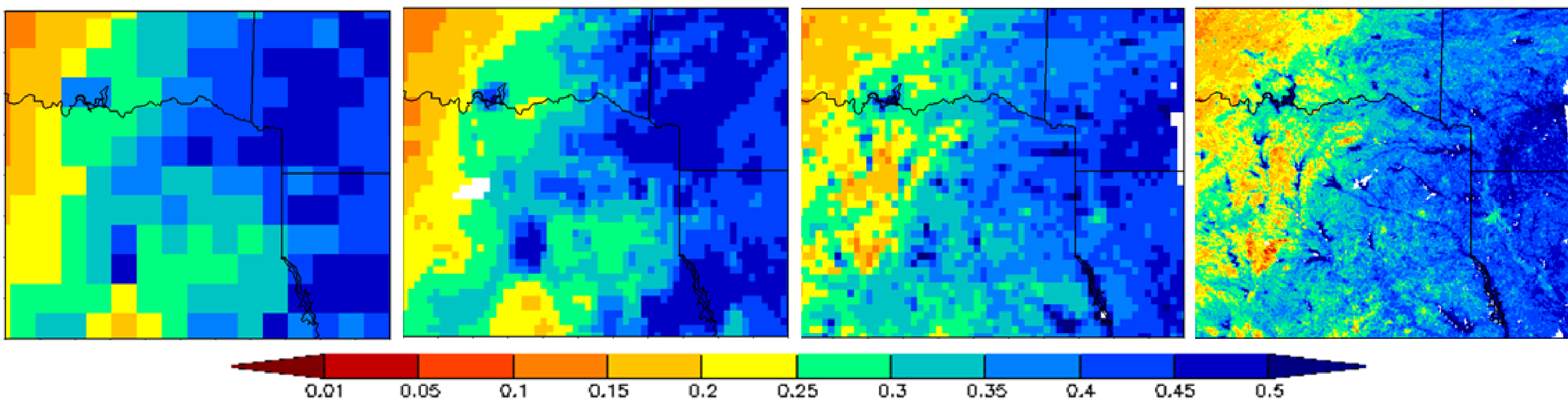


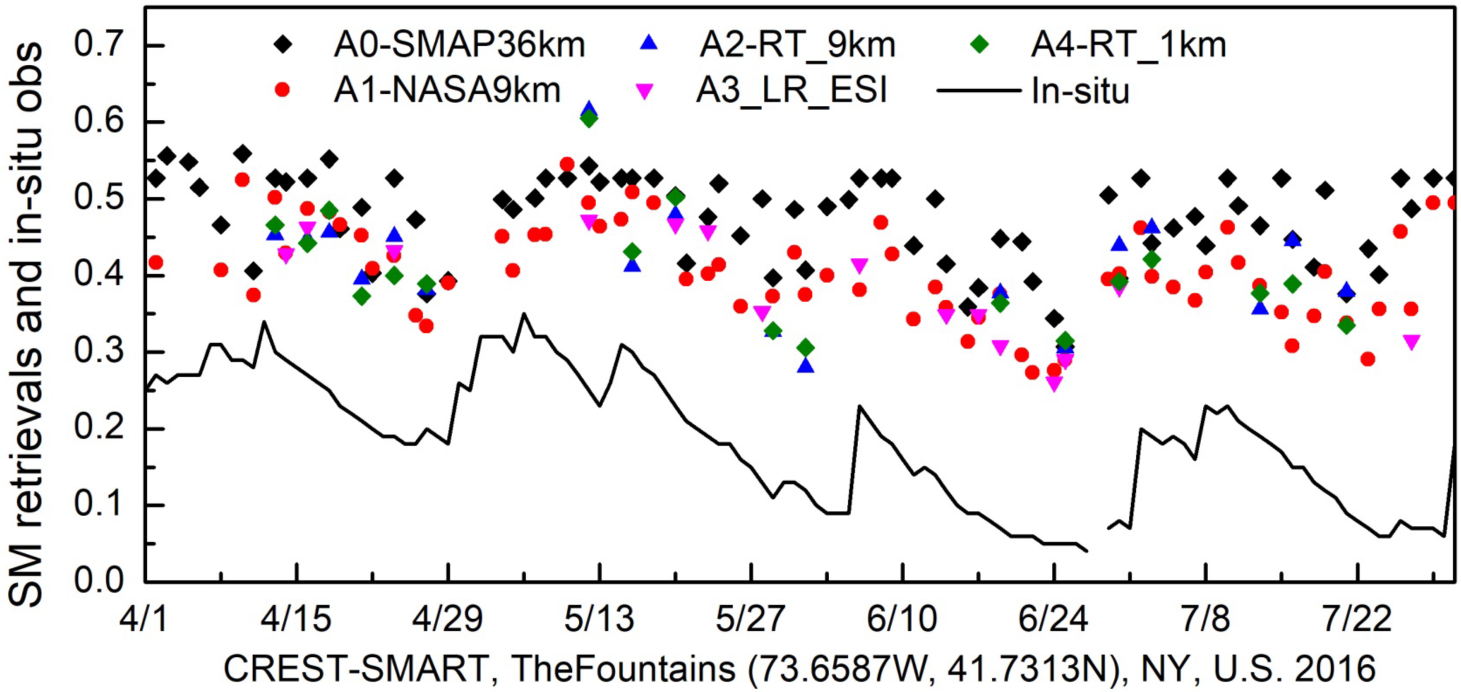
Figure 2. Comparison of SMAP SM data sets to be validated, over Texas region (98W~ 92.5W, 31N~35N), on April 2nd, 2016, including 1) SMAP SM product at 36km (L3_SM_P); 2) Enhanced SMAP radiometer-based SM at 9km (L3_SM_P_E); 3) Downscaled SMAP SM at 9km based on ESI; 4) Downscaled SMAP SM at 1km based on Regression Tree Algorithm, using MODIS LST and LAI (1km)

Validation results

- Background & Objectives
- Data fusion algorithms
- SM in-situ measurements
- Methodology
- **Results**
- Summary

- **D1 - CREST-SMART Network**
- **D2 - USDA-ARS**
- **D3 - OzNet Hydrological Monitoring**
- **D4 - Tibetan Plateau SM Networks**

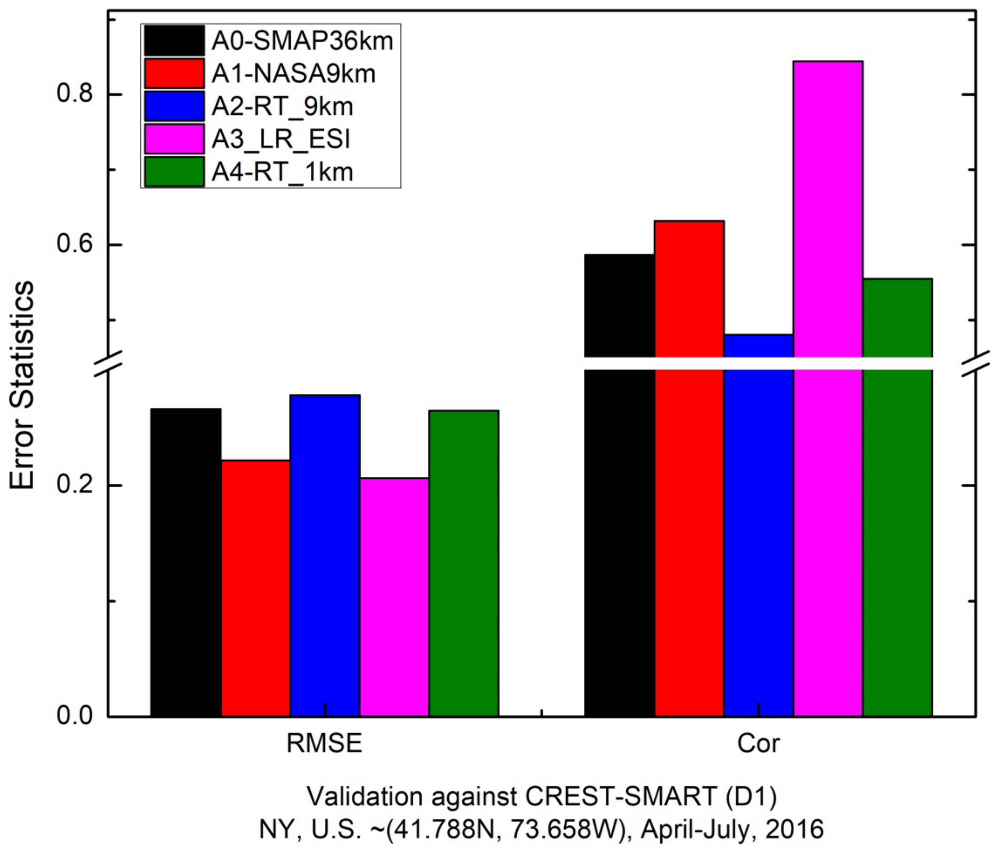
D1- CREST-SMART



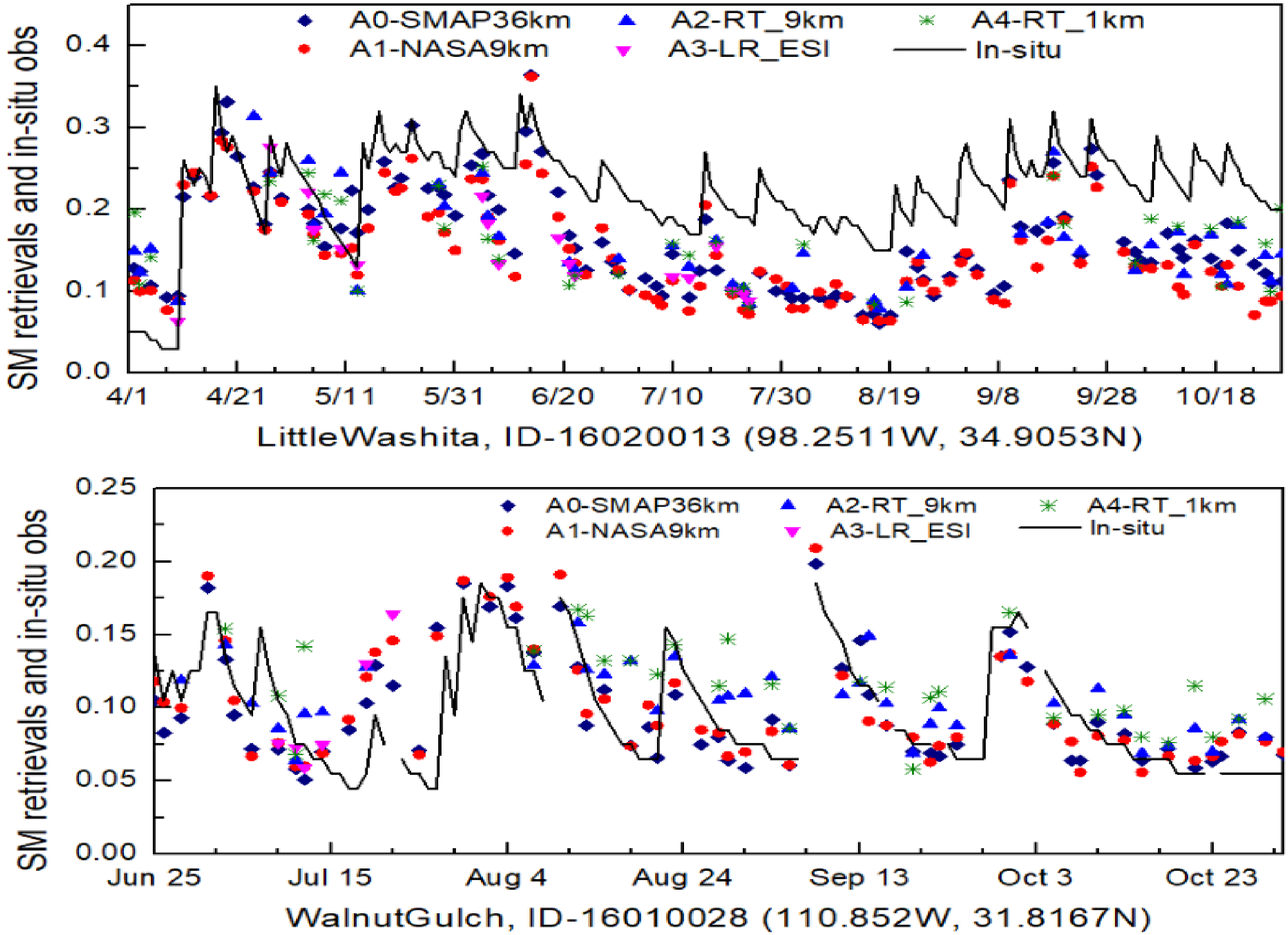
Product	A-SMAP36km	A1-NASA9km	A2-RT_9km	A3_LR_ESI	A4-RT_1km
ubRMSE	0.0692	0.062	0.0769	0.0372	0.0702
Cor	0.5514	0.6621	0.4778	0.8955	0.5703

D1- CREST-SMART

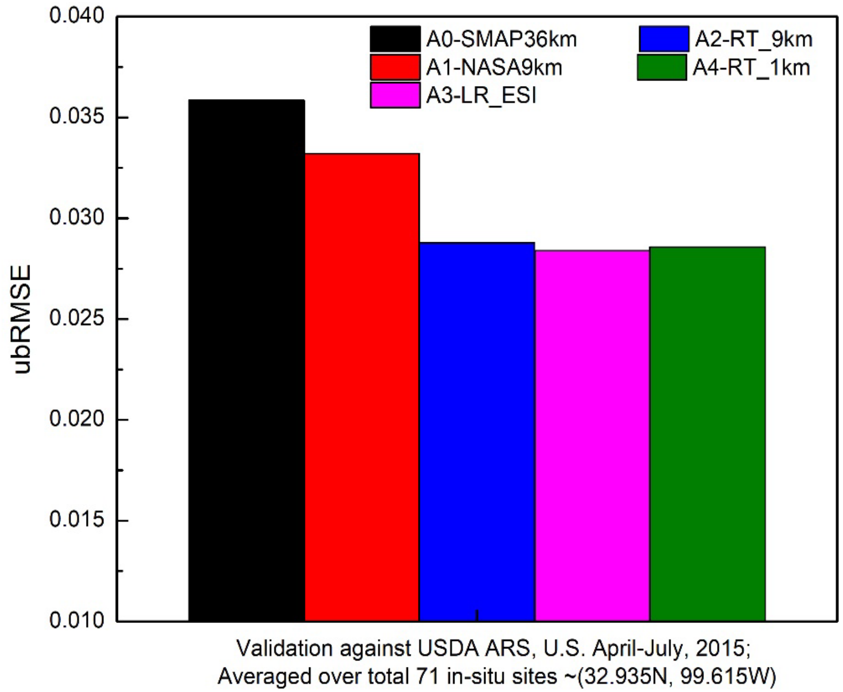
- Error statistics (RMSE and correlation) averaged from four ground stations in CREST-SMART network
- NASA Enhanced 9km product shows moderate improvement in accuracy
- The use of thermal inertial linear regression algorithm (A3) has seen the largest improvement, reducing RMSE by 0.059 and strengthens correlation by 0.257
- Downscaled products using data mining method have seen higher RMSE and lower Cor

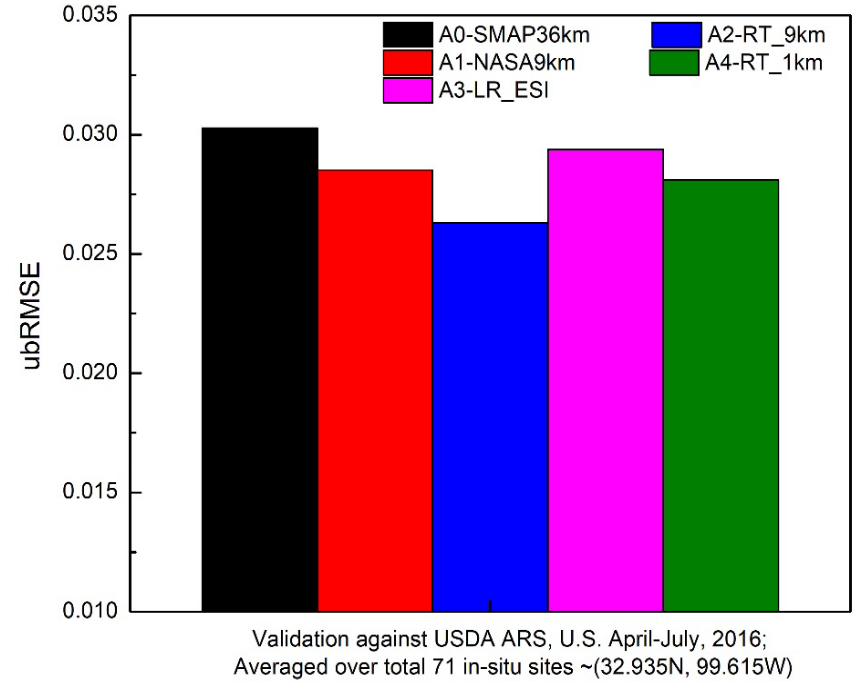


D2- USDA-ARS


A0-SMAP36km
A1-NASA9km
A2-RT_9km
A3-LR_ESI
A4-RT_1km
In-situ
SM retrievals and in-situ obs
0.0
0.1
0.2
0.3
0.4
4/1
4/21
5/11
5/31
6/20
7/10
7/30
8/19
9/8
9/28
10/18
LittleWashita, ID-16020013 (98.2511W, 34.9053N)
A0-SMAP36km
A1-NASA9km
A2-RT_9km
A3-LR_ESI
A4-RT_1km
In-situ
SM retrievals and in-situ obs
0.00
0.05
0.10
0.15
0.20
0.25
Jun 25
Jul 15
Aug 4
Aug 24
Sep 13
Oct 3
Oct 23
WalnutGulch, ID-16010028 (110.852W, 31.8167N)

D2- USDA-ARS

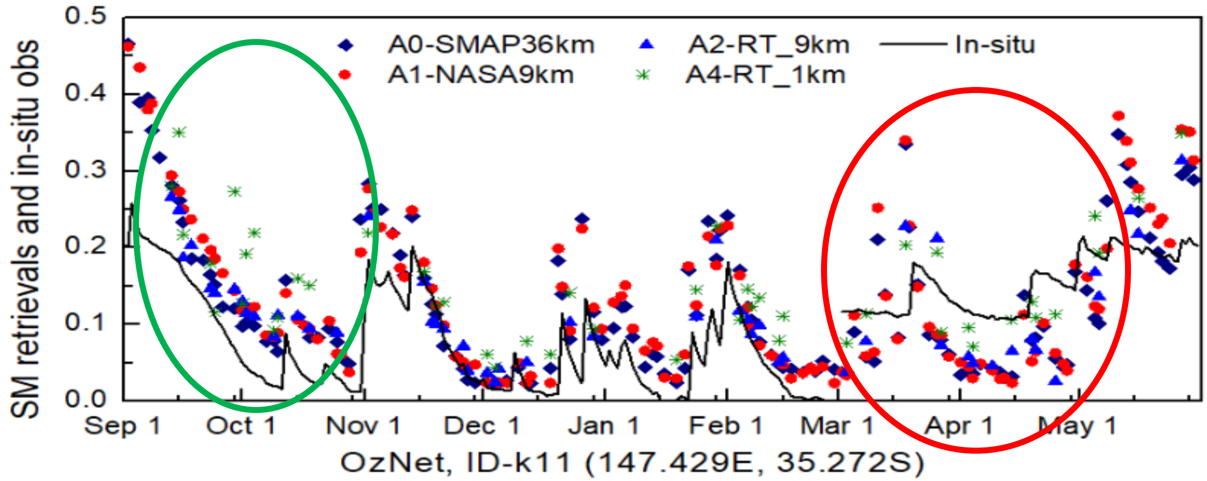


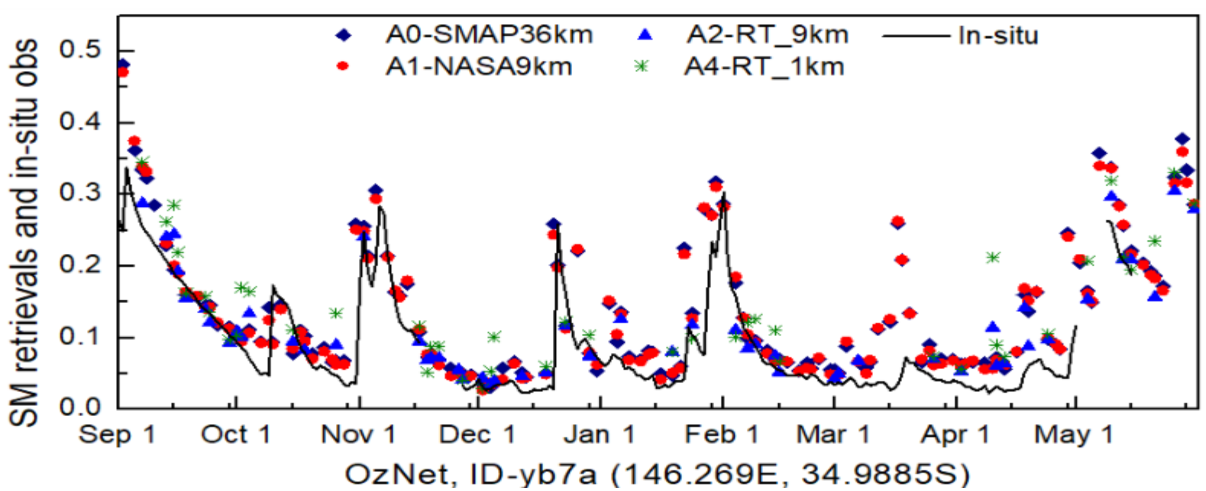


- Averaged ubRMSE of each involved satellite SM product for USDA-ARS networks over warm season (April – Oct.) in 2015 (left) and 2016 (right)
- Downscaled SMAP products have seen a decrease in ubRMSE in both years
- The improvement in 2015 is larger than that in 2016

D3- OzNet Network

- The OzNet network in Australia (D3) provides long-term field measurements in very high quality
- Both SMAP original and downscaled products agree well with the ground measurements

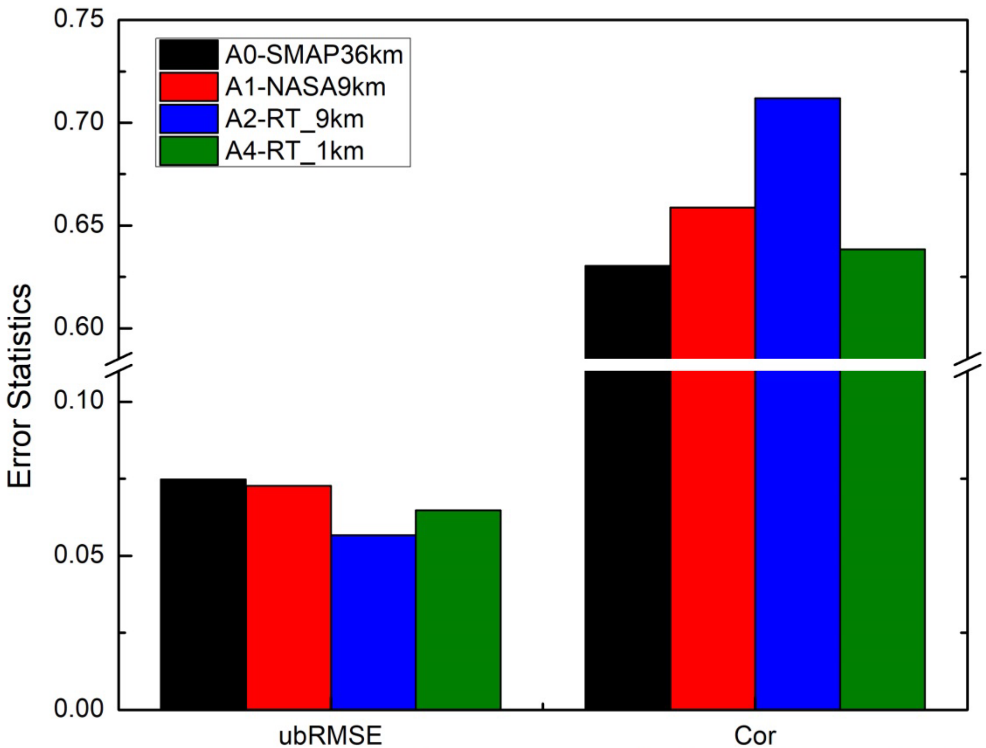




ubRMSE	A0-SMAP36	A1-NASA9	A2-RT_9km	A4-RT_1km
k11	0.0723	0.0748	0.0529	0.0621
yb7a	0.0556	0.0554	0.0434	0.0352

D3- OzNet Network

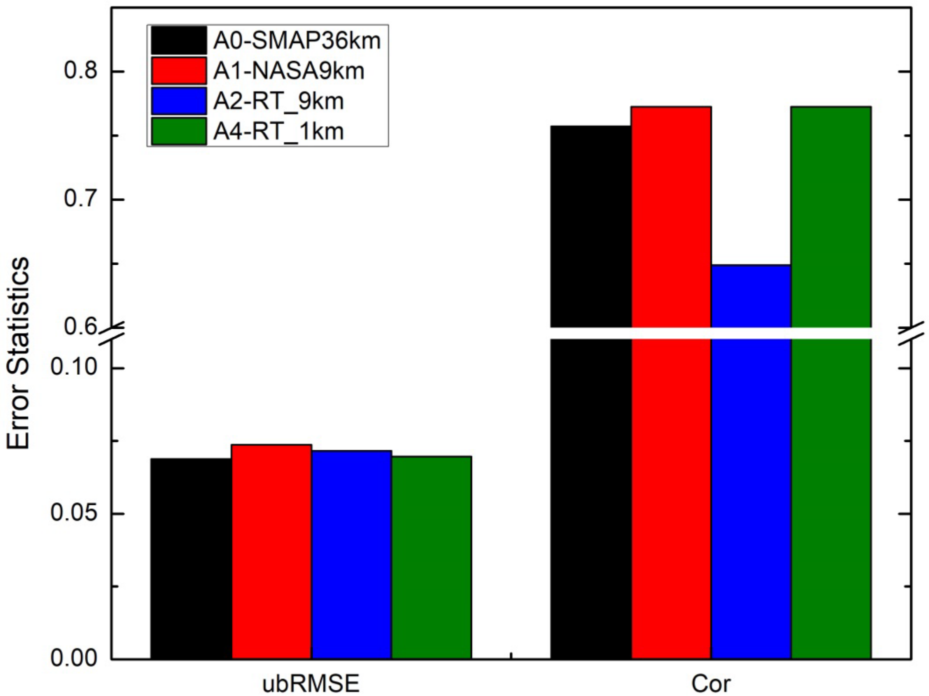
- A3 (ESI-based) is exclusive because current ESI product covers only the North America domain
- Validation period extends from Sept. 2015 to May 2016
- Downscaled products show lower ubRMSE and higher correlation than those from coarse scale SMAP SM product



Validation against OzNet network, Australia. Sept. 2015 -- May 2016; Averaged over total 38 in-situ sites ~(34.899S, 146.313E)

D4- Tibetan Plateau

- Validation period extends from April – June, 2015
- Downscaling did not give added value to data accuracy
- Finer resolution data have seen a rise in ubRMSE compared to SMAP 36km product
- Investigation on why downscaling performance is poor over that region is ongoing

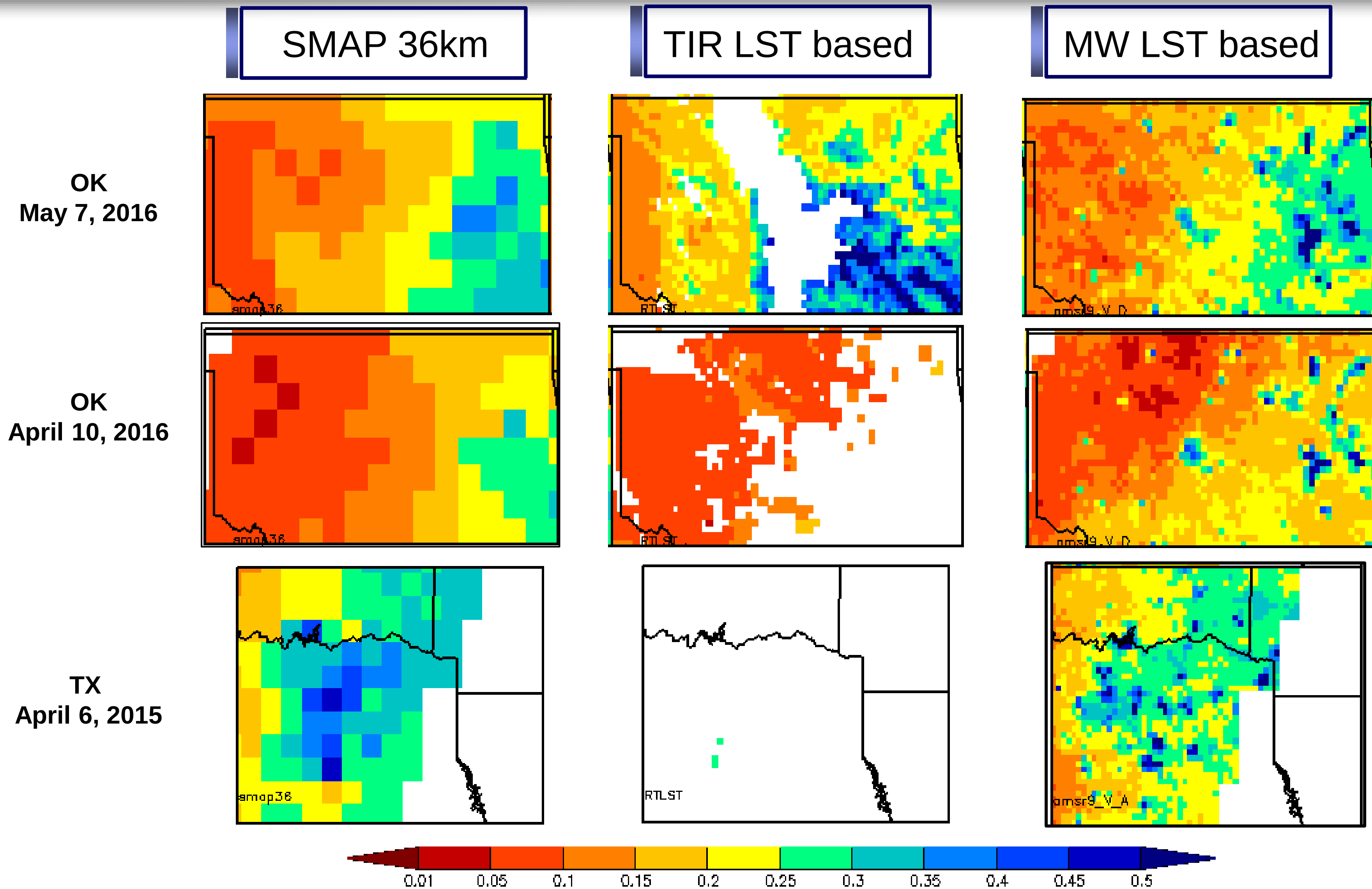


Validation against Maqu Network in Tibet (D4), China, April-July, 2015
Averaged over total 15 in-situ sites ~(33.867N, 102.23E)

Summary

- Downscaled SM products from all algorithms generally outperform the 36km product for most in situ data sets
- Downscaled 9km SM product based on ESI has the best agreement with the two in situ networks in the U.S.
- Data mining method using optical or thermal observations is promising for operational generation of fine resolution product
- Algorithms using optical/thermal observations could not be obtained for cloudy areas

Future work


SMAP 36km
TIR LST based
MW LST based
OK
May 7, 2016
OK
April 10, 2016
TX
April 6, 2015
smap36
RTLST
amsr9_V_A
0.01
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5

Future work

- Introduce MW brightness temperature observations (AMSR2) under cloudy conditions to improve spatial coverage
- Explore airborne SM data for validation
- Upscale in-situ measurements for validation
- Evaluate characteristics of different downscaling algorithms based on operationalization criteria
- Transition downscaled high resolution SMAP soil moisture product into NCEP operations

The end

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Back-up ALEXI