Design of efficient ground based soil moisture monitoring networks using cosmic-ray neutron probes and space-time data fusion

Trenton E. Franz

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With acknowledgements to: William Avery (MS Student), Catie Finkenbiner (UCARE Student), Tiejun Wang (Postdoc), Foad Foolad (PhD Student), Chase Johnson (Crop consultant), Darin Desilets (HydroInnova LLC), Gary Womack (HydroInnova LLC), and Luca Brocca (IRPI)

Funding provided by: CRREL through the Great Plains CESU, NSF EPSCOR FIRST, USGS104b, and UNL Layman Award

What have I learned since last years workshop and where is my lab group going

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  - Commodity prices dictate level of risk for new monitoring solutions
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- Last years MOISST workshop led to new and fruitful areas of research

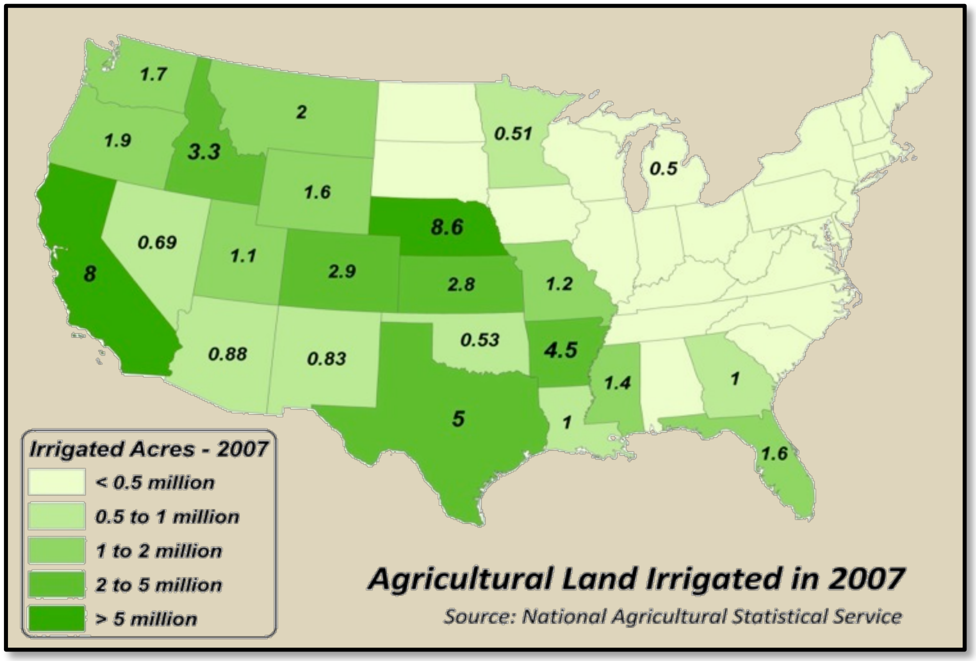
- Advanced center-pivot irrigation techniques can break apart field into 2 degree pie slices (Variable Speed, up to 180 management zones per field) and individual nozzle controls (Variable Rate, up to 5400 management zones field)

- Clear need for developing pragmatic soil moisture monitoring techniques to harness existing irrigation technology for optimal water management

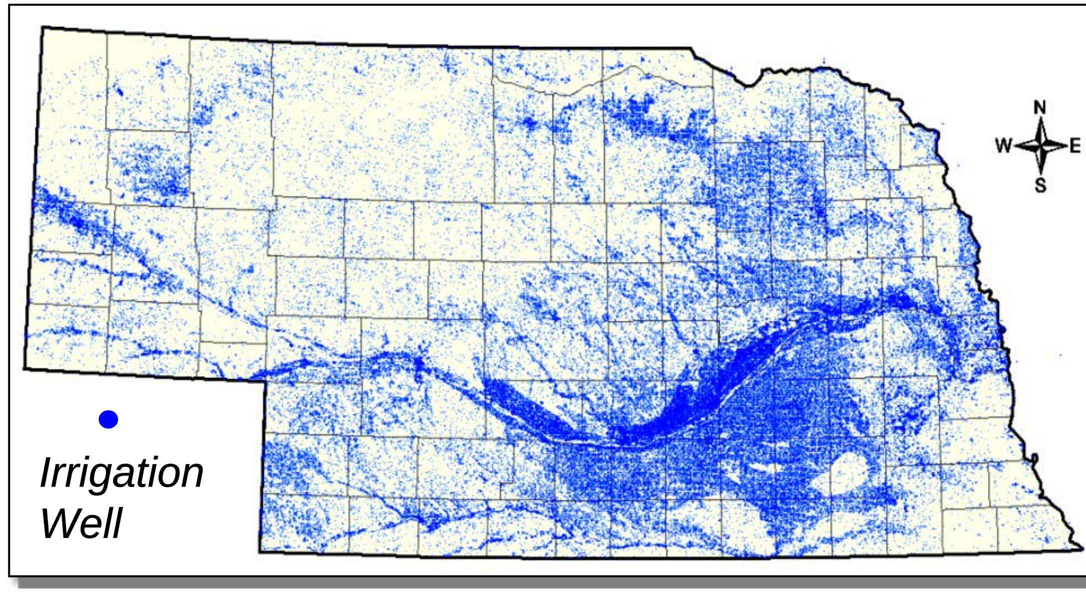

Images courtesy of Valmont Inc.

Irrigation Agriculture

~60,000 center-pivot irrigation systems in Nebraska alone!



- **16% Of National Irrigated Land Is In Nebraska**
- **90% Of Water Withdrawal Is For Irrigation**



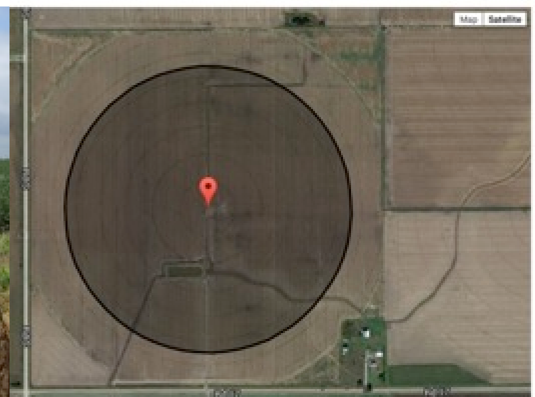
~ 93,000 Active Irrigation Wells
$6-8 Billion Investment

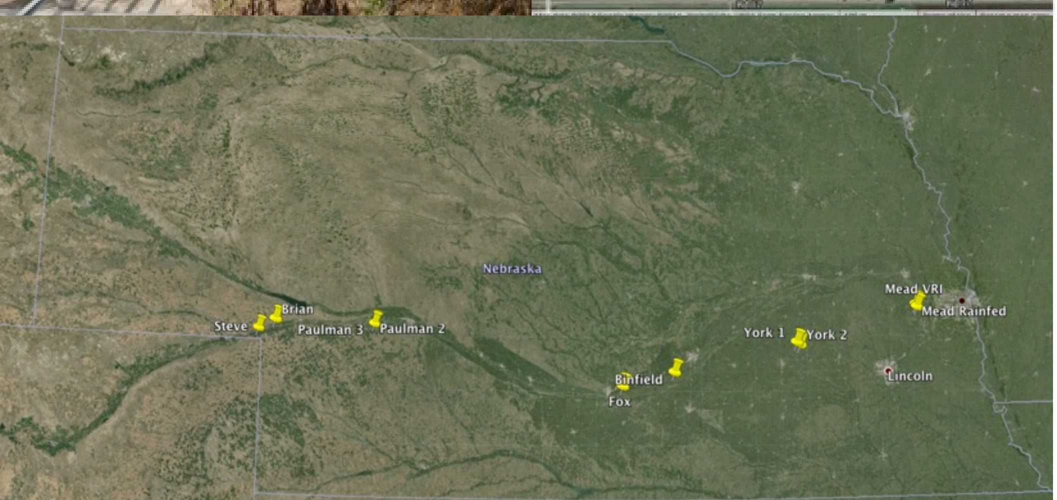
Figures courtesy of D. Martin (UNL)

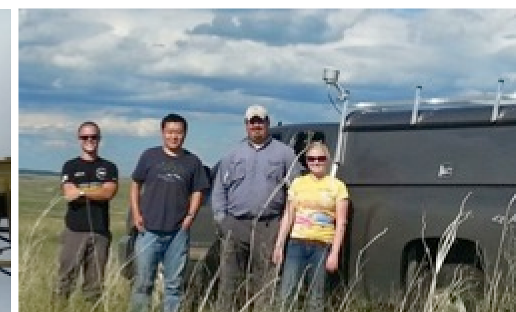
Lab Group Summary

Research: Understand the flow of water through natural and human dominated ecosystems

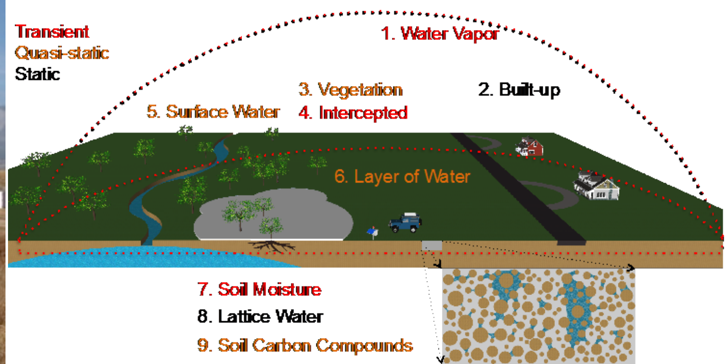
Extension: Expose or incorporate useful hydrogeophyscial technologies into practice of stakeholders across the state.
How many inches of water can this technology save?

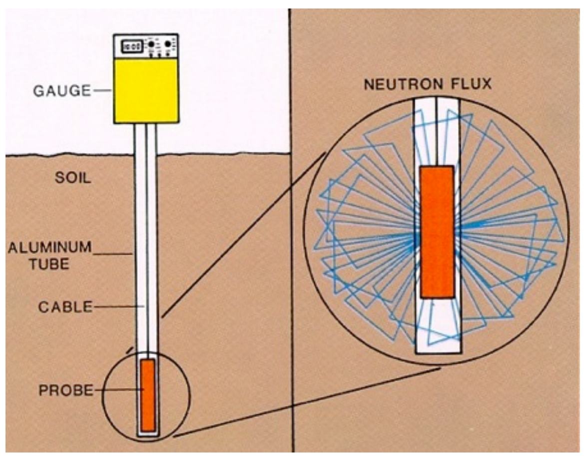






A Comparison of Neutron Probes

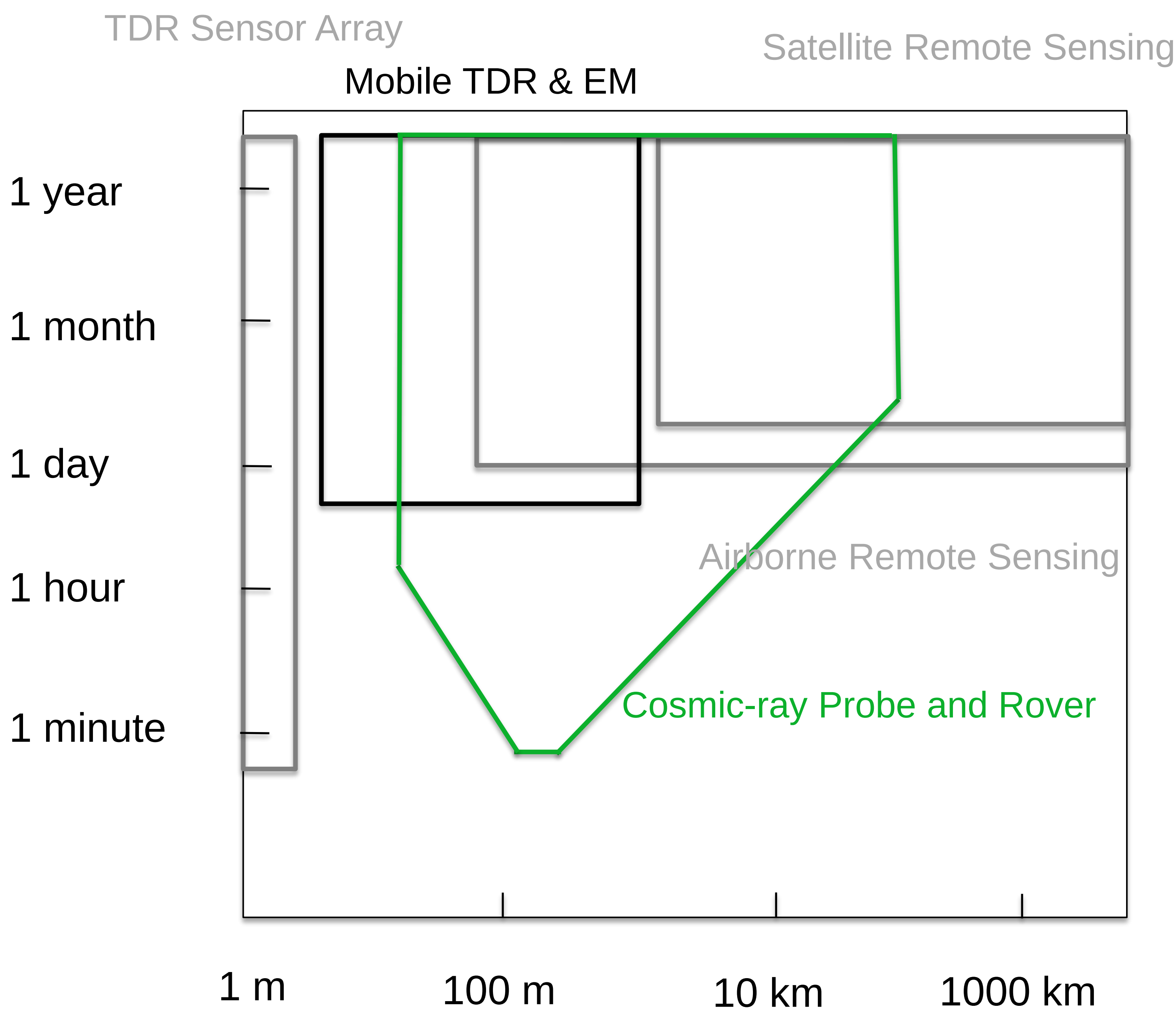




- Essentially same detector but with updated electronics and high voltage NPMs
- Same basic physics as in-situ neutron probe
- Passive sensor, uses cosmic-ray neutrons as source
- Relates fast neutrons to water content instead of slow or thermal neutrons
- Footprint is ~1000x larger (density of soil vs. air)
- Probe sees about top 30 cm
- In-situ probe considered gold standard in agronomy and soil physics

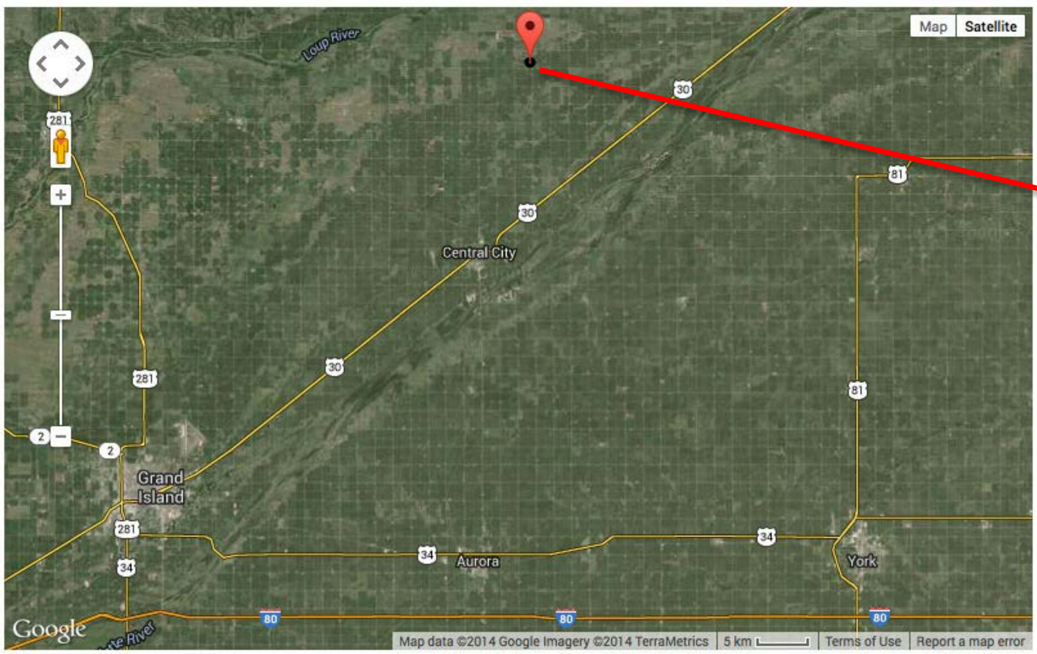
http://sanangelo.tamu.edu/agronomy/sorghum/neutron.htm

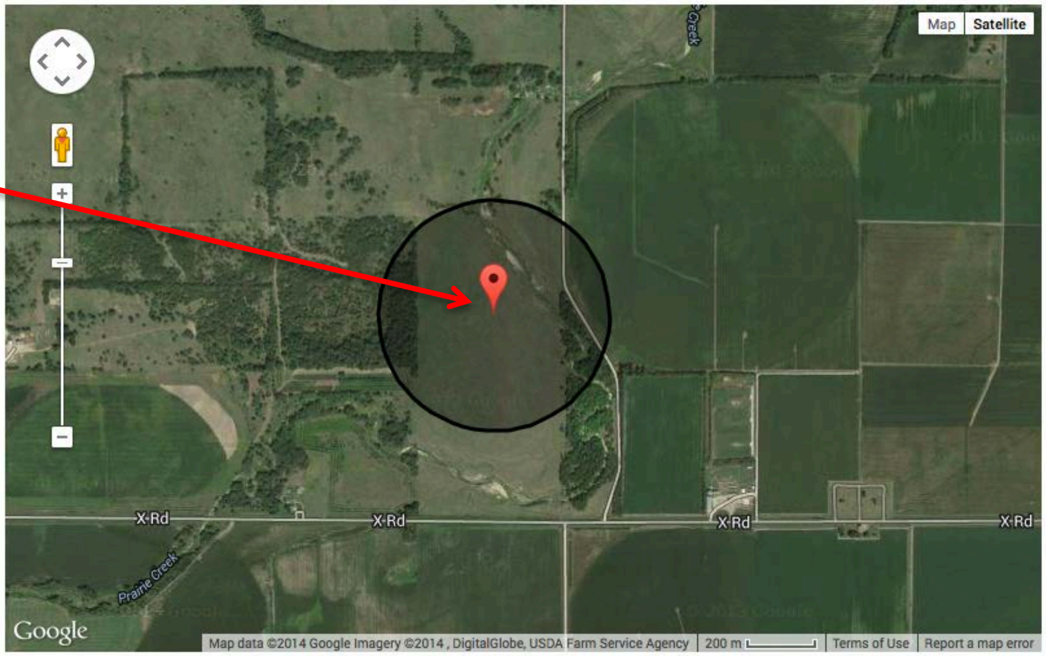
Measurements of Soil Moisture



Adapted from Robinson (2008)

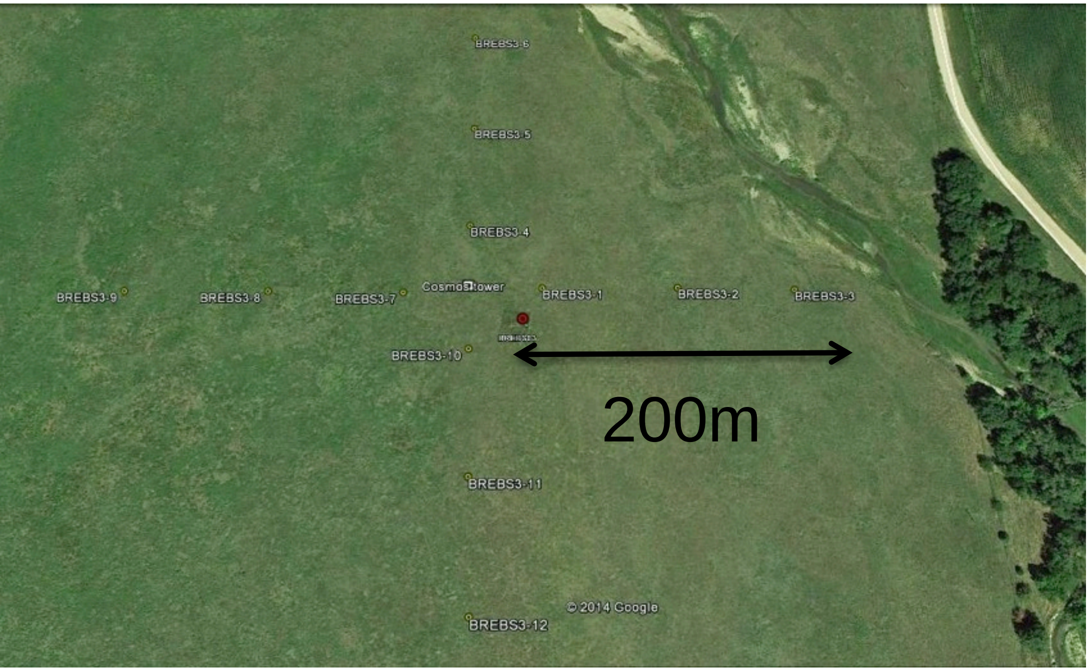
June-July 2014, near Central City, NE
Installed 12 profiles of Watermark sensors and 1 cosmic-ray sensor

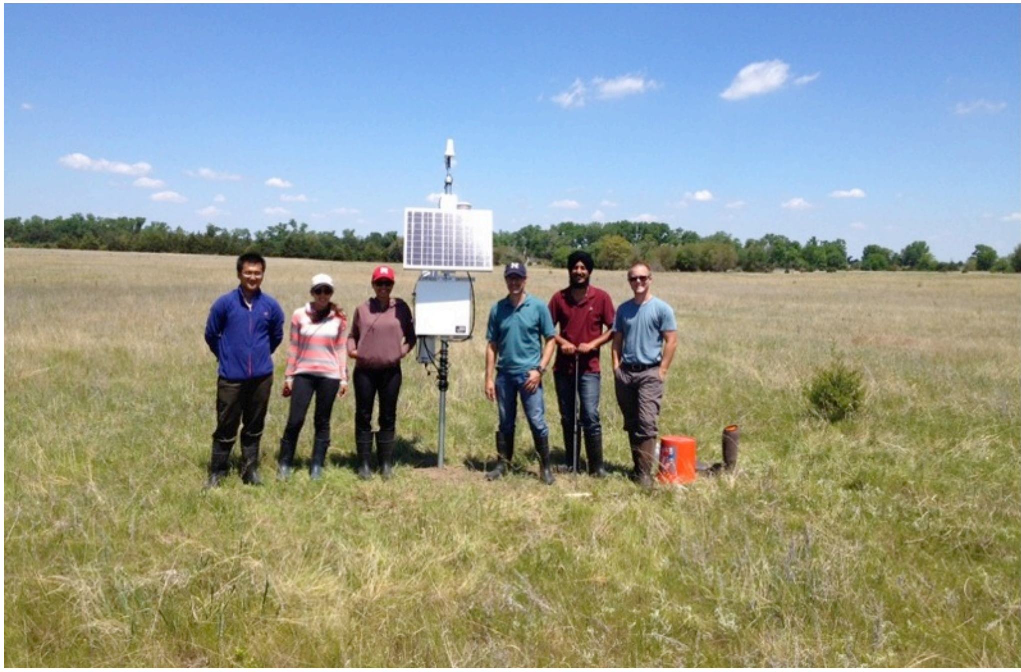




In collaboration with S. Irmak, A. Kilic, and A. Diotto

Field is fairly flat, homogeneous vegetation, sandy loam soil texture, ideal setting for homogeneity?





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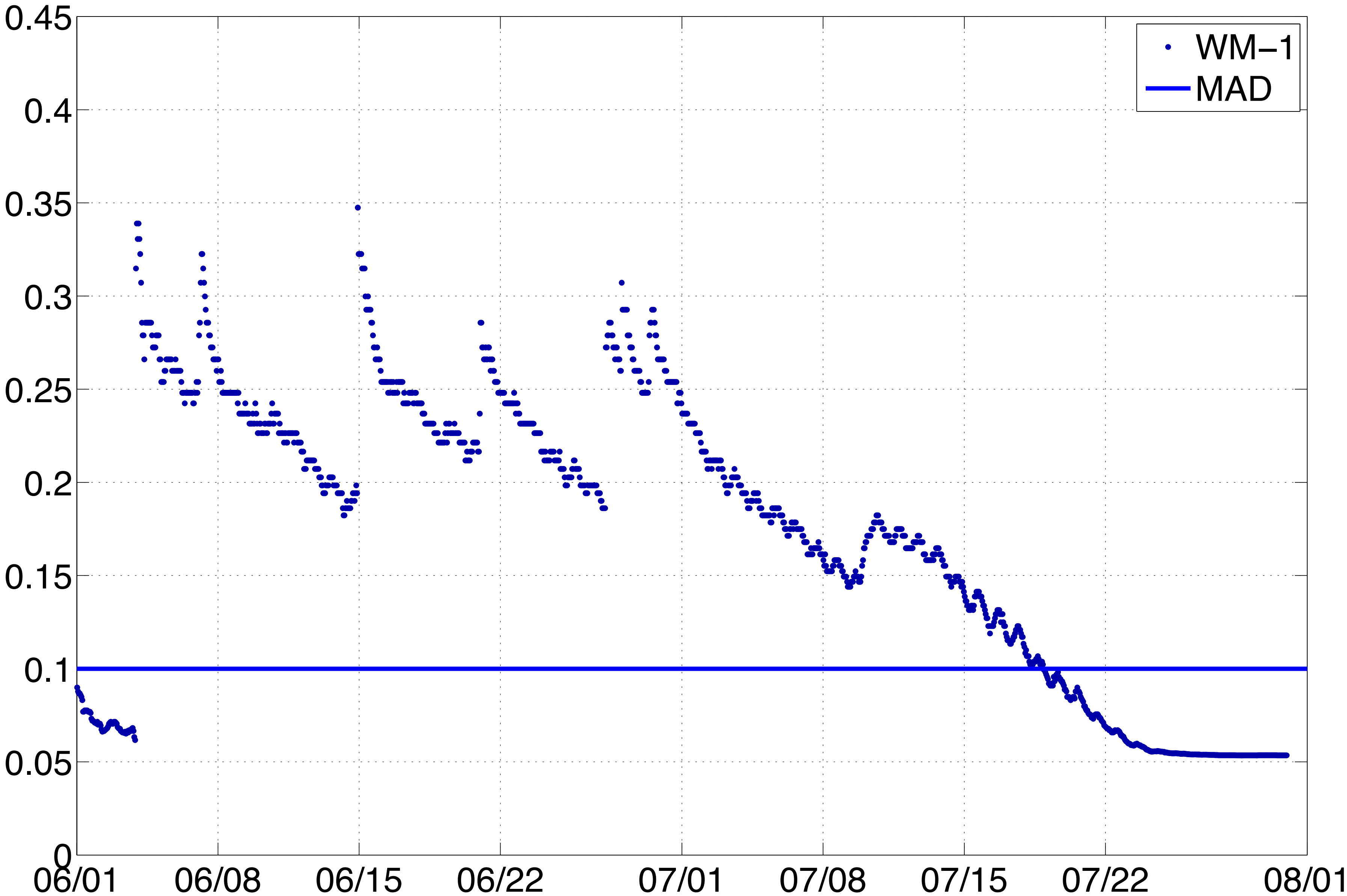
How to Train Your Point Sensor



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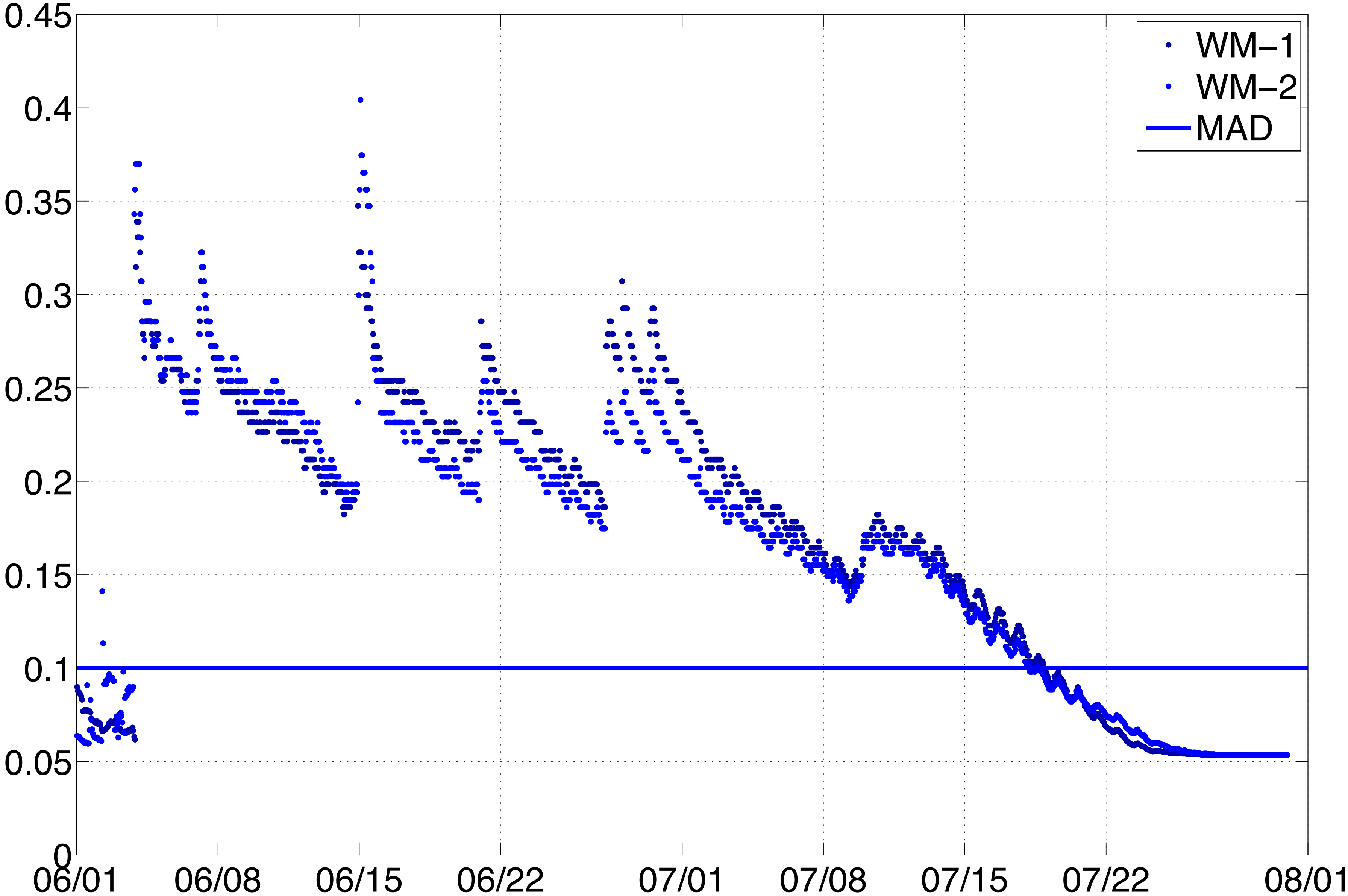

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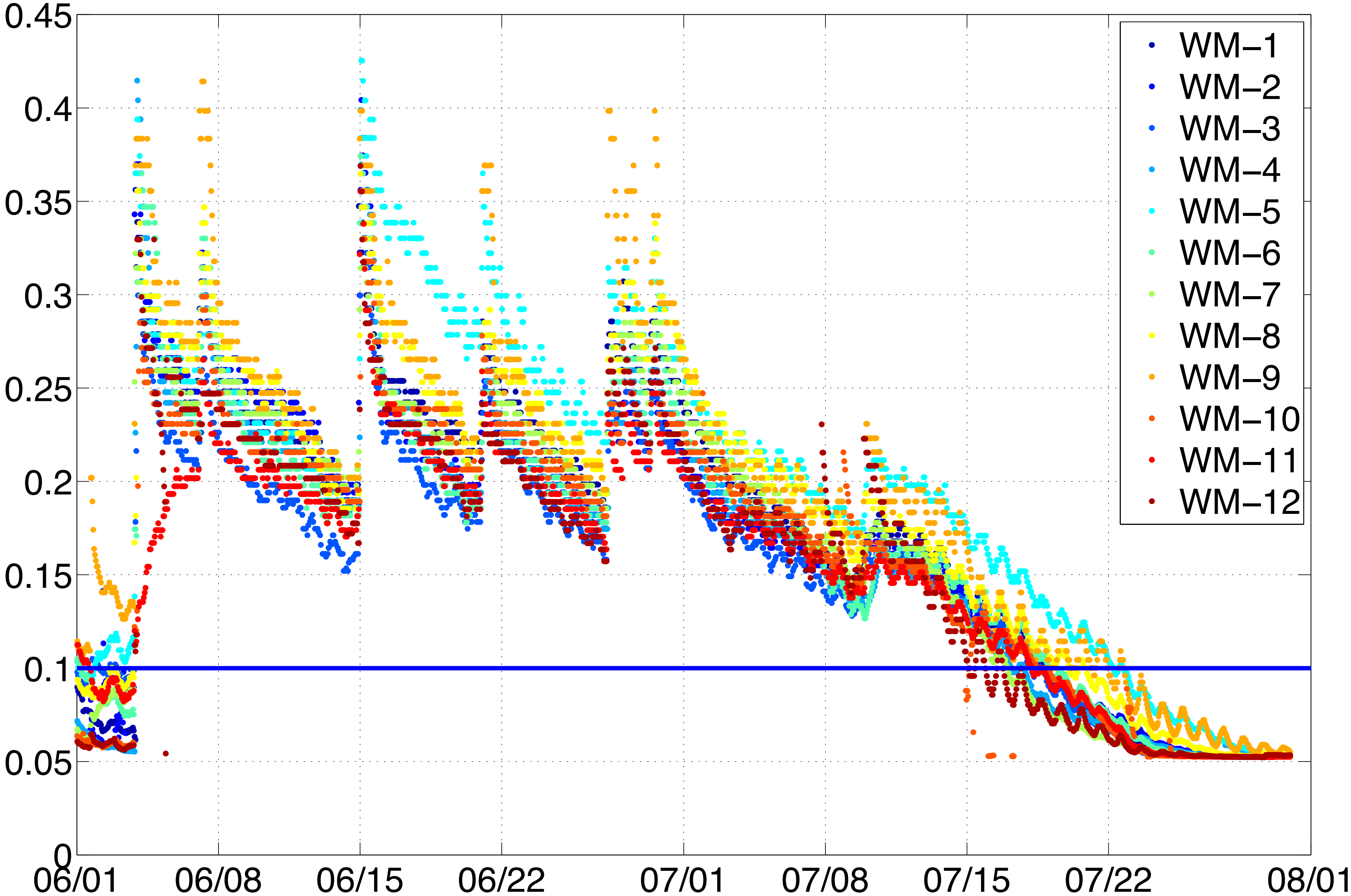

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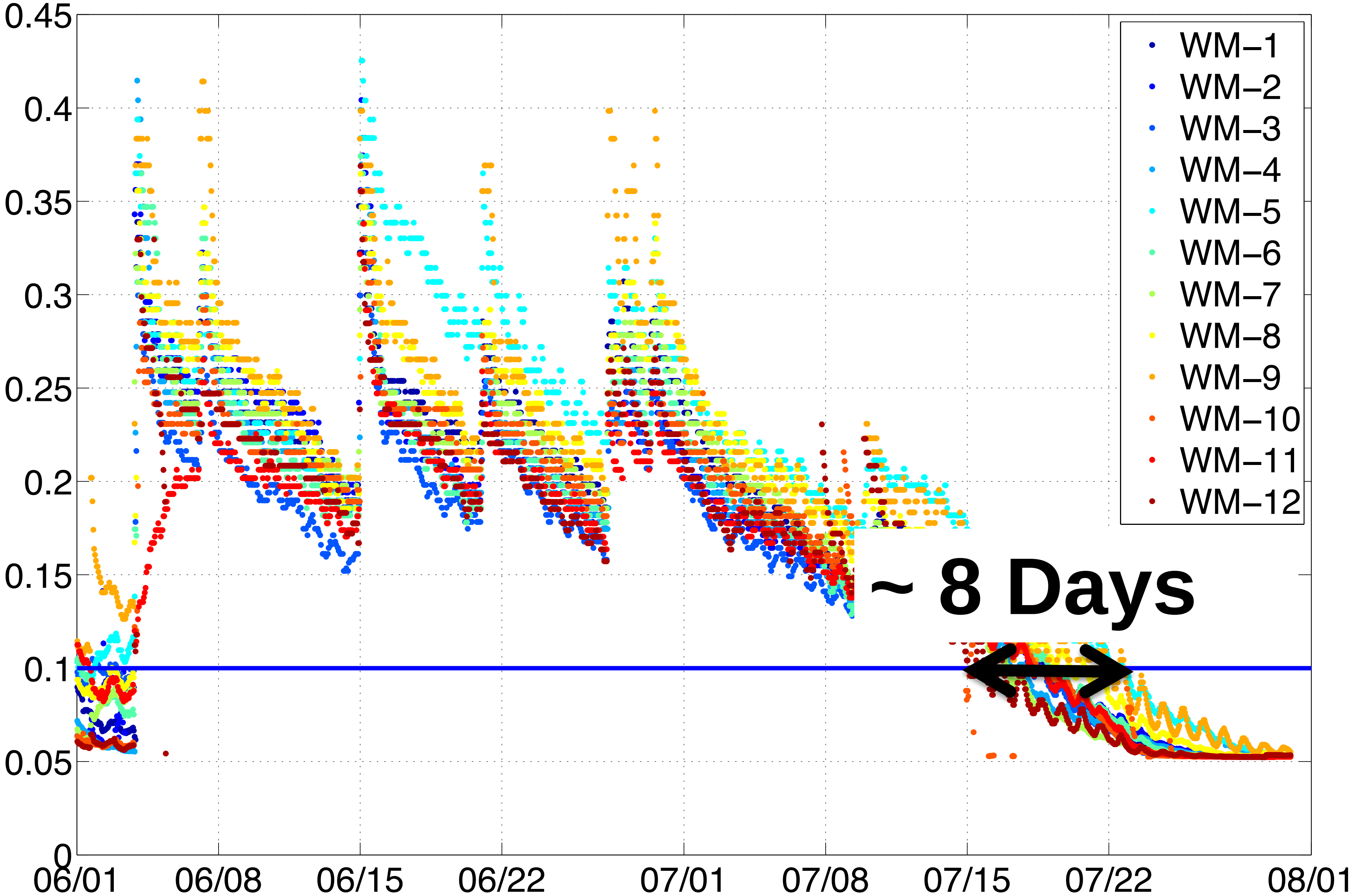

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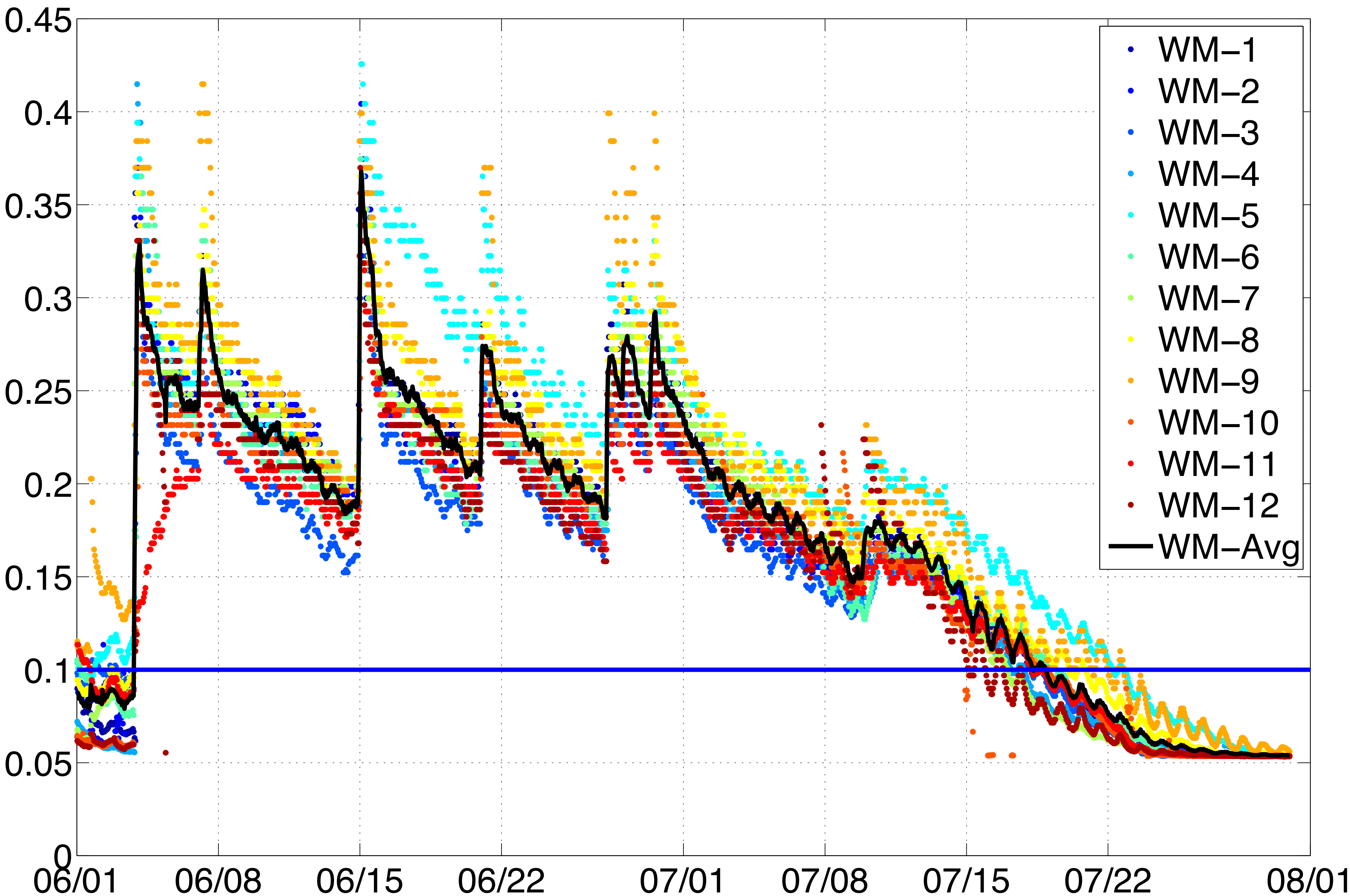

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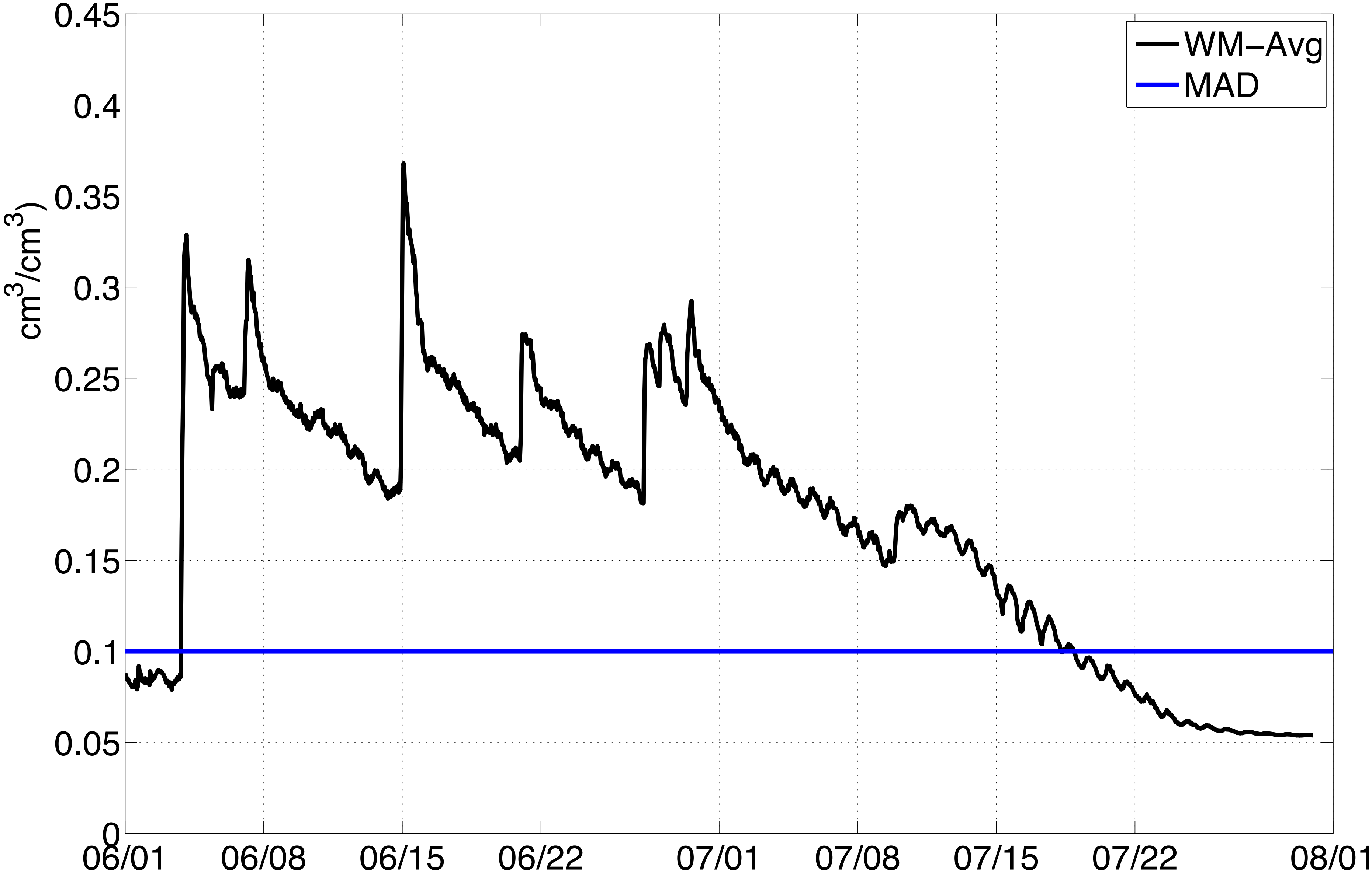

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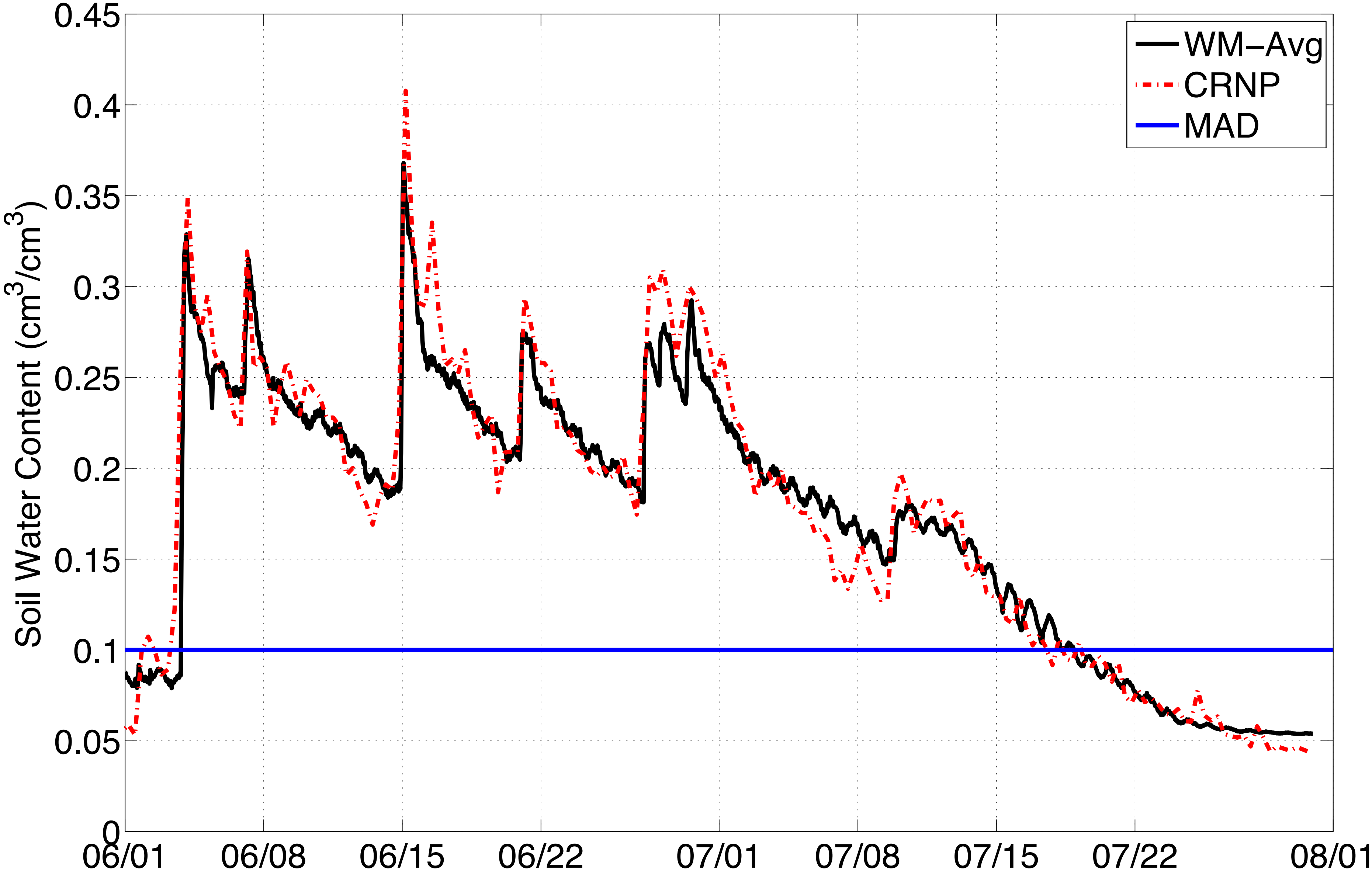

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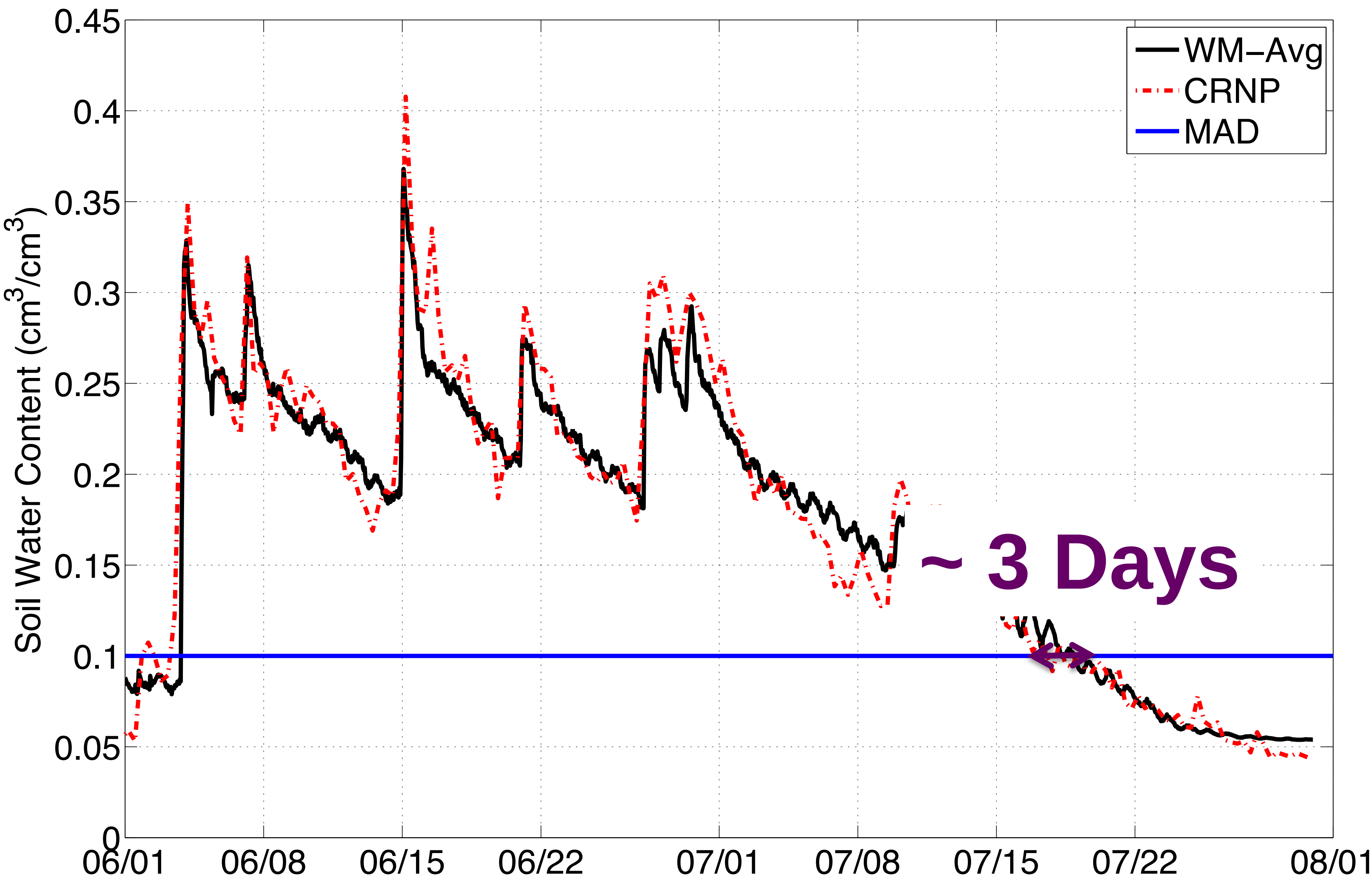

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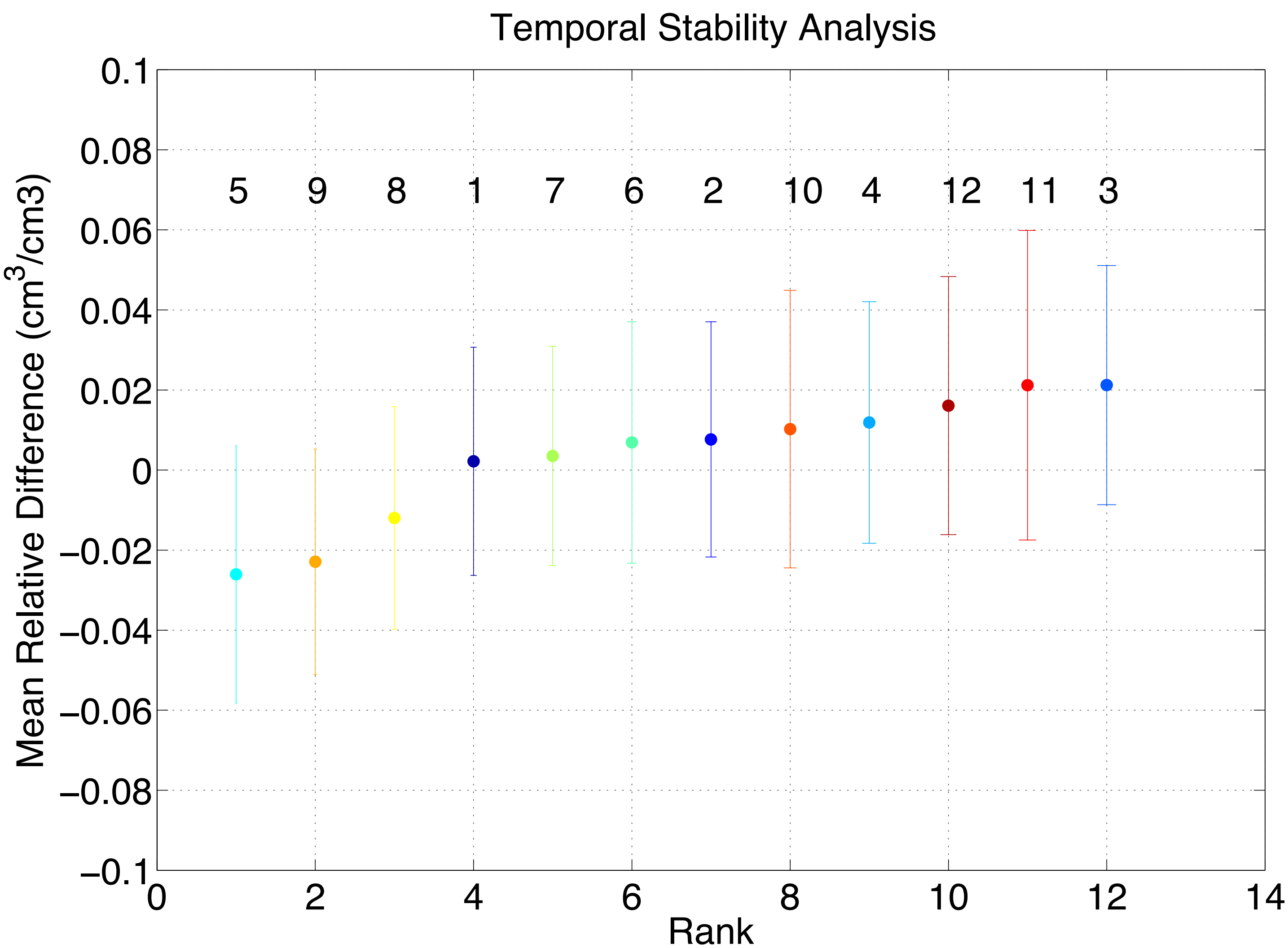
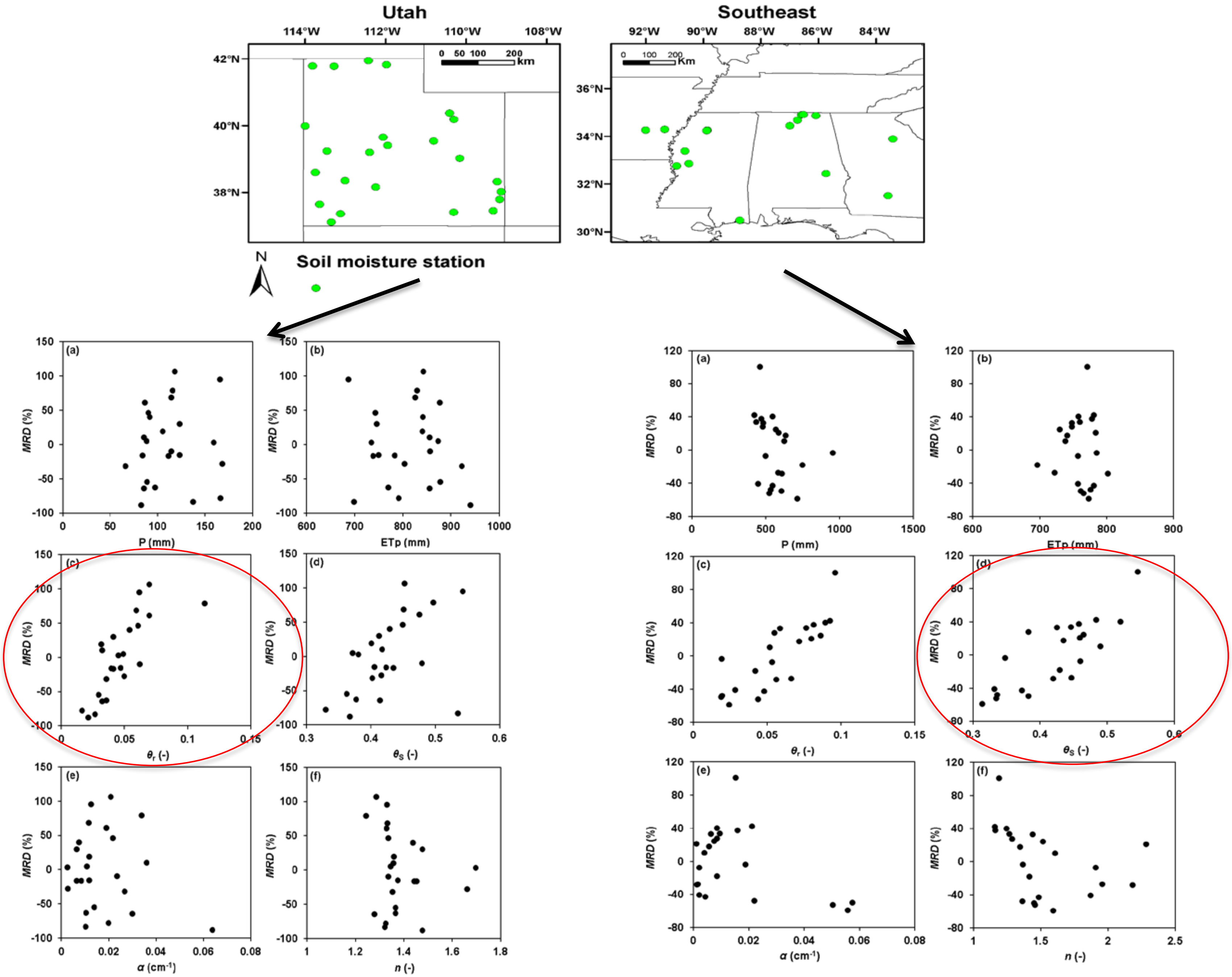


$$RD_{ij} = \frac{\theta_{ij} - \bar{\theta}_j}{\bar{\theta}_j}$$

$$MRD_i = \frac{1}{m}\sum_{j=1}^{m} RD_{ij}$$

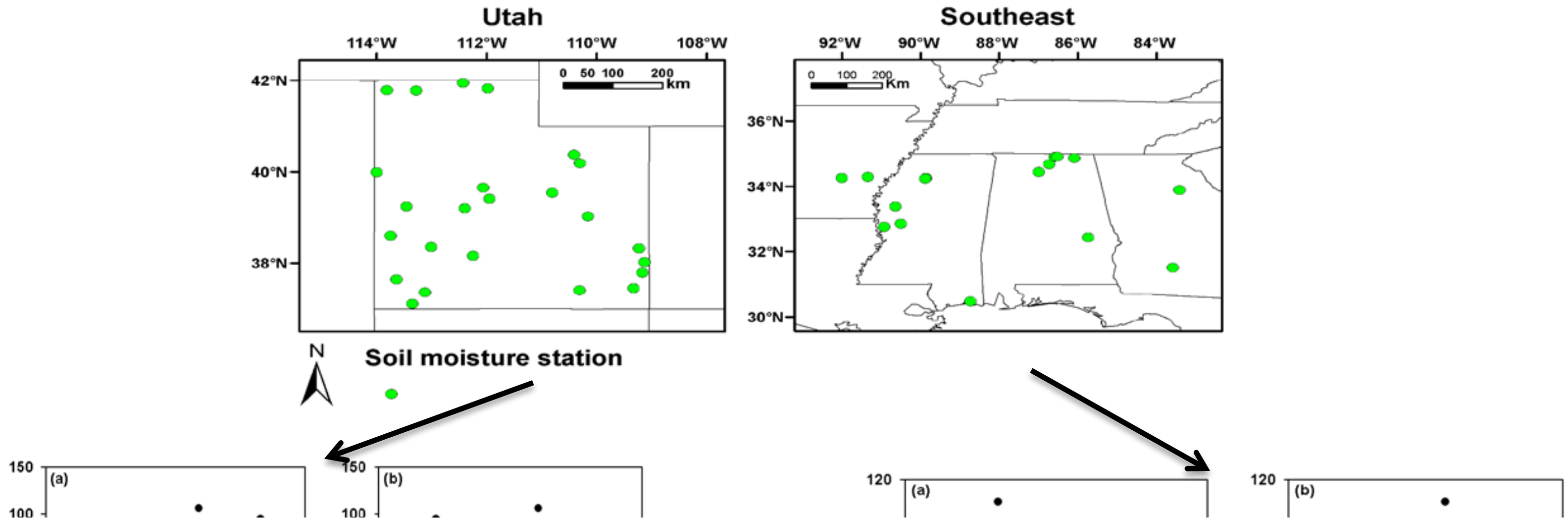
Following Vachaud et al. (1985) and others

How to Train Your Mesonet?



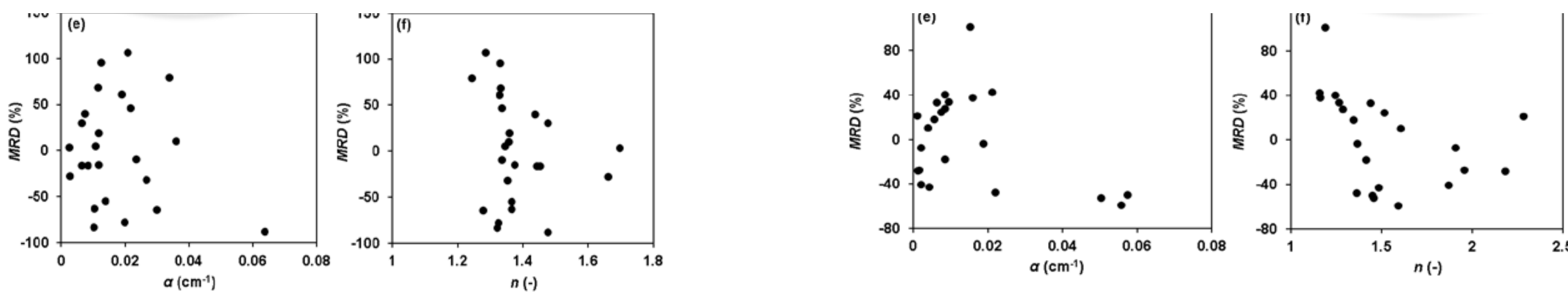
Wang and Franz (2015) VZJ in press

How to Train Your Mesonet?



Point scale soil moisture observations from SCAN mesonet shows MRD controlled by soil texture/hydraulic properties instead of climatology as previously thought.

Why?



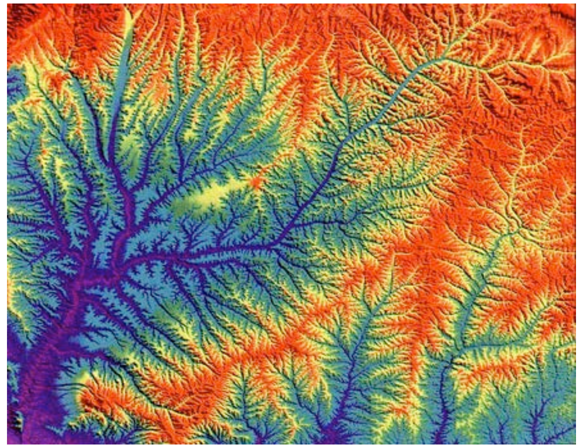
Wang and Franz (2015) VZJ in press

Scaling Problem, Fractals

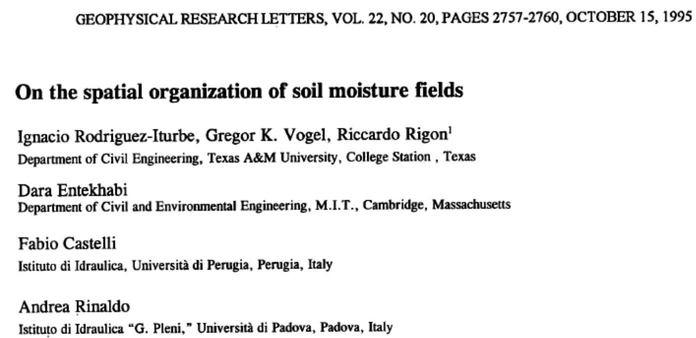
Canopy and Root Architecture

Koija Group Ranch, Kenya, Feb. 2007

River Basins/Channel Networks



https://uwana.wordpress.com/2012/07/



GEOPHYSICAL RESEARCH LETTERS, VOL. 22, NO. 20, PAGES 2757-2760, OCTOBER 15, 1995

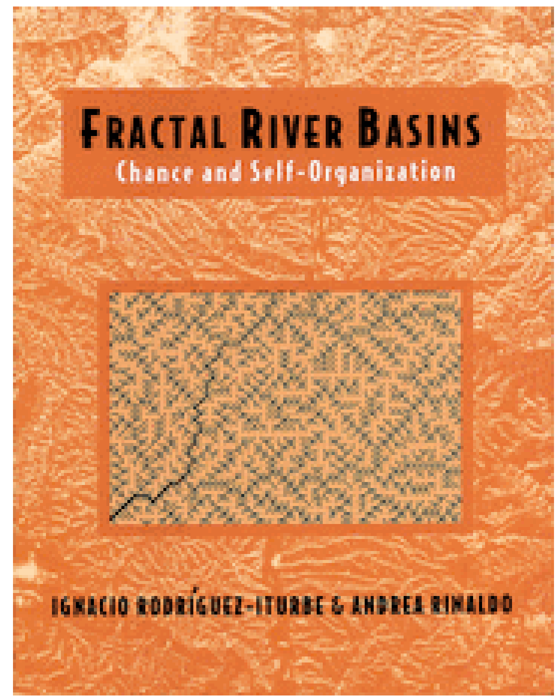
On the spatial organization of soil moisture fields

Ignacio Rodriguez-Iturbe, Gregor K. Vogel, Riccardo Rigon[1]
Department of Civil Engineering, Texas A&M University, College Station, Texas

Dara Entekhabi
Department of Civil and Environmental Engineering, M.I.T., Cambridge, Massachusetts

Fabio Castelli
Istituto di Idraulica, Università di Perugia, Perugia, Italy

Andrea Rinaldo
Istituto di Idraulica "G. Pleni," Università di Padova, Padova, Italy



Soil Properties

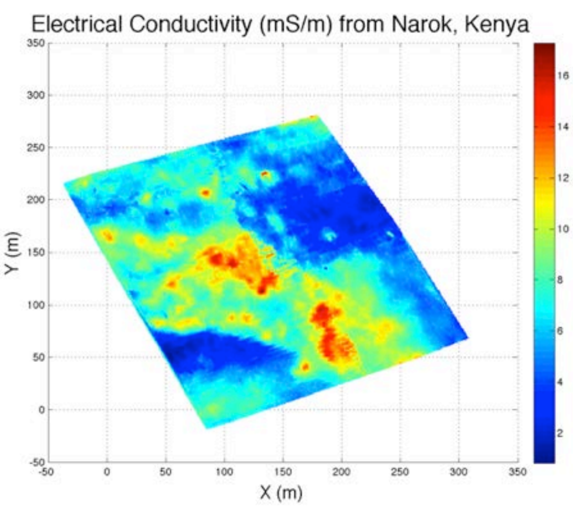
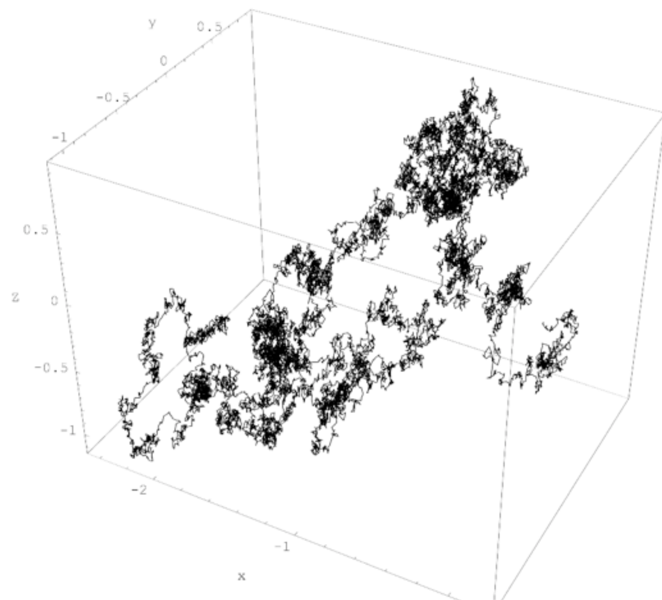


Image from Franz et al. (2011)

Brownian Motion



http://en.wikipedia.org/wiki/Wiener_process

Space-time Mapping of Soil Moisture

Deployed 3 stationary CRS sensors recording hourly soil moisture in irrigated maize, soybean and rainfed maize/soybean near Waco, NE.

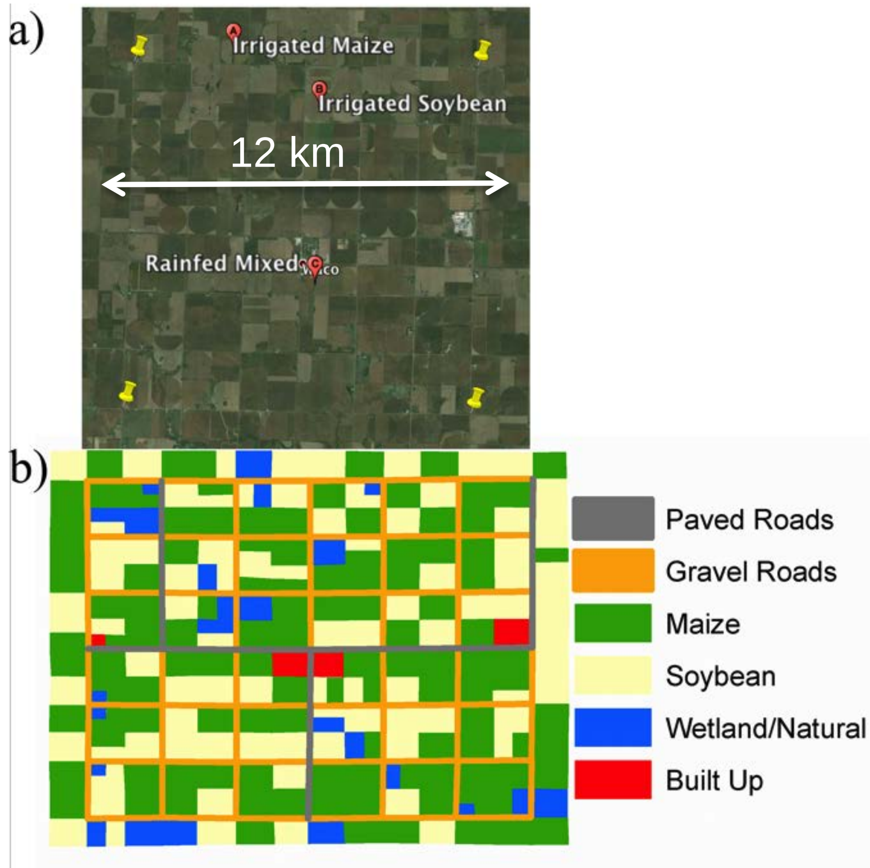
Used roving CRS to make daily soil moisture maps every week over a 12x12 km grid with 1.6 km spacing between May and September 2014.

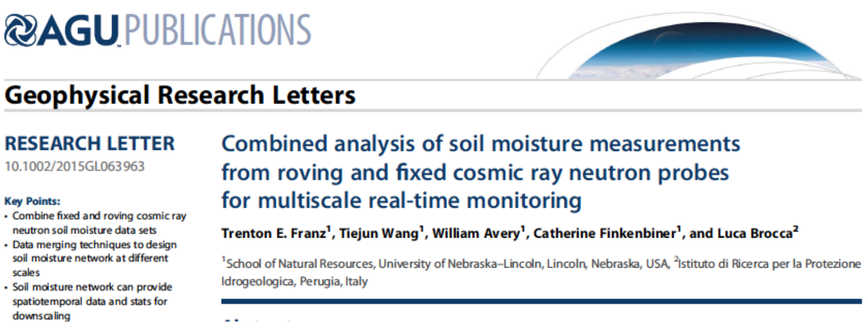
Goal to make continuous soil moisture estimates at individual quarter section level (~0.8 km) using statistical methods

Roving Sensor

Stationary Sensor

Study Area and Layout of Sensors





AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER
10.1002/2015GL063963

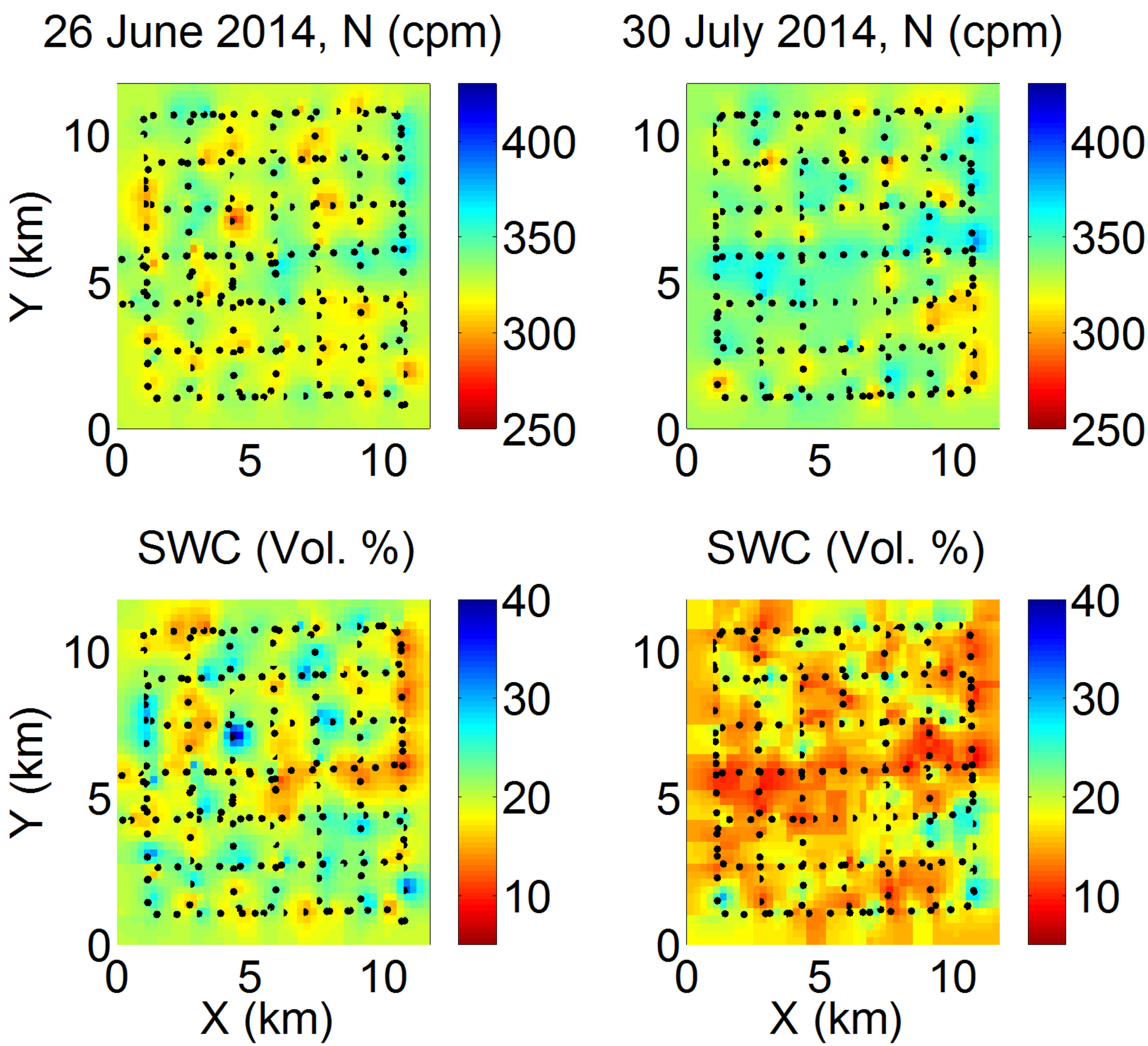
Key Points:
- Combine fixed and roving cosmic ray neutron soil moisture data sets
- Data merging techniques to design soil moisture network at different scales
- Soil moisture network can provide spatiotemporal data and stats for downscaling

Combined analysis of soil moisture measurements from roving and fixed cosmic ray neutron probes for multiscale real-time monitoring

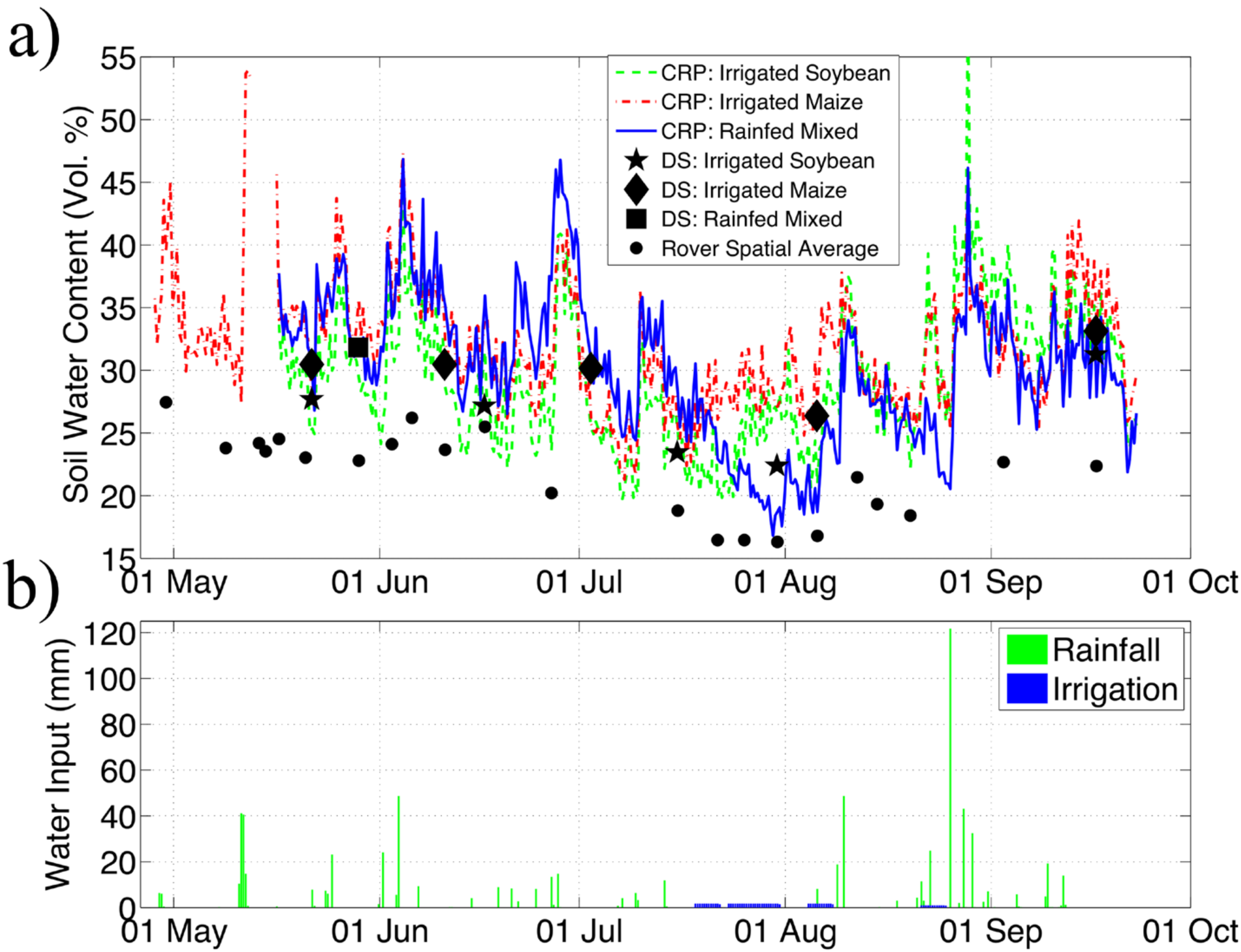
Trenton E. Franz[1], Tiejun Wang[1], William Avery[1], Catherine Finkenbiner[1], and Luca Brocca[2]

[1]School of Natural Resources, University of Nebraska–Lincoln, Lincoln, Nebraska, USA, [2]Istituto di Ricerca per la Protezione Idrogeologica, Perugia, Italy

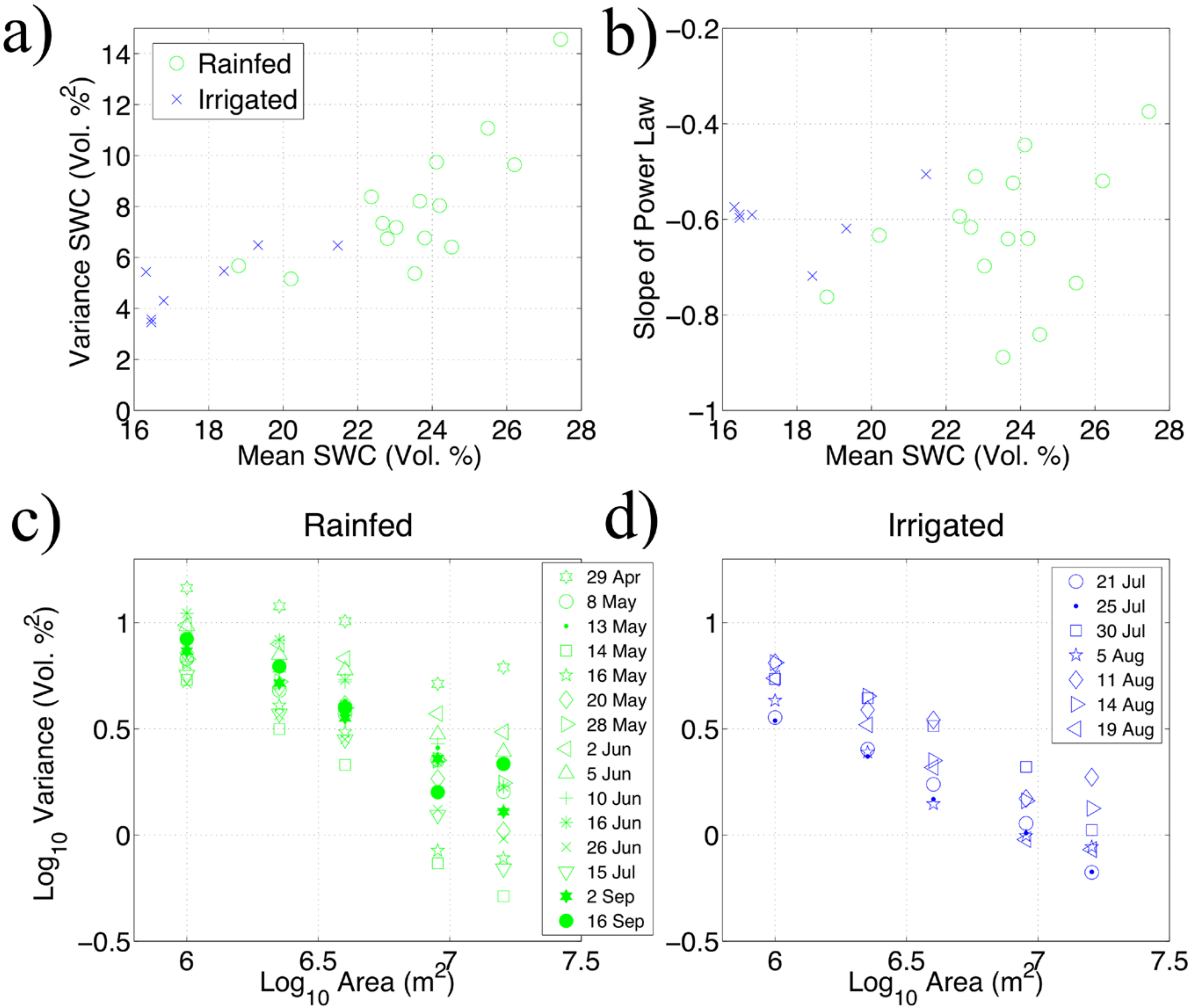
Roving CRS Results



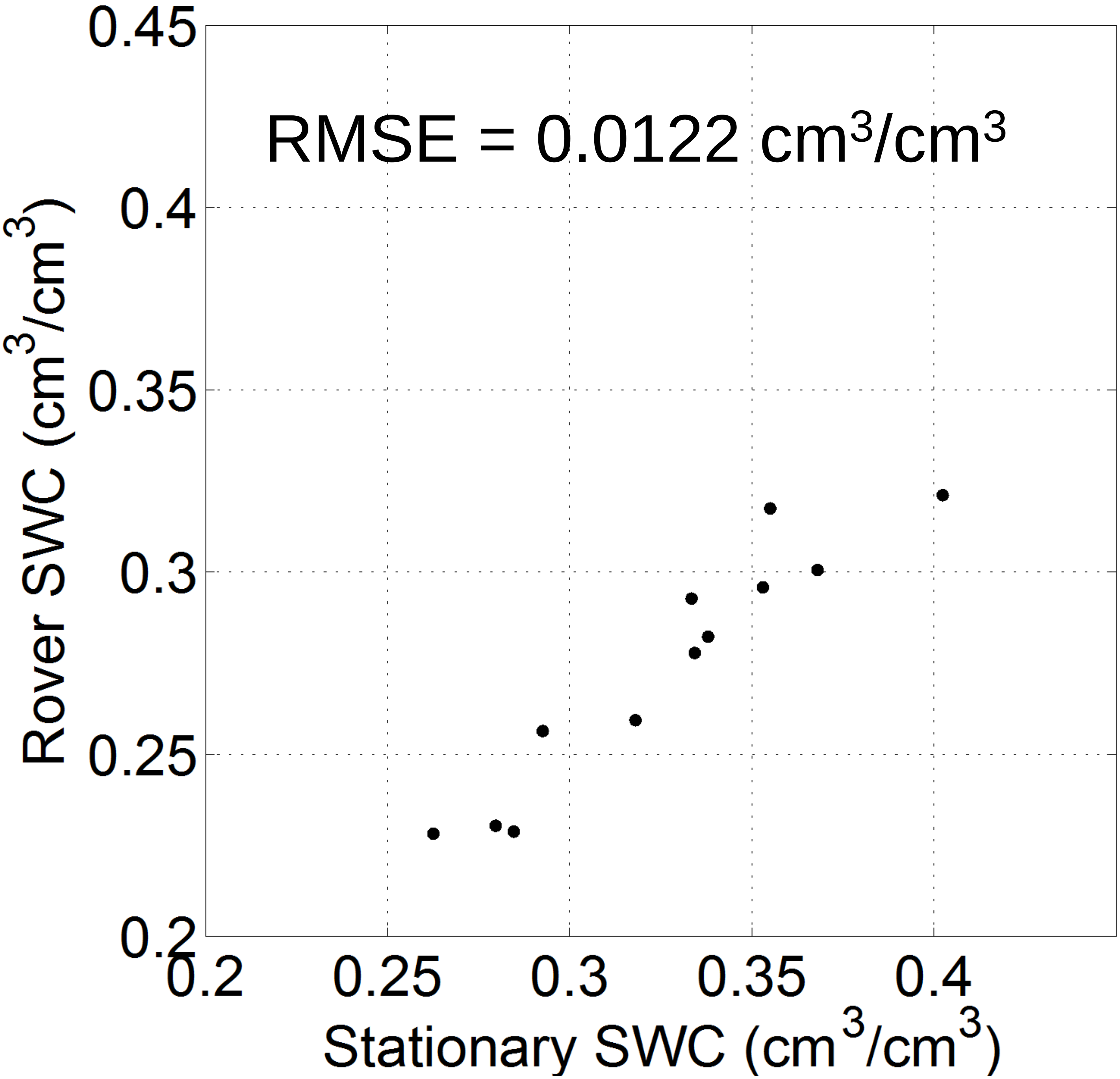
CRS and Rover Validation



Statistical Properties

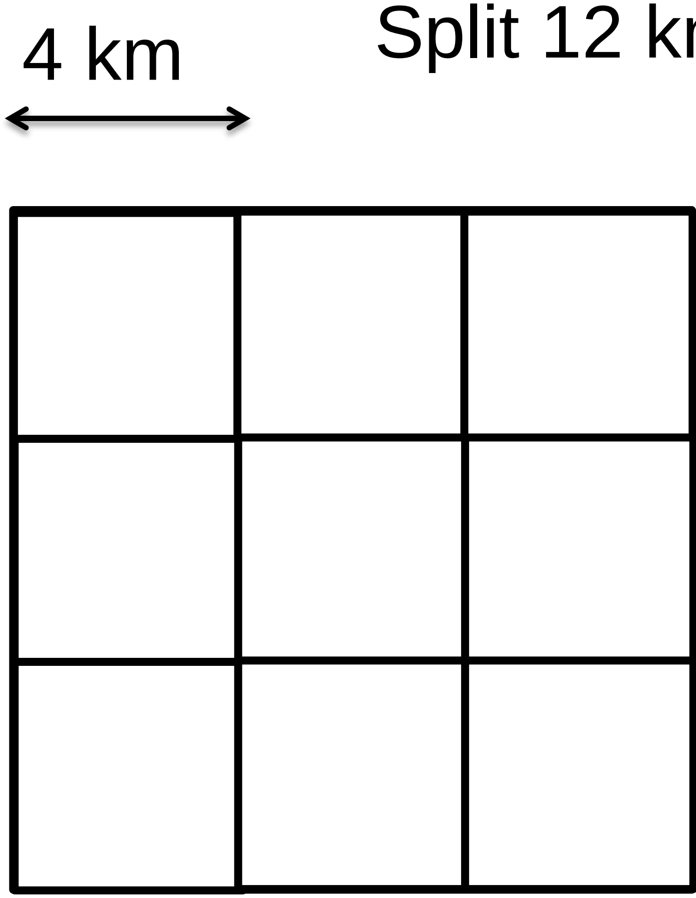


Correlation Between Probes



Correlation Between Probes

Split 12 km domain into 9 4x4 km subdomains



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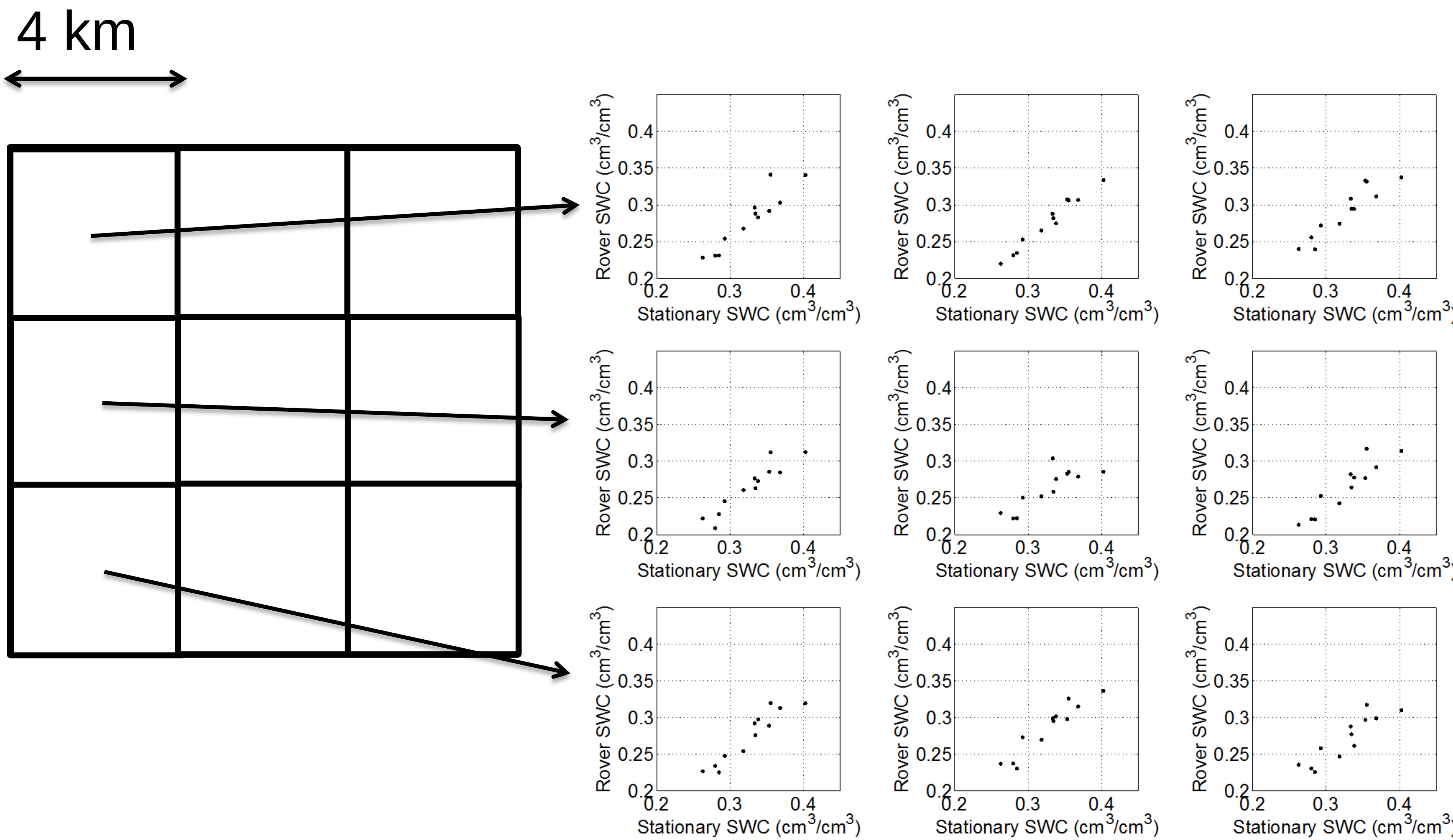

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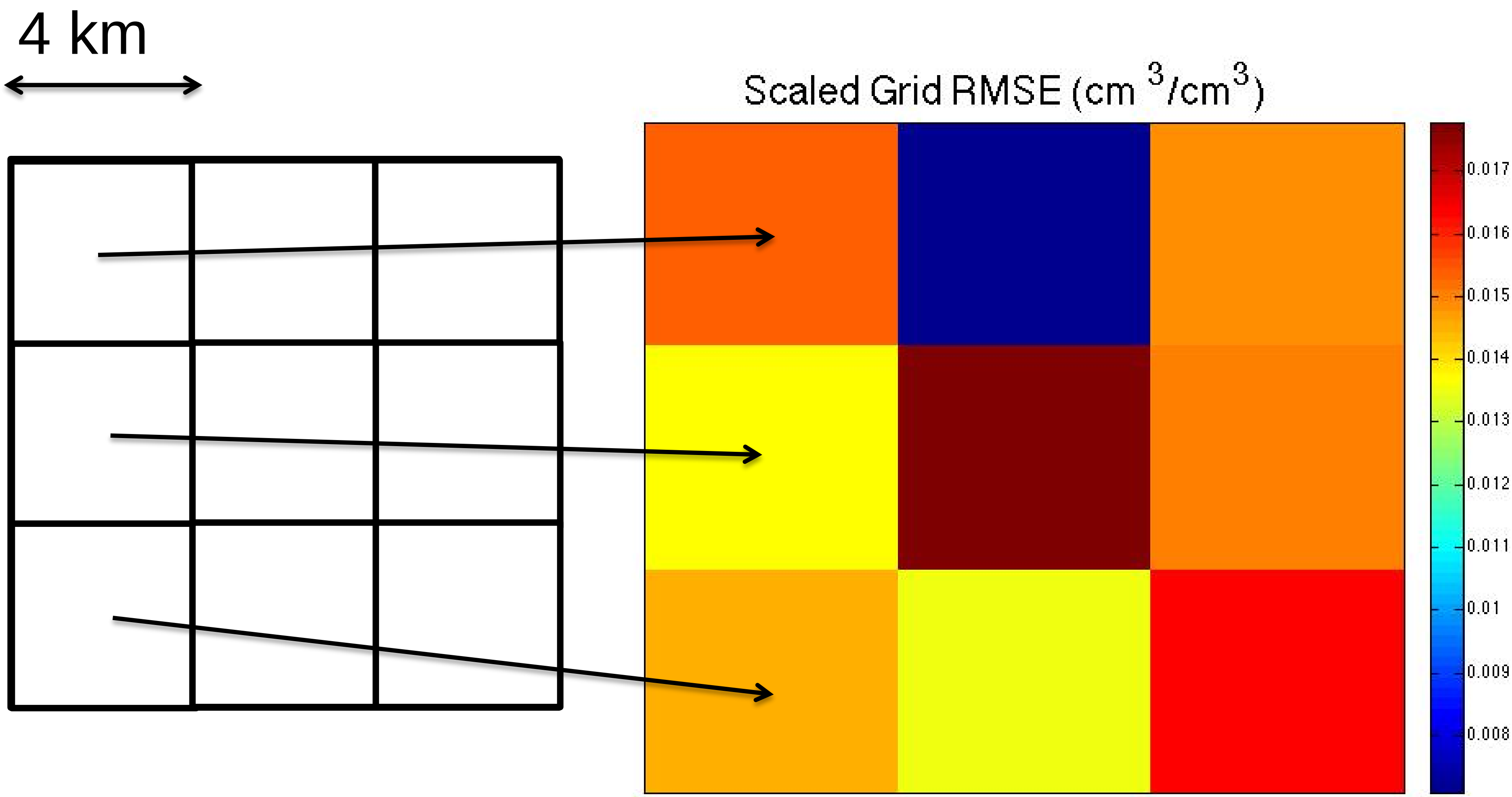
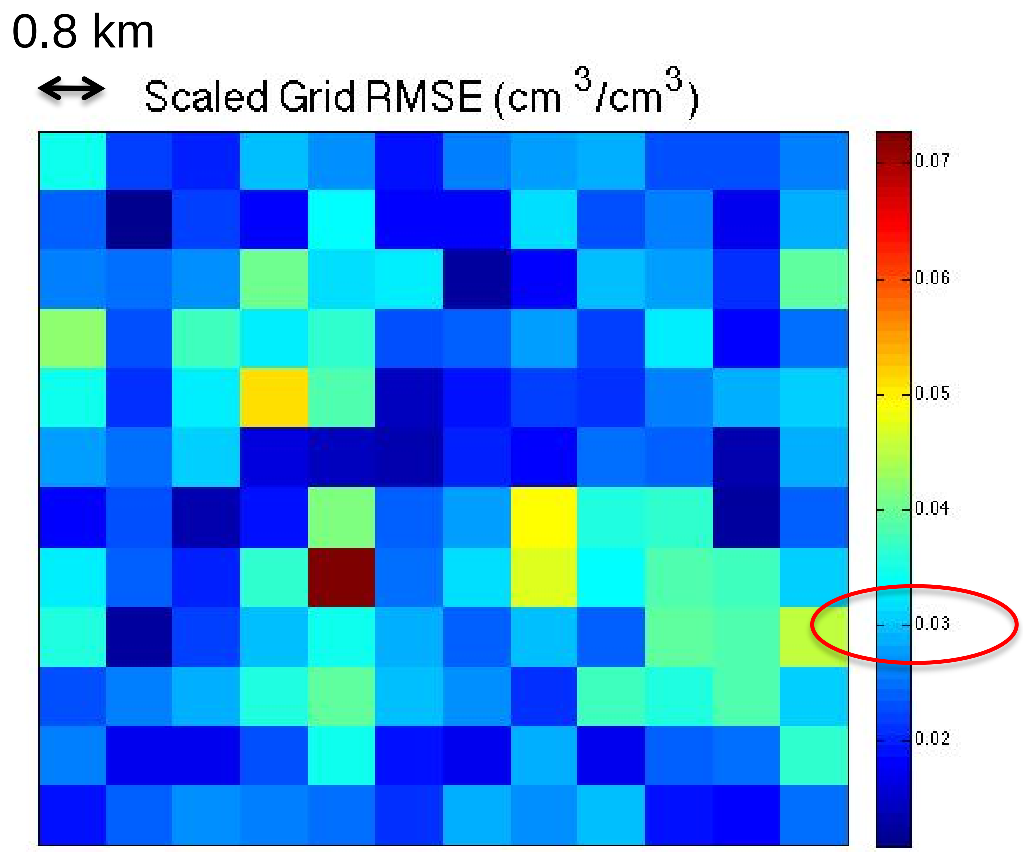


Correlation Between Probes

Split 12 km domain into 144 quarter section subdomains



CRP Network Design

- Combined fixed and mobile cosmic-ray probes to provide a realtime SWC monitoring network at ~1 km resolutions over a 144 km^2 domain with 3 stationary CRS and 20 CRS rover surveys with RMSE< ~3%
- Rover mapping can provide invaluable information to remote sensing
  - i.e. comparison of mean, relationship between mean and variance, spatial and temporal covariance matrices for downscaling
- Is the network cost effective? Are there better ways to design the network?

Previous work on network design

VOL. 10, NO. 4 WATER RESOURCES RESEARCH AUGUST 1974

The Design of Rainfall Networks in Time and Space

IGNACIO RODRÍGUEZ-ITURBE

Department of Civil Engineering, Massachusetts Institute of Technology, Cambridge, Massachusetts 02139

JOSÉ M. MEJÍA

Instituto Venezolano de Investigaciones Científicas, Caracas, Venezuela

3. For estimating long-term areal mean values of precipitation the commanding factor is the length of time that the network has been in operation.
4. Trading time versus space is possible in many cases when long-term areal mean values are estimated. Nevertheless, it is an expensive proposition.

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Soil moisture

Effective infiltration from rainfall

Losses

$$nZ_r \frac{dS(\mathbf{u},t)}{dt} = (1-\phi)Y(\mathbf{u},t) - VS(\mathbf{u},t),$$

WATER RESOURCES RESEARCH, VOL. 42, W05409, doi:10.1029/2005WR004548, 2006

On the spatial and temporal sampling of soil moisture fields

Salvatore Manfreda[1,2] and Ignacio Rodríguez-Iturbe[1]

Received 1 September 2005; revised 10 January 2006; accepted 24 January 2006; published 3 May 2006.

greatest gain in information for the estimation of the long-term mean daily soil moisture in a region is obtained with an initial, relatively small, number of stations.

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WATER RESOURCES RESEARCH, VOL. 42, W06D05, doi:10.1029/2005WR004497, 2006

Space-time modeling of soil moisture: Stochastic rainfall forcing with heterogeneous vegetation

I. Rodríguez-Iturbe,[1] V. Isham,[2] D. R. Cox,[3] S. Manfreda,[1,4] and A. Porporato[5]

[63] The standard deviation of the averaged relative soil moisture is particularly sensitive to the averaging spatial scale. Averaging in space considerably smoothes the relative soil moisture process; this effect depends on the the vegetation characteristics (small scale) and the structure of the rainfall process (large scale). By contrast, averaging in

[64] Comparison of the derived analytical results with the space-time correlation structure of soil moisture fields is a research priority of the authors. We are not aware of empirical soil moisture data available in space and time that will enable a strict validation of the theory. For this

The Way Forward?

Precision Agriculture

- Install network of 3-5 inexpensive point sensor profiles (1, 2, 3 ft.) with realtime data

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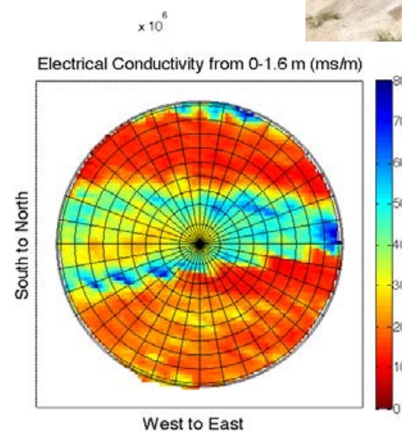
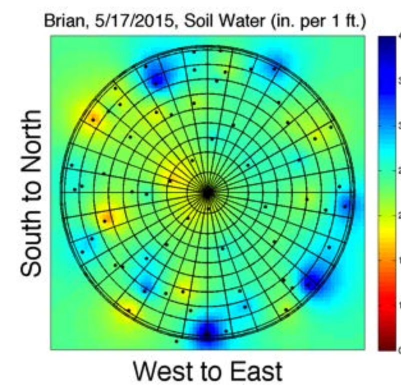
- Map field 4-6 more times with CR rover to form spatial calibration functions





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- Install network of 3-5 inexpensive point sensor profiles (1, 2, 3 ft.) with realtime data

- Map field with CREMISS for texture and soil moisture spatial patterns

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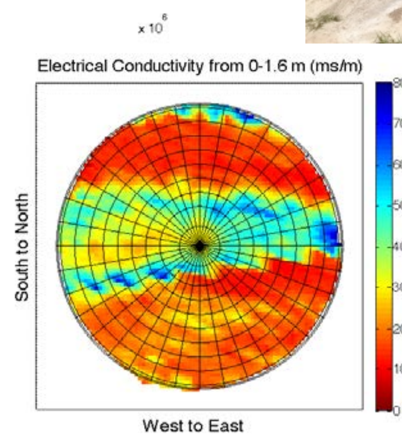
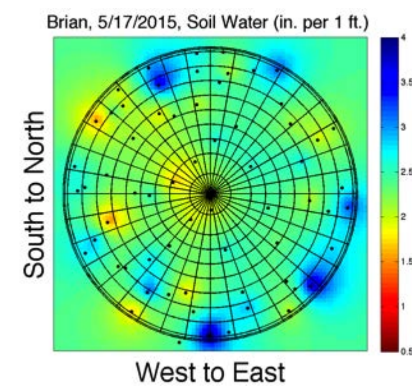
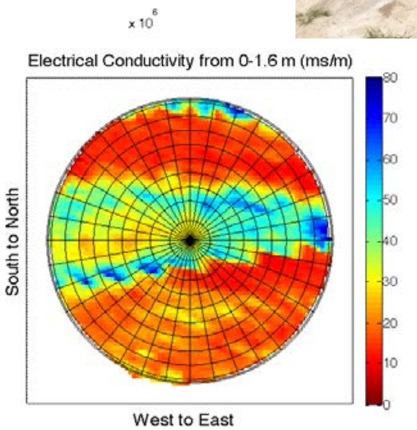
- Incorporate exponential filters for depth estimates down to 3 ft.

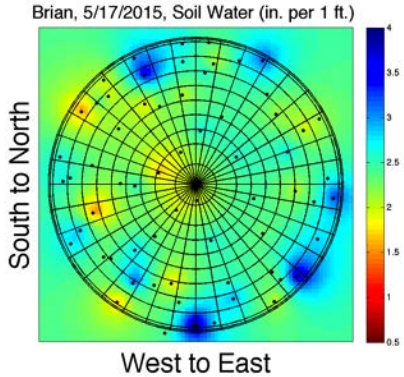


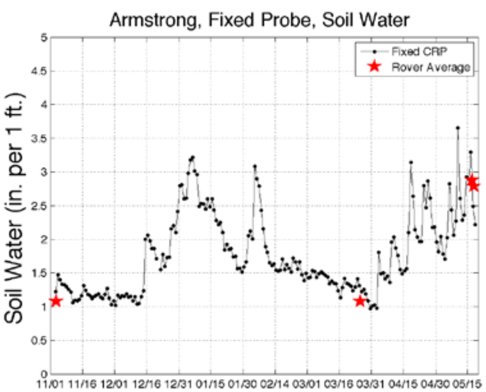


Precision Agriculture

- Install network of 3-5 inexpensive point sensor profiles (1, 2, 3 ft.) with realtime data
- Map field with CREMISS for texture and soil moisture spatial patterns
- Map field 4-6 more times with CR rover to form spatial calibration functions
- Incorporate exponential filters for depth estimates down to 3 ft.
- Provide realtime SWC statistical estimates by pivot section and 1 ft. depth increments by combining point sensor information with CREMISS mapping, spatial regression, and exponential filters

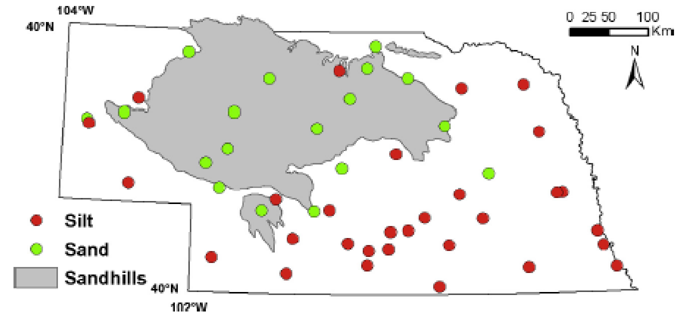






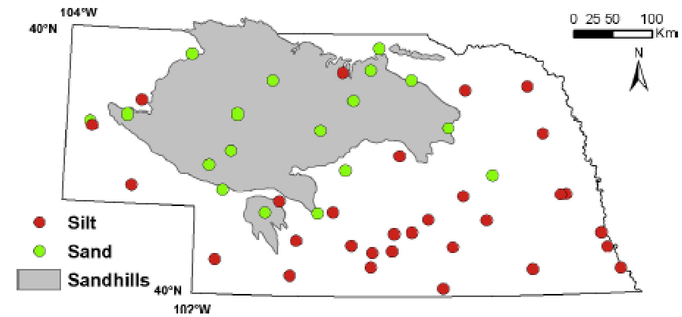
The Way Forward?

Integration with Mesonets



- Map areas with rover around longterm stations (SCAN, ADWN, OK. Mesonet, etc.), 10-15 times?

Integration with Mesonets



- Map areas with rover around longterm stations (SCAN, ADWN, OK. Mesonet, etc.), 10-15 times?

- Investigate spatial calibration functions between rover and longterm station values (0-30 cm avg.)

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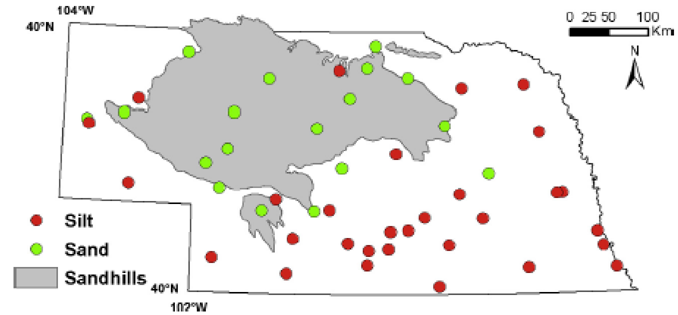

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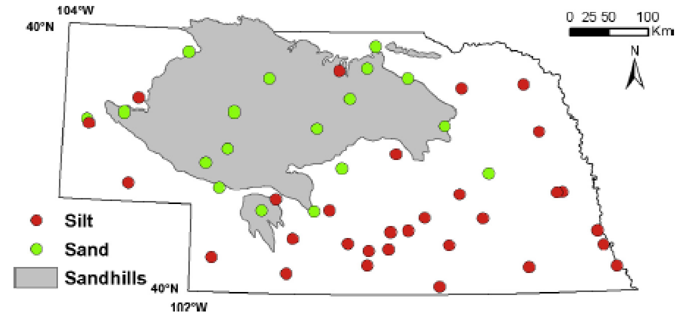

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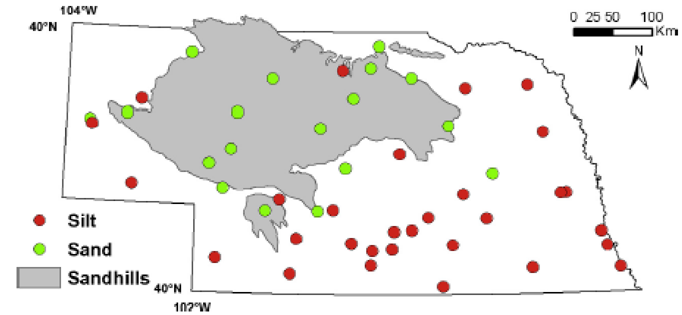

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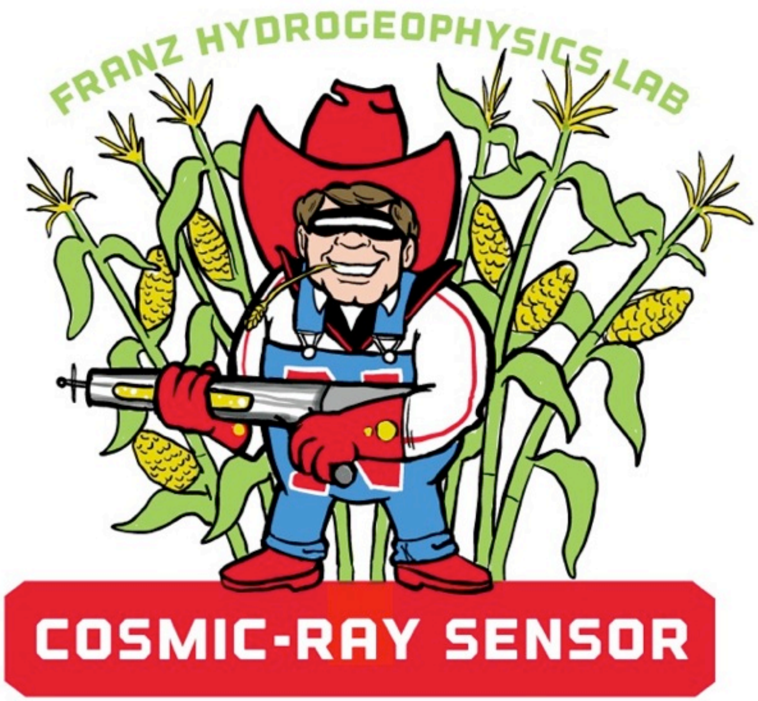
- Incorporate texture, elevation, vegetation characteristics, in geostatistical/data mining analyses
- Use statistical models to provide realtime spatial estimates of landscape scale soil moisture patterns
- Historical reconstruction of soil moisture fields for LSM initial conditions, LSM validation, and/or remote sensing analyses?

Questions?



See posters by Will and Catie tomorrow on CRS vegetation and soil calibration using remote sensing and global databases.

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