

1 Deploying temporary networks for upscaling of sparse network stations

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12 Abstract

13 Soil observations networks at the national scale play an integral role in hydrologic
14 modeling, drought assessment, agricultural decision support, and our ability to
15 understand climate change. Understanding soil moisture variability is necessary to apply
16 these measurements to model calibration, business and consumer applications, or even
17 human health issues. The installation of soil moisture sensors as sparse, national
18 networks is necessitated by limited financial resources. However, this results in the
19 incomplete sampling of the local heterogeneity of soil type, vegetation cover, topography,
20 and the fine spatial distribution of precipitation events. To this end, temporary networks
21 can be installed in the areas surrounding a permanent installation within a sparse network.
22 The temporary networks deployed in this study provide a more representative average at
23 the 3-km and 9-km scales, localized about the permanent gauge. The value of such
24 temporary networks is demonstrated at test sites in Millbrook, New York and Crossville,
25 Tennessee. The capacity of a single U.S. Climate Reference Network (USCRN) sensor
26 set to approximate the average of a temporary network at the 3 km and 9 km scales using
27 a simple linear scaling function is tested. The capacity of a temporary network to provide
28 reliable estimates with diminishing numbers of sensors, the temporal stability of those

29 networks, and ultimately, the relationship of the variability of those networks to soil
30 moisture conditions at the permanent sensor are investigated. In this manner, this work
31 demonstrates the single-season installation of a temporary network as a mechanism to
32 characterize the soil moisture variability at a permanent gauge within a sparse network.

33 **Introduction**

34 National soil-observation networks offer a valuable mechanism for understanding below-
35 ground climate change by providing a critical scientific data record (Schaefer et al. 2007;
36 Bell et al. 2013). Data from these networks can be used for understanding drought,
37 calibration of land surface models, validation of remotely sensed soil moisture, and even
38 topics related to human health (Beck et al., 2000). Understanding changes in soil
39 moisture dynamics gained national attention with the historic 2012 drought in the United
40 States (Bell et al., 2015; Blunden and Arndt, 2013) and recent outbreaks of
41 coccidioidomycosis (Valley Fever) that are shown to be related to changes in soil
42 moisture (Stacy et al., 2012). However, knowledge of soil moisture variability is still
43 incomplete (Ochsner et al., 2013; Palecki and Bell, 2013). Further research is still
44 required to understand how effectively a single station represents its surrounding area,
45 as *in situ* measurements of soil moisture are often too sparse to fully characterize soil
46 dynamics at broader spatial scales (Cosh et al., 2013). Given the considerable importance
47 of these measurements for drought-monitoring, agricultural yield estimation, and ground
48 validation of soil moisture from satellite and land-surface models, research characterizing
49 the representativeness of a single station to its surrounding area is critical for maximizing

50 the value of soil moisture measurements from any network collecting data (Kornelsen et
51 al. 2015).

52 Soil monitoring networks are expensive to operate and difficult to maintain (Schaefer et
53 al. 2007; Bell et al. 2013; Temimi et al, 2014). Any effort to provide national, high-
54 density soil moisture monitoring is too costly and time intensive to be sustainable. Efforts
55 are being made to assemble existing soil monitoring network data into larger databases
56 with uniform quality control procedures (Dorigo et al. 2011, 2013; Quiring et al., 2016),
57 and apply spatial interpolation techniques (Ford and Quiring, 2014). There is also
58 growing interest in ingesting soil moisture observations into weather and climate models
59 that normally depend on modelled soil moisture inputs (Dirmeyer et al., 2016). However,
60 soil moisture is highly variable and a dense network of stations is required to accurately
61 characterize spatial variability (Magagi et al., 2013). In order to reduce cost and improve
62 spatial coverage, previous studies have been conducted to temporarily deploy a higher
63 density network to determine a scaling function for that network (Cosh et al., 2006; Cosh
64 et al., 2013; Scaini et al., 2015). By identifying the scaling relationship of a station to the
65 larger domain, researchers and land managers may be able to use measurements of soil
66 moisture from sparse data networks more accurately for a variety of scientific and
67 societal needs. However, none of those studies were focused on singular permanent
68 stations. Before this relationship is established, work needs to be done on understanding
69 the limitation and similarities of soil moisture variability at different geographic locations
70 and soil types. By characterizing the spatial soil moisture variability surrounding
71 locations, it may be possible to apply a scaling strategy to all stations (Vachaud et al.,
72 1985; Crow et al., 2012; Cosh et al., 2013). This scaling strategy can then be deployed to

73 generalize the relationship of soil moisture measurements from a single point to the larger
74 domain.

75 To characterize the representativeness of a single station to its surrounding area,
76 installations of temporary networks of stations monitoring soil moisture were deployed to
77 evaluate the spatial variability surrounding two permanent stations in a sparse national
78 network. By instrumenting a variety of landscapes near each station, we will be able to
79 identify the spatial representativeness of individual stations and determine the limitations
80 of scaling a single station to a larger domain. This work will serve as a platform for
81 improving the utility of sparse data networks. As NASA's Soil Moisture Active Passive
82 (SMAP) satellite mission (Chan et al. submitted) was recently launched, this work will be
83 able to directly contribute to better calibration/validation of the satellite's soil moisture
84 measurements with sparse data networks. The outcome of this pilot project is to develop
85 1) a better understanding of spatial representativeness of a common station to the
86 surrounding area, 2) a scaling strategy that can be used for the life of any permanent soil
87 observing station, 3) an improved metric for scaling any single point measurement to the
88 surrounding area, and 4) an improved methodology for using scaling individual point soil
89 moisture measurements for calibration/validation of larger-scale, remotely-sensed and
90 modeled soil moisture data products.

91 **Test Sites and Data Collection Methods**

92 NOAA's US Climate Reference Network (USCRN) is a sparse data network that records
93 a variety of homogenous above- and below-ground climate data (Bell et al. 2013).
94 USCRN stations normally have soil-monitoring probes at five depths: 5 cm (the focus of

95 this study), 10 cm, 20 cm, 50 cm, and 100 cm. Soil probes are installed in three plots
96 around the station tower; the triple redundancy of measurements at each depth aids
97 quality control and allows for a continuous data record. USCRN locations are evenly
98 distributed across the United States and generally located in remote areas that are stable
99 with respect to human development (Diamond et al. 2013). Because of the placement of
100 USCRN gauges, each station is located in areas with topography, landscape, and soil
101 types that may or may not differ substantially from their surroundings. As a consequence,
102 spatial variability in the surrounding area can be challenging to characterize. The two
103 stations selected for this pilot study were near Crossville, Tennessee and Millbrook, New
104 York (Temimi et al, 2014). Station positions were selected with consideration towards
105 representing the diversity of soil textures and topographies present within the watershed,
106 maintaining an appropriate spatial distribution, and minimizing inconvenience to the
107 local landowners who allow installation of these gauges on private property.

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115 **Figure 1 –Design of the network of temporary stations installed around the USCRN**
116 **station at Millbrook, NY (top) and Crossville, TN (bottom).**

117 The Millbrook USCRN station is located at the Cary Institute for Ecosystems Studies,
118 while the stations of the temporary networks were installed across the land parcels of a
119 variety of landowners in the surrounding area (Figure 1, top). The installation of the
120 temporary network at Millbrook lay across a variety of diverse locations and topography;
121 including fields, pastures, and wooded areas. At each temporary installation, the top layer
122 of soil was carefully removed for the insertion of a Stevens Hydra Probe into the vertical
123 soil profile at 5cm depth to replicate the USCRN installation (which is intended to
124 estimate soil moisture at the 5cm depth) and to represent the soil moisture depth of the
125 NASA SMAP mission. The removed soil is replaced around the probe to fill the hole and
126 cover the exposed probe. The top layer of soil that contains the aboveground biomass is
127 placed over the hole and compacted to remove air pockets. Twenty-five temporary
128 stations were installed in a random pattern around the USCRN station. The design of the
129 temporary network allows for an examination of a 9-km SMAP satellite product,
130 intended to estimate soil moisture at the 5cm depth. The layout also provides an
131 opportunity for the temporary network to be divided into 16 stations that can represent
132 the 3-km SMAP product (also intended to provide a 5cm-depth estimate). Soil cores and
133 gravimetric soil samples were extracted near the probe. Samples were brought back to the
134 lab for drying and analysis of soil type, bulk density and gravimetric soil moisture. Near
135 the temporary probe installation sites, a metal fence post is driven into the ground and the
136 data-logger box and solar panel are attached. Periodically, the sites were visited for visual
137 inspection, downloading data, and gathering the requisite gravimetric soil samples for
138 calibration. Downloaded soil moisture observations were then processed and inspected
139 for quality assurance.

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141 **Analytical Methods**

142 Five primary approaches were deployed to assess the spatial robustness and temporal
143 variability of the temporary networks as they related to the permanent network sites.
144 This section will outline the techniques used and the insights to be gained that are
145 applicable to understanding sparse network representativeness.

146 **1. Temporal Stability Analysis**

147 In this analysis, the relative conditions of soil moisture at the temporary network sensors
148 and at the permanently-installed USCRN station are compared. In a temporally-stable
149 network, one expects specific sensors to remain among the wettest in the network,
150 regardless of conditions, while others remain among the driest. For each sensor, a
151 normalized soil moisture time-series is obtained by subtracting the mean soil moisture
152 value over all temporal network sensors from each individual sensor's time series. By
153 calculating the mean and standard deviation at each temporary network location, the
154 mean-relative-difference (MRD) for each sensor emerges. In turn, if the standard
155 deviation, a representation of the variability at each sensor, is small relative to the scale
156 of MRD values, one can conclude that a network is temporally stable. This analysis
157 method is analogous to work performed in Cosh et al. (2008; 2013).

158 **2. Linear Scaling Functions**

159 In this case, a simple linear regression is generated to relate the values of the single,
160 permanent, USCRN gauges to the weighted average of sensors in the temporary networks
161 that form either the 3-km or 9-km estimated average. This structure of these relationships
162 is shown in Equations 1 and 2, below:

$$163 \quad \theta_{ave} = \beta_1 \theta_{USCRN} + \beta_0 \quad (\text{Equation 1})$$

$$164 \quad \theta_{ave} = \sum_{i=1}^n \omega_i \theta_i \quad (\text{Equation 2})$$

165 In the above equations, ω_i denotes the weight associated with a given temporary network
166 sensor's soil moisture value, θ_i . The sum of all values of ω_i is unity. This yields the
167 weighted average, θ_{ave} , which represents the average soil moisture over the 3-km or 9-
168 km pixel in which we are interested in assessing temporal and spatial stability. θ_{USCRN}
169 signifies the soil moisture value from the permanent station, which is in turn, scaled via a
170 slope, β_1 , and an intercept, β_0 . The values of these parameters are calibrated using a
171 randomly-selected 80% of the soil moisture data set and validated on the 20% that remain.

172 **3. Sub-network Analysis**

173 Utilizing this approach, a temporary network average consisting of n-sensors is
174 compared with various sub-networks containing n-1 sensors, then n-2 sensors, etc.
175 Considering an average of a temporary network with n sensors, the number of
176 combinations of r sensors (for $r < n$) is given in Equation 3:

$$177 \quad \binom{n}{r} = \frac{n!}{(n-r)!*r!} \quad (\text{Equation 3})$$

178 If $\binom{n}{r} < 1000$, all such combinations are evaluated, and for each an RMSE value is
179 calculated between the sub-network and the full temporary network. The average RMSE
180 represents the error between a sub-network of size r , and the complete temporary network.
181 If $\binom{n}{r} > 1000$, for computational expediency, a randomly selected set of 1000
182 combinations of size r are chosen and the reported RMSE is the average thereof. This
183 analysis is performed for $r = 1$ through $r = n-1$, allowing a determination of how many
184 sensors can be removed from a temporary network without substantial degradation of
185 performance.

186 **4. Variability vs. Wetness**

187 Intuition might suggest that the variability across a network of temporary sensors would
188 be largest during periods of wetting and drying. After a prolonged period without rain,
189 all proximally-located sensors should stabilize at a low level at or near the residual soil
190 moisture contents of the area in question. Similarly, after substantial precipitation events,
191 all sensors should approach their levels of saturation. It is within the intermediate soil
192 moisture levels where one might expect to observe the greatest variability across the
193 temporary network. To this end, analysis is performed comparing the standard deviations
194 of all reporting sensors within the temporary network as a function of the average of
195 same.

196 **5. Network variability vs. 3-Profile Variability**

197 By design, the USCRN soil moisture values reported at sites of permanent installations
198 are the average of three co-located (separated by distances of several meters), but

199 independent instrument measurements. Assessments of the random errors at USCRN
200 installations via triple collocation are analyzed and discussed in greater detail in
201 Coopersmith et al (2016, i). In this case, we investigate briefly whether the variability
202 within the triad of USCRN measurements is related to the variability across the sensors
203 comprising the temporary network. As there are only three USCRN profiles available
204 (and the calculation of standard deviation is generally dubious for such small sample
205 sizes), an RMSD calculation about the mean value of the three profiles is obtained in
206 Equation 4.

$$207 RMSD = \sqrt{\sum_{i=1}^3 (\theta_i - \bar{\theta})^2} \quad (Equation\ 4)$$

208 In the above, θ_i denotes the soil moisture reading at one of the three USCRN profiles and
209 $\bar{\theta}$ signifies the average of those three measured values. These RMSD values are, in turn,
210 compared with the variability of the temporary network sensors at the 3-km and 9-km
211 scales.

212 **Results**

213 The soil probes of the temporary network were calibrated initially to the soil type located
214 at each individual location. The gravimetric measurements that occurred at each
215 temporary station throughout the life of the temporary networks served as a set of quality
216 measurements to calibrate the dielectric measurements. These calculations are applied
217 across all stations uniformly which is not unreasonable for the Crossville site. The
218 Millbrook site contained slightly more variation with respect to the soil textures, but the
219 heterogeneity is not expected to influence the results of the analysis significantly.

220 Calibrated values were used for evaluation of the spatial and temporal variability of soil
221 moisture across the entire network.

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224 **1. Temporal Stability Analysis**

225 Figure 2 illustrates that despite the 0.2-0.3 m³/m³ range in soil moisture values observed,
226 relative positioning of sensors is temporally stable to a large degree at the Millbrook site.
227 The red line in Figure 2 also suggests that the USCRN sensor is, in general, likely to
228 produce values that are drier than those reported by the temporary network at 9-km scale
229 (blue line) or 3-km scale (green line). As the plots show, a great deal of variability
230 occurs across the temporary networks at Millbrook site. However, despite this variability,
231 temporal patterns of the average 9-km and 3-km soil moisture values replicate the wetting
232 and drying cycles of the USCRN station. Average soil moisture values for the entire
233 period of record confirm that the USCRN station was slightly drier (mean =
234 0.2066/standard deviation = 0.0525) than the 9-km (mean = 0.2587/standard deviation =
235 0.0541) and 3-km (mean = 0.2364/standard deviation = 0.0465) grids at Millbrook.

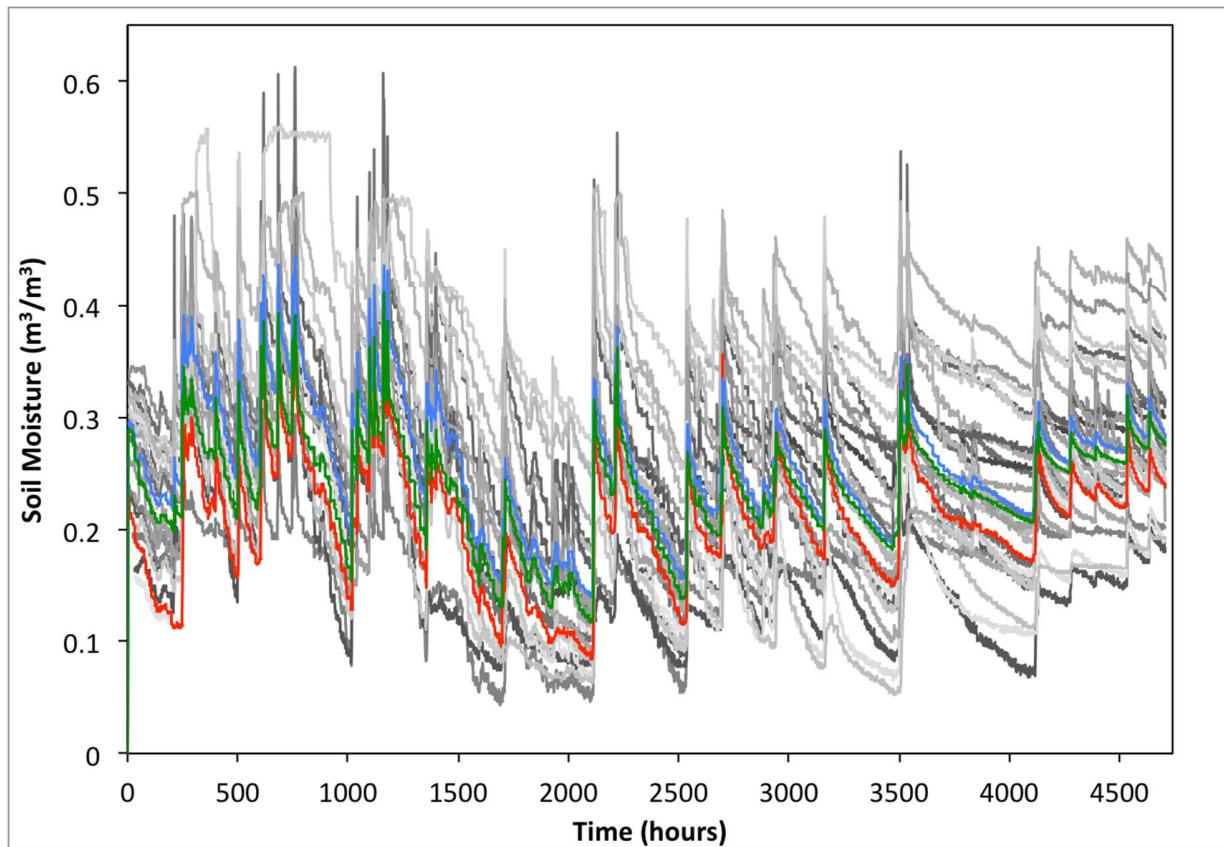
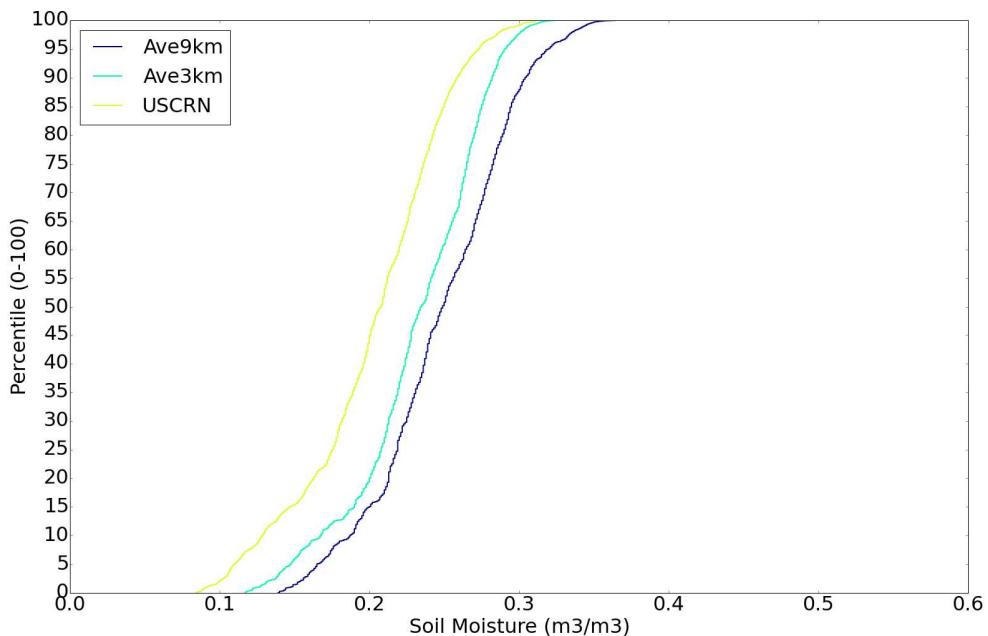
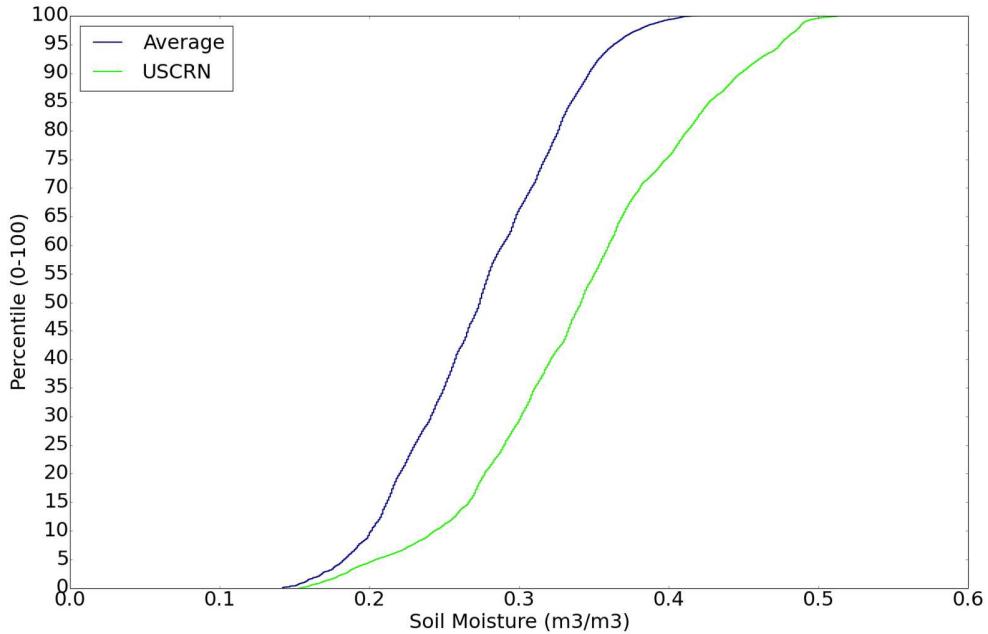


Figure 2. Mean soil moisture variability of the temporary network at Millbrook, NY.
The red line denotes the USCRN value, the blue line represents the 9-km average, and the green line signifies the 3-km average.
The various shades of grey represent the individual probe values within the temporary network.



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Figure 3. CDF plots for Millbrook (top, at 3-km and 9-km scales) and Crossville (bottom) USCRN gauges and temporary networks.

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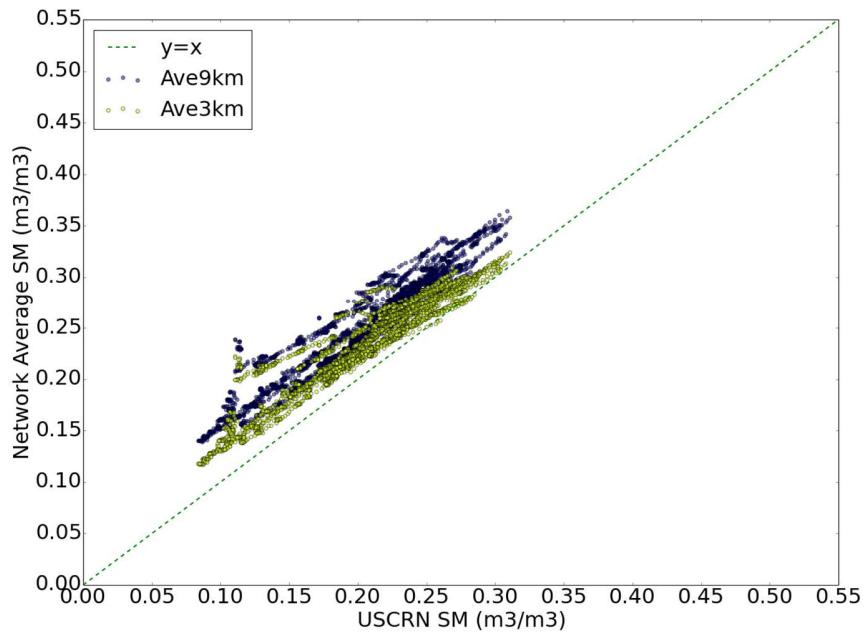
Cumulative distribution frequency plots were constructed to evaluate the population of USCRN values and compare them to 9-km and 3-km grid average value populations

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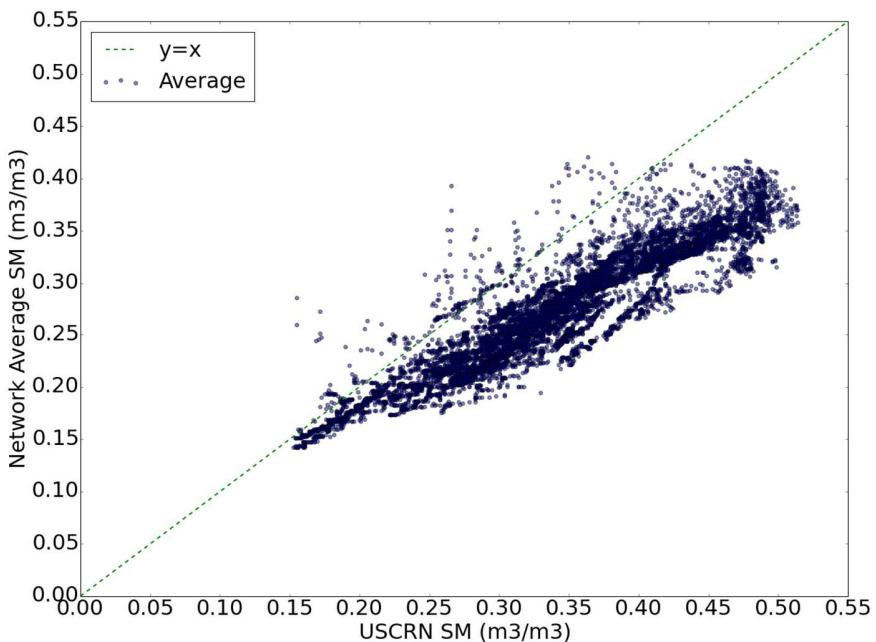
(Figure 3). The cumulative distribution frequency plots show that the three time series at

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9 Millbrook display similar patterns of soil moisture for the period of record. Again, as
10 expected, USCRN values were consistently drier than the 9-km values. The 3-km values
11 were wetter than the USCRN values in the lower soil moisture percentages but were more
12 similar to the USCRN values in the higher soil moisture conditions. In the lower panel,
13 at Crossville, we observe that the USCRN gauge is considerably wetter than the
14 distribution describing the surrounding temporary network. In contrast with the
15 Millbrook site, the USCRN station at Crossville was more similar to the temporary
16 network when drier - the values diverged as the conditions became wetter.



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19 **Figure 4. USCRN soil moisture vs. temporary network average at 3km (green dots)**
20 **and 9km (blue dots) scales at Millbrook (top) and USCRN vs. temporary network at**
21 **Crossville (bottom).**

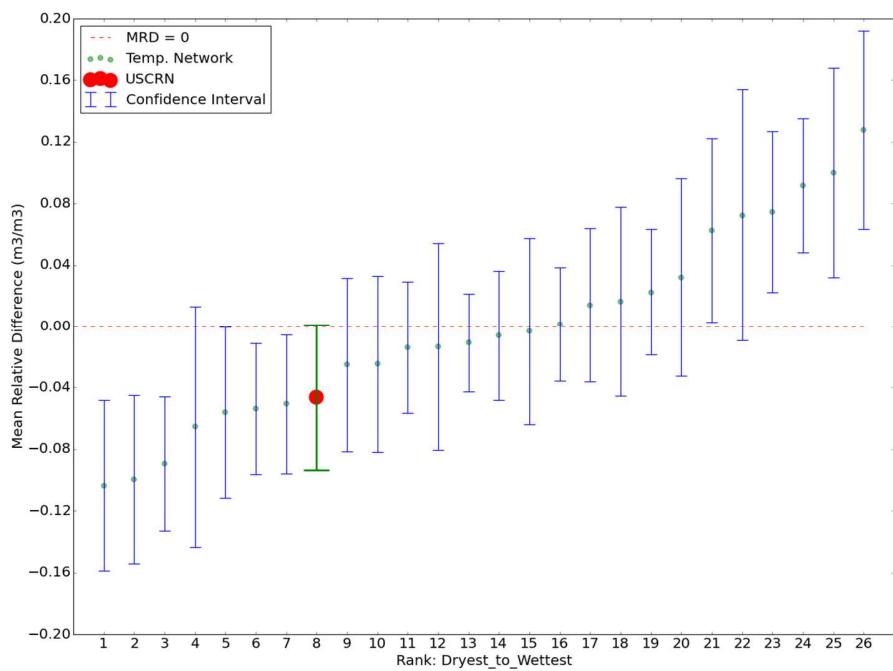
22

23 Correlations between the USCRN values and the Millbrook temporary network's 3-km

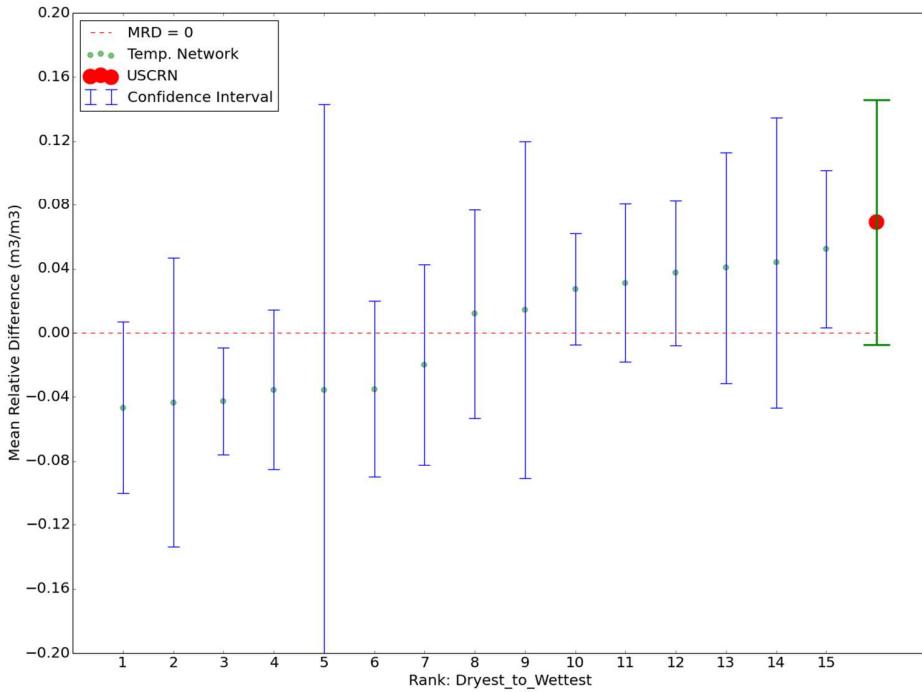
24 and 9-km products yield strong relationships (Figure 4, top panel). The 3-km temporary

25 network grid had a higher correlation ($r^2 = 0.90$) than the 9-km grid ($r^2 = 0.84$). As would
26 be expected, the correlation between the 3-km vs. 9-km grids was even higher ($r^2 = 0.94$).
27 In Crossville (Figure 4, bottom panel), the correlation between the USCRN and
28 temporary network average is comparable, at $r^2 = 0.85$, but demonstrates considerable
29 non-linearity at volumetric soil moisture amounts above $0.3 \text{ m}^3/\text{m}^3$ (a value rarely
30 exceeded at Millbrook).

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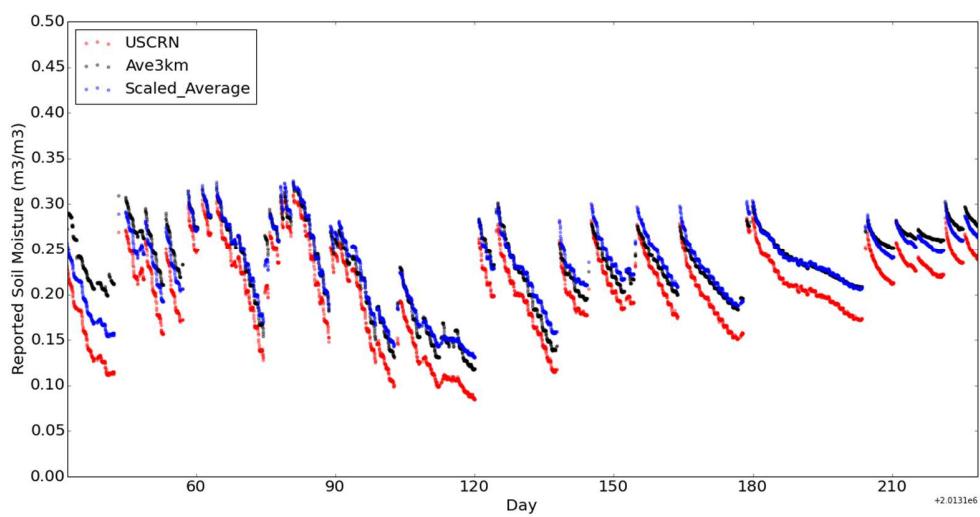
33
34 **Figure 5. Mean relative difference plot of the Millbrook (top) and Crossville**
35 **(bottom) temporary networks. Error bars represent the standard deviations of the**
36 **relative differences for each station with the remaining stations.**

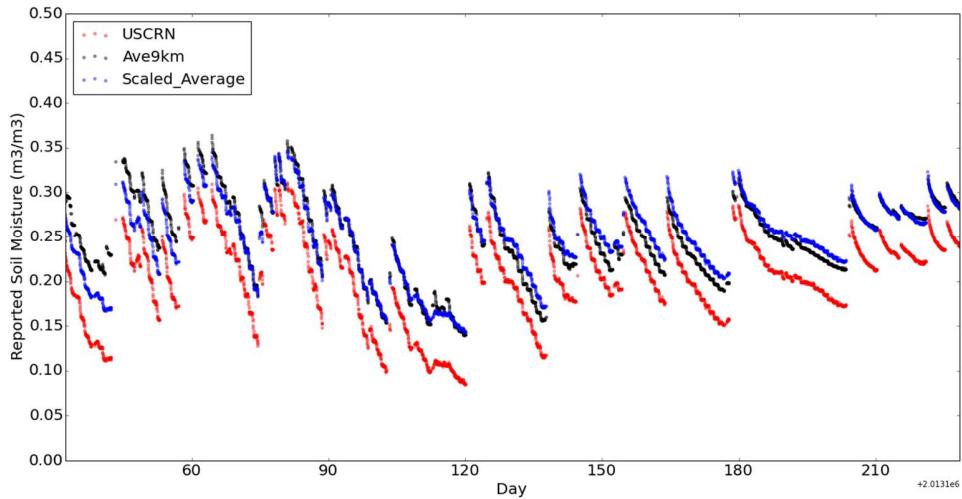
37
38 Figure 5 provides a summary of the temporal stability of the temporary networks. With
39 mean-relative-difference (MRD) values at Millbrook spanning a range of over $0.2 \text{ m}^3/\text{m}^3$,
40 while the standard deviation of readings at each sensor tend to hover near $0.05 \text{ m}^3/\text{m}^3$, the
41 top panel of Figure 5 confirms what Figure 2 suggests – wetter and drier sensors tend to
42 remain so. In contrast to some extent, at the Crossville location, the range of MRD
43 values falls below $0.10 \text{ m}^3/\text{m}^3$ while the standard deviations are often above $0.10 \text{ m}^3/\text{m}^3$.
44 In some cases, standard deviations are considerably larger than the MRD range displayed
45 by the temporary network. For this reason, fewer sensors seem consistently wetter or
46 drier. Additionally, these paired images illustrate that, within the Millbrook network, the
47 USCRN gauge has been installed in a location that is slightly drier than its surroundings,

48 whereas in Crossville, the installation site is substantially wetter than the peripheral
49 landscape.

50 **2. Linear Scaling Functions**

51 For the Millbrook location, time series data displayed in Figure 6 show the adjustment of
52 the USCRN soil moisture (red series) to a scaled average (blue series) via an optimal gain
53 and offset derived using Equation 1. The top panel represents the scaling for the 3-km
54 grid and the bottom panel represents the scaling for the 9-km grid. For the purposes of
55 data reliability, all time series values while rain is falling and during the four hours
56 immediately thereafter were removed from the regression analysis. Rain requires some
57 non-zero quantity of time to infiltrate to the depth of the sensor and short-term sensor
58 flooding is also possible. A four-hour removal of this nature, used for calibration of
59 USCRN sensors in Coopersmith et al, 2015(a) and Coopersmith et al, 2015(b) resolves
60 this issue.



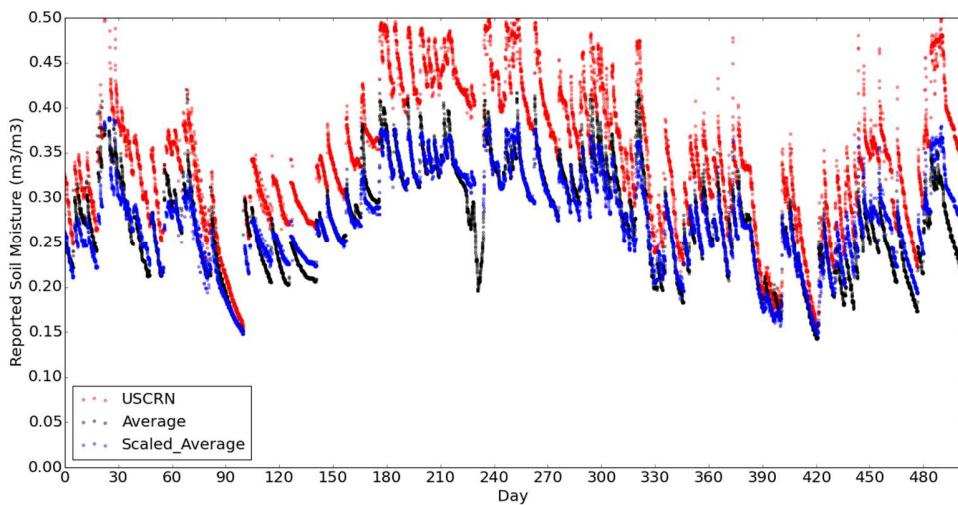


62
63 **Figure 6. Gain and offset adjustments of USCRN values to approximate the average**
64 **of the Millbrook temporary network at the 3km (top) and 9km (bottom) scales.**

65 The correlations between the Millbrook USCRN values and the temporary network 3-km
66 and 9-km averages are strong ($r^2 = 0.90$ and 0.89 respectively). These values are
67 obtained, as discussed in the methodology section by random selection of 80% of the
68 time series data. Validating on the remaining 20% yields comparable values ($r^2 = 0.89$
69 and 0.90 respectively). RMSE values prior to the introduction of optimal gains and
70 offsets were 0.033 and 0.049 m^3/m^3 at 3-km and 9-km scales, respectively. After the
71 introduction of these adjustments, RMSE values fall to 0.013 and 0.015 m^3/m^3 during
72 calibration for the 3-km and 9-km average respectively and 0.014 m^3/m^3 during
73 validation.

74 Within Crossville, an analogous analysis is performed and presented in Figure 7. The
75 correlation between the USCRN values and the temporary network average are strong in
76 calibration ($r^2 = 0.86$) and validation ($r^2 = 0.85$), though perhaps not as high as those
77 observed in Millbrook. The RMSE value prior to the introduction of an optimal gain and
78 offset is 0.076 m^3/m^3 , which falls to 0.021 m^3/m^3 (calibration) once an optimal linear

79 correction is implemented and is only marginally worse (0.021 m³/m³) during validation.
80 These results suggest that a single point of observation can effectively approximate the
81 behavior of a small area network through calibration, even if the site location is not in the
82 ideal position to represent the central tendency of the area soil moisture distribution.

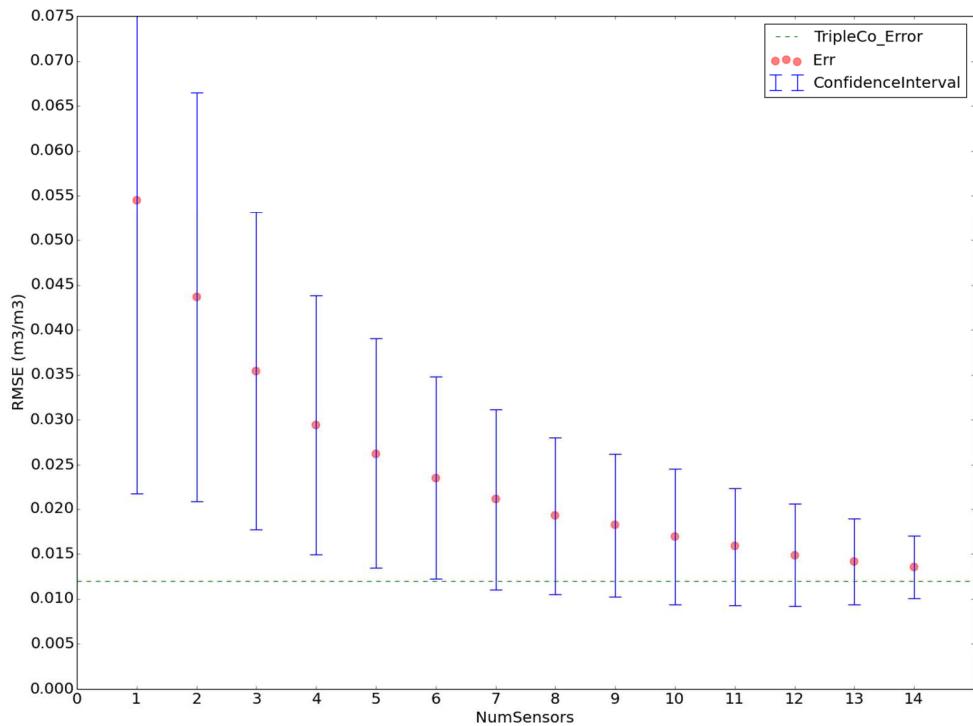


83
84 **Figure 7. Gain and offset adjustments of the USCRN gauge values to approximate**
85 **the average of the Crossville temporary network.**

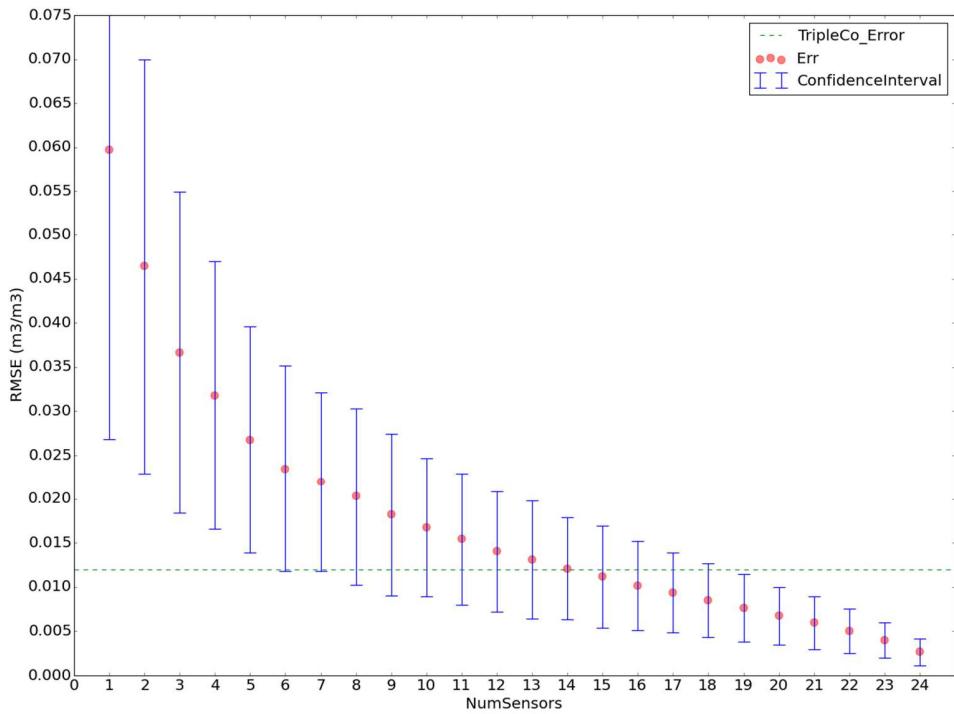
86 **3. Sub-network Analysis**

87 As temporary networks are still resource intensive, a sub-network analysis will help
88 determine the number of sensors needed to achieve results that would appear comparable
89 to that of the complete network. Figure 8 presents the RMSE between the various
90 combinations of sub-networks as compared to the 3-km (top) and 9-km (bottom) products,
91 respectively. In both panels, a green, dotted-line presents the approximate random error
92 associated with a hydaprobe measurement at this depth, as determined by the triple-
93 collocation analysis performed in Coopersmith et al (2016, i). The confidence intervals
94 are determined as the standard deviation of all combinations of the size listed on the x-

95 axis chosen from the complete network of size 15 (3-km product) or 25 (9-km product).
96 Where the number of such combinations is computationally-cumbersome, 1,000 random
97 combinations are selected and used to generate the confidence intervals illustrated.



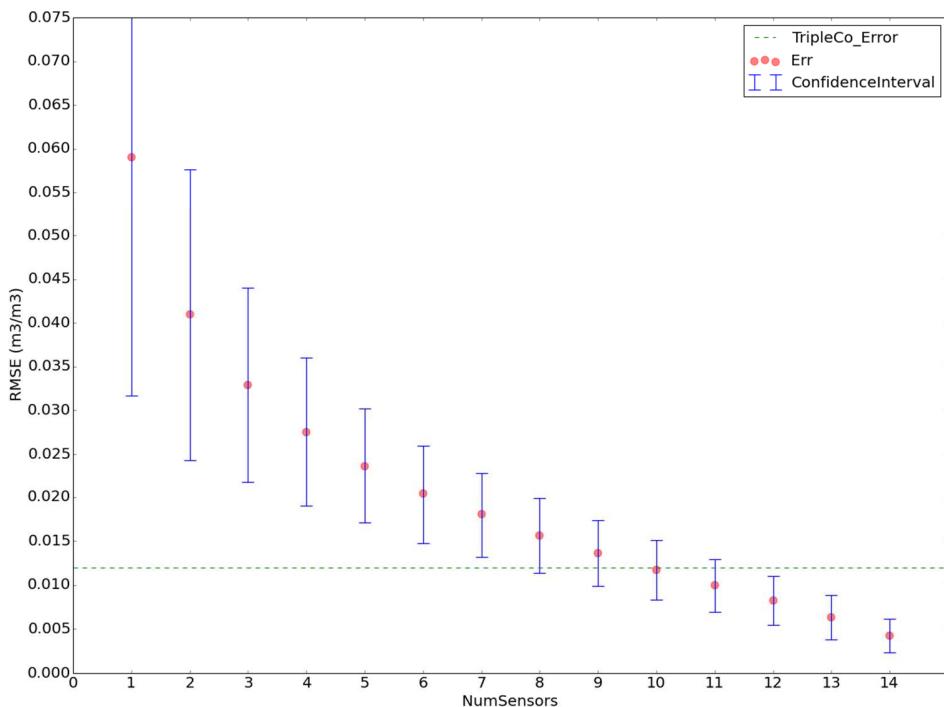
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100 **Figure 8. RMSE between complete Millbrook temporary network and combinations**
101 **of lesser numbers of sensors at 3-km (top) and 9-km (bottom) scales.**

102
103 At both 3-km and 9-km scales, we observe that even without the full contingent of
104 sensors, RMSE values against the complete temporary network average that fall below
105 the inherent random error in hydraphobe measurements are attainable. As the presented
106 confidence intervals illustrate a range of one standard deviation above or below the mean,
107 the probability of a random combination of sensors of size r (see Equation 3) presenting
108 an RMSE below the upper-end of the confidence interval is $\sim 84\%$. This suggests, that if,
109 of the 25 sensors comprising the 9-km average, 14 are installed, the expected value of the
110 RMSE would be roughly the value of random measurement error. If 19 are available, we
111 would expect that RMSE to be below the random measurement error with 84%
112 confidence. At the 3-km scale, errors are slightly larger, as we are removing sensors

113 from a group of 15 rather than 25. We observe that the expected RMSE value
114 asymptotically approaches the random error associated with a hydroprobe measurement.
115 Figure 9 presents the analogous plot at the Crossville location.



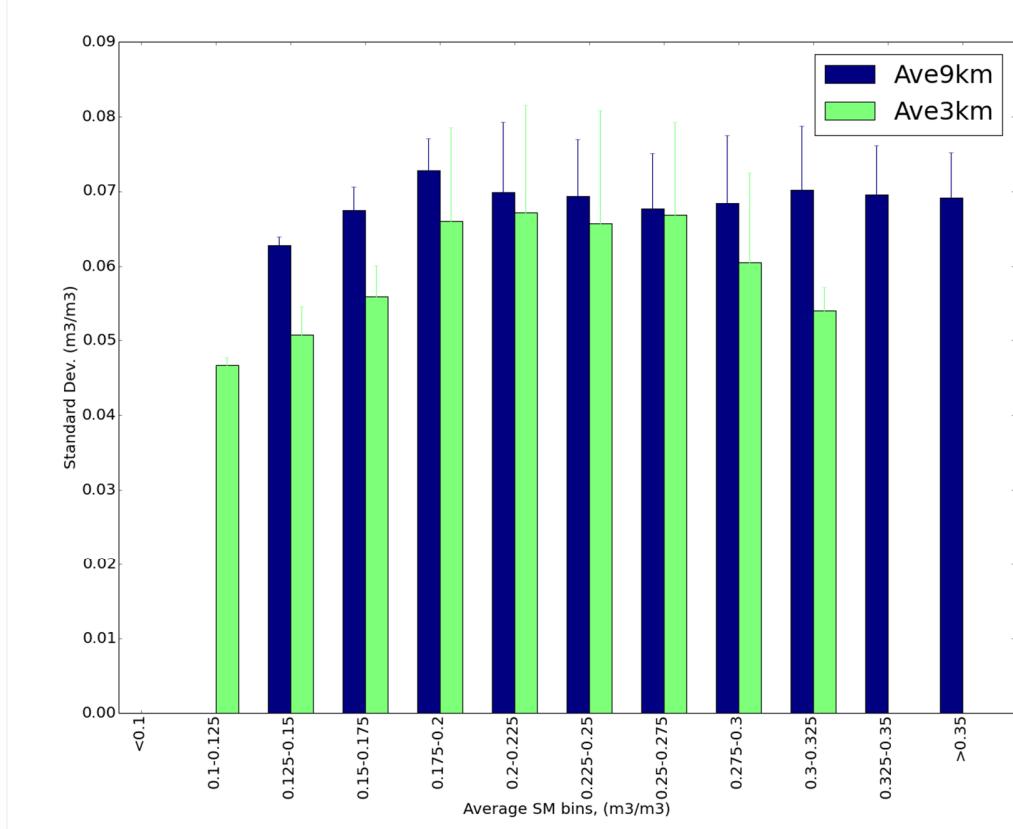
116
117 **Figure 9. RMSE between complete Crossville temporary network and combinations**
118 **of lesser numbers of sensors.**

119 These results suggest that even fewer sensors (of a 15-sensor temporary network) will be
120 required to achieve errors below the level of random measurement error, in this case only
121 10 will lead to expected RMSE values below the random error level and 12 sensors will
122 achieve this standard with 84% confidence.

123 **4. Variability vs. Wetness**

124 The average standard deviation among the temporary network's constituent sensors as a
125 function of the average soil moisture values reported by those sensors was calculated at

126 3-km and 9-km scales at Millbrook, and 3-km scale at Crossville. At Millbrook, it is
127 evident at the 3-km scale (Figure 10) that soil moisture variability across the temporary
128 network is largest during intermediate conditions, tapering off at both the upper and
129 lower ends of the distribution when all sensors are fully dried or fully saturated.
130 However, at the 9-km scale, the same relationship is no longer observed. In this case, the
131 variability across the temporary network may be the result of unevenly received
132 precipitation events in addition to topographic, vegetative, or edaphic variability. The
133 network at Crossville also shows no systematic relationship between variability and
134 wetness, even at the 3-km scale (not shown). Possibly, this may result from wet
135 conditions at the Crossville site – considerable rainfall arrived while the temporary
136 stations were installed.

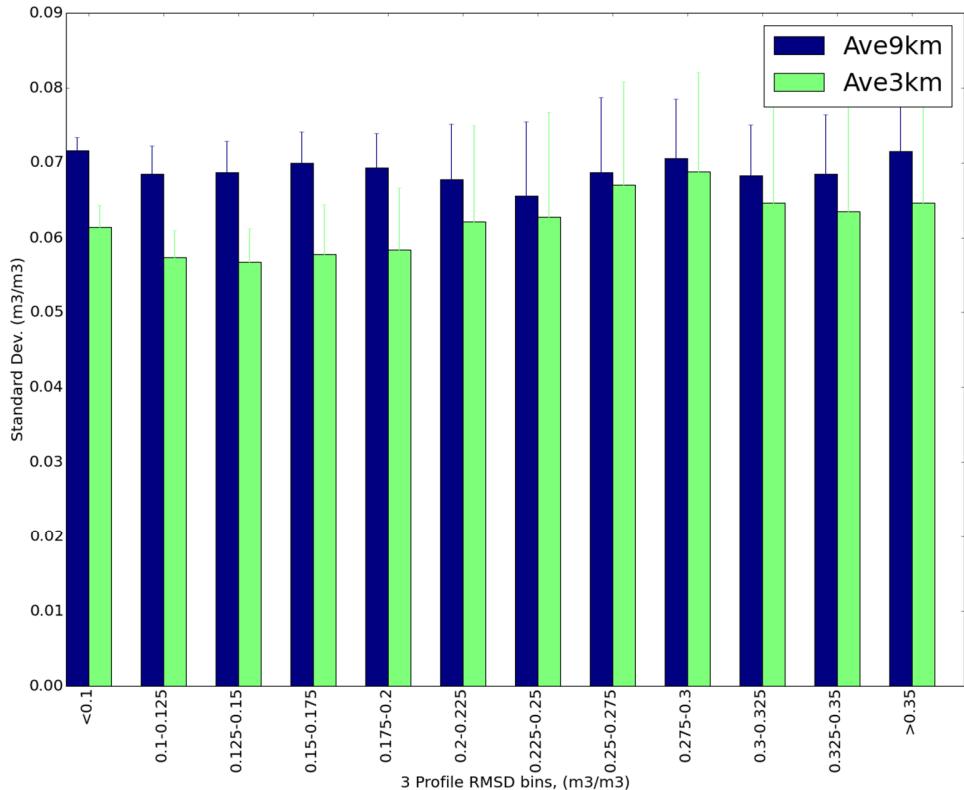


137

Figure 10. Standard deviation of Millbrook temporary network sensors vs. average soil moisture

5. Variability vs. 3-Profile Variability

Taking advantage of the USCRN's unique acquisition of three soil moisture profiles, it would be interesting to see if the near-point variability relates in any way to the 3-km or 9-km scale spatial variability around the site. Figure 11 presents the variability of the temporary network at Millbrook as a function of the variability observed in the three profiles of the USCRN installation (Equation 4). At neither the 3-km, nor the 9-km scale does the variability of the network seem dependent upon the consistency of the three-profile measurements at the single, permanent gauge. Though the 3-km scale does seem to present slightly less variability at the drier end of its distribution, the overall results seem to suggest that the variability in terms of precipitation, topography, soil texture, and vegetation cover all explain the temporary network's variability rather than specific conditions that manifest themselves as differences in the three profile measurements. Crossville displayed a similar lack of a relationship (not shown).



156
157 **Figure 11. Standard deviation of temporary network sensors at Millbrook vs. three-**
158 **profile variability of the USCRN station.**

159
160 **Discussion**

161 Previous research has demonstrated that a dense network of sensors can be deployed to
162 produce estimates at the 500m resolution by leveraging a combination of *in situ* sensory
163 resources, and if needed, knowledge of topographic and edaphic features (Coopersmith et
164 al., 2015, iii). By matching smaller 500m x 500m squares with models calibrated at
165 sensors located in similarly textured soils of similar topographic features, accurate
166 estimates within each square are possible. Essentially, this methodology enables the
167 creation of estimates in every 500m x 500m square within a larger (~40km x ~40km in
168 the article referenced above), then subsequently upscaling those estimates to 3km, 9km,
169 or 36km (the scales employed by the SMAP satellite mission) by aggregating and

170 averaging the constituent 500m x 500m boxes. This facilitates more direct validation of
171 satellite estimates (Coopersmith et al., 2015, iii).

172 The findings in this analysis suggest that errors decrease to the levels of random errors
173 inherent in *in situ* sensor measurement (Coopersmith et al, 2016, i) with a network of
174 approximately one-dozen sensors. As many dense permanent and temporary networks
175 contain more than this quantity of sensory resources, these findings suggest upscaling can
176 occur using even few sensors than are typically installed in dense networks. The number
177 of sensors is likely to be even fewer if care is taken to ensure the chosen sensor locations
178 represent the diversity of textures and topographies present within the test area. These
179 upscaled estimates can be compared, in turn, with remotely-sensed estimates from
180 satellites.

181 In addition to comparisons with remote sensing, these upscaled estimates can be
182 deployed within various dense networks (or sparse networks with lower resolutions than
183 the aforementioned 500km) as a means of assessing drought. Given this analysis's
184 findings of stable relationships for wetter and drier sensors within a given network,
185 characterization of potential drought risks could be informed by knowledge of which
186 sensors tend to be atypically wet or dry.

187 Previous research suggests that these findings are applicable in other locations and within
188 different hydroclimates and soil textures (Coopersmith et al, 2015, i). The models
189 calibrated during that analysis at both USCRN and the Soil Climate Analysis Network
190 (SCAN; Schaefer et al, 2007) sites, produced low RMSE values in over 40 states
191 throughout the continental USA. With respect to temporal stability, preliminary analyses

192 in the Agricultural Research Service test watersheds (located in Arizona, Oklahoma,
193 Idaho, Georgia, Iowa, and Indiana) suggest similar performance as sensors are removed
194 can be achieved (Coopersmith and Cosh, 2016, ii, in-progress).

195
196 **Conclusions**

197 The results of this pilot study indicate that it is possible to accurately represent the spatial
198 and temporal variability of a larger domain with an individual station with considerable
199 accuracy, once a scaling relationship has been developed. Deploying a temporary
200 network around a permanent station provides an estimate of the soil moisture
201 characteristics for that location and these results suggest that approximately one dozen
202 sensors distributed around a site for an entire seasonal cycle is likely to be sufficient to
203 characterize the variability of the domain average. The accuracy of the USCRN, once
204 scaled to the surrounding 3-km or 9-km average demonstrated RMSE values below 0.015
205 m^3 during both calibration and validation. Temporal stability analysis reveals that wetter
206 and drier sensors within the domain are robust in terms of their mean relative differences.
207 Finally, while wetter and drier conditions do affect network variability (at least at the
208 3km scale), the variability of the USCRN's three co-located profiles do not. This work
209 describes a successful approach for using a sparse data network station for validation of a
210 satellite remote sensing product.

211 Additional work is needed to characterize the differences seen at other locations with
212 varying soil conditions and landcover type. The study at Millbrook demonstrates that the
213 analytic approaches presented in this paper are useful even with a target area that has
214 substantial soil moisture variability due to a heterogeneous landscape. The study at

215 Crossville shows that even a primary station located in a less representative soil moisture
216 environment can still be successfully related to the variations in soil moisture for the
217 surrounding area. A similar study at a location with a less heterogeneous landscape or
218 more consistent soil type would likely produce even less variability and a more accurate
219 representation of the local area with a properly calibrated single point observation. The
220 utility of *in situ* soil moisture measurements at point locations in sparse networks can be
221 increased substantially through the use of temporary networks for area calibration.

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