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Key Points:

- Hourly soil water content at 42 stations and five depths across 37 ha farm, in operation since 2007
- Sensors distributed across complex terrain and dryland no-till crops in a Mediterranean climate
- Includes soil temperature, texture, bulk density, EC, Bt horizon, crops, and terrain

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A Field-Scale Sensor Network Data Set for Monitoring and Modeling the Spatial and Temporal Variation of Soil Water Content in a Dryland Agricultural Field

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Abstract We describe a soil water content monitoring data set and auxiliary data collected at a 37 ha experimental no-till farm in the Northwestern United States. Water content measurements have been compiled hourly since 2007 by ECH2O-TE and 5TE sensors installed at 42 locations and five depths (0.3, 0.6, 0.9, 1.2, and 1.5 m, 210 sensors total) across the R.J. Cook Agronomy Farm, a Long-Term Agro-Ecosystem Research Site stationed on complex terrain in a Mediterranean climate. In addition to soil water content readings, the data set includes hourly and daily soil temperature readings, annual crop histories, a digital elevation model, Bt horizon maps, seasonal apparent electrical conductivity, soil texture, and soil bulk density. Meteorological records are also available for this location. We discuss the unique challenges of maintaining the network on an operating farm and demonstrate the nature and complexity of the soil water content data. This data set is accessible online through the National Agriculture Library, has been assigned a DOI, and will be maintained for the long term.

1. Introduction

Spatiotemporal soil water content measurements are useful for understanding soil water dynamics in the vadose zone (see reviews by Ochsner et al., 2013; Robinson et al., 2008; Vereecken et al., 2008), for upscaling and linking in situ soil water measurements with remotely sensed imagery (Bandara et al., 2014; Brocca et al., 2010; Cosh et al., 2006; Crow et al., 2012; Wang et al., 2015), and for providing measurements for the calibration and validation of hydrology and biophysical models (Brooks et al., 2007; Johnson et al., 2003; Mehta et al., 2004; Stöckle et al., 2003). High temporal resolution soil water measurements are commonly obtained at the profile and continental scales, using point monitoring and remote sensing, respectively, while data at intermediate scales are less common, particularly for agricultural catchments. Availability of data at the field and landscape scales can assist in understanding and managing water resources in relation to climate (Cantón et al., 2004), terrain (Brocca et al., 2007; Western et al., 1999), vegetation (Korres et al., 2015), and in response to land use manipulations (Al-Mulla et al., 2009; Ibrahim & Huggins, 2011). Knowledge of soil water dynamics may be particularly important in dryland annual croplands that depend on stored soil water—particularly over the long term and with regard to predicted changes in future precipitation patterns.

Numerous diverse soil water data sets have been made publicly available to support water research and modeling efforts. These data sets have been described in publications and hosted by local websites (e.g., the Tarrawarra data set (Western & Grayson, 1998) and national-scale environmental observatory data sets (Keller et al., 2008b; Zacharias et al., 2011)) or have been compiled, organized, and distributed by data networks, including by the USDA's Long-Term Agro-Ecosystem Research (LTAR) network. Available soil water data sets vary in their spatial extent and arrangement, temporal frequency, measurement methods, cocollected auxiliary data, and dominant land use—although soil water monitoring is more common in wildland and rangeland settings than on intensively managed farmlands. As a contribution to the existing body of data that strives to advance our understanding of soil water dynamics across diverse landscapes, we present a soil water data set in a dryland annual crop field; we anticipate its use by interested research and modeling communities.

The objective of this paper is to describe data collection by an automated soil water content monitoring network at the 37 ha experimental R.J. Cook Agronomy Farm (CAF). Our network provides a 9 year record of hourly soil water content readings at 42 locations and five depths—spanning complex topography, soils, and cropping schedules. Sensor network operation is ongoing and will be maintained for the long term. We also discuss challenges that we have encountered in network implementation, we demonstrate the nature of soil water at CAF, and we provide full details for data access.

2. The Cook Agronomy Farm Network Description

2.1. Field Site Details

The R.J. Cook Agronomy Farm (CAF) is a Long-Term Agro-Ecosystem Research (LTAR) Site operated by Washington State University, located near Pullman, WA (46°47′N, 117°5′W). The 37 ha farm lies in the hilly Palouse region of the Inland Pacific Northwest (Figure 1). The region receives an annual average of 550 mm of precipitation (Pullman, WA climate summary available from the Western Regional Climate Center, www.wrcc.dri.edu/), primarily as rain and snow in November–May. Soil series at CAF include Naff, Palouse, and Thatuna, all of which are deep silt loam soils formed on loess hills with argillic silty clay loam horizons often occurring within 1.5 m of the surface (Whitman County, WA soil survey, available from the Natural Resource Conservation Service, websoilsurvey.sc.egov.usda.gov). The complex terrain of the farm provides variable soils, microclimates, and hydrological characteristics.

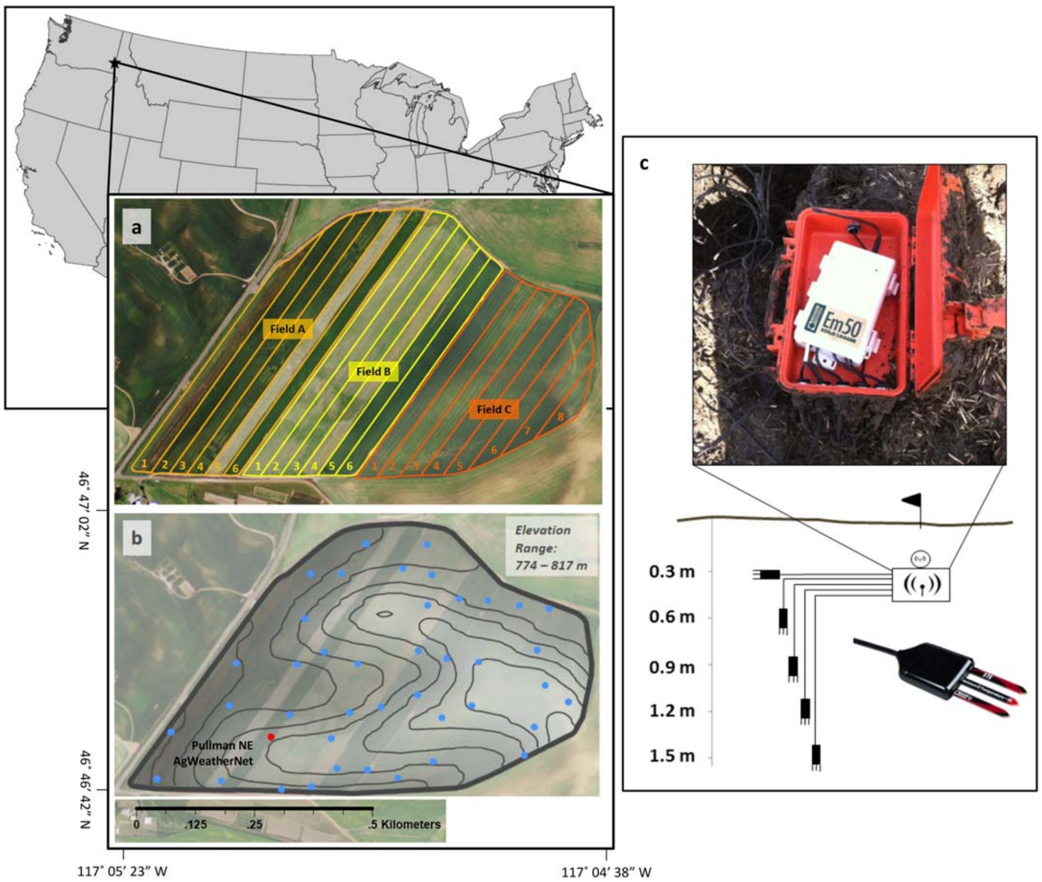

Figure 1. Location of the 37 ha Cook Agronomy Farm Long-Term Agro-Ecosystem Research Site, near Pullman, WA, with inset maps of (a) the crop rotation strips, (b) sensor locations with elevation (dark shading in low elevations) and 5 m contours, and sensor and data logger configuration. Blue points in Figure 1b indicate the 42 locations instrumented with soil water content sensors. The red hexagon in Figure 1b indicates the location of the meteorological station. (c) Sensors are installed at five depths and connected to a data logger housed in a water-resistant case and marked with a radio ball marker and surface flagging.

Farming practices at CAF are representative of regional dryland, no-tillage, annual cropping systems. The farm is divided into three experimental subfields, each further divided into 30 m wide strips, which serve as the basis for crop rotation (Figure 1a). In general, spring and winter wheat (*Triticum aestivum* L.) are planted two out of every 3 years, with the remaining year planted with an alternative crop (canola (*Brassica napus annua* Koch), chickpea (*Cicer arietinum* L.), pea (*Pisum arvense* L.), barley (*Hordeum vulgare* L.), or triticale (x*Triticosecale* Wittm.)). The CAF is host to multiple agricultural research projects conducted by interdisciplinary teams from multiple institutions. Research foci include climate change, sustainable agriculture, and precision agriculture, with data collected on soil biogeochemical processes (Chi et al., 2016; Shrewsbury et al., 2016; Waldo et al., 2016), weeds, pests, and pathogens (Paulitz et al., 2003; Smitchger et al., 2012), residue, yield, and seeding management (Huggins et al., 2014), biophysical modeling (Kemanian et al., 2007; Magney et al., 2016a, 2016b), landscape hydrology (Bellmore et al., 2015; Keller et al., 2008a; Kelley et al., 2017), and economic analyses (Painter & Huggins, 2007).

In general, with the exception of deep frozen soil events, the long-term no-tillage practices implemented at CAF have eliminated any infiltration-excess surface runoff. Saturation-excess surface runoff does occur in convergent topographic positions where the presence of hydraulically restrictive (e.g., argillic) soil horizons lead to seasonal perched water tables and subsurface lateral flow (Brooks et al., 2004, 2012; McDaniel et al., 2008). These seasonal perched water tables can delay spring seeding and fertilizing; as a result, artificial drains have been installed at a $\sim$1 m depth along toe slope positions in affected parts of the farm (Keller et al., 2008a).

2.2. Sensor Network Design and Components

Much of the monitoring and sampling at CAF occurs on a nonaligned systematic grid (369 georeferenced points, approximately 30 m spacing), such that diverse data collections over many years are spatially aligned. From the 369 grid points established on CAF, we installed ECH2O-TE sensors (Decagon Devices, Inc., Pullman, WA) at 12 of the 369 locations, at five depths: 0.3, 0.6, 0.9, 1.2, and 1.5 m, in April of 2007. In May 2009, we installed 5TE sensors (Decagon Devices, Inc.) at the same five depths at an additional 30 locations (see Figures 1b and 1c; Gasch et al., 2017 for a complete description of sensor installation). The 42 locations were chosen to maximize variability in elevation, slope, insolation, and topographic wetness index (Beven & Kirkby, 1979), and to ensure dispersal over the highly variable field conditions. The 42 locations span lag distances of 60–905 m.

The installed TE sensors interrogate approximately 0.33 L of soil to measure volumetric water content (m^3/m^3), soil temperature (°C), and bulk soil electrical conductivity (dS/m). All sensors are connected to an Em50R data logger (Decagon Devices, Inc.), powered by five AA batteries. Data loggers have recorded sensor measurements hourly since installation. The data loggers temporarily store a sensor reading each minute, and the hourly value that is recorded represents the mean of 60 readings stored within the hour. The data logger and its antenna are currently housed within a water-resistant case (Pelican Products, Inc., Torrance, CA) modified for sensor cable entry. The case is buried at approximately 0.3 m depth, with an EMS 1402 Power XR radio frequency identification ball marker (3M Company, St. Paul, MN). The sensor components and their configuration are illustrated in Figure 1c. Data are periodically retrieved from the data loggers using a RM-1 radio receiver (Decagon Devices, Inc.) and ECH2O utility software (Decagon Devices, Inc.). Our purpose does not require real time access to sensor data, but this system could be modified to provide that.

2.3. Network Challenges, Troubleshooting, and Adaptations

The CAF is a working farm, and farming operations have posed some challenges to the network design and maintenance that may not be encountered by networks installed in a wildland setting. Here we describe how we have overcome these and additional challenges, and we have identified points for improvement that may be relevant to similar sensor networks.

At installation, data loggers were not buried, but rather mounted to a post above ground. Data loggers were equipped with antennae, and data were automatically transmitted and stored on a single, centrally located DataStation (Decagon Devices, Inc.), accessible via URL through a data logger (CR1000, Campbell Scientific, Logan, UT) and cellular modem (AirLink Raven, Sierra Wireless, Richmond, BC, Canada). Above ground storage allowed for easy access to download data via USB connection, to change batteries, and to scan for errors, but the data station was not able to consistently receive data from all 42 locations. Furthermore, field operations (seeding, spraying, and harvest) required that cables be disconnected and buried, and posts be removed, resulting in multiple data gaps throughout the growing season. In some instances, sensors could not be located after field operations, which required that we completely reinstall sensors for those locations. For this reason, we adopted a below ground storage system in the spring of 2013. Since this change, we excavate once or twice per year to change batteries and perform maintenance. We also added desiccant packs (10–50 g) to the waterproof case to collect condensation, which accumulates during the winter months in the Mediterranean climate. Some of the cases at locations that experience seasonal saturation near the soil surface have flooded. At those locations, we store the case above ground during winter and spring, and we are exploring options to reinforce the cases to resist water entry.

Sensor life-span is estimated at 3–5 years for older models, and 7–10 years for sensors manufactured in recent years (e.g., since 2013, Decagon Support Staff, personal communication). Across the 210 sensor and 42 data logger installations, we have replaced 68 sensors (some up to three times), spliced 33 sensor cables, and replaced five data loggers due to failure, flooding, or damage. Sensor failure frequency is higher in soils that experience extended periods of saturation. When a sensor requires complete replacement, insertion of a new sensor must occur at a different location. In an effort to keep soil disturbance to a minimum, we leave exhausted sensors in place (particularly at deeper depths). We coil all operating cables together and nest them beneath the waterproof case for protection from farm equipment; however, sensor cables have occasionally been severed and data loggers have been crushed by farm equipment. Aside from missing data gaps resulting from sensor damage, sensor expiration, and battery death, the network has provided continuous data collection for the duration of its existence. The total number of hourly readings (accounting for different installation dates) is 14,127,840. Of those, 5,121,639 are missing a water content reading, and 5,070,945 are missing a temperature reading. Individual sensors have between 9 and 79% of the records missing, with an average of 35% (and a median of 34%) across all sensors.

Sensor data from each data logger (each location) is downloaded as a single spreadsheet file. We screen each spreadsheet for blatant sensor errors (volumetric water content values less than 0 or greater than 1, indicating sensor failure), which are replaced with "NA" values, and we confirm that all records have the correct date and time stamps. The volumetric water content readings are then calibrated. The TE sensors are factory calibrated in a variety of soil types and materials of varying dielectric permittivity (Decagon Devices, Inc., 2014; Kizito et al., 2008). However, specific soil conditions at the point of insertion can influence the variability of the sensors (Ojo et al., 2015; Rosenbaum et al., 2010; Spelman et al., 2013). Laboratory calibrations on individual sensors prior to installation may not represent the specific soil conditions in the field, and this approach is unrealistic for a large number of sensors in a heterogeneous setting, such as CAF. To calibrate the CAF sensor network, we developed a retroactive calibration, described in detail by Gasch et al. (2017) wherein a two-step calibration process is used to provide corrections based on static soil physical properties of installation sites. With this calibration method, the network-wide root-mean-squared error of volumetric water content readings is 0.049 m^3 m^{-3}. Sensor readings of temperature and electrical conductivity are not validated or calibrated, and bulk electrical conductivity readings should be converted to pore water conductivity (Hilhorst, 2000) prior to interpretation. Daily readings are computed as the arithmetic mean of hourly readings, with "NA" values removed prior to averaging.

After calibration, the sensors are screened and flagged for the following anomalies: missing data, flat-lining, values out of range (0–0.6 m^3/m^3 for water content and <0°C for temperature), spikes, and breaks (either drops or jumps) based upon the criteria described by Dorigo et al. (2011, 2013). A collection of files containing flags for each type of sensor anomaly is included in the data set, along with code for implementing the quality control screening in R (R Core Team, 2017).

2.4. Auxiliary Data From CAF

The water content data are available as a single file for each instrumented location. All records span the exact same time period (20 April 2007 to 16 June 2016, by hour and day—please contact the authors for uncalibrated bulk electrical conductivity readings). A set of files for hourly and daily soil temperature is also provided. Missing data exist for each sensor's record. A point shapefile accompanies the set of files, providing the spatial coordinates for each monitoring location.

In addition to the sensor data, we include the cropping history of each subfield and strip for each year, as a shapefile and in tabular form. We also include a 10 × 10 m digital elevation model (DEM) for CAF. The DEM was developed from points collected at high density by a differential global positioning system survey, and then subject to a local polynomial interpolation, described in detail by Huggins et al. (2014).

Soil data in the CAF data set includes bulk density and particle size to 1.5 m depth at each of the 42 instrumented locations. Volumetric soil cores at each location were extracted using a slide-hammer corer (5 cm diameter, AMS, Inc., American Falls, ID), in 10 cm increments, to 1.5 m depth (Blake & Hartge, 1986). We also extracted soil cores with a hydraulic coring device (2.75 cm diameter probe, Giddings Machine Company, Windsor, CO) to a depth of 1.5 m at each instrumented location. For 10 cm segments around each sensor depth, we obtained particle size distribution using the pipette method (Gee & Bauder, 1986). The range of soil particle sizes across the 42 locations and five depths at CAF were 42–75% silt, 12–46% clay, and 7–25% sand, and the bulk density ranged from 1.01 to 1.62 g/cm^3. Because the argillic horizons can influence soil water dynamics at CAF, we have included prediction surfaces for presence of a Bt horizon at the five sensor depths. The probability surfaces were interpolated from soil profile descriptions using a three-dimensional logistic regression-kriging model, described in detail by Gasch et al. (2015).

We also include two surfaces of apparent electrical conductivity (ECa), representing wet (spring, 6 May 2013) and dry (fall, 20 September 2013) conditions at CAF, which can serve as covariates for soil and water mapping. Surveys of ECa were conducted using an EM38-MK2 (Geonics Limited, Mississauga, ON, Canada) coupled with an AgGPS 132 differential global positioning system (Trimble, Sunnyvale, CA). The readings from the EM38 were attached to their location every second using the Handheld Geographic Information Systems software package (StarPal, Fort Collins, CO). The effective measurement depth (in vertical dipole orientation) was 1.5 m (Sudduth et al., 2001) with units of milliSiemens per meter (mS/m). In the spring, we walked the field to take readings at points on a 30 × 30 m grid (420 locations). At every other grid point (209 locations), we added a measurement point at short range, alternating in distance by 1 or 3 m and in orientation by the four cardinal directions. Thus, the spring survey had a total of 629 reading locations. For fall surveys, the instrument was placed in a polyvinyl chloride pipe carrier that was pulled behind an all-terrain vehicle, which was driven in a north-south, east-west grid across the field. The fall survey included a total of 13,232 reading locations. The ECa surface (10 × 10 m) for the spring survey was created using a regression-kriging model (Hengl et al., 2007), with elevation, topographic wetness index (Beven & Kirkby,

Table 1
Data Components and Summaries Included in the Described Data Set

Data set component	Comments	Format
Soil water content and temperature	Hourly and daily water content (m^3/m^3) and soil temperature (°C) readings collected at 42 locations and 5 depths (0.3, 0.6, 0.9, 1.2, and 1.5 m) for the time period 20 April 2007 to 16 June 2016.	.txt file for each location
Sampling/monitoring locations	Coordinates for each of the 42 locations.	.shp file (point)
Field and crop delineations	Boundaries of subfields and strips and cropping history and crop identity codes for 2007–2016.	.shp file (polygon) .txt file
Digital elevation model	10 × 10 m grid for elevation (in m)—can be used to derive terrain indices.	.tif (GeoTiff)
Bt horizon probability surfaces	10 × 10 m grids for 0.3, 0.6, 0.9, 1.2, and 1.5 m depths.	.tif (GeoTiff)
Spring and Fall ECa	10 × 10 m grids for spring (wet) and fall (dry) apparent electrical conductivity (ECa, mS/m), collected in 2013.	.tif (GeoTiff)
Soil properties	Bulk density (g/cm^3) at sensor depths at 42 locations.	.txt file
	Soil particle size (% clay, silt, and sand) at sensor depths at 42 locations.	.txt file
Meteorological data	Access via AgWeatherNet or Western Regional Climate Center.	
Quality Control files	Flags for locations, dates, and times for anomalous sensor readings.	.txt files
	List of current sensor models for each installation site	

Note. All spatial data have the spatial reference NAD83 UTM 11N. Soil water content, soil temperature, bulk density, and particle size files contain unique identities, which coincide with spatial point identities.

1979), and easting and northing coordinates as spatially exhaustive covariates. The fall ECa surface (10 × 10 m) was created with an ordinary kriging model. For each prediction surface, we randomly split the data into a training set used for model fitting (70% of points), and a validation set used to assess prediction accuracy (30% of points). The spring ECa surface accuracy, as measured by the root-mean-squared error (RMSE), was 2.94 mS/m (based on ten iterations of training and validation, range of ECa values = 11–78 mS/m); the fall ECa surface had a mean RMSE of 2.93 mS/m (based on ten iterations of training and validation, range of ECa values = 1–50 mS/m). All geostatistical analyses were conducted in R (R Core Team, 2017), using the "gstat" package (Pebesma, 2004), with assistance from the "rgdal" (Bivand et al., 2015), "raster" (Hijmans, 2015), and "plyr" (Wickham, 2011) packages.

Meteorological data are collected by a station located at CAF (see Figure 1b for location); measured properties include air temperature, relative humidity, and dew point temperature at 1.5 m height, soil temperature at 20 cm depth, rainfall, wind speed, wind direction, solar radiation, and leaf wetness at 2 m height. Properties are recorded every 5 s and summarized every 15 min by a data logger. The CAF station is a member of Washington State University's AgWeatherNet and data and sensor details can be obtained at http://weather.wsu.edu/. The CAF station name is "Pullman, NE" and was installed on 8 June 2011. Meteorological records from 21 October 1940 to 16 January 2015 can be obtained from a different weather station located 7.5 km southwest of CAF. Properties measured by this station (identifier: "Pullman 2 NW, Washington

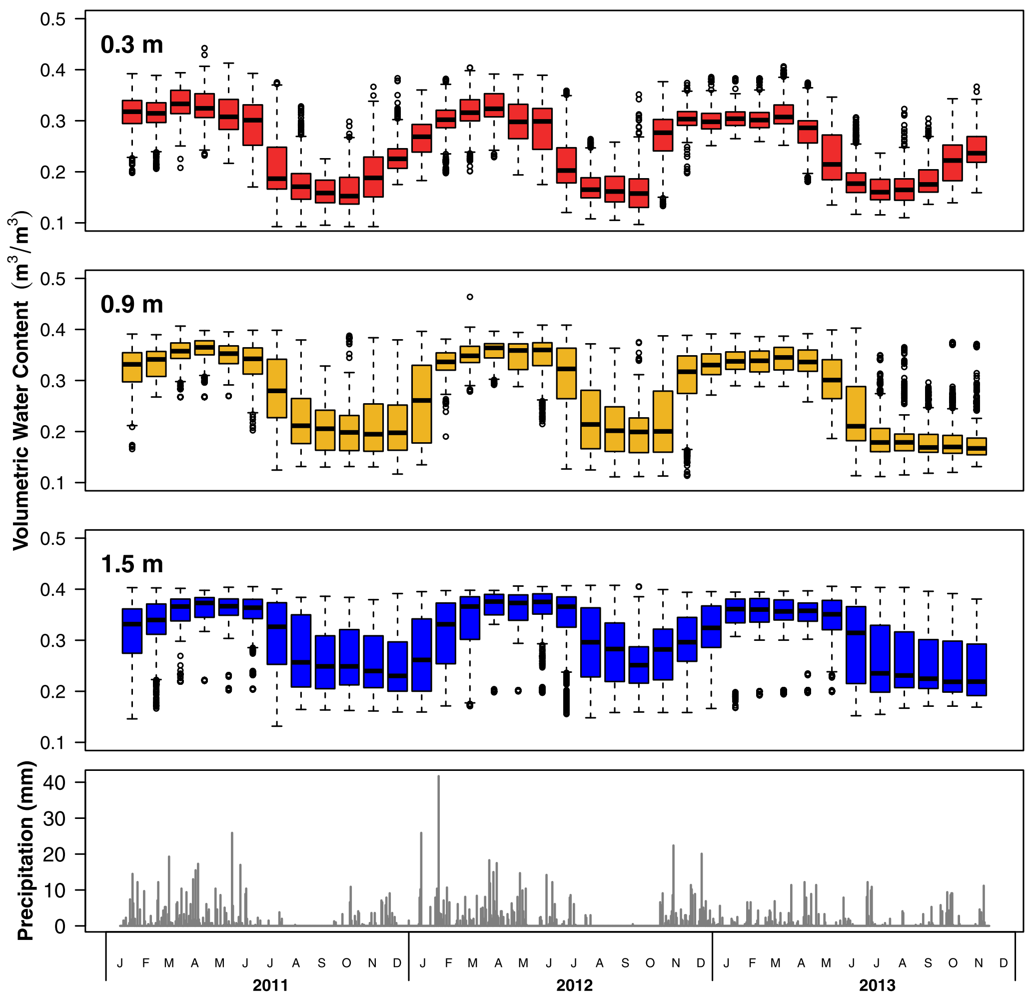

Figure 2. Box-and-whisker plots of field-wide volumetric water content for each month in 2011–2013 at three depths (0.3, 0.9, and 1.5 m). The bottom plot shows daily precipitation for the same time period. The line within the box represents the median value, the box represents the lower and upper quartiles, the whiskers represent the minimum and maximum, and the dots represent outliers.

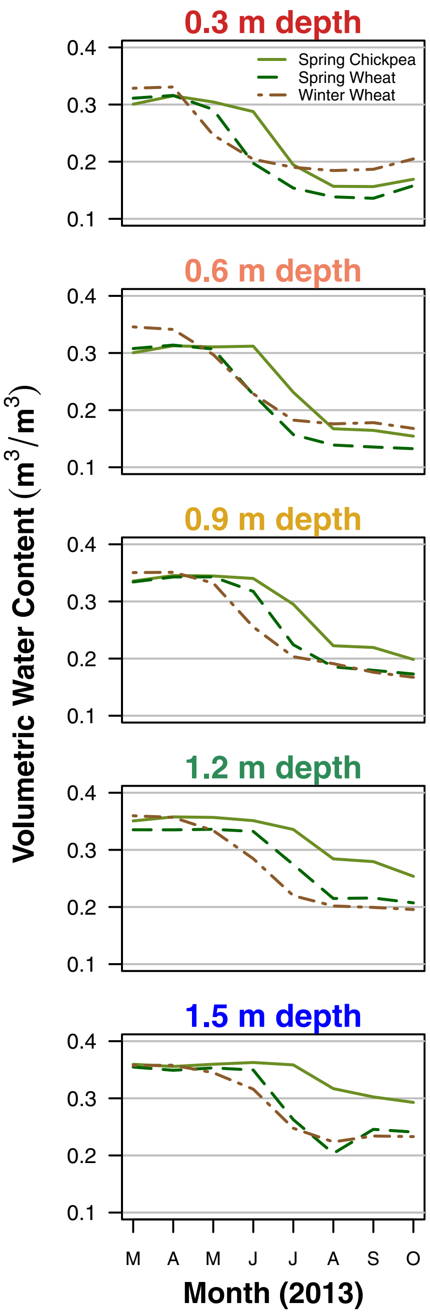

Figure 3. Mean monthly soil water content plotted for each depth, under each of three crops, for the 2013 growing season ($n = 11$ locations for spring chickpea, 14 locations for spring wheat, and 14 locations for winter wheat).

(456789)") include daily minimum and maximum air temperature, total precipitation, total snowfall, and total snow depth. These data and sensor details are available through the Western Regional Climate Center (www.wrcc.dri.edu).

2.5. Data Set Access

The entire data set is available through the National Agriculture Library. It has an assigned https://doi.org/10.15482/USDA.ADC/1349683, and it can be accessed at https://goo.gl/JYAIT3. Table 1 summarizes data components and their formats included in this data set. Use of the data is encouraged but must credit the authors and reference this publication.

3. Demonstration of the Data Set

The sensor network provides soil water content data as space-time points across CAF, which can be analyzed at any level of spatial and/or temporal aggregation, or treated in a spatially or temporally explicit manner. Here we present some descriptive summaries and illustrations to demonstrate the nature of the data set.

CAF soil receives water as precipitation (not irrigation), so soil water content displays a cyclic pattern, with four distinct seasonal phases:

1. late winter to early spring: cold soils receive precipitation and maintain high water content;
2. late spring to early summer: temperatures increase and soil water fluctuates in response to crop growth and precipitation;
3. late summer to mid-autumn: temperatures are high and soil water rapidly decreases through evapotranspiration and reduced precipitation; and
4. late autumn to early winter: temperatures decrease and dry soil is gradually recharged with precipitation.

The field-wide water content adheres to this seasonal cycle. Figure 2 illustrates the water content values across the field, with daily readings grouped into monthly boxplots for three depths (0.3, 0.9, and 1.5 m). The water content values at the 0.3 m depth display a stronger seasonal pattern (more temporal variability), whereas the values at 1.5 m display a weaker seasonal pattern and more variability across locations, particularly during late summer to early spring (indicated by longer boxes and whiskers). Also visible in Figure 2 is a delay in the cyclic pattern with increasing depth. The water content begins to drop in April at 0.3 m, May at 0.9 m, and June at 1.5 m; there is a less pronounced delay during the wetting period at the deeper depths. At most CAF locations, water content at all depths experiences the seasonal fluctuation, but a few locations do not exhibit this pattern.

Variability in soil water dynamics and patterns at individual sites is influenced by landscape position and soil profile characteristics. Crop identity can also affect soil water content patterns. Figure 3 presents the mean soil water content plotted for each depth under each of three crops in the 2013 growing season (locations for all crops span the topography of CAF). Soil drying under spring legume and spring wheat was similar at 0.3 and 0.6 m, but as the season progressed, water content under spring wheat was lower at deeper depths compared with spring legume. Soils under winter wheat had slightly higher mean water content at the beginning of the growing season, and soil drying appears to have been more uniform from the entire profile. These drying patterns during the growing season may relate to rooting depth differences between the crops. Winter wheat has the advantage of developing a larger root system, including at depth, which can extract water from the entire rooting profile (Winter & Musick, 1993). Additionally, there is a seasonal shift in soil dry-down between winter and spring crops, with winter crops extracting soil water earlier in the growing season, compared with spring crops. Roots of spring crops develop over much shorter time periods, and may be more reliant on shallow soil water. Spring legumes likely do not produce as much root biomass, or as many fine roots as wheat (Hamblin & Tennant, 1987), although our data and other reports (Benjamin & Nielsen, 2006; Thomas et al., 1995) indicate that they can still access soil water at 1.5 m. Information about root biomass, distribution, and architecture at CAF would complement this soil water content data for understanding crop water use patterns, and for partitioning evaporation and transpiration processes (Vereecken et al., 2015).

4. Concluding Remarks

The CAF soil water content data set presented here provides high frequency measurements that we have obtained over a heterogeneous, active farm, over 9 years. Even with 42 monitoring stations, each station provides a unique set of soil, terrain, microclimate, and crop conditions that provide insight into soil water content dynamics under particular site specific conditions. This data set has supported and will continue to support plot-level and field-level experimental, monitoring, and modeling work at CAF. However, we also anticipate that it can provide data for conducting point validation of local and regional systems models. Additionally, we hope that our experiences provide some insight into establishing and maintaining a soil sensor network in an intensively managed agricultural setting. This network will continue to be maintained, improved, and the data will be made available to the research community for the foreseeable future.

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