In-season Drought Monitoring: Testing Instrumentation and Developing Methods of Measurement Analysis

In-season Drought Monitoring: Testing Instrumentation and Developing Methods of Measurement Analysis

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by

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Abstract

Soil moisture sensor use in crop production systems has the potential to give inference on plant water status for the purpose of irrigation scheduling and site-drought characterization. These processed measurements could serve as the framework on which to compile trial results across locations, thereby more accurately defining varietal yield response to drought. Still, the ability to characterize drought within a given field or initiate irrigations from these data hinge upon the ability of the instrument to characterize soil moisture at the sampled point and extrapolate that information across the landscape and time. Therefore, the objectives of this research were to: (1) test the response of the Watermark 200SS (Irrometer Company, Inc., Riverside, CA) and Decagon 10HS (Decagon Devices, Inc., Pullman, WA) to changes in water content of three dissimilar soils representing common soils in row-crop production under variable environmental conditions; (2) develop a soil moisture-based index to quantify drought stress in dryland cotton cultivar trials; and (3) determine if a limited number of soil moisture sensors deployed into a dryland cultivar trial could accurately characterize the VWC at a given point within the field and if this measurement could be extrapolated out to the field scale from the very small sphere of influence characterizing the utilized soil moisture sensors. During the 2012 and 2013 growing seasons soil moisture sensors were deployed into over 14 cotton cultivar trials across the U.S. Cotton Belt and into a water-input controlled container study. Tested sensors' inability to accurately predict container VWC emphasized the relatively small quantity of soil on which these sensors rely and the variability in soil moisture within a very limited volume. Results from the drought-index studies suggested both the Accumulated Soil Moisture Stress Index (ASMSI) and the relative reduction in evapotranspiration ($1-(ET_{c\ adj}/ET_c)$) appear to have potential in characterizing the amount of stress experienced within dryland cultivar trials.

Analysis of spatial and temporal stability suggested trends between sensors were consistent, but absolute node readings varied. Optimism concerning the potential of these measurements/approaches for increasing water use efficiency is coupled with a call for more arbitrary, universal methods of measurement analysis.

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CHAPTER I

Introduction

The physiological processes associated with the onset and progression of drought in cotton (*Gossypium hirsutum*, L.) have been well characterized (Loka et al., 2011; Pettigrew, 2004a; Pettigrew, 2004b; Ball et al., 1994; Guin and Mauney, 1984a; Guin and Mauney, 1984b; Grimes et al., 1970). Each of these processes ultimately aggregate to curtail yield, resulting in a gap between yield potential and realized yield driven by water deficit stress. Producers have several management tools at their disposal to increase the soil water reserve or attempt to avoid historically water-deficit periods of the year. However, cotton producers in the Mid-South and Southeastern regions of the United States only have two substantial approaches to mitigate or manage drought stress: irrigate or plant drought-tolerant cultivars.

As of 2007, Arkansas ranked fourth in the U.S. in states with the largest acreage of irrigated land (2007 Census of Agriculture, NASS). This is in part due to the ease of access and low-overhead cost associated with the furrow system coupled with a relatively long growing season and fertile soils. However, row crop production in Mid-South region of the US, traditionally characterized by an over-abundant water supply, has recently seen an emphasis placed on water use efficiency. Many factors have contributed to this shift. These include escalating conflicts in the Western US between rural and urban water demand exacerbated by dwindling water supplies (Gleick et al., 2003), unsustainable depletion of several nonrenewable aquifers located across the Cotton Belt, even in the Mississippi River Delta (Konikow, 2013; Scott et al., 1998), and record drought in the 2011 and 2012 seasons, resulting in the most extensive drought since the 1950s (USDA-ERS, 2012). As a result, a large number of researchers are currently working on increasing the amount of crop yield which is produced from a given measurement of water (water use efficiency (WUE)) in the production system, or. These approaches can be categorized in three main goals: (1) increase the efficiency of the irrigation system, (2) better time each irrigation event, and (3) select cultivars which are more drought-tolerant.

Approaches to increase the efficiency of the furrow irrigated system are somewhat limited compared to other, more controllable irrigation systems. Most of these programs are focused on increasing the uniformity of each application, decreasing the amount of water allowed to run off the field, and increasing water infiltration into the profile. Methods to accomplish these goals vary but can include the use of surge flow, computerized hole selection (CHS), land grading, proper pipe placement, and tail water recovery. Programs such as the Pipe Hole and Universal Crown Evaluation Tool (PHAUCET) and Pipe Planner ™ by Delta Plastics (Little Rock, AR) are designed to accomplish many of these afore-mentioned goals.

In contrast to increasing the efficiency of the application, another method to increase WUE currently being explored is irrigation timing. Irrigation events are frequently scheduled by “balance sheet” or “checkbook” methods, which calculate water to be applied by subtracting modeled evapotranspiration from rainfall. Although better than an arbitrary time-interval based irrigation regime, many of these programs are based on estimated levels of crop water use instead of experimental verification (Vories et al., 2004). These methods may fail to estimate soil moisture at planting, runoff, or deep percolation.

Another method of increasing the irrigation efficiency of the production system would be the selection of drought tolerant cultivars. Currently, varietal drought tolerance is derived from yield responses noted in dryland cultivar trials. Although there are a large number of these trials located throughout the Cotton Belt, these are typically characterized by rainfall amounts alone.

Specific drought parameters necessary to accurately characterize seasonal growing conditions include timing, magnitude, and length of water deficit. Due to runoff, deep percolation, and a lack of information on soil moisture at planting and rainfall timing, accumulated seasonal rainfall often fails to characterize experienced drought and therefore prevent an accurate characterization of a cultivar's susceptibility to drought. For these reasons, producers lack the tools required to evaluate the benefit of the drought tolerant genes expected to be available in the near future and more basically, drought tolerance of current commercially available cultivars. Failure to collect and rapidly disseminate information on experienced drought stress is potentially limiting WUE.

Adoption of PHAUCET, the Arkansas Irrigation Scheduler, and a Pumping Cost Calculator have helped AR producers increase the efficiency of each irrigation event (Tacker, 2006) and decreased amounts of water applied (McClelland et al., 2012). Similar programs and results have been noted in other Mid-South and Southeastern States (Sassenrath et al., 2012). Still, the use of some in-season measurement to give inference on plant water status has the potential to remove many uncertainties associated with checkbook methods of irrigation scheduling. Concerning selection of drought-tolerant cultivars, these in-season measurements could be used to better characterize locational drought stress and serve as the basis on which to compile varietal yield response across locations.

Introduction of in-season plant-water-status-monitoring sensors has the potential to provide insight into yield-reducing stresses. This information could be used to initiate fewer, better-timed irrigation events which ameliorate the drought stress before a yield penalty is realized. If further developed, yield-reducing stresses quantified by in-season plant-water-status-monitoring sensors could be accumulated to describe seasonally experienced drought stress. This information could then be used as the parameter on which to compile dryland cultivar trial yield results and therein define very robust information on varietal yield response to drought possibly within one year from commercial release. Therefore, the objectives of this dissertation were to:

(1) examine the accuracy and precision of in-season soil moisture monitoring sensors to determine volumetric water contents of three dissimilar soils across varying environmental conditions,

(2) develop and test a soil moisture sensor-reliant drought-characterizing index to serve as a variable on which to compile dryland cultivar trial results and subsequently define varietal yield responses to stress, and

(3) determine if measurements of volumetric water content made by soil moisture sensors consisting of very small spheres of influence and corresponding drought-stress indices could be extrapolated to the field scale.

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CHAPTER II

Literature Review

Water Deficit Stress Indices

The accumulated stress/yield concept is based on the negative relationship of yield and water deficit stress. If no water stress is experienced during the growing season, yield will simply be a function of other genotypic and environmental limitations. As water-deficit stress occurs and 'stress units' are accumulated, yield penalties ensue. Accumulated stress units are therefore theoretically negatively correlated to crop yield. Most agriculture-based stress indices have been developed to increase WUE by more efficient irrigation scheduling. The index framework is also fairly consistent from author to author; however, authors typically diverge on stress definition and determination as well as the incorporation of a crop susceptibility factor.

Early Development

Some of the first authors to develop a primitive water stress index concept were Nix and Fitzpatrick (1969). Through soil water modeling and estimated potential evapotranspiration authors were able to determine periods of water stress and correlate these stress index 'units' to yield of wheat (*Triticum aestivum,* L.) and sorghum *(Sorghum bicolor,* L.). The defined 'stress index' represents the time in weeks which the current level of available water would sustain the crop if the rate of potential evaporation remained consistent. Noted yields of grain sorghum and wheat were positively correlated to increases in the stress index. This 'stress index', which would have more appropriately been deemed an 'available water index', is determined at the beginning of the pre-determined, 'critical' growth stage. Therefore, water stress experienced prior to, or after the 'critical' period is not included in the calculation.

A much more refined, season-encompassing Stress Day Index (SDI) was introduced by Hiler and Clark (1971) as a method of increasing water use efficiency by optimizing irrigation scheduling. Accumulated SDI values are calculated by summing the product of a stress day factor (SD) multiplied by a crop susceptibility factor (CS). Length, magnitude, and timing of stress are dictated by the SD factor. Proposed parameters to calculate SD included coarse-resolution plant measurements or estimated meteorological data. The CS factor serves as a method of decreasing or increasing SDI depending upon species and growth stage sensitivity to stress. Authors found this index to be acceptable for irrigation scheduling and predicting yields under crop water stress conditions. Weaknesses of this index hinged on the large number of samples required to define changes in plant water potential (the author selected SD factor) over time restricted its use in most production systems. Still, the SDI successfully advanced the stress index concept to include seasonal stress and growth stage sensitivity.

Canopy Temperature and the Stress Day Concept

A few years prior, Wiegand and Namken (1966) began examining the influence of plant moisture stress, solar radiation, and air temperature on cotton leaf temperature. Authors used an infrared thermometer to measure leaf temperature and a thermocouple in each plot to determine air temperature. Results indicated increases in leaf temperature were associated with decreases in relative turgidity, the authors' chosen indicator of plant moisture stress. Leaf temperature was also described to be sensitive to solar radiation and air temperature. Conclusions stated plant moisture stress significantly altered leaf temperature with respect to ambient air temperature, but caution should be taken under cloudy conditions due to the influence of solar radiation on leaf temperature. Several years later, Aston and van Bavel (1972) published research examining the relationship between soil surface water depletion and leaf temperature in order to determine the feasibility of remote-detection of cropped-field water depletion. Specifically, authors tested the theory that increases in leaf temperature were associated with increases in shortwave radiation from drying soil. Although this publication failed to consider transpiration as the major control for leaf temperature, the authors did suggested drought onset could be detected remotely through measurement of canopy temperature. These publications, along with several others, served as the framework for the incorporation of other drought stress indicators to serve as the SD factor.

Recognizing the shortcomings of the SD component of the SDI and the ability of canopy temperature to indicate stress, Idso et al. (1977) and Jackson et al. (1977) proposed canopy-air temperature differences to be an appropriate SD indicator. Both publications referred to this index as a Stress Degree Day (SDD). According to the authors, this measurement could be monitored remotely and prevented the labor intensive plant water potential measurements of Hiler and Clark (1971). To test this new SD indicator, Idso et al. (1977) predicted final wheat yield with accumulated stress units determined from canopy temperature. As predicted, strong negative relationships were noted between grain yield and accumulated stress units. Jackson et al. (1977) further tested this method by examining stress thresholds on which to base irrigations. Authors used a derived evapotranspiration equation to relate canopy-air temperature differences to soil water depletion. Even though several parameters in this equation were estimated, results suggested canopy-air temperature differences could serve as irrigation scheduling tools for large irrigation districts. In a later critique, however, Idso et al. (1981) found the SDD to be sensitive to several parameters beyond the parameter of interest, soil moisture.

During this period other indices were also being developed. Similar to the SDD, the Temperature Stress Day (TSD), developed by Gardner et al. (1981), utilized no atmospheric measurements. The TSD also differed from the SDD by utilizing a well-watered canopy temperature instead of an ambient air temperature for index calculation. Authors noted moderate relationships between cumulated TSD and relative yields of sorghum. Clawson and Blad (1982) were successful in scheduling corn (*Zea may*, L.) irrigations from measured TSD, but a critique of the TSD method by Clawson et al. (1989) displayed the sensitivity of the TSD to changes in vapor pressure deficits at a constant stress level, similar to the findings of Idso et al. (1981) concerning the SDD.

Crop Water Stress Index

In an effort to reduce sensitivity of these indices to parameters other than soil moisture, Jackson et al. (1981) modified the SDD introduced in 1977 and introduced this index as the Crop Water Stress Index (CWSI). This index is strongly rooted in the energy balance concept of crop production. Calculation of this index also requires wet-bulb air temperature and an estimation of net radiation in addition to the standard dry-bulb air temperature and canopy temperature measurements required by the SDD. These measurements are used to determine lower and upper limits of the canopy-air temperature difference, which represent well-watered and completely water deficit-stressed conditions, respectively. The index is then calculated by normalizing readings, resulting in values from zero (no water-deficit stress) to one (complete water-deficit stress). The CWSI was intended to be calculated from a single measurement taken between 1340 and 1400 each day. Studies examining the sensitivity of this index indicated the CWSI correlated strongly to extractable soil water and was less sensitive to other environmental factors (Idso et al., 1981).

One major limitation of adoption of the CWSI is the requirement for a wet-bulb temperature, which must be either estimated or determined experimentally. Estimation of this baseline requires information on multiple environmental parameters which are difficult to measure. Furthermore, experimental determination of the non-water-stressed baseline is site and season specific, and is only valid during clear skies. As a result, several authors tested a slightly modified CWSI which included a well-watered canopy temperature. Berliner et al. (1984) found this method buffered measurements against wind gusts and resulted in strong correlations with leaf water potential and stomatal resistance. Clawson et al. (1989) proposed a merging of the CWSI and the TSD. Specific modifications included the theoretical and empirical replacement of several difficult to determine CWSI parameters with a well-watered canopy temperature reading of the TSD. Each of two methods displayed stability to changes in environmental factors at constant levels of experienced stress, suggesting both could be acceptable crop water stress indicators. Similar work was conducted by Alves and Pereira (2000), who proposed and tested replacement of the wet-bulb temperature with monitored canopy temperature of a well-watered irrigation control. Conclusions were similar to other mentioned studies. Alves and Pereira (2000) concluded this adjustment would allow for crop water stress monitoring even under overcast conditions.

Additionally, Colaizzi et al. (2003a) conducted a trial comparing the CWSI to a Soil Water Stress Index (SWSI) based on available water in the effective rooting zone in Maricopa, AZ. Results showed a strong linear correlation between the CWSI and SWSI (r^2=0.86), confirming the ability of canopy temperature to serve as an indicator of available soil moisture and therefore crop water stress in arid environments. However, authors were forced to remove 4 growing season days from the analysis, three of which corresponded to rainfall events of 5, 3, and 5 mm, and one of which resulted in no rainfall but was characterized by overcast conditions.

Water Deficit Index

Another weakness of many canopy temperature measurements, and therefore the CWSI, is the inclusion of soil in the field of view, particularly prior to canopy closure (Moran et al., 1994). This has led some investigators to exclude time periods in which canopy development was not sufficient enough to prevent soil interference (Wanjura et al., 2004). Unfortunately, full canopy closure in many environments occurs at a point well past irrigation initiation timing, and due to the very substantial influence of soil moisture on soil temperature, a linear canopy closure and soil temperature correction fails to accurately remove soil interference. In an attempt to increase the utility of CWSI prior to canopy closure, Moran et al. (1994) developed a water deficit index (WDI) which is capable of detecting water stress in full-cover and partially vegetated fields using remotely sensed data. In order to accomplish this goal, authors utilized a vegetation index/temperature trapezoid to remove soil interference. Additional measurements required to calculate the WDI include red and infrared reflectance. Simulations and field trials suggested the WDI was capable of indicating relative field water deficit and field evapotranspiration rates.

A more recent evaluation of the WDI by Colaizzi et al. (2003b) compared the index to a soil water deficit index (SWDI), calculated from soil moisture measurements. Results indicated coefficients of determination between the two indices ranged from 0.84 to 0.87. According to the authors, failure of the relationships to be greater was due to the instantaneous point nature associated with the WDI in comparison with the average day nature of the SWDI. Still, the authors highlighted the potential of the remotely-sensed WDI to increase water use efficiency by increasing producer knowledge of water-stressed areas which would most likely not be noted from ground observations.

Canopy Time Temperature Thresholds

The canopy time temperature threshold (TTT) process and device, patented by Upchurch et al. (1996), varies substantially from the CWSI. This method requires constant monitoring of canopy temperature to determine when thermal stress occurs. Stress units are accrued when the monitored canopy temperature rises above the established temperature threshold and humidity is considered to be non-restrictive to plant cooling. According to Wanjura and Upchurch (1997) the threshold for cotton is 28°C. If cotton's canopy temperature remains below the threshold temperature or humidity is considered restrictive to plant cooling, stress units are not accrued. If the threshold is violated and the relative humidity is considered to be non-limiting, stress units begin to accrue. These stress units are accrued until an accumulated unit threshold is met, at which point an irrigation event is made.

Wanjura et al., (2004) further evaluated this method in Lubbock, TX with the objective of more accurately defining the relationship of irrigation water quantities and cotton yields to differing time thresholds (TT). The authors defined TT as the irrigation trigger associated with accumulated stress time (ST) above a temperature threshold. Authors observed canopy temperature under well watered and 50% of well watered irrigation regimes. In this study, the TT of 330 min/day was established and maintained. Results indicated increases in average calculated daily ST were associated with decreases in lint yield, total applied water and irrigation. Surprisingly, however, average daily ST was greater than the established TT. Authors suggested this was due to fluctuating canopy temperature of well-watered cotton when atmospheric environment was also fluctuating.

More recently, O'Shaughnessy and Evett (2010) attempted to schedule irrigation by using an automatic, canopy temperature time threshold-based system in comparison with a manual system. Research was conducted under a center pivot irrigation system in Bushland, TX.

Authors found inconsistent yield responses from the treatments, but noted increased irrigation water use efficiency (IWUE) with the automatic irrigation treatments. Still, authors concluded further research was needed due to the limited scope of the trials and the variability associated with the TX climate.

As defined, this approach is capable of quantifying length of deficit, timing of deficit, and frequency of deficit; however, no incorporation of the magnitude of the deficit is included. To best understand this error, it is useful to consider two stressed plants, one of which is growing at a soil moisture content just below a restrictive volume and one of which at a soil moisture content at or near permanent wilting point (PWP). Regardless of soil water content, the time temperature threshold at a given mid-afternoon point within the day will be the same. Although accrued stress units throughout the day will be theoretically greater for the plant which has no available water (increased time during the day at which the canopy temperature exceeds the threshold) it is logical to expect some increase in the relationship between accumulated stress units and yield to result from the incorporation of information on the magnitude of the deficit.

Humid Climates and Canopy Temperature

It is important to note that the CWSI was developed in the arid Southwest and Midwest regions of the US and an important source of error described by Jackson et al. (1981) was rapidly changing cloud conditions. According to the authors, quality measurements were possible during clear or overcast conditions but serious errors were associated with periods of intermittently cloudy conditions. More recent work by Colaizzi et al. (2003a) also indicated difficulty relating the CWSI to soil water under conditions of low vapor pressure deficits. According to Idso et al., (1981), “defining stress in this fashion limits our ability to confidently quantify (the onset of crop water stress) under conditions of low vapor pressure deficit, where the entire range of foliage to air temperature variability approaches the degree of scatter inherent in the data."

Utilization of the CWSI in the humid Mid-South or Southeast therefore poses many challenges, most of which stem from canopy temperature relationships to soil water in more meteorologically inconsistent locations. First, the recommended early-afternoon measurement times coincide with times of cloud formation, and variations in sensing time to calculate CWSI have been shown to influence CWSI values (Taghvaeian et al., 2012). Rainfall may or may not occur during these isolated thunderstorms, but as a response of the storm building, weather conditions across the region become very inconsistent. These inconsistencies result in highly variable air temperature, wind, and humidity, all of which change atmospheric moisture demand and transpiration. As a result, accurate site characterization in humid regions may prove difficult by the single measurements of canopy temperature or meteorological parameters proposed for arid climates. Critiques of the CWSI have alluded to this issue (Colaizzi et al., 2012; Idso et al., 1981; Jackson, 1982).

In theory, the canopy TTT concept would be less susceptible to such errors since measurements are conducted continuously. Nonetheless, research examining the TTT has also shown mixed results. Bockhold et al. (2011) tested this method in Portageville, MO with well watered, semi-stressed, and stressed crops of corn, cotton and soybeans. The canopy temperature time-threshold irrigation scheduling method failed to significantly increase yields or IWUE for any of the examined crops. Furthermore, differences in cotton canopy temperature between the well-watered and semi-stressed treatments were frequently insignificant. Although some results indicate potential of canopy temperature to determine water-stressed conditions, authors concluded these measurements have limitations and more research is necessary before these instruments can be effective, particularly in humid environments.

Soil Moisture and the Stress Day Concept

All aforementioned indices rely on the relationship of some measured or predicted parameter (most frequently canopy temperature) to the depletion of available soil water. Initial development of canopy-temperature based measurements relied heavily on handheld infrared thermometers or the use of thermal imaging to detect temperature differences. These methods allow canopy temperature readings to be taken over a large area at a fine scale with little difficulty. Still, plant-based sensing is associated with a number of practical difficulties which have, to this point, prevented large commercial adoptions (Jones, 2004). Indirect soil moisture measurements, in contrast, are most commonly characterized by very small fields of influence. For example, the neutron probe, considered to have one of the larger fields of influence, is only sensitive to soil within a 4-16 inch radius (Muñoz-Carpena et al., 2004). As a result, a large number of measurements must be conducted at a very high spatiotemporal frequency to characterize field-scale soil moisture over time. Consequently, soil moisture measurements have in the past been characterized as labor intensive and expensive, therefore more spatially coarse and less practical for field-scale drought characterization.

Recent advancements in electronics have resulted in a dramatic increase in the number of commercially available soil moisture sensors, many of which vary substantially in cost and application (Chávez and Evett, 2012; Muñoz-Carpena et al., 2004; Robinson et al., 2008). Still, only a few of these sensors are inexpensive enough to be appropriate for large deployments necessary for spatially dense readings. Two sensor types which currently meet these criteria are granular matrix sensors and low-frequency, capacitance-based sensors. Granular matrix sensors have been commercially available for many years and use resistance between two electrodes to infer soil water potential. Low-frequency, capacitance-based sensors have been commercially introduced more recently. In contrast to the granular matrix sensors, the low-frequency, capacitance based sensors rely on the dielectric characteristics of the sensing medium to infer volumetric water content (VWC).

Tensiometric Sensors

Sensors estimating soil matric potential include tensiometers, gypsum blocks, granular matrix sensors, heat dissipation sensors, and soil psychrometers (Muñoz-Carpena et al., 2004). The majority of these sensors estimate the amount of energy with which soil water is held by monitoring water movement through a porous material in contact with the soil. Granular matrix sensors are widely used for large deployments due to their low cost. These sensors are typically composed of two electrodes embedded into a cylindrical granular matrix which is buried in the soil. The granular matrix equilibrates to soil water content by the transfer of water from the surrounding soil. Moisture in the sensor is measured by the change in resistance between the two embedded electrodes. Specifically, a decrease in resistance is associated with an increase in soil moisture. One of the most commonly used granular matrix sensors is the Watermark Model 200SS (Irrometer Company, Inc., Riverside, CA).

Although the reported sensitivity for the Watermark 200SS sensor ranges from 0-200 kPa, erratic measurements have been reported during prolonged drying cycles exceeding 90 kPa (Berrada et al., 2001). Increased variability was suggested by Berrada et al. (2001) to be due to reduced soil contact with the porous matrix. Subsequently, use of these sensors in swelling soils should be avoided (Muñoz-Carpena et al., 2004). More concerning for quantification of seasonal drought stress, however, is the reported failure of the sensor to respond to rapid changes in soil water (Berrada et al., 2001; Muñoz-Carpena et al., 2004). McCann et al. (1992) reported accurate measurements during standard drying periods which were followed by complete re-wetting; however, poor results were noted under partial rewetting or rapid drying conditions. After a prolonged drying period, authors suggested accurate measurements taken during the following drying cycle would only be accurate if soil water reached or exceeded field capacity, or a threshold of -10 kPa. Furthermore, McCann et al. (1992) concluded that many deep sensors could fail to meet this re-wetting threshold and therefore these sensors could provide a limited amount of useful information for irrigation scheduling. These errors were also highlighted by Shock et al. (1998) while developing calibration equations for the Watermark 200, 200SS and the 200SSX. According to other reasearch, a minimum of 24 hours should be given after a rainfall or irrigation event to allow the sensor time to respond (Enciso et al., 2007). Although these issues are less of a concern in a well-managed irrigated cropping system (Berrada et al., 2001), the re-wetting requirement and slow response time pose significant challenges for the objective of drought quantification or under low-frequency irrigation regimes.

Still, the low sensor cost has made these sensors very appealing for the large deployments necessary for field soil water characterization. Fisher and Kebede (2010) utilized the Watermark 200SS Sensor in an effort to build a very low cost canopy, soil, and air temperature monitoring device for the Mid-south region of the U.S. The developed monitoring device was capable of measuring each of these aforementioned parameters for under 85 USD. Measurements of soil moisture and soil, leaf, and air temperature made by this system were later shown to be capable of detecting genotypic differences in corn response to stress (Kebede et al., 2012).

Additionally, Vellidis et al. (2008) utilized a 12 node, wirelessly-monitored system in a Georgia cotton field to monitor soil moisture and temperatures. Each node consisted of three

Watermark sensors and a thermocouple. Slight modifications in the sensor array resulted in a system which could be deployed early during the growing season and remain reliable until harvest without adjustment. Results indicated deployments of 2-3 nodes allowed for sufficient characterization of each irrigation management zone. Authors concluded that this technology was capable of driving variable rate irrigations to fields containing multiple irrigation management zones, thereby efficiently supplying irrigation water to spatially variable water demand.

Volumetric Sensors

A large percentage of VWC sensors utilize dielectric permittivity characteristics to make inferences on soil water content of the tested medium. This dielectric measurement of soil moisture is based on the concept that air and solid mineral particles are characterized by small dielectric constants (3-5 for most mineral components of soils, 1 for air). These small, consistent readings greatly contrast the large dielectric constant of water (78.9 at 23°C). Therefore, shifts in composite dielectric readings are noted even during small shifts in VWC (Kizito et al., 2008).

Several equations which range from simple to highly complex have been proposed to calculate VWC from measured composite dielectrics (Alharthi and Lange, 1987). The most frequently used is an empirical equation outlined by Topp et al. (1980). Dielectric responses of soils, as defined by Topp et al. (1980) are a function of texture, structure, soluble salt concentration, temperature, density, measurement frequency, and water content. The influence of water content on the dielectric constant is so dominant, however, that often the response of the constant can be considered “almost independent” of the other parameters (Topp et al., 1980).

Time domain reflectometry (TDR), frequency domain reflectometry (FDR), water content reflectometery (WCR), capacitance techniques, amplitude domain reflectometry, and phase transmission techniques are all based on the composite dielectric properties of soil composite and frequently utilize some form of the Topp equation (Chávez and Evett, 2012; Muñoz-Carpena et al., 2004). These sensor types vary slightly in methodology but all characterize the water content of a very limited soil area immediately adjacent the sensor. Extrapolation from these very small spheres of influence to the field-scale is often complicated due to the spatial variability of soil characteristics. One way to compensate for this variability is to increase the number of deployed sensors. Historically, large deployments have been financially impractical.

One notable exception to this financial restriction are VWC utilizing low-frequency, capacitance-based techniques (Kizito et al., 2008; Czarnomski et al., 2005; Seyfried and Murdock, 2004). Due to their cost, these sensors are frequently utilized for continuous logging in large deployments. Capacitance sensors correlate to soil moisture by measuring the charge time of a ground electrode buried in the soil (Kizito et al., 2008). The medium immediately surrounding the positive and ground capacitors increases or decreases charge time and this charge time is exponentially more dependent upon soil moisture than other parameters. The resulting relationship between capacitance charge times and VWC is fairly strong.

One concern with relatively in-expensive capacitance sensors are their low-frequency. Low-frequency sensors are more susceptible to the dielectric constants of soil texture, electrical conductivity (EC) and temperature, and therefore shifts in readings are not as strongly associated to changes in VWC. Sensitivities to medium characteristics beyond VWC have been reported to increase below frequencies of 100 MHz (Chen and Or, 2006). Unfortunately, higher frequencies are directly related to greater cost of sensor production, and most commercially produced, low cost, low-frequency, capacitance-based sensors are below the reported 100 MHz threshold.

In an attempt to more thoroughly define the sensitivity of a low-cost, low-frequency, capacitance-based sensor, Kizito et al. (2008) monitored the response of an ECH_2O-TE, 70 MHz Capacitance Sensor (Decagon Devices, Inc., Pullman, WA) to changes in frequency, temperature, and EC in a wide variety of soil types. Results suggested the sensor, when used in cooperation with a generic calibration curve, was capable of accurately determining VWC while relatively insensitive to other dielectric influencing parameters. These authors also monitored changes in sensor sensitivity as frequency was altered. Substantial decreases in sensitivity to EC, temperature and soil type were noted as frequency was increased from 10 MHz to 70 MHz. Although sensitivities continued to decrease until 150 MHz, no substantial decreases were noted at frequencies higher than 150 MHz. Results are in agreement with other research by Bogena et al. (2007), who noted increases in temperature and EC sensitivity associated with a 5MHz Decagon EC-20 sensor relative to a 70 MHz Decagon EC-5. Even so, a moderately strong temperature sensitivity of the Decagon 5TE sensor has been reported by Chávez and Evett (2012) in a study comparing five commercially produced soil moisture sensors.

A variety of studies have examined the use of the low-frequency, dielectric permittivity sensors in comparison to other, more costly dielectric permittivity sensors. Czarnomski et al. (2005) compared the use of a Decagon ECH_2O capacitance sensors, TDR sensors, and WCR sensors to determine VWCs of undisturbed, extracted soil profiles as well as mixed soil profiles. Authors noted all three sensors failed to reasonably determine VWC with the use of standard calibration equations; however, after soil specific calibration equations were developed, relationships strengthened greatly. The only sensor significantly influenced by temperature was the ECH_2O, as reported VWC decreased linearly by 0.1% for every 1°C increase in temperature. Even so, the authors concluded after evaluating cost, accuracy, and precision that the capacitance soil moisture sensors were appropriate for studies requiring high frequency observations at multiple sites over time.

Similarly, Seyfried and Murdock (2004) compared the low-frequency, capacitance-based 50 MHz Hydra Probes (Stevens Water Monitoring Systems, Inc., Portland, OR) to TDR sensors in a variety of fluids, soils, temperatures and ECs. One notable characteristic of the Hydra Probe is the unit's ability to also measure temperature and soil EC, making the unit comparable to the Decagon 5TE sensor. Authors concluded differences between the low-frequency, capacitance sensors and the TDR sensors were due to frequency differences. Still, Seyfried and Murdock (2004) reported both sensor estimated VWCs to correlate well with actual VWC under most soils.

Since the energy with which the water is held does not directly indicate amount of water held at the sampling time, conversion from matric potential to VWC requires a texture-specific soil water release/retention curve. These curves and a program used to derive them have been described in detail by multiple authors (Fredlund and Xing, 1994; Saxton et al., 1987; Saxton et al., 2006). Difficulties have been reported with this conversion as bulk density changes with inconsistent soil layers (Chávez and Evett, 2012), but strong coefficients of determination and low root mean square errors (RMSEs) have characterized some conversions of soil matric potential to VWC (Eldredge et al., 1993).

Comparisons between Low-cost Sensor Systems

Direct comparisons of similar low-cost sensors have been conducted, but construction of concrete conclusions has been difficult. Sui et al. (2012) compared of Decagon EC-5 and 5TM capacitance, frequency domain sensors to Watermark 200SS granular matrix sensors in a 10 ha cotton field in Stoneville, MS. Soil texture at this site ranged from a silt to a silt loam. Sensor nodes were deployed in 10 plots and each node monitored soil moisture at 3 depths (15, 30, and 60 cm). Authors noted substantially more soil-water depletion at the 15 and 30 cm depths than at the 60 cm depth from planting until 60 days after planting (DAP). From 60 to 80 DAP, a substantial decline occurred in soil moisture at the 60 cm depth. Difficulty was noted in comparing the reported soil water potential from the 200SS and the reported VWC from the Decagon sensors. Qualitative comparisons were made by monitoring trends over time. Resulting graphs were interpreted as displaying consistent behaviors between sensors at similar depths. Authors concluded that both sensors were capable of monitoring soil water status throughout the growing season.

Similarly, Varble and Chávez (2011) compared Decagon 5TE sensors with Watermark 200SS sensors under laboratory and field conditions. Measurements were then compared to VWCs determined by gravimetric sampling. Authors suggested each sensor required a unique calibration for every soil type and location within field. Although increasing soil EC in laboratory tests did not significantly influence 200SS readings, increasing soil EC did increase errors in 5TE reported VWCs. Authors concluded that field-based calibrations were more appropriate than laboratory-based calibrations, since laboratory conditions fail to represent specific, representative field operating conditions for each sensor.

Plant Available Water and Crop Stress

Plant available water (PAW), from a volumetric standpoint, is defined as follows:

$$\theta_{PAW}=\theta_{FC}-\theta_{PWP}$$

where: θ_{PAW} = Volumetric water content of plant available water (PAW)

θ_{FC} = Volumetric water content of field capacity (FC)

θ_{PWP} = Volumetric water content of permanent wilting point (PWP)

In this calculation of θ_{PAW}, θ_{FC} represents the amount of water held after gravitational water has drained away and represents the upper threshold of PAW. The lower limit, or θ_{PWP}, varies by species and cultivar, and represents the VWC at which the plant can no longer extract any water. From a tensiometric definition, this point is generally assumed to occur at -1500 kPa (Tolk, 2003). Subsequently. θ_{PAW} varies with soil texture. As texture becomes finer, PAW increases to a maximum near a texture of silt loams and then decreases (Brady and Weil, 2002).

Many studies have described water-deficit stress in terms of PAW. Meyer and Green (1980) determined 50% and 30% of PAW were safe irrigation scheduling values for crops of wheat and soybeans, respectively, as these values were associated with the onset of stress. Al-Khafaf et al. (1978) monitored evapotranspiration of cotton in arid New Mexico and suggested a substantial decline occurred at 40% PAW. In contrast, research in Arizona examining soil depletion levels of 35%, 50%, 65%, and 80%, found significant decreases in yield associated with each decrease in PAW (Husman et al., 1999). This research suggested yield-limiting water stress may occur at a PAW above 50%. Rosenthal et al. (1987) noted decreases in relative transpiration of cotton at 25% and decreases in relative leaf extension rate at 51% PAW. Similarly, Colazzi et al. (2003a) found cotton stress to be minute at levels of available soil water greater than 60%. These studies and others have led to the general recommendation of a 50% PAW for management allowable depletion (MAD) in cotton (Lieb and Fisher, 2012; Martin, 2001).

Cotton, Water Use, and the Crop Susceptibility Factor

The second major component of many water-deficit stress indices is the CS factor. As mentioned before, this component serves as a method of decreasing or increasing index readings depending upon species and growth stage sensitivity to stress. In order to formulate a CS factor, some background on cotton's physiological sensitivity to drought stress and water use is necessary.

Cotton Susceptibility

The physiological and morphological response of cotton to water-deficit stress is complex and has been well described elsewhere (Ball et al., 1994; Loka et al., 2011; Pettigrew, 2004a; Pettigrew, 2004b). Ultimately, this stress results in decreased lint yield by decreasing fruiting body production and by increasing abortion of present fruiting bodies (Guinn and Mauney, 1984a; Guinn and Mauney, 1984b; Orgaz et al., 1994). Increased boll numbers are typically associated with more bolls on higher nodes and more distal branch locations in comparison to drought-stressed plants (Pettigrew, 2004a). Water-deficit stress has also been noted to increase earliness (Orgaz et al., 1994). The broad physiological growth stage most sensitive to water stress in determinant crops is commonly considered to be flowering (Stewart et al., 1975). Cotton, an indeterminate, has also been shown to be most sensitive during flowering, although its fruiting period is considerably longer than most determinant row crops.

Guinn et al. (1981) examined the effects of irrigation initiation and stress timing on multiple growth parameters of Arizona cotton. These authors noted great yield reductions when irrigation initiation occurred after flowering, as this water deficit decreased number of produced fruiting positions and increased earliness. However, notable yield reductions and increased earliness were not associated with irrigation initiation immediately prior to flowering. Authors concluded that the crop was less susceptible to water stress prior to flowering but that it become much more susceptible during the flowering period. Results from this study are in agreement with those of Grimes et al. (1978), who noted decreases in lint yield associated with exceptionally late or early irrigation initiations during the flowering period. Research by Teague et al. (1999) also examined irrigation initiation beginning one week prior to first flower, during first flower, and one week after first flower. Significant decreases were noted in cotton yield response for each week delay in irrigation initiation, with the greatest yield associated with initiation beginning one week prior to first flower. Similarly, Radin et al. (1992) examined furrow irrigation during flowering in comparison with season-long, surface drip irrigation and noted comparable WUE (ratio of seedcotton yield to applied irrigation water and precipitation) and yields between these two treatments.

In contrast, recent research by Teague et al. (2012) noted significant increases in yield when irrigation initiation occurred more than 30 days prior to flowering when compared to irrigation timing 4 days prior to flowering. Since this trial examined irrigation and fertilizer treatments, only two irrigation initiation treatments were included. Still, these data do not concretely assert the squaring stage as the most sensitive growth stage to water-deficits. It is theoretically possible that several of these early irrigation events did not increase yield by reducing plant stress during the early squaring stage, but instead recharged the soil profile, therefore reducing the amount of stress experienced immediately prior to and during the flowering period. Some evidence of this can be seen through comparisons of irrigation squaring node curves to the COTMAN target development curve and through monitored soil matric potential. A third irrigation treatment, beginning roughly 14 days prior to first flower, would have given some insight to this relationship and irrigation water use efficiency (IWUE), or ratio of seedcotton yield to applied irrigation water.

Since flowering in cotton encompasses a considerable amount of time compared to determinant row crops, many studies determining the specific period during flowering of greatest sensitivity have been conducted. Research by Grimes et al. (1970) indicated stress during the middle (peak) flowering period resulted in the greatest yield reductions, as it caused both significant increases in square shedding prior to flowering and reduced boll retention. In contrast, early flowering stress (prior to peak) only significantly increased square shed and late stress (after peak) only significantly reduced flowering rates and boll retention. Authors also found very strong relationships between boll number and pounds of lint per acre, suggesting differences in boll size and lint percentage were not substantial. The ability of the cotton plant to drop fruiting bodies, therefore, allows the plant to sufficiently support and maintain the retained bolls.

Cotton Water Use

Although a partial objective of many water deficit-stress indices is irrigation scheduling, the crop susceptibility factor differs (at least theoretically) from a crop coefficient since it does not describe water use. Still, the theoretical trend of crop susceptibility conceptually mirrors the trend of a crop coefficient. Methods to determine evapotranspiration of a cropped surface have been thoroughly defined by Allen et al. (1998). Crop evapotranspiration (ET_c) is a function of the crop coefficient (K_c) multiplied by a reference evapotranspiration (ET_o). The K_c can be defined through a single parameter approach or a dual parameter approach. The differences here are on the quantification of soil evaporation. In the single parameter approach, deemed suitable for most irrigation needs, K_c equals the average system (soil + crop) evapotranspiration over a period of time. Increases in soil evaporation after rainfalls or irrigation events are not directly quantified, but averaged across the quantified period. In contrast, the dual parameter approach considers the K_c to equal the sum of a basal crop coefficient (K_{cb}) and soil evaporation (K_e). In this calculation, the K_{cb} refers to the ratio of ET_c to ET_o when adequate soil moisture is present to support transpiration but soil evaporation is essentially null. Unlike the single parameter approach, the dual parameter approach includes differences in ET relative to a damp soil surface following irrigation or rainfall. According to Allen et al. (1998), this method is most appropriate for soil water balance calculations, high frequency irrigations, or studies sensitive to day-to-day variations in ET_c. These authors also outlined specific K_c for multiple crops in both single and dual parameter methods, which vary by growth stage. During the initial stage, K_c is generally constant and small. As the crop begins to develop, K_c increases linearly until the mid-season plateau is reached. During the mid-season stage, the K_c represents the highest value of the growing season. Finally, the K_c declines linearly through the late-season growth stage.

Inferences on seasonal K_c are frequently determined by the use of weighing lysimeters. These are typically characterized by an inner field-buried container placed on a scale mounted in an outer field-buried container. Although numerous studies have been conducted to determine the K_c of field-grown cotton, several studies utilizing lysimeters have recently been conducted on modern cotton cultivars in the Mid-South and corresponding K_c have been reported. Fisher (2012) observed two weighing lysimeters over a four year period in Stoneville, MS. Due to large differences in crop growth patterns during the observed years, Fisher reported difficulty in constructing an average K_c curve. Early season values varied from 0.2-0.6, while maximum values varied from 1.1-1.3. Research by Kumar (2011) in St. Joseph, LA observed two lysimeters during the 2010 growing season. The measured K_c graphed by days after planting appeared to represent a quadratic relationship. Reported average K_c were 0.42, 0.89, and 1.41 for initial, developmental, and mid-season growth stages, respectively. Both of these studies indicated an initial low, increasing developmental, mid-season plateau, and end-of-season decline in K_c, which is in agreement with the standard K_c progression with growth stage outlined by Allen et al. (1998). These trends suggest the crop susceptibility factor should follow a similar trend; however, the CS factor must be calibrated and validated against observed site-relative yields.

Cotton root growth has been studied by many scientists but research which accurately mimics field conditions is difficult to conduct. Still, this information is critical to defining the effective rooting zone. Klepper et al. (1973) examined the rooting characteristics of two cotton plants in the Auburn rhizotron (Taylor, 1969); one of which underwent a drought stress beginning 68 days after planting, and another which was maintained as well-watered. Several findings from this study are applicable for the development of a drought stress index. First, roots had reached the bottom of the rhizotron (180cm) by the initiation of stress (68 days). Conditions in the uniform- textured rhizotron will definitely not characterize all profiles, but it is important to note the cotton's potential rooting depth. Furthermore, authors noted a decrease of root density at shallow depths and an increase at deeper depths four weeks after the onset of stress. This pattern was assumed to be associated death of upper roots and preferential growth into the more moist, lower profile regions.

Cotton Cultivar Trials and Drought

According to Cotton Incorporated, 17 states across the Cotton Belt conduct cultivar trials which include reports on lint yield, fiber quality, and other agronomic traits. Due to the lack of rainfall in some states, several do not have large numbers of dryland acres and therefore do not conduct dryland cultivar trials in addition to irrigated cultivar trials. Some of these states conducting irrigated cultivar trials still describe irrigation timings and accumulated monthly rainfall during the growing season (Bourland et al., 2013; McWilliams, 2007), but some, including CA and AZ, for example, do not. More concerning, however, is the failure of some states containing dryland cultivar trials to collect and report rainfall data. Although not particularly common, lack of reported rainfall data greatly limits the interpretation of the cultivar trial yields particularly when comparing relative varietal yields of regional trials.

Even when this information is supplied, no observed 2012 reports made adjustments to account for variations in the water holding capacity of the soil, the soil profile at planting, timings of rainfall events or intensities. Interpretation of only rainfall quantities can result in an overestimation of plant utilizable water (Dastane, 1978). Utilization of a PAW-based index could support a regional construction of varietal response to varying drought stress. Dryland producers could then use this tool to examine the response of each cultivar to drought conditions experienced across the Southeast and Mid-south. These index values could also be reported relative to individual varietal growth stage; thereby allowing the producer to understand which cultivars best fit the historical rainfall patterns at their location. Furthermore, this information could also benefit irrigated producers who have limited access to water or are interested in increasing IWUE by planting more drought-tolerant cultivars.

Rainfall information is generally not as critical for interpretation of irrigated trials as for dryland trials, but some quantification of irrigation amounts or characterization of water-deficit stress experienced even in irrigated trials may provide useful information to end-users. This information could specifically contribute to a more accurate curve describing varietal yield response to water. During the 2012 Arkansas Cotton Variety trials, for example, yield differences of just under 1000 lb of lint per acre were noted between the highest and lowest yielding cultivars (Bourland et al., 2013). Theoretically, there may be a strong interaction of varietal yield by water-deficit stress resulting in a reversal of this yield relationship at very low levels of PAW.

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CHAPTER III

Response of Two Inexpensive Commercially Produced Soil Moisture Sensors to Changes in Water Content and Soil Texture

Abstract

The use of low-cost (< 200 USD) soil moisture sensors in crop production systems has the potential to give inference on plant water status and therein drive irrigation events. However, commercially available sensors in this price range vary in sensing methodologies and limited information on sensor to sensor relationship is available. The objective of this research was to test the response of the Watermark 200SS (Irrometer Company, Inc., Riverside, CA) and Decagon 10HS (Decagon Devices, Inc., Pullman, WA) to changes in water content of three dissimilar soils representing common soils in row-crop production under variable environmental conditions.

Both tested sensors were influenced by changes in soil temperature but the magnitudes of the temperature responses were small relative to the moisture responses. Furthermore, the 10HS sensor did not indicate a significant impact of soil texture on estimated VWCs. The small sphere of influence on the tested soil moisture parameters coupled with the substantial evaporative demands and temperatures under which this experiment was conducted resulted in suspected non-uniform drying of the tested containers. Subsequently, non-linear relationships were noted between 10HS estimated VWCs and actual container VWCs and the 200SS predicted lower water potentials than calculated by converting container VWC to soil water potential. The failure of the sensors to accurately predict container VWC highlights the importance of understanding the relatively small quantity of soil on which these sensors rely as well as the potential variability in soil moisture within a very limited volume.

Introduction

The most critical step in irrigation scheduling is the determination of plant available water (PAW) relative to a yield-reducing lower water limit. In the humid Mid-South and Southeastern regions of the USA, this step has traditionally consisted of an indirect inference on water status through a visual inspection of the crop or soil. In more recent years more advanced water balance, or 'checkbook' methods have been introduced. Although typically better than arbitrary time-based irrigation scheduling regimes, these methods may fail to estimate runoff, leaching, or soil moisture at initiation. Furthermore, some of these methods rely on estimated volumes of daily crop water use instead of experimentally verified volumes (Vories et al., 2004). The characterization of in-field soil moisture conditions through some real-time measurement has the potential to give producers insight into actual crop water status and remove many uncertainties associated with more arbitrary methods of irrigation scheduling.

Recent advancements in electronics have resulted in a dramatic increase in the number of commercially available soil moisture sensors, many of which vary substantially in cost and application (Chávez and Evett, 2012; Muñoz-Carpena et al., 2004; Robinson et al., 2008). Still, only a few of these sensors are inexpensive enough to be appropriate for large deployments necessary for spatially dense readings. Two sensor types which currently meet these criteria are granular matrix sensors and low-frequency, capacitance-based sensors. Granular matrix sensors have been commercially available for many years and use resistance between two electrodes to infer soil water potential. Low-frequency, capacitance-based sensors have been commercially introduced more recently. In contrast to the granular matrix, tensiometric sensors, the low-frequency, capacitance based sensors rely on the dielectric characteristics of the sensing medium to infer volumetric water content (VWC).

Tensiometric Sensors

Sensors estimating soil matric potential include tensiometers, gypsum blocks, granular matrix sensors, heat dissipation sensors, and soil psychrometers (Muñoz-Carpena et al., 2004). The majority of these sensors estimate the amount of energy with which soil water is held by monitoring water movement through a porous material in contact with the soil. Granular matrix sensors are widely used for large deployments due to their low cost. These sensors are typically composed of two electrodes embedded into a cylindrical granular matrix which is buried in the soil. The granular matrix equilibrates to soil water content by the transfer of water from the surrounding soil. Moisture in the sensor is measured by the change in resistance between the two embedded electrodes. Specifically, a decrease in resistance is associated with an increase in soil moisture. One of the most commonly used granular matrix sensors is the Watermark Model 200SS.

Although the reported sensitivity for the Watermark 200SS sensor ranges from 0-200 kPa, erratic measurements have been reported during prolonged drying cycles exceeding 90 kPa (Berrada et al., 2001). Increased variability was suggested by Berrada et al. (2001) to be due to reduced soil contact with the porous matrix. Subsequently, use of these sensors in swelling soils should be avoided (Muñoz-Carpena et al., 2004). More concerning for quantification of seasonal drought stress, however, is the reported failure of the sensor to respond to rapid changes in soil water (Berrada et al., 2001; Muñoz-Carpena et al., 2004). McCann et al. (1992) reported accurate measurements during standard drying periods which were followed by complete re-wetting; however, poor results were noted under partial rewetting or rapid drying conditions. After a prolonged drying period, authors suggested accurate measurements taken during the following drying cycle would only be accurate if soil water reached or exceeded field capacity, or a threshold of -10 kPa. Furthermore, McCann et al. (1992) concluded that many deep sensors could fail to meet this re-wetting threshold and therefore these sensors could provide a limited amount of useful information for irrigation scheduling. These errors were also highlighted by Shock et al. (1998) while developing calibration equations for the Watermark 200, 200SS and the 200SSX. According to other research, a minimum of 24 hours should be given after a rainfall or irrigation event to allow the sensor time to respond (Enciso et al., 2007). Although these issues may not be a concern in a well-managed irrigated cropping system (Berrada et al., 2001), the re-wetting requirement and slow response time pose significant challenges for the objective of drought quantification or under low-frequency irrigation regimes.

Still, the low sensor cost has made these sensors very appealing for the large deployments necessary for field soil water characterization. Fisher and Kebede (2010) utilized the Watermark 200SS Sensor in an effort to build a very low cost canopy, soil, and air temperature monitoring device for the Mid-south region of the U.S. The developed monitoring device was capable of measuring each of these aforementioned parameters for under 85 USD.   Measurements of soil moisture and soil, leaf, and air temperature made by this system were later shown to be capable of detecting genotypic differences in corn response to stress (Kebede et al., 2012).

Additionally, Vellidis et al. (2008) utilized a 12 node, wirelessly-monitored system in a Georgia cotton field to monitor soil moisture and temperatures. Each node consisted of three Watermark sensors and up to four thermocouples. Slight modifications in the sensor array resulted in a system which could be deployed early during the growing season and remain reliable until harvest without adjustment. Results indicated deployments of 2-3 nodes allowed for sufficient characterization of each irrigation management zone. Authors concluded that this technology was capable of driving variable rate irrigations to fields containing multiple irrigation management zones, thereby efficiently supplying irrigation water to spatially variable water demand.

Volumetric Sensors

A large percentage of VWC sensors utilize dielectric permittivity characteristics to make inferences on soil water content of the tested medium. This dielectric measurement of soil moisture is based on the concept that air and solid mineral particles are characterized by small dielectric constants (3-5 for most mineral components of soils, 1 for air). These small, consistent readings greatly contrast the large dielectric constant of water (78.9 at 23°C). Therefore, shifts in composite dielectric readings are noted even during small shifts in VWC (Kizito et al., 2008).

Several equations which range from simple to highly complex have been proposed to calculate VWC from measured composite dielectrics (Alharthi and Lange, 1987). The most frequently used is an empirical equation outlined by Topp et al. (1980). Dielectric responses of soils, as defined by Topp et al. (1980) are a function of texture, structure, soluble salt concentration, temperature, density, measurement frequency, and water content. The influence of water content on the dielectric constant is so dominant, however, that often the response of the constant can be considered “almost independent” of the other parameters (Topp et al., 1980).

Time domain reflectometry (TDR), frequency domain reflectometry (FDR), water content reflectometery (WCR), capacitance techniques, amplitude domain reflectometry, and phase transmission techniques are all based on the composite dielectric properties of soil composite and frequently utilize some form of the Topp equation (Chávez and Evett, 2012; Muñoz-Carpena et al., 2004). These sensor types vary slightly in methodology but all characterize the water content of a very limited soil area immediately adjacent the sensor. Extrapolation from these very small spheres of influence to the field-scale is often complicated due to the spatial variability of soil characteristics. One way to compensate for this variability is to increase the number of deployed sensors, but historically, large deployments have been financially impractical.

One notable exception to this financial restriction are VWC sensors utilizing low-frequency, capacitance-based techniques (Kizito et al., 2008; Czarnomski et al., 2005; Seyfried and Murdock, 2004). Due to their cost, these sensors are frequently utilized for continuous logging in large deployments. Capacitance sensors correlate to soil moisture by measuring the charge time of a ground electrode buried in the soil (Kizito et al., 2008). The medium immediately surrounding the positive and ground capacitors increases or decreases charge time and this charge time is exponentially more dependent upon soil moisture than other parameters. The resulting relationship between sensor charge times and VWC is fairly strong.

One concern with relatively in-expensive capacitance sensors are their low-frequency. Low-frequency sensors are more susceptible to the dielectric constants of soil texture, EC and temperature, and therefore shifts in readings are not as strongly associated to changes in VWC. Sensitivities to medium characteristics beyond VWC have been reported to increase below frequencies of 100 MHz (Chen and Or, 2006). Unfortunately, higher frequencies are directly related to greater cost of sensor production, and most commercially produced, low cost, low-frequency, capacitance-based sensors are below the reported 100 MHz threshold.

In an attempt to more thoroughly define the sensitivity of a low-cost, low-frequency, capacitance-based sensor, Kizito et al. (2008) monitored the response of an ECH_2O-TE, 70 MHz Capacitance Sensor (Decagon Devices, Inc., Pullman, WA) to changes in frequency, temperature, and EC in a wide variety of soil types. Results suggested the sensor, when used in cooperation with a generic calibration curve, was capable of accurately determining VWC while relatively insensitive to other dielectric influencing parameters. These authors also monitored changes in sensor sensitivity as frequency was altered. Substantial decreases in sensitivity to EC, temperature and soil type were noted as frequency was increased from 10 MHz to 70 MHz. Although sensitivities continued to decrease until 150 MHz, no substantial decreases were noted at frequencies higher than 150 MHz. Results are in agreement with other research by Bogena et al. (2007), who noted increases in temperature and EC sensitivity associated with a 5MHz Decagon EC-20 sensor relative to a 70 MHz Decagon EC-5. Even so, a moderately strong temperature sensitivity of the Decagon 5TE sensor has been reported by Chávez and Evett (2012) in a study comparing five commercially produced soil moisture sensors.

A variety of studies have examined the use of the low-frequency, dielectric permittivity sensors in comparison to other, more costly dielectric permittivity sensors. Czarnomski et al. (2005) compared the use of a Decagon ECH_2O capacitance sensors, TDR sensors, and WCR sensors to determine VWCs of undisturbed, extracted soil profiles as well as mixed soil profiles. Authors noted all three sensors failed to reasonably determine VWC with the use of standard calibration equations; however, after soil specific calibration equations were developed, relationships strengthened greatly. The only sensor significantly influenced by temperature was the ECH_2O, as reported VWC decreased linearly by 0.1% for every 1°C increase in temperature. Even so, the authors concluded after evaluating cost, accuracy, and precision that the capacitance soil moisture sensors were appropriate for studies requiring high frequency observations at multiple sites over time.

Similarly, Seyfried and Murdock (2004) compared the 50 MHz Hydra Probes (Stevens Water Monitoring Systems, Inc., Portland, OR) to TDR sensors in a variety of fluids, soils, temperatures and ECs. One notable characteristic of the Hydra Probe is the unit's ability to also measure temperature and soil EC, making the unit comparable to the Decagon 5TE sensor. Authors concluded differences between the low-frequency, capacitance sensors and the TDR sensors were due to frequency differences. Still, Seyfried and Murdock (2004) reported both sensor estimated VWCs to correlate well with actual VWC under most soils.

Since the energy with which the water is held does not directly indicate amount of water held at the sampling time, conversion from matric potential to VWC requires a texture-specific soil water release/retention curve. These curves and a program used to derive them have been described in detail by multiple authors (Fredlund and Xing, 1994; Saxton et al., 1987; Saxton et al., 2006). Difficulties have been reported with this conversion as bulk density changes with inconsistent soil layers (Chávez and Evett, 2012), but strong coefficients of determination and low root mean square errors (RMSEs) have characterized some conversions of soil matric potential to VWC (Eldredge et al., 1993).

Comparisons between Low-cost Sensor Systems

Direct comparisons of similar low-cost sensors have been conducted, but construction of concrete conclusions has been difficult. Sui et al. (2012) compared of Decagon EC-5 and 5TM capacitance, frequency domain sensors to Watermark 200SS granular matrix sensors in a 10 ha cotton field in Stoneville, MS. Soil texture at this site ranged from a silt to a silt loam. Sensor nodes were deployed in 10 plots and each node monitored soil moisture at 3 depths (15, 30, and 60 cm). Authors noted substantially more soil-water depletion at the 15 and 30 cm depths than at the 60 cm depth from planting until 60 days after planting (DAP). From 60 to 80 DAP, a substantial decline occurred in soil moisture at the 60 cm depth. Difficulty was noted in comparing the reported soil water potential from the 200SS and the reported VWC from the Decagon sensors. Qualitative comparisons were made by monitoring trends over time.

Resulting graphs were interpreted as displaying consistent behaviors between sensors at similar depths. Authors concluded that both sensors were capable of monitoring soil water status throughout the growing season.

Similarly, Varble and Chávez (2011) compared Decagon 5TE sensors with Watermark 200SS sensors under laboratory and field conditions. Measurements were then compared to VWCs determined by gravimetric sampling. Authors suggested each sensor required a unique calibration for every soil type and location within field. Although increasing soil EC in laboratory tests did not significantly influence 200SS readings, increasing soil EC did increase errors in 5TE reported VWCs. Authors concluded that field-based calibrations were more appropriate than laboratory-based calibrations, since laboratory conditions fail to represent specific, representative field operating conditions for each sensor.

More information concerning the response of low-cost soil moisture sensors to VWC changes under similar soil textures and environmental conditions as those experienced in the field will be necessary before these instruments can be adopted to quantify drought our schedule irrigations. The objective of this research was to test the responses of two commercially produced, low cost soil moisture sensors to changes in water content of three dissimilar soils representing common soils in row-crop production under variable environmental conditions.

Materials and Methods

A container experiment was conducted at the Lon Mann Cotton Research Station in Marianna, AR during 2013. Three dissimilar soils were selected for inclusion in the study. Tested soils included an Alligator silty clay loam (34°46'9.82"N, -90°35'57.35"W), a Calloway silt loam (34°44'5.72"N, -90°45'53.81"W), and a Robinsonville sandy-loam(34°48'26.41"N, -90°41'5.42"W). Physical and chemical properties of these soils are described in Table 3.1. Prior to the initiation of the study, roughly 60 kg of each soil was dried, ground, and sieved through a number 4 mesh screen. After processing, 17kg of each soil was placed in a plastic, 19 L container. This process was repeated three times for each soil resulting in nine total containers.

In order to allow each soil to drain, five (2 mm) holes were drilled through each container side and four (2 mm) holes were drilled through the each container bottom. All containers were then placed outdoors on a 4m by 4m square cement pad elevated 1m above a grass surface. This concrete surface was selected over other natural surfaces due to its consistency and low maintenance requirements. Each container remained open to environmental conditions and was located far enough from nearby buildings to only experience shading very early and very late during the day. Measured environmental parameters at the site included air temperature, wind speed, solar radiation, and rainfall. Soil samples were taken at the beginning of the experiment in order to determine EC and bulk density (Table 3.1).

Periods from saturation to near permanent wilting point (PWP) were created by either allowing rainfall to wet the containers or by pouring water into the containers. These re-wetting events occurred on 2 June, 26 June, 13 July, 12 August, and 19 September 2013. After these saturating events, the containers were left exposed to the atmosphere. If rainfall was expected, containers were covered with a plastic tarp. These practices ensured saturation was reached and a substantial, prolonged dry-down period occurred. Each container was weighed daily at 0800 CST on a Cen-Tech 130 Lb. Electric Platform Scale (Cen-Tech Inc., Camarillo, CA). Gravimetric water content was then calculated by subtracting the mass of the container and the dried soil and dividing the remaining mass by the mass of the dried soil. VWC was calculated by multiplying gravimetric water content by the bulk density determined on 25 May 2013.

Two low-cost soil moisture sensors and their associated data loggers were selected based on price and availability. These included the Decagon 10HS and Em50 Data Logger and the Watermark 200SS and Watermark 900M Monitor.

The Decagon 10HS Soil Moisture Sensor Probe is a 70 MHz capacitance/frequency domain sensor. This probe also infers soil moisture by measuring the dielectric constant of the surrounding media. The output range of the unit is isolated from input voltage by an internal voltage regulator; as a result, excitation can vary from 3-15 V. This unit is composed of two independent probes and can also be installed into undisturbed soil horizons. According to the manufacturer, this device is accurate to within ±3% VWC when utilizing the standard calibration equation. This equation is as follows:

$$VWC = (1.17*10^{-9}*RC^{3}) - (3.95*10^{-6}*RC^{2}) + (4.90*10^{-3}*RC) - 1.92$$

where:

RC= raw counts reported by the sensor

VWC= % VWC (m3/m3)

In contrast to the Decagon 10HS sensor, the Watermark 200SS sensor estimates soil water potential by monitoring electrical resistance. The 200SS consists of two electrodes placed in a granular matrix surrounded by stainless steel mesh which allows the sensor to equilibrate with the surrounding soil after installation. Although Irrometer does not state the conversion equation from resistance to soil water potential in the sensor or data logger manual, Thompson et al. (2005) indicated the manufacturer utilizes the conversion equation published by Shock et al. (1998), which the authors noted was only valid from -10 to 75 kPa. This equation is as follows:

$$S= -(4.691+3.599R)/1-0.009733\ R\ -0.01205T$$

where:

S= soil water potential (kPa)

R= measured resistance of the sensor (ohms)

T= temperature (°C)

One sensor from each manufacturer was placed in each container within 1 cm of the soil surface in a vertical orientation. Each sensor was connected to the aforementioned data loggers produced by the same manufacturer. Data were collected from each sensor at an hourly interval and the manufacturer provided conversions were used to convert from sensor readings to either soil water potential or VWC.

Statistical analysis was conducted in JMP 11 (SAS Institute Inc., Cary, NC) and SigmaPlot 11 (Systat Software, Inc., San Jose, CA). The gravimetric water contents of each container were analyzed by a repeated measure ANOVA procedure. Parameters included date, texture, texture by date interaction, and treatment nested in replication. Replication effects were considered to be random. Subsequent relationships between sensors and soil moisture contents were compared through regression.

Results

Environmental Parameters

From the initiation of the study on 25 May 2013 until termination 17 Sept 2013 the buckets were covered with a waterproof tarpaulin when rain was forecasted. After this date the buckets were left exposed to the atmosphere. This created four investigator-manipulated, saturation-to-severe-drought stress periods and an additional, more naturally fluctuating period. The first four periods do not directly mimic typical rainfall patterns in the Mid-South but these periods are most appropriate for evaluating the aforementioned soil moisture sensors.

Average soil temperatures monitored every hour are displayed in Fig. 3.1. Due to the concrete surface and the large surface area associated with each individual container, large diurnal fluctuations of soil temperatures were observed. These fluctuations are much larger than would typically be observed in row-crop agriculture, since soil temperatures within a production system are buffered by the surrounding soil and the surface area exposed to the ambient environment is greatly reduced relative to the utilized containers.

Measured Gravimetric Water Content

All tested parameters (texture, sampling time, texture by sampling time interaction, and replication) were significant ($p \leq 0.05$) (Fig. 3.2). As expected, textural differences were evident at every measured point during the study with the largest and smallest water contents measured in the silty clay loam and sandy loams, respectively. The noted texture by date interaction is most likely a function of inconsistent differences during re-wet periods and prolonged dry-down periods. These trends can be observed in the first dry-down period, beginning on 2 June (Figs. 3.2 & 3.3). Immediately after the wetting event the water content of the sandy loam declines rapidly, until roughly 12 June, at which point the water content begins to decline at a much slower rate. The different rates of decline in the sandy loam are pronounced and could be fairly well characterized by two straight lines. In contrast, the silty clay loam and silt loam containers were not characterized by such a pronounced difference in the rate of decline curves.

Two factors of this experiment caused much of this within-texture variability. These can best be described by considering the dry-down period to be composed of two main periods of water extraction; first, a rapid runoff/drainage event which composes the largest percentage of water loss within a few days of the water application and second, an evaporative event which begins to dominate water loss three or four days after the application of water. Differences in drainage characteristics within texture containers were difficult to manage, particularly in the higher shrink-swell potential silty clay loam soils. The orientation of cracks relative to the drilled drainage holes could have provided a shorter path for some applied water to exit the containers. In the silt loam and sandy loam containers, cracking was not as severe. Variability in the initial dry-down period all containers was likely influenced by differences in soil-to-drainage- hole and container-to-soil contact noted immediately after each re-wetting event (Fig. 3.3). During the slower, more evaporative-driven water loss period, within-treatment variability was generally more consistent; for example, as the second, third and fourth dry-down periods progressed, the third container holding the silty clay loam treatment always contained less water than the other two silty clay loam containers (Fig. 3.3). This variability is most likely due to slight variations in container temperatures driven by differences in intercepted solar radiation, differences in soil-container contact, etc.

Sensor Results

Decagon 10HS Sensors

All nine Decagon 10HS sensors reported logical, consistent data throughout the examined time period. Trends are displayed in Fig. 3.4. Diurnal fluctuations noted are interpreted as a function of temperature. Still, these fluctuations across such broad ranges in soil temperatures (Fig. 3.1) are dwarfed by fluctuations in readings in response to changes in moisture content. Due to the noted significant differences in within-texture container VWC variability, it is not possible to differentiate between the variability caused by within-texture VWC differences by time and error in Decagon estimated 10HS water content. In order to isolate sensor error, individual sensor responses to measured VWC were plotted in Fig. 3.5. Since container mass was usually measured once during a 24 hour period, the 10HS reading closest to the measurement time was used to test the relationship between estimated and actual soil moisture. The subsequent relationship of measured container VWC to 10HS estimated VWC is best predicted by a three parameter, nonlinear exponential rise to a maximum curve. Since this relationship was hypothesized to be linear, trends over time were further examined and can be seen in Fig. 3.6. Several very important points should be made here. First, outside of a three or four day buffer immediately prior to and following the re-wetting events, the 10HS sensors consistently over-predicted soil moisture at most sampling points. This relationship is evident by observing the increasing divide between 10HS estimated VWC and container VWC immediately after re-wetting but prior to progression into the late secondary dry-down period. Average discrepancy between the estimated and measured VWC can be noted in Fig. 3.6 by the separation of the average 10HS estimated VWC (straight red line) versus the average container VWC (straight black line) determined by container weight.

These large differences, which are evidently influenced by soil texture, can be best explained by non-uniform drying of the soil container. At peak soil moistures, the differences between 10HS estimated VWC and measured VWC are minute. However, as the containers begin to lose water, even in the rapid dry-down period, measured VWC falls at a much faster rate than 10HS estimated VWC. As the containers move into the evaporation-dominated dry-down period, the 10HS estimated VWC remains substantially higher than the measured VWC. Differences again become minute during re-wetting events, after which the cycle resets. It is hypothesized that the small sphere of influence on the 10HS sensors relative to the large volume of soil placed in each container led to these substantial differences between absolute 10HS estimated VWC and measured VWC. Since sensors were placed near the center of each container, it is believed that as the soil dried from the exterior and upper portions of the container, the measured VWC of the container declined more rapidly than the soil which was contained in the sensor's sphere of influence at the center of the container. This hypothesis is supported by the relationship between container VWC and 10HS estimated VWC observed in Fig. 3.5. The proximal position of the sensor appears to buffer the estimated VWC from the more rapidly declining VWC along the more distal regions of the container. The nonlinear, exponential rise to a maximum relationship as VWC increases also supports this non-uniform drying hypothesis, since at very low moisture contents the 10HS estimated VWC and measured VWC begin to converge. This relationship is best visualized by examining the first, second, or fourth prolonged dry-down period in Fig. 3.6. From these curves, it is evident that immediately prior to the re-wetting event the rate of container VWC decline had drastically decreased. In contrast, the rate of decline in the 10HS estimated VWC was still substantial. Given these two rates of change, it does appear that if the dry-down periods had been longer, 10HS estimated VWC and container VWC would eventually meet.

The problem of non-uniform container drying could be partially addressed by reducing the size of the tested containers to better match the sphere of influence of the tested sensors and reducing the dramatic diurnal trends in environmental conditions (mainly temperature) associated with the concrete slab by placing containers in the ground. The introduction of a crop into the container would also contribute to more uniform dry-down throughout the container but this approach would not be as desirable due to the implications increases in biomass would have on calculation of gravimetric water content. Still, it is important to note that the differences in within-container soil water contents suspected in this trial will most likely not be noted in above-ground container plant production systems.

The Watermark 200SS sensor responses over time for individual containers generally followed the inverse of the container VWC (Fig. 3.7). Diurnal fluctuations were noted from each sensor, and although temperature corrections were applied by the Irrometer data logger, these fluctuations are interpreted as temperature-based. Still, these fluctuations associated with temperature were much smaller than observed fluctuations in readings in response to changes in soil moisture content. As expected, the response of each soil water potential sensor was highly influenced by soil texture (Fig. 3.7). This response is most evident when considering the rate of soil water potential decline immediately following each irrigation event by soil texture. Watermark 200SS sensors placed in the silty clay loam containers were characterized by a very rapid decline in soil water potential which began almost immediately after the saturating event. In contrast, sensors placed in the sandy loam containers were best characterized an initial, fairly slow rate of decline followed by a much more rapid rate of decline. The initial dry-down rate was substantially slower than the silty clay loam containers; near the end of the ‘slow’ sandy loam dry-down period at roughly 40 kPa, sensors in the silty clay loam containers had exceeded their reliable range and were near 239 kPa. Rates of declining soil water potential reported by the Watermark sensors located in the silt loam containers fell consistently between the silty clay loam and sandy loam containers. Due to this strong texture response, the sensors were grouped by corresponding texture in order to examine the response of the sensors to changes in VWC (Fig. 3.8). Insensitivity of instruments during the initial re-wetting period noted at extreme soil water potentials did weaken the relationship between these variables some (Fig. 3.8A), but these faults were associated with soil water potentials out of the reported usage ranges. More concerning, however, is the scatter of points within the reported usage ranges in the silty clay loam and silt loam containers (Figs. 3.8A, 9B). Ideally, these relationships would be more similar to the relationship observed in the sandy loam containers (Fig. 3.8C). These trends may be in part explained by the greater hysteresis experienced in silty clay loam and silt loam soils and issues with soil-to-sensor contact, which are generally less of an issue in coarser-textured soils.

Relationships between 10HS estimated VWCs and 200SS estimated soil water potentials graphed by texture can be found in Fig 3.9. The most consistent relationships between these two sensor types are found in the coarser sandy loam containers (Fig. 3.9C). The much weaker relationships observed in the finer textured silt loam and silty clay loam containers (Figs. 3.9A, 3.9B) can be partially attributed to hysteresis of the 200SS sensor, changes in soil-to-sensor contact of both the 10HS and 200SS sensors, and slight variations in water content immediately adjacent to each tested sensor. Fig.3.9 highlights the narrow range of water potentials in which useful data can be collected with the 200SS sensor. Although the 200SS may perform well under near-field capacity levels of soil water, another sensor, such as the 10HS, may be more appropriate for deployments designed to characterize drought stress instead of scheduling irrigation events.

Conclusions

The small sphere of influence on the tested soil moisture parameters coupled with the substantial evaporative demands and temperatures under which this experiment was conducted resulted in non-uniform drying of the tested containers. Subsequently, non-linear relationships were noted between 10HS estimated VWCs and actual container VWCs. Similarly, the 200SS predicted lower water potentials than calculated by converting container VWC to soil water potential. Fortunately the preferential drying of soil in the containers in this trial will most likely not be experienced in field deployments or above-ground containers which contain plants. Still, the failure of the sensors to accurately predict container VWC highlights the importance of understanding the relatively small quantity of soil on which these sensors rely as well as the potential variability in soil moisture within a very limited volume. This study did indicate that texture response for the 10HS sensors was not substantial and neither the 10HS nor 200SS was highly influenced by the drastic variations in soil temperature. Further research should be conducted in weighing field lysimeters or containers which would be characterized by more uniform within-container VWCs.

Table 3.1 Physical properties of three dissimilar soils included in this trial.

Textural Class	**Particle Analysis (%)**			**Bulk Density**	**Electrical Conductivity**
	Sand	**Silt**	**Clay**	**(g/cm^3)**	**(dS/m)**
Sandy Loam	78	11	11	1.56	3.1
Silt Loam	4	72	23	1.28	4.0
Silty Clay Loam	18	43	39	1.27	2.5

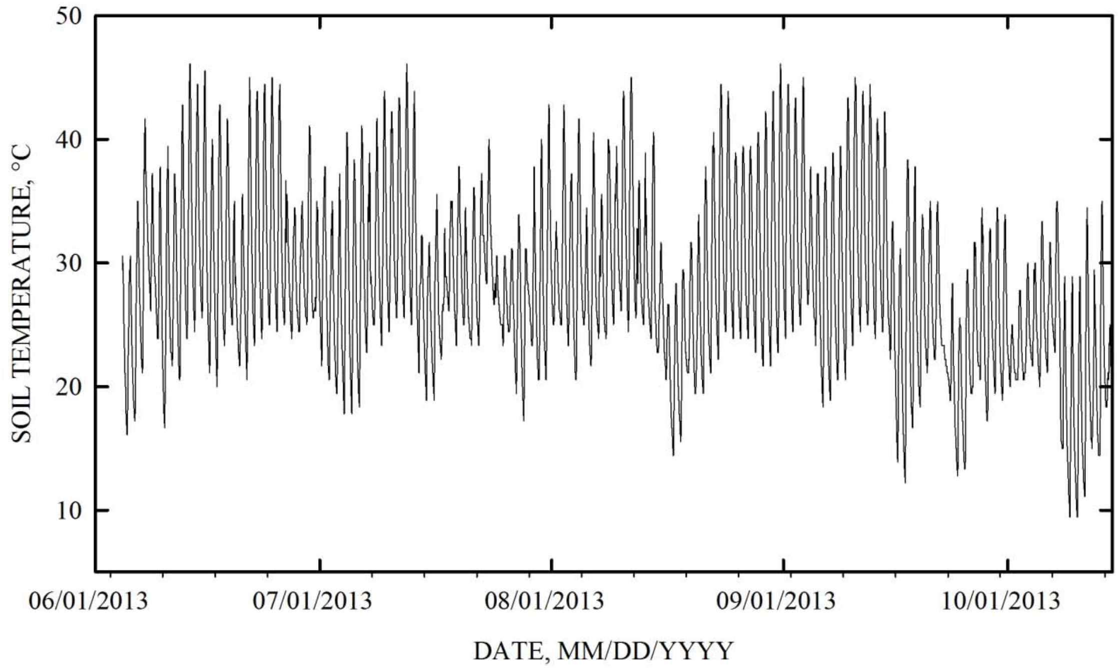

Figure 3.1 Average soil temperature of the containers during the period of the study.

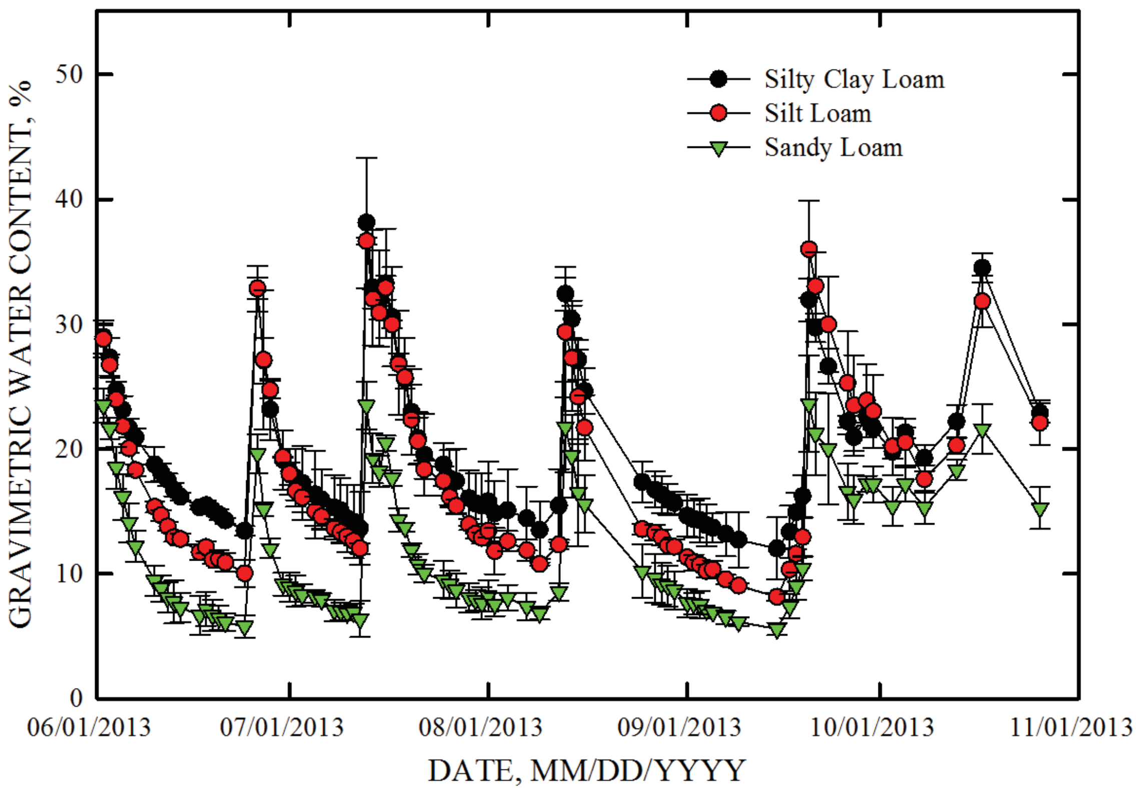

Figure 3.2 Average gravimetric water content by texture of all containers during the trial. Gravimetric water content was determined by measuring each container daily. Each point represents the mean water content calculated from three replications of each texture. Error bars represent 95% confidence intervals.

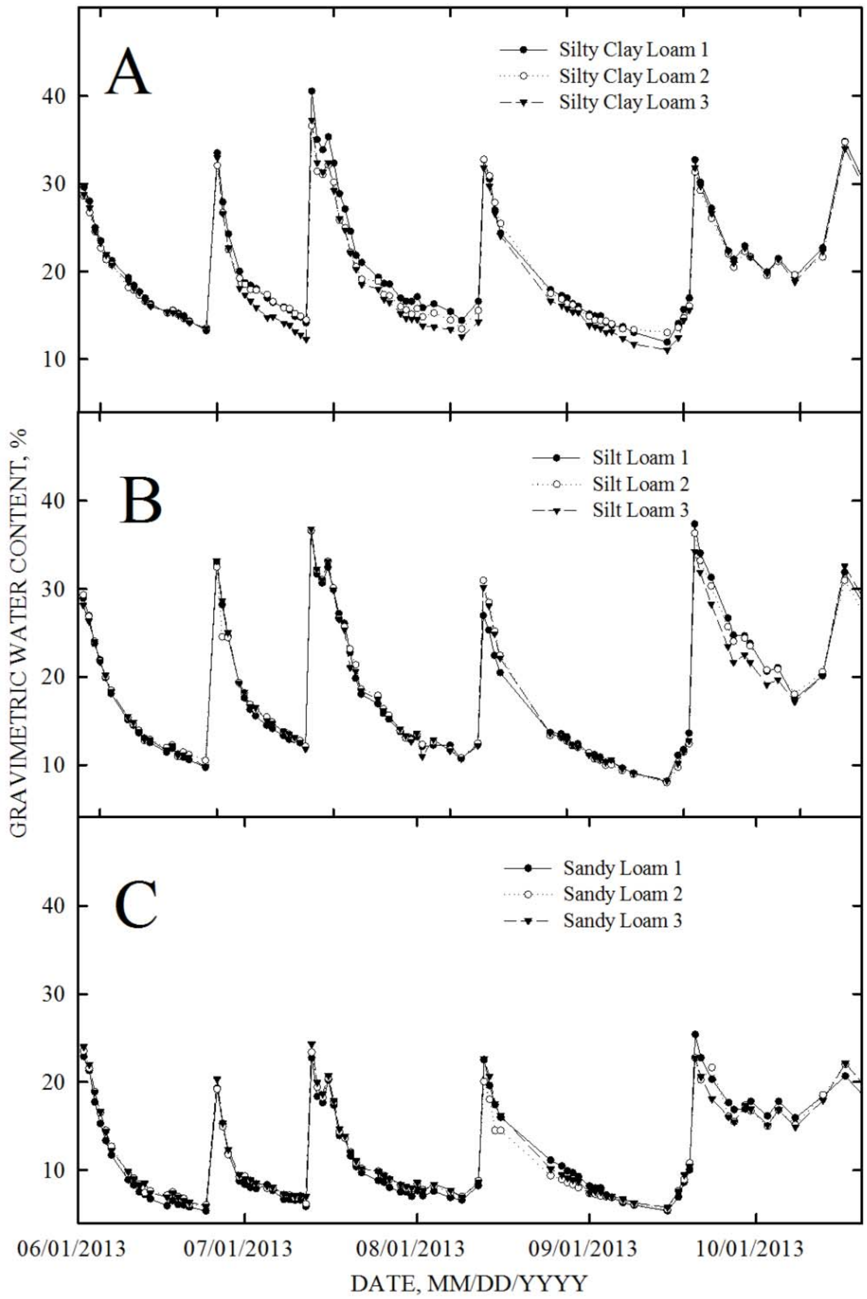

Figure 3.3 Gravimetric water content of the three silty clay loam containers (A), three silt loam containers (B) and three sandy loam containers (C) from 3 July 2013 to 1 October 2013.

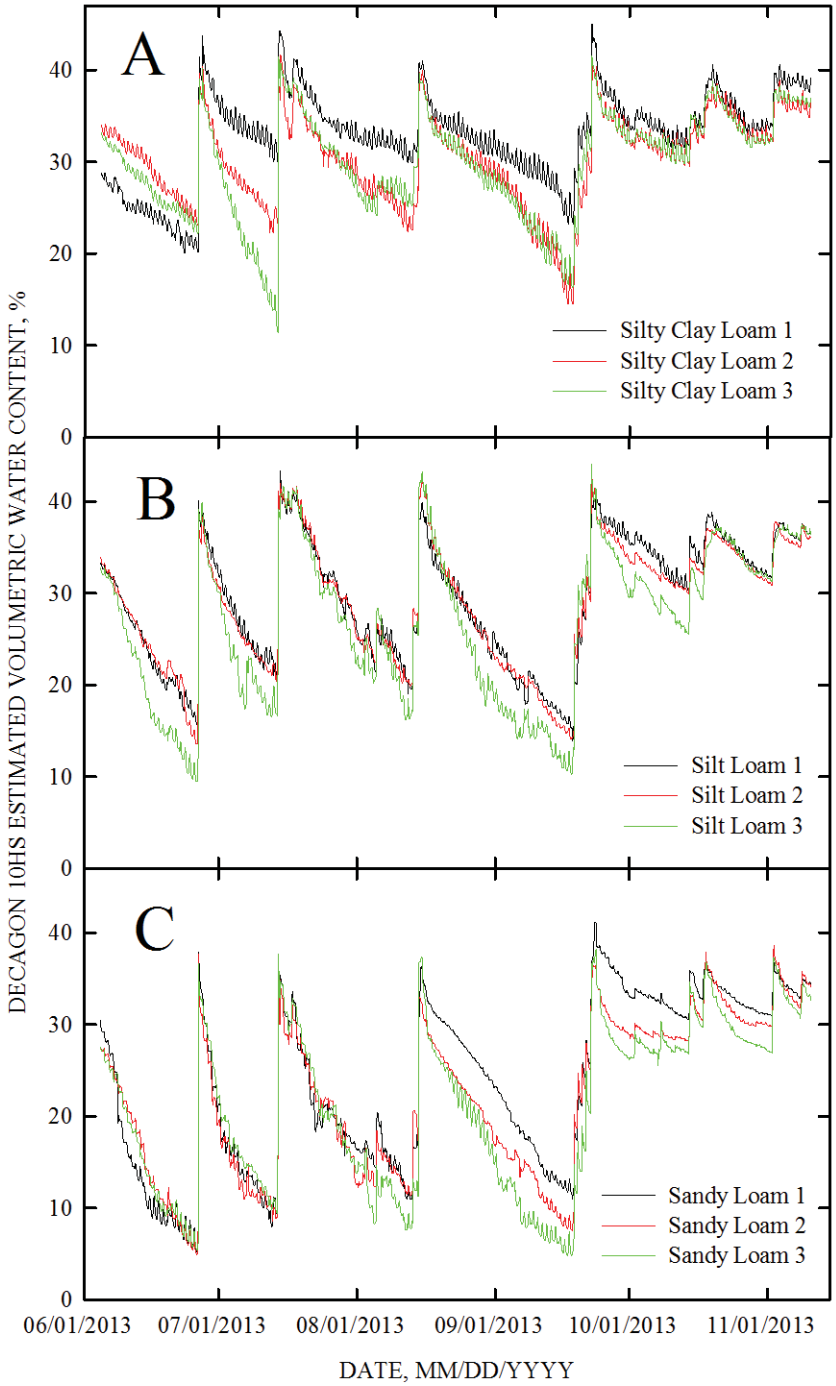

Figure 3.4 Decagon 10HS estimated volumetric water contents for the silty clay loam (A), silt loam (B), and sandy loam (C) containers during the trial period from 1 June 2013 to 15 November 2013.

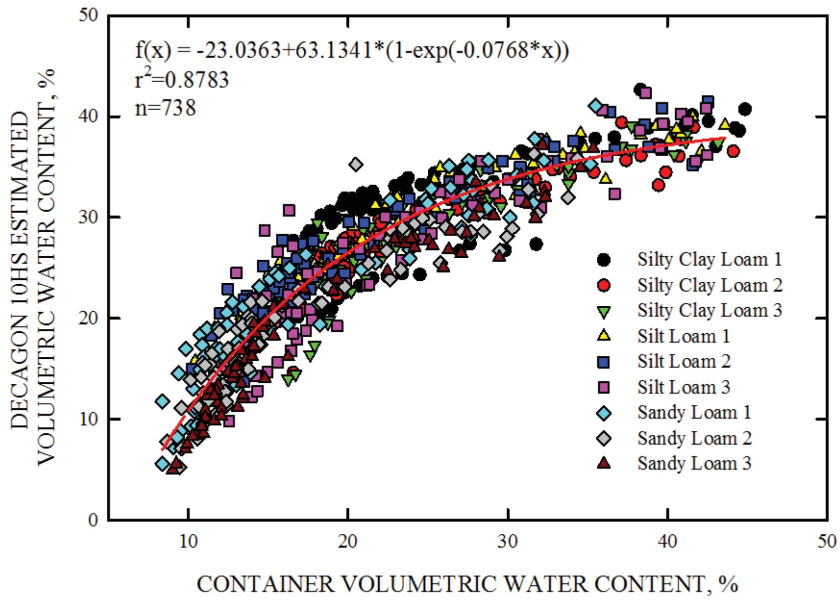

Figure 3.5 Relationships between measured volumetric water content, where VWC=Db*Gravimetric water content, and predicted VWC by the Decagon 10HS Sensors.

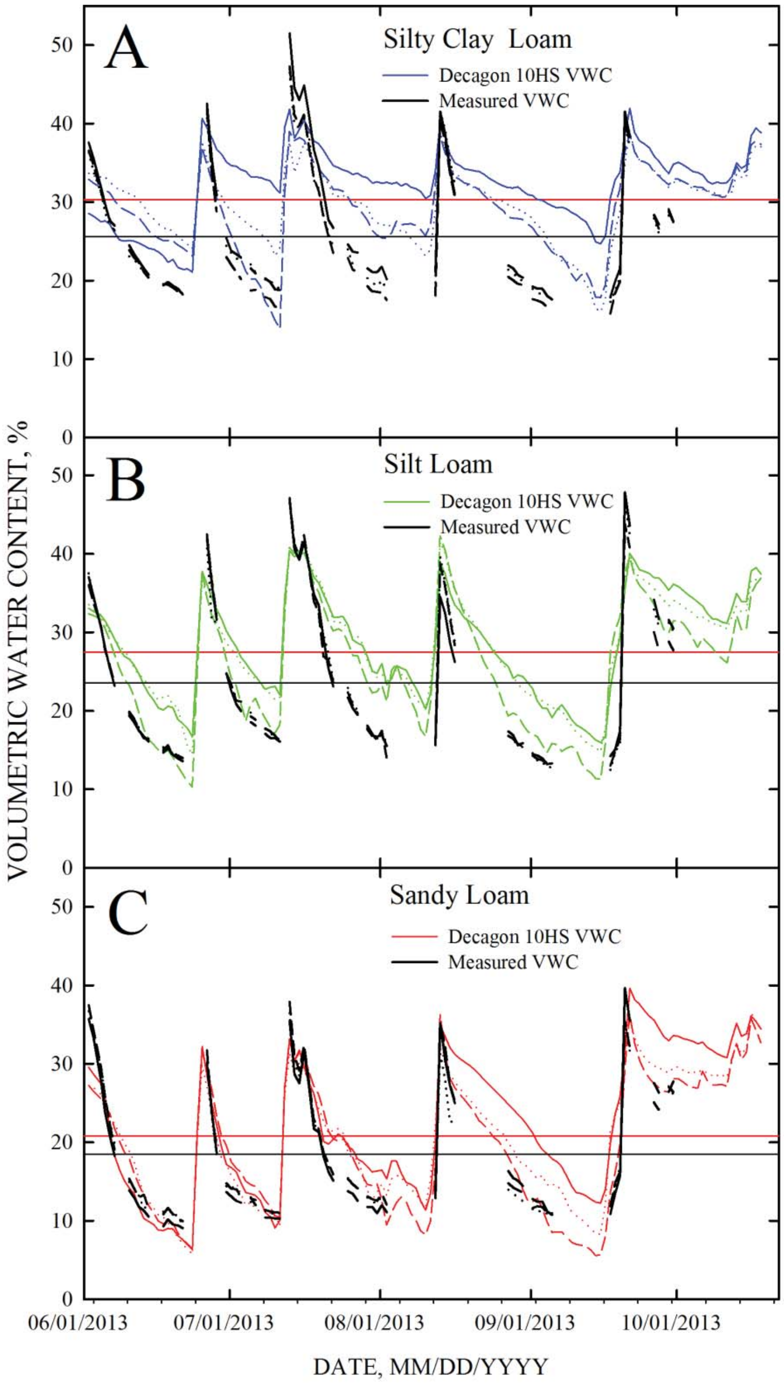

Figure 3.6 The difference between calculated VWC, derived from gravimetric water content, and the Decagon 10HS estimated water contents for the silty clay loam (A), silt loam (B), and sandy loam (C) containers. Solid reference lines represent mean differences.

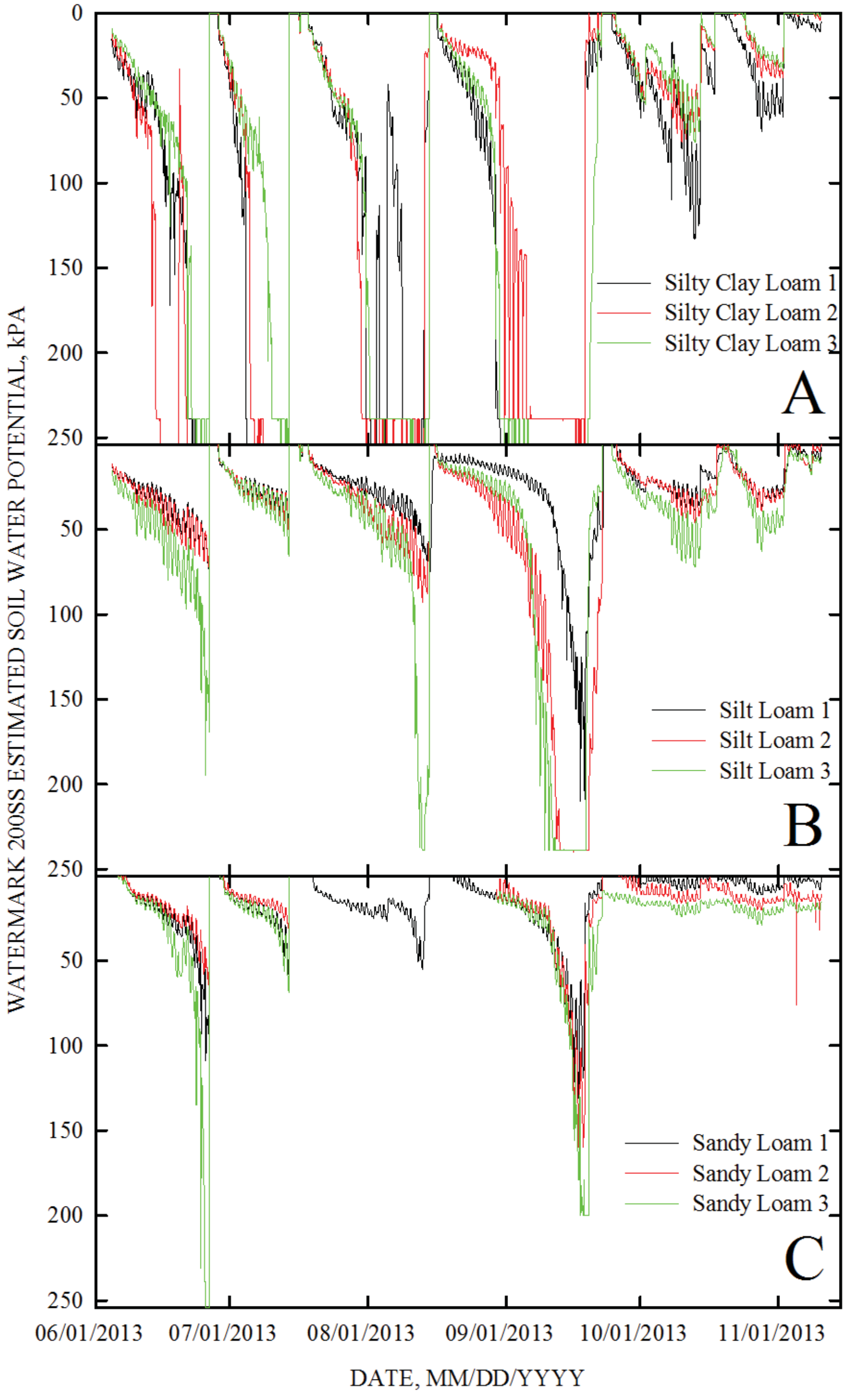

Figure 3.7 Watermark 200SS estimated soil water potentials or the silty clay loam (A), silt loam (B), and sandy loam (C) containers during the trial period.

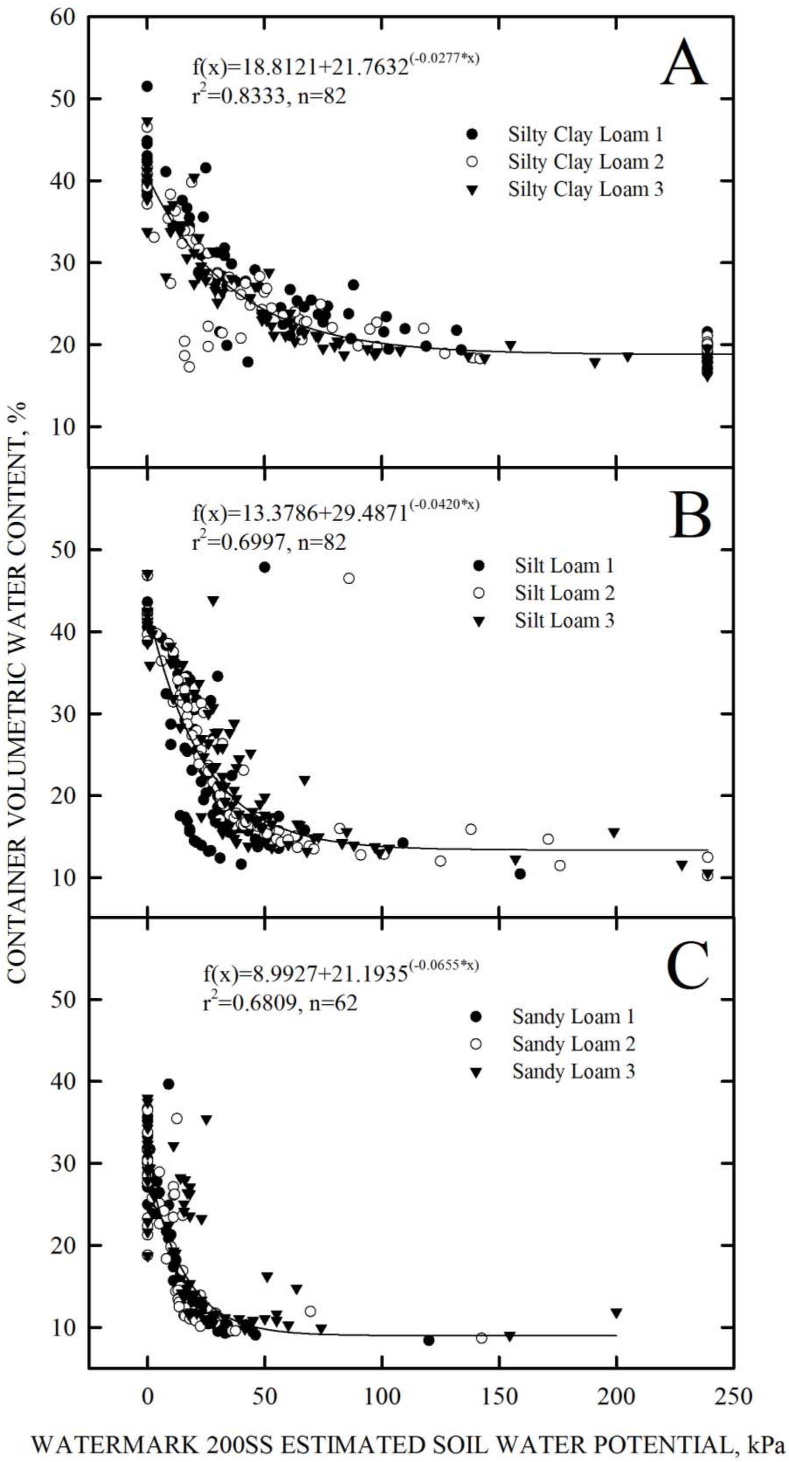

Figure 3.8 Relationships between container volumetric water content and Watermark 200 SS sensor estimated soil water potentials graphed by texture for the silty clay loam (A), silt loam (B), and sandy loam (C) containers.

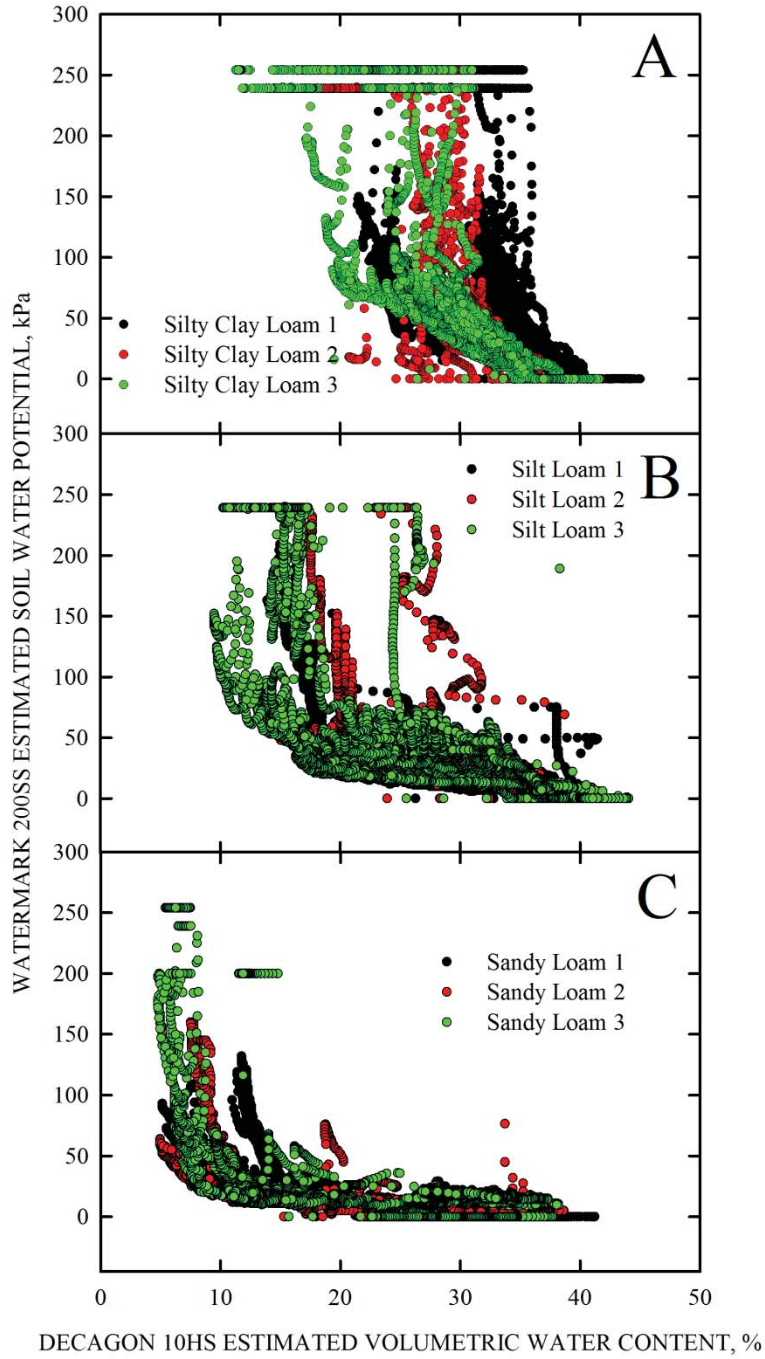

Figure 3.9 Relationship between Watermark 200SS estimated soil water potential and Decagon 10HS estimated volumetric water content for the silty clay loam (A), silt loam (B), and sandy loam (C) containers.

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CHAPTER IV

Development of a Soil Moisture Stress Index for Site Drought Characterization

Abstract

Although the large number of dryland cotton (*Gossypium hirsutum*, L.) cultivar trials conducted each year allow producers to examine the yield response of cultivars in similar growing conditions to their own, local trials may not fully express all varietal characteristics, specifically those of drought stress. A method to quantify experienced drought in these trials could serve as the framework on which to compile trial results across locations and thereby more accurately define varietal yield response to drought stress. Therefore, the main objective of this research was to develop a soil moisture-based index to quantify drought stress in dryland cotton cultivar trials. Five field trials consisting of a range of replicated cultivars under water-deficit stressed conditions and a well-watered strip were conducted across the Cotton Belt during the 2012 and 2013 growing seasons. Soil moisture in each plot profile was inferred by (4) Decagon 5TE sensors (Decagon Devices, Inc., Pullman, WA). These data were then used to calculate an adjusted soil moisture stress index (ASMSI) and a relative reduction in evapotranspiration (1-($ET_{c\ adj}/ET_c$)). Results indicate both approaches appear to have potential in characterizing the amount of stress experienced within dryland cultivar trials. The utility of these approaches will depend on the quality of the soil moisture and meteorological measurements collected to calculate these indices and the soundness of the assumption that yield is restricted by water-deficit stress. More research should be conducted on reducing these location responses before maximum separation between varietal responses will be recognized.

Introduction

Escalating conflicts between agricultural and urban entities and reported unsustainable depletion of multiple Mississippi Delta aquifers over the past few years have highlighted the importance of sustainable water use, even in the humid Mid-south and Southeastern regions. These issues, coupled with the exceptionally dry growing seasons experienced recently (with the exception of 2013) have further fueled interest in drought-tolerant cotton cultivars. Other commodities have already seen the release of drought-tolerant genes into their markets and a drought-tolerant gene for cotton is expected. Therefore, it is becoming increasingly imperative that producers be provided with timely, accurate, robust information on varietal drought tolerance from an un-biased source.

Most producers gather information on varietal drought tolerance through dryland cultivar trials. Although these trials are quite effective in relaying varietal yield response to drought experienced at one trial location in one growing season, drought in these trials is typically characterized by accumulated rainfall. This measurement does not fully characterize drought stress, specifically the frequency, timing, severity, and length of water-deficit stress experienced. Subsequently, producers interested in understanding varietal response to drought stress under conditions different to those experienced at their trial location must either attempt to combine trial data by making some estimation of experienced drought in another trial or estimate from the single-point observation. If the actual drought experienced could be more accurately characterized the results from multiple trials could be combined easily, thereby allowing for characterization of varietal drought stress across a range of deficit parameters (timing, length, frequency, magnitude of deficit).

A drought stress index which utilizes in-field, sensor measurements has the potential to define these parameters, and therefore serve as the framework for compiling regional yield responses to drought stress. The main benefit of this compiled data set would be the ability of the producer to examine the relative varietal yield response to a range of drought timings, magnitudes, and lengths. This type of data set would be much more powerful than single point observations of individual cultivar trials.

The accumulated stress/yield concept is based on the negative relationship of yield and water-deficit stress. If no water stress is experienced during the growing season, yield will simply be a function of other genotypic and environmental limitations. As water-deficit stress occurs and 'stress units' are accumulated, yield penalties ensue. Therefore, accumulated stress units are negatively correlated to crop yield. Most agriculture-based stress indices were developed for the purpose of irrigation scheduling. The index framework is also fairly consistent from author to author; however, authors typically diverge on stress definition and determination as well as the incorporation of a crop susceptibility factor.

Early Development

Some of the first authors to develop a primitive water stress index concept were Nix and Fitzpatrick (1969). Through soil water modeling and estimated potential evapotranspiration these authors were able to determine periods of water stress and correlate these stress index 'units' to yield of wheat (*Triticum aestivum*, L.) and sorghum (*Sorghum bicolor,*L.). The defined 'stress index' represents the time in weeks which the current level of available water would last the crop if the rate of potential evaporation remained consistent. Noted yields of grain sorghum and wheat were positively correlated to increases in the stress index. This available water index is determined at the beginning of the pre-determined, 'critical' growth stage. Therefore, water stress experienced prior to- and following the 'critical' period is not included in the calculation.

A much more refined, season-encompassing Stress Day Index (SDI) was introduced by Hiler and Clark (1971) as a method of increasing water use efficiency by optimizing irrigation scheduling. This equation hinges on two main parameters: the Stress Day (SD) parameter, which was originally defined as a function of early morning, profile soil water potential multiplied by the daily evaporative demand calculated by the van Bavel method (1966, 1967), and the Crop Susceptibility (CS) factor, which corresponds to yield response to the soil water deficit. Length, magnitude, frequency and timing of stress are therefore dictated by the SD factor, while the CS factor serves as a method of decreasing or increasing SDI depending upon species and growth stage sensitivity to stress. The resulting SDI values are then accumulated on a daily timestep and related to yield. Authors found this approach to be acceptable for irrigation scheduling and yield prediction under crop water stress conditions. Weaknesses of this index included the large number of samples required to define changes in the water-deficit status of the crop over time. Still, the SDI successfully advanced the stress index concept to include seasonal stress and growth stage sensitivity.

Canopy Temperature and the Stress Day Concept

Recognizing the shortcomings of the SD component of the SDI and the ability of canopy temperature to indicate stress, Idso et al. (1977) and Jackson et al. (1977) proposed canopy-air temperature differences to be an appropriate SD indicator. Both publications referred to this index as a Stress Degree Day (SDD). According to the authors, this measurement could be monitored remotely and prevented the labor intensive plant/soil water potential measurements of Hiler and Clark (1971). To test this new SD indicator, Idso et al. (1977) predicted final wheat yield with accumulated stress units determined from canopy temperature. As predicted, strong negative relationships were noted between yield and accumulated stress units. Jackson et al.

(1977) further tested this method by examining stress thresholds on which to base irrigations. These authors used a derived evapotranspiration equation to relate canopy-air temperature differences to soil water depletion. Even though several parameters in this equation were estimated, results suggested canopy-air temperature differences could serve as irrigation scheduling tools for large irrigation districts. In a later critique, however, Idso et al. (1981) found the SDD to be sensitive to several parameters beyond the parameter of interest, soil moisture.

Many canopy temperature derived stress approaches have been constructed since Jackson and Idso developed the CWSI in the late 1970s. These include, but are not limited to: the Temperature Stress Day (TSD), (Gardner et al., 1981), the Crop Water Stress Index (CWSI) (Jackson et al., 1981), the Water Deficit Index (WDI) (Moran et al., 1994), and the Canopy Time Temperature Threshold (TTT) (Upchurch et al., 1996; Wanjura and Upchurch, 1997; Wanjura et al., 2004).

Humid Climates and Canopy Temperature

It is important to note that many of these canopy-based approaches were developed in the arid Southwest and Midwest regions of the US, and an important source of error described by Jackson et al. (1981) was rapidly changing cloud conditions. According to the authors, quality measurements were possible during clear or overcast conditions but serious errors were associated with periods of intermittent clouds and clear conditions. More recent work by Colaizzi et al. (2003a) also indicated difficulty relating the CWSI to soil water under conditions of low vapor pressure deficits. According to Idso et al., (1981), “defining stress in this fashion limits our ability to confidently quantify (the onset of crop water stress) under conditions of low vapor pressure deficit, where the entire range of foliage to air temperature variability approaches the degree of scatter inherent in the data."

Utilization of several of these canopy temperature approaches in the humid Mid-south or Southeast therefore pose many challenges, most of which stem from canopy temperature relationships to soil water in more climacterically inconsistent locations. Concerning the CWSI, the recommended early-afternoon measurement times coincide with times of cloud formation, and variations in sensing timing to calculate CWSI have been shown to influence CWSI values (Taghvaeian et al., 2012). Rainfall may or may not occur during these isolated thunderstorms, but as a response of the storm building, weather conditions across the region become very inconsistent. These inconsistencies result in highly variable air temperatures, wind speeds and directions, and humidity, all of which change atmospheric moisture demand and transpiration. As a result, accurate site characterization in humid regions may prove difficult by the single measurements of canopy temperature or meteorological parameters proposed for arid climates. Critiques of the CWSI have alluded to this issue (Colaizzi et al., 2012; Idso et al., 1981; Jackson, 1982).

In theory, the canopy TTT concept would be less susceptible to such errors since measurements are conducted continuously. Nonetheless, research examining the TTT has also shown mixed results. Bockhold et al. (2011) tested this method in Portageville, MO with well watered, semi-stressed, and stressed crops of corn (*Zea mays*, L.), cotton (*Gossypium hirsutum*, L.) and soybeans (*Glycine max*, L.). The canopy temperature time-threshold irrigation scheduling method failed to significantly increase yields or irrigation water use efficiency for any of the examined crops. Furthermore, differences in cotton canopy temperature between the well-watered and semi-stressed treatments were frequently insignificant. Although some results indicate potential of canopy temperature to determine water-stressed conditions, authors concluded these measurements have limitations and more research is necessary before these instruments can be effective, particularly in humid environments.

Soil Moisture and the Stress Day Concept

Initial development of canopy-temperature based measurements relied heavily on handheld infrared thermometers or the use of thermal imaging to detect temperature differences. These methods allow canopy temperature readings to be taken over a large area at a fine scale with little difficulty. Still, plant-based sensing is associated with a number of practical difficulties which have, to this point, prevented large commercial adoptions (Jones, 2004). Indirect soil moisture measurements, in contrast, are most commonly characterized by very small fields of influence. For example, the neutron probe, considered to have one of the larger fields of influence and used in the original Hiler and Clark (1971) approach, is characterized by a 10-40 cm radius sphere of influence (Muñoz-Carpena et al., 2004). As a result, a large number of measurements must be conducted at a very high spatiotemporal frequency to characterize field-scale soil moisture over time. Consequently, soil moisture measurements have in the past been characterized as labor intensive and expensive, therefore more spatially coarse and less practical for field-scale drought characterization.

Recent advancements have resulted in a drastic increase in the variety of commercially available sensors. These vary substantially in cost and application (Chávez and Evett, 2012; Muñoz-Carpena et al., 2004; Robinson et al., 2008). Currently, capacitance/frequency domain sensors are capable of large deployments necessary for temporally and spatially dense readings. Ergo, soil moisture measurements to quantify water-deficit stress in humid regions should be re-evaluated. Given these advancements and sensor properties it is hypothesized that small deployments of soil moisture sensors in dryland cultivar trials will be able to characterize experienced stress at the location and therefore serve as the basis on which to combine yield responses across multiple locations. Therefore, main objective of this research was to develop a soil moisture-based index to quantify drought stress in dryland cotton cultivar trials.

Materials and Methods

During the 2012 and 2013 growing seasons, five trials were established across the Cotton Belt. An emphasis was placed on selecting locations at both humid and arid extremes in order to insure a wide range of precipitation quantities would be realized and to determine the environmental reliance of the developed index. The trial locations, treatment descriptions, design, irrigation type (if applicable) and included cultivars are described in Table 4.1. Each specific trial was managed to either create a range of drought statuses within one field or examine the influence of varietal water uptake on calculation of the developed index. Included cultivars varied based on commercially available cultivars of the region, but every trial included the standard cultivar of PHY 499 WRF.

Inference on volumetric water content (VWC) was made by low-frequency, capacitance-based, dielectric permittivity sensors. Decagon 5TE sensors (Decagon Devices Inc., Pullman, WA) were installed after emergence in a 15 cm diameter, augured hole, positioned within a harvested yield row near the center of each instrumented plot. The 70 MHz 5TE sensor measures VWC through a capacitance technique, which relies on the dielectric permittivity of the surrounding medium. Measurements of soil temperature and electrical conductivity (EC) are also made separately by each 5TE sensor. Sensor depths were consistent within location but varied across locations as a function of perceived effective rooting depth for the trials conducted in 2012 (Table 3.1). In order to create more arbitrary, less user-influenced insight into soil moisture, 2013 sensor depths were consistent within and across locations.

Sensors were deployed after emergence at a stage which principal investigators were confident a re-plant was not necessary; this typically corresponded to a 1 to 5 true leaf stage. Augured soil was mixed as little as possible and sorted by depth during sensor installations. After sensors were installed the disturbed soil was backfilled by depth and re-packed to reduce the influence of the disturbed soil in the hole on sensor readings. Three of the four sensors installed in each profile were inserted horizontally in the sidewall of the augured hole. The deepest sensor was inserted vertically at the bottom of the augured hole without an insertion tool. Un-installation occurred as close to- or post- defoliation applications. To maintain a consistent sensing window at each location, stress units were thereby accumulated from sensor installation until the date of first defoliation.

Data from all four sensors in each plot were collected at 15 minute intervals by an eKo PRO node (Memsic Inc., Andover, MA) and wirelessly transmitted to an edge-of-field base station. Meteorological parameters of rainfall, humidity, temperature, and estimated daily potential evapotranspiration were measured on a 15 minute interval and also transmitted to the base station. From the base station, data were then cellularly transmitted to PureSense servers (Puresense Environmental, Inc., Fresno, CA) at which point it was accessible by the end user through a smart-phone application or a computer program. Sensor output was converted from dielectric permittivity to VWC using the Topp equation (Topp et al., 1980). This conversion is described in the Decagon 5TE manual as:

$$VWC = 4.3 * 10^{-6}({}_{a}{}^{3}) - 5.5 * 10^{-4}({}_{a}{}^{2}) + 2.92 * 10^{-2}({}_{a}) - 5.3 * 10^{-2} \qquad \{1\}$$

Yield was collected at the end of the growing season by mechanical spindle-type pickers outfitted with load cells. Regression analysis was conducted to determine the relationship between the tested drought indices and seedcotton yields for each location. In order to maximize the relationship between drought indices and seedcotton yields across locations, relative yield was calculated by dividing observed yields by theoretical maximum yields for the given season. Maximum yields were defined from adjacent well-watered plots (if applicable) or through the y intercept of the stress by yield response for each location. Relative yield was then modeled in JMP Version 11 (SAS Institute Inc., Cary, NC) to be a function of cultivar, site-year, stress, stress*cultivar, and stress*site-year. Effects were deemed significant at the α=0.05.

Results

Each sensor was installed in 2013 by hand. This was particularly important for the Tifton, GA deployments as increasing coarse fragments at depth frequently lodged between sensor prongs during installation, increasing prong separation distances. The increased resistance associated with these fragments separating prongs was notable if installing by hand and served as an indicator to the installer to remove and re-install the sensor. Installation was also challenging at some locations due to the presence of fragi- or plow-pans at the 30 cm depths.

Planting date, initiation of data collection from soil moisture sensors, termination of data collection from soil moisture sensors, the first defoliation event and the harvest dates are summarized in Table 4.2. On average, a two to three week window existed between planting and deployment. Meteorological parameters for each location, as collected by the base-station and adjacent NOAA weather stations, are located in Figs. 4.1-5.

Volumetric Water Content to Plant Available Water

The first step in converting the raw VWC data to a useful PAW format was calculation of a weighted VWC for the monitored profile at time t.

$$\overline{VWC}_{lxt} = \frac{\sum_{z=1}^{n}[(\mathrm{VWC}_{lxtz}) \times (\mathrm{w}_{lz})]}{\sum_{z=1}^{n}(\mathrm{w}_{lz})} \qquad \{2\}$$

where: VWC_{xt} = Weighted average of volumetric water contents reported by all sensors at location *l*, node *x*, time *t*.

VWC_{xtz} = Volumetric water content reported by sensor at location *l*, node *x*, time *t*, depth *z*.

w_{lz}= Weighting factor based on distance between sensors at location *l*, depth *z*, and assumed rooting depth.

z= Sensor number at a given node, progressing from 1-n with depth

Since VWC does not give direct information on plant water status, VWC_{lxt} must then be converted to PAW_{lxt}.

$$PAW_{lxt} = \frac{\overline{VWC}_{lxt} - LL_l}{UL_l - LL_l} = \frac{\overline{VWC}_{lxt} - LL_l}{TAW_l} \qquad \{3\}$$

where: PAW_{lxt}= Plant available water at location *l*, node *x*, time *t*.

LL_l= Lower limit of PAW, or permanent wilting point at location *l*

UL_l= Upper limit of PAW, or field capacity at location *l*

TAW_l= Maximum total available water for location *l*

The upper and lower limits of PAW are a function of soil properties including, but not limited to: soil texture, porosity, salinity, organic matter, gravel content, and compaction. As a result, determination of PAW is often cumbersome. Moreover, the heterogeneity of soils even within a very small sensor sphere of influence, inherent errors in absolute sensor readings relative to other sensors and deployment influence on sensor readings, it is often more appropriate to determine these thresholds from in-season observed sensor readings. The methods used to determine these lower and upper limits of PAW in these studies are described below:

$$LL_l = \frac{\sum_{z=1}^{n} \left[\min_{x,t}(\mathrm{VWC}_{lxtz}) \times (\mathrm{w}_{lz})\right]}{\sum_{z=1}^{n}(\mathrm{w}_{lz})} \qquad \{4\}$$

This calculation determines the locational lower limit from minimums observed across all nodes and times and minimums associated with each individual depth are not necessarily selected from one point in time. Still, determination of the lower limit for the location from the above equation depends upon multiple assumptions: first, PAW-dependent soil characteristics noted at a given depth are consistent across the location; second, that a severe water deficit occurred in at least one period during the monitored growing season and that this stress was severe enough to deplete the VWC to a point very near the permanent wilting point (PWP); and third, the absolute VWC reported by deployed sensors equals the VWC of the surrounding soil medium.

In contrast to the lower limit calculation, determination of the upper limit cannot be calculated from a noted maximum for each depth across time, as the resulting PAW upper limit would represent the VWC more near saturation than field capacity. Instead, the upper limit from each location is calculated from the following equation:

$$UL_l = \frac{\sum_{z=1}^{n} \left\{\left[\max_{x,t} \frac{\left(\sum_{\mathrm{i}=1}^{h} \mathrm{VWC}_{(lxzt-\mathrm{i})+1}\right)}{h}\right] \times (\mathrm{w}_{lz})\right\}}{\sum_{z=1}^{n}(\mathrm{w}_{lz})} \qquad \{5\}$$

where: h= Total number of hours on which the moving average is based

This calculation determines the locational upper limit from maximums of a moving average calculated from all nodes and times, and similar to the minimum calculation individual depths are not necessarily restricted to one point in time. Again, there are multiple assumptions on which this calculation is dependent. First, that PAW-dependent soil characteristics noted at depth are consistent across the location. Second, that a near-saturating input of either irrigation or rainfall spiked at one time during the growing season and then decreased. Finally, that the time frame selected for d is large enough to prevent selection of a VWC near saturation but small enough to prevent selection of a VWC lower than field capacity.

There are also several overarching assumptions inherent in all four of these equations. First, regardless of depth, all water in the root zone is considered to have the same impact on yield regardless of root-depth densities (Taylor and Klepper, 1971). Second, effective rooting depth during the monitored time frame will not drastically increase or decrease average VWC or the upper and lower thresholds of PAW, as rooting depth is not included in this calculation.

These assumptions will rarely be met. If these assumptions are substantially violated, another method of limit selection, such as a hand-fitting method, should be considered. Still, the more arbitrary, less user-dependent calculations described here will prevent user error in the selection of improper limits and will at least theoretically remove much of the sensor error associated with absolute reading discrepancies due to the aforementioned sensor and soil factors. Furthermore, these calculations will at a minimum provide the investigator with initial limits on which further adjustments can be made from more specific site knowledge.

Stress-Day-Index Based Accumulated Soil Moisture Stress Index

After determination of PAW_{lxt}, severity of stress at the given location, node, and time can be determined from the following equation:

$$SD_{lxt} = ET_o * (1 - PAW_{lxt})^5 \quad \{6\}$$

where:

SD_{lxt}= Stress Day at location *l*, node *x*, and time *t*.

ET_o= Reference Potential Evapotranspiration, calculated by the Penman-Monteith Method (FAO-56) on a daily time interval.

The remaining parameter required for the calculation of the SMSI for one point in time is the Crop Susceptibility factor, which is a function of physiological growth stage and species. This parameter was calculated from days after planting (DAP) as follows:

$$\begin{gathered} CS_t = IF(DAP_t < DAP_{es})\ THEN(CS_{es}), \\ IF\left(DAP_t < DAP_{ef}\right) THEN\left(\frac{DAP_{ef} - DAP_{es}}{CS_{ef} - CS_{es}} \times DAP_t\right), \\ IF\left(DAP_t < DAP_{pf}\right) THEN(CS_{pf}), \\ IF(DAP_t < DAP_{ct})\ THEN\left(\frac{DAP_{ct} - DAP_{pf}}{CS_{ct} - CS_{pf}} \times DAP_t\right) \end{gathered} \quad \{7\}$$

where:

CS_t= Crop susceptibility to water stress at time t

DAP_t= Days after planting at time t

$_{es}$= Early square

$_{ef}$= Early flower

$_{pf}$=Peak Flower

$_{ct}$= Physiological cutout

Calculation of the SMSI for one point in time will therefore be described by the following equation:

$$SMSI_{lxt} = SD_{lxt} \times CS_t \quad \{8\}$$

Finally, the Accumulated SMSI (ASMSI) was calculated as follows:

$$ASMSI_{lx} = \sum_{t=1}^{n} SMSI_{lxt} \quad \{9\}$$

FAO-33 Crop Water Production Function

After determination of PAW_{lxt}, severity of stress at the given location, node, and time was related to the reduction in crop transpiration by the FAO 56 equation below:

$$ET_{C\ adj} = K_s K_c ET_o \qquad \{10\}$$

where: K_s= A water stress coefficient, which reduces potential evapotranspiration as a function of soil moisture.

K_c= A crop-specific coefficient, which relates water use of the modeled crop to a reference crop.

ET_o= Reference crop (0.12m, well-watered grass) evapotranspiration, calculated by the Penman-Monteith Method (FAO-56) on a daily time interval.

The water-stress coefficient, K_s, was defined in FAO 56 by the following equation:

$$K_s = \min_t\left(\frac{TAW_l - D_r}{(1-p)*TAW_l}, 1\right) \qquad \{11\}$$

where: D_r= root zone depletion (mm)

p= fraction of TAW that a crop can extract from the root zone without suffering stress

By substituting PAW_{lxt} in the above equation and defining TAW as 100%, it is possible to relate PAW to K_s:

$$K_s = \min_t\left(\frac{PAW_{lxt}}{(1-p)*TAW_l}, 1\right) \qquad \{12\}$$

From the soil moisture reduced $ET_{c\ adj}$, reduction in yield can be modeled by the following equation, defined in FAO 33 (Doorenbos and Kassam, 1979):

$$\left(1-\frac{Y_a}{Y_m}\right)=K_y\left(1-\frac{ET_{c\,adj}}{ET_c}\right) \qquad \{13\}$$

where: ET_c=Reference crop evapotranspiration, ET_o, multiplied by the modeled crop's crop coefficient, K_c

K_y= a yield response factor necessary to relate a relative reduction in evapotranspiration to relative reduction in yield

Y_a= actual yield

Y_m= Estimated yield potential

In contrast to the seasonal approach established in the proceeding equation, a daily approach can be calculated as follows:

$$\left(1-\frac{Y_a}{Y_m}\right)=\sum\nolimits_{t=1}^{n}\left(Ky_t\left(1-\frac{ET_{c\,adj}}{ET_c}\right)_t\right) \qquad \{14\}$$

The remaining parameter required to relate a soil moisture deficit reduction in evapotranspiration to relative crop yield at one point in time is the yield response factor, K_y, which is a unitless function of physiological growth stage and crop. This factor was designed to relate the actual evapotranspiration relative to that of potential crop evapotranspiration to realized relative yields (actual yields divided by potential). Subsequently, for crops that are fairly water-deficit tolerant, K_ys will be less than one and for more water-sensitive crops K_ys will be greater than one. These values were assumed to vary throughout the growing season with the most susceptible time frames surrounding flowering and early reproductive growth stages relating to the greatest yield reductions and periods in the vegetative and ripening stages relating to reduced yield reductions (Loka et al., 2011).

This parameter was calculated from days after planting (DAP) as follows:

$$Ky_t = IF(DAP_t < DAP_{es})\,THEN(K_{y\,es}), \qquad \{15\}$$

$$IF\left(DAP_t < DAP_{ef}\right) THEN \left(\frac{DAP_{ef} - DAP_{es}}{K_{y\,ef} - K_{y\,es}} \times DAP_t\right),$$
$$IF\left(DAP_t < DAP_{pf}\right) THEN (K_{y\,pf}),$$
$$IF(DAP_t < DAP_{ct})\, THEN \left(\frac{DAP_{ct} - DAP_{pf}}{K_{y\,ct} - K_{y\,pf}} \times DAP_t\right)$$

where: $K_{y\,t}$= Crop susceptibility to water stress at time t

Computational Procedures

Volumetric Water Content to Plant Available Water

Diurnal trends were noted in reported VWCs. These were most likely due to the temperature sensitivities of the utilized low-frequency, capacitance based sensors and in part due to hydraulic lift and subsequent moisture re-distribution during periods of low atmospheric demand. Barring days on which irrigation and rainfall events occurred, readings varied only slightly throughout the day. Subsequently, the majority of aforementioned calculations were conducted on a daily interval in order to reduce computation time. In contrast, the determination of upper and lower limits (equations 4 & 5) were calculated from hourly data. The time period over which the moving average was calculated for the determination of the upper limit (equation 5) was 72 hours due to a suspected under-prediction of the upper limit from a time period of 96 hours. The reduction in included time frame increased the selected upper limit to a point which appeared to better match predicted field capacity VWCs estimated by Saxton et al. (1986) and Saxton et al. (2006) equations.

After the arbitrary, user-independent calculations of the upper and lower thresholds, limits were inspected to insure values were logical. Next, accumulated stress units for the location of interest were regressed with yields. Outliers were examined and if justification existed, adjusted. Whenever possible, the same upper and lower limits of PAW were used across the location and similar limits were used from year to year. This was based on the assumption that installations were made uniformly, soil profile characteristics might vary on a z plane but are consistent on the x and y planes, and absolute reading variability from sensor to sensor is minute.

Calculation of Stress Indices

As mentioned in the methods, the measurements collected in these trials were volumetric. This measurement contrasts the required parameter of the absolute value of the soil water tension $|\psi_s|$ for the calculation of the SD in the SDI approach (Hiler and Clark, 1971) on which the ASMSI is based. Volumetric water content sensors were preferred for multiple reasons. First, many dryland cultivar trails are not located in the immediate proximity of the principal investigator and are therefore not frequently visited. Under these conditions, long-term deployments of soil moisture sensors would be preferred over more expensive, accurate instrumentation operated by the investigator. Furthermore, low-cost tensiometers designed for long-term deployments are typically not capable of making measurements beyond 150 kPa and have been characterized by delayed responses after prolonged dry-down periods (Berrada et al., 2001; McCann et al., 1992; Shock et al., 1998). Since dryland fields may spend a substantial amount of the season below this 150 kPa threshold, the capacitance-based, low-frequency dielectric permittivity sensors better fit this objective. Due to the exponential increase in soil water potential associated with declining VWC, it was deemed necessary to incorporate an exponential trend in the relationship between PAW and stress as a method of retaining an approach similar to the original SDI. This incorporation was derived in this study, is described by equation 6 and the resulting relationship is graphed in Fig. 4.6.

Potential reference evapotranspiration was calculated on a daily time step from the modified Penman-Monteith approach described in FAO-56 (Allen et al., 1998). An abbreviated description of these calculation procedures can be found in Zotarelli et al. (2009). Data used in this calculation were collected by an edge-of-field base station which collected data every 15 minutes. If the weather station went down for any period of time, replacement data were collected from a nearby Global Historical Climatology Network Weather Station (Table 4.1).

Dates for each growth stage were estimated from the traditional cotton plant growth describing publication from Oosterhuis (1990). Resulting points of change occurred at 35, 85, 105, and 155 days after planting, respectively (Fig. 4.7). Exact DAP of each relative growth stage will vary from year to year and therefore the use of Degree Day 60s (DD60s) may be preferred over the more simplistic DAP method; however, given drastic differences in these parameters for contrasting growth stages are not selected, this approach for defining the K_c , K_y, and CS factors results in fairly stable values over the span of seven days. Therefore, slight variations in GDD relative to DAP should not drastically shift the factors.

The values for both the K_y and CS factors were closely related to previously defined values. The season-long K_y factor initially introduced for cotton in the FAO Irrigation and Drainage Paper No. 33 and referred to in the FAO-56 manuscript was 0.85. This lower-than-one value relates to cotton's lower susceptibility to yield reductions from drought in comparison with many other, less drought-tolerant crops. In order to incorporate growth-stage sensitivities, K_y factor values of 0.7, 0.7, 0.95, 0.95, and 0.825 were used in this manuscript at 35, 85, 105, and 155 days after planting, respectively (Fig. 4.7).

Procedures to experimentally determine the CS factor were described by Hiler and Clark (1971). Outlined approaches relied on varying the amount of stress during growth stages in order to determine yield response to drought in the corresponding period. The CS used in the calculation of the ASMSI was a merger between reported cotton CS values (Hiler and Clark, 1971) and reported crop coefficients (Fisher, 2012) (Fig. 4.7). Values of the CS used were 0.1, 0.1, 0.3, 0.3, and 0.2 at 35, 85, 105, and 155 days after planting, respectively. This approach was taken due to a lack of scientifically robust, numerical quantification of a drought susceptibility parameter for cotton and the strong correlation assumed to exist between water use (crop coefficient) and susceptibility to drought.

The crop coefficient used for the calculation of $ET_{c\ adj}$ and ET_c in this publication was recently published by Ko et al. (2009) (Fig. 4.8). These values are very similar, albeit slightly higher, than the values published in FAO 56. Still, the more precise range of values reported by Ko et al. (2009) and the similarities between other published K_c over a range of environments (Fisher, 2012; Grismer, 2002) suggest the utilized K_c are robust and accurate.

Location Upper and Lower Limits of Plant Available Water

2012 Marianna, AR

The 2012 Marianna, AR trial was conducted on the Lon Mann Cotton Research Station of the University of Arkansas. Soils in this trial consisted of relatively uniform Memphis Series (fine-silty, mixed, active, thermic Typic Hapludalfs). Textures in these deep soils shift from silt loam to silty clay loam and then back to silt loam at deeper depths. The fine textures and deep profile at this location results in moderate water holding capacity but restrictive features such as plow pans can reduce rooting depths. Mean precipitation for this series is 125 cm.

Water deficit stress was created in the 2012 AR trial by re-routing the furrow irrigation to exclude the water-stressed block beginning on 7/17/2012 and ending on 8/9/2012. Irrigation water was applied to the well watered PHY 499 WRF strip three times during this period (Fig. 4.1). This allowed a severe water stress to develop in the water-deficit treatment by 8/1/2012. Severity of the stress was visible through substantial wilt noted by 9:00 AM CST in many plots and severe square shed, particularly those near the south end of the trial. The two southern-most replications were most frequently characterized by earlier, more prolific wilt. These differences can be explained by a greater slope which subsides in the third and fourth reps. The resulting cotton yields from this trial varied substantially by replication and by irrigation treatment. Higher yields were noted in the third and fourth replications than the more severely water-deficit-stressed first and second replications. Greatest yields were noted in the well-watered PHY 499 WRF plots.

The aforementioned period of stress matched a period of peak water demand for the cotton crop and great atmospheric demand. Subsequently, very low VWC readings were noted by the soil moisture sensors during this period. The rate of soil moisture decline was very low prior to re-applying irrigation water. Based on these observations, it was assumed that a water status very near that of PWP was reached. The upper and lower limits were initially established by equations 4 and 5 before making final adjustments. The profile upper and lower limits of PAW at 'normal' nodes were accepted to be 29.76% and 8.83%, respectively. Three deployments were deemed 'abnormal' due to differences in absolute values reported by the utilized soil moisture sensors and required post-hoc adjustment. The upper limit of one profile was reduced to the maximum of a three day moving average noted at these three sensor depths, resulting in a upper limit of 20.87%. Two other locations within the field reported significantly lower absolute VWCs relative to the other monitored profiles in the field. Similarly, the lower limits in both of these profiles were lowered to match the minimums observed within these profiles; the resulting lower limits for these two profiles were 15.20% and 10.49%. These adjustments were considered to be acceptable given the variability in soil texture and water holding capacity of plots within the Marianna trial coupled with the variability associated with absolute readings from differing capacitance-based, low-frequency soil moisture sensors.

2013 Marianna, AR

The 2013 Marianna, AR trial was conducted within the same field as 2012. Again, the trial was uniformly irrigated until 7/15/2013, at which point only the well-watered PHY 499 WRF strip received irrigation water (Fig. 4.2). This allowed a severe water stress to develop in the majority of the trial by 8/1/2013. Similar to 2012, the severity of the stress was visible through substantial wilt noted by 9:00 AM CST in many plots and very low VWC readings were noted by the soil moisture sensors located in the water-stressed treatments. Based on these observations, it was again assumed that VWC very near that of the PWP was reached. Disregarding outliers, profile upper and lower limits for all 'normal' nodes after adjustment were 28.97% and 7.64%, respectively. The reduced upper and lower thresholds in comparison with the 2013 season can be partially explained by the shallower deployment of three of the four sensors in each profile during the 2013 season. A large portion of this difference was evident when contrasting the range and median readings from the 2013 7.5 cm sensors and 2012 15 cm sensors.

There were two sensor failures at two different nodes at the Marianna AR location during the 2013 growing season and two 'abnormal' deployments. The missing sensors were ignored in the calculation of stress; VWC of these profiles were assumed to be a function of the three remaining sensors. The weight of the missing sensor was then divided up equally between the remaining sensors. Both sensor failures were at the 7.5 cm depth, which was typically characterized by lower VWCs. As a result, the upper and lower limits were shifted up for these locations to total 30.32% and 12.98%, respectively.

One 'abnormal' 2013 Marianna deployment was characterized by a range of reported absolute VWCs which varied substantially from other noted deployments. Still, the sensor response curves to changes in soil moisture appeared to be relatively similar to other corresponding sensors at similar depths in the profile. In order to compensate for the differences in absolute reported VWCs, the lower limit of the plot was adjusted from 7.64% to 15.61%. Again, these adjustments were considered to be acceptable given the variability associated with absolute readings from differing capacitance-based, low-frequency soil moisture sensors. This variability is partially characterized by examining the PAW trends between well-watered and water-stressed plots in Fig. 4.9. Although both plots received similar irrigations early during the season, substantial differences in PAW were noted very early within the trial.

2012 Maricopa, AZ

The Maricopa, AZ trial was conducted on the University of Arizona Maricopa Agricultural Center. Soils in this trial were classified as Casa Grande Series (Fine-loamy, mixed, speractive, hyperthermic Typic Natrargids). Textures in these deep soils shift from fine sandy loam to clay loam and then back to sandy clay loam at depth. Mean precipitation in for these soils is 18 cm.

Irrigation regime in this trial was based on a modeled soil water balance approach. Two irrigation treatments were established; the first treatment received irrigation when 50% PAW remained and the second received irrigation when 25% PAW remained. Triggered irrigation events, precipitation, and maximum and minimum temperatures are graphed in Fig. 4.3. Greater yields were associated with the 50% PAW triggered treatments.

The 2012 Maricopa, AZ trial data greatly contrasted that of both AR site years. These differences could be caused by the drastically more arid environment or differences in soil properties. Two very noticeable differences were the very rapid responses of the deep soil moisture sensors at the AZ site to the application of irrigation water and the rapid, uniform soil water decline throughout the profile following an irrigation event. Subsequently, drought at the

AZ trial occurred over a wider time frame during the season but this stress was not allowed to develop into the severe deficits which were observed at the AR site in both 2012 and 2013. Six sensors failed during this trial, but since the response of each sensor to changes in soil moisture did not vary much relative to depth, little difficulty was noted when profile PAWs were calculated from profiles with failed sensors.

Eight of the eleven remaining deployments (six failed sensors were located in five plots) appeared to behave normally relative to the other deployments. Thresholds were calculated by equations 4 and 5 and then adjusted to maximize relationships with yield. Upper and lower limits for these eight locations were 27.62% and 14.92%, respectively. The five deployments which contained the failed sensors required hand fitting of upper and lower thresholds, as equation 4 & 5 determined upper and lower limits resulted in illogical trends between perceived stress and seedcotton yields (data not shown). The three remaining, 'abnormal' deployments were characterized by higher absolute values at depth than noted at the other sensors. Subsequently, the lower limits of these three profiles were adjusted to either 17.05% or 19.76%, which corresponded to minimums calculated from each profile by equation 4.

2013 Tifton, GA

The Tifton, GA trial was conducted on the University of Georgia Lang-Rigdon Research Farm. Soils in this trial consisted of relatively uniform Tifton Series (fine-loamy, kaolinitic, thermic Plinthic Kandiudults). Textures in these deep soils shift from loamy sand to sandy clay loam at deeper depths. Coarse fragments and root-restricting pH at depth limits the effective water holding capacity of the Tifton location. Still, the mean annual precipitation of near 135 cm results in a large portion of this series to be cultivated for row-crop production.

The water stress treatment in this trial represented dryland management; only the well-watered PHY 499 WRF strip received irrigation water from a moving linear sprinkler system. However, a very wet June and July resulted in only one irrigation event during these two months (Fig. 4.4). As a result, inconsistent yield responses were noted between water-stressed and well-watered plots. Five sensor failures were noted within the trial; two of these were at the shallowest depth, two were at the deepest depth, and one was at the second depth. Substantial variability in yields were noted, but these did not correlate strongly to stress most likely due convolution of the relationship by water-logging stress observed during this extremely wet season. Severe violations of assumptions surrounding the calculation of the lower limit of PAW prevented the calculation by equation 4.

2012 Florence, SC

The Florence, SC trial was conducted on Clemson University's Pee Dee Research and Extension Center. Soils in this trial consisted of relatively uniform Goldsboro Series (fine-loamy, siliceous, subactive, thermic, Aquic Paleudults). Textures in these deep soils shift from loamy sand to sandy clay loam at deeper depths. The mean annual precipitation for this series is 122 cm.

The use of consistent location upper and lower limits used at several other locations resulted in illogical trends at the 2012 SC site. The resulting relationship between seedcotton yield and stress suggested yields increased as soil deficit stress increased (data not shown). Due to these illogical trends, within-plot, equation 4 & 5 calculated upper and lower limits were accepted for eight of the twelve 2012 SC deployments. For these eight profiles, the average upper limit was 24.63% with a standard deviation of 0.92% and the average lower limit was 13.36% with a standard deviation of 1.31%. The four remaining deployments were located adjacent to one another but did not appear to experience severe water depletions which characterized the other plots. In contrast to the other nine deployment limits, equations 4 & 5 calculated upper and lower limits across the three 'abnormal' plots were selected for use in each plot. The selected upper and lower limits for these plots were 20.98% and 9.83%.

By-location Relationships between Indices and Seedcotton Yields

Differences in coefficients of determination between the two stress-quantifying approaches (ASMSIs and 1-($ET_{c\ adj}/ET_c$)) varied only slightly for all trials with neither approach resulting in consistently higher relationships with seedcotton yields (Fig. 14.10-14.14). Varietal yield response at each location was variable and generally weak. This variability can be partially explained by inherent measurement variability and the very small sample size for each regression equation (n=4 to 8). Moderate to strong relationships between seedcotton yields and both stress indices were noted in both the 2012 and 2013 Marianna, AR trials (r^2=0.755-0.884) (Fig. 4.10 & 4.11). Slightly weaker, moderate coefficients of determination were noted at the 2012 Maricopa, AZ (r^2=0.649, 0.717) and 2013 Florence, SC trials (r^2=0.684, 0.706) (Figs. 4.12 & 4.14). As previously described, prolonged dry periods in each of these trials allowed a severe water deficit to develop and subsequently no clear violation of the assumptions associated with the stress approaches were made. In contrast, the relationship between seedcotton yields and stress indices from the 2013 Tifton, GA location were very poor (r^2=0.005, 0.014) (Fig. 4.13). This failure was due to an overall lack of water stress during the growing season and the presence of some other yield-limiting factor which resulted in seedcotton yields for the well-watered PHY 499 WRF treatment varying in excess of 1800 kg seedcotton ha^{-1}.

Across-location Relationships between Indices and Seedcotton Yields

In order to increase the number of modeled observations, to test the ability of the indices to remove location factors and differentiate between varietal yield response to experienced drought, all data (with the exception of the 2013 GA location) were combined and the yield response to the effects of interest were tested (Fig. 14.15, Table 4.3). Model fit for both indices was strong with adjusted coefficients of determination equaling 0.729 and 0.726 for the ASMSI and 1-($ET_{c\ adj}/ET_c$) approaches, respectively. Furthermore, both models indicated significance of site-year and stress index effects on yield ($p \leq 0.05$) (Table 4.3). However, neither model indicated a significant interaction of stress index and cultivar. Therefore, neither approach was capable of describing the unique characteristics of varietal response to drought.

Discussion

Large within-field variations of estimated water-deficit stress were noted in each of the locations. Although the AR and AZ trials both had two defined irrigation regimes, plots receiving these treatments did not separate out with respect to yield or stress-unit response (Figs. 4.10-4.12). Similar responses were noted in the uniformly-dryland SC location; within-cultivar yield responses varied in excess of 1000 kg ha^{-1} (Fig. 4.14) Some of this variability does appear to be due to variable soil water characteristics since relationships between seedcotton yield response to increasing stress at each location were generally moderate to strong. Still, the large range of stress units (both ASMSI and 1-($ET_{c\ adj}/ET_c$)) and yields noted at the SC site highlight major challenges for this type of approach on a larger scale. Dryland cultivar trials are frequently strip-replicated and may cover multiple acres. This large-plot approach increases the chances of separating cultivar response. However, relationships between seedcotton yield and accumulated stress could potentially deteriorate as discrepancies between the area on which the yield measurement is conducted and the area on which soil moisture measurement is bound diverge. In order to protect these moderate relationships, deployments must be made into soil profiles which characterize the majority of the field.

The general failure of either index to identify unique varietal responses to drought may be attributed to several factors. First, it is possible that varietal water uptake characteristics and transpiration rates influenced the estimated stress values which accrued at each node. Theoretically, these varietal water use characteristics could vary seasonally and be based upon available water. As a result, both intercept and slope of each cultivar yield response curve to accrued stress units could be shifted by these characteristics. Second, it is possible that the varietal response to drought among these three cultivars is either non-existent or too miniscule to be measured through the utilized approaches. Finally, it is possible that user adjustments to upper and lower limits at each location (defined in the results) could have been made in error and actually removed the varietal effect.

Although the latter factor is very difficult to prevent due to the nature of the instruments used to measure VWC in these trials, the other two factors can be at least partially addressed. By holding the cultivar under which deployments are made constant across all locations, the single-factor varietal water uptake characteristic error would be diminished, leaving only error associated with potential cultivar by environment interactions to convolute results. Furthermore, an increase in the number of tested cultivars and locations would increase the potential to quantify the varietal yield response to drought.

Similarities and Discrepancies with Other Approaches

Both of these approaches are at least partially similar to the Nix and Fitzpatrick (1969) approach of accumulating stress in the ‘critical’ periods. Although the ‘critical’ period here encompasses stress from two to three weeks after emergence up to a point very near defoliation, stress outside of the monitored window was assumed to have no impact on yield. This is a physiologically sound approach when considering the very low yield sensitivity of the crop in the weeks following emergence and the period between defoliation and harvest. Furthermore, ignoring these periods prevents the need to extrapolate soil moisture readings into these periods, and therefore protects the simplicity of the approaches.

These additive approaches could also be compared to numerous other additive and multiplicative approaches based on far more complex soil water budgets. Multiple similarities exist, but the approach outlined in this publication is far more simplistic for several reasons. First, measurements of runoff, deep percolation, interception, evaporation, transpiration, irrigation and precipitation are not of direct interest; these volumes ultimately impact the yield dependent factor of PAW which is indirectly measured by sensor deployments. Other approaches often model soil evaporation, intercepted precipitation/irrigation evaporation and transpiration separately, account for percent root distribution, adjust for effective rooting depth and address effects of rate of canopy development, CO_2 availability, or photosynthetic rate. Instead, these factors were disregarded in an attempt to limit the number of inputs required for the calculation while focusing on the sole purpose of quantifying experienced yield-reducing drought stress and maintaining field applicability, as stated by Sudar et al. (1981).

The single most important assumption on which this approach relies is the difference between site yield potential and actual yield is solely due to deficits in PAW observed during the growing season. Some errors in yield prediction will undoubtedly be driven by improper upper and lower PAW limit selection, establishment of the onset of stress threshold and the rate and manner in which stress increases as the PAW between the threshold and the lower limit declines, selection of the crop yield parameter values for each growth stage and prediction of growth stage, sensor error, etc; however, these errors pale in contrast to errors associated with violation of an assumption that yield in the modeled trial is solely restricted by water deficits. If yield restrictions are due to other parameters, the feebleness of this approach and the robustness of others becomes most evident.

Assuming drought is the sole yield-restricting parameter, indirect, temporally dense measurements of PAW allow for an empirical bypass of the aforementioned parameters frequently contained in modeling approaches. This is due to the fact that these parameters either drive or are dependent upon PAW, which ultimately governs relative yield.

Conclusions

Both the ASMSI and the 1-($ET_{c\ adj}/ET_c$) approaches appear to have potential in characterizing the amount of stress experienced within dryland cultivar trials. The utility of these approaches will depend on the quality of the soil moisture and meteorological measurements collected to calculate these indices and the soundness of the assumption that yield is restricted by water-deficit stress. However, both the ASMSI and 1-($ET_{c\ adj}/ET_c$) approaches resulted in substantial location-based responses. More research should be conducted on reducing these location responses before maximum separation between varietal response will be recognized.

Table 4.1 Trial locations, years, varieties, irrigation type, irrigation treatment, layout, and sensor depths for the included trials.

Location	Year	Cultivars	Irrigation	Irrigation treatments/ layout/ position		Sensor Depth				Weather Station
Lat, Lon‡			Type	Well	Stressed	z_1	z_2	z_3	z_4	GHCND‡ ID
Marianna, AR 34.731010°, -90.759010°	2012	PHY 499 WRF DP 0912 B2RF ST 5458 B2RF	Furrow	PHY 499 WRF strip, adjacent	All Cultivars 4 Replicates RCBD	15	30	60	75	USC00034638 34.7391°, - 90.7663°
Maricopa, AZ 33.059915°, -111.965275°	2012	PHY 499 WRF DP 164 B2RF ST 4498 B2RF	Furrow	PHY 499 WRF strip, adjacent	All Cultivars 4 replicates RCBD	15	30	60	90	USC00025270 33.1139°, - 112.0303°
Florence, SC 34.287215°, -79.744040°	2012	PHY 499 WRF DP 0912 B2RF ST 5458 B2RF	None	None	All Cultivars, 4 Replicates RCBD	7.5	15	30	60	USC00383111 34.2933°, -79.7400°
Marianna, AR 34.731010°, -90.759010°	2013	PHY 499 WRF DP 0912 B2RF ST 5458 B2RF	Furrow	PHY 499 WRF strip	All Cultivars 4 Replicates RCBD	7.5	22.5	45	75	USC00034638 34.7391°, - 90.7663°
Tifton, GA 31.520930°, -83.545612°	2013	PHY 499 WRF DP 0912 B2RF ST 5458 B2RF	Overhead	PHY 499 WRF strip	All Cultivars 4 Replicates RCBD	7.5	22.5	45	75	N/A†

†Weather station queried for missing data was located on the research station and was not a Global Historical Climatology Network station.

††Lat= latitude, lon= Longitude

‡GHCN= Global Historical Climatology Network

Table 4.2 Location planting dates, installation and un-installation dates of volumetric water content sensors, date of first defoliation, and date of harvest for the 2012 and 2013 growing seasons.

Location	**Year**	**Planting Date**	**VWC start date**	**VWC end date**	**Date of first Defoliation**	**Harvest**
Marianna, AR	2012	05/14/2012	06/07/2012	09/24/2012	09/22/2012	10/23/2012
Maricopa, AZ	2012	04/17/2012	05/07/2012	10/22/2012	09/28/2012	10/22/2012
Florence, SC	2012	05/03/2012	06/11/2012	09/21/2012	10/16/2012	10/25/2012
Marianna, AR	2013	05/16/2013	05/27/2013	10/08/2013	09/24/2013	10/09/2013
Tifton, GA	2013	05/08/2013	05/31/2012	09/25/2013	09/17/2013	10/16/2013

Table 4.3 Fixed effects from combined AR, AZ and SC results for the 2012 and 2013 seasons.

Source	DF	ASMSI Sum of Squares	ASMSI Mean Square	ASMSI F Ratio	$1-(ET_{cadj}/ET_c)$ Sum of Squares	$1-(ET_{cadj}/ET_c)$ Mean Square	$1-(ET_{cadj}/ET_c)$ F Ratio
Model	15	0.84716	0.05647	10.5112	0.84462	0.056308	10.3510
Error	38	0.20417	0.00537	Prob>F	0.20671	0.005440	Prob>F
C.Total	53	1.05134		<.0001	1.05134		<.0001

Summary of Fit	ASMSI	$1-(ET_{cadj}/ET_c)$
Adjusted r^2	0.72913	0.72576
RMSE	0.07330	0.07375
Mean of Response	0.74276	0.74276

Effect	DF	ASMSI Sum of Squares	ASMSI F Ratio	ASMSI Pr>F	$1-(ET_{cadj}/ET_c)$ Sum of Squares	$1-(ET_{cadj}/ET_c)$ F Ratio	$1-(ET_{cadj}/ET_c)$ Pr>F
Site Year	3	0.21895	13.5836	<.0001*	0.06909	4.2340	0.0112*
Cultivar	4	0.02891	1.3452	0.2711	0.01292	0.5942	0.6690
Stress	1	0.06839	12.7288	0.0010*	0.03907	7.1829	0.0108*
Stress*SiteYear	3	0.03288	2.0400	0.1246	0.00468	0.9319	0.4347
Stress*Cultivar	4	0.01214	0.5650	0.6895	0.01520	0.2153	0.9283

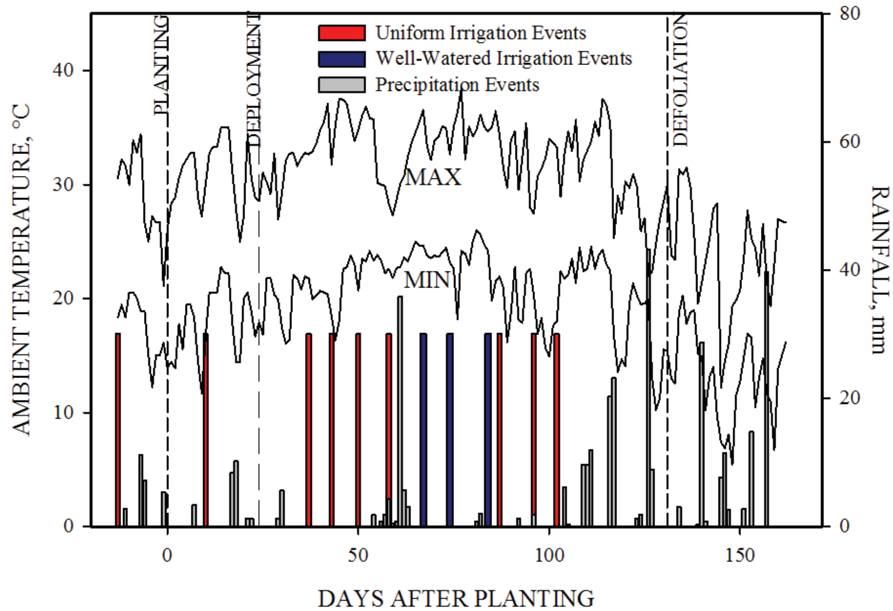

Figure 4.1 Maximum and minimum air temperatures, irrigation dates, and precipitation dates and quantities for the 2012 Marianna, AR trial. Volume of irrigation water was not measured.

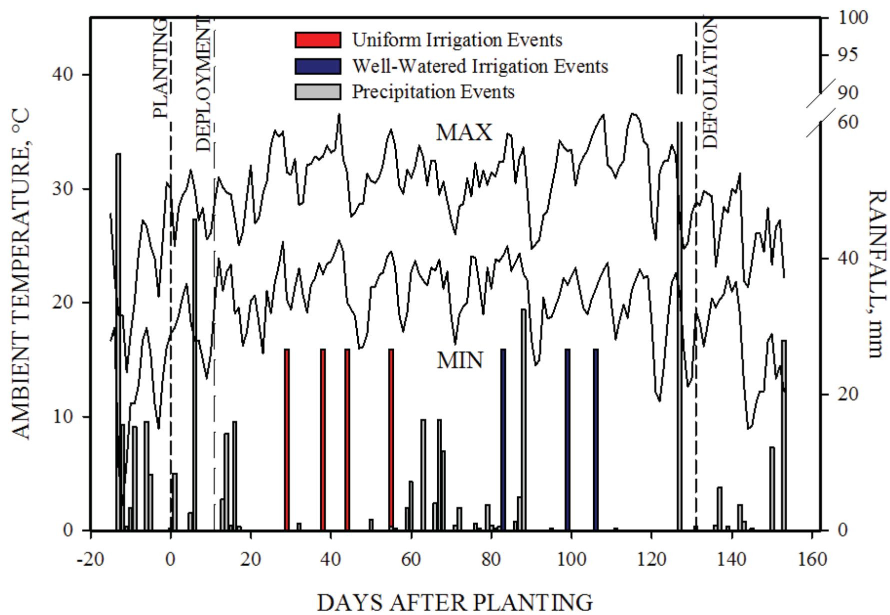

Figure 4.2 Maximum and minimum air temperatures, irrigation dates, and precipitation dates and quantities for the 2013 Marianna, AR trial. Volume of irrigation water was not measured.

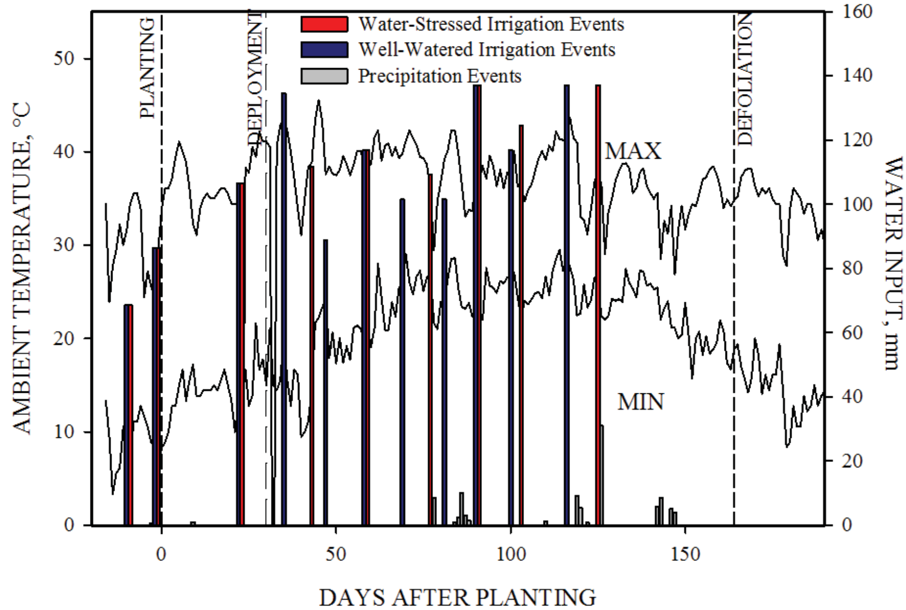

Figure 4.3 Maximum and minimum air temperatures, irrigation dates and quantities, and precipitation dates and quantities for the 2012 Maricopa, AZ trial.

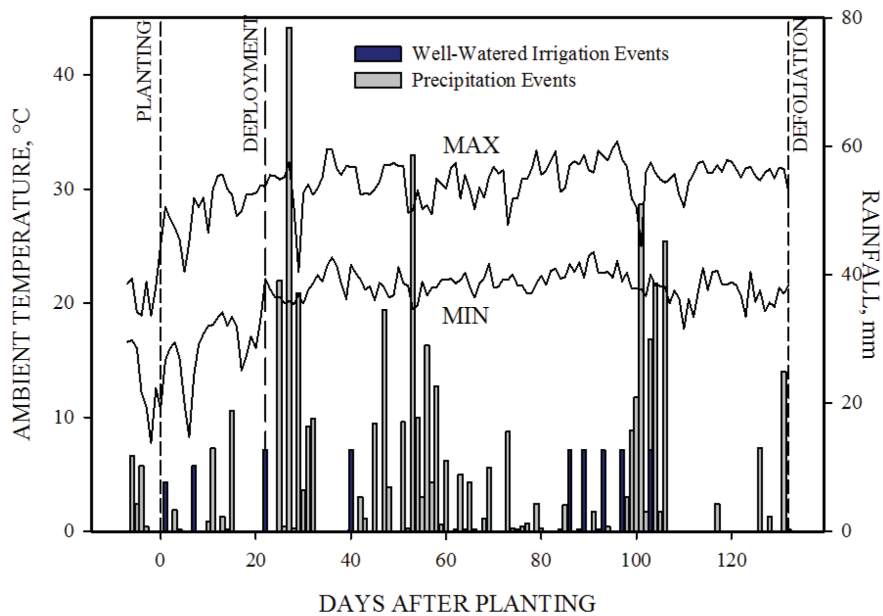

Figure 4.4 Maximum and minimum air temperatures, irrigation dates and quantities, and precipitation dates and quantities for the 2013 Tifton, GA trial.

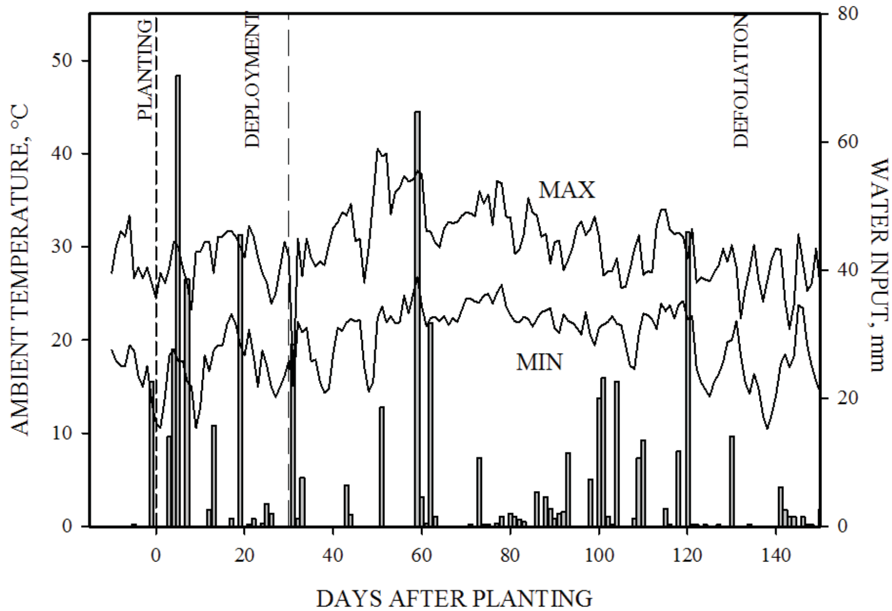

Figure 4.5 Maximum and minimum air temperatures, precipitation dates and quantities for the 2012 Florence, SC trial.

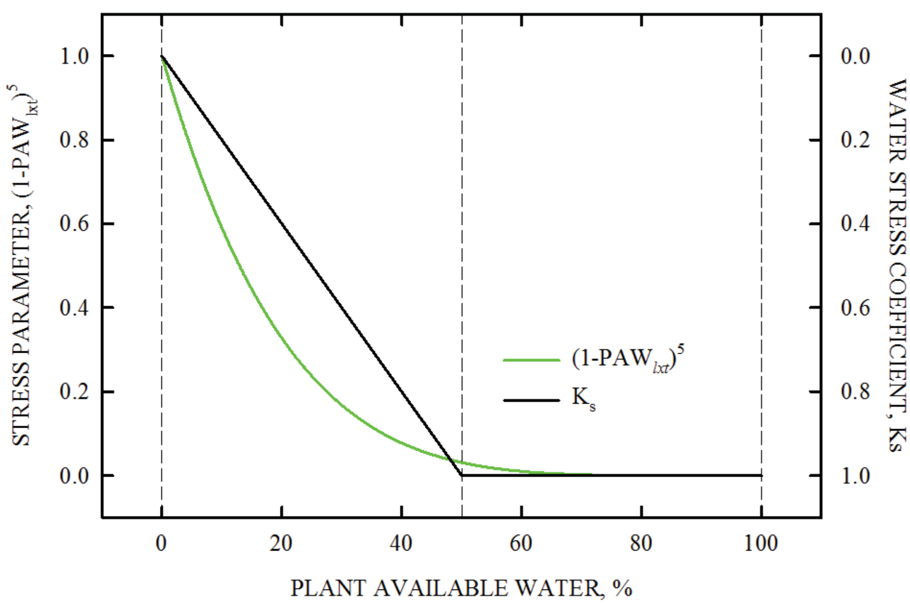

Figure 4.6 Responses of the Stress Parameter ($(1\text{-}PAW_{lxt})^5$) and Water Stress Coefficient, Ks (Allen et al., 1998), to changes in Plant Available Water, PAW.

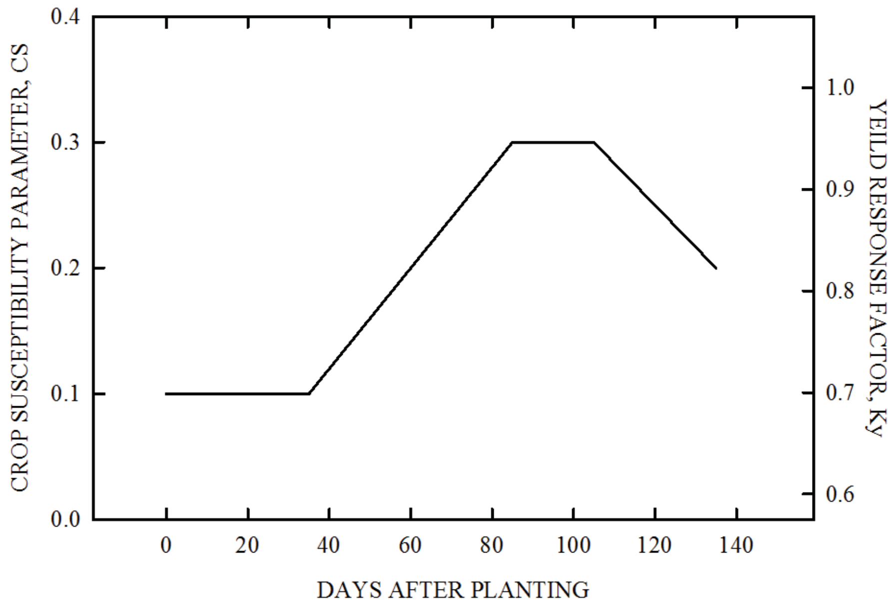

Figure 4.7 Changes of the Crop Susceptibility, CS, and Yield Response, Ky, factors in response to days after planting.

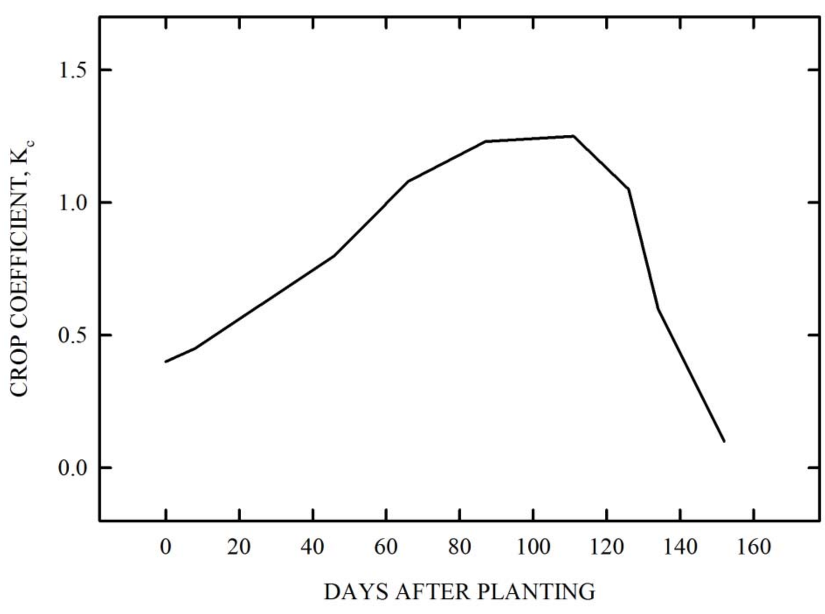

Figure 4.8 Cotton crop coefficients (K_c) defined by Ko et a. (2009) and used in this publication.

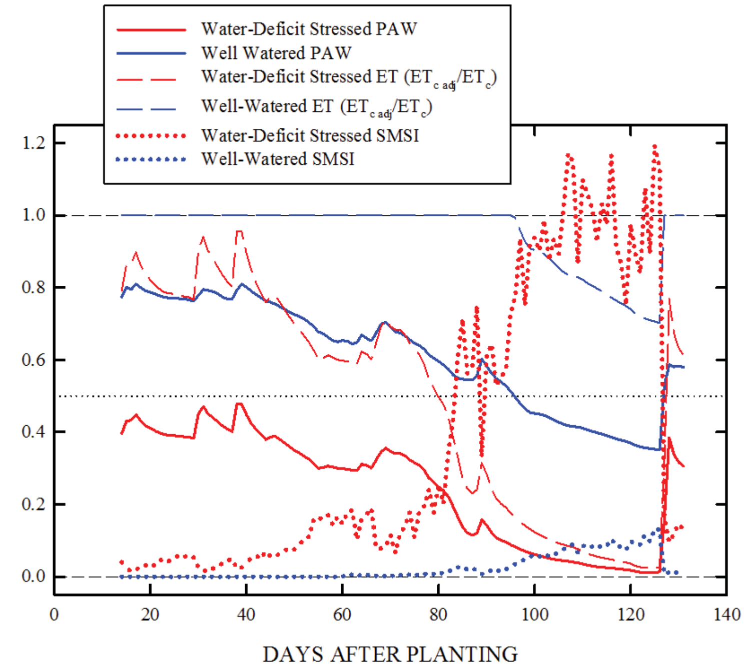

Figure 4.9 Decreases in plant available water (PAW) from a water-deficit stressed plot and a well-watered plot at the 2013 Marianna, AR location. Dashed lines represent estimated actual evapotranspiration ($ET_{c\ adj}$) divided by crop coefficient (K_c) adjusted evapotranspiration potential (ET_c). Dashed line represents the lower limit of readily available water (RAW), or p.

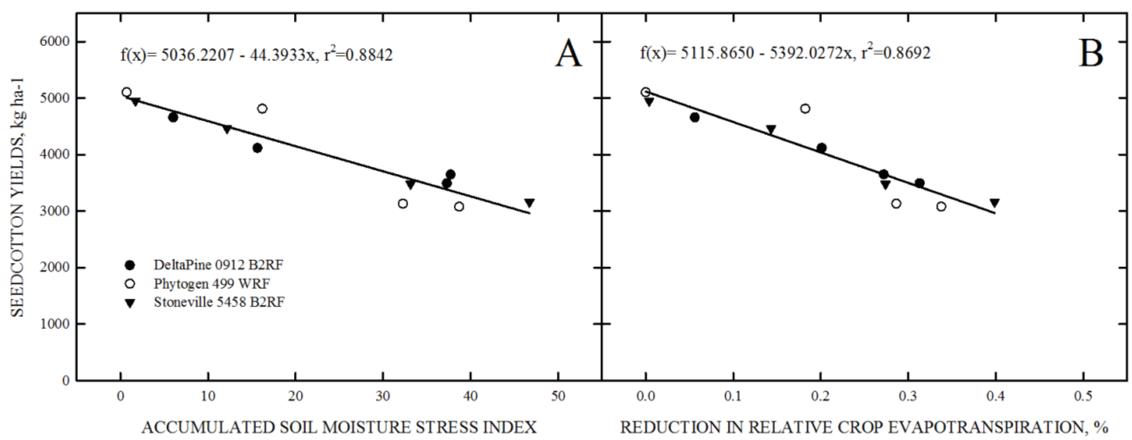

Figure 4.10 Seedcotton yield response to accumulated soil moisture stress index units and reduction in relative crop evapotranspiration at the 2012 Marianna, AR trial.

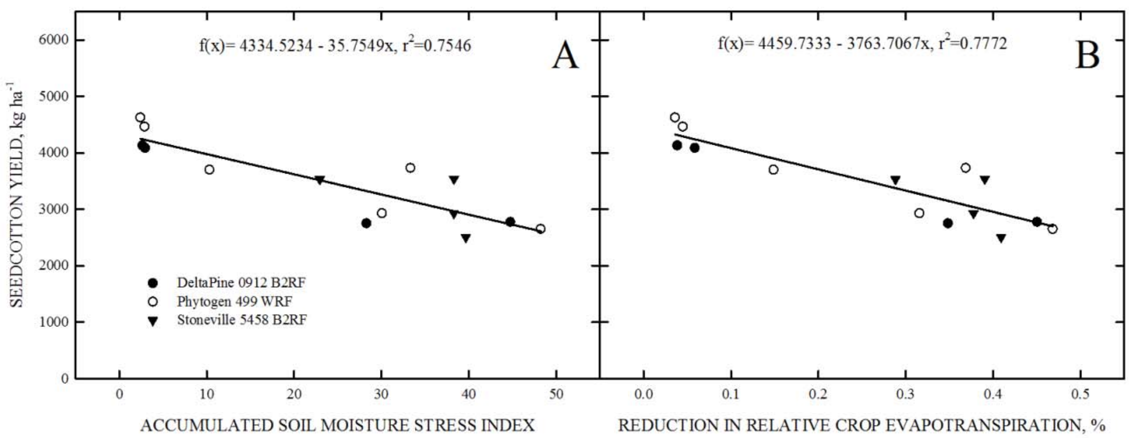

Figure 4.11 Seedcotton yield response to accumulated soil moisture stress index units and reduction in relative crop evapotranspiration at the 2013 Marianna, AR location.

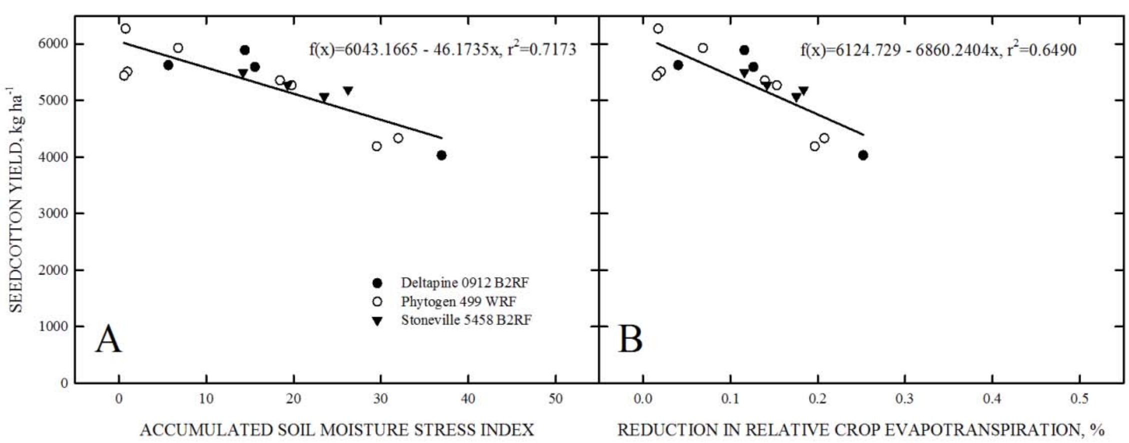

Figure 4.12 Seedcotton yield response to accumulated soil moisture stress index units and reduction in relative evapotranspiration at the 2012 Maricopa, AZ location.

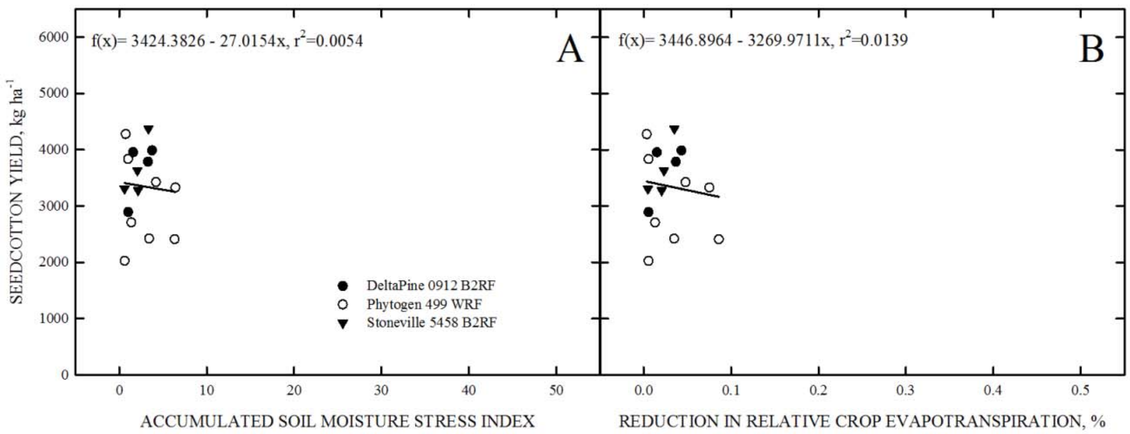

Figure 4.13 Seedcotton yield response to accumulated soil moisture stress index units and reduction in relative evapotranspiration at the 2013 Tifton, GA location.

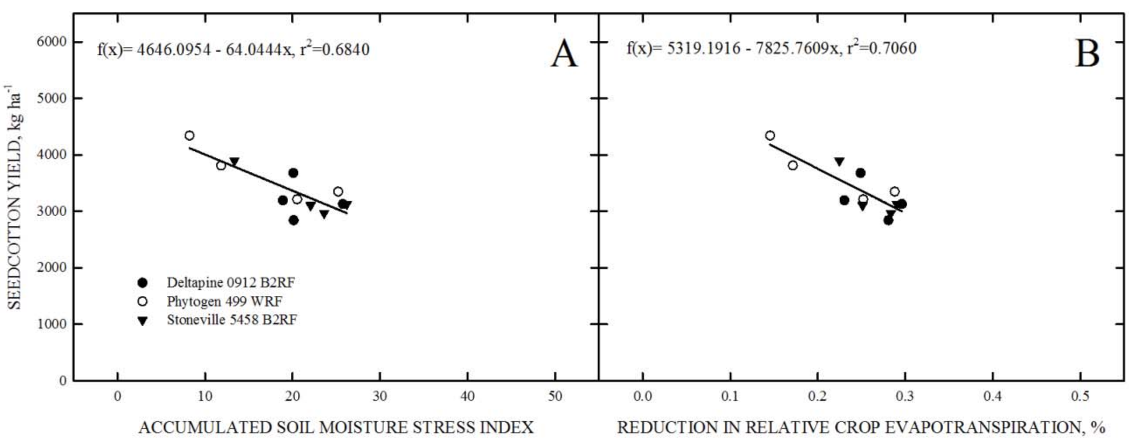

Figure 4.14 Seedcotton yield response to accumulated soil moisture stress index units and reduction in relative evapotranspiration at the 2012 Florence, SC location.

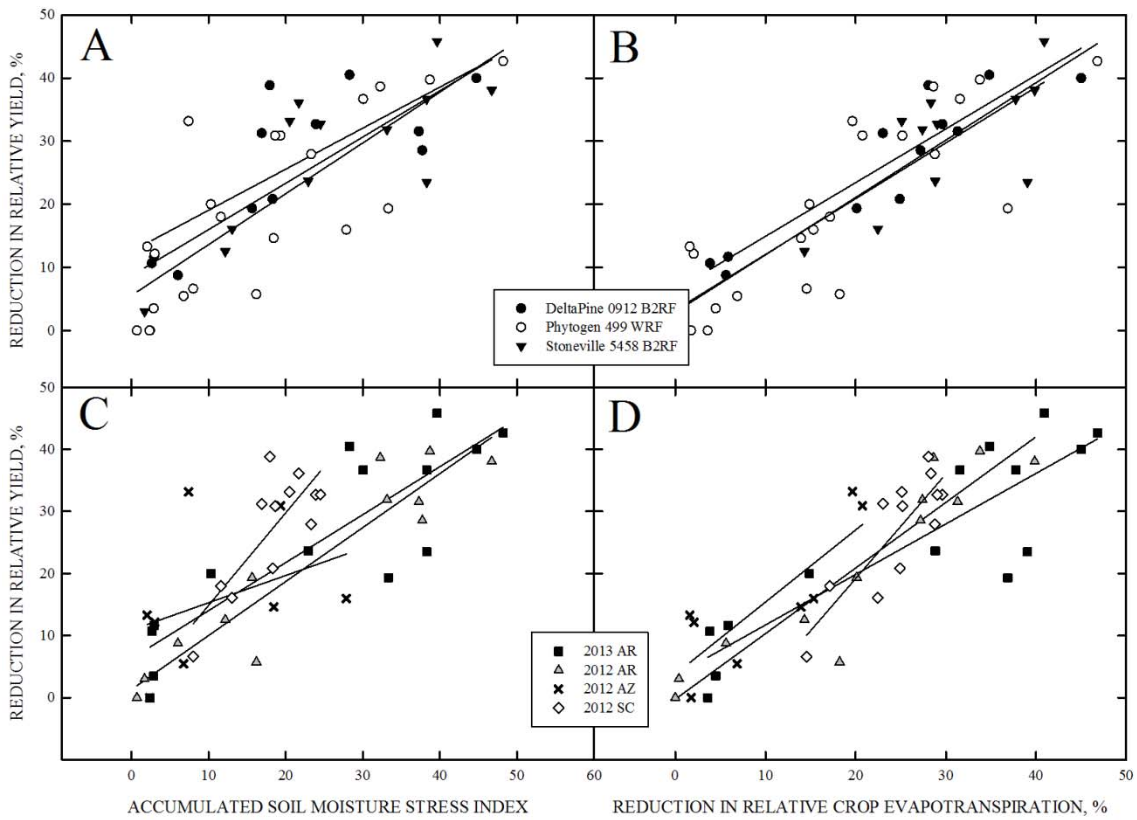

Figure 4.15 Reduction in relative seedcotton yield as a function of accumulated soil moisture stress index units graphed by cultivar (A) and location (C) and reduction in relative seedcotton yield as a function of a reduction in relative crop evapotranspiration graphed by cultivar (B) and location (D). Included data were collected from the Arkansas, Arizona, and South Carolina trials..

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CHAPTER V

Testing the Spatiotemporal Variability of Measured Soil Moisture across Multiple Cropped Agricultural Fields

Abstract

The ability to characterize drought within a given field or initiate irrigations from monitored soil moisture data hinges upon the ability of the instrument to characterize soil moisture at the sampled point and extrapolate that information across the landscape and time. Therefore, the objective of this study was to determine if a limited number of soil moisture sensors deployed into a dryland cultivar trial could accurately characterize the volumetric water content (VWC) at a given point within the field and if this measurement could be extrapolated out to the field scale from the very small sphere of influence characterizing the utilized soil moisture sensors. During the 2013 growing season soil moisture sensor deployments were made into seven dryland cotton (*Gossypium hirsutum*, L.) cultivar trials across the Mid-South and Southeastern Regions of the U.S. Inference on VWC of each monitored profile was determined by (4) Decagon EC-5 sensors (Decagon Devices Inc., Pullman, WA) installed at depths of 7.5, 22.5, 45, and 75 cm. Sensor reported VWCs related well to soil water content measured at installation (r^2=0.617). Relationships between within-location nodes varied but were typically moderate to strong ($0.646 \leq r^2 \leq 0.988$). Mean relative difference analysis indicated a minimum of one node in six of seven instrumented trials was characterized as temporally stabile (σ<5%). The moderate relationships noted between sensor-estimated and measured VWC and the presence of temporal stability noted at each location suggest a limited number of soil moisture sensors deployed into a dryland cultivar trial could accurately characterize the VWC of the trial. Still, further research should be conducted to see if trends in temporal stability remain through

multiple seasons and to investigate the relationship between varietal yield responses to the calculated drought stress-indices in more rainfall-normal years.

Introduction

Soil moisture contents vary temporally across the growing season as a function of water inputs and outputs and spatially across each cropped field as a function of changes in soil properties, slope, magnitudes of water inputs and outputs, etc. This spatiotemporal variability complicates drought quantification and the within-season management of irrigation water. The ability to characterize drought within a given field or initiate irrigations from monitored soil moisture data hinges upon the ability of the instrument to characterize soil moisture at the sampled point and extrapolate that information across the landscape and time.

Several attempts to extrapolate soil moisture measurements to the field or catchment scale have been made with limited success. Martínez-Fernández and Ceballos (2003) attempted to characterize the temporal stability of profile soil moisture (depths included 5, 25, 50 and 100 cm) across a 1285 km^2 basin in Spain. Data were collected at over 23 locations every two weeks during a 36 month period by a Time Domain Reflectometer (TDR). Authors noted stable temporal patterns across the monitored 36 months, even under very dry and very wet soil moisture conditions. Greater stability was noted under dry conditions than wet conditions, with the lowest stability occurring during periods of transition (between wet and dry).

Similarly, Brocca et al. (2010) used a TDR probe to monitor surface soil moisture (0-15 cm) in seven fields in Italy for the purpose of characterizing the temporal patterns of soil moisture at the catchment-scale. Authors stated that the temporal variability in soil moisture exceeded the spatial variability and therefore predicted that a limited network of soil moisture sensors monitoring moisture on a fine temporal scale could accurately estimate temporal patterns over large areas.

Jacobs et al. (2004) also monitored surface (0-6 cm) soil moisture but used a dielectric permittivity-based ML2 theta probe (Delta-T Devices, Cambridge, England) in an attempt to characterize field mean VWC of four fields in Iowa. Results indicated a range of 3-32 independent measurements would be required to determine field VWC with a ±2% bias and 95% confidence interval. The greatest amount of measurement variability (and therefore, the greatest number of measurements required to accurately characterize field soil moisture) was noted at field mean soil moistures between 10 and 25%. Still, authors concluded that an appropriately selected single sampling point was capable of providing accurate information on average field moisture and this point would ideally be located on a mild slope and be characterized by elevated clay contents relative to the remainder of the field. These results are in agreement with research conducted by Starks et al. (2006) who analyzed TDR data at eight locations across a 610 km2 watershed in Oklahoma. Starks et al (2006) concluded watershed mean values of profile soil moisture could be determined by inaccurate but precise soil moisture monitoring locations given the offset (discrepancy between estimated and actual value) was known a priori.

More recent research by Heathman et al. (2012a) monitored Frequency Domain Reflectometry Hydra Probes (Stevens Water Monitoring Systems, Inc.) installed both temporarily in agricultural fields and permanently in grassed easements at 5 and 20 cm depths in an effort to scale point data up to a 2 ha field. Although authors noted agreement between sensor readings and rainfall dynamics, these trends were complex and the permanently deployed sensors were concluded to require offset correction before being capable of characterizing mean field soil moisture (sensors were characterized as inaccurate but precise). However, further analysis of these data by Heathman et al. (2012b) noted difficulty in offset correction of permanent sensor deployment data. Authors concluded topography, rainfall interception differences associated with field measurements under soybeans (*Glycine max*, L.) versus edge-of-field measurements in grassed easements and differences in plant water uptake between the two systems likely combined to bias sensor readings and result in increased variability. Han et al. (2012) attempted to correct for this bias and variability through a cumulative distribution approach but was unsuccessful in accurately characterizing the mean field soil moisture from the permanently deployed sensors.

It should be noted that many of these aforementioned projects were designed to extrapolate readings to the catchment scale for validation of remotely sensed data or hydrological modeling. Subsequently, these studies were typically characterized by coarse temporal sampling regimes at coarse spatial resolutions by expensive instrumentation. Although these studies shed light on many data processing and deployment techniques, the coarse temporal resolution and high instrumentation cost limit the utility of the subsequent results to agronomic applications. Limited research has been conducted on determining the spatiotemporal pattern of yield-influencing soil moisture at relatively small-field scales from low-cost, low-frequency sensors. This information could provide great insight into crop water use and drought status and potentially serve as tools to schedule irrigations. Therefore, the objective of this study was to determine (1) if a limited number of soil moisture sensors deployed into a dryland cultivar trial could accurately characterize the VWC at a given point within the field and (2) if this measurement could be extrapolated out to the field scale from the very small sphere of influence characterizing the utilized soil moisture sensors.

Materials and Methods

During the 2013 growing season soil moisture sensor deployments were made into seven dryland cultivar trials across the Mid-South and Southeastern Regions of the U.S. Deployments were concentrated in states where cotton production is largely dryland. The trial locations, treatment descriptions, design, planting dates and nearby National Oceanic and Atmospheric Administration weather station locations are described in Table 5.1. Included cultivars varied based on commercially available cultivars of the region but every monitored trial included the standard cultivar of PHY 499 WRF. In order to prevent a genotypic effect from influencing soil moisture levels and therein the quantified stress index, all sensor deployments were made into replications of the PHY 499 WRF cultivar.

Experimental design varied from site to site but every deployment consisted of four data loggers, each of which collected information on soil moisture from four sensors. Each data logger will from here-on be referred to as a 'node.' Nodes were deployed in areas which appeared to represent median site properties. The spatial distribution of nodes within each field represented an attempt to minimize the distance between nodes while minimizing the distance between any given within-field point to the closest-proximity node. For trials which were strip-replicated, this typically resulted in a N, E, S, and W diamond-shaped deployment into PHY 499 WRF plots. In contrast, the spatial distribution nodes within trials which were designed as randomized complete blocks were less consistent. Plot selection was still based on minimizing distance between nodes while minimizing distance between any given within-field point to the closest-proximity node, but deployment was most influenced by PHY 499 WRF plot location.

Inference on VWC at each node was made by four low-frequency, capacitance-based, dielectric permittivity Decagon EC-5 sensors (Decagon Devices Inc., Pullman, WA). Sensors were installed after emergence in a 15 cm diameter, augured hole, positioned within a harvested yield row. The 70 MHz EC-5 sensor measures VWC through a capacitance technique based on the dielectric permittivity of the surrounding medium. Each node was characterized by sensors at 7.5, 22.5, 45, and 75 cm. Depths were consistent within and across locations regardless of perceived effective rooting depth.

Sensors were deployed after emergence at a stage which principal investigators were confident a re-plant was not necessary. Augured soil was mixed as little as possible and sorted by depth during sensor installations. After sensors were installed the disturbed soil was backfilled by depth and re-packed to reduce the influence of the disturbed soil on sensor readings. Three of the four sensors installed in each profile were stabbed horizontally in the sidewall of the augured hole. The deepest sensor was stabbed vertically into the bottom of the augured hole. Un-installation occurred as close to- or post- application of a defoliator. To maintain a consistent sensing window at each location, stress units were thereby accumulated from sensor installation until the date of first defoliation.

Data from all four sensors in each plot were collected at hourly intervals by a Decagon Em5B data logger (Decagon Devices, Inc., Pullman, WA) housed in a polyvinyl chloride, weather-resistant case. Data were manually downloaded twice during the growing season. Sensor output was converted from dielectric permittivity to VWC using the Topp equation (Topp et al., 1980). This conversion is described in the Decagon EC-5 manual as:

$$VWC = (8.5 * 10^{-4}) * (RAW) - 0.48 \qquad \{1\}$$

where: RAW= Decagon EC-5 output corresponding to 3V excitation from a Decagon Em5B data logger.

Four disturbed soil samples were collected at depths corresponding to sensor position from the augured installation hole at the time of sensor installation. These samples were placed in sealed water-proof bags to prevent evaporation and later weighed, dried, and weighed again to determine gravimetric water content. The University of Arkansas Agriculture Diagnostic Laboratory (Fayetteville, AR) ground and analyzed the dried samples to determine texture using the hydrometer method (Gavlak et al., 2003). Texture data were then used to estimate bulk density by using the Saxton and Rawls equation (Saxton and Rawls, 2006). Estimated bulk density was then multiplied by the corresponding measured gravimetric water content to yield an estimated VWC which was subsequently correlated to Decagon EC-5 estimated VWC. Yield was collected at the end of the growing season by mechanical spindle-type pickers. Plot weight was determined by either on-board weigh cells or a weighing boll-buggy.

Sensor readings from each node were used to calculate a weighted profile VWC from the following equation:

$$VWC_{lxt} = \frac{\sum_{z=1}^{n}[(\mathrm{VWC}_{lxtz}) \times (\mathrm{w}_{lz})]}{\sum_{z=1}^{n}(\mathrm{w}_{lz})} \qquad \{2\}$$

where: VWC_{lxt} = Weighted average of volumetric water contents reported by all sensors at location *l*, node *x*, time *t*.

VWC_{lxtz} = Volumetric water content reported by sensor at location *l*, node *x*, time *t*, depth *z*.

W_{lz}= Weighting factor based on distance between sensors at location *l*, depth *z*, and estimated rooting depth.

z= Sensor number at a given node, progressing from 1-n with depth

Profile weighted VWCs at each node were then used to calculate location mean VWCs:

$$\overline{VWC}_{lt} = \frac{1}{n}\sum_{x=1}^{n} \mathrm{VWC}_{\mathrm{lxt}} \qquad \{3\}$$

The spatial variability in node-reported VWCs was then examined by calculating the standard deviations (σ) and coefficient of variations (CV) for each location from the below equations:

$$\sigma_{lt} = \sqrt{\frac{1}{n-1}\sum_{x=1}^{n}(VWC_{lxt} - \overline{VWC}_{lt})^2} \qquad \{4\}$$

$$CV_{lt} = \frac{\sigma_{lt}}{\overline{VWC}_{lt}} \qquad \{5\}$$

Temporal stability of sensor measurement was calculated by the method defined by Vachaud et al. (1985). Relative differences in node-observed VWC and field average VWC for each observation time were calculated from:

$$\delta_{lxt} = \frac{(VWC_{lxt} - \overline{VWC}_{lt})}{\overline{VWC}_{lt}} \qquad \{6\}$$

where: δ_{lxt}= Relative differences in observed VWC at location *l*, node *x* and time *t*.

The average temporal difference was then calculated by averaging over all sampling times, *m*, by the following equation:

$$\bar{\delta}_{lx} = \frac{1}{m}\sum_{t=1}^{m}\delta_{lxt} \qquad \{7\}$$

Finally, the standard deviation of the temporal mean relative difference ($\varsigma(\bar{\delta}_{lx})$) was calculated as follows:

$$\varsigma(\bar{\delta}_{lx}) = \left[\sum_{t=1}^{m}\frac{(\delta_{lxt} - \bar{\delta}_{lx})^2}{m-1}\right]^{1/2} \qquad \{8\}$$

Within-field consistencies between nodes and discrepancies between reported values were further examined by correlating within-field nodes. These data were combined with meteorological parameters collected at nearby weather stations (Table 5.1) to calculate the relative reduction in potential evapotranspiration due to soil moisture stress, 1-($ET_{c\ adj}/ET_c$), and an adjusted soil moisture stress index (ASMSI) (Chapter IV). Reference evapotranspiration used in these approaches was estimated from observed maximum and minimum air temperatures from the nearby weather station by a modified Turc (1961) and Hargreaves and Samani (1982) approach defined by Fisher and Pringle (2013). All regression analysis and statistical calculations were conducted in JMP Version 11 (SAS Institute Inc., Cary, NC).

Results

Rainfall and Sensor-reported Volumetric Water Contents

The 2013 growing season was characterized by exceptionally frequent and large rainfall events (Fig. 5.1). As a result, VWCs of most locations remained well above the estimated permanent wilting point (PWP) for the majority of the season and very few indications of drought stress were noted. All locations were characterized by a general trend of increasing VWCs at greater depths (Fig. 5.1). The 75 cm sensors were less responsive to both rainfall events and prolonged-dry down periods, but sensitivity of the 75 cm depth did range from very well buffered at the Hazlehurst, GA location (Fig. 5.1C) to fairly responsive at the Florence, SC location (Fig. 5.1G).

Texture Analysis

Texture analysis indicated very little within-field variability in surface texture properties at each within-field node location (Fig. 5.2). This universal, within-location consistency, particularly concerning clay content, was not noted for all locations at deeper sampling depths. A substantial amount of variability in clay content was noted at the 22.5, 45, and 75 cm samples for the Cordele, GA, Lenox, GA, Starkville, MS and Florence, SC locations. In contrast, the variability in clay contents with depth at the Prattville, AL, Hazlehurst, GA, and Eupora, MS locations did not drastically increase. With the exception of the Starkville, MS location, all sites generally increased in clay content with depth.

Sensor Accuracy and Precision

The relationship between sensor readings immediately following installation and estimated VWCs determined by GWC multiplied by the Saxton and Rawls (2006) estimated bulk density from texture data can be found in Fig. 5.3. A moderate coefficient of determination was noted (r^2=0.617). Regression slope and intercept were very close to one and zero, respectively, which suggest the standard, manufacturer-provided mineral soil calibration (equation 1) performed moderately well for the tested soils. Low accuracy but moderate precision was noted in the Starkville, MS observations; reasons for this separation are not clear, but may be partially due to near-saturation conditions at some depths and the subsequent moisture loss during the time between auguring and placing the very moist samples in the sealed sample containers.

Sensor-reported Volumetric Water Content stability

Average location VWCs, standard deviations, and coefficients of variation at each sampled hour for the seven instrumented trials can be found in Fig. 5.4. Standard deviations ranged from near 0 to just under 8% VWC but most observations were within the 1-3% range. Coefficients of variation ranged from near 0 to in excess of 30% of the profile weighted VWC with the majority of readings falling between the 5 and 15% of the profile weighted VWC readings. Standard deviations during prolonged dry-down periods were often stable and low compared to periods following rainfall events but declining VWCs at a rate greater than decreasing standard deviations (equation 5) frequently resulted in increasing coefficients of variations during these periods. The greatest spikes in standard deviations and coefficients of variation were associated with hours immediately following rainfall events (Fig. 5.4 H, L, M, N, O, S, T, and U). It is suspected that these spikes are a function of the short term variability across the landscape of water movement into the profile. These results are in agreement with findings by Martínez-Fernández and Ceballos (2003), who defined transient periods between dry and wet soil conditions to be the periods of greatest uncertainty. In contrast, sustained trends of increasing standard deviations and coefficients of variation during prolonged dry-down periods were noted at the Cordele, GA and Starkville, MS locations.

Standard deviation and coefficients of variation relationships with profile weighted VWC for all instrumented sites can be found in Fig. 5.5. Trends across location were weak but generally standard deviations decreased as VWCs increased. Coefficients of variation also generally decreased as VWCs increased. However, both of these trends were typically noisy and with respect to the Prattville, AL and Lenox, GA locations, almost non-existent (Fig. 5.5A, H, D, and K).

Several factors contribute to the weak and inconsistent nature of observed standard deviations and coefficients of variation for the tested locations relative to trends reported elsewhere. The fairly consistent trends noted by Brocca et al. (2010) represented TDR measurements at one sampling depth and the temporal sampling period equaled one week. In contrast, observations from this study were collected by an inherently more variable instrument throughout the profile at an hourly interval. This approach adds much more variability by introducing greater sensor error, depth effects and captures data both during and immediately following rainfall events. Subsequently, greater variability in this data set was expected.

Temporal Stability

Node mean relative differences, ranked by increasing value by location are graphed in Fig. 5.6. Considerable within-site variability with respect to temporal stability (magnitude of standard deviation) was noted at the Cordele, GA, Lenox, GA and Starkville, MS locations. Other locations instrumented during the 2013 season were characterized by more consistent standard deviations. The only location which did not report a node with standard deviations of relative differences lower than 5% was Cordele, GA (Fig. 5.6B). The very small standard deviations of percent mean relative differences noted within six of the seven 2013 deployed locations suggest an appropriate deployment of one node with a priori knowledge of the mean relative difference offset could be used to characterize a four-node calculated field mean. Still, further research must be conducted to determine if these trends are stable across time; although the number of observations on which each mean relative difference was calculated exceeded 2700 points, each of these observations were dependent.

Within-field Node Relationships

Very strong coefficients of determination between node-reported VWCs within each location would indicate consistency in trends of VWC. This is important because it characterizes the uniformity of the spatial wetting and dry-down periods. However, this statistic is independent of bias, or discrepancies between predicted and observed values. In contrast, the Root Mean Square Error (RMSE) is a function of both the error in predicted values relative to those observed (bias, or accuracy) and the precision of the estimator. Another method capable of indicating discrepancies between predicted and observed values would be interpretation of values of slope and intercept of the linear regression describing each node-to-node relationship. Reasons for potential discrepancies in reported VWCs are numerous and therefore are difficult to fully interpret with respect to PAW but include known error in sensor prediction of ±3%VWC (Decagon Devices, 2014) and differences in soil properties across x,y and z planes, in addition to the possibility of non-uniform spatial distribution of water across the landscape. Although these statistics and parameters would not be independently capable of describing the relationship of the sensor readings to actual VWC, it would suggest that there would be no additional utility in deploying more than one node into the tested field.

Coefficients of determination between profile weighted VWCs at same-location nodes varied by location but all were moderate to strong (Figs. 5.7-5.14). Coefficients of determination ranged from 0.646 between two nodes at the Prattville, AL location (Fig. 5.7) to 0.988 between two nodes at the Eupora, MS location (Fig. 5.12). The average coefficient of determination between nodes across all locations during the 2013 season was 0.893 with a standard deviation of 0.074. Interpolating relationships from Fig. 5.4 to those noted in Figs. 5.7-5.14, the strongest coefficients of determination were noted at locations which were characterized by very pronounced, stable periods of soil moisture decline and the weakest coefficients of determination were noted at locations which were characterized by rapidly fluctuating VWCs. Examples of these relationships can be noted at the Eupora, MS and the Florence, SC locations, respectively (Figs. 5.7 & 5.12). Again, this variability may be partially attributed to the short term variability of water movement into the profile across the landscape. The same properties of preferential flow which may have contributed to spikes in standard deviations and coefficients of variations in Figs. 5.4 and 5.5 would also decrease coefficients of determination noted between within field nodes. Similar trends in RMSE were noted by locations. The average RMSE for all locations equaled 1.180 with a standard deviation of 0.381 (Figs. 5.7-5.14).

Regression equation intercepts and slopes of comparing node VWCs encompassed a wide range of values. Averaged across all locations and sorted by node ranges, the average intercept equaled 5.730 with a standard deviation of 4.569. The corresponding average slope equaled 0.842 with a standard deviation of 0.166. These intercepts and slopes suggest discrepancies in reported VWCs by node vary substantially across the landscape. Some of the slope and intercept variability can be partially explained by interpreting the texture data from Fig. 5.2. As previously mentioned, texture analysis on at each sensing depth indicated relatively small differences in within-location shallow clay contents; however, some locations were characterized by substantial differences in clay contents at greater depths. By grouping the more clay-content variable Cordele, GA, Lenox, GA, Starkville, MS, and Florence, SC locations, the average regression intercept was found to equal 8.454 with a standard deviation of 5.001 and the average slope equaled 0.738 with a standard deviation of 0.162. In contrast, the less-clay content variable Prattville, AL, Hazlehurst, GA, and Eupora, MS sites were characterized by an average intercept of 3.251 and a standard deviation of 2.580 and an average slope of 0.929 and a standard deviation of 0.113. These reductions in regression parameter variability and reduced differences between within-field reported VWCs suggests soil texture variability at depth influenced on node relationships.

Drought Stress Characterization

Actual seedcotton yield responses to (1-(ET_{cadj}/ET_c)) and the ASMSI are displayed in Fig. 5.15. Due to severe violations of multiple underlying assumptions associated with the user-independent upper and lower calculations of plant available water (PAW) outlined in Chapter IV, the Saxton and Rawls (2006) calculated upper and lower thresholds from collected texture data were used at several locations. The illogical, increasing lint yield trend associated with greater levels of estimated drought stress noted during 2013 can be attributed to (1) water-logging stress and prolonged cloudy conditions, which have been characterized elsewhere as reducing yield through square shed (Guinn, 1982) and (2) failure of a non-normalized approach to characterize the yield potential of the location. One method to normalize the data would be to use the response of one cultivar contained in each trail on which to base observations. Subsequently, the two lower panes of Fig. 5.15 represent the response of observed seedcotton yields normalized by PHY 499 WRF seedcotton yields to (1-(ET_{cadj}/ET_c)) and the ASMSI. Each line can be interpreted as the response of an individual cultivar to changes in stress in relation to the response of PHY 499 WRF. Points above 1 suggest the cultivar outperformed the 'standard' at that stress level and location. Positive slopes indicate yields for the cultivar increase relative to PHY 499 WRF yields as stress accrues. From this analysis, it appears that the drought-stress response of PHY 499 WRF is strong relative to the other tested cultivars. Still, both the (1-(ETcadj/ETc)) and ASMSI approaches rely heavily on the assumption that water-stress is the sole factor causing discrepancies between seasonal yield potential and observed yields. Since this assumption was violated in multiple locations during the 2013 growing season, interpretation of individual varietal yield responses to drought stress should be made with caution.

Discussion

The responsiveness of the utilized soil moisture sensors to precipitation events, the moderate relationships with gravimetrically estimated VWC, the very strong coefficients of determination and the low RMSEs noted between almost every within-field node, and the temporal stability noted for a minimum of one node for each location provides strong support for an approach to characterize experienced drought stress through small deployments of soil moisture sensors. Still, limitations to these observations should be addressed. First, the temporal stability analysis conducted here was a function of a limited number of sampling sites across one season and temporal measurements collected were not independent. Future years of research should be aimed at examining this stability across years to see if either this stability or relative rank in relationship to the mean is variable with season, as Heathman et al. (2012b) noted.

Second, these data emphasize the relative nature of sensor readings even within fairly uniform locations characterized by consistent deployments. Although user-guided deployments did result in a very small amount of variability in surface texture properties (Fig. 5.2), textures at four of the seven instrumented sites were characterized by within-depth shifts in clay content exceeding 10%. This variability most likely contributed to the very large range of the within-field, node-to-node regression parameters of slope and intercept.

Conclusions

Deployments of soil moisture sensors responded rapidly and precisely to changes in VWC. Relationships between within-location nodes varied but were typically moderate to strong. Mean relative difference analysis indicated a minimum of one node in six of seven instrumented trials was characterized as stabile (σ<5%). Logical trends of varietal yield response to drought stress estimated through the (1-(ET_{cadj}/ET_c)) and ASMSI approaches were not noted in actual yields, and although normalization of these data did appear to increase the utility of the data, trends were inconsistent. Further research should be conducted to see if trends in temporal stability remain through multiple seasons and to investigate the relationship between varietal yield responses to the calculated drought stress-indices in more rainfall-normal years.

Table 5.1 Descriptions of the 2013 testing locations.

Location			Cultivar Trial Design, # Replications	NOAA Weather Station info	Planting Date	Additional Comments
City, ST	**County**	**Latitude, Longitude**				
Prattville, AL	Autauga	32.425415 -86.443870	RCBD, nearest neighbor, four replications	US1ALAT0010 32.4262°, -86.539°	4/29/2013	Temperature data collected from: USW00013895 32.2997°, -86.4075°
Cordele, GA	Crisp	31.926123 -83.701294	Strip, three replications	USC00092361 31.8453°, -83.9409°	5/20/2013	
Hazlehurst, GA	Jeff Davis	31.800328 -82.635142	Strip, three replications	USC00094204 31.8878°, -82.5808°	5/20/2013	
Lenox, GA	Cook	31.26852 -83.489160	Strip, three replications	USC00098703 31.4461°, -83.4767°	5/14/2013	
Starkville, MS	Oktibbeha	33.467055 -88.760868	Strip, three replications	USC00228374 33.4691°, -88.7822°	5/15/2013	
Eupora, MS	Webster	33.519721 -89.286429	Strip, two replications	USC00222896 33.5627, -89.2358	5/16/2013	
Florence, SC	Darlington	34.310507 -79.746050	Strip, two replications	USC00382260 34.3011°, -79.8766°		Sensors deployed onto large-PHY 499 WRF plots near the Florence, SC official variety trial

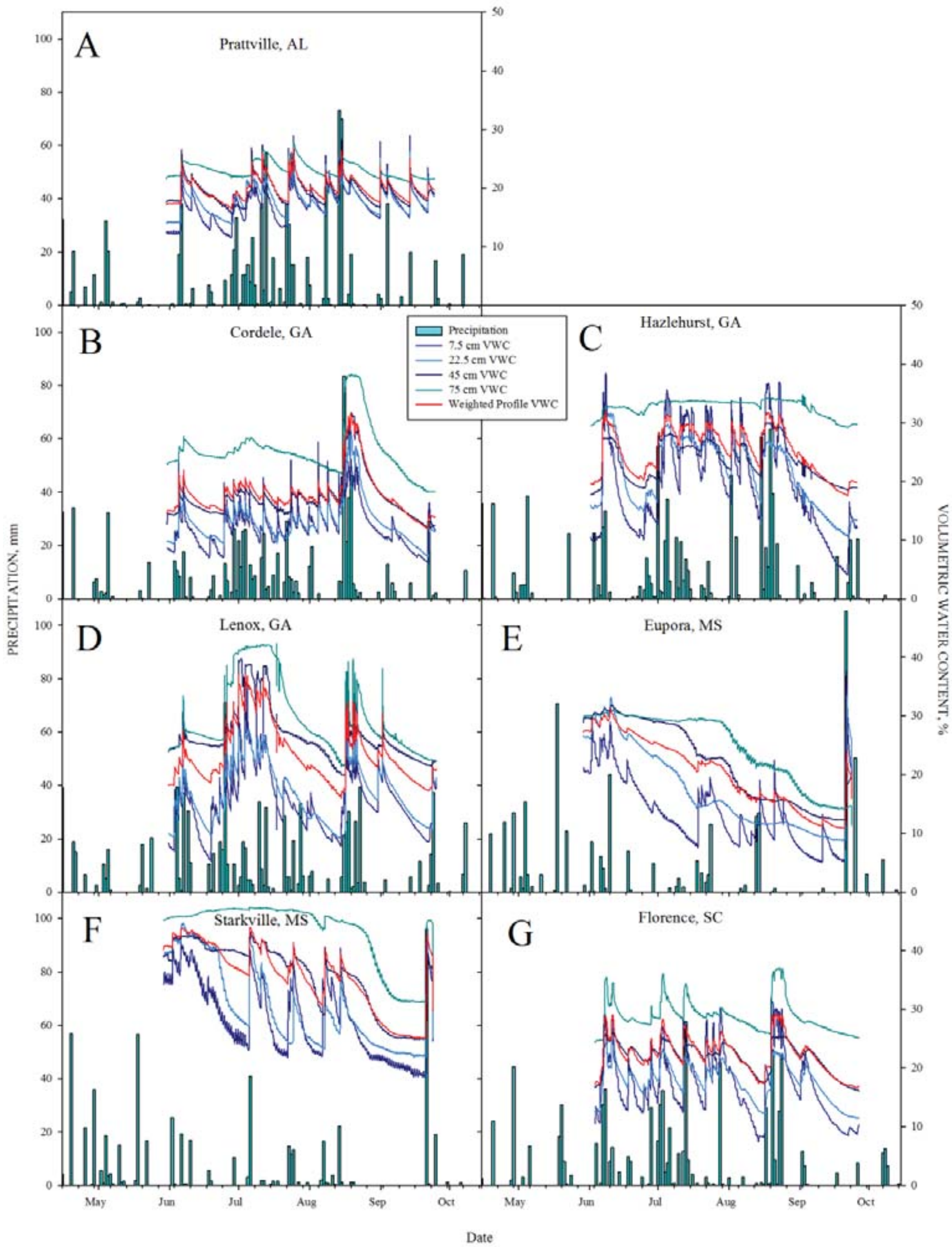

Figure 5.1 Precipitation dates and quantities, average reported volumetric water contents by depth across nodes, and average weighted volumetric water content across nodes and depths for each location (A-G) during the 2013 growing season. Due to single-sensor failures at the Lenox, GA, Starkville, MS, and Florence, SC locations, calculations for these locations were made with a sample size of 3 observations per hour. All other locations were calculated on a sample size of 4 observations per hour.

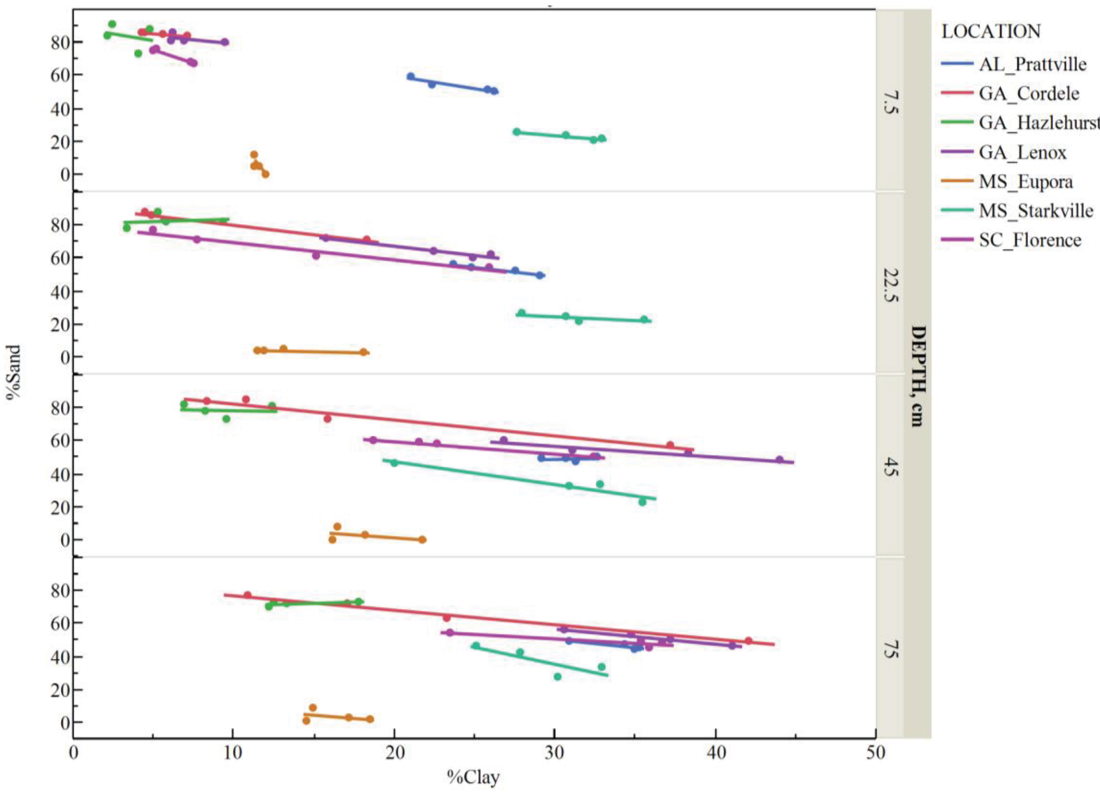

Figure 5.2 Results of texture analysis from samples collected at sensor installation graphed by depth with location overlain for the seven instrumented 2013 locations. Line length corresponds to within-site variability at each location.

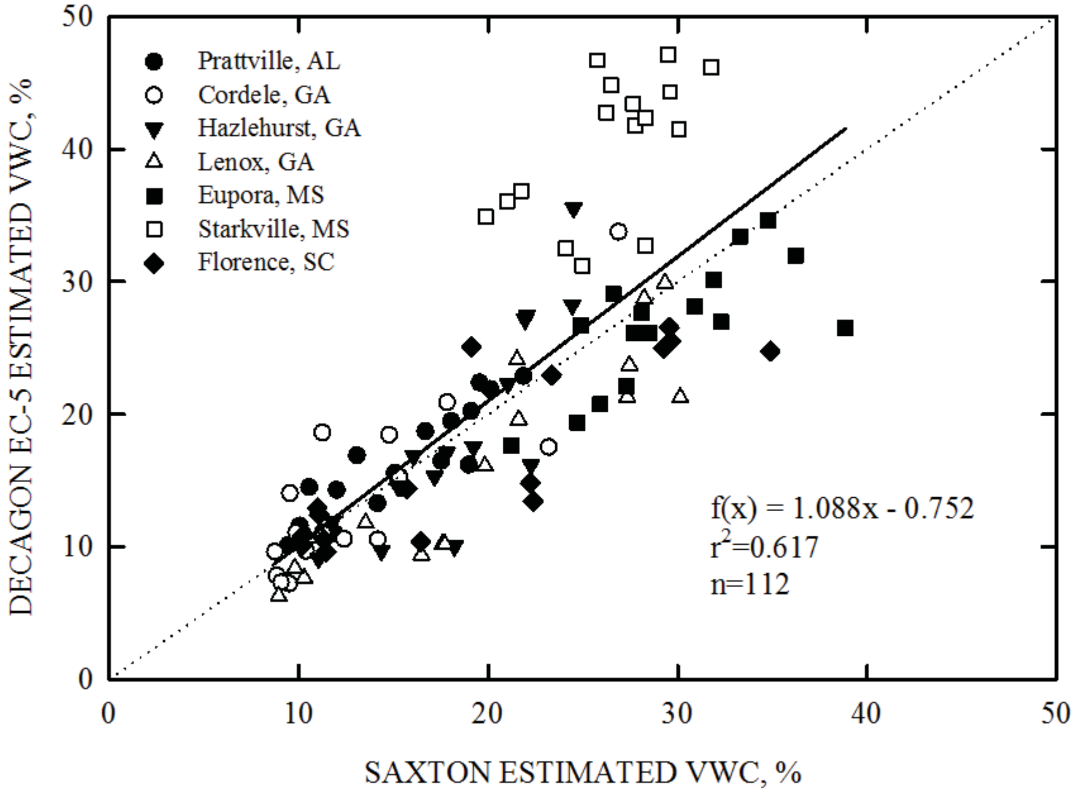

Figure 5.3 Relationship between Decagon EC-5 estimated volumetric water contents and Saxton estimated volumetric water contents, calculated from gravimetric water contents from samples collected at installation. Gravimetric water contents were multiplied by Saxton and Rawls (2006)-predicted bulk densities derived from textural analysis. Dashed line represents a slope of one with an intercept of zero.

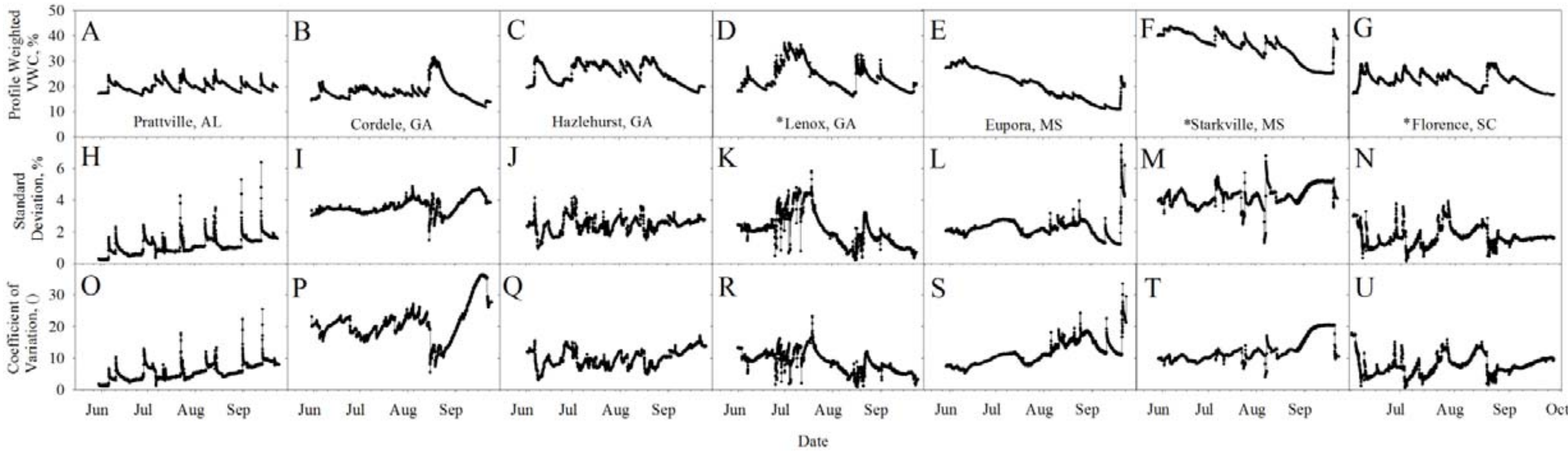

Figure 5.4 Profile weighted volumetric water contents across within-field locations, corresponding standard deviations, and corresponding coefficients of variation across the growing season for each tested 2013 location. Due to single-sensor failures at the Lenox, GA, Starkville, MS, and Florence, SC locations, calculations for these locations were made with a sample size of 3 observations per hour. All other locations were calculated on a sample size of 4 observations per hour.

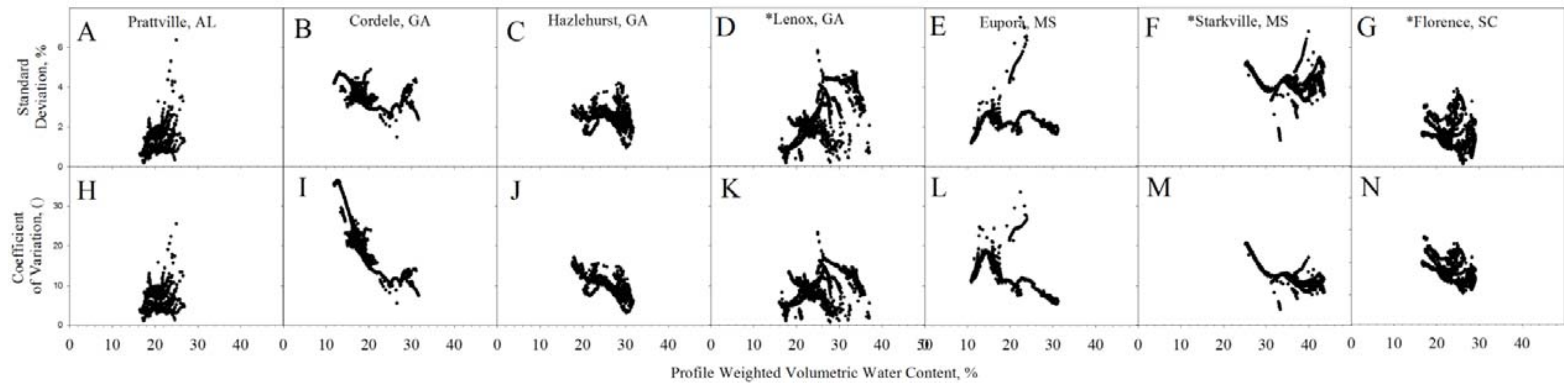

Figure 5.5 Relationships of standard deviations and coefficients of variation to profile weighted volumetric water contents for each tested 2013 location. Due to single-sensor failures at the Lenox, GA, Starkville, MS, and Florence, SC locations, calculations for these locations were made with a sample size of 3 observations per hour. All other locations were calculated on a sample size of 4 observations per hour.

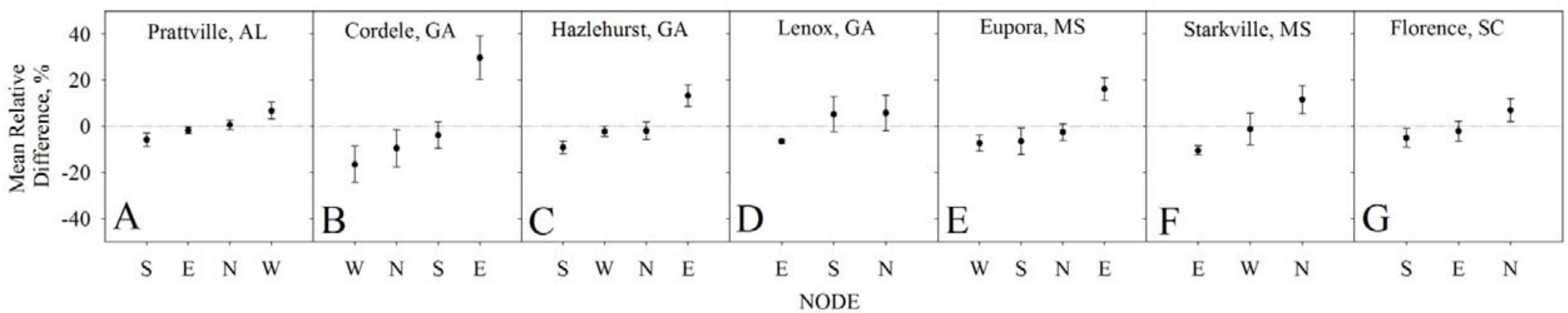

Figure 5.6 Ranked mean relative differences for each node within each location. Points represent mean relative differences and error bars represent ±one standard deviation. Due to single-sensor failures at the Lenox, GA, Starkville, MS, and Florence, SC locations, calculations for these locations were made from 3 nodes. All other locations were calculated on from four nodes.

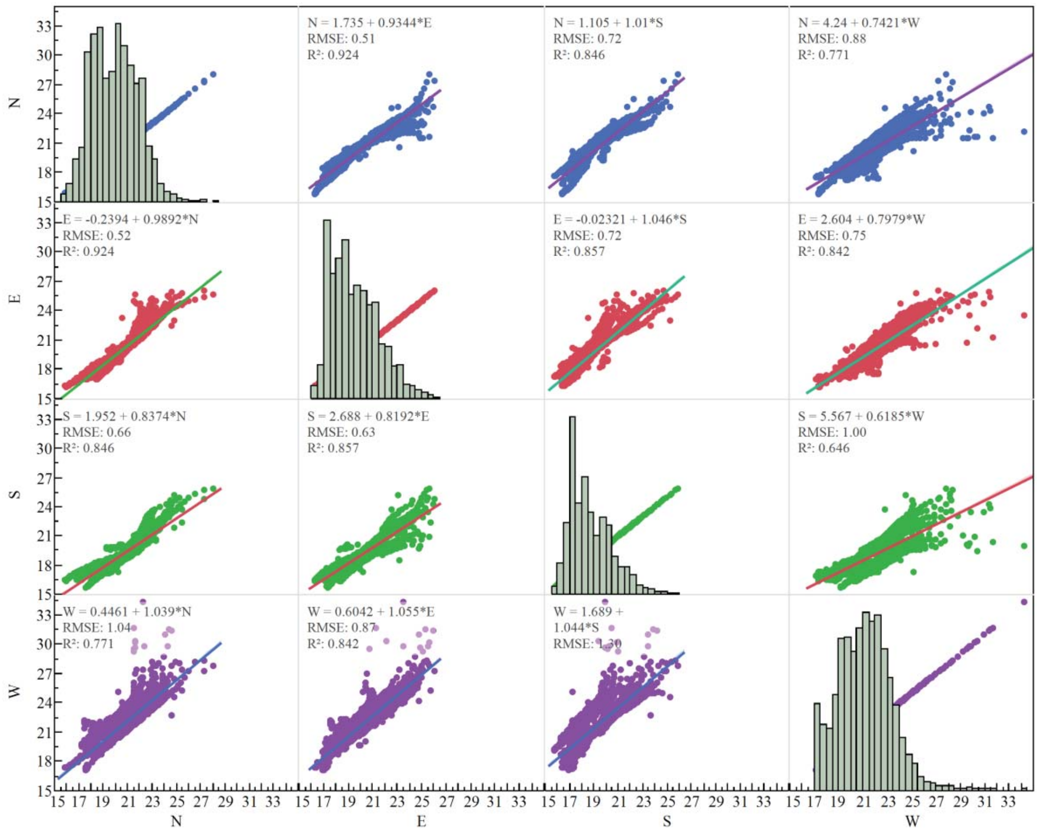

Figure 5.7 Relationships between profile weighted volumetric water contents reported by nodes located at the Prattville, AL location. Histograms represent measurement distributions.

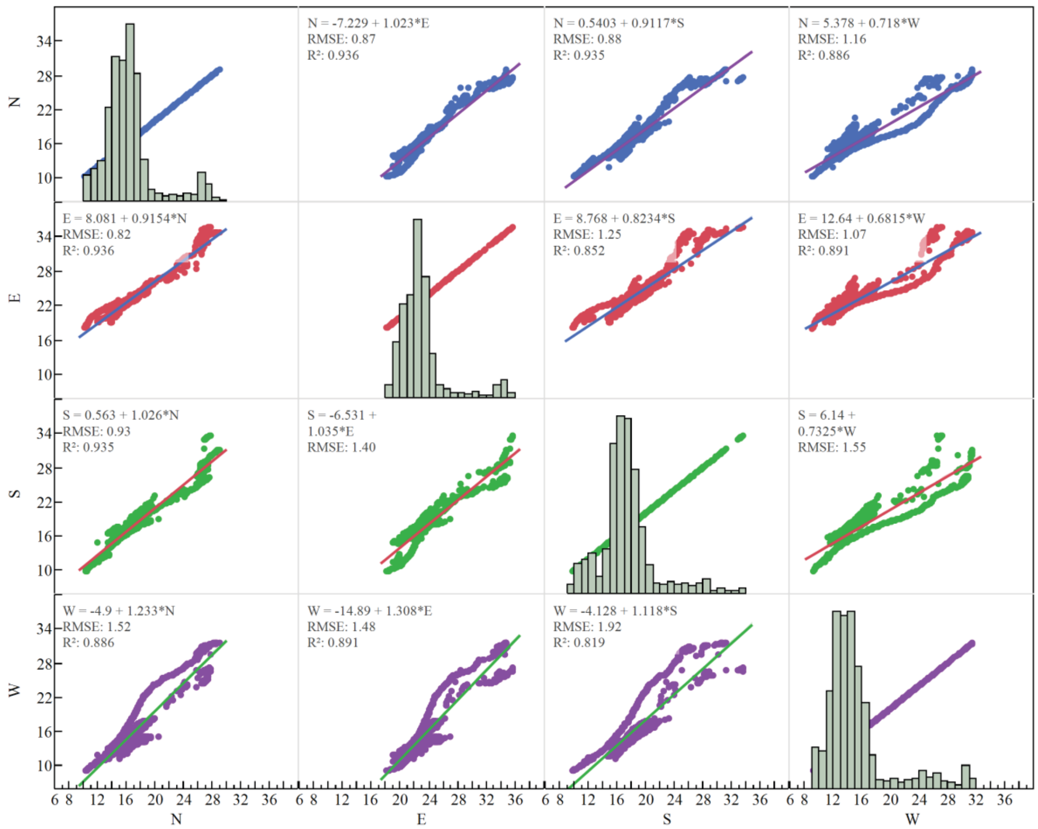

Figure 5.8 Relationships between profile weighted volumetric water contents reported by nodes located at the Cordele, GA location. Histograms represent measurement distributions.

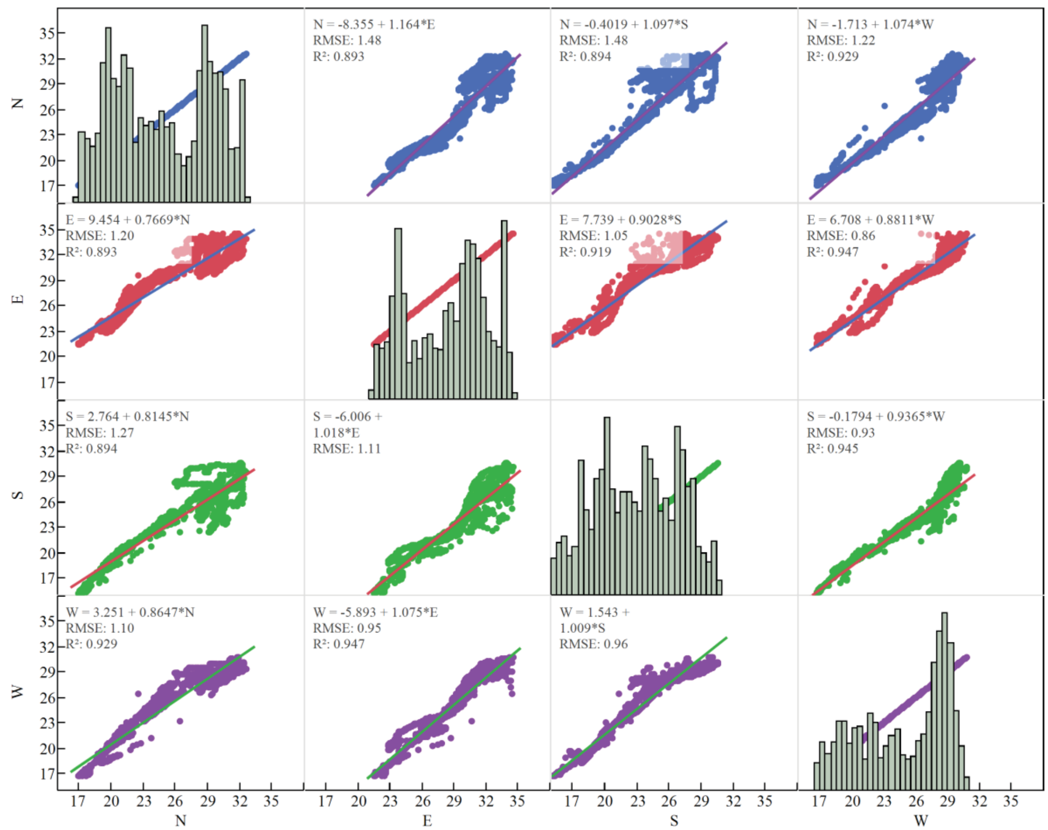

Figure 5.9 Relationships between profile weighted volumetric water contents reported by nodes located at the Hazelhurst, GA location. Histograms represent measurement distributions.

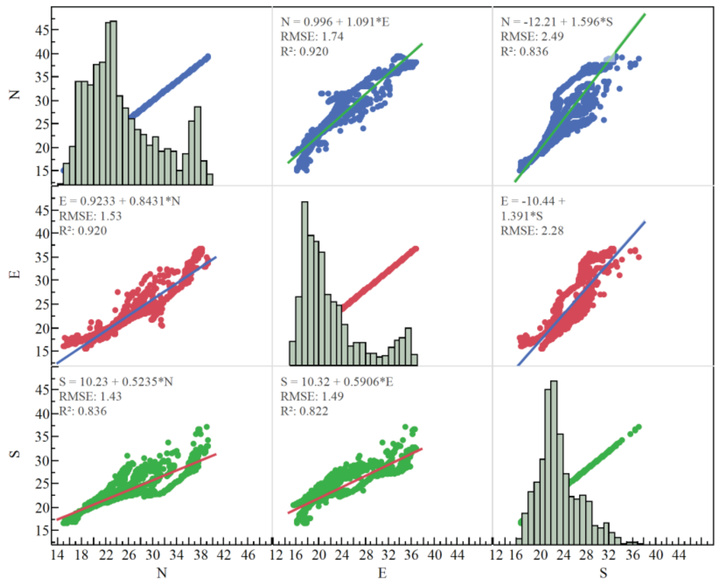

Figure 5.10 Relationships between profile weighted volumetric water contents reported by the N, E, and S nodes located at the Lenox, GA location. Histograms represent measurement distributions. Due to a sensor failure at the W node, only three node comparisons were constructed.

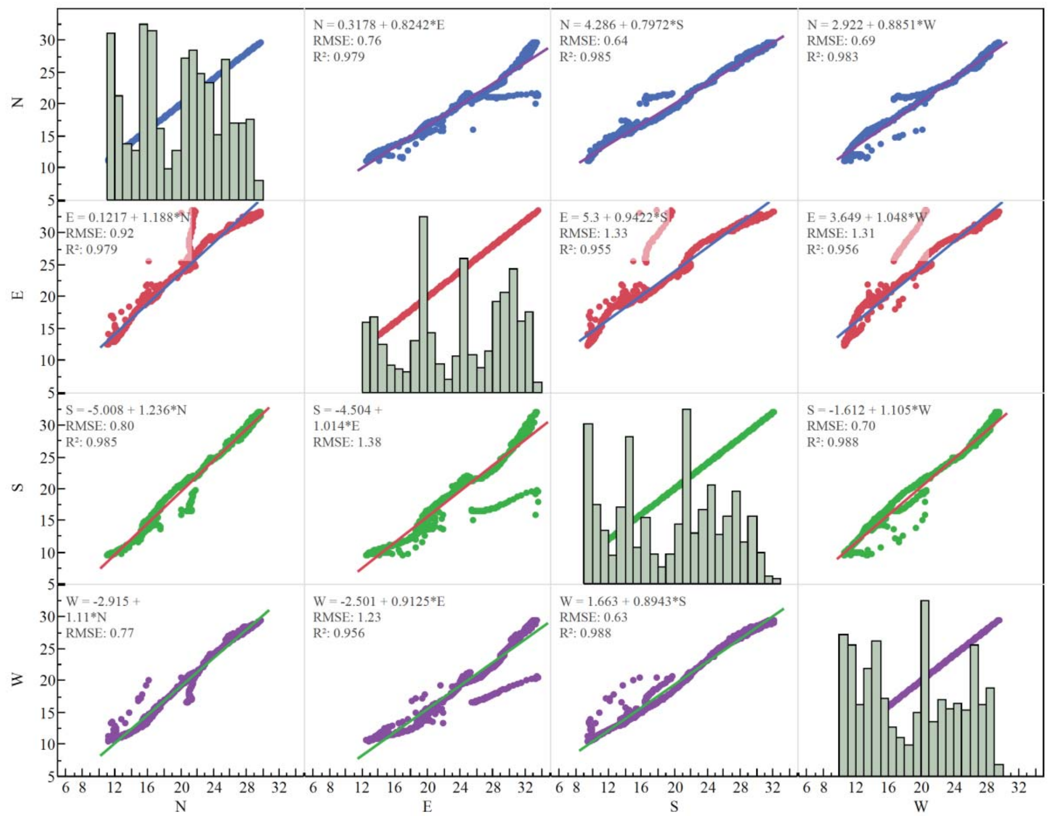

Figure 5.11 Relationships between profile weighted volumetric water contents reported by nodes located at the Eupora, MS location. Histograms represent measurement distributions.

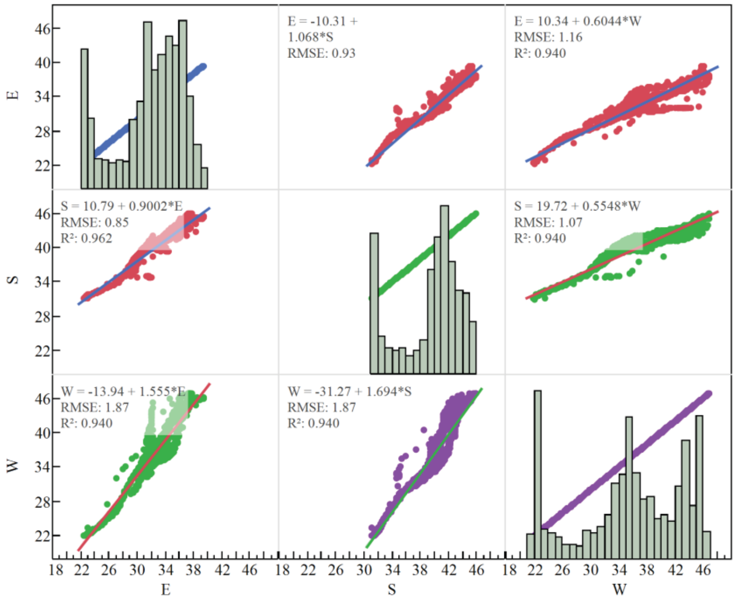

Figure 5.12 Relationships between profile weighted volumetric water contents reported by the E, S, and W nodes located at the Starkville, MS location. Histograms represent measurement distributions. Due to a sensor failure at the N node, only three node comparisons were constructed.

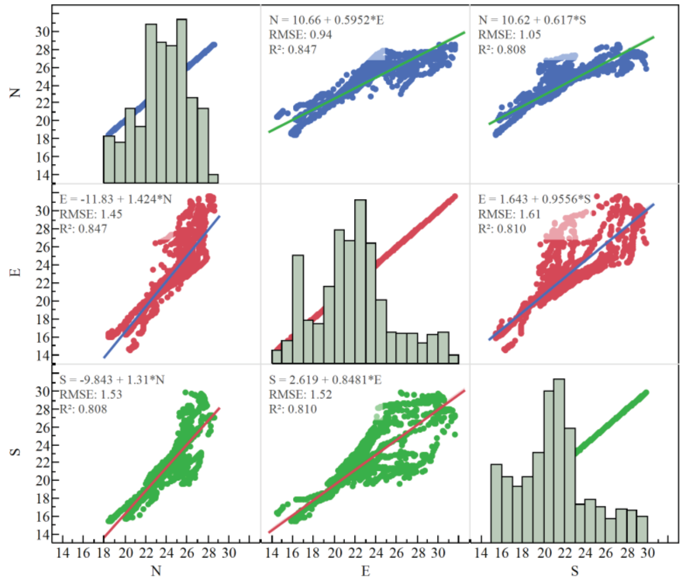

Figure 5.13 Relationships between profile weighted volumetric water contents reported by N, E, and S nodes located at the Florence, SC location. Histograms represent measurement distributions. Due to a sensor failure at the W node, only three node comparisons were constructed.

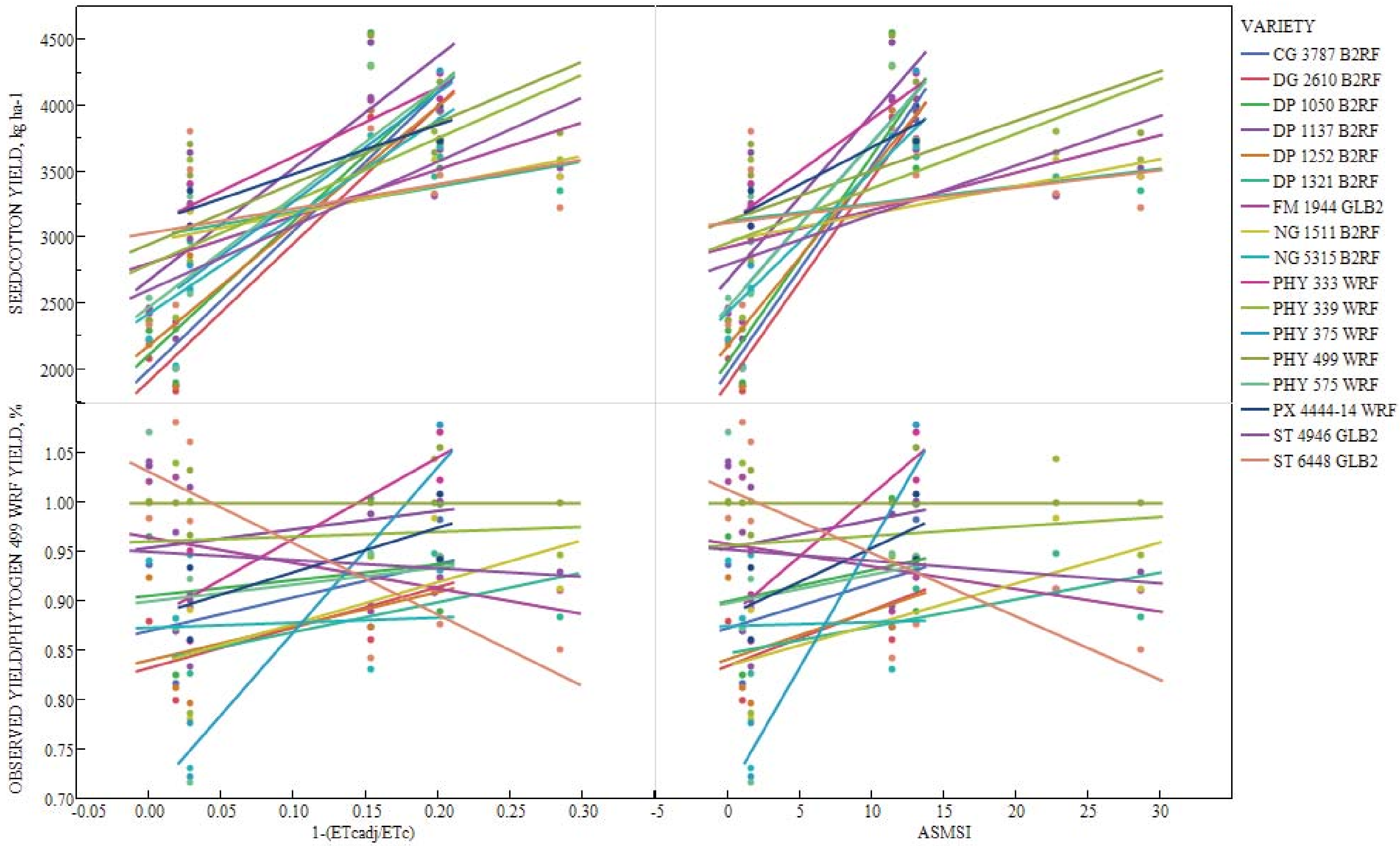

Figure 5.14 Actual seedcotton yield response (kg/ha) and PHY 499 WRF normalized seedcotton yield (%) of all tested cultivars to stress indices of relative reduction in potential evapotranspiration (1- ET_{cadj}/ET_c) and the accumulated soil moisture stress index (ASMSI).

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CHAPTER VI

Conclusions

In-season measurements of soil moisture for the purpose of irrigation scheduling and drought characterization have the potential to increase the water use efficiency of almost every crop production system by providing producers with reliable information on plant water status. This information could refine irrigation timings, frequencies, and reduce the total amount of water applied in irrigated production and serve as a parameter to define cultivar drought tolerance. Still, this research suggests that the currently produced, inexpensive (<200 USD) soil moisture sensors frequently require either additional verification of plant water status beyond reported readings or are not capable of monitoring soil moisture at moderately-dry to dry conditions. Subsequently, a substantial amount of user guidance is required, regardless if the information generated from these sensors will be used for irrigation scheduling or quantifying drought stress experienced at a given location. However, this research does suggest that measurements made by the Decagon EC-5 sensor are stable relative to the field mean across the tested locations and that these measurements correlate well to gravimetrically estimated volumetric water content. Further research should examine the temporal stability of sensor readings over multiple growing seasons. Although a considerable amount of additional information is required to quantify drought stress with this technology and several of the tested locations experienced above average rainfall events during the 2013 season, this research suggests a very limited number of sensors placed in a limited number of locations within a field do appear to be capable of characterizing experienced drought stress across the field within a given growing season.