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# Characterizing the Spatial Variation of Crop Water Productivity for Variable-Rate Irrigation Management

Jeffrey David Svedin
*Brigham Young University*

Characterizing the Spatial Variation of Crop Water Productivity

for Variable-Rate Irrigation Management

Jeffrey David Svedin

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Master of Science

Bryan G. Hopkins, Chair
Neil C. Hansen
Steven L. Petersen

Department of Plant and Wildlife Sciences

Brigham Young University

ABSTRACT

Characterization of Crop Water Productivity
for Variable-Rate Irrigation Management

Jeffrey David Svedin
Department of Plant and Wildlife Sciences, BYU
Master of Science


Irrigated agriculture is the primary consumer of limited worldwide freshwater resources. Drought, growing world populations, and environmental demands compete with irrigation for freshwater resources—threatening sustainable global food, fuel, and fiber production. This escalating global crisis demands that agriculture produce more food using less water. Traditional irrigation management has used technology to apply uniform irrigation rates across landscapes—ignoring natural environmental variation. This provides inherent inefficiencies of over- or under-irrigation within individual fields. Variable-rate irrigation (VRI) is modern technology that employs global positioning systems and geographic information systems to match irrigation to spatially variable crop water demands within a field. Although commercially available, VRI lacks scientifically validated decision support systems to determine spatially and temporally variable crop water demand. The purpose of this research is to explore spatial and temporal variations in crop water demand to inform growers utilizing VRI. This research consists of four seasons of winter wheat (Triticum aestivum L.) production on a commercial farm in Idaho that employs a VRI system. In Chapter 1, the spatial variation of crop water productivity (CWP, the grain produced per unit of water consumed), is characterized for two seasons (2016-2017) and we propose a unique conceptual strategy for VRI management targeted at CWP. Observed CWP ranged from 4.1-21 kg ha$^{-1}$ mm$^{-1}$ with distinct spatial variation that, when considered together with grain yield, were shown to be useful for VRI management. During the 2017 growing season, VRI zones conserved 25% of irrigation compared to traditional uniform irrigation management. In the second chapter the spatial variation of soil water holding capacity (SWHC) was measured at 90 sampling points throughout the field. Then, during the 2016-2017 growing seasons, the spatial and temporal variation of soil moisture were modelled to characterize crop stress and its influence on grain yield. Soil within the field showed large spatial variation of SWHC, ranging from 147-369 mm. Under uniform irrigation in 2016, the natural variation of TAW created 21 day variation in the onset of crop stress throughout the field and under VRI in 2017 the onset of crop stress spanned 56 d. Surprisingly the variations in TAW did not statistically influence yield in 2016, and in 2017 the rate of irrigation predicted yield and TAW again did not statistically predict yield. This suggests that other environmental variables should be included when delineating irrigation zones and rates for VRI.

Keywords: variable-rate irrigation, crop water productivity, soil water holding capacity, evapotranspiration, soil moisture depletion modeling

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CHAPTER 1

# Characterizing the Spatial Variation of Crop Water Productivity in Winter Wheat to Inform Variable-Rate Irrigation

Jeffrey D. Svedin[a], Neil C. Hansen[a], Ruth Kerry[b], Bryan G. Hopkins[a]
[a]Department of Plant and Wildlife Science, Brigham Young University, Provo, UT
[b]Department of Geography, Brigham Young University, Provo, UT

## ABSTRACT

Expanding worldwide populations and water scarcity create a significant challenge of producing more food with less water. Variable-rate irrigation (VRI technology shows promise for improving crop production per unit of water consumed, or crop water productivity (CWP, through spatially variable irrigation rates that match localized crop water demand. However, the spatial variation of CWP at the field scale is largely unknown and management recommendations employing VRI to promote CWP are limited. The objectives of this work are to address these research gaps by: (i describing the spatial variation of CWP on a commercial winter wheat field outfitted with VRI technology and (ii measure the spatial response of yield and CWP to the proposed conceptual model for delineation of VRI management zones. Measured values at 90 points in the field near Grace, Idaho, USA in 2016 were used to describe the spatial variation of CWP. Seasonal evapotranspiration (ET was calculated using a water balance approach. Then, in 2017, irrigation treatments were imposed based on a conceptual model utilizing three years of historic yield and the 2016 CWP map. Irrigation was increased or decreased 30% relative to the grower standard practice rate (GSP where CWP and historic yield were both high or both low, respectively. The spatial variation of CWP for both years were large, ranging from 4.7-21 kg $ha^{-1}$ $mm^{-1}$. Under VRI management 25% less irrigation was applied and CWP variance decreased by 0.8 suggesting VRI management has the potential to improve uniformity of CWP across the field. Where irrigation rate was increased, yield improved 6% but

CWP decreased 7%. Where irrigation was decreased, yield decreased 11% but CWP was equal to the GSP. This confirms that VRI can be used to manipulate CWP. Yield and CWP correlation coefficients were 97% (2016) and 75% (2017), but with minimal correlation between CWP and seasonal ET. This demonstrates that agronomic and environmental factors that control yield had a more important influence on CWP than those that directly influenced ET. Because of the large influence of yield on CWP, future approaches to managing VRI to improve CWP will require algorithms that include a suite of agronomic and environmental variations with strong influences on the spatial variation of yield.

## INTRODUCTION

Prolonged droughts, growing populations, increased urban demand, and changes in climate trends are causing water shortages worldwide. World population is projected to reach 10 billion by 2050 (United Nations 2017) and the demand for already scarce freshwater will increase, along with the demand for food, fuel, and fiber. Agriculture faces the need to increase production while using less freshwater resources. Irrigated land comprises produces 40% of the world's agricultural products on 17% of cultivated farmland (Abdullah 2006; Evans et al. 2013; Schaible and Aillery 2012). This high production of agricultural products on irrigated fields consumes four-fifths of the global available freshwater resources annually (Postel 1999). Improved water conservation and irrigation management practices are critical to achieve improved water-use efficiency.

Traditional irrigation approaches seek uniform water applications across fields to maximize yield, but this approach ignores inherent spatial variability in crop response to water and may result in water deficits in some places and surpluses in others (King et al. 2006). Spatial variability in crop water demand is driven by factors that influence plant health, rooting depth, and water and nutrient uptake. Among spatially variable factors are relatively permanent soil properties, such as topography, soil texture, organic matter content, and water-holding capacity. The challenge is further complicated by temporally variable factors such seasonal variation in solar angles, weather, microclimates, pests, pathogen pressure, crop response to management practices, and soil temperature, fertility status, and compaction. Significant spatial variation in soil and crop water status has been reported, even in mechanically leveled fields (Daccache et. al. 2014; Longchamps et al. 2015). Sadler et al. (2005) demonstrated that spatially varying irrigation rates to match crop water demand could conserve up to 50% of applied water. Variable-rate irrigation (VRI) refers to spatial and temporal variation of irrigation application rates to optimize plant responses for each unit of water applied (Evans and King 2012).

Variable-rate irrigation is most commonly implemented with center pivot and linear move systems and include zone control (site-specific) and speed control systems. Site-specific VRI has the capability to alter the water application rate at each nozzle of a center-pivot irrigation system. Combining the use of geographic information systems (GIS) with geographic positioning systems (GPS) and VRI systems, irrigation application rates can be altered to match predetermined spatially variable growing conditions. This is accomplished by defining irrigation zones (zones throughout the field with similar crop water demand) to inform the computer controlled system to adjust the irrigation rate as sprinkler nozzles move over the field. Sadler et al. (2002) conserved 8-21% of irrigation water using VRI techniques over three seasons of maize (*Zea mays* L.) production. Al-Kufaishi et al. (2006) conserved 13% with VRI in one season of sugarbeet (*Beta vulgaris* L.) production. In a three-year simulation of potato (*Solanum tuberosum* L.), alfalfa (*Medicago sativa* L.), and maize production, Hedley and Yule (2009b) reduced irrigation by 20-26% in three-year modeling of pasture and maize production, and Hedley et al. (2009) in one season of VRI management of pasture, potato, and maize reduced drainage 25-

45% and applied 9-19% less total irrigation. West and Kovacs (2017) suggested the adoption of VRI in the Arkansas basin would lead towards sustainable groundwater withdrawals. These VRI systems are available commercially and demonstrate the potential to conserve water, but scientifically defined and user-friendly decision support systems to guide grower's VRI management decisions need further development (Evans and King 2012; Evans et al. 2013).

Current VRI support systems use irrigation zones based on soil water holding capacity (SWHC) to match VRI to soil hydraulic properties and avoid over- and under-irrigation (Al-Kufaishi et al. 2006; Daccache et al. 2015; de Lara et al. 2017; Hedley and Yule 2009a; Hedley and Yule 2009b; Hedley et al. 2009; King et al. 2006; Li et al. 2007; Messick et al. 2017). This maximizes crop production per unit of land. However, Westfall et al. (2009) observed that in water scarce regions maximizing the yield produced per unit of water, or crop water productivity (CWP), is desired. Additionally, Evans et al. (2013) noted that VRI research needs to address the spatial variation of CWP for sustainable water use.

Management of CWP requires large enough variations in CWP to justify the added time and costs of VRI. Most CWP research reports field averages or is conducted on research plots designed to limit the influence from spatial variation. As such, CWP field averages for well managed fields are understood (Passioura 2005) but the range of values and spatial variation of CWP at the field level is largely unexplored. Filling this research gap is required to justify the management approach suggested by Evans et al. (2013). Additionally, VRI management designed to improve CWP requires a characterization of the spatial variation of CWP and subsequent response to VRI management. Very little research has been conducted on the spatial variation of yield response to water (Salder et al. 2005; and Haghverdi et al. 2016) with no research on the field scale spatial response of CWP to water to date.

In this study we (i) quantify the spatial variation of CWP in winter wheat (ii) propose and test a conceptual model for delineating VRI zones. The conceptual model is based on separating the field into four zones created from combinations of high and low relative historic yield and high and low crop water productivity (Figure 1). Within the conceptual model, areas where both CWP and yield are observed to be relatively high (Figure 1: lower right quadrant) are most likely to benefit from increased irrigation. In contrast, areas where yields are relatively high but CWP is low (Figure 1: lower left quadrant) are likely over-irrigated and reduced irrigation should be explored. In areas where both historic yields and CWP are low (Figure 1: upper left quadrant) factors other than irrigation (soil fertility, soil physical properties, topsoil depth, pests, etc.) are limiting yield. In these zones, one of two approaches need to be taken—depending upon the situation. If the factors limiting yield can be reasonably and economically remediated (e.g. fertilizer, pH, salts, sodium absorption ratio, compaction, organic matter, and certain weed, insect, and pathogen pressures) then irrigation rates are likely needed to remain the same and reevaluated over time. If the factors negatively impacting yield are not reasonably or economically able to be remediated, irrigation should be reduced to better match the yield potential. Finally, areas where yields are relatively low but CWP is high (Figure 1: upper right quadrant) are irrigated optimally, and unless it is possible to amend the cause of low yields, irrigation should not be altered.

In this study, we evaluate the application of this conceptual model. The specific objectives are to: (i) describe the spatial variation of CWP and (ii) investigate the spatial response of yield and CWP to the proposed conceptual model for delineation of VRI management zones.

# METHODS

## *Site Description and Management*

The CWP was evaluated during two years of winter wheat (*Triticum aestivum* L.) production for a commercial field (23 ha) managed in a three-year cropping system of potato-wheat-wheat. The field is located near Grace, ID, USA (42.60904, -111.788; elevation 1687 m). The soil is a Rexburg-Ririe complex with 1-4% slopes. Rexburg and Ririe soils are both coarse-silty, mixed, superactive, frigid Calcic Haploxerolls derived from loess or loess influenced alluvium with five percent rock outcroppings. The soil texture is a silty clay loam. There is a 6m difference between lowest and highest elevation within the field. About 0.3 ha of the field has emerged basalt bedrock (Figure 2) and, thus, was not farmed. Irrigation water was not applied to these areas and, as such, was not included in the study even though this is certainly part of the water savings for this field as a function of VRI.

The semi-arid climate typically has hot days and cool nights during the growing season with a typical annual growing season comprising 80-110 frost-free days. Average annual precipitation is 392 mm with most of the precipitation occurring during the cold months and minimal amounts during the summer. The historical average precipitation for May-August months is 150 mm. However, precipitation was relatively sparse during the time of this trial with precipitation between soil sampling at spring green-up and at harvest totaling 95 and 90 mm in 2016 and 2017, respectively. During the growing season, irrigation is applied with a 380 m center pivot with 5 m nozzle spacing equipped with a Variable-rate Irrigation System (GrowSmart Precision VRI, Lindsay Zimmatic, Omaha, NE, USA). There were 11 irrigation events in 2016, and 14 in 2017 with irrigation events occurred every 5-7 d in spring and every 3-5 d during peak evapotranspiration (ET) rates for 2016 and 2017.

Planting dates were 5 Oct. 2015 and 10 Oct. 2016. Conventional best practices for soil, pest, and crop management were utilized by the grower. Harvest dates were 16 Aug. 2016 and 30 Aug. 2017. In 2016, the grower standard practice (GSP) VRI prescription was used, which was a uniform irrigation rate except for no irrigation being applied in field areas with emerged bedrock and a 10% decrease in a few areas defined by the grower as visibly having more soil water (Figure 3). Irrigation for 2016 was considered uniform because where the grower decreased irrigation 10% the total impact on seasonal ET was less than 5% compared to the standard irrigation rate. Irrigation contributed 43% of seasonal ET, which is why the 10% reduction in irrigation had limited influence on the total ET (Table 1). The 2017, the VRI pattern was developed based on the conceptual model (Figure 1) and GSP control strips.

*Yield Data Collection*

Two years of historic yield data for winter-wheat (2013-2014), without information on ET, was evaluated together with two years of yield data with measured seasonal ET (2016-2017). Wheat was harvested with a commercial combine and all yield was collected with a calibrated yield monitor (New Holland Inteliview 4, Turin, Italy) using a mass flow sensor collecting yield data ever 10 $m^2$ spatial density. The yield data was processed as described by Kerry and Oliver (2003). Erroneous data points were defined as outside the limits of ± 75% of the median. In addition, points where the combine did not harvest the full header width were removed. Yield data was calibrated using a weigh cart and validated with wheat bin storage showing an overall accuracy of ±1%.

*Crop Water Productivity Analysis*

A CWP analysis was used to describe the spatial variability of water utilization throughout the field. Crop water productivity was calculated as:

$$CWP = Y/ET \tag{1}$$

Where Y is yield (kg ha$^{-1}$) and ET is evapotranspiration (mm) calculated at sample points (Figure 2) as the total of crop transpiration and evaporation from spring green-up through harvest. Total seasonal ET was calculated with the following water balance equation:

$$ET = P + I + \Delta S - RO - D \tag{2}$$

where P is precipitation, I is irrigation, ΔS is the difference between soil water content sampled to 1.2 m depth at spring green-up and at harvest, RO is surface water runoff, and D is soil water drainage to below sampling depth. Seasonal RO was assumed negligible because the greatest daily precipitation intensities were 16 and 14 mm with infiltration rates greater than this amount and no visible indications of surface water movement.

A soil water depletion model was developed to estimate D with initial values measured as soil water content at spring green up and with a daily timestep of water depletion calculated made using the water balance equation. For those calculations, daily ET rates were obtained by calculating reference ET using a standardized Penman-Monteith equation and a crop coefficient (Allen et al. 1998). When soil moisture exceeded site-specific field capacity values to 1.2 m deep, excess water was assumed to be lost as deep percolation. Daily deep percolation values were summed for the total deep percolation used in the season water balance equation. Inputs for daily ET and precipitation were measured at the Grace, ID AgriMet weather station located approximately 2 km east from the field site (US Department of Interior Bureau of Reclamation, Pacific Northwest Region; https://www.usbr.gov/pn/agrimet/wxdata.html).

Sample locations were located on a 70 m grid (46 samples) with random nested points (44) to collect sufficient samples to compute reliable variograms for kriging, the geostatistical estimation procedure (Webster and Oliver 2001). Soil samples were collected at the beginning of the growing season on 20 April 2016 and 4 May 2017 and after harvest on 16 August 2016 and 1 September 2017 using hand augers or a trailer mounted hydraulic drilling auger (Giddings Machine Company, Inc., Windsor, CO, USA). Soil cores were collected to the approximate depth of the rooting zone at four increments of 0-0.3, 0.3-0.6, 0.6-0.9, and approximately 0.9-1.2 m to capture the distribution of moisture throughout the soil profile. Soil samples were stored in plastic bags to eliminate evaporation losses until lab analysis for gravimetric water content ($\theta_g$). The $\theta_g$ was multiplied by the soil bulk density, and then divided by the density of water to calculate volumetric soil moisture ($\theta_v$) for each sample (Qiu et al. 2001). Bulk densities were calculated from spring 2016 soil samples by weighing the dry soil and dividing by the volume of the soil auger used for sampling.

*Geostatistical Methods and Interpolation*

A variogram of the normalized difference vegetation index (NDVI) from bare soil imagery of the field site was computed to identify the scale of soil spatial variation. The variogram had a range of ~140 m. Following the 'rule of thumb' developed by Kerry and Oliver (2003) that one should sample at an interval of approximately half the variogram range, the interval of 70 m was used for the main sampling grid (46 samples). Additional sample points (44 samples) were located at random points along the grids to strengthen the sensitivity of the geostatistical analysis. This sampling scheme was used to calculate spatial variation of $\Delta S$. Prior to geostatistical analysis of each variable, summary statistics were calculated and histograms plotted. If the skewness of the data set was outside the bounds of ±1, then the data was transformed to logarithms for variogram computation and back transformed to the original scale following kriging (Kerry and Oliver 2007). Where notable trends were identified in the data, variograms were computed using regression models fitted on the coordinates of the data and analyses performed on the residuals of the fitted function. Following variogram computation, each variable was ordinary kriged to a 2 m grid. All variograms were computed and kriging done using SpaceStat (BioMedware, SpaceStat 4, Ann Arbor, MI, USA) and ArcMap's Geostatistical Analyst (Environmental Systems Research Institute [ESRI] 2011, ArcGIS desktop: Release 10, Redlands, CA, USA). Geographically weighted regression (GWR) was used to analyze the spatial relationships between CWP constituents. A GWR employs a moving window approach to identify correlations between variables to indicate spatial ranges of correlation between variables dependent upon the spatial location. All GWR analysis was done in SpaceStat.

*2017 Variable-Rate Irrigation Treatments*

The objectives for the second year were to measure the spatial variation of yield and CWP in response to a variable-rate irrigation scheme derived from the conceptual model (Figure 1). The irrigation treatments were designed using historic yield (Figure 4) and the 2016 CWP spatial variation as inputs to the conceptual model. A High irrigation treatment was applied to areas where both CWP and yield were high (Figure 1: lower right quadrant) and the Low treatment was applied to areas where both CWP and yield were low (Figure 1: upper left quadrant). In lieu of individual irrigation treatments for the two remaining quadrants in the conceptual model, duplicate control zones that followed the GSP were utilized. High and Low irrigation treatments were relative to the GSP rate (15 mm per irrigation event) where the High treatment received 30% more irrigation water (20 mm) per event while the Low treatment received 30% less (11 mm; Figure 5). These treatments were applied at each irrigation excluding two fertigation events, where a uniform rate (15 mm) was applied across the field to avoid N fertilization differences.

A Paired t-test was performed along the GSP irrigation zones to evaluate responses in yield and CWP (Figure 5). Data within 5 m of the treatment edge were not included to avoid irrigation rate overlap between zones. Paired treatments included 10 $m^2$ plots parallel to treatment boundaries (Figure 5). One center pivot joint leaked across treatments—resulting in bias in several treatments locations. These erroneous data points were located with the yield map and not included in analysis. JMP Pro 13 (SAS Institute, Cary, NC, USA) was used for paired t-test and regional analysis.

## RESULTS AND DISCUSSION

### *Spatial and Temporal Yield Variations*

Average yields were 6.2, 4.1, 7.5, and 5.8 Mg $ha^{-1}$ for 2013, 2014, 2016, and 2017, respectively (Table 2). The wheat crops grown during 2013 and 2016 were planted in the year following a potato crop and produced the greatest yield. The second consecutive year of wheat (2014, 2017) produced markedly lower yields, with 34 and 23% reductions compared to the wheat the previous year. Reduced yield in the second year of wheat is a phenomenon commonly observed in potato-wheat-wheat cropping systems (potato was grown in 2012 and 2015). Potato has a shallow and inefficient root system with relatively high fertilizer and irrigation applications which potentially results in increased residual water and nutrients available for the first-year wheat in the deeper soil profile (Hopkins 2015; Hopkins and Hirnyck 2007; Miller and Hopkins

2007). Additionally, pests and pathogens are often crop specific and, thus, the yields are commonly reduced in the successive year of growing the same species (Hopkins 2010; Hopkins and Hirnyck 2007; Miller and Hopkins 2007). Symptoms and crop damage from greater pest and pathogen populations were not readily observed in this field, but this is common to have reduced yields due to a lack of rotation without any major visible difference. It is not possible to attribute which of these factors affected the second-year wheat yields, but it is likely a combination effect. Notably, in the season with employed VRI treatments (2017), the yield reduction was not as dramatic.

Based on the topography and variation of yield, the field was divided into four general areas, namely: 1) ridge, 2) western toe slope, 3) eastern plateau, and 4) field edges and exposed bedrock (Figures 2 and 4C). The ridge is located beginning west of center at the third span of the center pivot and extending nearly directly north (Figure 2). There is a zone of below-average yield that runs along and at the top of this ridge (Figure 4) possibly from the loss of topsoil and exposed calcareous subsoil from erosion or pre-season water runoff and/or horizontal movement of soil moisture from this area of slightly higher elevation. The western toe slope is an area west of the base of the ridge with the lowest field elevations (Figure 2) and is a zone of above-average yields (Figure 4). This is likely due to an accumulation of topsoil and residual nutrients, as well as possible subsurface water accumulation. The eastern plateau is an area east of the top of the ridge that has minimal slope (Figure 2) and tends to produce greater than average yields, with relatively more temporal variability than the ridge and western toe slope (Figure 4). The field edges and rock outcroppings, as expected, have the lowest yields. This was especially the case for the north and eastern field edges (Figure 2). In all four years, there is a semi-circle (following the third from the center pivot wheel track as seen in Figure 2, of high yield crossing the eastern plateau, ridgeline, and western toe slope. This is attributed to a leak at the pivot joint with the yield response from the additional water and nitrogen applied during irrigation and fertigation events (Figures 4 and 5).

*Spatial Variation in Crop Water Productivity under Uniform Irrigation*

The field average ΔS for 2016 was a 227 mm decrease in soil moisture with a range of 146-278 mm across the field (Figure 6A; Table 1). The eastern edge of the field showed the greatest ΔS with the least in the north and southeast corner. The soil profiles began the season at or near field capacity and were near wilting point in the fall, indicating that nearly all the plant available soil moisture was consumed during the season. Stored soil moisture, as measured by ΔS, contributed an average of 50% of the total seasonal ET in 2016 (Table 1).

The field average ET was 520 mm, with a range of 315-571 mm (Figure 6C; Table 1). The largest ET is found on the southeast corner of the field and generally decreases moving west across the field where the lowest values are found in the southwest corner of the field. The spatial pattern of ET closely resembles the variation in ΔS ($r^2$=0.91; Figures 6A and 6C; Table 3). This high correlation between ET and ΔS is because the spatial variation between points for the other components of ET (drainage, irrigation, and precipitation) was minimal. Seasonal ET was not significantly related to yield in 2016 ($r^2$=0.15; Figures 6C and 6E; Table 3). Given the large spatial variation in ET, the low correlation between yield and ET was surprising. This may suggest the 1.2 m sampling did not capture the full root zone soil moisture and access to deeper moisture reservoirs was not included in the ET water balance (Thorup-Kristensen et al. 2009; Sauer et al. 2002). Ideally, we would have sampled at deeper depths, but sampling below 1.2 m was prohibited in most locations because of the presence of rock. Therefore, we elected to focus on the upper root zone where >90% of the root biomass is active.

The field average CWP for 2016 was 14 kg $ha^{-1}$ $mm^{-1}$ ranging from 4.7 - 21 kg $ha^{-1}$ $mm^{-1}$ (Table 1; Figure 6G). The lowest values are near emerged bedrock and field edges while the largest are located at the westerly toe slope (Figure 6G). The high CWP values that follow the leaky pivot joint are in error because water added from the leak was not included in the ET calculation; consequently, these CWP values were not included in any field means or statistics. The field average CWP for this site and season was greater than the global average of 10.9 kg $ha^{-1}$ $mm^{-1}$ identified by Zwart and Bastiaanssen (2004) and greater than USA averages reported by Liu et al. (8.1 kg $ha^{-1}$ $mm^{-1}$; 2007), Chapagain and Hoekstra (11.8 kg $ha^{-1}$ $mm^{-1}$; 2004), and Zwart et al. (7.9 kg $ha^{-1}$ $mm^{-1}$; 2010).

The spatial variation of CWP closely follows yield patterns with 95% of the CWP variation being related to yield (Figures 6E and 6G; Table 3). The high correlation between yield and CWP compared to ET and CWP indicates that, for this season and field location, yield variation was driving the spatial variation in CWP. The negative correlation ($R = - 0.18$, $r^2 = 3$) between ET and CWP for 2016 suggests an increase in water efficiency of the crop probably stimulated by physiological responses to water stress where there were lower ET rates (Table 3).

*Spatial Variation in Crop Water Productivity under Variable-Rate Irrigation*

The 2017 average yield was 5.8 Mg $ha^{-1}$ ranging between 1.8-8.4 Mg $ha^{-1}$ (Table 2). Crop yield exhibited similar spatial patterns in 2017 compared to 2016 with the greatest yields west of the toe slope and the lowest yields near the exposed bedrock and field edges (Figure 6F). As in 2016, a pattern of high yield was associated with a leak in the pivot, which was apparent even in the High irrigation zone (Figure 6F). The overall field production was 23% less compared to 2016, which is a common phenomenon with the second year of consecutive wheat crops.

Irrigation treatments did influence yield with the Low, GSP, and High treatments averaging 4.9, 6.0, and 6.4 Mg $ha^{-1}$ respectively. From the 30% irrigation increase, the High treatment paired t test plots had 7% higher yield relative to the GSP (*p*-value < 0.0001) and yield in the Low treatment decreased 11% compared to the GSP (*p*-value = 0.0040; Table 4). There was high correlation between yield and ET in 2017 (R= 0.68, $r^2$= 46) compared to 2016 with very low correlation (Table 3). Under VRI in 2017, the stronger correlation between ET and yield shows that yields are more water dependent when broader ranges in ET exist, as compared to the 2016 data.

The 2017 field average ΔS was 190 mm ranging from 100-269 mm (Figure 6B; Table 1). The range in values was similar to 2016 and again did not reflect the spatial variation of yield (Figures 6A and 6E). It was hypothesized that the spatial variability of ΔS would reflect plant health and yield (healthier plants would remove more water from the soil) or irrigation rates. However, the spatial patterns between the two seasons of yield are very different from those observed for ΔS and the relationship was poor for both seasons (Figures 6A and 6E; Table 3). It appears that different environmental factors dictate the spatial variation of ΔS compared to yield and these factors resulted in different ΔS spatial patterns between seasons (Figures 6A and 6B).

Applied irrigation for the Low, GSP and High irrigation treatments were 158, 225, and 291 mm during the 2017 season compared to 198 mm applied in 2016 (Table 1). The greater GSP application in 2017 was largely a response to greater ET rates compared to 2016. The VRI in 2017 resulted in 25% less total irrigation than would have been applied with uniform GSP rates. The field average ET for 2017 cropping season was 497 mm, with a range of 255-620 mm (Figure 6D; Table 1). The spatial patterns of ET were largely dictated by irrigation treatments, with some in-treatment variation, but spatial patterns were quite different from 2016 (Figures 6C and 6D). In 2016, stored soil moisture, as measured by ΔS, was highly correlated with ET (r =

0.91) and explained 83% of the variation in ET. While in 2017 ΔS correlation was lower (r = 0.35) and explained only 13% of the variation of ET (Table 3). The 2017 low, GSP, and high irrigation treatments contributed 36, 43, and 52% of the total seasonal ET respectively (Table 1). This demonstrates that in heavily irrigated conditions, as VRI is implemented, the spatial variation of ET will reflect VRI management instead of the moisture removed from the soil.

The field average CWP for 2017 was 11 kg $ha^{-1}$ $mm^{-1}$ with a range of 4.1-19 kg $ha^{-1}$ $mm^{-1}$ (Table 1). The range and spatial variation of CWP were similar to those observed in 2016, with the lowest values near emerged bedrock, some field edges, and the eroded ridge, with the greatest values at the western toe slope (Figure 6H). Similar to 2016, the high CWP values that follow the leaky pivot joint are incorrect because the water added from the leak is not included in the ET water balance equation (Figure 6H). Crop water productivity variance was 4.2 in 2017, compared to 5.5 in 2016. The lower variance shows that VRI management has the potential to improve uniformity of CWP across the field.

The High treatment paired t test plots average CWP decreased 0.90 kg $ha^{-1}$ $mm^{-1}$ relative to the GSP, a 7% decrease (*p*-value $<0.0001$; Table 4). The Low treatment paired t test plots average improved CWP by 0.40 kg $ha^{-1}$ $mm^{-1}$, a 3% increase relative to the GSP (*p*-value = 0.15; Table 4). Where 30% more irrigation was applied yields improved (6%), but CWP decreased (7%). In contrast, where irrigation was decreased 30% yields decreased (11%) and CWP improved (Table 4). This suggests an inverse relationship between CWP and yield when manipulated with irrigation, or the 30% irrigation changes were too extreme causing the decreased in CWP in the High treatment and yield decrease in the Low treatment. Further research is required to identify methods to alter irrigation rates bother temporally and spatially to promote CWP without compromising yield.

For the two seasons yield explained 94% (2016) and 55% (2017) of the variation of CWP (Table 3). Additionally, the 21% decrease in CWP between 2016 and 2017 (Table 1) is almost equal to the 23% decrease in yield (Table 2). A GWR analysis of CWP and yield additionally exhibited high correlation between yield and CWP with correlations ranging from 0.78-0.99 for 2016 and 0.98-0.99 for the 2017 season respectively. Further GWR analysis with CWP and ET resulted in spatial coefficient range from (-) 0.57 – 0.19 and 0.362 – 0.796 for 2016 and 2017 respectively. The differences in the GWR correlations between seasons are largely explained by the difference in irrigation management but suggest the relationship between ET and CWP is both spatially and temporally variable. The close association between yield and CWP indicate that agronomic management that strongly influenced yield, such as crop rotation, had a greater influence on CWP than manipulating CWP through irrigation treatments.

Regarding management, this data indicates the spatial management of CWP with VRI requires additional agronomic practices. In fields with similar properties to this study site, managing spatial CWP will require a complete approach, including soil fertility, soil hydraulic properties, topography, etc. as suggested by King et al. (2006). The conceptual model improved the field uniformity of CWP, but further research is required to develop irrigation rate recommendations for yield and CWP combinations. Finally, the design of the experiment measured CWP response to irrigation, independent of other agronomic variables. Coupling VRI with other precision agriculture techniques such as variable-rate fertilization or planting may alter the response of CWP.

## CONCLUSIONS

This study evaluated the spatial variation of yields, ET, ΔS, and CWP in two consecutive years of irrigated winter wheat and proposed a unique conceptual strategy for VRI management targeted at CWP. Spatial and temporal variability of historic annual yields, ET, ΔS, and CWP was surprisingly large despite this field being relatively uniform in appearance, topography, texture, etc. Field averages of 11 and 14 kg $ha^{-1}$ $mm^{-1}$ CWP values were relatively high, but within the range of other values reported for US and world wheat production. Additionally, the first steps were taken in developing a conceptual model for VRI. Adjusting irrigation rates according to the proposed conceptual model had significant influence on the response of CWP and yield. The spatial variation in CWP and yield were highly correlated for both seasons. Surprisingly, correlation between ET and CWP was low for both seasons. Consequently, agronomic and environmental variations that strongly influenced yield altered CWP. This indicates that future approaches to manage CWP through VRI will likely require the development of algorithms that include a suite of agronomic management practices and environmental variations that have significant influence on the spatial variation of yield. Future research in fields with diverse environmental conditions is required to determine important variables to include in the characterization of VRI algorithms to conserve freshwater resources. Future research should also focus on finding inexpensive ancillary data that are related to CWP to determine irrigation application rates and zones.

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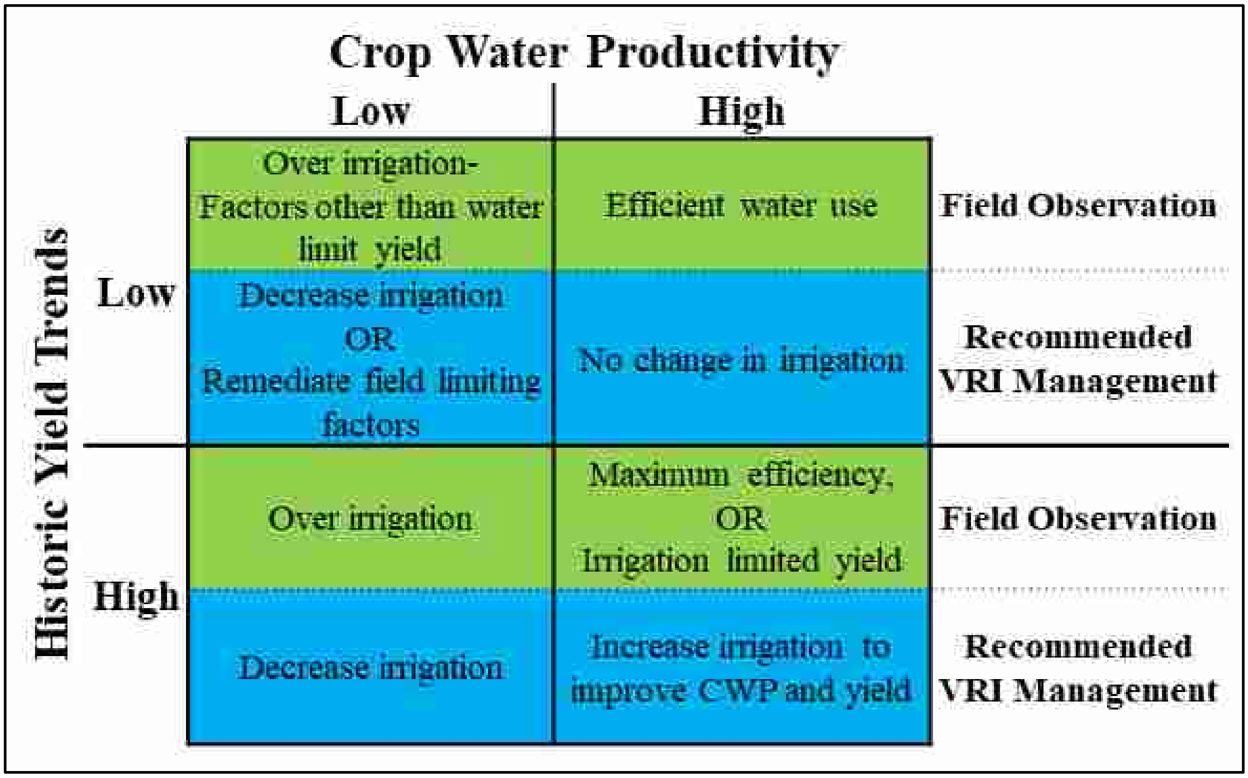


Figure 1-1. Conceptual model for delineation of variable-rate irrigation (VRI) zones based on separating the field into combination zones of high and low relative historic yield and crop water productivity (CWP). The four resulting quadrants each represent different field observations and recommended VRI management.

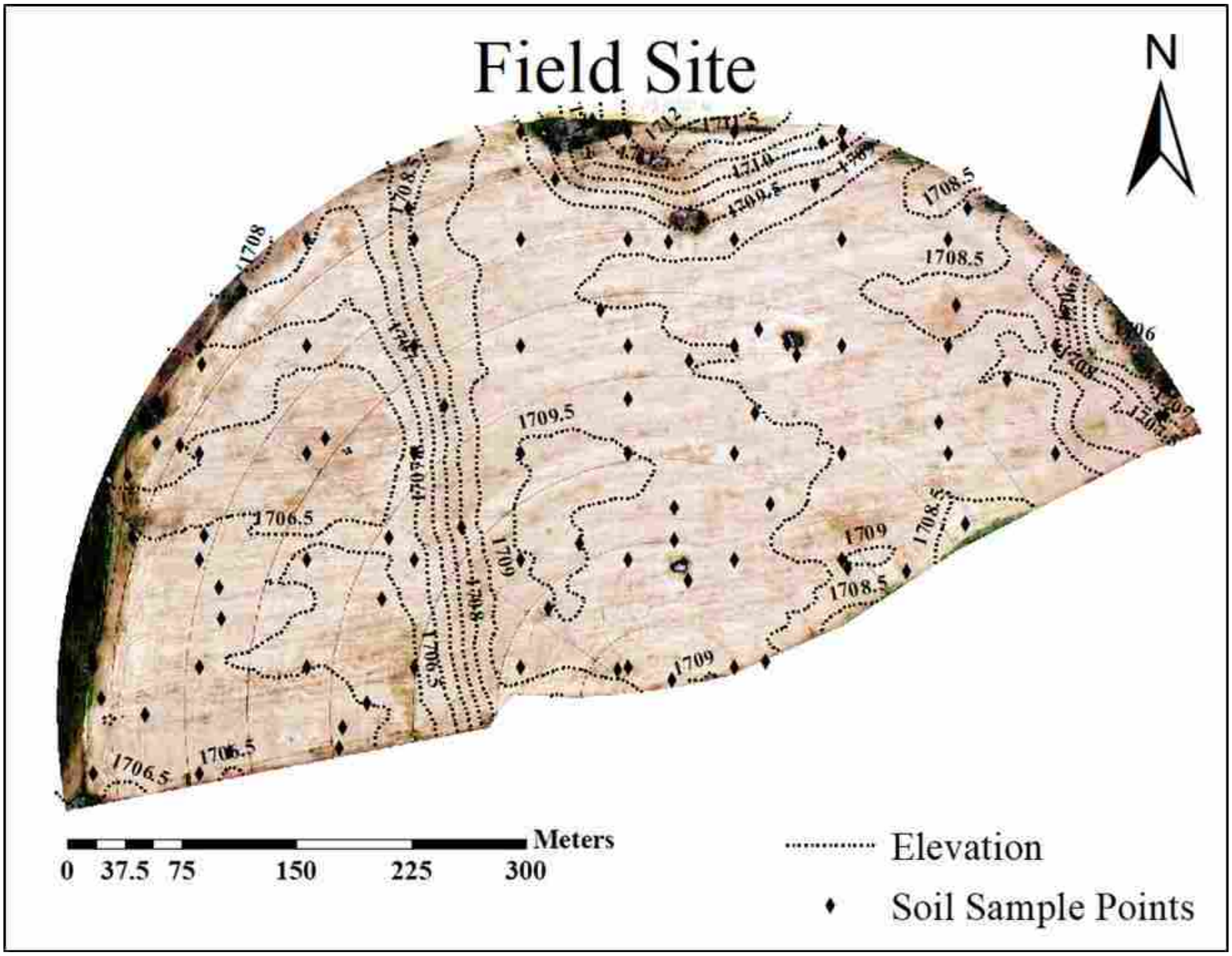


Figure 1-2. Bare soil image of the field research site near Grace, ID, USA with elevation contour lines (m) and soil sample points. Dark colored areas in the field and along edges are locations of unfarmed emerged bedrock.

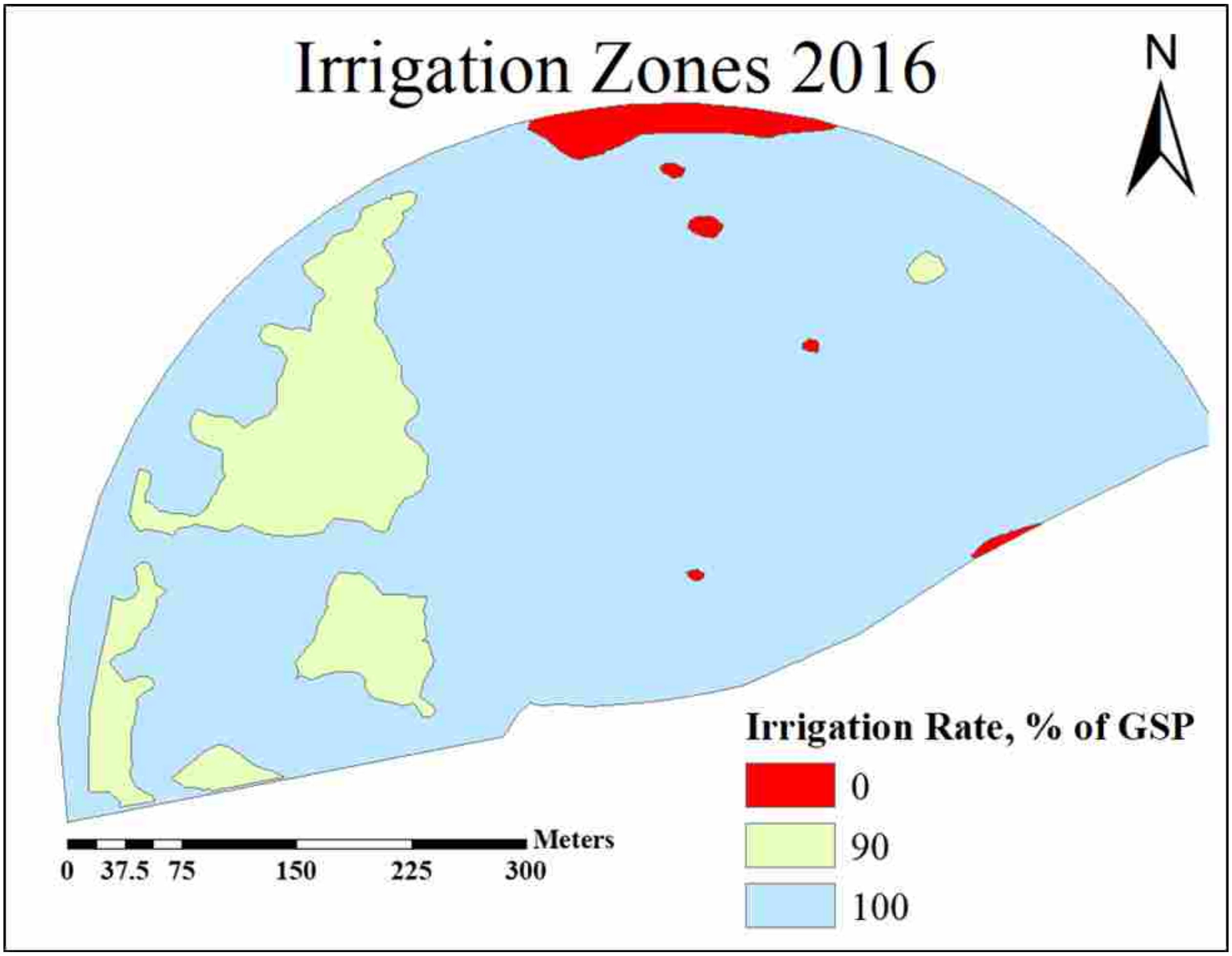


Figure 1-3. Grower developed irrigation zones used in the 2016 season. Irrigation zones are a percentage of the grower's standard practice (GSP) and were applied for each irrigation event excluding fertigation events.

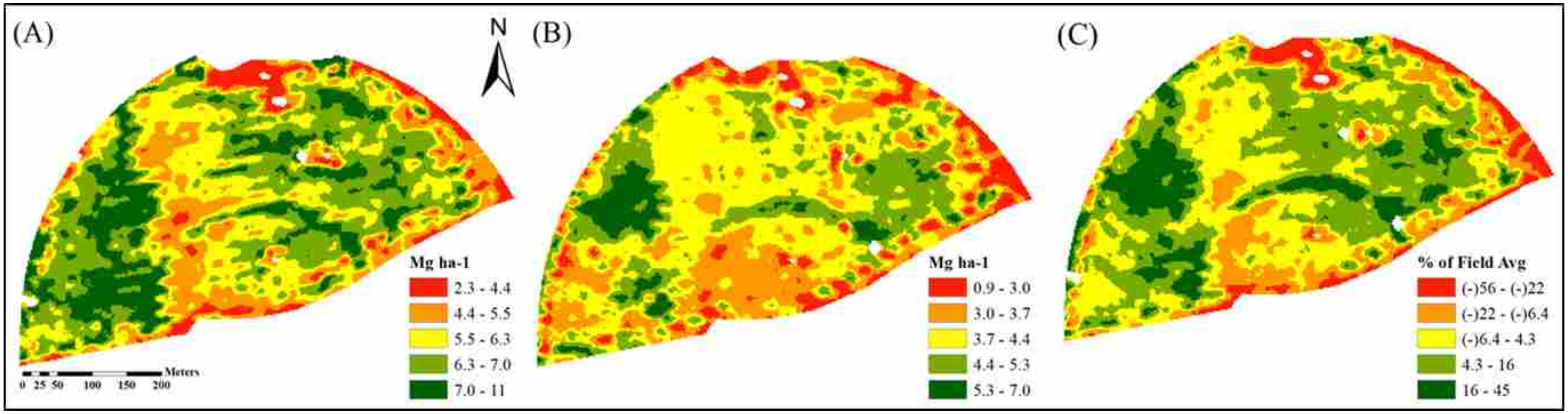


Figure 1-4. Historic yield maps for (A) 2013 and (B) 2014 were combined with yields measured in 2016 (see Figure 6) to create (C) a relative yield map (combined across 2013, 2014, and 2016).

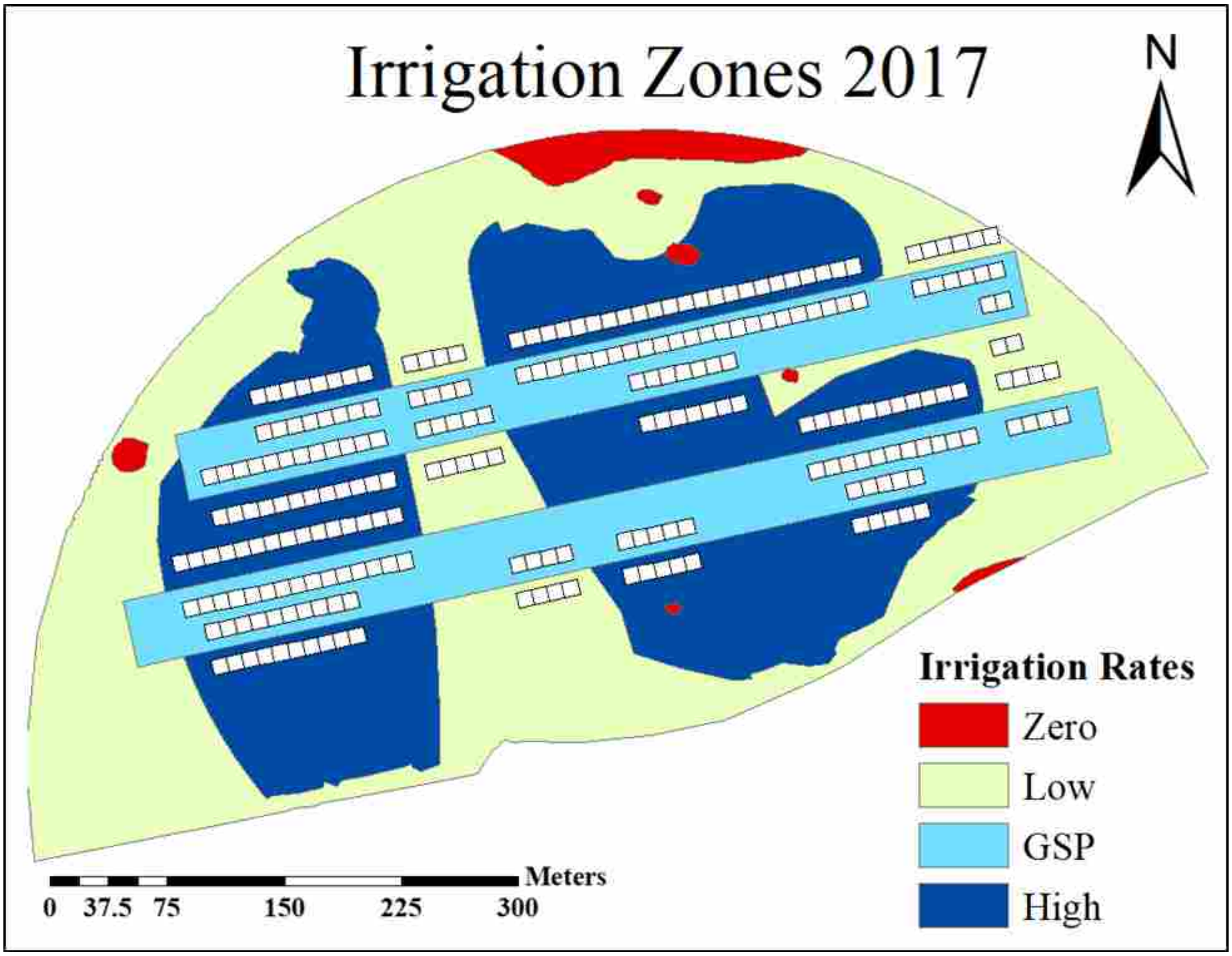


Figure 1-5. Developed irrigation zones based on historic yield and 2016 crop water productivity analysis with paired t-test plots outlined. The Low and High treatments received ± 30% of total irrigation relative to the grower standard practice (GSP). Paired T-test plots used for analysis are outlined in white boxes.

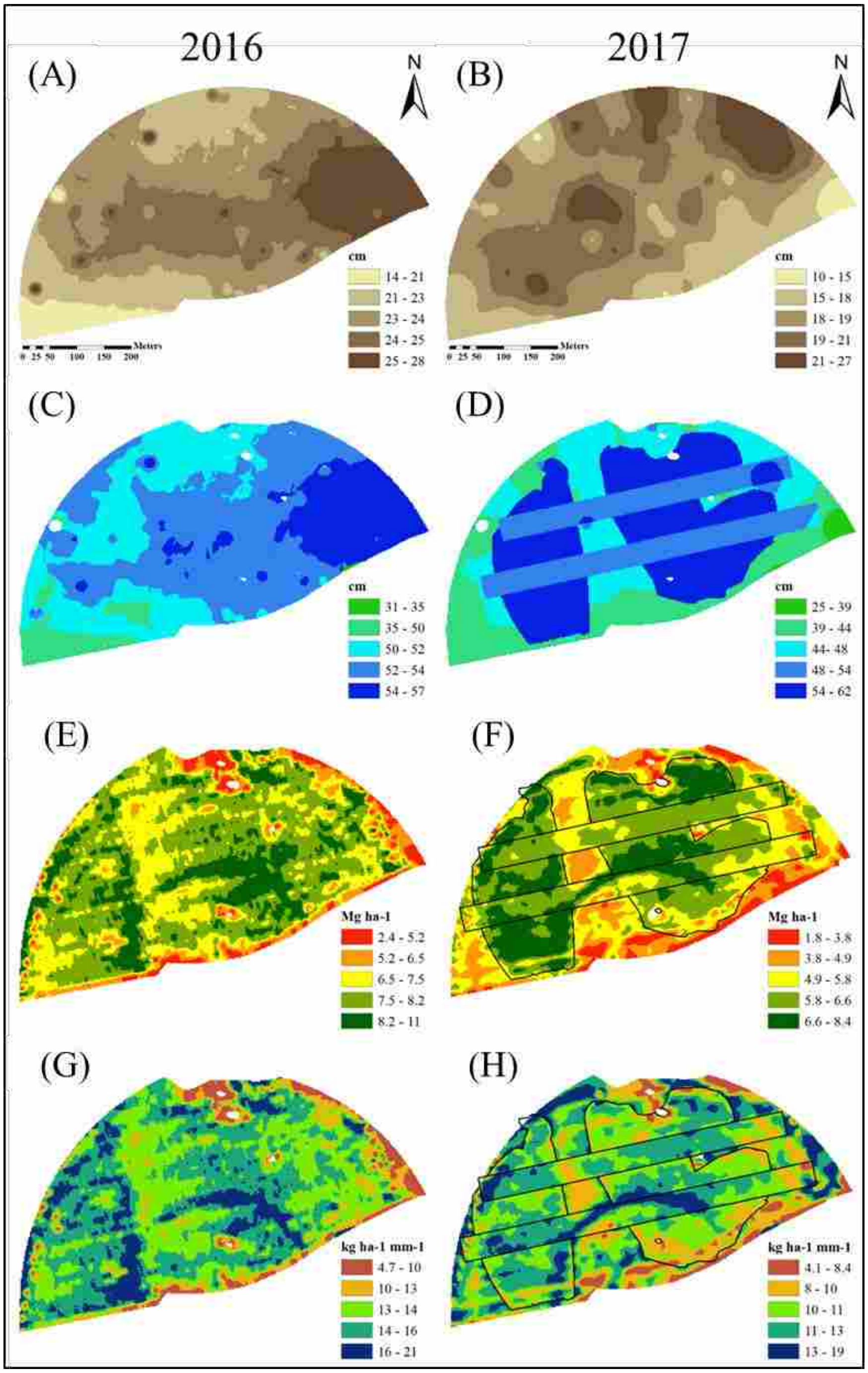


Figure 1-6. The spatial variation of 2016 and 2017 crop water productivity (CWP) constituents including: (A) 2016 change in soil moisture (ΔS) between spring green up and post-harvest, (B) 2017 ΔS between spring green up and post-harvest, (C) 2016 seasonal evapotranspiration (ET), (D) 2017 seasonal ET, (E) 2016 yield, (F) 2017 yield with irrigation treatments outlined in black, (G) 2016 spatial variation of crop water productivity (CWP), (H) 2017 spatial variation of CWP with irrigation treatments outlined in black.

TABLES

Table 1-1. Seasonal field and treatment averages and minimum and maximum values (shown in parenthesis after the average) of: precipitation (P), decrease in soil moisture between spring green-up and post-harvest (ΔS), irrigation (I), evapotranspiration (ET), and crop water productivity (CWP). Values in parentheses are the minimum and maximum values for that variable. In 2016, irrigation was nearly uniform, but in 2017 irrigation treatments were applied—values for each treatment and the average of all are shown for that year.

| Treatment | **P** | **ΔS** | **I** | **ET** | **CWP** |
|---|---|---|---|---|---|
| | **---mm---** | | | | **kg ha$^{-1}$ mm$^{-1}$** |
| | | **2016** | | | |
| **Average** | 95 | 227 (146-278) | 198 | 520 (315-571) | 14 (4.7-21) |
| | | **2017** | | | |
| **Average** | 90 | 190 (100-269) | | 497 (255-620) | 11 (4.1-19) |
| **Low** | | 190 (100-269) | 158 | 437 (255-518) | 11 (4.1-17) |
| **GSP** | | 195 (154-260) | 225 | 509 (434-574) | 12 (5.2-19) |
| **High** | | 195 (154-240) | 291 | 573 (525-620) | 11 (4.5-16) |

Table 1-2. Whole field yield data from winter wheat harvested in 2013-2014 and 2016-2017 with descriptive statistics. Also, yields for areas with irrigation treatments for 2017. The Low and High treatments received ±30% irrigation rates relative to the grower standard practice.

| | **Average** | **St Dev.** | **Min** | **Max** |
|---|---|---|---|---|
| | --------------------Mg ha$^{-1}$--------------------- | | | |
| **2013** | 6.2 | 0.98 | 2.4 | 10.8 |
| **2014** | 4.1 | 0.81 | 0.96 | 7.03 |
| **2016** | 7.5 | 1.01 | 2.4 | 10.7 |
| **2017** | 5.8 | 1.04 | 1.8 | 8.4 |
| **2017 Treatments** | | | | |
| **Low** | 4.9 | 0.91 | 1.8 | 7.6 |
| **GSP** | 6.0 | 0.61 | 2.2 | 7.9 |
| **High** | 6.4 | 0.69 | 3.0 | 8.4 |
| **Average** | 5.9 | 0.77 | | |

Table 1-3. Correlation coefficients (R) and $r^2$ (in parenthesis) between crop water productivity measurements including: crop water productivity (CWP), yield, seasonal evapotranspiration (ET), and decrease in soil moisture between spring green-up and post-harvest (ΔS).

| | | CWP | Yield | ET |
|---|---|---|---|---|
| **2016** | | | | |
| | **CWP** | | | |
| | **Yield** | 0.97 (94) | | |
| | **ET** | -0.18 (3) | 0.04 (0) | |
| | **ΔS** | -0.10 (1) | 0.09 (1) | 0.91 (83) |
| **2017** | | | | |
| | **CWP** | | | |
| | **Yield** | 0.74 (55) | | |
| | **ET** | 0.03 (0) | 0.68 (46) | |
| | **ΔS** | 0.03 (0) | 0.26 (7) | 0.35 (12) |

Table 1-4. Paired t-test results for 2017 irrigation treatments for yield and CWP. Significance at the 0.05 level marked with ** and 0.15 level marked with *.

| Treatment | | High | GSP | | Low | GSP | |
|---|---|---|---|---|---|---|---|
| **Yield** | Mg $ha^{-1}$ | 6.6 | 6.2 | ** | 5.0 | 5.6 | ** |
| **CWP** | kg $ha^{-1}$ $mm^{-1}$ | 11.4 | 12.3 | ** | 11.0 | 10.6 | * |

CHAPTER 2

# The Spatial Variability in Soil Water Holding Capacity and Modeling Spatiotemporal Soil Water Depletion and Crop Stress

Jeffrey D. Svedin[a], Neil C. Hansen[a], Ruth Kerry[b], and Bryan G. Hopkins[a]
[a]Department of Plant and Wildlife Sciences, Brigham Young University, Provo, UT
[b]Department of Geography, Brigham Young University, Provo, UT

## ABSTRACT

Variable-rate irrigation (VRI) is a technology that seeks to apply spatially and temporally variable irrigation rates to match site-specific crop water demand. The spatial variation of soil water holding capacity (SWHC) is an important physical soil property for delineating VRI zones. The objectives of this study were to: (i) characterize the spatial variation of SWHC, (ii) model subsequent spatiotemporal variation of soil water depletion and crop stress, and (iii) compare winter wheat (*Triticum aestivum* sp.) crop yield responses to the spatiotemporal variation in crop stress and ET to inform future VRI management. Soil samples at 90 locations in a 22 ha field were collected at spring green-up and post-harvest for two growing seasons of winter wheat (*Triticum aestivum* sp.) in Grace, Idaho, USA. The SWHC was characterized and daily soil moisture and crop water stress modelled between sampling points using a daily soil water balance. The range in SWHC for a 1.2 m deep profile was 144-369 mm, a large variation given a field with limited variation in topography and soil texture. The modelled variation in the day of stress onset was large under uniform irrigation in 2016, spanning a 21 d period. In 2017, with irrigation treatments employed in the field, the onset of crop stress spanned 56 d. In 2017 with irrigation zones implemented, 25% less water was applied with the VRI system compared to uniform irrigation. Interestingly the spatial variation of SWHC, and the subsequent modeled crop water stress was not significantly related to the spatial variation of yield in the two seasons. This

is surprising considering the large temporal variation of the onset of crop stress in both seasons. This suggests that interactions between the spatial variation of soil hydraulic properties and other environmental factors dictate the variation of yield in this field. Developing VRI prescriptions may require an approach that including environmental variables such as soil hydraulic properties, soil fertility, topography, and crop growth to match irrigation application to spatial crop water demand.

## INTRODUCTION

Irrigation consumes 80-90% of fresh-water use in the United States and two-thirds of freshwater resources are altered for human use (Postel 1999). Irrigated agriculture produces 40% of the world's food and fiber on 17% of cultivated land—producing nearly twice as much food per unit area compared to non-irrigated lands (Abdullah 2016; Evans et al. 2013; Shaible and Aillery 2012). Demand is increasing for existing water resources around the world from growing global population, declining groundwater levels, deteriorating water quality, increasing environmental regulations, rising recreational demands, and increasing international and interstate agreements, environmental regulation, water quality, and declining groundwater levels (Evans et al. 2013). In addition to the rising demand, the Food and Agriculture Organization of the United Nations (FAO) estimated that, under current management practices, by 2030, withdrawals for irrigation alone would need to increase by 14% to meet the world food demand (Abdullah 2016). These future projections clearly suggest that farmers will be required to increase food production with decreasing cultivatable land while at the same time reducing irrigation requirements. From these pressures, farmers are required to increase irrigation efficiency and food production per unit of applied water (Evans et al. 2013).

Traditional irrigation practices intend to apply uniform rates across farm fields to meet field average crop water demands. Spatial variability in crop water demand is driven by factors that influence plant health, rooting depth, and water and nutrient uptake. Among spatially variable factors are relatively permanent soil properties, such as topography, soil texture, organic matter content, and water-holding capacity. The challenge is further complicated by temporally variable factors such seasonal variation in solar angles, weather, microclimates, pests, pathogen pressure, crop response to management practices, and soil temperature, fertility status, and compaction. Thus, traditional irrigation contains inherent inefficiencies where portions of the field are over- or under-irrigated.

Variable-rate irrigation (VRI) employs state of the art technology to spatially match irrigation application rates to crop water demand. King et al. (2006) compared VRI and uniform irrigation in a two-year potato (*Solanum tuberosum* L.) experiment and observed greater water productivity under VRI management. West and Kovacs (2017) suggested adoption of VRI irrigation and other precision agriculture techniques would lead to sustainable groundwater withdrawals in the Arkansas valley. Lo et al. (2016) found that VRI techniques were effective in mining undepleted soil water in field regions with greater soil water holding capacity (SWHC) — resulting in at least a potential 25 mm $yr^{-1}$ irrigation reduction for 13% of Nebraska agricultural fields with center-pivot systems based on variations of soil properties.

Soil water holding capacity is a static soil property that reflects the water available to the plant and has been shown to influence yield and crop water use (Sadler et al. 2005; Zhao et al. 2017) and field scale have been observed (Haghvardi et al. 2015; Longchamps et al. 2015). As such, VRI zones are commonly delineated from the variation in SWHC (de Lara et al. 2017, Haghvardi et al. 2015, Hedley and Yule 2009; King et al. 2006; Lo et al. 2017). Therefore, effective VRI management requires accurate and precise spatial information regarding soil properties and crop water status.

Coupling daily estimates of crop ET with known spatial variation of SWHC can be a basis for managing VRI with the goal of using soil water efficiently and triggering irrigation before soil moisture fall below a crop specific threshold (Allen et al. 1998). The crop specific threshold is identified as the readily available water (RAW) or as management allowed depletion (MAD). When soil moisture falls below the threshold, the crop transpiration is reduced and yield is likely affected. The objectives of this study were to: (i) characterize the spatial variation of SWHC, (ii) model subsequent spatiotemporal variation of soil water depletion and crop stress, and (iii) compare winter wheat (*Triticum aestivum* sp.) crop yield responses to the spatiotemporal variation in crop stress and ET to inform future VRI management.

## METHODS

### *Site Description*

The study was conducted for two winter wheat growing seasons (2016-2017) in a commercial production field (22 ha) following a seed potato crop located near Grace, ID, USA, (42.60904, -111.788). The site is characterized by a growing season with 80 to 110 frost-free d and is located 1687 m above sea level (Figure 1). The soil is a silty clay loam Rexburg-Ririe complex and classified as coarse-silty, mixed, superactive, frigid Calcic Haploxerolls with 1-4% slopes. The field site contains 0.3 ha of unfarmed rock outcroppings (Figure 1). The mean annual precipitation is 392 mm with much of the precipitation falling as winter snowfall and spring rain.

*Management Description*

The winter wheat crop was grown using best management practices regarding crop, soil, fertilizer, water, and pest management (Table 1). Nitrogen applications were 59 kg $ha^{-1}$ and 175 kg $ha^{-1}$ of N for 2016 and 2017, respectively. Irrigation at the site is performed using a 380-m long center pivot sprinkler equipped with a Variable-Rate Irrigation System (Growsmart Precision VRI, Lindsay Zimmatic, Omaha, NE, USA). The relatively small adjustments of VRI rates in 2016 did not influence the model statistically and, coupled with inherent non-uniformity that accompanies sprinkler irrigation, the 2016 season is classified as “uniform irrigation”. Variable irrigation treatments were applied in 2017 during each event with ±30% relative to the GSP rate being applied. Irrigation treatments were delineated from historic yield and crop water productivity (See Chapter 1; Figure 2).

Yield was determined with a calibrated yield monitor (New Holland Inteliview 4, Turin, Italy) using a mass flow sensor attached to the harvester, collecting yield with point measurements approximately every 1.5 m. Planting dates were 5 and 10 October in 2015 and 2016, respectively. Harvest dates were 16 and 30 August in 2016 and 2017, respectively. The yield data was processed as described by Kerry and Oliver (2003). Erroneous data points were defined as outside the limits of ± 75% of the median. In addition, points where the combine did not harvest the full header width were removed. Yield data was calibrated using a weigh cart and validated with wheat bin storage showing an overall accuracy of ±1%.

*Spatial Statistics and Interpolation*

Geostatistical methods were used to explore spatial variation in yield, seasonal ET, soil moisture, and crop stress throughout the study period. A sampling scheme with 90 points was developed using the variogram of normalized difference vegetation index of bare soil aerial imagery of the field site. The variogram had an approximate range of 140 m so a sampling interval of 70 m (46 points) was used to capture spatial structure of variation in permanent soil properties following the approach suggested by Kerry and Oliver (2003). The gridded points were supplemented with randomly located points (44 points) to achieve a degree of nesting, to collect sufficient points for reliable variogram estimation (Webster and Oliver, 1992), and to better estimate the nugget component of the variogram. Careful attention was given to the distribution of the sampled and modeled soil water properties. The data was transformed to meet normality if the skewness of the data set was ±1, as departures from normality affect the stability of the variances and the corresponding variogram (Kerry and Oliver, 2008). All experimental variograms were modeled using SpaceStat (BioMedware, SpaceStat 4, Ann Arbor, MI, USA) and ArcMap's Geostatistical Analyst (Environmental Systems Research Institute (ESRI] 2011, ArcGIS desktop: Release 10, Redlands, CA, USA). All spatial maps were classified using Jenks' natural breaks classification which determines the best arrangement of values into classes and identifies breaks in the ordered distribution of values that minimizes the within-class sum of squared differences (Hedley and Yule 2009).

*Soil Water Depletion Modeling*

Soil water depletion modeling followed Allen et al. (1998) and the FAO Penman-Monteith estimation of ET to adjust daily soil water levels. Allen et al. (1998) describe the $ET_o$-$K_c$ approach where $ET_o$ represents the evapotranspiration on that d from a reference crop and the $K_c$ represents the adjustment for the growth stage of the specific crop being grown. Daily plant available soil water was modeled at the 90 soil sample points beginning with soil water measured at spring green-up through post-harvest. A non-stressed spatially uniform reference evapotranspiration ($ET_o$) and crop coefficient ($K_c$) was used over the field to estimate daily water removed from the soil. If, however, the daily soil moisture fell below a site-specific readily available water (RAW) point, a stress coefficient ($K_s$) was used to modify the non-stressed $ET_c$ and estimate $ET_{c\text{-}adj}$. The soil water depletion was used to estimate the spatial and temporal variation of the crop stress coefficient (Ks). The model was validated by comparing the sum of modeled growing season daily ET with ET as measured from the following seasonal water balance approach:

$$ET = P + I + \Delta S - D \qquad (1)$$

where P represents the seasonal precipitation, ΔS represents the difference in measured soil moisture between spring green-up and harvest, I is irrigation, and D is drainage during the season. Spring green-up and harvest soil samples were collected on April 18 and August 20, 2016 and on May 4 and September 1, 2017, respectively. Soil cores were collected at four depths 0-0.3 m, 0.3-0.6 m, 0.6-0.9 m, and 0.9-1.2 m with a 51 mm diameter auger to describe the moisture removed from the soil at 90 field locations (Figure 1). Drainage was calculated using the daily soil water depletion model (equation 6) whenever water inputs resulted in soil water that exceeded SWHC. Statistical measures of model fit followed Miner et al. (2013) including: (1) relative error (RE) (2) normalized objective function (NOF) and (3) root mean square error (RMSE). Where RE represents model bias, NOF indicates the fit of the model (where NOF $< 1$ is less than one standard deviation from the mean), and RMSE is the weighted differences between predicted and measured values in the same units as the modeled variables.

Weather data to calculate daily evapotranspiration was collected at a weather station 2,000 m from the field site (42.51496 N, -111.73606 W; Cooperative Agricultural Weather Network AgriMet). The weather data was used to calculate daily evapotranspiration ($ET_o$) for a reference crop using the American Society of Civil Engineers (ASCE) Standard Penman-Monteith Evapotranspiration model (Allen et al. 1998). The crop coefficient approach (Allen et al. 1998) was used to calculate daily $ET_{c\ adj}$ using the following equation:

$$ET_{c\ adj} = K_s * K_c * ET_o \tag{2}$$

where $ET_{c\ adj}$ is the adjusted ET from water stress and winter wheat crop specific conditions, $K_s$ is the transpiration reduction factor reflecting the available soil water, $K_c$ is the crop coefficient that reflects the winter wheat crop development stage, and $ET_o$ is the reference crop ET. The $K_c$ curve was estimated from table values in a similar environment (Allen et al. 1998) and validated with field observations. The dimensionless transpiration reduction factor is represented as $K_s$ and calculated as:

$$Ks = \frac{\mathrm{SWHC} - \mathrm{Dr}}{(1 - \mathrm{p}) * \mathrm{SWHC}} \tag{3}$$

where SWHC is the soil water holding capacity in the root zone (mm), *p* is the table value 0.55 from Allen et al. (1998) that represents the average fraction of SWHC that can be depleted before crop stress, and $D_r$ is the current root zone water depletion in mm.

Daily soil moisture was modeled based on the SWHC and the readily available soil water (RAW) using:

$$\mathrm{SWHC}=1000* (\theta_{FC}-\theta_{WP})*Z_r \tag{4}$$

$$\mathrm{RAW} = \mathrm{p}*\mathrm{SWHC} \tag{5}$$

where SWHC is defined as above and calculated for each sampling depth in mm and summed across the crop rooting depth for a soil profile, $\theta_{FC}$ is the volumetric water content ($m^3\ m^{-3}$) at field capacity, $\theta_{WP}$ is the volumetric water content at wilting point ($m^3\ m^{-3}$), and $Z_r$ is the estimated rooting depth of the crop (1.2 m; Weaver, 1925). RAW is the readily available soil water content in the root zone (mm), and p is as defined above.

For each sample location, the soil was assumed to be at field capacity for the greater of the two green-up observed water content values for each soil sample depth.  This follows the guidelines from Martin et al. (1990)—that sampling 1-3 d after a thorough soil-wetting event when crop water use is small is a good indication of FC. Winter precipitation, mostly in the form of snow, acted as the wetting event for this field. We assumed fall soil samples were at WP because the soils had been dried down for harvest with 15 and 7.1 mm of rainfall since the last irrigation event 18 and 16 d for 2016 and 2017, respectively.

The WP assumption was validated on 39 samples using a Decagon WP4C (WP4C Dewpoint PotentiaMeter, Decagon Devices, Pullman WA, USA) to estimate the relationship between volumetric soil moisture and water potential. For each validation sample, 4-5 known volumetric moisture values were analyzed on the WP4C to calculate water potential. Using a logarithmic fitted line, volumetric soil moisture was estimated at -1500 Kpa for each sample and compared to field estimated WP. All measured volumetric WP values were within ±10% of the fall soil moisture values for individual depths, and within 5% error when averaged for the whole soil profile, verifying the assumption that fall soil samples were at or very near WP.

Daily root zone depletion was estimated using the following equation:

$$D_{r,i} = D_{r,i-1} - P_i - I_i + ET_{c,i} + DP_i \quad (6)$$

where $D_{r,i}$ is the soil moisture depletion in the root zone at the end of d i, $D_{r,i-1}$ is the root zone depletion at the end of the previous d, $P_i$ is the precipitation on d i, $I_i$ is the irrigation depth on d i, $ET_{c,i}$ is the crop evapotranspiration on d i, and $DP_i$ is water loss out of the root zone by deep percolation on d i.

# RESULTS

## *Spatial Variation of Soil Water Properties and Yield*

The amount of water at FC for the 1.2 m deep soil profile varied spatially, with an average of 389 mm and range of 373 - 422 mm (Figure 3A). The semivariogram ranges for FC and WP were 574 and 30 m, respectively and is shown by the larger size of zones with similar values in FC. In contrast, for WP, although some larger structure is present, the variation is dominated by small, somewhat random structure. Because SWHC is the difference between FC and WP, the spatial randomness in WP is found in SWHC—giving the map a spotty appearance (Figure 3B). The field average SWHC is 258 mm in the 1.2 m deep soil profile, with a large range from 147 - 369 mm (Figure 3B). The soil moisture accounted for 50% of the seasonal ET in 2016 and 43, 38, 33% for the Low, GSP, and High 2017 treatments, respectively.

The spatial variation of yield for each year did not reflect patterns in FC, SWHC, or WP. Linear regression analysis between yield and SWHC was not significant (Table 3)—suggesting the variation of yield was not statistically influenced by the spatial variation of SWHC during either season (Figure 4). The 2016 yield average was 7.5 Mg ha$^{-1}$, ranging from 2.4 - 11 Mg ha$^{-1}$; while the 2017 average was 5.8 Mg ha$^{-1}$, ranging from 1.8 - 8.4 Mg ha$^{-1}$ (Figures 5 and 6). The western toe slope and eastern plateau produced the greatest yields in both seasons (Figures 5 and 6), as well as in 2013 - 2014 (See chapter 1). The areas with the lowest yields in 2016 were found at the eroded slope area, in addition to field edges and emerged bedrock (Figures 1 and 5). The areas with the lowest yields in 2017 followed this same pattern, but was exacerbated by the Low irrigation treatment. A semi-circle of high yield is found at the leaky third pivot joint in both years as a response from leaks during irrigation and fertigation events. Irrigation treatments significantly influenced yield in 2017, with highest yield associated with the High irrigation treatment (Figure 5; Table 2). Interestingly, this semi-circle from the pivot leak is evident across all treatments, demonstrating yield responded to the extra water and nutrients regardless of irrigation rate.

The field average yield was 23% lower in 2017, which is a common response to this crop rotation. Potatoes have inefficient root systems and demand high applications of nutrients and water potentially leaving residual nutrients and water available to the first-year wheat in the deeper soil profile (Hopkins, 2015; Hopkins and Hirnyck, 2007; Miller and Hopkins, 2007). Additionally, pests and pathogens are often crop specific and, thus, the yields are commonly reduced in the successive year of growing the same species (Hopkins 2010; Hopkins and Hirnyck 2007; Miller and Hopkins 2007). The grower confirmed that historically first year wheat produces much greater yields. Symptoms and crop damage from greater pest and pathogen populations were not readily observed in this field, but this is common to have reduced yields due to a lack of rotation without any major visible difference. It is not possible to attribute which of these factors affected the second-year wheat yields, but likely a combination effect. Notably, in the season with employed VRI treatments (2017), the yield reduction was not as dramatic.

*Model Evaluation*

The two measures used to validate the daily soil moisture were the seasonal ET and the soil moisture at harvest. Modelled predictions of seasonal ET matched well with seasonal ET calculated from a water balance (RMSE 73 mm), with a moderate bias towards over-prediction (1.3%; Figure 7). Model predictions of soil moisture at harvest also matched well with measured values (RMSE 81 mm, Figure 7), with bias towards under prediction (RE -5%; Figure 7). For seasonal ET and soil moisture at harvest, model predictions were within one standard deviation of the mean for both years (NOF <1). For both comparisons, model fit was better in 2016 than in 2017 (Figure 7). The likely reason for the greater RMSE in 2017 is that daily ET was calculated using a spatially uniform crop coefficient—even while using variable-rate irrigation zones. Effectively the uniform crop coefficient treated the whole field crop growth as uniform regardless of environmental variability. This strongly indicates that using spatially variable crop coefficients in a dynamic VRI management systems has the potential for additional water conservation.

*2016 Model: Uniform Irrigation*

The 2016 model covered d 111 - 230 with 11 total irrigation events (Figure 8). Irrigation began on d 151 with 11 events applying 198 mm over 11 events occurring nearly every 4 d (Table 2). Because the model uses a spatially uniform crop coefficient, modeled rates of soil moisture depletion are the same at each site until soil moisture at individual sites is predicted to go below RAW, at which time a $K_s$ factor is introduced (Figure 8). The modelled variation in soil water depletion demonstrates the hypothesized importance of spatial variation of FC, WP, RAW, and SWHC for VRI management.

The onset of modelled crop water stress, where soil moisture depletion fell below RAW, began on d 175 (point 20) with the last location falling below RAW on d 196 (point 37), showing a range of 21 d (Figure 8). When the last modeled location reached stress (d 196) the adjusted $ET_{c\text{-}adj}$ was 8.4 mm, compared to 5.4 mm when the first modeled location to reached stress (d 175). Therefore, the differences in SWHC and crop water stress reduced ET by 36% between the first and last points to experience water stress. The 2016 season was uniformly irrigated so the variation of soil moisture depletion was a direct result of the variation in SWHC and the spring soil moisture levels. Therefore, the three-week range in the onset of crop stress derived from the field's natural variation in SWHC (Figure 8).

The spatial variation of crop water stress was represented as the seasonal average $K_s$ for each location, where a $K_s$ of 1.0 indicates there was no crop water stress. The seasonal average $K_s$ ranged from 0.76 – 0.83 and were not significantly correlated with yield (Figure 9; $p$-value = 0.54). This suggests that during 2016 other environmental and/or soil factors dictated yield variability and that the variation of SWHC did not play a critical role in the 2016 yield variation (Figure 9).

*2017 Model: Variable-Rate Irrigation*

The 2017 model began on d 125 and ended on d 244 with 14 irrigation events (Figure 10). Variable irrigation treatments were applied during each event with ±30% relative to the GSP rate being applied. Irrigation began d 143 with events occurring, on average, every 5 d. Total irrigation for Low, GSP, and High treatments were 158, 225, 291 mm total for the 2017 season. A total 25% less water was applied to the field, compared to the amount that would have been applied if the GSP were utilized during the 2017 season.

The first onset of stress was modeled on d 155 at (point 112) and the last occurred d 211 (point 36)—spanning 56 d. The temporal variation in the onset of stress resulted in a spatial variation of stress on d 211 with point 35 $ET_{c\text{-}adj}$ at 7.0 mm and point 112 $ET_{c\text{-}adj}$ at 2.9 mm; a 59% reduction in daily $ET_{c\text{-}adj}$ from crop water stress. The irrigation treatments exacerbated the extremes in crop stress but the variations in crop stress were also a function of soil SWHC (Figure 10). Meaning some points that received the High irrigation rate experienced stressed before points that received the GSP rate and the same for the Low and GSP treatments. For example, the temporal range of when the first and last point experienced modeled water stress was d 155 - 187, d 158 - 195, and d 186 - 211 (32, 37, and 25 d) for the Low, GSP, and High zones, respectively (Figure 10). This indicates that the Low treatment modelled points experienced stress, on average, much earlier in the season compared to the other irrigation rates.

The 2017 seasonal average $K_s$ values ranged from 0.63-0.86, with the field average $K_s$ value of 0.78. The 2017 field average Ks value was 5% lower (5% greater crop water stress) compared to 2016—with a standard deviation of 0.07 compared to 0.03 for 2016. Multi-linear regression analysis predicting yield by irrigation treatment, $K_s$, and SWHC resulted in irrigation treatment as the only significant variable in predicting yield (Figure 11; Table 4) with SWHC significant at the 0.15 level (*p*-value 0.12). This shows that the field variation of SWHC is of lesser importance for crop yield than irrigation. Therefore, based on the 2016 and 2017 field data, for this site additional variables and SWHC could improve irrigation zone delineation.

## DISCUSSION

The objectives of this research were threefold (i) characterize the spatial variation of SWHC, (ii) model subsequent spatiotemporal variation of soil water depletion and crop stress, and (iii) compare winter wheat (*Triticum aestivum* sp.) crop yield responses to the spatiotemporal variation in crop stress and ET to inform future VRI management. Spatial variation in soil water properties was observed for FC (373 - 422 mm), SWHC (147 - 369 mm), and WP (106 - 221 mm) despite limited spatial variations in soil texture and topography. The range in SWHC was surprisingly large, but similar variation in SWHC has been observed at the field scale in other studies (de Lara et al. 2017; Daccache et al. 2015; Lo et al. 2017; Longchamps et al. 2015; Haghverdi et al. 2015). The WP spatial patterns appear random with variations too small (approximately 30 m variogram range) to be desirable to manage or to properly address with 5 m nozzle spacing on the VRI center-pivot (Figure 3). The random behavior of the WP properties may be from the variation of the depth to bedrock and the random mixture of rocks in the deeper soil profile that influence the SWHC. The SWHC is influenced by WP and some of the random variation of WP is seen in the SWHC map (Figure 3).

Surprisingly, despite the large spatial variation of SWHC, there was limited correlation with yield. This observation is different from Haghverdi et al. (2015) where strong correlations were observed between SWHC and cotton and soybean yield. Additionally, Zhao et al. (2017) observed yield and water productivity responses to field zones delineated by SWHC with less variability (158.1 - 168.7 mm). Fraisse et al. (2001) observed that with adequate soil moisture the number of management zones decreased, and DeJonge et al. (2007) observed that large seasonal irrigation applications can reduce spatial yield variability. Irrigation contributes over 50% of the total seasonal ET, which may explain the poor relationship between yield and SWHC for this field.

The temporal range of the onset of crop water stress for the whole field was 21 and 56 d for 2016 and 2017 respectively. The GSP in 2017 was 37 d with 32 and 25 d ranges for the Low and High treatments respectively. The 2017 irrigation rates created the larger temporal variation of crop stress which lead to significant variation in yield between irrigation rates. However, controlling for irrigation treatment, the variation of crop water stress did not significantly predict yield for either season (Table 4). The variation in yield throughout the field demonstrates that there are variations in crop water demand throughout the field (Figures 5 and 6). Study results suggests that environmental factors other than soil water properties dictated this variation.

Regarding the specific management of this field, this information is useful in determining field scale allocation of water resources when water resources are scarce. For example, the grower is forced to decide whether to allocate freshwater resources to the greatest soil SWHC or to the greatest yield. Our data suggests that the spatial variation of SWHC does not dictate the variation of yield and allocating irrigation to the historically greater yield zones would be a better use of a limited water supply. Preliminary research investigating the variation of crop water productivity, crop produced per unit of applied water, is very closely related to the variation of yield (Chapter 1). These data sets suggest that historic yield patterns are valuable in identifying irrigation zones that conserve water and are economically profitable. However, further research is required in deciding where to allocate irrigation to gain the greatest water productivity and key temporal triggers to maximize yield and water productivity spatially across the field.

While increasing irrigation during peak ET rates may not be possible, early spring irrigations can create a buffer against crop water stress during peak crop demand and improve yields. Additionally, the lack of correlation between soil hydraulic properties and yield indicate that other environmental factors (such as soil borne pests/pathogens; weeds; topography; local variations in sunlight due to aspect and/or soil organic matter, fertility, depth, etc.) are driving yield variation in this field when receiving adequate, or nearly so, water. This shows the importance of a comprehensive agronomic approach to VRI, in this field the interaction with SWHC with other variations is required to determine the variable crop water demand. This compliments the suggestion from Evans and King (2012) that integrated comprehensive decision support tools are required to optimize the allocation of limited water and should include holistic approaches. Plant feedback systems, such as thermal stress indices, to diagnosis crop water stress have shown promise in using VRI to address spatial crop water demand (O'Shaughnessy et al. 2015). These systems, coupled with knowledge regarding the spatial variation of fertility and SWHC could lead to spatially variable irrigation recommendations that describe the spatial and temporal crop water demand.

## CONCLUSIONS

The spatial variation of SWHC and spatiotemporal relationships of modelled daily soil moisture depletion with yield were characterized in two seasons of winter wheat. Modelled spatiotemporal variations of SWHC and crop stress were large, but irrigation treatment was the only significant variable in predicting yield. Therefore, for this field VRI management is not justified simply because of large SWHC variations exist. Instead coupling variation in soil hydraulic properties with supplementary data regarding the spatial variation of crop water status, potential yield, and other environmental factors are required for VRI management. Further research is required in adapting spatial and temporally variable crop coefficients and integrating proximal and remote sensing to estimate spatial soil properties, crop coefficients, and crop water demand to inform variable-rate irrigation.

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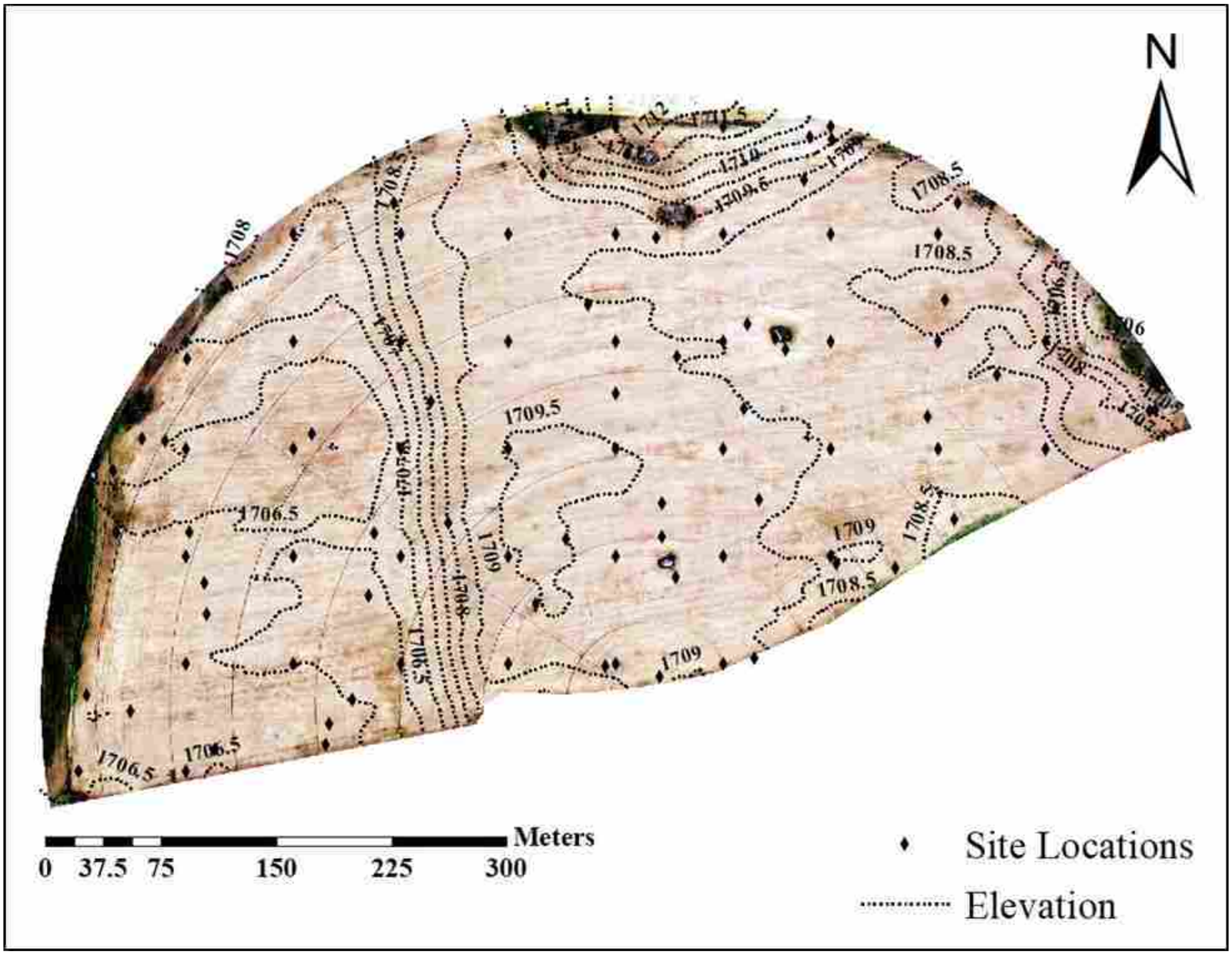



Figure 2-1. Irrigation treatments for the 2017 growing season. The Zero zone received no irrigation on unfarmed rock outcroppings. The Low and High zones received ± 30% irrigation relative to the grower standard practice (GSP).

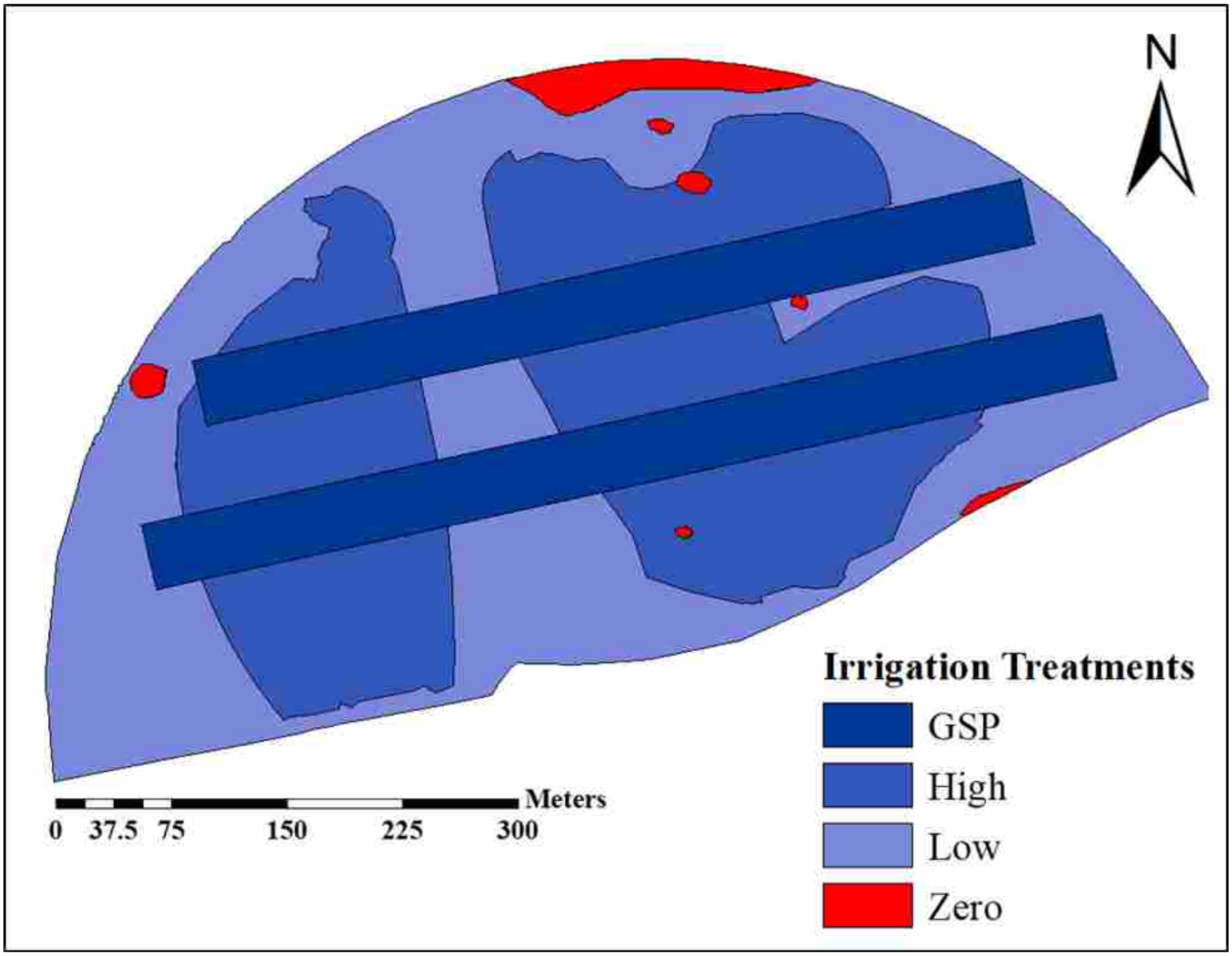



Figure 2-2. Irrigation treatments for the 2017 growing season. The Zero zone received no irrigation on unfarmed rock outcroppings. The Low and High zones received ± 30% irrigation relative to the grower standard practice (GSP).

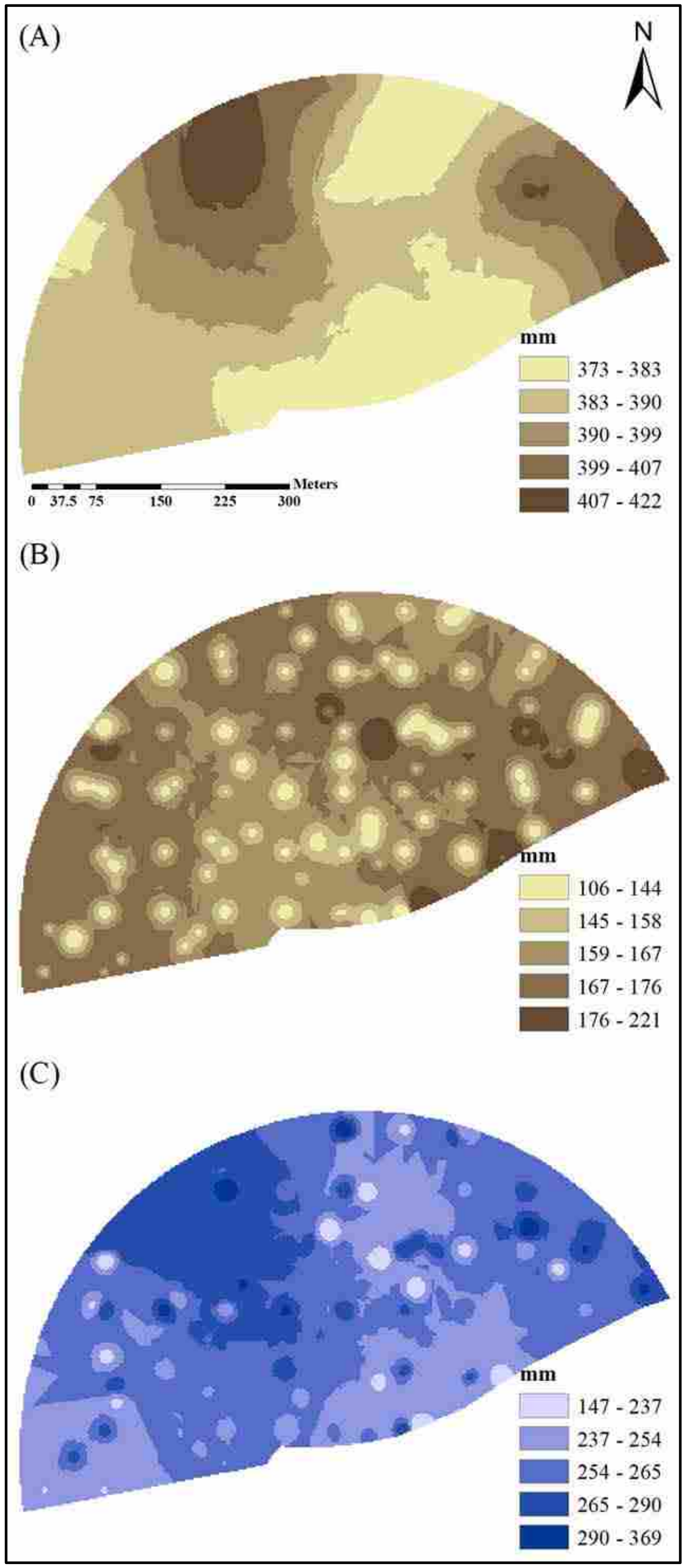



Figure 2-3. Spatial variation of measured soil hydraulic properties including (A) field capacity (B) wilting point and (C) soil water holding capacity. All zones were created using the Natural Jenks method to create zones with the least in-zone variation.

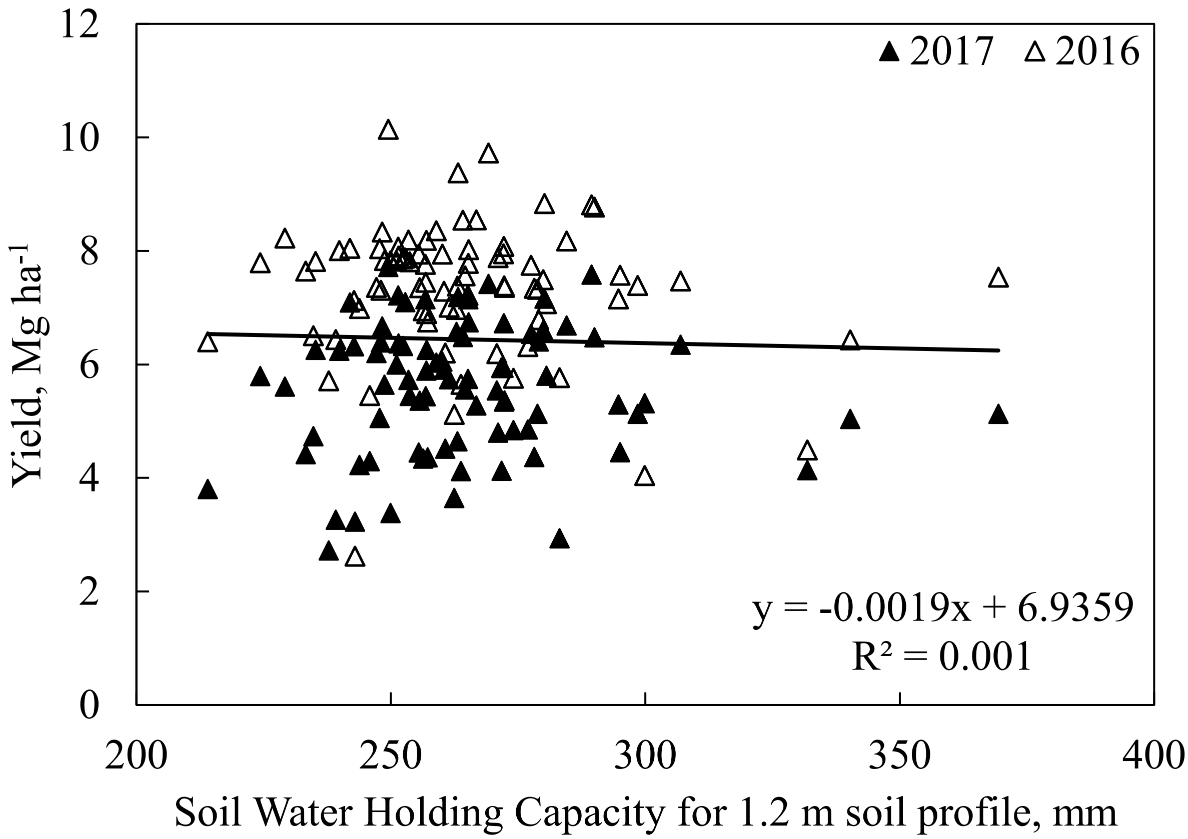



Figure 2-4. Linear relationship between 2016-2017 measured yield and total available soil water in the root zone (1.2 m depth) measured at 90 points at the study site.

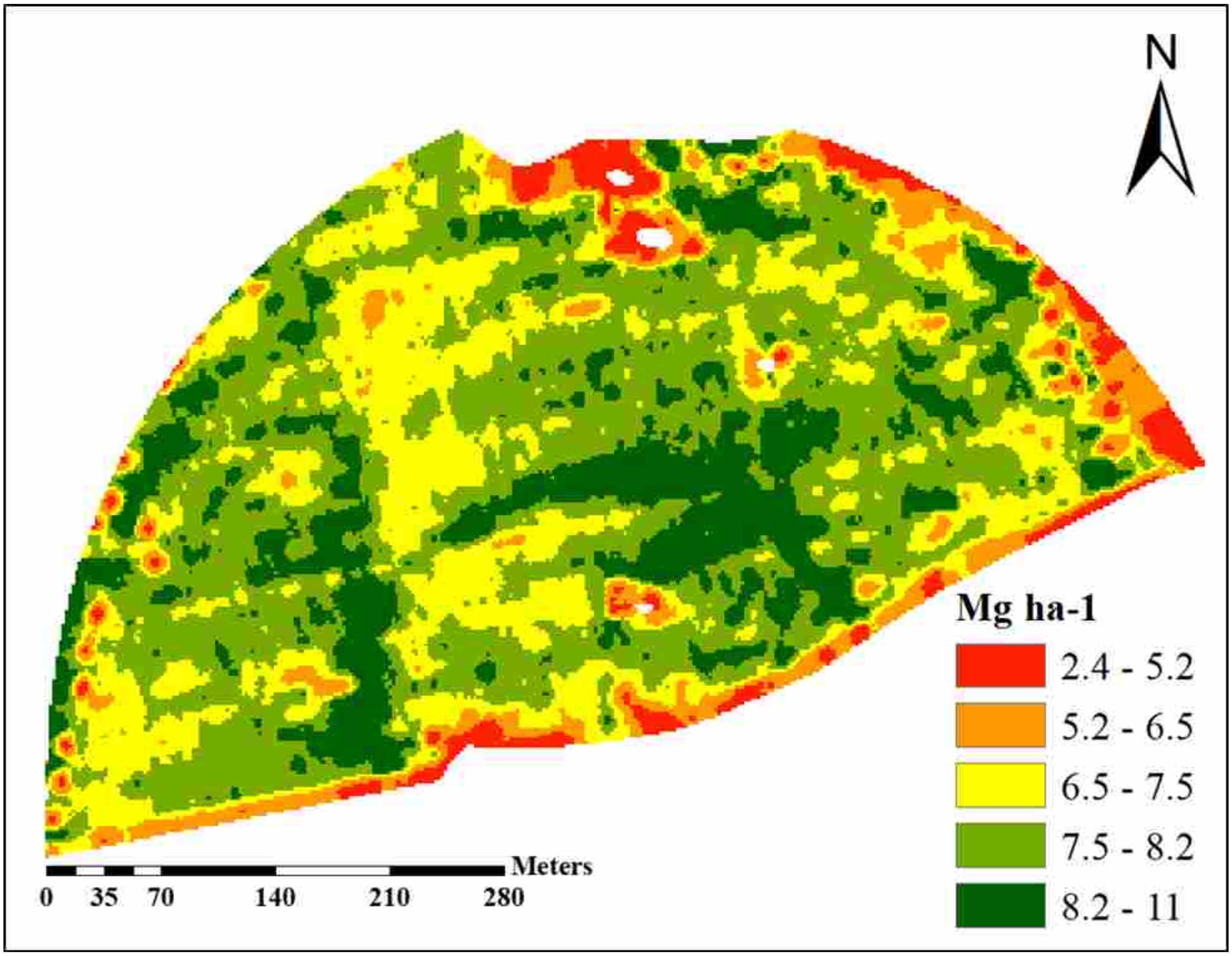



Figure 2-5. The spatial variation of measured winter wheat yield for the 2016 season.

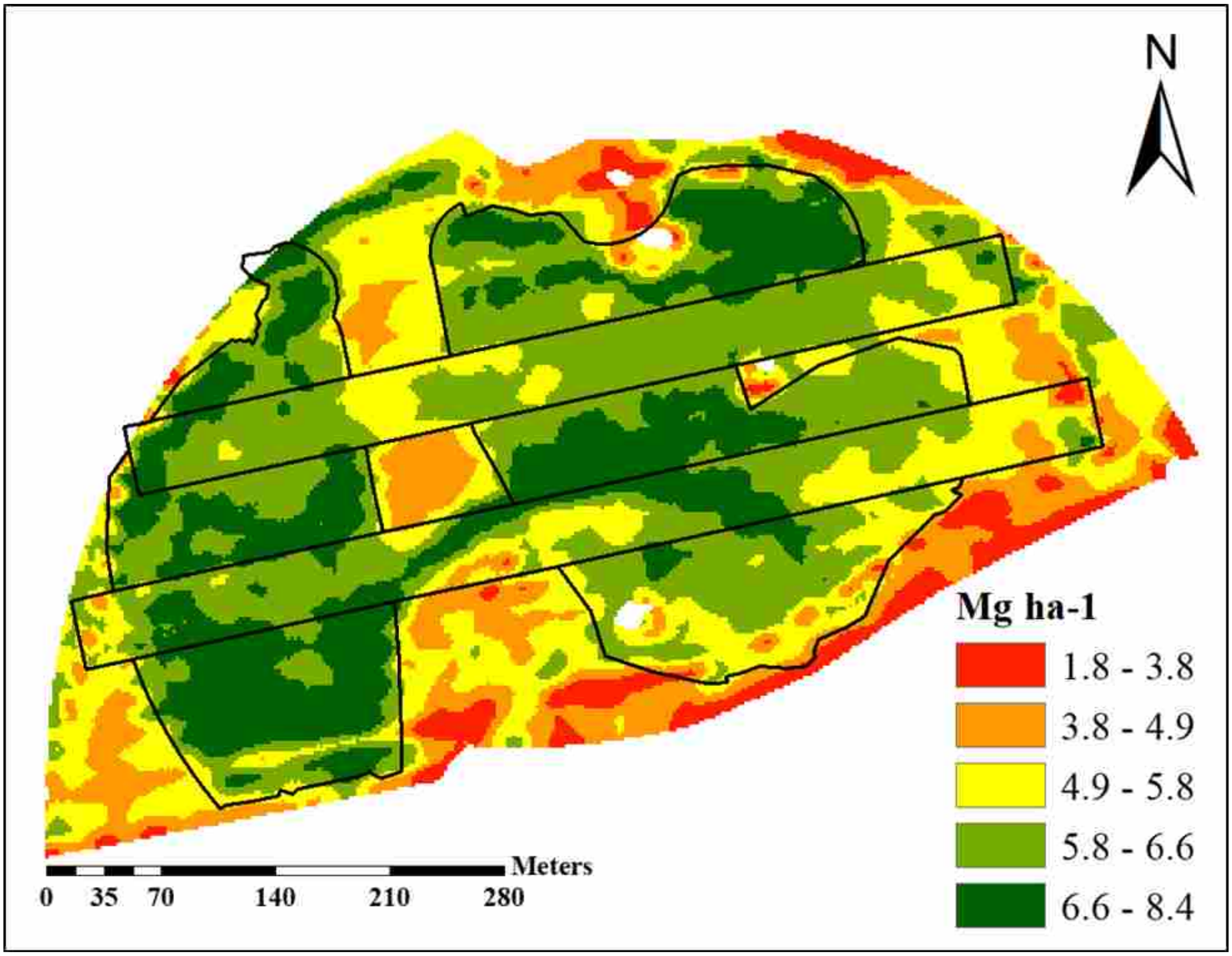
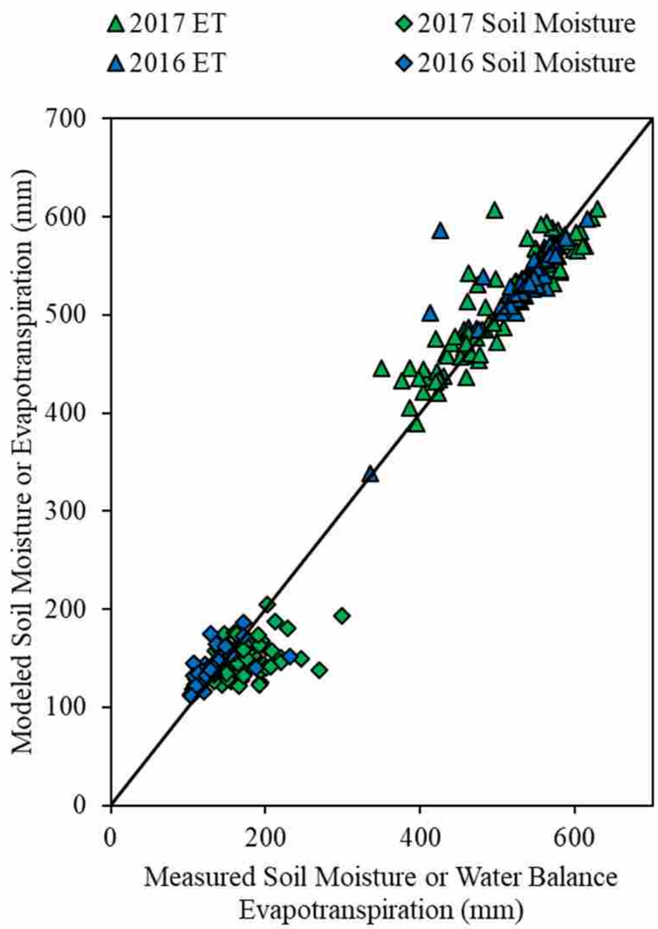



Figure 2-6. Spatial variation of winter wheat yield for the 2017 seasons with irrigation treatments (Figure 2) outlined in black.




Model fit statistics root mean square error (RMSE), relative error (RE), and normalize objective function (NOF).

| **Year** | **RE %** | **NOF** | **RMSE mm** |
|---|---|---|---|
| **Seasonal Evapotranspiration** | | | |
| 2016 | 0.1% | 0.10 | 53 |
| 2017 | 2.4% | 0.18 | 91 |
| Mean | 1.3% | 0.14 | 73 |
| **Soil Moisture at Harvest** | | | |
| 2016 | 8% | 0.2 | 27 |
| 2017 | -13% | 0.8 | 132 |
| Mean | -5% | 0.5 | 81 |

Figure 2-7. Modeled soil moisture for the fall sample dates in both 2016 and 2017 versus the measured soil moisture for both years and modeled total seasonal ET versus the water balance calculated ET. Model fit statistics include relative error (RE), normalized objective function (NOF), and root mean square error (RMSE).

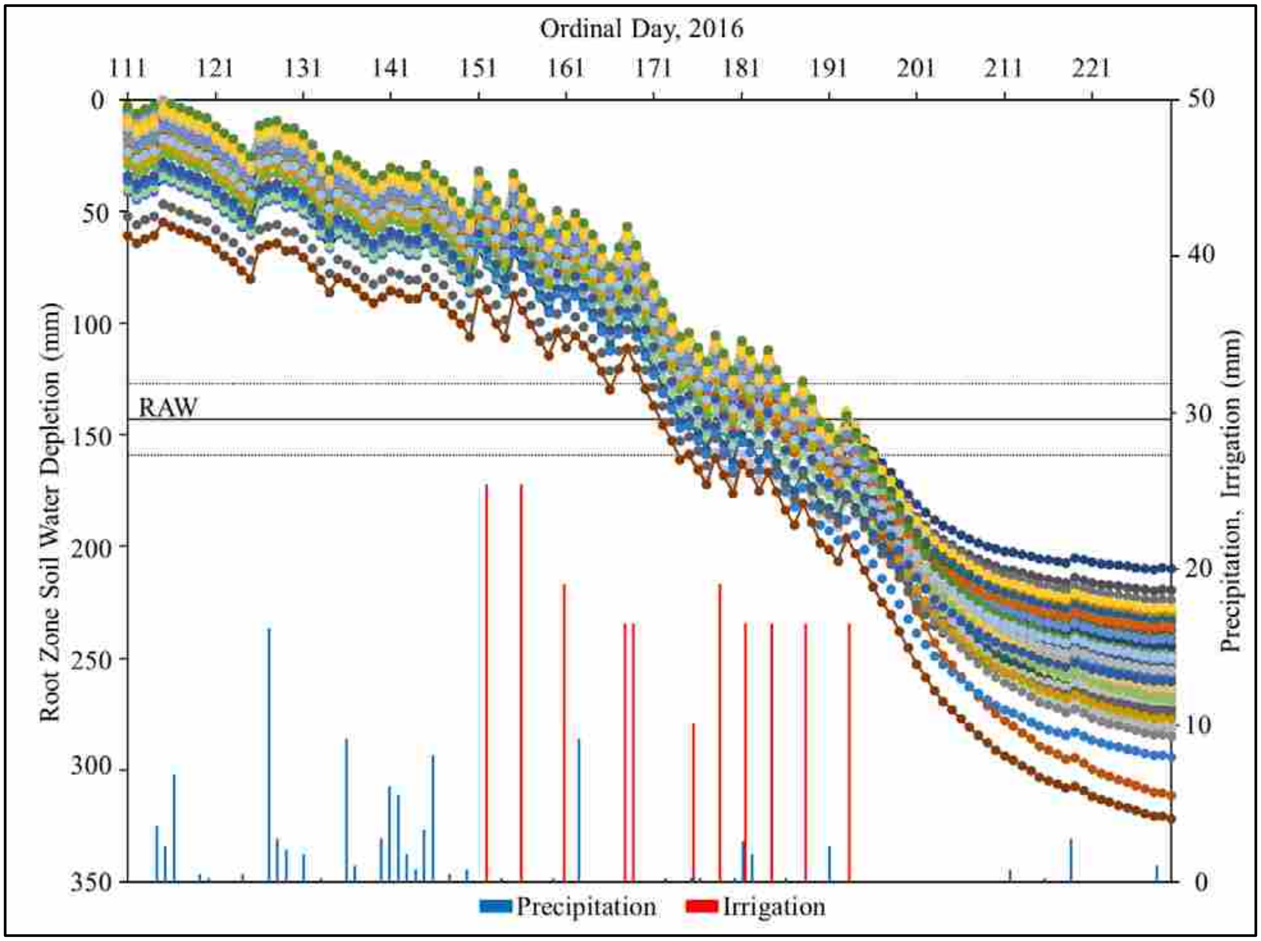



Figure 2-8. Modeled root soil moisture depletion for 85 spatially variable points beginning at spring green up and ending at harvest under uniform irrigation in 2016. Rain and irrigation events are identified on the second axis on their respective d. Field average readily available water (RAW) and one standard deviation above and below the mean are identified with dashed lines. The figure illustrates that there is significant spatial variation in when soil water falls below RAW, which translates to spatial variation in crop water stress.

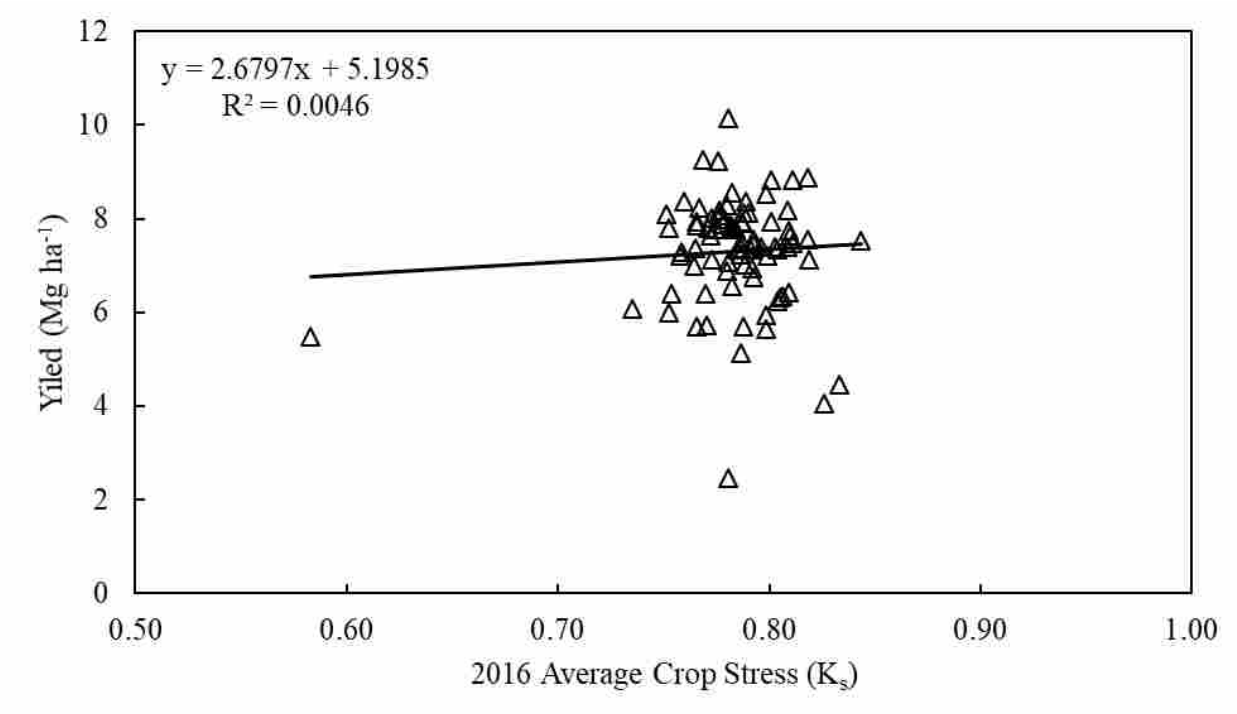



Figure 2-9. Linear fit for modelled average crop stress (Ks) and winter wheat yield for the 2016 season. Linear fit not statistically significant ($p$-value = 0.64)

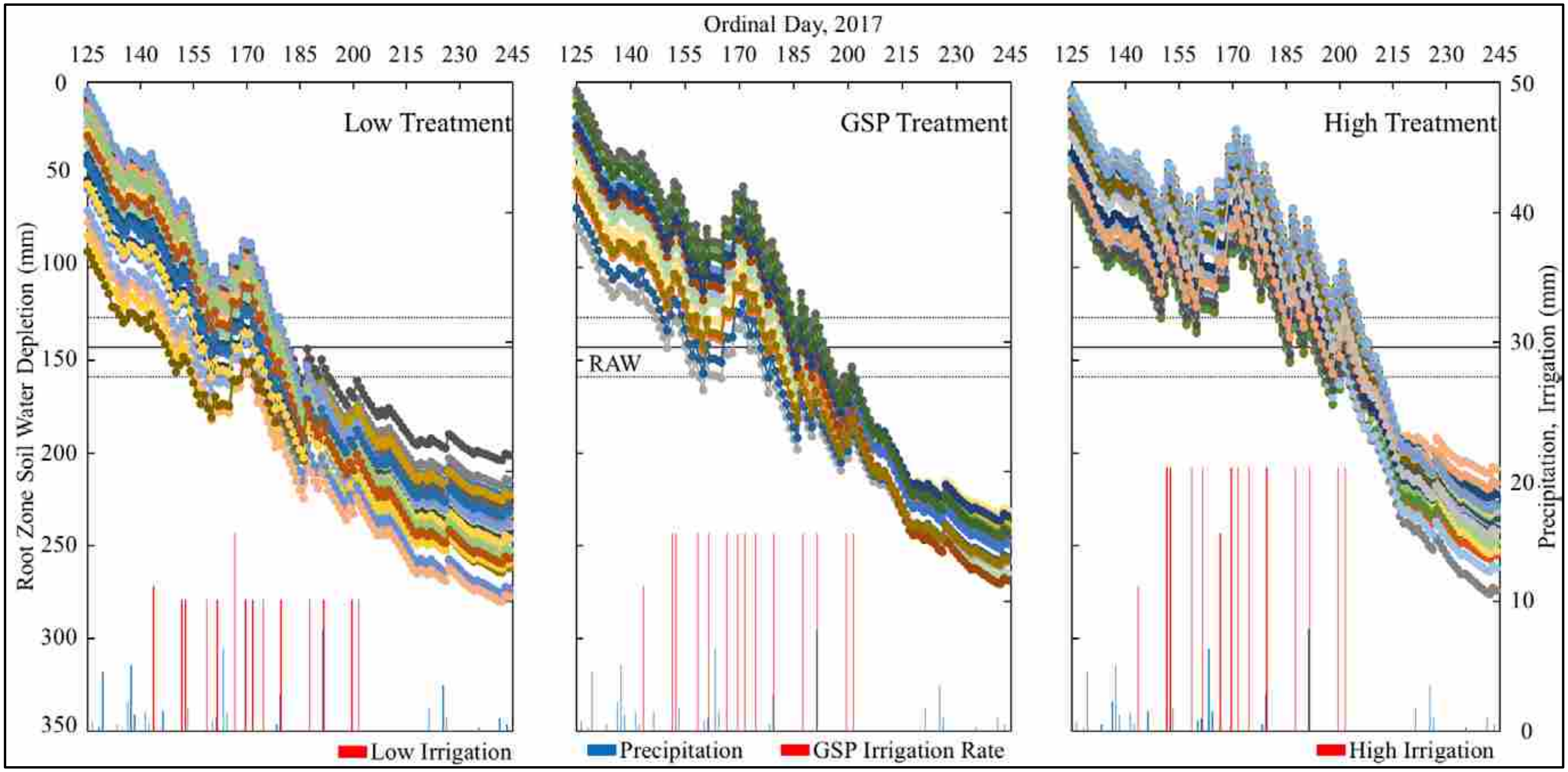



Figure 2-10. Modeled root soil moisture depletion for 90 spatial points beginning at wheat spring green up and ending at harvest. Each graph represents the irrigation treatment that the respective points received with rain and irrigation rate identified on the secondary y-axis. Field average readily available water (RAW) identified with one standard deviation from the mean identified with dashed lines, when points fall below their respective RAW during growth or maturity the crop is stressed and yield is reduced.

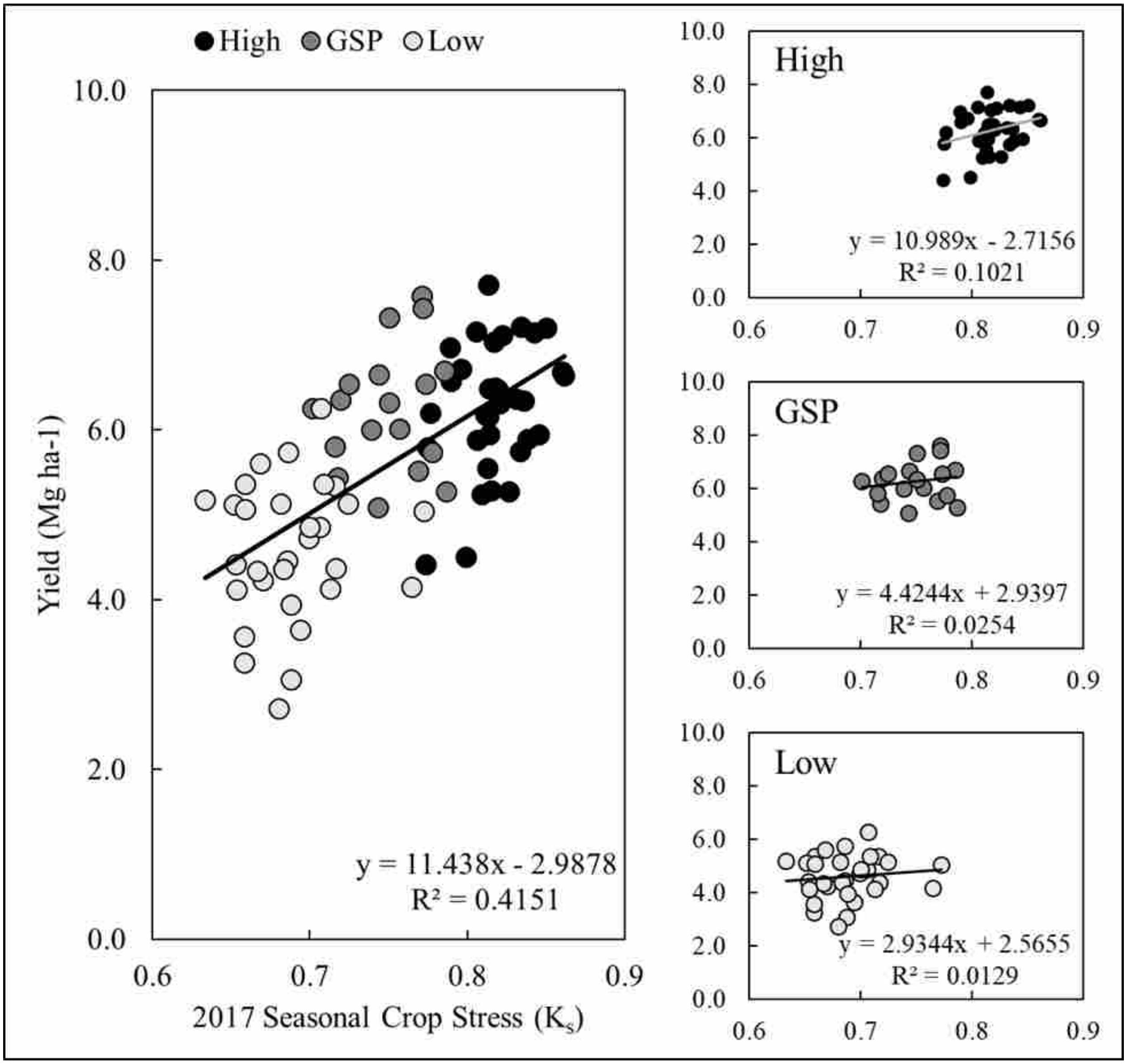



Figure 2-11. Linear fit for seasonal modeled crop stress coefficients ($K_s$) and yield for the 2017 growing season and for irrigation treatments. The 2017 seasonal average crop stress was statistically significant across all points for the 2017 season (*p*-value< 0.001) but within treatment variation of crop stress and yield was not statistically significant, meaning statistical significance is from irrigation treatments.

TABLES

Table 2-1. Field average soil test results 0-30 cm depth. This sampling depth is typical where the topsoil is mixed every 3 years from potato harvest.

| Phosphorus | Potassium | Nitrogen | Organic Matter | $CaCO_3$ | Clay | Silt | Sand | Texture | pH |
|---|---|---|---|---|---|---|---|---|---|
| ---------- ppm ---------- | | ---------------------------------------- % ---------------------------------------- | | | | | | | |
| 30 | 234 | 0.13 | 1.7 | 2.8 | 34 | 58 | 8 | Silty Clay Loam | 7.6 |

Table 2-2. Seasonal data for the two study years and irrigation treatments in 2017. Letters signify statistical differences at $p < 0.05$

| Season | Precipitation | Irrigation | ET | Yield |
|---|---|---|---|---|
| | --------------------cm-------------------- | | | Mg $ha^{-1}$ |
| 2016 | 10 | 20 | 53 | 7.5 |
| 2017 | 9 | 23 | 50 | 5.8 |
| | **2017 Irrigation Treatments** | | | |
| Low | | 16 | 44 | 4.9a |
| GSP | | 23 | 52 | 6.0b |
| High | | 30 | 57 | 6.4c |

Table 2-3. Regression analysis of year and total plant available soil water (SWHC) in predicting yield for the 2016 and 2017 seasons. Statistical significance marked with asterisks where *p*-value < 0.05

| Variable | Estimate | Standard Error | p-value |
|---|---|---|---|
| Intercept | 6.01645 | 0.75187 | < 0.0001* |
| Year[2016] | 0.89451 | 0.08865 | < 0.0001* |
| SWHC (mm) | 0.01532 | 0.28942 | 0.5973 |

Table 2-4. Regression analysis of 2017 irrigation treatments, average crop stress, and total plant available water in predicting yield. Asterisk signifies statistical significance where $p < 0.05$

| **Source** | **Sum of Squares** | **p-value** |
|---|---|---|
| Irrigation Treatments | 19.591987 | <0.0001* |
| Average Ks | 0.958153 | 0.2406 |
| SWHC (mm) | 16.69818 | 0.1227 |