2021-03-01

Spatiotemporal Analysis of Variability in Soil Volumetric Water Content and Spatial Statistical Methods for Management Zone Delineation for Variable Rate Irrigation

Isak Lars Larsen
Brigham Young University

Spatiotemporal Analysis of Variability in Soil Volumetric Water Content and Spatial Statistical Methods for Management Zone Delineation for Variable Rate Irrigation

Isak Lars Larsen

A thesis submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Master of Science

Neil Hansen, Chair
Bryan Hopkins
Tom Smith

Department of Plant and Wildlife Sciences

Brigham Young University

ABSTRACT

Spatiotemporal Analysis of Variability in Soil Volumetric Water Content and Spatial Statistical Methods for Management Zone Delineation for Variable Rate Irrigation

Isak Lars Larsen
Department of Plant and Wildlife Sciences, BYU
Master of Science

Irrigated agriculture is the largest user of freshwater in a world experiencing increased water scarcity and water demands. Variable rate irrigation (VRI) aims to use water efficiently in crop production, resulting in good yields and water conservation. With VRI, the grower is able to employ custom irrigation rates for different parts of a field. Adoption of VRI has been limited due to the complexity of matching irrigation to spatiotemporal crop water needs and the cost/benefit economics of VRI equipment. The goal of this study was to quantify spatiotemporal variability of VWC in a field that has uniform soil type and discuss the driving factors that contribute to that variability. Soil samples were acquired at 66 and 87 locations during the 2019 growing season at two study sites. Soil samples from 32 and 48 locations within each study site were selected to be analyzed for soil texture properties. The USGS Web Soil Survey was also referenced. Both, the USGS data and the data collected for this project showed very uniform soils across both fields. The objectives of this study were i) to show variability of VWC within fields that contain uniform soil texture using univariate Local Moran's I (LMI) and ii) to compare static VRI zones based on spatial patterns of readily available field data that might serve as surrogates for VRI zones created from measured variation of soil volumetric water content (VWC). Management zones created using readily available field data had reasonable correlations with VWC. In both study sites, elevation was found to be the best variable for delineating VRI zones that imitate measured VWC.

Keywords: crop water productivity, evapotranspiration, soil moisture, soil water holding capacity, variable rate irrigation, volumetric water content, VRI zone delineation

ACKNOWLEDGEMENTS

I would like to express my gratitude for my family's support as I have pursued an education. My mother and father taught me how to work hard and to push myself beyond the expectations of those around me. I have enjoyed extraordinary opportunities in my life thanks to the way they raised me.

I would like to thank my committee for their advisement throughout my research and personal mentorship. Each committee member has been a great example of how to balance professional success with family and hobbies. I want to thank Dr. Hopkins for lending his knowledge of agriculture whenever needed and also Dr. Smith for helping me develop my writing skills and keep my focus on my long-term goals. I would like to specifically thank Dr. Hansen for his animated words of encouragement throughout my graduate studies. He reached out to me before I even started the program. I will be forever grateful for that.

This project required many individuals' hard work, and I would like to thank the many students, teachers and working professionals who helped along the way. I want to give a special thanks to Dr. Ruth Kerry for the many hours spent teaching me one on one.

Finally, I give the utmost thanks to Ryan Christensen and BYU Idaho for providing the field sites equipped with variable-rate irrigation equipment necessary for this project's success. My hope is that my research results will assist them and others with their future irrigation management decisions.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Spatiotemporal Variability of Soil Volumetric Water Content in Texturally Uniform Fields

Isak L. Larsen[a], Ruth Kerry[b], Bryan G. Hopkins[a], Matthew Heaton[c],
Tom Smith[a], Neil C. Hansen[a]
[a]Department of Plant and Wildlife Sciences, Brigham Young University, Provo, UT
[b]Department of Geography, Brigham Young University, Provo, UT
[c]Department of Statistics, Brigham Young University, Provo, UT

ABSTRACT

Irrigated agriculture is the largest user of freshwater in a world experiencing increased water scarcity and water demands. Variable rate irrigation (VRI) aims to use water efficiently in crop production, resulting in good yields and water conservation. Adoption of VRI has been limited due to the complexity of matching irrigation to spatiotemporal crop water needs and the cost/benefit economics of VRI equipment. The objective of this study was (i) to examine the spatial variability of soil texture in two wheat fields and (ii) to investigate the spatiotemporal variability of VWC in those fields. Soil samples were acquired at 66 and 87 locations during the 2019 growing season at the two study sites. Pearson's correlation coefficients as well as univariate Local Moran's I (LMI) were used to study the VWC data. Soil samples from 32 and 48 locations within each study site were selected to be analyzed for soil texture properties. The USGS Web Soil Survey was also used for reference. Both, the USGS data and the data collected for this project showed very uniform soils across both fields.

INTRODUCTION

Irrigated agriculture is the largest global consumer of freshwater. As demands for freshwater increases worldwide, irrigation water use efficiency must improve in order to sustain agricultural production. Many irrigated farms today use "linear-move" or, more commonly, "center-pivot" overhead sprinkler irrigation systems to achieve mostly uniform irrigation rates across the field. A shortcoming of uniform irrigation is that it does not address spatial variation of soil properties and crop water requirements within fields, which can result in over-irrigation or under-irrigation in many parts of each field. Water requirements within fields vary as a function of topography and soil properties. Variable rate irrigation (VRI) is emerging as an approach to achieve precision water management by addressing within-field variation (King et al., 1995; O'Shaughnessy et al., 2019; Svedin et al., 2018).

Generally, the two types of VRI are speed control and zone control (O'Shaughnessy et al., 2019). Speed control VRI is limited to wedge- or rectangle-shaped zones for center-pivot or linear-move systems, respectively. These zones are created by changing the travel speed of the irrigation system. Zone control VRI systems have greater zone formation flexibility as they allow differing irrigation rates by regulating nozzles variably, resulting in management zones that can take almost any shape. For the remainder of this paper, use of the term VRI refers to zone control VRI systems. Despite over 26 years of research and more than 17 years of public availability, commercial adoption of VRI has been minimal King et al. 1995; O'Shaughnessy et al. 2019). However, increased availability of VRI systems, drought, and scarcity of freshwater have continued to drive interest and development of VRI (O'Shaughnessy et al. 2019).

VRI is often perceived as only being relevant in fields with high topographic variability, but soil properties can also impact patterns of VWC. Hawley et al. (1983) studied the interactions between different field characteristics with surface VWC and found topography to be the most influential factor in determining the spatial distribution of VWC. It was concluded that for many purposes, topography can be the only necessary variable for modeling spatial variability of

VWC, and that minor variations in soil properties were typically inconsequential in affecting VWC (Hawley et al., 1983). However, several studies have shown that factors other than topography can cause significant spatial variability in VWC. Baroni et al. (2013) found that spatial variability of VWC was affected by the variation of soil texture in wet conditions, but in dry conditions spatial variation of VWC was affected more by interactions with vegetation. Longchamps et al. (2015) studied leveled fields and found statistically significant variation in soil water content over time, suggesting potential value of implementing VRI even in fields with minimal topographic variation. For leveled fields, they showed significant spatial variation in soil VWC and suggested that variation was connected to differences in soil texture.

While static management zones are typically used for precision nutrient management, some have suggested that VRI might require dynamic zones. O'Shaughnessy et al. (2015) created a spatiotemporal VRI prescription map using automatic plant feedback from thermal sensors mounted on the pivot arms. Their system successfully provided site specific irrigation rates throughout the growing season. However, automatic feedback systems are still in early development and may depend on the crop experiencing some stress in order to separate zones. While the complexities of dynamic VRI zones are being studied, development of simple approaches for static VRI zone delineation is still needed.

.This paper seeks to clarify the apparent discrepancy between Hawley et al. (1983) and Lonchchamps et al. (2015) with the intent to understand spatiotemporal variation of VWC as it relates to potential implementation of VRI. The objective was to describe the spatiotemporal variability of soil VWC for two irrigated wheat fields with relatively uniform soil texture but significant topographic variation. It was hypothesized that significant spatial variability of VWC will be observed and that patterns of VWC will be relatively stable over time and space.

MATERIALS AND METHODS

Study Locations

The study was conducted at two field locations, one near Grace, ID, USA (42.60904, -111.788; elevation 1687 m) and the other in Rexburg, ID, USA (43.800966, -111.790141; elevation 1509 m). The Grace field site (22 ha) grew seed potato (*Solanum tuberosum* L.) in 2018 and winter wheat (*Triticum* spp.) in 2019-2020. The Rexburg study field (13 ha) produced alfalfa (Medicago sativa L.) from 2013-2017, and spring wheat (*Triticum* aestivum spp.) from 2018-2020. The Grace site contains areas, totaling 0.3 ha, of shallow and emerged basalt bedrock that are not farmed.

Average annual precipitation in Grace is 392 mm with most of the precipitation occurring during the cold months and minimal amounts during the summer. A typical annual growing season comprises of 80-110 frost-free days. Average annual precipitation in Rexburg is 393 mm with the majority of the precipitation typically falling as snow in the spring and winter months. . A typical annual growing season comprises of 80 to 100 frost-free days.

Irrigation was applied at both locations with a center-pivot sprinkler system with 5 m nozzle spacing and equipped with VRI (GrowSmart Precision VRI, Lindsay Zimmatic, Omaha, NE, USA). In Grace, planting occurred on September 20, 2018 (winter wheat is planted in the fall) and harvest took place on September 5, 2019, with 17 irrigation events. In Rexburg, planting occurred on April 5, 2019 and harvest took place on August 18, 2019, with 15 irrigations events.

Soil Sampling and Analysis

A hand-held, gas-powered hammer probe (AMS, Inc., American Falls, ID USA) and a trailer mounted hydraulic probe (Giddings Machine Company, Inc., Windsor, CO, USA) were utilized to take soil samples in Grace on April 23, May 30, June 25, and September 5 and in Rexburg on April 29, May 31, June 25, and August 29. Samples were collected on a nested grid with sufficient samples to compute reliable variograms for kriging (102 samples locations in Grace and 66 in Rexburg, Figure 1-1AB).

Soil cores were collected at four depths of 1.2 m to capture the distribution of moisture throughout the soil profile and to cover the entire root zone. Soil samples were stored in sealed plastic bags and placed on ice in insulated containers for transport to the laboratory. Soil wet weights were obtained prior to transferring to paper bags and drying in a forced air oven at 105^{o}C for 24 hours to determine dry weights. Soil VWC, averaged over all depths, was then calculated and kriged to a uniform five meter grid in preparation for subsequent analysis. After analysis for VWC was completed, 48 and 32 samples from the 0-0.3 m depth were taken at Grace and Rexburg respectively to be analyzed for soil texture by the hydrometer method (Miller et al., 1997)

Statistical Analysis

Correlation analysis was achieved using Pearson's correlation. Correlations were considered significant when $\alpha < 0.05$. Correlation analysis was used to determine whether spatial patterns of VWC were consistent over time. Univariate Local Moran's I (LMI) maps were produced for each sampling date in both fields to determine field areas with significant clustering of relatively high or low VWC ($\alpha < 0.05$). This analysis determined the extent of spatial autocorrelation.

Kriging, correlation analysis and univariate LMI were produced using SpaceStat (BioMedware, SpaceStat 4, Ann Arbor, MI, USA), and ArcGIS Pro (Release 10, Redlands, CA, USA). Soil texture results were plotted over univariate LMI maps to illustrate any apparent interactions between soil texture and VWC.

RESULTS

Soil Texture and Elevation

The objective of this study is to evaluate the spatiotemporal variation of VWC at field locations with relatively uniform soil texture and significant topographical variation. The USDA web soil survey classified the soil for nearly the entire field at Grace as Rexburg-Ririe complex with 1-4% slope and with a silt loam texture. Both Rexburg and Ririe soils are coarse-silty, mixed, super-active, frigid Calcic Haploxerolls derived from alluvial influenced loess (USDA et al., 2019). The soil at the Rexburg site was classified by the USDA with 55% of the site as a Pocatello Variant Silt Loam and the remaining 45% as a Ririe Silt Loam with 2-8% slopes. Pocatello and Ririe soils are coarse-silty, mixed, calcareous, frigid, Typic Xerorthents and coarse-silty, mixed, frigid, Calcic Haploxerolls (USDA et al., 2019).

In slight contrast with the USDA data (USDA et al., (2019), our analysis showed that the soil texture at the Grace location was silty clay loam (n = 48). Of the 48 samples, 45 were classified as silty clay loam texture, while the remaining three were classified as clay loam, silt loam, and silty clay (Figure 1-2A). All samples at Grace had an average of 31.5% clay (SD = 2.9), and an average of 9.3% sand (SD = 3.2). Average soil texture at the Rexburg location was classified as a sandy loam (n = 32). Of the 32 samples, 27 were classified as sandy loam texture, while the five remaining samples were classified as loam (Figure 1-2B). Among all Rexburg samples had an average of 8.4% clay (SD = 1.6), and an average of 58.6% sand (SD = 8.6). There is no obvious relationship of soil textural class and elevation for the Grace site (Figure 1-2A), however, in the Rexburg site, the five soil samples that were classified as loams, are all in the highest area of the field (Figure 1-2B). Measured soils' textural classes did not match the USDA classifications for either site, but textural class was mostly uniform for both field sites (Figure 1-3).

Detailed elevation maps were created for both the Grace and Rexburg locations (Figure 1-2). Elevation ranged from 1705 m to 1712 m at the Grace location, with seven m difference between lowest and highest areas of the field (Figure 1-2A). Field areas with relatively low elevations were found on the western one-third of the field and a small area at the eastern extreme. Field areas with relatively high elevations were found in the center one-third of the field. For the Rexburg location, elevation ranged from 1515 m to 1532 m, with a 17 m difference between lowest and highest elevation within the field (Figure 1-2B). The relatively high areas in the south-east of the field sloped down to the relatively low areas in the northwest of the field.

Spatial Variability of VWC

The kriged maps of VWC depict the spatial distribution of data as well as the range of values for each sample date (Figure 1-4). For the April sampling date in Grace (Figure 1-4A), the average VWC was 38.9 cm (R = 3.6 cm, SD = 0.74 cm). For the May sampling date (Figure 1-4B), the average VWC was 39.4 cm (R = 5.6 cm, SD = 1.0 cm). For the June sampling date (Figure 1-4C), the average VWC was 33.1 cm (R=3.9 cm, SD = 1.0 cm). For the September sampling date (Figure 1-4D), the average VWC was 21.2 cm (R = 3.6 cm, SD = 0.74 cm).

For the April sampling date in Rexburg (Figure 1-5A), the average VWC was 20.0 cm (R =10.4 cm, SD = 2.1 cm). For the May sampling date (Figure 1-5B), the average VWC was 21.4 cm (R = 10.5 cm, SD = 2.1 cm). For the June sampling date (Figure 1-5C), the average VWC was 20.0 cm (R = 8.2 cm, SD = 1.7 cm). For the September sampling date (Figure 1-5D), the average VWC was 7.6 cm (R = 10 cm, SD = 1.7 cm).

The univariate LMI maps of VWC for the Grace location (Figure 1-6) show distinct and significant ($p < 0.001$) patterns of variability of VWC for all four sampling dates. For the April sampling date (Figure 1-6A), 33% of the field area was clustered as relatively high VWC and 23% as relatively low VWC. For the May sampling date (Figure 1-6B), 26% of the field area was clustered as relatively high VWC and 24% as relatively low VWC. For the June sampling date (Figure 1-6C), the LMI map showed 34% of the field area was clustered as relatively high VWC and 35% as relatively low VWC. For the September sampling date (Figure 1-6D), 20% of the field area was clustered as relatively high VWC and 26% as relatively low VWC.

The univariate LMI maps of VWC for the Rexburg location (Figure 1-7) also showed distinct and significant ($p < 0.001$) patterns of variability of VWC for all four sampling dates. For the April sampling date (Figure 1-7A), 23% of the field area was clustered as relatively high VWC and 26% as relatively low VWC. For the May sampling date (Figure 1-7B), 30% of the field area was clustered as relatively high VWC and 22% as relatively low VWC. For the June sampling date (Figure 1-7C), the LMI map showed 24% of the field area was clustered as relatively high VWC and 29% as relatively low VWC. For the August sampling date (Figure 1-7D), 30% of the field area was clustered as relatively high VWC and 25% as relatively low VWC.

Temporal Variability of VWC

To evaluate whether or not the spatial patterns of VWC were consistent over time, a spatial regression was done to compare VWC patterns among dates (Table 1-1). For the Grace location, all the correlation coefficients were significant ($p < 0.001$). The Pearson correlation coefficients for April VWC were 0.704 with May, 0.618 with June, and -0.254 with September. The Pearson correlation coefficient for May VWC and June VWC had was 0.542. The September VWC correlations coefficients with VWC from April, May, and June were -0.254, -0.234, and -0.152, respectively.

The correlation matrix for Rexburg showed April correlating even higher than Grace with the VWC from subsequent sampling dates (0.861, 0.894, and 0.546 respectively). May VWC showed slightly higher correlation with June VWC (0.895) than with August VWC (.0.657). June VWC showed the lowest correlation coefficient with the August VWC (0.604). Correlations were lowest between both sites for the latest sampling date (September 5th in Grace). This is also apparent in the univariate LMI maps, as the September map exhibits patterns that are noticeably different when compared with the first three sample dates.

DISCUSSION

Spatial Variation of VWC

Understanding the spatial variation of VWC within irrigated fields is critical for successful implementation of VRI. Some have argued that variation of VWC is controlled by topography and that variation of soil properties has a minor effect (Hawley et al., 1983). Others have shown significant variation in VWC especially in leveled fields (Longchamps et al., 2015). In this study, we evaluated variation of VWC in irrigated wheat fields with little variation in soil textural class.

Our results showed significant clustering of VWC during the irrigation season over soils with minimal spatial variation in soil textural classes. Differences in elevation explained much, but not all, of the variation in VWC and topography had a stronger effect at the Rexburg location, which had a more coarse soil texture. Similar to results from Hawley et al. (1983), minor differences in soil textural class appeared to have an inconsequential effect on the distribution of VWC in both sites. It is likely that, as Hawley et al. (1983) concluded, the VWC is most influenced by topography in these fields. Baroni et al. (2013) found that patterns of VWC variability are affected by the distribution of soil texture more in wet conditions, however effects of the patterns of soil textural class on VWC were negligible in both Grace and in Rexburg. Longchamps et al. (2015) found that the variation in soil VWC was linked to soil texture variability, but effects from those features of soil texture may have had increased influence due to the uniform topography in the fields in that study.

The results of both the univariate LMI maps, and the correlation matrix supported the findings of Longchamps et al. (2015) that found there to be stability in the spatial patterns of soil VWC, which would justify the use of static VRI management zones. Patterns of VWC did however seem to change more drastically under the extremely dry conditions exhibited post-harvest (after the intentional dry-down period that prepares the wheat crop for harvest). This result is less important, as the crop is not affected by soil VWC conditions post-harvest.

Temporal Variability of VWC

While static management zones are typically used for precision nutrient management, some have suggested that VRI might require dynamic zones. O'Shaughnessy et al. (2015) looked at the viability of using dynamic VRI management zones, and this study shows that patterns of VWC do change over the course of a growing season, however it is unclear how to accurately modify management zones mid-season, and if it would be cost-effective to do so. More research in this area could be advantageous. While the complexities of dynamic VRI zones are being studied, results of this study suggest that using static VRI zones could be an effective approach in fields similar to the ones studied here. Fields that exhibit more complex variation may produce different results.

CONCLUSION

Characteristics conducive to the use of VRI were discovered in this study. Univariate LMI maps of VWC and Global LMI numbers revealed significant variation of VWC in texturally uniform fields. Additionally, through correlation matrices the patterns of spatial variability of VWC were shown to be relatively stable throughout the season suggesting that static VRI zones could be effective in irrigation management. Also, significant discrepancies between USDA-derived soil data and these study results should deter growers from relying solely on USDA soil data/maps (USDA et al., 2019).

LITERATURE CITED

Baroni, G., Ortuani, B., Facchi, A., & Gandolfi, C. (2013). The role of vegetation and soil properties on the spatio-temporal variability of the surface soil moisture in a maize-cropped field. *Journal of Hydrology (Amsterdam), 489*, 148-159. https://doi.org/10.1016/j.jhydrol.2013.03.007

Hawley, M. E., Jackson, T. J., & McCuen, R. H. (1983). Surface soil moisture variation on small agricultural watersheds. *Journal of Hydrology (Amsterdam), 62*(1), 179-200. https://doi.org/10.1016/0022-1694(83)90102-6

King, B. A., Brady, R. A., McCann, I. R., & Stark, J. C. (1995). Variable rate water application through sprinkler irrigation. *Site-Specific Management for Agricultural Systems, 33*, 485-493.

Longchamps, L., Khosla, R., Reich, R., & Gui, D. W. (2015). Spatial and temporal variability of soil water content in leveled fields. *Soil Science Society of America Journal, 79*(5), 1446-1454. https://doi.org/10.2136/sssaj2015.03.0098

Miller, R. O., Kotuby-Amacher, J., & Rodriguez, J. B. (1997). *Particle size analysis (hydrometer)* (4th ed.)

Nijbroek, R., Hoogenboom, G., & Jones, J. W. (2003). Optimizing irrigation management for a spatially variable soybean field. *Agricultural Systems, 76*(1), 359-377. https://doi.org/10.1016/S0308-521X(02)00127-0

O'Shaughnessy, S. A., Evett, S. R., & Colaizzi, P. D. (2015). Dynamic prescription maps for site-specific variable rate irrigation of cotton. *Agricultural Water Management, 159*, 123-138. https://doi.org/10.1016/j.agwat.2015.06.001

O'Shaughnessy, S. A., Evett, S. R., Colaizzi, P. D., Andrade, M. A., Marek, T. H., Heeren, D. M., Lamm, F. R., & LaRue, J. L. (2019). Identifying advantages and disadvantages of variable rate irrigation: An updated review. *Applied Engineering in Agriculture, 35*(6), 837-852. https://doi.org/10.13031/aea.13128

Svedin, J. D. (2018). *Characterizing the Spatial Variation of Crop Water Productivity for Variable-Rate Irrigation Management*. MSc thesis, Brigham Young University.

USDA. (2019). *Web soil survey.https://websoilsurvey.sc.egov.usda.gov/App/* WebSoilSurvey.aspx

FIGURES

Figure 1-1AB. Soil volumetric water content (VWC) sample locations overlain on aerial imagery of field sites near Grace (1A) and Rexburg (1B).

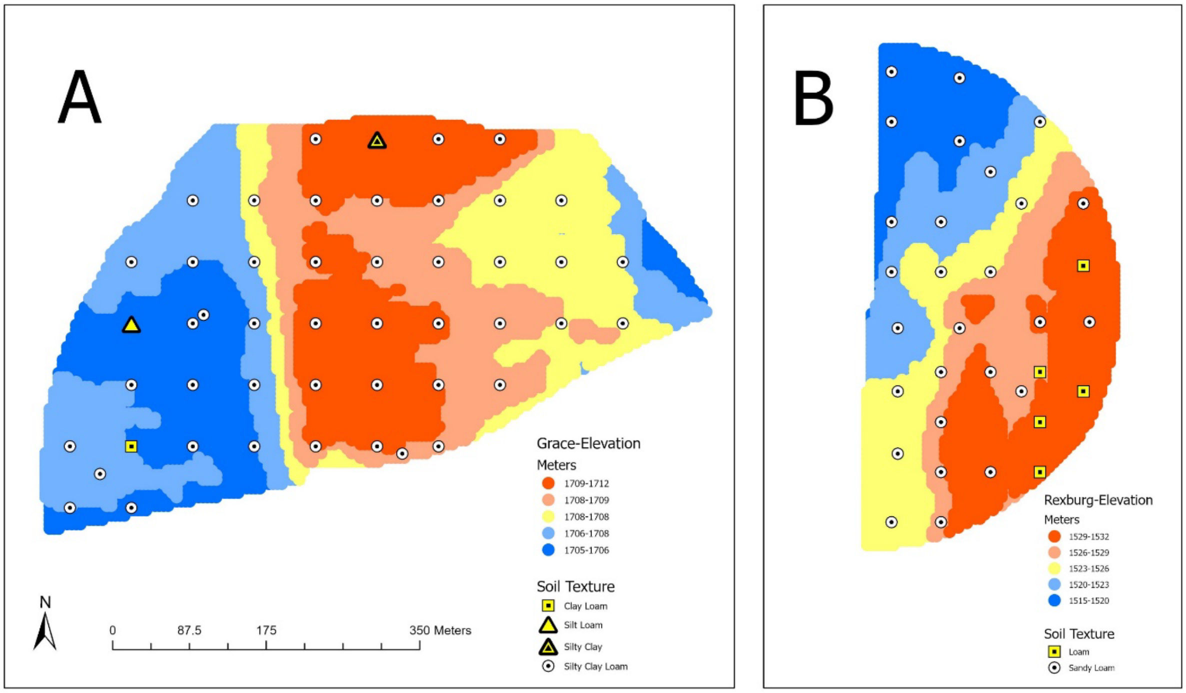


Figure 1-2AB. Soil texture sample locations overlain on the elevation maps for field sites near Grace (2A) and Rexburg (2B).

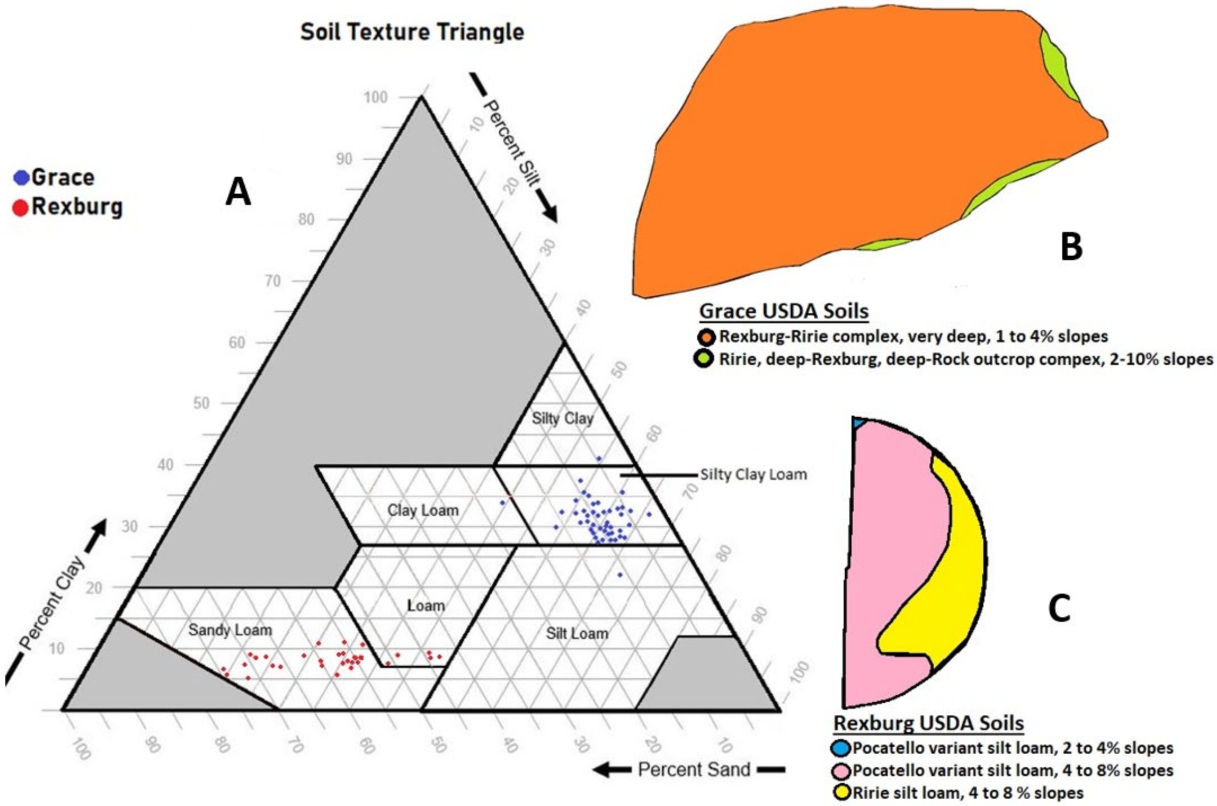


Figure 1-3AC. Soil texture triangle (A) showing the various soil texture readings for sample sites at Grace and Rexburg, ID, USA. USDA soil taxonomic maps and soil descriptions for Grace (B) and Rexburg (C) field sites (USDA et al., 2019).

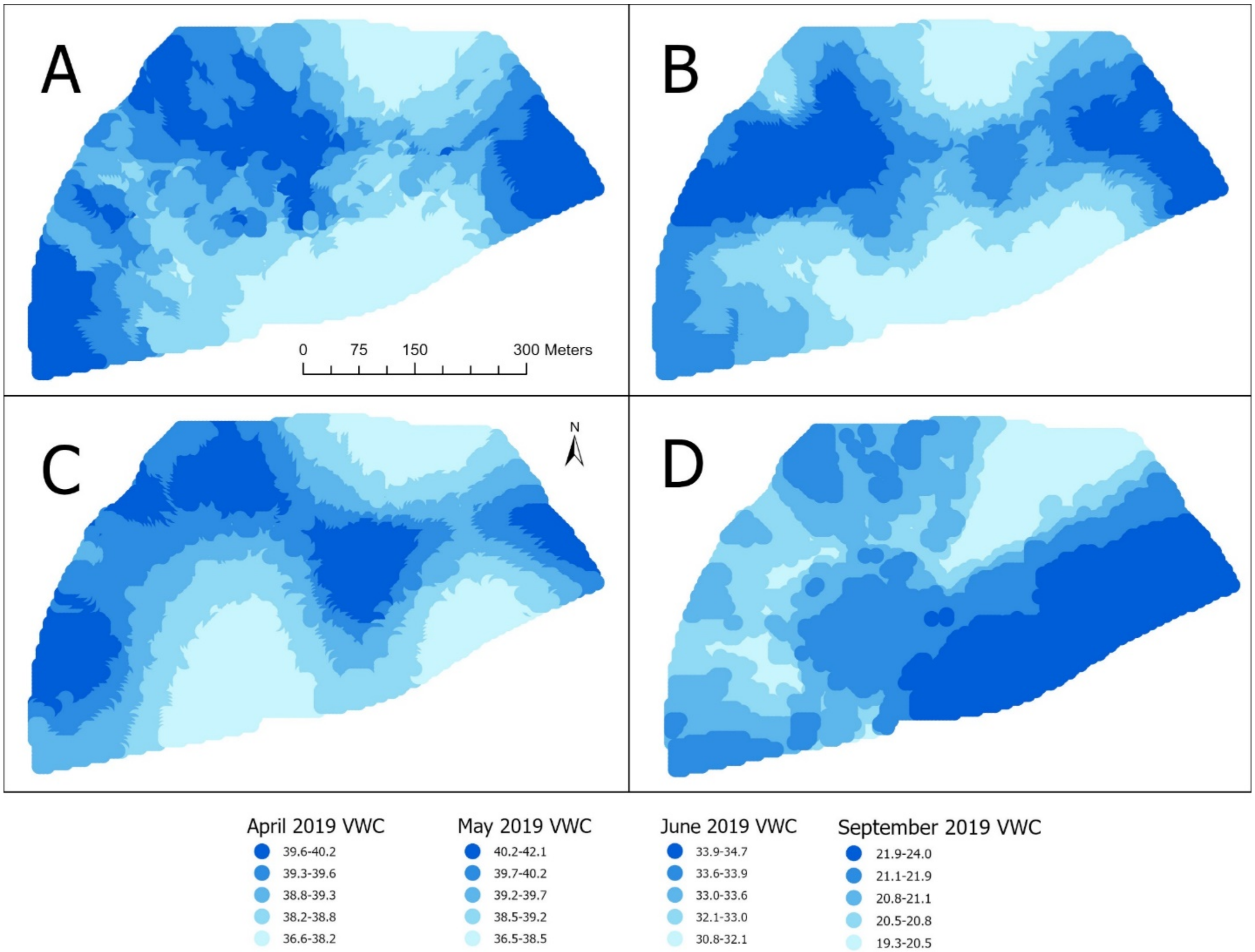


Figure 1-4AD. Kriged volumetric water content (VWC) maps for 2019 field site near Grace, ID, USA: April 23rd, 2019 (4A), May 30th, 2019 (4B), June 19th, 2019 (4C), September 5th, 2019 (4D).

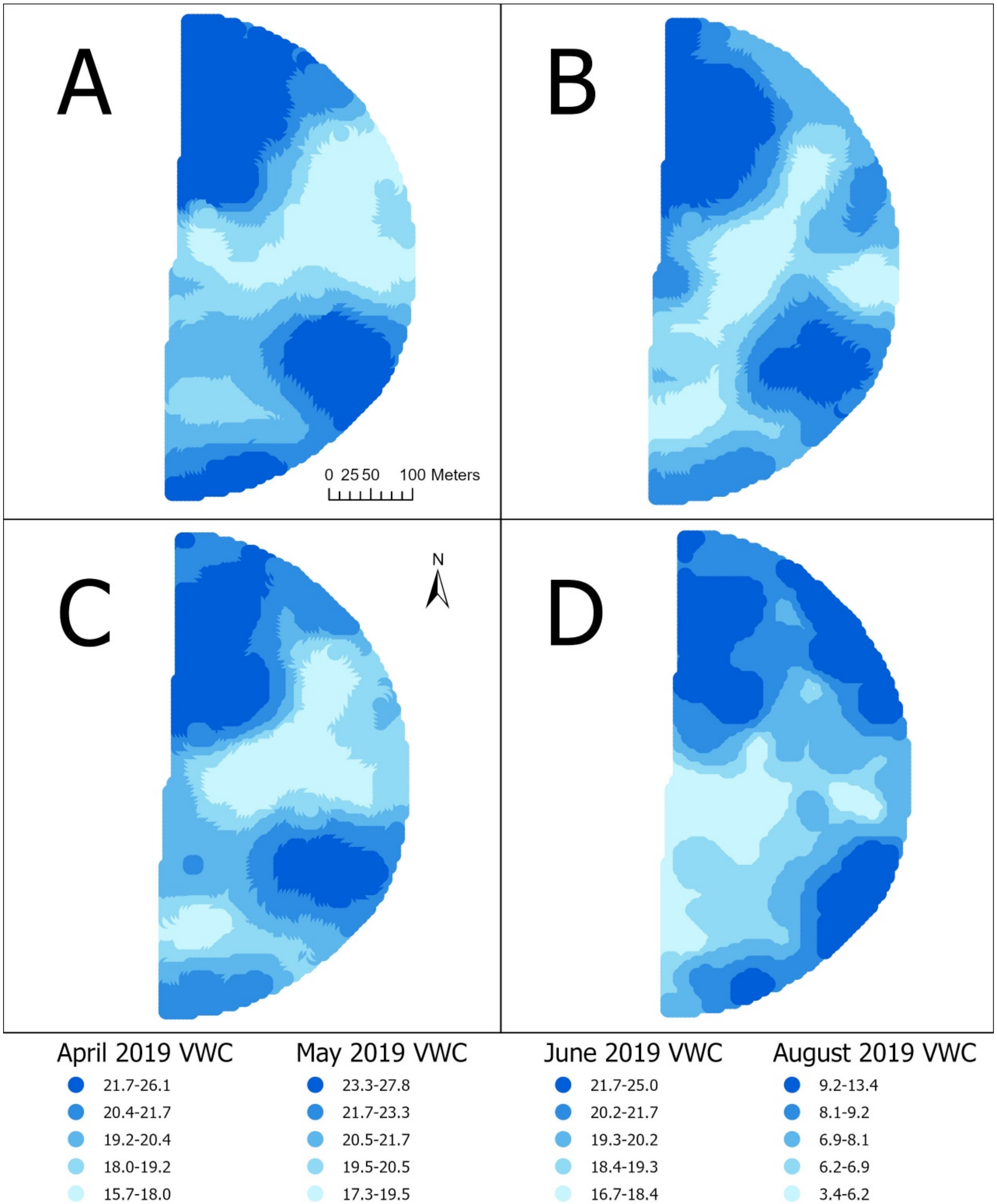


Figure 1-5AD. Kriged volumetric water content (VWC) maps for 2019 field site in Rexburg, ID, USA: April 29th, 2019 (5A), May 31st, 2019 (5B), June 25th, 2019 (5C), August 29th, 2019 (5D).

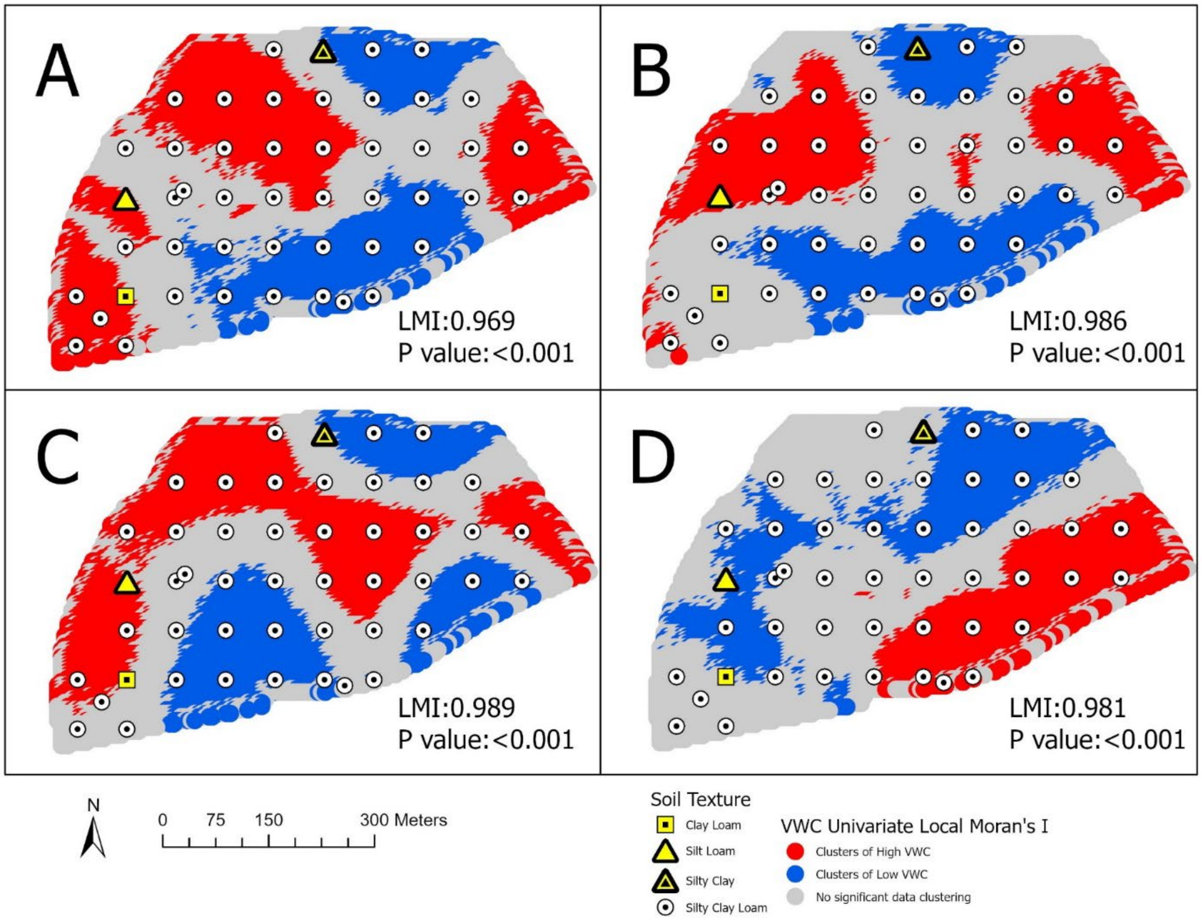


Figure 1-6AD. Univariate Local Moran's I (LMI) maps for four sample dates: April 23rd, 2019 (6A), May 30th, 2019 (6B), June 19th, 2019 (6C), September 5th, 2019 (6D). Soil Texture points overlay the maps.

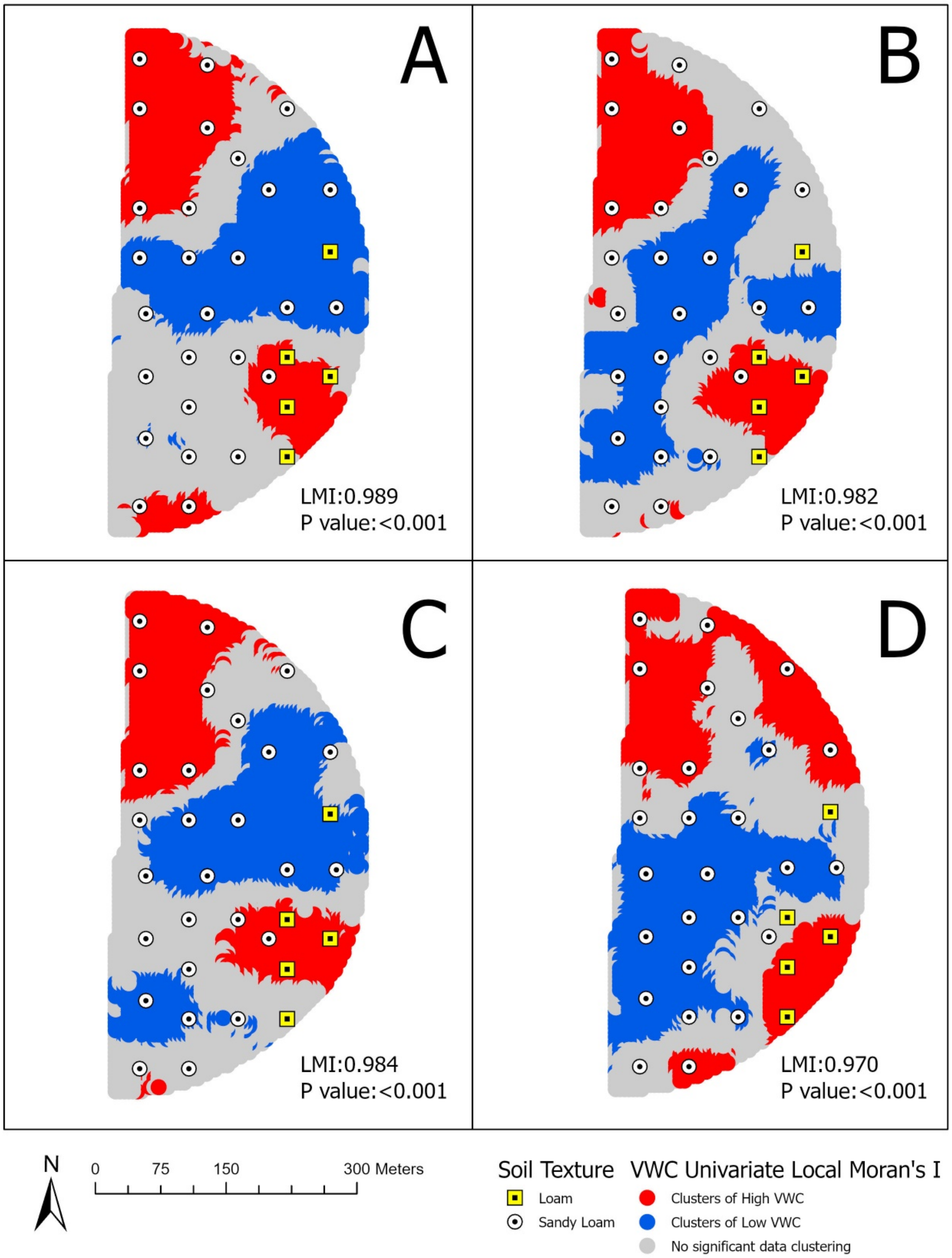


Figure 1-7AD. Univariate Local Moran's I (LMI) maps for four sample dates: April 29rd, 2019 (7A), May 31th, 2019 (7B), June 25th, 2019 (7C), August 29th, 2019 (7D). Soil Texture points overlay the maps.

TABLES

Table 1-1. Correlation Matrix displaying Pearson correlation coefficients to show relationships between VWC data from four different sampling dates for both the Grace location, and the Rexburg study location.

Grace VWC Pearson Coefficients	April 23	May 30	June 19	September 5
April 23 VWC	-	-	-	-
May 30 VWC	0.704**	-	-	-
June 19 VWC	0.618**	0.572**	-	-
September 5 VWC	-0.254**	-0.234**	-0.152**	-
Rexburg VWC Pearson Coefficients	April 29	May 31	June 25	August 29
April 29 VWC	-	-	-	-
May 31 VWC	0.861**	-	-	-
June 25 VWC	0.894**	0.895**	-	-
August 29 VWC	0.546**	0.657**	0.604**	-

** Correlation is significant at the 0.01 level (2-tailed).

CHAPTER 2

Management Zone Delineation for Variable Rate Irrigation Using Spatial Statistical Methods

Isak L. Larsen[a], Neil C. Hansen[a], Ruth Kerry[b], Bryan G. Hopkins[a]
Matthew Heaton[c], Tom Smith[a]
[a]Department of Plant and Wildlife Sciences, Brigham Young University, Provo, UT
[b]Department of Geography, Brigham Young University, Provo, UT
[c]Department of Statistics, Brigham Young University, Provo, UT
Master of Science

ABSTRACT

Irrigated agriculture is the largest user of freshwater in a world experiencing increased water scarcity and water demands. Variable rate irrigation (VRI) aims to use water efficiently in crop production, resulting in good yields and water conservation. VRI allows the grower to employ custom irrigation rates for different parts of a field. Adoption of VRI has been limited due to the complexity of matching irrigation to spatiotemporal crop water needs and the cost/benefit economics of VRI equipment. The objective of this study is to compare static VRI zones based on spatial patterns of readily available field data that might serve as surrogates for VRI zones created from measured variation of soil volumetric water content (VWC). Management zones created using readily available field data had reasonable correlations with VWC. In both study sites, elevation was found to be the best variable for delineating VRI zones that imitate measured VWC.

INTRODUCTION

Irrigated agriculture is the largest global consumer of freshwater. As demands for freshwater increases worldwide, irrigation water use efficiency must improve in order to sustain agricultural production. Many irrigated farms today use “linear-move” or, more commonly, “center-pivot” overhead sprinkler irrigation systems to achieve mostly uniform irrigation rates across the field. A shortcoming of uniform irrigation is that it does not address spatial variation of soil properties and crop water requirements within fields, which can result in over-irrigation or under-irrigation in many parts of each field. Water requirements within fields vary as a function of topography and soil properties. Variable rate irrigation (VRI) is emerging as an approach to achieve precision water management by addressing within-field variation (O'Shaughnessy et al. 2019).

Generally, the two types of VRI are speed control and zone control (O'Shaughnessy et al. 2019). Speed control VRI is limited to wedge- or rectangle-shaped zones for center-pivot or linear-move systems, respectively. These zones are created by changing the travel speed of the irrigation system. Zone control VRI systems have greater zone formation flexibility as they allow differing irrigation rates by regulating nozzles variably, resulting in management zones that can take almost any shape. For the remainder of this paper, use of the term VRI refers to zone control VRI systems. Despite over 26 years of research and more than 17 years of public availability, commercial adoption of VRI has been minimal (King et al., 1995; O'Shaughnessy et al., 2019). However, increased availability of VRI systems, drought, and scarcity of freshwater have continued to drive interest in and the development of VRI (O'Shaughnessy et al. 2019).

Research on the effectiveness of VRI has varied in method and results. Many studies comparing VRI and uniform irrigation have used water balance simulations to estimate potential water savings, yields, and economic returns. Ritchie et al. (1999), Nijbroek et al. (2003), Al-Kufaishi et al. (2006), DeJonge et al. (2007), Hedley, et al. (2009), and Daccache et al. (2015) all utilized crop simulation models to compare VRI with uniform irrigation and found that high VRI implementation costs and low commodity prices resulted in an economic loss. However, various model parameters could change the predicted economic costs and benefits of VRI, such as higher water costs, higher crop prices, and/or reduced equipment/implementation costs. For example, Nijbroek et al. (2003) used a ten-year low soybean price and concluded that VRI was not economical, but those conclusions would be different if a high price estimate were used. One study that demonstrated the benefits of VRI documented a four percent improvement in potato (*Solanum tuberosum* L.) yield in six of nine comparisons (King et al., 2006). In that study, total water application was the same between uniform irrigation and VRI, but the spatiotemporally variable patterns of water application resulted in VRI producing an average of \$159 ha^{-1} greater income based on improved tuber quality and price (King et al. 2006). Potato is the highest value and most widely grown vegetable crop and is relatively more valuable per unit of land than most grain crops, especially in "high-yield systems" (Hopkins et al., 2019). Thus, VRI would likely be more profitable in high value fruit and vegetable cropping systems than with relatively lower value grain and forage crops. Nevertheless, grain crops are far more commonly grown (Hopkins et al., 2019) and finding profitable ways to enable water conservation in these cropping systems is important.

Successful VRI requires the implementation of management zones that reflect the spatial variability within each field. VRI is often perceived as only being relevant in fields with large amounts of topographic variability. However, Longchamps et al. (2015) studied a leveled field and found statistically significant variation in soil water content over time, suggesting that benefits from VRI may exist even in fields that appear topographically uniform. The most common parameter used in the creation of VRI management zones has been soil available water holding capacity (AWC) which is often estimated from apparent soil electrical conductivity (EC_a). Hedley et al. (2009) used AWC to delineate management zones for pasture, maize, and potato fields in New Zealand, and found that VRI reduced irrigation and drainage. King et al.

(2006) suggested that AWC may not be the best parameter to use for VRI zone creation because other factors affect yield and water use (O'Shaughnessy et al., 2019). This was supported by others who found that AWC and evapotranspiration alone were poor indicators of good irrigation zones for VRI in winter wheat cropping systems (Svedin et al., 2018).

More research has been done for delineating within-field management zones for precision nutrient management than for VRI. Some common methods have utilized remotely sensed data (either satellite or from an unmanned aerial vehicle), yield, soil type and/or EC_a. VRI management zones are potentially more difficult to create accurately because soil VWC is constantly changing, both spatially and temporally throughout a growing season. Yield mapping has long been studied for its utility for zone delineation for variable nutrient management. Yield maps provide spatially dense data at a very low cost, and spatial variability in yield data reflects the integration of all of the factors that affect crop development (Stafford et al., 1999). Stafford et al. (1999) found large variations in within-season yield, but also found that these yield patterns varied greatly from season to season within the same fields. Yield data may be less applicable to VRI zones than they are to nutrient management zones, as they may be reflecting features that don't affect variation in VWC.

While static management zones are typically used for precision nutrient management, some have suggested that VRI might require dynamic zones. O'Shaughnessy et al. (2015) created a spatiotemporal VRI prescription map using automatic plant feedback from sensors mounted on the pivot arms. Their system successfully provided site-specific irrigation rates throughout the growing season. However, automatic feedback systems are still in early development and may depend on the crop experiencing some stress in order to separate zones. While the complexities of dynamic VRI zones are being studied, development of simple approaches for static VRI zone delineation is still needed.

The objective of this paper is to evaluate the use of easily obtained ancillary data to delineate static VRI zones. Simple topographic (slope, elevation), soil (EC_a), and crop (yield) factors were compared with measured within-field variability of VWC. These easily obtained ancillary data were selected because they are generally available in most settings without additional fieldwork or cost, which may lead to more feasible adoption of VRI. It was hypothesized that topographic data would relate best to the measured variability in VWC data because it is assumed that spatial variation of VWC is highly impacted by topographic factors.

MATERIALS AND METHODS

Study Locations

The study was conducted at two field locations, one near Grace, ID, USA (42.60904, -111.788; elevation 1687 m) and the other in Rexburg, ID, USA (43.800966, -111.790141; elevation 1509 m). The Grace field site (22 ha) grew seed potato (*Solanum tuberosum* L.) in 2018 and winter wheat (*Triticum* spp.) in 2019-2020. The Rexburg study field (13 ha) produced alfalfa (Medicago sativa L.) from 2013-2017, and spring wheat (*Triticum* aestivum spp.) from 2018-2020. The soil at the Grace site is classified as a Rexburg-Ririe complex with 1-4% slopes with a silty clay loam texture. Rexburg and Ririe soils are both coarse-silty, mixed, superactive, frigid Calcic Haploxerolls derived from alluvial- influenced loess. The soil at the Rexburg site is classified as a Pocatello Variant Silt Loam and a Ririe Silt Loam with 2-8% slopes and a sandy loam texture. Pocatello and Ririe soils are coarse-silty, mixed, calcareous, frigid, Typic Xerorthents and coarse-silty, mixed, frigid, Calcic Haploxerolls. There is a 6 m difference between lowest and highest elevation within the field in Grace, and a 17 m difference between lowest and highest elevation within the field in Rexburg. In Grace, about 0.3 ha of the field contains emerged basalt bedrock and thus, was not farmed or sampled.

In 2016 in Grace, and in 2019 in Rexburg, spatial variation in soil VWC under uniform irrigation was measured at the beginning and the end of the growing season. Irrigation was applied in both locations with a center pivot with five meter nozzle spacing equipped with a Variable-rate Irrigation System (GrowSmart Precision VRI, Lindsay Zimmatic, Omaha, NE, USA). In Grace there were 11 irrigation events applied uniformly, with irrigation events occurring every 5-7 days in spring and every 3-5 days during peak evapotranspiration (ET) rates for 2016. Planting occurred on October 5, 2015 and harvest took place on August 16, 2016. In Rexburg, there were 15 uniform irrigations events, with 1.5 cm of irrigation applied in events being occurring every 2-6 days. Planting occurred on April 5, 2019 and harvest took place on August 18, 2019.

Soil Volumetric Water Content Analysis

Soil samples were taken in both fields at the beginning and end of the growing season on a random-nested grid with sufficient samples to compute reliable variograms for kriging. Soil samples were collected on April 20, 2016 and August 16, 2016 in Grace. In Rexburg the samples were taken on April 29, 2019 and August 29, 2019. A hand-held, gas-powered hammer probe (AMS, Inc. American Falls, ID USA) and a trailer-mounted hydraulic probe (Giddings Machine Company, Inc., Windsor, CO, USA) were utilized. Soil cores were collected at four depths of 0-0.3, 0.3-0.6, 0.6-0.9, and 0.9-1.2 m to capture the distribution of moisture throughout the soil profile. Soil samples were stored in sealed plastic bags and placed on ice in insulated containers for transport to the laboratory. There, soil wet weights were obtained prior to transferring to paper bags and drying in a forced air oven at 105°C for 24 hours to determine dry weights.

Ancillary Variables

In Grace, crop yield was measured at harvest using a New Holland Inteliview 4 (Turin, Italy) that used a RangePoint RTX GPS with a relative accuracy of +/- 15 cm. In Rexburg the yield was measured using an Ag Leader Versa (Ames, IA, USA) that used a TerraStar-C Pro GPS with a relative accuracy of +/- 5 cm. At both sites, yield monitors were calibrated using a mass flow sensor collecting yield data at a 10 m^2 spatial density. 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. The Grace site had yield data available to represent three years of wheat production (2013, 2014 and 2016), while Rexburg had two years of yield data available for wheat production (2019 and 2020).

Topographic ancillary data included slope and elevation. Both slope and elevation were measured using the GPS units on the yield monitors for both study locations and their data were compared with data obtained from the USDA et al. (2019). Soil apparent electrical conductivity (EC_a) was used as the ancillary soil factor. EC_a was measured in Grace in the fall of 2016 using a direct contact system (Veris, V3150, Veris Technologies, Salina, KS, U.S.A.) and in the spring of 2020 in Rexburg using an electromagnetic induction system (Duelem 1S, Duelem Inc., Minton, Ontario, Canada). At both sites, EC_a was measured on bare soil at two depths, 50cm and 150cm.

Mapping and Geo-statistical Analysis

Data for each map variable were kriged to a uniform five meter grid for both sites so that they would be on the same coordinate systems and have the same number of data points. A correlation matrix composed of Pearson's Correlation Coefficients was created to evaluate the relationships between ancillary variables and measured VWC variables. Ancillary variables included slope, elevation, measured yield for different individual years or multi-year averages, shallow and deep EC_a.

A k-means clustering algorithm was used in SPSS (IBM-statistics software) to group the VWC and ancillary variables individually into VRI management zones. For kriged data that were significantly skewed, a transformation to reduce the skewness was performed prior to performing the k-means clustering and creating zones. The zone map created using average VWC data was chosen as a reference against which to compare zone maps created from each of the ancillary variables. For the average VWC, k-means clustering was performed multiple times for 2-6 data clusters. Each number of data clusters was plotted against mean square error to help determine the optimum number of data clusters or zones. Two approaches were used to compare the agreement between zones created from average VWC and the ancillary variable, namely average percent agreement and bivariate Local Moran's I. Kriging, correlation coefficients, and bivariate Local Moran's I (LMI) were produced using SpaceStat (BioMedware, SpaceStat 4, Ann Arbor, MI, USA).

Overall percent agreement between the reference zone map created using average VWC and zone maps created from each ancillary variable was calculated using the Crosstabs tool in SPSS. This method gave an additional way of ranking the different predictor variables with regardto how well they represent average VWC.

The Moran's I statistic tests to what extent a set of spatial data exhibits clustering in patterns of variation (positive spatial autocorrelation) or dispersion with many spatial outliers (negative spatial autocorrelation). The bivariate LMI statistic identifies significant data clusters ($\alpha < 0.05$) for two different variables at the same time. The bivariate LMI maps compare the kriged average VWC data against the ancillary variables. For each bivariate LMI map, a bivariate LMI number was included to quantify how strongly two data sets were spatially clustered (Figures 2-7AD and 2-8AD). A positive, or negative, bivariate LMI number specifies if the positive or negative correlations dominated between the two variables being used. The percentage of area that showed positive and negative correlation for each map was also calculated.

RESULTS

Correlation Matrix

A correlation matrix composed of Pearson's Correlation Coefficients was created to evaluate relationships between measured VWC variables and ancillary variables (Table 2-1). In Grace, slope had a significant positive correlation with spring VWC, average VWC, and the change in VWC, while it had a negative correlation with fall VWC. At Rexburg, slope had significant negative correlations with all of the VWC variables. At both sites, slope better represented the spring VWC when the field was near field capacity, than fall VWC, when fields were very dry.

Elevation had significant negative correlations with all VWC variables at both sites. Elevation had a stronger correlation with the fall VWC (-0.371) than with the spring VWC (-0.199) in Grace, but the opposite was true for Rexburg. Elevation showed very low correlation with the change in VWC at Grace (0.055). Correlation coefficients for elevation with both average VWC (-0.396) and change in VWC (-0.326) were higher than most other individual ancillary variables.

For the Grace site, there were no significant correlations between 2013 yield data and the 2016 VWC variables. Correlation coefficients were significant but very low for 2014 yield data. There was stronger correlation with the 2016 VWC data (-0.202 for spring VWC, 0.202 for fall VWC, -0.075 for average VWC and -0.319 for change in VWC). The three year average yield generally showed poor relationships with VWC variables. For Rexburg, the 2019, 2020, and two-year average yield data were significantly and positively correlated with all of the VWC variables.

In Grace, EC_a did not show significant correlations with the spring VWC (0.005 for shallow EC_a, and -0.018 for deep EC_a) as observed in spring VWC (0.393 for shallow EC_a, and 0.383 for deep EC_a). The correlation coefficient for shallow EC_a with average VWC was significant (0.038), but not significant for deep EC_a with average VWC (0.019). In Rexburg, both shallow and deep EC_a were significantly correlated with each VWC variable. Shallow EC_a had the highest correlation with the average VWC (0.269), followed by correlations with fall VWC, spring VWC, and the change in VWC (0.248, 0.228, and 0.036 respectively). Deep EC_a in Rexburg correlated best with the change in VWC (0.483), second best with the spring VWC (0.351), third best with the average VWC (0.178), and the fall VWC showed the lowest correlation coefficient (-0.089).

Based on results from the correlation matrix, and the goal of showing spatial and temporal variability of soil VWC, the average VWC was selected as the primary variable for comparison with individual ancillary variables. The ancillary variables were further simplified to include only slope, elevation, shallow EC_a and a single year of yield data.

Overall Percent Agreement

For both locations, three-zone maps created from ancillary variables were compared to three zone maps created from average VWC using overall percent agreement calculations (Figures 2-5AF and 2-6AF). This method worked better in Rexburg, as the observed spatial patterns were similar. For the Grace location, zone patterns varied widely among ancillary variables, but there were visible similarities between the slope, and elevation zone maps, and the average VWC zone map. Agreement with zones created from average VWC for the Grace site was 39% (slope), 53% (elevation), 27% (yield), and 40% (Shallow EC_{a}). Agreement with zones created from average VWC for the Rexburg site was 40% (slope), 48% (elevation), 46% (yield), and 40% for EC_a, elevation, yield, and slope, respectively.

Bivariate Local Moran's I

A bivariate local Moran's I (LMI) analysis was performed to assess how spatial variability of the ancillary variables related to the spatial variability of average VWC. In addition to the LMI statistics, this analysis compared the percentage of field area where there was significant positive (high-high and low-low relationships), negative (high-low and low-high relationships), and total percentage of area with any correlation between the ancillary variables and VWC. The LMI value was significant for all slope, elevation, and 2016 yield at the Grace location, but was not significant for EC_a (Figure 2-7). The LMI values were significant for all ancillary variables for the Rexburg location (Figure 2-8). At the Grace location, the percentage of total area with significant correlation was 63% for slope and 64% for elevation. However, for slope, the area of significant correlation was divided nearly equally between positive and negative correlation, while for elevation, the majority of the area was negatively correlated (Figure 2-7).

The bivariate map comparing elevation with average VWC in Grace showed continuity that matched reasonably well with the elevation zone map. The Grace bivariate Moran's I number for elevation was -0.219 and it had the highest percentage of area with significant correlation with average VWC (64%). Elevation performed similarly in Rexburg, matching its zone map, and displaying the highest percentage of area showing significant correlation (65%). It also displayed the highest bivariate LMI number (-0.394). For both sites, yield produced choppy bivariate LMI maps and the lowest percentage of significantly correlated area (38% for Grace and 43% for Rexburg). In Grace, the bivariate Moran's I number for yield was the second lowest (-0.118) and in Rexburg it was the second highest (0.391). Shallow EC_a in Grace showed a poor clustering with a very low bivariate LMI number (0.005) and had the second lowest percentage of significantly correlated area (56%). In Rexburg, the continuity of correlated areas was far better and mirrored the shallow EC_a zone map. It had a bivariate Moran's I value of 0.266 and the second best percentage of area showing significant correlation (52%).

DISCUSSION

Slope and Elevation

Topographic ancillary data have a few distinct advantages. First, they can easily be obtained online or in many cases, from data collected by the GPS that may already be installed on the combine at the time of harvest and second, they are static over time. Also, they are more likely to create fairly continuous zones on the first try, requiring fewer subjective and tedious map modifications.

Though slope performed relatively well in Grace, it performed relatively poorly in Rexburg. However, elevation performed very well in both sites. In Grace, the elevation zone map showed the highest percent agreement with the average VWC zone map (53%) and in Rexburg the elevation zone map shared the highest percent agreement (48%) with the shallow EC_a. The elevation zone maps also showed patterns that were easily discernible in the bivariate LMI maps, which suggests that zones represent areas that correlate with the average VWC data. In the bivariate LMI data for both study sites, we see almost the same percentage of total area showing significant correlation for elevation with average VWC (64% for Grace and 65% for Rexburg). In addition, both Rexburg and Grace showed nearly the same percentage of area with positive correlation (17% Grace and 18% for Rexburg), and the exact same percentage of area showing negative correlation (47%). These results are likely due to the average VWC data being high in areas of low elevation and vice versa, as a result of soil VWC moving through the soil.

Shallow EC_a

EC_a was found to be a much better indicator for irrigation zones in Rexburg than in Grace, possibly because of the time of year in which the measurements were taken. The correlation matrix shows how in Rexburg, EC_a correlated better with the Spring VWC while in Grace, the EC_a correlated better with the Fall VWC. The EC_a was measured in Grace in the fall right after harvest, and in Rexburg EC_a was measured in the spring at the beginning of the growing season. This difference may explain why the EC_a in Grace correlated better with the fall VWC than with the spring, and the EC_a in Rexburg correlated a little better overall with the spring VWC than with the fall VWC. Perhaps this difference in sampling caused the EC_a to perform better in subsequent tests in Rexburg than in Grace. EC_a measurements can also be affected by many other factors, such as salt accumulation, nutrient management issues and other conditions at the time of measurement.

Yield

Yield likely produced poor results due to overwatering in parts of the field. Overwatering weakens the correlation between yield and VWC. This problem is worse in a slow draining soil like in Grace, where soils drain slower due to higher clay content. Not only should a field be divided into irrigation zones based on different water needs, custom irrigation rates (likely using soil sensors) ought to be implemented within each zone to optimize benefits.

Combining different years' yield data did not yield a significant increase in correlations in this study. However, combining multiple years of yield data is a way to make up for errors associated with unique factors that affected individual years' yield. The 2016 yield in Grace showed relatively low correlation with average VWC (-0.113) but in Rexburg, 2019 yield data was among the most correlated ancillary variables with the 2019 average VWC (0.396).

It is also important to note, that many of zone maps would likely have to be altered significantly for actual VRI use due to poor zone continuity. However, these maps were left as they were after k-means clustering, as to remove any subjectivity that might skew results. Modifying these maps for better zone continuity would likely improve their overall agreement. Additionally, if any of these variables were to be used for VRI implementation, the number of zones used should be adjusted depending on unique features of each dataset.

O'Shaughnessy et al. (2019) concluded that although the adoption of VRI technology has been low, it is expected to increase over time, and that researchers should continue to report findings so that end users may implement effective VRI. This study had the end user in mind, as it analyzes some of the simplest approaches for the delineation of management zones for the benefit of new adopters of VRI. Hedley et al. (2009) had success implementing VRI using EC_a for zone delineation, and found that the shallow EC_a was the second-best ancillary variable for predicting patterns in average VWC. However, EC_a produced relatively poor results for the Grace Study site. King et al. (2006) and (Svedin, et al. 2018) suggested that EC_a may not be the best parameter to use for VRI zone delineation and this was supported by our results, as the elevation data in both sites exhibited a stronger correlation in each test with the average VWC data.

Stafford et al. (1999) discovered that yield patterns varied greatly from season to season within the same fields, making them difficult to use reliably for delineating management zones. These findings were corroborated by those of this study at Grace as they showed that correlation coefficients change from -0.016 in 2013 to 0.036 in 2014, and then back down to -0.113 in 2016. Because correlation went from negative to positive and then back down to negative, the average yield had an extremely low correlation of only 0.006. However, yield had better and more consistent correlations for 2019 (0.396) and for 2020 (0.270) in Rexburg. Yield mapping provides spatially dense data at a very low cost to the grower, however due to its inconsistent nature, it may not be a reliable option for VRI zone delineation.

CONCLUSION

Though slope delineated good zones in Grace, it was a poor indicator for zone delineation in Rexburg. Yield and shallow EC_a both worked relatively well in Rexburg, but were not useful in Grace. Elevation performed well at both sites, and is easily obtainable and implementable. . Also, elevation has the advantage of being static over time and of producing good zone continuity. Both of these fields have relatively uniform soils across the fields, which was likely a factor in the performance of elevation in this study.

LITERATURE CITED

Al-Kufaishi, S., Blackmore, B., & Sourell, H. (2006). The feasibility of using variable rate water application under a central pivot irrigation system. *Irrigation and Drainage Systems, 20*(2), 317-327. https://doi.org/10.1007/s10795-006-9010-2

Daccache, A., Knox, J. W., Weatherhead, E. K., Daneshkhah, A., & Hess, T. M. (2015). Implementing precision irrigation in a humid climate – recent experiences and on-going challenges. *Agricultural Water Management, 147*, 135-143. https://doi.org/10.1016/j.agwat.2014.05.018

DeJonge, K. C., Kaleita, A. L., & Thorp, K. R. (2007). Simulating the effects of spatially variable irrigation on corn yields, costs, and revenue in iowa. *Agricultural Water Management, 92*(1), 99-109. https://doi.org/10.1016/j.agwat.2007.05.008

Hedley, C. B. (2009). Key performance indicators for simulated variable-rate irrigation of variable soils in humid regions. *Transactions of the ASABE, 52*(5), 1575-1584. https://doi.org/10.13031/2013.29146

Hopkins, B. G., & Hansen, N. C. (2019). Phosphorus management in High-Yield systems. *Journal of Environmental Quality, 48*(5), 1265-1280. https://doi.org/10.2134/jeq2019.03.0130

King, B. A. (2006). Comparison of site-specific and conventional uniform irrigation management for potatoes. *Applied Engineering in Agriculture, 22*(5), 677-688. https://doi.org/10.13031/2013.22000

King, B. A., Brady, R. A., McCann, I. R., & Stark, J. C. (1995). Variable rate water application through sprinkler irrigation. *Site-Specific Management for Agricultural Systems, 33*, 485-493.

Nijbroek, R., Hoogenboom, G., & Jones, J. W. (2003). Optimizing irrigation management for a spatially variable soybean field. *Agricultural Systems, 76*(1), 359-377. https://doi.org/10.1016/S0308-521X(02)00127-0

O'Shaughnessy, S. A., Evett, S. R., & Colaizzi, P. D. (2015). Dynamic prescription maps for site-specific variable rate irrigation of cotton. *Agricultural Water Management, 159*, 123-138. https://doi.org/10.1016/j.agwat.2015.06.001

O'Shaughnessy, S. A., Evett, S. R., Colaizzi, P. D., Andrade, M. A., Marek, T. H., Heeren, D. M., Lamm, F. R., & LaRue, J. L. (2019). Identifying advantages and disadvantages of variable rate irrigation: An updated review. *Applied Engineering in Agriculture, 35*(6), 837-852. https://doi.org/10.13031/aea.13128

Ritchie, J. T., Gerakis, A., & Suleiman, A. (1999). Simple model to estimate field-measured soil water. *Transactions of the ASAE, 42(6)*, 1609-1614. https://elibrary.asabe.org/pdfviewer.asp?param1=s:/8y9u8/q8qu/tq9q/5tv/J/9HPPP/KI/M/HMGPHMHK.5tv&param2=I/HN/IGIH&param3=HIO.HON.HHI.HN&param4=13326

Stafford, J. V., Lark, R. M., & Bolam, H. C. (1999). Using yield maps to regionalize fields into potential management units. *Proceedings of the fourth international conference on precision agriculture* (pp. 225-237). American Society of Agronomy, Crop Science Society of America, Soil Science Society of America. https://doi.org/10.2134/1999.precisionagproc4.c20

Svedin, J. D., Hansen, N. C., Kerry, R., & Hopkins, B. G. (2018). *Characterizing the spatial variation of crop water productivity for variable-rate irrigation management.* Unpublished manuscript.

Svedin, J. D., Hansen, N. C., Kerry, R., & Hopkins, B. G. (2018). *Characterizing the Spatial Variation of Crop Water Productivity for Variable-Rate Irrigation Management*. MSc thesis, Brigham Young University.

USDA. (2019). *Web soil survey.* USDA.gov. https://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx

FIGURES

Figure 2-1AB. Map of research site near Grace, ID, USA (A), and research site in Rexburg, ID, USA (B) with VWC sample locations.

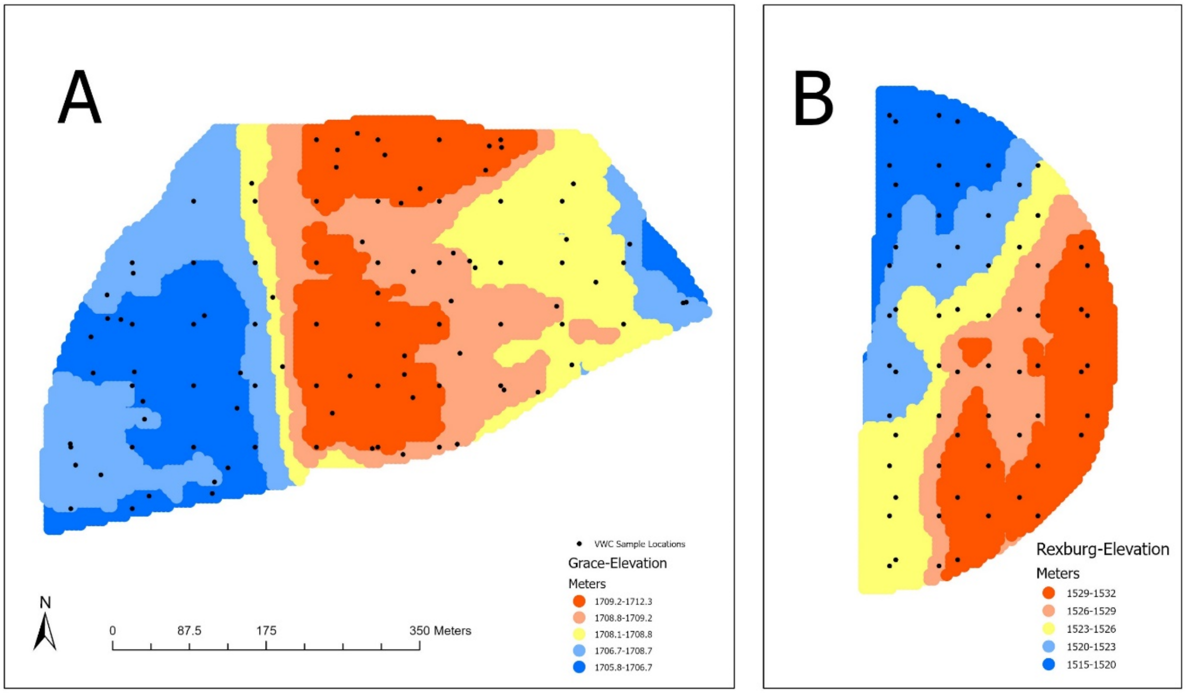


Figure 2-2AB. Map of elevation for the research site near Grace, ID, USA (A), and for the research site in Rexburg, ID, USA (B) with VWC sample locations.

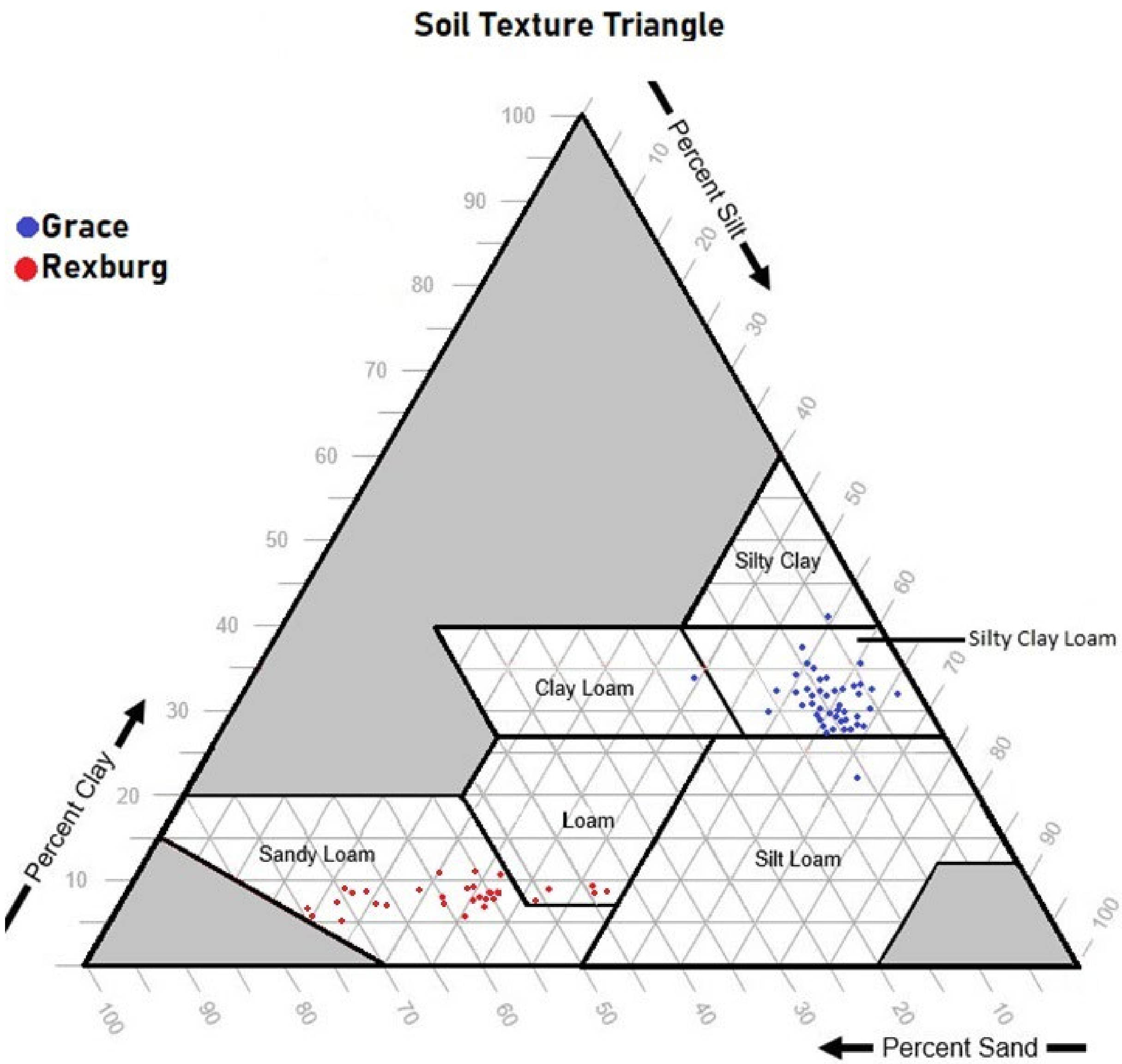
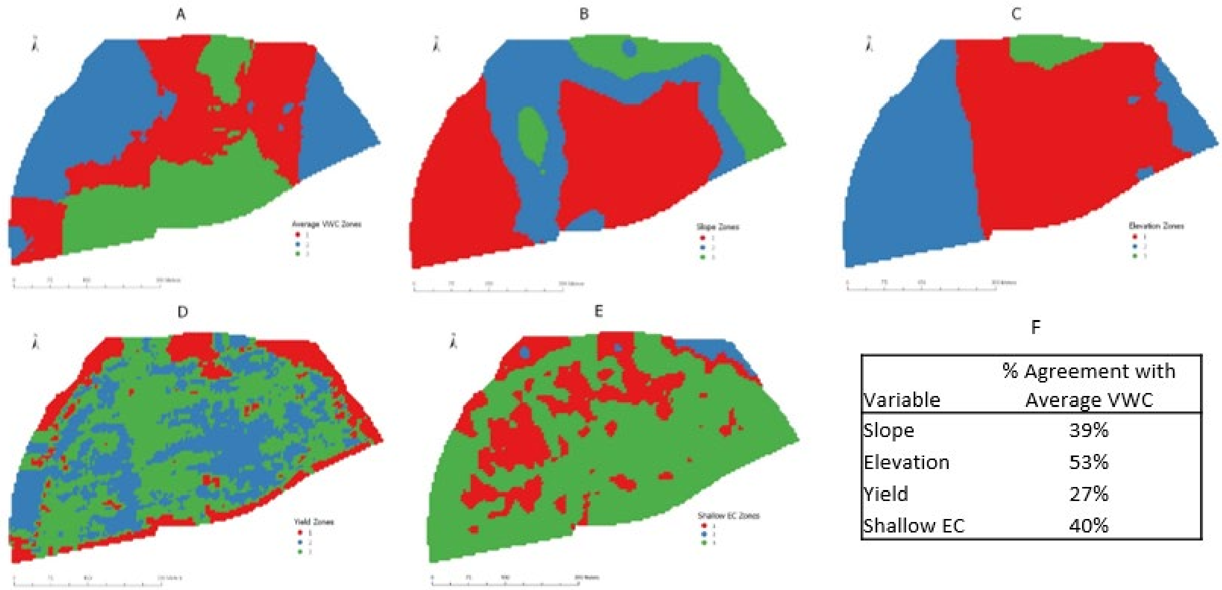


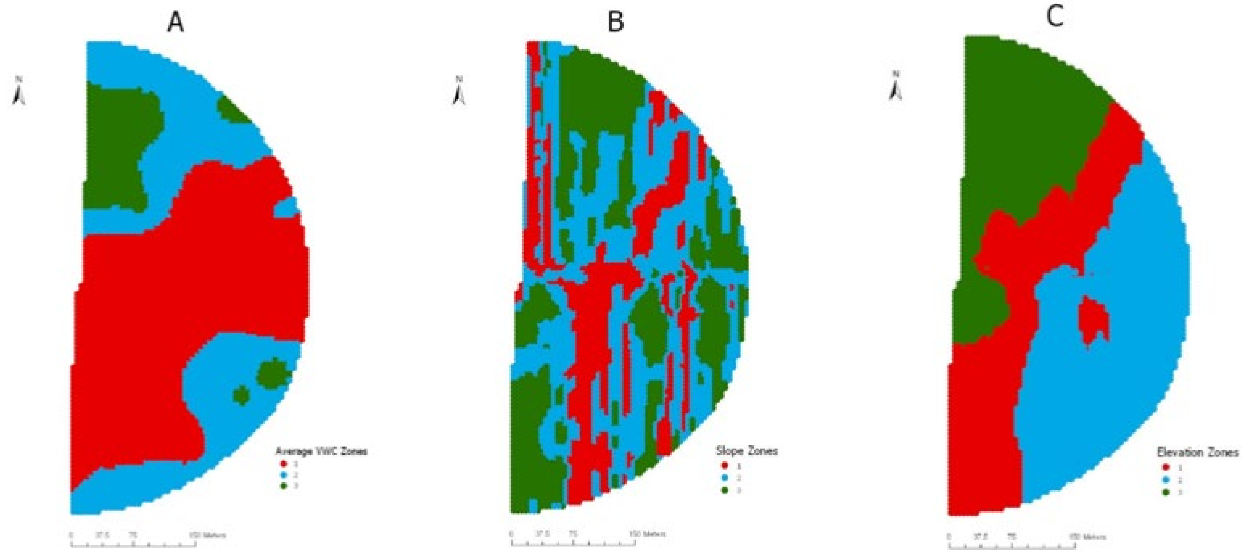
Figure 2-3. Soil texture triangle showing soil texture for the Grace site in blue and for the Rexburg site in red.

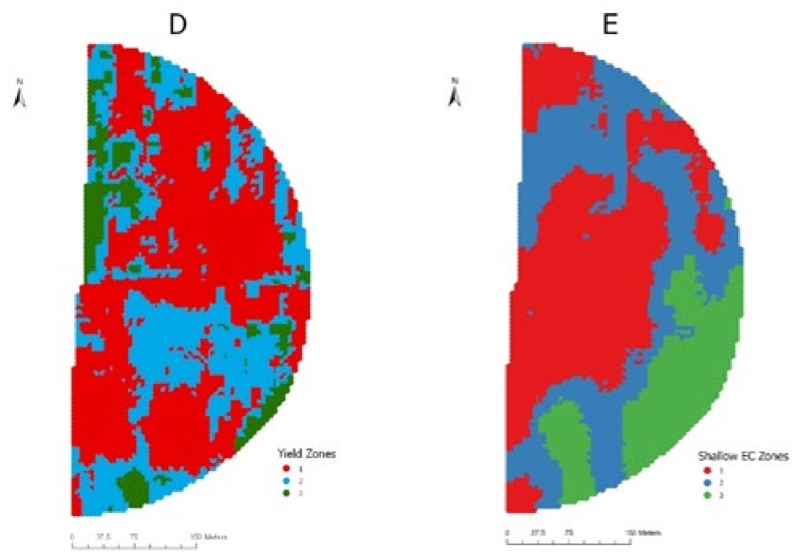


F

Variable	% Agreement with Average VWC
Slope	39%
Elevation	53%
Yield	27%
Shallow EC	40%

Figure 2-4AF. Three zone maps for the Grace site: average 2016 VWC (4A), slope (4B), Elevation (4C), Yield (4D), shallow EC_a (4E), and overall percent agreement for each ancillary variable (4F).

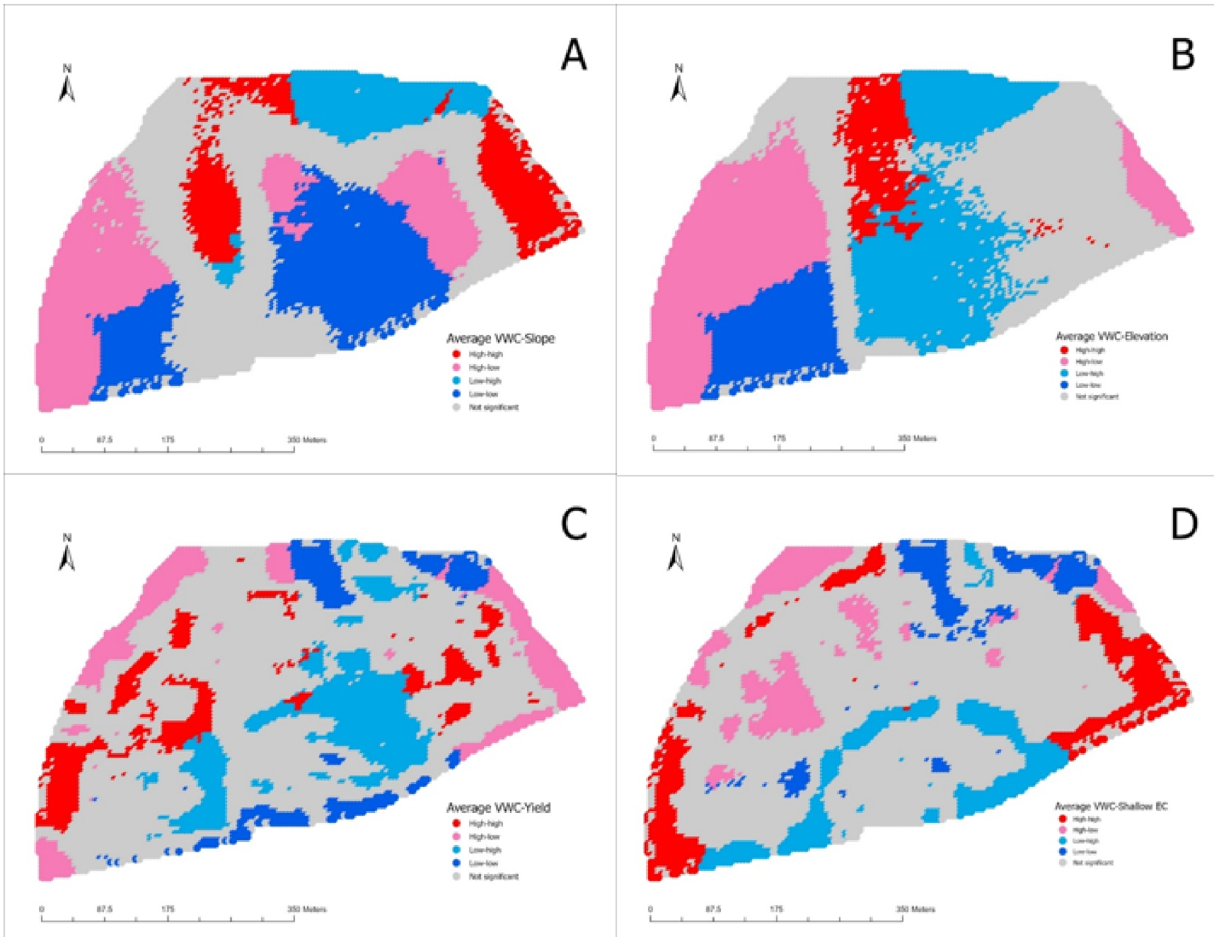




F

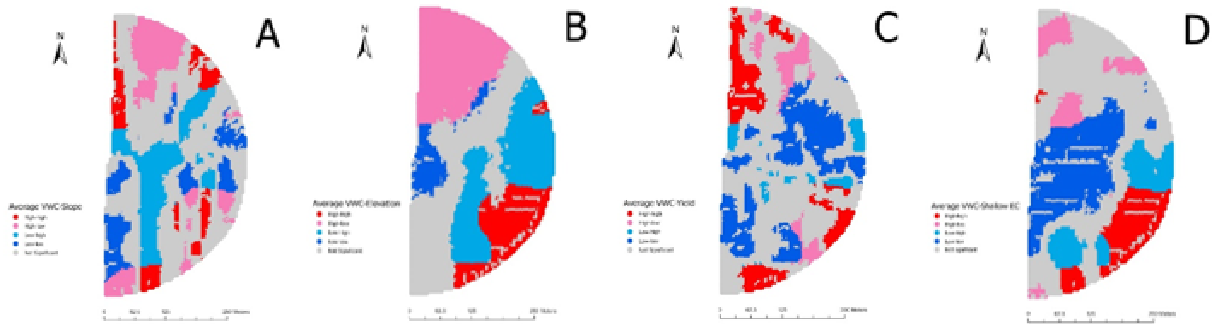
Variable	% Agreement with Average VWC
Slope	40%
Elevation	48%
Yield	46%
Shallow EC	48%

Figure 2-5AF. Three zone maps for the Rexburg site: average 2019 VWC (5A), slope (5B), Elevation (5C), Yield (5D), shallow EC_a (5E), and overall percent agreement for each ancillary variable (5F).



GRACE SITE					
Variables with 2016 Average VWC	Bivariate LMI	Global P-value	Total % of Area with Significant Correlation	% of Area with Positive Correlation	% of Area with Negative Correlation
Slope	0.304	0.001	63%	33%	30%
Elevation	-0.219	0.001	64%	17%	47%
2016 Yield	-0.118	0.001	38%	15%	23%
Shallow EC	0.005	0.306	56%	24%	32%

Figure 2-6AD. Bivariate Local Moran's I (LMI) maps comparing the average 2016 VWC with slope (6A), Elevation (6B), Yield (6C), and shallow EC_a (6C). The table displays data associated with the LMI maps (A-D).



REXBURG SITE					
Variables with 2019 Average VWC	Bivariate LMI	Global P-value	Total % of Area with Significant Correlation	% of Area with Positive Correlation	% of Area with Negative Correlation
Slope	-0.145	0.001	49%	19%	30%
Elevation	-0.394	0.001	65%	18%	47%
2016 Yield	0.391	0.001	43%	33%	10%
Shallow EC	0.266	0.001	52%	34%	18%

Figure 2-7AD. Bivariate Local Moran's I (LMI) maps comparing the average 2019 VWC with slope (7A), Elevation (7B), Yield (7C), and shallow EC_a (7C). The table displays data associated with the LMI maps (A-D).

TABLES

Table 2-1. Correlation Matrix showing Pearson correlation coefficients that show relationships for both study locations between ancillary data (slope, elevation, four yield variables, and two EC_a measurements) and four VWC variables (spring, fall, average, and change).

Grace Correlations	Spring VWC	Fall VWC	Average VWC	Change in VWC
Slope	0.479**	-0.163**	0.305**	0.547**
Elevation	-0.200**	-0.371**	-0.219**	0.054**
2013 Yield	-0.002	-0.015	-0.016	0.008
2014 Yield	0.047**	-0.001	0.036**	0.044**
2016 Yield	-0.188**	0.064**	-0.113**	-0.215**
3 Year Average Yield	0.024*	-0.013	0.006	0.030**
Shallow EC	0.005	0.393**	.038**	-0.248**
Deep EC	-0.018	0.383**	0.019	-0.263**
Rexburg Correlations				
Slope	-0.162**	-0.074**	-0.140**	-0.119**
Elevation	-0.455**	-0.216**	-0.396**	-0.326**
2019 Yield	0.402**	0.281**	0.396**	0.206**
2020 Yield	0.248**	0.224**	0.270**	0.081**
2 Year Average Yield	0.255**	0.228**	0.276**	0.085**
Shallow EC	0.228**	0.248**	0.269**	0.036**
Deep EC	0.351**	-0.089**	0.178**	0.483**

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).