Summer 8-2014

Estimating Potential Water Pump Reductions Based on Soil Water Content, Geospatial Data Layers, and Variable Rate Irrigation (VRI) Pivot Control Resolution

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ESTIMATING POTENTIAL WATER PUMP REDUCTIONS BASED ON SOIL WATER CONTENT, GEOSPATIAL DATA LAYERS, AND VARIABLE RATE IRRIGATION (VRI) PIVOT CONTROL RESOLUTION

by

Keith A. Miller

A THESIS

Presented to the Faculty of

The Graduate College at the University of Nebraska

In Partial Fulfillment of Requirements

For the Degree of Master of Science

Major: Agricultural and Biological Systems Engineering

Under the Supervision of Professor Joe D. Luck

Lincoln, Nebraska

August, 2015
Increasing concern for sustainable water use has the agriculture industry working toward higher efficiency use of irrigation water. The average irrigation water use efficiency throughout the United States is 45%, which is extremely poor. Advancements in crop management have continued to allow producers to know more about the conditions in their field from nutrient management and pest control, to understanding yield spatially.

Recent mechanical advancements have improved the capabilities of center pivot irrigation systems to water various depths throughout the field. This technology is known as variable rate irrigation (VRI). With VRI comes a whole new strategy for irrigation. Advancements in remote and mobile sensing have played a major role in collecting data spatially throughout a field in order to aid in the management of VRI.

The goal of this study was to provide a method for potential VRI technology adopters to evaluate potential water savings using datasets collected with varying levels of complexity. The proposed method was based on estimating root zone water holding capacity (RZWHC) spatially across two case study fields and treating each with URI and both sector and zone-controlled VRI.
Estimation of RZWHC was defined with three different levels of data input. The first method was created from a database of gridded SSURGO data. The second method included linear regression between mobile sensed soil apparent electrical conductivity (ECa) data along with pedo-transfer function (PTF) determined RZWHC. The third method utilized soil moisture sensing data from a neutron gauge along with various spatial data layers to develop a regression to model RZWHC.

These maps were sampled by applying irrigation management zones that include sector and zone control options. Irrigation was simulated and managed based upon the 10th percentile management allowed depletion (MAD) of 50% of the RZWHC. Results were determined with field averaged water application reduction (up to 9 and 14 mm for the two studied fields) as a result of VRI implementation along with the associated pumping energy reduction. Conclusions determine that not all fields may result in pumping water reductions, but rather a better water distribution can be achieved throughout the field.
Dedication

I dedicate this thesis to my family and close friends. I would like to extend a special thanks to all who have provided me with words of encouragement and also supporting prayer. I would also like to dedicate this work to God who has provided me with a tremendous opportunity to expand my knowledge; His strength has helped guide me along the way.
Acknowledgments

The author would like to acknowledge all the people who helped make this project a success. A special thanks to Alan Boldt and Tyler Smith for their help throughout all the field work. A special thanks also goes to Himmy Lo and John Barker for their help with the project in its entirety. I would also like to thank Dr. Joe Luck who has provided me with guidance and encouragement, and for also all his assistance in writing of this thesis.

Support for this project comes the Water, Energy and Agriculture Initiative, the latter made possible with funding from the Nebraska Corn Board, the Nebraska Soybean Board, the Agricultural Research Division at the University of Nebraska-Lincoln (UNL) and Nebraska Public Power District through the Nebraska Center for Energy Sciences Research at UNL.
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Chapter 1. Introduction

Water applied for plant survival and production, including horticultural and agricultural purposes, is considered irrigation water. All irrigation water withdrawals are fresh water and come from either surface or ground water sources. Irrigation withdrawals in 2000 were estimated at 18.9 billion hectare-millimeters per year over 25,000 hectares in the United States alone. Irrigation withdrawals account for about 65 percent of all freshwater withdrawals excluding thermoelectric power with the water for irrigation servicing nearly 25 million hectares. Nebraska withdrawals totaled nearly 1.22 billion hectare-millimeters in 2000 with the total land being irrigated of 3.64 million hectares, of which 1.7 million hectares were sprinkler irrigated. (U.S. Geological Survey, 2014). The average irrigation water use efficiency, which is the percent of water applied is actually utilized by the crop, for the agricultural sector does not exceed 45% which is very poor. Therefore, significant water savings are possible within the agricultural sector through improved irrigation management. Increased management through site-specific crop management (i.e., precision agriculture) is often more sustainable and efficient (Hezarjaribi & Sourell, 2007).

Traditionally, water has been an abundant resource in areas such as Nebraska, but advancements in water management technologies have resulted in new opportunities for stewardship of this precious resource. Variable rate irrigation (VRI) is a technology developed in recent decades that may aid in improving water-use efficiency of irrigated crop land. VRI has the potential to conserve and allow for more efficient use of water by varying the rate or depth of water applied to different crops and soils (Hedley & Yule, 2009; Evans et al., 2012).
Developments in technology have provided agricultural producers with new resources to become more efficient with energy and time while thriving to maximize profit. Today, most agricultural equipment allows producers to spatially monitor crop yields on-the-go and to vary nutrient and seeding rates throughout a field. Variable rate application of crop inputs has been studied for decades as a method to improve crop input use efficiency (Hedley, 2014). Improving irrigation practices to conserve water pumped and lower pump energy requirements has recently become a topic of interest for producers. VRI technology allows for precision water application throughout various field regions to improve water use efficiency by giving producers the ability to control application to smaller irrigation management zones (IMZs) (Daccache et al., 2014).

To enable VRI, a prescription map needs to first be defined by the irrigator and continually managed throughout the irrigating season to meet crop water needs. Technology advancements have provided the necessary hardware, software, and communication systems to successfully manage and apply prescriptions to irrigated fields. The major limitation lies not in the mechanical operation of the pivot but the management of spatial data and writing of prescription maps to address for the numerous factors that impact yield and soil available water (Evans et al., 1996).

One necessity to writing a prescription map is defining IMZ. There are different methods for delineating an IMZ; one common method is based on observed changes in soil types. This method of IMZ classification and the root zone water holding capacity (RZWHC) range determines the number, size, and distribution of IMZs (Daccache et al., 2014). RZWHC is defined as the difference between field capacity (FC) and permanent wilting point (WP), this is also considered to be the water available for plant uptake. Field
capacity is the amount of water in the soil after the downward flow of water due to gravity is negligible. Permanent wilting point occurs when plants can no longer readily extract water from the soil (Scherer, et al., 1999). Field capacity can be determined with different laboratory techniques where the matric potential of the soil is between -10 and -15 kPa. A good estimate can be determined from field sampling following a thorough wetting event one to three days prior (Martin et al., 1990)

VRI is currently underutilized with most VRI applicators that have zone control technology being primarily used to address regions of a field that do not receive irrigation. These regions are often waterways, ponds, roads, drainage ways, or rocky outcrops (Evans et al., 2012). Current VRI options for the most part include sector control and zone control. Sector control is the simplest form of VRI; this system has the capability to change irrigation rotation speed throughout the field applying different amount of water in sector slices at any defined position. Various different manufacturers offer zone control with various different capabilities. It has the capability to pulse sprinklers, either in banks where multiple sprinklers are controlled the same or as a single sprinkler. The ability to pulse sprinklers offers the option of watering various different regions anywhere in the field.

Uniform rate irrigation (URI) for a field generally ignores in-field variation in soil texture or terrain since there is no ability to vary rates throughout the field, but variability between fields exist which call for additional management from field to field. It is common for URI to be scheduled for the lowest RZWHC regions within the field to prevent under-irrigation (Daccache et al., 2014). VRI has the potential to manage in-field variation, but like URI, VRI should be managed separately among differing fields. At the
sub-field level, many factors may vary which include: topography, soil texture, cropping practices (e.g., tillage and soil compaction), fertility differences, and localized pest distributions (Kranz et al., 2012; Evans et al., 1996).

Precision agriculture first focused on managing in-field variations in soil nutrients with management decisions based around grid-sampling fields for variable rate fertilizer application (Wibawa et al., 1993). Spatial yield maps have revealed relationships among field properties such as topography and soil physical properties related to water distribution rather than soil nutrients (Sudduth K. et al., 1996). Obtaining accurate soil moisture-related properties has been challenging, often requiring intense field work and laboratory analyses. As a result, the spatial resolution of these data has been relatively low, historically because of the difficulty of collecting these data. The scale at which they need to be collected has made it impractical to map sub-field variations (Sudduth et al., 2001; Hezarjaribi & Sourell, 2007). Understanding soil texture distribution and how RZWHC is related may lead to further management decisions based upon any quantifiable variation (Godwin & Miller, 2003).

Mobile sensors combined with global positioning systems (GPS) provide higher resolution spatial maps of field properties. Proximal soil sensing can provide fine-resolution maps of apparent soil electrical conductivity (ECa), optical reflectance, mechanical resistance, capacitance, and other properties for non-saline soils. The relationships between the sensor-based soil properties and the agronomic soil properties are often site-specific, requiring additional field sampling to properly utilize the data (Pan et al., 2013; Sudduth, et al., 2004). With the amount of information gained with soil ECa, soil moisture monitoring sites can be targeted (Godwin & Miller, 2003) and an RZWHC
map can be generated at a higher resolution allowing for delineation of spatial variation in soil water (Hezarjaribi & Sourell, 2007) (Hedley & Yule, 2009).

Today, EC$_a$ sensing is offered by many commercial operators. Often times, the EC$_a$ map is directly compared to the yield map while considering yield variation resulting from soil properties. A recognized approach that would relate better the field conditions and yield results would be to first relate the sensor based EC$_a$ data to the soil properties. Further explanation for yield variations might be better explained considering climate and other seasonal field conditions (Sudduth, et al., 2004).

Topography affects the hydrologic response of rainfall catchment and impacts the available water for crop production. Access to more accurate digital elevation models (DEMs) such as LIDAR has become easier through public datasets and RTK GPS elevation values recorded during field operations. Computerized terrain analysis tools have made it possible to readily quantify topographic attributes (Kitchen et al., 2003). One in particular is terrain analysis using digital elevation models (TauDEM). TauDEM is free software accessible using a geographic information system (GIS) software which can compute various topographic layers from DEMs (Tarboton, 2013). Topographic wetness index (TWI) is widely-used in precision agriculture, and has been utilized in modeling the spatial distribution of soil moisture and surface saturation. TWI is a steady state wetness index. It’s most common use is to quantify topographic control on hydrological processes.

Soil texture and its relationship with available water content have been thoroughly studied and documented. Useful tools have been developed such as the soil water characteristics tool which combines textural analysis and results soil water characteristic
estimates such as wilting point and field capacity under different situations allowing for the determination of available water content (Saxton & Rawls, 2006).

Previous work has been done in monitoring of temporal soil water content and acquiring proximal soil sensing data to obtain high resolution maps relating to different soil properties (Pan et al., 2013). The resulting product from this study was a water stress index (WSI) that related field soil EC<sub>a</sub> and elevation to soil moisture data collected throughout the growing season. The WSI method utilized spatial data with soil water holding capacity to identify monitoring locations which include the entire range of water storage indicated (Pan et al., 2013).

While great advances in irrigation technology have occurred with VRI systems, irrigation decision support systems have not developed at a similar pace. Knowledge of plant available water on a spatial, daily timescale throughout the soil is critical for optimal irrigation management. Work has been done on modeling plant available water using a water balance approach or by soil moisture sensing. Using RZWTHC and soil EC<sub>a</sub> researchers have developed daily soil water status maps that could assist in VRI management (Hedley & Yule, 2009).

To summarize, irrigation water is becoming more limited as a result of increasing concern for the sustainability of fresh water sources. VRI is expected to potentially improve placement of irrigation water, coupled with irrigation decision support systems that accurately indicate crop water needs. These advances should greatly improve irrigation efficiency. Adoption of VRI has been relatively slow; there is a need for increased management support and estimates of potential economic impact (Feinerman & Voet, 2000; Evans et al., 1996; Evans et al., 2012).
Further work is needed to help justify the implementation of VRI. Traditionally most work has been done on the mechanical operations of VRI and on the management of VRI. With increasing producer interest in VRI it is important for further understanding of what benefits are to be expected. The initial cost of VRI systems varies depending upon what system is selected and historically have been a large investment for most producers. In order to provide some guide to help producers make decisions on implementation of VRI, a method of field analysis was conducted in this paper. Two fields were specifically considered for VRI with potential water and energy savings based upon three different methods for spatially mapping RZWHC. Different VRI management zone sizes were considered during the analysis along with URI to determine differences in management strategies.
Chapter 2. Goals and Objectives

The goal of this study was to provide a method for potential VRI technology adopters to evaluate potential water savings using datasets collected by varying levels of complexity. The proposed method was based on estimating RZWHC spatially across two case study fields and treating each with URI and both sector and zone-controlled VRI. Irrigation events were determined by calculating the 10\textsuperscript{th}-percentile management allowed depletion (MAD) per zone. Irrigation depth differences were calculated between URI and VRI based upon the goal of mining the RZWHC.

Specific objectives were to:

1) Develop RZWHC maps using three methods which included gridded SSURGO data, field collected EC\textsubscript{s} and PTF determined FC and WP (which required soil textural analysis), and finally soil moisture content measurements to determine observed FC and PTF WP coupled with regression data using multiple datasets.

2) Simulate irrigation events for varying levels of irrigation control (URI to zone-controlled VRI) using 10\textsuperscript{th}-percentile MAD per zone to manage RZWHC.

3) Estimate pumping and energy reductions for different levels of VRI control for the study fields.
Chapter 3. Materials and Methods

3.1 Field Study Site Descriptions
Field data were collected during the 2014 growing season at two locations in Nebraska. The first field study site (Field A) consisted of a 42-ha center pivot irrigated field located in Saunders Co., Nebraska (41.164798, -96.430352) that consisted of Fillmore, Filbert, and Tomek silt loam, and Yutan silty clay loam soil types (NRCS, 2014). The field has been managed as two 21-ha fields in which crops were rotated on north and south halves (typically soybeans and corn) from year to year with no tillage practices. The field site has some historic roadways that impact the topography of the field. Average annual precipitation for this field has been approximately 29.4 inches (National Climatic Data Center, 2015).

An additional study field (Field B) was located in Hamilton Co., Nebraska (40.792732, -98.173270) and consisted of a 25.6-ha field irrigated by a wiper center pivot. This wiper pivot does not travel 360 degrees in one direction, but rather travels a partial circle and then generally travels the opposite direction for the next irrigation pass. The field is also on a year-to-year rotation schedule between corn and soybeans along with some tillage practices. The field consisted of Crete and Hastings silt loam soil types (NRCS, 2014) with minimal slopes. Average annual precipitation for a nearby location has been 28.8 inches (National Climatic Data Center, 2015).

3.2 Field Data Acquisition
3.2.1 Soil Map
Multiple spatial data layers were obtained for the study fields. The Web Soil Survey (WSS) is a useful web-based tool (Staff, 2014) that can provide knowledge about a
field’s soil properties. WSS is open to the public as a free service operated by the USDA Natural Resources Conservation Service (NRCS). Information about soil boundaries and textural properties can lead to further understanding variability within a field. The WSS was used to begin understanding variations in field soil texture properties before visiting the field sites and allowed for preliminary study. WSS soil maps for fields A and B can be found in Figure 3.1 and Figure 3.2, respectively.

![Figure 3.1: Field A soils and their corresponding boundaries (NRCS, 2014) and the separately managed halves of the field.](image)

![Figure 3.2: Field B soils and their corresponding boundaries (NRCS, 2014).](image)

3.2.2 Soil Apparent Electrical Conductivity

Apparent electrical conductivity (EC_a) data were collected in November, 2014 after harvest for Field A, while Field B EC_a data were collected prior to planting in April,
2014. A Veris mobile sensor platform (MSP) was used to collect the EC$_a$ data at depths of zero to 30 cm (EC$_{a\text{-shallow}}$) and zero to 1 m (EC$_{a\text{-deep}}$) with spacing between passes approximately 20 m apart. An integrated Differential Global Positioning System (GPS) provided coordinates for each measurement recorded by the Veris MSP. Soil EC$_a$ data were recorded on a 1-s interval and the accuracy of the GPS reading was within 1.5 m (Sudduth et al., 2001).

Based on visual inspection of the data once interpolated to a raster, there appeared to be some outliers in both the EC$_{a\text{-deep}}$ and EC$_{a\text{-shallow}}$ datasets. The raw data were post-processed (i.e., cleaned) by removing any points outside the range determined by the following procedure. The soil EC$_a$ data cleaning process began by determining Quartile 1 (Q1) and Quartile 3 (Q3) for the data using Microsoft Excel and its built-in quartile function. The inter-quartile range (IQR) was then calculated as the difference between Q1 and Q3. The IQR was multiplied by three and added to Q3 (Q3 + 3IQR) and subtracted from Q1 (Q1 – 3IQR). The lower range (Q1-3IQR) was set to zero and not allowed to include negative values. Field A data were used as an example in Figure 3.3 and Figure 3.4 to show points (as a cumulative distribution) that were deleted along with a summary of these points in Table 3.1. Field B is displayed in Figure 3.5 and Figure 3.6 a summary of deleted points from Field B is displayed in Table 3.2. It should be noted that these data from Field B include additional data collected in Field B to the south of the study area. The cleaned point data for both fields (Figure 3.7 and Figure 3.8) are displayed as a point shapefile in ArcMAP which indicates the Veris MSP path and areas where data were not collected due to the center pivot or road.
Figure 3.3: Field A raw soil EC₄ collected with Veris

Figure 3.4: Field A soil EC₄ after post-processing.

Table 3.1: Field A soil EC₄ data edited out from raw EC₄ data.

<table>
<thead>
<tr>
<th>Total Data Points</th>
<th>Points Removed EC₄-shallow</th>
<th>Points Removed EC₄-deep</th>
</tr>
</thead>
<tbody>
<tr>
<td>13466</td>
<td>13 (&lt;0.1%)</td>
<td>7 (&lt;0.1%)</td>
</tr>
</tbody>
</table>
Figure 3.5: Field B raw soil EC$_a$ collected with Veris.

Figure 3.6: Field B soil EC$_a$ after post-processing.

Table 3.2: Field B number of points edited out of raw EC$_a$ data.

<table>
<thead>
<tr>
<th>Total Data Points</th>
<th>Points Removed</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EC$_a$-shallow</td>
<td>EC$_a$-deep</td>
</tr>
<tr>
<td>38,178</td>
<td>180</td>
<td>1086</td>
</tr>
<tr>
<td></td>
<td>(0.5%)</td>
<td>(2.8%)</td>
</tr>
</tbody>
</table>
Previous work with EC_a has provided spatial information throughout research fields relating to soil texture and WHC. It is common practice to have soil samples throughout a field where EC_a was recorded to develop relationships between various soil properties (Sudduth, et al., 2004). The EC_a point data were spatially interpolated in ArcMap v10.2 (ESRI, Redlands, CA) to a 10 m raster using the Raster Interpolation toolbox (Figure 3.9 and Figure 3.10). The Inverse distance weighted (IDW) technique (ESRI, 1999) was used to perform the interpolation, a method which assumes objects closer to one another are more alike than those far apart. Options within the IDW tool were kept at default within the GIS software (power = 2 and search radius of 12 points). The result was a spatial data...
layer used to further identify potential soil zone boundaries and soil layers with differing EC$_a$ values. The EC$_a$ can be used as an indirect measurement for multiple soil properties or with enough variation may be calibrated and used as a direct property (Sudduth et al., 2001). Soil samples that were collected in May 2014 were used to compare texture properties at sampling locations with the EC$_a$ value for the 10 m grid cell by extracting points in ArcGIS using GPS coordinates recorded from the sampling locations.

3.2.3 Elevation Data
A 2-m LIDAR dataset (Nebraska Department of Natural Resources, 2014) was obtained to provide accurate elevation data for the terrain analysis for Field A. The LIDAR data were resampled from 2-m to 10-m grid rasters for analyses due to the desired grid size.
and consistency between data layers. It was determined that a 10 m grid for all spatial layers would be preferred for the sake of uniformity. This common grid size allowed for multiple rasters to be snapped together so the grid cells for each data layer would line up. Because the spatial data analysis used layers based on less dense sample points (e.g., EC<sub>a</sub> collected at a 20 m spacing), the 10 m grid allowed for less uncertainty in grid estimates for those data layers. To resample the LIDAR elevation data layer, the 2 m raster was converted to points, thus each grid cell value was converted to a point value. The point to raster tool was used with an output grid cell size of 10 m, which resulted in a 10 m grid cell representing an average of 25 2-m points. The range in elevation change throughout the field A is relatively moderate. The result of the LIDAR (Figure 3.11) indicates 5 meter of elevation change throughout the field.

![Figure 3.11: Fields A elevation data from LIDAR (2m) displayed on a 10 m raster.](image)

RTK elevation data were collected during field harvest operations during the 2013 growing season and used to develop an elevation map (Figure 3.12) for Field B since LIDAR data was unavailable. The raw data were in a point file so in order to develop a 10 m grid, the points had to be interpolated to create a continuous surface. The point data
were spatially interpolated in ArcMap v10.2 (ESRI, Redlands, CA) to a 10 m raster using the Raster Interpolation toolbox. Inverse distance weighted (IDW) technique (ESRI, 1999) was used to perform the interpolation, a method which assumes objects closer to one another are more alike than those far apart. Options within the IDW tool were kept at default within the GIS software (power = 2 and search radius of 12 points). The resulting map was snapped to the soil ECa map which allowed for different maps to have 10 m cells that are exactly in the same locations.

The topographic map (Figure 3.12) appears to have very gradual slopes with a relatively small vertical change throughout the field of four meters. For the most part the west end of the field is the highest point while the southeast corner is the lowest with a small drainage path that is cropped cutting through the middle of the field from northwest to southeast.

![Figure 3.12: Field B elevation data from RTK displayed on 10 m raster.](image)

### 3.2.4 Terrain Analysis

Using a topographic map, multiple terrain attributes were calculated. Slope, specific catchment area (SCA), and topographic wetness index (TWI) were all calculated and considered in the analysis for both fields. Slope can have an impact on time of infiltration along with the amount of surface storage that can be achieved. Sloping terrain contributes
to the potential for runoff which can result in the movement of soil and chemicals across the field and even out of the field. This water movement can result in lack of soil moisture in some locations while others receive an excess resulting in deep percolation (Scherer, et al., 1999). SCA analyzes water flow on hill slopes; it is a ratio of contributing area to contour length with units of $m^2\cdot m^{-1}$. Soil moisture can be indicated by SCA since the larger the catchment area, the more moisture is contributed throughout the hill slope by overland flow.

TWI was computed (Equation 1) in ArcGIS to identify locations where topography may have had an impact on hydrologic processes (Qin, et al., 2011). TWI can be used to locate potential areas subject to runoff and run-on as a result of topography. Water-related soil properties including soil-surface water storage along with soil infiltration rates vary throughout different hill slopes. As, TWI was selected to identify any relationships among these varying properties and assist in spatial field analysis by providing insight to varying soil moisture levels.

TWI was calculated as follows:

$$\text{TWI} = \ln \left( \frac{\alpha}{\tan(\beta)} \right)$$

Equation (1)

Where:

$\alpha$ = specific catchment area and

$\beta$ = slope.

A combination of TauDEM toolset (Tarboton, 2013) and Spatial Analyst toolset were used in ArcMap to calculate TWI. Spatial Analyst was used to fill sinks (results in a depressionless DEM) in the LIDAR dataset as opposed to TauDEM due to more desirable flow direction results from visual inspection of water flow paths observed.
throughout the field during the 2014 growing season. *TauDEM* was then used to complete the actions of computing specific catchment area (SCA) and slope (Figure 3.13 and Figure 3.14) which were used in the TWI calculation (Figure 3.15). TWI for field B was computed completely in *TauDEM* using the RTK elevation data (Figure 3.16).

The slope grid for field A indicates slopes up to 9.3 percent; however, higher slopes are not wide spread and consist of a very small portion of the field where a railroad previously crossed through the field. The slope grid for field B has some data streaks from north to south throughout the field; this is thought to be a result of harvester RTK collection path. For use in this field with relatively flat terrain the data is felt to still be beneficial to use.

![Figure 3.13: Field A 10 m slope (percent slope) grid.](image)

![Figure 3.14: Field B 10 m slope (percent slope) grid.](image)
3.2.5 Soil Moisture Monitoring and Textural Analysis

The neutron probe requires calibration to measure the soil water content. Volumetric water content was determined using the ratio of observed counts and standard counts from time of installation, with linear calibration from laboratory determined volumetric water content which was determined from intact soil cores collected during access tube installation with a Giddings probe (Windsor, Colo.). Volumetric water content from neutron probe readings at each location was summed to estimate a root zone management depth of 1.2 m. The calibration plots and linear equations are displayed in Figure 3.17 and Figure 3.18 along with Table 3.3.
Intact soil cores that were collected during access tube installation were also used for soil textural analysis. Field A consisted of ten locations while field B had six (Figure 3.19).
The soil samples were analyzed for volumetric water content by weighing the sample and then recording the weight after oven drying. Sample bulk densities were also determined by analyzing the intact soil cores for volume and moisture content, of which some results were undesirable and therefore an average bulk density was determined. A laboratory textural analysis was also conducted for percent sand, silt, and clay along with organic matter content which were analyzed by Ward Laboratories Inc. (Kearney, NE) (Table 3.4 and Table 3.5).

The intact soil cores allowed for determination of bulk density, as a result of uncertainty in the data collected the average bulk density was used for the analysis. A PTF (Saxton & Rawls, 2006) used the textural analysis and average bulk density of the samples to determine FC and WP (33 kPa and 1500 kPa respectively), which was then used to determine RZWHC. The results were compared with the actual measured data from the neutron gauge monitoring. Comparison between the PTF and neutron gauge observed RZWHC, along with graphical comparisons of soil texture with the two methods of determining RZWHC were analyzed to consider possible relationships that would aid in spatially predicting RZWHC.

Figure 3.19: Field A (left) and Field B (right) soil moisture sensing locations
Table 3.4: Field A root zone (RZ) textural analysis.

<table>
<thead>
<tr>
<th>Soil Depth (m)</th>
<th>OMC (%)</th>
<th>Sand (%)</th>
<th>Silt (%)</th>
<th>Clay (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0 to 0.15</td>
<td>3.0 ±0.2</td>
<td>16.9 ±4.9</td>
<td>55.0 ±5.0</td>
<td>28.1 ±5.0</td>
</tr>
<tr>
<td>0.15 to 0.46</td>
<td>2.2 ±0.5</td>
<td>15.6 ±5.8</td>
<td>53.1 ±3.9</td>
<td>31.3 ±6.2</td>
</tr>
<tr>
<td>0.46 to 0.76</td>
<td>1.8 ±0.5</td>
<td>13.2 ±2.1</td>
<td>53.4 ±2.3</td>
<td>33.4 ±1.6</td>
</tr>
<tr>
<td>0.76 to 1.07</td>
<td>1.5 ±0.3</td>
<td>13.6 ±2.8</td>
<td>55.1 ±3.6</td>
<td>31.3 ±4.2</td>
</tr>
</tbody>
</table>

Table 3.5: Field B root zone (RZ) textural analysis.

<table>
<thead>
<tr>
<th>Soil Depth (m)</th>
<th>OMC (%)</th>
<th>Sand (%)</th>
<th>Silt (%)</th>
<th>Clay (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0 to 0.15</td>
<td>2.4 ±0.2</td>
<td>17.2 ±1.9</td>
<td>55.2 ±5.1</td>
<td>27.7 ±6.0</td>
</tr>
<tr>
<td>0.15 to 0.46</td>
<td>2.0 ±0.5</td>
<td>15.3 ±1.4</td>
<td>53.8 ±3.0</td>
<td>30.8 ±3.3</td>
</tr>
<tr>
<td>0.46 to 0.76</td>
<td>1.5 ±0.2</td>
<td>15.7 ±1.9</td>
<td>57.0 ±6.6</td>
<td>27.3 ±5.2</td>
</tr>
<tr>
<td>0.76 to 1.07</td>
<td>1.4 ±0.1</td>
<td>15.5 ±1.0</td>
<td>60.7 ±2.6</td>
<td>23.8 ±2.9</td>
</tr>
</tbody>
</table>

3.2.5.1 Soil Moisture Monitoring: Field A

Soil moisture monitoring was accomplished with ten neutron gauge monitoring sites installed across the field to measure depths of up to 183 cm. A neutron probe (503 Elite Hydroprobe, CPN, Concord, Cal.) was used to measure root zone soil moisture at depths of 15, 46, 76, and 107 cm at sampling periods of one to two weeks.

Locations for moisture monitoring were selected based on topography produced from LIDAR, NRCS soil maps, and historic yield maps. Yield maps allowed for further understanding of regions in the field that were poorly drained or had other factors such as pests that affect the ability to obtain a good crop stand which makes for a poor monitoring location. Field A sensors were placed to monitor variation in soil type and terrain within the field. Six monitoring locations were focused in major soil types along a hill slope on the north half of the field (Yutan silty clay loam, terrace, 2 to 6 percent slopes, eroded; and Tomek silt loam, 0 to 2 percent slopes) to monitor soil moisture at the top, middle, and bottom of the hillslope. The other four locations were on the south half of the field where two locations were in the majority soil type (Yutan silty clay loam,
terrace, 2 to 6 percent slopes, eroded) and two locations in next majority soil (Filbert silt loam, 0 to 1 percent slopes) (NRCS, 2014) while one location fell into a hydric soil by definition of the observed soil condition.

3.2.5.2 Soil Moisture Monitoring: Field B
Soil moisture was monitored throughout the growing season at six locations within the irrigated field. A neutron probe (503 Elite Hydroprobe, CPN, Concord, Cal.) was used to monitor soil moisture. Access tubes were installed down to 183 cm and intact soil samples were taken at the time of installation and used to determine volumetric water content and bulk density which are used to calibrate the probe. The soil samples were later used for textural analysis at Ward Laboratories Inc. (Kearney, NE). Soil moisture readings were taken every one to two weeks for this analysis at depths of 15, 46, 72, and 107 cm.

Locations selected for monitoring were based upon a soil EC$_a$ map that was previously collected. The locations were chosen to monitor between the distinctly differing EC$_a$ zones. The goal of this strategy was to monitor differing soil moistures as a result of soil texture since this field had minimal topography impacts.

3.3 Development of Root Zone Water Holding Capacity Maps
3.3.1 SSURGO
SSURGO was used to develop a preliminary analysis since the data required and analysis does not require any field collected data. NRCS WSS data were used to develop Root Zone Water Holding Capacity (RZWHC) maps for the two study fields. This first method for map development was selected because RZWHC could be spatially estimated without the need for field data collection. The WSS maintains published WHC values for soil
horizons, along with the depth of their existence allowing for RZWHC to be determined between varying soil types without having to visit the field. Previous work done by (Lo, et al., 2015) summed the WHC to a depth of 120 cm from gridded SSURGO 2014 to represent the root zone on a 10 m grid which was then resampled to a one meter grid. This previous work provided access to RZWHC data layers for the two study fields; for additional details refer to the methods section of (Lo, et al., 2015).

### 3.3.2 $EC_a$ and PTF

A second method for developing spatial RZWHC maps utilized spatial soil $EC_a$ and field collected soil sample analysis. The soil sample analysis results were used in a pedo-transfer function (PTF) (Saxton & Rawls, 2006) to estimate the soil hydraulic properties including field capacity (FC) and permanent wilting point (PWP). FC and PWP were estimated using tensions of 33 and 1500 kPa respectively and their difference estimated the AWC (Rudnick & Irmak, 2014). Each depth (0.15, 0.46, 0.76, and 1.07 m) was determined separately and then summed to obtain water holding capacity (WHC) for the root zone (RZWHC). This method is commonly used for loam soils, but we acknowledge it may not be the best estimate due to textural variations and layering soils for the fields that were sampled. To develop a RZWHC map, soil $EC_a$ was extracted from a 10 m grid where the soil samples were collected. Next the $EC_a$ results were plotted in relation to the RZWHC from the PTF for the sampled locations. A linear regression relationship was used to relate the two (Hezarjaribi & Sourell, 2007) which can be used in conjunction with the spatial $EC_a$ to predict RZWHC throughout the field for a 1.2 m root zone.
3.4 Field Data Analysis

3.4.1 Methods to Analyze Field Collected Data

Soil layering in the field was expected to impact the results from Saxton and Rawls (2006) PTF which doesn’t account for the layering, therefore to effectively simulate root zone water holding capacity both field measured and PTF methods were used. Observed FC was determined from neutron gauge monitoring and WP was determined from Saxton and Rawls (2006). Observed FC was observed under natural conditions in contrast to being artificially inundated for observed FC.

For field A, the top foot observed FC was determined from a reading taken on September 17, 2014 after a total of 61.5 mm rainfall events have previously occurred on September ninth through the 15th while the evaporation rate was minimal with quality crop cover and transpiration rates minimal with a senescing crop. The observed FC for the remaining three feet was determined from a reading taken on May 28, 2014 before any water had been taken up by the crop with rains starting April 13 until May 26 totaling in 164 mm (HPRCC, 2014). Field B observed FC was determined from moisture readings on June 26, 2014 when the soil moisture profile was assumed to be full as a result of minimal ET and seasonal rains (35.8 mm over previous 10 days) exceeding ET. The volumetric water content measured one to three days after a thorough wetting event is a good indication of FC (Martin et al., 1990). This observed FC value can be determined by monitoring the soil moisture in situ over time, or by collecting samples at a point in time and determining volumetric water holding capacity in the laboratory.

Observed RZWHC for the monitoring sites indicated the spatial RZWHC variability throughout the field which could be used to estimate the RZWHC across the whole field.
Topography features along with soil (EC\textsubscript{a-deep} and EC\textsubscript{a-shallow}) were considered to develop regression equations that would be used to spatially map RZWHC. Topography features were determined on a 10 m grid cell size which included slope, specific catchment area, and TWI.

Statistical correlations were determined and used to predict the spatial variation of RZWHC. Statistical software R was used to conduct regression models between RZWHC and values extracted from the various dense spatial data layers such as EC\textsubscript{a}, topographic layers, and TWI with the goal of developing an equation to spatially predict RZWHC throughout the field.

3.4.2 Theoretical RZWHC
The regression model relating the selected field characteristics with RZWHC was an estimate; the actual RZWHC across the field will have additional random variability not explained by the independent variable(s). An error strategy using the residual error of the regression model was used to create a RZWHC map that could display the naturally occurring spatially variable RZWHC. The Create Random Raster tool in ArcGIS was used to create a 1-m and 10-m random error raster with a distribution that fits the residual error of the developed model. The observed FC determined RZWHC map with the random error raster added to it was considered “theoretical RZWHC” which was used to compare the three different levels of spatially estimating RZWHC. A sensitivity analyses was conducted on the difference between 1 m and 10 m RZWHC maps to determine how the increase in level of precision affects the outcome by simulating irrigation for both maps and using the results to draw conclusions.
3.5 Development of VRI center pivot control scenarios

Today’s options on the market for VRI vary by manufacturer. Two common VRI application practices are sector and zone control. Sector control allows for VRI in only a radial direction while zone control allows for VRI laterally throughout the irrigation. For this project, sector control was limited to 2°, 5°, and 10° while zone control added irrigation zones to the sectors at the span and twice the wetted sprinkler diameter (12.6 m). Various irrigation control scenario polygons were developed by building polygons in AutoCAD to simulate VRI application zones. An example of the pivot polygon control scenarios for 10° sectors, and the corresponding zone control scenarios is displayed in Figure 3.20. It is important to note that the most inside zone was removed due to the lack of data for the zone scenarios with a distance of 12.6 m.

Figure 3.20: 10-degree pivot polygon control scenarios including sector (left), span (middle), and 12.6 m (right).

The control scenarios discussed above were used to sample spatial RZWHC maps developed from the three strategies (SSURGO, ECₐ and PTF, Observed FC) and compare them to the theoretical RZWHC map. Methods used to complete the sampling procedure in ArcGIS were first defined by developing a manual procedure in ArcGIS. Once the methodology was finalized, programming code was written in Python to simulate the
Irrigation scheduling for each IZ was based on a MAD of 50%. The theoretical scenario was treated with URI and the irrigation was initiated when the field’s 10th-percentile RZWHC reached MAD. Basing irrigation on the 10th-percentile RZWHC was chosen to
acknowledge that the produced RZWHC maps are not perfect, this acknowledges that and gives a good base for irrigation. The seasonal irrigation depth can be understood with (Equation 2) where the application depth is uniform. The cumulative distribution for the theoretical RZWHC whole field can be seen in Figure 3.22. The entire field consists of a total of 418,578 1 m grid cells. These points include error at the 10 m scale; therefore there are steps that define these zones but are not easily visible because of the large number of points and the range of the values.

\[ I_{n Irr} = ET_c - P_{eff} - RZWHC_{10th-percentile} \times MAD \]  

Equation (2)

Figure 3.22: CDF of zonal and whole field RZWHC

To simulate VRI, irrigation for the control scenarios was based on irrigating each zone individually (Equation 3) which did not account for edge effects. Irrigation for a particular zone was determined based on the 10th-percentile of the RZWHC MAD contained in that zone. This method allowed for various depths to be watered throughout the field and to distribute water more effectively to differing defined irrigation zones.
In vri = ET, - P_eff - RZWHC zone 10th-percentile * MAD  \hspace{1cm} \text{Equation (3)}

A CDF for a zone is displayed in Figure 3.22; a total of 1,429 1-m grid cells populated this zone (5° by tower). Steps between values of zonal RZWHC existed in Figure 3.22 because the original RZWHC map was a 10 m grid. The 10-m grid was resampled to 1 m so each grid cell was made up of 100 points of the same value. This allowed for improved sampling resolution near zone boundaries compared to using 10 m grid cells.

To quantify any potential water savings with a VRI approach, the VRI control scenarios were compared to the theoretical RZWHC scenario. The RZWHC 10th-percentile of the whole field (URI) minus the RZWHC 10th-percentile of each zone results in irrigation savings for each zone as a result of VRI (Equation 4). To determine the water savings over the entire field, equation 5 was used. This accounted for each 1 m grid cell in order to account for the entire area of the field.

$$\Delta I_{ni} = I_{nuri} - I_{nvr} = (RZWHC_{10th-percentile,field} - RZWHC_{10th-percentile,zone}) \times \text{MAD}$$  \hspace{1cm} \text{Equation (4)}

Where: $$\Delta I_{ni} = \text{depth of irrigation savings per zone i}$$

$$\Delta I_{nfield} = \sum_i^m \Delta I_{ni} \times \frac{n_i}{n_{total}}$$  \hspace{1cm} \text{Equation (5)}

Where: m = number of zones in the field
n_i = number of cells in the zone i
n_{total} = number of 1 m cells
$$\Delta I_{nfield} = \text{depth of irrigation savings for the field}$$

To compare excesses and deficits between URI (Equation 6) and VRI (Equation 7), they were quantified and graphically displayed. The URI calculation is based only on the “theoretical RZWHC” map where URI was applied. The VRI excess and deficit was determined by determining each grid cell “theoretical RZWHC” (RZWHC_j) and
subtracting the prescription map zone RZWHC and multiplying by the MAD. If the result calculated is a negative excess, it is then considered to be a deficit.

\[
\text{URI Excess} = (RZWHC_j - RZWHC_{10\text{th-percentile,field}}) \ast \text{MAD} \quad \text{Equation (6)}
\]

\[
\text{VRI Excess} = (RZWHC_j - RZWHC_{10\text{th-percentile,zone}}) \ast \text{MAD} \quad \text{Equation (7)}
\]

**Chapter 4. Results and Discussion**

**4.1 SSURGO**
The first method for creating RZWHC maps utilized tabular gridded SSURGO data provided by the NRCS web soil survey. This data resource provides spatial information about the range in RZWHC and the approximate area impacted within the field.

The RZWHC map created for Field A based on the SSURGO data layer is illustrated in Figure 4.1. It should be noted that only four distinct values were estimated based on this method (Figure 4.1). The histogram highlights the distribution of RZWHC versus field area for Field A (Figure 4.2). These data indicate that substantial portions of the field may contain soil profiles where RZHWC values differ by well over 25 mm. Based on the amount of variation exhibited within this field, VRI could prove useful in addressing this imbalance in RZWHC.
Field B RZWHC results based upon SSURGO showed three varying regions throughout the field with a total range in RZWHC from 210 mm to 229 mm (Figure 4.3). The lowest RZWHC (210 mm) contained the most area in the field (Figure 4.4). VRI opportunities are presented to address the different water needs between the different RZWHCs (about 20 mm different) to mine the water as effectively as possible.
4.2 Soil ECₐ and PTF
The second method for creating a spatial RZWHC map utilized soil ECₐ and the Saxton and Rawls (2006) PTF. A linear regression equation was developed to predict RZWHC (Hezarjaribi & Sourell, 2007) based on georeferenced ECₐ values throughout the field (Figure 4.5 and Figure 4.6). While both corn and soybeans were grown during the 2014 season in Field A, the two cropped areas were treated as one for this analysis. This was justified because at the time the ECₐ data were collected (April), there was likely little impact due to the different cropping systems. The soil textural analysis would also have been minimally affected. The ECₐ-deep and ECₐ-shallow were treated separately for the analysis and the regression results are displayed in Table 4.1. The ECₐ-shallow was used for both locations (R² = 0.085 and R² = 0.028 for Fields A and B, respectively) instead of ECₐ-deep (R² = 0.034 and R² = 0.002 for Fields A and B, respectively). These relationships were poor according to the R²; a direct relationship was developed for Field A while an inverse relationship was developed for Field B as a result from the ECₐ and PTF data. It is recognized that this method is not a good resource for predicting RZWHC spatially.
Based on the data collected, RZWHC regression equations (Table 4.1) using $EC_a$-shallow as the independent variable for both fields (A and B) provided the better results compared to $EC_a$-deep. It is understood that in order for this method to work, what affects the change in $EC_a$ must also affect the RZWHC, this is not the case for these fields. Using ArcGIS, the $EC_a$-shallow 10 m raster and regression equations were used to predict the RZWHC throughout the irrigated fields (Figure 4.7 and Figure 4.8). Relatively small ranges in RZWHCs were developed by this process (95% of the area was within 5 mm for Field A). The areas impacted by different ranges in RZWHC are displayed in Figure 4.9 and
Figure 4.10. It was concluded that Field A has a right skew with area concentrated on the lower end of the RZWHC range. Field B is a left skew; more area is concentrated on the upper end of the RZWHC depth. Understanding where the majority of the field is impacted may aid in further decisions about how to address various differences in spatial data and measured data. Larger areas might be more important to thoroughly address. Avoidance of over addressing the larger areas in attempt to address the smaller field areas affected will greatly benefit the field.

Table 4.1: Linear regression results from ECa and PTF RZWHC.

<table>
<thead>
<tr>
<th>Field</th>
<th>Linear Regression Equation</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$RZWHC = -87.133 + 0.581 \times (Ec_{a\text{-shallow}})$</td>
<td>0.084</td>
</tr>
<tr>
<td></td>
<td>$RZWHC = -71.18 + 0.618 \times (Ec_{a\text{-deep}})$</td>
<td>0.034</td>
</tr>
<tr>
<td>B</td>
<td>$RZWHC = 96.54 - 0.2949 \times (Ec_{a\text{-shallow}})$</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>$RZWHC = 68.06 - 0.0739 \times (Ec_{a\text{-deep}})$</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Figure 4.7: Field A RZWHC (mm) map produced using EC$_{a\text{-shallow}}$ and PTF (Saxton & Rawls, 2006).
4.3 Field Study Results: Field A
Neutron gauge observed FC and PTF (Saxton & Rawls, 2006) estimated wilting point was determined at four depths throughout the 122-cm root zone (Table 4.2). Low wilting points in the top 61 cm for location 10 greatly increased its RZWHC. At the time soil
samples were collected for this location, the soil conditions were indicative of it being a hydric soil. A hydric soil is defined by the NRCS to be “a soil that formed under conditions of saturation, flooding or ponding long enough during the growing season to develop anaerobic conditions in the upper part” (Staff, 2014). Based on visual inspection, various regions throughout the field consisted of hydric soil, but only one monitoring location was located in a hydric area and was kept in the analysis. The relating soil water tension in centibars for each observed FC measurement is displayed in Appendix D.

Table 4.2: Field A neutron gauge determined $\theta_{fc}$ and Saxton & Rawls (2006) PTF determined $\theta_{wp}$ resulting in RZWHC for 0 to 122 cm.

<table>
<thead>
<tr>
<th>Location</th>
<th>0-30 cm $\theta_{fc}$</th>
<th>0-30 cm $\theta_{wp}$</th>
<th>30-61 cm $\theta_{fc}$</th>
<th>30-61 cm $\theta_{wp}$</th>
<th>61-91 cm $\theta_{fc}$</th>
<th>61-91 cm $\theta_{wp}$</th>
<th>91-122 cm $\theta_{fc}$</th>
<th>91-122 cm $\theta_{wp}$</th>
<th>RZWHC (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.39</td>
<td>0.19</td>
<td>0.38</td>
<td>0.21</td>
<td>0.38</td>
<td>0.22</td>
<td>0.38</td>
<td>0.21</td>
<td>215</td>
</tr>
<tr>
<td>2</td>
<td>0.39</td>
<td>0.19</td>
<td>0.38</td>
<td>0.23</td>
<td>0.39</td>
<td>0.22</td>
<td>0.39</td>
<td>0.21</td>
<td>210</td>
</tr>
<tr>
<td>3</td>
<td>0.38</td>
<td>0.16</td>
<td>0.37</td>
<td>0.19</td>
<td>0.37</td>
<td>0.21</td>
<td>0.39</td>
<td>0.21</td>
<td>230</td>
</tr>
<tr>
<td>4</td>
<td>0.39</td>
<td>0.20</td>
<td>0.39</td>
<td>0.19</td>
<td>0.38</td>
<td>0.20</td>
<td>0.37</td>
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<td>5</td>
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<td>0.20</td>
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<td>0.34</td>
<td>0.18</td>
<td>205</td>
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<tr>
<td>6</td>
<td>0.37</td>
<td>0.20</td>
<td>0.37</td>
<td>0.20</td>
<td>0.37</td>
<td>0.20</td>
<td>0.38</td>
<td>0.20</td>
<td>211</td>
</tr>
<tr>
<td>7</td>
<td>0.39</td>
<td>0.16</td>
<td>0.38</td>
<td>0.21</td>
<td>0.38</td>
<td>0.20</td>
<td>0.40</td>
<td>0.24</td>
<td>222</td>
</tr>
<tr>
<td>8</td>
<td>0.38</td>
<td>0.17</td>
<td>0.40</td>
<td>0.24</td>
<td>0.38</td>
<td>0.21</td>
<td>0.37</td>
<td>0.16</td>
<td>228</td>
</tr>
<tr>
<td>9</td>
<td>0.39</td>
<td>0.20</td>
<td>0.38</td>
<td>0.17</td>
<td>0.34</td>
<td>0.20</td>
<td>0.35</td>
<td>0.16</td>
<td>222</td>
</tr>
<tr>
<td>10</td>
<td>0.39</td>
<td>0.13</td>
<td>0.38</td>
<td>0.12</td>
<td>0.41</td>
<td>0.20</td>
<td>0.39</td>
<td>0.18</td>
<td>291</td>
</tr>
</tbody>
</table>

Neutron gauge determined RZWHC were graphically compared with multiple spatial layers including topography features and soil $EC_a$ (Figure 4.11). One location’s result appeared to act as an outlier; it was understood that the location of this monitoring site was the hydric soil. It was concluded that TWI and SCA did not have a linear relationship with the RZWHC estimate as a result of poorly dispersed data. The resulting $R^2$ for SCA and TWI was an improvement over the other considerations but a majority of the strength is a result of one data point located away from a cluster of data points. Soil $EC_a$ and
topographic slope had the best distribution for fitting a line to build a regression equation which relates RZWHC throughout the field. The resulting linear regressions from Figure 4.11 are displayed in Table 4.3.

Table 4.3: Linear regression results of field collected RZWHC and spatial data layers.

<table>
<thead>
<tr>
<th>Regression Equation</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>RZWHC = 271.94 - 0.9112*ECₐ-deep</td>
<td>0.3321</td>
</tr>
<tr>
<td>RZWHC = 258.39 - 1.1938*ECₐ-shallow</td>
<td>0.2048</td>
</tr>
<tr>
<td>RZWHC = 153.66 + 24.136*O.M.</td>
<td>0.0605</td>
</tr>
<tr>
<td>RZWHC = 216.47 + 0.0476*SCA</td>
<td>0.8658</td>
</tr>
<tr>
<td>RZWHC = 249.62 - 993.79*Slope</td>
<td>0.4176</td>
</tr>
<tr>
<td>RZWHC = 163.02 + 7.4572*TWI</td>
<td>0.8291</td>
</tr>
</tbody>
</table>
Field area affected by various ranges and zones in spatial data layers aids in understanding the magnitude of field variability that may exist. Field area results of 10 m spatial data grids for TWI, EC$_{a\text{-deep}}$, EC$_{a\text{-shallow}}$, and slope were tabulated (Table 4.4). It is clear that Field A was not uniformly dispersed over the different ranges in spatial data but rather a majority of the field fell within two to four range classifications. Slope for instance contained 80% of the field area in the range of 0.017-2.68%, while the higher slopes impacted small areas of the field. It is unlikely that by developing linear regression relationships between a single field spatial data layer and measured RZWHC that the entirety of the field will be properly treated. Rather than analyzing and treating an entire field, it might be more beneficial to focus on the regions that contain the most area. When trying to encompass an entire range in spatial data it can be difficult to address accurately its entirety; therefore error and over fitting of data can become prevalent. Understanding different classification ranges of spatial data and the area impacted is an important factor when addressing a field in order to minimize the amount of error introduced as a result of regions with limited area.

Table 4.4: Spatial data layers ranges and the area impacted.

<table>
<thead>
<tr>
<th>TWI</th>
<th>Area (ha)</th>
<th>EC$_{a\text{-deep}}$ Area (ha)</th>
<th>EC$_{a\text{-shallow}}$ Area (ha)</th>
<th>Slope (%)</th>
<th>Area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.4-5.9</td>
<td>2.15</td>
<td>11.9-27.3</td>
<td>0.49</td>
<td>11.44-18.5</td>
<td>2.21</td>
</tr>
<tr>
<td>6-7.9</td>
<td>23.21</td>
<td>27.4-42.7</td>
<td>12.04</td>
<td>18.6-25.5</td>
<td>13.21</td>
</tr>
<tr>
<td>8-9.9</td>
<td>10.43</td>
<td>42.8-58.1</td>
<td>11.15</td>
<td>25.6-32.5</td>
<td>8.75</td>
</tr>
<tr>
<td>10-11.9</td>
<td>2.37</td>
<td>58.2-73.5</td>
<td>13.69</td>
<td>32.6-39.5</td>
<td>9.29</td>
</tr>
<tr>
<td>12-13.9</td>
<td>1.57</td>
<td>73.6-88.9</td>
<td>4.27</td>
<td>39.6-46.5</td>
<td>6.67</td>
</tr>
<tr>
<td>14-15.9</td>
<td>1.16</td>
<td>89.0-104.3</td>
<td>0.2</td>
<td>46.6-53.5</td>
<td>1.46</td>
</tr>
<tr>
<td>16-18.8</td>
<td>0.9</td>
<td>104.4-119.76</td>
<td>0.02</td>
<td>53.6-60.14</td>
<td>0.27</td>
</tr>
</tbody>
</table>
R software (R Core Team, 2015) was used to perform statistical data analyses. Various linear regression, multiple linear regression, and interaction terms were considered using slope and ECₐ as the variables ( 
Table 4.5). Further considerations were taken to exclude the outlying hydric soil data point to better predict the majority of the field while disregarding the hydric soil regions (Table 4.6) as they accounted for minimal field areas. When the hydric point was eliminated from the analysis the $R^2$ decreased while the $SE_{resid}$ improved. Thus, a linear regression using all data points with slope as the independent variable was determined to be the best ($R^2 = 0.4176$) estimate based on the amount of data used. Using slope as a predictor for RZWHC has certain implications that should be considered. Slope at the top, middle, and bottom of hills can be difficult to predict because slope (as a percent) on a grid can be the same at the top and bottom of the hill while the location affects the runoff or run-on of water. However, the impacts of hydrologic processes in both areas would likely be different. Along a hillslope soil layers and depths of soil horizons often change as a result of erosion over time. This can change the rate and amount of water infiltrated throughout a slope. Another important hydrologic event is that runoff from the slope feeds downslope areas. As a result the further downslope water travels, the longer the infiltration time over these areas is, resulting in increased water available for storage.
Table 4.5: Field A regression considerations and results (hydric soil data point included).

<table>
<thead>
<tr>
<th>Regression Equation</th>
<th>$R^2$</th>
<th>df</th>
<th>SE resid (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RZWHC = 249.62 - 993.79*Slope</td>
<td>0.418</td>
<td>8</td>
<td>19.62</td>
</tr>
<tr>
<td>RZWHC = 254.2 - 905.99<em>Slope - 0.25</em>EC$_{a\text{-shallow}}$</td>
<td>0.423</td>
<td>7</td>
<td>20.88</td>
</tr>
<tr>
<td>RZWHC = 292.5 - 2527.61<em>Slope - 1.8</em>EC$<em>{a\text{-shallow}}$ + 58.42*(Slope * EC$</em>{a\text{-shallow}}$)</td>
<td>0.527</td>
<td>6</td>
<td>20.42</td>
</tr>
<tr>
<td>RZWHC = 251.66 - 1459.51<em>Slope + 12.52</em>(Slope* EC$_{a\text{-shallow}}$)</td>
<td>0.432</td>
<td>7</td>
<td>20.71</td>
</tr>
<tr>
<td>RZWHC = 294.72 - 2590.70<em>Slope - 1.0486</em>EC$<em>{a\text{-deep}}$ + 33.94*(Slope*EC$</em>{a\text{-deep}}$)</td>
<td>0.584</td>
<td>6</td>
<td>19.15</td>
</tr>
<tr>
<td>RZWHC = 252.6 - 1767.95<em>Slope + 11.48</em>(Slope*EC$_{a\text{-deep}}$)</td>
<td>0.443</td>
<td>7</td>
<td>20.52</td>
</tr>
</tbody>
</table>

Table 4.6: Field A regression considerations excluding the outlying hydric soil data point.

<table>
<thead>
<tr>
<th>Regression Equation Excluding Hydric Soil</th>
<th>$R^2$</th>
<th>df</th>
<th>SE resid (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RZWHC = 227.81 - 332.57*Slope</td>
<td>0.271</td>
<td>7</td>
<td>8.306</td>
</tr>
<tr>
<td>RZWHC = 227.49 - 0.2987*EC$_{a\text{-shallow}}$</td>
<td>0.088</td>
<td>7</td>
<td>9.294</td>
</tr>
<tr>
<td>RZWHC = 227.55 - 0.1597*EC$_{a\text{-deep}}$</td>
<td>0.058</td>
<td>7</td>
<td>9.445</td>
</tr>
<tr>
<td>RZWHC = 201.48 + 736.47<em>Slope + 0.4879</em>EC$<em>{a\text{-deep}}$ - 18.55*(Slope*EC$</em>{a\text{-deep}}$)</td>
<td>0.438</td>
<td>5</td>
<td>8.63</td>
</tr>
</tbody>
</table>

A 10-m RZWHC grid was created in ArcMap by applying the resulting regression equation (Equation 8) to the 10 m grid slope raster. A 10 m raster of RZWHC throughout the field was created (Figure 4.12) and used to predict soil water capacity throughout the field. Two different thresholds were applied to the RZWHC raster to avoid unreasonable quantities and to also test the sensitivity of the application of setting bounding limits (the upper and lower bounds above and below field collected samples were set to +/- 25.4 and 12.7 mm). RZWHC was calculated using a linear regression with the slope grid as follows:

$$\text{RZWHC (mm) = 249.62 - 993.79 \times \text{Slope}}$$  \hspace{1cm} \text{Equation (8)}$

Where: Slope is in (m/m)
Resulting thresholds were 190.5 mm to 304.8 mm and 177.8 mm to 317.5 mm for the 12.7 mm and 25.4 mm thresholds, respectively. The results computed in ArcMap indicated that the upper threshold was not reached while the lower thresholds for both were reached. For the 12.7 mm threshold, the RZWHC ranged from 191 mm to 250 mm in the resulting map, a total of 59 mm difference on a 10 m grid between the lowest and highest values observed (Figure 4.12). In this case, 59 mm would likely be equivalent to two irrigation applications and represented 24% of the entire RZWHC for the 250 mm depth. The 25.4 mm threshold resulted in a RZWHC map which ranged from 177.8 mm to 250 mm (Figure 4.13). While the lower thresholds were reached, it is indicated that very little field area is included in these lower regions of RZWHC (Figure 4.14) and they might not be the best areas to target for management.
The field “theoretical RZWHC” map was developed from the slope regression (equation 8). The threshold used was +/- 19 mm from the observed minimum and maximum neutron gauge determined RZWHC. This threshold is exactly half-way between the two thresholds (25.4 mm and 12.7 mm) which were used in the irrigation scenario slope regression maps. In addition this map also included an error term to simulate unknown and real life error throughout the field. The error term was determined from the regression results residual standard error. The residuals did not look normally distributed so a better fitting statistical distribution was used; for this case it happened to be a log
normal distribution (standard deviation of 0.25). The error term was determined both on a 1-m and 10-m raster (Figure 4.15 and Figure 4.16).

As shown in Figure 4.15, adding error at the 1 m level allows for error within the 10 m grids and results in many more grid values which can average throughout generally small regions; it also increased the range in RZWHC significantly. Adding error at the 10 m grid level did not introduce error within the 10 m grids (Figure 4.16). Visual observation suggests that with fewer grid cells (1 cell vs. 10 cells), adding the 10-m error may not average as well over an irrigation zone, therefore some small zones might be highly influenced by one 10-m grid cell.

Figure 4.15: Field A "theoretical RZWHC" 1 m map.
Estimated RZWHC (PTF and gSSURGO) was plotted against neutron gauge measured RZWHC in Figure 4.17. The results indicated what appeared to be over-estimation of the gSSURGO RZWHC map and under-estimation of the PTF RZWHC map (Figure 4.17). The one-to-one line represented an ideal relationship between measured and estimated RZWHC. The ECₐ and PTF regression results were undesirable, it is expected that the complexity of the soil layering makes it hard to accurately apply only textural properties for a given depth without considering the surrounding soils. The PTF is a laboratory based determined soil properties which only consider the soil sample, in the field for example, constricting soils may lie above limiting the soil beneath it. There is also possible contribution to error in the PTF determination of FC. Field capacity is difficult to predict and can range from 1/10⁰ to 1/3 bar, resulting in large ranges of FC values without a pressure plate laboratory analysis. To obtain a better estimate of the RZWHC one might consider using Hydrus to model the root zone since it can adjust for layering of soils and other surrounding conditions.
The field “theoretical RZWHC” (1 m and 10 m) layers were sampled using the VRI pivot polygons consisting of two, five, and 10 degree sectors along with each sector having two zone sizes laterally. Each zone’s standard deviation of RZWHC was computed to determine if the decreasing size of irrigation zones becomes more uniform (Figure 4.18). As a result the standard deviation, mean, and quartile one and three become closer between scenarios. The range between high and low standard deviations increases with decreased zonal size, resulting in uncontrollable error. As zones become finer, some zones are primarily made up of only one or very few RZWHC values. The step from including error at the 10 m and then the 1 m level does have an impact on the range of RZWHC experienced indicating the impact from including 1 m verses 10 m error.
Each zone’s water requirements were based upon the 10\textsuperscript{th} percentile MAD for the zone. Analyzing the 10\textsuperscript{th} percentiles for the entire field to see how the various irrigation zones affect the 10\textsuperscript{th} percentile (Figure 4.19) resulted in conclusions similar to the standard deviation. The 10\textsuperscript{th} percentile increased as the zone size decreased (opposite of standard deviation). The range in values increase but the lower range tends to increase more than the upper range. The mean of the 10\textsuperscript{th} percentiles also remains more consistent throughout the differing irrigation zones; the largest improvement is seen when going from sector to zonal control. Defining the zonal control further (span to 12.5 m) for this field has less of an impact than the going from sector to zone control by span. Going from a 1 m map to a 10 m map increases the spread and range of 10\textsuperscript{th} percentiles (Figure 4.19).
Figure 4.19: Field A Pivot control scenario sampled zonal 10th-percentiles of RZWHC (mm) for grid size of 1 m and 10 m

Applying four prescription maps to the “theoretical RZWHC” map allowed for testing the accuracy of prescription map development. The VRI maps were compared to uniform irrigation which allowed for calculation of field water savings in (mm) after the savings were averaged over each 1 m grid cell and summed to give a whole-field depth. Negative values for savings were noticed which indicated increased water application above the uniform rate application based upon the 10th percentile MAD of the field. Results indicate that the regression analysis performed with slope results in the highest water savings while the gSSURGO prescription also offers improvements from uniform rate irrigation except for the sector control option (Figure 4.20). The explanation for additional irrigation requirement with sector control resulted from the method for determining irrigation needs. When the sector’s 10th-percentile MAD, which is not the majority of the sector, is lower than the field 10th-percentile MAD, the result will be over-irrigation. The sensitivity of the slope regression RZWHC map bounds (+/- 25.4 mm or 12.7 mm) were minimal with very minor gains below one-tenth of a millimeter in water savings from one to the other. A direct regression between ECa and PTF actually introduces irrigation error above URI; as a result more irrigation is required for this prescription than URI without any benefits. It is assumed that since URI was based on the field’s 10th percentile, few areas would be subject to water stress, thus the additional irrigation water would not be utilized by the crop.

Slight increase in water savings were noted using a 10 m “theoretical RZWHC” compared to the 1 m map, but the trends were similar between the two (Figure 4.20). The difference in irrigation depth between the two methods is about 2 mm. This depth is
minimal with the resulting increase in savings smaller than the uncertainty in measurement error and would change with different irrigation water application techniques. The resulting suggestions are that for the control scenarios tested in this study, the 1 m and 10 m error raster had little to no impact on the results; therefore either one is as sufficient as the other.

Figure 4.20: Field A calculated savings from applying VRI polygons and different RZWHC maps.

To further illustrate the spatial distribution of potential savings using VRI, Figure 4.21, Figure 4.22 and Figure 4.23 were developed in ArcGIS. Each control zone was an average determined from analyzing the 1 m grid cells and averaging the grid cells within the polygon. The result was a depth (mm) of water saved or added for that zone. It should be noted that each scenario contained regions throughout the field that required more or less water than what the URI applied. The figures visually offer further understanding how increased control offers more precise zonal water application. Decreasing the zone
degree level allows for more precise on/off control of irrigation sprinklers in order to water the edges of different zones more effectively and efficiently.

Figure 4.21: Field A 10 degree VRI irrigation savings and additions for four prescription maps.

The increase in irrigation zone definition from the sector control to the zonal span control further defines the target areas within the zones. The zone control breaks up the irrigation zones to irrigate throughout the span more effectively. By visual comparison the easiest and largest difference to notice is between the sector control of the gSSURGO map compared to the tower zone control (Figure 4.21 and Figure 4.22).
Figure 4.22: Field A 10 degree by tower VRI irrigation savings and additions for four prescription maps. Further defining the 10 degree sectors to a small distance which requires nozzle control allows for applying various water depths with each nozzle by pulsing on and off. The increase in control from tower control to 12.5 m lateral distance has smaller beneficial gains than stepping from sector control to zonal control. It is visually observed that the increased control is existent but with limited beneficiary increases (Figure 4.22 and Figure 4.23).
4.4 Field Study Results: Field B

Soil moisture was measured at four depths with a neutron gauge and determined to be representative of observed FC for a root zone of 122 cm. Saxton and Rawls (2006) PTF was used to determine volumetric wilting point for the same depths where soil moisture was measured. The volumetric FC and WP along with the corresponding depths and also the RZWHC are displayed in Table 4.7. The range in RZWHC depth between locations was 50 mm, which would be greater than a single irrigation application depth for this field. Thus, VRI may have the potential to reduce irrigation in some areas. The corresponding soil water tension in centibars for the observed FC is displayed in Appendix D.
To estimate RZWHC throughout the field, spatial data layers including soil EC<sub>a</sub> and topography were collected and studied to develop a relationship with RZWHC in order to further extrapolate RZWHC spatially throughout the field. Spatial data were extracted in ArcMap based upon GPS coordinates of monitoring locations allowing for comparison with measured RZWHC for each location (Figure 4.24). Soil EC<sub>a-shallow</sub> appears to cover a wide range of well dispersed data, considering a limited amount of six data points. EC<sub>a</sub> and slope appear to have the best distribution which fit the data with RZWHC while SCA and TWI is rather clustered resulting in undesirable results. The resulting linear regression equations along with the R<sup>2</sup> fit are displayed in Table 4.8.
Figure 4.24: Field B measured RZWHC compared with available spatial data layers.

Table 4.8: Field B linear regression results from RZWHC and differing spatial data.

<table>
<thead>
<tr>
<th>Regression Equation</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RZWHC = 292.55 - 1.3474*EC$_{a\text{-deep}}$</td>
<td>0.5108</td>
</tr>
<tr>
<td>RZWHC = 271.38 - 1.3956*EC$_{a\text{-shallow}}$</td>
<td>0.6985</td>
</tr>
<tr>
<td>RZWHC = 141.82 + 9.0029*TWI</td>
<td>0.2458</td>
</tr>
<tr>
<td>RZWHC = 219.62 + 0.0175*SCA</td>
<td>0.0094</td>
</tr>
<tr>
<td>RZWHC = 266.58 - 4391.6*Slope</td>
<td>0.6104</td>
</tr>
</tbody>
</table>

Further understanding the extent of the spatial data above, such as the ranges in the data along with the area of field affected, allows for suggestions to be made about variability. Results from the 10 m grids for TWI, EC$_{a\text{-deep}},$ EC$_{a\text{-shallow}},$ and slope are tabulated (Table
It can be concluded for the spatial data extent that a majority of the field’s area is contained within two to four of the evenly spaced range classifications. For example, EC_{a-deep} has a range of 7.3 mS/m to 110.7 mS/m while 82% of the field area falls within two classifications ranges of 36.9 mS/m to 51.7 mS/m and 51.7 mS/m to 66.5 mS/m.

When managing a field it is important that the entire area is considered, but focusing on the major target areas where the most impact will be to more accurately address these major areas might be the most beneficial.

<table>
<thead>
<tr>
<th>TWI</th>
<th>Area (ha)</th>
<th>Slope (%)</th>
<th>Area (ha)</th>
<th>EC_{a-deep}</th>
<th>Area (ha)</th>
<th>EC_{a-shallow}</th>
<th>Area (ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>6.0 - 7.75</td>
<td>5.49</td>
<td>0 - 0.38</td>
<td>3.74</td>
<td>7.3 - 22.1</td>
<td>0.11</td>
<td>5.6 - 13.9</td>
<td>0.04</td>
</tr>
<tr>
<td>7.75 - 9.5</td>
<td>11.21</td>
<td>0.38 - 0.76</td>
<td>9.43</td>
<td>22.1 - 36.9</td>
<td>1.85</td>
<td>13.9 - 22.1</td>
<td>0.77</td>
</tr>
<tr>
<td>9.5 - 11.25</td>
<td>5.75</td>
<td>0.76 - 1.14</td>
<td>7.16</td>
<td>36.9 - 51.7</td>
<td>11.55</td>
<td>22.1 - 30.5</td>
<td>10.64</td>
</tr>
<tr>
<td>11.25 - 13</td>
<td>2.07</td>
<td>1.14 - 1.52</td>
<td>3.32</td>
<td>51.7 - 66.5</td>
<td>9.42</td>
<td>30.5 - 38.8</td>
<td>6.96</td>
</tr>
<tr>
<td>13 - 14.75</td>
<td>0.87</td>
<td>1.52 - 1.9</td>
<td>1.22</td>
<td>66.5 - 81.3</td>
<td>2.57</td>
<td>38.8 - 47.1</td>
<td>4.74</td>
</tr>
<tr>
<td>14.75 - 16.5</td>
<td>0.17</td>
<td>1.9 - 2.28</td>
<td>0.47</td>
<td>81.3 - 96.1</td>
<td>0.1</td>
<td>47.1 - 55.4</td>
<td>2.02</td>
</tr>
<tr>
<td>16.5 - 18.2</td>
<td>0.07</td>
<td>2.28 - 2.66</td>
<td>0.27</td>
<td>96.1 - 110.7</td>
<td>0.02</td>
<td>55.4 - 64.1</td>
<td>0.45</td>
</tr>
</tbody>
</table>

Statistical software R (R Core Team, 2015) was utilized to conduct further analyses. The same linear regressions as Table 4.8 are considered and the results are displayed in

**Error! Reference source not found.**. As a result of EC_{a-shallow} having the best linear fit, interaction terms with the additional data were considered by plotting against the EC_{a-shallow} residual standard error (Figure 4.25). The residual standard error is interpreted to be the difference between the regression line and the actual measured value. If an interaction term that would result in a more accurate regression was existent, there would be a stable trend with the residual standard error of EC_{a-shallow}. The graphs indicate there is not an interaction term that would strengthen the regression as a result of scatter in the plots,
therefore the linear regression between RZWHC and $EC_{a\text{-shallow}}$ was determined to be the best estimate ($R^2$ is 0.70).

The resulting linear regression equation ($RZWHC = 271.38 - 1.4 \times EC_{a\text{-shallow}}$) was used in ArcGIS to calculate the spatial RZWHC on a 10 m grid throughout the field. Two different thresholds were incorporated to limit the upper and lower range for the calculated RZWHC to avoid unrealistic results. Threshold depths of RZWHC were ±254 and ±127 mm from the range of neutron gauge measured RZWHC.

The resulting RZWHC layers have ranges of 182 mm to 241.3 mm for the 12.7 mm threshold and 182 mm to 254 mm for the 25.4 mm threshold. Results can be seen in Figure 4.26 and Figure 4.27, to obtain a further understanding of the distribution throughout the field of differing RZWHC depths, Figure 4.28 shows representative field area for different ranges of RZWHC. The result is a right skew with more area impacted...
on the upper end of the RZWHC range. 91% of the field area has a RZWHC between 215 mm and 241.3 mm, leaving the remaining 9% to be in the 182 mm to 215 mm range.

Another RZWHC map developed is “theoretical RZWHC”. This map was developed to represent the actual field RZWHC by using the same map as the field measured RZWHC and EC\textsubscript{a-shallow} regression, but now changing the limits and adding an error term that fits
the residual error from the regression. By adding the error term, the result was a more realistic map since in reality there are subtle variations throughout the field that impact how much moisture the rootzone holds. A 19.5 mm threshold was used to limit the variation in values, this threshold was applied before the error was added to the map. The error was added to the map at one m and 10 m levels. One meter grids allowed for variation within the 10 m grids which were used for the other three methods of RZWHC map making (Figure 4.29). By including this error the range in RZWHC greatly increased (164.7 mm to 265 mm). Error was also added at a 10 m level which resulted in a more realistic range of RZWHC values but also makes the field become more uniform since the error is so course and relatively large (Figure 4.30).

The neutron gauge measured RZWHC is considered to be the most accurate value for RZWHC. It was desired to compare the measured results with the results from
gSSURGO and the PTF/EC\textsubscript{a-shallow} regression. The results are slightly under predicted from the gSSURGO and PTF/EC\textsubscript{a-shallow} regression of the RZWHC. The gSSURGO had four out of six points under predicted, while the PTF had five out of six points under predicted, refer to Figure 4.31. The one to one line represents the measured RZWHC, therefore any points to the right are under predicted while the points to the left are over predictions and any points close to the line are relatively accurate predictions of RZWHC. Possible avenues for error is with complex soil layering, field practices, and in the determination of FC for all methods since this value can range from 1/10\textsuperscript{th} bar to 1/3 bar.

![Figure 4.31: Field B estimated RZWHC vs. measured RZWHC.](image)

Each of the three RZWHC maps created was compared to the “theoretical RZWHC” map to simulate irrigation and determine zonal water applications compared to URI. The “theoretical RZWHC” layers (one m and 10m) were sampled with the VRI pivot polygons to see the impact on the standard deviation and 10\textsuperscript{th}-percentile between zones as the zone sizes decrease (Figure 4.32 and Figure 4.33). For both the one meter and 10 m
maps, as irrigation zone sizes decrease, so does the mean, quartile 1, and quartile 3 of the standard deviations indicating more uniformity within the zone. The minimum and maximum range increases as zones become finer. This is expected since smaller zones are made up of very few points of which some can be very low or high as a result of the random error which did not averaged out as well as it did with larger zones. The overall range in standard deviations is higher for the 10 m grid, since fewer values get average throughout smaller irrigation zones resulting in some higher extremes.

![Figure 4.32: Pivot control scenario sampled standard deviations from "theoretical RZWHC" map for grid cell size of 1 m and 10 m.](image)

Each zone’s irrigation depth calculations were based on the 10\textsuperscript{th}-percentile MAD within the zone. The result is increasing zonal 10\textsuperscript{th}-percentiles as irrigation zone sizes decrease. The mean, quartile one, and quartile three are similar for the sector control zones. Increases between sector and zone control remained relatively similar, not showing much increase in precision when advancing to higher levels of control for both the 1 m and 10 m grids. The difference between the 1 m grid and 10 m grid is an increase in overall range while the mean, quartile 1, and quartile 3 remain relatively consistent (Figure 4.33).
Each RZWHC map was also sampled with the same pivot polygons. These results are compared to the “theoretical RZWHC” map under which URI is simulated. The product is a calculation that determines the amount of water applied to each zone, the VRI polygons indicate additional water applied or water saved throughout the different zones. The water savings calculations were determined on 1 m grids, summed and averaged over the whole field to determine the whole-field depth of excess or deficit. Each zone was irrigated based upon the 10th-percentile MAD for the zone, while the “theoretical RZWHC” was treated with URI and also irrigated based upon the 10th-percentile of the entire field’s MAD.

Results indicate that the gSSURGO and field RZWHC measured linear regression maps (ECa-shallow (+/- 25.4 and 12.7 mm)) offered similar field averaged savings. The PTF and ECa-shallow had much lower field savings and very little variation between differing pivot application scenarios. There is an increase in water savings for gSSURGO and RZWHC measured linear regression map when decreasing the zone size both by degree (10, 5, and 2 degree) and along the lateral Figure 4.34.
Figure 4.34: Field B calculated savings from applying VRI polygons and different RZWHC maps.

VRI water savings were determined for each irrigation zone by comparing to URI. The savings include both positive and negative values as a result of not every zone required less water than URI. Applying this field with VRI allows for smaller and larger depths to be applied strategically. Increasing the application depth in areas and decreasing in others allows for increased management in water application which might result in higher water use efficiency. Figure 4.35 displays water savings for the various 10 degree polygons and four different RZWHC maps that were compared with the “theoretical RZWHC” URI treatment. Similar to Field A, it is also visually apparent that the increase from sector control to zone control allows for a great deal of additional management options, but also increased decisions for water application practices.
Figure 4.35: Field B VRI water savings example for 10 degree pivot polygons.
4.5 Energy Analysis

An energy analysis was performed to quantify potential savings directly related to the depth of water pumped using an electric motor. A variable frequency drive was not considered. Pump well information was obtained through the State of Nebraska Department of Water Resources Water Well Registration (Registered Groundwater Wells Data Retrieval, 2015) along with irrigation operating requirements. Methods for calculating the energy usage for pumping water was determined from (Martin et al., 2010). Pump efficiency was determined from pump curves. Field A energy requirements along with a potential economic cost are displayed in Table 4.10, where the cost of a kWh was estimated to be $0.10 USD. It is concluded that for Field A the highest energy savings are around 1180 kWh which is a result of the finest level of irrigation control tested (2 degree sector with 12.5 m laterals). The negative energy values indicate an increase in energy requirements as a result of pumping more water with the VRI application.

<table>
<thead>
<tr>
<th>Pivot Scenario</th>
<th>gSURGO</th>
<th>PTF &amp; ECshallow Regression</th>
<th>Slope regression (+/-25.4 mm)</th>
<th>Slope regression (+/-12.7 mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 deg Sector</td>
<td>-49</td>
<td>-90.91</td>
<td>6.4</td>
<td>62.93</td>
</tr>
<tr>
<td>2 deg x Span</td>
<td>54</td>
<td>8.30</td>
<td>9.8</td>
<td>90.80</td>
</tr>
<tr>
<td>2 deg x 12.5 m</td>
<td>203</td>
<td>25.27</td>
<td>11.6</td>
<td>117.24</td>
</tr>
<tr>
<td>5 deg Sector</td>
<td>485</td>
<td>-86.46</td>
<td>6.2</td>
<td>61.65</td>
</tr>
<tr>
<td>5 deg x Span</td>
<td>21</td>
<td>2.13</td>
<td>9.5</td>
<td>94.08</td>
</tr>
<tr>
<td>5 deg x 12.5 m</td>
<td>16</td>
<td>16.75</td>
<td>11.1</td>
<td>110.47</td>
</tr>
<tr>
<td>10 deg Sector</td>
<td>2160</td>
<td>-50.32</td>
<td>6.2</td>
<td>61.83</td>
</tr>
<tr>
<td>10 deg x Span</td>
<td>65</td>
<td>1.08</td>
<td>8.8</td>
<td>88.93</td>
</tr>
<tr>
<td>10 deg x 12.5 m</td>
<td>402</td>
<td>9.40</td>
<td>10.1</td>
<td>100.63</td>
</tr>
</tbody>
</table>

For Field B there were no additional depths of water required from the VRI system, only water savings were experienced for an average of the field (Table 4.11). While there is little improvement in energy savings with implementation of a VRI for this field, it can be concluded that the increase from sector control VRI to zone control VRI is a
quantifiable difference. For this application it is also noticeable that our results indicate
the 2 degree sector with 12.5 m lateral zones having the highest energy savings.

Table 4.11: Field B energy and economic impacts from VRI water savings.

<table>
<thead>
<tr>
<th>Pivot Scenario</th>
<th>gSSURGO</th>
<th>PTF &amp; EC</th>
<th>Regression</th>
<th>EC regression (+/-25.4 mm)</th>
<th>EC regression (+/-12.7 mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>field depth (mm)</td>
<td>Volume (m³)</td>
<td>kWh</td>
<td>Cost ($)</td>
<td>field depth (mm)</td>
</tr>
<tr>
<td>2 deg Sector</td>
<td>3.6</td>
<td>934</td>
<td>24.69</td>
<td>2.2</td>
<td>298</td>
</tr>
<tr>
<td>2 deg x Tower</td>
<td>7.1</td>
<td>1815</td>
<td>47.98</td>
<td>1.4</td>
<td>360</td>
</tr>
<tr>
<td>2 deg x 12.5 m</td>
<td>7.5</td>
<td>1917</td>
<td>50.69</td>
<td>1.6</td>
<td>398</td>
</tr>
<tr>
<td>5 deg Sector</td>
<td>3.6</td>
<td>934</td>
<td>24.69</td>
<td>1.2</td>
<td>295</td>
</tr>
<tr>
<td>5 deg x Tower</td>
<td>7.0</td>
<td>1796</td>
<td>47.49</td>
<td>1.4</td>
<td>356</td>
</tr>
<tr>
<td>5 deg x 12.5 m</td>
<td>7.5</td>
<td>1909</td>
<td>50.48</td>
<td>1.5</td>
<td>386</td>
</tr>
<tr>
<td>10 deg Sector</td>
<td>3.6</td>
<td>934</td>
<td>24.69</td>
<td>1.1</td>
<td>293</td>
</tr>
<tr>
<td>10 deg x Tower</td>
<td>7.0</td>
<td>1791</td>
<td>47.35</td>
<td>1.3</td>
<td>345</td>
</tr>
<tr>
<td>10 deg x 12.5 m</td>
<td>7.3</td>
<td>1870</td>
<td>49.45</td>
<td>1.4</td>
<td>370</td>
</tr>
</tbody>
</table>

The economic impact from energy savings for these two field sites is not enough to
justify implementing a VRI. If more restrictive water limitations are put into practice
which jeopardize reaching full yield potential, then water application strategies might
become more significant. Even though this analysis did not support implementing VRI at
these field sites, the methodology developed for analysis is thought to be applicable to
most fields for a preliminary analysis.
Chapter 5. Summary and Conclusion

Three methods for mapping RZWHC were achieved in this study, all of which required different input data. Numerous spatial data layers are available; this study was limited to elevation layers which were used to conduct hydrologic analysis and soil ECa which indicates soil properties (Sudduth, et al., 2004). Methodology for consistent cleaning and spatial interpolation were important in utilizing the data. The three methods for mapping RZWHC vary in cost for obtaining the data, with more data often associated with higher costs.

Data obtained from gSSURGO is the easiest to collect; this was the basis for the gSSURGO RZWHC map. Soil ECa collection (for our case a Veris MSP was used) is offered through various different cropping consultants which often also conduct a soil textural analysis. The method for developing a soil ECa and PTF linear regression based map did not prove to be highly effective for the fields tested (Field A (R² = 0.085) and Field B (R² = 0.028)). Mild costs are often associated with data collection for this level of study. The third method of RZWHC map required further sampling which included soil moisture sampling. Soil moisture monitoring was conducted throughout the season. A very wet off-season and growing season was experienced; therefore the soil profile was determined to be at field capacity. Measurements taken by soil moisture monitoring allowed for RZWHC to be determined for the monitoring locations. This data was used along with topographic analysis and soil ECa analysis to develop regression equations that allowed for spatial prediction of RZWHC. Resulting equations included linear models; Field A encompassed a slope term with an R² of 0.42 and Field B had a linear regression with the variable being ECa-shallow with an R² of 0.70. For both Fields A and B
a “theoretical RZWHC” was created based on the sampled soil moisture and an additional error term equal to the residual error from the regression which was fitted to the distribution and added at both 1 m and 10 m grid cell sizes.

A total of nine irrigation zone control layers were analyzed (2, 5, and 10 degree radial sectors along with lateral zones at the span length and 12.5 m). The three methods for developing RZWHC maps were sampled with these field polygon files where the 10\textsuperscript{th}-percentile of the 1 m points in the polygons were used to determine RZWHC MAD which controlled the irrigation. The irrigation determined from the polygon files was compared by applying URI to the “theoretical RZWHC” map where the 10\textsuperscript{th}-percentile RZWHC of the field was used to determine irrigation MAD. Minimal water savings were quantified for the fields, but the use of VRI showed its ability to spatially distribute various depths of water throughout the field to better manage the different zones. Therefore, often times irrigation zones received more or less water than what was applied with the URI treatment. The highest field averaged water depth savings were a result of the soil moisture sampling regression in which Field A saved around 14 mm and Field B saved around 9 mm.

Further work is needed to test the methods produced in this paper. Also further defining of sampling techniques is needed to acquire the necessary data for RZWHC map development and continuation of field soil moisture monitoring. Numerous options are available on the market when considering VRI that include a multitude of options for management practices. The higher precision levels of the irrigation system, the more precise the irrigation application achievable throughout different management zones. While it is beneficial to have a high precision system for the accuracy of turning on and
off sprinklers, it may be less beneficial to have really small management zones. Changes in crop condition and AWC throughout the field can cause a great deal of error when trying to manage for small zones. Also, there is error due to sprinkler overlap that gets introduced when starting and stopping sprinklers, an area of meshing between two assigned depths. Currently the economic impact on implementing a VRI is unrealistic for the two sites considered in this analysis where water restrictions do not play a role in limiting irrigation.
5.1 References


R Core Team. (2015). R: A language and environment for statistica computing. Ver. 3.2.0, Vienna, Austria.


Appendix A: Python Code for Simulating GIS Sampling

```python
import csv, os, sys, tkFileDialog

mapDir = tkFileDialog.askdirectory(title = "Please choose the folder in which the RZWHC maps are located (".../1m/"")
mapList = os.listdir(mapDir)
mapCount = 0
while mapCount < len(mapList):
    if ("WHC" not in mapList[mapCount]) or (mapList[mapCount][-4:] != "\.tif") or ("3qrt" in mapList[mapCount]):
        mapList.pop(mapCount)
    else:
        mapCount += 1
zoneDir = tkFileDialog.askdirectory(title = "Please choose the folder in which the previously rasterized zone polygons are located (".../PolygontoRaster/"")
zoneList = os.listdir(zoneDir)
zoneNames = []
zoneCount = 0
while zoneCount < len(zoneList):
    if zoneList[zoneCount][-8:] != "rast.shp":
        zoneList.pop(zoneCount)
    else:
        if "x" in zoneList[zoneCount]:
            if "41" in zoneList[zoneCount]:
                zoneNames.append(zoneList[zoneCount].split("x", 1)[0].zfill(2) + "deg41")
            else:
                zoneNames.append(zoneList[zoneCount].split("x", 1)[0].zfill(2) + "degTR")
        else:
            zoneNames.append(zoneList[zoneCount].split("deg", 1)[0].zfill(2) + "degSP")
        zoneCount += 1
spatialJoinDir = mapDir.replace("1m", "SpatialJoin", 1)
if not os.path.exists(spatialJoinDir): # if folder doesn't exist, create it now
    os.makedirs(spatialJoinDir)
inputDir = mapDir.replace("1m", "Input", 1)
if not os.path.exists(inputDir): # if folder doesn't exist, create it now
    os.makedirs(inputDir)
for m in xrange(mapCount):
    mapName = mapList[m].rsplit(".", 1)[0]
    arcpy.RasterToPoint_conversion(mapDir + "\" + mapList[m], mapDir + "\" + mapName + "\" + Value")
    for z in xrange(zoneCount):
        arcpy.SpatialJoin_analysis(zoneDir + "\" + zoneList[z], mapName, spatialJoinDir + "\" + mapName + "\" + zoneNames[z] + "\" + Value")
        rows = arcpy.da.SearchCursor(mapName + "\" + zoneNames[z], ["GRIDCODE", "GRID_CODE"])
        spatialJoinTable = [["ZoneID", "RZWHC"]
        for row in rows:
            spatialJoinTable.append(row)
        inputFile = open(inputDir + "\" + mapName + "\" + zoneNames[z] + "\" + Value")
```

inputWriter = csv.writer(inputFile, delimiter = ",")
inputWriter.writerows(spatialJoinTable)
inputFile.close()
print "Done with " + mapName + "" + zoneNames[z] + "!"
print "Done with " + mapName + "!"
print "All done!"
Appendix B: Python Code for Simulating Irrigation Depth Calculations

```python
# import required modules
import csv, math, os, sys, tkFileDialog

# set up
inputDir = tkFileDialog.askdirectory(title = 
    "Please choose input directory (".../Input/...")")
inputList = os.listdir(inputDir) # list all files in folder
scenarioList = []
realityScenarios = []
prescriptionScenarios = []
realityScenariosCount = 0
maxNumPrescriptions = 0
for inputName in inputList:
    scenario = inputName.rsplit('_', 2)[1]
    if scenario in scenarioList:
        scenarioNum = scenarioList.index(scenario)
        if "reality" in inputName.lower():
            realityScenarios[scenarioNum].append(inputName)
            realityScenariosCount += 1
        else:
            prescriptionScenarios[scenarioNum].append(inputName)
            if len(prescriptionScenarios[scenarioNum]) > maxNumPrescriptions:
                maxNumPrescriptions = len(prescriptionScenarios[scenarioNum])
    else:
        scenarioList.append(scenario)
        if "reality" in inputName.lower():
            realityScenarios.append([inputName])
prescriptionScenarios.append([])
            realityScenariosCount += 1
        else:
            realityScenarios.append([])
prescriptionScenarios.append(inputName)
            if len(prescriptionScenarios[-1]) > maxNumPrescriptions:
                maxNumPrescriptions = len(prescriptionScenarios[-1])

if inputDir.count("Input") == 1:
    outputDir = inputDir.replace("Input", "Output", 1) # create output folder name
    if not os.path.exists(outputDir):
        os.makedirs(outputDir) # if output folder doesn't exist, create it now
    else:
        print "Please modify input directory " + inputDir + " so that it contains "Input" exactly once!"
        sys.exit()

MAD = 0.5
realityNum = 0
realizonalZonalStdDevs = []
summaryTable = [["realityName"], [
    "fieldCellCount"] + ["" for i in xrange(realizonalScenariosCount)], [
    "field10thPctile (mm)"] + ["" for i in xrange(realizonalScenariosCount)], [
    "URIFieldAvgExcess (mm)"] + ["" for i in xrange(realizonalScenariosCount)], [
    "URIFieldAvgDeficit (mm)"] + ["" for i in xrange(realizonalScenariosCount)], [
    "minZonalStdDevs (mm)"] + ["" for i in xrange(realizonalScenariosCount)], [
    "q1ZonalStdDevs (mm)"] + ["" for i in xrange(realizonalScenariosCount)], [
    "medZonalStdDevs (mm)"] + ["" for i in xrange(realizonalScenariosCount)], [
    "q3ZonalStdDevs (mm)"] + ["" for i in xrange(realizonalScenariosCount)], [
    "maxZonalStdDevs (mm)"] + ["" for i in xrange(realizonalScenariosCount)], [
    "minZonal10thPctile (mm)"] + ["" for i in xrange(realizonalScenariosCount)], [
    "q1Zonal10thPctile (mm)"] + ["" for i in xrange(realizonalScenariosCount)], [
    "medZonal10thPctile (mm)"] + ["" for i in xrange(realizonalScenariosCount)], [
    "q3Zonal10thPctile (mm)"] + ["" for i in xrange(realizonalScenariosCount)]
```

for n in xrange(maxNumPrescriptions):
    summaryTable.extend(["prescriptionName"] + ["" for i in xrange(realityScenariosCount)],
    ["fieldCellCount"] + ["" for i in xrange(realityScenariosCount)],
    ["minZonal10thPctile (mm)"] + ["" for i in xrange(realityScenariosCount)],
    ["maxZonal10thPctile (mm)"] + ["" for i in xrange(realityScenariosCount)],
    ["zonal10thPctile (mm)"] + ["" for i in xrange(realityScenariosCount)],
    ["maxZonalSavings (mm)"] + ["" for i in xrange(realityScenariosCount)],
    ["VRIFieldAvgSavings (mm)"] + ["" for i in xrange(realityScenariosCount)],
    ["VRIFieldAvgExcess (mm)"] + ["" for i in xrange(realityScenariosCount)],
    ["VRIFieldAvgDeficit (mm)"] + ["" for i in xrange(realityScenariosCount)])
# repeat for each scenario
for s in xrange(len(realityScenarios)):
    # repeat for each reality
    for r in xrange(len(realityScenarios[s])):
        # read and store RZWHCs of each reality cell
        realityFile = open(inputDir + "/" + realityScenarios[s][r], "rb")
        realityReader = csv.reader(realityFile, delimiter = ",")
        skipRows = 1
        realityCellRZWHCsByZone = []
        realityRZWHCList = []
        # skip first row and read in the rest
        for row in realityReader:
            if skipRows <= 0:
                for z in xrange(int(float(row[0]) - len(realityCellRZWHCsByZone) + 1):
                    realityCellRZWHCsByZone.append([])
                realityCellRZWHCsByZone[int(float(row[0]))].append(float(row[1])) # list RZWHC by zones
                realityRZWHCList.append(float(row[1]))
            else:
                skipRows -= 1
        realityFile.close()
        # calculate realityFieldCellCount, realityField10thPctile, and realityFieldAD
        realityFieldCellCount = len(realityRZWHCList)
        if realityFieldCellCount > 1:
            realityField10thPctilePos = max(realityFieldCellCount / float(10) - 0.5, float(0)) # calculate the position of realityField10thPctile
            realityRZWHCList.sort() # sort RZWHC in ascending order
            realityField10thPctile = (realityRZWHCList[int(realityField10thPctilePos)] + (realityRZWHCList[int(realityField10thPctilePos) + 1] - realityRZWHCList[0]) * (realityField10thPctilePos - int(realityField10thPctilePos))) # calculate realityField10thPctile using the position by linear interpolation
            realityFieldAD = realityField10thPctile * MAD
        else:
            print "Please put more than one cell in " + realityScenarios[s][r] + "!"
            sys.exit()
        # calculate realityZoneCount, realityZonalCellCounts, realityZonalMeans, zonal10thPctiles for this reality,
        realityZonal10thPctilesList = []
        # realityCellADsByZone, zonalAvgBalances, URIFieldAvgExcess, URIFieldAvgDeficit, realityZonalStdDevs, and realityZonalStdDevsList
realityZoneCount = len(realityCellRZWHCsByZone)
if realityZoneCount > 1:
    realityZonalCellCounts = []
    realityZonalMeans = []
    zonal10thPctiles = [['' for j in xrange(2 +
    len(prescriptionScenarios[s]) * 2)]
    for z in xrange(realityZoneCount)]
    realityZonal10thPctilesList = []
    realityCellADsByZone = []
    zonalAvgBalances = [['' for j in xrange(2 +
    len(prescriptionScenarios[s]) * 2)]
    for z in xrange(realityZoneCount)]
URIFieldAvgExcess = 0
URIFieldAvgDeficit = 0
realityZonalStdDevs.extend([['' for j in
    xrange(realityScenariosCount * 2)]
    for z in xrange(realityZoneCount -
    len(realityZonalStdDevs))])
for z in xrange(realityZoneCount):
    realityZonal10thPctilePos = max(realityZonalCellCounts[z] / 10.0 - 0.5, float(0))
    realityCellRZWHCsByZone[z].sort()
    zonal10thPctiles[z][0] = z
    zonal10thPctiles[z][1] =
    (realityCellRZWHCsByZone[z][int(realityZonal10thPctilePos)] +
     realityCellRZWHCsByZone[z][int(realityZonal10thPctilePos) + 1] -
     realityCellRZWHCsByZone[z][int(realityZonal10thPctilePos)]) *
    (realityZonal10thPctilePos -
     int(realityZonal10thPctilePos)))
    realityZonal10thPctilesList.append(zonal10thPctiles[z][1])
    varPop = 0
    realityCellADsByZone[z].append([])
    zonalAvgBalances[z][0] = z
    zonalAvgBalances[z][1] = 0
    for RZWHC in realityCellRZWHCsByZone[z]:
        varPop += (RZWHC - realityZonalMeans[z]) ** 2 / float(realityZonalCellCounts[z])
        realityCellADsByZone[z].append(RZWHC * MAD)
        zonalAvgBalances[z][1] += (realityCellADsByZone[z][-1] -
        realityFieldAD) / float(realityZonalCellCounts[z])
        if RZWHC >= realityField10thPctile:
            URIFieldAvgExcess += (realityCellADsByZone[z][-1] -
            realityFieldAD) / float(realityFieldCellCount)
            else:
                URIFieldAvgDeficit += (realityFieldAD -
                realityCellADsByZone[z][-1]) / float(realityFieldCellCount)
        realityZonalStdDevs[z][2 * realityNum] = z
        realityZonalStdDevs[z][2 * realityNum + 1] =
        math.sqrt(varPop)
        realityZonalStdDevsList.append(realityZonalStdDevs[z][2 *
        realityNum + 1])
    elif realityZonalCellCounts[z] == 1:
        realityZonalMeans.append(realityCellRZWHCsByZone[z][0])
        zonal10thPctiles[z][0] = z
        zonal10thPctiles[z][1] = realityCellRZWHCsByZone[z][0]
        realityZonal10thPctilesList.append(zonal10thPctiles[z][1])
realityCellADsByZone.append([realityCellRZWHCsByZone[z][0] - MAD])

zonalAvgBalances[z][0] = z
zonalAvgBalances[z][1] = realityCellADsByZone[z][0] - realityFieldAD

if realityCellRZWHCsByZone[z][0] >= realityField10thPctile:
    URIFieldAvgExcess += (realityCellADsByZone[z][0] - realityFieldAD) / float(realityFieldCellCount)
else:
    URIFieldAvgDeficit += (realityFieldAD - realityCellADsByZone[z][0]) / float(realityFieldCellCount)

reali

realityZonalStdDevs[z][2 * realityNum] = z
realityZonalStdDevs[z][2 * realityNum + 1] = 0
realityZonalStdDevsList.append(realityZonalStdDevs[z][2 * realityNum + 1])

else:
    print "Please put at least one cell in zone " + str(z) + " of " + realityScenarios[s][r] + "!"
    sys.exit()
else:
    print "Please put more than one zone in " + realityScenarios[s][r] + "!"
    sys.exit()

# calculate min, Q1, median, Q3, and max of realityZonalStdDevsList and
# realityZonal10thPctilesList;
# fill in elements of summaryTable corresponding to this reality
qlPos = max(realityZoneCount / float(4) - 0.5, float(0))  # separating zones into four quartiles and then determining q1, etc.
medPos = max(2 * realityZoneCount / float(4) - 0.5, float(0))
q3Pos = max(3 * realityZoneCount / float(4) - 0.5, float(0))

realityZonalStdDevsList.sort()
realityZonal10thPctilesList.sort()

summaryTable[0][realityNum + 1] = realityScenarios[s][r]
summaryTable[1][realityNum + 1] = realityFieldCellCount
summaryTable[2][realityNum + 1] = realityField10thPctile
summaryTable[3][realityNum + 1] = URIFieldAvgExcess
summaryTable[4][realityNum + 1] = URIFieldAvgDeficit
summaryTable[5][realityNum + 1] = realityZonalStdDevsList[0]
summaryTable[6][realityNum + 1] = realityZonalStdDevsList[qlPos] + (realityZonalStdDevsList[qlPos + 1] - realityZonalStdDevsList[qlPos]) * (qlPos - int(qlPos))
summaryTable[7][realityNum + 1] = realityZonalStdDevsList[medPos] + (realityZonalStdDevsList[medPos + 1] - realityZonalStdDevsList[medPos]) * (medPos - int(medPos))
summaryTable[8][realityNum + 1] = realityZonalStdDevsList[q3Pos] + (realityZonalStdDevsList[q3Pos + 1] - realityZonalStdDevsList[q3Pos]) * (q3Pos - int(q3Pos))
summaryTable[9][realityNum + 1] = realityZonalStdDevsList[qlPos]
summaryTable[10][realityNum + 1] = realityZonal10thPctilesList[0]
summaryTable[11][realityNum + 1] = realityZonal10thPctilesList[qlPos] + (realityZonal10thPctilesList[qlPos + 1] - realityZonal10thPctilesList[int(qPos)]) * (qlPos - int(qPos))
summaryTable[12][realityNum + 1] = realityZonal10thPctilesList[medPos] + (realityZonal10thPctilesList[medPos + 1] - realityZonal10thPctilesList[int(medPos)]) * (medPos - int(medPos))
summaryTable[13][realityNum + 1] = realityZonal10thPctilesList[q3Pos] + (realityZonal10thPctilesList[q3Pos + 1] - realityZonal10thPctilesList[int(q3Pos)]) * (q3Pos - int(q3Pos))
summaryTable[14][realityNum + 1] = realityZonal10thPctilesList[qlPos]
prescriptionZonalSavings = [["" for j in xrange(2 *
len(prescriptionScenarios[s])]
    for z in xrange(realityZoneCount)
    # repeat for each prescription
    for p in xrange(len(prescriptionScenarios[s])):
        # read and store RZWHCs of each prescription cell
        prescriptionFile = open(inputDir + "/" +
            prescriptionScenarios[s][p], "rb")
        prescriptionReader = csv.reader(prescriptionFile, delimiter = ",")
        skipRows = 1
        prescriptionCellRZWHCsByZone = []
        prescriptionFieldCellCount = 0
        # skip first row and read in the rest
        for row in prescriptionReader:
            if skipRows <= 0:
                for z in xrange(int(float(row[0])) -
                    len(prescriptionCellRZWHCsByZone) + 1):
                    prescriptionCellRZWHCsByZone.append([])
                    prescriptionCellRZWHCsByZone[z].append(float(row[1]))
                    RZWHC by zones
                    prescriptionFieldCellCount += 1
            else:
                skipRows -= 1
        prescriptionFile.close()
    # calculate prescriptionZoneCount, prescriptionZonalCellCounts,
    zonal10thPctiles for this prescription, minPrescriptionZonal10thPctile,
    # prescriptionZonalSavings, maxZonalSavings, VRIFieldAvgSavings,
    zonalAvgBalances for this prescription, VRIFieldAvgExcess, and
    VRIFieldAvgDeficit
    prescriptionZoneCount = len(prescriptionCellRZWHCsByZone)
    if (prescriptionFieldCellCount > 1) and (prescriptionZoneCount ==
        realityZoneCount):
        prescriptionZonalCellCounts = []
        minPrescriptionZonal10thPctile = 9999
        maxZonalSavings = -9999
        VRIFieldAvgSavings = 0
        VRIFieldAvgExcess = 0
        VRIFieldAvgDeficit = 0
        for z in xrange(prescriptionZoneCount):
            prescriptionZonalCellCounts.append(len(prescriptionCellRZWHCsByZone[z]))
            # count number of cells in zone z
            if prescriptionZonalCellCounts[z] > 0:
                if prescriptionZonalCellCounts[z] > 1:
                    prescriptionZonal10thPctilePos =
                        max(prescriptionZonalCellCounts[z] / float(10) - 0.5, float(0))
                    prescriptionCellRZWHCsByZone[z].sort()
                    zonal10thPctiles[z][2 * p] = z
                    zonal10thPctiles[z][2 * p + 1] =
                        (prescriptionCellRZWHCsByZone[z][int(prescriptionZonal10thPctilePos)] +
                            (prescriptionCellRZWHCsByZone[z][int(prescriptionZonal10thPctilePos) + 1] -
                                prescriptionCellRZWHCsByZone[z][int(prescriptionZonal10thPctilePos)]) *
                                (prescriptionZonal10thPctilePos -
                                    int(prescriptionZonal10thPctilePos)))
                else:
                    zonal10thPctiles[z][2 * p] = z
                    zonal10thPctiles[z][2 * p + 1] =
                        prescriptionCellRZWHCsByZone[z][0]
if zonal10thPctiles[z][2 * p + 1] < minPrescriptionZonal10thPctile:
    minPrescriptionZonal10thPctile =
    zonal10thPctiles[z][2 * p + 1]  
    prescriptionZonalAD = zonal10thPctiles[z][2 * p + 1] * MAD
    prescriptionZonalSavings[z][2 * p] = z
    prescriptionZonalSavings[z][2 * p + 1] = prescriptionZonalAD - realityFieldAD
    if prescriptionZonalSavings[z][2 * p + 1] > maxZonalSavings:
        maxZonalSavings = prescriptionZonalSavings[z][2 * p + 1]
        VRIFieldAvgSavings += prescriptionZonalSavings[z][2 * p + 1] * realityZonalCellCounts[z] / float(realityFieldCellCount)  # use reality cell counts
        zonalAvgBalances[z][2 * p + 2] = z
        zonalAvgBalances[z][2 * p + 3] = 0
        for realityCellAD in realityCellADsByZone[z]:
            zonalAvgBalances[z][2 * p + 3] += (realCellAD - prescriptionZonalAD) / float(realityZonalCellCounts[z])
            if realityCellAD >= prescriptionZonalAD:
                VRIFieldAvgExcess += (realCellAD - prescriptionZonalAD) / float(realityFieldCellCount)
            else:
                VRIFieldAvgDeficit += (prescriptionZonalAD - realityCellAD) / float(realityFieldCellCount)
    else:
        print("Please put at least one cell in zone "+ str(z) + " of "+ prescriptionScenarios[s][p] + ")!
        sys.exit()
    else:
        print("Please put more than one cell in "+ prescriptionScenarios[s][p] + " and/or put the same number of zones (i.e., "+ str(realityZoneCount) + ") in "+ prescriptionScenarios[s][p] + " as "+ realityScenarios[s][r] + ")!
        sys.exit()
# fill in elements of summaryTable corresponding to this prescription
summaryTable[7 * p + 15][realityNum + 1] = prescriptionScenarios[s][p]
summaryTable[7 * p + 16][realityNum + 1] = prescriptionFieldCellCount
summaryTable[7 * p + 17][realityNum + 1] = minPrescriptionZonal10thPctile
summaryTable[7 * p + 18][realityNum + 1] = maxZonalSavings
summaryTable[7 * p + 19][realityNum + 1] = VRIFieldAvgSavings
summaryTable[7 * p + 20][realityNum + 1] = VRIFieldAvgExcess
summaryTable[7 * p + 21][realityNum + 1] = VRIFieldAvgDeficit

# export zonal10thPctiles
zonal10thPctilesFile = open(outputDir + "/" + realityScenarios[s][r].rsplit('_', 1)[0] + "_zonal10thPctiles.csv", "wb")
zonal10thPctilesWriter = csv.writer(zonal10thPctilesFile, delimiter = ",")
header = ["realityName", realityScenarios[s][r]],
        ["zoneFID", "10thPctile"] * (len(prescriptionScenarios[s]) + 1)
for p in xrange(len(prescriptionScenarios[s])):
    header[0].extend(["prescriptionName", prescriptionScenarios[s][p]])
zonal10thPctilesWriter.writerow(header)
zonal10thPctilesWriter.writerow(zonal10thPctiles)
zonal10thPctilesFile.close()}
# export zonalAvgBalances
zonalAvgBalancesFile = open(outputDir + "/" + realityScenarios[s][r].rsplit("_", 1)[0] + "_zonalAvgBalances.csv", "wb")
zonalAvgBalancesWriter = csv.writer(zonalAvgBalancesFile, delimiter = ",")
header = [("realityName", realityScenarios[s][r]),
(["zoneID", "avgURIBalance"] + ["zoneID", "avgVRIBalance"] * len(prescriptionScenarios[s]))]
for p in xrange(len(prescriptionScenarios[s])):
    header[0].extend(["prescriptionName", prescriptionScenarios[s][p]])
zonalAvgBalancesWriter.writerows(header)
zonalAvgBalancesWriter.writerows(zonalAvgBalances)
zonalAvgBalancesFile.close()

# export prescriptionZonalSavings
prescriptionZonalSavingsFile = open(outputDir + "/" + realityScenarios[s][r].rsplit("_", 1)[0] + "_prescriptionZonalSavings.csv", ",")
prescriptionZonalSavingsWriter = csv.writer(prescriptionZonalSavingsFile, delimiter = ",")
header = [("realityName", realityScenarios[s][r]),
(["zoneID", "savings"] * len(prescriptionScenarios[s]))]
for p in xrange(len(prescriptionScenarios[s])):
    header[1].extend(["prescriptionName", prescriptionScenarios[s][p]])
prescriptionZonalSavingsWriter.writerows(header)
prescriptionZonalSavingsWriter.writerows(prescriptionZonalSavings)
prescriptionZonalSavingsFile.close()

realityNum += 1

# export realityZonalStdDevs
realityZonalStdDevsFile = open(outputDir + "/realityZonalStdDevs.csv", "wb")
realityZonalStdDevsWriter = csv.writer(realityZonalStdDevsFile, delimiter = ",")
header = [[],
(["zoneID", "stdDev"] * realityNum)]
for s in xrange(len(realityScenarios)):
    for r in xrange(len(realityScenarios[s])):
        header[0].extend(["realityName", realityScenarios[s][r]])
realityZonalStdDevsWriter.writerows(header)
realityZonalStdDevsWriter.writerows(realityZonalStdDevs)
realityZonalStdDevsFile.close()

# export summaryTable
summaryFile = open(outputDir + "/summary.csv", "wb")
summaryWriter = csv.writer(summaryFile, delimiter = ",")
summaryWriter.writerows(summaryTable)
summaryFile.close()
### Appendix C: Soil Data

**Field A:**

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<tr>
<th>Location</th>
<th>Depth (cm)</th>
<th>Organic Matter LOI %</th>
<th>% Sand</th>
<th>% Silt</th>
<th>% Clay</th>
<th>Texture</th>
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Appendix D: Observed FC relative soil water tension

Field A: Soil water tension determined using Saxton and Rawls (2006) PTF.

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Field B: Soil water tension determined using Saxton and Rawls (2006) PTF.

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