Managing Available Water Differences with Increasing Levels of Variable Rate Irrigation

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Introduction

Differences in field productivity result from a combination of many different field characteristics including but not limited to soil texture, topography, and fertility. In addition to field characteristics, considerations for seasonal differences along with year to year variations of water application and cropping systems need to be considered when determining water related stress.

Center pivot Variable-Rate Irrigation (VRI) systems vary by manufacturer but are commonly grouped into sector or zone control options. The decision of whether or not to invest in a VRI system, along with what level of control are primary considerations for potential adopters of this technology.

Specific objectives for this study were to:

- Identify relationships between available water and spatial data layers (e.g., topography and electrical conductivity) collected for the study fields.
- Create spatial prediction maps for available water from significant spatial data layers to estimate field variation.
- Spatially compare different levels of VRI control to determine how increasing control resolution may help address available water variation for the study fields.

Materials and Methods

- Study performed on 42 ha irrigated field located in Saunders Co., NE over the 2014 growing season.
- Field consisted of Fillmore, Filbert, and Tomek silt loam soils, and Yutan silty clay loam (from NRCS web soil survey, Figure 1).
- The field was managed as Field B (north 21 ha in soybeans) and Field A (south 21 ha in corn).
- Soil moisture monitoring included 11 neutron gauge access tubes (Figure 2) to a depth of 183 cm. A Troxler 4302 was used to measure soil moisture at depth of 15, 46, 72, and 107 cm.

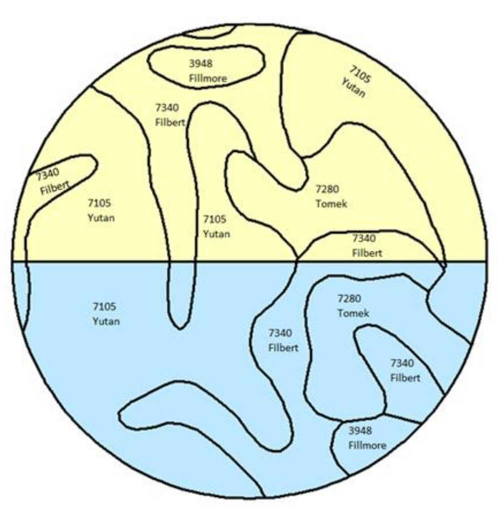

Fig. 1: NRCS soil map

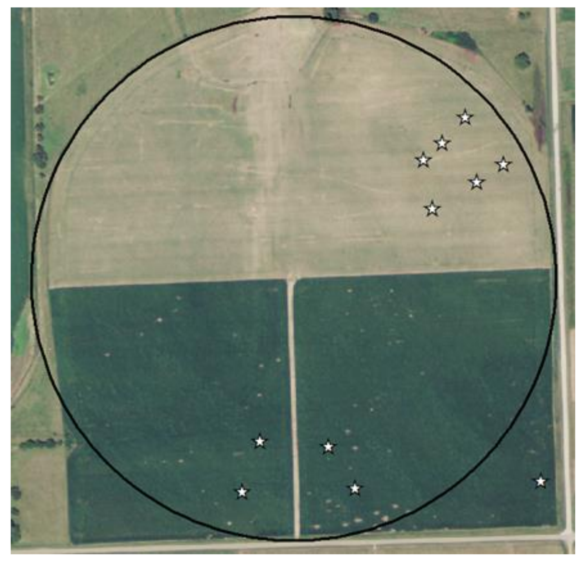

Fig. 2: 2014 moisture monitoring locations

- Soil apparent electrical conductivity (EC_a) was collected in fall of 2014 with a Veris MSP.
- Spatial variations in measured soil moisture were evaluated using Δ_{ij} which determined the difference between available water and the mean available water at each monitoring location.

$$\Delta_{ij} = AW_{ij} - \overline{AW_j}$$

- Regression equations were developed in statistical software (R) to spatially predict Δ based upon field properties.

- Topography characteristics were computed using 2m LIDAR data set obtained from Saunders County, this provided higher accuracy compared to RTK elevation data.
- Topographic Wetness Index (TWI) was computed in ArcGIS to quantify topography impacts on hydrologic processes (Equation 1).

$$TWI = \ln\left(\frac{\alpha}{\tan(\beta)}\right) \quad Eqn. 1$$

Where:
α = specific catchment area and
β = slope.

- Water Stress Index (WSI) is a regression equation developed by previous soil moisture monitoring throughout the growing season.

$$WSI = -0.26 - 0.13 * EC_a - 0.40 * Elev_{rel} + 0.08 * EC_a * Elev_{rel}$$

- A 10 x 10 grid was used to calculate WSI, the input fields were interpolated using Inverse Distance Weighting in ArcGIS.
- Water holding capacity was determined using soil sample characteristics and Saxton and Rawls pedo-transfer function.

Results and Discussion

- Seasonal average available water was determined by averaging neutron gauge soil moisture measurements from throughout the growing season.
  - North (Field B): Measurements used four pre-irrigation readings.
  - South (Field A): Nine measurements throughout the growing season.
- Available water was compared to field properties to identify correlations (Figure 3).

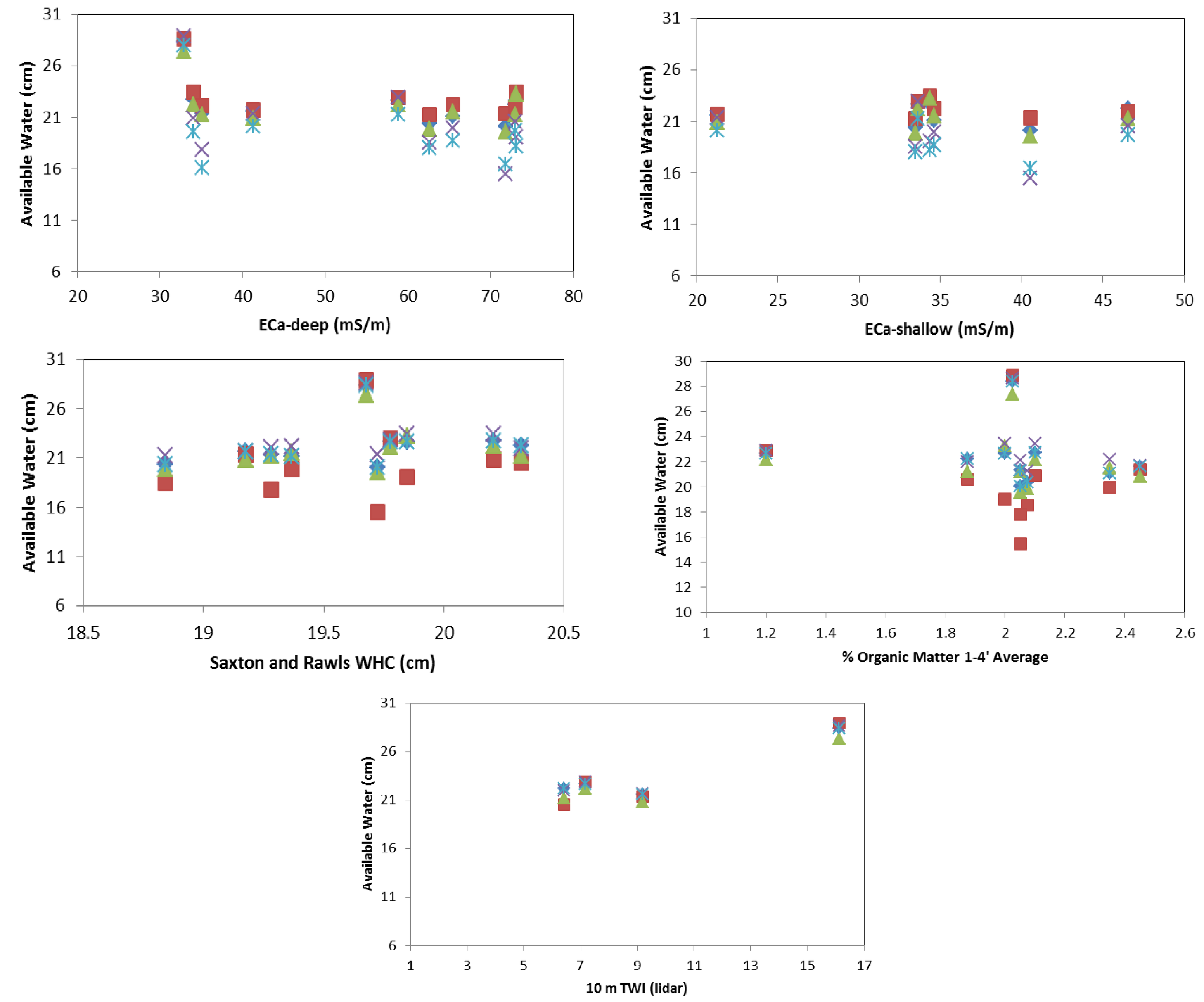

Fig. 3: Available water plotted versus five spatial data layers utilized during this analysis.

- Topography appeared to impact spatial variations in seasonal average soil moisture.
- Understanding variation in available water may lead to soil moisture monitoring and potential VRI management strategies.
- To develop a field raster to predict available water, Δ was determined for both fields (Figure 4).

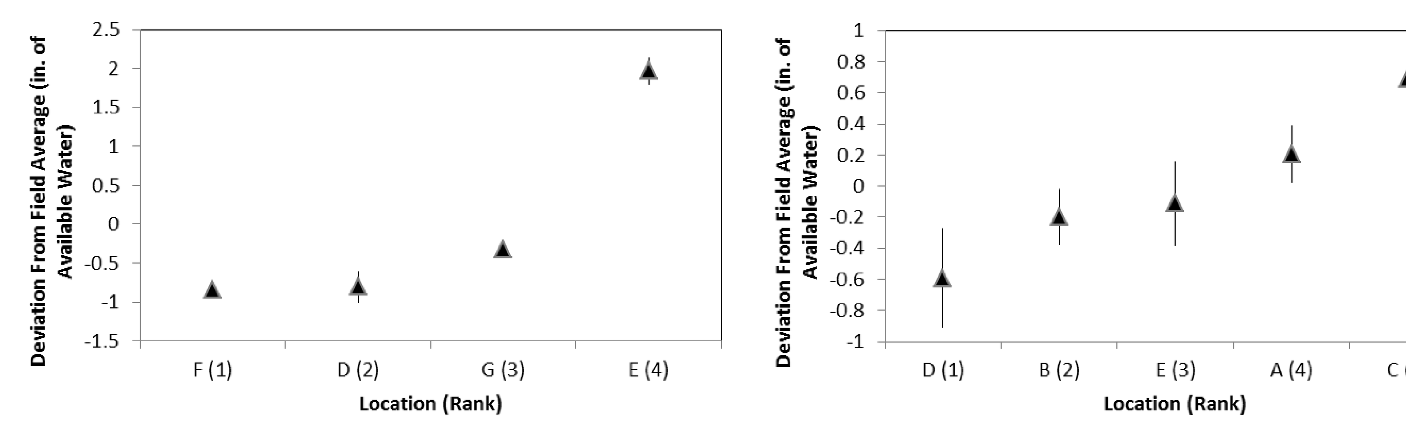

Fig. 4: Specific location deviations from field average available for south (left) and north (right) fields.

- Δ was mapped spatially for the fields using a regression. Average Δ was determined based upon neutron gauge measurements.
  - Varying field properties considered: Slope, Specific Catchment Area, $Ec_{a\text{-deep}}$, $EC_{a\text{-shallow}}$, TWI, along with variations of Log().
- The resulting regression equations were produced:

Field A	Avg Δ	R^2	RMSE (in)	df	SE_{resid} (in.)
Model 1	-2.7412472 + 0.2818521 * TWI_LDR_10	0.872	0.4137	2	0.585
Model 2	-5.760290905 + 0.283424844 * TWI_LDR_10 + 0.007374902 * TWI_LDR_10 * ECd_IDW_10	0.998	0.0502	1	

Field B	Avg Δ	R^2	RMSE (in)	df	SE_{resid} (in.)
Model 1	-2.6431764 + 0.3456924 * TWI_LDR_10	0.423	0.2572	3	0.332
Model 2	-0.324255071 + 0.147836376 * TWI_LDR_10 - 0.002036804 * TWI_LDR_10 * ECd_IDW_10	0.495	0.2405	2	
Model 3	-0.3352791 + 0.2809551 * log(SCA_LDR_10) - 0.2633137 * SLP_LDR_10	0.658	0.1981	2	
Model 4	-0.6421808 + 0.3773683 * log(SCA_LDR_10) - 0.8556817 * log(SLP_LDR_10)	0.685	0.1899	2	
Model 5	-1.3032730 + 0.5865203 * log(SCA_LDR_10) - 0.2429881 * log(SCA_LDR_10) * log(SLP_LDR_10)	0.717	0.1801	2	0.285

Results and Discussion

- Model 1 was used to determine Δ on a 10 m grid for both fields. Because Δ was an estimate, an error term was added at the 1 m level, which had a mean of zero and standard deviation (SD) which equaled the model residual error (Figure 5).

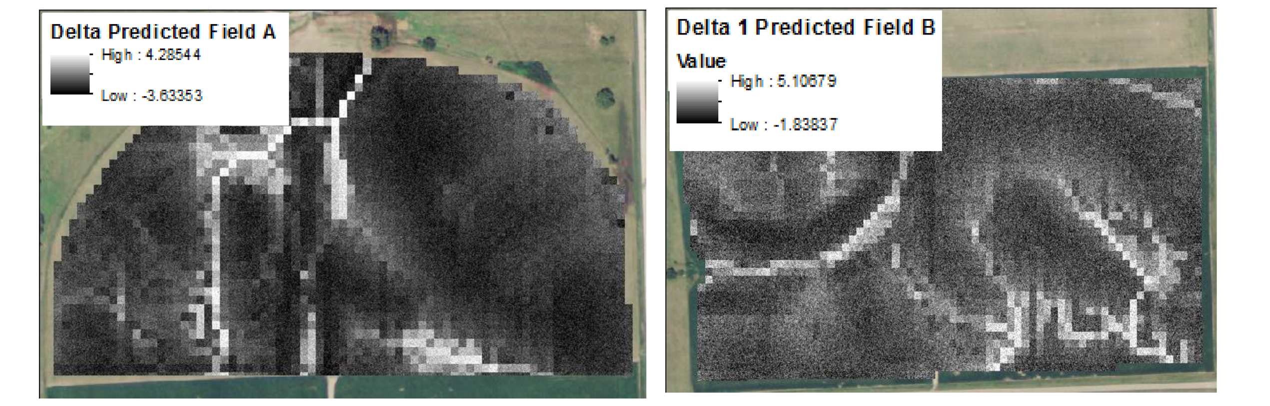

Fig. 5: 10 m rasters of predicted delta (Δ) including error for Field A (right) and Field B (left).

- The theoretical range of Δ (based upon porosity and average wilting point) was determined to be -6.48 to 6.48.
- The SD of Δ values were calculated for each zone within three VRI control scenarios. The SDs are displayed below (Figure 6) along with box & whisker plots created from the SD (Figure 7) for each VRI control scenario.

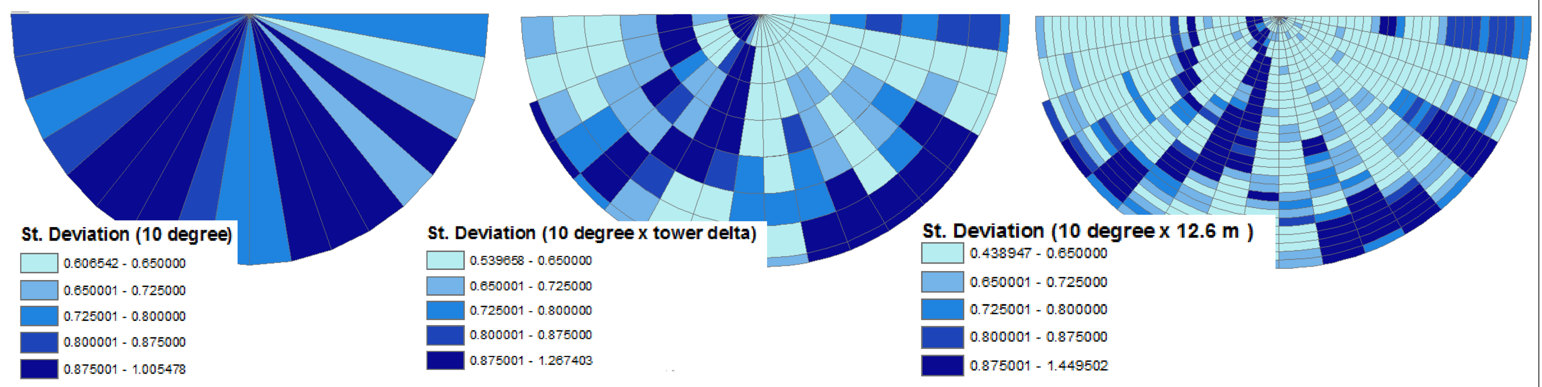

Fig. 6: SD of Δ shown for three VRI control scenarios within Field A.

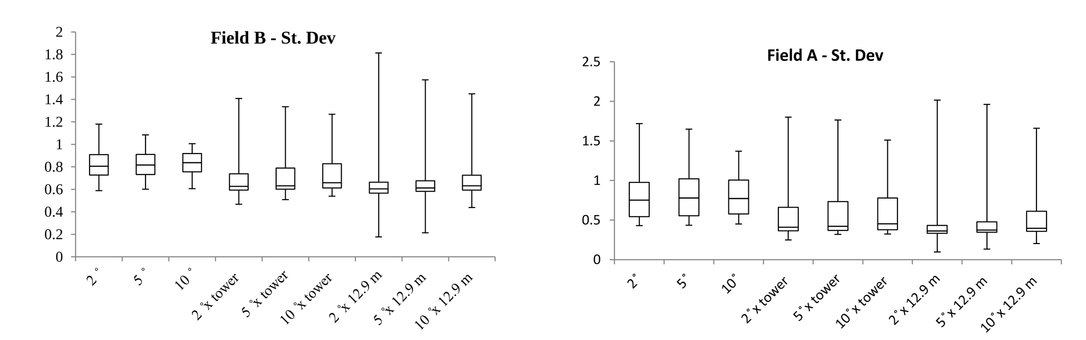

Fig. 7: Box and whisker plots of SD versus VRI control scenario for Fields A and B.

Conclusions

- For the two study fields, topography appeared to most directly affect seasonal available water.
- A model was created to predict available water from TWI; which was applied across the field to create a data layer for Δ that estimated available water deviation from field average.
- Nine VRI control scenarios were considered. The number of zones increased as the size per control zone decreased. Increasing the number of control zones reduced the overall SD in Δ for the study fields. This highlights the fact that higher control resolution could address field variation more successfully.
- The overall range in Δ SD increased as the number of zones increased which represented unmanageable differences.

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