PRECISION MAPPING TECHNOLOGY IN DRYLAND CROPPING SYSTEM

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ABSTRACT

Increasing availability of cropland geospatial data are providing farmers with opportunities but also challenges in interpreting these data for precision cropland management decisions. The objective of this study is to evaluate spatial variability and precision management decisions using mapping technology in dryland cropping system. The study was initiated in 2018 in Akron, Colorado on field size plots ranged from 2.4 to 4.5 ha (6-11 acres) with substantial production variability. The cropping system consists of (i) Business-As-Usual (BAU) management with wheat-fallow cropping under reduce tillage (WF-RT) and (ii) Aspirational (ASP) with four-year cropping of winter wheat-corn-millet-flex under no tillage (WCMFlex-NT). Each phase of each rotation was included in each year of the study with three replications. Soil samples in each field were taken in a 30-m (100-ft) georeferenced grid. Two or three management zones were defined in each field by yield, soil properties, and elevation. Veris-EC/pH was used as a tool to evaluate some aspects of soil properties. Two eddy covariance towers were installed to estimated carbon and water fluxes. High-resolution topographical maps reveal elevation changes of more than 2 m (6.5 ft) in some fields. Yield differences between high and low yielding zones within each field varied by as much as 135 bu ac^{-1} (8.5 Mg ha^{-1}) for corn and 85 bu ac^{-1} (5.3 Mg ha^{-1}) for wheat. Preliminary geospatial analyses are showing promise in guiding precision farming decisions and could provide a unique opportunity to dryland farmers for optimizing crop production, reducing inputs, and enhancing economic return in the central Great Plains Region.

INTRODUCTION

Precision Agriculture is a farming concept that accounts for spatial and temporal variability in crop production and soil resources. This can be done by using global positioning system (GPS) to coordinate collection of soil, site, and plant information; generating maps and relationships between spatial variability of soil and site properties in correlation with crop yield; and applying those relationships to guide variable-rate inputs for seed, fertilizer, and pesticides. The increase in world's population and the demand for food and fiber challenge the agriculture industry to increase food production, maximize profits, and conserve available resources. Adaptation of precision farming strategy may help increase food production, reduce inputs, enhance resource use efficiency, and improve economic return (Franzen and Mulla, 2016).

The usage of Unmanned Aerial Vehicles (UAV) technology with high resolution imaging equipment assists researchers and producers to identify spatial variability of key factors in the field and apply appropriate management strategies. The UAV provides assessments of crop yield, crop water and nutrient stress, weed problems, insect and pathogen infestation, soil characteristics, and other field conditions, all of which can contribute to maximize land sustainability (Olson and Anderson, 2020). The spectral cameras in these UAV can be used to identify crop stand count (Torres-Sánchez et al., 2015), weed detection (Hansen et al., 2013), and biotic stress detection (Bock et al., 2008). The incorporation of remote sensors and UAV technology allow plant breeders and researchers to gather phenotypic information quickly and efficiently for making management decision that enhance production (Yang et al., 2017). Crop yield and quality assessment, for a specific year, can be influenced by crop genetics, weather pattern, soil nutrients, and land management decisions (Raun et al., 2001). The usage of UAV-based imagery have enhanced crop assessment accuracy (Mekonnen et al., 2020) due to real time evaluation of crop progress though the life cycle (Ballester et al., 2017).

Soil water is the most limiting factor for crop production in dryland agricultural systems. Monitoring crop water stress with UAV technology can assess fluctuations in crop water needs throughout the season (Santestaban et al., 2017) and allow for improved irrigation scheduling (Crusiol et al., 2019) Crop nutrients such as nitrogen (N), phosphorus (P), and potassium (K) are essential for crop production and are applied regularly to soil. Crop nutrient-use efficiency could vary from year to year depending on water availability and ambient temperature. Insufficient synchronization between crop nutrient needs and available soil nutrients may cause deficiencies or lead to leaching of nutrients with harmful effects on the environment (Olson and Anderson, 2020). The UAV can be equipped with spectral sensors for crop nutrient assessments to indirectly assess real-time nutrient deficiencies (Liu et al., 2018). This also could improve estimates of fertilizer requirements and associated costs (Olson and Anderson, 2020).

In precision agriculture, mapping soil characteristics is important for management decisions due to spatial soil heterogeneity (Govers et al., 2013). The UAV provides precise and high-resolution soil mapping, which helps with enhanced input efficiency. Veris instrument that use measured soil electrical conductivity (EC) to estimate soil properties that can be transferred into maps (Pei et al, 2018; Azhar et al., 2021). Soil properties informed by Veris data may include soil organic carbon (SOC), total nitrogen (TN), moisture, soil texture (clay, silt, and sand), cation exchange capacity (CEC), calcium (Ca), magnesium (Mg), potassium (K), and pH (Pei et al., 2018).

The semiarid region of the Great Plains exhibit erratic weather patterns with low precipitation, high evaporation, and high temperature during summer months. The production in dryland cropping systems of this region depends on soil water storage that is influenced by land topography, cropping intensity, and tillage practices (Kühling et al., 2017). There is an information gap linking land topography, soil water storage, crop soil water availability, soil properties, and crop yield (Brown et al., 2020). The objective of this study is to evaluate precision management decisions for enhancing land productivity in dryland cropping system in Akron, Colorado. In this report we will focus on precision technologies in relation to productivity.

MATERIALS AND METHODS

The precision management approach initiated in 2018 at Akron, CO on field size plots that exhibited high degree of variability in crop production, soil nutrients, and soil water content. Two management practices have been implemented: (i) Business-as-

Usual (BAU) that consist of wheat-fallow rotation with reduce tillage (WF-RT) and (ii) Aspirational (ASP) that consist of a four-year rotation with winter wheat-corn-millet-fallow/flex (WCMFlex) and no-tillage. The choice between fallow and an appropriate crop (flex) in the fourth year will depend on the available soil moisture at planting for that year. Each phase of rotation is included in each year with 3 replications. The field plots size ranged from 6-11 acres (2.4-4.5 ha). Average annual precipitation over the previous 29 years (1991-2020) was 16.2 inches (410.5 mm). In 2018, soil samples were taken using a gridded sampling design of 100 ft x 100 ft equidistant spacing with georeferenced grid points to generate field maps (Figure 1). Soil samples were taken from 0-6 inches (0-15 cm) and 6-12 inches (15-30 cm) depth.

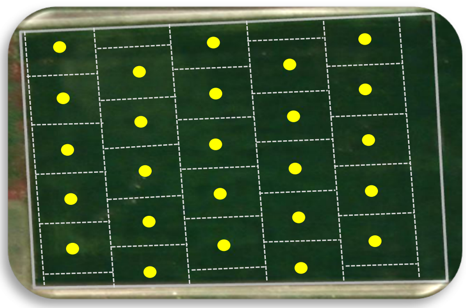


Figure 1. Soil sampling points diagram. Soil samples were taken using grid of 100 ft x 100 ft equidistant spacing and georeferenced each grid point.

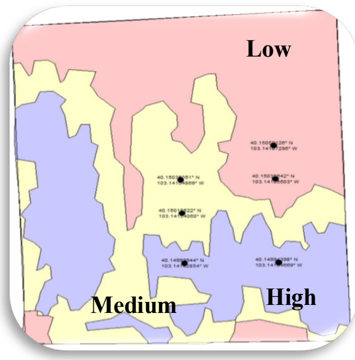
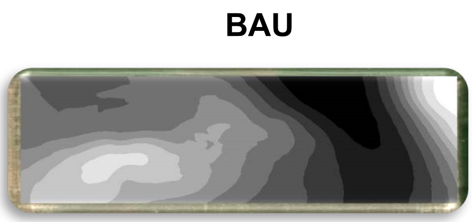


Figure 2. Diagram of the neutron tubs installed in each field plots at low, medium, and high yield zones.

Soil samples were analyzed for chemical properties such as EC, pH, N, P, K, organic matter. Crop yield was evaluated using yield combine harvester equipped with georeferenced instrument to establish yield maps. Crop yield in each field plot was organized in three zones (High, Medium, and Low) by yield, soil properties, and elevation. Soil moisture is being evaluated using neutron probe measurements from two tubes installed in each zone within the same field (Figure 2). Correlation among different parameters (yield, soil nutrients, soil water content, etc.) and crop yield was evaluated using Random Forest models.

RESULTS AND DISCUSSION

Field plots varied in land elevation (Figure 3). The differences in elevations within the same field plot ranged between 7-10 ft (2.1-3.0 m) with BAU and ASP. In 2019 corn and wheat yield ranged from 25.0 bu/ac in the low yielding zone to 160 bu/ac in some high yielding zone for corn and 110 bu/ac for wheat (Figure 4). The yield differences between the high and the low yielding zones was about 135 bu/ac (8.5 Mg ha^{-1}) for corn and 85 bu/ac (5.3 Mg ha^{-1}) for wheat. This represents about 8.5 Mg/ha differences with corn yield and 5.3 Mg/ha for wheat yield within the same field plot. Yield in each field plot exhibited 7 zones blended with each other (Figure 4) which could cause some management challenges regarding inputs. Therefore, organizing the field plot into three management zones may help with improving field management efficiency.



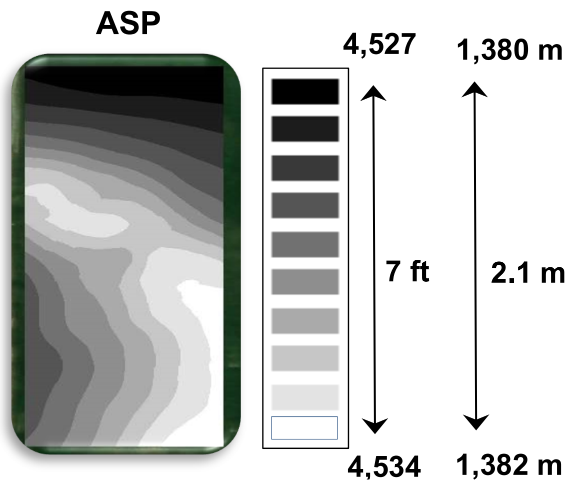


Figure 3. Variability in some field plot elevation associated with Business-as-Usual (BAU) and Aspirational (ASP) management

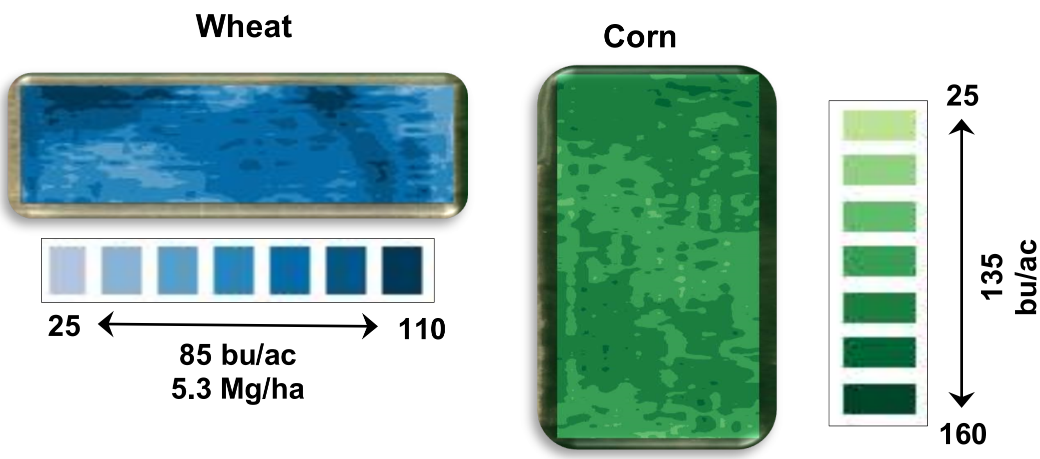


Figure 4. Wheat (blue color) and corn (green color) yield variability within the field plot associated with Business-as-Usual (BAU) and Aspirational (ASP) management decisions.

The 2019 yield data were correlated with field elevation (Figure 3 and 4). The higher elevation areas of the field exhibited lower yield, while the yield decreased with elevation. The yield dynamic for corn and wheat was expected because soil water is the most limiting factor in dryland system. Land topographies contribute to soil differences, soil water differences, and nutrients differences, as nutrients are transported from higher elevation to lower elevation area of the field. This process can translate into enhanced yield in the low elevated section of the field plot compared with high elevated section of the field. Topography is just a surrogate parameter, however, so the next step is to differentiate the contribution of each of these factors, and others, to the observed yield differences.

The influence of different parameters studied on crop yield were evaluated using Random Forest models (Figure 5). These preliminary data showed elevation to be the most influential factor on crop yield. This could be related to soil water and nutrient availability in this dryland cropping system.

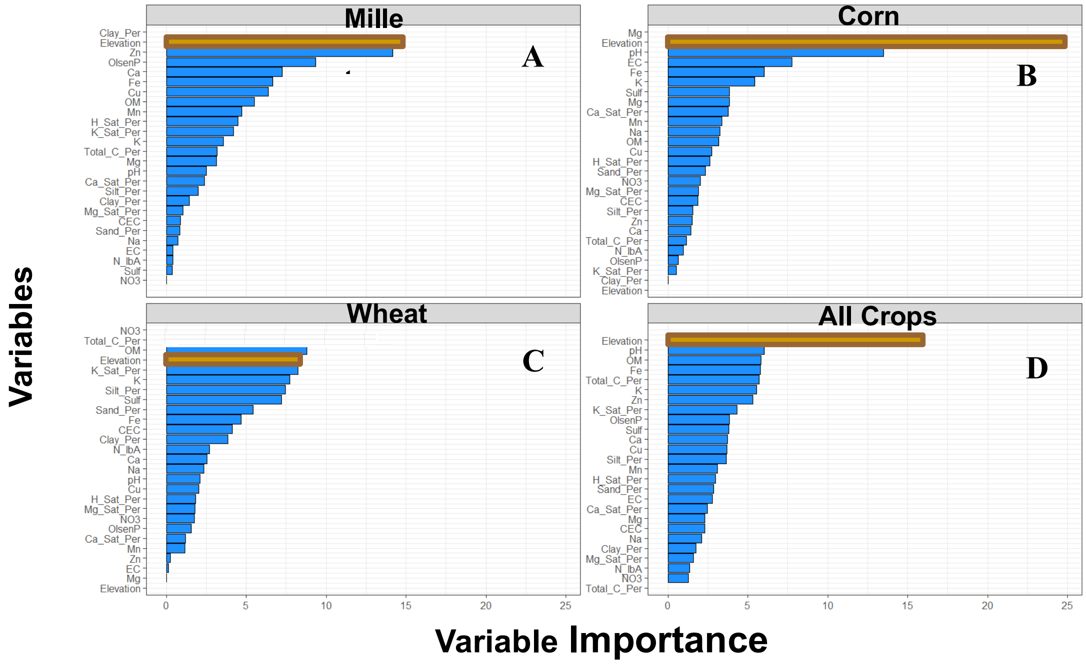


Figure 5. The influence of different studied parameters on crop yield (A, B, and C) individually and on all crops combined (D).

CONCLUSIONS

The data collection and usage of precision technologies and analyses for soil nutrients, crop monitoring, and field mapping will be continued till 2023. This information could improve the application of precision farming in this region. Overall, this project provides a unique opportunity to evaluate precision farming practices for the dryland cropping system in the Central Great Plains Region.

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