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Processes for Improved Variable Rate Irrigation and Nitrogen Within Potato-Wheat-Wheat Cropping Systems

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PROCESSES FOR IMPROVED VARIABLE RATE IRRIGATION AND NITROGEN WITHIN POTATO-WHEAT-WHEAT CROPPING SYSTEMS

by

Elisa A. Flint

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ABSTRACT

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Elisa A. Flint

Utah State University, 2024

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Understanding spatial and temporal dynamics of multiple factors within a field is critical for effective variable rate irrigation (VRI) and variable rate nitrogen (VRN) management. Data were retrieved near Grace and Rexburg Idaho, USA to collect volumetric water content samples, delineate zones for VRI and VRN and manage irrigation throughout zones and collect yield data. Three studies were conducted to (1) examine spatial variation of measured volumetric water content (VWC) over time and assess theoretical soil sensor placement methods with a farmer-informed method, elevation, yield and crop water productivity (CWP) and compare to the VWC at each sensor location along with the mean value and temporal stability of VWC within that zone; (2) estimate VWC with satellite imagery to improve efficiency of determining irrigation zones, as well as understanding spatial patterns and differences of VWC within each zone during the growing season for irrigation management decisions and (3) create and evaluate a simple VRN management plan to improve yield and yield quality, and economics within a wheat-wheat-potato cropping system.

The sensor placement analysis resulted in the farmer-informed method with the smallest mean relative difference (MRD) and VWC difference to the average VWC across all depths and zones. The yield method had the smallest standard deviation of relative difference (SDRD) over all soil depths and zones. These results suggest that farmer's experience combined with yield maps are reliable tools for placing soil moisture sensors that capture soil VWC variability for precision irrigation. Results from the analysis with satellite imagery suggest that imagery coupled with soil sensor data can depict differences in VWC between irrigation zones. Further, utilizing NDVI during crop growth can be useful in estimating VWC. Additional vegetative indices should be explored when estimating VWC when bare soil dominates the imagery, when the crop is senesced and in different crops. Within the VRN study, higher N rates generally increased potato productivity in areas of fields with high yield potential and lower N rates were able to maintain similar productivity with less N in areas with low yield potential, thus showing how a simple VRN design could benefit potato production.

(158 pages)

PUBLIC ABSTRACT

Processes for Improved Variable Rate Irrigation and Nitrogen
within Potato-Wheat-Wheat Cropping Systems

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Proper irrigation and nutrient management are vital for optimal crop production within agricultural fields. Improving irrigation and nutrient application through precision agriculture is necessary to conserve the limited resources available, while improving yield and quality of crops produced through such a system. Variable rate irrigation (VRI) and variable rate nitrogen are systems used to apply water and nitrogen more precisely to agricultural fields to reduce runoff, deep percolation, leaching, and other negative impacts of over application, while providing the optimal rates to produce maximum yields. However, the processes to utilize these systems have proven to be more difficult than expected, and the technology has developed at a faster rate than the knowledge to manage such systems. Much research has been performed to determine different ways to use VRI and VRN, but many studies have been more technical than application based.

This research has focused on farm-scale trials to assist in further exploration of managing VRI and VRN in three ways. First, determine sensor placements based on resources available to the farmer to assist in making in-season irrigation decisions. Second, utilize satellite imagery to estimate in-season variation of soil moisture throughout fields that could assist with irrigation management. Third, trial a zone

delineation and management plan for VRN that utilizes resources readily available to growers.

These analyses found that farmer's experience combined with yield maps are reliable tools for placing soil moisture sensors that capture soil VWC variability for precision irrigation. Utilizing satellite imagery with some vegetative indices were useful in estimating soil moisture throughout a field, and exploring some soil indices could prove useful in estimating soil moisture at different crop growth stages. These studies also found that sectioning a field into high and low yield productivity areas and applying different rates of N based on those productivity areas resulted in higher crop yields and improved nitrogen use efficiency. Overall, these results show the benefit of utilizing resources readily accessible to the farmer, as well as the experience of the farmer to implement VRI and VRN systems to improve crop production as well as conservation in resources.

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Finally, I would like to express my sincere gratitude to my husband, family, friends, and fellow students. I could not have succeeded without the love, support, advice and confidence you all have given me.

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CHAPTER 1

INTRODUCTION

Agriculture is the largest principal user of freshwater resources (Postel, 1999). As the global human population grows, there is the need to increase crop production while using less water. It is known that water is a scarce resource in semi-arid and arid regions, and many of the crops in these regions rely on irrigation. Soil moisture is a variable that drives irrigation needs in production fields (Svedin et al., 2019). Soil moisture is rarely uniform within agricultural fields, even in fields that are leveled and have fairly uniform soil textures and properties (Daccache et al., 2015; Longchamps et al., 2015). Variable rate irrigation (VRI) can assist in correcting over- or under-watering throughout fields that generally occurs when uniform irrigation is practiced (King et al., 2006).

Understanding the spatial and temporal variation of soil moisture throughout a field can assist in making more accurate irrigation management decisions under traditional uniform and variable rate irrigation (VRI) practices. Soil sensors can assist VRI management by determining volumetric water content (VWC) levels for irrigation decisions for each irrigation zone (Flint et al., 2023; Zhao et al., 2018). While each sensor increases the cost of the VRI system, the need to know the optimal count and placement is critical in optimizing the VRI management system and thus improving crop yields, water usage, economics, and decreasing environmental concerns (Evans et al., 2013).

Sensor placement based on spatially and temporally dense VWC data is a promising method to provide confident locations for making irrigation decisions. If VWC measurements are collected at the same locations over time, this can provide the ability to find spatial and temporal patterns within a given area (Biswas & Si, 2011). This process can assist in finding the optimal sensor locations within a field. However, measuring the variation of soil properties can be time consuming and costly, creating an unsuitable process for growers in making sensor placement decisions (Barker et al., 2017; Kaleita et al., 2007; Hedley & Yule 2009a, 2009b).

Temporal stability of soil moisture patterns over time can be simpler to find in landscapes with varying topography (Biswas & Si, 2011), and soil textures (Zhao et al., 2018), but may be more difficult to extract when fields have little topography changes, similar spatial patterns of soil texture, and receive uniform irrigation throughout a field (Barker et al., 2017). Utilizing data that is readily accessible to many farmers via their own yield and other GPS monitors, or data they could calculate if desired to determine how they correlated to VWC could be used to relate to average VWC and temporal stability of VWC within each irrigation zone. If this process is successful, it should reduce barriers to placing sensors for irrigation decisions.

While utilizing sensors to assist with understanding the temporal variation of soil moisture within irrigation management zones throughout a season is beneficial, knowing the spatial variation of soil moisture throughout a field can also aid VRI management decisions. Measuring soil moisture throughout the field with soil samples can give accurate data on the spatial variation of volumetric water content (VWC), but this is only at specific times of sampling within the season. However, this process can be time consuming and costly (Barker et al., 2017; Headley & Yule 2009a, 2009b; Kaleita et al., 2007).

Soil moisture sensors only measure VWC in their locations of placement, but they give continuous data throughout the growing season, which can assist with irrigation timing decisions. Many studies have been performed to understand what static soil property or properties best explain spatial and temporal trends in VWC (Barker et al., 2017; Baroni et al., 2013; Biswas & Si, 2011; Kaleita et al., 2007; Phillips et al., 2014). Utilizing different vegetative indices from readily available satellite imagery coupled with static field properties or other variables that correlate well to VWC within a particular field could more precisely estimate or predict spatial variability of VWC (Phillips et al., 2014).

While VRI is a very important aspect within agriculture to be improved upon, variable rate nitrogen (VRN) is also an important part of precision agriculture that can decrease environmental concerns as well as improve crop production. With ebbs and flows in fertilizer costs, and the growing environmental concerns that fertilizers have in water bodies and other environments, implement VRN within agriculture has potential to conserve resources as well as increase yields with the land and resources available.

Crops are generally not grown in isolation, but rather as part of a cropping system. A system that is economically, environmentally, and socially sustainable is highly dependent upon effective nutrient stewardship (Hopkins, 2020; Westermann, 2005; Zebarth & Rosen, 2007). This is especially true for nitrogen (N), which often has a larger impact on production than all other nutrients. Best management practices (BMPs) for N can vary by crop species, especially when the cropping system includes species with vastly different soil-plant relations, such as wheat (*Triticum* spp.) grown in rotation with potato (*Solanum tuberosum* L.).

Crop N needs are spatially variable based on topography, soil properties, microenvironments, and biotic/abiotic stresses (Ruffo et al., 2006). Proper N management, which could include applying variable rate N (VRN), or specific N sources, rates and timings could improve crop growth, optimize tuber size, production, grade specific gravity and other qualities in potato (Hong et al., 2006; Hopkins et al., 2020; Stefaniak et al., 2021; Westermann, 2005; Zebarth & Rosen, 2007). Improving N management through VRN also has the potential to decrease input costs, and/or minimize negative environmental impacts (Bragagnolo et al., 2013; Hong et al., 2006; Hurley et al., 2004; Koch et al., 2004; Mamo et al., 2003; Scharf et al., 2005).

Determining N rates for VRN in potato has been explored with several approaches. While VRN research has been performed on potato, most of the work has focused on in-season VRN without the pre-emergence VRN (Bohman et al., 2019, 2020; Kempenaar et al., 2017). These studies referenced above were also performed on small plot scales and not at the field scale. There is also the need to evaluate VRN approaches in different climates, such as semi-arid Idaho where potato production is common. There is also a sparsity of data on how VRN performs on various potato cultivars that have different optimal N rates, or where optimal N rates are unknown (Westermann, 2005; Whitley & Davenport, 2003; Zebarth & Rosen, 2007).

Historical yield maps (Robertson et al., 2008) as well as other layers of information (such as crop canopy sensors), have been used to improve VRN in wheat production (Stamatiadis et al., 2018; Thomason et al., 2011). This approach could also be utilized in potato to assess effectiveness in N management and production. When determining N zones for VRN management, evaluation of yield patterns throughout a field could be a meaningful predictor of spatially variable N needs. If a portion of a field historically yielded high, one might determine this area has a high yield potential zone, thus assigning a higher N rate than the other areas of the field. If a portion of a field historically yielded low it could receive a lower N rate than the other areas of the field. This process leverages the spatial variability of historical performance throughout a field to potentially increase production where possible and decrease input costs where increased production is not expected or attainable.

This research has focused on farm-scale trials to assist in further exploration of managing VRI and VRN in three ways. First, determine sensor placements based on resources available to the farmer to assist in making in-season irrigation decisions. Second, utilize satellite imagery to estimate in-season variation of soil moisture throughout fields that could assist with irrigation management. Third, trial a zone delineation and management plan for VRN that utilizes resources readily available to growers. The goal of this research was to find easily-adoptable ways to improve management of VRI and VRN systems through agricultural production.

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CHAPTER 2

SOIL MOISTURE SENSOR PLACEMENT FOR IRRIGATION SCHEDULING

2.1 | INTRODUCTION

Understanding the spatial and temporal variation of soil moisture throughout a field can assist in making more accurate irrigation management decisions under traditional uniform and variable rate irrigation (VRI) practices. Soil sensors can assist VRI management by determining volumetric water content (VWC) levels for irrigation decisions for each irrigation zone (Flint et al., 2023, Zhao et al., 2018). While each sensor increases the cost of the VRI system, the need to know the optimal count and placement is critical in optimizing the VRI management system and thus improving crop yields, water usage, economics, and decreasing environmental concerns (Evans et al., 2013).

Sensor placement based on spatially and temporally dense VWC data is a promising method to provide confident locations for making irrigation decisions. If VWC measurements are collected at the same locations over time, this can provide the ability to find spatial and temporal patterns within a given area (Biswas & Si, 2011). This process can assist in finding the optimal sensor locations within a field. However, measuring the variation of soil properties can be time consuming and costly, creating an unsuitable process for growers in making sensor placement decisions (Barker et al., 2017; Kaleita et al. 2007; Hedley & Yule 2009a, 2009b).

Van Pelt and Wierenga (2001) utilized the mean soil water content to place soil moisture sensors for making irrigation decisions. However, temporal and spatial variability in VWC can make it difficult to determine the average VWC location for a zone or a field without taking ground measurements. Temporal stability, which ranks the magnitude of VWC relative to the spatial mean, can be correlated with other static, non-changing properties to assist in describing patterns over time (Barker et al., 2017; Biswas & Si, 2011; Kachanoski & de Jong 1988; Kaleita et al., 2007; Vachaud et al., 1985; Wang et al., 2015). Static, non-changing properties can include soil texture and topography that can either individually or interactively impact VWC (Baroni et al., 2013; Biswas & Si, 2011). For example, Zhao, et al. (2018) found that utilizing clay percentile with mean soil water content supplied proper locations for soil sensors using both uniform irrigation and VRI. Van Pelt and Wierenga (2001) found temporal stability of soil moisture that was highly correlated to soil texture, but it is important to note their experiment site had little to no topography changes. Another study by Kachanoski and de Jong (1988) found that topographical features, specifically curvature, were significantly related to soil moisture pattern changes in the event of the soil profiles being recharged. Utilizing variables such as these could assist in depicting spatial and temporal variation of VWC, but understanding which of these variables relate to VWC the most spatially and temporally by field is difficult to determine.

Temporal stability of soil moisture patterns over time can be simpler to find in landscapes with varying topography (Biswas & Si, 2011), and soil textures (Zhao et al., 2018), but may be more difficult to extract when fields have little topography changes, similar spatial patterns of soil texture, and receive uniform irrigation throughout a field (Barker et al., 2017). Soil matric potential has also been used to assist in making irrigation decisions, but the temporal stability of the respective variable has not been studied as aggressively as soil water content (Barker et al., 2017; Van Pelt & Wierenga, 2001). The process of defining temporal stability of soil moisture in field soils with a variety of conditions such as crop type, yield patterns, climate, soil type, topography and so on needs further analysis in order to assist in sensor placement decisions (Barker et al., 2017).

While utilizing spatially dense soil texture and topographical data can be valuable in correlating to VWC, the purpose of this study was to use data that was readily accessible to many farmers via their own yield and other global positioning system (GPS) monitors, or data they could calculate if desired such as crop water productivity (CWP) to determine how they correlated to VWC. These variables were used to evaluate their utility in determining sensor placements in relation to average VWC. If this process is successful, it should reduce barriers to placing sensors for irrigation decisions. Thus, the objectives of this study were to: (i) understand the variation of soil moisture throughout a field, (ii) determine how the placement of the soil sensors within each zone represented the average VWC in each zone, and (iii) assess how different accessible variables such as average elevation, yield, and CWP related to the average VWC and the most temporally stable VWC location within each zone and sampling depth.

2.2 | MATERIALS AND METHODS

2.2.1. Site Description and Background

This study was conducted on a winter wheat (*Triticum aestivum* ‘UI Magic’) field (23 ha) located near Grace, ID, USA (elevation 1706 m above sea level; 42.609 latitude and -111.788 longitude) in 2019. This location is in a semi-arid region with a climate typified with relatively hot days and cool nights during the summer growing season, with about 80 to 110 frost-free days. Average annual precipitation is 390 mm (Bureau of

Reclamation, 2017) with most of the precipitation occurring during the winter as snow. The historical average precipitation for the May-August wheat growing season is 150 mm based on the Cooperative Agricultural weather network AgriMet (Bureau of Reclamation, 2017).

The soil is a silty clay loam Rexburg-Ririe complex, with 1 to 4 % slopes (Soil Survey Staff, 2023). The field has a 6 m difference between the lowest and highest elevation. Soil texture was measured at four 0.3-m depth increments from surface level down to 1.2 m at 46 spatially distributed sites (70 m grid) across the field. Forty two sample sites were classified as silty clay loam and silty clay for the remaining four sample sites (Flint et al., 2023). Soil texture was analyzed at the Environmental Analytical Lab at Brigham Young University in Provo, Utah, USA using the hydrometer method.

2.2.2 Irrigation Management

Irrigation was applied using a 380-m center pivot with a 1.5 m nozzle spacing equipped with a zone-control VRI system (GrowSmart Precision VRI, Lindsay Corporation, Omaha, NE, USA). Irrigation zones were created from yield and evapotranspiration (ET) data collected from 2016 and 2017 using a water balance based on soil water content samples collected at the given sampling locations (Fig. 2–1; Flint et al., 2023; Svedin, 2018; Svedin et al., 2019). A regression analysis was performed on data from 2016 and 2017 with yield as the response variable and ET as the explanatory variable. Then, a k-means clustering was performed from the regression’s slope to determine five irrigation zones, with constraints to spatial contiguity (Flint et al., 2023).

Irrigation rates in 2019 for each zone were derived by comparing soil water content measured by sensors in each zone to the respective zone average field capacity values and applied to bring the upper 300 mm soil depth to a soil water content approximately equal to field capacity (Flint et al., 2023). Irrigations were timed to keep water depletion from decreasing below readily available water levels where plants experience crop water stress and yields are reduced (Fig. 2–2; FAO 56).

2.2.3 Soil Sampling Method

The scale of soil spatial variation was determined from a variogram of the normalized difference vegetation index from bare soil imagery of the field site (Flint et al., 2023). The variogram had a range of ~140 m. Following methods of Kerry and Oliver (2003) we used 70 m for the main sampling grid (46 samples) to represent approximately half the variogram range. Additional samples points (56 samples) were located at random nested points along the grids to strengthen the sensitivity of the geostatistical analysis for a total of 102 sampling points. This sampling scheme was used to calculate spatial variation of soil VWC and soil water depletion over time via soil sampling.

Soil samples were collected at the beginning of the growing season, and two times mid-season (Fig. 2–2). All 102 locations were sampled in April and May. In June, sampling was reduced to 56 sampling locations due to how wet the field was shortly after an irrigation event. Soil samples were collected using soil probes with an inner diameter of 19 mm. These were driven into the profile with a modified gas-powered post driver (AMS, Inc. American Falls, ID, USA). At each sampling point, a soil core was taken at increments of 0.0-0.3, 0.3-0.6, 0.6-0.9, and 0.9-1.2 m to represent the rooting zone. Samples were sealed for transport to the laboratory where gravimetric soil water content was determined by drying in a forced-air oven at 105°C until consistent weights were reached. Soil gravimetric water content was converted to VWC using soil bulk density values determined for each sampling location in 2016 from previous samples (Flint et al., 2023; Svedin, 2018; Svedin et al., 2019).

2.2.4 Statistical Analysis Procedure

Prior to geostatistical analysis of soil VWC, elevation, yield and CWP, summary statistics were calculated, and histograms plotted. If the skewness of the data was outside the bounds of ±1, then the data were transformed to logarithms for variogram computation and back-transformed to the original scale following kriging (Flint et al., 2023; Kerry & Oliver 2008). Following variogram computation, each variable was ordinary kriged to a 5-m grid. All variograms and kriging were completed using SpaceStat (BioMedware, SpaceStat 4, Ann Arbor, MI, USA), and ArcGIS desktop: Release 10 (Redlands, CA, USA).

2.2.5 Soil Moisture Variation and Sensor Placement Scenarios

Values of VWC across sampling dates were evaluated for temporal stability using a Pearson's rank correlation coefficient (Table 2–S1, 2–S2). The temporal and spatial coefficient of variation (CV) of VWC was calculated at each depth. Temporal CV were calculated from individual sampling locations at a given depth across all sampling dates. Spatial CV was calculated across all sampling locations at a given depth and at a given sampling date. Then, the soil moisture from each zone's sampling and sensor locations was compared to the average VWC of that zone at each sampling date and depth using boxplots (R version 4.2.3, RStudio).

Next, scenarios of placing sensors from different field variables were evaluated. The variables used were the farmer-informed method (cooperating farmer input and knowledge of field conditions) used for actual placement of sensors in 2019. Sensors installed in 2019 were TEROS 12 VWC sensors (METER Group, Pullman, WA, USA) installed at 30 cm deep. The other three variables were readily available data layers such as yield, elevation, and CWP. Crop water productivity was derived by the same method used by Flint et al. (2023), a calculation based on yield from combine yield monitor data divided by seasonal evapotranspiration based on a water balance. Average values of yield, elevation and CWP were determined for each zone, and the VWC value at the sampling location closest to the average value of each of those field variables was selected for sensor placement evaluations. The farmer-informed method used the VWC at the sensor site from the ground soil samples for consistency in comparison. These VWC values for each of these scenarios were then compared to the average VWC within each zone, at depths 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m. Differences in VWC were evaluated over the three sampling dates.

Estimated ratios of irrigation rates for the two in-season sampling dates were evaluated by taking the irrigation rates calculated from the VWC data for the farmer-informed sensor placement method and comparing those irrigation rate values to the irrigation rates that would have been calculated for the different scenario (yield, elevation, CWP) placements. Because these sampling dates were not on dates where irrigation occurred, these are simply estimations of how the irrigation might be different between scenarios for the different irrigation zones.

Temporal stability of all VWC values from the sampling dates were calculated by irrigation zones and the depths described above (Wang et al., 2015) and ranked according to their mean relative difference (MRD). Standard deviations of the relative differences

(SDRD) were also computed for each sampling location by zone and depth across time. The standard deviation of relative difference describes the temporal variability of the relative difference in VWC over all sampling dates at each sampling location by zone and depth (Barker, et al., 2017; Wang et al., 2015). The MRD and SDRD values at each of the sensor placement scenario locations described above were then compared to the sampling locations with the smallest MRD and SDRD by zone and depth. The values of the MRD and SDRD for each sensor placement scenario were then ranked against each other for each zone and depth. The difference in average VWC from the method described above was also ranked for each sensor placement scenario at each zone and depth. Rankings were labelled 1-4, 1 being the scenario with the smallest MRD, SDRD, and difference from the average VWC, and 4 being the scenario with largest MRD, SDRD, and difference from the average VWC within the respective zone and depth. These rankings were then added together to determine which sensor placement scenario had the smallest accumulation of rankings by depth, zone, and overall for MRD, SDRD and difference from the average VWC.

2.3 | RESULTS

2.3.1 Variation in Volumetric Water Content

Spatial variation of VWC was assessed for each sampling date, which occurred during spring green-up on 23 April, and during the growing season on 30 May and 25 June (Fig. 2–3). Variation of soil VWC was observed through spatial CV and temporal CV (Fig. 2–4, Table 2–1) at depths 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m. Spatial variation increased in the later sampling date within the irrigation season (25 June) but the average spatial CV remained small and was 0.12, 0.11, and 0.08 for depths 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m, respectively, across the entire field (Table 2–1). Temporal CV was similar for all depths and zones across the growing season, with average temporal CV values of 0.10, 0.09, and 0.07 for depths 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m, respectively, across the entire field (Fig. 2–4, Table 2–1). The means of VWC within each zone and depth differed from the overall mean VWC of the field at each depth, illustrating the value of using irrigation zones (Fig. 2–5). Ranges of VWC were also smaller within each zone compared to the range of the VWC of the entire field.

2.3.2 Soil Sensor Locations Representation of Average VWC

Soil samples at the sensor locations were collected to see how closely they related to the average values of VWC within their zone. The percentage of soil samples at the sensor locations that were within their respective quantiles for the three sampling dates at depths 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m were as follows: 68, 78, 89, 56, and 56% for zones 1, 2, 3, 4, and 5 (Fig. 2–5). When comparing the VWC values at the sensor locations to the average VWC values within each zone averaged across the different sampling dates, the average differences in VWC for all zones was 0.02, 0.01, and 0.01 m^3 m^{-3} above the average VWC for depths 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m (Fig. 2–6). The percentage of soil samples where VWC at the soil sensor locations were within one standard deviation of the average VWC for their respective zones at the depths 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m were 89, 89, 100, 78, and 89% for zones 1, 2, 3, 4, and 5, respectively across the three sampling dates. Across all depths and irrigation zones, the percentage of VWC values at the sensor locations that were within one standard deviation of the average VWC for their respective zone was 87%. One standard deviation ranged between 0.02 – 0.03 m^3 m^{-3} for all zones and depths at the April and May sampling dates.

Potentially due to the reduced number of samples in June, the standard deviation range increased from 0.02 – 0.05 m^3 m^{-3} for all zones and depths compared to the earlier sampling dates. Generally, VWC at the sensor locations tended to have higher VWC than their respective zone's average VWC. The percentage of samples at the sensor locations that had VWC values above their respective zone's average VWC across all sampling dates and depths 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m were 56, 78, 89, 100, and 78% for zones 1, 2, 3, 4, and 5, respectively.

2.3.3 Sensor Placement Scenarios

Volumetric water content values at each of the sensor placement scenarios were compared to the average VWC in each zone by depth 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m across all sampling dates (Fig. 2–6). All sensor placement methods resulted in varying differences from the average VWC across zones, depths, and sampling dates (Fig. 2–6). Across all zones and sampling dates the farmer-informed sensor placement had VWC values closest to the average VWC for depth 0.0 – 0.3 m with a difference of 0.02 m^3 m^{-3} above the average VWC for across zones and dates. The CWP scenario had VWC values closest to the average VWC for depth 0.3 – 0.6 m with a difference of 0.01 m^3 m^{-3} above the average VWC. The yield scenario had VWC values closest to the average VWC for depth 0.0 – 1.2 m with a difference of 0.01 m^3 m^{-3} above the average VWC.

Estimations of the potential irrigation differences in the form of ratios from the average elevation, yield, and CWP locations compared to the current sensor placement location irrigation rates were calculated from the two in-season sampling dates (Table 2–2). The sensor placement based on historical yield had the closest estimated irrigation rates to the farmer-informed method's irrigation rates across irrigation zones, as well as averaged over all zones. The large, negative irrigation ratios in zone 4 across all three sensor placement options (yield, elevation, CWP) compared to the farmer-informed sensor placement may suggest the sensor location in zone 4 for the 2019 growing season was not representative of the average VWC.

2.3.4 Temporal Stability of Volumetric Water Content

Temporal stability of all soil sampling locations over the three sampling dates within each zone and depth were evaluated to determine which location most consistently represented the average VWC of that zone and depth over a growing season (Fig. 2–7, Table 2–3). The temporal stability of soil samples within the different zones and depths ranged from -20 to 30% of the MRD.

The locations of the actual farmer-informed sensor placements and potential placements based on average elevation, yield, and CWP were also marked to see where they ranked within the temporal stability range for each zone and depth (Fig. 2–7). The placement scenarios that were closest to the MRD with the smallest SDRD varied by zone. Sensor placement locations with the values that were closest to the optimal MRD (i.e., zero) across all depths and sampling dates for zones 1, 2, 3, 4 and 5 were farmer-informed method and CWP, farmer-informed method, CWP, elevation and yield, and all scenarios except CWP, respectively (Table 2–3, 2–4). Sensor placement locations with the values that had the smallest SDRD across all depths and sampling dates for zones 1, 2, 3, 4, and 5 were yield, farmer-informed method and yield, farmer-informed method, CWP, and all scenarios except CWP, respectively (Table 2–3, 2–4). Sensor placement locations with the values closest to the optimal MRD across all zones and sampling dates for depths 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m were the farmer-informed method, CWP and farmer-informed method, respectively. Sensor placement locations with values that had the smallest SDRD across all zones and sampling dates for depths 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m were elevation, farmer-informed method, and yield, respectively. When looking at all zones and depths together, the scenario with the smallest MRD and SDRD was the farmer-informed method and yield, respectively.

When observing where the temporally stable locations were compared to the sensor placement scenario locations across zones and depths, there were three locations where sensor placement scenario locations were at the same location as the temporally stable location (Fig. 2–8). In general, the sensor placement scenario locations were within the same proximity as the temporally stable locations, with the exception of the average elevation locations in zones 2 and 3 across all depths (Fig. 2–8). The temporally stable location in zone 4 for depth 0.0 – 1.2 m was 150 m away from the nearest sensor placement scenario location for that zone.

2.4 | DISCUSSION

2.4.1 Variation in Volumetric Water Content

Spatial variation of VWC was not consistent throughout the growing season. It is important to note that soil sampling dates occurred at differing intervals from irrigation or rain events. The sampling date in April occurred 2-3 days after snowmelt, and thus the field was considered to be at or as close to field capacity as possible. The sampling date in May occurred 9 days after a precipitation event and 15 days after an irrigation. The sampling date in June occurred the day following an irrigation event. While the soils throughout this field were all very similar, slight changes in soil texture, structure, and properties can impact the water holding capacity of soils throughout the field, thus impacting the spatial variability across the field (Biswas & Si, 2011), as well as temporal variability. Elevation changes can also impact soil moisture, as runoff and/or subterranean flow can occur if rain or irrigation events are large enough, changing the soil moisture across space and depth.

Spatial differences of water uptake from the crop can also affect the spatial variability of VWC (Svedin et al., 2019). If some areas are more productive where the plant is healthier than other areas, then the productive areas may uptake more water than areas where the crop can be negatively impacted by shallow soils, pest pressures, diseases, nutrient deficiencies, weed competition and so forth. Irrigation nonuniformity can also greatly impact plant health and soil VWC variability.

2.4.2 Representation of Average VWC with Existing Sensor Placement Based on Farmer-Informed Placement Method

Soil samples closest to the existing sensor locations (based on farmer-informed placement) generally represented the average VWC within their zone as most samples were within one standard deviation of the mean for their respective zone, depth, and sampling date. Within depth 0.0 – 0.3 m, two of the three of soil sensor samples from the different sampling dates were below the average VWC for zone 1, with the only sampling date (April) with VWC above average. This location for a soil sensor may be on the drier side of the zone for most of the season depending on the depth used to make irrigation decisions. Knowing that depth 0.0 – 0.3 m was used to make irrigation decisions in this study, this zone could have potentially been over watered based on its patterns of VWC being below the average for that zone. This location was also below the MRD in the temporal stability analysis and had a large SDRD, further suggesting that this location was not an optimal location for sensor placement.

Zone 2's VWC samples within depth 0.0 – 0.3 m at the sensor location consistently trended above the average VWC for that zone at all three sampling dates. This location was also above the MRD by 8% in the temporal stability analysis with a 5% SDRD. This could mean that the zone may have received less irrigation than needed. However, lateral movement of water from zone 3 into zone 2 could have kept the VWC at a high enough level to keep the plants from reaching crop water stress and negatively impacting yields.

Soil VWC samples nearest zone 3 soil sensor locations at depth 0.0 – 0.3 m were slightly above average at the April and May sampling dates, and slightly below average at the June sampling date. This sensor location was considered the most temporally stable location of all the samples in zone 3 at depth 0.0 – 0.3 m, making it a beneficial sensor location for irrigation management. While all the samples at the sensor location were very close to the average zone VWC, this zone includes a ridge where some portions of the zone may have been drier than the location at the ridge. However, placing the sensor on the ridge was intentional and desired by the cooperating farmer so the zone was not over-irrigated, which can cause elevated disease pressure for potato production.

Zone 4's VWC samples nearest the sensor location at depth 0.0 – 0.3 m were all above the average zone VWC across all sampling dates. Two of the three sampling dates at the sensor location were within one standard deviation of the average VWC, and the June sample at the sensor location was within two standard deviations. The location of this sensor was also above the MRD by 10% with a 13% SRDR in the temporal stability analysis. These values and statistics show that this sensor was likely not placed in a location that accurately represented the average VWC of that zone and was potentially under irrigated compared to the average VWC for the growing season. It is important to note that the sample that was within two standard deviations of the mean in zone 4 was for the June sampling date, which had half as many samples compared to the rest of the sampling dates due to how wet the field was shortly after an irrigation event. The decrease in soil samples could have an impact on the average VWC for that sampling date, as well as the standard deviation for that zone on that date.

The VWC samples nearest the sensor location in zone 5 was above the average VWC for that zone at the April and June sampling date and below the average VWC at the May sampling date for depth 0.0 – 0.3 m. There were some fluctuations in VWC compared to the average VWC in that zone in depth 0.0 – 0.3 m. The VWC at this zone's sensor location fluctuated between one standard deviation from the mean at the April and June sampling dates and two standard deviations at the May sampling date. This may show that this location was likely not the best location for a sensor as the VWC was not consistently over or under the average VWC. This could be because this zone is slightly sloped and bedrock can be shallow in this region with basalt outcrops being visible throughout fields, and thus lateral water movement could have occurred beneath the surface during the growing season. This sensor location within zone 5 was 7% above MRD with a SDRD of 9%, and was not closest to an MRD of zero at this depth, suggesting a different sensor location may have been better for irrigation management purposes.

Evaluating Alternate Sensor Placement Scenarios

No single soil sensor placement method outperformed all other methods consistently across all zones and depths. The two variables that were closest to the average VWC over all depths, dates and zones, were the farmer-informed sensor locations that were used, and average yield. Utilizing the grower knowledge of the field could have played a big role in predicting areas that were representative of the average VWC within each zone, as they may have known the patterns of VWC based on experience with the spatial variability of crop production and dry down patterns. Average yield could be comparable to average VWC, as generally areas that are limited by water tend to have lower yields, and areas that have greater amounts of water can either have higher yields, or lower yields depending on whether the VWC values are too high for the crop in that area. Baroni et al. (2013) noted that dry conditions can be related to vegetation, and vegetation can be correlated with yield and therefore it was inferred that yield may have a potential relationship with VWC. Yield could be a spatially dense resource that many growers have from their yield monitors and could omit the need for extensive soil sampling to determine sensor placement locations.

Using average elevation within each zone as the determining factor for sensor placement may not be the best approach, particularly in zones where there are topographical changes that can impact water movement. Areas with relatively similar elevation through the entirety of a zone may be a useful variable in determining a location that is close to the average VWC for that specific zone. In this study zone 4 did not have large elevation changes and the VWC at the average elevation was closest to the average VWC, and it had the smallest standard deviation compared to the VWC at the other variables (farmer-informed method, yield and CWP). However, Kaleita et al. (2007) noted that in their study, topographic data did not have strong correlations with VWC, and this might be explained by the minor topographical changes within the field (1.2% slopes, and 4.6 m elevation difference). The elevation changes in the study by Kaleita et al. (2007) were similar to elevation range of 6 m of our study, which could explain why using elevation in some zones did not relate well to average VWC but would counter the reasoning for elevation being a useful variable in zone 4. While some studies have found that topographical features, such as elevation can be a determining factor in understanding VWC patterns, other studies have not found these as useful (Barker et al., 2017; Baroni et al., 2013; Biswas & Si, 2011; Zhao et al., 2018). Therefore, more research is required to understand what specific topographical characteristics relate to VWC in certain fields.

Crop water productivity was a variable that generally did not represent the average VWC within most zones at most depths. This could be because of the way CWP is calculated by using multiple variables (evapotranspiration and yield), and thus the variation between the two variables throughout the season could not properly represent VWC. While studies have not utilized this variable specifically to relate to spatial and temporal variation of VWC, it was used in this study to observe if it had strong correlations with VWC and would be worth the time and effort to calculate and apply.

2.4.3 Temporal Stability of Volumetric Water Content

When looking at the temporal stability of VWC within the entire profile (0.0 – 1.2 m) for each zone compared to depths 0.0 – 0.3 and 0.3 – 0.6 m, the most temporally stable sample locations were not consistent between depths. This was also seen in the study by Barker et al. (2017) where temporally stable locations were not consistent between shallow soil depths and the entire soil profile. Barker et al. (2017) correlated elevation, deviation from mean elevation (DEV) and apparent electrical conductivity (EC_a) to the MRD values and found varying instances where DEV had strong correlations, followed by EC_a. While the present study used average elevation rather than DEV, the results were somewhat similar to the study by Barker et al. (2017) in that average elevation was closest or close to MRD throughout a few irrigation zones and depths. Barker et al. (2017) also noted that areas in their field that were wetter than others had a stronger correlation to ECa than DEV. Baroni et al. (2013) found that VWC was more related to soil texture than topographical or vegetative variables in wet conditions, and more related to vegetation in dry conditions. Differences in wet and dry conditions within our study field could explain why yield (i.e., vegetation) could be more closely representative of temporally stable location in certain zones and depths than others.

Differences in temporally stable locations between depths could be due to even slight soil textural differences or topographical differences that may impact VWC patterns in the top two depths more than in the entire profile, particularly in zone 3 where there is a west-facing ridge with elevation change around 5 m and zone 2 where there is a swale below and to the west of zone 3. There is also a slight ridge within zone 5 that slopes to the east and away from the field. Larger ranges in MRD and SDRD within the 0.0 – 0.3 and 0.3 – 0.6 m depths could be explained by the amount of water entering and leaving the 0.0 – 0.3 and 0.3 – 0.6 m depths during the growing season, as well as subsurface lateral water movement from zone 3 where there is a ridge moving into zone 2 where the swale is located. While there are some topographical changes within zones 2, 3 and 5, using sensor locations based on average elevation did not result in VWC values closest to the most temporally stable VWC in these zones. The VWC at the average yield location within zone 2 tended to be closer to the most temporally stable VWC compared to all other VWC values at the other sensor placement scenarios. zone 3 had even more elevation differences due to the ridge, and the VWC for both the average elevation and yield placement methods were not closest to the temporally stable value, except for yield at the profile depth (0.0 – 1.2 m). The VWC at the locations predicted by the average elevation and yield methods for the upper depths may have seen more water movement throughout the growing season, and both depths for these two scenarios were near 10% above or below the MDR in zone 3.

The existing farmer-informed sensor placement scenario used for making irrigation decisions in this study had a VWC that was closest to the most temporally stable VWC value for all three depths in zone 3. However, the SDRD in depth 0.3 – 0.6 m was 8%, which shows that VWC varied over time. Sensor placement in zone 3 where there was quite a bit of elevation change benefited from the grower knowledge of that zone and the crop patterns that occurred during the growing season, as well as their experience with the water needs and patterns.

The sensor location predicted by the average elevation scenario was the closest to the most temporally stable location for all depths in zone 4. This zone generally has small elevation change, but more rock outcroppings, where topsoil depths vary and subsequently impact yield. This potentially explains why yield may not be the best variable to depict sensor placement in this zone. The farmer-informed method was not close to the most temporally stable VWC value across all depths in Zone 4, and in fact was consistently well over the average VWC for that zone. This may have resulted in improper irrigation recommendations for this zone. zone 5 is a relatively small zone with less soil samples compared to all other irrigation zones within this study. All scenarios except CWP could have been an option to place sensors for this zone, although the farmer-informed method, elevation and yield scenarios were never closest to the MRD of zero nor had the lowest SDRD compared to other sample locations within zone 5. Using CWP may not be a reputable variable due to situations where yield is low, but ET is high. This will result in a low CWP but will not represent average VWC in some cases.

5. Conclusion

Variable rate irrigation approaches that section fields into static zones can benefit from installing sensors in each zone to assist in making irrigation decisions specific to that zone. Placing sensors within zones to represent the zonal average VWC is challenging and can be accomplished in many ways. It requires understanding of spatial and temporal trends in VWC. Spatial and temporal variability in VWC were measured in a field near Grace, Idaho. Trends showed that while spatial and temporal variability may be relatively small, changes in VWC throughout a growing season and within zones are difficult to determine without dense collection of soil VWC. Our study evaluated our existing approach of sensor placement (farmer-informed placement) and three alternative methods (elevation, yield and CWP) that are generally easily accessible to the grower or can be calculated fairly quickly to provide spatially dense information throughout a field. When comparing the farmer-informed method of placing sensors to average elevation, yield, and CWP based on ability to represent average VWC within irrigation zones and represent variability, the optimal method varied by zone and by soil depth. This indicates that different variables may need to be considered within each irrigation zone. However, when averaged across all conditions, the farmer-informed and yield methods for placing sensors most frequently represented the average and variability of VWC. These results suggest that a combination of yield data and farmer's experience are suitable methods for placing soil moisture sensors for use in precision irrigation. These methods should be evaluated in other fields with dense soil sample VWC to validate whether it is successful in other applications. Soil sensor placement based on yield maps and farmer knowledge rather than difficult and laborious deep soil sampling has the potential to save much time, cost, and effort and to improve the adoption of practical precision irrigation management.

2.6 | TABLES AND FIGURES

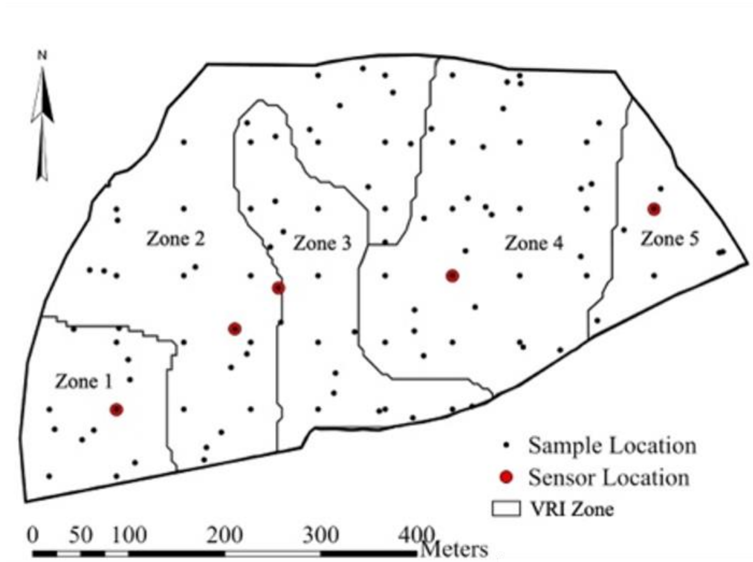

Figure 2–1. Soil sampling locations, farmer-informed soil sensor locations, and variable-rate irrigation (VRI) management zones for the 2019 growing season

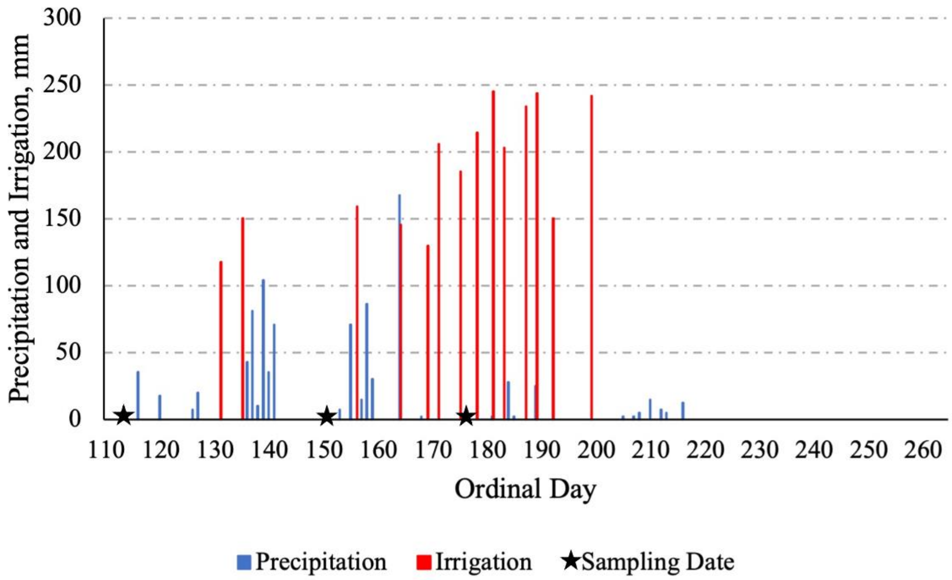

Figure 2–2. Precipitation (blue bars) and irrigation (red bars) applied to field during the 2019 growing season, with stars on the x-axis representing the soil sampling dates

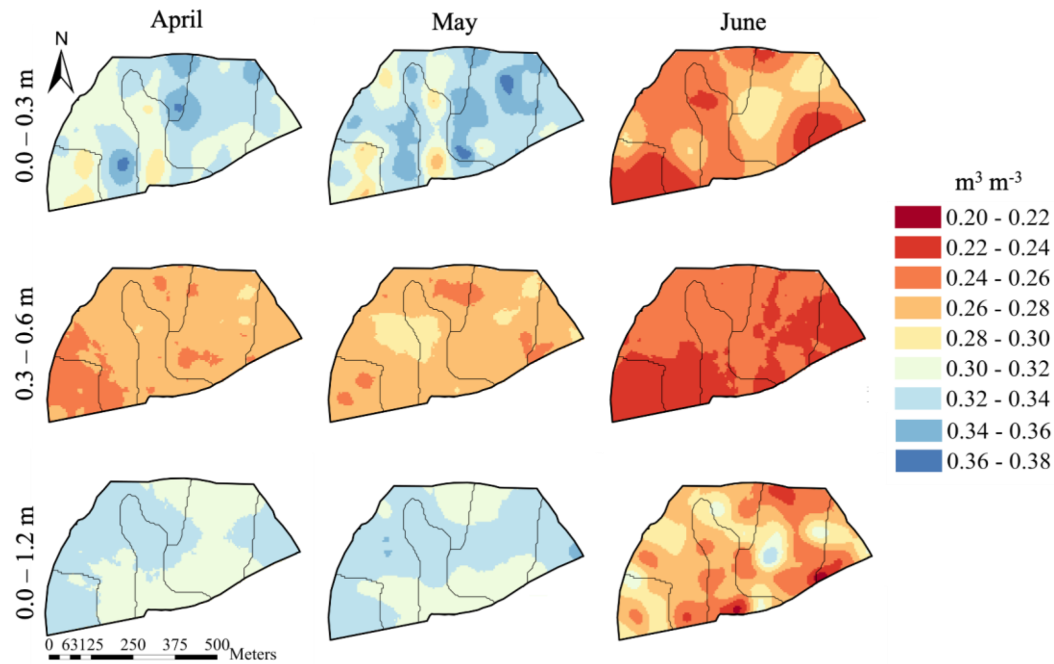

Figure 2–3. Spatial variation of soil volumetric water content (VWC) at three depths (rows) and three dates (columns)

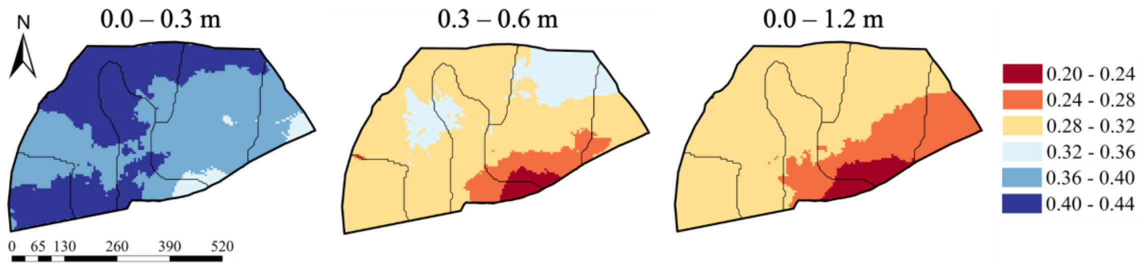

Figure 2–4. Temporal coefficient of variation in soil volumetric water content (VWC) for all sampling dates in 2019 at depths 0.0 – 0.3, 0.3 – 0.6, and 0.0 – 1.2 m

Table 2–1. Average temporal and spatial coefficient of variation (CV) of soil volumetric water content (VWC) by soil depth and irrigation zone of the four soil sampling dates within the 2019 growing season

Average Temporal CV						
Depth (m)	Zone					
	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Full Field
0.0 – 0.3	0.10	0.10	0.10	0.09	0.16	0.10
0.3 – 0.6	0.06	0.10	0.09	0.08	0.11	0.09
0.0 – 1.2	0.06	0.07	0.07	0.07	0.11	0.07
Average Spatial CV						
Depth (m)	Zone					
	1	2	3	4	5	Full Field
0.0 – 0.3	0.14	0.12	0.12	0.11	0.11	0.12
0.3 – 0.6	0.09	0.10	0.10	0.11	0.13	0.11
0.0 – 1.2	0.08	0.07	0.07	0.08	0.11	0.08

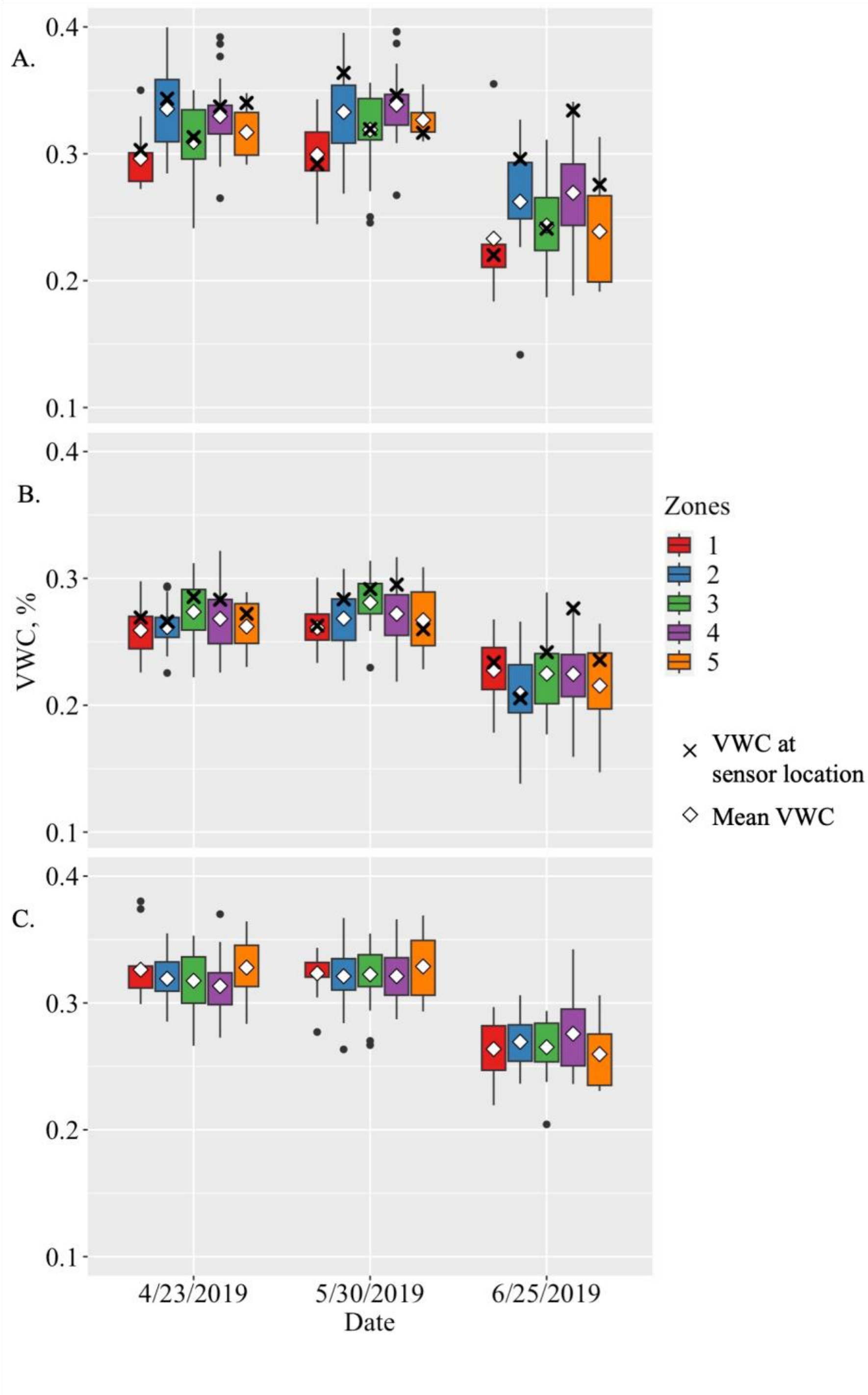

Figure 2–5. Ranges of soil volumetric water content (VWC) at each sampling date and irrigation zone for depths 0.0 – 0.3 (A.), 0.3 – 0.6 (B.), and 0.0 – 1.2 m (C.). White diamonds represent the mean VWC for each zone, and the × markers represent the VWC at each sensor location for the respective zone.

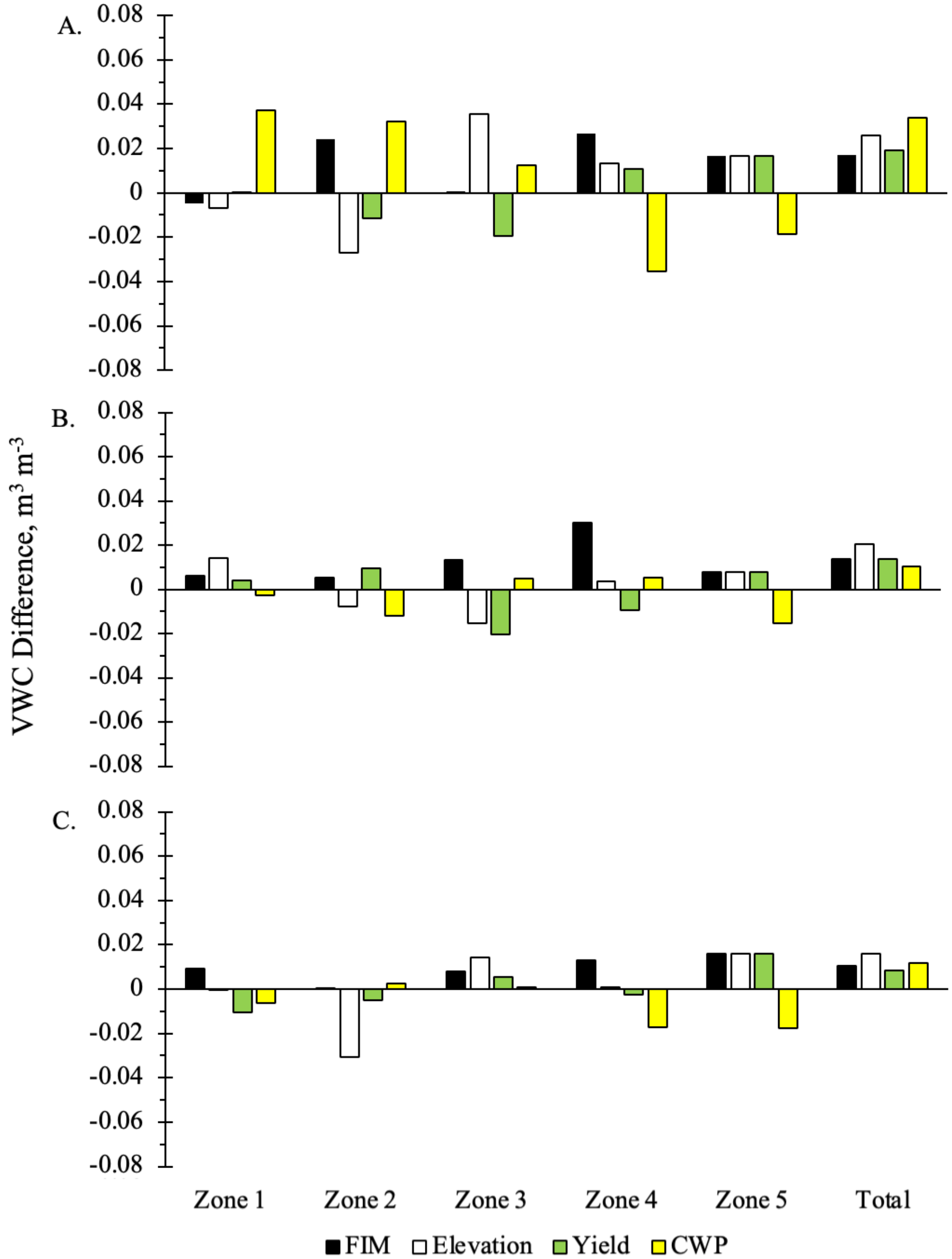

Figure 2–6. Seasonal average difference of soil volumetric water content (VWC) from average VWC across all sampling dates within each irrigation zone (VWC at sensor placement location – average VWC) at farmer-informed method and average elevation, yield, and crop water productivity (CWP) locations for the respective zone at depths 0.0 – 0.3 (A), 0.3 – 0.6 (B), and 0.0 – 1.2 (C) m.

Table 2–2. Average potential irrigation amount ratios from the May and June soil samplings of different sensor placement scenarios (elevation, yield, and crop water productivity (CWP) to the farmer-informed actual sensor placement in each zone at depth 0.0 – 0.3 m.

Zone	Sensor Placement Scenario (cm cm^{-1})		
	Elevation	Yield	CWP
1	1.0	1.0	0.3
2	-0.4	1.3	2.0
3	1.8	0.7	0.5
4	-5.5	-4.0	-5.7
5	1.0	1.0	1.8
Average	-0.4	0.0	-0.2

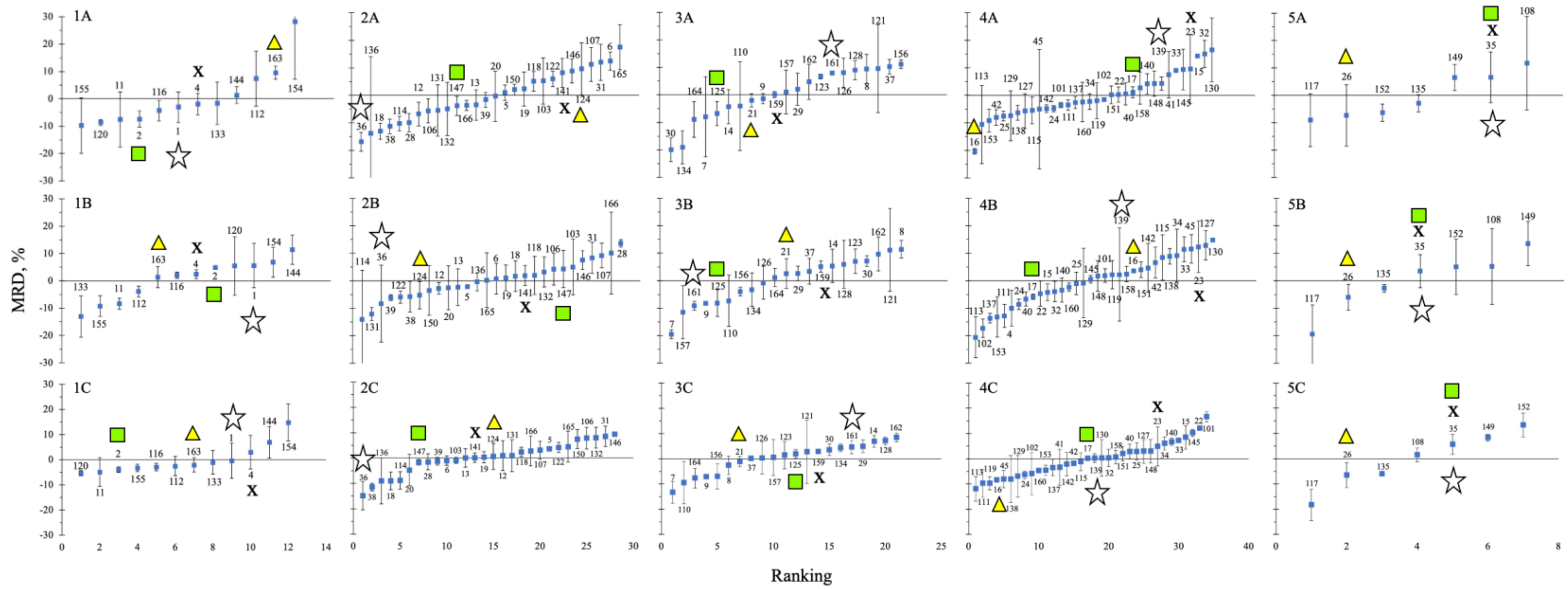

Figure 2–7. Temporal stability of soil samples in each irrigation zone (1-5) for depths 0.0 – 0.3 (A), 0.3 – 0.6 (B), and 0.0 – 1.2 m (C). Blue boxes represent the mean relative difference (MRD) percentage of soil volumetric water content (VWC) and the whiskers represent the standard deviation of relative difference (SDRD). Green square, yellow triangle, white star and the black x symbols represent average yield, CWP, elevation, and the farmer-informed sensor placement scenarios, respectively.

Table 2–3. Temporally stable locations (TSL) from all soil samples throughout each irrigation zone with mean relative difference (MRD), and standard deviation of relative difference (SDRD) values of samples closest to zero, representing the most temporally stable locations, by zone and depth, as well as the MRD and SDRD values of the locations at each sensor placement scenario [farmer informed method (FIM), elevation (E), yield (Y) and crop water productivity (CWP)]. The scenario with the MRD and SDRD closest to zero for each zone and depth is in **bold-face type** text.

		Depth 0.0 - 0.3 m					Depth 0.3 - 0.6 m					Depth 0.0 - 1.2 m				
Zone	Metric	TSL	FIM	E	Y	CWP	TSL	FIM	E	Y	CWP	TSL	FIM	E	Y	CWP
1	MRD	1.3	-2	-10	**-7**	10	2	2	6	**5**	1	-1.0	3	-0.4	**-4**	-2
	SDRD	3	4	10	**3**	2	1	2	8	**1**	4	5	7	7	**1**	3
2	MRD	0.9	8	-17	**-4**	10	-0.4	**2**	-8	4	-5	0.2	0.2	-15	**-2**	1
	SDRD	3	5	3	**4**	9	3	**4**	14	7	5	2	2	6	**1**	5
3	MRD	0.1	**0.1**	8	-7	-2	1	**5**	-9	-8	3	0.1	**3**	5	2	-1
	SDRD	1	**1**	0.3	4	2	3	**2**	2	5	5	1	**1**	3	2	2
4	MRD	1.1	10	4	**1**	-20	1	12	2	-6	**4**	0.1	5	0.2	**0.1**	-8
	SDRD	2	13	2	**2**	1	1	9	17	1	**0.1**	0.5	8	2	**0.5**	1
5	MRD	-3	**7**	**7**	**7**	-7	-3	**4**	**4**	**4**	-6	1	**6**	**6**	**6**	-6
	SDRD	3	**9**	**9**	**9**	11	1	**6**	**6**	**6**	5	3	**4**	**4**	**4**	5

Table 2–4. Ranking of sensor scenarios [farmer intuitive method (FIM), elevation, yield, and crop water productivity (CWP)] with 1 representing the location with the smallest MRD, SDRD, and volumetric water content (VWC) difference from average, and 4 representing the largest MRD, SDRD, and VWC difference from average for each zone and depth. All rankings are then added by depth and zone for each scenario. The scenario with the smallest ranking for all depths, zones, and depths and zones combined are in **bold-face type** text.

		0.0 - 0.3 (m)			0.3 - 0.6 (m)			0.0 - 1.2 (m)			All Depths		
Zone	Scenario	MRD	SDRD	AVG	MRD	SDRD	AVG	MRD	SDRD	AVG	MRD	SDRD	AVG
1	FIM	1	3	2	2	2	3	3	2	3	**6**	7	8
	Elevation	4	4	3	4	4	4	1	3	1	9	11	8
	Yield	2	2	1	3	1	2	4	1	4	9	**4**	**7**
	CWP	3	1	4	1	3	1	2	2	2	**6**	6	**7**
2	FIM	2	3	2	1	1	1	1	2	1	**4**	**6**	**4**
	Elevation	4	1	3	4	4	2	4	4	4	12	9	9
	Yield	1	2	1	2	3	3	3	1	3	6	**6**	7
	CWP	3	4	4	3	2	4	2	3	2	8	9	10
3	FIM	1	2	1	2	2	2	3	1	3	6	**5**	6
	Elevation	3	1	4	4	1	3	4	4	4	11	6	11
	Yield	4	4	3	3	3	4	2	2	2	9	9	9
	CWP	2	3	2	1	4	1	1	3	1	**4**	10	**4**
4	FIM	3	4	3	4	3	4	3	4	3	10	11	10
	Elevation	2	3	2	1	4	1	2	3	1	**5**	10	**4**
	Yield	1	2	1	3	2	3	1	1	2	**5**	5	6
	CWP	4	1	4	2	1	2	4	2	4	10	**4**	10
5	FIM	1	1	1	1	2	1	1	1	1	**3**	**4**	**3**
	Elevation	1	1	1	1	2	1	1	1	1	**3**	**4**	**3**
	Yield	1	1	1	1	2	1	1	1	1	**3**	**4**	**3**
	CWP	2	2	2	2	1	2	2	2	2	6	5	6
All	FIM	**8**	13	9	10	**10**	11	**11**	10	**11**	**58**	66	**62**
	Elevation	14	**10**	13	14	15	11	12	15	**11**	80	80	70
	Yield	9	11	**7**	12	11	13	**11**	**6**	12	64	**56**	64
	CWP	14	11	16	**9**	11	**10**	**11**	12	**11**	68	68	74

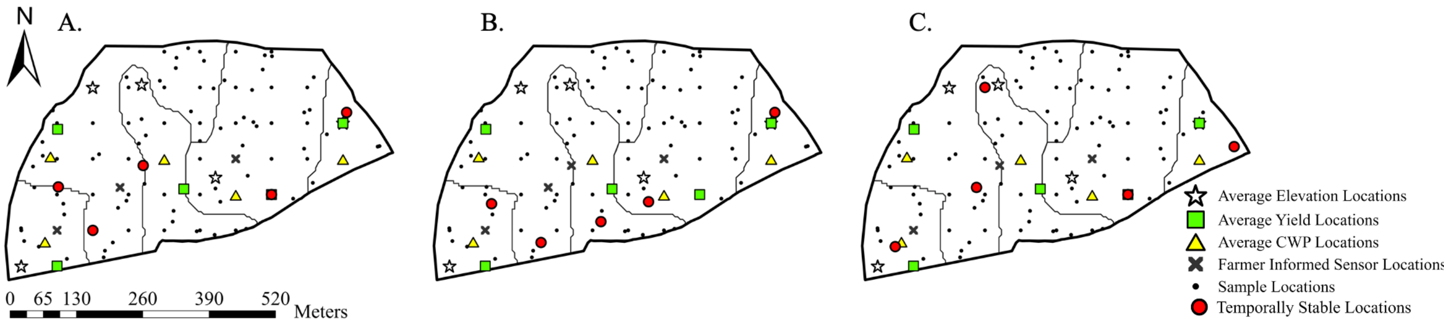

Figure 2–8. Locations of temporally stable samples (red circle), farmer-informed method location (black x), average elevation method (white star), average yield method (green square), and average crop water productivity (CWP) method (yellow triangle) within each irrigation zone, with zones 1-5 running from west to east in the field at depths 0.0 – 0.3 (A.), 0.3 – 0.6 (B.), and 0.0 – 1.2 (C.) m

2.7 | SUPPLEMENTARY MATERIAL

Table 2–S1. Pearson's correlation matrix values (r) for VWC sampling dates

		23-Apr	30-May	25-Jun	5-Sep
Depth (m)	Date	0.0 - 0.3 (m)			
0.0 - 0.3	23-Apr	1.00	0.85	0.52	0.48
	30-May	0.85	1.00	0.45	0.47
	25-Jun	0.52	0.45	1.00	0.45
	5-Sep	0.48	0.47	0.45	1.00
		0.3 - 0.6 (m)			
0.3 - 0.6	23-Apr	1.00	0.58	0.53	0.09
	30-May	0.58	1.00	0.53	0.02
	25-Jun	0.53	0.53	1.00	0.47
	5-Sep	0.09	0.02	0.47	1.00
		0 6 - 0.9 (m)			
0 6 - 0.9	23-Apr	1.00	0.80	0.74	0.35
	30-May	0.80	1.00	0.75	0.27
	25-Jun	0.74	0.75	1.00	0.35
	5-Sep	0.35	0.27	0.35	1.00
		0.9 - 1.2 (m)			
0.9 - 1.2	23-Apr	1.00	0.87	0.75	0.44
	30-May	0.87	1.00	0.85	0.52
	25-Jun	0.75	0.85	1.00	0.41
	5-Sep	0.44	0.52	0.41	1.00
		0.0 - 1.2 (m)			
0.0 - 1.2	23-Apr	1.00	0.67		0.31
	30-May	0.67	1.00	0.60	0.25
	25-Jun	0.69	0.60	1.00	0.38
	5-Sep	0.31	0.25	0.38	1.00

Table 2–S2. Pearson's correlation matrix values (r) of static and dynamic field variables with each sampling date and depth

	April	May	June	September	Average
			0.0 - 0.3 (m)		
Elevation	0.20	0.27	0.02	0.22	0.18
Yield	-0.16	-0.21	-0.20	-0.25	0.21
CWP	-0.15	-0.24	-0.12	0.03	0.14
			0.3 - 0.6 (m)		
Elevation	0.26	0.19	0.08	0.44	0.24
Yield	0.03	0.00	-0.07	-0.25	0.09
CWP	-0.07	-0.21	-0.07	0.08	0.11
			0 6 - 0.9 (m)		
Elevation	0.07	0.13	-0.14	0.18	0.13
Yield	-0.07	-0.10	-0.14	0.10	0.10
CWP	-0.18	-0.23	-0.15	0.25	0.20
			0.9 - 1.2 (m)		
Elevation	-0.16	-0.03	-0.02	-0.10	0.08
Yield	0.11	0.02	-0.28	0.18	0.15
CWP	0.02	-0.03	-0.31	0.38	0.18
			0.0 - 1.2 (m)		
Elevation	0.08	0.20	-0.02	0.20	0.13
Yield	-0.01	-0.12	-0.27	-0.08	0.12
CWP	-0.14	-0.27	-0.25	0.32	0.25

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CHAPTER 3

ESTIMATING AND INVESTIGATING ZONE AND FIELD VARIABILITY OF SOIL MOISTURE WITH SATELLITE IMAGERY

3.1 | INTRODUCTION

Agriculture is the largest principal user of freshwater resources (Postel, 1999). As the global human population grows, there is the need to increase crop production while using less water. It is known that water is a scarce resource in semi-arid and arid regions, and many of the crops in these regions rely on irrigation. Soil moisture is a variable that drives irrigation needs in production fields (Svedin et al., 2019). Soil moisture is rarely uniform within agricultural fields, even in fields that are leveled and have fairly uniform soil textures and properties (Daccache et al., 2015; Longchamps et al., 2015). Variable rate irrigation (VRI) can assist in correcting over- or under-watering throughout fields that generally occurs when uniform irrigation is practiced (King et al., 2006).

Understanding the spatial and temporal variation of soil moisture throughout a field can aid VRI management decisions. Measuring soil moisture throughout the field with soil samples can give accurate data on the spatial variation of volumetric water content (VWC), but this is only at specific times of sampling within the season. This process can be time consuming and costly (Barker et al., 2017; Headley & Yule 2009a, 2009b; Kaleita et al., 2007).

Soil moisture sensors only measure VWC in their locations of placement, but they give continuous data throughout the growing season, which can assist with irrigation timing decisions. Many studies have been performed to understand what static soil property or properties best explain spatial and temporal trends in VWC (Barker et al., 2017; Baroni et al., 2013; Biswas & Si, 2011; Kaleita et al., 2007; Phillips et al., 2014).

While Biswas and Si (2011) noted that topography influences VWC, Baroni et al. (2013) found that the following factors reflect the level of moisture: soil texture was more influential in wet conditions and spatial variability of vegetation in dry conditions. Other researchers have noted that using clay content or soil types within a field could be useful in estimating soil moisture (Oltra-Carrio et al., 2015; Yue et al., 2019). Kaleita et al. (2007) noted that some areas within their study had good correlation between topographic features and VWC. These collective results suggest that the soil properties that influence soil moisture variability are likely different from field to field, or that there is a deep and complex interaction among several factors that determine the moisture content of soils. Exploring these connections and simultaneously evaluating additional soil and field properties are important for the advancement of precision irrigation.

Utilizing different vegetative indices from readily available satellite imagery coupled with static field properties or other variables that correlate well to VWC within a particular field could more precisely estimate or predict VWC (Phillips et al., 2014). Many studies have utilized remote sensing, Sentinel and Landsat data specifically, to estimate leaf area index and evapotranspiration within a variety of crops (Anderson et al., 2012; Hammond et al., 2023; Herrmann et al., 2011; Richter et al., 2012; Verrelst et al., 2015). Other studies have used Sentinel-2A data to help optimize irrigation events (Vanino et al., 2018), have utilized Sentinel 2 and Landsat 8 for exploring how normalized difference vegetation index (NDVI) and Red Edge can depict crop stress (Vlachos, 2018), and have combined Sentinel 2 imagery with hyperspectral data to predict soil moisture (Ainiwaer et al., 2020).

Previous studies have also used shortwave infrared bands to assist in estimating soil moisture in bare soil fields (Oltra-Carrio et al., 2015; Yue et al, 2019). While there are many studies utilizing different indices from satellite imagery in a variety of methods for agricultural use, estimating soil moisture in individual fields during the growing season with Sentinel 2 and Landsat 8 imagery combined with ground truth measurements are lacking.

The objective of this study was to determine whether elevation coupled with, NDVI, normalized difference water index (NDWI), normalized difference red edge index (NDRE), and red, blue, and green (RGB) bands from satellite imagery could be used to accurately estimate within zone and field variation of soil moisture measured with soil samples and soil moisture sensors. Since soil moisture sensors were installed in pre-determined static management zones, a secondary aim of the work was to assess how irrigation zones based on water productivity and farmer knowledge represented soil moisture variation.

3.2 | MATERIALS AND METHODS

This study was conducted on two fields with different crops. Field A was based on data gathered in 2019 from a 22 ha field located near Grace, Idaho, USA (elevation 1687 m above sea level; 42.60904 latitude and -111.788 longitude). The crop rotation at the site is a wheat (*Triticum aestivum*)-wheat-potato (*Solanum tuberosum* L.) rotation. In 2019, the wheat cultivar ‘UI Magic’ was grown and was the first wheat crop following potato. The soil is a silty clay loam Rexburg-Ririe complex with 1 to 4% slopes. Field B was 23 ha and was located near Rexburg, Idaho, USA (elevation 1483 m above sea level;

43.800622 latitude and -111,79 longitude) (Soil Survey Staff, 2023). The crop rotation at the site is alfalfa (*Medicago sativa)*-wheat-alfalfa. Data were collected in 2021 on a 3 yr-old alfalfa stand. The soil is a silt loam Pocatello variant (Soil Survey Staff, 2023). These fields are in a semi-arid region with a climate typified with relatively hot days and cool nights during the summer growing season.

The average annual precipitation near Field A is 390 mm with the majority of the precipitation occurring during winter as snow (Bureau of Reclamation, 2017), which often blows and accumulates variably based on topography and surface soil tillage/plant residue. This was seen at the beginning of the growing season, where ponding occurred in the west side of the field, due to snow melt. This caused late growth in that area compared to the rest of the field. Average annual precipitation near Field B is 340 mm with the majority of precipitation occurring during winter and early spring as snow (Bureau of Reclamation, 2017), which also blows and accumulates variably, similar to field A.

Volumetric water content was measured four times in the growing season at field A on 23 April, 30 May, 25 June, and 05 September 2019 at 46 sample locations throughout five irrigation zones (Fig. 3–1) collected on a 70 m grid with 56 additional nested samples collected at random locations throughout the five irrigation zones in the field. Additionally, VWC was measured four times during the growing season at field B on 12 May, 09 June, 17 July, and 15 September 2021 at 66 sample locations throughout the west half of the field on a 60 m grid coupled with a 75 m offset grid (Hammond et al., 2023) (Fig. 3–1). Soil samples at both locations were collected at four depths (0-0.3, 0.3-0.6, 0.6-0.9, and 0.9-1.2 m) using a modified gas-powered post driver (AMS, Inc.

American Falls, ID, USA). Gravimetric water content from the soil samples was determined by weighing wet samples and then drying them in a forced air oven at 105ºC until consistent dry weights were reached. Volumetric water content was then calculated using gravimetric water content values and soil bulk density values determined in 2016 from previous samples (Svedin, 2018; Svedin et al., 2019) for field A. A single bulk density value was used for field B from averaging the individual bulk density values at each soil sensor location. The VWC data were kriged to a 5 m grid for each date (Fig. 3–2).

Irrigation zones for field A in 2019 were created by analyzing patterns in 2016 and 2017 crop water productivity (CWP), which was calculated from yield and evapotranspiration (ET) data (Flint et al., 2023). This was accomplished by using a regression analysis where yield was the response variable and ET was the explanatory variable. Then, a k-means clustering algorithm with constraints for spatial contiguity was used to map the five irrigation zones. The irrigation rate applied to each zone was derived from a combination of the data provided by these soil sensors and the averaged field capacity (FC) from nearby soil samples to irrigate up to estimated field capacity. Irrigation zones were not implemented for field B, although a variable rate irrigation system was installed on the center pivot. Irrigation was managed by the farm manager, with uniform irrigation applied throughout the field.

A data logger (ZL6, Meter, Pullman, WA, USA) with an attached VWC sensor (TEROS 12 [field A], TEROS 10 [field B], Meter, Pullman, WA, USA) was installed in each zone to record changes in VWC throughout the growing season at a depth of 0.3 m. Data were logged every 15 minutes. The loggers and sensors were installed in field A on

23 April and removed just prior to harvest on 20 August. The loggers and sensors were installed in field B by 25 May and removed on 15 September, but not all sensors were reading properly on 15 September to use for analysis in this study.

Sentinel 2 and Landsat 8 images near soil sampling dates were downloaded from earthexplorer.usgs.gov and dataspace.copernicus.eu. All images were then clipped to the field boundaries in Arc GIS Pro (ArcGIS Pro 3.2.2, Redlands, CA, USA). The NDVI, NDRE and RBG bands from Sentinel 2 and Landsat 8 imagery were calculated, kriged, and extracted in both Spacestat (BioMedware, SpaceState 4.0.21, Ann Arbor, MI, USA and ArcGIS Pro (Table 3–1, Fig. 3–2, 3–3). Different sub-points (15 VWC subpoints, 5 VWC subpoints at each sensor location, and sensor VWC data from 5 sensor locations) from the VWC data for depth 0.0 – 0.3 m in both fields were chosen and used for the regressions explained below. The 15 sub-points were randomly selected, three within each zone at field A, and randomly chosen throughout field B. The 5 VWC sample subpoints were selected from each sensor location for both fields. The 5 sensor VWC subpoints were data used from the sensors in both fields. Average VWC values within each irrigation zone were also used in regressions for field A. These average VWC values were calculated from the total VWC samples used at each sampling date at field A. Average VWC values were not used in regressions for field B, as the field did not have delineated VRI zones and was irrigated uniformly. These different subsets were used in regressions to reduce or possibly omit the amount of soil samples needed in order to estimate VWC with the satellite imagery and other static, ground data. Elevation from both fields and 2016 (first-year wheat) yield, and aspect data from field A were also collected and kriged to a 5-m grid (Fig. 3–3) for correlation purposes. Elevation had some of the best correlations with VWC at each sampling date for field A compared to aspect, slope, and yield and was used in the regressions described below.

Three indices (NDVI, NDRE and average RGB) calculated from satellite imagery at or near each specified soil sampling date were correlated with four sets of VWC data including all VWC sample points, 15 VWC sample points, 5 VWC sample points at the sensor locations and 5 sensor VWC values at the 0.0 – 0.3 m soil sampling depth. The VWC samples from the deeper depths were not used in this analysis due to low correlations with vegetative indices. The average VWC was not correlated with the satellite imagery, but the correlations from all VWC sample points with satellite imagery was used. For each soil sampling date and VWC subset, regressions with VWC as the dependent variable and the most highly correlated imagery data and elevation data as independent variables were calculated for both field A and B. The regression equations were applied to the kriged (5-m^2) imagery to estimate VWC and compared to the original kriged VWC maps.

3.3 | RESULTS AND DISCUSSION

Satellite imagery proved useful in estimating VWC throughout both fields. However, some indices had better estimations than others, and the timing within the growing season often influenced the accuracy of VWC estimation. A general pattern of better correlation or larger r^2 values of 0.37, 0.33, and 0.81 occurred on the May date for 15 points, 5 points, and 5 sensor data points, respectively, than the subsets on the other sampling dates in field A regressions (Table 3–2). Field B had a mixed response with variable correlation coefficients across the different sampling dates and subsets (Table 3–2). In field A, the May sampling date had an established crop, but only had two irrigations prior to the sampling date, which may explain why r^2 values were higher and more consistent at this date. Irrigation can increase soil VWC uniformity, which in turn may cause more uniform crop water status, vegetative and visual indices, and less correlation with satellite imagery.

In field B, the May sampling date only had a single irrigation event the day before the sampling event. Water was potentially still moving through the soil profile and would have less impact of spectral signatures. The June sampling date in field B was just prior to the first harvest with a fully established crop. Eight irrigation events had occurred leading up to that sampling. The July sampling date was also just prior to the second alfalfa harvest with multiple irrigation events preceding that time. The September sampling date was a week prior to harvest.

On the first sampling date (23 April) for field A, the crop may not have been sufficiently established for the vegetative indices to represent soil moisture. The vegetative indices used in this study may not have captured the variation in soil moisture as well as other indices available that were not used in this study. Thus, exploring soil indices at this time of year in fields with wheat may have resulted in regressions with higher r^2 values that would have better represented the soil moisture at that time. Utilizing a soil index to estimate soil moisture has been evaluated in a situation with bare soil. A study looking at determining soil moisture in bare soil fields found that utilizing indices that included ShortWave InfraRed (SWIR) coupled with clay content was useful and had promising results with r^2 values above 0.76 and root mean square error (RMSE) values below 0.08 m^3 m^{-3} (Oltra-Carrio et al., 2015). The SWIR bands are more sensitive to changes in water at the surface level in bare soil than other spectral bands. Utilizing indices with SWIR could improve VWC estimation when fields do not have established or fully established crops.

At the June sampling date for field A, the crop had surpassed row closure and multiple VRI events had occurred up to that point. This potentially manipulated the soil moisture, making it more difficult for one vegetative index coupled with elevation data to predict soil moisture at this stage. Baroni et al. (2013) discussed utilizing the combination of different variables to assist in describing VWC at varying stages of wet and dry soils. This could translate to using different or multiple vegetative indices during the growing season where temperatures are generally high, there is an increase in evapotranspiration, and irrigation is occurring. This process could potentially estimate VWC more precisely throughout a field.

On the September sampling date in field A, the r^2 values from the 15 and 5 sampling data point regressions were the smallest with values of 0.28 and 0.03, respectively (Table 3–2). The wheat had just previously been harvested and only the stubble remained in the field at the time of soil sampling. The vegetative indices may not have correlated to soil moisture as well that day because of the dry matter and no growing plant material. When the crop was actively growing there was a higher reflectance due to scattering within the spongy mesophyll cells (Richter et al., 2012). This would be captured by NIR bands better during the growing stage of a plant rather than at the senescence stage of a plant. Other indices at this stage of wheat may need to be explored to improve the accuracy of estimating soil moisture.

Field B did not have the same trends as field A with the outcomes from the regressions. Across all sampling dates at field B, the regressions from the 15 subset data points had the lowest r^2 values compared to the other subset regressions, with r^2 values of 0.24, 0.55, 0.35 and 0.43 for the May, June, July, and September sampling dates, respectively. The 5 sample subset points had the highest r^2 values across all dates, except for the July regression that had an r^2 of 0.51, while the May, June, and September r^2 values were 0.99, 0.96, and 0.87, respectively.

The r^2 value at the sensor points in July had a much higher r^2 value of 0.97 than the sampling points as close as possible to the sensor locations with an r^2 value of 0.51. While the 5-sample subset regression used NDVI from Landsat 8 imagery, the sensor subset regression at the July sampling date used RGB from Sentinel 2 imagery. The images were taken three days apart. Such differences in outcomes could be due to the different vegetative indices used, or the date at which the images were taken compared to the VWC soil sampling and sensor data retrieval date.

Vlachos (2018) noted that NDVI was not as useful in detecting stress in plants as indices that include red edge. While the majority of vegetative indices in the results did not include red edge, NDRE was included in the analysis. However, NDRE only correlated well with the ground VWC data at the May and September sampling date for field B. Although vegetative indices with the red bands generally had the highest correlations with the VWC sample data in most situations, there is a decrease in correlations and r^2 values at the June and July sampling dates for fields A and B, respectfully, following the previous sampling date. Utilizing an index with red edge could increase correlations but needs additional validation. This method of using vegetative indices with red edge may be questionable, as many of the indices used in the regressions were NDVI, and most of the indices did not have red edge within the vegetative index for the regressions, particularly in periods of water stress. Richter et al. (2012) also found that using NIR and red edge bands were most useful in estimating leaf area index due to higher reflectance of these bands, and that implementing Sentinel 2 data could be useful for agricultural settings. Although their study did not relate imagery to soil VWC, the more information there is on what indices and bands relate to different variables within a field, the better these data can be utilized to assist in precision agriculture.

It was also discovered that regression methods from the 5 sensor data points at field A were better than the regression methods from the 5 sampling points. Regression output for the 5 sensor data points had r^2 values of 0.81 and 0.58 (Table 3–2) during May and June, respectively in field A. These results suggest the sensor data coupled with elevation and imagery may be useful to estimate within zone variability. The 15 subset data point regressions for field A had slightly larger r^2 values than the 5 subset data point regressions across sampling dates with a general pattern of smaller RMSE values. While this option may have better r^2 and RMSE values, when it was correlated with all the soil samples throughout the field, it did not have as strong of a correlation as did the regressions with the 5 sensor data points and will be discussed more below (Table 3–3). The zone average models did give promising r^2 values of 0.83, 0.91, 0.92, and 0.71 in April, May, June, and September, respectively (Table 3–2), but as this method utilizes the 102 sampling points, it would not be as economically favorable as other options with less soil sampling points. Therefore, this option was not further evaluated.

The regressed, kriged soil sensor VWC means and standard deviations were highly correlated with the original, kriged VWC mean and standard deviation values. These correlation coefficients values were 0.93 and 1.00 for the means and 0.39 and 1.00

for the standard deviations for field A and B, respectively (Table 3–3, 3–4). This suggests the current method of using soil moisture sensors may be valuable in predicting VWC. However, the inconsistency of vegetation indices used to predict VWC between fields at similar dates is not practical and needs further research. Determining a specific vegetative index predictor per crop and time period would be necessary for more efficient and practical use. The spatial variation of estimated VWC from the 5 soil samples at the sensor locations has visually more apparent spatial patterns in VWC in relation to the 102 and 66 soil samples than the 5 soil sensors for fields A and B, respectively (Fig. 3–4). However, the correlation coefficients of the regressed 5 soil samples at the sensor locations with the original VWC means and standard deviations were not as strong with mean correlations of 0.94 and 0.97, and standard deviation correlations of 0.25 and 0.16 for field A and B, respectively (Table 3–3, 3–4). This suggests that the estimation from the 5 soil sensors better represents the VWC from the 102 and 66 samples for fields A and B, respectively. Part of this could be explained by human error when collecting soil samples by hand. If sensors are properly calibrated and installed within a field, they typically have accurate readings of soil moisture. This could also be explained by the smaller number of mean and standard deviation points correlated from the sensor subsets compared to the 5 sample subsets.

The irrigation method used at field A during the 2019 growing season should have resulted in a relatively uniform distribution of VWC within and between zones at field A. As differences in VWC between zones at the May and June sampling dates were not significant with *p*-values of 0.095 and 0.449, respectively, this suggests that irrigation was applied to a level that was near field capacity across the entire field (Table 3–5).

However, on the April and September sampling dates, VWC was significantly different between zones with *p*-values of 0.005 and 0.002, respectively. Zone three had consistently lower VWC compared to zones 1 and 2.

Zone 3 was on the slope of the field compared to zones 1 and 2 that were below it and were relatively flat. The slope in zone 3 may have caused lateral movement of water, which creates difficulty in irrigating the whole field to field capacity at one time during certain times of the year. As was seen in the kriged estimated VWC data, there were significant differences in VWC between zones at all sampling dates. While the original VWC does not show that there are significant differences in VWC between zones in May and June, there are still differences in VWC between and throughout the zones during these two months, but not near as many differences between zone variability as in April or September.

Kruskal-Wallis H tests were performed on the 102 VWC soil samples for each sampling date and showed significant ($p<0.05$) differences in the VWC between the zones in April and September (Table 3–5). These are dates when irrigation was not being applied and given the irrigation strategy of applying irrigation to reach field capacity, less difference between the zones would be expected in May and June when irrigation was being applied. Nevertheless, the difference between zones was close to significant in May as there were only three irrigation events up to that point.

Kruskal-Wallis H tests were also performed on the estimated VWC based on the regressions from the 15 soil sample, 5 soil sample, and 5 sensor data subsets. The subset of averaged VWC by zone from all the soil samples was discarded as gathering data for this involves taking 102 soil samples and is still a costly and timely process that most farmers would unlikely employ. The results for this test on the regressed VWC values showed significant differences in VWC between the zones at all sampling dates, but this is likely due to the large number of points in these data and the presence of some spatial autocorrelation. However, larger H values indicate increased significant differences in VWC between the zones. For each regressed dataset the VWC was most different between zones for May and least for June.

Measured VWC was lowest in zone 3 on all sampling dates and highest or second highest for zone 1 on each date (Table 3–3). For the regressed data, similar, but not as well-defined, patterns could be observed. The standard deviations of the VWC from the 102 soil samples are evidence of variation within each zone at each sampling date, even on dates where irrigation events were aiming to irrigate to the zone's predicted FC. However, when standard deviations of the different subsets were correlated with the standard deviations from the original VWC values, the best correlation came from the 5 soil sensor data subset.

The means for each zone were closest to those for the 102 measured samples for the 15 samples regression in April and May, for the five sensors in June, and for the 5 soil points in September. But the regressed values tended to have similar ranks of VWC to the 102 VWC samples on each date. When estimated mean VWC values from the different subsets were correlated with the mean VWC from the 102 soil samples at each sampling date, the 15 sampling points had the strongest correlation, but correlations with the 5 sample and 5 sensor points were also strong. The correlations for the standard deviations were far weaker, but strongest for the five sensors. This suggests that although the approach using remotely sensed imagery and elevation data gives a good estimate of the average VWC in each zone, the approach using the five sensors is the best at indicating the variation within zones.

3.4 | CONCLUSIONS

Satellite imagery can be useful in determining VWC at certain stages of winter wheat and alfalfa growing seasons. Soil sensor data does prove useful and comparable to actual VWC data from soil samples during the growth period of the crop and therefore can provide useful data for irrigation recommendations. Utilizing satellite imagery coupled with soil sensor data can also assist in depicting differences in VWC between irrigation management zones. NDVI for example is clearly less useful when bare soil dominates the imagery (April) or when the crop is senesced (September). Different vegetative indices may more accurately represent VWC for different crops depending on their growth patterns, growth ranges, and irrigation needs. Further work is needed to know which imagery will be best for depicting VWC within winter wheat and alfalfa crops at different growth stages of the crop.

3.5 | TABLES AND FIGURES

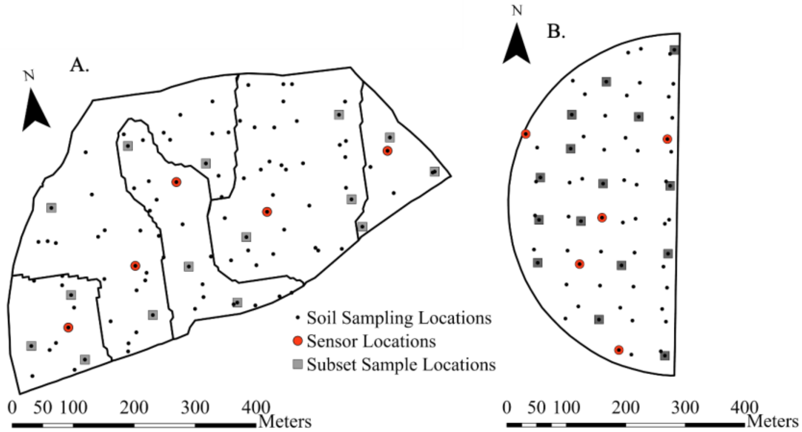

Figure 3–1. Maps showing the location soil sampling points, sensor locations and a directed subset of sample locations in relation to the irrigation management zones (black lines) in the field for field A and field B

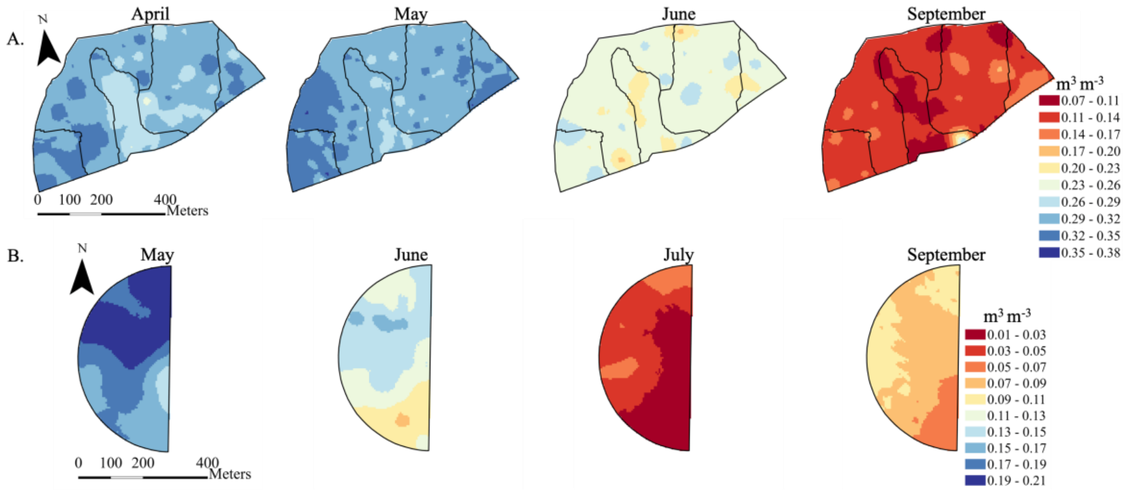

Figure 3–2. Kriged spatial variation of volumetric water content (VWC) at the 0-0.3 m depth throughout A) field A at each sampling date within the 2019 growing season and B) field B within the 2021 growing season

Table 3–1. Vegetation indices and formulas used in regression for estimating VWC.

Vegetation Index	Formula
NDVI	(NIR – Red) ÷ (NIR + Red)
NDRE	(NIR – Red Edge) ÷ (NIR + Red Edge)
Average RGB	(Red + Green + Blue) ÷ 3

Sentinel 2 Band information

Band	Central Wavelength	Description
	- - - - - nm - - - - - -	
B2	490	Blue
B3	560	Green
B4	665	Red
B5	705	Red Edge
B8	842	VNIR
B8a	865	VNIR

Landsat 8 Band Information

Band	Central Wavelength	Description
	- - micrometers - -	
B2	0.45 - 0.51	Blue
B3	0.53 - 0.59	Green
B4	0.64 - 0.67	Red
B5	0.85 - 0.88	NIR

NDVI: Normalized difference vegetative index
NDRE: Normalized difference red edge index
Average RGB: average of red, green, and blue bands
VNIR: Visible and Near Infrared
NIR: Near Infrared

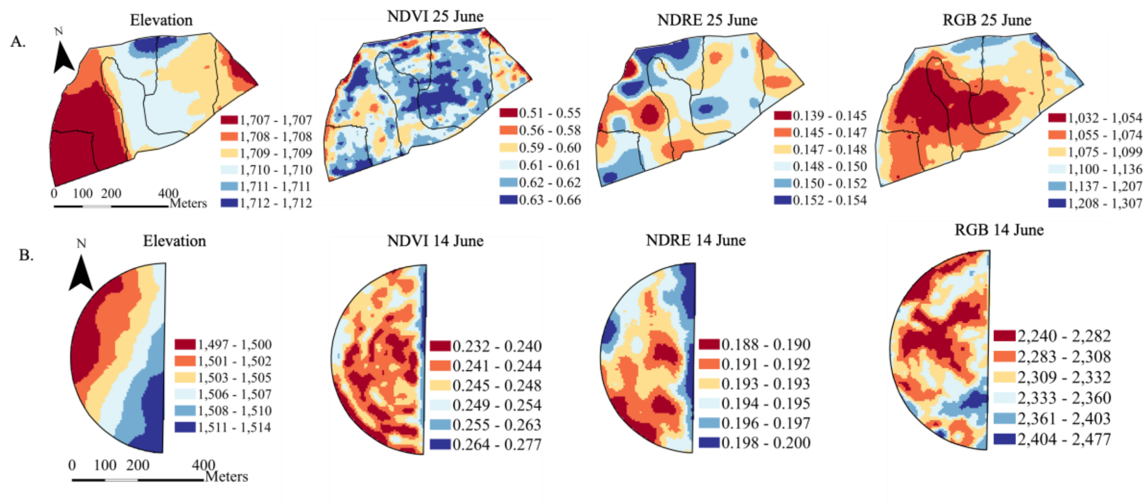

Figure 3–3. Spatial variation of selected satellite imagery near the June sampling dates and field data used in analysis for field A and B

Table 3–2. Summary of model fit statistics with the best fit vegetative indices and dates from satellite imagery collection used for each regression of the subset of points for estimating soil moisture in fields A and B

Field	Sampling dates	Subset	Vegetative index	Satellite	Date of imagery	Correlation coefficient	r2	*p*-value	Kriged RMSE
Field A	23-Apr	15 points	RGB	S2	3-May	0.57	0.32	0.098	0.02
		5 points	RGB	S2	18-Apr	0.86	0.73	0.266	0.07
		Avg zones	RGB	S2	3-May	0.83	0.69	0.315	0.05
	30-May	15 points	NDVI	L8	26-Jun	0.61	0.39	0.053	0.01
		5 points	RGB	S2	11-May	0.57	0.33	0.671	0.02
		5 sensors	RGB	S2	11-May	0.90	0.80	0.198	0.02
		Avg zones	NDVI	L8	26-Jun	0.91	0.83	0.172	0.01
	25-Jun	15 points	NDVI	S2	5-Jun	0.63	0.40	0.363	0.03
		5 points	NDVI	S2	5-Jun	0.54	0.29	0.711	0.06
		5 sensors	NDVI	S2	5-Jun	0.76	0.57	0.428	0.03
		Avg zones	NDVI	S2	5-Jun	0.92	0.85	0.151	0.01
	5-Sep	15 points	NDVI	L8	29-Aug	0.53	0.28	0.143	0.02
		5 points	NDVI	L8	29-Aug	0.17	0.03	0.972	0.01
		Avg zones	NDVI	L8	29-Aug	0.71	0.51	0.494	0.01
Field B	12-May	15 points	NDRE	S2	9-Jun	0.49	0.24	0.191	0.18
		5 points	NDVI	L8	12-Apr	0.99	0.99	0.014	0.04
	9-Jun	15 points	NDVI	S2	9-Jun	0.74	0.55	0.008	0.02
		5 points	NDVI	S2	30-Apr	0.98	0.96	0.038	0.04
		5 sensors	NDVI	L8	5-May	0.83	0.69	0.313	0.05
	15-Jul	15 points	RGB	L8	8-Jul	0.60	0.36	0.071	0.18
		5 points	NDVI	L8	22-Jun	0.71	0.51	0.492	0.02
		5 sensors	RGB	S2	19-Jun	0.87	0.99	0.119	0.12
	15-Sep	15 points	NDRE	S2	23-Aug	0.66	0.43	0.035	0.01
		5 points	RGB	S2	7-Sep	0.93	0.87	0.132	0.05

NDRE: Normalized difference red edge
NDVI: Normalized difference vegetation index
RGB: Red, green, and blue bands, averaged
S2: Sentinel 2
L8: Landsat 8
RMSE: root mean square error

Table 3–3. Mean and standard deviations of measured and regressed VWC for each management zone on each sampling date at field A

		Mean				Standard Deviation			
Date	Zone	102 VWC samples	5 Samples regressed	5 Sensors regressed	15 Samples regressed	102 VWC samples	5 Samples regressed	5 Sensors regressed	15 Samples regressed
23-Apr	1	0.321	0.435	n/a	0.311	0.011	0.136	n/a	0.017
	2	0.313	0.388	n/a	0.322	0.012	0.167	n/a	0.017
	3	0.289	0.317	n/a	0.292	0.013	0.031	n/a	0.011
	4	0.299	0.321	n/a	0.315	0.013	0.066	n/a	0.017
	5	0.303	0.433	n/a	0.303	0.015	0.162	n/a	0.015
30-May	1	0.323	0.331	0.299	0.327	0.007	0.010	0.012	0.006
	2	0.313	0.333	0.311	0.302	0.012	0.022	0.011	0.020
	3	0.297	0.297	0.285	0.277	0.011	0.008	0.006	0.008
	4	0.307	0.299	0.287	0.298	0.010	0.011	0.010	0.013
	5	0.320	0.336	0.318	0.310	0.007	0.015	0.010	0.009
25-Jun	1	0.251	0.282	0.270	0.241	0.011	0.082	0.048	0.018
	2	0.242	0.254	0.250	0.221	0.011	0.073	0.044	0.031
	3	0.237	0.236	0.233	0.195	0.009	0.041	0.024	0.012
	4	0.244	0.283	0.260	0.204	0.012	0.068	0.040	0.019
	5	0.244	0.270	0.259	0.221	0.011	0.063	0.036	0.017
5-Sep	1	0.129	0.121	n/a	0.120	0.006	0.002	n/a	0.005
	2	0.122	0.124	n/a	0.114	0.008	0.003	n/a	0.006
	3	0.116	0.128	n/a	0.110	0.021	0.002	n/a	0.006
	4	0.126	0.128	n/a	0.108	0.011	0.002	n/a	0.005
	5	0.134	0.125	n/a	0.113	0.009	0.007	n/a	0.016
Correlation with zone means & standard deviations for 102 VWC samples			0.940	0.929	0.986	n/a	0.252	0.386	0.125

Table 3–4. Mean and standard deviations of measured and regressed (Reg) VWC for each sampling date at field B near Rexburg, ID

	Mean				Standard Deviation			
Date	66 VWC Samples	5 Samples Reg	5 Sensors Reg	15 Samples Reg	66 VWC Samples	5 Samples Reg	5 Sensors Reg	15 Samples Reg
12-May	0.182	0.208	n/a	-0.001	0.017	0.053	n/a	0.006
9-Jun	0.126	0.153	0.173	0.118	0.017	0.046	0.045	0.025
15-Jul	0.033	0.020	0.108	0.038	0.014	0.013	0.091	0.024
15-Sep	0.083	0.122	n/a	0.074	0.0113	0.0502	n/a	0.0111
Correlation with field means & standard deviations for 66 VWC samples		0.972	1.000	0.230	n/a	0.158	1.000	0.088

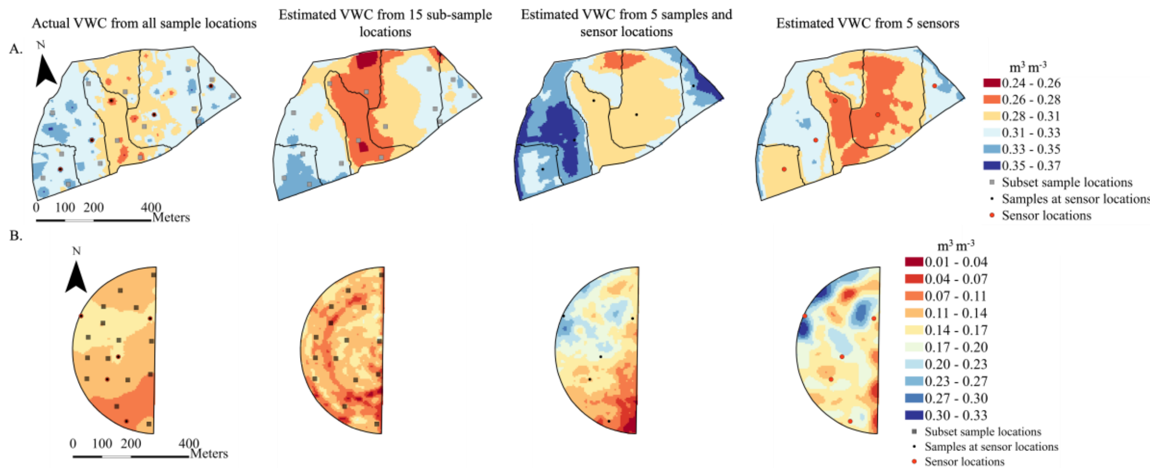

Figure 3–4. Comparing spatial variation of soil VWC from all the soil sample locations to the spatial variation of estimated VWC from three reduced datasets (15 and 5 soil sample locations, and 5 sensor data) at the May sampling date at field A with 102 total sampling points (top row) and at the June sampling date with 66 sampling points at field B (bottom row).

Table 3–5. Kruskal Wallis H test values and probability levels for differences in measured and regressed VWC between management zones at each soil sampling date in field A. Dates with NA were due to sensors not installed at those dates.

	Date of Observations			
	23-Apr	30-May	25-Jun	5-Sep
H value measured 102 Samples	14.94	7.92	3.695	17.27
p-value measured 102 Samples	0.005	0.095	0.449	0.002
H value regressed 5 Sample Points	2692	5080	1216	3748
p-value regressed 5 Sample Points	0.000	0.000	0.000	0.000
H value regressed 5 Sensor Points	n/a	5699	1266	n/a
p-value regressed 5 Sensor Points	n/a	0.000	0.000	n/a
H value regressed 15 Sample Points	3058	4339	3223	2808
p-value regressed 15 Sample Points	0.000	0.000	0.000	0.000

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CHAPTER 4

ON-FARM VARIABLE-RATE NITROGEN MANAGEMENT IN POTATO

4.1 | INTRODUCTION

Crops are generally not grown in isolation, but rather as part of a cropping system. A system that is economically, environmentally, and socially sustainable is highly dependent upon effective nutrient stewardship (Hopkins, 2020; Westermann, 2005; Zebarth & Rosen, 2007). This is especially true for nitrogen (N), which often has a larger impact on production than all other nutrients. Best management practices (BMPs) for N can vary by crop species, especially when the cropping system includes species with vastly different soil-plant relations, such as wheat (*Triticum* spp.) grown in rotation with potato (*Solanum tuberosum* L.).

Globally, wheat is first in acreage and third in value among all crops; while potato is first in acreage and value among annual vegetable and fruit crops (Hopkins & Hansen, 2019). Although generally higher in value, potato is necessarily grown in rotation with other crops (Hopkins & Hirnyck, 2007; Hopkins et al., 2020; Myers et al., 2008; Zebarth & Rosen, 2007). In many regions, wheat is included as a component of the cropping system or as the sole rotational crop with potato (Myers et al., 2008). This is a common system in the Pacific Northwest where the majority of the US potatoes are grown,

Although commonly grown in the same cropping systems, morphological and physiological characteristics of wheat and potato are not the same, requiring different management practices. While irrigated wheat roots can reach a depth of 1.5 – 1.8 m (Hopkins & Hansen, 2019; Weaver, 1926), most potato roots are shallow and only reach a depth of 0.6 m with the majority of those roots within the top 0.3 m (Hopkins & Hansen, 2019; Hopkins et al., 2020; Ojala et al., 1990). Potato roots also have about half the amount of root hairs as most other crops, including wheat, which lowers uptake and negatively impacts nutrient use efficiency (Hopkins et al., 2020). While wheat roots are still extending 2-3 months into the growing season (Weaver, 1926), potato roots have usually completed their development by that time and roots have started to decline (Hopkins et al., 2020). These features of potato and their root systems cause the application rate of nutrients, particularly N, to be higher than other crops such as wheat, even if the uptake rate of N in these two crops are similar. Wheat and, especially, potato require careful N management as it is also an expensive component of crop production (Hopkins et al., 2007, 2020; Schwalbert et al., 2019).

Potato requires an optimal amount of N, with both deficiencies and excesses negatively impacting crop production (Geary et al., 2015; Jones & Painter 1974; Ojala et al., 1990; Pedersen et al., 2021; Stark et al., 2004). Deficient N can reduce vine canopy growth, resulting in early onset of senescence and a reduction in yields. Excess N in the early season delays tuber elongation and reduces yield. Excess N can also increase vegetative growth while slowing tuber bulking if applied in excess during mid-growing season. If levels of N are inconsistent throughout the tuber bulking stage, yield quality (internal and external qualities) of tubers can be negatively impacted.

Excess N can also be harmful to the environment, with concerns of NO_3-N in drinking water, eutrophication of surface water, reactive NH_3 volatilization, and greenhouse gas emission of N_2O (Holland & Schepers, 2010; Hong et al., 2006; Hopkins, 2020; LeMonte et al., 2016, 2018; Stefaniak et al., 2021; Whitley & Davenport, 2003).

Excess soil moisture can cause N to leach past the shallow root zone of potato and in turn be unavailable to the plant. This can lead to leaching into groundwater. Denitrification can also be an issue if N on the surface of soils is not able to move into the soil for root uptake.

Crop N needs are spatially variable based on topography, soil properties, microenvironments, and biotic/abiotic stresses (Ruffo et al., 2006). Proper N management, which could include applying variable rate N (VRN), or specific N sources, rates and timings could improve crop growth, optimize tuber size, production, grade specific gravity and other qualities in potato (Hong et al., 2006; Hopkins et al., 2020; Stefaniak et al., 2021; Westermann, 2005; Zebarth & Rosen, 2007). Improving N management through VRN also has the potential to decrease input costs, and/or minimize negative environmental impacts (Bragagnolo et al., 2013; Hong et al., 2006; Hurley et al., 2004; Koch et al., 2004; Mamo et al., 2003; Scharf et al., 2005).

Determining N rates for VRN in potato has been explored with several approaches including remote sensing. A two-year study on VRN in potato found that utilizing VRN with remote sensing decreased N and resulted in increased NUE while maintaining tuber yield (Bohman et al., 2019, 2020). Another VRN study evaluated several indices that might best guide VRN applications and found that relative chlorophyll meter reading, relative chlorophyll index and relative normalized differential vegetation index were beneficial in predicting N stress at different growth stages of potato (Giletto & Echeverria, 2016). While VRN research has been performed on potato, most of the work has focused on in-season VRN without the pre-emergence VRN (Bohman et al., 2019, 2020; Kempenaar et al., 2017). These studies referenced above were also performed on small plot scales and not at the field scale. There is also the need to evaluate VRN approaches in different climates, such as semi-arid Idaho where potato production is common. There is also a sparsity of data on how VRN performs on various potato cultivars that have different optimal N rates, or where optimal N rates are unknown (Westermann, 2005; Whitley & Davenport, 2003; Zebarth & Rosen, 2007).

Past research has used crop sensing, modeling, yield maps, topography and soil properties to create N management zones for VRN, some collectively and some individually (Bourdin et al., 2017; Holland & Schepers, 2010; Koch et al., 2004; Pedersen et al., 2021; Schwalbert et al., 2019). While some studies have shown success with VRN zones, others have not (Koch et al., 2004; Long et al., 2015; Schwalbert et al., 2019). Hong et al. (2006) studied VRN in a soybean-wheat-maize-wheat crop rotation and found that utilizing remote sensing to set N rates improved yields or N:harvest ratios in all three years of their study. The authors also observed increases of NO_3-N in groundwater from additional N in high zones with VRN use. This study implies caution must be taken to avoid negative environmental impacts from potential increased N rates within high VRN management zones.

Historical yield maps (Robertson et al., 2008) as well as other layers of information (such as crop canopy sensors), have been used to improve VRN in wheat production (Stamatiadis et al., 2018; Thomason et al., 2011). This approach could also be utilized in potato to assess effectiveness in N management and production. When determining N zones for VRN management, evaluation of yield patterns throughout a field could be a meaningful predictor of spatially variable N needs. If a portion of a field historically yielded high, one might determine this area has a high yield potential zone, thus assigning a higher N rate than the other areas of the field. If a portion of a field historically yielded low it could receive a lower N rate than the other areas of the field. This process leverages the spatial variability of historical performance throughout a field to potentially increase production where possible and decrease input costs where increased production is not expected or attainable.

To address literature gaps in practical field scale pre-emergence evaluations of VRN, a simple approach to VRN management that utilizes readily available resources such as field history and grower knowledge is needed to advance field-scale precision N management in a cost-effective way for growers in the western region of the United States for multiple potato cultivars. Therefore, the objective of this study was to determine how pre-emergence VRN impacted yield, crop quality, and NUE of various potato cultivars in on-farm trials.

4.2 | MATERIALS AND METHODS

4.2.1 Site Description and Management

Trials were conducted on 10 commercial, center-pivot-irrigated, seed potato fields (50, 35, 18, 35, 23, 25, 9, 40, 49 and 26 ha for fields 1-10, respectively). These fields were located near Grace, Idaho, USA (elevation 1687 m above sea level) in 2022 and 2023 (Fig. 4–1). This area has a semi-arid climate typified by relatively hot days and cool nights during the growing season. The 30-year normal annual precipitation is 382 mm with the majority occurring during the winter as snow (NOAA, 2023). Weather conditions were mostly typical during the trial period with average precipitation 0.5 mm higher and 64 mm lower for years 2021 and 2022, respectively, and average temperatures 1.3 and 0.70 oC higher than the 1991-2020-year normal for 2021 and 2022, respectively

(Bureau of Reclamation, 2017; NOAA, 2023).

The soils are calcareous with a silt loam texture (Table 4–1; Soil Survey Staff, 2023). The taxonomic class of fields 3, 4, 6, 7 and 10 are coarse-silty, mixed, superactive, frigid Calcic Haploxerolls, which is a Rexburg series. The taxonomic classes of fields 1, 5, 8 and 9 are coarse-silty, mixed, superactive, frigid Calcic Haploxerolls and fine-silty, mixed, superactive, frigid Calcic Argixerolls, which is a Bancroft series. The taxonomic classes of field 2 are fine-silty, mixed, superactive, frigid Pachic Haploxerolls (Lanoak series) and coarse-silty, mixed superactive, frigid Calcic Pachic Haploxerolls, which is a Rexburg and Kucera series. Nutrient analyses of soil samples were performed by Servi-Tech Laboratories at Dodge City, Kansas, USA (Table 4–1).

Most fields had a wheat-wheat-potato cropping system. Wheat was the previous crop in the two years prior to the study except for field 2 where alfalfa was the crop for the four years and a year of wheat prior to potato. In the year of the study, potato seed pieces (~50-100 g each) were planted at ~0.25 m spacing in rows 0.86 m apart at a planting rate of ~2.2 Mg ha-1. Russet Burbank (fields 1, 6, 8, and 10), Frito Lay 2137 (fields 2, 4, and 9), Actrice (fields 3 and 7), and Waneta (field 5) were planted between 11 and 15 May 2021 and 13 and 20 May 2022. In general, BMPs were used by the cooperating grower for soil, nutrient, water, crop, and pest management (Hopkins et al., 2020). No significant stresses or pest or pathogen outbreaks occurred in any of the fields.

4.2.2 Zone Delineation

Two to four N zones were identified within each field based on yield potential (Fig. 4–1). The zones were delineated using various information layers, including: grower field knowledge, topography, bare soil imagery, historical in-season visible and normalized difference vegetation index (NDVI) imagery, and yield map histories of potato and rotational crops. Bare soil imagery was collected from imagery at either the beginning of that growing season or at the end of the previous growing season depending on the crop rotation using FarmShots (FarmShots, Durham, North Carolina, USA) with permission from the farmer.

At least one years' worth of yield history was included, preferably a potato yield map. In cases where multiple yield maps of the same or differing crops did not align in yield patterns, the yield was discussed with the farmer to understand the general patterns of yield, and specifically the yield patterns for potato. In general, the "high" zones had relatively better growing conditions resulting in relatively higher yields while the "low" zones were opposite. The "medium" zones generally had average and/or sporadic yield history. Two fields (fields 2 and 5) in 2021 had an additional zone that was "medium-low". Zone delineation was determined simply by combining all these layers together to see where patterns overlapped that would represent the same yield potential zone of high, medium or low.

4.2.3 Pre-Emergence Nitrogen Rates

Soil samples (12-15 cores per sample) were collected to a 0.3 m depth randomly throughout each zone between 18-19 May 2021 and 6-8 April 2022 and were air dried, ground (< 2 mm), and analyzed for NO_3-N (Table 4–2). Analysis for fields 1-5 (year 2021) was performed by the Utah State University Analytical Lab (USUAL) at Logan, Utah, USA and Servi-Tech Laboratories (STL) at Dodge City, KS, USA for fields 6-10 (year 2022). A potassium chloride (KCl) extraction followed by analysis on a flow injection analyzer (FIA) using a cadmium reduction technique was used for the NO_3-N analysis (Miller et al., 2013). Base N rates for each zone were determined using the equation of Hopkins et al. (2020), specifically factoring in soil and water NO_3-N concentrations, cultivar specific needs, yield goal, crop residue, and legume credits. None of these fields had a history of recent manure application and, thus, no manure N credit was given. The residual soil NO_3-N at the beginning of the growing season commonly was relatively low (Table 4–2) for fields with two years of wheat as the previous crops. As field 2 had alfalfa prior to wheat as the previous crop and had residual NO_3-N approximately twice as high as the other fields, both a legume credit and a residual NO3-N credit were applied in formulating the base rate.

In all fields prior to planting each year, banded P and micro-nutrient fertilizer was applied in the hills about ~8-10 cm from the seed pieces. A combination of 11-37-0, Nutrilink HP (Helena Agri-Enterprises, LLC, Collierville, Tennessee, USA), and Bio-Release with Micro (AgSciTech Inc., Aztec, New Mexico, USA) was applied each year. The total applied N in these products was 14 and 13 kg ha^{-1} in 2021 and 2022, respectively. The additional N predicted to be needed for the season (Table 4–3) was applied via broadcast with a Miller Condor fertilizer spreader (St. Nazianz, Wisconsin, USA) shortly after planting between 27 May and 3 June 2021, and 2-9 June, 2022 using a polymer coated urea product [Environmentally Smart N (ESN); Nutrien, Saskatoon, Canada]. The normal rate applied by the grower was applied uniformly in strips through all zones as a positive control. The justification of using the grower standard rate as the positive control is discussed below. The N was incorporated into the soil during cultivation (hilling), which occurred shortly after fertilization.

The amount of N applied within the VRN zones in each field was comparable to the amount of N that would have been used with the uniform grower standard practice (GSP) control rate. Applied N differences of VRN rate – GSP had a range of ±10 kg N ha^{-1} applied across fields 1-10, with an average difference over all 10 fields of <1 kg N ha^{-1}. The VRN treatments had minor impacts on total N rates applied across the field, as N was reappropriated from low to high productivity areas.

4.2.4 In-Season Nitrogen Rates

The crop canopies were monitored at least twice weekly for spatial differences in remotely sensed visible and NDVI imagery (Sentinel 2 and Landsat 8 satellite imagery; FarmShots, Durham, North Carolina, USA). Composite petiole samples (Hopkins et al., 2020) were taken in the uniform control N strips three times starting near canopy row closure around early to mid-July, then near the end of July and finally at beginning of August to evaluate overall nutrition and NO_3-N trends. Based on these data and canopy imagery, additional composite petiole samples were taken in every zone once in 2021 and twice in 2022 and analyzed for NO_3-N. If NO_3-N levels were low (Hopkins et al., 2020; Jones & Painter, 1974; Stark et al., 2004), additional N was planned to be applied variably to subplots to test additional responsiveness to fertilizer. Surprisingly, in-season assessment of N status via visible scouting, NDVI imagery, and petiole tissue sampling revealed no signs of N deficiency inducing chlorosis, stunted growth, or low levels of NO_3-N based on petiole NO_3-N ranges from Hopkins et al. (2020), thus, this planned portion of the study was omitted.

4.2.5 Harvest Measurements

The potato vines were chopped and then sprayed with sulfuric acid ~21 d prior to harvest to aid in thickening of skins in preparation for handling during harvest and storage. Harvest occurred 17-27 September 2021 and 19-29 September 2022. Field-scale yields were determined with the grower's harvester in real-time with a RiteYield yield monitor (Greentonics, Ontario, Canada). In addition, yields were also measured from samples collected manually at four to six locations within each zone in a paired sampling structure. Each pair consisted of a sampling from the control strip and the VRN zone approximately 35 m apart. These tubers were dug using commercial four or six row windrowers ("crossovers"). All tubers from a 3 to 4 m section of all rows were then separated by grade (US No. 1, US No. 2, and malformed; USDA, 2011), counted, and weighed by grade. Total yields included the combined yield of all grades. Marketable yield included the yields of U.S. No. 1 plus US No. 2. Average tuber size was calculated by dividing the weight of all tubers within a specified grade by the respective count. A random subsample of 16 US No. 1 tubers were collected from within each sampling area for determining solids percentages (specific gravity) (Kleinkopf et al., 1987) and internal and external quality (brown center, hollow heart, stem end, and disease, insect or nematode infestations; USDA, 2011). The subsample of only U.S. No. 1 tubers was collected as the respective tuber grade represents the majority of yields within each field and is the desired grade in the production process.

Nitrogen use efficiency (NUE) was calculated using the following equation:

$$NUE = Y \div N$$

Where Y is yield (kg ha^{-1}) and N is the N rate (kg ha^{-1}) applied.

To evaluate the impacts of VRN on yield and quality values, three-way analyses of variance (ANOVA) at $P < 0.05$ were conducted using the MIXED procedure of SAS (SAS 9.4, Cary, North Carolina, USA) to determine the fixed effects of field, zone (high, control, and low), and treatment (VRN and control) and their interactions. Medium zones were not included in analysis as N rates for respective zones were the same as the control, and it was expected that no differences would be observed. All Medium-Low zones were considered a Low zone for ease of comparison.

The replications within each treatment, and their interaction with fixed effects were considered random effects. Assumptions were assessed via residuals, distribution and QQ-residual plots. All response variables were normal with the exception of malformed yield, and US No. 2 and malformed tuber size, which were transformed with a square root transformation. Least squares mean separations were performed using the PDIFF procedure of SAS at the 0.05 probability level.

4.3 | RESULTS

Applying VRN resulted in significant differences for all measured parameters (Table 4–4). The three-way interaction of VRN applications with zones in each field was generally significant for tuber size and NUE. This suggests that the impact of VRN was not consistent across fields for these variables. Thus, tuber size and NUE were evaluated in each field separately. In contrast, the three-way interaction was not significant for any yield or quality variable. Rather, the two-way interactions were generally significant. As expected, there were significant differences across fields when averaged over the other variables and, more importantly, zone and treatment (VRN) were generally significant. An orthogonal comparison was made between Russet Burbank cultivars and all other cultivars combined using the same three-way ANOVA for the same response variables as in table 4–5.

4.3.1 Yields

The average field yield, based on the grower's yield monitor, were: 38, 44, 43, 26, 37, 35, 49, 39, 34 and 45 Mg ha^{-1} for fields 1-10, respectively. These are considered slightly above average for this high elevation seed potato region (personal communication). When averaged across fields (treatment × zone interaction), the VRN approach of increasing N application rate in high yield potential zones significantly increased total, marketable, and US No. 1 potato yields by 4.6, 4.6 and 4.8 Mg ha^{-1}, respectively (Table 4–4, Table 4–S1, 4–S2, Fig 4–2). The increase in US No. 1 yield was not coupled with a decrease in US No. 2 and/or malformed tubers, although it was trending in that direction, which is often the case when there is increased tuber quality (US No. 1 tubers are considered higher quality than US No. 2 and, especially, malformed tubers). The VRN approach of decreasing N application rate in low yield potential zones followed similar trends, although the differences between these zones and the control were not significant. It is noteworthy that a decrease in N in these low zones did not result in decreased yields.

When averaged across zones (field × treatment interaction), the VRN approach resulted in significant yield increases in four of the fields and trended in this direction in three others, resulting in a significant increase for the treatment effect as well (Table 4–4, Fig. 4–3). The VRN zones significantly increased total, marketable, and US No. 1 potato yields in fields 1, 6, 8 and 10. It is noteworthy that all of these fields had Russet Burbank as the variety. The VRN zones did not negatively impact the yields in the other fields for these three grades, although it trended in that direction for two fields. There were significant differences in US No. 2 and malformed yields (Fig. 4–3). Overall, there were statistically lower yields within these two grades within VRN zones compared to control strips, although the magnitude was small. These significantly lower yields within VRN zones were measured in three fields for US No. 2, and two fields for malformed compared to their respective control strips.

Fields 1, 6, 8 and 10 had significantly higher potato yield with VRN compared to the control (Fig. 4–3). All of these fields were planted with the Russet Burbank cultivar. An orthogonal comparison of Russet Burbank vs. all other cultivars combined (labeled as "Other cultivars") showed that the three-way interaction of treatment, zone, and field did not result in significant differences for the Russet Burbank or Other cultivars, nor was the treatment by zone interaction significant for Russet Burbank. The treatment by zone interaction was significant, however for other cultivars for total, marketable and US No. 1 tuber yields, but the *F*-value was only slightly larger in magnitude than the *F*-value for the main effect of treatment. Therefore, the treatment effect was explored for both Russet Burbank and Other cultivars (Fig. 4– 4). Significant increases in yields of 6.5, 7.0 and 7.7 Mg ha^{-1} were observed for the Russet Burbank cultivars for total, marketable and US No. 1 tuber grades, respectively, from utilizing VRN compared to the control while no significant differences were observed within the Other cultivars for those respective tuber grades. Significant decreases in yields from utilizing VRN were observed in the Russet Burbank cultivars by 0.7 and 0.5 Mg ha^{-1} for US No. 2 and malformed tuber grades, respectively. No significant differences in yields were observed for US No. 2 and malformed grades with the Other cultivars (Fig. 4–4).

4.3.2 Tuber Size

Total tuber size averages were 158, 144, 157, 136, 144, 145, 158, 139, 152 and 145 g $tuber^{-1}$ on average for fields 1-10, respectively (Table 4–S3). Tuber size increases followed a similar pattern as yield, although the three-way interaction of treatment, zone, and field was significant for most categories (Table 4–4). The increases in size were only significant in some fields (Tables 4–4, 4–S3, 4–S4, Fig. 4–5). Overall, tuber size increased with VRN in most fields, with significant increases in four to five fields for the high yield potential zones for total, marketable, and US No. 1 tubers (Fig. 4–5, Table 4–S4).

Tuber size increased with VRN compared to the control in one field in the low yield potential zones, while another field had a significant decrease in tuber size in the high yield potential zones. Low VRN zones had a mixture of increased and decreased tuber size in all fields except field 4 that resulted in a significant decrease in tuber size for total, marketable, US No. 1 and US No. 2 grades. Significant differences in the field × treatment interaction occurred for malformed tuber size (Fig. 4–S1). Significantly smaller malformed tubers occurred in fields 1, 9 and 10 (Fig. 4–S1). Overall, the trend of malformed tuber size decreased within VRN zones compared to control strips, but differences were not statistically significant. Three of the ten fields showed significant differences in tuber size with control strips resulting in increased malformed tuber sizes compared to VRN zones. Further, tuber size increased by 10, 8, and 11 g tuber^{-1} for total, marketable and US No. 1 grades in the high yield potential zones.

Tuber size was also analyzed with orthogonal comparisons for Russet Burbank vs. Other cultivars. While the three-way interaction was not significant for Russet Burbank cultivars, it was significant for Other cultivars (Fig. 4–6). Significant increases of 11, 10 and 12 g tuber^{-1} on average were observed in field 2 as well as significant increases of 33, 23 and 33 g tuber^{-1} in field 5 for total, marketable, and US No. 1 tuber grades, respectively, within the high yield potential zones. Tuber size decreased in the high zones compared to the control in field 9 by an average of 12 g tuber^{-1} for total, marketable and US No. 1 tuber grades. No significant differences were observed within the low zones for any fields with Other cultivars. The treatment × zone interaction was also significant for both Russet Burbank and Other cultivars, with significant increases occurring in the high zones for total, marketable and US No. 1 tuber grades (Fig. 4–6). No significant differences were observed within the low zones.

4.3.3. Tuber Quality

Specific gravity averages across all treatments within each field were 1.078, 1.088, 1.058, 1.095, 1.075, 1.083, 1.076, 1.086, 1.089 and 1.085 for fields 1-10, respectively (Table 4–S5). The treatment × zone interaction was significant for specific gravity (Table 4–4). The zone effect essentially cancelled out specific gravity differences with VRN resulting in a non-significant decrease of 0.002 in the high zones and a significant increase of 0.002 in the low zones (Fig. 4–S2). When analyzed with the orthogonal comparison of Russet Burbank vs. Other cultivars, the three-way interaction was not significant, and treatment × zone was only significant in Other cultivars (Fig. 4–S3) with an increase of 0.002 in the low VRN zone compared to the control.

Internal measurements of US No. 1 tubers showed that stem end discoloration was impacted by the treatment × zone interaction (Table 4–4; Fig. 4–S4) and insect damage by the field × treatment interaction (Table 4–4; Fig. 4–S6). Elevated stem end discoloration counts occurred in the high zones compared to the control across all 10 fields combined, with a numerical but non-significant decrease in stem end discoloration counts in low zones compared to the control. Significant increases in insect damage occurred within VRN zones in field 4, and significant decreases in insect damage occurred within the VRN zones of field 8. Overall, there were few differences in stem end and insect damage between VRN zones and control strips.

When Russet Burbanks and Other cultivars were compared, the three-way interaction was not significant for either stem end or insect damage, but the treatment × zone interaction was significant for both groups of cultivars (Fig. 4–S5). Elevated stem end discoloration counts occurred in high zones compared to control strips for the Other cultivars across all fields. The low zones across fields with Other cultivars had a numerical, but not significant, decrease in stem end counts compared to the control. For insect damage, the field × treatment interaction was not significant for Other cultivars but was significant for Russet Burbank. Although the field × treatment interaction was significant, the *F*-value was lower in magnitude than the treatment interaction for Russet Burbank, with VRN areas resulting in significantly lower insect damage counts by an average of 1.3 counts tuber^{-1} of US No. 1 tubers than the control across all Russet Burbank fields combined.

4.3.4 Petiole Nitrate

The petiole tissue NO_3-N concentrations overall showed no need for in-season VRN except for field 4 that had low N towards the end of the season (Table 4–6). However, due to the timing of a scheduled early harvest, additional N was not applied in field 4. This suggests that pre-season VRN with slow-release N fertilizers such as ESN may remove the need for in-season VRN management. This could simplify VRN approaches and save growers time and application costs.

4.3.5 Nitrogen Use Efficiency (NUE)

Total (all tuber grades combined) NUE averages across all treatments within each field were: 235, 323, 375, 243, 239, 197, 255, 196, 302 and 202 kg ha^{-1} for fields 1-10, respectively. There was a significant three-way interaction impacting NUE (Table 4–4). The majority of fields in the low yield potential zones had significantly greater NUE (Fig. 4–7) than the control due to lower N rates in the VRN zones (Table 4–3) that did not generally cause yield reductions (Table 4–4; Figs. 4–2, 4–3). Increased N rates in the high yield potential zones (Table 4–3) generally increased yields (Figs. 4–2, 4–3), but not enough to increase NUE, thus showing the numerical decrease in NUE in four fields, and significant decrease in NUE in three fields (Fig. 4–7). Overall, when the main effect of treatment, the differences in NUE between VRN treatments and control strips were significant, with an increase in NUE of 25 kg ha^{-1} (Table 4–4; Fig. 4–7).

When the NUE of Russet Burbank was compared to Other cultivars, the three-way interaction for Other cultivars was significant, but the F-value for treatment × zone was much larger and there was a significant difference for both Russet Burbank and Other cultivars in this two-way interaction (Fig. 4–8). Significant increases in NUE of 77 and 66 kg ha^{-1} in the low zones were observed for both Russet Burbank and Other cultivars, respectively. A significant decrease of 39 kg ha^{-1} in NUE was observed in the high zones compared to the control for Other cultivars. When looking at the treatment effect, Russet Burbank saw a significant increase in NUE, while the Other cultivars saw a numerical, but not significant, increase in NUE.

4.4 | DISCUSSION

4.4.1 Yield

Yield levels from this study were comparable to other studies that had yield increases when N rates were increased within VRN zones (Bohman et al., 2019, 2020; Bowen et al., 2005; Morier et al., 2015; van Evert et al., 2012) (Table 4–7). However, the approach to VRN differed in the current study and previous studies. These differences included differing climates, the scale of study being field scale compared to plot studies, and the VRN plots in the other studies did not base N rates on yield potential. While many variables from these other studies were different, greater yields with increased N rates were similar (Table 4–7).

A plot-scale study with similar high and low N rates for Russet Burbank in Minnesota showed similar results to this study in that increased rates (270 kg N ha^{-1}) improved total and US No. 1 yields compared to the control (45 kg N ha^{-1}) and lower rates (180 kg N ha^{-1}) (Bohman et al., 2019). Yield levels in these previous trials have ranged from 41.5 – 82.9 Mg ha^{-1} across treatments. Bowen et al. (2005) studied the use of managing in-season N with optical sensing instrumentation in four different Russet Burbank fields in eastern Idaho with six different N rates (0, 78, 157, 235, 314, and 392 kg N ha^{-1}) and found positive responses in yields with higher N rates, and also did not find any significant negative yield impacts from lowered N rates. Morier et al. (2015) performed a plot-scale study near Quebec City, Canada and evaluated how five N rates (0, 60, 120, 200, 280 kg N ha^{-1}) that were split applied at planting and then hilling affected Russet Burbank performance. The purpose of their study was to determine how to best detect N status and tuber yield with different hyperspectral vegetation indices. The authors observed significant yield increases between the negative control (0 kg N ha^{-1}) and all other N rates in the first and second year. However, in the first year, they did not see significant differences in yields between the four other N rates but did see a significant increase in yield the second year between the 60 kg N ha^{-1} rate and the 200 and 280 kg N ha^{-1} rates.

Yield increases were similar in this study compared to other studies when N was increased and compared to a control (Bohman et al., 2019, 2020; Bowen et al., 2005; Morier et al., 2015). While for most of the fields in the current study, the high VRN zones increased yields, fields 2 and 3 did not result in significant increases in yield for total, marketable, and US No.1 tubers. Field 2's lack of yield response was likely impacted by the increased residual N from the previous alfalfa crop. Field 3 and 7 had the Actrice cultivar that is known to be more N efficient, and while VRN rates were implemented, they were greater than the recommended rate for this cultivar and may be the reason for the lack of response (Agroplant, nd).

Regarding the low VRN zones that had low yield potentials, it was important to document that yields were not significantly and negatively impacted by the reduced N rates. Bowen et al. (2005) also did not find any significant negative yield impacts from lowered N rates. However, in a study by Bowen et al. (2019), while lower N rates yielded more than the control for both total and US No. 1, the control rate was 135 kg N ha^{-1} less than the low N rate. According to Bohman et al. (2019), reduced rates in N (by 90 kg ha^{-1}) without any in-season crop monitoring resulted in reduced tuber yields and did not improve economic return with the savings from reduced N rates.

The current study showed improved potato yield and quality with VRN simply by reallocating N throughout fields. The reason VRN may have been more beneficial in the current study compared to others is likely related to delineating zones based on historical yield patterns of high, medium and low, and combining those patterns with topography, bare soil imagery, and historical in-season NDVI imagery to better represent spatially variable N needs throughout each field. The benefits of VRN were especially beneficial for the Russet Burbank cultivar. Russet Burbank in the current study responded to VRN similarly to other studies including this cultivar (Bohman et al., 2019, 2020; Bowen et al., 2005; Morier et al., 2015). In the present study, significant increases in yield in the high yield potential zones were found in the 'Russet Burbank' cultivar when utilizing VRN, while all other cultivars combined did not see significant increases in yield with VRN. This could be due to the sensitivity to N in 'Russet Burbank', and the negative effects improper N management can have on this variety (Hopkins et al., 2020), some of which can produce more US No. 2 and malformed tubers. This could be why a larger difference in yields were seen within these fields compared to fields with other cultivars. This could not be validated with results from similar studies (Bohman, et al., 2019, 2020; Bowen et al., 2005; Morier et al., 2015) because they did not report US No. 2 or malformed tuber yields. Although total and/or US No. 1 tuber grades are generally the most studied and typically the most produced, understanding the effect N management has on US No. 2 and malformed tubers and knowing they can be decreased to in turn increase US No. 1 production can improve profits for growers. Therefore, future work including these grades should be included in VRN studies.

4.4.2 Tuber Size

Tuber size had mixed responses to VRN, although there was an overall positive trend of increased tuber sizes within the high zones across all fields and this response was comparable to other potato studies (Bohman et al., 2019; Zebarth & Rosen, 2007) (Fig. 4–4). This was expected with increased N rates, as more N will generally increase tuber size. When Russet Burbank was analyzed separately from Other cultivars, surprisingly Russet Burbank did not have a significant difference in the zone × treatment × field effect like it did with tuber yields. However, Other cultivars did show a positive response in tuber size in the high yield potential zones. While Russet Burbank is more sensitive to N management and tuber outcomes than other cultivars, these results suggest that other cultivars like Frito Lay and Waneta, which are cultivars used for potato chips, may be more sensitive in terms of tuber size with N management than Russet Burbank.

4.4.3 Tuber Quality

Relatively high N nutrition is known to result in decreased potato specific gravity, but these values did not decrease enough within the high VRN zones to impact the value of the crop for most contracts (values between 1.080 and 1.092 are generally acceptable). Bohman et al. (2019) found similar results showing significant differences in specific gravity between VRN and control treatments, and that higher rates of N reduced specific gravity. Other internal quality factors measured in the current study were generally not impacted by the VRN treatments. This aligns with results from Bohman et al. (2019).

4.4.4. Petiole Nitrate

Other studies have shown the need to apply in-season VRN (Bohman et al., 2019, 2020; Morier et al., 2015), while this study did not. Surprisingly, in-season visible and NDVI imagery revealed minimal spatial variability in crop growth within zones and across zones, especially near the first two petiole sampling dates. Petiole tissue NO_3-N concentrations are known to drop steadily throughout the growing season (Hopkins et al., 2020; Jones & Painter, 1974; Stark et al., 2004; Zebarth & Rosen, 2007), which is what was observed in these fields (Table 4–4).

The fields in the current study generally had ample N through July but were likely slightly N deficient towards the end of the season in Aug 2021. We were prepared to variably apply N in-season, but it was decided to not do so for any of the fields based on the lack of variability across zones in 2021 [all zones were classified as low (Hopkins et al., 2020; Jones & Painter, 1974; Stark et al., 2004; Zebarth & Rosen, 2007), but the grower was harvesting relatively early and opted for no in-season N]. Field 4 had low NO_3-N concentrations (150, 850 and 110 mg kg^{-1} within high, control strip, and low zones, respectively) towards the end of the season. However, due to the timing of a scheduled early harvest, additional N was not applied.

In 2022, fields had reasonable tissue NO_3-N levels (820 - 11270 mg kg^{-1}) at the last sampling date (1 and 2 Aug, 2022) with minimal variability between zones, so no in-season VRN was applied. The reason for this could be due to the higher rates of N and a more efficient slow-release fertilizer applied at pre-emergence in our study compared to others.

If pre-emergence rates in this study were initially lower, differences in NDVI and petiole NO_3-N concentrations could have been greater within and across zones, thus requiring in-season VRN applications. Further, although fields were being observed with NDVI from satellite imagery, subtle changes within small areas of the fields may not have been detected due to the lower resolution from the satellite imagery compared to remote sensing data that was gathered by handheld sensors or other high-resolution sensors in other studies (Bohman et al., 2019, 2020; Bowen et al., 2005; Giletto & Echeverria, 2016; Morier et al., 2015). While no in-season VRN was needed in the current study, this result may be desirable by growers to help simplify their VRN management with single, less expensive applications of VRN at pre-emergence.

Bohman et al. (2019) found that using a N sufficiency index predicted crop N status that compared well to petiole samples. The in-season NDVI imagery for these fields did follow the trend of the petiole sample results via visual comparisons, but more research is needed to know if NDVI accurately reflects the details of N status throughout each zone within a field, as there are still many variables within a field-scale study that can affect NDVI values other than N deficiencies (Janssens et al., 2020). Furthermore, studies assessing different vegetative indices did note that NDVI may not be the best index to correlate to petiole NO_3-N concentrations and/or N stress within the plant (Bohman et al., 2019; Morier et al., 2015; van Evert et al., 2012).

The source of N that was used in this study was different from the majority of N sources used in other potato VRN and N rate studies. Environmentally smart N (ESN) is a polymer coated urea that releases N at a slower rate than urea throughout the growing season, essentially spoon feeding N to potato. While potato N application is generally high (135 – 191 kg ha^{-1} for potato seed crops) compared to some other field crops and the demand for N during the vegetative growth stage is critical for optimal yields as potato uptake efficiency is much lower than many other crops. Nitrogen values within the plant during the vegetative growth stage must stay relatively high and then the N need decreases as potato approaches the tuber bulking stage (Hopkins et al., 2020; Jones & Painter, 1974; Stark et al., 2004). One previous study compared multiple ESN rates at the beginning of the growing season to multiple split urea rates during the growing season (Bohman et al., 2019) and found that both were equally effective fertilization strategies. Split applications of N increase application costs and require additional time and effort to apply. Utilizing a polymer coated urea reduces labor costs by only requiring one N application event that can last for the entirety of the growing season. It has also been shown to reduce losses to the environment while providing the needed N for the crop (Hopkins et al., 2020). While fertigation is an option for in-season application of N, studies have not utilized fertigation in VRN studies and VRN application with fertigation can be more difficult to achieve than with broadcast application.

4.4.5 Nitrogen Use Efficiency (NUE)

The fact that NUE decreased in high zones is evidence that excess N was applied in these zones and N rates could have been reduced to more closely match the NUE of the control rates. Fields 4 and 7 did not result in significant NUE differences within the low zones like the other fields did. For field 7, this could be because the cultivar ‘Actrice’ requires a lower optimal rate of N, but a greater rate of N was applied across the field for all zones, thus potentially influencing NUE. Field 4 yielded lower overall, and it was speculated to have some unknown, underlying conditions within the low zones that could be negatively impacting yields and thus lowering the relative NUE. Although NUE could have been improved, the cooperating grower recorded that they increased profits by an average of \$900 ha^{-1} with VRN compared to several previous years across fields 6-10 in 2022 alone (personal communication). These profit gains validate that our simple approach to VRN improved field scale profits in most fields and that it could likely be used to improve profits in other regions.

It is common to observe a decrease in NUE with increased rates of N, which this study did show for the high VRN zones. However, assessing NUE at the treatment level resulted in a significant increase in NUE, which is not commonly observed in most VRN studies. Koch et al. (2004) performed an economical analysis of strip trials for three site years in the Great Plains with maize (*Zea mays* L.) and found that VRN increased NUE compared to uniform rates due to decreased N rates with no yield decrease. Although the current study's and results by Koch et al (2004) indicated improved profits with VRN, Watkins et al. (1998) found that VRN in seed potato and the other crops in rotation in eastern Idaho, USA did not result in increased profits. Differences in these results could be due to the inconsistent methods of VRN zones, N applications, and economic calculations. Bohman et al. (2019) found that decreasing the N rates in potato did not improve the economic outcome enough to justify the decreased N rates. The outcomes from the Bohman et al. (2019) study differed from the current study's results which measured statistically significant increases in NUE from the low VRN zones. This demonstrates that the current study's VRN approach can increase yields while also increasing NUE, positively impacting profits as well as possibly reducing potential environmental concerns.

This study demonstrated many positive outcomes from VRN, but the approach needs to be validated in other regions and improved to further refine N use as well as the in-season assessments for potential in-season VRN applications. Combining the pre-season and in-season VRN opportunities into a management system has the potential to improve precise applications needed to avoid over and under application of N to potato and to reach full yield and quality potential. This could be performed by determining zones and yield potentials similar to the process used in this study, but with further in-depth assessment of the historical yields and potential yields. It is recommend based on the findings of this study, especially with Russet Burbank, to adhere to the following guidelines for applying pre-emergence VRN:

- consistently average yielding areas = keep N the same as recommended practices
- consistently high yielding areas with no inherent limitations = increase N
- consistently low yielding areas with limitations that are not reasonably possible to correct (e.g., shallow soil, persistent hard pans, soil textural problems, steep slopes, north facing slopes, and certain soil borne pest/pathogen infestations) = decrease N
- consistently low yielding areas with limitations that are possible to correct (e.g., low soil fertility of nutrients other than N, low organic matter, simple compaction, and correctable soil borne pest/pathogen infestations) = correct limitations, then potentially increase N
- sporadically yielding areas with limitations that are often not readily apparent = keep N the same as recommended practices.

4.5 | CONCLUSIONS

The VRN approach used in this study reappropriated fertilizer N spatially based on yield potential, with nearly equivalent overall N rate compared to the grower standard uniform N rates. It was among the first studies to evaluate how VRN impacted potato production at the field-scale. This VRN approach resulted in greater yields and larger tuber sizes in high yield potential zones. There were no negative impacts on yield or tuber size from lower N rates applied within the low yield potential zones. These results imply that VRN can be successfully implemented by combining patterns of historical yield, elevation maps, and bare soil and NDVI to identify VRN zones that reallocate N according to their respective yield potentials. Through this process of zone delineation and N rates based on the yield potential for each zone, yields, tuber size and in some cases NUE can be improved. In order to improve NUE, a lower rate of N than what was applied in this study, depending on the zones and yield goals throughout the field, could be applied at the beginning of the growing season. Potato would be assessed during critical growth stages to determine if additional N is needed to ensure it reaches its yield potential in each zone. Evidence from the 10 fields used in this study indicate that this simple and straightforward VRN method that could be readily adopted by growers is likely to increase potato yield and profit and should be considered.

4.5 | TABLES AND FIGURES

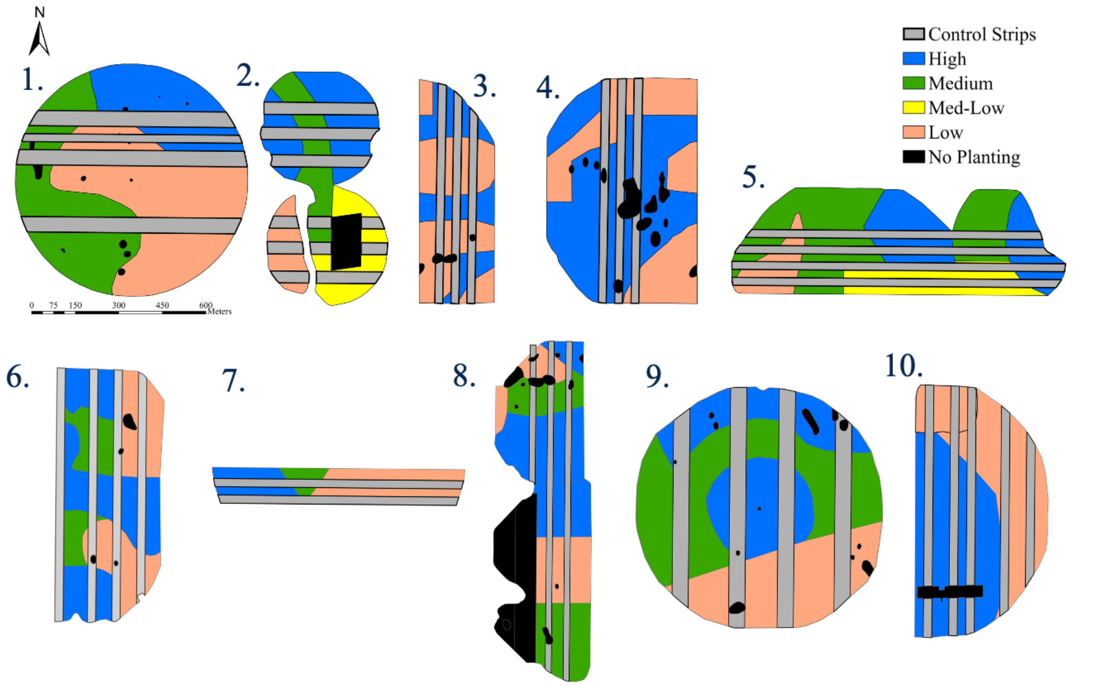

Figure 4–1. Potato field sites (fields 1-5 in 2021 and 6-10 in 2022) with N zones based on high, medium, medium-low, or low yield potential with uniform N rate grower standard practice control strips.

Table 4–1. Background soil properties to 30 cm depth and GPS coordinates for 10 trials near Grace, Idaho in 2022 and 2023 taken prior to the start of the growing season

Test[1]	Field ID									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
pH	8.3	7.8	7.9	7.9	8.3	8.4	8.4	8.3	8.3	8.2
	- - - - - mmho cm^{-1} - - - - -									
EC	1.4	0.65	0.36	0.36	0.41	0.26	0.27	0.26	0.26	0.22
	- - - - - g kg^{-1} - - - - -									
OM	0.25	0.26	0.21	0.21	0.25	0.16	0.16	0.16	0.17	0.17
	- - - - - mg kg^{-1} - - - - -									
P	32	37	31	31	25	45	54	28	42	46
K	286	552	330	330	550	317	453	303	432	407
S	20	25	21	21	25	20	17	18	20	11
Na	115	83	88	88	68	84	119	94	83	52
Ca	2220	4710	3870	3870	3680	3530	3640	4180	2570	3250
Mg	936	699	616	616	817	1045	900	931	933	471
Zn	2.2	2.1	2.0	2.0	1.6	2.9	1.2	1.7	1.5	1.0
Fe	9	17	13	13	11	7	8	8	7	10
Mn	8.9	4.2	2.6	2.6	2.6	1.9	2.1	1.7	2.2	2.1
Cu	1.2	0.8	0.8	0.8	0.7	0.8	0.9	0.8	0.9	0.7
	- - - - - $cmol_c$ kg^{-1} - - - - -									
CEC	20	31	26	26	27	28	27	30	22	21
Lat.	42.631103	42.560716	42.609212	42.609291	42.690295	42.623642	42.641091	42.614429	42.61647	42.62377
Lon.	-111.803448	-111.840395	-111.751039	-111.755864	-111.765133	-111.791368	-111.793557	-111.794753	-111.783954	-111.742997

[1]pH and EC (electroconductivity) analyzed with 1:1 water-soil.
OM (organic matter) analyzed with loss on ignition.
P, K, S, and Na analyzed using the Mehlich-3 method, with Inductively Coupled Plasma-Optical Emission Spectrometry (ICP-OES).
Ca and Mg analyzed using the Ammonium Acetate method, with ICP-OES.
Zn, Fe, Mn, and Cu analyzed with the diethylenetriaminepentaacetic acid (DTPA) micronutrient extraction method with ICP-OES.
CEC (cation exchange capacity).
Miller et al., 2013.

Table 4–2. Pre-plant soil NO_3-N concentrations to 0.3 m in the spring of 2020 or 2021 for each zone in 10 potato fields. Zones were based on yield potential, with some fields not having all zones (not applicable = n/a).

	Field ID									
Zone	1	2	3	4	5	6	7	8	9	10
	NO_3-N mg kg^{-1}									
High	17	22	8	7	9	5	6	5	7	3
Medium	12	23	n/a	n/a	9	4	5	4	6	n/a
Medium-Low	n/a	22	n/a	n/a	10	n/a	n/a	n/a	n/a	n/a
Low	10	21	9	11	8	4	8	5	5	4

Table 4–3. Pre-emergence N rates for each zone in 10 potato fields. Zones were based on yield potential, with some fields not having all zones (not applicable = N/A). Difference in N rate calculated as variable-rate N (VRN) in all zones minus the control.

Zone	Field										
	1	2	3	4	5	6	7	8	9	10	Mean
	- kg N ha^{-1} -										
Control	179	135	146	146	157	179	146	179	146	191	160
High	213	168	179	179	191	213	179	213	179	224	194
Medium	178	135	n/a	n/a	157	179	146	179	146	n/a	160
Med-Low	n/a	118	n/a	n/a	135	n/a	n/a	n/a	n/a	n/a	127
Low	146	101	112	112	123	146	112	146	112	157	127
N Difference	-8	3	-9	9	2	6	-10	6	2	1	0.1

Table 4–4. Statistical significance of the impacts of field, treatment, zone and their interactions on potato yield and tuber quality. Probability values with significance at 0.05 are shown in **bold-face** type for the two-way and three-way interactions.

Response Variable	Field (F)	Treatment (T)	Zone (Z)	F × T	F × Z	T× Z	F × T × Z
				P > F			
				Yield			
Total	<0.0001	<0.0001	0.0022	**0.0034**	0.5045	**0.016**	0.5862
Marketable	<0.0001	<0.0001	0.0006	**0.0009**	0.3942	**0.0249**	0.5463
US No. 1	<0.0001	<0.0001	0.0002	**0.0001**	0.2265	**0.0307**	0.5849
US No. 2	<0.0001	0.0242	0.0174	**0.0424**	**0.0028**	0.5965	0.9992
Malformed	<0.0001	0.2078	0.009	**0.0026**	**0.0336**	0.4978	0.4703
				Tuber Size			
Total	<0.0001	0.0025	0.0652	**0.0003**	**0.0325**	**0.0001**	**0.0121**
Marketable	<0.0001	0.0222	0.0743	**0.0003**	0.075	**0.0014**	**0.0097**
US No. 1	<0.0001	0.0002	0.0298	**0.0002**	0.091	**<0.0001**	**0.0165**
US No. 2	<0.0001	0.0011	0.1467	0.0952	0.4451	0.3243	**0.0317**
Malformed	<0.0001	0.4003	0.0827	**0.0422**	0.4077	0.0717	0.8869
				Tuber Quality and Nitrogen Use Efficiency (NUE)			
Specific Gravity	<0.0001	0.8439	0.0012	0.0671	**0.0005**	**0.0034**	0.4695
Stem End	0.0240	0.3428	0.0275	0.1796	0.4275	**0.0008**	0.1500
Insect Damage	<0.0001	0.5622	0.1313	**0.0308**	**<0.0001**	0.3470	0.5215
NUE	<0.0001	<0.0001	<0.0001	0.089	**0.007**	**<0.0001**	**0.0061**

Table 4–5. Statistical significance of the impacts of field, treatment, zone and their interactions on orthogonal comparisons between Russet Burbank and other potato cultivar yield and tuber quality. Probability values with significance at 0.05 are shown in **bold-face** type.

Cultivar	Response Variable	Field (F)	Treatment (T)	Zone (Z)	F × T	F × Z	T× Z	F × T × Z
				P > *F*				
				Yield				
Russet Burbank	Total	**<0.0001**	**<0.0001**	**0.0103**	0.4244	0.7863	0.2297	0.9446
Other Cultivars		**<0.0001**	0.6246	0.0522	0.3293	0.301	**0.0345**	0.2877
Russet Burbank	Marketable	**<0.0001**	**<0.0001**	**0.0016**	0.4815	0.6645	0.3325	0.8829
Other Cultivars		**<0.0001**	0.6734	**0.0467**	0.353	0.3093	**0.0375**	0.2777
Russet Burbank	U.S. No. 1	**<0.0001**	**<0.0001**	**0.0001**	0.3277	0.3872	0.3539	0.8644
Other Cultivars		**<0.0001**	0.7332	0.0555	0.3152	0.3596	**0.0442**	0.3254
Russet Burbank	U.S. No. 2	**0.0042**	**0.0003**	**<0.0001**	0.1874	0.0796	0.7907	0.9389
Other Cultivars		0.0228	0.7439	0.4994	0.3093	**0.0222**	0.2297	0.9396
Russet Burbank	Malformed	0.0631	**0.0086**	**0.0023**	**0.012**	**0.0225**	0.4483	0.2088
Other Cultivars		**<0.0001**	0.4049	0.1078	0.4466	0.5455	0.8042	0.903
				Tuber Size				
Russet Burbank	Total	**0.0068**	**0.0066**	0.3061	0.4643	0.4905	**0.0031**	0.3865
Other Cultivars		**<0.0001**	0.0987	**0.0008**	**<.0001**	**0.0481**	**0.0094**	**0.0032**
Russet Burbank	Marketable	**0.0095**	**0.0357**	0.7108	**0.0361**	0.6424	**0.0186**	0.1495
Other Cultivars		**<0.0001**	0.2488	**0.0058**	**0.0004**	**0.025**	**0.0309**	**0.0066**
Russet Burbank	U.S. No. 1	**0.0084**	**0.0003**	0.7054	0.7663	0.5391	**0.0026**	0.5655
Other Cultivars		**<0.0001**	0.1149	**0.0009**	**<.0001**	0.0665	**0.0114**	**0.0031**
Russet Burbank	U.S. No. 2	**<0.0001**	**0.0012**	0.2574	**0.0467**	0.0829	**0.0165**	0.1672
Other Cultivars		**<0.0001**	0.0774	0.3797	0.2849	0.7704	0.0659	0.4299
Russet Burbank	Malformed	**0.0001**	**0.0071**	0.3238	0.1593	0.8768	0.2333	0.538
Other Cultivars		**<0.0001**	0.3334	0.058	0.2292	**0.0323**	0.1169	0.8997
				Tuber Quality and Nitrogen Use Efficiency (NUE)				
Russet Burbank	Specific Gravity	**0.0131**	0.8983	**0.0127**	0.545	**0.0369**	0.135	0.3612
Other Cultivars		**<0.0001**	0.6832	**0.0384**	**0.0094**	**0.0012**	**0.0081**	0.3655
Russet Burbank	Stem End	**0.0123**	0.7253	0.2339	0.1196	0.8712	**0.0166**	0.1752
Other Cultivars		.	0.2815	**0.0484**	.	.	**0.0249**	.
Russet Burbank	Insect Damage	0.5567	**0.0007**	0.0907	**0.0059**	0.8185	0.882	0.9092
Other Cultivars		**<0.0001**	0.5472	0.0514	0.2247	**0.0009**	0.3234	0.3967
Russet Burbank	NUE	**<0.0001**	**<0.0001**	**<0.0001**	0.3875	0.5398	**<0.0001**	0.9484
Other Cultivars		**<0.0001**	0.0548	**<0.0001**	0.4444	0.0567	**<0.0001**	**0.0083**

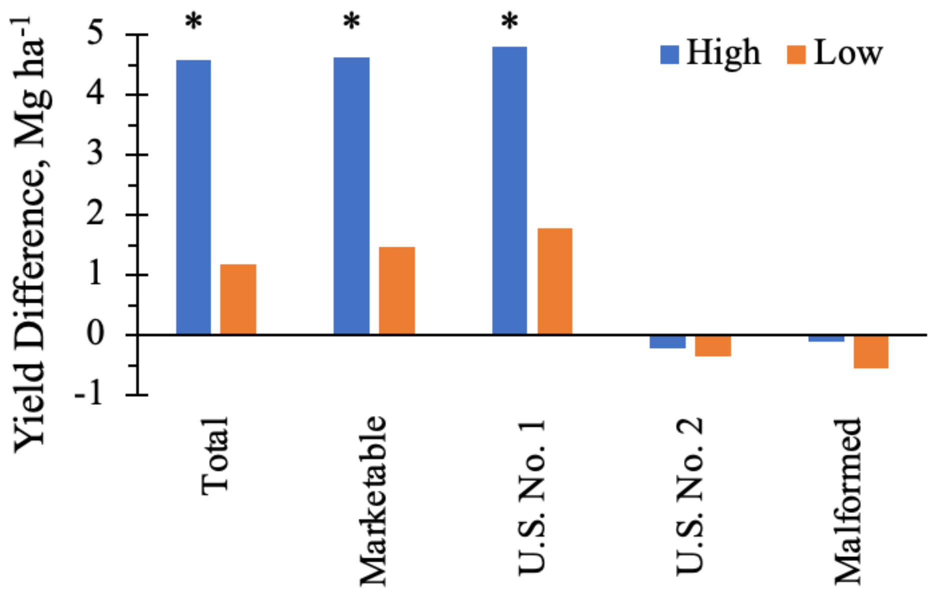

Figure 4–2. Yield difference [Variable Rate N (VRN) minus control] averaged across ten fields for the high and low yield potential zones for total, marketable, US No. 1, US No. 2, and malformed potato yields, with significant differences ($P < 0.05$) shown with an *

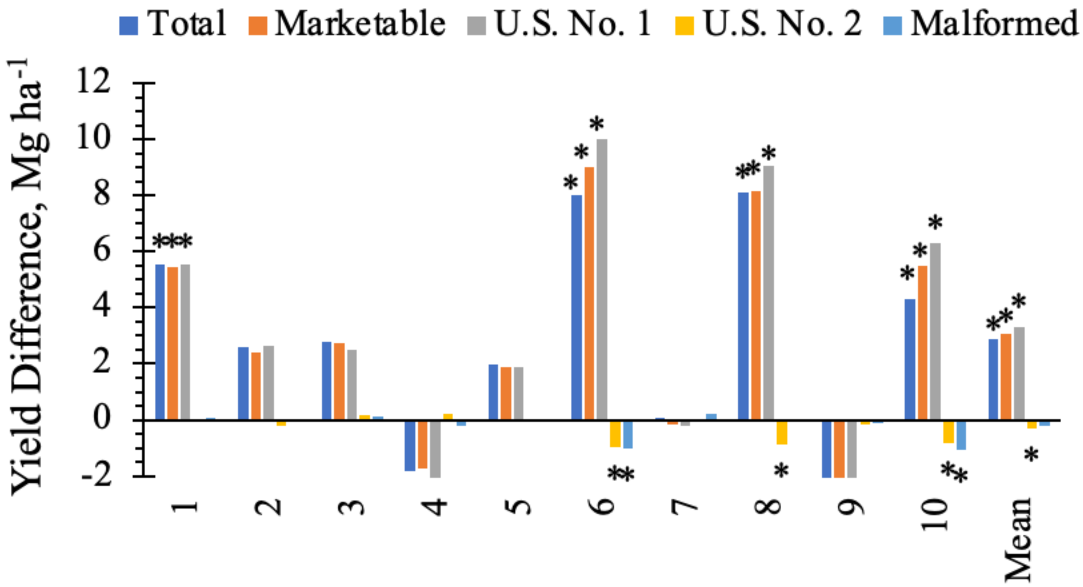

Figure 4–3. Yield difference [Variable Rate N (VRN) minus control] averaged across all yield potential zones for individual fields (1-10) for total, marketable, US No. 1, US No. 2 and malformed potato yields, with significant differences ($P < 0.05$) shown with an *

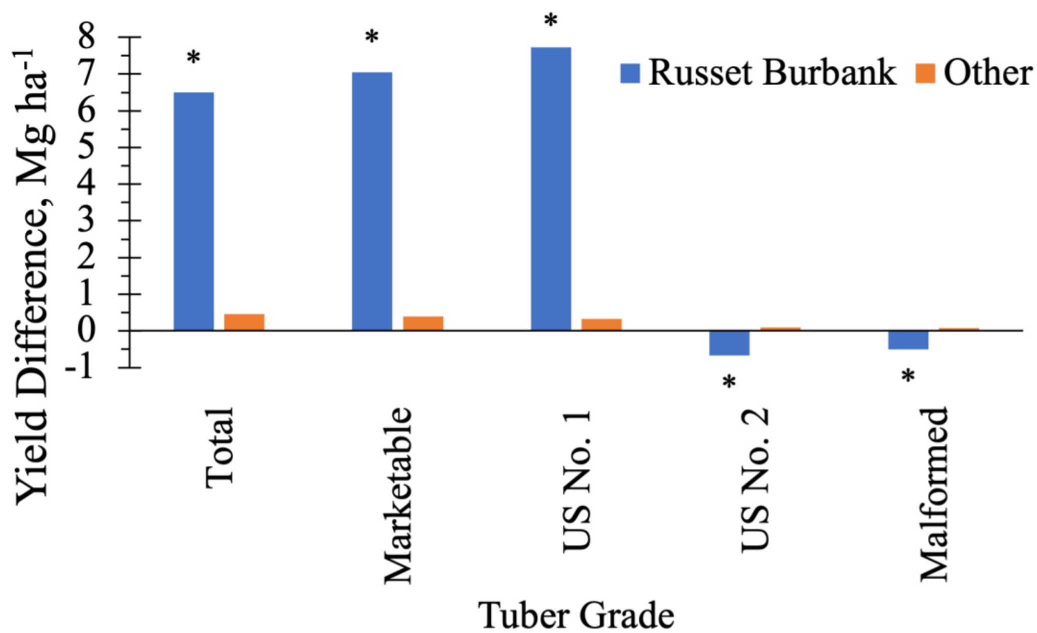

Figure 4–4. Yield difference [Variable Rate N (VRN) minus Control] averaged across all fields for the Russet Burbank cultivar and Other cultivars for total, marketable, US No. 1, US No. 2, and malformed potato yields, with significant differences shown with an * ($P < 0.05$)

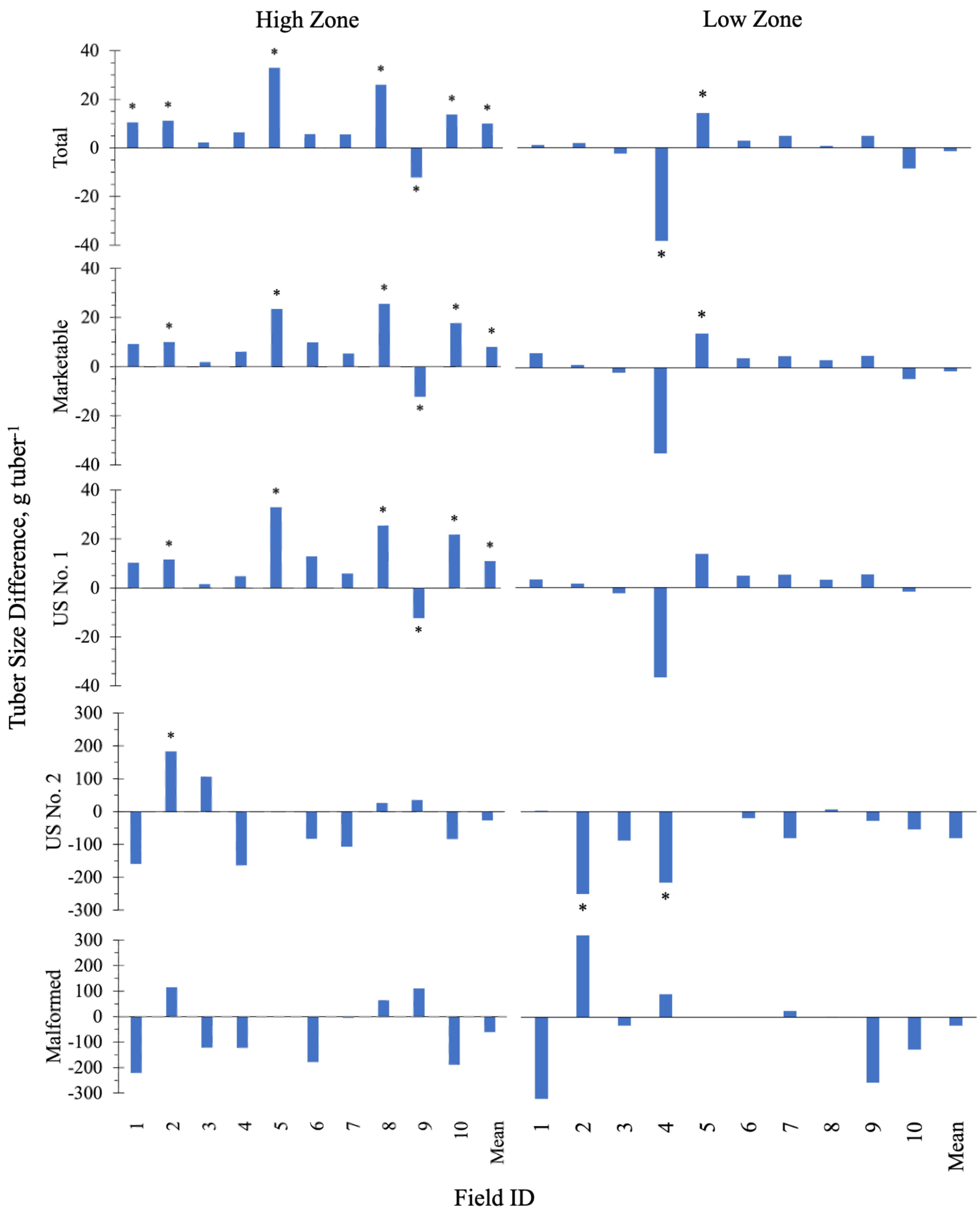

Figure 4–5. Differences of average size per tuber [Variable Rate N (VRN) minus Control] by high zones (left graphs) and low zones (right graphs) by field for total, marketable, US No. 1, US No. 2, and malformed tuber sizes, with significant differences ($P < 0.05$) shown with an *

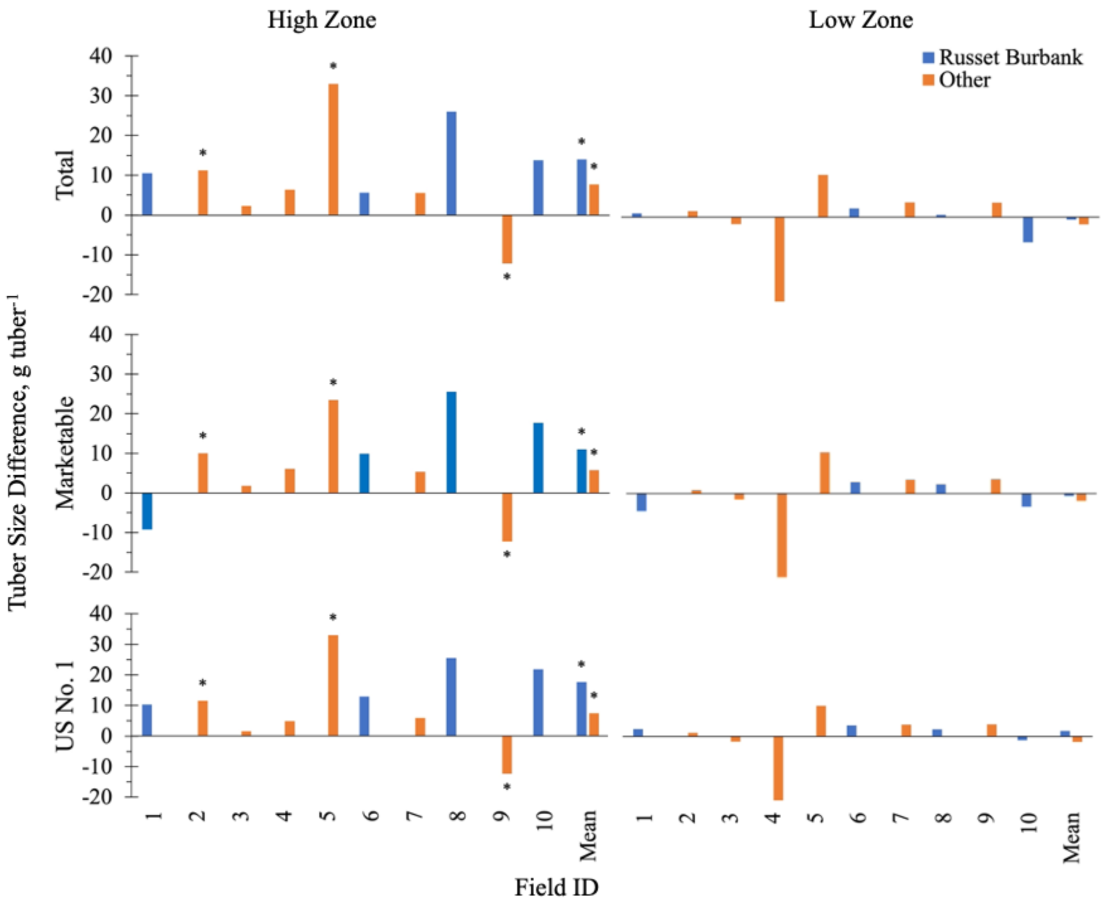

Figure 4–6. Relative differences of average size per tuber [Variable Rate N (VRN) minus Control] by high zones (left graphs) and low zones (right graphs) by field for total, marketable and US No. 1 tuber sizes, with significant differences ($P < 0.05$) shown with an *

Table 4–6. Composite (non-replicated) in-season petiole NO_3-N concentrations for early, middle, and late season sampling dates in control strips (uniform N application) and low to high yield potential zones receiving variable rate N.

	Field ID									
Zone	1	2	3	4	5	6	7	8	9	10
	- NO_3-N, g kg^{-1} -									
	Early									
Control	24	25	23	19	23	19	23	22	25	17
	Middle									
Control	13	9	9	5	12	11	15	18	11	4
High						13	16	18	12	3
Medium-Low										
Low						11	13	14	6	3.5
	Late									
Control	3	3	0.3	1	2	6	9	11	2	1
High	5	4	1	0.2	0.3	9	9	10	3	1
Medium-Low		2			2					
Low	2	3	0.4	0.1	0.2	8	11	7	2	1.5

Early: 2 July 2021, 14 July 2022
Middle: 23 July 2021, 23-26 July 2022
Late: 31 July/06 August 2021, 01-02 August 2022

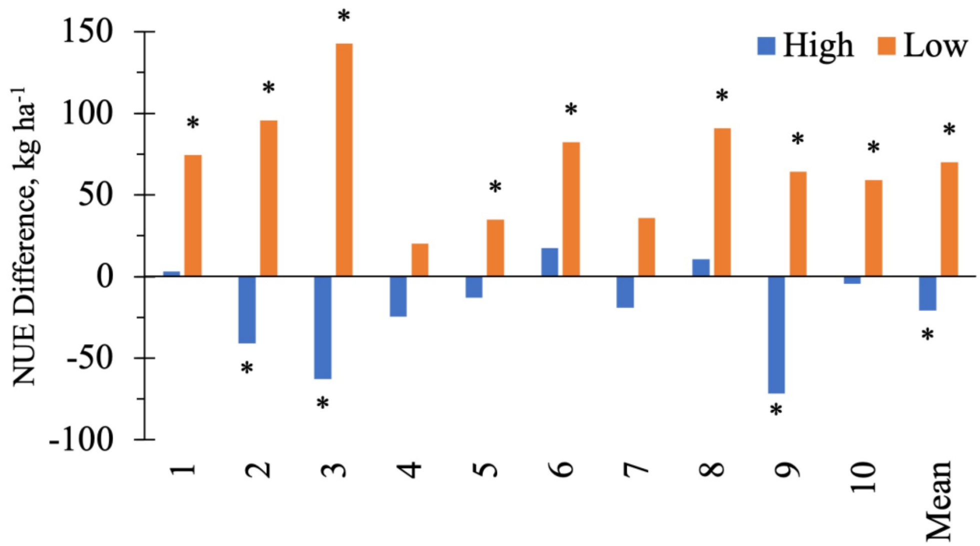

Figure 4–7. Nitrogen use efficiency (NUE) differences [Variable Rate N (VRN) minus Control] by field and zones for total tubers, with significant differences ($P < 0.05$) shown with an *

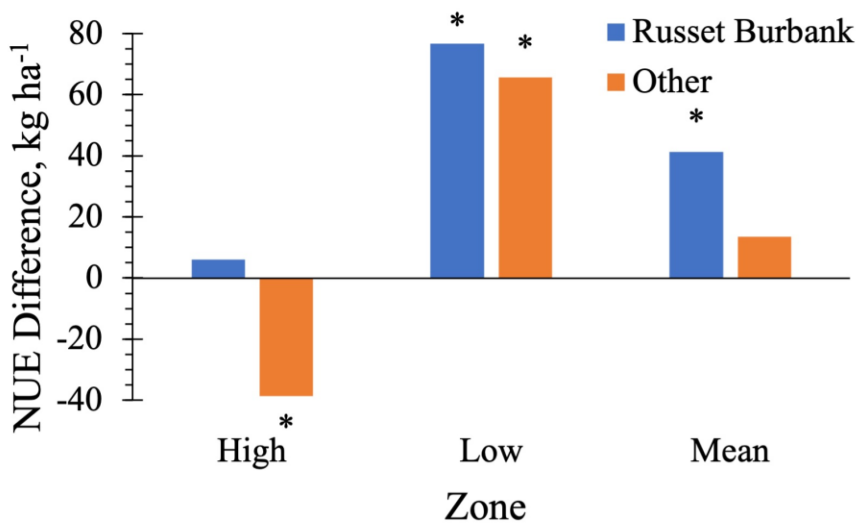

Figure 4–8. Nitrogen use efficiency (NUE) differences [Variable Rate N (VRN) minus Control] by zones for both Russet Burbank and Other cultivars, with significant differences ($P < 0.05$) shown with an *

Table 4–7. Comparison of results of current study with other published studies utilizing variable rate N (VRN) and/or differing rates of N in potato crops

Author	Type	Variety	VRN Zone	Total	Marketable	US No. 1	US No. 2	Malformed	Size	Specific Gravity	Internals	Externals	NUE
Flint et al., 2024	Field	RB, W, FL, AC	High	+*	+*	+*	-	-	+	-	+	Mixed	-
			Low	+	+	+	-	-	-	+	-	Mixed	+
Bohman et al., 2019	Plot	RB	High	+	n/a	+	n/a	n/a	+	-	+	n/a	+
			Low	-	n/a	-	n/a	n/a	-	+	n/a	n/a	-
Bowen et al., 2005	RB	High	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
		Low	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Morier et al., 2015	Plot	RB	High	+	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
			Low	-	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
van Evert et al., 2012	Plot	A, F	High	+	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
			Low	-	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

RB: Russet Burbank, W: Waneta, FL: Frito Lay 2137, AC: Actrice, A: Agria, F: Felsina
*: indicates significant increase (+) or decrease (-) with VRN compared to control; mixed: indicates there were increases and decreases

4.6 | SUPPLEMENTARY MATERIAL

Table 4–S1. Yield of each grade (total, marketable, U.S. No. 1, U.S. No. 2, and malformed) by treatment (VRN or Control) and zone (high or low)

Field	Treatment	Zone	Total	Marketable	U.S. No. 1	U.S. No. 2	Malformed
			- - - - - - - - - - - - - - - -	**Mg ha^{-1}**	- - - - - - - - - - - - - - - -		
1	VRN	High	46	45	44	1	2
2	VRN	High	44	44	44	0	1
3	VRN	High	56	54	54	1	1
4	VRN	High	36	35	35	1	1
5	VRN	High	43	42	42	0	0
6	VRN	High	41	40	39	1	1
7	VRN	High	41	41	40	1	0
8	VRN	High	40	39	38	1	1
9	VRN	High	43	43	42	0	0
10	VRN	High	43	42	41	1	1
1	Control	High	39	38	37	1	1
2	Control	High	41	41	40	1	1
3	Control	High	54	54	53	1	1
4	Control	High	33	32	32	1	1
5	Control	High	37	37	37	0	0
6	Control	High	31	29	28	2	2
7	Control	High	36	36	36	1	0
8	Control	High	32	31	29	2	1
9	Control	High	45	45	45	0	0
10	Control	High	37	36	34	2	2
1	VRN	Low	43	42	41	1	1
2	VRN	Low	45	44	44	1	1
3	VRN	Low	54	53	52	0	1
4	VRN	Low	32	32	31	1	1
5	VRN	Low	35	34	34	0	1
6	VRN	Low	37	35	32	2	2
7	VRN	Low	33	32	32	0	0
8	VRN	Low	37	36	34	2	1
9	VRN	Low	41	41	40	0	0
10	VRN	Low	38	37	34	2	1
1	Control	Low	39	38	37	1	1
2	Control	Low	43	42	42	1	1
3	Control	Low	49	48	48	0	1
4	Control	Low	39	38	38	1	1
5	Control	Low	36	36	36	0	0
6	Control	Low	30	27	24	3	3
7	Control	Low	37	37	37	0	0
8	Control	Low	29	27	25	3	2
9	Control	Low	44	43	43	1	0
10	Control	Low	34	32	29	3	2

Table 4–S2. Relative yield (VRN - Control) across all fields and zones for total, marketable, U.S. No. 1, U.S. No. 2, and malformed grades. Significant differences shown with bold-face ($P < 0.05$)

Field	Treatment	Total	Marketable	U.S. No. 1	U.S. No. 2	Malformed
		- - - - - - - - -	- - - - - - - - -	Mg ha^{-1}	- - - - - - - - -	- - - - - - - - -
1	High	7.4	6.8	6.9	-0.1	0.6
2	High	3.1	3.1	3.4	-0.2	-0.1
3	High	1.1	0.8	0.6	0.3	0.2
4	High	3.0	2.8	2.3	0.3	-0.1
5	High	5.6	5.5	5.5	0.0	0.1
6	High	9.6	10.9	11.7	-0.8	-1.3
7	High	4.8	4.6	4.3	0.2	0.3
8	High	8.3	7.8	8.5	-0.7	0.5
9	High	-2.6	-2.6	-2.6	0.0	0.1
10	High	5.5	6.6	7.5	-0.9	-0.9
1	Low	3.7	4.1	4.2	0.1	-0.4
2	Low	2.0	1.7	1.9	-0.1	0.1
3	Low	4.5	4.7	4.4	0.1	0.0
4	Low	-6.7	-6.3	-6.5	0.1	-0.3
5	Low	-1.6	-1.7	-1.7	0.0	0.6
6	Low	6.4	7.2	8.3	-1.2	-0.8
7	Low	-4.7	-4.9	-4.7	-0.1	0.2
8	Low	7.9	8.6	9.6	-1.0	-0.4
9	Low	-2.9	-2.9	-2.9	-0.3	-0.2
10	Low	3.2	4.4	5.1	-0.8	-1.2
Mean	High	**4.6**	**4.6**	**4.8**	-0.2	-0.1
Mean	Low	1.2	1.5	1.8	-0.3	-0.2
Mean	All Zones	**2.9**	**3.1**	**3.3**	**-0.3**	-0.2

Table 4–S3. Tuber size for each grade (total, marketable, U.S. No. 1, U.S. No. 2, and malformed) by treatment (VRN or Control) and zone (high or low)

Field	Treatment	Zone	Total	Marketable	U.S. No. 1	U.S. No. 2	Malformed
			- - - - - - - -	- - - - - - - -	grams	- - - - - - - -	- - - - - - - -
1	VRN	High	161	149	157	273	356
2	VRN	High	149	147	148	552	636
3	VRN	High	159	157	156	451	344
4	VRN	High	148	146	145	358	315
5	VRN	High	164	151	164	-	114
6	VRN	High	146	146	148	110	125
7	VRN	High	165	165	165	167	219
8	VRN	High	151	150	150	164	233
9	VRN	High	148	148	148	199	246
10	VRN	High	153	154	156	119	125
1	Control	High	151	158	147	432	577
2	Control	High	138	137	137	369	521
3	Control	High	157	156	155	345	466
4	Control	High	142	140	140	521	438
5	Control	High	131	127	131	-	-
6	Control	High	140	137	135	193	304
7	Control	High	159	160	159	274	223
8	Control	High	125	124	124	138	170
9	Control	High	160	160	160	163	136
10	Control	High	139	136	134	202	314
1	VRN	Low	161	155	158	267	436
2	VRN	Low	145	144	144	404	702
3	VRN	Low	155	154	153	354	341
4	VRN	Low	113	112	111	260	450
5	VRN	Low	146	145	146	-	620
6	VRN	Low	151	147	147	144	235
7	VRN	Low	156	156	156	144	175
8	VRN	Low	139	138	138	144	262
9	VRN	Low	152	153	153	150	-
10	VRN	Low	140	140	140	149	158
1	Control	Low	160	159	156	265	704
2	Control	Low	144	143	143	609	435
3	Control	Low	157	155	155	427	370
4	Control	Low	140	139	138	437	375
5	Control	Low	136	135	136	-	-
6	Control	Low	149	144	144	160	235
7	Control	Low	153	153	152	210	154
8	Control	Low	139	136	136	138	261
9	Control	Low	149	149	149	173	214
10	Control	Low	146	144	141	193	264

Table 4–S4. Relative tuber size (VRN - Control) across all fields and zones for total, marketable, U.S. No. 1, U.S. No. 2 and malformed grades. Significant differences shown with bold-face (*P* < 0.05)

Field	Zone	Total	Marketable	US No. 1	U.S. No. 2	Malformed
		- - - - - - - - - - - - - - - - - -	grams	- -		
1	High	**11**	-9	10	-159	-221
2	High	**11**	**10**	**12**	**183**	115
3	High	2	2	2	106	-122
4	High	6	6	5	-164	-123
5	High	**33**	**23**	**33**	-	-
6	High	6	10	13	-83	-179
7	High	6	5	6	-107	-4
8	High	**26**	**26**	**25**	26	63
9	High	**-12**	**-12**	**-12**	35	110
10	High	**14**	**18**	**22**	-84	-189
1	Low	1	-4	2	3	-268
2	Low	1	1	1	**-205**	268
3	Low	-2	-1	-2	-72	-28
4	Low	**-27**	**-27**	**-27**	**-177**	75
5	Low	**10**	**10**	10	-	-
6	Low	2	3	3	-16	0
7	Low	3	3	4	-66	21
8	Low	1	2	2	6	1
9	Low	3	3	4	-23	-214
10	Low	-6	-3	-1	-44	-106
Mean	High	**10**	**8**	**11**	-27	-61
Mean	Low	-1	-1	0	-66	-28
Mean	All Zones	**4**	**3**	**6**	**-47**	-44

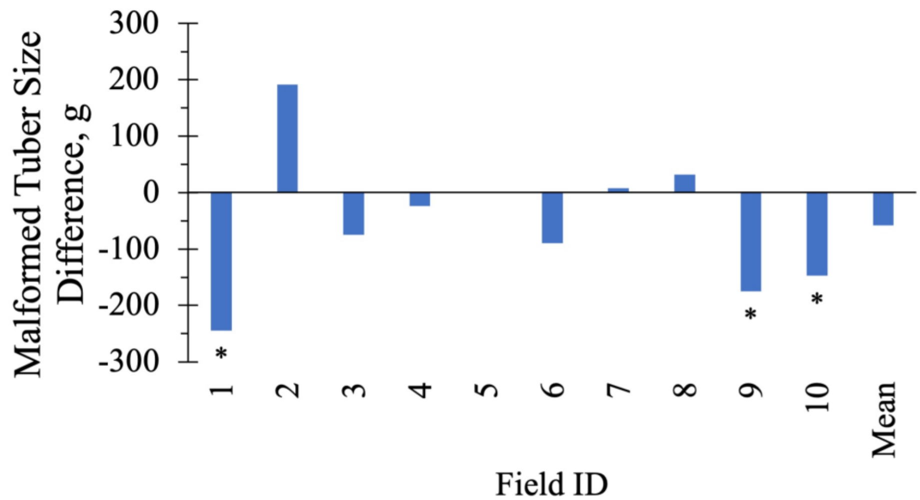

Figure 4–S1. Malformed tuber size (g) difference (VRN – Control) by field. Significant differences are shown with an * (*P* < 0.05).

Table 4–S5. Specific gravity for US No. 1 tuber grades by zone (high or low) and treatment (VRN or Control)

		------ Field ------									
Zone	Treatment	1	2	3	4	5	6	7	8	9	10
High	VRN	1.0789	1.0895	1.0560	1.0922	1.0712	1.0834	1.0733	1.0785	1.0886	1.0830
	Control	1.0810	1.0910	1.0574	1.0953	1.0741	1.0824	1.0757	1.0847	1.0877	1.0832
Low	VRN	1.0789	1.0864	1.0594	1.0975	1.0764	1.0845	1.0783	1.0918	1.0948	1.0874
	Control	1.0808	1.0853	1.0585	1.0965	1.0793	1.0800	1.0761	1.0876	1.0829	1.0878

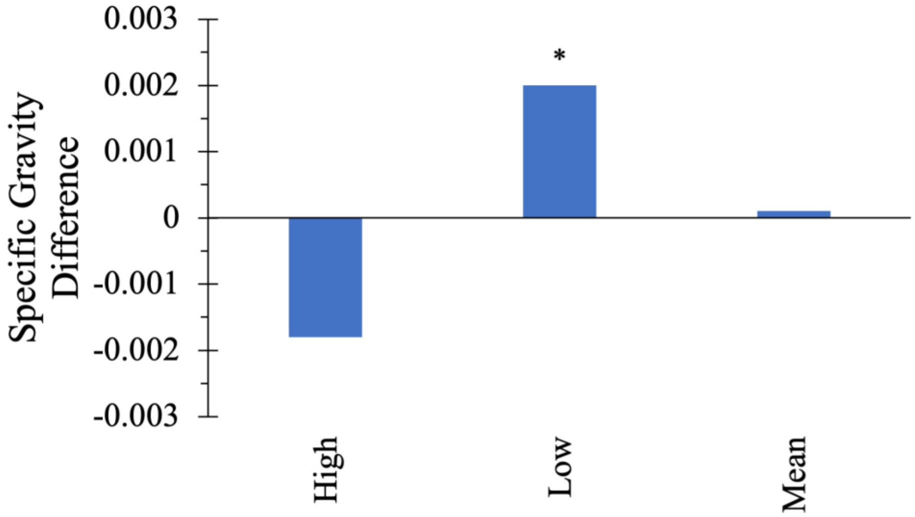

Figure 4–S2. Tuber solid (specific gravity) difference (VRN – Control) within a subsample of U.S. No. 1 tubers across VRN zones. Significant differences shown with an * (P < 0.05).

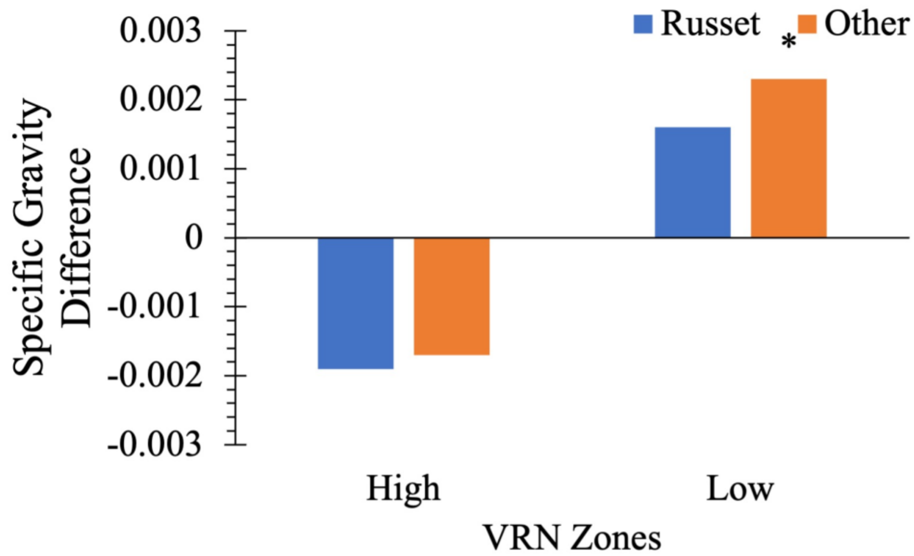

Figure 4–S3. Tuber solid (specific gravity) difference (VRN – Control) within a subsample of US No. 1 tubers across VRN zones for the Russet Burbank cultivar and Other cultivars. Significant differences shown with an * (P < 0.05).

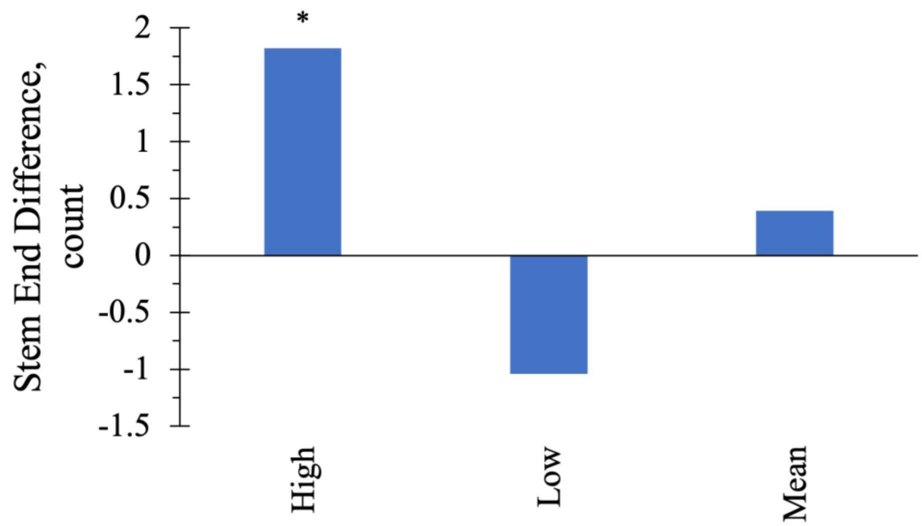

Figure 4 –S4. Count of stem end difference (VRN – Control) within a sub-sample of U.S. No. 1 tubers across VRN zones. Significant differences shown with an * (P < 0.05).

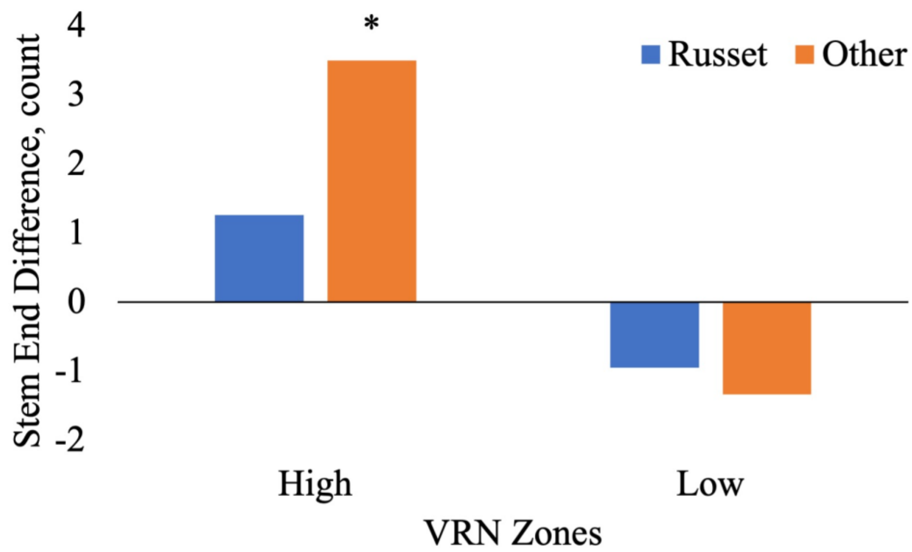

Figure 4–S5. Count of stem end difference (VRN – Control) within a sub-sample of U.S. No. 1 tubers across VRN zones for 'Russet Burbank' and Other cultivars. Significant differences shown with an * ($P < 0.05$).

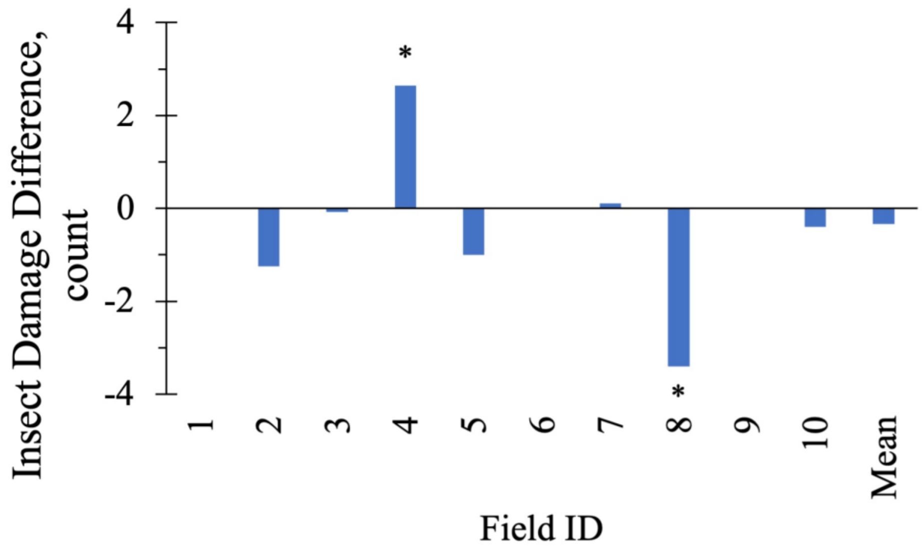

Figure 4–S6. Count of insect damage difference (VRN – Control) in sub-sample tubers across fields. Significant differences shown with an * (P < 0.05).

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CHAPTER 5

CONCLUSION

The studies presented in Chapters 2-4 evaluated different approaches and aspects of managing VRI and VRN with data either from cooperating grower or that are publicly available. Variable rate irrigation approaches that section fields into static zones can benefit from installing sensors in each zone to assist in making irrigation decisions specific to that zone. Placing sensors within zones to represent the zonal average VWC is challenging and can be accomplished in many ways. Our study (Chapter 2) evaluated our existing approach of sensor placement (farmer-informed placement) and three alternative methods (elevation, yield and CWP) that are generally easily accessible to the grower or can be calculated quickly to provide spatially dense information throughout a field. The results from this study suggest that a combination of yield data and grower’s experience are suitable methods for placing soil moisture sensors for use in precision irrigation. These methods should be evaluated in other fields with dense soil sample VWC to validate whether it is successful in other applications.

Satellite imagery can be useful in determining VWC at certain stages of winter wheat and alfalfa growing seasons. Soil sensor data does prove useful and comparable to actual VWC data from soil samples during the growth period of the crop and therefore can provide useful data for irrigation recommendations (Chapter 3). Utilizing satellite imagery coupled with soil sensor data can also assist in depicting differences in VWC between irrigation management zones. NDVI for example is clearly less useful when bare soil dominates the imagery (April) or when the crop is senesced (September). Different vegetative indices may more accurately represent VWC for different crops depending on their growth patterns, growth ranges, and irrigation needs. Further work is needed to know which imagery will be best for depicting VWC within winter wheat and alfalfa crops at different growth stages of the crop.

The VRN approach used in this study reappropriated fertilizer N spatially based on yield potential, with nearly equivalent overall N rate compared to the grower standard uniform N rates (Chapter 4). This VRN approach resulted in greater yields and larger tuber sizes in high yield potential zones. There were no negative impacts on yield or tuber size from lower N rates applied within the low yield potential zones. These results imply that VRN can be successfully implemented by combining patterns of historical yield, elevation maps, and bare soil and NDVI to identify VRN zones that reallocate N according to their respective yield potentials. Through this process of zone delineation and N rates based on the yield potential for each zone, yields, tuber size and in some cases NUE can be improved. Evidence from the 10 fields used in this study indicate that this simple and straightforward VRN method that could be readily adopted by growers is likely to increase potato yield and profit and should be considered.

Overall, these studies suggest that readily available data are beneficial in assisting in management of VRI and VRN in agricultural settings. Utilizing these variables with the equipment available to enhance precision agricultural practices can reduce costs and labor, and environmental impacts of overfertilization, and can benefit growers through improved crop yield and quality. Additional research in application based precision agriculture in different crops and regions of the country are necessary to determine processes most optimal for different situations.

APPENDIX

CURRICULUM VITAE

ACADEMIC EDUCATION

Utah State University

- *PhD Plant Sciences*
  - GPA 3.86 — January 2021 – Current
  - *Processes for Improved Variable Rate Irrigation and Nitrogen within Potato-Wheat-Wheat Cropping Systems.* PhD dissertation. Utah State University. Logan, UT

Brigham Young University

- *MS Environmental Science*
  - GPA 3.58 — December 2020
  - *Soil Water Dynamics within Variable Rate Irrigation Zones of Winter Wheat.* M.S. thesis. Brigham Young University, Provo, UT

- *BS Landscape Management*
  - GPA 3.43 — August 2015
  - *Business Management Minor*

PROFESSIONAL EXPERIENCE

Utah State University

- *Project Coordinator III* — June 2023 - Current
  - Direct the farmer participant portion of AG-DRIP throughout Utah
  - Manage installation and set-up of equipment and resources to all farms
  - Educate farmers of irrigation management opportunities
  - Assist farmers in all aspects throughout the program
- *Research Assistant* — 2021-June 2023
  - Manage data collection for research
  - Coordinate all steps of research with the cooperating grower
  - Teach and oversee undergraduate students in assisting with lab research
  - Assist professors and other graduate students in collecting data for soil, crop, and water research studies in greenhouse, lab, and field environments
- *Teaching*
  - PSC 4280 - World Food Crops — Jan 2022 – April 2022
    - Assist in teaching & coordinating guest lectures while professor was on sabbatical
    - Prepare class materials, grade exams & assignments

BYU Environmental Biophysical Chemistry Lab

- *Lab Manager* — 2018-2020

- Oversee multiple undergraduate student research projects (5-7 Students)
- Assist professors in collecting data for soil, crop, and water research studies in greenhouse, lab, and field environments

➢ *Teaching*

- Turf Science, Soil Science & Urban Soils and Water 2018 – 2020
  - Assist in teaching lectures with and without professor
  - Preparing trips and materials for class
  - Grading quizzes and assignments
- Medicinal Plants 2013 – 2014
  - Prepared lectures with professor
  - Taught lecture and held office hours to help with questions
  - Graded tests, quizzes and assignments

Intermountain Plantings, LLC February 2017 – April 2018

➢ *Maintenance Management*

- Responsible for overall landscape management of multiple LDS church sites, including irrigation management, enhancement projects, weekly services and special requests from customers
- Assisted in management commercial site enhancement projects from planning to completing the project
- Scheduled work for maintenance crews

➢ *Office Administration* June 2016 – February 2017

- Performed all invoicing within accounts receivables for the Maintenance Division
- Assisted in office administrative work such as payroll, contracts, estimating, HR, and accounts payable
- Implemented time/cost tracking software for Maintenance Division

➢ *Montage Landscape Attendant* June 2015 – June 2016

- Directed all landscape management responsibilities for Deer Valley's Resort
- Coordinated with Montage management and Intermountain crews

Internship – High Grove April 2014 – August 2014

➢ *Commercial Landscape Maintenance*

- Adjusted quickly in working with different crews
- Learned skills in irrigation, spray, maintenance and installation

AWARDS AND HONORS

➢ 2022 International Society of Precision Agriculture Outstanding Graduate Student Award

- 2020 Brigham Young University Plant and Wildlife Sciences Exception Scholarship
- 2019 Irrigation Association Scholarship
- 2019 Graduate Student Presentation 1st Place at Western Nutrient Management Conference
- 2018-2019 Brigham Young University Plant and Wildlife Graduate Student Scholarship

GRANTS AND PROPOSALS

- Yost, M. A, Flint, E. A., and Hopkins, B. B. Variable Rate Nitrogen Management in Southeast Idaho Irrigated Winter and Spring Wheat. USU. 2023-2024. $10,394.00
- Yost, M. A, Flint, E. A., and Hopkins, B. B. Variable Rate Nitrogen Management in Southeast Idaho Irrigated Winter and Spring Wheat. USU. 2022-2023. $33,374.00
- Hansen, N., R. Kerry, M. Heaton, R. Jensen, and B.G. Hopkins. Integrating Remote Sensing and Spatiotemporal Statistics to Develop Prescription Maps for Variable Rate Irrigation Systems. BYU. 2018-2020. $120,000.00

PUBLICATIONS

Turner, I., Kerry, R., Jensen, R., Flint, E. A., Svedin, J. D., Hansen, N. C., Hopkins, B. G., Hammond, K. 2023. Automated Analysis of Snowmelt from Sentinel 2 Imagery to Determine Variable Rate Irrigation Zones in the American Mountain West. *Geocarto International*, 38, 1. https://doi.org/10.1080/10106049.2023.2230939

Flint, E. A., Hopkins, B.G., Svedin, J. D., Kerry, R., Heaton, M., Jensen, R.R., Campbell, C., Yost, M.A., & Hansen, N.C., 2023. Irrigation Zone Delineation and Management with a Field-Scale Variable Rate Irrigation System in Winter Wheat. *Agronomy*, 13, 1125. https://doi.org/10.3390/agronomy13041125

Smith, R., Oyler, L., Campbell, C., Woolley, E. A., Hopkins, B.G., Kerry, R., Hansen, N.C. 2021. A New Approach for Estimating and Delineating Within-Field Crop Water Stress Zones with Satellite Imagery. *International Journal of Remote Sensing*, 42:16, 6005-6024, DOI: 10.1080/01431161.2021.1931536

PUBLICATIONS IN PREPARATION

Flint, E. A., Hopkins, A. P., Svedin, J. D., Kerry, R., Jensen, R., Hansen, N.C., Yost, M. A., Hopkins, B.G. 202x. Sensitivity Analysis of Modeled Soil Water Dynamics within Variable Rate Irrigation Zones of Winter Wheat. *Precision Ag. J.*

Flint, E. A., Yost, M. A., Hopkins, B.G. 202x. Variable Rate Nitrogen Zone Delineation and Management in Potato. *Precision Ag. J.*

Flint, E. A., Yost, M. A., Hopkins, B.G. 202x. Variable Rate Nitrogen in Wheat Crops. *Precision Ag. J.*

Hopkins, A. P., Jensen, R., Hopkins, B. G., Flint, E. A., Hansen, N. C. 202x. Visible Vegetation Indices, Spatial Resolution, and Resampling Methods for Modeling Leaf Area Index of Irrigated Wheat. *Remote Sensing*

Martini, M. E., Hopkins, A. P., Ransom, C. J.., LeMonte, J. J., Flint, E. A., Buck, R. L., Hopkins, B. G. 202x.Struvite as a Phosphorus Source: Potato. *Resources, Conservation and Recycling*

Stapley, S., Yost, M. A., Flint, E. A., Seely, C., & Hopkins, B. G. 202x. Staked 4R Impacts on Potato Yield and Quality. *Soil Science Society of America*

DISSERTATION

Flint, E. A. 2024. *Processes for Improved Variable Rate Irrigation and Nitrogen within Potato-Wheat-Wheat Cropping Systems.* PhD dissertation. Logan, UT. Utah State University

THESIS

Woolley, E. A. 2020. *Soil Water Dynamics within Variable Rate Irrigation Zones of Winter Wheat.* M.S. thesis. Provo, UT. Brigham Young University

PUBLISHED CONFERENCE PROCEEDINGS

Flint, E. A., Hopkins, B. G., Yost, M. A. 2023. Variable Rate Nitrogen in Potato. (Oral Presentation) *In Proceedings*, 14th European Conference on Precision Agriculture. 2-6 Jul. 2023. International Society of Precision Agriculture, Monticello, IL.

Hansen, N. C., Flint, E. A., Hopkins, A. P., Larsen, I., Kerry, R., Hopkins, B. G., Yost, M. A., Jensen, R., Heaton, M. 2023. On-Farm Evaluation of Variable Rate Irrigation for Winter Wheat in Semi-arid Western U.S.A. (Oral Presentation) *In Proceedings*, 14th European Conference on Precision Agriculture. 2-6 Jul. 2023. International Society of Precision Agriculture, Monticello, IL.

Flint, E. A., Hopkins, B. G., Yost, M. A. 2023. Impact of Variable-Rate Nitrogen on Potato Yield, Nitrogen Use Efficiency, and Profit. (Oral Presentation) *In Proceedings*, Western Nutrient Management Conference. 9-10 Mar. 2023. WERA-103, Monticello, IL.

Flint, Elisa A., Hopkins, B. G., Yost, M. 2022. On-Farm Evaluations of Pre- and In-Season Variable Rate Nitrogen For Potato (Oral Presentation) *In Proceedings*, 15th International Conference on Precision Agriculture. 26-29 Jun. 2021. International Society of Precision Agriculture, Monticello, IL.

Turner, I., Kerry, R., Jensen, R., Flint, E. A., Svedin, J. D., Hansen, N. C., Hopkins, B. G 2022. Investigation and Development of Automated Analysis of Snowmelt from Time-series Sentinel 2 Imagery to Determine Variable Rate Irrigation Zones in the American Mountain West (Oral Presentation) *In Proceedings*, 15th

International Conference on Precision Agriculture. 26-29 Jun. 2021. International Society of Precision Agriculture, Monticello, IL.

Stapley, S. H., Hansen, N. C., Yost, M. A., Woolley, E. A., Hopkins, B. G. 2022. Stacking Nutrient 4Rs on Potato and Wheat. Great Plains Annual Conference Session 2022. 08-11 Jun. 2022. Great Plains United Methodists, Topeka, KS.

Woolley, Elisa A., Kerry, R., Hansen, Neil C., Hopkins, B.G. 2020. Variable Rate Irrigation: Investigating Within Zone Variability (Oral Presentation) *In Proceedings*, 13th European Conference on Precision Agriculture. 19-22 Jul. 2021. International Society of Precision Agriculture, Monticello, IL.

Fisher, J., Woolley, E. A., Svedin, J. D., Hopkins, B.G. 2019. Struvite Phosphorous Fertilizer on Sugar Beet (Poster and oral presentation.). *In Proceedings of the Western Nutrient Management Conference (WNMC);* 7-8 Mar. 2019; Reno, NV. Peachtree Corners, GA: International Plant Nutrition Institute (IPNI). 13:87-95

Woolley, E. A., Searle, T. G., Hopkins, T. J., Williams, J. D., Hopkins, B.G. 2019. Boron Fertilization with Aspire® in Alfalfa and Potato. (Poster and oral presentation.). *In Proceedings of the Western Nutrient Management Conference (WNMC);* 7-8 Mar. 2019; Reno, NV. Peachtree Corners, GA: International Plant Nutrition Institute (IPNI). 13:118-126

Woolley, R. K., Svedin, J. D., Woolley, E. A., Hopkins, B.G. 2019. Struvite Phosphorus Fertilizer on Potato. (Poster and oral presentation.). *In Proceedings of the Western Nutrient Management Conference (WNMC);* 7-8 Mar. 2019; Reno, NV. Peachtree Corners, GA: International Plant Nutrition Institute (IPNI). 13:127-137

EXTENSION ARTICLES

Flint, E., Yost, M., Peters, T., Anderson, C., Barker, B., & Hansen, N. (2023). *Precision irrigation guide for center pivots* [Fact sheet]. Utah State University Extension.

PROFESSIONAL MEETINGS WITH PUBLISHED ABSTRACTS

Hopkins, A. P., Flint, E. A., Hopkins, B. G., Hansen, N. C. 2023. Spatial Variability of Leaf Area Index from Drone Imaging of Two irrigated Wheat Fields. (Oral Presentation). *In Abstracts*, EGU General Assembly, 23-28 Apr. 2023. EGS-EUG, Munich, Germany.

Taghizadeh-Mehjardi, R., Kerry, R., Flint, E. A., Svedin, J. D., Hopkins, A. P., Hansen, N. C., Hopkins, B. G., Jensen, R. 2023. Mapping Volumetric Water Content at Multiple Depths to Inform Variable Rate Irrigation using UAV and Yield Monitor data with Random Forests. (Poster Presentation). *In Abstracts*, AAG Annual Meeting, 23-27 Mar. 2023. AAG, Washington, DC.

Flint, E. A., Hopkins, B. G., Hansen, N. C., Yost, M. A. 2022. Temporal Stability of Soil moisture and Static Variables to Determine Optimal Sensor Placements within Variable Rate Irrigation Systems. (Oral Presentation). *In Abstracts*, ASA•CSSA•SSSA International Annual Meetings, 6-9 Nov. 2022. ASA-CSSA-SSSA, Madison, WI.

Flint, E. A., Hopkins, B. G., Yost, M. A. 2022. Variable Rate Nitrogen Approach in a Potato-Wheat-Wheat Cropping System. (Poster Presentation). *In Abstracts*, ASA•CSSA•SSSA International Annual Meetings, 6-9 Nov. 2022. ASA-CSSA-SSSA, Madison, WI.

Woolley, E. A., Yost, M. A., Kerry, R., Hansen, N. C., Hopkins, B. G. 2021. Optimal Number of Sensors and Sensor Placement for Sensor-based Irrigation Scheduling for a Variable Rate Irrigation System. (Oral Presentation). *In Abstracts*, ASA•CSSA•SSSA International Annual Meetings, 7-10 Nov. 2022. ASA-CSSA-SSSA, Madison, WI.

Bonsrah, D. K. A., Kobza, S. J., Woolley, E. A., Hopkins, B.G. 2020. Boron Distribution and Uptake: Homogeneous Vs. Heterogeneous Fertilizer Blends. (Poster Presentation) *In Abstracts*, ASA•CSSA•SSSA International Annual Meetings, Virtual. 9-13 Nov. 2020. ASA-CSSA-SSSA, Madison, WI.

Woolley, Elisa A., Svedin, J.D., A. P., Hopkins, Kerry, R., Hansen, Neil C., Jensen, R., Hopkins, B.G. 2020. Comparing Spatial Variation of Crop Water Productivity and Moisture Relations in Multiple Years of Wheat. (Oral Presentation) *In Abstracts*, ASA•CSSA•SSSA International Annual Meetings, Virtual. 9-13 Nov. 2020. ASA-CSSA-SSSA, Madison, WI.

Woolley, E. A., Svedin, J.D., Kerry, R., Hansen, Neil C., Jensen, R., Hopkins, A. P., Hopkins, B.G. 2019. Comparing Spatial Variation of Crop Water Productivity and Moisture Relations in Potato and Wheat. *In* Abstracts, ASA•CSSA•SSSA International Annual Meetings, San Antonio, TX. 10-13 Nov. 2019. ASA-CSSA-SSSA, Madison, WI.

Hopkins, A. P., Woolley, Elisa A., Hansen, N. C., Kerry, R., Jensen, R., Hopkins, B.G. 2019. Remote Sensing Approaches for Maximizing Productivity of Variable-Rate Irrigation Systems. *In* Abstracts, ASA•CSSA•SSSA International Annual Meetings, San Antonio, TX. 10-13 Nov. 2019. ASA-CSSA-SSSA, Madison, WI.

Nolan, E.A., Woolley, E. A., Searle, T. G., Hopkins, T. J., Williams, J. D., Hopkins, B.G. 2019. Boron Update Efficiency With a Homogenous Potassium Granule As a Function of Root System Diameter. *In* Abstracts, ASA•CSSA•SSSA International Annual Meetings, San Antonio, TX. 10-13 Nov. 2019. ASA-CSSA-SSSA, Madison, WI.

Svedin, J.D., Woolley, E. A., Hansen, Neil C., Kerry, R., Hopkins, B.G. 2018. Spatio-Temporal Soil Water and Crop Stress Modeling for Variable Rate Irrigation. *In* Abstracts, ASA•CSSA•SSSA International Annual Meetings, Baltimore, MA. 5-7

Nov. 2018. ASA-CSSA-SSSA, Madison, WI.

FUTURE PROFESSIONAL MEETINGS WITH PUBLISHED ABSTRACTS

Ekadu, S., Flint, E. A., Barker, J. B., Yost, M. A. 2024. Participatory On-Farm Irrigation Water Optimization for Water Conservation and Increased Resilience to Drought in the Colorado River Basin; Ag-DRIP. (Lightning Talk). *In Abstracts*, ASABE 2024 Annual International Meeting, 28-31, Jul. 2024. St. Joseph, MI.

PRESENTATIONS AT PROFESSIONAL MEETINGS

Flint, E. A., Ekadu, S., Barker, J. B., & Yost, M. A., 2024. Agriculture – Demonstration, Research and Implementation Program (AG-DRIP). (Oral presentation) *Carbon County Crop School*, 14, Feb. 2024; Price, UT: Utah State University

Flint, E. A., Yost, M., Kerry, R., Hansen, N. C., Hopkins, B. G. 2022. Optimal Sensor Placement for Sensor-Based Irrigation Scheduling in a Variable Rate Irrigation System. (Poster presentation) *USU Interdisciplinary Water Science & Education*; 20, Mar. 2022; Logan, UT: Utah State University

Woolley, E. A., Svedin, J. D., Kerry, R., Hansen, N. C., Jensen, R., Hopkins, B.G. 2020. Soil Water Dynamics within Variable Rate Irrigation Zones of Winter Wheat. (Oral presentation) *BYU PWS Graduate Research Conclave;* 05 Nov. 2020; Provo, UT: Brigham Young University

Woolley, E. A., Svedin, J. D., Kerry, R., Hansen, N. C., Jensen, R., Hopkins, A. P., Hopkins, B.G. 2019. Comparing Spatial Variation of Crop Water Productivity and Moisture Relations in Potato and Wheat. (Oral presentation) *BYU PWS Graduate Research Conclave;* 21 Nov. 2019; Provo, UT: Brigham Young University

Woolley, E. A., Svedin, J. D., Hansen, N. C., Kerry, R., Hopkins, B.G. 2018. Spatio-Temporal Soil Water and Crop Stress Modeling for Variable Rate irrigation. (Poster presentation) *BYU PWS Graduate Research Conclave;* 15 Nov. 2018; Provo, UT: Brigham Young University

ARTICLES

Hopkins, B. G., Woolley, E. A., 2019. Biostimulants – Boom or Bull? *Sports Turf Mag*. 35(6): 26-29