Time-lapse mapping of crop and tillage interactions with soil water using electromagnetic induction

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Abstract
Assessing spatiotemporal variations in soil water is critical to many decisions in precision agriculture. In dryland crop production regions with marginal precipitation, growers use crop rotations and surface preparation practices to build soil water natural capital over preceding seasons for cash crop production. However, significant gaps exist in quantifying linkages between topography, soil properties, and site-specific agronomic practices to crop water use, and to predict temporal changes in soil water storage. In this study, we used time-lapse electromagnetic induction to measure apparent electrical conductivity (ECₐ) to infer spatiotemporal variability of soil water while comparing crop (winter wheat [Triticum aestivum L.], spring peas [Pisum sativum L.], and spring barley [Hordeum vulgare L.]) as well as tillage (no till and chisel plow) on a split-plot design in the Palouse region of northern Idaho. Weekly measurements of ECₐ were converted to soil water content using multiple linear regression with the help of principal component analysis. Separating factors of temporal stability and variability allowed us to derive crop-specific calibrated relationships between soil water content and the additional variables growing degree days, elevation, clay content, and silt content. Results suggest that spring peas retained the highest water content, followed by spring barley and winter wheat. Resultant maps show highly structured and consistent patterns in ECₐ being driven primarily by crop type that are apparent even in uncalibrated imagery. Although soil ECₐ tended to be greater in no-tillage compared with chisel plow treatments, we found no significant differences in soil water content between the two. This may be partially due to the limited number of years of no-till practice at this site.

Abbreviations:  BD, bulk density; CoV, condensed variable; CP, conservation tillage (chisel plow); DEM, digital elevation model; ECₐ, soil apparent electrical conductivity; ECₑ, electrical conductivity of the pore fluid; EMI, electromagnetic induction; GDD, growing degree days; MV, measured variable; NT, no tillage; PCA, principal component analysis; PCR, principal component regression; RSSD, response surface sampling design; SB, spring barley; SP, spring peas; TWI, topographic wetness index; WW, winter wheat.

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INTRODUCTION

Dryland crop production depends on stored soil water, which organizes in patterns linked in part to topography (Beven & Kirby, 1979; Wilson, Western, & Grayson, 2005), cropping sequences (Schlegel et al., 2017), and tillage practices (Fuentes, Flury, Huggins, & Bezdicek, 2003; Jin et al., 2007; Kühling, Redozubov, Broll, & Trautz, 2017). Interactions among these factors can make it difficult to predict soil water and associated responses, especially in the context of climate change in dryland ecosystems (Bradford, Schlaepfer, Lauenroth, & Palmquist, 2020). Improved ability to assess soil moisture storage at the field scale is also important to realizing gains in nutrient use efficiency and protection of water quality through variable rate technologies, especially in topographically complex cropping regions (Yoursek, Brooks, Brown, Poggio, & Gasch, 2019).

Soil water storage fluctuates temporally and spatially (Eagleson, 1978) due to climate, heterogeneity of soil profiles (Sheets & Hendrickx, 1995), topography (Burt & Butcher, 1985), and vegetation (Cassiani et al., 2012; Eagleson, 1978). Although topography-based surface and subsurface lateral flow is a main determinant of water movement and storage in winter and spring months (Western, Grayson, & Blöschl, 2002; Zhu, Lin, & Doolittle, 2010), soil properties such as texture, porosity, and hydraulic conductivity become increasingly important as soils dry, runoff ceases, and unsaturated flow dominates (Grayson, Western, Chiew, & Blöschl, 1997; Vereecken et al., 2014), presenting distinct states in soil water patterns (Martini et al., 2015). In the topographically complex Palouse bioregion, Ibrahim and Huggins (2011) confirmed that elevation and the topographic wetness index (TWI, upper slope-dependent water accumulation originally proposed by Beven and Kirby, 1979) were the most influential variables in determining soil water distribution in the spring months, and that soil properties, such as apparent electrical conductivity (ECa) and bulk density (BD), were better descriptors with the onset of summer and drier conditions. Although it is well known that both topography and soil properties influence water distribution, it is important to note that these relationships are site specific (Corwin & Lesch, 2005a, 2005b).

Sources of site-specific variability may also arise from differences in tillage management. Conservation tillage practices such as chisel plow (CP) and no-till (NT) result in greater amounts of residue remaining on the soil surface and less soil disturbance as compared with complete inversion tillage (Lal, 2007). Crop residues help to trap snow, resulting in greater snow accumulation in the winter and more water being added to soil during snow melt in the spring. Qiu et al. (2011) found that when more crop residue was left on a field with rolling topography, snow accumulation tended to be more evenly distributed across the landscape. In contrast, conventional tillage fields, with little residue to hold the snow in place, showed larger spatial variation for snow accumulation, which likely leads to a larger variation of stored water across the landscape (Qiu et al., 2011). The lack of disturbance in conservation tillage systems may also lead to improved soil structure over time and greater infiltration and water storage capacity (Shukla, Lal, Owens, & Unkefer, 2003). Conservation tillage, therefore, may moderate the impact of topography on soil–water relationships across complex landscapes. However, the scale gap between point-scale sensors and remote sensing continues to limit the assessment of the combined effects of factors such as topography and tillage on soil water patterns and crop soil water use.

Electromagnetic induction (EMI) methods have been used widely for soil mapping and assessment, as measurement shows close correlation with key soil properties, and because spatially exhaustive data can be collected rapidly and at comparatively little cost (Doolittle & Brevik, 2014). The high resolution of EMI data and derivative products make EMI particularly well suited to support precision agriculture (Brogi et al., 2019; Corwin & Lesch, 2003, 2005a; McCutcheon, Farahani, Stednick, Buchleiter, & Green, 2006; Rosenzweig et al., 2004). Electromagnetic induction surveys the ECa of the soil, which can be related to the soil water content (Archie, 1942; Friedman, 2005). The ECa(θv) relationship (where θv is volumetric water content) depends on additional soil and environmental attributes such as the salinity, temperature, mineralogy, soil organic matter, as well as particle shape and distribution, which suggest site-specific ECa(θv) like the ones summarized in Calamita, Perrone, Brocca, Onorati, and Manfreda (2015). In nonsaline soils, ECa has been shown to be linearly related to water content (Khakural, Robert, & Hugins, 1998; Rhoades, Raats, & Prather, 1976; Sheets & Hendrickx, 1995; Tromp-van Meerveld & McDonnell, 2009), but topographic attributes (Sauer et al., 2013), changes in temporal soil water composition (Martini, Werban, et al., 2017;
Martini, Wollschläger, Musolff, Werban, & Zacharias, 2017), and soil properties such as clay content (Corwin & Lesch, 2003; Robinson et al., 2008) and salinity (Yao et al., 2016) may be important site conditions for calibration of EC\textsubscript{a}(θ\textsubscript{v}) data that may be nonlinear and dynamic.

Time-lapse EMI imaging has long been known to improve soil water content estimations, starting with work in California by Sheets and Hendrickx (1995) and in Missouri by Sadduth, Drummond, and Kitchen (2001). The spatiotemporal changes in EC\textsubscript{a} have been shown to improve the estimation of water content under the assumption that soil properties such as clay content remain static (Robinson et al., 2009, 2012), and that the EMI instrument interaction with the soil is not changing significantly. Researchers have begun to exploit time-lapse EMI to study intraseason soil water use within-and across plant species such as chickpeas (Cicer arietinum L.; Huang, Purushothaman, McBratney, & Bramley, 2018) and wheat (Triticum aestivum L.; Shanahan, Binley, Whalley, & Watts, 2015). Time-lapse measurements of EC\textsubscript{a} have further been used to quantify root activity in wheat, as demonstrated by Whalley et al. (2017) and Blanchy et al. (2020). Other examples of the use of EMI in crop water use studies include Cassiani et al. (2012), who demonstrated positive feedbacks in EC\textsubscript{a} between soil and root development, as well as water uptake; Yao et al. (2016), who suggested the need for long-range EMI surveys and data collection to capture the spatial and temporal variability of soil and crop yield; and Moghadas, Jadoon, and McCabe (2017), who used EMI to study temporal root zone soil moisture variations with depth.

Despite the demonstrated utility of EMI data for visualizing soil spatial variability and assessment of soil water content changes with time-lapse imaging, datasets collected specifically for assessing impacts of management such as crop sequencing and tillage remain sparse. This study aims at providing a spatial view of temporal crop water uptake patterns, using an existing tillage comparison study located within the topographically complex Palouse bioregion. In this study, repeated EMI surveys were used to characterize the spatial distribution and temporal dynamics of root zone soil water during a growing season based upon ancillary data, and to quantify differences between crops and tillage in light of the spatial patterns. This work was conducted in the Palouse bioregion within southeastern Washington State and north-central Idaho (USA), which is characterized by rolling loess hills with steep slopes and Mediterranean climate with distinct wet and dry periods (Mulla, 1986; Schillinger & Papendick, 2008). The primary objectives were (a) to establish a relationship between root zone water content and the EMI measurements using principal component analysis (PCA) and principal component regression (PCR) with covariates sampled using a response surface sampling design (RSSD), (b) to evaluate the spatial distribution and temporal changes of EC\textsubscript{a} throughout a growing season and to investigate the influence of crop type and tillage practices, and (c) to spatially estimate root zone water content using the EMI measurements and covariates as a predictive tool for land management decisions including the selection of crop rotations.

2 | MATERIALS AND METHODS

2.1 | Field location, climate, and soil descriptions

The study was conducted at an experimental field on the University of Idaho Kambitsch Farm near Genesee, ID. The farm is in the Palouse region of northern Idaho characterized by a mesic temperature regime (Soil Survey Staff, 2020) with a mean annual temperature of 8.5°C with cold winters and hot summers (Western Regional Climate Center, 2020). Although the mean precipitation is 605 mm yr\textsuperscript{-1}, being in a xeric precipitation regime (Soil Survey Staff, 2020), the majority of the precipitation occurs during winter and spring months (Figure 1). During our study, the annual precipitation was 591 mm in 2012 (Western Regional Climate Center, 2013). The dominating soil series is a Palouse silt loam, classified by the NRCS as a fine-silty, mixed, superactive, mesic Pachic Ultic Haploxeroll (Soil Survey Staff, 2020). The fine textures, high cation exchange capacity, and deep A horizon of a Mollisol give the soil naturally high fertility and high water-holding capacity. The depth to water table is generally >200 cm deep (Soil Survey Staff, 2020).

2.2 | Experimental design

The 1.6-ha (192 × 82 m) tillage study site (Figure 2) was created in 2000 when CP and NT treatments were established in eight alternating strips in an east–west direction along the slope contour. Each tillage strip was divided into three equal sections, in the north–south direction, and planted to one of the following crops: winter wheat (WW), spring pea (Pisum sativum L.; SP), spring barley (Hordeum vulgare L.; SB). Crops were rotated annually across the three tillage strips. The experimental design was modified in 2010 to include five replicate CP–NT treatment plot pairs with each tillage plot. Each tillage plot was further divided into three subplots and planted to the rotational crops (WW–SP and SB). Except for one newly created replicate, each tillage treatment remained in the same location as in the previous design. Each subplot measured 6 × 82 m with 1.2 m of unplanted soil between each main plot. At the time of sampling for this study, the tillage treatments had been in place for either 10 (four replicate tillage treatment pairs) or 2 yr (one replicate tillage pair). The current design (created in 2010) is a split-plot design with tillage (CP or NT) and crop (WW–SP–SB) treatments.
Winter wheat (528/523 blend) was planted on 27 Oct. 2011 at a rate of 123 kg ha\(^{-1}\) with 130 kg of 31–10–0–7.5 deep-banded dry fertilizer. The entire field was top-dressed via a plane with 40–0–0–6 (urea mixed with KCl) fertilizer on 9 Apr. 2012 at a rate of 112 kg ha\(^{-1}\). Spring peas (Aragorn peas) were planted the following spring on 14 May 2012 at 134 kg ha\(^{-1}\). Spring barley was planted on 16 May 2012 at 90 kg ha\(^{-1}\) with 118 kg of 31–10–0–7.5 deep-banded dry fertilizer applied at the same time. The drill used for all planting was a 20’ Flexi-Coil no-till drill with a 1720 air cart and Barton II openers on the tool bar at 25-cm row spacing. On the Barton II openers, there is a larger leading disk that places the dry fertilizer about 10 cm deep. Then, the rear smaller disk, which is angled in the other direction, places the seed above and slightly to the side of the fertilizer furrow, at a depth of about 3 cm. The CP plots were tilled (4-m-wide Glencoe Soil Saver with a row of straight coulter disks in front and behind a row of 7-cm-wide shanks with 10-cm-wide twisted shovels spaced 30 cm apart in the fall to a depth of 20 cm) and cultivated twice in the spring (11-m-wide Wil-Rich 2500 cultivator with 1-cm-wide shanks spaced 18 cm apart and attached tines spaced 8 cm apart). The depth of cultivation was 8–10 cm. The prior year planting for WW, SB, and SP was SP, WW, and SB, respectively.

At the end of the growing season, SB yield averaged 4.8 t ha\(^{-1}\) and SP averaged 0.6 t ha\(^{-1}\). The yields in the NT and CP plots were not significantly different. Winter wheat averaged 5.5 t ha\(^{-1}\) (82.2 bu acre\(^{-1}\)). The yields of CP plots were
significantly greater ($p < .05$): 5.8 t ha$^{-1}$ compared with the NT plot yields of 4.9 t ha$^{-1}$ (Bull, University of Idaho Farm Technician, personal communication, 2012).

### 2.3 Spatial measurements of soil variability

We used the noninvasive CMD-1 EMI conductivity meter (GF Instruments) to collect subsurface $EC_a$. The instrument collected a georeferenced datum (including elevation) every second (approximately every 1.3 m) using a submeter accuracy GPS receiver (SX BlueII, Geneq). The EMI instrument was carried at a walking pace between crop rows, perpendicular to the slope, with ~84-cm linear distance between each measurement path. There were four measurement paths per each subplot (i.e., four transects per crop strip). The instrument was held ~8 cm above the ground on the vertical co-planar (VCP) setting for an effective depth of ~1.5 m (Callegary, Ferré, & Groom, 2007; McNeill, 1980). This depth range was chosen to maximize sensitivity to root zone moisture, as suggested by Corwin and Lesch (2005a). Throughout the 2012 growing season (May–October), 13 time-lapse field-scale EMI measurements were collected (Figure 2). Approximately 8,000 $EC_a$ data points were collected per field measurement.

The $EC_a$ data were normalized to a reference temperature of 25 °C using the equation found in Reedy and Scanlon (2003):

$$EC_{25} = EC_a \left[0.4779 + 1.3801e^{-\left(\frac{T}{25.541}\right)}\right]$$

(1)

In lieu of measured soil temperatures profiles, we estimated the depth-weighted temperature $T$ based on the model found in Van Wijk and Vries (1963) using mean daily air temperature and diurnal amplitude as input parameters derived from daily measurements at the field location weather station. The characteristic damping depth and phase constant were estimated by fitting the model to observations of daily average soil temperatures over 1 yr measured at the 10-cm depth using a standard Levenberg–Marquardt least squares algorithm implemented in Matlab (The Mathworks). Depth weighing of $T$ used the sensitivity distribution in McNeil (1980) to calculate an effective temperature for conversion to $EC_{25}$. From this point forward, $EC_a$ will represent $EC_{25}$ as temperature-corrected $EC_a$.

In addition to the spatial measurements of $EC_a$, site-specific covariate spatial data was calculated for elevation, slope, aspect, and TWI based on a digital elevation model (DEM). The DEM was derived by fitting a local linear regression surface to pooled GPS data collected along with the EMI measurements throughout the year. Slope and aspect were derived from the DEM using scripts in TopoToolbox (Schwanghart & Kuhn, 2010). The TWI was calculated following Beven and Kirkby (1979).

### 2.4 Calibration data

Soil samples were collected and analyzed to determine volumetric water content ($\theta_v$), particle size, soil pH, BD, bulk electrical conductivity, and electrical conductivity of the pore fluid ($EC_v$). Figure 2 gives the locations of the 60 BD and 12 soil property sampling sites. Bulk density samples were collected using a Giddings probe (Giddings Machine Company) to a depth of 150 cm or refusal and were collected on 31 Oct. 2012. Bulk density was determined in 10-cm increments from 0 to 30 cm and in 30-cm increments from 30 cm to maximum depth. The 12 soil sampling locations were selected using ESAP-RSSD software (U.S. Salinity Laboratory) to optimize sampling design based on a response surface sampling design (Lesch, Rhoades, & Corwin, 2000). The response surface sampling design used the spatial variability in $EC_a$ derived from the EMI measurements in the wet state (8 Dec. 2011) to create a regression model and sample sites that represent the electrical conductivity data (Lesch et al., 2000). At each site, soil samples were collected at depths of 0–10, 10–20, 30–40, 50–60, and 90–100 cm with a 2.5-cm-diam. soil probe.

Soil texture was determined by pipette procedure per Kilmer and Alexander (1949) based on USDA-NRCS standards for classification using collected soil samples from each of the 12 sites and 30 of the 60 locations (approximately every other location going up the hill) from the BD measurements, for a total of 42 samples. Texture analyses were performed for samples comprising the lower and upper 50 cm to a depth of 100 cm. Samples tested negative for carbonates and had organic matter (Mikhail & Briner, 1978) and excess ions (95% methanol and 95% ethanol washings) removed.

Volumetric water content and bulk electrical conductivity were measured using a Trime-Pico IPH/T3 soil moisture sensor (IMKO) starting 17 June 2012 (Figure 2). At each of the twelve sites TECANAT PC plastic access tubes were augered without pre-boring to a soil depth of 80 cm. The tubes allowed repeated measurements on days of EMI data collection in 15-cm depth increments.

Soil pH and the $EC_v$ were determined using the saturated paste extract method (Burt, 2004). The $EC_v$ and pH data from soil samples collected on 8 and 24 Ma were compared via a paired t test for differences. The two dates bracketed fertilizer applications and were used to determine if the fertilizer applications caused detectable changes in $EC_a$ and pH.

We used growing degree days (GDD) as a crop-relevant time measurement. Cumulative GDD started on 1 Apr. 2012 and were determined based on temperatures recorded at a nearby weather station, using 0 °C as a reference. On dates
TABLE 1  Summary statistics and variogram parameters for kriged variables (clay, silt, sand, bulk density [BD], and apparent electrical conductivity [ECₐ] with date collected)

| Variable | Date      | Mean | Min. | Max. | Range | Sill | Nugget | Model type |
|----------|-----------|------|------|------|-------|------|--------|------------|
| Clay, %  | –         | 30.0 | 23.0 | 37.0 | 392.9 | 2.95 | 0.21   | Spherical  |
| Silt, %  | –         | 64.0 | 58.0 | 71.0 | 392.9 | 3.03 | 0.20   | Spherical  |
| Sand, %  | –         | 6.0  | 5.0  | 8.0  | 392.9 | 0.12 | 0.90   | Spherical  |
| BD, g cm⁻³ | –       | 1.6  | 1.4  | 1.8  | 137.1 | 0.96 | 0.39   | Cubic      |
| ECₐ, mS m⁻¹ | 17 Apr. | 36.7 | 18.8 | 62.7 | 488.3 | 3.84 | 0.06   | Cubic      |
|          | 24 May    | 41.6 | 23.0 | 69.9 | 314.2 | 2.48 | 0.07   | Cubic      |
|          | 10 June   | 38.6 | 17.4 | 66.6 | 310.6 | 2.44 | 0.09   | Cubic      |
|          | 17 June   | 41.0 | 16.6 | 72.6 | 464.2 | 3.65 | 1.11E-07 | Cubic    |
|          | 2 July    | 35.0 | 8.5  | 76.7 | 395.3 | 3.52 | 0.27   | Cubic      |
|          | 11 July   | 28.8 | 13.6 | 72.1 | 485.1 | 3.31 | 0.28   | Cubic      |
|          | 19 July   | 28.5 | 13.6 | 75.1 | 428.4 | 3.28 | 0.44   | Cubic      |
|          | 30 July   | 22.4 | 5.2  | 58.5 | 486.4 | 4.47 | 3.16E-07 | Cubic    |
|          | 19 Aug.   | 24.3 | 6.2  | 65.8 | 454.1 | 3.12 | 6.23E-08 | Cubic    |
|          | 27 Aug.   | 24.4 | 10.1 | 60.8 | 422.9 | 3.39 | 0.38   | Cubic      |
|          | 15 Sept.  | 25.5 | 11.5 | 59.8 | 418.7 | 3.51 | 0.33   | Cubic      |
|          | 4 Oct.    | 24.3 | 11.9 | 58.2 | 418.8 | 3.50 | 0.32   | Cubic      |

where temperature data was missing (3% of dates), we interpolated temperatures.

2.5  | Statistical analysis

The average ECₐ within plots planted to WW, SB, and SP under CP or NT management were compared. Each plot consisted of one type of tillage and three crops, or three subplots per plot (Figure 2). There were 30 subplots in the field or 10 per crop type and 15 per tillage type. The average ECₐ of the subplots were compared with a paired t test for comparing WW with SB, WW with SP, SP with SB, NT with CP, and crop and tillage combinations. A correlation matrix was used to determine the correlation coefficients between the GDD, elevation, sand, silt, and clay percentage, θᵥ, BD, TWI, slope, and aspect.

To obtain continuous maps of ECₐ and soil variables, we fitted theoretical variogram models to experimental variograms (Table 1) in Spacestat (Biomedware, Michigan, USA, version 3.8.5) using normal-score-transformed data. Soil variables such as θᵥ, BD, and texture were depth weighted based on the sensitivity distribution given by McNeill (1980) before normal-score transform. Univariate ordinary kriging in Spacestat (Biomedware, Michigan, USA, version 3.8.5) was used to estimate spatial distributions of elevation, BD, clay, silt, and sand percentages, as well as ECₐ. Continuous maps of the variables were created with a back transformation of the kriged data (see for example Figure 3).

Lastly, we used PCR to derive a model for θᵥ. In PCR, PCA is used to decompose the independent measured variables (MVs) into an orthogonal basis (eigenvectors) and select a subset of those components as the variables to predict θᵥ. Principal component regression and PCA are useful techniques for dimensionality reduction and are especially useful when the independent variables are highly colinear, which is typical for soil data. Generally, one selects the principal components with the highest variance because the subspace defined by these principal components captures most of the variation in the data, and thus captures most of the qualities of the data. We used PCA in Spacestat. Resultant eigenvectors represent condensed variables (CoVs) of the original MVs and are thus defined by the dataset at hand, not a priori (Jolliffe & Cadima, 2016). The CoVs are ordered in such a way that the first component describes the largest fraction of the original data variance. Since θᵥ data were collected at the 12 collection sites, data used in the PCA were limited to these 12 locations for all collection dates (Figure 2). The resulting CoVs, along with categorical values for crop and tillage type, were used to predict θᵥ using multiple linear regression. The predicted θᵥ was then compared with the measured θᵥ for the 12 sites from April to October. We tested several PCR models determined by leaving out one or combinations of the MVs from the PCA and selecting the one that presented the highest correlation coefficient. The resulting CoVs and the categorical values, crop, and tillage type were then used in a multiple linear regression to predict θᵥ for the entire field for all collection dates.
Figure 3 illustrates kriged maps of (a) clay content, (b) bulk density, (c) topographic wetness index (TWI), and (d) apparent electrical conductivity (ECa) for select dates. Clay content and TWI are depicted as examples of soil textural and topographic variables considered in predicting volumetric water content. The time-lapse maps of kriged and temperature-corrected ECa show linear patterns (east–west direction) that correspond with crop strips but also reveal the influence of soil properties and topography on the observed ECa. Not all ECa maps are shown. July images are highlighted as a transition.

3 RESULTS

3.1 Soil properties

Kriged clay content and BD distributions are shown in Figure 3a,b. Seventy four percent of the field was classified as silty clay loam, and 26% was silt loam. The clay percentage ranged from 23 to 37%, with an average of 30%. The lower half of the field had a higher clay content than the upper portion of the field, with notably higher clay content on the southeast side. Silt content was greatest on the upper northern half of the field and decreased on the lower half. Silt ranged from 57 to 71% and averaged 64% for all soil samples. Bulk density was lowest on the upper half of the field and on the lower southwest side and ranged from 1.44 to 1.7 g cm⁻³, with an average of 1.61 g cm⁻³ (Figure 4c). Bulk density increased towards the east and midsection of the field, as did clay content.

Soil samples collected on 8 and 24 May 2012 were analyzed to determine the impact of fertilizer application on pH and ECe. The soil pH and ECe before and after fertilizer application did not differ significantly for the surface nor any other depth (paired t test, α = .05). The average pH for all depths (maximum depth of 55 cm) before and after fertilizer application was 4.98 and 4.84, respectively. The average ECe for all depths (maximum depth of 55 cm) before and after fertilizer application was 0.34 and 0.40 mS m⁻¹, respectively. Due to the relative stability in soil pH and ECe over time with fertilizer application, they were not included as factors that influence transient ECa for this field in the PCA and linear regression discussed below.

3.2 Agronomic differences

Figure 3d show kriged maps of ECa. Patterns of ECa among crops changed distinctly between the beginning and the end of the growing season (Figure 4). Spring rains resulted in slight increases in ECa between April and June (compare Figure 1). With precipitation for the growing season ending in July, ECa began to decrease. From August through October, the ECa remained relatively constant with no precipitation during these dates. These trends were consistent for all
FIGURE 4  Mean apparent electrical conductivity ($Ec_a$) of winter wheat (WW), spring barley (SB), and spring pea (SP) subplots compared over the growing season. Within-date differences between crops or tillage practice are indicated by the lettering above columns (paired $t$ test, $\alpha < .05$). Dotted and dashed lines show the mean $Ec_a$ for each crop comparing chisel plow (CP) and no-till (NT) plots, respectively.

crops (Figure 4a). At the beginning of the crop season (May–2 July), SP (42 mS m$^{-1}$) and SB (40 mS m$^{-1}$) had greater average $Ec_a$ than WW (35 mS m$^{-1}$). At the end of the season (August–October), SB (23 mS m$^{-1}$) and WW (23 mS m$^{-1}$) had lower average $Ec_a$ values compared with that measured in SP (28 mS m$^{-1}$). Between 17 April and 17 June 2012, SP did not show significantly different $Ec_a$ compared with SB (paired $t$ test, $\alpha = .05$). Winter wheat $Ec_a$ was $\sim17\%$ less than that of SP and $12\%$ less than that of SB from 24 May to 19 July and remained $\sim19\%$ less than SP $Ec_a$ for the majority of the rest of the season. Spring barley $Ec_a$ became significantly less than SP $Ec_a$ starting on 11 July and continued to be $\sim18\%$ less for most of the season. In the latter portion of the growing season, from 30 July to 4 Oct. 2012, WW and SB were not significantly different. On 30 July, the SP $Ec_a$ did not match its $Ec_a$ pattern of the rest of the season. This may be partially true due to the growth stage of the peas and the difficulty of transporting the EMI instrument through the tightly wound tendrils causing the meter to be held at a greater distance from the ground. Between 24 May and 4 Oct. 2012, $Ec_a$ in WW, SB, and SP subplots decreased by 46, 43, and 36%, respectively.

Chisel plow plots were between 6 and 12% lower in $Ec_a$ compared with NT for all collection dates (Figure 4b). From April to October, average $Ec_a$ decreased by 12.3 mS m$^{-1}$ for CP and 12.9 mS m$^{-1}$ for NT. The difference in means between $Ec_a$ in NT and CP at any date ranged from 2.2 and 4.4 mS m$^{-1}$, with NT maintaining greater $Ec_a$, with the beginning of the season having the largest difference.

Tillage had a stronger influence on $Ec_a$ within SB and WW sections than within SP sections. Between April and July, SB NT maintained similar $Ec_a$ to SP subplots. Spring barley CP had lower $Ec_a$ values than did SB NT and was at about the same level of $Ec_a$ as WW NT from May to July. Winter wheat CP had the lowest $Ec_a$ from May to July. From August to October, SP NT and CP plots maintained the greatest $Ec_a$, followed by SB NT and WW NT, with SB CP and WW CP having similar relatively lower mean $Ec_a$. Spring barley NT had significantly greater average $Ec_a$ on 17 April and 11 July, with all other dates having no significant difference between NT and CP SB subplots. Barley NT averaged 32.9 mS m$^{-1}$, whereas SB CP averaged 28.6 mS m$^{-1}$ from April to October. Winter wheat NT had greater average $Ec_a$ than WW CP subplots on 10 June, 2 July, 11 July, 19 July, 30 July, 19 Aug., and 15 Sept. 2012, with an average of 27.2 mS m$^{-1}$ for CP and 30.4 mS m$^{-1}$ for NT. Spring peas NT and CP did not have different average $Ec_a$ between subplots for any collection date, with an average of 34.2 and 33.1 mS m$^{-1}$ across dates, respectively.

3.3 Soil water prediction

The MVs of GDD, elevation, aspect, slope, TWI, $Ec_a$, $\theta_v$, BD, and sand, silt, and clay percentage, were compared in a correlation matrix (Table 2). The $Ec_a$ was highly correlated with many of the other variables, contrasting with $\theta_v$, which was only highly correlated to three of the MVs according to the correlation matrix. The main variables that correlated with $Ec_a$ were silt ($r = -.68, p = 1.43 \times 10^{-16}$), clay ($r = -.65, p = 6.2 \times 10^{-15}$), elevation ($r = -.63, p = 1.1 \times 10^{-13}$), $\theta_v$ ($r = .60, p = 2.2 \times 10^{-12}$), GDD ($r = -.48, p = 9.9 \times 10^{-9}$), BD ($r = .40, p = 1.4 \times 10^{-5}$), and TWI ($r = .30, p = 1.5 \times 10^{-3}$). The main MVs that correlated
TABLE 2  Correlation matrix of growing degree days (GDD), elevation, aspect, slope, topographic wetness index (TWI), sand, silt, and clay content (as a fraction), electrical conductivity (ECa), bulk density (BD), and volumetric water content (VWC) is shown. The values indicate the correlation coefficient (r) between two variables

| Variable | GDD       | Elevation | Aspect | Slope     | TWI       | Sand | Silt | Clay | ECa     | BD | VWC |
|----------|-----------|-----------|--------|-----------|-----------|------|------|------|---------|----|------|
| GDD      | 1.000     |           |        |           |           |      |      |      |         |    |      |
| Elevation| .031      | 1.000     |        |           |           |      |      |      |         |    |      |
| Aspect   | −.034     | −.230     | 1.000  |           |           |      |      |      |         |    |      |
| Slope    | .088      | .495      | −.201  | 1.000     |           |      |      |      |         |    |      |
| TWI      | −.052     | −.689     | .411   | −.604     | 1.000     |      |      |      |         |    |      |
| Sand     | −.038     | .195      | −.201  | −.098     | 1.000     |      |      |      |         |    |      |
| Silt     | −.019     | .762      | −.127  | −.269     | −.438     | .426 | 1.000|      |         |    |      |
| Clay     | .023      | −.735     | .049   | −.218     | .419      | −.549| −.990| 1.000|         |    |      |
| ECa      | −.477     | −.629     | .185   | −.215     | .295      | −.152| −.680| .652 | 1.000   |    |      |
| BD       | .031      | −.324     | .211   | −.080     | .224      | .001 | −.687| .635 | .398    | 1.000 |      |
| VWC      | −.594     | −.338     | −.123  | −.055     | .120      | .006 | −.197| .181 | .601    | .069 | 1.000 |

TABLE 3  The measured variables (MVs) and their corresponding influence on the condensed variable (CoV). The larger the absolute value, the greater the influence the MV has on that CoV. Above the MVs is the cumulative variance for each CoV. This represents the amount of variance in the data that is accounted for by the corresponding CoV

| MVa | CoV1 | CoV2 | CoV3 |
|-----|------|------|------|
| GDD | 0.09 | 0.87 | −0.05|
| Elevation | 0.48 | −0.11 | 0.85 |
| Silt | 0.53 | −0.19 | −0.34|
| Clay | −0.52 | 0.20 | 0.41 |
| ECa | −0.46 | −0.38 | 0.02 |
| Axis variance | 0.65 | 0.24 | 0.06 |
| ΣVariance | 0.65 | 0.89 | 0.96 |

aGDD, growing degree days; ECa, apparent electrical conductivity.

with θv were ECa (r = .60, p = 2.2 × 10−12), GDD (r = −.59, p = 4.7 × 10−12), and elevation (r = −.34, p = 2.7 × 10−4). Slope and aspect were not highly correlated with either ECa or θv.

For the prediction of θv using a PCA the MVs ECa, GDD, elevation, silt, and clay content were used due to their correlation with θv and ECa. In addition, the PCA was done repeatedly with all variables and compared with respect to the correlation coefficient when certain variables were excluded. For example, silt and clay were part of the final PCA as their inclusion resulted in a greater correlation coefficient and therefore prediction of θv. Apparent electrical conductivity, GDD, elevation, silt, and clay content MVs were used in a PCA by creating the three CoVs that account for 96% of the variability in the data (Table 3). The first CoV, which accounted for the most variability in the data (65%) had high loadings for several of the variables including elevation, silt, clay, and ECa. The second CoV had a high loading for GDD and accounted for an additional 24% of the variability in data. The main contributor to the third CoV was elevation and, to a lesser extent, clay content and accounted for another 6.5% of the variability, giving a total of 96% of the variability accounted for in the PCA.

To predict spatiotemporal changes in θv, we used a multiple linear regression in PCR transformations of MVs to CoVs (eigenvectors). The created CoVs in combination with crop type were used to create a linear regression equation to predict θv. Including tillage type in this regression did not increase the predictability of θv, as evident by no change in the correlation coefficient with its addition, and was not considered significant in the regression (p > .05) and was therefore not included.

A prediction model for θv in a field with WW, SB, and/or SP gives the following regression equation:

\[
\theta_v = 24.9 - 2.25225CV1 - 2.90325CV2 + 2.228952CV3 + 6.304125BV + 9.951404PV
\]

where CoVs represent the variables created by PCA using a combination of ECa, GDD, elevation, silt, and clay contents. BV represents whether or not the field was planted with SB (1 for barley, 0 for no), and PV represents whether or not the field had SP (1 for peas, 0 for no). A 0 for both SB and SP indicates WW. Figure 5 regresses the predicted θv using Equation 2 with the measured θv.

Figure 6b depicts spatiotemporal maps of the predicted θv. Predicted maps show many of the same trends seen in Figures 3 and 7, generally showing significantly lower water content under WW throughout most of the growing season compared with the other crop types (Figures 6a). Although the crop-specific predictions artificially increase the abruptness of changes in water content between crops, these abrupt changes agree with the transitions seen in Figure 7b. Beginning in July, ECa and θv decrease in step with crop growth with a notable transition in ECa where SB switches
4 | DISCUSSION

4.1 | Correlation of variables

For this study, EC\textsubscript{a} was shown to be an important factor in the prediction of \( \theta_v \) \((r = .60, p = 2.2 \times 10^{-12})\) and having a larger impact than GDD, elevation, silt, clay, aspect, TWI, BD, or slope \((r = -.60, -.34, -.2, .18, -.12, .12, .07, -.06, \text{ respectively})\). Elevation was the main topographic feature that correlated with EC\textsubscript{a} \((r = -.63, p = 1.0 \times 10^{-12})\) and, to a lesser extent, \( \theta_v \) \((r = -.34, p = 2.7 \times 10^{-4})\). This is consistent with Ibrahim and Huggins (2011), who found that topography was the main contributor and EC\textsubscript{a} was the second most important variable in the prediction of soil water content on a site 40 km northwest of our study site with similar soil types. The low correlation between TWI and \( \theta_v \) and EC\textsubscript{a} found in our study was also found by Robinson, Abdu, Lebron, and Jones (2012). The combination of catchment area and slope variation was not enough to predict locations of water accumulation. Robinson et al. (2012) suggested that TWI would likely be more useful with the incorporation of spatial soil texture. This proved to be successful, as with our study, soil texture was the main correlated factor with EC\textsubscript{a} (clay: \( r = .65, p = 6.2 \times 10^{-15} \); silt: \( r = -.68, p = 1.4 \times 10^{-16} \)), contrasting with \( \theta_v \), which was not well correlated to soil texture (clay: \( r = .18, p = .06 \); silt: \( r = -.20, p = .04 \)). Sand content was not correlated with EC\textsubscript{a} or \( \theta_v \) \((r = -.15, p = .11; r = .01, p = .95, \text{ respectively})\). Despite the lower correlation with \( \theta_v \) for the entire growing season, soil texture was still an important variable in predicting water. For our study, fertilizer additions did not appear to result in significant changes in EC\textsubscript{a}, which has been suggested as a major limitation in the applicability of EMI in accurately capturing EC\textsubscript{a}(\( \theta_v \)) relationships (Altdorff et al., 2017; Kaufmann et al., 2020). This may be partially due to possibly not capturing the localized fertilizer effect with banding application.

4.2 | Differences between crops and tillage

Few studies have addressed using EC\textsubscript{a} or EC\textsubscript{a}–based estimates of water content to study difference between crops, crop rotations, crop sequencing, or tillage despite the increased use of EMI as a noninvasive option for sensing water content at the field scale. The large amount of data collected per each subplot (~283 per subplot per date in our study) allows for a more explicit representation of variability within and across each subplot when comparing treatments. Our data showed that this is especially important when analyzing data on a hillslope. For this study, the spatial variation in soil properties and topographic features was apparent in both EC\textsubscript{a} and \( \theta_v \), which if not considered might mask significant differences in treatments.

In our study, mean EC\textsubscript{a} comparisons by crop and tillage in Figure 4 showed that the EC\textsubscript{a} of SB transitioned from aligning closely with the EC\textsubscript{a} observed in SP in the wet spring (until approximately the end of June) to aligning more closely with observations of EC\textsubscript{a} in WW in the summer dry period starting in August. Winter wheat consistently had lower EC\textsubscript{a} than SP and SB, with the exception of the first reading on 17 April. Whether it remained a significant difference or not, SP maintained the highest EC\textsubscript{a} throughout the growing season. This overall trend was mirrored by the \( \theta_v \) predictions (Figure 6), with SP retaining the highest amount of water, followed by SB. Winter wheat maintained the lowest amount of water throughout the growing season. However, the state transition of SB from the close alignment with SP early in the growing season to a close alignment with WW later in the growing season was not captured in the PCR-based water content prediction.

Since crop type was a factor in the multiple linear regression, the differences in predicted \( \theta_v \) between crops remained relatively constant over the growing season. Similar spatial heterogeneities of the EC\textsubscript{a}(\( \theta_v \)) relationship at the field scale related to crop varieties have been found by Blanchy

**FIGURE 5** Predicted and measured volumetric water content \( (\theta_v) \) from April to October, 2012. Predicted water contents are based on a linear regression model using condensed variables derived using principal component analysis calibrated on data from co-measured water content at 12 sampling sites. The correlation coefficient \( r = .89 \) for all crops combined from being similar to WW to being more similar to SP. From August to October, a drier state is predicted where the predicted \( \theta_v \) does not stay as constant temporally as EC\textsubscript{a} and continues to decrease with time due to GDD in the regression equation. Although a trend can be seen with the NT having greater \( \theta_v \) than CP subplots of SB and WW, the differences were not significant (paired t test, \( \alpha = .05 \)). The SP NT and CP subplots maintained 10 and 5% higher \( \theta_v \) than WW and SB, respectively, through the course of the entire season. No-till and CP SB also maintain ~5% more \( \theta_v \) than the WW NT and CP.
et al. (2020), who suggested using plot-specific parameters that can be estimated from baseline measurements. In our case, the variability in EC₄ was much greater compared with the crop-specific θᵥ predictions. Predicted θᵥ of individual crops decreased nearly linearly with time rather than matching the EC₄ temporal changes of more pronounced decreases from June to July and remained static from August to October (compare Figures 6 and 7). However, the percentage change from April to October was not different between EC₄ and predicted θᵥ for WW, SB, and SP (41, 36, and 25% and 41, 33, 28%, respectively; paired t test, α = .05).

Although the general behavior was concordant between EC₄ and θᵥ, discrepancies were noticeable in the dynamics amongst EC₄, θᵥ, and crop type. Our results suggest that WW extracted significantly more water than SB or SP over the entire growing season. Although our predicted water content suggests near linear depletions with time and constant offsets between crops (see Equation 2), changes in EC₄ revealed dynamics between crops that appear to better elucidate dynamics in root water uptake. Looking at Figure 4, during the wet stage until about the end of June, there is no significant difference between SB and SP, whereas the
The apparent electrical conductivity ($EC_a$) in WW, which started higher than that in SB and SP, rapidly fell to significantly below that of SB and SP, indicating a higher degree of water uptake at a time when spring rains continued to replenish water contents at the soil surface. This finding is consistent with an earlier root development of WW resulting in a greater root length for WW early in the season (Entz, Gross, & Fowler, 1992) and a significantly higher water uptake from the top 50–100 cm of the soil profile compared to SB and SP (Cann, Schillinger, Hunt, Porker, & Harris, 2020). For WW, it has been suggested that the root mass increases exponentially until the start of rapid above-ground growth and then increases linearly until anthesis (Gregory, McGowan, Biscoe, & Hunter, 1978). Over time, WW and SB both develop deep roots of 0.8–1.8 m (Cann et al., 2020; Gregory et al., 1978; Kirkegaard & Lilley, 2007) with similar root architectures. However, the highest rooting depths are associated with WW (Thorup-Kristensen, Salmerón Cortasa, & Loges, 2009), whereas peas have the shallowest rooting profile of annual crops, with 90% of all roots contained in the top 60 cm (Gregory, 1988; Liu, Gan, Bueckert, & Van Rees, 2011) with a similar trend in root length densities. Returning to Figure 4, the $EC_a$ of SB then declines faster.
than that of SP and is not significantly different from WW postharvest. We thus hypothesize that the earlier development of WW compared with SB resulted in a greater root length and water uptake for WW by the end of the wet season, but at least in terms of EC$_a$, that advantage over SB was lost by maturity, at which point there was no significant difference in EC$_a$ between WW and SB, which is consistent with findings of similar root length densities and growth rates between winter and spring plantings, but differing maximum rooting depths (Thorup-Kristensen et al., 2009). Compared with WW and SB, SP extracted water from the profile at a similar rate, but presumably mainly from shallower depths. The significantly higher EC$_a$ after the August harvests indicate SP left more soil water unused at maturity. Unused water stored at depth would benefit deep rooting crops in the subsequent season. This can be seen in Figure 4, where the EC$_a$ of WW is significantly higher than that of the spring-planted crops for the 17 April map because of the prior year pea sequence for WW. The postharvest maps with significantly higher EC$_a$ for SP are expected to lead to higher soil water maintained until the following year. Thus, we believe that that site- and crop-specific models such as ours bear potential to assess retained soil water storage either postharvest or prior to planting.

No-till and CP sections showed similar trends for the crop subplots in regard to EC$_a$ and $\theta_v$ prediction maps. No-till had greater EC$_a$ and predicted $\theta_v$ than CP for the entire season, but the difference was only significant for EC$_a$ ($p < .05$). The multiple linear regression equation did not have tillage as a specified factor in the analysis, as it did not increase the correlation between measured and predicted $\theta_v$. It is possible that PCA and regression analysis did not include tillage practices because the differences in EC$_a$ between crop types was so much greater than the differences for EC$_a$ between tillage practices, suggesting that vegetation has a much larger impact on stored soil water than tillage practices. It could also suggest NT and CP sections have similar rates of change in $\theta_v$ over the growing season. The differences between mean EC$_a$ of NT and CP plots increased notably during precipitation events (Figure 4b, April–July) and decreased during the later portion of the summer (July–October). The changes in differences between CP and NT were minimal and not apparent when looking at the $\theta_v$ prediction (Figure 6). It is likely that over time minimal amounts of increased infiltration would cause larger differences between NT and CP (Williams & Wuest, 2011). Robertson (2010) compared NT and CP soil water content on the same field as this study and showed that it can take 9 yr for NT to have greater water content than CP. The plot design for Kambitsch farm was changed after the Robertson study was completed and became the current split plot design one year prior to this study. It is suggested that the timeframe of NT conversion be taken into consideration when applying multiple linear regression for prediction of soil water content using EC$_a$.

5 SUMMARY AND CONCLUSIONS

This study described how spatial and temporal EC$_a$ data can be used in combination with elevation, soil texture, crop type, and possibly tillage practices to predict water content over time in dryland agriculture. For our study location, texture (silt and clay content), elevation, and volumetric water content were more correlated than aspect, TWI, slope, or BD was to EC$_a$. Apparent electrical conductivity, GDD, elevation, and texture (silt and clay content) were the most important site-specific variables for prediction of soil water content. Soil water content increased in areas with lower elevation and greater EC$_a$, and to a lesser extent greater silt content and lower clay content.

The addition of crop type in a model was key to predicting soil water content. We found that spring pea had the greatest retention of soil water at the end of the growing season, followed by SB and WW. The differences in soil water content between CP and NT sections were not significant. In addition, WW and SB sections were not significantly different towards the end of the growing seasons. The differences in water content between crop sections was 10 times greater than the differences between NT and CP, causing the difference in crop type to be dominant in the prediction of water. The field had only been in its current crop rotation and tillage setup for 1 yr prior to this study. Other studies with longer term NT practices would be beneficial to further understand the dynamics between tillage practices and crop rotations on soil water distribution.

While the measured EC$_a$ provides a good basis for predicting water content with more ease and spatial coverage, the measured EC$_a$ of crop subsections was more dynamic than the predicted water content. Spring pea and SB subsections had similar EC$_a$ until July, after which spring pea subsections maintained greater conductivity values for the rest of the season presumably due to a shallower root system. Spring barley subsections, starting with higher conductivity values, approached the same conductivity as WW starting in July in part due to presumably similar root length densities at maturity. Apparent electrical conductivity-based water estimates may be improved by adding a more mechanistic time component than GDD to better capture EC$_a$ changes such as a growth-stage-dependent root growth or crop coefficient model. The water content and EC$_a$ of the subsections had the same percentage decrease between April and October, indicating the potential for EC$_a$ to be able to predict water content changes for the growing season. Future work should include the comparisons between EC$_a$ and soil water content on an annual basis, to better evaluate their differences over time.

Soil water content was predicted based on EC$_a$ and site-specific variables. Using EMI-derived EC$_a$ for soil water content prediction will be very useful for farmers that are interested in quantifying how crop sequencing, intercropping,
and precision agriculture more generally affect productivity and yield. Specifically, they could have a better understanding of when spring soil moisture storage becomes depleted. Volumetric water content prediction based on $EC_a$ could also be useful for researchers trying to understand the dynamics of climate change on water distribution spatially and temporally and how different agricultural practices are affected by any changes. Lastly, $EC_a$ is more sensitive to soil water content than matric potential. The latter, however, may be a better indicator of agronomically important crop water uptake patterns and indicate more precisely when storage depletion becomes limiting to crop development, but there is no spatially exhaustive measurement technique for this assessment at this time.

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AUTHOR CONTRIBUTIONS
Meghan Brown: Conceptualization; Formal analysis; Investigation; Methodology; Writing-original draft; Writing-review & editing. Robert Heinse: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Resources; Software; Supervision; Visualization; Writing-review & editing. Jodi Johnson-Maynard: Methodology; Resources; Writing-review & editing. David Huggins: Conceptualization; Methodology; Writing-review & editing.

CONFLICT OF INTEREST
The authors declare no conflict of interest.

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