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On-farm evaluation of regenerative land-use practices in a semi-arid pasture agroecosystem in West Texas, USA

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ABSTRACT: Continually rising scarcity in water and nutrient resources, especially in semi-arid agricultural systems, combined with increased frequency of extreme weather events such as drought, contribute to a growing need for resilient and regenerative agricultural ecosystems. However, evaluating a myriad of combinations of producer-led sustainable management practices in on-farm research remains challenging. Few studies have elucidated spatial variability in measured soil properties across the study area due to logistical and economic constraints. As such, this study aimed to: 1) establish soil health assessment and landscape variability data immediately after land-use change to a sustainable pasture management system, and 2) delineate relationships and predictive capability between measured soil health parameters. Soil samples were collected on May 23, 2018 in a grid pattern across two adjacent pastures on a farm in the semi-arid Southern High Plains (Texas, USA) that had recently been converted from long-term continuous cotton production to grazed pasture. Significant differences were found in soil chemical and biological properties between pastures (e.g., ~37 % reduction in microbial community size and 36 and 178 % greater electrical conductivity (EC) and Na contents, respectively, in the East pasture) that likely resulted from recent tillage and receiving irrigation compared to similar soil types and management history in the West pasture. Spatial diagrams of measured parameters revealed localization of measured properties, such as higher clay content and soil organic matter in the southeastern portion of the study area, and clear boundaries between pastures in terms of arbuscular mycorrhizal fungi (AMF) distribution. Soil physical and chemical properties were sufficiently correlated with biological measurements to predict soil microbial community size based on routine soil test analyses. The patterns of distributed elements evaluated in this study can provide a basis for management decisions on soil health and potential contaminant monitoring across the study area. These findings provide insight as to how novel, producer-designed soil health management practices in small semi-arid production systems impact soil properties, as well as help develop cost-effective predictive modeling solutions that aid long-term monitoring efforts. Such strategies will be critical tools in resource-scarce semi-arid regions such as those found in the current study region of Texas, as well as similar semi-arid regions such as northern China and northeastern Brazil. Overall, the results of this study provide direction for long-term soil health monitoring at this site, as well as a critical evaluation of relationships between soil health indicator measurements that aids interpretation and management planning.

Keywords: grazing, tillage, EL-FAME, PXRF, landscape variability.

INTRODUCTION

Increased demand for high-quality agricultural food and fiber products combined with rising input costs, declining irrigation water resources, and increasing frequency and intensity of extreme weather events such as drought, have created an urgent need to sustainably maintain or increase agricultural productivity and profitability. Given the reliance of agricultural productivity on soil ecosystem functions such as nutrient cycling and water storage, practices that improve the soil capacity to provide these functions (termed "soil health") are a critical component of ensuring long-term food system sustainability.

Developing management practices that increase soil health and reduce agricultural reliance on irrigation will be especially critical to maintain or increase productivity in semi-arid regions such as the Texas Southern High Plains (SHP), which must also navigate declining groundwater resources, high susceptibility to soil erosion, and soil nutrient depletion in continuous cropping systems (Cano et al., 2018). Transitioning from continuous row crop systems to pasture-based livestock systems, as well as integrating pasture production into crop rotations, are economically viable options for reducing dependence on irrigation resources while improving soil health in the SHP region (Acosta-Martínez et al., 2004; Allen et al., 2012; Zilverberg et al., 2014; Bhandari et al., 2018). The sustainability and adaptation challenges faced in the SHP are similar to challenges in other semi-arid regions across the globe that rely heavily on agriculture, such as in Sub-Saharan Africa and South Africa, Inner Mongolia and the Loess Plateau of northern China, and the northeastern region of Brazil.

When establishing forage-based livestock systems for improving soil health and agricultural productivity, producers may adopt conservation management practices such as rotational grazing and providing diverse forage mixtures (Sanderson et al., 2007). In addition, studies demonstrated improved animal health and forage management with multispecies grazing, such as through chicken predation on cattle pests or weed suppression by complementary grazing habits (Hassan et al., 1991; Glatz et al., 2005a,b). Despite the potential benefits of these individual strategies, few studies have investigated the ecosystem outcomes of novel grazing systems that support multiple livestock species on diverse pasture mixes in semi-arid environments, especially at a small farm scale.

In addition, uncertainty remains as to how long it takes to improve soil health or gain associated benefits when transitioning to dryland pasture or no-till systems in a variety of semi-arid environments or in producer-managed ecosystems. For example, substantial improvements to common soil health indicator measurements such as soil organic matter (SOM), soil organic carbon (SOC), soil test nutrients, and soil microbial community size or relative abundance can take years to decades to develop in semi-arid soils with coarse textures that are limited by moisture and vegetative productivity (e.g., Bronson et al., 2004; Li et al., 2017; Lewis et al., 2018).

To address these research gaps, monitoring long-term changes in soil health at the local farm scale with diverse vegetation and livestock management strategies is critical. Production systems recently converted from continuous row crop systems to pasture with co-grazed cattle and chicken rotations designed to mimic natural ecological interactions are an ideal target for this study. In addition to capturing immediate effects of altered management in this system, the relationships between physical, chemical, and biological soil properties must be considered and how either inherent differences in soil texture or changes in easily-measured properties such as nutrients determine the strength and speed of response in other indicator measurements such as microbial community size that are not commonly available to producers.

In addition, because of the high spatial variability of soils across even small landscape scales, spatial heterogeneity of the study landscape must also be considered to enable effective sampling strategies and continued long term monitoring (Robert, 1993). In our semi-arid smallholder study system, we hypothesized that: 1) establishing grazed dryland perennial forages in the West pasture would improve soil measured properties and soil health compared to recent tillage and irrigation in the East pasture, driven largely by soil disturbance and management for increased soil vegetative cover, and 2) physical (i.e., soil textural fraction) and chemical (i.e., SOM, pH, total C and N, and elemental contents) soil properties most commonly available for producers through soil testing laboratories would be useful predictors of more specialized soil health indicators such as microbial community size and community composition, which will further help producers decide on economically feasible long-term assessment and management targets. As such, the objectives for this study were to: 1) establish soil health assessment and landscape variability data immediately after diverging land-use change in two adjacent pastures with similar management histories, and 2) delineate relationships and predictive capability between measured soil health parameters.

MATERIALS AND METHODS

General occurrence and features

The study was conducted on farmland in Major Land Resource Area (MLRA) 77C: Southern High Plains – Southern Part (Soil Survey Staff, 2006). The surface of this area is covered primarily by eolian deposits in the Blackwater Draw Formation of Pleistocene age. Lacustrine deposits of dolomite with interbedded clastic sediments are both laterally extensive where they are of Pliocene age (Blanco Formation) and more local where they are of Pleistocene age (Tule, Double Lakes, and Tahoka Formations). Locally, it draws inset alluvial deposits in the Ogallala Formation of Miocene-Pliocene age. The dominant soil orders in this MLRA are Alfisols, Inceptisols, Mollisols, and Vertisols. The soils in the area dominantly have a thermic soil temperature regime, an ustic soil moisture regime, and mixed mineralogy. Soils of the area are generally moderately deep to very deep, well drained, and clayey, loamy, or sandy (Soil Survey Staff, 2006). According to Köppen classification system (Peel et al., 2007), the climate of this area is considered BSk (Tropical and Subtropical Steppe).

The study site included ~65 ha located at Alcove Farms in Lubbock, TX (between latitude 33° 35′ 6″ and 33° 35′ 32″ N and longitude 101° 59′ 12″ and 102° 0′ 2″ W). All management strategies described below were designed and implemented by the producers. This study site had historically supported continuous irrigated row crop production, predominantly cotton (*Gossypium hirsutum*). In 2016, ~28 ha was converted to a dryland mixed grass-forb-legume pasture (West side, 11 species sown), and ~32 ha was converted to pivot-irrigated bermudagrass (*Cynodon dactylon* (L.) Pers.) pasture (East side, Tifton 85 variety). In the West pasture, the grass-forb-legume mix applied at a rate of 15.3 kg ha^{-1} included the following plants in a commercial mix (Stark Ranch - Vegetable Mix, Green Cover Seed, Bladen, NE): watermelon (*Citrullus lanatus* (Thunb.) Matsum. & Nakai var. *lanatus*), cantaloupe (*Cucumis melo* L.), squash 'Golden Summer Crookneck' (*Cucurbita moschata* Duchesne), cucumber 'Marketmore 76' (*Cucumis sativus* L.), okra 'Clemson Spineless 80' (*Abelmoschus esculentus* (L.) Moench), sunflower 'Black Oil Seed' (*Helianthus annuus* L.), green beans 'Bush Blue Lake 274' (*Phaseolus vulgaris* L.), brown top millet (*Urochloa ramosa* (L.) Nguyen), hybrid sudangrass (*Sorghum bicolor* (L.) Moench ssp. *drummondii* (Nees ex Steud.) de Wet & Harlan), buckwheat (*Fagopyrum esculentum* Moench), and Phacelia Angelia (*Phacelia tanacetifoia* Benth.). Half-ha paddocks were grazed by cattle every 70 days, although cattle were rotated earlier if forages had been grazed below approximately 0.10 m in height before the 70 day period had passed, followed by chickens on a three-day rotation in the mixed dryland pasture. The Soil Survey Staff (2020) noted two soil map units at the study site: Acuff (Fine-loamy, mixed, superactive, thermic Aridic Paleustoll) loam (79 % of the area) and Amarillo (Fine-loamy, mixed, superactive, thermic Aridic Paleustalf) fine sandy loam (21 % of the area); both occurred on slopes of 0 to 1 %. The World Reference Base (WRB) classification for these Paleustoll and Paleustalf soils was Kastanozems and Planosols, respectively (IUSS Working Group WRB, 2015).

Field sampling and laboratory analysis

Surface soil samples to a maximum depth of 0.10 m were collected from 80 total sites across the East and West study pastures on May 23, 2018 (Figure 1) per Schoeneberger et al. (2012). A 1.5 cm diameter push probe was used to collect approximately five soil sub-samples to composite for each of the 80 total sites. A portable GPSmap 60CSx (Garmin Ltd., Olathe, KS, USA) was used to locate pre-determined surface soil samples (geo-referenced field sites). Surface samples were characterized for chemical, physical, and biological properties. Air-dried, disaggregated soil (passed through a 2 mm sieve) was subjected to particle size analysis for soil textural class using the hydrometer method (Gee and Bauder, 1986) with an ASTM 152H hydrometer. Clay and sand readings were made at 1440 min and 40 sec, respectively. Samples were not treated to remove carbonates prior to analysis, as carbonate content was negligible in the surface soils. Soil elemental analysis was determined in oven-dried (105 °C), ground sub-samples using a Vanta M series (Olympus, Waltham, MA, USA) portable X-ray fluorescence (PXRF) spectrometer per Weindorf and Chakraborty (2016). The instrument was standardized with a 316 calibration alloy coin prior to scanning. Operated on line power (110 VAC), the PXRF featured a Rh X-ray tube, and a silicon drift detector operated in *Geochem mode* with scanning (dwell time) set to 45 s beam^{-1} at 10-40 keV. Instrument performance was validated using National Institute of Standards and Technology (NIST) certified reference materials. A recovery percentage relative to NIST 2711a was calculated per Koch et al. (2017) on an element by element basis yielding the following (NIST/PXRF): Ca 24,200/21,711 mg kg^{-1} (1.11); K 25,300/21,221 mg kg^{-1} (1.19); Ti 3,170/3,221 mg kg^{-1} (0.98); Cr 52/46 mg kg^{-1} (1.13); Mn 675/653 mg kg^{-1} (1.03); Fe 28,200/26,535 mg kg^{-1} (1.06); Cu 140/147 mg kg^{-1} (0.95); Rb 120/115 mg kg^{-1} (1.04); Pb 1,400/1,473 mg kg^{-1} (0.95).

Routine soil test nutrients were determined in air-dried soil samples via Mehlich 3 extraction and analysis using an inductively coupled plasma (ICP) atomic emission spectrometer in the Soil Testing and Plant Analysis Lab at Louisiana State University (LSU) (Mehlich, 1984). Soil pH and electrical conductivity (EC) levels were also determined at the LSU soil testing facility in a 1:1 (*v/v*) soil:water mixture with an electrometric meter (McLean, 1982). Soil organic matter was determined via loss on ignition (LOI) per Nelson and Sommers (1996) at 400 °C for 24 h. Total soil carbon (C) and nitrogen (N) contents were measured via high temperature combustion analysis on a LECO TruSpec CN analyzer (LECO corporation, St. Joseph, MI). Microbial community size and structure were determined via ester-linked fatty acid methyl ester (EL-FAME) analysis (Schutter and Dick, 2000).

Statistical and spatial analysis

All statistical analyses were executed in R version 3.6.0 (R Development Core Team, 2020) and XLstat software version 2019 (Addinsoft, Paris, France). Significant differences between East and West pastures for each measured variable were determined using Student's t-tests (α = 0.05). Pearson correlation analysis was initially executed to examine any linear relationship among analyzed soil physical, chemical, and biological properties using Pearson's r-values. Principal component analysis (PCA) was performed using function 'prcomp' in R to observe the clustering of soil samples coming from the East and West pasture using all chemical, physical, and biological properties. Generally, PCA indicated the linear combination of the original input variables and analyzed the structure of their correlation matrix. In this study, PCA biplot was produced to investigate the relationship among individual sample and variables used for PCA. Furthermore, to evaluate whether a combination of all analyzed soil properties could classify the samples coming from the East and West pasture, discriminant analysis (DA) was executed (Tharwat et al., 2017). Discriminant analysis was used to analyze the data when the dependent and independent variables were categorical and numeric, respectively. The DA confusion matrix summarized the reclassification of the observations and exhibited the percent (%) of correctly classified samples, which indicated the ratio of the number of correctly classified samples over the total number of samples. Additionally, nine soil biological properties including total microbial community size and the relative abundance of selected microbial FAME groups were predicted using soil physical and chemical properties via partial least squares regression (PLSR) (Wold et al., 2001) with full cross-validation. This technique has been used as a rapid, efficient, and widely used covariance-dependent regression algorithm and useful when there are many correlated explanatory variables in the model.

Finally, for all analyzed parameters (physical, chemical, and biological) of the collected soil samples, spatial analysis was applied to determine the distribution of those properties across both pastures. The Geostatistical Analyst extension in ArcMap (ESRI, The Redlands, CA, USA) was used, and the kriging method was employed as one of the most recommended spatial interpolation techniques. The best fitting variogram model was examined, and the variogram parameters (nugget, sill, and range) were calculated. The semivariogram parameters that were obtained from the fitted semivariogram models included nugget (C0), sill (C0 + C), where (C) is structured variance, and range (A). The spatial dependence was calculated for each parameter based on the ratio between nugget and sill ratio, C0/(C0 + C), as suggested by Cambardella et al. (1994). A nugget/sill ratio ≤25 % indicated a strong nugget effect with strong spatial dependency, while a nugget/sill ratio >75 % indicated weak nugget effect with weak spatial dependency, and the ration 25-75 % indicated moderate nugget effect and moderate spatial dependency. The spatial distributions of soil pH, EC (dS m^{-1}), and Mehlich 3 available Ca, P, K, S, Cu, Mg, Zn, and Na contents of collected surface soil samples were determined. Soil textural fractions (sand, silt, and clay g kg^{-1}), organic matter (LOI g kg^{-1}), and total N (TN) and C (g kg^{-1}) were also spatially interpolated. The presence of spatial patterns in the distribution of the microbial parameters (nmol FAME g^{-1} soil) such as total microbial community size, total bacteria, total fungi, protozoa, AMF, and F:B Ratio (fungal-to-bacterial ratio) were examined. Additionally, the spatial patterns of 19 elements scanned by PXRF were evaluated in this study. The examined elements included Mg, Si, Al, S, K, Ti, Ca, V, Cr, Fe, Mn, Ni, Cu, As, Zn, Rb, Sr, Y, and Pb (mg kg^{-1}). Spatial variability and distribution of selected parameters were illustrated in Figures 2, 3, and 4, with the data breaks for measured parameters chosen according to the data range and the resulting classes from the kriging interpolation as in Shit et al. (2016).

RESULTS

Physical and chemical properties

Soil textures at the site were within the range of characteristics expected for the Amarillo (Paleustoll/Kastanozem) and Acuff (Paleustalf/Planosol) soil series. Surface

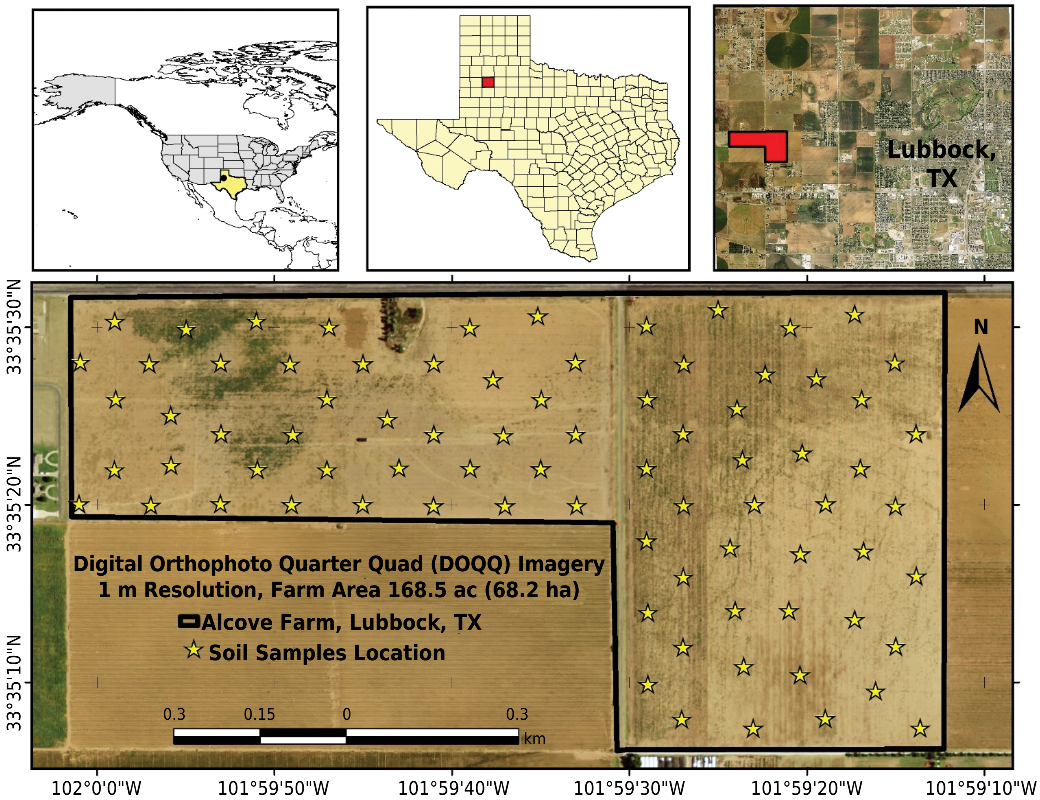

Figure 1. Location and field layout of Alcove Farm near Lubbock, TX, USA. In the top left panel, the black dot indicates the general location of the present study. In the bottom panel, the East and West pastures are separated by a vertical road transecting the total study area as seen in the satellite imagery, which is outlined in black.

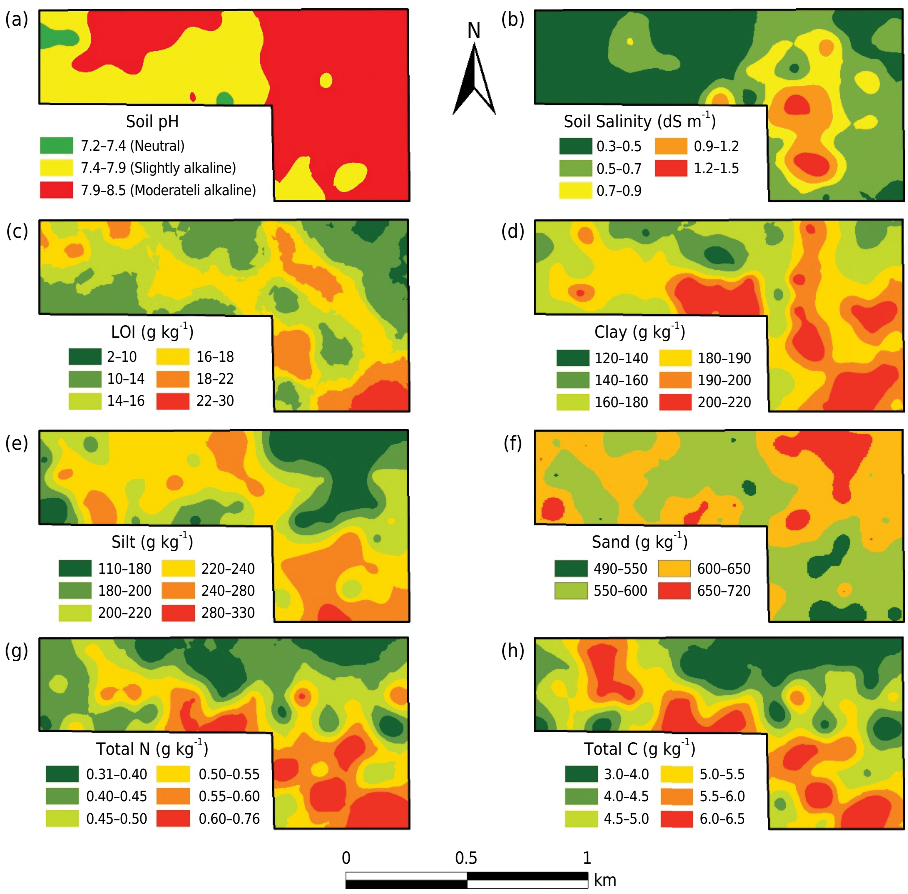

Figure 2. Spatial variability in surface (0.00-0.10 m) soil physiochemical properties at Alcove Farm near Lubbock, TX, USA.

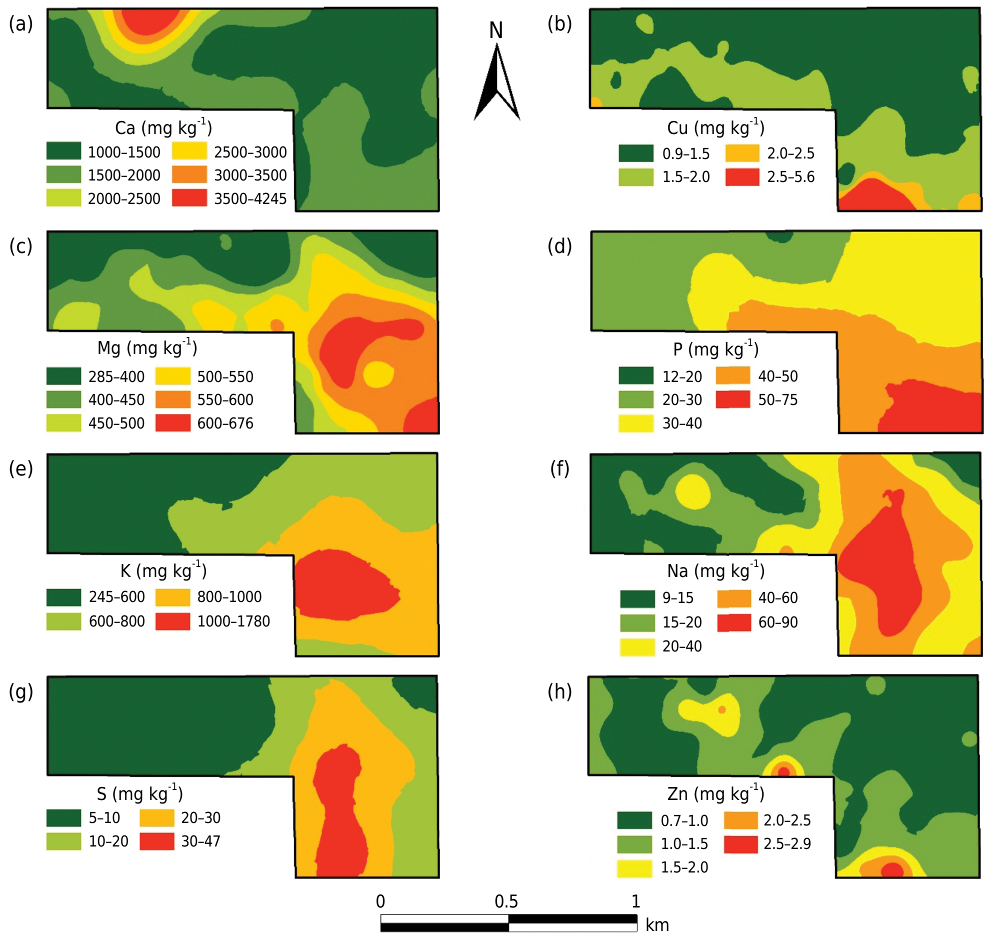

Figure 3. Spatial variability of nutrient contents (mg kg^{-1}) in the soil surface (0.00-0.10 m) of Alcove Farm near Lubbock, TX, USA.

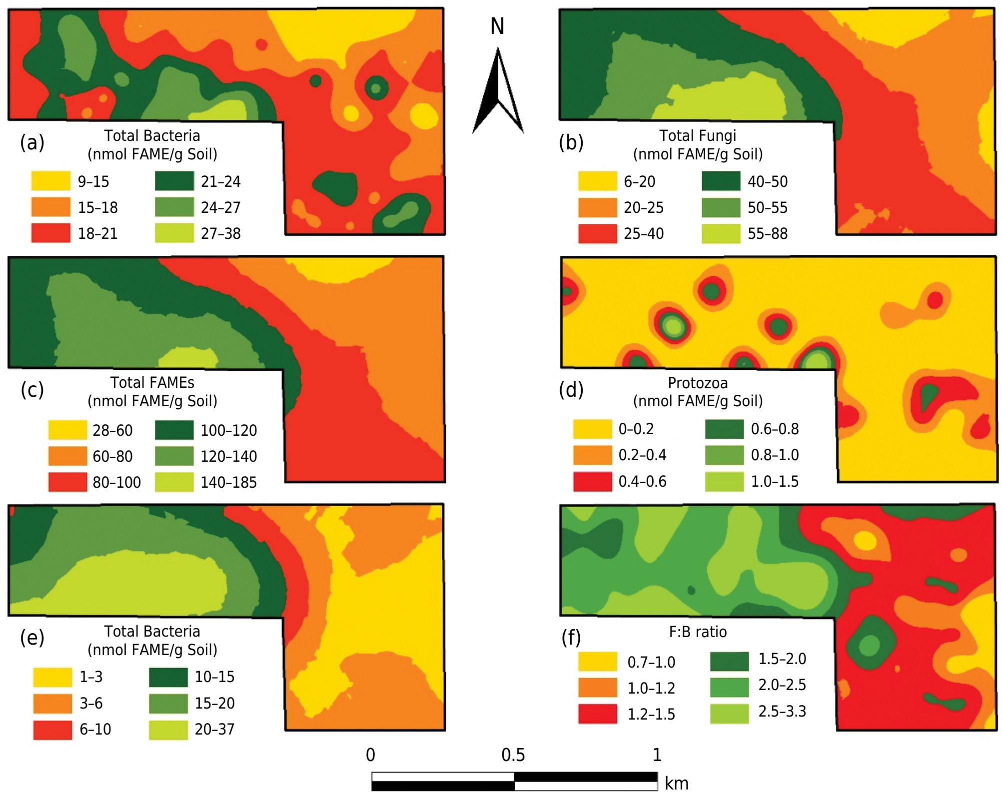

Figure 4. Spatial variability of total bacterial biomass, total fungal biomass, and total arbuscular mycorrhizal fungi (AMF) biomass in the soil surface (0.00-0.10 m) of Alcove Farm near Lubbock, TX, USA.

soil textures (0.00-0.10 m) were dominantly sandy loam (Amarillo) and sandy clay loam (Acuff). Clay and sand content averaged 182 and 602 g kg^{-1}, respectively, and neither of these were significantly different between pastures (Table 1). Electrical conductivity was low, ranging from 0.28 to 1.50 dS m^{-1} ($\bar{x}$ = 0.58 dS m^{-1}), and was significantly higher in samples from the East pasture (Table 1). Soil reaction (pH) was also significantly higher in the East pasture and ranged from 7.23 to 8.59 ($\bar{x}$ = 7.93) across both pastures (Table 1); 31 samples featured a pH(H_2O) ≥8.0. Increased pH was significantly associated with PXRF-determined Ca (r = 0.249), Na (r = 0.391), and EC (r = 0.246). Total N content ranged from 0.21 to 0.76 g kg^{-1} ($\bar{x}$ = 0.49 g kg^{-1}) while total C ranged from 2.77 to 7.13 g kg^{-1} ($\bar{x}$ = 4.92 g kg^{-1}). Loss on ignition (LOI) organic matter (OM) was generally low, ranging from 2.4 to 29.9 g kg^{-1} ($\bar{x}$ = 15.3 g kg^{-1}); only 22 samples featured OM ≥20.0 g kg^{-1}. However, none of these three variables (i.e., total N and C, and OM) significantly differed between East and West pastures when samples were averaged within each pasture (Table 1).

Spatial representation of data revealed more nuanced differences in the distribution of measured parameters across the study area than pasture-averaged comparisons alone. For example, higher clay content was more prevalent and evenly distributed in the East pasture relative to the West pasture (Figure 2d). Although subtle, the East pasture also featured higher LOI that was more concentrated in the southeastern portion of the pasture (Figure 2d). We observed a strong spatial dependency (nugget/sill ratio ≤25 %) for most parameters, which indicated that structural factors played a significant role in the degree of spatial variability (Shit et al., 2016). In contrast, both structural and stochastic factors resulted in a moderate spatial dependency (nugget/sill ratio between 25 and 75 %) for total FAMEs and total fungi as well as soil K, V, Rb, and Sr contents (Shit et al., 2016).

Elemental analysis

All nutrients measured via ICP analysis were present in significantly greater contents in the East pasture compared to the West pasture when samples were averaged within each pasture, with the exception of Cu, Zn, and Ca (Table 1). However, the West pasture contained significantly higher Ca contents than the East pasture as measured by ICP, but not as measured by PXRF (Table 1). The elemental analysis via PXRF revealed few differences in macro- and micronutrients, including low contents of naturally-occurring heavy metals, between pastures (Table 1).

Spatial analysis of soil test nutrients across both pastures (Figure 3), revealed that elements such as Cu and Zn were not significantly different between pastures but exhibited distinct localization during spatial analysis. Despite no differences in pasture-averaged samples (Table 1), higher contents of both Cu and Zn were found in the southeast area of the East pasture, with localized portions in the southern half of the West pasture also containing elevated contents (Figure 3).

Biological properties

Soil microbial community size (total nmol FAME g^{-1}) and the abundance of selected microbial groups of bacteria and fungi differed significantly between pastures, with greater abundance in the West pasture for all measured soil biological parameters (Table 1). Total microbial abundance levels ranged from 27.68 to 184.72 nmol FAME g^{-1} ($\bar{x}$ = 98.28 nmol FAME g^{-1}) across pastures. Similar to spatial distribution of soil physical and chemical properties, spatial assessment of soil biological responses such as bacterial and fungal abundance revealed distinct patterns of distribution across the East and West pastures (Figure 4). Total bacterial abundance was concentrated in a few areas across both pastures, while there was sharp contrast in fungal abundance, particularly of AMF, in the West pasture compared to the East pasture (Figure 4).

Table 1. Field-averaged study results for measured parameters in the East and West pastures in surface soils (0.00-0.10 m) of Alcove Farm near Lubbock, TX, USA

Study Parameter	East (n = 41)	s.e.	West (n = 39)	s.e.	p-value
Microbial biomass					
Total FAMEs (nmol FAME g^{-1} soil)	76.39	4.04	121.29	4.89	**<0.01**
Protozoa (nmol FAME g^{-1} soil)*	0.53	1.07	0.94	1.12	**<0.01**
Total Bacteria (nmol FAME g^{-1} soil)*	17.12	1.05	21.13	1.04	**<0.01**
Gram + bacteria (nmol FAME g^{-1} soil)*	9.30	1.05	11.68	1.04	**<0.01**
Gram − bacteria (nmol FAME g^{-1} soil)*	2.05	1.04	2.61	1.04	**<0.01**
Actinobacteria (nmol FAME g^{-1} soil)	5.91	0.22	6.95	0.22	**<0.01**
Total Fungi (nmol FAME g^{-1} soil)	23.79	1.50	51.07	2.38	**<0.01**
AMF (nmol FAME g^{-1} soil)	3.02	0.21	19.18	1.15	**<0.01**
F:B ratio	1.30	0.04	2.36	0.07	**<0.01**
Soil texture					
Sand (g kg^{-1})	600	8.9	610	8.1	0.29
Clay (g kg^{-1})	190	2.7	180	3.7	0.07
Silt (g kg^{-1})	220	7.7	210	5.6	0.65
Soil chemical properties					
EC (ds m^{-1})	0.69	1.05	0.42	1.05	**<0.01**
pH (1:1 soil:water)	8.06	0.03	7.80	0.04	**<0.01**
LOI (g kg^{-1})	16.0	1.3	14.6	0.9	0.39
Total N (g kg^{-1})	0.51	0.02	0.47	0.01	0.16
Total C (g kg^{-1})	4.82	0.17	5.02	0.15	0.38
Soil nutrients (mg kg^{-1})					
Ca*	1455.60	1.03	1626.75	1.05	**0.05**
Cu	1.58	0.12	1.45	0.04	0.28
Mg	529.43	14.25	425.68	11.90	**<0.01**
P*	40.42	1.04	26.51	1.08	**<0.01**
K*	850.29	1.06	572.03	1.03	**<0.01**
Na*	43.62	1.08	15.70	1.05	**<0.01**
S*	20.83	1.09	6.95	1.04	**<0.01**
Zn*	0.97	1.05	1.06	1.05	0.19
Elemental analysis (mg kg^{-1})*					
Mg	5646.46	236.63	5084.00	217.59	0.09
Al	78578.49	697.00	78501.54	669.23	0.94
Si	299917.44	3186.21	299985.67	1872.78	0.99
S**	103.09	1.14	60.61	1.14	**0.01**
K	12253.88	241.90	11388.38	212.95	**<0.01**
Ca**	1122.89	1.41	763.68	1.46	0.46
Ti	2937.24	55.22	2878.21	43.17	0.40
V	62.80	1.42	60.21	1.31	0.18
Cr	52.37	1.88	51.95	1.43	0.86
Mn	288.56	8.88	274.64	7.98	0.25
Fe	15393.56	304.05	14659.74	292.16	0.09
Ni**	32.49	1.04	32.22	1.03	0.88
Cu**	13.34	1.03	12.90	1.03	0.37
Zn	38.83	0.93	38.38	0.86	0.73
As**	6.31	1.02	5.39	1.03	**<0.01**
Rb	57.51	1.13	54.38	1.02	**0.04**
Sr	87.12	2.75	76.92	1.82	**<0.01**
Y	15.34	0.43	14.36	0.32	0.07
Hg**	2.45	1.12	2.33	1.08	0.71
Pb**	11.13	1.02	10.73	1.03	0.27

* Elements not detected in study samples included P, Co, Se, Mo, Ag, Cd, and Au. ** Data were log-transformed for statistical analysis to satisfy assumptions of normality. Back-transformed means and standard error (s.e.) are reported. Significant p-values (α = 0.05) for differences between pasture means for each variable are highlighted in bold text. Values are means, with the standard error (s.e.) reported beside each mean. P-values from Student's t-test results for two samples to determine significant differences between fields is also reported.

Correlations between variables

Pearson correlation analysis between all measured variables revealed several relationships between soil textural fraction, chemical, and biological properties that informed and supported further analyses. Analytical focus was primarily on linkages observed between soil texture or chemical study variables and biological parameters (Tables 2 and 3). Significant positive linear correlations were observed between the total soil microbial community size (total FAMEs) and soil properties such as silt content, TN, and TC; significant negative correlations were found with sand content and pH (Table 2). Similar negative relationships were observed with the abundance of microbial groups including total bacteria, Gram+ bacteria, Gram− bacteria, and actinobacteria, with the addition of a significant positive relationship with clay content (Table 2). Abundance of total fungi and AMF were not significantly correlated with soil textural fraction but were negatively

Table 2. Pearson correlation coefficients (r-values) calculated between selected soil physical and chemical properties and soil microbial measurements in surface soils (0.00-0.10 m) of Alcove Farm near Lubbock, TX, USA

Measured parameter	Total FAME	Protozoa	Total Bacteria	Gram+ Bacteria	Gram− Bacteria	Actino-bacteria	Total Fungi	AMF	F:B ratio
Sand	**-0.28****	-0.15	**-0.36*****	**-0.32*****	**-0.37*****	**-0.44*****	-0.20	-0.09	0.00
Clay	0.18	0.15	**0.29****	**0.26***	**0.28****	**0.34*****	0.11	-0.03	-0.10
Silt	**0.27***	0.12	**0.32*****	**0.27****	**0.33*****	**0.40*****	0.20	0.12	0.04
LOI	0.11	0.01	0.16	0.15	0.11	0.19	0.07	-0.04	-0.03
salinity	-0.18	-0.15	0.01	0.03	-0.07	-0.01	**-0.29****	**-0.46*****	**-0.42*****
pH	**-0.34*****	0.00	**-0.25***	**-0.25***	**-0.29****	-0.21	**-0.37*****	**-0.38*****	**-0.37*****
TN	**0.45*****	0.15	**0.66*****	**0.65*****	**0.61*****	**0.68*****	**0.29****	0.01	-0.07
TC	**0.66*****	0.12	**0.77*****	**0.74*****	**0.73*****	**0.82*****	**0.53*****	**0.25***	0.20

Statistically significant correlations between variables are indicated with bold type, and the level of significance is indicated by asterisks (* significant at p<0.05; ** significant at p<0.01; *** significant at p<0.0001).

Table 3. Pearson correlation coefficients (r-values) calculated between selected soil nutrient properties and soil microbial measurements in surface soils (0.00-0.10 m) of Alcove Farm near Lubbock, TX, USA

Measured parameter	Total FAME	Protozoa	Total Bacteria	Gram+ Bacteria	Gram− Bacteria	Actino-bacteria	Total Fungi	AMF	F:B ratio
ICP analysis (mg kg^{-1})									
Ca	0.19	-0.07	0.10	0.07	0.12	0.14	0.21	**0.22***	**0.25***
Cu	0.05	-0.02	0.11	0.08	0.11	0.16	0.00	-0.03	-0.09
Mg	-0.09	0.05	0.07	0.05	0.06	0.12	-0.18	**-0.30****	**-0.36*****
P	0.03	-0.12	**0.24***	**0.27****	0.21	0.17	-0.09	**-0.28****	**-0.32*****
K	-0.17	0.07	0.05	0.05	-0.03	0.07	**-0.29****	**-0.43*****	**-0.45*****
Na	**-0.42*****	-0.13	-0.21	-0.18	**-0.26***	**-0.23***	**-0.52*****	**-0.65*****	**-0.63*****
S	**-0.41*****	-0.16	**-0.23***	-0.21	**-0.28****	-0.22	**-0.50*****	**-0.60*****	**-0.57*****
Zn	0.20	-0.04	**0.25***	**0.25***	**0.26***	0.22	0.17	0.11	0.07
PXRF analysis (mg kg^{-1})									
Ca	-0.11	-0.13	-0.17	-0.16	-0.15	-0.17	-0.08	-0.06	-0.01
Cu	0.16	0.00	**0.24***	0.19	**0.26***	**0.32*****	0.12	0.04	-0.04
Mg	0.01	0.01	0.11	0.10	0.11	0.13	-0.05	-0.12	-0.16
P	**0.27****	-0.05	**0.39*****	**0.43*****	**0.42*****	**0.25***	0.19	0.03	0.00
K	0.10	0.07	**0.28****	**0.25***	**0.25***	**0.35*****	0.00	-0.12	**-0.23***
S	**-0.23***	-0.14	-0.11	-0.09	-0.16	-0.13	**-0.27****	**-0.37*****	**-0.34*****
Zn	**0.34*****	0.10	**0.41*****	**0.36*****	**0.41*****	**0.49*****	**0.27****	0.12	0.06

Statistically significant correlations between variables are indicated with bold type, and the level of significance is indicated by asterisks (* significant at p<0.05; ** significant at p<0.01; *** significant at p<0.0001).

correlated with both EC and pH (Table 2). Arbuscular mycorrhizal fungi abundance exhibited negative linear correlations with Mg, P, K, Na, and S measured via ICP, and had a positive correlation with soil Ca (Table 3). In general, the amount of total microbial community size was not strongly associated with most soil nutrients measured in this study, except for a negative linear correlation with Na and S, and a positive relationship with Zn and P as measured by PXRF (Table 3). Especially in the case of elemental contents measured by PXRF, soil Zn had a positive linear correlation with each microbial parameter except protozoa and AMF abundance and the F:B ratio (Table 3).

PCA, DA, and PLSR analyses

From the PCA bi-plot (Figure 5), it was clear that PC1 and PC2 combined explained ~55 % of the total variance. A clear location pattern among the samples was discernible. The PC1 mainly showed the direction for most of the PXRF and ICP reported elements. The PC2 mainly exhibited the directions of soil biological properties while samples with large PC2 had large values on these variables. Notably, all biological properties were closely correlated with each other. As expected, PXRF-determined Si and sand fraction were closely related to each other while the Si and sand fraction were negatively correlated to other PXRF and ICP reported elements. Notably, PXRF Si and pH had very small loading values on PC1 and PC2, respectively. Most importantly, samples from two locations (East vs. West pastures) were separated along PC2 while the samples from the West pasture showed more influence from the biological properties. The excellent location-wise separation of samples via PCA was further corroborated by the DA analysis, which exhibited perfect classification with 0 % misclassification rate (Table 4). Summarily, both PCA and DA indicated the clear differences of the samples coming from two different locations while combining the physical, chemical, and biological properties. Additionally, PLSR was able to predict most of the biological properties with reasonable accuracy. Except for protozoa (R^2 = 0.06), all other biological properties exhibited coefficient of determination ranging from 0.44 to 0.58 (Figure 6).

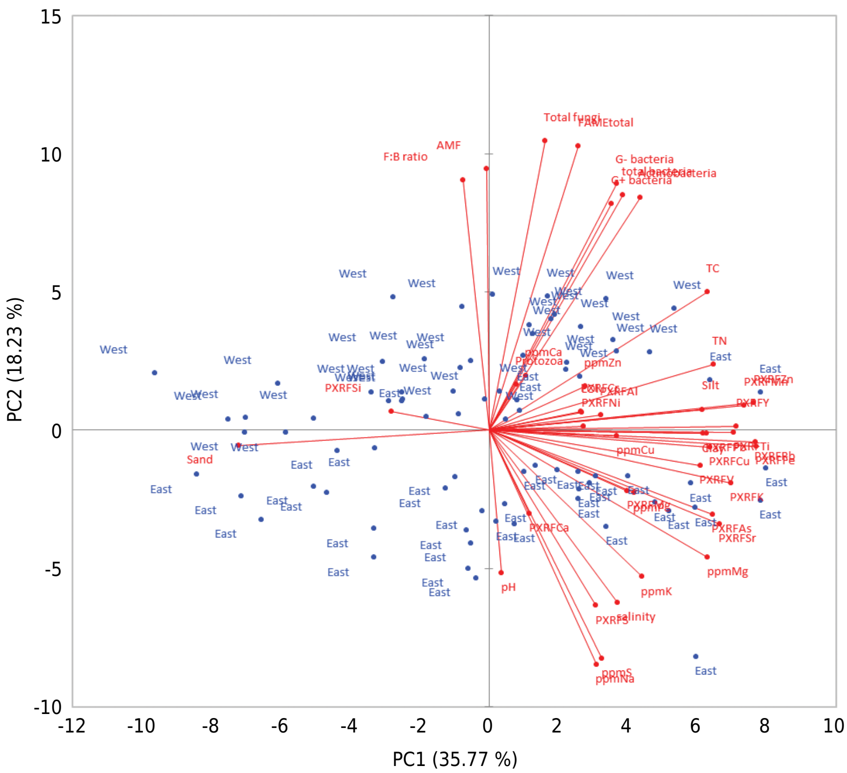

Figure 5. Principal components bi-plot illustrating the association of soil physical, chemical, and biological factors of surface soils (0.00-0.10 m) at Alcove Farm near Lubbock, TX, USA. Clear differentiation can be observed between the East and West parts of the farm along PC2.

Table 4. Confusion matrix from discriminant analysis showing the classification accuracy of surface soil samples (0.00-0.10 m) from the East and West pastures of Alcove Farm near Lubbock, TX, USA

from \ to	East	West	Total	% correct
East	41	0	41	100
West	0	39	39	100
Total	41	39	80	100

DISCUSSION

The purpose of this study was to examine differences between two adjacent semi-arid pastures under contrasting management practices, with the West pasture supporting dryland grazing of cattle and chickens, and the East pasture subjected to recent tillage and receiving irrigation to support forage production for cattle. Both were recently converted from similar histories of continuous tillage cotton row crop production and are strategies employed in the semi-arid Texas Southern High Plains (SHP) to restore degraded soil and reduce overall agricultural reliance on groundwater resources. To aid in long-term soil health monitoring and interpretation, we also sought to establish predictive relationships between routinely-measured soil physical and chemical properties and more intensive characterizations of microbial community size and composition.

Differences between pastures after land-use divergence

Significant differences between pastures were found for several soil chemical properties, including EC, pH, and soil test nutrients such as Ca, Mg, P, K, Na, S, and Zn (Table 1). Compared to the West pasture, significantly greater pH, EC, and Na in the East pasture (Table 1) most likely resulted from higher amounts of irrigation applications, including more recent irrigation events prior to sampling, given that the groundwater used for irrigation in this region has been subjected to increased temporal salinization (Chaudhuri and Ale, 2014). In addition, spatial diagrams revealed that many soil measured properties were highly localized across the study area and likely linked to similar spatial patterns of other study variables, such as textural differences. For example, patchy increases in soil OM and total soil C may be partially explained by higher clay contents in certain areas of the study pastures (Figure 2). Generally, the clay fraction of agricultural soils has been reported to accumulate more soil organic carbon than other fractions under long-term agricultural management practices (Burke et al., 1989; Jagadamma and Lal, 2010). Because of the high charge and specific surface area, soil clay minerals are the most active constituents in the formation of organo-mineral complexes, resulting in higher soil organic carbon concentration in the clay fraction that favors more biological activity. While the differences were modest, higher clay and organic matter content often facilitate higher soil cation exchange capacity (CEC), especially at more alkaline soil pH levels (Helling et al., 1964), and have subtle yet positive effects on soil water holding capacity (Hudson, 1994). Despite no significant differences between pasture mean values for total C, total N, and SOM parameters, visualization of inherent soil physical properties (e.g., textural fraction) that heavily influence important properties such as biological functioning, as well as targeted soil health indicators such as SOM, will aid producers in making site specific management decisions for vegetation and soil management across the study pasture. For example, areas that may benefit from the targeted improvement of vegetative cover and reduced disturbance to increase SOM include the northeast corner of the East pasture, and the southwest corner of the West pasture (Figure 2).

Overall, routine soil test nutrients were often significantly depleted in the West pasture compared to the East pasture (Table 1). This was likely due to the fact that the East pasture had been only recently tilled and converted to bermudagrass cover that was still in the early stages of plant growth and establishment, while the West pasture was

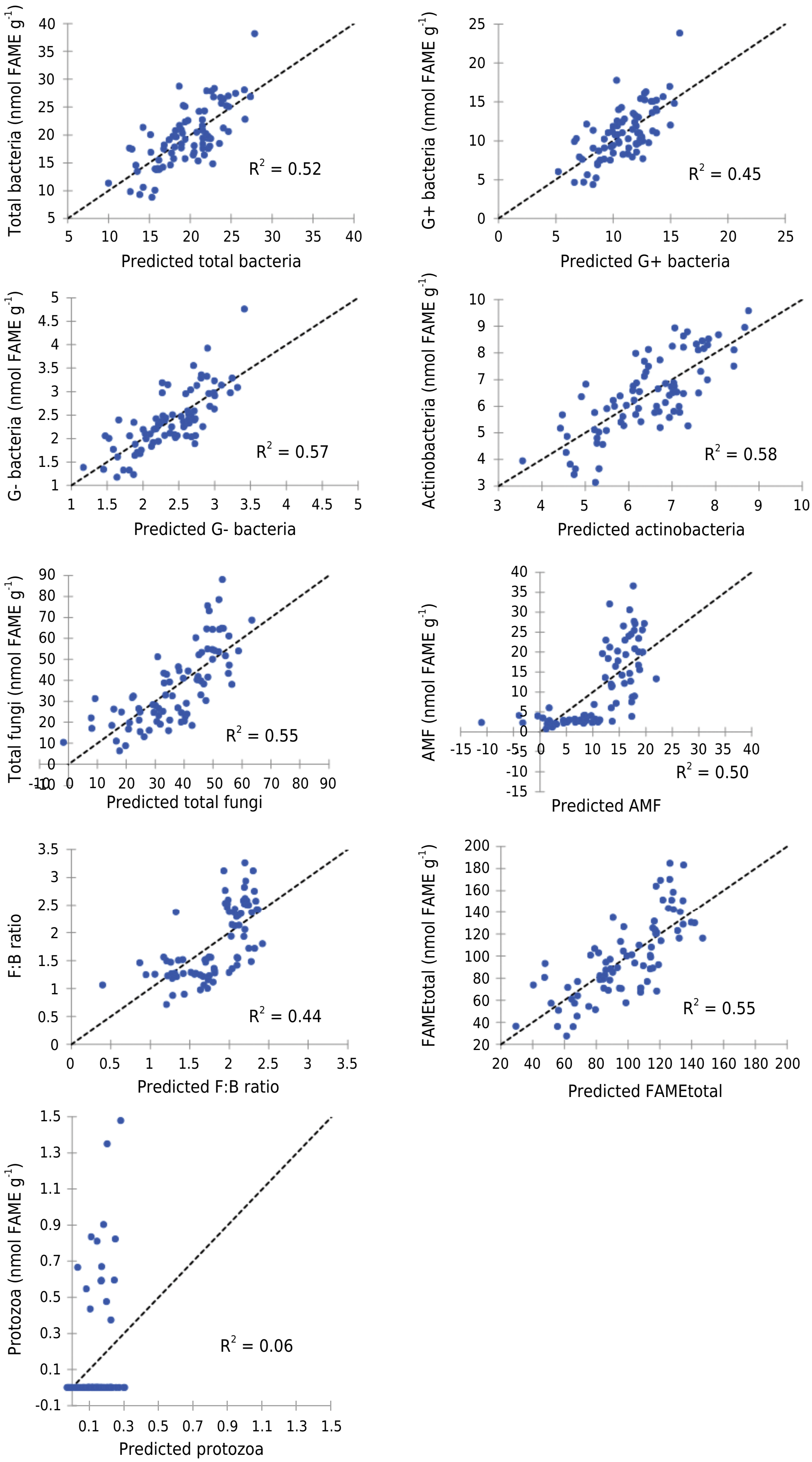

Figure 6. Cross-validated partial least squares regression of measured vs. predicted biological properties in surface soils (0.00-0.10 m) of Alcove Farm near Lubbock, TX, USA. With the exception of protozoa, coefficient of determination values ranged from 0.44 to 0.58.

already vegetated and in use for grazing. Spatial analysis of soil test nutrients across both pastures (Figure 3), however, provided more relevant information regarding localized areas of concern for nutrient and land management to enhance land productivity and support more uniform agricultural production. Especially in the case of soil nutrient and potential contaminant monitoring across the study area, spatial analysis provided more detailed visualization and interpretive capacity for management decisions than comparisons between pastures alone. For example, because poultry litter can contribute to As contamination of soil (Rutherford et al., 2003), knowledge of both elevated As levels and spatial distribution of As relative to chicken coop locations and heavy grazing use are critical for effective long-term soil management.

Significant differences between pastures were also observed for all soil biological parameters measured in the study, where the East pasture typically supported lower microbial community size compared to the West pastures (Table 1). The total microbial community size results from the present study (average 76.39 and 121.29 nmol FAME g^{-1} in the East and West pastures, respectively) are in some cases similar to Ghimire et al. (2019) or lower than the levels observed by Bhandari et al. (2018) in other long-term grazed pastures of this semi-arid region measured using the same laboratory techniques, and within the range of levels typically found in continuous cotton pastures (Pérez-Guzmán et al., 2020). With significantly increased microbial community size in the West pasture that had been undisturbed in the past year and sown with a diverse forage cover compared to the East pasture that had been irrigated and recently tilled (Table 1), it is likely that differences in total microbial FAMEs between pastures were due largely to disturbance of surface soil and presence of vegetative cover. Microbial abundance, including AMF, has been shown to decrease rapidly in response to tillage disturbance in this region (Cotton and Acosta-Martínez, 2018), which was reflected by the present study findings. With time, increased microbial community size is expected in the East pasture after cessation of tillage and with the continued establishment of vegetative cover.

In addition, spatial diagrams of soil microbial characteristics reinforced clear differences between the East and West pastures for certain variables such as total microbial FAMEs and the abundance of fungal FAME biomarkers such as for AMF discussed above, yet also revealed localized patterns in bacteria and protozoa distribution (Figure 4). Visualization of these findings is important because of rotational cattle and chicken grazing practices at this location that in future years will be heterogeneously distributed across both the East and West pastures. Producers can evaluate how specific rotations of both cattle and chicken coops impact heavily utilized areas within the pasture using spatial maps, and assess whether management practices successfully increase soil microbial community size across the pastures. Further, the patterns of spatially distributed biological properties observed in this study would be useful for other semi-arid pastures aimed at evaluating soil health indicators for grazing management.

Correlative and predictive relationships between soil properties

To help interpret significant differences between pastures and spatial distribution of measured soil properties, potential correlations between measured study variables were investigated, focusing on microbial characteristics. This revealed significant correlations between several biological parameters and physical or chemical properties such as soil particle size distribution, pH, EC, soil total N, and total C (Table 2). Herein, AMF biomarker abundance in soil was negatively correlated with EC and pH, which differs from other studies that suggest AMF is often associated with enhanced plant salinity tolerance (Hajiboland et al., 2010; Wang et al., 2019). Recent tillage in the East pasture likely disrupted AMF hyphal growth. Higher pH and salinity also observed in the East pasture was likely due to irrigation, as the remaining groundwater resources for irrigation in the SHP have been increasingly affected by high salt contents (Scanlon et al., 2010). Therefore, it is more likely that concomitant effects of tillage and irrigation on pH, salinity, and AMF abundance contributed to this result more than direct cause-and-effect linkages between AMF and salinity or pH.

As expected, several physical and chemical properties measured in the study exhibited reasonable predictive relationships with microbial parameters via PCA, DA, and PLSR methods (Figures 5 and 6; Table 4). Physical and chemical properties such as texture, pH, and soil organic carbon are well-known regulators of microbial community size (Dequiedt et al., 2011) and community structure (Fierer, 2017). A commonality among these physical and chemical measurements is that their analyses require little specialized sample storage or preparation beyond air-drying compared to the soil biological characterization such as microbial community size and structure that requires fresh or frozen soil samples. Commercial soil testing laboratories are also more commonly able to offer routine physical and chemical analyses compared to more intensive sample preparation and data analyses required for microbial community size and structure assessments. For producers interested in more intensive soil sampling strategies for precision agricultural management but who may also be limited by available funds for soil testing, a cost-effective solution may be to focus on routine testing of soil physical and chemical properties that are likely linked to concomitant changes in soil biological properties. More frequent investigation and characterization of relationships between soil physical, chemical, and biological soil health indicators across a variety of soil types, climates, and production systems as provided in this study are required to aid future interpretation of soil testing results for producers and subsequent soil health management decisions.

CONCLUSIONS

This study characterized soil physical (i.e., soil textural fraction), chemical, and biological properties and associated relationships during the establishment of soil health management practices in a semi-arid production system. Significant differences were observed in properties such as pH, EC, soil C and TN, nutrients, and microbial community size between pastures during the first year of management that will inform future monitoring and analyses.

Spatial analysis across the study area using a grid sampling strategy was more helpful than pasture-averaged data alone to aid interpretation and producer management decisions. The distribution of elements evaluated in this study correlated well with biological properties such as the total microbial size and the abundance of specific microbial groups such as AMF, and can therefore inform management decisions on soil health and potential contaminant monitoring across the study area.

Our results help farm managers and landowners in the SHP and other producers in semi-arid systems such as in northern China or northeastern Brazil who may be interested in soil health assessment, but have limited funding that inhibits measuring soil biological characteristics, interpret and focus on measurement of affordable routine soil test results while still gaining and expanding ideas of how management outcomes impact soil biota. Overall, the results of this study provide useful direction for long-term soil health monitoring at this site, as well as a critical evaluation of relationships between soil health indicator measurements that aids interpretation and management planning.

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SUPPLEMENTARY DATA

Supplementary data to this article can be found online at https://www.rbcsjournal.org/wp-content/uploads/articles_xml/1806-9657-rbcs-45-e0200163/1806-9657-rbcs-45-e0200163-suppl01.pdf

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