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ORIGINAL ARTICLE

Characterization of spatial variability of soil physicochemical properties and its impact on Rhodes grass productivity

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Abstract Characterization of soil properties is a key step in understanding the source of spatial variability in the productivity across agricultural fields. A study on a 16 ha field located in the eastern region of Saudi Arabia was undertaken to investigate the spatial variability of selected soil properties, such as soil compaction 'SC', electrical conductivity 'EC', pH (acidity or alkalinity of soil) and soil texture and its impact on the productivity of Rhodes grass (*Chloris gayana L.*). The productivity of Rhodes grass was investigated using the Cumulative Normalized Difference Vegetation Index (CNDVI), which was determined from Landsat-8 (OLI) images. The statistical analysis showed high spatial variability across the experimental field based on SC, clay and silt; indicated by values of the coefficient of variation (CV) of 22.08%, 21.89% and 21.02%, respectively. However, low to very low variability was observed for soil EC, sand and pH; with CV values of 13.94%, 7.20% and 0.53%, respectively. Results of the CNDVI of two successive harvests showed a relatively similar trend of Rhodes grass productivity across the experimental area ($r = 0.74$, $p = 0.0001$). Soil physicochemical layers of a considerable spatial variability (SC, clay, silt and EC) were utilized to delineate the experimental field into three management zones (MZ-1, MZ-2 and MZ-3); which covered 30.23%, 33.85% and 35.92% of the total area, respectively. The results of CNDVI indicated that the MZ-1 was the most productive zone, as its major

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areas of 50.28% and 45.09% were occupied by the highest CNDVI classes of 0.97–1.08 and 4.26–4.72, for the first and second harvests, respectively.

1. Introduction

Farming systems have various types of soils, habitats, microclimatic features, and crop varieties, which result in wide variations in soil fertility, water retention and crop productivity (Sciarretta and Trematerra, 2014). Crop yield variability can be caused by many factors, including spatial variability of soil type, landscape position, crop history, soil physical and chemical properties and nutrient availability (Wibawa et al., 1993). Understanding the spatial variability of soil physicochemical characteristics, in both its static (e.g. texture and mineralogy) and dynamic (e.g. water content, compaction, electrical conductivity and carbon content) forms is necessary for site-specific management of agricultural practices, as it is directly contributing to variability in crop yields and quality (Jabro et al., 2010; Silva Cruz et al., 2011). Site-specific practices could help significantly in managing the spatial variability in the productivity of agricultural soils by tailoring the agricultural inputs to fit the spatial requirements of soil and crop (Fraisse et al., 1999). Spatial variations of soil properties across agricultural fields have been reported by many scientists as a major source of variability in crop yields (Gaston et al., 2001). Therefore, determination of the major sources of variation in productivity is a key parameter in achieving efficient site-specific management practices (Mzuku et al., 2005). Variability in agricultural soils is a function of both soil structure and the imposed management practices for crop production (Hulugalle et al., 1997).

Soil Physicochemical properties that are important in crop production are characterized as those that directly affect crop growth, such as water, oxygen, temperature and soil resistance, and others, such as bulk density, texture, aggregation and pore size distribution, that indirectly affect crop growth (Letey, 1995). Soil compaction risk occurs when soil density reaches a critical value, beyond which soil performance is affected considerably. Such critical soil densities are different for different crops in different soils and different climatic regions (Bouma, 2012). Soil compaction negatively affects essential soil properties and functions, such as hydraulic properties and gas-phase transport or root growth; hence, it is associated with various environmental and agronomic problems, such as erosion, leaching of agrochemicals to water bodies, emissions of greenhouse gases and crop yield losses (Keller and Lamandé, 2012). The susceptibility of agricultural soils to soil compaction depends mainly on soil type and moisture status. In general, for moist soils, soil compaction increases with the decrease in soil particle size (Sutherland, 2003).

Spectral vegetation indices are being successfully used as effective measures of vegetation activity and are considered as useful parameters to characterize differences in crop canopy characteristics; hence, for the assessment of spatial variability in agricultural fields (Al-Gaadi et al., 2014; Henik, 2012). The Normalized Difference Vegetation Index (NDVI) is considered by many scientists and researchers as one of the most important vegetation indices utilized for the prediction of crop production, because of its strong relationship with crop yield (Yin et al., 2012; Bhunia and Shit, 2013; Matinfar, 2013; Sheffield and Morse-McNabb, 2015).

Geostatistical methods are essential for the investigation of spatial variations of soil and crop parameters across agricultural fields, which can lead to the efficient implementation of site-specific management systems (Najafian et al., 2012). An experimental variogram is usually used to measure the average degree of dissimilarity between locations that are not sampled and nearby data values (Deutsch and Journel, 1998). Hence, correlations at various distances can be established to come up with values for non-sampled field locations.

Soil parameters are the most important factors in crop production systems. Hence, understanding their spatial variability across agricultural fields is essential in optimizing the application of agricultural inputs and crop yield. Therefore, the objectives of this study were: (i) to characterize the spatial variability of selected soil physicochemical properties across an agricultural field, and (ii) to investigate the spatial correlation between the studied soil properties and CNDVI as an indicator of Rhodes grass productivity.

2. Materials and methods

2.1. Experimental site

The study was conducted on a 16 ha field irrigated by a center pivot system in a commercial farm located in the eastern region of Saudi Arabia that extended between the latitudes of 23° 48′ 46.85″ and 24° 14′ 22.65″ N and the longitudes of 48° 49′ 48.98″ and 49° 20′ 55.45″ E (Fig. 1). The farm was laid out along a valley area with small undulations under an arid climatic zone. The study area experienced hot summers with mean temperature of 42 °C and cold to moderate winter with a mean temperature of 18 °C. The mean annual rainfall was in the range from 60 to 90 mm. The major crops cultivated in the experimental farm include potatoes, wheat, alfalfa, corn, Rhodes grass and Sudanese grass.

2.2. Sampling strategy

The field was sampled on a 40 m × 40 m grid strategy described by Mallarino and Wittry (2001) and Franzen (2011). This sampling strategy resulted in 96 sampling locations (field data points) covering the whole experimental field (Fig. 2). Of the 96 sampling locations of the experimental field, data of 86 sampling points within the actual experimental area were used for this study. The preparation of the sampling grid map was generated using ArcGIS (Ver. 2010) software program, while a GPS-receiver was used for locating the predetermined sample points in the field, for the collection of soil samples in the period from 10 to 15 April, 2013.

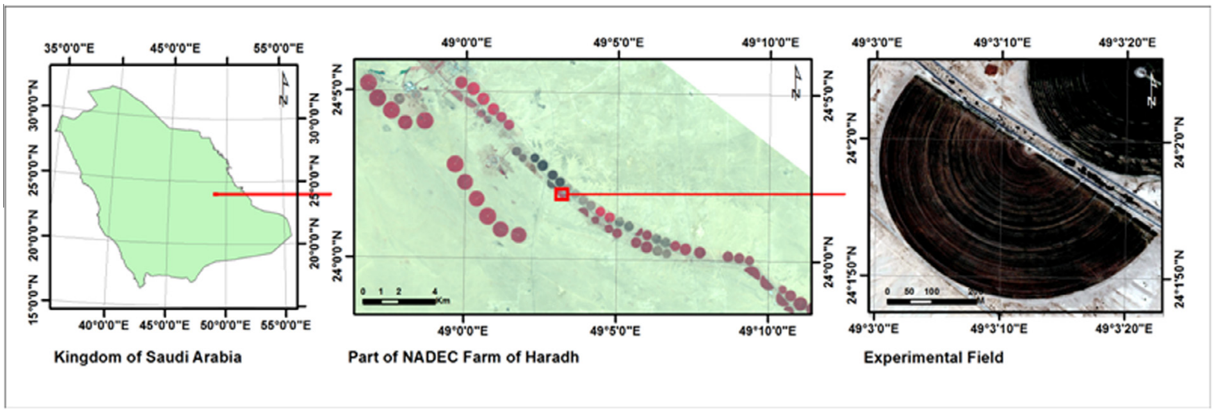

Figure 1 Location map of the experimental field.

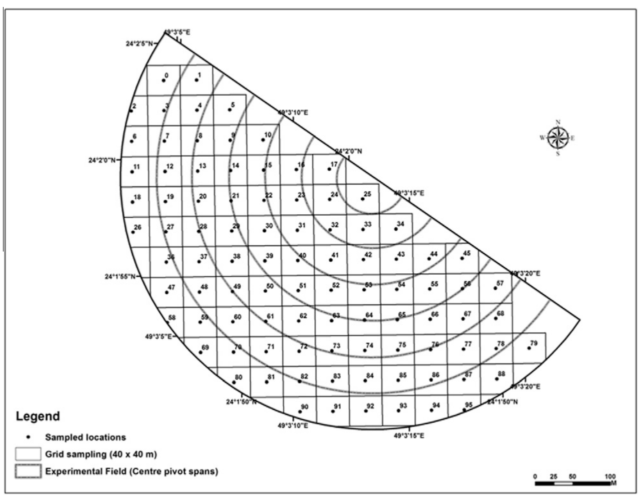

Figure 2 Grid sampling map of the experimental field.

2.3. Field data collection

Geo-referenced soil samples were collected from the top soil layer at a depth of 0–20 cm and analyzed for soil electrical conductivity (EC) and soil pH as described by Estefan et al. (2013). The same samples were analyzed for soil texture analysis, adopting the hydrometer method (Ryan et al., 2001). In addition, soil compaction measurements were also recorded at a soil depth of 0–15 cm using the soil cone penetrometer (Model: Field Scout SC 900). While taking soil measurements, average soil moisture of 13% (d.b.) was maintained.

2.4. Geostatistical analysis

Geostatistical techniques play an important role in the quantitative evaluation of spatial variability within a field (Yang et al., 2011). Kriging, for example, is characterized as a method of optimal prediction or estimation in geographical space and is often referred to as being the best linear unbiased predictor (Oliver, 2010). Hence, the collected soil physicochemical data (EC, pH, texture and SC) were assigned to the respective geo-coordinates and exported to a GIS domain (Arc GIS Software of ESRI, Inc., 2010) as a shape file for geostatistical analysis. The longitude and latitude of each sampled location were designated with x and y variables, respectively. The field data sets, soil EC, pH, soil texture and SC were termed as $z_1, z_2, z_3, \ldots z_n$.

In kriging (ordinary), interpolation algorithm was developed and tested, by using the collected observations from 96 sampling locations, according to the ratio distribution of 6:4 (58 locations as training samples and the remaining 38 categorized as test samples). Training sampling (58 locations) was used for kriging interpolation; however, the 38 test samples validated the ability tointerpolate unknown values of soil EC, pH, SC and soil texture (Childs, 2004). The variance was calculated on 0.0–1.0 scales. Kriging estimation was made and compared with the measured values. Thus, for each sampled location, the collected observations included the measured value, $Z(x_i)$ and the estimated value, $Z'(x_i)$, as well as their standard values of $Z_1(x_i)$ and $Z_2(x_i)$. The performance statistics were assessed in terms of Mean Error (ME), Mean Standard Error (MSE), Average Standard Error (ASE), Root Mean Square Error (RMSE) and Root Mean Square Standardized Error (RMSSE) as described in Yang et al. (2011) and illustrated in Eqs. (1)–(5). Geostatistical software program (Gamma Design Software) was used to construct semivariograms and to address the spatial structural analysis for the variables.

$$\mathrm{ME} = \frac{1}{N}\sum_{i=1}^{N}[Z(x_i) - Z'(x_i)] \quad (1)$$

$$\mathrm{ME} = \frac{1}{N}\sum_{i=1}^{N}[Z_1((x_i) - Z_2(x_i)] \quad (2)$$

$$\mathrm{ASE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[Z'(x_i) - \left(\sum_{i=1}^{N}Z'(x_i)\right)\Big/N\right]^2} \quad (3)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[Z(x_i) - Z'(x_i)]^2} \quad (4)$$

$$\mathrm{RMSSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[Z_1(x_i) - Z_2(x_i)]^2} \quad (5)$$

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2.5. Rhodes grass crop productivity

Eight Landsat-8 cloud-free images, corresponding to Rhodes grass growth period, were downloaded from the Earth explorer portal of the USGS (http://earthexplorer.usgs.gov), Table 1. The spatial variability of the experimental field was investigated through the Normalized Difference Vegetation Index (NDVI) resulting from Rhodes grass reflectance at red and Near Infrared (NIR) channels captured by Landsat-8 (OLI) images. Consequently, the vigor/productivity of Rhodes grass was assessed against the recorded soil physicochemical properties.

Initially, the downloaded cloud free images were subjected to radiometric calibration (top of atmosphere – TOA correction) for surface reflectance using ENVI (ver. 5.1) software program. Then, the NDVI image was developed from the surface reflectance image, using Eq. (6).

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{6}$$

where NIR is the reflectance from the near infrared portion (i.e. band 5) and Red is the reflectance from the red portion (i.e. band 4) of the electromagnetic spectrum detected by landsat-8 (OLI) sensors.

The NDVI of the experimental field was calculated for all acquired images (Table 1). Subsequently, a cumulative NDVI (CNDVI) was determined for each of the two Rhodes grass cuts/harvests. The obtained CNDVI maps, for the growth period of each of the two harvests, were overlaid on soil physicochemical maps (i.e. soil EC, pH, SC and texture), in order to visualize their impact on the spatial variability in Rhodes grass productivity. In addition, Rhodes grass crop performance was also assessed against the management zones delineated in accordance with the studied soil physicochemical properties of the experimental area.

2.6. Delineation of management zones (MZ)

The generated maps of soil physicochemical properties and CNDVI were subjected to fuzzy c-means clustering analysis and used as inputs to determine MZ using Management Zone Analyst (MZA) software (Fridgen et al., 2004). Harvest-wise generated CNDVI of Landsat-8 data was integrated with the thematic maps of soil physiochemical properties. The output file of MZA was imported to ArcGIS (Ver. 2010) software program to generate management zone map of the experimental field. The management zones were determined based on the representation of Fuzziness Performance Index (FPI) and Normalized Classification Entropy (NCE) performance indices as described by Fraisse et al. (1999) and Lark and Stafford (1997).

Table 1 Details on Rhodes grass sowing, harvesting and satellite overpass (images) dates.

Description	Date	Crop age (days)	Remarks
Sowing date	25 April, 2013	00	Cut/harvest number 1
Image 1	11 May, 2013	16	
Image 2	27 May, 2013	32	
Harvesting date	7 June, 2013	43	
Image 3	12 June, 2013	05	Cut/harvest number 2
Image 4	28 June, 2013	21	
Image 5	14 July, 2013	37	
Image 6	30 July, 2013	53	
Image 7	15 August, 2013	69	
Image 8	31 August, 2013	85	
Harvesting date	7 September, 2013	92	

3. Results and discussion

The analysis of the collected data of soil physicochemical parameters (soil EC, pH, SC, and soil texture components) was first achieved through the conventional statistics (minimum, maximum, arithmetic mean, median, mode, standard deviation, standard error, coefficient of variation (CV), Kurtosis and Skewness) as given in Table 2. However, spatial variability of each parameter was assessed using semivariogram measures (range, nugget, sill and nugget ratio), Table 3; and the maps of the studied parameters were generated using the kriging (ordinary) technique (Osama et al., 2005). Results of the descriptive statistics indicated that the observations of soil pH, SC and clay content showed almost symmetric data. However, the distribution of sand and silt observations skewed to the left and soil EC observations skewed to the right. Kurtosis results indicated that except for sand, all physicochemical parameters revealed a lower and broader central peak with shorter and thinner tails, while the distribution of sand observations exhibited a higher and sharper central peak with longer and fatter tails.

3.1. Soil texture

Soil texture data were analyzed (Table 2) and subsequently subjected to geospatial analysis (Table 3) to investigate the spatial variability of sand, clay and silt components across the experimental field. The results revealed that sand was the dominant soil texture component in the experimental field (80.53%), followed by clay (10.84%) and silt (8.63%). As indicated by the values of the coefficient of variation (CV), it was observed that the spatial variability of the clay component across the experimental field was the highest (CV of 21.89%) compared to silt (CV of 21.02%) and sand (CV of 7.20%). This was also shown from the results of geostatistical analysis (Table 3), as the least variance was shown for sand (0.04), followed by clay (0.19) and silt (0.12), with semivariogram range values of 99.11, 5.22 and 76.58 m, respectively. The RMSSEE values for sand (0.819), silt (0.921) and clay (1.161) indicated a slight under-estimation of sand and silt components and an over-estimation of the clay component. In general, the results revealed that, in terms of soil texture components, the experimental field was relatively homogeneous in sand with a low spatial variability in clay and silt components. The spatial variability maps of soil sand, silt and clay are provided in Figs. 3–5, respectively.

3.2. Soil electrical conductivity (EC) and soil pH

The results of the descriptive statistics (Table 2) revealed that the values of soil EC across the experimental field varied

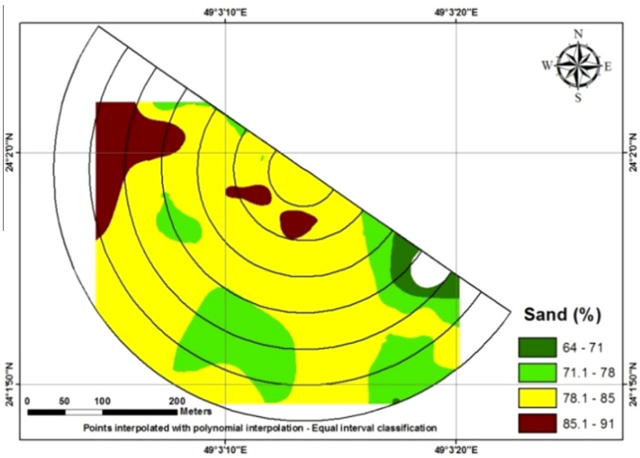

Figure 3 Spatial variability of sand component across the experimental field.

between 0.70 and 1.19 dS m^{-1} and the values of soil pH varied between 7.82 and 7.98. As per the standards of soil EC and pH scales (Soil Survey Division Staff, 1993), the field soil was characterized as non-saline and moderately alkaline soil. The spatial distribution of both soil EC and soil pH across the experimental field is illustrated by Figs. 6 and 7, respectively. The soil pH showed a very low variability across the experimental field, as indicated by the very low value of CV of 0.53%. However, low variability of EC was observed across the experimental field with a CV value of 13.94%. Furthermore, geostatistical analysis (Table 3) showed a variance value of 0.28 for soil EC across the study field, while for pH it was 0.02. The variance strength was also assessed through the RMSSEE, which resulted in a variogram of 0.862 for EC and 1.379 for pH. The variance and its associated RMSSEE results also indicated that the experimental field was relatively homogeneous in terms of soil pH with low to moderate spatial variation in soil EC with semivariogram range values of 28.2 and 16.6 m, respectively.

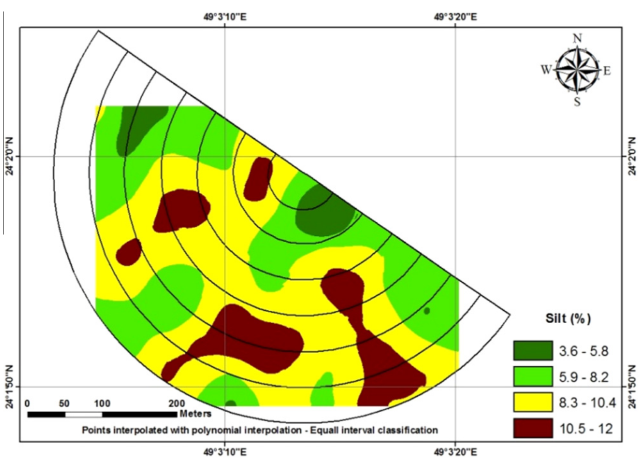

Figure 4 Spatial variability of silt component across the experimental field.

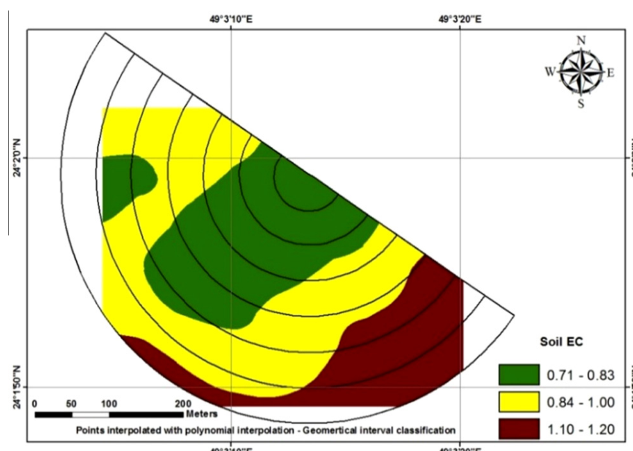

Figure 6 Spatial variability map of soil EC.

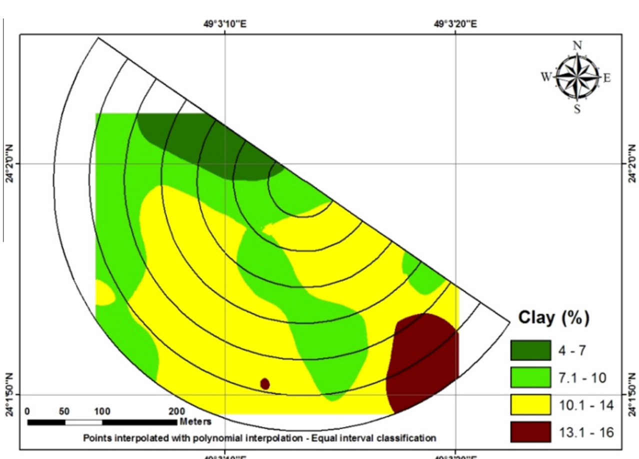

Figure 5 Spatial variability of clay component across the experimental field.

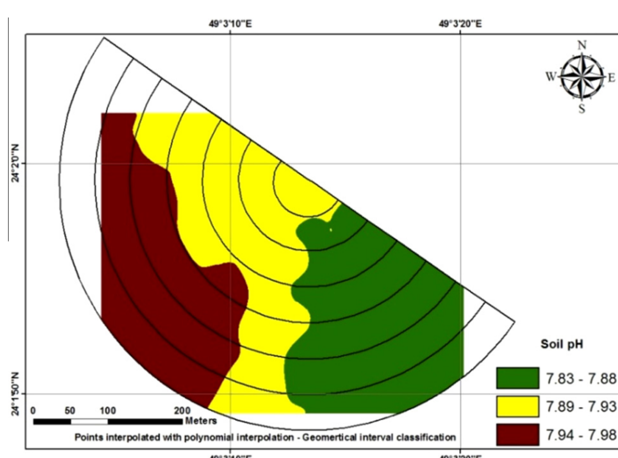

Figure 7 Spatial variability map of soil pH.

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3.3. Soil compaction (SC)

The descriptive statistics (Table 2), as well as the geostatistical results (Table 3), showed a considerable variability of SC across the experimental field (CV of 22.08%), with values of soil resistance to penetration ranging between 617 and 2264 kPa. The generated SC map (Fig. 8) showed its spatial distribution across the experimental field. In terms of spatial variation of SC, variogram analysis showed a variance value of 0.29 across the sampled data (Table 3) with an associated RMSSE value of 0.904.

3.4. Rhodes grass productivity

Rhodes grass productivity was assessed through the spatial variability of the Cumulative Normalized Difference Vegetation Index (CNDVI), which was determined from two Landsat-8 images for the first Rhodes grass harvest and six images for the second harvest. The spatial distribution of the CNDVI across the experimental field is illustrated by the results of the descriptive statistics and the geostatistical analysis (Tables 2 and 3). The spatial variability of CNDVI was very low as reflected in the values of CV of 3.88% and 6.79% for the first and second harvests, respectively. Similarly, variances of 0.69 and 0.76 with semivariogram range values of 32.77 and 38.90 m were observed for CNDVI data of the first and second harvests, respectively.

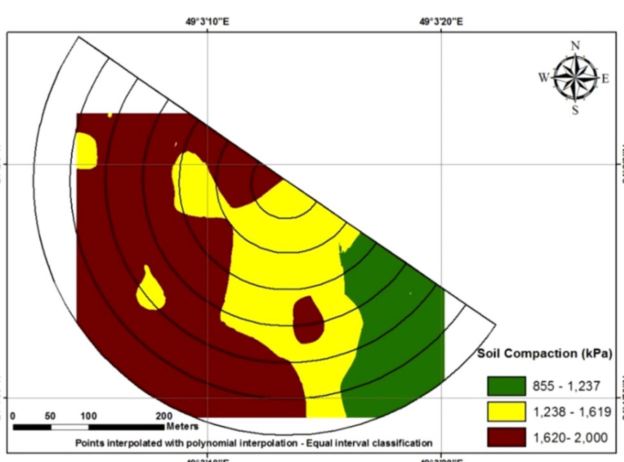

Figure 8 Spatial distribution of soil compaction across the experimental field.

3.5. Interrelations between soil parameters and their impact on CNDVI

To study the interrelations among soil physicochemical properties, as well as, between soil properties and Rhodes grass productivity, the collected observations were subjected to correlation matrix. The results shown in Table 4 indicated that soil texture components correlated significantly with soil EC. For example, the clay component showed a significant direct correlation with soil EC. However, the sand component of the soil texture showed a significant inverse correlation with soil EC, which coincided with the findings reported by Heil and Schmidhalter (2012). Although, soil compaction showed no significant effects on Rhodes grass performance, it showed a significant inverse correlation with the clay component of soil texture, and a high significant inverse correlation with soil EC. However, a direct relationship of high significant correlation was observed between soil compaction and pH.

The spatial variability of Rhodes grass productivity was observed to be of the same trend as indicated by the highly significant spatial correlation between the CNDVI values of the first and second harvests, with a correlation coefficient (r) of 0.74 (p = 0.0001). The results of this study also revealed that all soil texture components (sand, silt and clay) showed significant spatial correlations with Rhodes grass productivity represented by the CNDVI. Among soil texture components, the silt component showed the most significant correlation with CNDVI; with (r, p) values of (0.22, 0.043) and (0.32, 0.002) for the first and second Rhodes crop harvests, respectively. Although, the results showed inverse correlations between the CNDVI and other tested soil parameters (SC, EC and pH), significant correlation was observed only between CNDVI and soil pH for the first harvest (r = −0.22, p = 0.041).

According to the results of geostatistical analysis for soil texture components, soil EC and SC, it can be concluded that low to moderate spatial variability in these parameters was observed across the experimental field. These components were ranked in a descending order based on the degree of variability (CV, Table 2) as: SC > clay > silt > EC. To address the cumulative impact of soil parameters on Rhodes grass

Table 2 Descriptive statistics of the measured soil physicochemical properties.

Description	Soil EC (dS m^{-1})	Soil pH	SC (kPa)	Soil texture			CNDVI	
				Sand %	Clay %	Silt %	Harvest No. 1	Harvest No. 2
Minimum	0.70	7.82	617	53.47	4.18	3.55	0.76	3.35
Maximum	1.19	7.98	2264	97.01	17.36	12.77	1.08	4.72
Mean	0.91	7.90	1600	80.53	10.84	8.63	0.96	4.39
Median	0.89	7.91	1614	80.08	10.96	8.79	0.98	4.45
Mode	0.86	7.93	1614	81.48	11.54	10.56	0.98	4.57
Standard Deviation (SD)	0.13	0.04	353.28	5.80	2.37	1.81	0.04	0.30
Standard Error (SE)	0.01	0.004	38.09	0.62	0.26	0.20	0.007	0.028
CV, %	13.94	0.53	22.08	7.20	21.89	21.02	3.88	6.79
Skewness	0.46	0.01	−0.17	−0.80	−0.10	−0.35	−1.51	−2.47
Kurtosis	−0.61	−1.09	0.12	5.37	0.78	−0.39	3.97	7.05

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Table 3 Geostatistical analysis results for soil physicochemical properties.

Description	Soil texture components			Soil EC (dS m^{-1})	Soil pH	SC (kPa)	CNDVI	
	Sand %	Clay %	Silt %				Harvest No. 1	Harvest No. 2
Model	G	G	G	G	G	G	G	S
Nugget (C_0)	0.01	0.02	0.00	0.00	0.00	0.02	0.02	0.01
Sill (C_0 + C)	0.23	0.24	0.04	0.10	0.20	0.25	0.06	0.06
Range (A)	99.11	76.58	5.22	16.60	28.18	63.80	32.77	38.90
Variance	0.04	0.19	0.12	0.28	0.02	0.29	0.69	0.76
R^2	0.91	0.91	0.81	0.98	0.98	0.97	0.94	0.95
RSS	3.0E−04	1.2E−04	7.4E−05	2.3E−04	5.5E−04	1.8E−04	2.5E−05	2.1E−05
ME	0.0045	0.0004	0.0051	0.0027	0.0034	0.0003	0.0069	0.0048
RMSE	0.0920	0.0640	0.0780	0.0570	0.0590	0.0390	0.0450	0.0580
ASE	0.0460	0.0570	0.0680	0.0490	0.0360	0.0420	0.0590	0.0420
MSE	0.0090	0.0059	0.0028	0.0052	0.0060	0.0038	0.0046	0.0019
RMSSE	0.819	1.161	0.921	0.862	1.379	0.904	1.112	0.864

G – Gaussian; S – spherical; E – exponential; RSS – residual sums of squares.

Table 4 Correlation coefficient (*r*) between soil properties and NDVI.

	CNDVI (1st harvest)	CNDVI (2nd harvest)	Clay	EC	Sand	Silt	Compaction	pH
CNDVI (1st harvest)	–							
CNDVI (2nd harvest)	0.74**	–						
Clay	0.16	0.24*	–					
EC	0.00	−0.06	0.24*	–				
Sand	0.22*	0.17	−0.27*	−0.25*	–			
Silt	0.22*	0.32**	0.31**	0.12	−0.30**	–		
Compaction	−0.08	0.00	−0.27*	−0.31**	0.11	0.06	–	
pH	−0.22*	−0.11	−0.19	−0.46**	0.23*	−0.14	0.53**	–

* Significant ($p < 0.05$).
** Highly significant ($p < 0.01$).

productivity, the selected soil physicochemical layers were subjected to management zone analysis for the characterization of the experimental field (Fig. 9). The delineated MZ map resulted in three distinct zones: MZ-1, MZ-2 and MZ-3, which covered 35.78%, 37.66% and 26.56% of the experimental field area, respectively.

The spatial layers of CNDVI for the first and second harvests (Figs. 10 and 11) were overlaid on the generated MZ map, and quantitatively assessed for CNDVI distribution across the experimental field (Table 5). The major areas of MZ-1 were occupied by the high CNDVI classes under both first (50.28%) and second (45.09%) harvests. The major areas

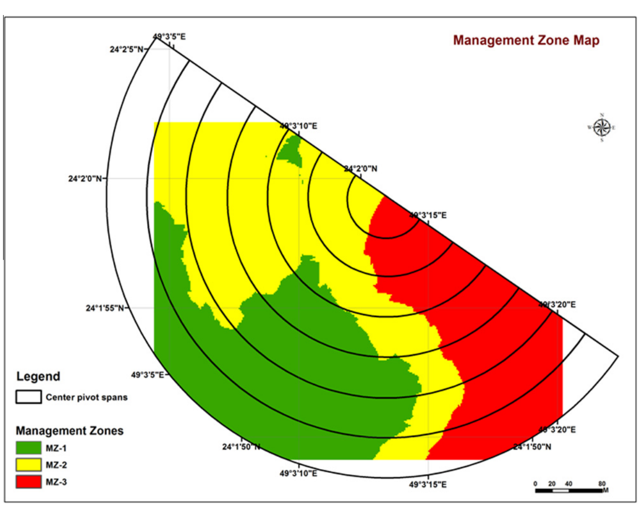

Figure 9 Management zone map of the experimental field.

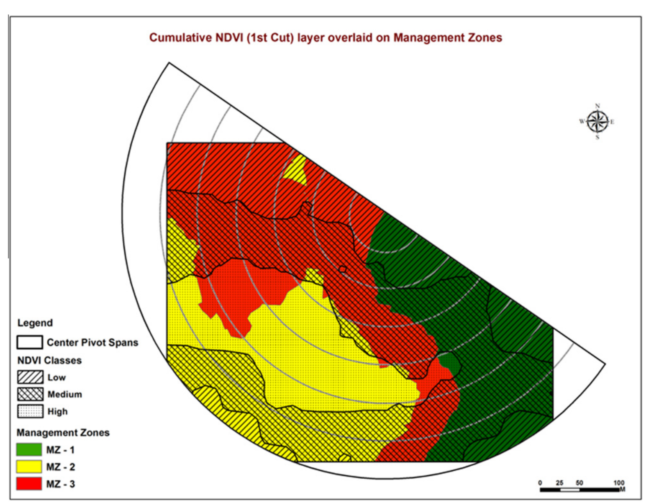

Figure 10 CNDVI of the 1st harvest overlaid on the MZ map.

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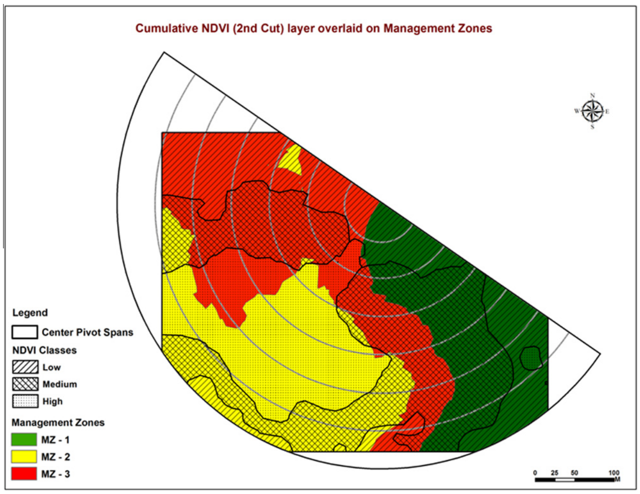

Figure 11 CNDVI of the 2nd harvest overlaid on the MZ map.

Table 5 CNDVI distribution across the management zones as a percentage of total experimental area.

Harvest No.	CNDVI	(Area, %)			
		MZ-1	MZ-2	MZ-3	Total
1	Low (0.76–0.86)	4.31	14.77	25.23	44.31
	Medium (0.87–0.96)	10.72	14.08	10.32	35.13
	High (0.97–1.08)	15.20	5.00	0.37	20.57
	Total area (%)	30.23	33.85	35.92	100.00
2	Low (3.35–3.80)	4.27	13.83	24.01	42.11
	Medium (3.81–4.25)	12.34	15.54	11.61	39.48
	High (4.26–4.72)	13.63	4.48	0.30	18.41
	Total area (%)	30.23	33.85	35.92	100.00

of MZ-3 were occupied by the low CNDVI classes for both first (70.24%) and second (66.84%) harvests. However, low and medium CNDVI classes occupied relatively the same areas of MZ-2 for both first and second harvests. In general, MZ-1 showed the highest Rhodes grass productivity followed by MZ-2, while MZ-3 was characterized as the least productive zone in the experimental field. These results indicated that the experimental field was successfully delineated into three distinct management zones based on Rhodes grass productivity.

4. Conclusions

A field study was conducted to investigate the spatial variability of soil physicochemicals and to study its impact on the productivity of Rhodes grass. The following conclusions are inferred from the study:

- Low to moderate spatial variability in soil physicochemical properties was observed across the experimental field. The four soil properties that showed a considerable degree of variation were soil compaction (CV of 22.08%), clay (CV of 21.89%), silt (CV of 21.02%) and soil EC (CV of 13.94%).
- Based on soil physicochemical layers, the experimental field was delineated into three distinct management zones (MZ-1, MZ-2, and MZ-3), which covered 30.23%, 33.85% and 35.92% of the experimental area, respectively.
- Soil texture components showed a significant correlation with Rhodes grass productivity. Silt component showed a high significant spatial correlation with CNDVI ($r = 0.32$ and $p = 0.002$), while, clay ($r = 0.24$, $p = 0.025$) and sand ($r = 0.22$, $p = 0.042$) components showed a low significant correlation with the CNDVI.
- Although, the results showed inverse correlations between Rhodes grass CNDVI with SC, EC and pH, significant correlation was observed only between CNDVI and soil pH for the first harvest ($r = -0.22$, $p = 0.041$).

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