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Spatial analysis of soil physicochemical and hydraulic properties in the Libga irrigation scheme in northern Ghana using geostatistics and GIS approach

Yakubu Saaka Zakaria[1]*, Abdul-Ganiyu Shaibu[2], Bernard N. Baatuuwie[3]

[1] University for Development Studies, Faculty of Agriculture, Department of Agricultural Mechanisation and Irrigation Technology, Nyankpala, +233, Tamale, Ghana
[2] University for Development Studies, School of Engineering, Department of Agricultural Engineering, Nyankpala, +233, Tamale, Ghana
[3] University for Development Studies, Faculty Natural Resources and Environment, Department of Geo-Information Sciences, Nyankpala, +233, Tamale, Ghana

* Yakubu Saaka Zakaria, zakaria_yakubu_saaka@yahoo.com, ORCID iD: 0000-0002-4213-1418

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Abstract

This study was undertaken to determine the spatial variability of soil physicochemical and hydraulic properties in the Libga irrigation scheme in order to make appropriate recommendations for site-specific management on irrigation and soil/plant nutrition. Soil samples were collected from 0–30 cm and 30–60 cm depths from 50 geo-referenced points located at the nodes of a 100 m × 100 m regular grid. Particle size distribution (PSD), bulk density (BD), total porosity (TP), field capacity (FC), permanent wilting point (PWP), available water capacity (AWC), saturated hydraulic conductivity (Ksat), electrical conductivity (EC) and pH were determined following standard laboratory protocols at the AGSSIP Laboratory of the University for Development Studies, Nyankpala. Generally, soils in the scheme had relatively high bulk densities and were slightly acidic. Electrical conductivity displayed the highest variability with CVs of 154.6% at 0–30 cm and 178.7% at 30–60 cm whereas BD displayed the lowest variability (CVs of 4.43% and 4.8% at 0–30 cm and 30–60 cm). Most of the soil properties exhibited moderate to strong spatial dependence indicating that they were mainly influenced by intrinsic or soil forming factors. Spatially, the soil properties showed a continuous distribution pattern over relatively longer distances indicating that site-specific irrigation and fertilization could be implemented in the scheme.

1. Introduction

Site-specific farming has gained a lot of attention (Lee et al., 2021) as a strategy to manage the inherent variability of soils. It involves the accurate matching of soil conditions and crop needs to specific input requirements (Weddell et al., 2017). In irrigation, soil properties such as texture, bulk density, total porosity, soil moisture constants, saturated and unsaturated hydraulic conductivity, pH and electrical conductivity play critical roles in the control, movement and availability of water and nutrients in the soil. For optimal irrigation planning, the spatial variability of these soil properties needs to be taken into account (Terribile et al., 2011). Knowledge of soil spatial variability is useful in deriving soil suitability classes for irrigation, determining production constraints and in promoting the rational use of water resources and fertilizers.

Again, studies of soil spatial variability help researchers and farmers to identify the source of variability of soil properties and to understand the evolution of soils in fields. For instance, it has been identified that, intrinsic factors such as parent material and topography are linked to the continuous pattern in the spatial variability of soil properties whereas extrinsic factors such as irrigation, fertilisation and tillage are associated with the random pattern in the spatial variability of soil properties (Iqbal et al., 2005).

Geostatistics is one of the methods which has been used to understand the spatial structure and variability of soil properties (Jabro et al., 2010). The main tool in geostatistics is the semivariogram. Through its parameters; the sill, range and nugget, the semivariogram provides the necessary information for determining the spatial dependence of soil properties and for interpolating soil properties at unsampled locations. Spatial dependence calculated as the ratio of the nugget to the sill (N/S ratio) was classified by Cambardella et al. (1994). According to this classification, a N/S ratio <25% indicates strong spatial dependence, a N/S ratio within 25–75% indicates moderate spatial dependence and a N/S ratio >75% indicates weak spatial dependence. Strong spatial dependence is influenced mainly by intrinsic factors whereas weak spatial dependence is influenced by management/extrinsic factors (Tuffour et al., 2016). Moderate spatial dependence has been linked to the interplay of soil forming factors and management factors (Rasekoele, 2016).

Advancement in geographic information systems (GIS) and the integration of geostatistics into GIS platforms such as ArcGIS has immensely contributed to the rapid assessment of soil spatial variability and mapping of soil properties. These maps serve as guide to irrigation managers and farmers in making informed decisions about input use, soil and water management. The Libga Irrigation Scheme is one of the major vegetable production sites in the Northern Region of Ghana. Since its completion in 1980, the scheme has been under intensive and continuous cultivation. However, the lack of previous studies on soil spatial variability and the lack of spatial distribution maps of soil properties present great challenges for its sustainable management. As indicated by Khan et al. (2021) land use without adequate planning leads to soil impoverishment and decline in crop yields. The aim of this study was to apply geostatistics to quantify and interpolate the spatial dependence and structure of soil physicochemical and hydraulic properties in order to provide accurate information for making informed site-specific management decisions in the Libga Irrigation Scheme.

2. Materials and methods

2.1. Description of study area

The study was conducted in the Libga Irrigation Scheme covering an area of about 56 hectares. The irrigation scheme is located between latitudes 9°35'48" and 9°36'12" and longitudes 0°51'07" and 0°51'25" (Fig. 1). The climate of the area is characterized by a unimodal rainfall pattern with mean annual rainfall and temperatures of 1099 mm and 28.2°C, respectively. The main crops grown in the irrigation scheme include rice (*Oryza sativa*), roselle (*Hibiscus sabdariffa*), jute mallow (*Corchorus olitorius*) and pepper (*Capsicum annuum*).

The topography is generally flat and the elevation is about 166 m a.s.l. The geology of the area is defined by the paleozoic consolidated sedimentary rocks developed mainly from sandstone, shale and mudstone (Mensah et al., 2014). The soils in this area are predominantly plinthosols. Planosols cover only a small area. These are moderately deep and consist of imper-

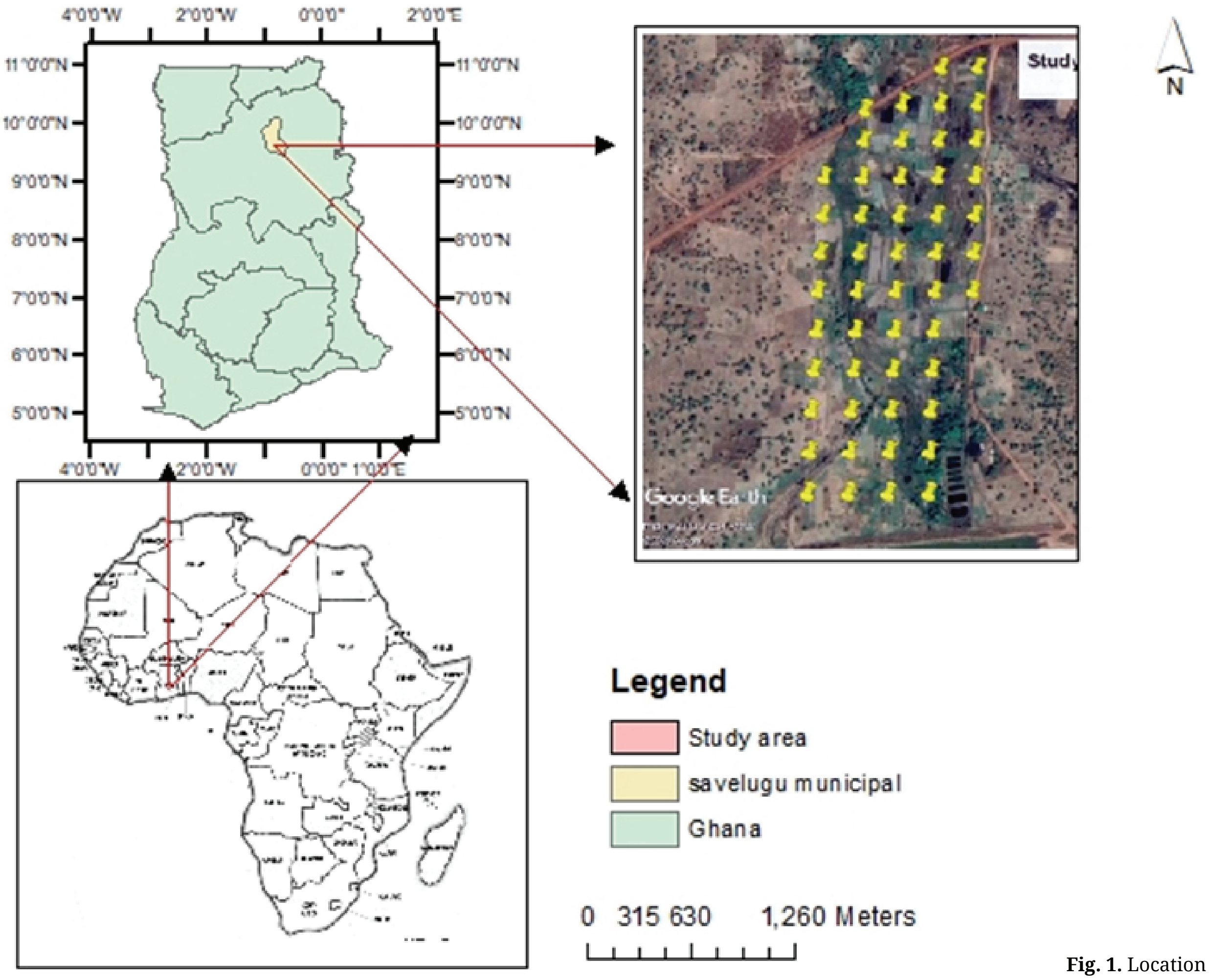

Fig. 1. Location of the study area

fectly drained, pale brown/yellowish-brown, porous and very fine sandy loam or silty-clay loam topsoil, usually less than 30 cm thick, overlying hard ironpan (Gyekye et al., 2020).

2.2. Soil sampling and analysis of samples

Soil samples were collected 0–30 cm and 30–60 cm depths from 50 georeferenced points located at the nodes of a 100 m × 100 m regular grid laid over the study area. The coordinates of the sampling points were recorded using a handheld Garmin global positioning system (GPS). Both disturbed and undisturbed soil samples were collected. The undisturbed samples were collected using cylindrical metal cores with height and diameter of 5 cm and 5.08 cm, respectively. Both the undisturbed and disturbed samples were collected following the procedure described by Agyare (2004).

Laboratory analysis was conducted at the Agricultural Services Sub-Sector Investment Programme (AGGSIP) Laboratory of the University for Development Studies, Nyankpala campus, Ghana. The disturbed soil samples were air-dried and sieved through a 2 mm mesh before analyzing for particle size distribution (PSD), soil pH and electrical conductivity (EC). The undisturbed soil samples were first saturated for 72 hours in plastic basins before the analyzing for bulk density (BD), total porosity (TP), saturated hydraulic conductivity (Ksat), soil moisture retention at field capacity (FC), soil water retention at permanent wilting point (PWP) and available water capacity (AWC).

Particle size distribution was determined using the Bouyoucos hydrometer method as described by Carter and Gregorich (2008). Bulk density was determined using the core method (Carter and Gregorich, 2008). Total porosity was calculated using Equation 1 as described by Ali (2010). Saturated hydraulic conductivity was determined using the falling-head permeameter method (Carter and Gregorich, 2008). Soil moisture retention at field capacity and permanent wilting point was determined using the pressure plate apparatus (Stolte, 1997). pH in water was measured in a 1 : 2.5 soil-water suspension using Crison pH meter as described by Carter and Gregorich (2008). Soil electrical conductivity was also measured in a soil-water suspension (ratio of 1 : 2.5) using a Crison conductivity meter as described by Jackson (1962).

$$TP = 1 - \frac{BD}{2.65} \times 100 \qquad \text{Equation 1}$$

2.3. Data Analysis

Descriptive statistics including minimum, maximum, mean, coefficient of variation (CV), skewness and kurtosis were determined using Genstat (12^{th} edition). Coefficient of variation was classified as described by (Wilding, 1985). Data was checked for normality by the Shapiro-Wilk test. Soil properties which were found to be non-normally distributed were log-transformed before using them to calculate semivariance. Paired two-tailed t-test was used to statistically test for differences between values of given soil properties within the two sampling depths.

Geostatistical analysis was performed using the geostatistical analyst tool in ArcMap® (ArcGIS 10.5). Semivariance was calculated using Equation 2 (Usowicz and Usowicz, 2004).

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=0}^{N(h)} \left[z(x_i + h) - z(x_i)\right]^2 \qquad \text{Equation 2}$$

where:
$\gamma(h)$ – the estimated semivariance at lag h (distance between observations), $z(x_i)$ – the value of the random variable Z at $x = x_i$, $z(x_i + h)$ – the value of Z at a distance h from x_i and N(h) – the number of pairs of points that are a distance h apart.

Ordinary kriging was employed in the interpolation and mapping of soil properties (Equation 3).

$$Z(x_0) = \sum_{i=1}^{n} \lambda_i \cdot Z(x_i) \qquad \text{Equation 3}$$

where:
$Z(x_i)$ is the measured value at a location (ith), λ_i is the unknown weight for the measured value at the location (ith) and x_o is the estimation location. The unknown weight (λ_i) depends on the distance to the location of the prediction and the spatial relationship among measured variables (Webster and Oliver, 2007).

Cross-validation of semivariogram models was based on the mean-squared error (MSE), root mean-squared error (RMSE) and root mean-squared standardized error (RMSS).

3. Results and discussion

3.1. Classical statistics of soil properties

As shown in Table 1, soils in the irrigation field are predominantly sandy loams as observed by Adongo et al. (2015). This implies that most of the soils in the field are free draining and plants must be frequently irrigated to supply them with their daily water requirements. Most of the soil properties varied significantly along the soil depth. Clay content, for instance, increased from the topsoil to the subsoil layer which could partly be attributed to eluviation/illuviation processes in the field (Iqbal et al., 2005). Bulk density was relatively high measuring 1.70 g cm^{-3} at 0–30 cm depth and 1.78 g cm^{-3} at 30–60 cm depth. This relatively high bulk density indicates restriction of downward movement of water into the soil (Iqbal et al., 2005) and could explain why many parts of the field experiences waterlogging. Similar to clay content, BD increased from the topsoil to the subsoil. This observation is in line with Foth (1990) who contends that clay accumulation in the B horizon results in the formation of Bt horizon which are associated with increased bulk density. Available water content was also observed to increase with depth. This is also related to clay as opined by Gulser et al. (2016) that hydraulic properties are controlled mainly by clay content. In contrast, saturated hydraulic conductivity decreased from the topsoil to the subsoil. This could be inversely related to BD. The inverse relationship between soil bulk density and saturated hydraulic conductivity has been reported by MacCarthy et al. (2013) who observed negative correlations of –0.05 and 0.20 at the topsoil and subsoil layers, respectively in an agricultural field in Navrongo, Ghana. Saturated hydraulic conductivity in the field was generally low, which indicates that water movement in the soils is restricted. Soils with low saturated hydraulic conductivity are generally prone to runoff, ponding and waterlogging. This increases erosional processes leading to deterioration of the capacity of soils to support proper plant growth. There was also a decrease in pH with depth. Generally, the soils were slightly acidic. This is attributable to excessive use of chemical fertilizers and the high leaching of basic cations resulting from high intensity rainfall in the study area (Agyare, 2004; Ali, 2010).

The coefficient of variability (CV) is an important indicator of variability. According to De Carvalho et al. (2012), the variability of soil properties measured by the CV may be considered as “the first indication of heterogeneity in the data”. As classified by (Wilding, 1985), a CV <15% indicates low variability, CVs within 15%–35% indicate moderate variability and CV >35% indicates high variability. Based on this, the results showed that the variability of the soil properties measured ranged from low to high. Bulk density recorded the lowest variability ab both depths whereas EC recorded the highest variability. The high variability of EC could be due to differences in fertilizer application levels on irrigation plots. In contrast to reports of many studies which found Ksat to be highly variable (Saglam et al., 2011; MacCharthy et al., 2013), the variability of Ksat in this study was low at the 0–30 cm with a CV of 14.2% and moderate at 30–60 cm with a CV of 20.5%). The low variability of Ksat in this study could be due to the method of measurement and the instruments used as explained by Shukla (2011).

3.2. Geostatistical analysis

The best-fit models for the soil properties studied are depicted in Figures 2a–2l. Eight isotropic semivariogram models namely K-Bessel, J-Bessel, Spherical, Hole Effect, Exponential, Gaussian, Rational Quadratic and Circular models were chosen. These isotropic models were selected due to the fact that the spatial dependency between data points developed in the same fashion in all directions (Schabenberger and Pierce, 2002). The best-fit models were selected through cross-validation and based on the root mean squared error (RMSE), mean squared error (MSE) and root mean squared standardized error (RMSS) (Webster and Oliver, 2014). According to Oliver and Webster (2014) the best-fit model should have a small RMSE as possible, an MSE close to zero and RMSS close to 1. The RMSS which is “the most telling” of the three parameters was given priority in the selection of the models as suggested by Oliver and Webster (2014). As presented in Table 2, most of the models selected had RMSS ranging from 0.91 to 1.04 indicating that the kriging prediction made were

Table 1
Classical statistics of the measured soil properties

Variable	Depth (cm)	Min.	Max.	Mean	Median	Kurt.	Skew.	SD	CV (%)	S-W test (p<0.05) Stat.	Prob.
Sand (%)	0–30	25.15	83.10	66.19	66.85	5.59	–1.86	9.98	15.1	0.82	<0.001
	30–60	37.80	81.45	64.37	64.85	1.89	–1.06	9.05	14.1	0.90	<0.001
Silt (%)	0–30	4.05	30.35	18.55	18.75	0.20	–0.24	5.31	28.6	0.99	0.878
	30–60	6.30	30.20	18.29	18.82	–0.67	–0.02	5.76	31.5	0.98	0.640
Clay (%)	0–30	5.30	46.90	16.12	15.20	8.76	2.63	7.34	45.6	0.69	<0.001
	30–60	7.80	34.40	18.10	17.35	1.16	0.92	5.84	32.3	0.93	0.005
BD (g cm^{-3})	0–30	1.49	1.82	1.70	1.73	–0.02	–0.74	0.08	4.4	0.93	0.005
	30–60	1.55	1.93	1.78	1.78	–0.02	–0.30	0.08	4.8	0.97	0.25
TP (cm^3 cm^{-3})	0–30	31.48	42.83	35.75	34.86	–0.02	0.74	2.85	8.0	0.93	0.005
	30–60	27.04	41.59	32.88	32.78	–0.02	0.30	3.22	9.8	0.97	0.25
FC (cm^3 cm^{-3})	0–30	17.32	52.43	23.79	23.67	27.31	4.62	4.65	19.5	0.52	<0.001
	30–60	21.55	40.20	25.68	24.80	7.46	2.39	3.20	12.4	0.77	<0.001
PWP (cm^3 cm^{-3})	0–30	4.75	16.57	8.73	8.48	1.75	1.05	2.30	26.3	0.94	0.010
	30–60	2.98	16.26	8.35	8.24	2.16	0.96	2.42	29.0	0.93	0.006
AWC (cm^3 cm^{-3})	0–30	11.60	20.33	16.53	16.42	0.13	0.00	1.78	10.7	0.98	0.595
	30–60	9.06	20.84	16.60	16.90	2.21	–1.17	2.34	14.1	0.92	0.002
Ksat (cm hr^{-1})	0–30	0.60	1.07	0.73	0.70	1.08	1.12	0.10	14.2	0.91	<0.001
	30–60	0.40	0.84	0.58	0.54	–0.26	0.77	0.12	20.5	0.92	0.002
EC (dS m^{-1})	0–30	0.011	0.62	0.11	0.03	3.09	2.06	0.17	154.6	0.60	<0.001
	30–60	0.011	0.49	0.06	0.01	7.46	2.81	0.10	178.7	0.51	<0.001
pH	0–30	4.44	6.20	5.23	5.24	–0.93	0.18	0.48	9.1	0.96	0.143
	30–60	4.25	6.46	5.53	5.56	–0.86	–0.21	0.57	10.3	0.97	0.214

SD – standard deviation, CV – coefficient of variation, Kurt. – kurtosis, Skew. – skewness, S-W test – Shapiro-Wilk test, FC – volumetric water content at field capacity, PWP – volumetric water content at permanent wilting point, AWC – available water content, Ksat – saturated hydraulic conductivity, EC – electrical conductivity

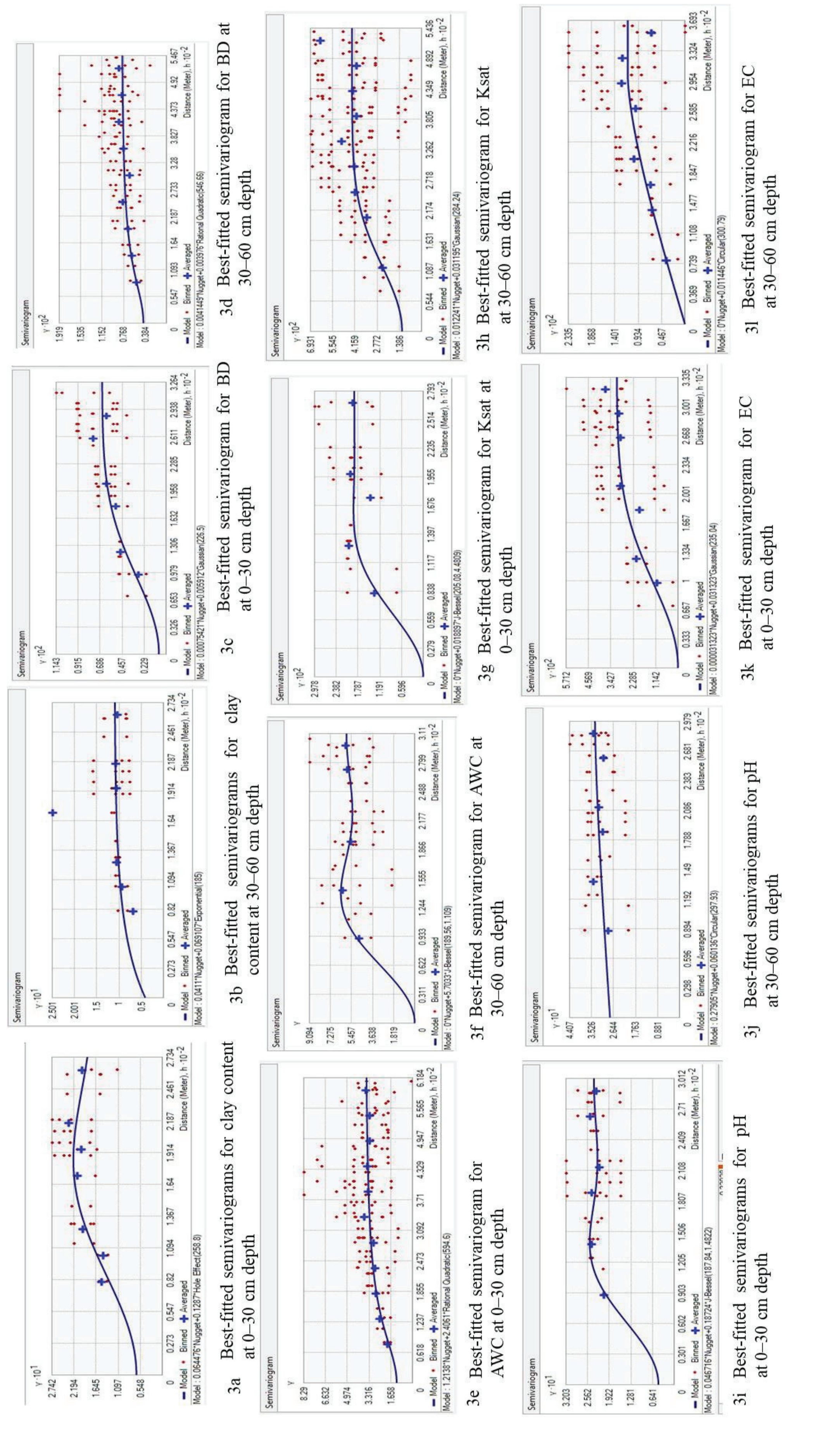

Fig. 2. Best-fitted semivariograms for the soil properties studied

of high accuracy (about 91% to 100% of the observed values in the field). A look at the semivariograms shows that most of the soil properties produced distinct sills which implies second-order stationarity of the respective data sets (Schabenberger and Pierce, 2002).

3.2.1. Spatial dependence

As indicated in Table 2, the soil properties studied displayed different spatial dependence and structure at both the 0–30 cm and 30–60 cm depths as indicated by the different semivariograms and semivariogram parameters namely the nugget, sill and the range.

The nugget effect describes the short-range variability at distances too small to be detected at the sampling interval used. It is attributed to measurement and sampling errors in the field (Tuffour et al., 2016). From the results, at the 0–30 cm depth, most of the soil properties, with the exception of saturated hydraulic conductivity, recorded nuggets ranging from 0.0007 (total porosity) and 18.84 (silt). Similarly, at 30–60 cm depth, except for sand, AWC and FC which were not associated with nugget effects, the rest of the soil properties had nuggets ranging from 0.004 (BD) and 5.72 (silt). The relatively small nuggets recorded by clay, BD, TP, FC, EC, pH and Ksat indicate smooth spatial continuity between neighboring points and good spatial structure at both sampling depths (Fathi et al., 2014). The relatively small nugget recorded by the soil properties is attributable to small and minimal measurement and sampling errors as well as micro-scale variability in the field. In effect, most of the soil properties studied displayed good spatial structure. The sill, which represents the total variability, has two components; the nugget or random component and the structural component. The structural component is the variability could be accounted for by the spatial pattern of the soil properties at sampling interval adopted. The small nuggets exhibited by the soil properties therefore means that a greater proportion of the variability of the soil properties was captured or accounted for at the sampling interval employed in this study. In related studies conducted by (Ayoubi et al., 2007) in Iran and by (Abu and Malgwi, 2011) in Nigeria, pH, EC, sand silt, clay, FC and PWP were found to be associated with very small nugget effects.

Range refers to the distance at which the maximum semivariance is reached on the semivariogram. It represents the minimum separation distance between statistically independent pairs of samples. Values of a variable separated at distances closer than the range are said to be spatially correlated while those separated at greater distances are said to be spatially independent (Webster and Oliver, 2007). From the results, the range showed wide variations among the soil properties investigated

Table 2
Best-fitted semivariograms and their parameters for the soil properties studied

Variable	Depth (cm)	Model	Nugget	Sill	Range (m)	N/S (%)	SD	Cross-validation RMSE	MSE	RMSS
Sand (%)	0–30	K-Bessel	2.062	144.242	185.0	1.4	Strong	7.78	0.002	0.91
	30–60	J-Bessel	0	95.528	209.0	0	Strong	8.84	–0.02	0.97
Silt (%)	0–30	K-Bessel	18.844	29.105	185.0	64.7	Moderate	5.22	0.008	0.97
	30–60	Spherical	5.724	37.756	185.0	15.2	Strong	5.39	0.03	0.98
Clay (%)	0–30	Hole Eff.	0.064	0.193	258.8	33.4	Moderate	7.19	–0.04	0.99
	30–60	Expon.	0.041	0.110	185.0	37.3	Moderate	5.67	–0.01	0.95
BD (g cm^{-3})	0–30	Gaussian	0.001	0.007	226.5	11.3	Strong	0.05	0.0004	1.04
	30–60	R. Quad.	0.004	0.008	546.7	51.0	Weak	0.07	–0.02	0.94
TP (cm^3 cm^{-3})	0–30	Gaussian	0.001	0.007	219.5	10.3	Strong	1.93	–0.007	1.04
	30–60	K-Bessel	0.008	11.568	380.8	0.07	Strong	2.77	0.02	0.93
FC (cm^3 cm^{-3})	0–30	Gaussian	0.004	0.005	176.4	71.2	Moderate	1.819	–0.025	1.03
	30–60	J-Bessel	0.362	0.779	195.4	46.5	Moderate	0.8766	0.023	0.98
PWP (cm^3 cm^{-3})	0–30	Hole Eff.	3.048	5.109	225.3	59.6	Moderate	2.21	–0.007	0.96
	30–60	J-Bessel	0.470	6.042	192.3	77.7	Weak	2.47	0.06	1.03
AWC (cm^3 cm^{-3})	0–30	R. Quad.	1.214	3.620	594.6	33.5	Moderate	1.47	–0.01	0.996
	30–60	J-Bessel	0	5.703	189.6	0	Strong	2.29	–0.052	0.989
Ksat (cm hr^{-1})	0–30	J-Bessel	0	0.019	205.1	7.7	Strong	0.09	–0.05	0.96
	30–60	Gaussian	0.012	0.043	284.2	28.2	Strong	0.078	–0.027	0.92
EC (dS m^{-1})	0–30	Gaussian	3.132E-5	0.031	235.0	0.001	Strong	0.058	0.0306	1.00
	30–60	Circular	0	0.011	300.8	0.0	Strong	0.06	0.0045	0.92
pH	0–30	J-Bessel	0.047	0.234	187.8	19.97	Weak	0.496	–0.056	1.01
	30–60	Circular	0.279	0.339	297.9	82.3	Moderate	0.578	–0.042	1.00

RMSE – root mean square error, MSE – mean standardized error, RMSS – root mean-square standardized error, N/S – nugget to sill ratio, SD – spatial dependency: <25% – strong, 25–75% – moderate, >75% – weak in this study. For instance, whereas AWC recorded a range of 594.6 m at 0–30 cm depth, FC had a range of 176 m. Similarly, at 30–60 cm depth, BD had a range of 546.7 m whiles silt and clay recorded a range of 185 m.

As posited by Fathi et al. (2014), the range is a very useful parameter which could be used as a guide to obtain independent datasets, determine where to resample where necessary and to design future field experiments. The ranges recorded in this study indicate that the soil properties studied could be sampled at distances ranging from 176 m to 547 m to obtain independent datasets for fertilizer experiments.

The nugget to sill ratio (N/S ratio) is the most widely used parameters for classifying the spatial dependence of soil properties. Based on the N/S ratio, the results showed that with the exception of pH which exhibited weak spatial dependence at the 0–30 cm depth, the rest of the soil properties exhibited strong to moderate spatial dependence. Similarly, at the 30–60 cm depth, most of the soil properties with the exception of BD and PWP were found to be strongly and moderately spatially dependent. These results are in conformity with the results of Iqbal et al. (2005) and Abu and Malgwi (2011) who found most of the soil properties studied to be moderately to strongly spatially dependent. The strong spatial dependence exhibited by most of the soil properties studied could be related to parent material and the influence of the relatively flat topography in the area.

3.2. Spatial distribution of the soil properties

The spatial distribution of the soil properties studied at 0–30 cm and 30–60 cm depths are depicted in the Figures 3a–3l. As shown in the figures, most of the soil properties displayed clustered spatial distribution pattern with varying ranges of patches. As shown in Figures 3g and 3h, Ksat was low across the field in both the surface and subsoil layers indicating that downward movement of water is impeded. This could be related to the fact that the soils in the area are predominantly plinthosols. These soils contain plinthite, an iron-rich, poor humus-poor mixture of kaolinite clay with quartz and other constituents that change irreversibly to a hardpan (Driessen and Deckers, 2001). Figure 3b, also shows that the subsoil layer (30–60 cm) recorded significantly higher clay content with higher values concentrated in the mid-eastern, middle and mid-western parts of the field. Again, this is typical of plinthosols and planosols which have AEBC profiles with subsoils significantly higher in clay (Driessen and Deckers, 2001).

4. Conclusions

- Soils in the irrigation scheme are slightly acidic and have high bulk density indicating possible limitations to the cultivation of vegetables such as tomatoes, cabbage and watermelon.
- Most of the soil properties studied showed moderate to strong spatial dependence indicating that their distribution was largely influenced by intrinsic factors such as parent material, topography and soil mineralogy.
- The study has provided useful information about the spatial structure and variability of soil properties in the Libga Irrigation Scheme which could serve as guide for managers of the scheme and farmers to make informed decisions about input use and tillage practices to adopt.
- The study has provided the foundation for the implementation and adoption of site-specific farming technologies by farmers.
- The study has demonstrated that with limited number of soil samples, ordinary kriging can be executed in ArcGIS (Arcmap) to adequately model the spatial structure and dependence of soil properties and produce accurate spatial distribution maps.

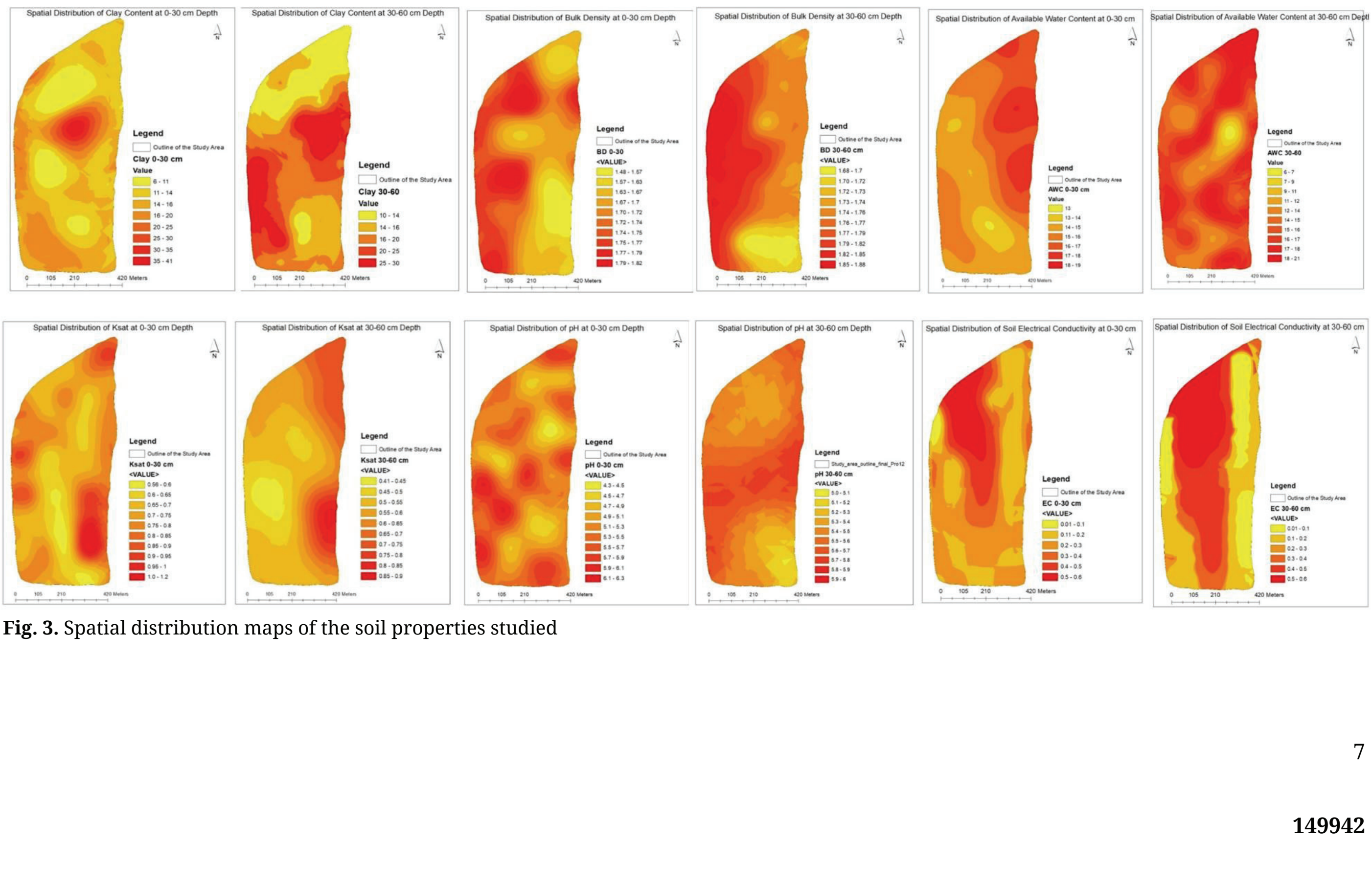

Fig. 3. Spatial distribution maps of the soil properties studied

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