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Geospatial distribution of soil organic carbon and soil pH within the cocoa agroecological zones of Ghana

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ABSTRACT

Geospatial distribution of soil organic carbon (SOC) and soil pH is an important component of soil fertility management in sustainable cocoa (*Theobroma cacao* L.) production. Spatial precision of cocoa soil fertility management in Ghana is rare due to paucity of spatially precise knowledge of farm soil properties. This study sought to provide spatially explicit knowledge of the underlying trends of SOC and pH in and across cocoa agroecological zones, covering 61 cocoa districts in Ghana. Soil samples collected at 20 cm depth from 739 newly established cocoa farms were analyzed using classical and geospatial statistical methods. We described the spatial pattern (clustering) of SOC and pH and predicted their spatial continuity from observed and unobserved locations. Results generally revealed unsuitably low SOC (0.39 ± 0.009 g/100 g) and strong acidity (5.35 ± 0.027). Univariately, SOC varied more continuously (58%) over a longer distance (1.424 km) than pH, which varied moderately around 55.7% over a shorter distance (0.598 km). Covariates improved the co-regionalized structure and homogeneity of the predictions. Thus, the spatial dependencies of SOC and pH were moderate but the risk of imprecision was higher for SOC than pH. This knowledge is crucial in our understanding of the geo-physicochemical phenomena controlling the spatial distribution of SOC and pH in the cocoa farms and districts across the agroecological zones. The findings underscored dwindling SOC and pH in line with historic boom-bust cycle of cocoa production hot and cold spots transitions. The findings are also indicative of the adverse implications of relying on current blanket fertilizer recommendations. Therefore, a change from the current agronomic practice of fertilizer use to one that recognizes the SOC and pH needs of specific areas, farms and cluster of districts is recommended.

1. Introduction

Geospatial distribution of soil organic carbon (SOC) and soil pH constitutes a salient component of soil management in sustainable cocoa (*Theobroma cacao* L.) production. The levels of SOC and pH are essential for soil microbial activities that stimulate mineralization of key soil nutrients such as potassium (K) and phosphorus (P) (Ahenkorah, 2016; Doran et al., 1987; van Vliet and Giller, 2017). According to Dawoe et al., (2014) and Dossa et al., (2018), cocoa soils are rapidly losing their SOC while acidity is increasing. This is attributed to intensive cocoa-monocropping system and blanket agrochemical dosage for short-term profits in Ghana (Asare et al., 2017). Identifying the location of deficient SOC and soil acidity hotspots in the agroecological landscape is essential for precision in maintaining cocoa soil fertility (IFDC, 2011). These hotspots will determine the type and dose of fertilizers required to elongate soil health and fertility in such locations (Snoeck et al., 2016, 2010; Snoeck and Dubos, 2018). Previous studies suggest that the current blanket cocoa fertilizer dose of 150 kg acre^{-1} regardless of soil conditions (IFDC, 2011) is inaccurate, costly and less profitable compared to site-specific trial results (Dossa et al., 2018; Snoeck et al., 2016, 2010; Asare et al., 2017). According to IFDC, (2011), Dossa et al. (2018), Asare et al. (2017) among others. Site-specific fertilizer recommendation is the way forward for sustainable cocoa production in Ghana. However, upscaling the gains from the available site-specific trials have been hampered by limited knowledge of the spatial structure of SOC and pH distribution. The co-regionalized or composite structure of SOC and pH that should incorporate secondary variables like clay, aluminium (Al) and iron (Fe) are also rare (Ahenkorah, 2016;

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Doran et al., 1987; van Vliet and Giller, 2017). Based on ecological concept of positive and negative feedbacks and feedback-loops of soil resilience (Folke et al., 2010; Lal, 2015), SOC may respond positively to clay and pH, while Al and Fe do exert negative feedback on soil pH. Both feedbacks affect soil fertility and health. For example, high clay content of soils has been reported to be critical for soil health and productivity (Calvo de Anta et al., 2020; Rial et al., 2017; Singh et al., 2018). Gérard (2016); Delhaize and Ryan (1995) in van Vliet and Giller (2017) and Ahenkorah (2016) have also reported that Al and Fe toxicities tie-up plant nutrients by creating "soil acidity complex" in soils that have low SOC and pH. This study attempts to map and predict the spatial distribution of SOC and pH at 20 cm depth in newly established cocoa farms; incorporate the impacts of clay, Al and Fe as covariates in the spatial structure of SOC and pH across the entire cocoa agroecological zones of Ghana. The study employed classical statistics, geospatial and geostatistical tools such as coefficient of variations (CV), local moran (LM), Kriging/cokriging (Goovaerts, 1999; Hengl et al., 2004; Minasny and McBratney, 2016) to achieve its objectives.

Soil organic carbon is derived from living and dead biota. It may more or less constitute 50–58% of soil organic matter (FAO, 2017; Pribyl, 2010). It stores the largest pool of the world's terrestrial carbon and serves as an indicator of soil health and fertility for crop production (FAO & ITPS, 2015; Lal, 2013; Rial et al., 2017). Soil microbes like phosphate mobilizing bacterial and mycorrhizae fungi feed on SOC to stimulate humification and mineralization of major plant soil nutrients such as phosphorus and potassium (Ahenkorah, 2016; Doran et al., 1987; Ingham, 2019; Rousk et al., 2009). As a carbon stock (FAO, 2017; Owusu et al., 2020), SOC helps to conserve biodiversity, regulates adverse global warming, climate change and variability (Lal, 2019, 2004).

Maintaining SOC is essential for sustainable soil productivity as it enhances good soil consistency and water retention capacity thereby buffering crops against delayed rainfall (Blanco-Canqui et al., 2013). With the current 2% annual rate of deforestation in Ghana (Asase et al., 2010; Doe et al., 2018; FAO, 2016), declining cocoa soil fertility (Wessel and Quist-Wessel, 2015) and climate change (Akpa et al., 2016; Anim-Kwapong and Frimpong, 2009; Schroth et al., 2016), the role of SOC needs to be emphasized. The role of SOC is apt for ecological intensification, organic farming (Tittonell and Giller, 2013), climate-smart agriculture (Schroth et al., 2016) and restoration of depleted cocoa soil nutrients (Dawoe et al., 2014; Dechert et al., 2004; Lal, 2019, 2015, 2004; Somarriba et al., 2013).

A poor balance of SOC and pH is unsafe for the health and productivity of soil (Rousk et al., 2010, 2009). Although pH enhances ionic mobility, extremes of soil pH negatively affect soil microbiology and nutrients dynamics. Farm soils of pH ≤ 4.5 limit bacterial activities just as soil pH ≥ 7.5 restrains fungal activities (Rousk et al., 2010, 2009). According to Rousk et al. (2009), bacterial activities decreased five-fold in contrast to a five-fold increase in fungal activities when soil pH was reduced from 8.3 to 4.5. Below 4.5, all microbial activities ceased, due to free release of Al that inhibits plant growth (Ingham, 2019; Rousk et al., 2009). Soils with pH of 5.6–7.4 and SOC above 3.5% are recommended as ideal for cocoa production in Ghana (Ahenkorah, 2016).

Ghanaian cocoa soils are generally acidic and low in carbon and this affects the uptake of plant-available nutrients (Ahenkorah, 2016; IFDC, 2011). Strong acidic soils (pH ≤ 5.5) tend to release aluminium (Al^{3-}), iron and (Fe^{2-}) hydroxides and oxides that limits the usefulness of major soil nutrients such as P and K. The Al^{3-} and Fe^{2-} form AlOH and FeOH respectively by taking up the hydroxide ion (HO^-) from soil mineral water ($H^+ + OH^-$) solution. The loosed hydrogen ion (H^+) increases soil acidity and when the pH is below 5.5 uptakes of plant-available nutrients becomes difficult (Ahenkorah, 2016).

On the other hand, high soil clay facilitates the release of plant-available soil nutrients (Ahenkorah, 2016; Cunningham, 1963; Nye and Bertheux, 1957). Clayey soils have a large surface area of tiny particles that are negatively charged. These negatively charged particulates hold loosed H^+ more rapidly than plant-available nutrients like Ca^{2+} and K^{2+}. Clay soils also preserve dissolved SOC from phyllosilicate, soil water run-offs and seepages (Barré et al., 2014; Singh et al., 2018).

Due to the aforementioned, previous studies have recommended the need to balance the use of acid-forming and base-forming fertilizers in line with site-specific soil requirements (Snoeck et al., 2016, 2010; Snoeck and Dubos, 2018).

However, fertilizer use and site-specific soil fertility management can only be possible when there is precise knowledge of the spatial variations in soil properties across location and space (Dossa et al., 2018; Lal, 2015; Wang et al., 2007). Although several studies have been conducted on the usefulness of cocoa fertilizers (Afrifa et al., 2007; Appiah et al., 2000; Snoeck et al., 2007), agroecological zones and soil properties differ spatially (Anim-Kwapong and Frimpong, 2009; Hall and Swaine, 1976; Owusu et al., 2020). Inherent site-specific soil variability makes the current blanket recommendation of cocoa fertilizers suboptimal and environmentally risky. Asare et al. (2017), observed in a fertilizer trial that the recommended dosage of P, calcium (Ca^{2+}) and magnesium (Mg^{2+}) in cocoa fertilizer did not produce the desired yield because of the spatial differences in soil properties. In another study, Dossa et al., (2018) found the site-specific treatment to be more effective and profitable than the blanket ones. Although the work of Owusu et al. (2020) on carbon stock was broad, it revealed the paucity of precise spatial information on underlying SOC and pH in Ghana. Therefore, this study attempts to fill the spatial knowledge gap on SOC and pH in the cocoa agroecological zones of Ghana. The main aim of this study was to determine the extent of geospatial variability in SOC and pH with underlying co-regionalized auxiliary or secondary variables (covariates) in the cocoa production zones of Ghana. Specifically, the study sought to describe the levels of SOC and pH, predict the magnitude of spatial autocorrelation, pattern, hot and cold spots of SOC and pH using clay, Al and Fe as secondary variables in the cocoa districts and within the cocoa agroecological zones of Ghana. In this study, the term spatial dependency is used interchangeably with spatial continuity and spatial auto-correlation. It is defined as the correlation between the primary values of SOC and pH over distance.

The study is relevant for precision of soil fertility management for sustainable cocoa production in Ghana. Knowledge of spatial variations of cocoa soil properties is required in improving the precision of fertilizer use and soil fertility management. This is important in curtailing the declining cocoa SOC and pH (Ahenkorah, 2016; Cunningham, 1963; Dawoe et al., 2014; IFDC, 2011). The spatial insights on SOC and pH observed in this current study serve as indicators of soil health status for the various cocoa districts. These insights are relevant to cocoa farmers as well as extension workers of the Cocoa Health and Extension Division (CHED) of Ghana Cocoa Board (COCOBOD), including other local and international stakeholders.

2. Materials and methods

2.1. Study area

The study area lies between latitude 4°3′0″ N to 8°0′0″ N and longitude 3°3′0″ W to 0° 2′0″ E in Ghana. There are 61 cocoa districts across six cocoa agroecological zones (Anim-Kwapong and Frimpong, 2009; Hall and Swaine, 1976) in seven cocoa regions (Fig. 1). The total land area of the cocoa districts is about 94,580.11 km^2 with an average size of 1576.34 km^2 (SD = 976.34 km^2) per district. The agroecological zones are made up of Dry Semi-Deciduous Fire Zone (DSFZ), Dry Semi-Deciduous Inner Zone (DSIZ), Wet Evergreen (WE), Moist Evergreen (ME), Moist Semi-Deciduous North West (MSNW) eco-type and Moist Semi-Deciduous Southeast (MSSE) eco-type. These ecological zones constitute about 86.19% (81,515.23 km^2, mean = 13.58 km^2, SD = 7.24 km^2) of the cocoa districts land surface area. The mean (μ) annual rainfall is about 1600 mm in the wet season and 1200 mm in the dry

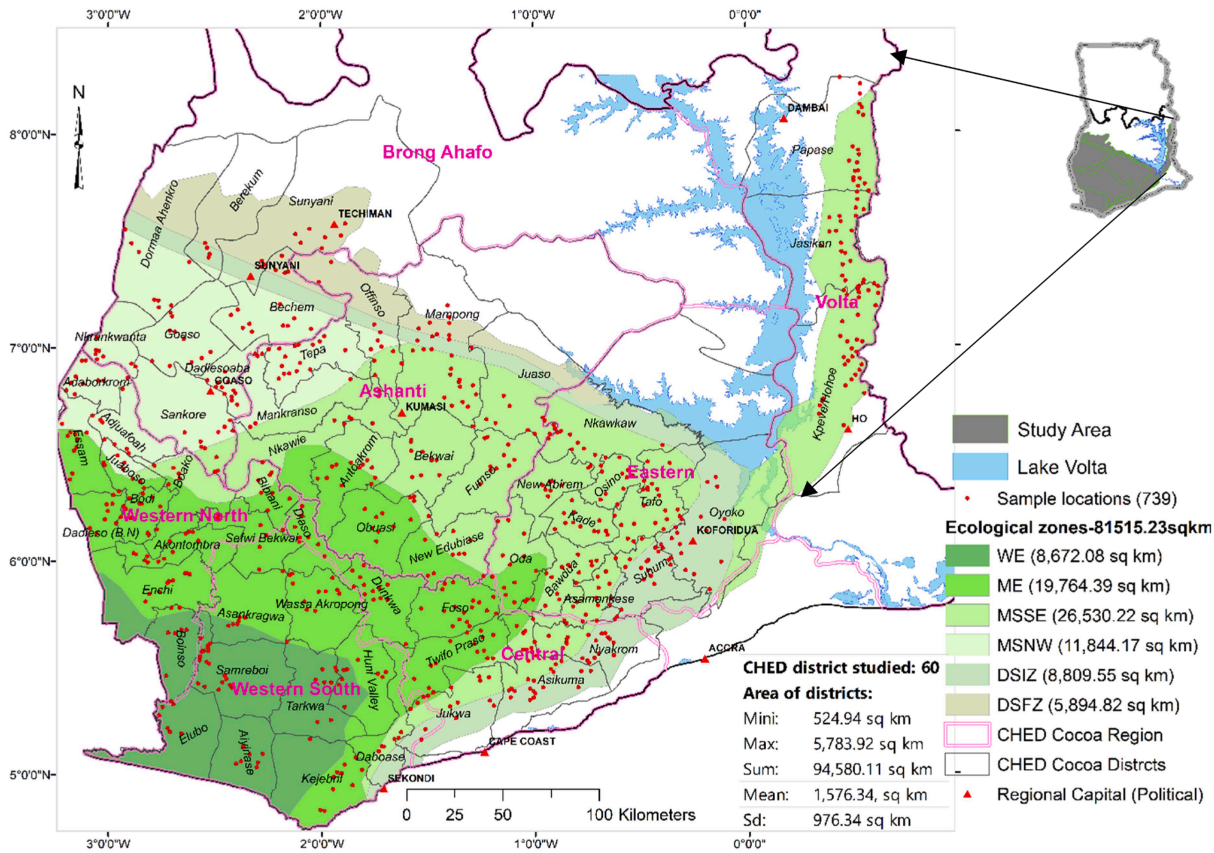

Fig. 1. Map of the study area showing soil sample locations in farms, agroecological zones, cocoa districts and regions of Ghana. Note: WE = Wet Evergreen; ME = Moist Evergreen; MSSE = Moist Semi-Deciduous Southeast eco-type; MSNW = Moist Semi-Deciduous North West eco-type; DSIZ = Dry Semi-Deciduous Inner Zone; DSFZ = Dry Semi-Deciduous Fire Zone.

season. Distribution of the rainfall increases from 1400 mm to 1800 mm with DSFZ < DSIZ < MSNW < MSSE < ME < WE. The mean daily temperature ranges from 18 °C to 26 °C and the elevation is 90–400 m above sea level (Anim-Kwapong and Frimpong, 2009; Hall and Swaine, 1976).

2.2. Study design and data source

Soil samples were collected at 20 cm depth from 739 newly established cocoa farms in the 61 cocoa districts between 2015 and 2017. The cocoa farms were hitherto fallowed for about five years or grubbed cocoa farmlands for that matter the soil sample locations were irregularly spaced. A stratified random sampling method was used to select representative farms for each cocoa district. A standard hand-held Global Position System (GPS) device of 2 m accuracy range was used to pick the geographical coordinates of the sample locations x_{ij}. The soils were air-dried and sieved using a 2 mm mesh. Particle size distribution was determined using the Hydrometer method, pH in a 1: 2.5 soil–water suspension using a glass electrode and pH meter. Organic carbon (OC) was analyzed by the Walkley and Black wet combustion method. Concentrations of Fe and Al in the soil were determined by the Mehlich-3 extraction method using 1: 10 (w/v) soil-extractant ratio, followed by atomic absorption spectrometry. The ecological attributes of the study area were obtained by plotting and clipping the sample coordinates to shapefiles of the ecological zones and cocoa districts.

2.3. Variables

The primary (dependent) variables of the study are SOC and pH and the secondary (covariates) variables are clay, Al and Fe. The soil pH doubles as a covariate for SOC. According to Hengl et al. (2004), covariates are useful for explaining the distribution and accuracy of spatial prediction of soil properties. The soil pH and clay were used to predict SOC while Al and Fe were employed to predict soil pH. In each case, ecological zones implicitly served as proxies for rainfall or available soil water.

2.4. Statistical methods

Both classical and geostatistical methods were employed to analyze the dataset (N). Classical descriptive statistics such as mean (μ), median, range (minimum and maximum values), standard deviation (σ) and coefficient of variation (CV_{x_i}) (Eq. (1)), and their probability density function (PDF), enabled description of the study variables (x_i). In this study, CV_{x_i} values for both SOC (CV_{SOC}) and soil pH (CV_{pH}) were classified into three categories, low variability ($\leq$25%), moderate variability ($<$25 to $\leq$ 75%) and high variability ($>$75%).

$$CV_{x_i} = \frac{\sigma}{\mu} \times 100\% \tag{1}$$

The PDF was estimated using kernel density estimator (KDE), a technique that enables fitting a smooth curve over the underlying distribution of x_i. The Gaussian (normal) kernel and a smoothing bandwidth (h) were chosen for any two observations where the variance (σ^2) was constant. The Shapiro Wilk test of normality was used to determine the normality of the distribution of x_i. This test informed the decision to transform the data or use a non-parametric test of the mean difference between the agroecological zones.

Well-known geostatistical methods, namely Global Moran's I (GMs), local Moran's I (LMs), semi-variance, ordinary Kriging (OK) and ordinary cokriging (OCK) were used to study the spatial distribution and to predict the structure of SOC and pH. The GMs and LMs are known for identifying aerial clustering and outliers (Anselin, 1995) while OK/OCK detect statistically significant hot and cold spots. In this study, hotspot refers to locations of rich SOC while cold spot denotes locations of low SOC and the same applies to pH.

2.4.1. Empirical modelling of cocoa soil organic carbon and soil pH within cocoa agroecological zones

Assuming x is a set of coordinates for a spatial variable Z_{x_i} (SOC or pH), with z_μ being the mean and w_i the weighting distance between any two observations at locations z_{x_i} and z_{x_i+h}. The stochastic error term $\varepsilon(.)$ of the spatial regression of Z_{x_i} (Anselin, 1995; Getis and Ord, 1992) is a measure of the total spatial variation from Z_{x_i} to z_{x_i+h}. As specified in Eqs. (2.1) and (2.2), the error terms $\varepsilon(.)$ are the estimates $(\widehat{Z_{x_i}})$ of Z_{x_i} from either a univariate (no covariate) or a multivariate regression.

$$\widehat{Z_{x_i}} = X\beta_i + \varepsilon_i \Rightarrow \widehat{SOC}_i = \left[X\beta_0 + \beta_1 Clay_{z_i} + \beta_2 pH_{z_i} + \beta_3 pH_{z_i} * Clay_{z_i}\right] + \varepsilon_i,\ \beta_i > 0 \tag{2.1}$$

$$\widehat{Z_{x_i}} = X\beta_i + \varepsilon_i \Rightarrow \widehat{pH_i} = \left[X\beta_0 - \beta_1 Al_{z_i} - \beta_2 Fe_{z_i} - \beta_3 Al_{z_i} * Fe_{z_i}\right] + \varepsilon_i,\ \beta_i < 0 \tag{2.2}$$

Both the univariate OK and multivariate OCK methods predict the clustering and distance of objects based on the spatial lag of each primary variable and the error term (ε_i) from Eq. (1) and Eq. (2) respectively. The univariate OK predicts the sole structure of the primary variables while the multivariate OCK approach predicts the co-regionalized structure of the primary variables based on the secondary variables (Goovaerts, 1999; Goulard and Voltz, 1992; Hengl et al., 2004).

Our apriori expectations about the relationships between SOC, clay and pH is positive $(\beta_i > 0)$ in line with Ahenkorah, (2016), Barré et al., (2014) and Singh et al. (2018). These authors suggested that the negatively charged colloids of clay particles retain SOC longer and their uptake of H^+ reduces soil acidity while leaving OH^- to increase basicity and plant-available nutrients in the soils. Hence, we expected the coefficients of clay $(\beta_1 > 0)$, pH $(\beta_2 > 0)$ and their joint-interaction $(\beta_3 > 0)$ to impact positively on the predicted SOC.

Concerning the soil pH, we expected the coefficients of Al (β_1), Fe (β_2) and their joint-interaction (β_3) as specified in Eq. (2.2) to exert negative $(\beta_i < 0)$ impacts on the prediction. Bioavailability of negatively charged plant nutrients such as Phosphate $(PO_4)^{3-}$ or $(H_2PO_4)^-$ anions is retarded by Al^{3+} and Fe^{2+} cations. These cations bind up HO^- from soil water leaving the (H^+), making the soil more acidic and unsuitable for microbial activities and crop growth (Ingham, 2019; Rousk et al., 2009). These apriori expectations buttress the reasons for using OCK in addition to the OK.

In the case of the univariate OK, the $\varepsilon(.)$ can be summarized by a semi-variance $\lambda(h)$ as given in Eq. (3) (Goovaerts, 1999; Simbahan et al., 2006).

$$\lambda_i(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[\widehat{\varepsilon}(Z_{x_i}) - \widehat{\varepsilon}(Z_{x_i+h})\right]^2 \tag{3}$$

where $\lambda(h)$ is the semi-variance estimator for any given spatial lag distance h between any two observations (Z_{x_i} and Z_{x_i+h}) and $N(h)$ is the total counts of h pairs. The $\widehat{\varepsilon}(Z_{x_i}) - \widehat{\varepsilon}(Z_{x_i+h})$ denote the error difference between the observed and unobserved locations of each primary variable.

The semi-variance is an indicator of dissimilarity and how closer values of Z_{x_i} are related (similarity). Let C_1 represent partial sill or the difference between the sill $(C_0 + C_1)$ and nugget (C_0) values of the semi-variance. If the nugget (C_0) and the sill $(C_0 + C_1)$ are the maximum similarity and maximum dissimilarity respectively, the nugget and sill ratio $(C_0/[C_0 + C_1])$ of <25%, 25–75% and above 75% is indicative of strong (high), moderate and weak (low) spatial dependence respectively (Cambardella et al., 1994; Goovaerts, 1999; Zhang et al., 2012). The major range determines the distance (m) at which values of Z_{x_i} become spatially independent of each other. In other words, the major range is the maximum distance (h) beyond which there is no spatial continuity (Goovaerts, 1999; Zhang et al., 2012). In line with Tobler's first law of geography concerning spatial dependency, we expected that all Z_{x_i} would be related but nearer Z_{x_i} will be more related.

The univariate OK as defined in Eq. (4) was used to interpolate (predict) the unobserved Z_{x_o} (SOC or pH) locations based on the observed ones Z_{x_i},

$$\lambda(h)_{\widehat{Z_{x_0}}} = \sum_{i=1}^{n} \gamma_i.\lambda_i() + \varphi = \lambda(x_i, x_o) \tag{4}$$

where $\sum_{i=1}^{n}\gamma_i = 1$, $\lambda()$ is the semi-variance between pairs of locations $Z_{x_{ij}}$, φ is a Lagrange multiplier for minimization (Zhang et al., 2012).

Goovaerts (1999), Hengl et al. (2004) and Simbahan et al. (2006) have described the OCK estimator as the multivariate extension of the OK, where the covariates of the primary variables are incorporated in the estimation of the unobserved locations Z_{x_o}. The auto-variogram of each variable and their cross-variograms can be linearly summed up into a co-regionalized structure (Goulard and Voltz, 1992; Simbahan et al., 2006), that estimates the unobserved locations Z_{x_o} using a multivariate OCK estimator (Eq. (5)).

$$\lambda(h)_{\widehat{Z_{x_0}}} = \gamma_1\lambda_1() + \gamma_2\lambda_2() + \cdots + \gamma_n\lambda_n() \tag{5}$$

2.5. Data analysis

We used R-software (Pebesma, 2004) for the OK and ESRI ArcGIS version10.4.1 Geostatistical Analyst for the OCK. In each variogram (semi-variances), we tested for normality and standardization $(z = (x-\mu)/\sigma)$ of the data. Outliers were addressed by activating Cressie-Hawkins robust estimator (Lark, 2000). Different variogram models were used to examine the auto and cross variograms to choose the best fit model that improves accuracy (Hengl et al., 2004), based on second-order stationarity of the random error term. We did not activate trend removal because of the relative smoothness of the transformed variables. Also, instead of the absolute distance (h), the data (Z_{x_i}) pairings were regrouped or rescaled into regular lag "bins" (lag distances h) to overcome the constraints of stationarity of the mean and regular sample spacing (Oliver and Webster, 2014; Webster and Oliver, 2007).

3. Results

3.1. Distribution of soil organic carbon and soil pH intensity in the entire study area

Visualizing the geospatial distribution of farm-level SOC and soil pH

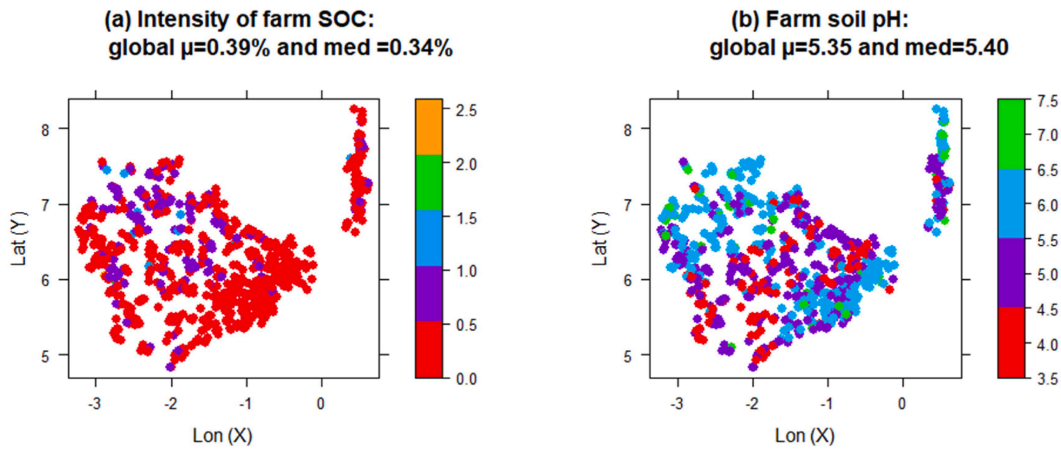

Fig. 2. Geospatial distribution of the density of (a) soil organic carbon (%) and (b) soil pH in newly established cocoa farms within the cocoa-growing zones of Ghana.

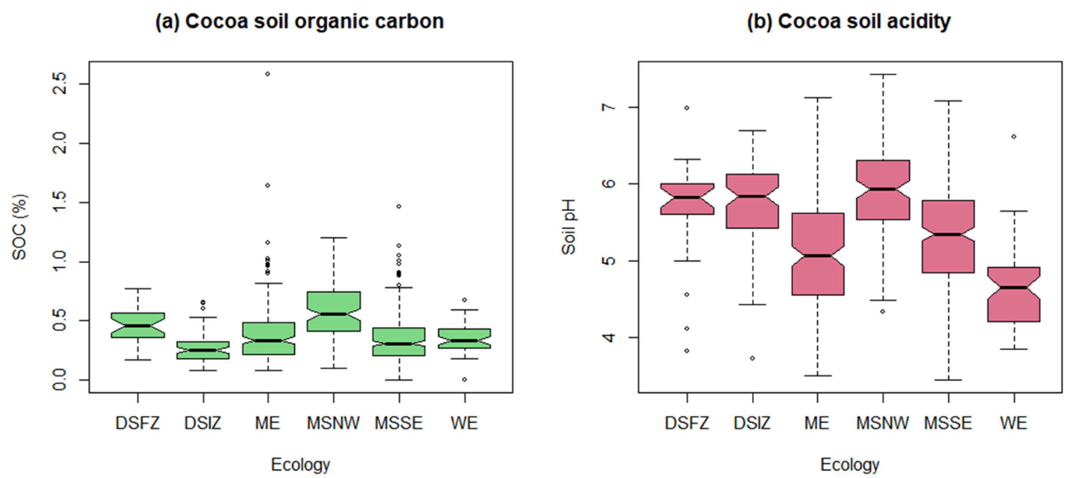

Fig. 3. A summary of the classical distribution of the median (a) soil organic carbon (%) and (b) soil pH in the different cocoa agroecological zones of Ghana.

(Fig. 2) suggests the presence of a spatial dependency (spatial pattern or continuity). A short-scale spatial continuity was dominant within range 0.00% to 0.50% of the SOC (Fig. 2a) whiles soil pH intensity varied within the range of 3.50–7.45 (Fig. 2b).

At the agroecological level, the spatial dependency is summarized in Fig. 3 showing the magnitude (intensity, concentration, density) and ranges of both SOC and pH. The sizes of the boxes and notches are respectively indicative of the extent of variability and confident intervals of the medians. The medians of the overlapping notches are statistically the same.

In Fig. 3a, it is observed that the ecological intensity of SOC declines in the following order: MSNW (0.55%) > DSFZ (0.46%) > WE (0.33%) > ME (0.33%) > MSSE (0.31%) > DSIZ (0.25%). Fig. 3b shows a decreasing sequence of soil pH that follows this trend: MSNW (5.93) > DSIZ (5.84) > DSFZ (5.82) > MSSE (5.34) > ME (5.06) > WE (4.65). The soil pH peaks (leptokurtic) within a relatively suitable median (5.8–5.9) for the DSFZ, DSIZ and MSNW. The ME and MSSE zones exhibited the widest pH range (3.45–7.12), exhibiting a platykurtic distribution. The WE zone was the strongest in terms of acidity, with a pH range of 3.85–6.61.

Generally, the ecological intensity of SOC ranged from 0.00 to 2.59% (med = 0.34%, μ = 0.39 ± 0.01, σ = 0.23) and the soil pH ranged from 3.45 to 7.43 (med = 5.40, μ = 5.35 ± 0.027, σ = 0.74) (Table 1 and Fig. 2). The Shapiro Wilk (SW) test of normality indicates that both the National (global) and ecological distributions of both SOC and pH are statistically different from normal (Table 1). The Kruskal-Wallis (KW) test of mean-difference in SOC (fisher exact) shows that the medians of SOC are not equal. A similar result was noticed for the soil pH (Table 1).

As shown in Table 1, the overall CV_{SOC} was generally moderate (CV_{x_i} = 59.5%, σ = 0.23) while that of CV_{pH} was low (CV_{x_i} = 13.92%, σ = 0.74). This is interpreted to mean that SOC is moderately heterogeneous while the pH is more homogeneous in the study area. High CV_{x_i} value is indicative of a high level of uncertainty (variability) while low values denote a high level of certainty (homogeneity).

The results in Table 1 reveal that ecological variation in CV_{SOC} is also moderate and decreases as follows: ME (0.69% σ = 0.28) > MSSE (0.56%, σ = 0.20) > DSIZ (0.49%, σ = 0.13) > MSNW (0.44%, σ = 0.25) > DSFZ (0.36%, σ = 0.18) > WE (0.35%, σ = 0.12). This implies that the precision or certainty of SOC increases sequentially as arrayed. In other words, the magnitude of homogeneity increases in that order.

Table 1 also shows a decreasing CV_{pH} (mean = CV_{x_i} ≤ 13.92%, σ = 0.74) across the agroecological zones in the following order: ME (13.6%, σ = 0.69) > DSFZ (12.0%, σ = 0.54) > MSSE (3.83%, σ = 0.72) > MSNW (0.92%, σ = 0.54), WE (0.11%, σ = 0.53) > DSIZ (0.1%, σ = 0.68). This means the ecological precision of soil pH is generally high or homogeneous and decreases sequentially as arrayed.

Table 1
Classical distribution of soil organic carbon and pH within cocoa agroecological zones of Ghana.

Variable(x_i)	Descriptive statistic		Cocoa agroecological zones						KWχ2 test***
		Overall	**DSFZ**	**DSIZ**	**ME**	**MSNW**	**MSSE**	**WE**	
		N = 739	n = 25	n = 75	n = 182	n = 103	n = 298	n = 56	ˆaˆ
SOC % (g/100g)	Median	0.340	0.460	0.250	0.330	0.550	0.310	0.330	107.760
	mean(μ)	0.390	0.465	0.268	0.401	0.579	0.357	0.354	
	σ	0.230	0.167	0.130	0.278	0.253	0.201	0.122	
	(%)	59.500	0.359	0.485	0.693	0.437	0.563	0.345	
	min	0.000	0.167	0.079	0.077	0.097	0.000	0.000	
	max	2.590	0.768	0.654	2.590	1.210	1.460	0.669	
	SW.test***	0.851	0.976	0.913	0.720	0.972	0.889	0.967	
Clay %	Median	20.760	22.760	14.760	22.760	22.700	18.760	24.760	
	μ	21.400	22.440	16.760	23.123	22.546	20.308	25.189	
	σ	8.738	7.063	6.746	11.025	6.555	7.970	7.461	
	min	2.760	8.760	4.760	2.760	8.760	4.760	10.760	
	max	54.760	34.760	30.760	54.760	40.760	48.760	44.760	
	SW.test***	0.975							
Soil pH	Median	5.400	5.820	5.840	5.060	5.930	5.340	4.650	170.490
	μ	5.350	5.660	5.750	5.080	5.910	5.320	4.630	
	σ	0.740	0.680	0.544	0.694	0.543	0.719	0.530	
	(%)	13.920	12.000	0.095	13.600	0.919	3.825	0.114	
	min	3.450	3.820	3.730	3.510	4.340	3.450	3.850	
	max	7.430	6.980	6.700	7.120	7.430	7.080	6.610	
	SW.test***	0.992	0.121	0.095	0.137	0.092	0.135	0.115	
Fe (cmol/kg)	Median	0.081	0.051	0.058	0.103	0.054	0.082	0.140	
	μ	0.087	0.630	0.645	0.106	0.057	0.085	0.132	
	σ	0.036	0.028	0.026	0.038	0.019	0.029	0.029	
	min	0.023	0.030	0.024	0.023	0.023	0.027	0.055	
	max	0.200	0.128	0.178	0.200	0.149	0.186	0.168	
	SW.test***	0.948							
Al (cmol/kg)	Median	4.880	2.762	5.929	6.786	4.846	9.039	8.585	
	μ	7.661	4.058	8.690	5.975	4.200	7.640	8.960	
	σ	6.970	2.800	7.590	4.593	2.373	5.243	2.188	
	min	0.190	0.190	1.460	1.420	0.640	1.480	3.120	
	max	37.370	9.820	25.890	30.060	12.060	37.370	12.980	
	SW.test***	0.975							

KW = Kruskal-Wallis rank sum test at df = 5, SW = Shapiro Wilk normality test, *** = significant at p < 0.000.

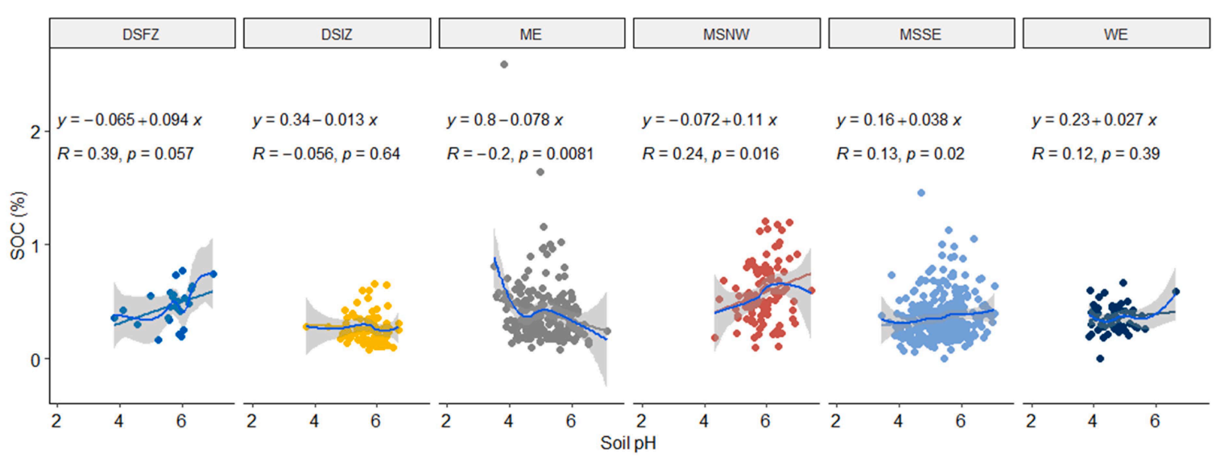

Fig. 4. Classical correlation of soil organic carbon and pH in the cocoa agroecological zones of Ghana.

3.2. *The relationship between soil organic carbon and pH with their covariates in the cocoa agroecological zones of Ghana*

The linear and polynomial relationship between the primary variables and the covariates in the agroecological zones are depicted in Figs. 4–7. The shaded area in each line denotes the precision level (σ) of the relationship. The R denotes R-square (R^2) and the p-value denotes probability of significance. The p-values that are <0.05 in Figs. 4–7, indicate that the relationship is significant. While the linear relationship between SOC and pH (Fig. 4) was positive in the MSNW and MSSE zones, it was negative in the ME zone. The coefficients were significant at 5%. In Fig. 5, the relationship between SOC and clay was significantly positive at 5% in the ME, MSSE and WE zones.

The relationship between soil pH and Al was positively significant at 5% in the WE zone but negative in the DSFZ, ME and MSSE zones (Fig. 6). This means that low concentrations of Al correspond to low pH and vice versa, in these zones. The relationship was insignificant in the DSIZ and MSNW zone. Also, the results showed a strong (6.1–19)

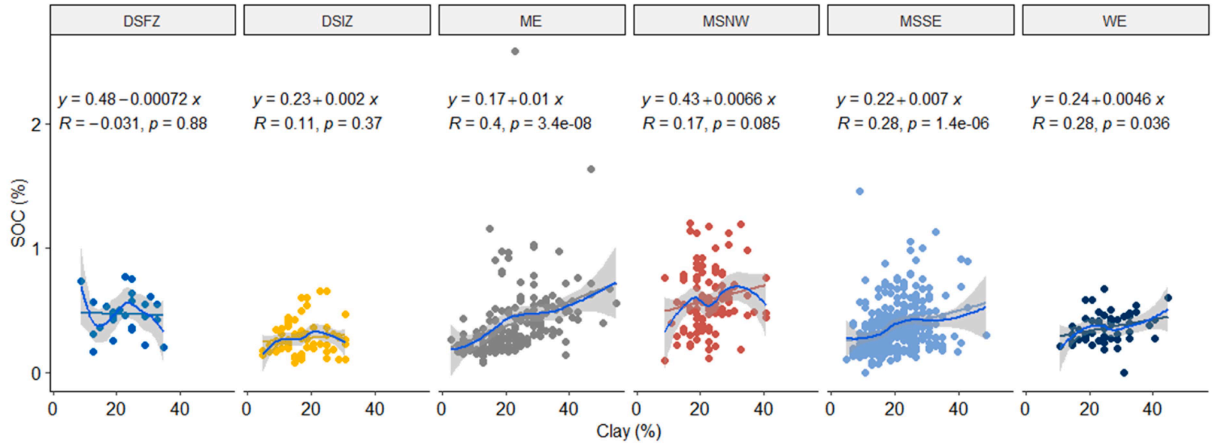

Fig. 5. Classical correlation of soil organic carbon and clay in the cocoa agroecological zones of Ghana.

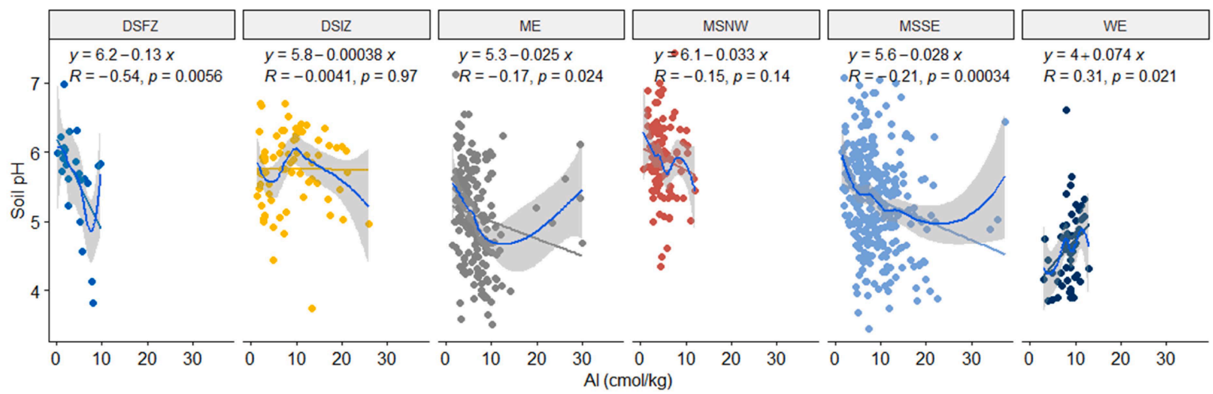

Fig. 6. Classical correlation of soil pH and aluminium in the cocoa agroecological zones of Ghana.

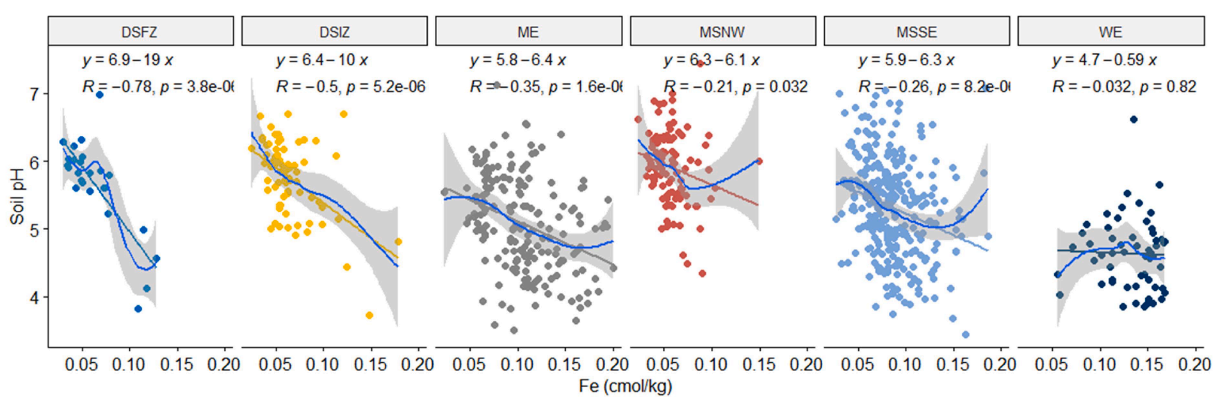

Fig. 7. Classical correlation of soil pH and iron in the cocoa agroecological zones of Ghana.

negative correlation of soil pH and Fe in five ecological zones excluding the WE which was insignificant (Fig. 7).

3.3. Spatial clustering of soil organic carbon and pH in the cocoa districts of Ghana

Fig. 8, illustrates the general distributions of the median, upper and lower quartiles of SOC (a) and pH (b) in the cocoa districts of Ghana. Note that SoC is the same as SOC. Mankranso and Obuasi in the Ashanti Region (AR), Dadiesoaba, Dormaa Ahenkro and Nkrankwanta in the Brong Ahafo Region (BA), Akontombra, Enchi, Swefi Bodi and Boako in Western North Regions (WN) had the richest SOC content. Elubo, Tarkwa, Kejebril and Boinso in the Western South Region (WS) recorded the most acidic soils. Adaborkrom in WN, Dadiesoba, Sunyani, Dormaa Ahenkro, Goaso, Bechem in BA, Mankranso, Tepa, Offinso, Nkawie in AR, Oyoko and Suhum in the Eastern Region (ER), including Papase in the Volta Region (VR) had relatively higher levels of soil pH than the rest of the cocoa districts. Fig. 9 presents the geographical mean of the SOC (Fig. 9a) and pH (Fig. 9b) in the cocoa districts and their correlation coefficients (Fig. 9c). The local Pearson's correlation coefficient is more negative toward the south-eastern districts but more positive in the north-west/south-west districts, meaning high SOC values associate with high pH values vice versa in the latter.

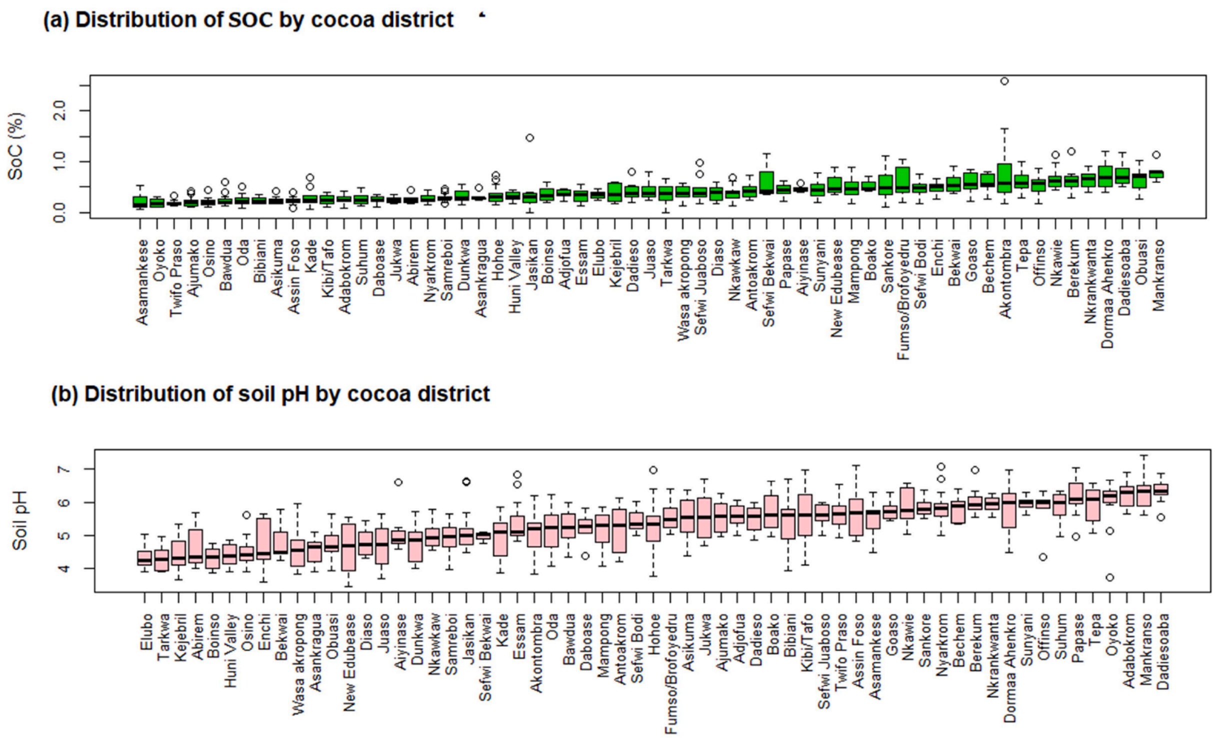

Fig. 8. Box plots of soil organic carbon (%) and pH distribution in the cocoa districts of Ghana.

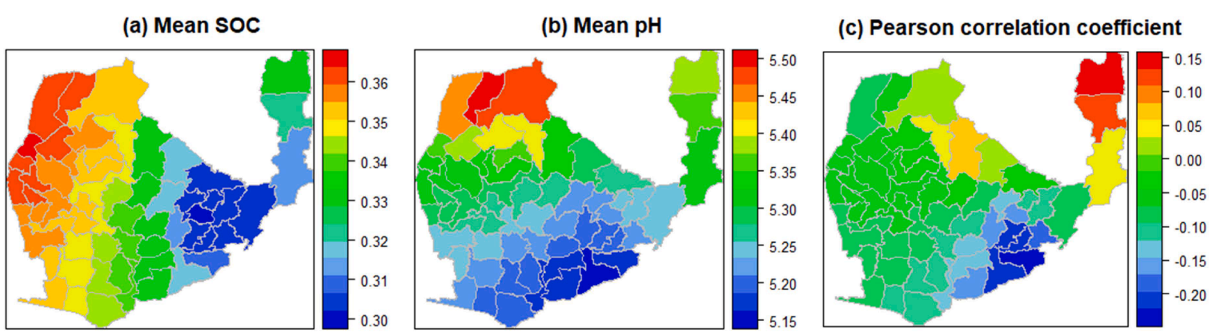

Fig. 9. Geographical correlation of soil organic carbon and pH in the cocoa districts of Ghana.

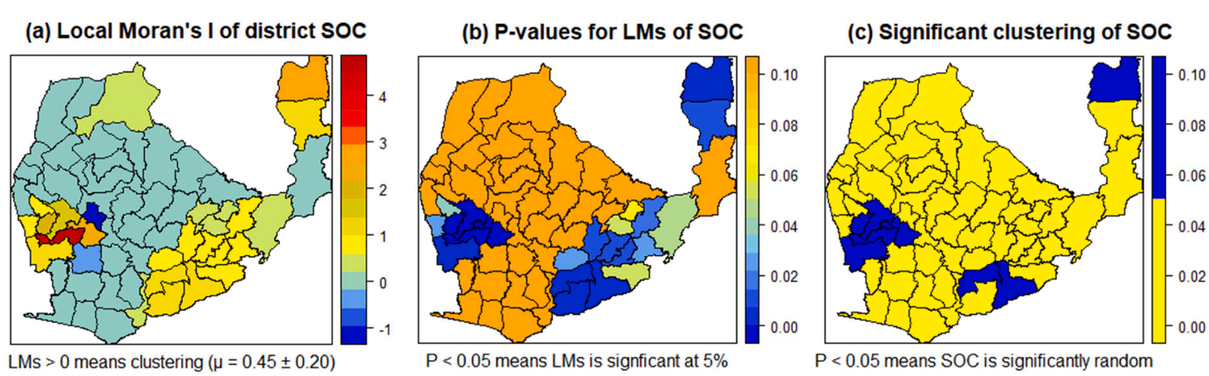

Fig. 10. Geospatial clustering of soil organic carbon in the cocoa districts of Ghana.

3.4. Geospatial clustering of soil organic carbon and pH in the cocoa districts of Ghana

The positive significant values of the GMs statistic for SOC (GMs = 0.447 ± 5.792, p-value = 0.000) and soil pH (GMs = 0.620 ± 7.629, p-value = 0.000) validated by Monte Carlo simulation showed a systemic spatial tendency that is of clustering for both primary variables. Fig. 10 presents the LMs statistics, indicating clustering of SOC in the cocoa districts (Fig. 10a) and the significance levels of the clustering (Fig. 10b) as wells groups of significant and non-significant clusterings (Fig. 10c).

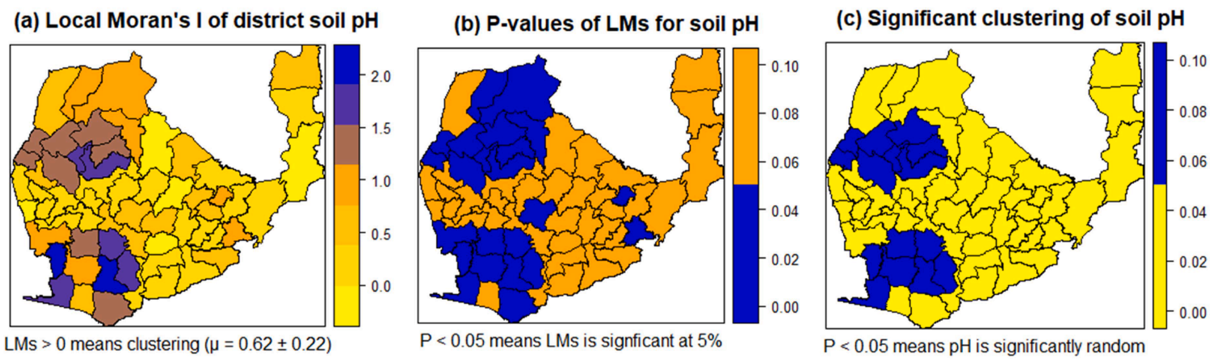

Fig. 11. Geospatial clustering of soil pH in the cocoa districts of Ghana.

Most of the local statistics centred around zero (random) and above zero (clustering) with a few negative (dispersed) ones. The LMs results showed that, apart from the Papase District in VR, Twifo Praso and Asikuma Districts in CR, Enchi, Akontombra, Bodi, Boako and Sefwi Bekwai Districts in WN, which were not significant, the probability of clustering was significant at 5% for all the remaining cocoa districts (Fig. 10c).

In terms of soil pH, the probability of clustering (Fig. 11a) was largely positive (LMs ≥ 0) and significant at 5% for most ($\geq$50%) of the districts while a few ones ($\leq$50%) were significantly dispersed (negative) (Fig. 11a). However, only about 23% of the districts namely, Nkrankwanta, Goaso, Bechem, Adobokrom, Sankore, Dadiesoba in BA,

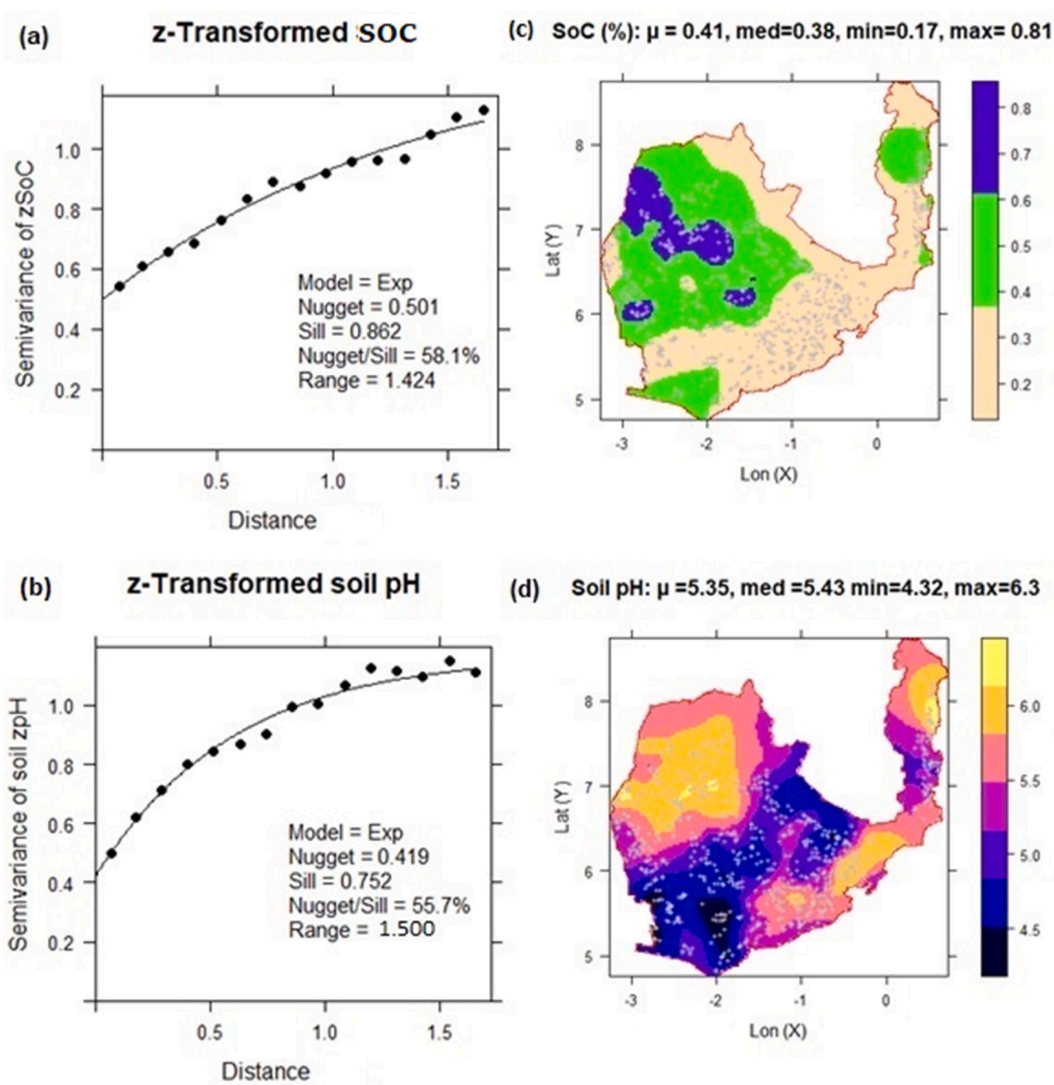

Fig. 12. Isotropic Variograms (●) of soil properties at 20 cm depths with fitted exponential models (solid lines) based on standardized z-scores of (a) soil organic carbon (%) and (b) soil pH. The corresponding maps of univariate ordinary kriged prediction of soil organic carbon (c) and soil pH (d) with sample locations in grey colour crosses(+). Note: SoC = SOC.

Tepa and Mankranso in AR and Elubo, Bionso, Samreboi, Asankragua, Wasa Akropong, Tarkwa and Huni Valley in WS experienced significant clustering (Fig. 11b). These GMs and LMs statistics mean there is spatial autocorrelation (clustering) in the distributions of SOC and pH in the districts' cocoa soils. (Anselin, 1995; Getis and Ord, 1992).

3.5. Predicting the spatial distribution of soil organic carbon and pH in the cocoa districts of Ghana

Fig. 12a and b show the experimental semi-variances of z-transformed SOC (zSOC) and soil pH (zpH) as well as the predictions of SOC (Fig. 12.c) and soil pH (Fig. 12.d) respectively, based on univariate OK. The variograms show the presence of a moderate spatial structure in both variables, indicating the extent of change in SOC and pH from one sample location to another. The slope of the curves near the origin of both variograms is not steep, suggesting that the closest neighbour locations have moderate variability. The nugget/sill ratios show the impacts on the short-scale spatial continuity of the variables. However, the SOC (Fig. 12b) appears to vary more continuously (58.1%) over a longer range (1.424 km) than pH, which also varied moderately (55.7%) up to range 1.500 km (Fig. 12b). This knowledge improves the understanding of geophysical phenomena controlling the estimated spatial pattern in Figs. 2,10,11.

3.6. Predicting the co-regionalized spatial distribution of soil organic carbon with clay and pH as covariates

Results of the multivariate OCK co-regionalized structure of SOC is presented in Fig. 13 and its variograms involving clay and soil pH as covariates are shown in Fig. 14. The mean residual error (MRE) and the standardized root mean square error (RMSE) of the prediction are approximately zero. The insignificance of these errors suggests a strong predictive accuracy of the predicted SOC map. The largest spatial continuity occurred in the fourth and third quartiles of the distributions, which coincided with the current high cocoa production hotspot in the WN and WS Regions of Ghana. The first and second quartiles dominate the low cocoa-producing areas. The multivariate OCK (Fig. 13) and the univariate OK (Fig. 12c) of SOC are quite similar in terms of spatial structure but different in terms of spatial distance.

The variograms in Fig. 14 show that SOC, clay and pH have similar spatial structure. At the major range of 113,080 m, the nugget/sill ratios exhibited moderate degrees of spatial dependencies in SOC (53.59%), clay (44.82%) and pH (48.28%). The nugget effects of SOC (0.478), clay (0.532) and pH (0.526) denote their individual effects on the predicted SOC map (Fig. 13). The covariance coefficients show the magnitudes of their joint-effects on the predicted SOC map, with the joint-effects of SOC*Clay (0.248), SOC*pH (0.062) and pH*Clay (−0.171) exhibiting strong spatial autocorrelation at very negligible distances. The dots (●) denote the distribution of the binned sample points in the empirical variograms at lag one while the crosses (+) represent the averages number of binned points that fall within the 8-angular sectors. The binned points depict local variation while the average values show the smoothness of variation in the data.

3.7. Predicting the co-regionalized spatial distribution of soil pH with aluminium and iron as covariates

The soil pH map (Fig. 15) predicts the multivariate OCK co-regionalized structure of soil pH with Al and Fe as covariates. The mean residual error of the prediction was approximately zero. Classifying the distribution into three quantiles, we found that the third (16.7%) and second quantiles (75.6%), which are below pH 5.5

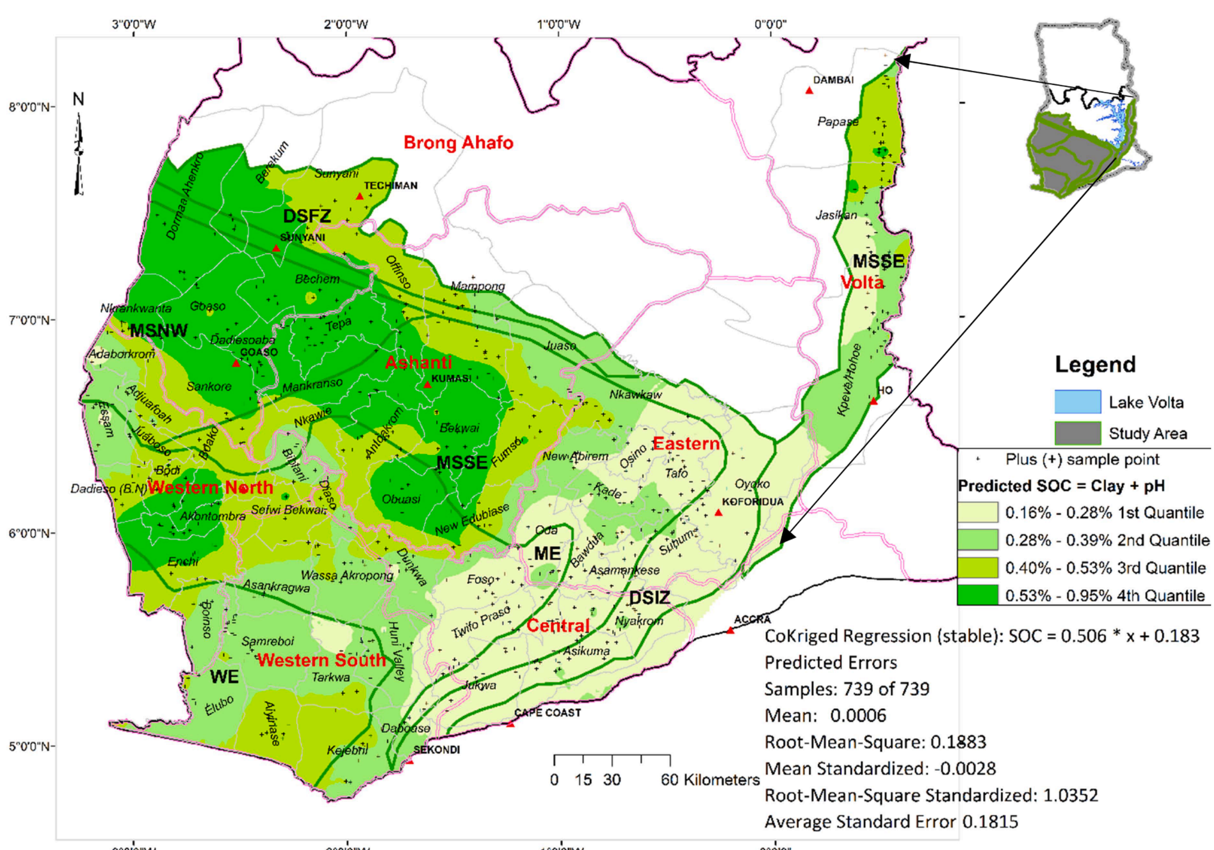

Fig. 13. Multivariate ordinary cokriging map of soil organic carbon (%) at farm-scale with clay and pH as covariates in the entire study area (81,515.23 km^2), overlaid by the agroecological zones boundary lines, the polygons of cocoa Districts and Regions in Ghana.

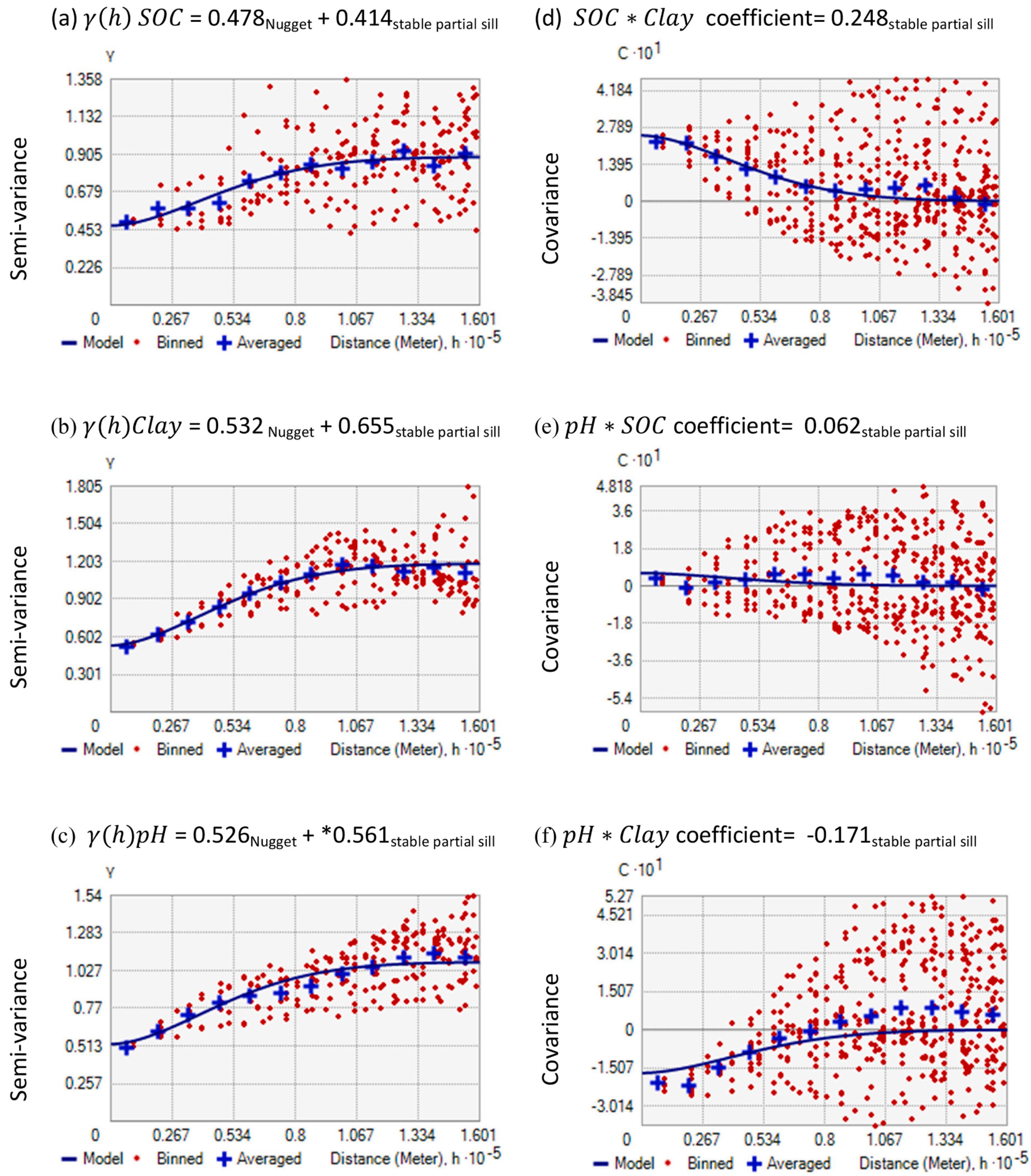

Fig. 14. Isotropic variograms of (a) soil organic carbon (%), clay (b) and (c) soil pHwith their covariance graphs (d, e and f) and the corresponding OCK prediction accuracy of SOC (g) showing the expected positive and negative relationships between the covariates. The stable semivariance models (solid line) were estimated using a maximum of 25 neighbours out of 739 soil samples, 12 lags, 13340.360 lag size, at 113,080 m major and 1.768 m minor. Red dots (●) denote binned sample point values; the blue crosses (+) represent the average number of binned points that fall within 8-angular sectors and a search radius of 182,955.6 km. The binned points depict local variation in the data while the crosses show the smoothness of variation in the data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

predominate the western-south to the central corridors of the study area while the first quantile with pH > 5.5 covers most of the western-north and the south-eastern diagonal of the study area. The predicted soil pH exhibited long-scale spatial continuity just as was observed in Fig. 12d.

The variograms (Fig. 16) reveal that soil pH; Al and Fe exhibit a similar spatial structure at the maximum range of 379,361.318 m. This means the combined effects of pH, Al and Fe, at any two locations of lag distance below 379.36 km are spatially correlated. The zero (0.000) nugget effects of pH, Al and Fe imply that at very short distances there is a high degree of homogeneity. The nugget/sill ratios of pH (0.14%) and clay (0.0002%) and Fe (1.32%) show a very strong homogeneous spatial continuity (dependencies). Apart from the joint-effects of pH*Al (-0.423), which is of a moderate spatial dependency the pH*Fe (0.009) and Al*Fe (0.009) were strongly spatially correlated.

4. Discussion

In improving the health of cocoa farm soils through precision-fertilizer use for cocoa sustainable farming, the spatial mapping of SOC and pH is as important as site-specific fertilizer upscaling. In this

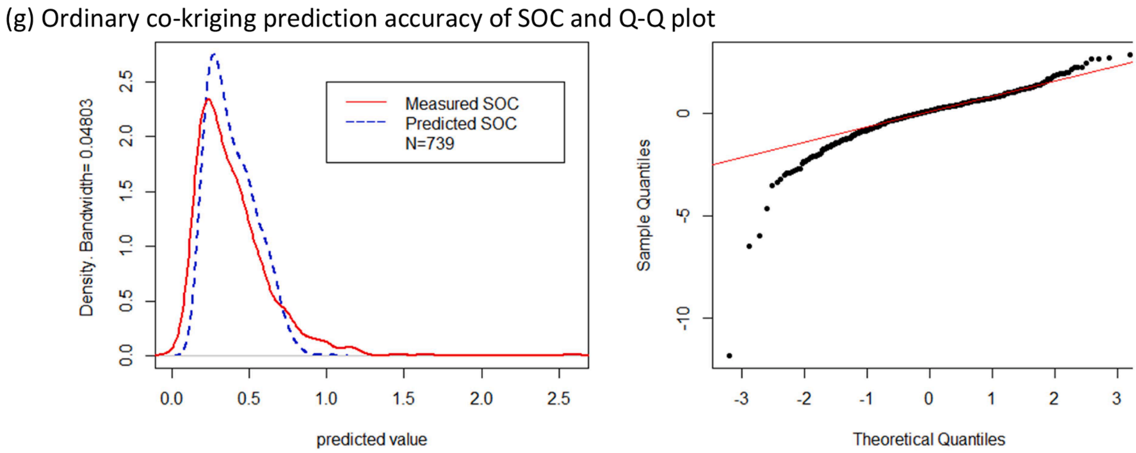

Fig. 14. (*continued*).

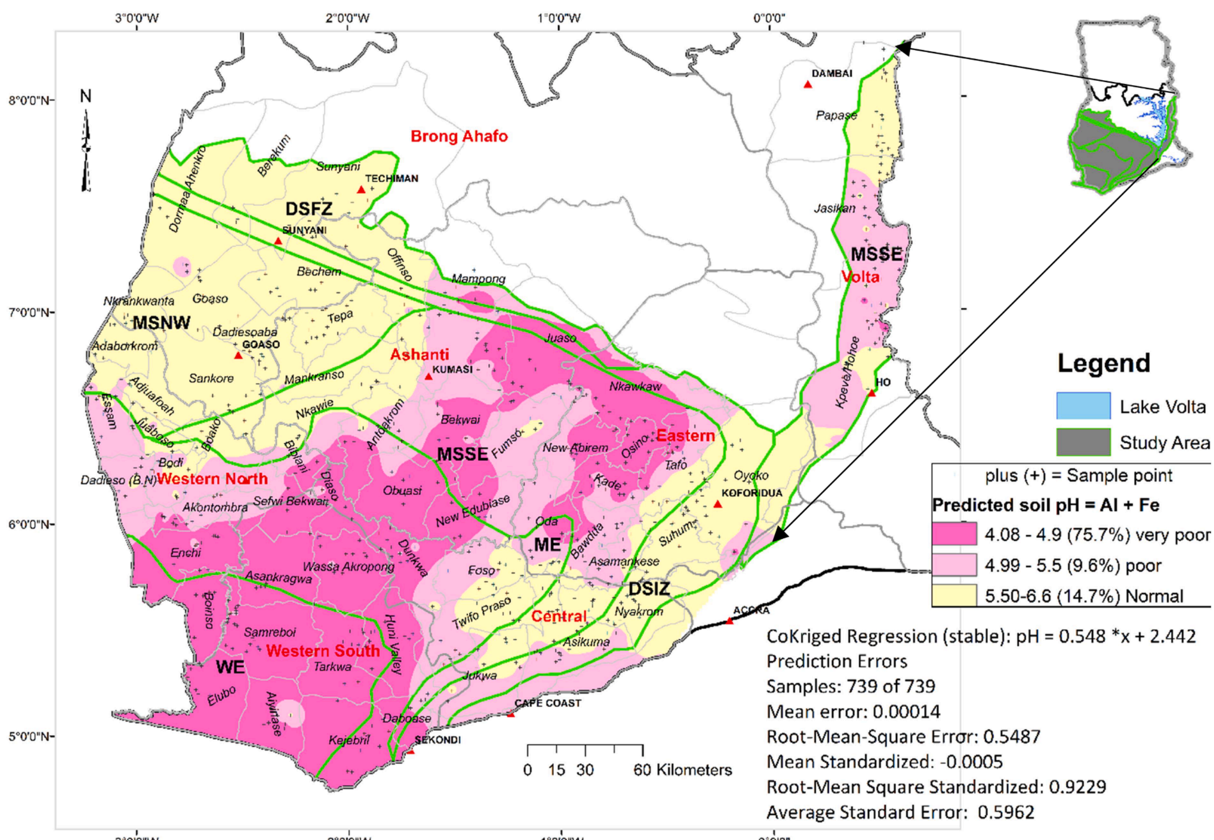

Fig. 15. Multivariate ordinary co-kriging prediction of soil pH concentration at farm-scale in the entire study area (81,515.23 km^2) overlaid by sample points (+), agroecological zone boundary lines, polygons of the cocoa Districts and Regions of Ghana.

study, the predicted spatial pattern of SOC and pH with their regionalized structures have been made spatially-explicit, as a guide for the precision-implementation of the fertilizer recommendations earlier proposed by Afrifa et al., (2009), Asare et al. (2017) and Dossa et al. (2018) among others in Ghana.

Specifically, this current study has established the extent of spatial dependency of farm and district SOC and soil pH. First, the study reveals (i) unsuitably low SOC and strong acidity across the different cocoa agroecological zones and cluster of districts, making the current blanket fertilizer recommendation highly unhealthy.; (ii) the univariate spatial structure of both SOC and pH generally dwindled in magnitude from South-East and peaks toward North-West of the whole study area, with SOC hotspots occurring in the Western-North while the pH coldspot dominates the Western-South zones. (iii) The co-regionalized spatial structure of SOC improves with soil pH covariate more than clay. In turn, Fe dominated soil pH more than Al covariates.

4.1. *Low soil organic carbon in and across the cocoa agroecological zones*

The low SOC (0.39% ± 0.23) which is equivalent to 3.9 g/kg was prevalent in all the six agroecological zones. The agroecological intensity of SOC significantly declines in the following order: MSNW > DSFZ > WE > ME > MSSE > DSIZ. The estimates were statistically the same for the WE, ME and MSSE. All the estimates were unsuitably low

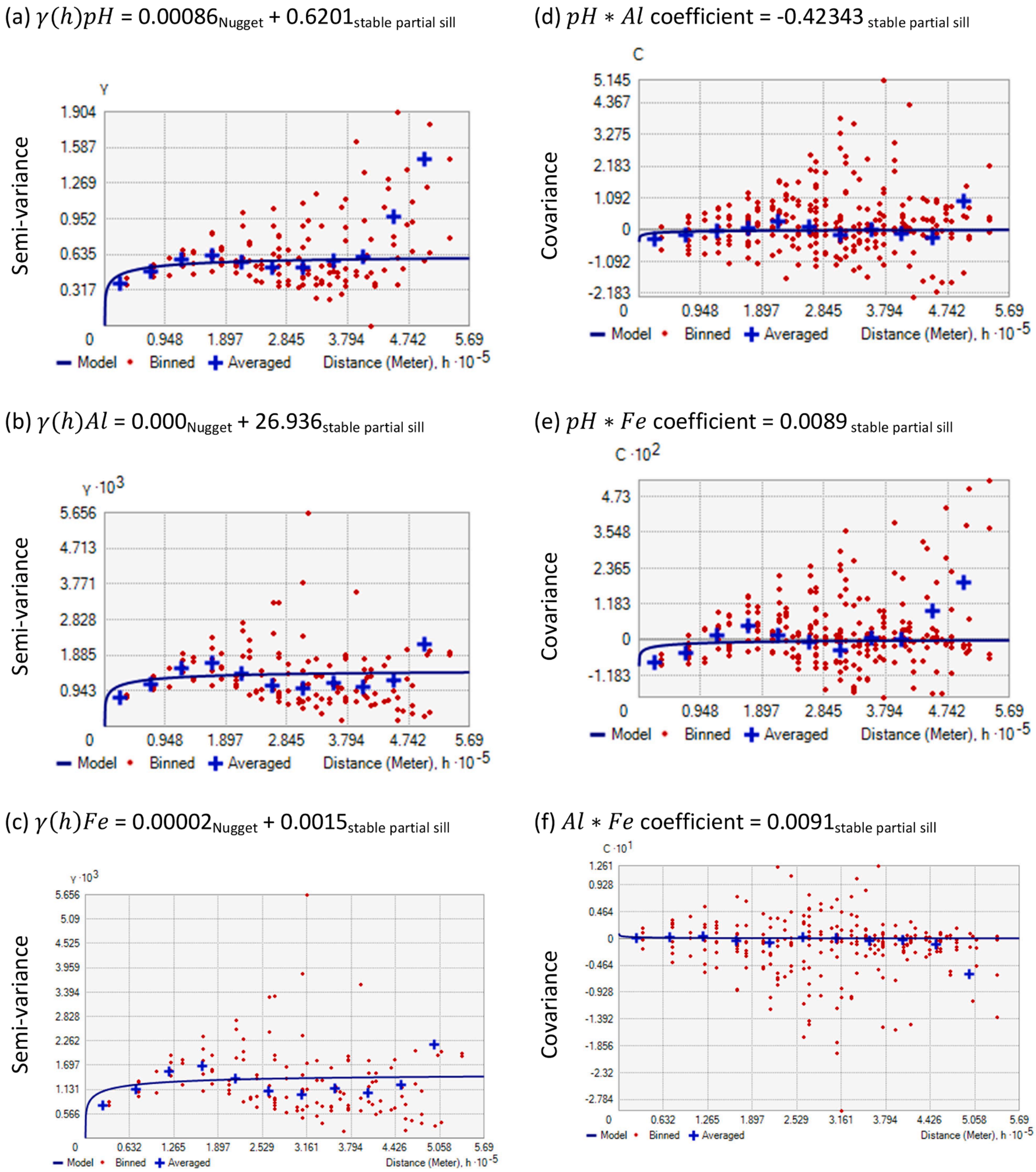

Fig. 16. Stable Isotropic variograms of soil pH(a), aluminium (b) and iron (c) with their covariance graphs (d, e and f) and the corresponding OCK prediction accuracy of pH (g) displaying the expected positive and negative relationship between covariates. The Stable semivariance models (solid line) were estimated using a maximum of 25 neighbours out of 739 sample points, 12 lags, 47,420.165 lag size, at 379,361.318 m and 0.3002 m. Red dots (●) are binned sample point values while blue crosses (+) are the average number of points generated by binning points in the empirical variogram that fell within 8-angular sectors and a search radius of 182,955.6 km. The binned points depict local variation while the average values show the smoothness of variation in the data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

compared to the required value of 2.2–3.5% for sustainable cocoa production (Ahenkorah, 2016; IFDC, 2011). The current estimates are more representative of the study area because of the large number of soil samples (739) involved in the study. The previous estimates of 1.37% (Dossa et al., 2018; IFDC, 2011), 0.78–2.7% (Arthur et al., 2017) and 1.05–1.4% (Asare et al., 2017) were based on smaller sample sizes ($\leq$50).

The current SOC estimate is not the total soil organic carbon (TSOC) stock in the study area. There is a deficit in terms of the TSOC (11.2–12.7 g/kg or 1.12–1.27%) reported by Owusu et al. (2020) in Ghana. In similar ecological zones in Nigeria, Akpa et al. (2016) found the TSOC to be 2.95 g/kg (0.295%) at 30 cm. The estimate for temperate zones in Spain was 1.51 g/kg (0.151%) at 30 cm (Calvo de Anta et al., 2020) and 6.28% at 20 cm for entire Europe (Rial et al., 2017).

According to Dechert et al. (2004), Somarriba et al. (2013) and Ahenkorah (2016), soils of cocoa agroforestry, planted with permanent shade trees should have high SOC build-up. Therefore, the current low SOC could be attributed to the younger ages of the new cocoa farms, less litter, continuous cropping, monocropping or full-sun cocoa, deforestation among other poor agricultural practices (Bationo and Fening, 2018).

This low SOC implies cocoa farm soils in Ghana are likely to develop

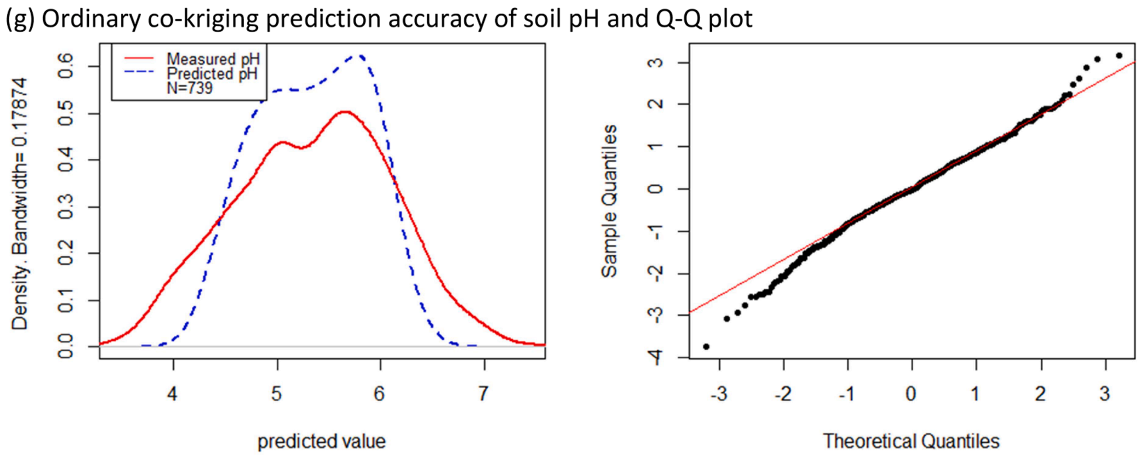

Fig. 16. (*continued*).

poorly in soil structure (Blanco-Canqui et al., 2013) and ecosystem services like improving water soil retention capacity, mineralization and retention capacity of available soil nutrients (Afrifa et al., 2007; Ahenkorah, 2016; Appiah et al., 2000; Snoeck et al., 2007). Therefore, ecologically friendly soil amendment practices are required to restore the SOC content in all the ecological zones. Some of the required practices to restore SOC should include the application of organic manure (Tittonell and Giller, 2013) and compost (Ingham, 2019; Rousk et al., 2009), integrating shade trees and refraining from the practice of full-sun cocoa monocropping (Dechert et al., 2004; Somarriba et al., 2013). Others are the application of cocoa-potash and biochar (Eduah et al., 2019). The precision dose of climate/ecologically friendly crop protection products (Dossa et al., 2018; Schroth et al., 2016) to avoid further soil toxification and deterioration of the SOC cold spots.

4.2. Low soil pH in and across the cocoa agroecological zones

The unsuitably low soil pH 5.35 (±0.027) denotes high soil acidity in the entire study area. Most (83.3%) of the soils have pH below 5.5 which is not suitable for sustainable cocoa farming (Ahenkorah, 2016). Only 14.7% of the soils were within the suitable range (pH > 5.5–7.5). The distribution of soil pH in the DSFZ and DSIZ was similar to that of the MSNW ecological zone. The pH distribution in the ME and MSSE was more platykurtic, plateauing within almost the entire range of the measured pH. The distribution can be considered unique for only WE, which stands aloft in a high concentration of hydrogen ions. These findings are consistent with Hall and Swaine, (1976) and other previous reports that most Ghanaian cocoa soils are generally acidic (Ahenkorah, 2016; Snoeck et al., 2016, Snoeck et al., 2010; Snoeck et al., 2007).

According to Dossa et al., (2018), Snoeck et al. (2016), Snoeck et al. (2010) and Asare et al. (2017) there are negative effects of strong soil acidity and heavy metals on cocoa soil health and farm profitability in the WE and MSSE. Afrifa et al (2009), IFDC (2011) and Dossa et al. (2018), ascribed the low soil pH to the predominance of soil types such as Acrisols (75%, pH = 5.66), Lixsols (10%, pH = 5.88), Ferrosol (9%, pH = 5.01) and Nitisols (3%, pH = 6.55) in the study area. In terms of site-specific fertilizer formulae implementation, the current study offers a spatial precise knowledge to address the spatial information gap in upscaling it.

The current study has explicitly demarcated the spatial extent of the low soil pH across all the six ecological zones with varying degrees of spatial continuity in the hot/cold spots. These spots will enhance precision in implementing the appropriate fertilizer recommendations. The existing cocoa fertilizer-formulae need to consider these hot/cold pH spots. Applying acid-forming fertilizers in the cold pH spots, for instance, would be economically irrational and ecologically toxic (Dossa et al., 2018; Asare et al., 2017; IFDC, 2011). Instead, base-forming fertilizers with some amount of lime, Ca and MgO to neutralize the strong-acidic soils are preferable (Afrifa et al., 2009; Snoeck et al., 2016, 2010; Snoeck and Dubos, 2018).

Apart from implementing appropriate fertilizer regimes (Dossa et al., 2018; Asare et al., 2017; IFDC, 2011), genetic advancement such as the breeding of low pH, high Fe and Al or acid-tolerant (Zhang et al., 2019) cocoa varieties are required. Other researchers have recommended the use of acid or metal tolerant organisms like some strains of earthworms such as *Metaphire posthuman*, *Bacillus megaterium*, *Staphylococcus haemolyticus* and *Bacillus licheniformis* (Biswas et al., 2018). These ecosystem engineers enhance the bioavailability of phosphorus in strong-acidic soils. Also, biochar produced from rice husks and corn cobs have been reported to increase soil pH, cation exchange capacity, P-absorption and carbon mineralization potential in strong-acidic soils (Eduah et al., 2019; El-Naggar et al., 2018). Therefore, the application of biochar is also recommended in the cold pH spots.

4.3. Implications of the univariate spatial structure of soil organic carbon and pH

As already pointed out, the LMs showed spatial clustering of SOC and pH at cocoa districts scale. The nugget/sill ratios of SOC (58.1%) and pH (55.7%) revealed a spatial structure of moderate variability across the entire study area. The spatial patterns from both the LMs and the OK suggest there is a major threat to sustainable cocoa production if the declining trends of SOC and pH are not curtailed in a spatially-explicit manner.

The spatial patterns of SOC and pH whether at the farm, district or ecological scales suggest that the current leading cocoa areas owe their high productivity to SOC mining and soil acidification. The low cocoa production zones or cold spots are in the ER and CR while the hot spots are in the WN and WS Regions where cocoa output is currently the highest (Ahenkorah, 2016). These patterns showed a loss of SOC from the ER of Ghana, where commercial cocoa production started to the current leading cocoa-producing districts in the WN and WS Regions (Ahenkorah, 2016; Anim-Kwapong and Frimpong, 2009). The Volta and Brong Ahafo cocoa Regions were relatively better in SOC and pH. The revelation corroborates Ahenkorah (2016) in terms of SOC and pH depletion. It is obvious from the study that, the leading cocoa-producing districts most of which produced >12,000 metric tons of cocoa per year in the past 10 years are at risk of severe decline in SOC and soil pH. This risk particularly holds for forest-fringe cocoa districts such as Enchi and Dadieso, Bonsu Nkwanta, Sefwi Wiawso and Debiso in the ME zone of the WN Region as well as Samreboi and Boinso in the WE zone of the WS Region. These findings are consistent with Akpa et al. (2016), Vaughan et al. (2019) and Owusu et al. (2020), who also observed dwindling SOC from dry to wet agroecological zones in unfarmed virgin forests.

4.4. Implications of the co-regionalized spatial pattern of low organic carbon and pH

To improve the precision of the univariate OK spatial structure, multivariate OCK covariates were used in this study. The results confirm that clay content (%) and pH impact positively on the predicted SOC. This finding corroborates (Ahenkorah, 2016); Barré et al., (2014) and Singh et al. (2018). The OCK predicted co-regionalized-structure confirms Owusu et al. (2020). Specifically, the resulting spatial clustering of SOC (OCK) revealed the presence of a co-regionalized structure that is moderately heterogeneous or homogenous. The highest level of homogeneity was found in the MSWN zone while the rest of the ecological zones exhibited moderate heterogeneity. Also, the co-regionalized structure varied more continuously over a longer distance when the covariates are present. The results imply that clay and pH improve the spatial precision of SOC and spatial structure, which is more accurate for planning site-specific fertilizer use.

The co-regionalized structure of soil pH in the WE and ME zones, were the strongest in low soil pH (<5.5) homogeneity over shorter ranges. This result confirms the report of Hall and Swaine, (1976) among others. Previously, Hall and Swaine, (1976), Ahenkorah, (2016) and Afrifa et al., (2009) stated that soils of these ecological zones in the southwestern part of the country were more acidic due to leaching caused by the frequent occurrence of high rainfall (Anim-Kwapong and Frimpong, 2009; Hall and Swaine, 1976). It could also be due to improper fertilizer use. The remaining ecological zones had varying levels of soil pH at shorter-scales over relatively long distances.

Generally, the soil pH varied moderately (55.7%) over short distances, corroborating Ahenkorah (2016), Gérard, (2016), Delhaize and Ryan (1995) in van Vliet and Giller (2017). According to these authors, the influence of Al and Fe on soil pH is negative. The contributions of Al and Fe have improved the homogeneity of the predicted soil pH cold/hot spots. The co-regionalized structure revealed a favourable pH ($\geq$5.5–6.6) in MSNW but poor pH levels in most of the remaining ecological zones, starting with WE followed by ME and MSSE. Nearly all the areas in the WE and central parts of ME were cold spots or strongly acidic (pH $<$ 5.5) as was previously reported by Afrifa et al (2009), IFDC (2011), Dossa et al. (2018) and Asare et al. (2017).

These revelations are useful information that would improve precision-implementation of the site-specific fertilizer-formulae recommendations because the ecological zones are not homogeneous. Irrespective of the ecological zones, strongly acidic areas need no further application of acid-forming fertilizers just as areas that are poor in SOC need no more of such fertilizers. Instead, improving the basicity and soil organic matter contents of the soil in those zones are crucial (Ahenkorah, 2016; Dossa et al., 2018; Asare et al., 2017; IFDC, 2011).

To sum up, the spatial patterns from the LMs, OK or OCK are generally consistent with the historic boom-bust cycle of cocoa transitions associated with soil nutrient mining (Clough et al., 2009; Gockowski et al., 2013; Lal and Stewart, 2013). This kind of situation was forewarned as far back as 1974 by Ahenkorah's (2016) end of shade and manurial study in New Tafo Akim, where 54.8 tons of humus/ha was lost within 15 years of continuous cocoa cropping. Inappropriate management of soil fertility jeopardizes the current and future suitability of cocoa soils (Ahenkorah, 2016; Wessel and Quist-Wessel, 2015). There is a major systemic SOC threat to sustainable cocoa production if recommendations on fertilizer use in Ghana continues at the current blanket application rate of 375 kg/ha irrespective of location and age of farm.

5. Conclusions

This study has shown a spatially explicit loss of SOC from the Eastern and Central through Ashanti and Brong Ahafo to the current cocoa hot spots in the Western North and South cocoa Regions of Ghana. These findings underscored the dwindling SOC and acidity in line with historic boom-bust cycle of cocoa production hot and cold spots transitions trends of Ghana. The current spatial structure of the predicted SOC and pH is new knowledge that would improve our understanding of the systemic trends in the geospatial distribution of SOC and acidity within the cocoa agroecological zones. This knowledge can help improve the precision of cocoa soil fertility management in the cocoa farms, districts and the agroecological zones of Ghana. The findings are also indicative of adverse implications of the current recommendation of blanket fertilizer use. It also shows the potential role that the cocoa agroforest land-use can play in global carbon sequestration if carbon credit and offsets are provided to cocoa farmers to engage in climate-smart agriculture. Hence the need for change to good agronomic practices and fertilizer use policies that recognize areas, districts, site-specific soil needs and ecological tolerance as in integrated soil fertility management, ecological intensification or precision agriculture. The authors recommend a further study to investigate the factors that account for the observed and predicted spatial dependency of the cocoa SOC and soil pH.

6. Authors' contributions

This work was a collaborative one among all authors. AKQ designed the original soil survey, designed the soil sampling scheme, led the field soil samples collections and supervised the laboratory technicians to ensure data quality. Authors YDN, led the team to collect geographical coordinates of the soil samples. Author DA led laboratory analysis of the soil samples. Author EKD designed the geospatial and geostatistical concepts applied in this paper, processed the data, performed the classical and geostatistical analyses including the spatial regression models and wrote the first and final drafts of the manuscript. Author JAD, AA and SK helped in the interpretation of data concerning cocoa soil nutrient management. Author EMA and GY did a critical review, provided valuable comments, suggestions and proof-reading of the paper provided academic mentorship and coaching to EKD on the application of physical geography, geospatial and geostatistical tools of soil health and ecology as employed in this paper. All authors read and approved the final manuscript.

7. Data Availability.

The study data will be available at the Cocoa Research Institute of Ghana, P.O. Box 8, New Tafo - Akim Ghana and the following ORICD numbers:

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.geoderma.2020.114921.

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