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Spatial Variability of Soil Fertility Using a Geostatistical Approach in Benin: A Case of Hlankpa Village, Adjohoun Commune

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Abstract

In Benin, agricultural soils are degraded by poor farming practices and flooding, which reduces their fertility. This study aimed to analyze the variability of physico-chemical properties on a 6-hectare farm in Adjohoun municipality to guide soil management and crop planning. A total of 93 soil samples were collected at 25-meter intervals. The following parameters were determined: pH, nitrogen (N), phosphorus (P), potassium (K), organic matter, cation exchange capacity (CEC), soil depth, and water table level. Four kriging methods (simple, ordinary, universal, indicator) combined with different variogram models (exponential, Gaussian, circular, spherical) were tested to identify the most suitable approach for spatial variability assessment. The performance of the variogram models and the kriging methods was evaluated and compared using the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) as validation criteria. The exponential variogram proved to be the most appropriate for pH (MAE = 0.003; RMSE = 0.979), soil depth (MAE = 0.019; RMSE = 0.887), and water table level (MAE = 0.001; RMSE = 1.033), while the Gaussian model better explained the variability of nitrogen, phosphorus, and cation exchange capacity. Simple kriging showed good performance for soil depth (MAE = −0.003; RMSE = 0.979), pH (MAE = −0.003; RMSE = 0.979), nitrogen (MAE = −0.006; RMSE = 1.078), and organic matter (MAE = 0.00003; RMSE = 1.025), while indicator kriging excelled for water table level and phosphorus. The soils overall have satisfactory chemical fertility (N ≈ 0.29%; P ≈ 19.3 mg/kg; K ≈ 0.40%;

organic matter ≈ 2.49%; CEC ≈ 15.9 cmol/kg) although the pH is slightly alkaline (≈7.51). The findings indicate that crops adapted to hydromorphic conditions are more suitable for the site. The geostatistical approach proved effective for precise mapping and soil fertility management, providing valuable insights for agricultural planning in Benin.

Keywords

Fertility, Geostatistics, Kriging, Precision Agriculture, Benin

1. Introduction

The soil represents a fundamental dimension of terrestrial resources and constitutes the basis for agricultural development and ecological viability [1]. It is a vital element for the survival of living beings, regardless of their living environment. Maintaining or even increasing soil fertility is a major challenge for food security [2]. Food security and sustainable agriculture are fundamental components of the sustainable development process [3]. Thus, sustainable soil management is a prerequisite for sustainable agriculture [4]. In Benin, agricultural soils are subject to severe degradation due, in particular, to poor farming practices and seasonal flooding, reducing their biological and chemical potential. Cultivated land is being depleted at an accelerated rate and crop yields are continuously decreasing, dangerously compromising the productivity and sustainability of the agricultural system. Given the crucial role of soils in maintaining the food and nutritional security of populations, important measures must be taken to sustain the sustainable management of this resource. For decades, nitrogen (N), phosphorus (P), and potassium (K) have been the most studied soil nutrients in precision agriculture due to their crucial importance. Nitrogen promotes plant growth and the formation of albumin and chlorophyll [5]. Phosphorus is essential for the transformation of energy substances, the formation of roots, flowers, and fruits, while potassium contributes to plant health and resistance to stress [5]. It is therefore imperative to have values for these chemical constituents in order to assess the fertility of the soil in a given area. Several methods are used for this purpose. The spatial correlation of soils means that geographically close samples exhibit similar properties [6]. In pedology, various methods are used to assess the fertility of unsampled soils. Traditional fertility mapping methods assume that the variability within the identified units is homogeneous [7]. Geostatistics is a statistical approach that characterizes the spatial structure of soil characteristics using sampled point data to estimate these characteristics at unsampled locations within the study area [8]-[10]. It improves the reliability of estimates [11]. Different spatial interpolation methods are available and the choice depends on the nature of the data and the final use of the results [12]-[14]. Kriging is one of the most effective geostatistical methods, comprising different techniques: simple kriging, ordinary kriging, universal kriging, and indicator kriging. In Benin, few studies have been conducted on identifying and assessing soil fertility levels by combining geostatistical and classical methods. The assessment of soil fertility in Southern and Central Benin based on the classical method was carried out by [15]. These approaches integrate all parameters for fertility assessment: pH, water table level, soil depth, cation exchange capacity (CEC), organic matter (OM) content, nitrogen (N), phosphorus (P), and potassium (K). To better assess soil fertility, it is necessary to experiment with a combination of a geostatistical approach and a comprehensive classical evaluation of physico-chemical and hydraulic parameters. This study aims to evaluate the spatial variability of soil physico-chemical properties (pH, N, P, K, OM, CEC), soil depth, and water table level, in order to identify fertility zones on the scale of Adjohoun Commune in Benin.

2. Materials and Methods

2.1. Study Area Description

Adjohoun is a commune in Benin located in the center of the Ouémé department, 32 km from Porto-Novo and 62 km from Cotonou, with a total area of 308 km^2. It is bordered to the South by Dangbo, to the North by Bonou, to the East by Sakété and Akpro-Missérété, and to the West by Abomey-Calavi and Zè. It is home to more than 90,000 inhabitants distributed across eight arrondissements: Adjohoun, Awonou, Azowlissè, Dèmè, Gangban, Kodé, and Togbota [16]. The study was conducted on a private six-hectare farm in the village of Hlankpa, Kodé arrondissement, owned by Mr. Behi OWA, Director of Solution Plus (**Figure 1**). The study area is characterized by alluvial sediments with relative pedological homogeneity.

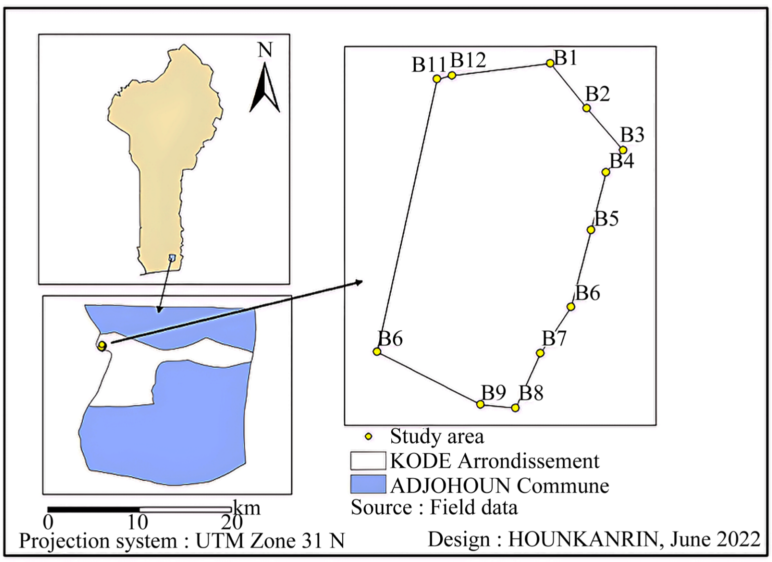

Figure 1. Geographical location of the study area.

2.2. Sampling and Data Collection

Field survey allowed for the *in-situ* collection of morphological and physical data.

A pedological reconnaissance carried out on the study perimeter confirmed the characteristic homogeneity of this alluvial sediment area. Using a GPS projected in linear metric units (WGS84; UTM Zone 31 N), the coordinates of each point were recorded. The study began with a systematic grid of the study area with equidistant sampling points spaced 25 m apart. Each point was subjected to a soil survey using a Dutch auger down to one meter depth. In total, 93 soil surveys were conducted (**Figure 2**). These surveys allowed for the assessment of the hydraulic characteristics of the soils in the field. Soil samples were taken at each sampling point, packaged in labeled polyethylene bags (sample point number, sample depth), and analyzed in the laboratory.

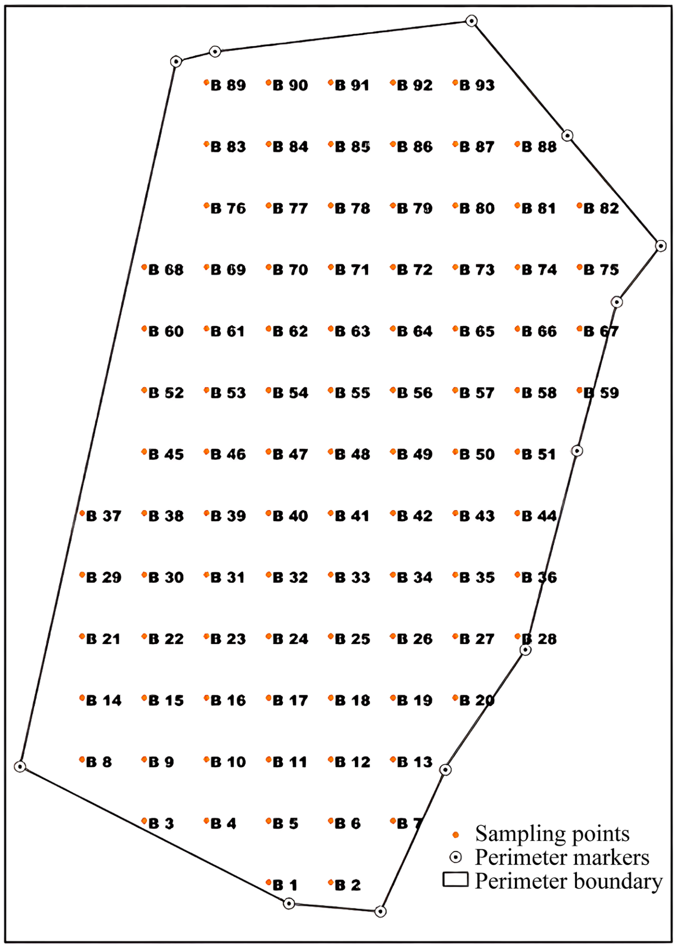

Figure 2. Grid of the perimeter with pedological sampling points.

2.3. Determination of Physico-Chemical Parameters

Hydrogen potential (pH) was measured using a pH meter in an aqueous solution (soil/water ratio 1:2.5). Total nitrogen (N) content was determined by the Kjeldahl method, involving mineralization with sulfuric acid followed by distillation and titration. Available phosphorus (P) was analyzed by the Olsen method using extraction with 0.5 M sodium bicarbonate at pH 8.5, while exchangeable potassium

(K) was measured by atomic absorption spectroscopy after extraction with 1 N ammonium acetate at pH 7. Organic matter (OM) content was determined by the Walkley and Black method, based on the oxidation of organic carbon by potassium dichromate in a sulfuric medium. Finally, the cation exchange capacity (CEC) was assessed by the 1 N ammonium acetate method at pH 7, allowing for the saturation of exchange sites and their subsequent displacement by ammonium ions.

2.4. Statistical Analyses

Data analysis was based on the geostatistical approach. As geostatistical methods are sensitive to data normality, a normality test was performed on all variables. In case of a significant deviation from normality, a logarithmic transformation was applied. The error metrics (Root Mean Square Error (RMSE) and Mean Absolute Error (MAE)) were calculated using the log-transformed data to ensure consistency with the fitted variogram models. However, for agronomic interpretation, the predicted values were back-transformed to original units. The very low MAE values (e.g., 0.00001 for Organic Matter) result from the logarithmic transformation and indicate a very close fit between observed and predicted values on the transformed scale; when back-transformed, these errors correspond to small relative errors in the original units (e.g., for OM with mean 2.49%, an MAE of 0.00001 on the log scale corresponds to a relative error of about 0.004%). ArcGIS version 10.1 and R software were used to generate continuous maps representative of the geostatistical variability of soil fertility. Several studies have compared geostatistical spatial interpolation methods [14] [17]. In this study, four models were fitted for each parameter: spherical Equation (1), exponential Equation (2), Gaussian Equation (3), and circular Equation (4). Spatial dependence was modeled using semivariograms. An empirical semivariogram was calculated and plotted to assess the spatial variability between neighboring observations. The appropriate model among the available theoretical models was chosen according to the criteria of [17] and [18]. The parameters of the variogram model (nugget effect, range, and sill) were determined to characterize the spatial dependencies of the different soil fertility-related variables. For each parameter, the single variogram model that showed the best performance according to the cross-validation criteria (lowest MAE, RMSE closest to 1) was selected and then applied consistently across all kriging methods (Simple, Ordinary, Universal, and Indicator Kriging) for that parameter. This ensured a fair comparison of the kriging methods while using the optimal spatial structure model for each soil property. The mathematical expressions of the variogram models used are:

- Spherical:

$$g(h)=\begin{cases} C_o+C\left(\dfrac{3h}{2a}-\dfrac{h^3}{2a^3}\right), if\ h\le a \\ C_0+C, if\ h>a \end{cases} \tag{1}$$

- Exponential:

$$g(h)=C_0+C\left(1-e^{-h/a}\right) \tag{2}$$

- Gaussian:

$$g(h)=C_0+C\left(1-e^{-\left(\frac{h}{a}\right)^2}\right) \tag{3}$$

- Circular:

$$g(h)=\begin{cases} C_o+C\left[1-\frac{2}{\pi}\cos^{-1}\frac{h}{a}+\frac{2h}{\pi a}\sqrt{1-\left(\frac{h}{a}\right)^2}\right], if\ h\le a \\ C_0+C, if\ h>a \end{cases} \tag{4}$$

with h: lag distance, C_0: nugget effect, C: sill, a: range.

For indicator kriging (IK), critical threshold values (cutoffs) were defined for each parameter based on agronomic standards or data percentiles to transform continuous data into binary indicators (1 if above the threshold, 0 otherwise). The thresholds used were: water table depth ≤ 20 cm (shallow), phosphorus ≤ 15 mg/kg (deficient), potassium ≤ 0.35% (deficient), and CEC ≤ 12 cmol/kg (low). These thresholds were chosen to identify areas requiring specific management interventions.

The variogram models were compared using cross-validation criteria: the Root Mean Square Error (RMSE, Equation (5)) and the Mean Absolute Error (MAE, Equation (6)). The best model is the one with MAE values closest to 0 and RMSE values closest to 1 [18]. The formulas used are as follows:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Z(x_i)-Z^*(x_i)\right)^2} \tag{5}$$

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|Z(x_i)-Z^*(x_i)\right| \tag{6}$$

where $Z(x_i)$ is the observed value, $Z^*(x_i)$ is the predicted value and n is the number of observations.

3. Results

3.1. Descriptive Statistics and Fertility Status

Descriptive statistical analysis (Table 1) revealed the variability of the physicochemical properties of the farm's soils. The pH is 7.51 ± 0.39, indicating slightly alkaline soils. Soil depth is 101.29 ± 13.29 cm, while the water table depth is 19.62 ± 14.24 cm. The contents are 0.29 ± 0.05% for nitrogen, 0.40 ± 0.11% for potassium, 19.26 ± 4.45 mg/kg for phosphorus, 2.49 ± 0.04% for organic matter, and 15.89 ± 3.27 cmol/kg for the cation exchange capacity. The standard deviations indicate that all parameters show low dispersion around the mean, except for the water table depth. None of the parameters followed a normal distribution ($p < 0.05$), which required a logarithmic transformation of the data prior to geostatistical analysis.

Table 1. Descriptive statistics of the studied parameters.

Parameters	pH	Soil depth (cm)	Water table depth (cm)	N (%)	P (mg/kg)	K (%)	MO (%)	CEC (cmol/kg)
Mean ± Standard deviation	7.51 ± 0.39	101.29 ± 13.29	19.62 ± 14.24	0.29 ± 0.05	19.26 ± 4.45	0.4 ± 0.11	2.49 ± 0.04	15.89 ± 3.27
Kurtosis	0.11	0.41	0.52	0.42	0.11	0.11	0.42	0.42
Skewness	−0.60	−0.63	1.19	0.74	0.60	0.60	−0.74	0.74
Minimum	6.5	70	5	0.19	11.32	0.21	2.38	10.33
Maximum	8.2	120	60	0.43	30.88	0.67	2.56	24.79

N: Nitrogen; P: Phosphorus; K: Potassium; MO: Organic Matter; CEC: Cation Exchange Capacity; pH: Hydrogen Potential.

3.2. Selection of Variogram Models

The comparative analysis of the four variogram models (Gaussian, exponential, circular, and spherical) reveals distinct performances depending on the parameters studied (Table 2). The exponential model best fits the spatial variability of pH (MAE = 0.003; RMSE = 0.979), soil depth (MAE = 0.019; RMSE = 0.887), and water table depth (MAE = 0.001; RMSE = 1.033), consistently presenting the lowest MAE values and RMSE values closest to 1 compared to the other models. The Gaussian model better explains the spatial variability of nitrogen (MAE = 0.006; RMSE = 1.077), phosphorus (MAE = 0.008; RMSE = 1.067), and cation exchange capacity (MAE = 0.006; RMSE = 1.078), demonstrating its superiority for these chemical parameters with optimal evaluation criteria. The circular and spherical models best fit potassium (MAE = 0.009; RMSE = 1.058) and organic matter (MAE = 0.00001; RMSE = 1.025), respectively, the latter showing exceptional performance with a quasi-null mean absolute error for organic matter.

Table 2. Comparison of variogram models.

Parameters	Criteria	Gaussian	Exponential	Circular	Spherical
pH	MAE	0.017	**0.003**	0.011	0.008
	RMSE	1.104	**0.979**	1.062	1.023
Soil depth	MAE	0.021	**0.019**	0.024	0.028
	RMSE	0.906	**0.887**	0.892	0.879
Water table depth	MAE	0.006	**0.001**	0.003	0.006
	RMSE	1.055	**1.033**	1.052	1.046
Nitrogen (N)	MAE	**0.006**	0.008	0.006	0.008
	RMSE	**1.077**	1.085	1.079	1.081
Phosphorus (P)	MAE	**0.008**	0.008	0.009	0.009
	RMSE	**1.067**	1.071	1.064	1.067
Potassium (K)	MAE	0.009	0.01	**0.009**	0.011
	RMSE	1.06	1.064	**1.058**	1.061

Continued

Matter organic (OM)	MAE	0.0004	0.0007	0.002	**0.00001**
	RMSE	1.025	1.03	0.038	**1.025**
Cation exchange capacity (CEC)	MAE	**0.006**	0.009	0.006	0.008
	RMSE	**1.078**	1.086	1.079	1.08

MAE: Mean Absolute Error; RMSE: Root Mean Square Error.

3.3. Comparison of Kriging Methods

Table 3 compares the performances of the different kriging methods based on cross-validation criteria. Simple kriging (SK) proves to be the most effective for soil depth (MAE = −0.003; RMSE = 0.979), pH (MAE = −0.003; RMSE = 0.979), nitrogen (MAE = −0.006; RMSE = 1.078), and organic matter (MAE = 0.00003; RMSE = 1.025), consistently presenting MAE values closest to zero and RMSE values closest to 1 compared to the other methods. Indicator kriging (IK) excels for water table depth (MAE = 0.003; RMSE = 0.948), phosphorus (MAE = 0.012; RMSE = 1.001), potassium (MAE = 0.011; RMSE = 1.005), and cation exchange capacity (MAE = 0.013; RMSE = 1.002), demonstrating optimal performance with very satisfactory evaluation criteria. In contrast, universal kriging (UK) shows poor performance with aberrant values for several parameters, notably pH (RMSE = 7.819), phosphorus (RMSE = 20.669), and CEC (RMSE = 17.39), confirming its inadequacy for this study.

Table 3. Comparison of kriging methods.

Parameters	Criteria	SK	OK	UK	IK
Soil depth	MAE	**−0.003**	−0.022	−0.01	0.021
	RMSE	**0.979**	1.002	1.005	1.249
Water table depth	MAE	0.02	−0.045	−0.167	**0.003**
	RMSE	0.887	0.870	0.976	**0.948**
pH	MAE	**−0.003**	−0.007	−0.037	−0.023
	RMSE	**0.979**	1.04	7.819	0.998
Nitrogen (N)	MAE	**−0.006**	−0.013	−0.004	0.013
	RMSE	**1.078**	1.094	0.314	0.5
Phosphorus (P)	MAE	−0.008	−0.017	−0.374	**0.012**
	RMSE	1.065	1.085	20.669	**1.001**
Potassium (K)	MAE	−0.009	−0.022	−0.007	**0.011**
	RMSE	1.058	1.089	0.401	**1.005**
Organic matter (OM)	MAE	**0.00003**	−0.008	0.013	−0.002
	RMSE	**1.025**	1.03	2.579	1.011
Cation exchange capacity (CEC)	MAE	−0.006	−0.015	−0.274	**0.013**
	RMSE	1.079	1.095	17.39	**1.002**

SK: Simple Kriging; OK: Ordinary Kriging; UK: Universal Kriging; IK: Indicator Kriging.

3.4. Mapping the Spatial Variability of Soil Parameters

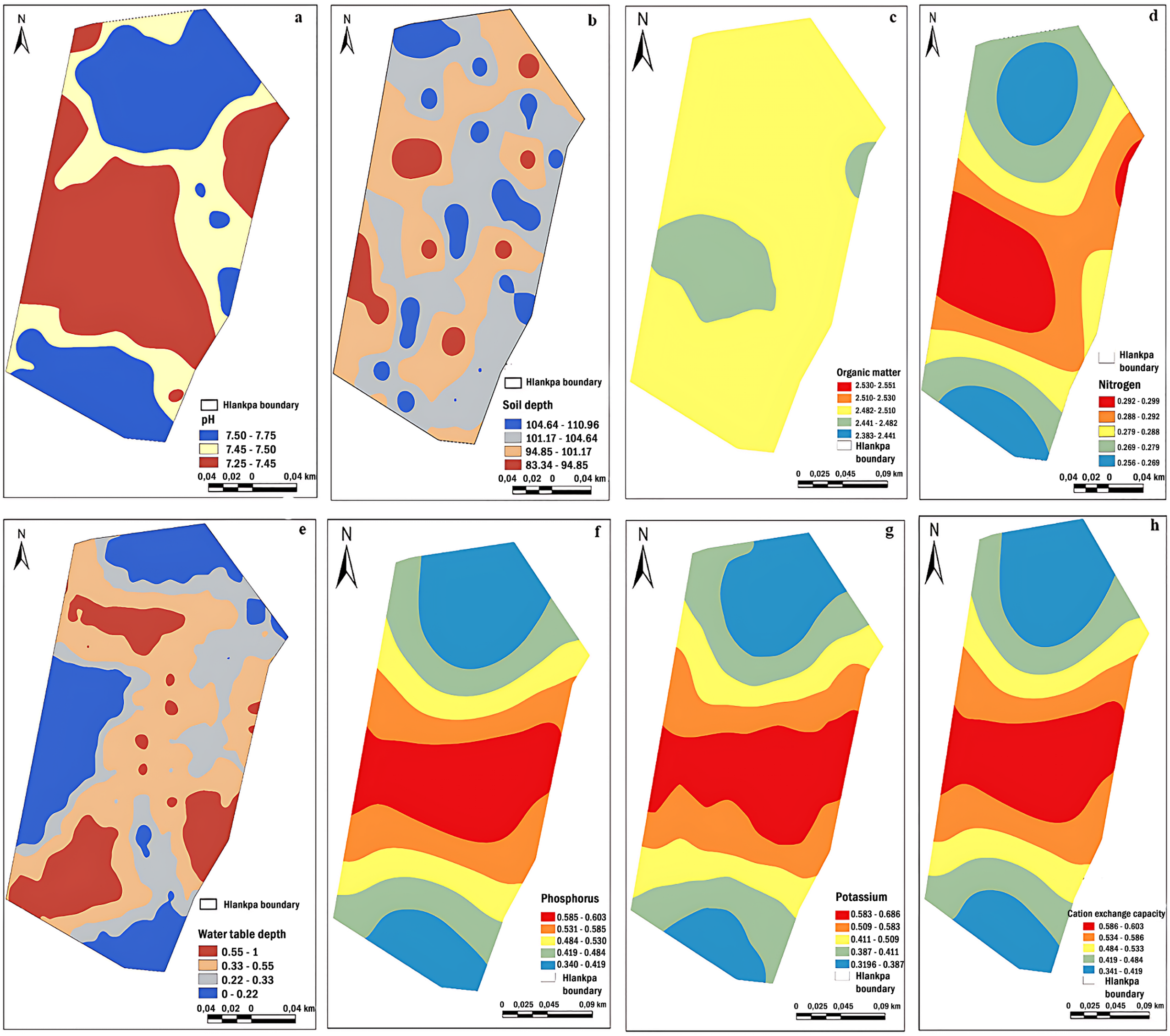

Figure 3. Spatial variability of soil parameters in Hlankpa village. (a) pH prediction by simple kriging; (b) Soil depth prediction by simple kriging; (c) Organic matter prediction by simple kriging; (d) Nitrogen prediction by simple kriging; (e) Water table depth prediction by indicator kriging; (f) Phosphorus prediction by indicator kriging; (g) Potassium prediction by indicator kriging; (h) Cation exchange capacity prediction by indicator kriging.

Figure 3 presents the spatial variability of eight soil parameters, offering a detailed visualization of their distribution within the Hlankpa farm. The spatial prediction maps reveal distinct patterns for each parameter. The pH map reveals strong spatial heterogeneity (Figure 3(a)). It is observed that the soil exhibits slightly alkaline zones in the North and South (pH > 7), contrasting with neutral zones in the West, Center, and East (pH between 6.5 and 7). The soil depth map indicates the presence of pockets of deep soils (>1 m) mainly in the North-East and from the North-West to the South of the farm. In contrast, shallower soils (<1 m) dominate in the North, Central-East, and South-East (Figure 3(b)). The organic matter map shows a generally high concentration across the entire plot. Areas of high concentration are noted in the center, which could be explained by the accumulation of crop residues or compost application (**Figure 3(c)**). Nitrogen exhibits strong spatial variability (**Figure 3(d)**). A high concentration is observed in the center of the farm, with values exceeding 0.25%, while the North-East and South areas show very low concentrations (<0.05%). The water table depth map indicates that the water is almost at the surface (<1 m) in the North-West, South-West, and East of the farm (**Figure 3(e)**). Conversely, it is deeper (>1 m) in the North-East, Center, and South-East.

The spatial distribution of phosphorus reveals a higher concentration in the center of the farm, reaching values > 100 mg/kg, with lower amounts in the South and North (**Figure 3(f)**). The predominance of areas with low phosphorus content is notable, suggesting that phosphorus fertilizer inputs are necessary to improve soil fertility over the majority of the plot. Similar to phosphorus, potassium is predominantly present in high amounts in the center of the plot, with high values (>120 mg/kg), and in low amounts in the South and North (**Figure 3(g)**). Targeted potassic fertilization in deficient areas is essential for crop development. The cation exchange capacity map shows a low chance of observing high CEC in the center of the farm, with even lower values in the South and North (**Figure 3(h)**). A low CEC indicates a low soil capacity to retain nutrients, which can lead to leaching and nutrient loss.

4. Discussion

This study confirms the effectiveness of the geostatistical approach to characterize the spatial variability of soil fertility with a significantly reduced number of samples. Unlike the study by [15], which required 2264 observations to map soil fertility in Southern and Central Benin, the geostatistical approach allowed for a precise characterization with only 93 samples, representing a 96% reduction in sampling, while maintaining satisfactory statistical reliability. The differential performance of the variogram models depending on the parameters studied is explained by the intrinsic nature of their spatial variability. The exponential model, optimal for pH (RMSE = 0.979), soil depth (RMSE = 0.887), and water table level (RMSE = 1.033), reflects spatial continuity with gradual transitions, characteristic of physical and hydraulic properties. Conversely, the Gaussian model, more effective for chemical parameters (nitrogen, phosphorus, CEC), reflects a smoother variability typical of biogeochemical processes [19]. These results converge with those of [20] on geostatistical variability in the Sudan-Guinea and Guinea zones of Benin. The demonstrated superiority of simple kriging and indicator kriging confirms the observations of [21] and [22] in the Beninese context. Simple kriging, optimal for five parameters, benefits from its ability to incorporate a known prior mean, particularly suited to the relatively homogeneous soils of the study area characterized by alluvial sediments. Indicator kriging, effective for the other four parameters, excels in predicting critical thresholds, essential for identifying areas of nutrient deficiency or excess. The inadequacy of universal kriging, with aberrant RMSE values reaching 20.669 for phosphorus, is explained by the absence of a marked spatial trend in the study area. This method, designed for data with a spatial drift, generates prediction artifacts in a context of stationary variability [23] [24]. The analysis reveals soils with an agronomic paradox: satisfactory chemical fertility (adequate levels of N, P, K, and high OM and CEC) but significant physical-hydraulic constraints. The slightly alkaline pH (7.51 ± 0.39) may limit the availability of certain micronutrients (iron, zinc, manganese) despite satisfactory nutrient levels [2]. The moderate soil depth (101.29 ± 13.29 cm) and especially the shallow water table (19.62 ± 14.24 cm) create temporary or permanent hydromorphic conditions. This pedological configuration naturally directs these soils towards crops adapted to hydromorphic conditions: flooded rice cultivation, dry-season market gardening (cabbage, carrot, lettuce), or forage crops tolerant to waterlogging. The areas with a very shallow water table (<10 cm) identified in the North-West and South-West of the farm present opportunities for rice farming or fish farming developments. The observed spatial heterogeneity justifies a spatially differentiated agricultural management approach. The central areas, enriched in nitrogen (>0.25%) and phosphorus (>100 mg/kg), according to information provided by the farm owner, Mr. Behi OWA, have indeed received regular applications of compost and crop residues over recent years, which explains the high fertility. These sectors can support demanding crops without immediate complementary fertilization. Conversely, the North-East and South areas, depleted in nutrients, require targeted inputs. The spatial correlation between the distribution of nutrients and the micro-local topography suggests redistribution processes through runoff or lateral leaching, classic phenomena in alluvial systems [25]. The relatively high cation exchange capacity (15.89 ± 3.27 cmol/kg) is a major asset for nutrient retention, limiting leaching risks despite the shallow water table. However, the spatial variability of this parameter (low zones in the South and North) requires differentiated improvement strategies: organic matter inputs in low CEC areas, and reasoned fertilization management in high CEC areas. The high organic matter content (2.49 ± 0.04%) reflects a preserved biological potential, favorable for microbial activity and soil structure. This characteristic, coupled with hydromorphic conditions, creates an environment conducive to anaerobic processes, beneficial for certain crops (rice) but potentially limiting for others requiring good root aeration.

5. Conclusion

This study demonstrated the effectiveness of the geostatistical approach to characterize the spatial variability of soil fertility. The Hlankpa soils exhibit satisfactory chemical fertility with adequate levels of main nutrients (N, P, K) and good cation exchange capacity. However, the slightly alkaline pH, moderate depth, and shallow water table direct these soils towards specific crops adapted to hydromorphic conditions. Simple and indicator kriging methods proved to be the most effective for the spatial prediction of fertility parameters, offering an efficient alternative to traditional assessment methods. Given the identified pedological specificities, several recommendations are essential for the optimal valorization of these soils. It is advisable to prioritize rice cultivation and market gardening adapted to hydromorphic conditions while implementing appropriate drainage systems to diversify crops and expand agronomic possibilities. Fertilization must be adapted according to the identified spatial variability, allowing for reasoned input management based on areas of deficiency or nutrient abundance. The use of geostatistics should be promoted as a standard method for assessing soil fertility, given its demonstrated efficiency. Finally, training farmers in farming practices adapted to the specific characteristics of their plots is a major challenge for the effective implementation of these recommendations and the sustainable improvement of agricultural productivity. It is important to note that this study was conducted on a single 6-hectare farm within Adjohoun Commune. While the geostatistical methodology is transferable to other sites, the specific spatial patterns of soil fertility are context-dependent and cannot be directly extrapolated to the entire commune without complementary studies.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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