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## Small-scale spatial variability of selected soil properties in a sloped cultivation area – A case study of Phetchabun province's highland region, Thailand

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**Abstract** Spatial variability analysis revealed distinct patterns among selected soil properties in a small-scale sloped cultivation area in the highland region of Phetchabun Province, Thailand. Descriptive statistics revealed low coefficients of variation (CV) for soil bulk density (BD), gravimetric soil water content (GWC), soil pH, soil organic carbon (SOC), and soil organic matter (SOM), indicating little variability. Exchangeable potassium ( $K_{\text{exch}}$ ), exchangeable calcium ( $Ca_{\text{exch}}$ ), and exchangeable magnesium ( $Mg_{\text{exch}}$ ) showed moderate variability, while both saturated soil hydraulic conductivity ( $K_{\text{sat}}$ ) and available phosphorus ( $P_{\text{avai}}$ ) displayed high variability. A geostatistical analysis, where residuals are kriged before adding with trend obtained through linear regression, reliably predicted BD, GWC, and  $K_{\text{exch}}$  under a small sample size; however, caution is needed for soil pH predictions. The study underscored the impact of a small sample size on log-transformed  $K_{\text{sat}}$ , SOC, SOM, log-transformed  $P_{\text{avai}}$ ,  $Ca_{\text{exch}}$ , and  $Mg_{\text{exch}}$  correlations. Overall, the findings are emphasized the importance of spatial variability analysis in guiding precise agricultural practices and resource utilization for small-scale sloped cultivation areas.

**Keywords:** Soil properties, Spatial variability, Geostatistics, Site-specific soil management, Slope

### Introduction

In Thailand, cultivation areas in highland areas encompass approximately 10.75 million hectares, representing 53% of land cover across 20 provinces. These areas comprise a mixture of hills and mountains, identified as highland

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region when the elevation exceeds 500 m a.s.l (Highland Research and Development Institute, 2014). Highland areas typically have limited agricultural potential due to their moderately low soil fertility and high soil erodibility, especially in areas with steep slopes (Sukanlaya *et al.*, 2014; Wicharuck *et al.*, 2023). However, agriculture is one of important economic activity and has been largely trans-formed into cash cropping on permanent fields in these areas (Trébuil *et al.*, 2006). It is also important to cultivate even in highland areas for food security reasons under uncertainties associated with global climate change and regional conflicts. Balancing agricultural, economic, and environmental benefits in these areas are then considered essential to prevent and control deforestation and land degradation. Phetchabun province, located in northern Thailand, is a prominent region for maize production. The choice of crops in the highland areas of Phetchabun province is influenced by factors such as soil fertility and market demand. Maize is preferred in the northern Phetchabun, while cassava is grown in the southern Phetchabun. Rubber plantations are widespread in the northern and southern Phetchabun. Specialty crops like exotic flowers, ornamental plants, temperate vegetables, and fruits are mainly found in the northern Phetchabun, where favorable temperature conditions support their cultivation alongside tourism activities (Sukanlaya *et al.*, 2014). Variation in crops, as indicated above, suggests that achieving sustainable agricultural productivity in the highland areas of Phetchabun province requires understanding and addressing soil properties.

Soil physical and chemical properties are key determinants of soil fertility, nutrient availability, water holding capacity, and overall ecosystem functioning (Bai *et al.*, 2018; Lal, 2020). Soil texture, structure, organic matter content, nutrient levels, pH, and electrical conductivity are among the important parameters that influence soil productivity and plant growth. Highland soils in Khao Kho area, Phetchabun province, Thailand, for example, exhibit specific characteristics. These soils have low bulk density in topsoil (1.07-1.16 Mg/m<sup>3</sup>) and low to moderately low in subsoil (1.09-1.63 Mg/m<sup>3</sup>). The hydraulic conductivity values of topsoil and subsoil range from moderately low to high, spanning a range of  $6.71 \times 10^{-3}$  to 16.1 cm/h<sup>1</sup> (Samrit *et al.*, 2008). Limitations for crop practices in these soils include attributes such as acidity, low phosphorus, low potassium, and aluminum toxicity. (Samrit *et al.*, 2008). In addition, slope stability is a crucial consideration in the highland region, where steep slopes are susceptible to erosion, landslides, and other forms of mass movement. The physical and chemical properties of the soil play a direct role in slope stability by influencing soil erodibility, shear strength, and water infiltration capacity (Havaee *et al.*, 2015; Sun *et al.*, 2020; Yalcin, 2007). Studies have shown that cultivated lands and steeper slopes tend to have higher bulk

density and lower total porosity, whereas forestland and gentler slopes exhibit lower bulk density and higher total porosity (Wubie and Assen, 2020).

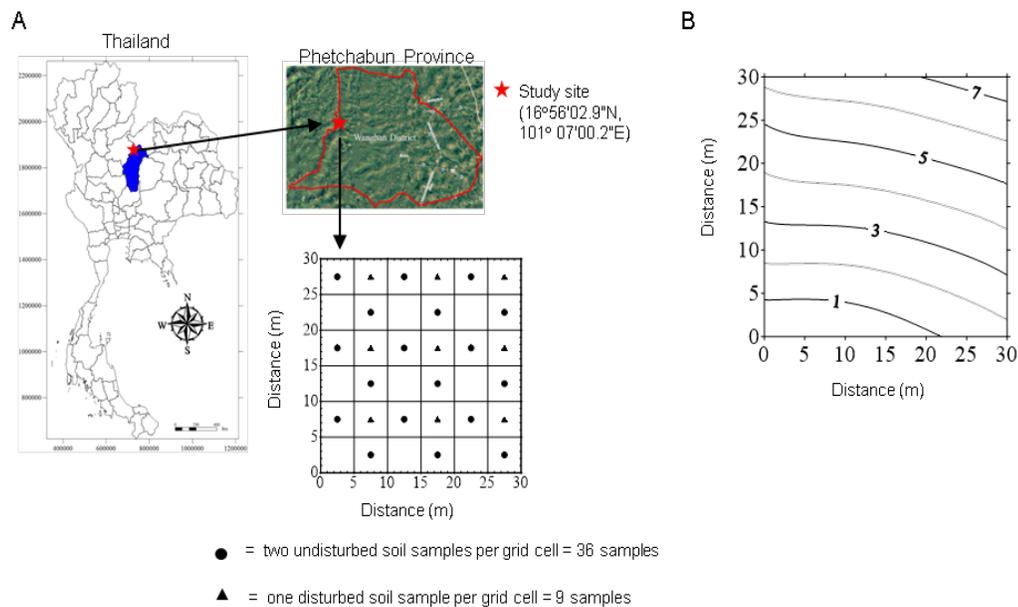
Soil properties in nature are known to be spatially variable. In agricultural practices, understanding the spatial variability of soil properties is crucial for making informed decisions about crop management practices, irrigation, fertilization, and soil conservation efforts. Geostatistics is then a valuable statistical tool that has been employed to assess the spatial variability of soil properties. It enables the analysis of soil variability across different spatial resolutions, ranging from a few meters (Negassa *et al.*, 2019; Wilcke, 2000) to regional scales (Liu *et al.*, 2009). The versatility and application in soil research make geostatistics an essential method for understanding and managing soil resources. In Thailand, there is a need for studies that specifically focus on highland agricultural areas, considering unique features and challenges of these regions. Small-scale evaluation of specific soil conditions in the highland region of Phetchabun Province was a case study that used geostatistics to assess and optimize land use and agricultural practices. Therefore, the objective of this study was to assess selected soil physical and chemical properties in a sloped agricultural area within the highland region of Phetchabun Province. The findings based on soil properties in this highland region can support sustainable land management practices, aid in crop selection for the region, and provided valuable insights for slope stability assessment and mitigation.

## **Materials and methods**

### ***Study area***

The study area is located at the Phetchabun Research Station of Faculty of Agriculture, Kasetsart University, which is situated in Phetchabun Province, Thailand, at 16° 56' 02.9" N and 101° 07' 00.2" E (Figure 1A). The study site exhibits mountainous topography, with elevation ranging from 1,000 to 1,300 m above sea level and 11-degree slope. The research station encompassed approximately 16 ha. The study area experiences a tropical monsoon climate. The summer season typically spans from February to May, with the highest temperatures occurring in April, reaching an average of about 37°C. The rainy season begins in May and extends through October, with an average annual precipitation of 1050 mm. The winter season occurs from November to February, with the lowest temperature observed in December, averaging around 18°C. In general, ploughing tillage system and crop rotation Jerusalem artichoke, rice, maize, and vegetables are commonly used in the experimental field.

In the dry season of 2020, the study area was cultivated with Jerusalem artichoke. The experimental field within the study site covers an area of 900 m<sup>2</sup> (30 m × 30 m). Land labeling was performed with grid points spaced evenly at 5-m apart, resulting in a total of 49 grid points. The elevation of each grid point was measured by using the telescope surveyor (Topcon AT-G4, USA) and the level staff. The coordinates of each grid point were entered into the Surfer 17 (Golden Software®, USA) for spatial interpolation and production of contour maps. Figure 1B shows the elevation of the experimental field. The difference between the highest and lowest elevation points within the study was approximately 7 m. Thus, relative elevations ranging from 0 to 7 m, where the lowest relative elevation of 0 m corresponds to the south-west corner of the field, are used hereafter. The soil textures varied; sandy clay loam was found at the elevation of 5 to 7 m, while clay loam was found at the elevation of 1 to 3 m (data not shown).



**Figure 1.** Location map of the study area (A) and the elevation of the experimental field (B)

### ***Soil sampling***

Soil samples were taken from the experimental field using the grid sampling method (Gandah *et al.*, 2000; Li *et al.*, 2019). A plot with a size of 30 m × 30 m (900 m<sup>2</sup>), featuring similar topography and vegetation, was divided into 36 grid cells of 5 m × 5 m.

Two undisturbed soil samples were individually collected from the center of each grid cell using core soil samplers (50 mm diameter and 55 mm height) from 18 grid cells, as illustrated in Figure 1A, resulting in a total of 36 samples. The undisturbed core samples were weighted to determine the fresh weight. Then, the undisturbed core samples were wrapped in plastic to prevent them from drying out and were sent to the laboratory. They were stored at a temperature of 5°C until processing to determine selected soil physical properties.

Nine disturbed soil samples, each comprising five subsamples, were collected within the center of each grid cell depicted as triangles in Figure 1A at a depth of 20 cm to determine specific soil chemical properties. These disturbed soil samples were dried at room temperature and kept under the same conditions until they were sent to the Soil Science Department, Faculty of Agriculture, Kasetsart University, Bangkok, Thailand, for analysis.

### ***Soil physical and GWC analysis***

Undisturbed core samples were used to determine soil bulk density (BD) and saturated soil hydraulic conductivity ( $K_{sat}$ ) and GWC of the soil at the time of sampling, at the Soil Science Department, Faculty of Agriculture, Kasetsart University, Bangkok, Thailand.  $K_{sat}$  determination was carried out using a falling head method (Klute and Dirksen, 1986). Following  $K_{sat}$  measurements, undisturbed core samples were oven dried at 105°C for at least 24 h to obtain dry weight of soil particles. This dry weight was used to determine BD and GWC using the direct core method and oven drying method, respectively.

Soil texture information was obtained from the soil test report of the disturbed soil samples serviced by the Soil Science Department, Faculty of Agriculture, Kasetsart University, Bangkok, Thailand. The soil texture was determined from their particle size distributions, which were determined using the hydrometer method (Gee and Bauder, 1986).

### ***Soil chemical analysis***

To determine soil pH, soil organic carbon (SOC), soil organic matter (SOM), available phosphorus ( $P_{\text{avai}}$ ), exchangeable potassium ( $K_{\text{exch}}$ ), calcium ( $Ca_{\text{exch}}$ ), and magnesium ( $Mg_{\text{exch}}$ ), disturbed soil samples were sent for analysis to the Soil Science Department, Faculty of Agriculture, Kasetsart University, Bangkok, Thailand. The used methods, according to the obtained soil test report, were as follows: soil pH was measured in water suspension at soil to water ratio of 1:1 (Thomas, 1996). The SOC was determined using the Walkley-Black method (Walkley and Black, 1934), while the SOM was obtained by multiplying the SOC content by the van Bemmelen factor of 1.724 (Van Bemmelen, 1890).  $P_{\text{avai}}$  was analyzed using the Bray II method (Bray and Kurtz, 1945). The  $K_{\text{exch}}$ ,  $Ca_{\text{exch}}$ , and  $Mg_{\text{exch}}$  in the  $NH_4OAc$  extracts (Pratt, 1965) were analyzed using atomic absorption spectrometer (AAS). For each soil sample, three technical replicates of each soil chemical analysis were performed.

### ***Statistical analysis***

Soil physical and chemical data were subjected to descriptive analysis using Statistical Tool for Agricultural Research (STAR) (Version 2.0.1). Statistical descriptive parameters including, mean, median, mode, minimum, maximum, standard deviation, skewness, kurtosis and coefficients of variation were calculated for each soil property to describe position, dispersion and distribution of soil physical and chemical dataset. The normality of soil physical and chemical data was assessed according to the Shapiro–Wilk’s W test. When data did not fit to a normal distribution, data were logarithmically transformed. In this study,  $P_{\text{avai}}$  and  $K_{\text{sat}}$  data were logarithmically transformed. Pearson correlation analysis was used to estimate all relationships between soil variables using STAR. The coefficient of variation (CV) for soil properties was used to classify the samples into three categories: low variation ( $CV < 15\%$ ), moderate variation ( $15\% < CV \leq 35\%$ ), and high variation ( $CV > 35\%$ ) (Wilding, 1985).

### ***Geostatistical analysis***

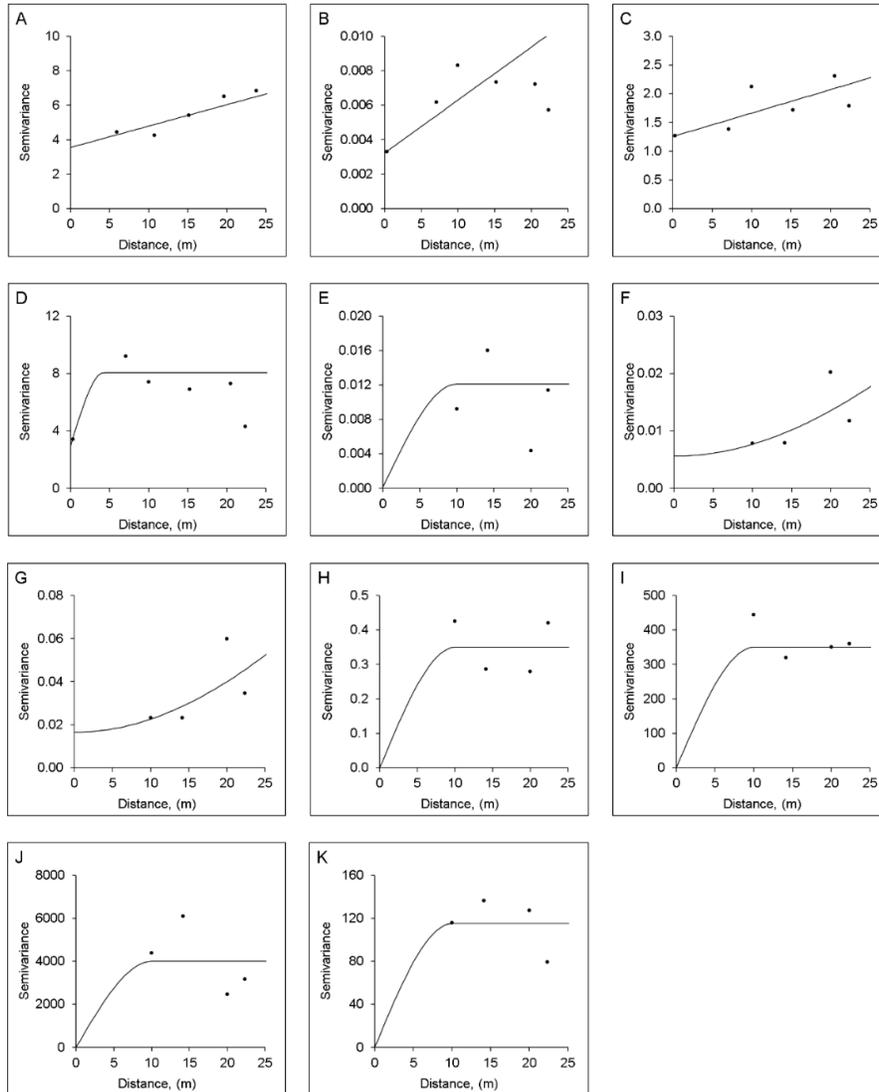
Simple kriging with varying local mean (SKlm) was performed, wherein the constant mean in SK was replaced by known varying means to account for the set of covariates available at each location being estimated (Goovaerts, 1997), to predict selected soil physical and chemical properties. In SKlm, the first step is to estimate varying local means. In this study, they were obtained through linear regression between the observed soil property values and the slope

gradient percentage. The soil property values estimated from the linear regression model were subtracted from the observed data to generate residuals. Given that the original values were influenced by slopes, the geostatistical analysis used these residual values to assess spatial correlation. Subsequently, these residual values were employed to compute experimental semivariograms for simple kriging (SK) of the residuals using the R version 4.1.1 (RCoreTeam, 2021) with the gstat package version 2.07 (Gräler *et al.*, 2016; Pebesma, 2004). Common semivariogram models including linear, exponential, spherical, and Gaussian models (Goovaerts, 1997), were fitted to the experimental semivariograms (Figure 2). The best-fit model for each soil physical and chemical parameter was selected through a combination of visual assessment and statistical methods, specifically by identifying the model with the lowest value of Mean Squared Error (MSE) or Root Mean Square Error (RMSE). The spatial dependence of each variable was assessed by calculating the nugget-to-sill ratio. Based on, the nugget-to-sill ratio, a given soil parameter can be classified as spatially independent ( $> 0.75$ ), moderately dependent (0.25 to 0.75), or strongly spatially dependent ( $< 0.25$ ) (Cambardella *et al.*, 1994). After performing SK to the residuals, the kriged residuals were added to the spatially varying local means, which were obtained from the linear regression model.

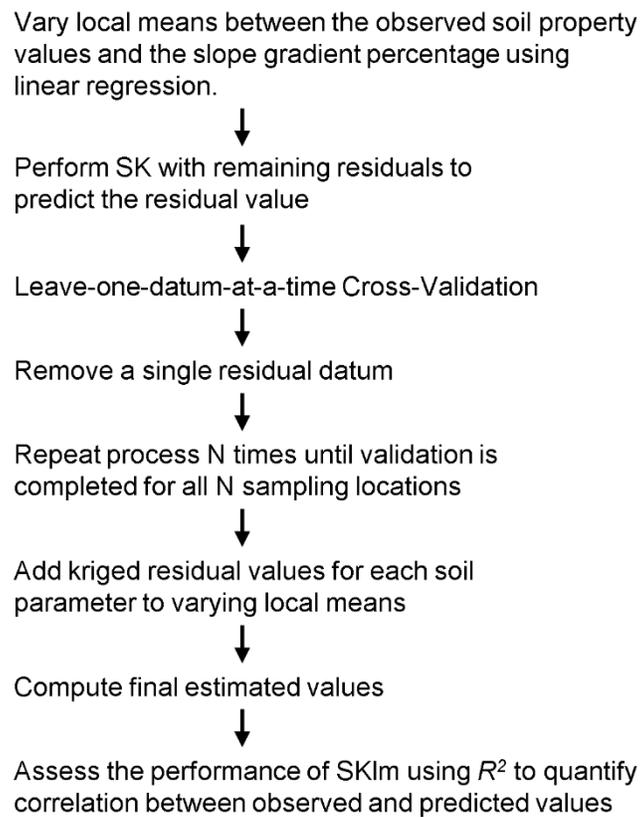
To assess the performance of SKlm, the leave-one-datum-at-a-time cross-validation was carried out (Saito *et al.*, 2009). The leave-one-out approach adopted in this study involved removal of a single residual datum, followed by performing SK with the remaining residuals to predict the residual value. This sequential process was repeated N times until validation was completed for all N sampling locations. Subsequently, the kriged residual values for each soil parameter through the leave-one-out approach were added to the varying local means, obtained from the linearly regressed equations, to compute the final estimated values. This final estimate was finally used to assess the performance of SKlm through with  $R^2$  serving to quantify the degree of correlation between observed and predicted values (Figure 3).

Non-point prediction of residuals on spatial maps was performed for each soil property. Within the SKlm framework, the slope gradient percentage was computed using a semivariogram and simple kriging, respectively. In a simple kriging process, 2,500 datapoints were used to estimate values and increase data resolution. The quantity of residual points for selected soil physical properties and GWC increased from 36 to 2,500 data points, and for chosen soil chemical properties, it expanded from nine to 2,500 datapoints. The estimated residuals from the 2,500 data points of each soil property were employed in their corresponding linear regression equations to calculate prediction values.

Following this, spatial distribution maps for each soil property were generated by utilizing predictions derived from the 2,500 datapoints.



**Figure 2.** Semivariogram results. (A) slope gradient percentage, (B) bulk density (BD), (C) a natural logarithmic transformation of saturated hydraulic conductivity ( $\ln K_{sat}$ ), (D) gravimetric soil water content (GWC), (E) soil pH, (F) soil organic carbon (SOC), (G) soil organic matter (SOM), (H) a natural logarithmic transformation of available phosphorus ( $\ln P_{avai}$ ), (I) exchangeable potassium ( $K_{exch}$ ), (J) exchangeable calcium ( $Ca_{exch}$ ), and (K) exchangeable magnesium ( $Mg_{exch}$ )



**Figure 3.** The flowchart of the leave-one-datum-at-a-time cross-validation

## Results

### *Descriptive statistics and correlation analysis*

The descriptive statistics of selected soil properties for both disturbed and undisturbed soil samples taken from the sloped area is shown in Table 1. The BD values ranged from 0.91 to 1.28 g/cm<sup>3</sup>, while the GWC varied from 20.08 to 33.27%, respectively. The  $K_{sat}$  values ranged from 4.05 to 816.34 mm/h. The soil pH, SOC, and SOM were in the range of 4.02 to 4.33, 1.37 to 1.65 t/ha, and 2.35 to 2.85 t/ha, respectively. The concentration of  $P_{avai}$ ,  $K_{exch}$ ,  $Ca_{exch}$ , and  $Mg_{exch}$  ranged from 14.40 to 95.10 mg/kg, 62 to 150 mg/kg, 264 to 452 mg/kg, and 16 to 52 mg/kg, respectively. The CV value is a commonly used measure of the variability of soil properties. According to Wilding (1985), CV values can be categorized as follows: 0 to 15% for little variability, 15 to 35% for moderate variability, and > 35% for high variability. It was found that the CV values for

BD, GWC, soil pH, SOC, and SOM were in the range of 2.63 to 10.19% (Table 1), indicating little variability. For  $K_{\text{exch}}$ ,  $\text{Ca}_{\text{exch}}$ , and  $\text{Mg}_{\text{exch}}$ , the CV values ranged from 18.72 to 30.69% (Table 1), suggesting a moderate variability. Both  $K_{\text{sat}}$  and  $\text{P}_{\text{avai}}$  displayed high variability, which is commonly found (Jury and Horton, 2004), with CV values of 97.02% and 73.83%, respectively. To assess the normality of the soil physical and chemical data distribution, the Shapiro–Wilk’s W test was conducted. The results of the test indicated that all selected soil physical and chemical data passed the Shapiro–Wilk’s W test at a significance level of 0.05, except for  $K_{\text{sat}}$  and  $\text{P}_{\text{avai}}$ . However, after applying a natural logarithmic (ln) transformation, the  $K_{\text{sat}}$  and  $\text{P}_{\text{avai}}$  data passed the normality test (Table 1).

Results of Pearson’s correlation analysis is shown in Table 2. The analysis revealed significant correlation between various properties. The BD showed a significant negative correlation with  $\ln K_{\text{sat}}$ , indicating that as the BD increased, the  $\ln K_{\text{sat}}$  decreased. The observed negative correlation between BD and  $\ln K_{\text{sat}}$  was due to increased soil compaction with higher BD, which reduces pore size and connectivity, leading to decreased hydraulic conductivity. Conversely, the BD showed a positive correlation with  $\ln \text{P}_{\text{avai}}$ , suggesting that higher BD values were associated with increased  $\ln \text{P}_{\text{avai}}$ . Soil pH exhibited a significant positive correlation with  $\text{Ca}_{\text{exch}}$ , and  $\text{Mg}_{\text{exch}}$ . This indicates that as soil pH increased, the concentration of  $\text{Ca}_{\text{exch}}$ , and  $\text{Mg}_{\text{exch}}$  also increased. Additionally, a significant positive correlation was also observed between  $\text{Ca}_{\text{exch}}$ , and  $\text{Mg}_{\text{exch}}$ , indicating that as the concentration of  $\text{Ca}_{\text{exch}}$ , the concentration of  $\text{Mg}_{\text{exch}}$  also increased.

### ***Linear regression of soil physical and chemical properties and GWC in relation to the slope gradient percentage***

The analysis incorporated observed values of BD, GWC, and  $\ln K_{\text{sat}}$  (referred to as  $\text{BD}_{\text{obs}}$ ,  $\text{GWC}_{\text{obs}}$ , and  $\ln K_{\text{sat-obs}}$ ), as well as observed values of soil pH, SOC, SOM,  $\ln \text{P}_{\text{avai}}$ ,  $K_{\text{exch}}$ ,  $\text{Ca}_{\text{exch}}$ , and  $\text{Mg}_{\text{exch}}$  (referred to as soil  $\text{pH}_{\text{obs}}$ ,  $\text{SOC}_{\text{obs}}$ ,  $\text{SOM}_{\text{obs}}$ ,  $\ln \text{P}_{\text{avai-obs}}$ ,  $K_{\text{exch-obs}}$ ,  $\text{Ca}_{\text{exch-obs}}$ , and  $\text{Mg}_{\text{exch-obs}}$ ) to evaluate the relationship between these soil properties and the slope gradient percentage in the sloped study area of the highland region in Phetchabun Province, Thailand.

**Table 1.** Descriptive statistics and Shapiro-Wilk normality test of data of selected soil physical and chemical properties on slope area cultivated with Jerusalem artichoke at the Phetchabun research station, Pechabun Province, Thailand

Parameters	Number of samples	Mean	Median	Min	Max	SD	Cs	Ck	CV (%)	S-W
BD (g/cm <sup>3</sup> )	36	1.13	1.13	0.91	1.28	0.09	-0.37	-0.20	7.96	0.977
$K_{sat}$ (mm/h)	36	230.29	124.26	4.05	816.34	223.42	1.04	0.01	97.02	0.857****
GWC (%)	36	25.61	25.59	20.08	33.27	2.61	0.39	0.68	10.19	0.979
$K_{sat}^a$ (mm/h)	36	4.80	4.82	1.40	6.70	1.36	-0.73	-0.24	28.33	0.936
Soil pH	9	4.18	4.16	4.02	4.33	0.11	0.11	-1.66	2.63	0.931
SOC (t/ha)	9	1.49	1.48	1.37	1.65	0.11	0.20	-1.70	7.38	0.923
SOM (t/ha)	9	2.56	2.54	2.35	2.85	0.19	0.20	-1.70	7.42	0.923
$P_{avai}^a$ (mg/kg)	9	36.61	24.70	14.40	95.10	27.03	1.12	-0.29	73.83	0.787**
$P_{avai}$ (mg/kg)	9	3.41	3.21	2.67	4.55	0.63	0.61	-1.18	18.48	0.916
$K_{exch}$ (mg/kg)	9	105.33	98	62	150	31.73	0.07	-1.58	30.12	0.916
$Ca_{exch}$ (mg/kg)	9	354.44	356	264	452	66.34	0.13	-1.37	18.72	0.922
$Mg_{exch}$ (mg/kg)	9	36.33	40	16	52	11.15	-0.33	-1.16	30.69	0.966

\*\* , \*\*\*\*Significant at  $p$ -value = 0.01 and 0.001 levels, respectively.

<sup>a</sup>Natural logarithmic transformed data, BD = soil bulk density,  $K_{sat}$  = saturated hydraulic conductivity, GWC = gravimetric soil water content, SOM = soil organic matter, SOC = soil organic carbon,  $P_{avai}$  = available phosphorus,  $K_{exch}$  = exchangeable potassium,  $Ca_{exch}$  = exchangeable calcium,  $Mg_{exch}$  = exchangeable magnesium, Min = minimum, Max = maximum, SD = standard deviation, Cs = coefficient of skewness, Ck = coefficient of kurtosis, CV = coefficient of variance and S-W = Shapiro-Wilk normality test.

**Table 2.** Pearson correlation coefficients (*r*) among the elevation and the selected soil physical and chemical properties of highland soil located in slope area cultivated with Jerusalem artichoke at the Phetchabun research station, Phetchabun Province, Thailand

Variable	Elevation	GWC	BD	$K_{sat}^a$	Soil pH	SOM	SOC	$P_{avai}^a$	$K_{exch}$	$Ca_{exch}$
GWC	-0.259									
BD	0.120	-0.401								
$K_{sat}^a$	-0.182	0.150	-0.807**							
Soil pH	-0.025	-0.145	-0.241	0.270						
SOM	0.188	0.244	0.190	-0.565	0.112					
SOC	0.207	0.229	0.177	-0.557	0.115	0.999				
$P_{avai}^a$	-0.284	0.601	-0.731*	0.490	-0.046	-0.042	-0.033			
$K_{exch}$	-0.551	0.384	-0.194	0.320	0.496	0.233	0.219	0.295		
$Ca_{exch}$	-0.105	-0.023	-0.470	0.564	0.904****	-0.226	-0.222	0.118	0.435	
$Mg_{exch}$	-0.320	0.244	-0.471	0.327	0.681*	0.034	0.036	0.388	0.456	0.781*

\*, \*\*, \*\*\*\*Significant at *p*-value = 0.05, 0.01 and 0.001 levels, respectively.

<sup>a</sup> Natural logarithmic transformed data, GWC = gravimetric soil water content, BD = soil bulk density,  $K_{sat}$  = saturated hydraulic conductivity, SOM = soil organic matter, SOC = soil organic carbon,  $P_{avai}$  = available phosphorus,  $K_{exch}$  = exchangeable potassium,  $Ca_{exch}$  = exchangeable calcium,  $Mg_{exch}$  = exchangeable magnesium

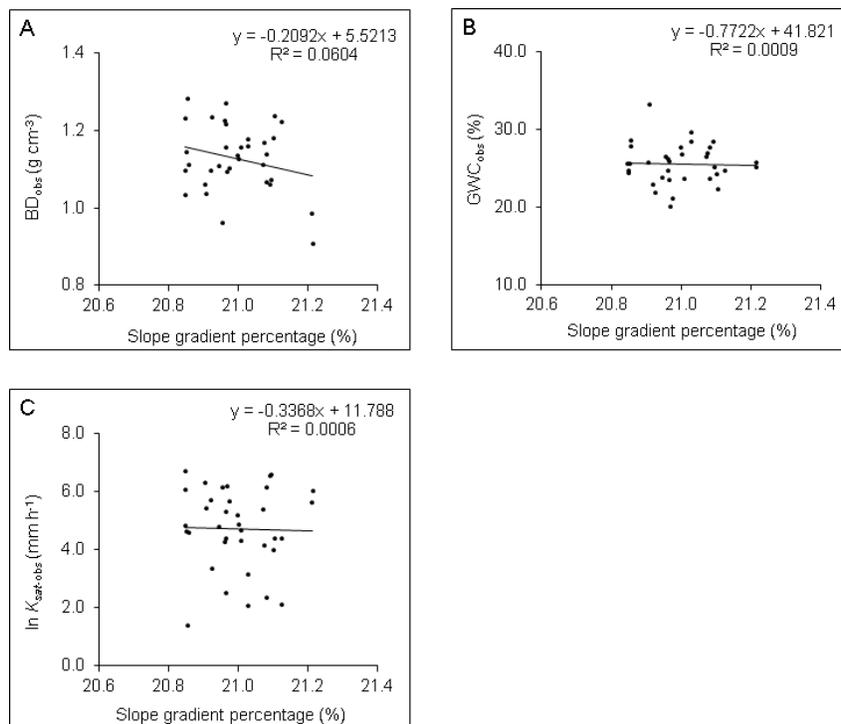
Result showed correlations between the observed soil physical properties, including GWC, and the slope gradient percentage, as well as the chemical properties and the slope gradient percentages (Figures 4 and 5). There was a negative correlation between  $BD_{obs}$ ,  $GWC_{obs}$ , and  $\ln K_{sat-obs}$  and the slope gradient percentage, with the  $R^2$  values of 6.04, 0.09, and 0.06%, respectively (Figure 5). A negative correlation was also found between soil  $pH_{obs}$ ,  $SOC_{obs}$ ,  $SOM_{obs}$ ,  $K_{exch-obs}$ ,  $Ca_{exch-obs}$ , and  $Mg_{exch-obs}$  and the slope gradient percentage with the  $R^2$  values of 13.25, 13.32, 13.32, 59.01, 3.81, and 1.19%, respectively (Figure 5). In contrast, a positive correlation was detected between  $\ln P_{avai-obs}$  and the slope gradient percentage with the  $R^2$  values of 5.23% (Figure 5D). The  $R^2$  values indicated a weak relationship between the selected soil physical and chemical properties and the slope gradient percentage, in general. This suggests that the slope alone accounted for only a small portion of the variability in these parameters. While slope alone might not fully account for the variability observed in these properties, it still plays an important role in how topographic characteristics shaped soil properties. Therefore, incorporating quantitative information of the slope into the estimation process was still comprehensive assessment of soil properties in relation to the topography of the study area.

### ***SKlm estimates of soil physical and chemical properties and GWC***

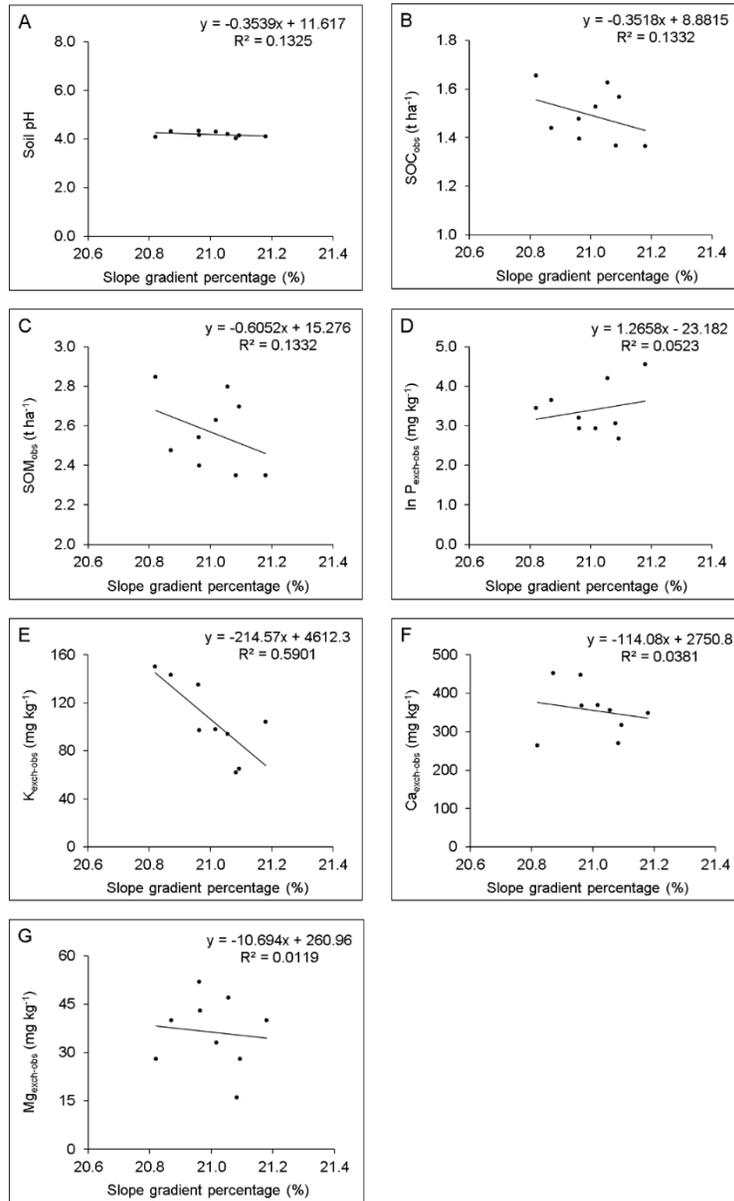
At first, to obtain the residuals of each property, the linear regression was used between each property and the slope gradient percentage. The regression results for BD, GWC, and  $\ln K_{sat}$  is shown in Figure 4. Similarly results of linear regression for soil pH, SOC, SOM,  $\ln P_{avai}$ ,  $K_{exch}$ ,  $Ca_{exch}$ , and  $Mg_{exch}$  are depicted in Figure 5.

The residual values were calculated for each property after regression. It was found that the range of residual for BD, GWC, and  $\ln K_{sat}$  extended from -0.18 to 0.14 g/cm<sup>3</sup>, -5.55 to 7.60%, and -3.36 to 1.94 mm/h, respectively (Table 3). Similarly, the range of residuals for soil pH, SOC, SOM,  $\ln P_{avai}$ ,  $K_{exch}$ ,  $Ca_{exch}$ , and  $Mg_{exch}$  in relation to the slope gradient percentage extended from -0.16 to 0.13, -0.11 to 0.15 t/ha, -0.19 to 0.26 t/ha, -0.85 to 0.93 mg/kg, -26.60 to 36.20 mg/kg, -111.53 to 87.52 mg/kg, and -19.50 to 15.19 mg/kg, respectively (Table 3). The residuals values obtained through the linear regression analysis of each soil property were employed to compute experimental semivariograms of the residuals. For the residual values of BD and  $\ln K_{sat}$ , the linear semivariogram model was found to be the most suitable with the least errors compared to other semivariogram models. In contrast, for the residuals of GWC, soil pH,  $\ln P_{avai}$ ,  $K_{exch}$ ,  $Ca_{exch}$ , and  $Mg_{exch}$ , the spherical semivariogram model was found to be the best. Moreover, for the residuals of SOC and SOM, the Gaussian semivariogram model fits well.

The nugget-to-sill ratios of the residual semivariograms revealed interesting patterns for different soil properties. For BD and  $\ln K_{sat}$ , the results indicated that their residuals were spatially independent. It suggested that the residual values of BD and  $\ln K_{sat}$  distributed randomly in space. The GWC residuals showed a moderate level of spatial dependence. On the other hand, the residuals of SOC and SOM exhibited strong spatial dependence. The semivariogram analysis of the residuals revealed a spatial range of correlation extending even up to a distance of 45 m (the maximum separation distance between the sampling locations at the site). It suggested that the residuals of SOC and SOM varied systematically with the slope gradient percentage over this distance. Similarly, the residuals of soil pH and the total nutrients ( $\ln P_{avai}$ ,  $K_{exch}$ ,  $Ca_{exch}$ , and  $Mg_{exch}$ ) also exhibited strong spatial dependence. The semivariogram analysis of the residuals showed a range of 10 m for the total nutrients indicating that their values exhibited a structured spatial pattern within this range (Table 4).



**Figure 4.** The correlation analysis of the relationship between observed (obs) soil physical properties and slope gradient percentage. (A) bulk density ( $BD_{obs}$ ), (B) gravimetric soil water content ( $GWC_{obs}$ ), and (C) a natural logarithmic transformation of saturated hydraulic conductivity ( $\ln K_{sat-obs}$ )



**Figure 5.** The correlation analysis of the relationship observed (obs) soil chemical properties and slope gradient percentage. (A) soil pH, (B) soil organic carbon (SOC<sub>obs</sub>), (C) soil organic matter (SOM<sub>obs</sub>), (D) a natural logarithmic transformation of available phosphorus (ln P<sub>avai-obs</sub>), (E) exchangeable potassium (K<sub>exch-obs</sub>), (F) exchangeable calcium (Ca<sub>exch-obs</sub>), and (G) exchangeable magnesium (Mg<sub>exch-obs</sub>)

**Table 3.** Goodness of fit model and estimated value range of soil parameters

Soil parameters	model equation	Range
BD (g/cm <sup>3</sup> )		
BD <sub>est-SLP</sub>	$y = -0.2092x + 5.5213$	1.08 - 1.16
Residual BD	-	-0.18 - 0.14
Residual BD <sub>SKlm</sub>	-	-
BD <sub>SKlm</sub>	-	1.01 - 1.22
ln $K_{sat}$ (mm/h)		
ln $K_{sat-est-SLP}$	$y = -0.3368x + 11.788$	4.64 - 4.77
Residual ln $K_{sat}$	-	-3.36 - 1.94
Residual ln $K_{sat-SKlm}$	-	-
ln $K_{sat-SKlm}$	-	4.59 - 4.90
GWC (%)		
GWC <sub>est-SLP</sub>	$y = -0.7722x + 41.821$	20.85 - 21.22
Residual GWC	-	-5.55 - 7.60
Residual GWC <sub>SKlm</sub>	-	-
GWC <sub>SKlm</sub>	-	22.53 - 30.00
Soil pH		
Soil pH <sub>est-SLP</sub>	$y = -0.3539x + 11.617$	4.12 - 4.25
Residual soil pH	-	-0.16 - 0.13
Residual soil pH <sub>SKlm</sub>	-	-
Soil pH <sub>SKlm</sub>	-	4.12 - 4.27
SOC (t/ha)		
SOC <sub>est-SLP</sub>	$y = -0.3518x + 8.8815$	1.43 - 1.56
Residual SOC	-	-0.11 - 0.15
Residual SOC <sub>SKlm</sub>	-	-
SOC <sub>SKlm</sub>	-	1.40 - 1.53
SOM (t/ha)		
SOM <sub>est-SLP</sub>	$y = -0.6052x + 15.276$	2.46 - 2.68
Residual SOM	-	-0.19 - 0.26
Residual SOM <sub>SKlm</sub>	-	-
SOM <sub>SKlm</sub>	-	2.42 - 2.63
ln $P_{avai}$ (mg/kg)		
ln $P_{avai-est-SLP}$	$y = 1.2658x - 23.182$	3.17 - 3.63
Residual ln $P_{avai}$	-	-0.85 - 0.93
Residual ln $P_{avai-SKlm}$	-	-
ln $P_{avai-SKlm}$	-	3.14 - 3.42
$K_{exch}$ (mg/kg)		
$K_{exch-est-SLP}$	$y = -214.57x + 4612.3$	67.80 - 145.00
Residual $K_{exch}$	-	-26.60 - 36.20
Residual $K_{exch-SKlm}$	-	-
$K_{exch-SK}$	-	63.28 - 144.37
$Ca_{exch}$ (mg/kg)		
$Ca_{exch-est-SLP}$	$y = -114.08x + 2750.8$	354.49 - 375.53
Residual $Ca_{exch}$	-	-111.53 - 87.52
Residual $Ca_{exch-SKlm}$	-	-
$Ca_{exch-SKlm}$	-	332.80 - 389.48

Soil parameters	model equation	Range
Mg <sub>exch</sub> (mg/kg)		
Mg <sub>exch-est-SLP</sub>	$y = -10.694x + 260.96$	34.46 - 38.31
Residual Mg <sub>exch</sub>	-	-19.50 - 15.19
Residual Mg <sub>exch-SKlm</sub>	-	-
Mg <sub>exch-SKlm</sub>	-	33.77 - 39.60

BD = soil bulk density,  $\ln K_{sat}$  = natural log-transformed saturated hydraulic conductivity, GWC = gravimetric soil water content, SOC = soil organic carbon, SOM = soil organic matter,  $\ln P_{avai}$  = natural log-transformed available phosphorus,  $K_{exch}$  = exchangeable potassium,  $Ca_{exch}$  = exchangeable calcium,  $Mg_{exch}$  = exchangeable magnesium

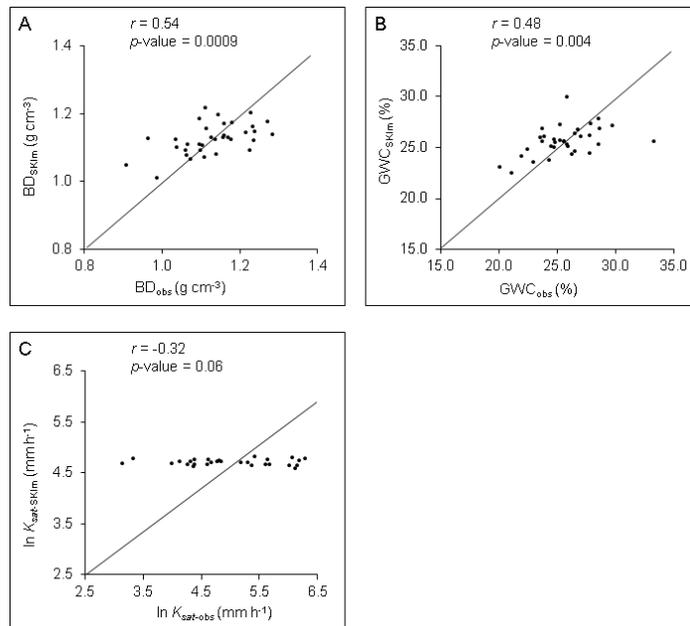
**Table 4.** Spatial correlation of selected soil physical and chemical properties of highland soil located in slope area cultivated with Jerusalem artichoke at the Phetchabun research station, Phechabun Province, Thailand

Parameter	Model	Nugget	Sill	Range (m)	Nugget:Sill ratio	MSE	RMSE
BD	Linear	0.0032	0.0003	-	10.485	1.740	1.319
$K_{sat}^a$	Linear	1.2536	0.0409	-	30.629	2.805	1.675
GWC	Spherical	2.9312	5.1275	4.234	0.572	1.080	1.039
SOC	Gaussian	0.0056	0.0906	66.030	0.062	1.000	1.000
SOM	Gaussian	0.0165	0.2676	65.974	0.062	1.193	1.092
Soil pH	Spherical	0.0001	0.0120	10	0.008	0.874	0.935
$P_{avai}^a$	Spherical	0.0001	0.3500	10	0.0002857	1.069	1.034
$K_{exch}$	Spherical	0.0001	350	10	0.0000003	1.179	1.086
$Ca_{exch}$	Spherical	0.0100	4000	10	0.0000025	1.058	1.029
$Mg_{exch}$	Spherical	0.0001	115	10	0.0000009	1.068	1.033

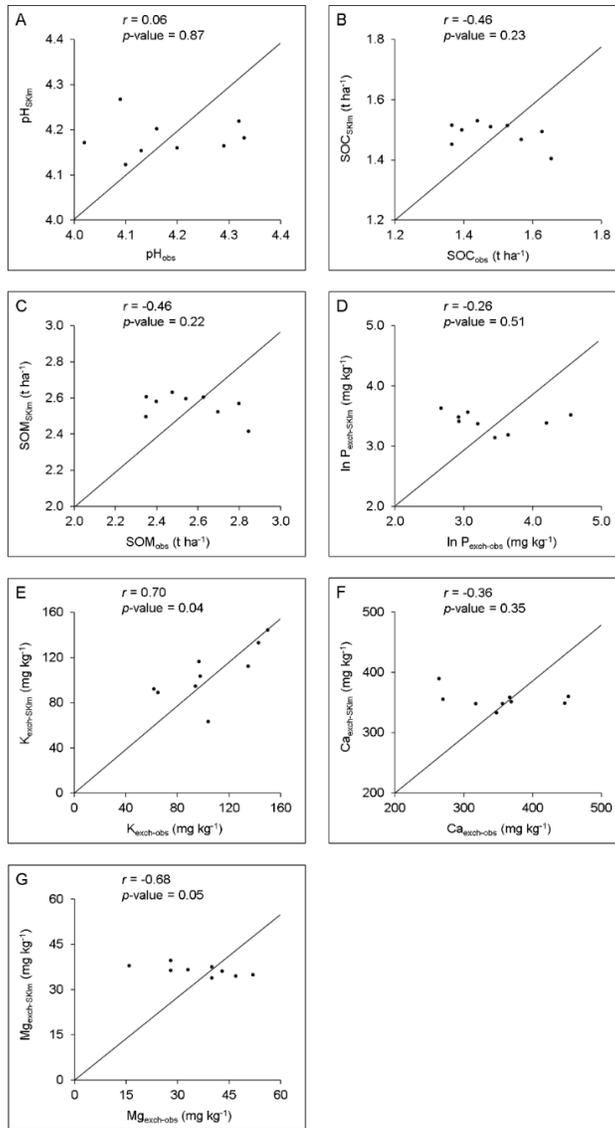
<sup>a</sup>Natural logarithmic transformed data, BD = soil bulk density,  $K_{sat}$  = saturated hydraulic conductivity, GWC = gravimetric soil water content, SOC = soil organic carbon, SOM = soil organic matter,  $P_{avai}$  = available phosphorus,  $K_{exch}$  = exchangeable potassium,  $Ca_{exch}$  = exchangeable calcium,  $Mg_{exch}$  = exchangeable magnesium

The predicted residuals obtained with simple kriging through the leave-one-out approach were added to the trend components that were obtained from their respective linear regression equations to finally obtain the soil property values at each sampling location. These values were subsequently subjected to correlation analysis with the observed values. It was found that the range of the predicted SKlm BD, GWC, and  $\ln K_{sat}$  values with SKlm across the entire slope area was 1.01 to 1.22 g/cm<sup>3</sup>, 22.53 to 30.00%, and 4.59 to 4.90 mm/h, respectively (Table 3). In case of the selected soil chemical properties, the calculations showed that predicted SKlm soil pH, SOC, SOM,  $K_{exch}$ ,  $\ln P_{avai}$ ,  $Ca_{exch}$ , and  $Mg_{exch}$  across the entire slope area was 4.12 to 4.27, 1.40 to 1.53 t/ha, 2.42 to 2.63 t/ha, 3.14 to 3.42 mg/kg, 63.28 to 144.37 mg/kg, 332.80 to 389.48 mg/kg, and 33.77 to 39.60 mg/kg, respectively (Table 3).

The scatter plots comparing the predicted values obtained through SKlm using the leave-one-out approach against the observed values is shown in Figures 6 and 7. The Pearson's coefficient of correlations ( $r$ ) and  $p$ -value summarizes the linear relationship between the predicted and observed values. A significant positive linear relationship was found between the predicted and observed values for BD, GWC, and  $K_{\text{exch}}$ , with the respective  $r$  values of 0.54, 0.48, and 0.70, indicating a moderate correlation (Figures 6A, 6B, and 7E, respectively). A weak positive linear relationship was also found for soil pH with an  $r$  value of 0.06, which was not statistically significant (Figures 5A). Alternatively, a moderate negative linear relationship was observed for  $\ln K_{\text{sat}}$ , SOC, SOM,  $\ln P_{\text{avai}}$ ,  $\text{Ca}_{\text{exch}}$  and  $\text{Mg}_{\text{exch}}$  with  $r$  value of -0.32, -0.46, -0.46, -0.26, -0.36, and -0.68, respectively (Figures 6C, 7B, 7C, 7D, 7F, and 7G, respectively). This indicates that even the moderate negative correlation was not statistically significant between the predicted and observed values for  $\ln K_{\text{sat}}$ , SOC, SOM,  $\ln P_{\text{avai}}$ ,  $\text{Ca}_{\text{exch}}$  and  $\text{Mg}_{\text{exch}}$ . It suggested that the effect of small sample size might lead to unreliable correlation estimates. However, the small sample size did not affect BD, GWC, and  $K_{\text{exch}}$ .



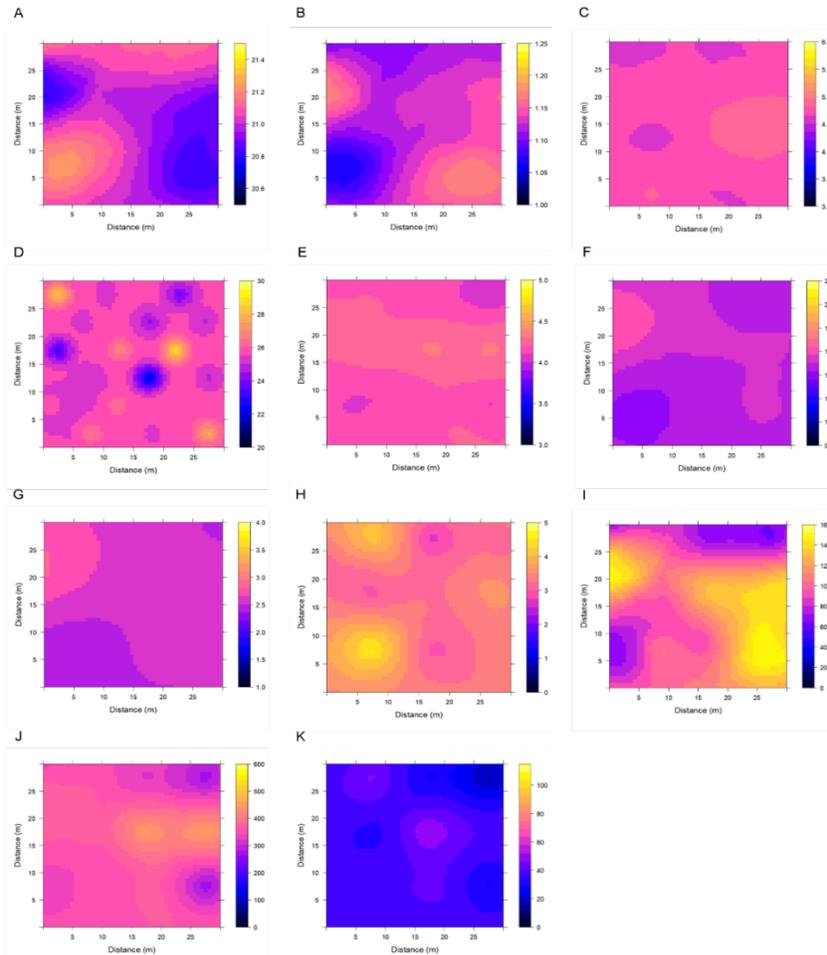
**Figure 6.** Scatter plot of the observed values (obs) and predicted values of selected soil physical properties obtained through the simple kriging with varying local mean (SKlm) using the delete-one cross validation. The Pearson's  $r$  coefficient of correlations and  $p$ -value are indicated for the observed values and predicted values for each soil property: (A) soil bulk density (BD), (B) gravimetric soil water content (GWC), and (C) a natural logarithmic transformation of saturated hydraulic conductivity ( $\ln K_{\text{sat}}$ )



**Figure 7.** Scatter plot of the observed values (obs) and predicted values of selected soil chemical properties obtained through the simple kriging with varying local mean (SKlm) using the delete-one cross validation. The Pearson's  $r$  coefficient of correlations and  $p$ -value are indicated for the observed values and predicted values for each soil property. (A) soil pH, (B) soil organic carbon (SOC), (C) soil organic matter (SOM), (D) a natural logarithmic transformation of available phosphorus ( $\ln P_{\text{avai}}$ ), (E) exchangeable potassium ( $K_{\text{exch}}$ ), (F) exchangeable calcium ( $\text{Ca}_{\text{exch}}$ ), and (G) exchangeable magnesium ( $\text{Mg}_{\text{exch}}$ )

### *Spatial map of predicted datapoints for each soil property*

Spatial maps presenting 2,500 predicted datapoints for each soil property in relation to slope gradient percentage were generated using the SKlm are shown in Figure 8. The analysis based on SK indicates a spatial variability across the for predicted BD, GWC, and  $\ln K_{sat}$ , soil pH, SOC, SOM,  $\ln P_{avai}$ ,  $K_{exch}$ ,  $Ca_{exch}$ , and  $Mg_{exch}$ .



**Figure 8.** Spatial maps of 2,500 predicted datapoints of slope gradient percentage (A) and 2,500 predicted datapoints of each soil property (B-K). (B) bulk density (BD), (C) a natural logarithmic transformation of saturated hydraulic conductivity ( $\ln K_{sat}$ ), (D) gravimetric soil water content (GWC), (E) soil pH, (F) soil organic carbon (SOC), (G) soil organic matter (SOM), (H) a natural logarithmic transformation of available phosphorus ( $\ln P_{avai}$ ), (I) exchangeable potassium ( $K_{exch}$ ), (J) exchangeable calcium ( $Ca_{exch}$ ), and (K) exchangeable magnesium ( $Mg_{exch}$ )

An inverse relationship was observed between slope gradient percentage and several soil variables (BD,  $\ln K_{sat}$ , SOC, SOM,  $\ln P_{avai}$  and  $K_{exch}$ ). In regions with low slope gradient percentage (Figure 8A), higher values of BD,  $\ln K_{sat}$ , SOC, SOM,  $\ln P_{avai}$  and  $K_{exch}$  were observed (Figures 8B, 8C, 8F, 8G and 8H). GWC exhibited a spot spatial distribution within a radius of 10 m (Figure 8D), which was not related to BD or  $\ln K_{sat}$ . The spatial map for GWC indicated localized variations rather than showing any correlation with BD or  $\ln K_{sat}$ . The spatial map for BD in relation to slope showed a distribution pattern similar to that of  $K_{exch}$  (Figures 8B and 8I). The spatial maps for SOC and SOM demonstrate similar spatial patterns, with relatively well distribution throughout the slope area (Figures 8F and 8G), indicating areas with potentially higher soil fertility. The soil pH spatial map revealed distinct patterns of soil acidity across the study area. Extremely acidic regions were observed in the middle of the slope. As the topsoil pH showed acidity, it potentially leads to high leaching (Table 1). This finding coincides with the spatial map of cations, where  $Ca_{exch}$ , and  $Mg_{exch}$  showed high levels downstream of the slope region (Figures 8J and 8K).

## Discussion

### *Descriptive statistics of the raw dataset of soil properties*

The coefficient of variation (CV) values calculated for the soil properties provided insights into their variability across the slope area. The CV values indicated the level and degree of variation in the data, reflecting the consistency or variability of each property. The low CV values for BD, GWC, soil pH, SOC, and SOM indicated a relatively uniform distribution. The consistent values of BD, GWC, soil pH, SOC, and SOM are important findings as BD and GWC are related to the water movement in the slope, while soil pH, SOC, and SOM indicate nutrient availability. The uniform distribution of these values suggests that at the small scale of the test plot area, soil management experiences, such as cultivation and crop residual management, were uniform. For  $K_{exch}$ ,  $Ca_{exch}$ , and  $Mg_{exch}$ , these properties showed a moderate variability. The moderate variability of  $K_{exch}$ ,  $Ca_{exch}$ , and  $Mg_{exch}$  may be influenced by localized variations in soil types, this is due to the variation in soil texture within the experimental field, which included sandy clay loam and clay loam (data not shown). The exchangeable cations showed potential leaching in these soils (Alfaro *et al.*, 2004; Rosolem *et al.*, 2010), which in turn might affect the variability of these elements in the experimental field. While both  $K_{sat}$  and  $P_{avai}$  displayed high variability, the high variability of  $K_{sat}$  is normally reported due to the complex and dynamic nature of soil properties and environmental factors influencing water flow in the soil. As a result,  $K_{sat}$  variability can be close to 100% or exceed

100% (Awal *et al.*, 2019; Warrick and Nielsen, 1980). On the other hand, the  $P_{\text{avai}}$  content often exhibits complex interactions with geology (Page *et al.*, 2005), land use (Liu *et al.*, 2009), clay soil texture, and SOM. These interactions contribute to the observed variation in the levels of  $P_{\text{avai}}$  in soils.

### ***Correlations among soil properties***

The correlation analysis revealed a significant negative correlation between BD and  $\ln K_{\text{sat}}$ , highlighting the impact of BD on water movement through the soil in this sloped area. As the BD increased, the soil became more compacted, leading to a reduction in the rate at which water could infiltrate. This, in turn, could potentially affect plant water availability, as compacted soil might hinder water penetration and retention. Conversely, a significant positive correlation was also found between BD and  $\ln P_{\text{avai}}$ , suggesting that compacted soils influence the availability of  $P_{\text{avai}}$ , with soil available P decreasing as BD increased (Barber, 1995; Jian *et al.*, 2022). Moving on the relationship between soil pH and exchangeable cations, the analysis showed significant positive correlations of soil pH with the  $\text{Ca}_{\text{exch}}$  and  $\text{Mg}_{\text{exch}}$ , indicating that as the pH increased, the negative charges on the soil colloids increased. Consequently, more positively charged cations, including Ca and Mg, were attracted to, and held onto by the soil.

### ***Semivariogram analysis***

The results highlighted the effectiveness of the semivariogram model accurately predicting certain soil parameters. The linear model fitted well with the BD, the spherical model for soil pH, and a Gaussian model for SOC and SOM, as evidenced by low MSE and RMSE values. The model also provided reasonably accurate predictions for GWC,  $\ln K_{\text{sat}}$ , and  $\ln P_{\text{avai}}$ , with moderate MSE and RMSE values. However, challenges were observed in predicting  $K_{\text{exch}}$ ,  $\text{Ca}_{\text{exch}}$ , and  $\text{Mg}_{\text{exch}}$ , as indicated by larger MAE and RMSE values, indicating that environmental factors (Wu *et al.*, 2021) other than slope have more control on these parameters. Further research and consideration of additional influencing factors may be necessary to improve the accuracy of predictions for these parameters in site-specific soil management.

The analysis based on the semivariograms of the residual soil physical and chemical parameters in relation to the slope gradient percentage has provided valuable insights into the spatial variability patterns within the study area. The nugget-to-sill ratio analysis revealed significant heterogeneity across the experimental field, which can be attributed to variations in soil conditions and

climate. At a small scale, our study revealed that GWC exhibited moderate spatial dependence (nugget-to-sill ratio is between 0.25 and 0.75) within a range of 4.2 m, and this could potentially be influenced by the precipitation pattern (Li *et al.*, 2019). In contrast, a study by Zhang *et al.* (2022) reported a strong spatial correlation of surface GWC on shady and sunny slopes at a depth of 0-20 m. To further explore spatial correlations for GWC, reducing the study's sampling scale is a potential approach (Cambardella *et al.*, 1994). The spatial independence observed for BD and  $\ln K_{sat}$  in our study, with nugget-to-sill ratio greater than 0.75 indicated that these parameters are spatially independent. This spatial independence can be attributed to the complex water movement and infiltration processes, resulting in increased variations within the slope gradient. However, to identify spatial correlations in such cases, strategies like reducing the study's sampling scale (Cambardella *et al.*, 1994) or implementing a classic randomization block design (Kravchenko *et al.*, 2006) can be effective.

From this study, it was found that the nugget-to-sill ratio of soil pH, SOC, SOM,  $\ln P_{avai}$ ,  $K_{exch}$ ,  $Ca_{exch}$ , and  $Mg_{exch}$  was less than 0.25, indicating a strong spatial dependence. Soil in humid climates are characterized by their acidic nature and low soil pH (Weil and Brady, 2016). The changing climate can have an impact on regional rainfall patterns, leading to increased precipitation in certain area. This rise in precipitation can cause the leaching of alkaline basic cations from the topsoil, resulting in a condition known as topsoil acidification. During this study, the soil was observed to display pH values ranging from 4.02 to 4.33, with a mean of 4.18 indicating an extremely acidic nature across the slop area. The spatial dependence of the selected soil chemical properties in this research area appeared to be primarily influenced by intrinsic soil factors (Cambardella *et al.*, 1994). Notably, the study suggests that intrinsic soil factors, such as parent materials and soil texture, may be affected by the precipitation patterns arising from climate change.

### ***SKlm estimates of soil properties***

The Pearson's correlation coefficients ( $r$  values) and  $p$ -value were used to evaluate the accuracy and reliability of SKlm through the leave-one-out approach estimations for each soil parameter. Significant moderate positive correlations for BD, GWC, and  $K_{exch}$  suggest that the model performed well in predicting these properties under a small sample size, but a weak prediction was observed in the model for soil pH. On the other hand, moderate negative correlations for  $\ln K_{sat}$ , SOC, SOM,  $\ln P_{avai}$ ,  $Ca_{exch}$ , and  $Mg_{exch}$  indicate the effect of a small sample size, demonstrating that a larger sample size might be required to provide a more reliable assessment of the relationship between observed and predicted soil

properties. Additionally, it emphasizes the need for caution when relying solely on the simple kriging approach for accurate estimation.

Alongside geostatistical analysis, digital soil mapping (DSM) methods based on machine learning such as support vector machines (SVM), quantile regression forest (QRF) or random forest (RF) have been considered effective for predicting the spatial distribution of soil properties (Biney *et al.*, 2021; Guo *et al.*, 2022; Zhou *et al.*, 2022). Therefore, further research will consider incorporating remote sensing data to address smaller sampling sizes.

### ***Implications for site-specific soil management***

In hilly regions, understanding the variation of soil chemical properties along slope position gradients is crucial for effective soil management. The influence of the slope factor on solute transport and accumulation was evident, resulting in higher pH, exchangeable Ca and Mg, and lower organic carbon, available N, and K, as well as extractable Zn in the depositional areas of the footslope (Liu *et al.*, 2020; Tsui *et al.*, 2004). In relation of slope to the crop system, the relationships between cropping systems, terrain, and soil nutrients were site- and scale-specific, with different aspects and slope positions influencing the distribution of crops and nutrient content in the soil (Gou *et al.*, 2015). In this study, the observed strong spatial dependence of selected chemical properties suggested that the sample plot design adequately captured the spatial structure characteristics of the entire selected soil chemical content, where their distribution might be influenced by the slope gradient percentage. The spatial map, with its enhanced resolution, further illustrated a reasonable distribution of soil nutrient stock (SOC and SOM) throughout the slope area indicating regions potentially characterized by higher soil fertility. In this slope area, farming integrates manual and mechanized practices to reduce soil degradation. Fertilizer application, which is manual due to small field size, can be improved through site-specific, variable-rate application, thereby enhancing agricultural practices. Consequently, implementing site-specific, variable-rate fertilizer application becomes crucial in optimizing resource utilization and advancing agricultural practices in this area.

The study highlights the significance of understanding the small-scale spatial variability of selected soil properties in a slope cultivation area. Through the evaluation of selected soil physical and chemical properties in a small-scale slope area in Phetchabun Province's Highland Region, Thailand. The descriptive statistics revealed low variability for BD, GWC, soil pH, SOC, and SOM, while  $K_{\text{exch}}$ ,  $Ca_{\text{exch}}$ , and  $Mg_{\text{exch}}$  displayed moderate variability, and  $K_{\text{sat}}$  and  $P_{\text{avai}}$  exhibited high variability. Geostatistical analysis further demonstrated that SKIm

showed reliable predictions for BD, GWC, and  $K_{\text{exch}}$  under a small sample size, with caution warranted for soil pH predictions. The impact of a small sample size on  $\ln K_{\text{sat}}$ , SOC, SOM,  $\ln P_{\text{avai}}$ ,  $\text{Ca}_{\text{exch}}$ , and  $\text{Mg}_{\text{exch}}$  correlations, emphasizing the need for caution when relying solely on the simple kriging approach. Overall, these findings underscore the importance of spatial variability analysis for precise agricultural practices in small-scale slope areas, emphasizing its crucial role in soil management in hilly regions. Specifically, the findings underscore the influence of slope gradient percentage on soil nutrient distribution, highlighting the need for site-specific fertilizer applications to optimize resource utilization and enhance agricultural productivity.

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### Conflicts of interest

The authors declare no conflict of interest.

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