Predictive Mapping for Soil pH and Phosphate based on Kriging Interpolation

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ABSTRACT
Spatial variability can be the main cause of uneven plant growth, but this has not received much attention in the field. Spatial variability in soil chemical properties (soil pH, P) can be calculated using a geostatistics approach. The main objective of this research was to make a predictive mapping for soil pH and phosphate based on Kriging interpolation. The research resulted that the maps generated by Kriging interpolation showed similar patterns of high leaching and erosion effects in the landscape. The range of spatial variability of soils was found between 250-350 m with an average value of 300 m. Therefore, an effective survey can be carried out with a density every 120 m (rounded up to 100 m). The elevation range with an average value of 700 m can be said to be a maximum of 50% causing the increase in spatial variability of soils. This was evidenced by the high difference between the soil characters range (250-350 m) and the elevation range (700 m). The spatial variability of soil characters did not only depend on the relief form, but also on the dynamics of the groundwater interflow. A combination of soil pH, available P provided good indices for high leaching in the landscape. The high spatial variability for soil pH and available P indicated the result of the weathering process of the parent material, which was influenced by slopes, land use, intensive vertical and lateral groundwater flows. Cation leaching was the main process causing systematic spatial variability of soils in the landscape. Therefore, this leaching process has to be managed.

Keywords: *Good interpolator, mapping, spatial variability, soils*

1. INTRODUCTION

The Ultisols landscape is classified as marginal soils, acidic, poor in nutrients and dominates about 68% of the terrestrial area of Sumatra, Indonesia [1, 2]. In reality very little attention has been researched to the spatial variability of soils for agricultural activities in a broad sense [3, 4, 5]. Soil heterogeneity was usually not considered to determine the level of soil fertility or soil quality, but the reality in the fields showed that crop production was uneven due to the spatial variability of soils [6, 7]. Spatial variability of soils in the fields directly affected agriculture performance, and will become a major problem in production if spatial variability of soils was ignored or not considered [8, 9, 10]. About 15-25% of the difference in agricultural production in the field was directly triggered by the spatial variability of soils [11, 12, 13].

Comprehensive research on spatial variability of soils has presented various important data and information about the main factors causing the spatial variability of soil characters [14, 15, 16] . The general view of now society was that any spatial variability of soils found in a given space and time was the result of soil physical, chemical, or biological processes that occurred in the soil. This view was acceptable and had only limited use at microscopic scales (e.g. studies of soil biological activity), whereas other processes, such as weathering of parent materials, erosion or solute transport can occur over large and longer distances [17, 18].

Site-specific soil and plant management practices require the need to display the spatial variability of soil characters. Land clearing, forest and land fires, accumulation of organic matter, ash deposits, free standing trees, tree stumps, erosion, planting alleys,

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mounds of ants and termites are the dominant factors causing the increase in spatial variability of soils in the fields [19, 20].

The spatial variability of soil characters can be analyzed using geostatistical techniques to research more deeply about the spatial variability of soil characters. Geostatistical techniques are able to combine various sources of spatial variability of soils to obtain a variogram of soil characters with certain structures. Each structure shows the influence of spatial factors that correspond to the spatial variability of soils. These factors affect soil characters in different ways in different space and time [21, 22].

Kriging interpolation can be mentioned as a multivariate method displaying spatial variability data of soils in unvisited areas. Correlation between real data and estimate data can be tested for each spatial scale, and spatial variability of soils can also be mapped [2]. Kriging interpolation can be applied to distinguish local and regional sources of spatial variability of soils [1]. The main objective of this research is to make a predictive mapping for soil pH and phosphate based on Kriging interpolation. The resulting map is useful for making a layout design (spatial) that is aligned for long-term field agricultural activities, so that agricultural management can be effective, efficient and sustainable.

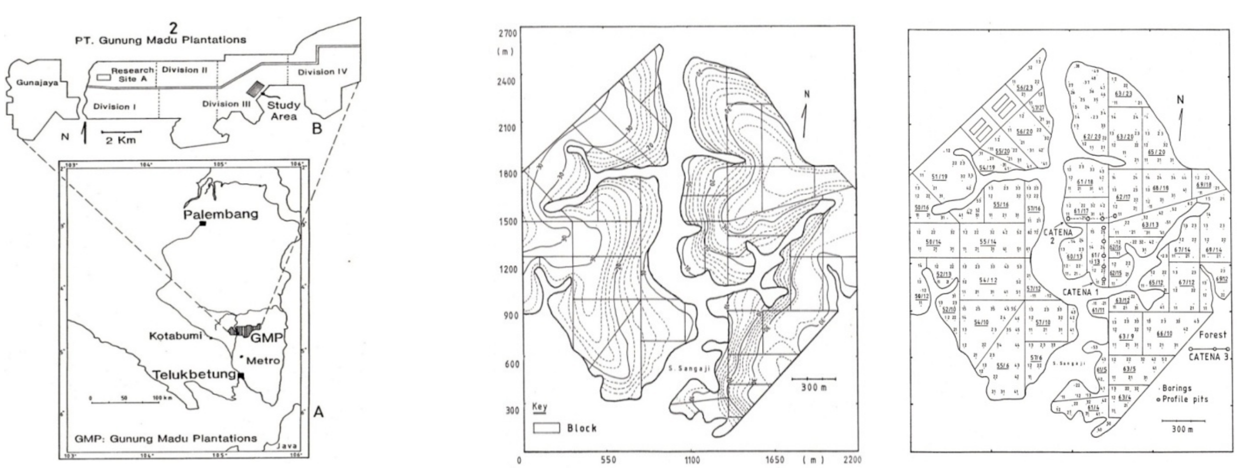
2. MATERIALS AND METHODS

This research was conducted on the Ultisols landscape of 405 ha in Lampung Province, Indonesia (Figure 1). The research area has an elevation ranging from 6-40 m above sea level. The slopes was classified as gentle (3-28%, average 8%) with the main slopes direction from West-East to East-West. The research site had soil parent material (volcanic tuff) and was cultivated with sugarcane monoculture for 45 years with intensive management, including high levels of P fertilization (100 kg P/ha*a). Therefore, a high level of productivity even on unfavorable land.

The soil sampling scheme used a 1:5,000 scale map and a very detailed survey method. The intensity of soil sampling was carried out in two ways (overall and transect). The overall survey was carried out for whole survey area. Soil samples were taken using an auger bore at the five levels of depths with amount of samples of around 1,800 soil samples. Three transects consisted of two transects under sugar cane and one transect under forest, and totally described. After describing the soil profile, composite soil samples were taken for analysis in the laboratory. A fragment > 2 mm (gravels) was separated by sieving. The soil pH data were measured in distilled water and 0.01 N KCl electrolyte solution with a glass electrode. The available P was extracted with Bray2 method and measured by spectrophotometer. The interpolation process followed the stages as stated in Figure 2. The Kriging interpolation were mapped to obtain a map of soil pH and available P and its geostatistical parameters.

3. RESULTS AND DISCUSSIONS

This research performed various important components related to how to make predictive mapping for soil pH and available phosphate based on Kriging interpolation. The main topics discussed include, namely magnitudes and scope for soil pH and available P; variogram analyses for soil pH and available P; cross-validation for optimal interpolator by Kriging; the Kriging map for soil pH values; the Kriging map for available P; and landscape analyses.



A: Research site B: Topography map C: Sampling area

Figure 1 Research site, topography map and sampling area

3.1. Magnitudes and Scope for Soil pH and Available P

Table 1 shows values of means; standard deviation; minimum and maximum values. The soil characters selected for analysis were soil pH (0-20 cm); soil pH is quite varied with a range of 4.40-5.72, the average value of soil pH is 4.76 for soil pH (0-20 cm) and the range is 3.59-4.55 (average value 4.21) for soil pH (35-60 cm). Soil pH data (0-20 cm) was found to be 1-2 units higher than soil pH (35-60 cm). This is because the surface soil was treated with liming and long-term fertilization, so that the soil pH increased, but it was still classified as acidic. The coefficient of spatial variability (CV) of soil pH was high, which was more than 36.71%).

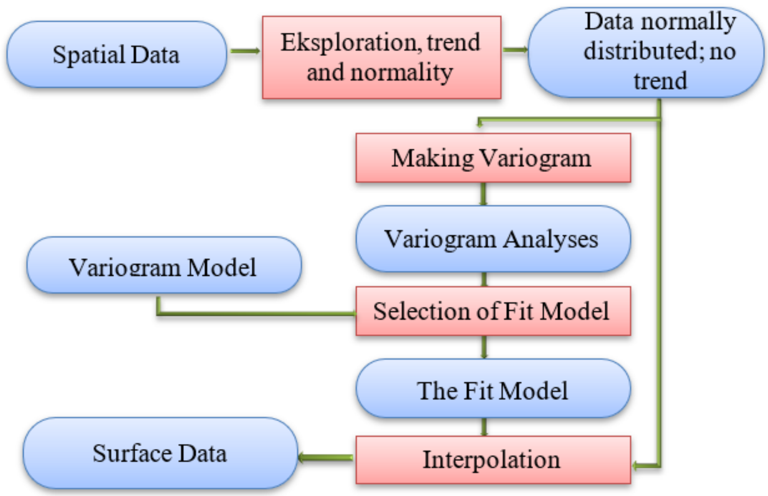


Figure 2 Interpolation procedure to analyze spatial variability of soils

Table 1. Statistic summary for raw data (n =405)

Soil Characters	Mean	Minimum	Maximum
Soil pH (0-20 cm)	4.76 ± 0.26	4.40	5.72
Soil pH (90-120 cm)	4.21 ± 0.24	3.59	4.55
Available P (ppm)	95.01 ± 4.87	62.02	127.21

Source: Results of field survey and laboratory data analyses (2022).

Available P data were in the range of 62.02-127.21 ppm with an average value of 95.01 ppm. This available P value was quite high because the soil was fertilized every year with natural phosphate which was able to improve P content in the soils for the long term and released it slowly according to the needs and uptake of plants. Data available P showed the highest CV compared, namely (63.35-112.67%). This means that the treatment of P fertilization in the field was less evenly distributed and spread due to soil management factors.

Soil character data with a high CV value means that the data were more varied than soil character data with a small CV value. This means that the higher the CV, the greater the spread of dispersion in the variable. Data with high CV have to be transformed before being processed. The lower the CV, the smaller the value relative to the predicted value, so that the recorded data was more uniform and can be used for data interpolation. Classification of CV values can be grouped, namely CV 0-15% (the lowest); 16-35% (moderate) and 36-51% (high); and > 51% classified as very high.

3.2. Variogram Analyses for Soil pH and Available P

Quantification of the spatial variability of soil characters can be done by making a variogram. The spatial variability analysis of soil characters is presented in Table 2. The variogram form presented is a spherical model for all soil characters. In general, the range of soil pH and available P was in the range of 250-350 m. The results of this range calculation were able to prove that the density of data collection in the field was considered sufficient to reveal regional relationships for all research areas.

The maximum range of 350 m proved that if sampling in the field with a distance of more than 350 m, then the data collected was useless (no meaning) for interpolation. In other word, that interpolation based on survey distance outside this range (over 350 m) was meaningless, whereas the effective survey distance aimed to predict 50% of the relevant variance (Figure 3).

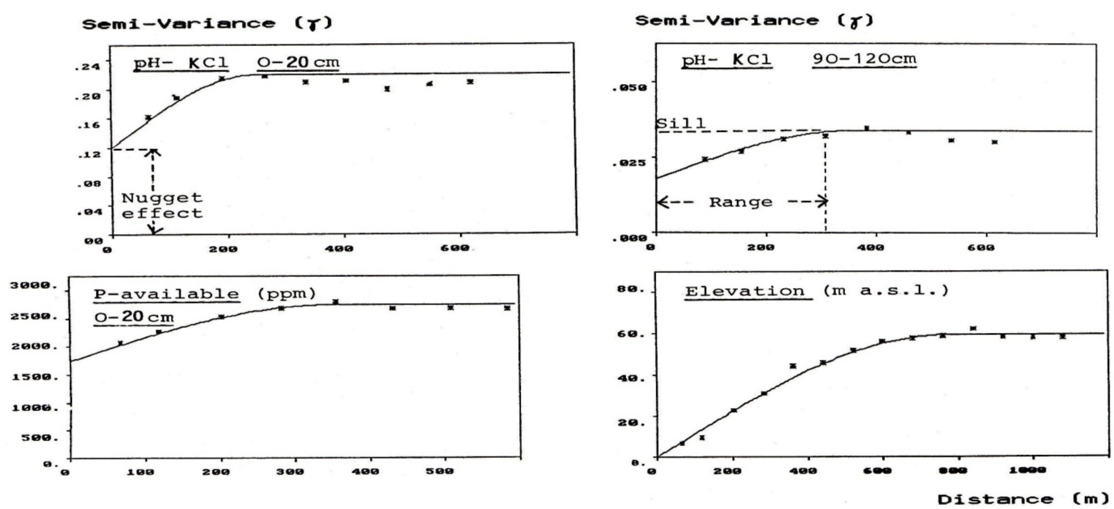
Most data of soil characters had an effective range of about 120 m. Therefore, field-intensive survey data can be taken to perform Kriging interpolation and created a soil character isoline map on the basis of the interpolated data. For simplification of calculations, field soil samples should be taken at a distance of 100 m (1 boring/ha). This means that the research area of 405 ha requires 405 borings and this is all fulfilled by the field survey that has been carried out. Therefore the data can be interpolated as shown in the result of Figure 3.

The soil pH and available P data were strongly spatially dependent. These highly spatially dependent data can be controlled by intrinsic variations in other soil characters, such as soil fractions (clay, silt, and sand). Weak spatial dependence means that spatial variability of soils was more dominantly controlled by extrinsic variations, such as tillage or fertilizer application. The spatial variation of available P in this research was influenced by the application of P fertilizer.

Table 2. Spatial variability analyses for soil characters (n = 405)

Soil Characters	Mean	Semi variance	Nugget effect (%)	Sill (%)	Range (m)	Effective distance (m)
Soil pH (0-20 cm)	4.76	0.22	55	45	250	100
Soil pH (90-120 cm)	4.21	0.034	53	47	300	120
Available P (ppm)	95.01	2750	64	36	350	140
Elevation (m)	25.15	60.03	2	88	770	-

Source: Results of field survey and laboratory data analyses (2022).



Source: Results of field survey and laboratory data analyses (2022).

Figure 3. Variogram analyses of soil pH; available P and elevation

The range of semi variogram displays the maximum distance between the actual data (measurement results), correlated and become an effective criterion for determining the sampling design. The results of the estimated distance of this soil sampling can be mapped. However, this distance must be considered was 250-350 m with an average value of 300 m, if it exceeded this distance, then sampling is not useful for Kriging interpolation.

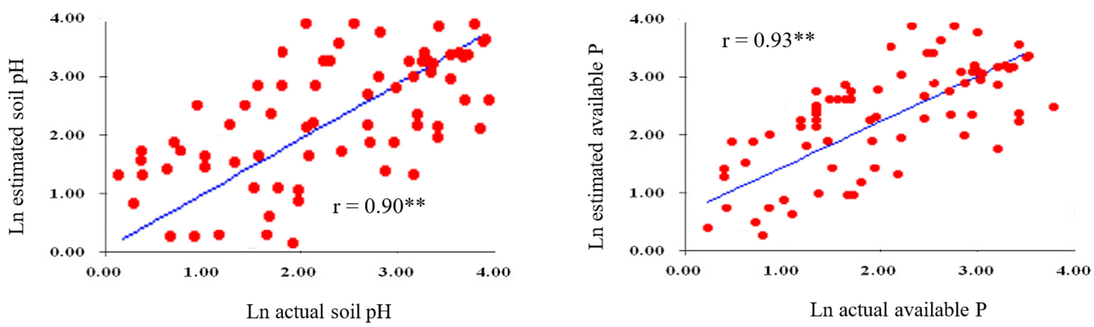
The elevation range (about 700 m) can determine a maximum of 50% of the spatial variability of the soil. Therefore, the character of the soil did not only depend on the shape of the relief, but also on the dynamics of the groundwater table.

The variation of the nugget effect lies between 55-64%, except for elevation. This nugget effect represented a measure of variance that cannot be avoided (constant, persists) even in very dense surveys (range is close to zero). The nugget effect reduces the value of the spatial correlation of soil characters. Nugget effects can be caused by various disturbances, such as land clearing (50 years ago), varying tillage depths (20-50 cm) and sampling schemes. The very low elevation nugget effect (2%) was due to the continuous descent of the slope from the top of the hill to the river. As a supplement to 100%, the spatial dependence of soil characters was low as measured by threshold (28-58% of semi-variance), except for elevation.

3.3. *Cross*-Validation for Optimal Interpolator by Kriging

Cross validation calculations are applied to perform the variogram model effectiveness (Table 3). The scattering plot between the actual data and the estimated data of soil pH and available P was shown in Figure 4. The actual data were obtained from the results of field surveys and laboratory analysis, while the estimated data were generated from calculations using Kriging interpolation. Since the two types of data are not normally distributed and there is a trend, then the data were normalized using the logarithm (Ln) and discarding the trend.

The results of cross validation showed a very good performance relationship. It means that the estimated soil pH and estimated available P data can be made on the basis of the actual data for these two parameters. The results of the estimated soil pH and available P showed the similar type pattern. Figure 4 shows a close and reliable relationship because it has a very significant correlation coefficient (r = 0.90 for soil pH, and r = 0.93 for available P). The calculation of the coefficient of determination (r^2) is determined by squaring the correlation coefficient (r).



Soil pH Available P

Source: Results of field survey and laboratory data analyses (2022).

Figure 4. Cross validation for soil pH and available P (log transformed data, n = 248)

Table 3. Cross validation for soil pH and available P

Soil characters	Correlation coefficient (r)	Determinant coefficient (r^2)	Significance at level of 1%
Soil pH	0.90	0.81	Very significant
Available P	0.93	0.86	Very significant

Source: Results of field survey and laboratory data analyses (2022).

For soil pH with r value is 0.90, thus the r^2 is 0.90 x 0.90 = 0.81, while for r2 from available P is 0.86. This means that the actual soil pH data is able to explain the estimated soil pH data around 81% and 86% for available P. This means that about 81% of the soil pH estimation data is determined by the actual soil pH data, while 19% (100-81%) of the soil pH estimation data is explained. by other factors. Likewise, the actual available P determines 86% of the data estimate available P and the rest (14%) is played by other factors.

However, these interpolated data cannot be utilized for developing daily data (for soil pH and available P) if the data amount was minimized. This interpolation was very good to perform network systems and to develop Kriging analyses. The interpolation was very helpful and can be used for understanding the spatial variability of soil pH and regional available P if data of soil pH and available P were not available, thus this interpolation may assess the dynamics of soil pH and available P for all area.

3.4. The Kriging Map for soil pH Values

There are only slight changes of soil pH observed in the landscape. The minimum values were determined in the depressions. Lowering mean values downslopes was connected to the leaching of most base cations and lateral moving of the groundwater table. High annual rainfall and good soil structure were very supportive of this leaching process. A similar downward trend in soil pH along slopes suggested a type of lateral transport which was an important soil formation process that caused systematic long-term spatial variability in the landscape.

Soil pH value (0-20 cm) was higher than soil pH (35-60 cm) because of the effect of P fertilization on topsoils. In general, the distribution of available P can be related to the soil pH map. The facts reveal that the higher the soil pH was, the higher the available P in the landscape was found (Figure 5). In addition, there was also a relationship between soil pH, available P and clay fraction in the landscape. Field observations revealed that an increase in the soil pH was followed by an increase in P, and vice versa.

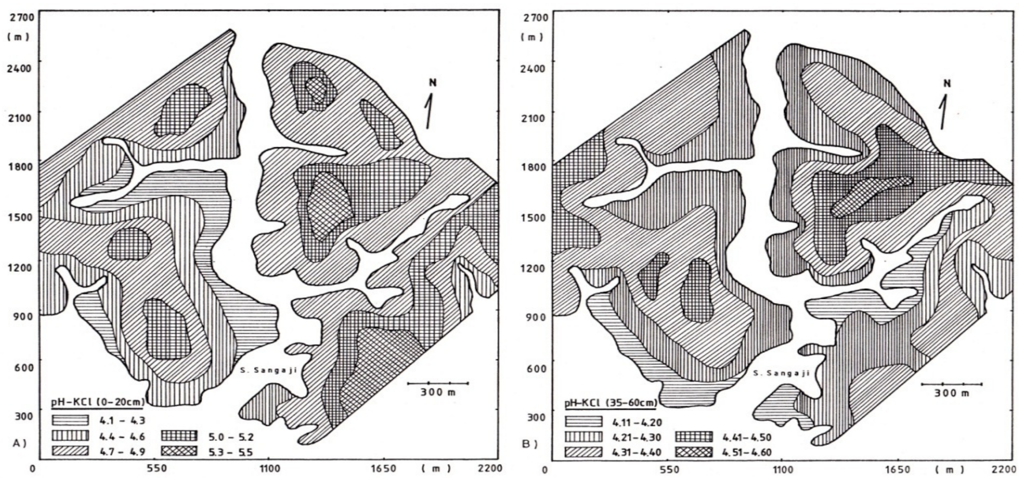
3.5. The Kriging Map for Available P

Generally the available P value decreases from hilltops to lower slopes or depression areas (Figure 6). This means that the maximum value of available P was found on the hilltops to the upper slopes and continues to decrease at the lower slopes. In addition, the maximum value of available P was always followed by the maximum clay content as well. The minimum available P value is followed by the minimum clay.

The occurrence process of the maximum P at the hilltops and minimum P at the lower slopes showed the phenomenon of high soil erosion and leaching. Available P at the hilltops is transported by erosion and leaching down the slopes. Due to the high energy of runoff water transportation which was able to carry all colluvium material into the nearest river, so that more than 90% of eroded material (colluvium) was lost in the rivers and no sedimentation occurred in the depression area. This condition caused most of the available P to be transported to the river together with the eroded soil fractions.

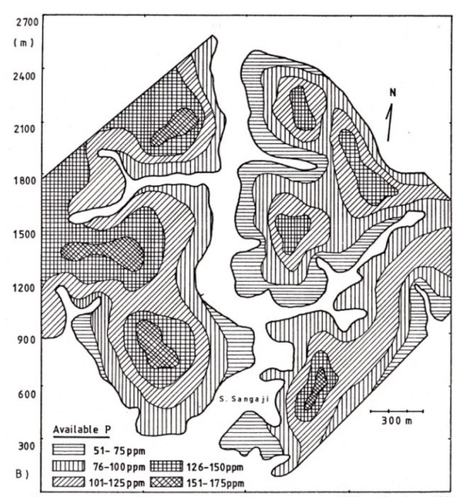
All maps (generated by Kriging interpolation) showed the similar pattern and showed high erosion and leaching effects in the landscape. The amount of soil fraction > 2 mm (gravels) apparently increased in line with the decreasing slopes. The minimum amount of gravels was recorded in the intensively eroded area and the maximum amount was found in the depression area. Field facts revealed that the steeper and longer the slopes were, the higher the dynamics of the gravels were identified. However, the slope steepness played more important role than the slope length. It means that there was a relationship between the level and selectivity of the erosion process with the slopes.

3.6. Landscape Analyses



Source: Results of field survey and laboratory data analyses (2022).

Figure 5. Kriging Maps for soil pH (0-20 cm, left) and soil pH (35-60 cm, right)



Source: Results of field survey and laboratory data analyses (2022).

Figure 6 Kriging maps for available P (0-20 cm)

Generally this soil system was called as an "open system" because of the high erosion rate and most of the material was eroded out of the landscape system. The formation of this open system was because the Lampung tuff is very porous and well drained, especially in the hilltops. The water infiltration rate in the hilltops was very high, therefore ground water levels are found very deep in the hilltops and moved sideways as inter or underflow due to the many flat areas on the hilltops found. When it rains heavily, this water continues to flow until the impermeable layer (Fe concretion layer). Furthermore, water was inundated in the impermeable layer, therefore the movement of groundwater inter or underflow will determine the increase in the spatial variability of soils.

Soil sub-orders are distinguished based on soil genetic differences, for example those related to the influence of water, moisture regime, main parent material, and vegetation. The high annual rainfall and the predominance of vertical and lateral transport of ions and other solutes have resulted in a deep, acidic, well-structured soil profile with the appearance of an argillic characterizing horizon at the hilltops. Generally, the soils at the hilltops are classified as Kanhapludults, Udults, and Hapludults. At the upper and middle slopes, the dominance of the redox process occurred due to increased wetness and the soils were classified as Aquults. This evolutionary sequence was found on most of the main slopes with the surface soil color changing from dark reddish brown to reddish brown and yellowish-reddish brown. In depression or downslopes areas, soils were classified as Dystrudept, Dystropept and Humaquept.

Soil weathering process in this landscape was dominated by leaching process, clay translocation, and lateral water movement was the dominant soil formation process for long and long term. As a result of all these processes, lateral leaching of acid cations (H, Al) occurred. Many soil nutrients were deeply leached in these areas, but groundwater come to the soil surface on lower and middle slopes and eroded the topsoil fractions sideways into nearby rivers. In addition to intensive erosion, excess water has formed Dystrudept, Dystropept and Humaquept at the lower slopes and depression area. The hydrological sequence occurred in a large landscape with a uniform and layered parent material such as Lampung tuff. This process causes the formation of an open system.

Soil morphology and spatial variability of soils were able to reflect the effects of erosion. However, the research was unable to reconstruct the initial soil conditions (before erosion occurred) because only < 10% colluvium was found in the landscape. More than 90% of the colluvium material was lost in the landscape due to the high energy of runoff water transport which was able to carry all the colluvium material into the nearby river. This condition triggered a landscape imbalance. Unbalanced landscapes were able to stimulate erosion and soil degradation. This erosion vulnerability was increasing in line with the high amount of rainfall.

4. CONCLUSIONS

The maps generated by Kriging interpolation showed similar patterns of high leaching and erosion effects in the landscape. The range of spatial variability of soils was found between 250-350 m with an average value of 300 m. Therefore, an effective survey can be carried out with a density every 120 m (rounded up to 100 m). The elevation range with an average value of 700 m can be said to be a maximum of 50% causing the increase in spatial variability of soils. This was evidenced by the high difference between the soil characters range (250-350 m) and the elevation range (700 m). The spatial variability of soil characters did not only depend on the relief form, but also on the dynamics of the groundwater interflow. A combination of soil pH, available P provided good indices for high leaching in the landscape. The high spatial variability for soil pH and available P indicated the result of the weathering process of the parent material, which was influenced by slopes, land use, intensive vertical and lateral groundwater flows. Cation leaching was the main process causing systematic spatial variability of soils in the landscape. Therefore, this leaching process has to be managed.

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