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The Use of DEM to Delineate Spatial Variability of Soil Nutrient Content in Apple Orchard Batu City, East Java Province, Indonesia

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Abstract. The spatial variability data on soil nutrient content is the key component in precision farming implementation. The kriging method that is widely used for interpolation is considered inefficient. This is an obstacle to the concept application of precision farming. Therefore, another method is needed to answer this problem. The purpose of this study was to assess whether DEM can be used to delineate the spatial variability of soil nutrient content. The research was conducted on an apple orchard in Batu City, East Java Province. Determination of sample points was using a stratified random sampling method, so the land was classified into 9 areas (Area 1-9). The data used for this purpose were high-resolution DEM. Statistical analysis was done using GLM Multivariate. The statistical analysis results show that the significance value is less than 0.05. This means that with a 95% degree of confidence the value of soil nutrients including soil pH, organic carbon, total P, and total K are significantly different in various Areas. The formation of Areas in this study derives from spatial analysis of the DEM. The conclusion of this research is that DEM can be used to delineate the spatial variability of soil nutrient levels in an apple orchard.

1. Introduction

The basic principle of precision agriculture concept is that the addition of agricultural inputs is in line with the soil fertility conditions. Therefore, mapping the variability of soil nutrient levels is a crucial point in applying this concept [9], [28]. The method widely used to map soil nutrient variability is the interpolation method, in which the determination of the sample point uses a grid method [13] [31], [4].

Testing the various types of interpolation methods include inverse distance weighting (IDW), kriging, spline, and trend surface that have been carried out [18]. The results show that the kriging produces the highest accuracy in the mapping of soil nutrient content [36], [39], [41], [12].

The consequence of using the kriging is that it needs a large number of sample points, so it takes a lot of time, effort, and cost. This is the weakness and constraint in applying the concept of precision farming [21], [22], [23], [35]. Therefore, research is needed to address these problems to obtain a new efficient method.

The development of remote sensing technology and geographic information systems has opened up opportunities to map soil properties more efficiently. The potential use of secondary variables for estimating soil properties has been carried out over the past decade [37], [9], [24]. The requirement for selecting secondary variables is easy to measure (availability) and inexpensive [3], [25].

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The secondary variable widely used in estimating the spatial distribution of soil properties is elevation [27]. Lately, elevation data have been widely available in a digital format in the form of digital elevation models (DEM) [6]. This variable can reflect the topographic conditions of an area which is quantitatively called relief. Topography is one of the factors soil formations beside climate, parent material, organism, and time [7]. Topography is the major factor influencing the soil's physical, chemical, and biological properties [19], [42], [8]. So the purpose of this study is to assess whether DEM can be used to delineate the spatial variability of soil nutrient content.).

2. Material and method

This research was located in Batu City, East Java Province, Indonesia (7 ° 52′S and 112 ° 31′E) (Figure 1). This region is in the geological formation of the ArjunaWelirang Volcano in the late Pleistocene. The elevation of the place is at 700-1900 masl with undulating reliefs to mountainous. Field observations show that the soil types belong to Humic Dystrudepts with silt loam soil texture, subangular blocky soil structure, 10YR3 / 2 soil color, and slightly hard soil consistency.

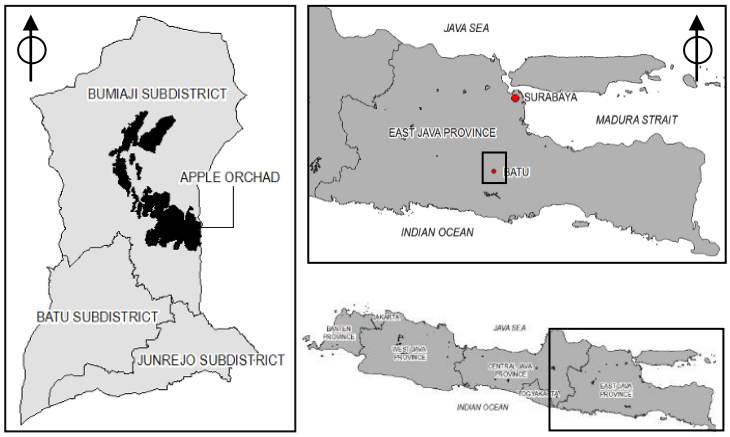


Figure 1. Research location at apple orchard in Batu City, East Java Province

This study focused on apple land use because the soil has undergone fertility degradation resulting in a decreasing production. In addition, this plant has a unique value, so it becomes a symbol of this region. The apple plant type that is cultivated is Ana Apple which is characterized by the thin and dominant reddish-colored peel. The average age of apple plants is 20 years with a spacing of 3 x 3 meters.

2.1. DEM generation

DEM data in this study were originated from the results of interpolation of 5-meter interval contour maps obtained from the Regional Development Planning Agency (Bappeda) in Batu City, East Java Province. Conversion of contour maps to 5-meter spatial resolution DEMs was done automatically using the spatial analysis method. DEM data accuracy test was carried out with a number of actual elevation points in the verification field using LE 90 method with the following formula [40]:

$$LE90 = \delta p \; x \; 1.6449., where \; \delta p: standard \; deviation \; (RMSE) \qquad (1)$$

DEM accuracy rate is quite good if the value of LE90 less than half the contour interval [40]. Contour data in this study was 5 meters so that relatively good accuracy DEM data when the value of LE 90 is less than 2.5. The meaning of this value is that the elevation information in the DEM data is the same as the real condition of the field.

2.2. Soil sampling

Obtaining 60 soil samples in the field were using a stratified random sampling method based on topography characteristics. Soil samples were taken at a depth of 60 cm around the tree canopy (a distance of 60 cm from the tree trunk). This adjusts to the crops zone and the width of the apple canopy. The coordinates of each soil sample were recorded using GPS Garmin 76CSX and recorded along with the sample code

2.3. Soil analysis

Soil samples were air dried and sieved with a 2 mm sieve diameter for the purpose of analyzing soil pH, soil organic carbon (SOC), soil total phosphorus (TP), and soil total calium (TK). Soil organic carbon was analyzed using Walkley and Black method. Soil TP and soil TK content were analyzed using extract HCL 25% method. The degree of acidity (pH) was measured using an electrical pH meter method with distilled water [14].

2.4. Statistical analysis

Descriptive statistical analysis included mean minimum, maximum, median, range, and coefficient of variance that were useful for determining data normality. Data normality indicators used the Skewness and Kurtosis index. Significance test of the research variables was using GLM Multivariate 5% with Pilla's Trace, Wilks' Lambda, Hotelling Trace, and Roy's largest Root indicators to simultaneously test the significance while testing individual significance was using Test of Between-Subject [32].

3. Result and discussion

The initial stage in this study is to assess the accuracy of DEM data using the LE90 vertical accuracy method. The basic principle of this method is to compare the elevation value between DEM data and field data [40]. The result of the calculation of the level of accuracy DEM data is 1.77, it means the DEM data is relatively good because the value of LE 90 is less than 2.5.

3.1. DEM extraction

DEM data that have been corrected was processed to be slope map and drainage flow map. Spatial analysis was done by stacking the two data and DEM visualization in hill shade form. This process could clearly show land surface relief, so visual interpretation could be carried out based on the topographic characteristics (Figure 2).

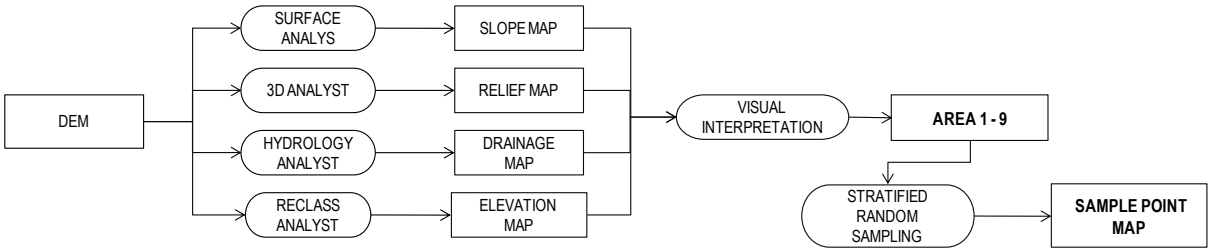


Figure 2. The flow chart of DEM extraction

The spatial analysis of the DEM produces slope maps, hill shade maps, drainage maps, and elevation maps (Figure 3). The results of this process formed 9 areas, in which each area has different topographic characteristics. This map was used as the basis for determining the sample points using a stratified random sampling method (Figure 3).

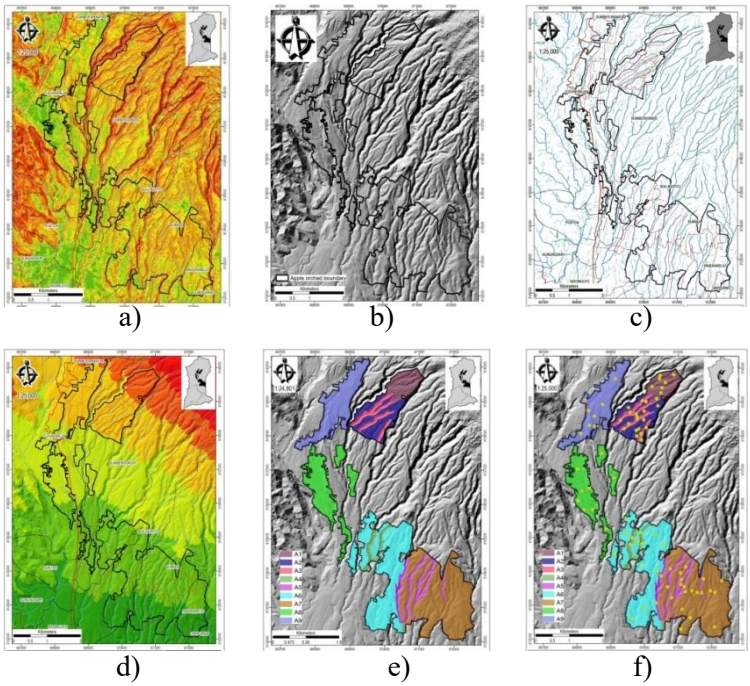


Figure 3. The result of DEM extraction i.e a) slope map, b) relief map, c) drainage map, d) elevation map, e) stratified area map, and f) sample point map

3.2. Descriptive statistics

The results of the descriptive analysis of soil nutrient content are presented in Table 1. The pH value of the soil is in the range of 4.2 - 6.1, this condition shows that the soil varies from very acid to neutral. Soil organic carbon content is very low to a very high level (0.49 - 4.93). Soil Total P is in the very low range (8.20) to very high (284.71). Soil Total K is also in the same range, which is very low (8.98) to very high (126.33). Skewness and kurtosis index of all variables indicate that the data distribution is relatively normal because it is in the range of -2 to 2.

Table 1. Results of descriptive statistical analysis of soil nutrient content data.

Variable	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
pH	4.200	6.100	5.045	0.549	0.056	-1.083
SOC	0.490	4.930	2.279	1.114	0.577	-0.311
TP	8.620	284.710	85.330	69.522	1.370	1.686
TK	8.980	126.330	41.577	26.825	1.173	0.977

3.3. Multivariate analysis

Multivariate analysis is a multivariable statistical analysis (more than two variables) in a bond that is carried out simultaneously or together [32]. This study used an analysis method of General Linear Model (GLM Multivariate) that consists of three stages of the process, namely: assumption test, significance test, and interpretation of the analysis results. The dependent variables in this analysis are pH, SOC, TP, and TK, while the independent variable is the Area. So the total number of variables in this study is 4 variables, meaning that the multivariate requirement is met.

Multivariate GLM analysis can be done if it meets the test criteria for assuming the Box's M method. The criterion is if the significance value (Sig.) more than 0.05 then all dependent variables have the same covariance-variant matrix in the existing group. The results of Box's M assumption test (Table 2) show the Sig. value as much as 0.127. This shows that the Sig.value is more than 0.05, meaning that pH, soil organic carbon, total P, and total K have the same variant-covariance matrix, so the next test could be continued.

Table 2. Assumption test results using Box's M method

Box's Test of Equality of Covariance Matricesa	
Box's M	178.437
F	1.176
df1	90
df2	1995
Sig.	0.127

The following analysis phase was the simultaneous and individual significance test. In this method, the decision making criteria are if the Sig. value < 0.05, the dependent variables simultaneouslyshow the real differences in various areas. This criterion also applies to testing individual variables.

The results of the simultaneous signification test (Table 3) show that the significance value of Pilla's Trace, Wilks' Lambda, Hotelling Trace, and Roy's largest Root in the Area row is 0,000 (all of Sig. is less than 0.05). This means that with a 95% confidence level the soil nutrient contents including pH, soil organic carbon, soil total P, and soil total K together show a significant difference between Areas.

Table 3. Results of simultaneous multivariate analysis (GLM Multivariate 5%)

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	0.998	5547.375	4	48	0.000
	Wilks' Lambda	0.002	5547.375	4	48	0.000
	Hotelling's Trace	462.281	5547.375	4	48	0.000
	Roy's Largest Root	462.281	5547.375	4	48	0.000
Area	Pillai's Trace	1.392	3.402	32	204	0.000
	Wilks' Lambda	0.074	5.739	32	178.610	0.000
	Hotelling's Trace	7.076	10.282	32	186	0.000
	Roy's Largest Root	6.356	40.521	8	51	0.000

The results of the significance test on the dependent variables individually for pH, organic C, and P total are 0.00, while for total K is 0.005 (Table 4). Based on the decision-making criteria, it shows all Sig. values are less than 0.05, meaning that with a 95% confidence levels pH, soil organic carbon, total P, total K individually show significant differences in various areas.

Table 4. Results of individual multivariate analysis (Test of Between-Subject)

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	pHH2O	13.300	8	1.662	18.805	0.000
	Corg	46.016	8	5.752	10.771	0.000
	Ptot	131900.350	8	16487.544	5.486	0.000
	Ktot	14284.350	8	1785.544	3.232	0.005
Intercept	pHH2O	1454.886	1	1454.886	16456.763	0.000
	Corg	315.558	1	315.558	590.895	0.000
	Ptot	429707.512	1	429707.512	142.992	0.000
	Ktot	95707.120	1	95707.120	173.260	0.000
Area	pHH2O	13.300	8	1.662	18.805	0.000
	Corg	46.016	8	5.752	10.771	0.000
	Ptot	131900.350	8	16487.544	5.486	0.000
	Ktot	14284.350	8	1785.544	3.232	0.005

The final stage of multivariate analysis is the interpretation of the result of the simultaneous and individual significance test. Based on the test results, it is indicated that soil nutrient contents

significance difference in various Areas, where the formation of Areas is based on topographic characteristics including slope, elevation, drainage density, and relief. This means that topography affects the spatial variability of soil nutrient content which is spatially presented in Figure 4.

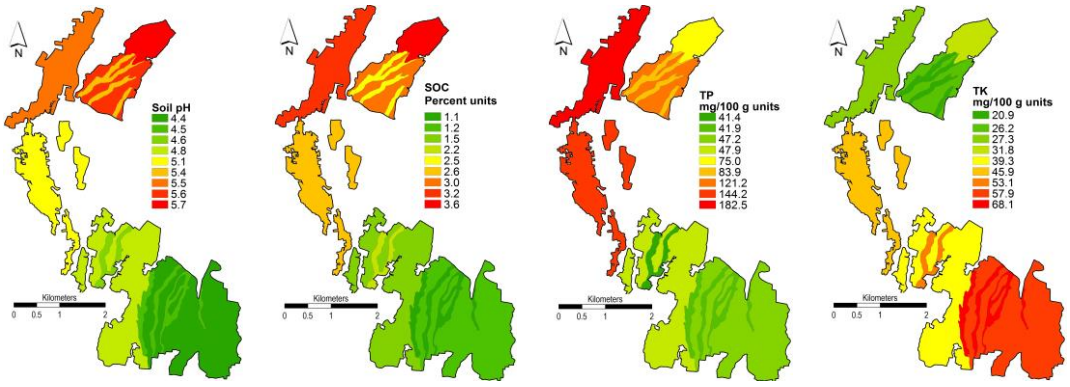


Figure 4. The spatial variability of soil nutrient content in apple orchard Batu City, East Java Province, i.e. soil pH, soil organic carbon (SOC), soil total phosphorus (TP), and soil total calium (TK).

In this study identification of topographic characteristics was using DEM data, meaning that DEM data can be used as a secondary variable to identify the spatial variability of soil nutrient levels. This is in accordance with the results of [20], topographic characteristics including altitude, slope, and drainage conditions can be used for mapping soil characteristics in precision agriculture.

Sewerniak [33] states that topographic conditions trigger differences in soil characteristics. This means that the topographic appearance can be used to estimate the spatial distribution of soil characteristics and its fertility. The results of a study by Clemen [8], [5] show that soil fertility is influenced by topographic conditions in the form of slopes. Land on the upper slope and the lower slope is more fertile than the land on the middle slope. This is because the upper slope is less eroded than the middle, while the lower slope is a zone of sediment accumulation thus it is more fertile.

In the study of Moser [26] show that topography influences the availability of soil nutrients through the redoximorphic process. Darke [10], [1] state that in wet soil conditions Fe element plays an important role in the availability, absorption, and retention of soil's P elements. This is because Fe and P bond will become weak in anaerobic soil so that P becomes available for plants. But on the contrary, in aerobic conditions, Fe and P bonds become stronger resulting in increased P retention [15].

The redoximorphic atmosphere of land is influenced by land topography conditions in the form of relief (surface roughness), so the availability of soil nutrients is also diverse [44]. De Souza [16] stated that the shape of relief affects the spatial distribution of soil chemical properties including pH, P, K, Ca, Mg, CEC, and base saturation.

Tsui [43] states that the movement and accumulation of nutrients in a particular land is affected by slope factor through groundwater movement. The lower slope generally has higher pH, CEC, Ca, and Mg than the middle slope. In addition, the slope is also a major factor in the pedogenic process. The greater the slope angle, the higher the material translocation through erosion process [7].

Shaoliang [34] states that the position of the slope affects soil fertility. The middle slope has the lowest soil fertility compared to the upper and lower slopes. This happens because the middle slope of the erosion process occurs more intensively than the upper slope, while the lower slope is the accumulation zone.

In terms of the number of samples, it is shown that DEM utilization provides efficient soil nutrient mapping results compared to the interpolation method. Pozdnyakova [29] report that co-kriging has

the best salinity mapping accuracy. This method involved 898 sample points on an area of 3375 hectares in California USA.

Ismail [17] report that there is spatial variability in soil nutrient levels (N, P, and K). The study involved 122 sample points on an area of 3,75 hectares in Durian Agrowisata, Malaysia. This result is in accordance with [11] that show significant differences in spatial soil fertility conditions. The number of samples used was 303 points.

Based on the explanation above, the mapping of soil nutrient levels using the interpolation method requires a large number of sample points. The consequence of this is that it takes time, effort, and high costs, thus it is not efficient. The use of DEM (topographic characteristics) in mapping soil nutrient levels is more efficient because it involves fewer soil samples compared to interpolation methods

4. Conclusion

One of the main objectives of the work was to obtain a very high-resolution DEM, which could be used as a tool to explain the relationships between topography and soil properties. We also evaluated different ways to account for exhaustively sampled secondary variables, such as the topographic information derived from the DEM, to improve the precision of soil nutrients contents delineation as primary information. The results of GLM Multivariate statistical analysis, both simultaneously and individually, show that the significance value is less than 0.05. This means that with a 95% degree of confidence the value of soil nutrients is significantly different between Areas (Area 1 to 9). The establishment of the Areas in this study uses DEM spatial data analysis. So, the conclusion of this study is that DEM can be used to delineate the spatial variability of soil nutrient content in apple orchard land.

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