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SPATIAL PATTERN OF RICE FIELD PRODUCTIVITY BASED ON PHYSICAL CHARACTERISTICS OF LANDSCAPE IN CITARUM WATERSHED, WEST JAVA

N. Purwono[a], A. Aprianto[b]

[a] *Geospatial Information Agency, Indonesia*
[b] *Master of Geography Science Program, University of Indonesia / Geospatial Information Agency, Indonesia*

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Corresponding Author:
Nugroho Purwono
Geospatial Information Agency, Indonesia
Email: Inugpurwono@gmail.com

Abstract: *This research to analyze the pattern of rice field productivity that is identified through landscape perspective. Identification of productivity pattern has been done partially based on each typology of land components into several segment of the Citarum watershed, West Java Province, Indonesia. Spatial autocorrelation through GIS tool is used as the method in this research. By using moran's I (index) measurement, degree of dependency of these variables are generated to find the spatial pattern. The result of this study is separated the value of productivity based on segments of watershed, the values of the average of productivity are upstream (6.39 ton/Ha), middle stream (6.52 ton/Ha), and downstream (7.17 ton/Ha), sequentially. The highest productivity is in the downstream area (9.83 ton/Ha) and the lowest is in the upstream area (4.55 ton/Ha). In accordance with physiographic typology showed the rice field in the middle stream has more variation than the upstream or the downstream area. The highest of average rice field productivity is on alluvial plain. Overall, the rice field productivity on the hills is higher rather that other types of landform the structural formation is more dominant, in addition. The spatial pattern shows the distribution of rice field productivity most likely to clustered based on the similarity of physiographic type. Statistically, it has p-value <0.01 and z-score >2.58 (239.26) correspond to Spatial Autocorrelation (Moron's I). This positive value means a less than 1% likelihood that this clustered pattern could be result of random choice, which the rice field productivity value has similar pattern to others. Thus, it can be generated that the pattern of rice field productivity has a very close relation with the physical characteristics which associated of each typology of land components.*

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1. INTRODUCTION

In the modern scientific context, many researchers express that, agricultural productivity is a multidimensional concept, which incorporates innovative headway, effective management of available resources and authoritative setup for the agricultural production (Kumar & Manimannan, 2014). These elements thus, influence the relative creation in any region. The term of productivity is viewed as the estimation of production and inputs required for the production of that output is known as agricultural productivity (Ogale & Nagarale, 2014).

Citarum watershed is one of the largest and strategic watersheds in West Java Province, Indonesia. The rice field area in the Citarum watershed is 17.7% of the rice field area in the whole province, which is the widest among other watersheds. According to the Indonesia the government's data, the rice field in Citarum watershed has a lot of potential and contribution to agricultural production in West Java Province. Thus, the existence of rice field area has an important role related to national food security (FAO, 2014; Nurliani & Rosada, 2016). However, there were several constraints on rice fields that cause problems in food sector. For instance, reducing rice-field area through land conversion. Several areas are expanded into urban areas, while the other district maintains as the buffer area. The development of many cities in West Java expands to other built-up area, for instance the residential and industrial area (Santoso et al., 2017). The expansion from agricultural areas to non-agricultural is dominant. The change of rice-field area was caused by low productivity of rice-field, decreasing quality of land, particularly physical condition (Nurliani & Rosada, 2016; Santoso et al., 2017).

West Java has great potential in agriculture, however the use of data and spatial analysis to support the process of decision making is still considered lacking. Spatial data and techniques are becoming an increasingly popular tool to identify potential opportunities in many sector (Mennis & Guo, 2009), in particular as agricultural sector (Jones et al., 2017). A wide variety of new spatial data have recently been developed using innovative data mining techniques, such as high-resolution satellite imagery and geo-referenced environmental data. On the agriculture side, there are several important international initiatives to examine current land use and potential crop productivity in connection to physical conditions of agricultural area (Iimi et al., 2015; Mennis & Guo, 2009).This research has examined the agricultural productivity of West Java, within Citarum watershed unit, by using spatial analysis through an examination of the characteristics of the land components. The objective is specifically aims at generating the spatial agricultural for rice field and potential data in the watershed area, and analyse the pattern of rice field productivity that is identified from the characteristics of the land component based on physiographic typology (Donfouet et al., 2017; Ziadat, 2007). In particular, this paper addresses the local pattern of rice field productivity through landscape variables by applying the spatial autocorrelation model (Moran's I Index) to find out the productivity pattern (Kumar & Manimannan, 2014; Ord & Getis, 1995).

2. DATA AND METHODS

2.1. Area of Study, Data and Work Processing

The Citarum Watershed is the largest watershed in West Java. The Citarum river as the main channel starts flowing from Mount Wayang and run out through the Java Sea. Geographically, The Citarum watershed area extends at 106 ° 58'30.22 "- 107 ° 54'7.92" E and 5 ° 57'44.13 "- 7 ° 13'58.86" S. The Department for Water Resource Management of West Java Province has stated this watershed covered 13 districts that consisted of Bandung, West Bandung, Bekasi, Bogor, Cianjur, Garut, Karawang, Subang, Sukabumi, Purwakarta, Sumedang, Bandung City and Cimahi City (Figure 1).

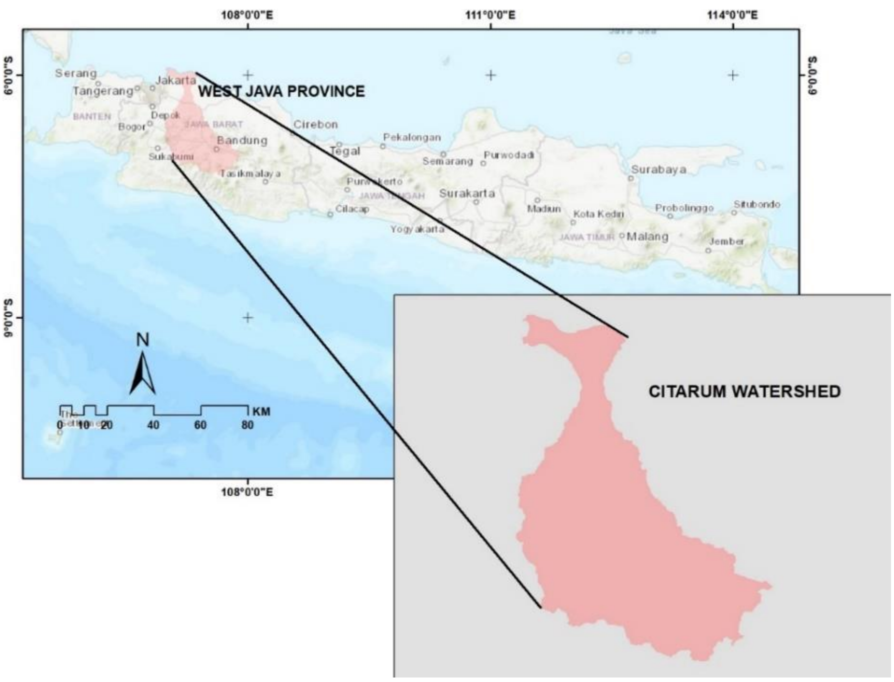


Figure 1. Area of study

The rice field area in the Citarum watershed are distributed in part of those districts entirely. To reach this objective, this research uses several data which are divided to determine two main indicators, these are land component and agriculture potency. Each variable of land component was obtained from certain data sources which consists of Indonesia Topographic Map (RBI), soil map, SPOT 6 Imagery and DEM derived from Shuttle Radar Topographic Mission (SRTM). While the data of agriculture potency was obtained from the statistical data for each administration unit, and rice field map was generated to obtain agriculture area in this research study unit. These data entirely compiled from 2014 to 2016. Further, the data in this research described by following table (Table 1).

Table 1. Relation data and variable trough this research

5	Variable	Data source	Instrument and method
Land component	1. Segment of watershed (upstream, middle stream, downstream)	DEM - SRTM	Extraction; Interpretation; Reclassification; Overlay
		Topographic Map (RBI)	
	2. Physiography	SRTM	
		Topographic Map (RBI)	
	3. Soil type	Soil Map	
Agriculture potency	1. Rice field	Rice field map (LP2B)	Updating; Spatial Join
		SPOT 6 Imagery	
	2. Administration	Topographic Map (RBI)	
	3. Productivity	Statistic data (BPS)	

In this study, data processing consisted of two main steps (Figure 2). First, built the typology components of rice field area. Second, identification of rice field productivity spatially by generated statistical data. Furthermore, results of these data processing are used to analyse productivity patterns based on typology of the land component (Álvarez-López et al., 2008). Spatial data of the rice field contains productivity information obtained from spatial analysis function (spatial joint) between rice field maps (LP2B) with topographic maps (RBI). Spatial data of the rice fields typology is derived from the land system map by reclassifying attributes related to land suitability criteria (Álvarez-López et al., 2008; Ziadat, 2007). The physiographic maps were generated from morphologic and topographic approaches. Morphology information was identified by analyzing the slope, consisting of plains, hills and mountains types (Mokarram & Hojati, 2017; Suwartha et al., 2017). The identification of morphogenesis was interpreted from shading map visualization including volcanic, structural, karst, fluvial and structural. Analysis of the patterns of rice fields productivity is compiled from overlaying the typology map of land components with rice fields productivity maps (Kumar & Manimannan, 2014; Ogale & Nagarale, 2014). Furthermore, the analysis of productivity patterns based on land components was accomplished related to rice fields area which have at least 60% of the area of rice fields in each typology of land component.

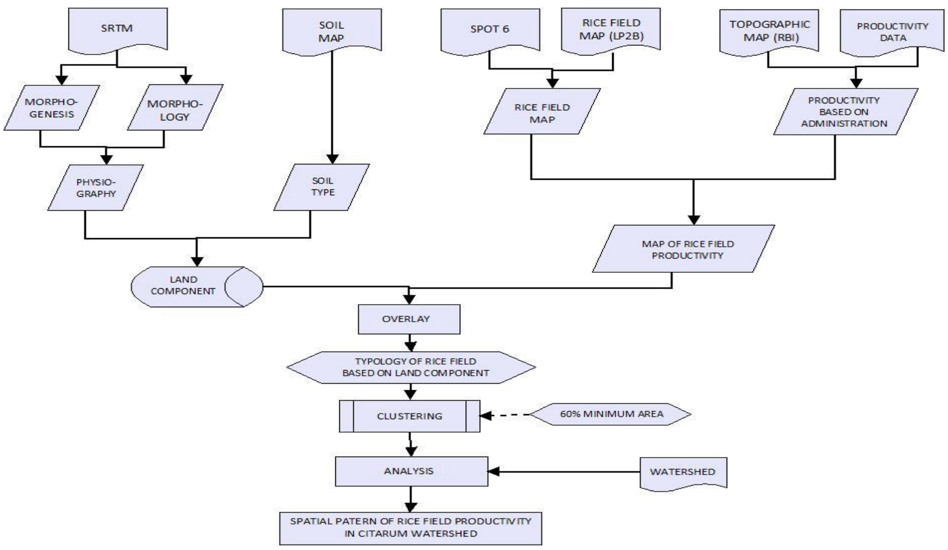
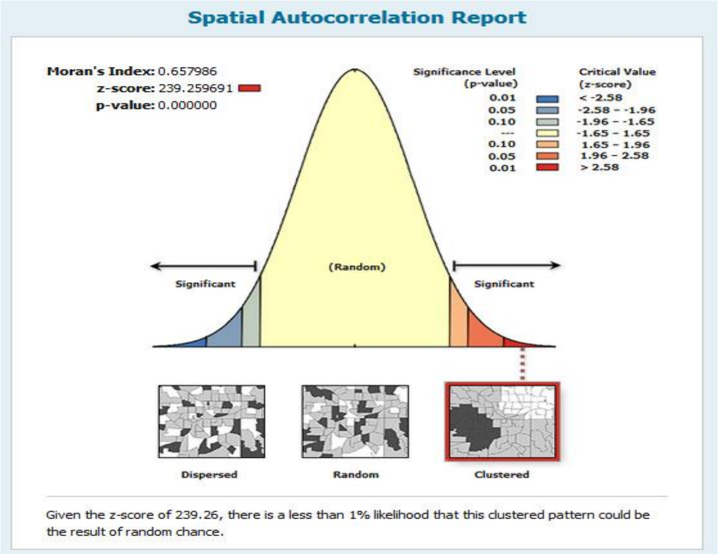


Figure 2. Flow of data processing

2.2. Approach and Analysis

Land component is identified by landscape approach (Álvarez-López et al., 2008; Dorner et al., 2002). The best productivity value for each type of land component typology is used as the reference productivity value to calculate the potential productivity by the similarity of land unit. Analysis of production component is performed into the same land units with different productivity levels.

Identification of productivity pattern is conducted to know the correlation between productivity level and land component typology (Álvarez-López et al., 2008; Kumar & Manimannan, 2014; Jiang et al., 2013). Identification of productivity pattern is generated partially by each land component. Then, all parameters of the land component are combined simultaneously. Spatial analysis is generated by the result of map overlay related to variation of productivity value (Álvarez-López et al., 2008; Diao et al., 2012; Jiang et al., 2013; Legendre, 1993; Saroinsong et al., 2007). The analysis of variation productivity patterns is based on land component typology that provides information of productivity levels in each typology (Kumar & Manimannan, 2014; Jiang et al., 2013). The range of highest, lowest and average productivity values reflects the productivity level of a land component typology (Álvarez-López et al., 2008; Saroinsong et al., 2007). That value can be compared between each typology of land component. Identification of productivity pattern includes variations of rice field productivity value related to spatial distribution of the land component typology. Identification of the variation pattern of productivity value is based on the unit of rice field area which considered representing typology of land component (Saroinsong et al., 2007). The rice field unit is mostly (60% or more) related in one typology of land component, and then it is necessary to sort the data by area distribution (Álvarez-López et al., 2008; Jiang et al., 2013).The pattern of rice field productivity is divided by each segment of watershed, and then analyzed based on two land components, including soil type and physiographic character. The analysis is done separately (by each land component) and simultaneously (combining all land components). Spatial pattern of rice field productivity is analyzed based on Spatial Autocorrelation Moran's I model (Diniz-Filho et al., 2009; Iimi et al., 2015a; Ord & Getis, 1995). Spatial analysis of Moran's I (Figure 3) is used to identified the spatial pattern of rice field distribution, whether the pattern will be clustered or random, and the pattern follows uniformity of productivity value. The Moran's I method gauges spatial autocorrelation based on geographic location and attribute data values using Global Moran I statistical model (ESRI, 2012; Legendre, 1993; Ord & Getis, 1995).



Moran's Index:	0.657986
Expected Index:	-0.000022
Variance:	0.000008
z-score:	239.259691
p-value:	0.000000

Figure 3. Spatial Autocorrelation Moran's I (ESRI, 2012)

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The spatial autocorrelation model (Global Moran's I) measures the correlation between objects in terms of location and attribute values simultaneously (ESRI, 2012). The model measures the location pattern and object attribute whether it is grouped, spread, or randomly based on the Moran Index value as indicated by the z (z-score) and p (p-value) which represented the significance number of the model. In this research context, statistical model that used is Anselin Local Moran's Index. Through Geographical Information System (GIS), the Anselin Local Moran's I was used in spatial autocorrelation calculation tool (ESRI, 2012). This model is used to identify spatial clusters of variables with high or low values. The model also identifies spatial outliers (Anselin, 1995). To performs this model, the tool calculates a local Moran's I value, a z-score, a p-value, and a code representing the cluster type for each statistically significant parameter. The z-scores and p-values represent the statistical significance of the computed index values. Thus, it’s formulated as following equations.

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j\neq i}^{n} w_{i,j}(x_j - \bar{X}) \qquad \text{.............................. (1)}$$

$$S_i^2 = \frac{\sum_{j=1, j\neq i}^{n} (x_j - \bar{X})^2}{n-1} - \bar{X}^2 \qquad \text{....................................(2)}$$

$$\begin{aligned} \mathrm{E}[I] &= -1/(n-1) \\ \mathrm{V}[I] &= \mathrm{E}[I^2] - \mathrm{E}[I]^2 \end{aligned} \qquad \text{...................................(3)}$$

$$z_I = \frac{I - \mathrm{E}[I]}{\sqrt{\mathrm{V}[I]}} \qquad \text{...................................(4)}$$

where

X_i	:	attribute for feature (variable) i	
Ẋ	:	mean of corresponding attribute	
$W_{i,j}$	:	the spatial weight between feature i and j	
z_i	:	deviation of *i* value against mean value ($x_i - X$)	
		$w_{i,j}$:	weighted factors by each data
		n :	sum of data
S_o	:	sum of weighted factors	

3. RESULTS AND DISCUSSION

3.1 Distribution of rice field productivity in Citarum Watershed

There are three categories resulted from the aggregation of rice productivity, they are: Low productivity (<6 ton/Ha), Moderate Productivity (6-7 ton/Ha) and High productivity (>7 ton/Ha). Entire area of the watershed, the proportion of rice field productivity detailed as follow (Figure 4).

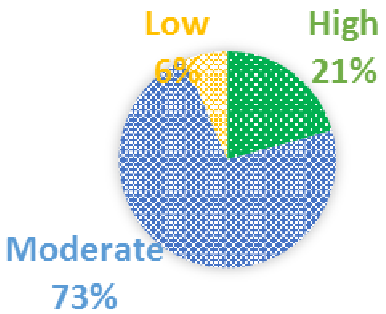

Figure 4. Proportion of rice field productivity within watershed area

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Distributions of rice field productivity values are grouped based on the segment of watershed. It consists of upstream, middle stream, and downstream. Moderate productivity dominates in whole areas with the proportion toward rice filed area in each segment of watershed is 88%, 70.4% and 51.22%. The average of rice field productivity in the upstream area (6.39 ton/Ha) is lower than the average of rice field productivity in the middle stream area (6.52 ton/Ha), and also lower than downstream area (7.17 tons/Ha). The highest productivity is in the downstream area (9.83 ton/Ha) and the lowest is in the upstream area (4.55 ton/Ha). The variation of rice field productivity in segments of watershed illustrated as follow (Figure 5). Spatial distribution of rice field productivity is shown in the Figure 6. Each color shown on the map illustrate the rice productivity in each segment of watershed. The level of productivity was described by the color gradation on the map, the light colors means low values and the darks colors means high values.

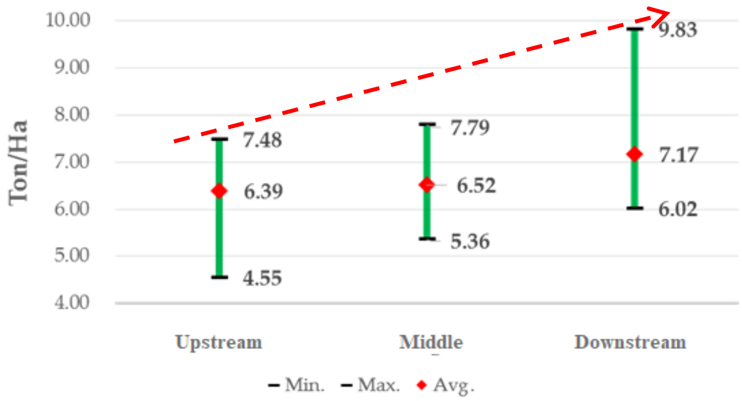

Figure 5. Variation of rice field productivity within the segments of watershed

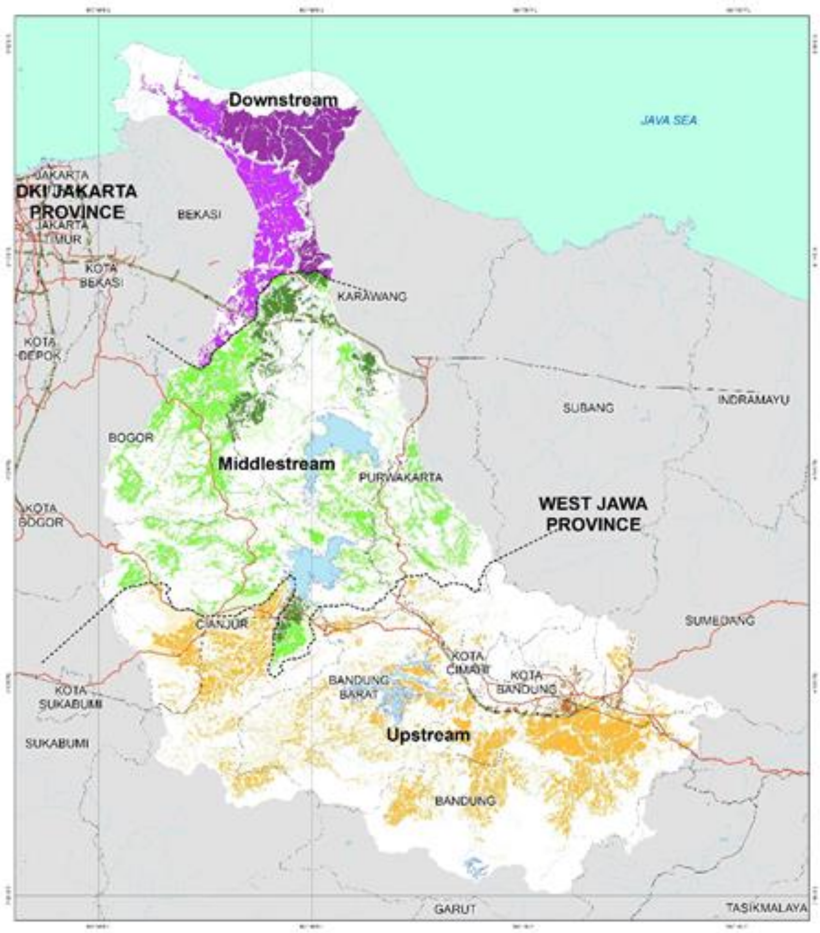

Figure 6. Spatial distribution of rice field productivity in Citarum Watershed

3.2 Distribution of Rice Field Productivity Toward Soil Type

The result of overlay between rice field productivity with soil type shows different proportions of productivity class in particular soil type. The dominant soil type across all segment of the Citarum watershed is Incept sols, involve 74.1% of whole rice fields area in the watershed. The second soil type is Andisols, with 6.7% of rice field area in the watershed. Distribution of rice field area based on productivity class and soil type is presented in Table 2.

Table 2. Distribution of rice field productivity class based on soil types

No	Soil type	Upstream (ha)			Middle stream (ha)			Downstream (ha)		
		Productivity Class			*Productivity Class*			*Productivity Class*		
		(High)	(Mod)	(Low)	(High)	(Mod)	(Low)	(High)	(Mod)	(Low)
1	Inceptisols	301.9	51,182.2	2,527.8	9,657.2	21,838.8	3,917.9	18,478.0	20,015.4	
2	Ultisols		906.8	0.8	2,493.9	4,307.8	1,505.1	0	884.2	
3	Alfisols		1,936.0	108.0	27.8	1,923.2	95.4			
4	Oxisols					934.6	352.3			
5	Andisols	236.2	4,879.4	2,475.6		3,893.3	83.9			
6	Entisols				619.1	225.7		1,402.2		
7	Mollisols		48.2							
8	*Residential area*	*1,597.8*		*73.8*						
9	*no data*	*809.8*	*1,091.4*	*51.3*	*35.6*	*62.8*	*24.1*	*34.7*	*8.0*	
10	*Bogor District*					*11,583.6*				
	Total	**2,945.7**	**60,044.0**	**5,237.4**	**12,833.6**	**44,769.7**	**5,978.7**	**19,915.0**	**20,907.7**	

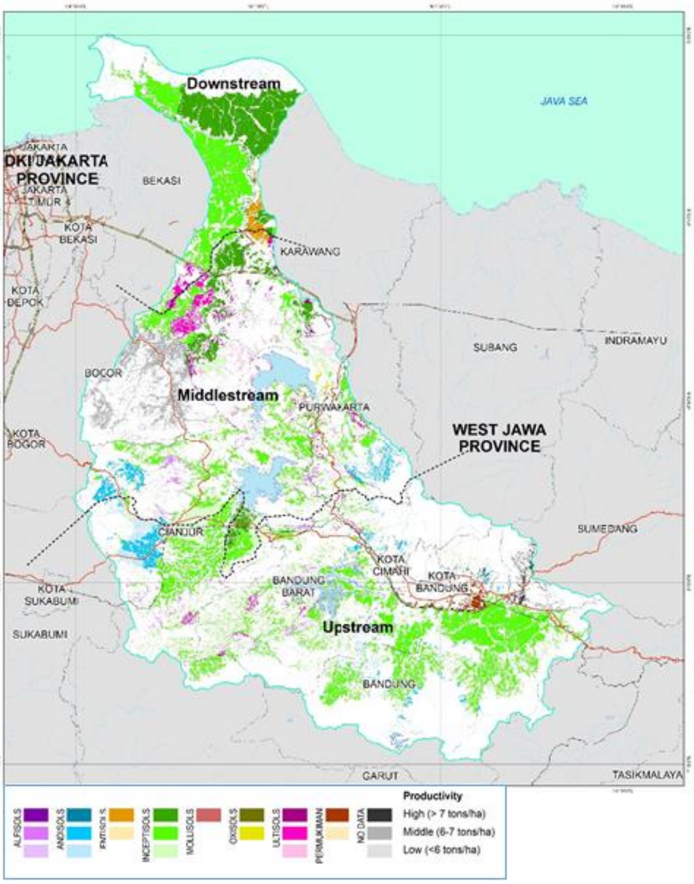

Figure 7. The class of productivity related to soil types

The spatial distribution shows the highest productivity is on Inceptisol that spread in the downstream area, these patterns illustrated as the Figure 7. Statistically, the Inceptisols type tend to increase rather than the productivity on Andisols soil type (Figure 8).

As the significant proportion, the result of analysis focuses on the dominant soil type (Incept sols and Andisols). The highest productivity was (9.83 ton/ha) found in rice field on Inceptisols type, while the lowest productivity (4.55 ton/ha) was found in rice field on Andisols type. Each averages value of both shows that Inceptisols is higher. Statistically, the value of the variation of the dominant soil types within watershed segments were showed as follow (Table 3).

Table 3. Variation of productivity according to soil type

No.	Soil type	Upstream			Middle			Downstream		
		Max	Min	Avg	Max	Min	Avg	Max	Min	Avg
1	Andisols	6,513	4,548	5.99	6.12	6.12	6.12	-	-	-
2	incept sols	7,793	5,589	6.40	7,793	5,589	6.65	9,834	6,018	7.17

According to statistical results, distribution of rice field productivity based on the type of soil can be spatially identified that the productivity of rice fields in the Inceptisols more increase in every segment of watershed, which compared to the Andisols. Inceptisols and Andisols are the main soil in the Citarum watershed, either were found in rice field area mostly.

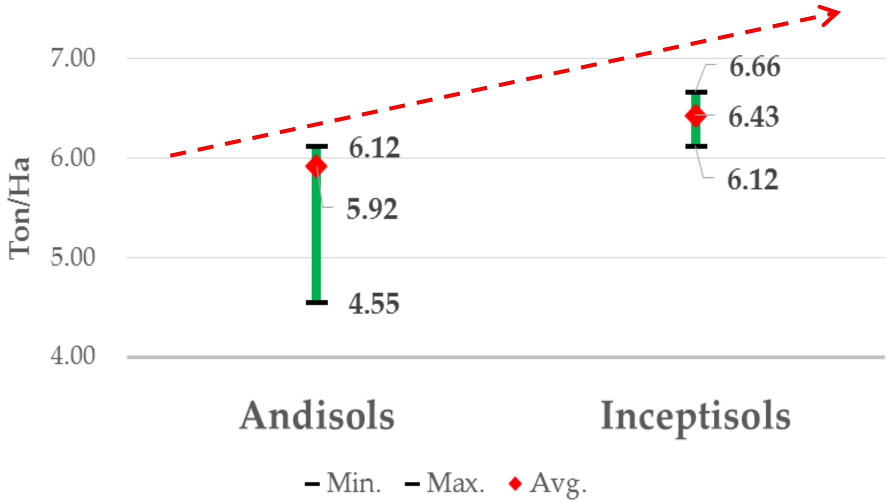

Figure 8. Variation pattern of productivity according to the dominant of soil types

3.3 Distribution of Rice Field Productivity According to Land Physiographic

Based on physiographic analysis, the physiographic type in the upstream is the volcanic plain. This type can be found in 35.2% number of the upstream area. Further, the proportion areas of each physiographic type are 20% for structural mountainous; 17.4% for the volcanic hills and 12.2% structural hills, respectively. The area with volcanic mountain is 3.3% by total area of rice field in the upstream watershed. Mostly, the class productivity was dominated by moderate value (Table 4).

In the middle stream area also dominated by moderate productivity class which is found in the structural hills with 17.5% area, 16,4% in structural mountains and 15.43% in the structural plain. While in the downstream area is in fluvial plains with high and medium productivity class, mostly. Overall, the proportion of rice field in the downstream area has high and medium productivity class by 53.1% and 45.2%.

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Table 4. Distribution of rice field productivity by physiographic types (ton/ha)

No	Physiography	Upstream (ha)			Middle stream (ha)			Downstream(ha)		
		Productivity Class			*Productivity Class*			*Productivity Class*		
		(High)	(Mod)	(Low)	(High)	(Mod)	(Low)	(High)	(Mod)	(Low)
1	Fluvial Plain				4,037.7	1,385.9		19,899.6	18,547.4	
2	Marine							15.4	621.8	
3	Structural Plain				2,777.3	10,610.0	1,195.7		1,130.5	
4	Volcanic Plain	2,096.8	23,953.1	1,990.3	1,519.1	2,253.7	2,245.3		97.8	
5	Structural Mointains	341.3	13,620.1	472.8		10,173.7	200.3		510.2	
6	Volcanic Mountain	1.2	2,244.2	876.2	56.4	2,629.3	443.7			
7	Karst Hills				19.7	8.8	56.2			
8	Structural hills	7.3	8,308.8	240.7	4,423.4	10,815.1	1,769.4			
9	Volcanic hills	499.0	11,917.8	1,657.4		6,893.3	68.3			
Total		**2,945.7**	**60,044.0**	**5,237.4**	**12,833.6**	**44,769.7**	**5,978.7**	**19,915.0**	**20,907.7**	

The highest productivity is found in rice field with fluvial plain whereas the lowest productivity was found in structural hills. Related to morphological types, the plains have the highest average productivity, followed by the hilly type. On the other side, the Volcanic Mountains has the lowest average productivity. Based on morphogenesis, the highest average productivity is found in fluvial, followed by structural and volcanic. Variation of rice field productivity related to physiographic types illustrated by Figure 9.

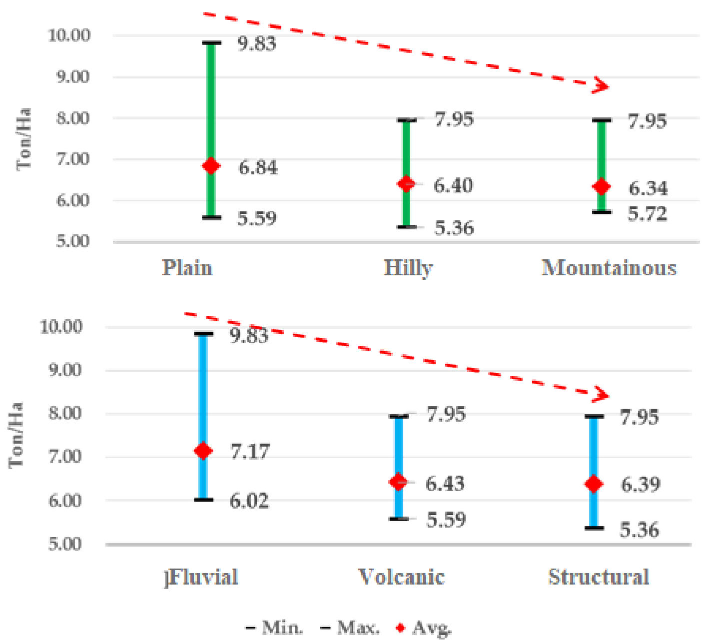

Figure 9. Variation of productivity based on physiographic (morphology)

Based on physiographical typology shows that rice field in middle stream of the Citarum Watershed has more variation than the upstream and downstream areas. Based on variation, the highest average productivity was in the alluvial plains. Amount of productivities in the Hills type was higher than the Mountains, while the Structural form has higher productivity than the Volcanic. The difference pattern of these values can explain the rice field productivity which is identified from the aspect of physiographic (Álvarez-López et al.,2008; Saroinsong et al.,2007). The distribution of productivity value toward physiographic types of rice field area illustrated as following figure (Figure 10). However, to know related factors that influence the difference of productivity level of rice field within same physiographic typology need to be analyzed by physical component deeply (Álvarez-López et al., 2008; Diao et al., 2012; Jiang et al., 2013; Legendre, 1993; Saroinsong et al., 2007). Furthermore, that factors should be studied comprehensively in particular correlated to others external factor, such as sociocultural and economic influence (Kumar & Manimannan, 2014; Mahananto, 2009; Ogale & Nagarale, 2014).

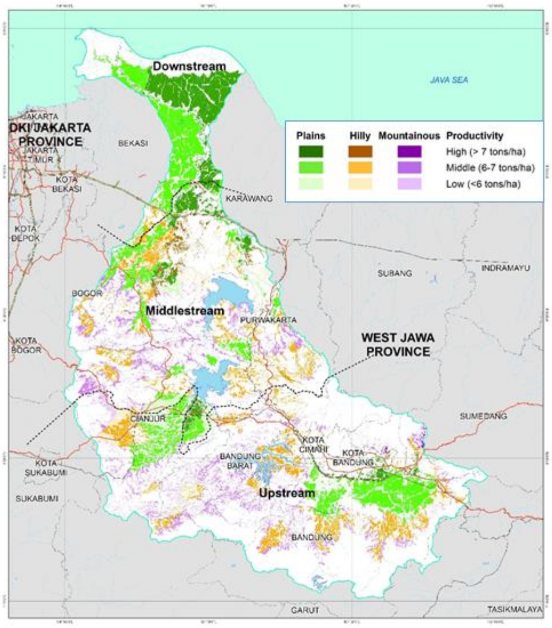

Figure 10. Distribution of rice field productivity based on physiographic (morphologic)

3.4 Spatial Pattern of Rice Field Productivity

The spatial pattern of rice field productivity was examined by using spatial autocorrelation of Moran's I, whether the results will be clustered or disperse. In this section, the spatial autocorrelations showed the size and distribution of the different types of productivity value, as well as the association between physiographical types in the segment of Citarum watershed. Based on the productivity and physiographical association, the current pattern should be separated according to its homogeny or heterogenic values. The result of typology clustered presented in Figure 11.

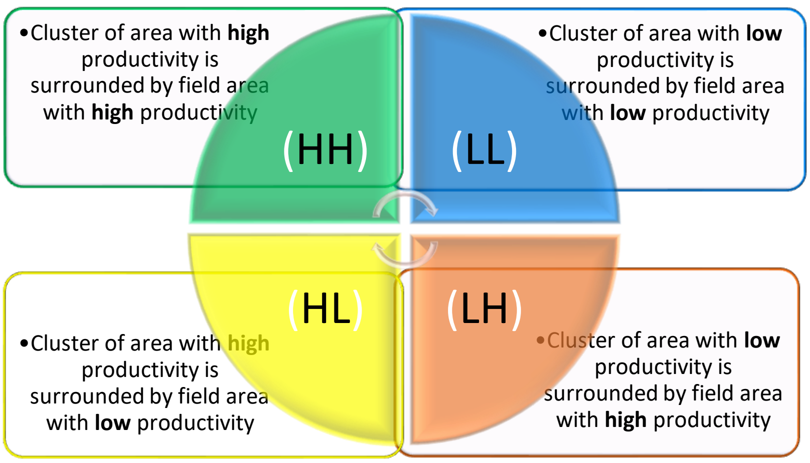

Figure 11. Cluster of typologies based on Moran's I spatial distribution pattern

The values for neighboring variable are either both larger than the mean or both smaller than the mean, so the cross-product will be positive. When one value is smaller than the mean and the other is larger than the mean, the cross-product will be negative. In this case, the larger the deviation from the mean, the larger the cross-product result. The values in the results tend to cluster spatially (high values cluster near other high values; low values cluster near other low values), the Moran's Index will be positive, vice versa. When high values eliminate other high values, and tend to be near low values, the Index will be negative. If positive cross-product values balance negative cross-product values, the Index will be near zero (Anselin, 1995).

The spatial pattern shows the distribution of rice field productivity tends most likely to be clustered based on the similarity of physiographic type (Álvarez-López et al., 2008; Diao et al., 2012). Statistically, it has p-value <0.01 and z-score >2.58 (239.26) correspond to Spatial Autocorrelation (Moran’s I). A high positive z-score indicates that the surrounding variable have similar values (either high values or low values). The variable field in the output be HH for a statistically significant cluster of high values and LL for a statistically significant cluster of low values. A low negative z-score indicates a statistically significant spatial data outlier. The variable field in the result will indicate if the variable has a high value and is surrounded by variable with low values (HL) or if the variable has a low value and is surrounded by variable with high values (LH).

According to the result of this analysis, it indicates that Type HH, HL, and LH, which are the three typologies of high productivity potential areas. This is followed by Type LL which can be attributed to the similarly physiographic types which has low productivity in Citarum Watershed. On the other hand, half of the rice field areas in Citarum watershed were characterized as HH primarily because of the physiographic characteristic that suitable for agriculture, in particular with rice field production. The results also show that the potential for rice field productivity and physiographic types are spatially correlated. The spatial distribution of rice field productivity depicted in this following figure (Figure 12).

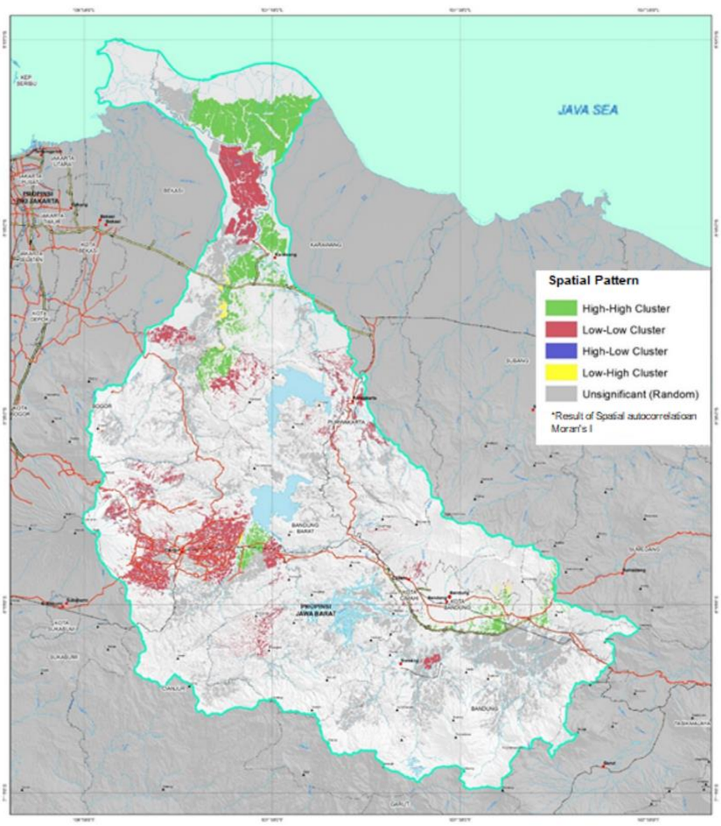

Figure 12. Spatial distribution pattern based on Moran’s Index

3.5 The Affect of Land Component Toward Rice Field Area Productivity Pattern

The identification of productivity based on land component is done to know the pattern of productivity based on physical characteristic which is more accurate, where each typology is clustered based on the same physical characteristic. Combination of land component shows the potential of the rice field area physically. Thus, it can be identified the impact of land component variety across to the productivity on each rice field area. According to combination of land component, it can be determined area which has the same typology related to class of productivity.

The overlay of land component with rice field area produce 365 typology which are the combination of 27 soil varieties and 9 class of physiographic. It differentiated based on the upstream, middle stream, and downstream area. Furthermore, the distribution of rice field based on administration area is representing 60% the same land component in each district. The result is 53 from 127 rice field area per district represents its land component typology. Those 53 field areas are consisted of 15 lands component typologies that are labeled from A to O. In detail are presented as the following (Table 5).

Table 5. Typology of land component of rice filed area in Citarum Watershed

No	Typology of land component	Land component character		Segment of Watershed	∑ District	Productivity variation
		Soil type	Physiographic			
1	A	Typic Endoaquepts	Fluvial plain	Downstream	1	Moderate
2	B	Typic Epiaquepts	Fluvial plain	Downstream	1	Moderate to high
3	C	Oxyaquic Dystrudepts	Structural hills	Upstream	1	Moderate
4	D	Residential	Volcanic plain	Upstream	1	High
5	E	Residential	Volcanic plain	Upstream	1	High
6	F	Typic Epiaquepts	Structural mountains	Upstream	1	High
7	G	Typic Endoaquepts	Volcanic plain	Upstream	1	Low to moderate
8	H	Typic Eutrudepts	Structural mountains	Upstream	1	Moderate
9	I	Typic Eutrudepts	Structural hills	Upstream	1	Moderate
10	J	Typic Eutrudepts	Volcanic hills	Upstream	1	Moderate
11	K	Typic Eutrudepts	Volcanic hills	Upstream	1	Moderate
12	L	Typic Hapludands	Structural mountains	Upstream	2	Moderate to high
13	M	Typic Hapludands	Volcanic hills	Upstream	1	Low to moderate
14	N	Typic Epiaquepts	Volcanic plain	Middle stream	1	Moderate to high
15	O	Typic Eutrudepts	Structural mountains	Middle stream	1	Moderate

4. CONCLUSION

Based on the result of the analysis spatial pattern of rice field area distribution and factors that affect to the value of productivity in Citarum Watershed, it can be concluded that physical factor of land component affects significantly toward the rice field productivity. Further, that determines the variation of the productivity on lowest and highest threshold. According to the result of the analysis, it shows that rice field productivity values increased sequentially, from the upstream to the downstream area. Based on morphological types, the rice field productivity values tend to increase from mountains, hills, and plain. According to the aspect of morphogenesis, the productivity rose from the structural landform, volcanic, and fluvial, respectively. In accordance with spatial distribution, the pattern shows the distribution of rice field productivity tends to clustered or grouped based on the similarity of physiographic type. Further, it delivered by the result of Spatial Autocorrelation (Moran's Index) that showed p-value <0.01 and z-score >2.58 (239.26). This value indicates statistical significance. Therefore, that correlation has tendency toward clustered of surrounding variable which have similar values. Thus, it can be concluded that the pattern of rice field productivity has a very close relationship with the physical characteristics which associated with each typology of land component.

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6. REFERENCES

Álvarez-López, C. J., Riveiro-Valiño, J. A., & Marey-Pérez, M. F. (2008). Typology, classification and characterization of farms for agricultural production planning. *Spanish Journal of Agricultural Research, 6*(1), 125–136. [Crossref]

Anselin, L. (1995). Local Indicators of Spatial Association - LISA. *Geographical Analysis, 27*(2), 93–115. [Crossref]

Diao, X., You, L., Alpuerto, V., & Folledo, R. (2012). Assessing Agricultural Potential in South Sudan – A Spatial Analysis Method. *Intech*, 139–152. [Crossref]

Diniz-Filho, J. A. F., Oliveira, G. de, Lobo, F., Ferreira, L. G., Bini, L. M., & Rangel, T. F. L. V. B. (2009). Agriculture, habitat loss and spatial patterns of human occupation in a biodiversity hotspot. *Scientia Agricola, 66*(6), 764–771. [Crossref]

Donfouet, H. P. P., Barczak, A., Détang-Dessendre, C., & Maigné, E. (2017). Crop Production and Crop Diversity in France: A Spatial Analysis. *Ecological Economics*, *134*, 29–39. [Crossref]

Dorner, B., Lertzman, K., & Fall, J. (2002). Landscape pattern in topographically complex landscapes: Issues and techniques for analysis. *Landscape Ecology, 17*(8), 729–743. [Crossref]

ESRI. (2010). *GIS Best Practices: Environmental Management*.

FAO. (2014). *a Regional Rice Strategy for Sustainable Food Security in Asia and the Pacific*.

Iimi, A., You, L., Wood-Sichra, U., & Humphrey, R. M. (2015). Agriculture Production and Transport Infrastructure in East Africa: An Application of Spatial Autoregression. *Policy Research Working Papers 7281*, (June).

Jiang, X. jian, Tang, L., Liu, X. jun, Cao, W. xing, & Zhu, Y. (2013). Spatial and Temporal Characteristics of Rice Potential Productivity and Potential Yield Increment in Main Production Regions of China. Journal of *Integrative Agriculture, 12*(1), 45–56. [Crossref]

Jones, J. W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., … Wheeler, T. R. (2017). Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. *Agricultural Systems, 155*, 269–288. [Crossref]

Kumar, C., & Manimannan, G. (2014). Spatial pattern of agriculture Productivity of Crop in Cauvery Delta zone of Tamilnadu. *IOSR Journal of Agriculture and Veterinary Science (IOSR-JAVS)*, *7*, 1–7. [Crossref]

Legendre, P. (1993). Spatial Autocorrelation : Trouble or New Paradigm? Author(s): Pierre Legendre Published by : Ecological Society of America Stable URL : http://www.jstor.org/stable/1939924 REFERENCES Linked references are available on JSTOR for this article : You may. *Ecology, 74*(6), 1659–1673. [Crossref]

Mahananto, S. S. dan C. F. A. (2009). Faktor-Faktor yang Mempengaruhi Produksi Padi Studi Kasus di Kecamatan Nogosari, Boyolali, *Jawa Tengah. Wacana, 12* No.1(1), 179–191.

Mennis, J., & Guo, D. (2009). Spatial data mining and geographic knowledge discovery-An introduction. Computers, *Environment and Urban Systems, 33*(6), 403–408. [Crossref]

Mokarram, M., & Hojati, M. (2017). Morphometric analysis of stream as one of resources for agricultural lands irrigation using high spatial resolution of digital elevation model (DEM). *Computers and Electronics in Agriculture, 142,* 190–200. [Crossref]

Nurliani, & Rosada, I. (2016). Rice-field Conversion and its Impact on Food Availability. *Agriculture and Agricultural Science Procedia, 9,* 40–46.[Crossref]

Ogale, S., & Nagarale, V. (2014). Agricultural Productivity of the Baramati Tahsil, Pune District \n(Maharashtra).\n. *IOSR Journal of Agriculture and Veterinary Science (IOSR-JAVS), 7*(5), 25–30.

Ord, J. K., & Getis, A. (1995). Local Spatial Autocorrelation Statistics: Distributional Issues and an Application. *Geographical Analysis, 27*(4), 286–306. [Crossref]

Santoso, P. B. K., Sabiham, S., & Wayan Rusastra, I. (2017). Analisis Pola Konversi Lahan Sawah dan Struktur Hubungan Penyebab dan Pencegahannya (Studi Kasus Kabupaten Subang, Provinsi Jawa Barat). *Jurnal Pengelolaan Sumberdaya Alam Dan Lingkungan, 7*(2), 184–194. [Crossref]

Saroinsong, F., Harashina, K., Arifin, H., Gandasasmita, K., & Sakamoto, K. (2007). Practical application of a land resources information system for agricultural landscape planning. *Landscape and Urban Planning, 79*(1), 38–52. [Crossref]

Suwartha, N., Maulani, I., Priadi, C. R., Felaza, E., Tjahjono, T., & Putri, G. L. (2017). Mapping land use suitability for development of recharge wells in the ciliwung watershed, Indonesia. *Water Practice and Technology, 12*(1), 166–178. [Crossref]

Ziadat, F. M. (2007). Land suitability classification using different sources of information: Soil maps and predicted soil attributes in Jordan. *Geoderma, 140*(1–2), 73–80. [Crossref]