Deciphering Spatial Variability and Kriging Mapping for Soil pH and Groundwater Levels

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Deciphering Spatial Variability and Kriging Mapping for Soil pH and Groundwater Levels

Menguraikan Keragaman Spasial dan Pemetaan Kriging untuk pH Tanah dan Level Muka Air Tanah

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ABSTRAK

Keragaman spasial lahan gambut bersifat alami, dapat dikelola dan terkait dengan variasi alam dan lingkungan. Penelitian ini bertujuan untuk menguraikan keragaman spasial gambut dan pemetaan kriging untuk pH dan muka air tanah. Lokasi penelitian ini adalah lahan gambut di Desa Seponjen, Kec. Kumpeh, Kab. Muaro Jambi, Jambi. Data penelitian dianalisis dengan ArcGIS 10.3 dan Geostatistik. Analisis validasi antara pH tanah aktual dan estimasi pH tanah memiliki pola fluktuasi yang sama, dengan reliabilitas tinggi (r = 0,94) dan akurasi (R^2 = 0,89) positif. Ini artinya kinerja interpolasi data pH dapat digunakan untuk membuat peta pH tanah. Sebaran pH gambut sangat tebal (area A) memiliki autokorelasi kuat dengan kisaran variogram 768 m, pada gambut sedang (area B) cenderung anisotropik terhadap sungai dengan keragaman maksimum 273 m. Kedalaman muka air tanah di kedua area itu bersifat autokorelatif, yaitu memiliki ketergantungan spasial dimana keragaman muka air tanah pada jarak dekat kecil dan meningkat pada jarak jauh.

Kata kunci: interpolator yang bagus, muka air tanah, pH tanah, keragaman tanah

ABSTRACT

Spatial variability of peatlands is mostly related to natural variations and environment. Thus, it is natural and manageable. This study aimed to determine deciphering spatial variability and kriging mapping for soil pH and groundwater levels. The study was conducted on peatlands in Seponjen Village, Kumpeh Sub-District, Muaro Jambi District, Jambi. The collected data were analyzed using ArcGIS 10.3 and Geostatistics. The validation analysis of soil pH showed good performance where the actual soil pH and the estimated results of soil pH had the same fluctuation pattern, with high reliability (r = 0.94) and accuracy (R^2 = 0.89) positive. It means that the interpolation performance of soil pH data can be used to create soil pH maps. The soil pH on very thick peat (the area A) showed a strong autocorrelation with a variogram range of 768 m, while on medium peat (the area B) it showed an anisotropic tendency towards rivers with a maximum variability of 273 m. The depth of the groundwater levels in the two areas is autocorrelative, it has a spatial dependence where the variability of the groundwater levels is small at close ranges and increases at long distances.

Keywords: good interpolator, groundwater levels, soil pH, spatial variability

INTRODUCTION

Peatlands have very diverse characteristics both spatially and vertically (El Falah et al., 2021; Al-Timimi, 2021). Their characteristics are closely related to their thickness, the mineral soil layer under the peat substratum, maturity, and enrichment level (from the overflow of the surrounding river water and the influence of sea water). Peatlands are generally categorized as marginal land for agriculture development (Zuhdi et al., 2019; Imanudin et al., 2019; 2020). The main limiting factor is the condition of the root media which is not conducive to the development of root crops, mainly due to the conditions of water saturation, acid, and containing toxic organic acids that are harmful to plants (Armanto, 2019a; 2019b; 2019c). Therefore, reclamation efforts are needed, so that land conditions become more suitable for plant development (Barchia et al., 2021; Zahri et al., 2019).

Spatial variability of peatlands is mostly related to natural variations and environment (Abdel Rahman et al., 2020; Dwiastuti et al., 2021). Thus, spatial variability of peatlands is natural and manageable (Maroeto et al., 2021. Determinant factors cause an increase of soil variability both geologically and pedologically, such as climate, plant residues, flora, fauna, topography as well as management (Imanudin et al., 2021a; 2021b; 2021c). Spatial variability analysis is a very useful tool for assessing peatland productivity and for the environment (Bhunia et al., 2018; Negassa et al., 2019). Geostatistics belongs to a method that is well known accepted to manage the spatial soil variability and is able to interpolate the relationship between reconstructions and variogram analysis. Kriging interpolation technique helps show regional character distributions with isoline (Kriging) maps (Sayer, 2020). For peatlands this information is still very much needed. This is because the use of soil characteristics can be used as the basis for making peatlands restoration policies, such as the paludiculture model (Varone et al., 2021; Wildayana & Armanto, 2021). Traditional soil sampling methods based on soil type are possible and do not adequately represent a very large area of peatlands. Therefore, it is necessary to propose a systematic soil sampling method, namely the grid sampling method. Collected data taken from the grid sampling method are able to be mapped or utilized to predict locations that were not sampled using spatial interpolation (Dietrich & MacKenzie, 2018). This study aimed to determine deciphering spatial variability and Kriging mapping for soil pH and groundwater levels. This research has been carried out in year of 2021 located in the peatlands, which are part of the Batanghari River-Air Hitam Laut KHG (Peat Hydrological Area) which is the most extensive KHG in Jambi.

MATERIALS AND METHODS

The Study Sites

This study was conducted on peatlands in Seponjen Village, Kumpeh Sub-District, Muaro Jambi District, Jambi Province Indonesia (Figure 1). Geographically, the study location was located between 103°58'20"–103°58'51" east and 1°27'35"–1°30'00" south. The peatlands are adjacent to two conservation areas, namely the Orang Kayo Hitam Grand Forest Park and the Berbak National Park.

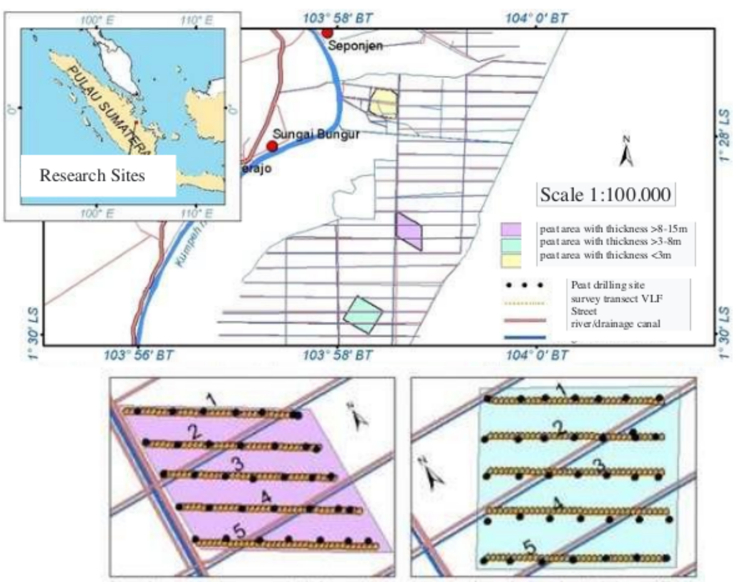
Survey Design, Method, Materials and Tools

This research used some tools and materials, namely peat drill, peat probe, GPS (Global Positioning System), compass, ruler of 20 m, plastic bag, label, permanent marker, tally sheet and stationery. Two grid sampling areas were designed with an area of around 25 ha each, i.e. the area A (having peat depths of around 8-15 m); and the area B (showing peat depths of around 3-8 m). On the sampling area, some transects were made in forms of row and column. This boring path was made in a direction more or less perpendicular to the river. The distance between the lines was 100 m. Observation of boring distance in each lane 80 m. The peat thickness was observed and measured directly during the main survey in the field, namely by boring at the planned point location. Sampling was carried out on transects with boring direction of Northwest to Southeast. The layout of the data collection locations was presented in Table 1 and Figure 1.

Data Collection and Analyses

The field survey was done in each sampling point. The collected data were analyzed using ArcGIS 10.3 software with the extension of Geostatistical Analyst. The data analysis aimed to perform data interpolation, which was to estimate the amount of data on the entire surface of the study area on the basis of the distribution of available data. Data normality was proved by histogram, QQ Plot (Quantile-Quantile Plot) and Voronoi Map.

Geostatistical interpolation was done to perform an estimate of the value of the data distribution across the surface based on the collected sample point data and based on a statistical model that calculates auto-correlation between samples by making some variogram models for peat depths. Some selected variogram models were made in order to find out optimal variogram models for peat depths. The geostatistical interpolation were to make mapping to obtain maps of levels of the peat depths by Kriging method and its geostatistical parameters.



A (very thick peats) B (thick peats)

Figure 1. Geographic location of study locations and layout of measurement area

Table 1. General description of sampling area

General Characters	Area A	Area B
Acreage (ha)	25	25
Direction of Bboring	Northwest-Southeast	Northwest-Southeast
Peat Depths (m)	8-15	3-8
Peat Thickness	Very Thick	Medium
Row (row)	5	5
Column (column)	7	7
Boring Distance (m)	80	80
Column Distance (m)	100	100
Boring Amount (boring)	35	36

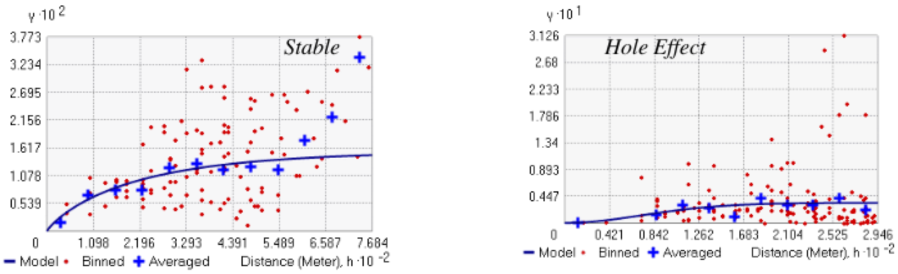
RESULTS AND DISCUSSION

The results and discussion of this study emphasized the discussion of general description of sampling area; variogram models for soil pH values and for groundwater levels; optimal interpolator by Kriging for soil pH; Kriging interpolation for soil pH values and for ground water levels; and correlation between peat depths with soil pH and ground water levels.

Variogram Models for Soil pH Values

The variogram representing the distribution pattern of soil pH in each area could be seen in Figure 2. Based on the distribution of red dots in Figure 2, it could be concluded that the very deep peat area (the area A) has a more auto-correlative pH distribution or has more spatial dependence. This means that the distance between locations greatly determines the difference in pH values, the closer the distance, the more likely the pH value will be the same. The further away the greater the possibility of differences in soil pH. In contrast to the area A, in the area B, the distance does not really affect the difference in soil pH. At close range the pH can be very different, conversely at a long distance the pH can be almost the same. Thus, it can be concluded that the distribution of soil pH in the area A has a higher spatial autocorrelation and tends to follow Tobler's Law of Geography. The model chosen to represent the variogram of the distribution of soil pH in each study area was the Stable model (RMSE, Root Mean Square Error = 0.077) for the area A, Hole effect (RMSE = 0.15) for the area B. For the chosen variogram, it was taken for the lowest RMSE. The parameters of the selected variogram model in both areas are presented in Table 2.

Nugget effect values that are low or close to zero in both study areas indicate that the mean prediction error of the selected model was very small and indicates that the prediction results using the model are very good. The range value indicates the maximum distance where autocorrelation still occurs, i.e. the range where the difference in measurement results was still influenced by the measurement distance. The area A shows a range value of approximately 768 m, meaning that the distribution of soil pH in very thick peat areas has a spatial dependence of up to a distance of 768 m. Where the diversity of pH values tends to be small at close distances and more varied at longer distances. However, at distances greater than 768 m, the soil pH was random. The range value in the measurement than in the area B is closer, which was 273 m. Therefore, the pH distribution in the area B appears to be more varied.

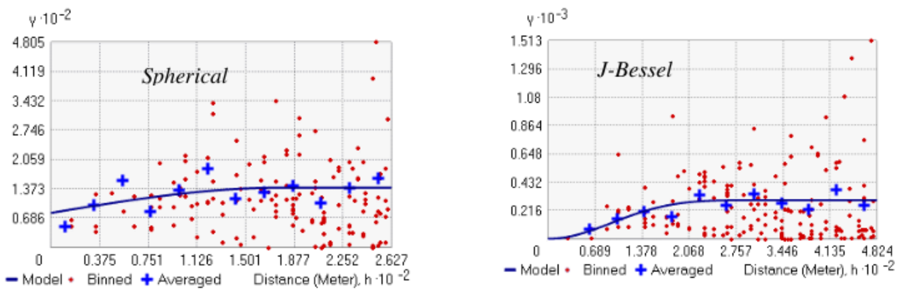


Area A Area B

Figure 2. Variogram model for soil pH values

Table 2. Parameters for the best selected variogram model

Parameter	Area A	Area B
For Soil pH Distributions		
Model Type	Stable	Hole Effect
Nugget Effect (%)	0.0000	0.0177
Range (m)	768.44	273.41
Sill (%)	0.0155	0.0070
For Groundwater Levels		
Model Type	Spherical	J-Bessel
Nugget Effect (%)	80.96	2.50
Range (m)	176.40	361.00
Sill (%)	58.83	293.89



Area A Area B

Figure 3. Variogram model for groundwater levels

Variogram Models for Groundwater Levels

Figure 3 presented the distribution of variogram points in the area A and the area B which are superimposed with the best variogram model. Based on Figure 3, it can be concluded that the depth of the groundwater levels in the two areas was autocorrelative, that was, it has a spatial dependence where the variability of the groundwater levels was small at close ranges and increases at long distances.

Area A shows a range value of around 176 m, meaning that the distribution of groundwater levels in the area A has a spatial dependence of up to a distance of 176 m. Where the diversity of pH values tends to be small at close distances and more varied at longer distances. However, at distances greater than 176 m, the groundwater levels are random. The range value in the measurement than in the area B was larger, which was 360 m. For distances greater than 360 m, the groundwater levels did not follow the model (random). In other words, the distribution of groundwater depths followed the pattern of Tobler's law of geography. The best model that describes the variogram of the groundwater tables in the area A was the spherical model, while the area B was the J-Bessel model which produces RMSE of 12.01 and 9.33, respectively.

Optimal Interpolator by Kriging for Soil pH

In fact, soil pH data on large areas of peatland are often incomplete or not measured due to the large area of peatlands, and the limited ability of measuring instruments or the presence of outliers (values) that differ greatly from the majority of the data we have. One way was to interpolate the available data. Interpolation was the process of "guessing" the data by taking into account other available data. Interpolation was a technique to find the value of a missing variable in a known data range.

To test the data interpolation can use the correlation coefficient or determinant coefficient. There are three interpretations of correlation analysis, including: looking at the strength of the relationship between two variables; looking at the significance of the relationship; and looking at the direction of the relationship. The relationship between actual soil pH and estimated soil pH of R = 0.945 means that the relationship between the actual pH variable and the estimated pH was very strong, positive and significant. The correlation coefficient was positive (unidirectional), then the relationship between the two variables was unidirectional, meaning that if the soil pH actual was high, then the pH estimated variable was also high. The termination coefficient (R^2) was the proportion of variability in a data that was calculated based on a statistical model. R^2 was the ratio of the variability of the estimated soil pH values made by the model to the variability of the actual soil pH data values, so that R^2 can be used as a measurement of how well the regression line approaches the original data values created by the model. In the case of soil pH, it turns out that R^2 = 0.89 means that 89% of the variation from the estimated pH can be explained by the actual pH variable; while the remaining 0.11 was influenced by unknown variables or inherent variability or 89% of the estimated pH was determined by the actual pH, while the remaining 11% was influenced by other factors.

Kriging interpolation using variogram model. The Kriging method was able to provide data at unrecorded points, unbiased soil sample parameter estimates with a minimum standard deviation, so the Kriging method was an optimal interpolator. Maps created with Kriging are able to visually display the distribution of data. Kriging was based on the theory of regionalized variables and was considered the best linear unbiased estimator. Statistical analysis for the results of cross-validation using soil pH data showed good performance where the results of soil pH measurements and soil pH estimation results had almost the same fluctuation pattern (Figure 4). The performance of the estimated soil pH data (interpolation) was good and this interpolation can be used to create soil pH data.

Kriging Interpolation for Soil pH Values

The results of the interpolation of soil pH data from each area were mapped geostatistical based on the variogram model with the smallest RMSE. Figure 5 showed how the pH distribution pattern of the peat soil is, it turns out that very thick peat areas (the area A) tend to have lower soil pH values (more acidic than medium peat areas or the area B), although the difference was small (< 1 pH unit). The lower pH in very thick peat areas was thought to be due to the greater mass of peats in this area, resulting in more production of organic acids such as humic acid, fulvic acid and others which are contributors to the low pH of peat soils in general. While the variation in pH in medium peat soils was understandable because medium peat areas are not completely peat soils. The presence of mineral soil, which was part of the area B, was thought to contribute to this variability.

Kriging Interpolation for Ground Water Levels

The results of geostatistical interpolation of groundwater depth data in the two peat areas produce a prediction map for the distribution of the groundwater table depth as showed in Figure 6. There was a difference in the depth of the groundwater table between very thick peat areas (left) and medium peat areas (right), where in very thick peat areas tend to have a greater depth of water table. While the spatial variability between the two does not seem much different.

Correlation Between Peat Depths with Soil Ph And Ground Water Levels

The relationship between the pixel values of the predicted peat thickness map with the predicted pH and groundwater depth was traced using correlation statistics in image processing software. The results in the form of coefficients are presented in Table 3.

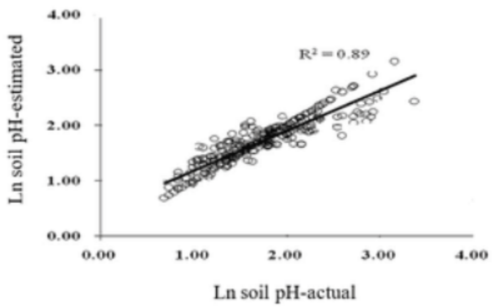


Figure 4. Cross validation for actual soil pH and estimated soil pH (log transformed data, n = 140)

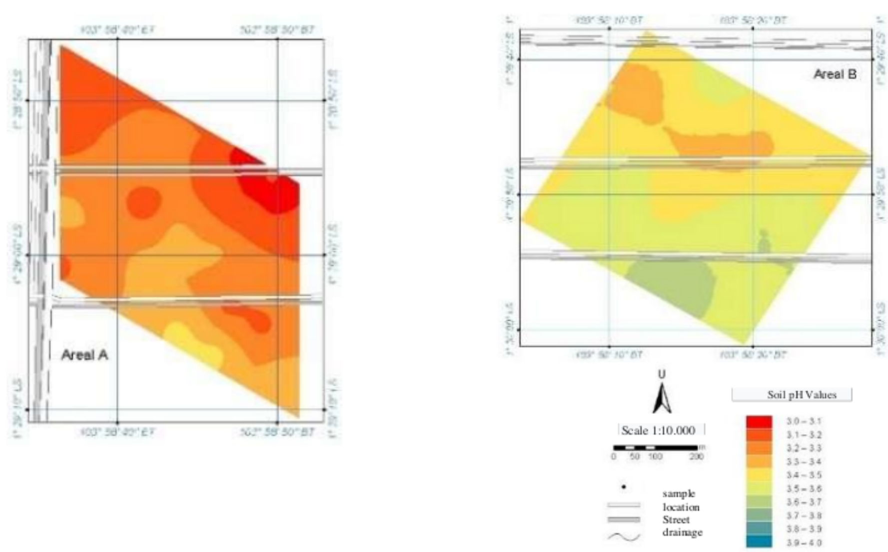


Figure 5. Kriging interpolation of soil pH values

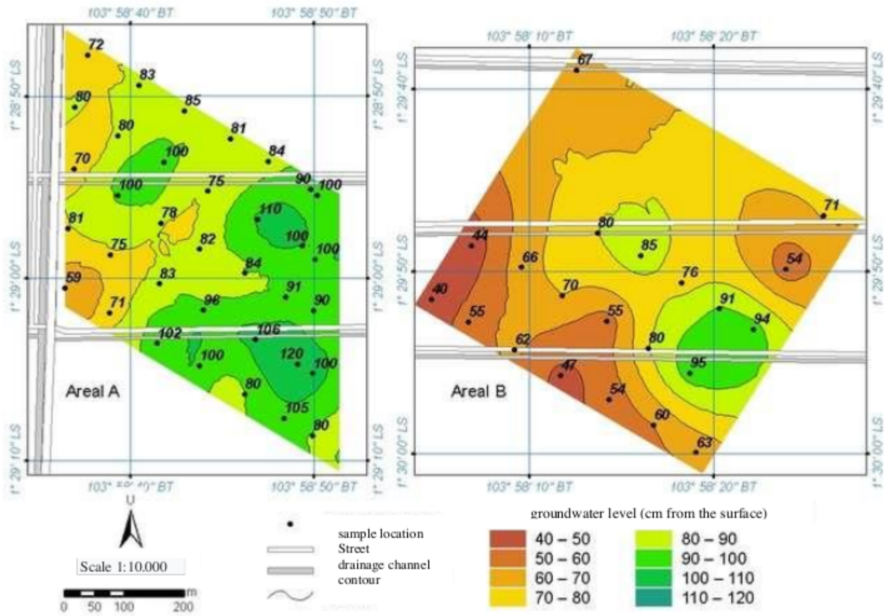


Figure 6. Kriging interpolation of ground water levels

Table 3. Correlation coefficient of peat depths with soil pH and groundwater levels

Area/Variable	Peat Depths (m)	pH Values	Groundwater Levels (cm)
	Area A		
Peat Depths	--	-0,78*/	-0,75*/
pH Values	-0,78*/	--	0,05
Groundwater Levels	-0,75*/	0,05	--
	Area B		
Peat Depths	--	-0,62*	-0,75*/
pH Values	-0,62*/	--	0,04
Groundwater Levels	-0,75*/	0,04	--

Note: */ significantly different at the level of 5%.

Peat thickness, soil pH and groundwater table depth are generally significantly negatively correlated with each other at the 5% test level in the two study areas. This was very reasonable because the pH value of the soil was not constant and was influenced by organic acids under the ground water. The more soil water, the more organic acids released by the system, so that the soil pH decreases. Therefore, the relationship between the two shows a real relationship.

CONCLUSSION

Based on the results and discussion of this study, it can be concluded validation analysis of soil pH data showed good performance where the actual soil pH and the estimated results of soil pH had the same fluctuation pattern, with high reliability (r = 0.94) and accuracy (R^2 = 0.89) positive. This means that the interpolation performance of soil pH data can be used to create soil pH maps. The distribution of soil pH on very thick peat (the area A) showed a strong autocorrelation with a variogram range of 768 m, while on medium peat (the area B) it showed an anisotropic tendency towards rivers with a maximum variability of 273 m. The variogram model for the area A is stable and the hole effect is for medium peat (the area B). The depth of the groundwater levels in the two areas is autocorrelative, that is, it has a spatial dependence where the variability of the groundwater levels is small at close ranges and increases at long distances.

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REFERENCES

Abdel Rahman MAE, Zakarya YM, Metwaly MM. Koubouris G. 2020. Deciphering soil spatial variability through geostatistics and interpolation techniques. *Sustainability*. 13 (1): 1–13. DOI: 10.3390/su13010194.

Al-Timimi Y. 2021. Monitoring desertification in some regions of Iraq using GIS techniques. *Iraqi Journal of Agricultural Sciences*. 52 (3): 620–625. DOI: 10.36103/ijas.v52i3.1351.

Armanto ME. 2019a. Comparison of chemical properties of peats under different land uses in South Sumatra, Indonesia. *J. Ecol. Eng*. 20 (5): 184–192. DOI: 10.12911/22998993/105440.

Armanto ME. 2019b. Soil variability and sugarcane (*Saccharum officinarum* L.) biomass along ultisol toposequences. *J. Ecol. Eng*. 20 (7): 196–204. DOI: 10.12911/22998993/109856.

Armanto ME. 2019c. Improving rice yield and income of farmers by managing the soil organic carbon in South Sumatra Landscape, Indonesia. *Iraqi Journal of Agricultural Sciences*. 50 (2): 653–661. DOI: 10.36103/ijas.v2i50.665.

Barchia MF, Ishak A, Utama SP, Novanda RR. 2021. Sustainability status of paddy cultivation on marginal peat soils in Indonesia. *Bulg. J. Agric. Sci*. 27 (2): 259–270.

Bhunia, GS, Shit PK, Chattopadhyay R. 2018. Assessment of spatial variability of soil properties using geostatistical approach of lateritic soil (West Bengal, India). *Annals of Agrarian Science*. 16 (4): 436–443. DOI: 10.1016/j.aasci.2018.06.003.

Dietrich ST, MacKenzie MD. 2018. Comparing spatial heterogeneity of bioavailable nutrients and soil respiration in boreal sites recovering from natural and anthropogenic disturbance. Front. *Environ. Sci* 6 (126): 1–13. DOI: 10.3389/fenvs.2018.00126.

Dwiastuti R, Setiawan NN, Aprilia A, Laili F, Setyowati PB. 2021. Land use management and carrying capacity of Bangsri Micro Watershed, East Java, Indonesia: A baseline study. *Bulg. J. Agric. Sci*. 27 (1): 38–50.

El Falah S, Dakki M, Mansouri I. 2021. Mapping analysis of the wetland loss in Loukkos (Morocco) under agricultural managements. *Bulg. J. Agric. Sci.*. 27 (1): 186–193.

Imanudin MS, Armanto ME, Bakri. 2019. Determination of planting time of watermelon under a shallow groundwater table in tidal lowland agriculture areas of South Sumatra, Indonesia. *Irrigation and Drainage*. 68 (3): 488–495. DOI: 10.1002/ird.2338.

Imanudin MS, Priatna SJ, Bakri, Armanto ME. 2020. Field adaptation for watermelon cultivation under shallow ground water table in tidal lowland reclamation area. *Journal of Wetlands Environmental Managements*. 8 (1): 1–10. DOI: 10.20527/jwem.v8i1.211.

Amandine MS, Priatna SP, Armanto ME, Prayitno MB. 2021a. Integrated Duflow-Drainmod Model for Planning of Water Management Operation in Tidal Lowland Reclamation Areas. *IOP Conf. Series: Earth and Environmental Science*. 871 (2021) 012035.

Imanudin MS, Bakri, Armanto ME, Wildayana E, Al Rasyid S. 2021b. Development of Control Drainage Operation Model and Utilization Planning of Post-Fire Peatlands. *Jurnal JWEM*. 9 (1): 1–21.

Imanudin MS, Sulistiyani P, Armanto ME, Madjid A, Saputra A. 2021c. Land suitability and agricultural technology for rice cultivation on tidal lowland reclamation in South Sumatra. *Jurnal Lahan Suboptimal : Journal of Suboptimal Lands*. 10 (1): 91–103. DOI: 10.36706/JLSO.10.1.2021.527.

Maroeto, Priyadarshini R, Santoso W. 2021. Integration GIS and multicriteria analysis critical land farming in Welang watershed. *Bulg. J. Agric. Sci*. 27 (2): 242–252.

Negassa W, Baum C, Schlichting A, Müller J, Leinweber P. 2019. Small-scale spatial variability of soil chemical and biochemical properties in a rewetted degraded peatland. *Front. Environ. Sci*. 7 (116): 1-15. DOI: 10.3389/fenvs.2019.00116.

Sayer AM. 2020. How Long is too Long? Variogram analysis of AERONET data to aid aerosol validation and intercomparison studies. *Earth and Space Science*. 7 (9): 1–19. DOI: 10.1029/2020EA001290.

Varone C, Lenti L, Martino S, Semblat JF. 2021. Spatial variability of the urban ground motion in a highly heterogeneous site-city configurations. *Bull Earthquake Eng*. 19 (1): 27–45. DOI: 10.1007/s10518-020-00965-2.

Wildayana E, Armanto ME. 2021. Empowering indigenous farmers with fish farming on south sumatra peatlands. *Jurnal Habitat*. 32 (1): 1–10.

Zahri I, Wildayana E, Thony Ak, Adriani D, Harun MU. 2019. Impact of conversion from rice farms to oil palm plantations on socio-economic aspects of ex-migrants in Indonesia. *Agricultural Economics-Czech*. 65 (12): 579–586. DOI: 10.17221/349/2018-AGRICECON.

Zuhdi M, Armanto ME, Setiabudidaya D, Ngudiantoro, Sungkono. 2019. Exploring peat thickness variability using VLF method. *J. Ecol. Eng*. 20 (5): 142–148. DOI: 10.12911/22998993/105361.

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