Journal of Smart Agriculture and Environmental Technology
e-ISSN:3021-8802
Vol. 2, No. 3, December 2024
https://josaet.com | https://doi.org/10.60105/josaet.2024.2.3.100-106

Research Paper

Mapping and Analysing Spatial Variability of Peat Depths by Using Geostatistics

M. Edi Armanto[1]*, Mohd Zuhdi[2], Dedi Setiabudidaya[3], Ngudiantoro[3], Elisa Wildayana[1]

[1] *Faculty of Agriculture, Sriwijaya University, South Sumatra, Indonesia 30662*
[2] *Faculty of Agriculture, Jambi University, Indonesia 54401*
[3] *Faculty of Mathematics and Natural Sciences, Sriwijaya University, South Sumatra, Indonesia 30662*
***Corresponding author**: mediarmanto@unsri.ac.id

Article History: Received: May 21, 2024, Accepted: July 15, 2024

Abstract

Determining peat depths can be done by intensive surveys which are expensive, inefficient, and ineffective, therefore, it is essential to find simple alternative methods for measuring peat depths. The research objective was to estimate and make maps of peat depths by applying Geostatistics analysis. This research was conducted on Muaro Jambi District, Jambi (Seponjen Village, Kumpeh) peatlands. The primary data was analyzed by ArcGIS 10.3 and Geostatistics programs. The spatial variability of peat depths on Site A (peat depth of 8.10–15.00 m) and Site B (3.10–8.00 m) showed maximum values at 271 and 242 m distances, respectively. On-Site C (0.00–3.00 m), maximum variability was found at the distance of 63 m. Peat depths variability may be interpolated at a maximum of 271 m (for Site A) and 242 m (for Site B). More than the above distances, peat depths cannot be interpolated. Site A must be conserved because of peat depths of > 3 m, only Site C can be cultivated for agriculture and plantations. Unfortunately, all areas have been cultivated for the oil palm plantation because the government has granted concession permits to plantations before knowing how deep the permissible peatlands are for the whole area.

Keywords

Estimated maps, Interpolation, Peat depths, Spatial variability

1. INTRODUCTION

Peatlands belong to deposits of incompletely decomposed remnants of past plant materials and are generally found in water-saturated areas (Armanto, 2019a). Generally, peatland ecosystems belong to marginal lands for agricultural activities in a broad sense, including fisheries, livestock, plantations, food agriculture, and forest plantations (Armanto and Wildayana, 2022; Imanudin et al., 2019). The dominant limiting factors for peatlands are the status of the groundwater table that is difficult to control, the peat depths are more than 3 m and are not conducive as media for rooting growth system (Holidi et al., 2019; Hu et al., 2021). This is because the conditions are saturated with water, acidic, and contain a lot of organic acids that are harmful to plants and other agricultural commodities (Bhunia et al., 2018; Armanto, 2019b). Thus, efforts of reclamation are necessary to make peatlands suitable for plant growth (Wildayana and Armanto, 2018; Armanto, 2019c). If the peat depths are more than 3 m and used for agriculture, thus natural disasters occur with high probability, such as floods, droughts, peat subsidence, and other environmental damage (Wildayana and Armanto, 2018b). Determining peat depths can be conducted in the fields by intensive surveys which are so expensive, inefficient, and ineffective, therefore it is essential to find simple alternative methods how to measure peat depths easily by using spatial variability analyses and Geostatistics (Negassa et al., 2019). Geostatistics is commonly applied to analyze spatial variability, namely combining spatial coordinates of data with attribute data. Besides that, Geostatistics can provide spatial analysis, thus enabling us to measure the spatial variability of data (Al-Timimi, 2021). Based on this spatial variability analysis, models can be formed to estimate the distribution of data on a large scale. Kriging is a spatial analysis to measure spatial data variability (Varone et al., 2021). Variogram models can provide information about the variability between available data and have a range of distances that are not different. This means that adjacent data generally has a low level of variability. Vice versa, the further distance between the data, the variability generally increases (Vilas-Boas et al., 2021).

Each site on the earth surface can be estimated by utilizing the most suitable model by interpolating data around that Site (Zuhdi et al., 2019). As a consequence, for several sample points, it is possible to obtain several estimated points aligned with the estimated variance values. Finally, if we have limited sample sizes, the Kriging will offer unbiased estimates based on available data with minimal variance. It can be concluded that kriging is classified as an optimal interpolator (Abijith and Saravanan, 2021). The research objective was to estimate and make a mapping of peat depths by applying Geostatistics analysis.

2. EXPERIMENTAL SECTION

2.1 Research Sites

This research was conducted on Muaro Jambi District, Jambi, Indonesia (Kumpeh, Seponjen Village) peatlands. The peatlands are a part of the Peat Hydrological Area (KHG) of the Batanghari River-Air Hitam Laut River, which is the largest KHG in Jambi (Figure 1). On the East of the research area, there are Orang Kayo Hitam Forest Park and Berbak National Park, both belong to the conservation areas (PMRA, 2022).

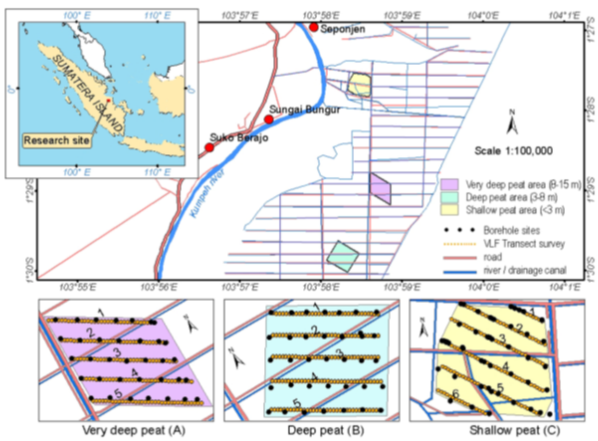

Figure 1. The Site of Research and Its Grids Sampling Layout

2.2 Survey Method and Distance between Sampling Points

GPS (Global Positioning System), compass, peat drill, peat probe, ruler, label, permanent marker, plastic bag, and stationery were used in this research. Three research Sites (around 30 ha each) were determined purposively, namely Site A (peat depth of 8.10 – 15.00 m); Site B (3.10 – 8.00 m); and Site C (0.00 – 3.00 m). Field observations were made by boring on the selected transect lines (Table 1). Peat depths were measured in the field (called manual probing or manual coring) by pushing metal sticks that can be extended (each 1 m) into the ground until they touched the mineral soil layer, then recording their depths and geographic position with the GPS.

2.3 Collecting Data and Analysis

The Geostatistics extension application and ArcGIS 10.3 were used to process the gathered data. The analyzed data were purposed to obtain interpolation and display of some data in maps. Data normality was monitored and analysed using histogram pictures, Voronoi maps as well as Quantile-Quantile plots. Data interpolation was calculated by using Geostatistics to have data distribution and estimation based on measured sampling point data and model statistics. Model statistics can display automatic correlations among sampling data by creating several variogram models. The selected variogram model will be tested to obtain the most optimal variogram model for peat depth. The geostatistical interpolations were displayed in the form of peat depth maps using Kriging. Interpolation stages and spatial variability analysis are given in Figure 2.

Table 1. Common descriptions of field data

Filed descriptions	Site A	Site B	Site C
Row totals (unit)	5 – 6	5 – 6	
Column totals (unit)	7 – 8	7 – 8	7 – 8
Site area (ha)	30	30	30
Thickness of peat	Very deep	deep	shallow
Depths of peat (m)	8.1 – 15.0	3.1 – 8.0	0.0 – 3.0
Distance among boring (m)	85 – 90	85 – 90	85 – 90
Distance among column (m)	95 – 110	95 – 110	95 – 110

Note : Borings were placed from Northwest to Southeast
Source : Field Survey Results (2023)

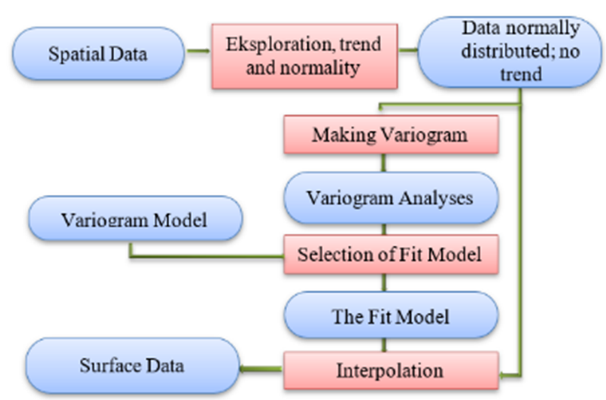

Figure 2. Interpolation stages and spatial variability analysis

3. RESULTS AND DISCUSSION

3.1 Statistical Analyses for Primary Data

Around 120 primary data of peat depths were collected from boring points in the selected transects and presented in Table 2. Each research Site (A; B; C) had several boring points of 35, 36, and 49 respectively. The main problem with this manual probing was that there was little local variability affecting results and the measurement volume was relatively small. Junedi et al. (2017) have analyzed the same phenomena of peatlands. The difference in the number of boring points was due to the different forms and sizes of each Site. Site C showed the highest number of boring points because Site C is located in a transitional area between mineral soils and peatlands, so the peat depths were greatly varied. The distance among the boring points at Site C is near each other (less than 10 m), thus the number of boring points has automatically increased. The research outcomes are consistent with the findings (Armanto et al., 2022).

Table 2. Basic Statistical Analysis of The Dataset

Statistics	Site A	Site B	Site C	Total
Boring totals (unit)	36	37	51	124
Minimum (m)	4.6	0.0	0.0	0.0
Maximum (m)	11.3	10.1	4.2	11.3
Mean (m)	9.27	3.34	1.19	4.60
Range (m)	6.42	11.01	4.22	11.01
Standard deviation	1.50	1.50	1.42	4.42
Skewness	−1.88	2.52	0.81	0.62
Kurtosis	6.51	13.02	2.22	−1.10
Variation	2.23	2.33	1.87	6.43
First quartile	9.32	2.70	0.02	0.66
Third Quartile	10.21	3.63	2.41	8.87
Median	9.50	2.89	0.42	2.97

Source: Statistical analysis of dataset (2023).

Running Kriging needed the input data were normally distributed and free from any trends of statistics. However, the dataset was not normally distributed due to data distribution far from 0 (zero) that indicating the abnormality of data distribution (Table 2). The data at Site A indicated dominant trends towards the right (high value), therefore skewness showed a negative value. The Site B and the Site C displayed positive skewness meaning that they tend to be left (low value). The data abnormality is presented in the histogram form (Figure 3). This abnormal distribution of data was also discovered by other researchers (Syakina et al., 2024a,b).

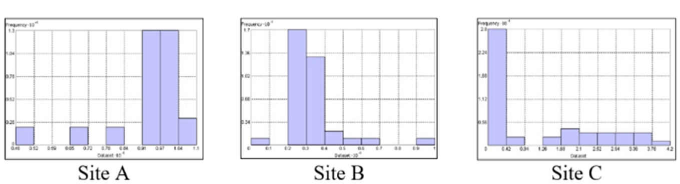

Figure 3. Histogram of Peat Depths Data

All histograms showed the data asymmetric of peat depths. Among these histograms, Site C showed the more extreme distribution of data, thus it needed a transformation process before geostatistics was conducted. Before the data was statistically processed, pre-processing was carried out in order to evaluate the trend of spatial data distribution (Figure 4). Figure 4 illustrates that the trends of peat depth occurred at Site C (shallow peat). It can be observed that the peat depth increased on the position of East to West (the x-axis) and from North to South (the y-axis). However, Site A and Site B did not show trends. These data abnormalities and trends at Site C required transformation treatment to minimize trends from data Site C. Data distribution was normalized by Box-Cox transformation, while the trends were removed by choosing order trend removal in geostatistical software.

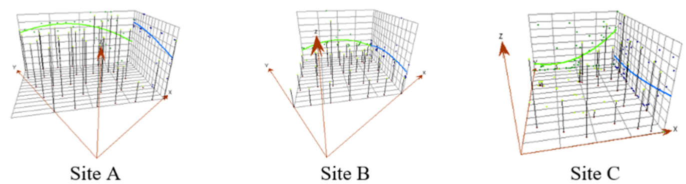

Figure 4. Trend Illustrations of Peat Depths Data

3.2 Variogram Models

There are four parameters to analyze the variogram model, namely: range (A); sills (C-Co); nuggets (Co); and scale (C). These four parameters will determine the shape and type of the resulting variogram. The range value figures the extent to which autocorrelation can still be produced. The Site A and Site B show high autocorrelation distances when compared to Site C. The variance improves following the variogram model selected. It starts from a very small at distance of 0, increasing as well as reaching a maximum value at the same distance as that distance and then appears to be constant. The Sill value indicates a variance (diversity value) of the dataset at the same distance as the range. The nugget effect value illustrates the average value of the prediction data deviation. The desired value of the nugget effect is small even close to zero as an indicator for selecting the best predictive model. The results of adjacent studies are in line with the findings (Armanto et al., 2013).

The spatial dependence of the dataset can be derived from testing the selected variogram models. At Site A and Site B, the variogram model had a low value at close range, then increased at long distances and remained constant at a certain distance. Meaning there is a spatial autocorrelation of peat depths at Site A. The distribution of the variogram adheres to Tobler's law pattern, meaning that everything is related to one another, but something that is very close means that it is more related than that which is far away (Figure 5). El Falah et al. (2021) explained that their abnormal distribution of data was also discovered by other researchers (Guth et al., 2022).

Site C shows clearly the existence of trends found along the transect. This means that the peat depths increase dominantly with increasing distance to the east. These trends must be removed before running Kriging and will be added back to the output surface. Lázaro-Lobo and Ervin (2021) have carried out the similar research. Site C proves that there is a weak automatic correlation (Figure 6). This proves that the variogram distribution pattern does not strictly follow Tobler's law. The research results do not conflict with the findings of other researchers (Zhang, 2023; Lázaro-Lobo et al., 2023).

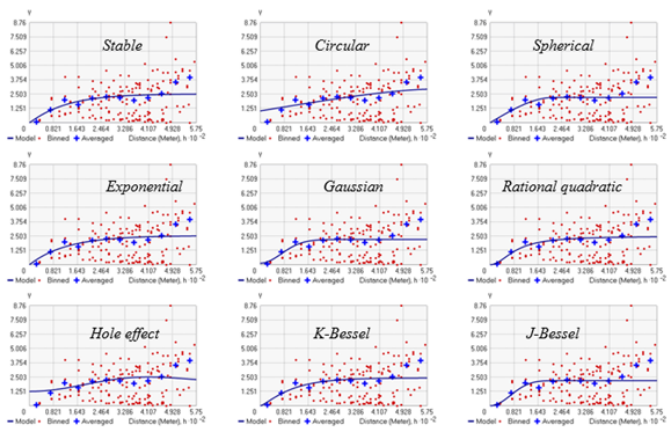

Figure 5. Selected Variograms for the Site A

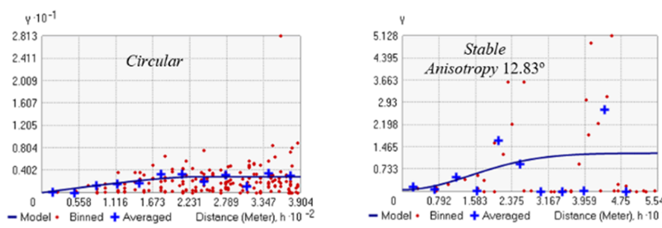

Figure 6. Selected variograms for Site B and Site C

3.3 Determining the Best and Most Appropriate Variogram Model

Based on the variogram analyses, it turned out that the best models were characterized by four important criteria, namely: (1) having the smallest RMSE (Root Mean Square Error); (2) the standard mean is close to zero; (3) having the average standard error is almost similar to the root-mean-squared prediction error; and (4) the root-mean-squared standard prediction error is close to 1.

It is relatively difficult to determine the best model to describe the empirical variogram. The easy way to point out the best model by adjusting the RMSE value of each model (Armanto et al., 2023a). The smallest RMSE indicated the best variogram model (Table 3 and 4). The dataset in Site A was more accurate if the dataset was displayed using the J-Bessel model. The circular model looked reliable for Site B because of showing the smallest RMSE value. Site C seems suitable for the stable anisotropy 12.83° model.

Table 3. The Best Variogram Models for Peat Depths

Parameter	Site A	Site B	Site C
The best model	J-Bessel	Circular	Stable
Sill	1.61	2.55	1.26
Nugget	0.004	0.000	0.064
Range (m)	230	275	40
Minor range (m)	-	-	35.48
Major range (m)	8.1 – 15.0	3.1 – 8.0	0.0 – 3.0
Lag (m)	9.37	22.96	4.58
Coefficient correlation (r)	0.92	0.55	0.68
RMSE	0.56	1.18	0.95
Direction for anisotropy	-	-	12.84

Note : RMSE (Root Mean Square Error)
Source : Geostatistical Analysis Results (2023).

Anisotropy trend reduced the variogram computation on the sample pairs pointing in a particular direction. The anisotropy direction indicated the direction of a longer spatial continuity. Anisotropy in the azimuth direction of +12.83° was shown by the variogram model at Site C, with a dominant range of 63.50 m and a minimum range of 35.48 m. Each model of variogram showed an optimum parameter and will be used for the interpolation. Thus, the estimated dataset can be used for mapping of unvisited peat depths (Table 4).

Table 4. RMSE values of the tested models

Model	Site A	Site B	Site C
Stable	0.74	1.75	0.97
Exponential	0.80	1.46	0.99
Hole Effect	1.37	1.52	0.99
Circular	1.14	1.18	0.98
Gaussian	0.59	1.62	0.97
K-Bessel	0.70	1.61	0.97
Spherical	0.70	1.50	0.97
Rational Quadratic	0.54	1.49	0.97
J-Bessel	0.57	2.44	1.07
Stable + anisotropy 12.83°			0.95

Note : */ The bold values show the smallest RMSE.)
Source : Geostatistical Analysis Results (2023).

3.4 Mapping of Estimated Peat Depths

After the best variogram models had been determined, the peat depths were mapped and displayed in Figure 7. On the map, it can be seen that the shallow peat is figured in light blue, while the deepest peat is determined brown red colors. Site A must be restored because having peat depths of more than 3 m, only Site C can be cultivated for plantation industry. All of these areas have been cultivated for the oil palm plantation industry. This occurred because the government had granted concession permits to the plantation industry before knowing how deep the permissible peatlands were for the whole area.

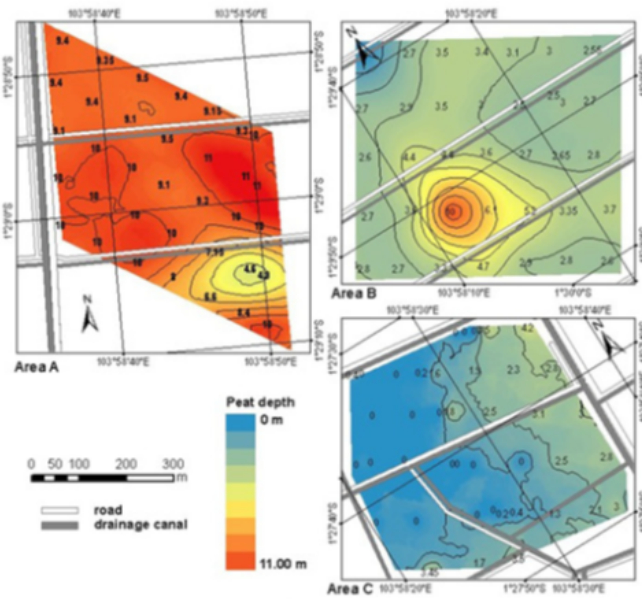

Figure 7. The map of estimated peat depths

3.5 Advantages of Estimated Peat Depths Maps

Maps of estimated peat depths are very useful not only for the Government, industry, but also for the general public. For the Government, maps of peat depths are mainly used to manage peatlands in an integrated manner, for example for granting concession permits. Peatlands (according to the Governmental Regulation nr 71/2014) can be utilized for agriculture and plantations if the peat depths are less than 3 m, or more than 3 m, peatlands have to be conserved or restored. It was explained by other researchers that peatland mapping is very important for agricultural management in a broad sense (Wildayana and Armanto, 2017; Armanto et al., 2023b). For industry, maps of estimated peat depths can be used as main references in managing the integrated plantation and forestry industry. Byg et al. (2023) found in their work that industrial activities on peatlands without mapping will cause serious environmental problems and be difficult to control, this statement was supported by Wildayana and Armanto (2018c,d). For the general public, maps of estimated peat depths are useful for basic references to find out which areas can be managed and which areas must be restored. Wildayana and Armanto (2021) suggested that any activity in fishery should be managed by using maps. For the environment, maps of estimated peat depths can offer quantification of carbon stored in peatlands, to minimize carbon emissions into the atmosphere and to ensure that peatland environmental services function optimally as mentioned and analyzed by Wildayana (2017). Maps of estimated peat depths will be made available to the public to stimulate our awareness and understanding of total peat resources and carbon. Armanto and Wildayana (2023) have provided examples of managing environmental parameters using maps. Peatlands are dominantly degraded by very dynamic causes, namely fires, drainage, land clearing, and illegal logging. The limited data availability of field measurements makes it difficult to map peatlands. Maps of estimated peat depths can only be created if the baseline maps are available, if it is not available, then field measurement data is also not available and maps of estimated peat depths are also hardly made.

4. Conclusion

The spatial variability of peat depths on Site A and Site B showed maximum values at the distances of 271 and 242 m respectively. On Site C, maximum variability was found at a distance of 63 m. Distance of peat depth variability may be interpolated maximum of 271 m (for Site A) and 242 m (for Site B). Peat depths cannot be interpolated if the distances are more than the above distances. For Site C, the estimated peat depth could not be interpolated up to the distance of 63 m. Site A must be conserved because having peat depths of more than 3 m, only Site C can be cultivated for plantation industry. All of these areas have been cultivated for the oil palm plantation industry. This occurred because the government had granted concession permits to the plantation industry before knowing how deep the permissible peatlands were for the whole area.

Acknowledgements

The authors were very grateful for all the help from everyone who cannot be mentioned one by one, especially for the assistance of students during field research and analysis in the laboratory.

REFERENCES

Abijith, D. and S. Saravanan (2021). Assessment of land use and land cover change detection and prediction using remote sensing and CA Markov in the Northern Coastal Districts of Tamil Nadu, India. *Environmental Science and Pollution Research*, **12**(09); 86055–86067. Https://doi.org/10.1007/s11356-021-15782-6

Al-Timimi, Y. (2021). Monitoring desertification in some regions of Iraq using GIS techniques. *Iraqi Journal of Agricultural Sciences*, **53**(3); 620–625. 10.12911/22998993/156056

Armanto, M. E. (2019a). Comparison of chemical properties of peats under different land uses in South Sumatra, Indonesia. *Journal of Ecological Engineering*, **20**(5); 184–192. Https://doi.org/10.12911/22998993/105440

Armanto, M. E. (2019b). 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. Https://doi.org/10.36103/ijas.v2i50.66

Armanto, M. E. (2019c). Soil variability and Sugarcane (Saccharum officinarum L.) biomass along Ultisol toposequences. *Journal of Ecological Engineering*, **20**(7); 196–204. Https://doi.org/10.12911/22998993/109856

Armanto, M. E., M. Adzemi, E. Wildayana, and M. S. Imanudin (2013). Land evaluation for paddy cultivation in the reclaimed tidal lowland in Delta Saleh, South Sumatra, Indonesia. *Journal of Sustainability Science and Management*, **8**(1); 32–42. Http://jssm.umt.edu.my/files/2013/07/4w.pdf

Armanto, M. E., A. Hermawan, M. S. Imanudin, S. E. Wildayana, and A. Triana (2023a). Biomass and soil nutrients turnover affected by different peat vegetation. *Journal of Wetlands Environmental Management*, **11**(1); 31–42. Http://dx.doi.org/10.20527/jwem.v11. i1.292

Armanto, M. E. and E. Wildayana (2022). Accessibility impact to government programs on the household income contribution at the various livelihood sources of farmers. *Agriekonomika Journal*, **11**(1); 62–75. Https://doi.org/10.21107/agriekonomika.v11i1.13191

Armanto, M. E. and E. Wildayana (2023). Predictive mapping for soil pH and phosphate based on Kriging Interpolation. In *International Conference on Sustainable Environment, Agriculture and Tourism (ICOSEAT), Advances in Biological Sciences Research*, volume 26. pages 254–262. Https://doi.org/10.2991/978-94-6463-086-2$_3$3

Armanto, M. E., E. Wildayana, and B. Syakina (2023b). Deciphering the anthropogenic challenges of peat swamp forest degradation to improve awareness and emphasis on restoration in South Sumatra. *Forestry Ideas*, **29**(2); 207–215. Https://forestry-ideas.info/issues/issues$_Index.php?journalFilter = 73$

Armanto, M. E., M. Zuhdi, D. Setiabudidaya, E. W. Ngudiantoro, A. Hermawan, and M. S. Imanudin (2022). Deciphering spatial variability and kriging mapping for soil pH and groundwater levels. *Suboptimal Land Journal*, **11**(2); 187–196. Http://www.jlsuboptimal.unsri.ac.id/index.php/jlso/article/view/577/526

Bhunia, G., P. Shit, and R. Chattopadhyay (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. Https://doi.org/10.1016/j.aasci.2018.06.003

Byg, A., P. Novo, and C. Kyle (2023). Caring for Cinderella - Perceptions and experiences of peatland restoration in Scotland. *People Nature*, **5**(-); 302–312. Https://doi.org/10.1002/pan3.10141

El Falah, S., M. Dakki, and I. Mansouri (2021). Mapping analysis of the wetland loss in Loukkos (Morocco) under agricultural management. *Bulgarian Journal of Agricultural Science*, **27**(1); 186–193. Https://agrojournal.org/27/01-25.pdf

Guth, M., S. Stępień, K. Smędzik-Ambroży, and A. Matuszczak (2022). Is small beautiful? Techinical efficiency and environmental sustainability of small-scale family farms under the conditions of agricultural policy support. *Journal of Rural Studies*, **89**(-); 235–247. Https://doi.org/10.1016/j.jrurstud.2021.11.026

Holidi, M. E. Armanto, N. Damiri, and D. D. A. Putranto (2019). Characteristics of selected peatland uses and soil moistures based on TVDI. *Journal of Ecological Engineering*, **89**(-); 235–247. Https://doi.org/10.12911/22998993/102987

Hu, X., P. Zhang, Q. Zhang, and J. Wang (2021). Improving wetland cover classification using artificial neural networks with ensemble techniques. *GIScience Remote Sensing*, **58**(4); 603–623. Https://doi.org/10.1080/15481603.2021.1932126

Imanudin, M. S., M. E. Armanto, and 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. Https://doi.org/10.1002/ird.2338

Junedi, H., M. E. Armanto, S. M. Bernas, and M. S. Imanudin (2017). Changes to some physical properties due to the conversion of secondary forest of peat into oil palm plantation. *Sriwijaya Journal of Environment*, **2**(3); 76–80. Http://ojs.pps.unsri.ac.id/index.php/ppsunsri/article/view/56

Lázaro-Lobo, A. and G. Ervin (2021). Wetland invasion: a multi-faceted challenge during a time of rapid global change. *Wetland*, **41**(5); 64. Https://doi.org/10.1007/s13157-021-01462-1

Lázaro-Lobo, A., P. Ruiz-Benito, V. Cruz-Alonso, and P. Castro-Díez (2023). Quantifying carbon storage and sequestration by native and non-native forests under contrasting climate types. *Global Change Biology*, **29**(16); 4530–4542. Https://doi.org/10.1111/gcb.16810

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

PMRA (2022). Performance report of peat and mangrove restoration agency [Laporan Kinerja. Badan Restorasi Gambut dan Mangrove. Technical Report -, PMRA (Peat and Mangrove Restoration Agency). Https://brgm.go.id/publikasi/

Syakina, B., R. Nor, and M. Armanto (2024b). Linkages of peatland degradation and rural poverty in development scenarios of peatland restoration. *Geografia-Malaysian Journal of Society and Space*, **20**(1); 85–98. Hhttps://doi.org/10.17576/geo-2024-2001-06

Syakina, B., R. M. Nor, and M. E. Armanto (2024a). Elucidating indigenous farmers' avoidance of deep peatlands for food crop farming in South Sumatra province, Indonesia. *Forestry Ideas*, **30**(1); 3–15. Https://forestry-ideas.info/issues/issues$_Index.php?journalFilter = 746$

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

Vilas-Boas, J., L. Klerkx, and R. Li (2021). Connecting science, policy, and practice in agrifood system transformation: the role of boundary infrastructures in the evolution of Brazilian pig production. *Journal of Rural Studies*, **89**(-); 171–185. Https://Doi.Org/10.1016/J.Jrurstud.2021.11.025

Wildayana, E. (2017). Challenging Constraints of Livelihoods for Farmers in The South Sumatra Peatlands, Indonesia. *Bulgarian Journal of Agricultural Science*, **23**(6); 894–905. Ttps://www.agrojournal.org/23/06-02.pdf

Wildayana, E. and M. E. Armanto (2017). Agriculture phenomena and perspectives of lebak swamp in Jakabaring South Sumatra, Indonesia. *Jurnal Ekonomi dan Studi Pembangunan*, **9**(2); 156–165. Http://journal.um.ac.id/index.php/jesp/article/view/8832

Wildayana, E. and M. E. Armanto (2018). Dynamics of landuse changes and general perception of farmers on South Sumatra Wetlands. *Bulgarian Journal of Agricultural Science*, **24**(2); 180–188. Http://www.agrojournal.org/24/02-02.html

Wildayana, E. and M. E. Armanto (2018b). Formulating popular policies for peat restoration based on livelihoods of local farmers. *Journal of Sustainable Development*, **11**(3); 85–95. Https://doi.org/10.5539/JSD.V11N3P85

Wildayana, E. and M. E. Armanto (2018c). Lebak swamp typology and rice production potency in South Sumatra. Agriekonomika. *Agriekonomika*, **7**(1); 30–36. Https://doi.org/10.21107/agriekonomika.v7i1.2513

Wildayana, E. and M. E. Armanto (2018d). Utilizing non-timber extraction of swamp forests over time for rural livelihoods. *Journal of Sustainable Development*, **11**(2); 52–62. Https://doi.org/10.5539/jsd.v11n2p52

Wildayana, E. and M. E. Armanto (2021). Empowering indigenous farmers with fish farming on South Sumatra Peatlands. *Jurnal HABITAT*, **32**(1); 1–10. Https://Doi.Org/10.21776/Ub.Habitat.2021.032.1.1

Zhang, Y. (2023). Building a bridge between biodiversity and ecosystem multifunctionality. *Global Change Biology*, **29**(16); 4456–4458. Https://doi.org/10.1111/gcb.16729

Zuhdi, M., M. E. Armanto, D. Setiabudidaya, Ngudiantoro, and Sungkono (2019). Exploring peat thickness variability using VLF method. *Journal of Ecological Engineering*, **20**(5); 142–148. Https://doi.org/10.12911/22998993/105361