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Using the kriging method to establish a spatially reliable interpolator for peat depth variability

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ABSTRACT

Peatlands (according to the Governmental Regulation nr 71/2014) can be utilized for agriculture and plantation if the peat depths are less than 3 m or more than 3 m, peatlands have to be conserved or restored. Determining peat depths can be conducted in the fields by intensive surveys which were so expensive, inefficient, and ineffective, therefore it was essential to find our simple alternative methods how to measure peat depths easily. The research aimed to establish a spatially reliable interpolator for peat depth variability by utilizing the kriging method. The research was conducted in Seponjen Village, Kumpeh, Muaro Jambi, Jambi Indonesia. Primary data were processed by applying ArcGIS 10.3 software. The interpolated dataset of peat depths validated their actual dataset and performed an excellent relationship (indicated by a positive correlation coefficient, r = 0.920) and a coefficient of determination (R^2 = 0.847). It indicated that the interpolated dataset could be utilized to make maps by kriging. The very deep peat (Site A) and the deep peat (Site B) showed a tendency for a strong autocorrelation of the data distribution of peat depths. Autocorrelation tended to be anisotropic towards the river on the shallow peat (Site C). A good interpolator of peat depth variability can be generated using the kriging method.

Keywords: good interpolator, Jambi, kriging analysis, peat depths, spatial variability

INTRODUCTION

Peatlands deeper than three meters have to be preserved, according to government regulations; those shallower than three meters could be used for general agricultural purposes and industrial plantations (Armanto, 2019a). The primary issue is that field operating scale maps of the peat depth distribution (scales 1:50,000 and 1:10,000) were still missing (Armanto et al., 2013). It is challenging for peatland users to identify their industrial plantations and field-based agriculture on the 1:250,000 or the available peat national scale maps (Al-Timimi, 2021).

One of the goals stated in the ASEAN Peatland Management Strategy (APMS) is the mapping of all the peatlands by generating peat maps at the operational level (Abijith & Saravanan, 2021). As part of the context of the ASEAN Agreement on Transboundary Haze Pollution, APMS seeks to assist in managing peatlands sustainably and minimizing fires and haze (Armanto et al., 2023b). Regretfully, due to these constraints, which include a lack of ability to track the APMS implementation progress, a lack of a consistent national budget, and a shortage of personnel, technical know-how, and a standardized mapping methodology, the mapping of peatlands is moving slowly, especially for smaller areas (Syakina et al., 2024a; 2024b). Other things impeding the mapping process are diverse definitions of peat and peatlands: One of the main difficulties is coming up with a standard set of peat classes and definitions. Currently, several industrial plantations lack an operationally accepted definition of peatlands (Armanto et al., 2023a). Lack of awareness: Many peatland users, from the government and communities, continue to lack information and awareness about peatland issues (Wildayana & Armanto, 2018d). One of the most important things to help maintain peatlands is to develop and execute sustainable policies and methods for managing peatlands (Wildayana, 2017). Another important thing is to educate the community about the value of preserving the environment (Wildayana & Armanto, 2018a; 2018b).

Difficult access: It is more challenging to perform ground observations in many peatland locations due to their inaccessibility (Wildayana & Armanto, 2018c). Problems with methodology (money and time): The currently popular approach for mapping peatlands is a measurement done on the ground. Peat mapping in the field takes a long time since it is expensive, labor-intensive (Wildayana & Armanto, 2017, 2021), and needs a large amount of peat drilling data. For example, creating maps at scales of 1:50,000 and 1:10,000, respectively, will need around 100 and 2500 persons to conduct ground surveys over an area of 70,000 ha; the survey is expected to take 20 days to complete. Ground-surveying is estimated to cost between \$0.3 and \$0.5 ha^{-1}, or between \$21,000 and \$35,000 for a 70,000-ha region.

One of the easiest and simplest approaches to producing maps with a scale of 1:50,000 and 1:10,000 is to interpolate the available peatland map data at a scale of 1:250,000 (national scale maps, PMRA, 2022). This interpolation can minimize technical difficulties and make mapping work more effective and efficient. Interpolation is theoretically defined as the process of making estimates of datasets on a location without sampling using surveyed actual datasets from observation points (Armanto, 2019b). Sampling points (actual dataset) may be obtained from field surveys, the available peatland map data at a scale of 1:250,000, and field measurements by moving sensors. For example, in smart agriculture, if we have a dataset of information for a certain parameter (e.g. peat depths), and want to create a map for peat depths over all fields (Guth et al., 2022; Bhunia et al., 2018). The dataset unavailability may be due to survey complexity, expensive, expensive, time-consuming or requiring too many sensors (Armanto & Wildayana, 2022; 2023a). Hence, it is very inefficient and ineffective to sample any square centimeter in the field, so it is necessary to use the interpolation method (Holidi et al., 2019).

The spatial interpolation technique consists of deterministic and kriging methods (Zuhdi et al., 2019). The deterministic approach does not encapsulate the spatial structure in the data structure, carried out by applying mathematical equations to estimated values at non-sampled points and conducted by collecting surface and trend analysis techniques (Varone et al., 2021). The kriging method can align the spatial model with the actual dataset so that predicted values can be obtained at not sampled locations (Lázaro-Lobo et al., 2023) and offer users an accurate estimated dataset (El Falah et al., 2021; Armanto et al., 2022). The interpolation technique depends on the fact that there are spatial correlations in the datasets. Tobler's law (1970) states that anything in this world is related to each other, but adjacent points are more related than distant points (Imanudin et al., 2019). Kriging is the most frequently used for interpolation techniques (Negassa et al., 2019). Kriging is generally an approach used to perform spatial interpolation.

The kriging technique is based on spatial models between actual observation points (analyzed by the variogram) to estimate the values of points at not surveyed locations (Hu et al., 2021; He et al., 2023). The kriging method focuses on the distance between actual observation points, describing the spatial structure in the dataset by comparing observation points separated by spatial distance (Zhang, 2023). The goal is to understand the relationship between actual observation points separated by different distances (Jamali et al., 2021). The kriging technique retains the dataset values of the actual observation points on the interpolation map (Zhu et al., 2021). The objective of this research was to establish a spatially reliable interpolator for peat depth variability by utilizing the kriging method.

MATERIALS AND METHODS

Research Locations

Peatlands in the Muaro Jambi District, Indonesia (Kumpeh Sub District, Seponjen Village) served as the research site. The Batanghari River-Air Hitam Laut River largest Peat Hydrological Unit (PHU), which includes the peatlands, was shown in Figure 1. The research area was East of Orang Kayo Hitam Forest Park and Berbak National Park, both of which were conservation areas (PMRA, 2022).

Field Survey, Procedures, Tools and Materials

In this study, we used a GPS (Global Positioning System), compass, ruler, peat drill, peat probe, label, permanent pen, plastic bag, and stationery. Purposively, three research sites, each covering around 30 ha, were identified: Site A, which had a peat depth of 8.10–15.00 m; Site B, which covers 3.10–8.00 m; and Site C, which covers 0.00–3.00 m. Boring on the chosen transect lines allowed for field observations (Table 1). By inserting metal sticks that could be stretched by one meter apiece into the ground until they hit the mineral soil layer, peat depths were recorded in the field using a technique known as manual probing or manual coring. The GPS was then used to record the depths of the sticks as well as their geographic position.

Gathering Information and Analysing It

Using ArcGIS 10.3 and the Geostatistics extension program, the gathered data was processed. The goal of the data analysis was to produce interpolation and map-based displays of part of the data. Quantile-quantile plots, Voronoi maps, and histogram images were used to monitor and analyze data normality. To have data distribution and estimation based on measured sampling point data and model statistics, data interpolation was computed using geostatistical methods. By building many variogram models, model statistics could show automatic relationships between sample data. To find the best variogram model for peat depth, the chosen model will be put to the test. Kriging was used to represent the geostatistical interpolations as peat depth maps. The use of kriging in this research (no other programs) was because kriging could perform interpolation and extrapolation, apart from that, kriging was technically easier and more effective when combined with a GIS program. Stages of interpolation and spatial variability analysis were stated in Figure 2. The ability to spatial interpolate and extrapolate was the novelty of this research, therefore the use of kriging was very relevant to display interpolated and extrapolated datasets.

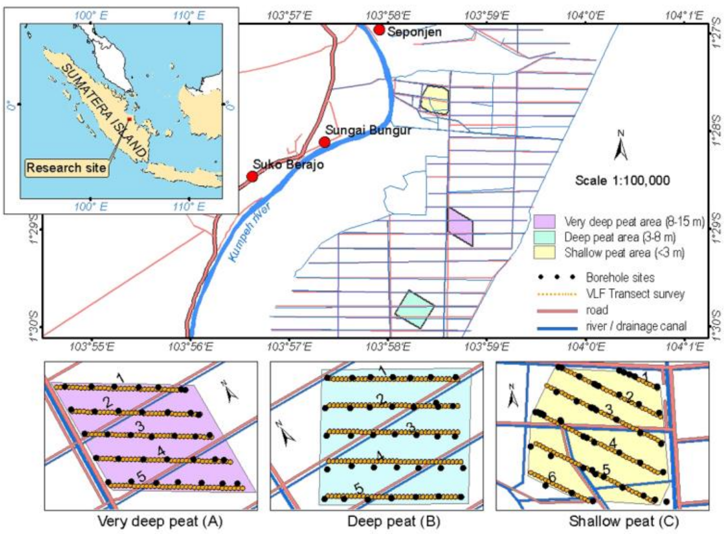

Figure 1. Research site and grid sample arrangement

Table 1. Typical field data descriptions

Filed Descriptions	Site A	Site B	Site C
Row Totals (unit)	5–6	5–6	6–7
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)	8.10–15.00	3.10–8.00	0.00–3.00
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. Field Survey Results in 2023

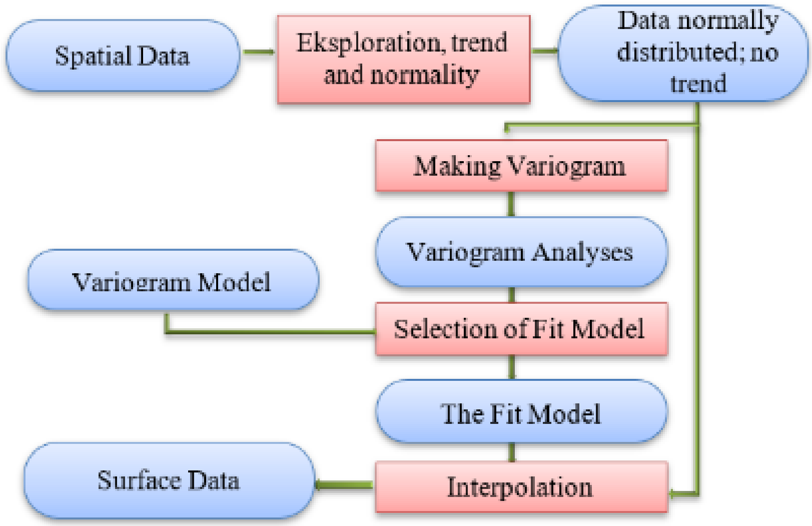

Figure 2. Spatial variability analysis and interpolation steps

RESULTS

Optimal Interpolator Validation by kriging

The kriging validity testing of the estimated dataset using a variogram illustrated that each interpolated point on the prediction grid was obtained from the actual measured points. Thus, for each actual dataset, the standard deviation of the dataset could be calculated. It was concluded that based on a limited actual dataset, the kriging could display the estimated dataset at points that were not surveyed. Dataset estimation did not rule out the actual field dataset and was followed by a minimum standard deviation. Hence, the kriging could be mentioned to be an optimal interpolator because the kriging was developed based on the regionalization theory and was stated as the best linear estimator. Kriging maps could be used to display peat depth distribution maps.

Figure 3 compares the scatter plot between the actual dataset and the estimated dataset. The estimated dataset could be cross-validated with the actual dataset. The validation concluded that the actual dataset and the estimated dataset had almost the same fluctuations with high reliability (demonstrated by the determination coefficient, $R^2 = 0.846$, and a strong correlation coefficient, $r = 0.93$). This indicates that about 84.62% of the estimated dataset was obtained from the actual dataset, and the rest 15.40% was determined by other factors. Based on the estimated dataset, maps could be made. The kriging could not interpolate the dataset globally if the amount of the actual dataset was minimal. It could be only used for the regional estimated dataset and it was not helpful if no dataset was available at all. This means if we only have a limited number of peat depth datasets, then based on that dataset we could make spatial interpolation and extrapolation to produce peat depth maps with high validation. The peat depth maps were very important in determining which peat areas could be cultivated and which areas had to be conserved. It supports the Governmental Regulation No. 71/2014 states that if the peat depth was less than 3 m, then peatlands may be used for agriculture and plantations; if the peat depth was greater than 3 m, then peatlands must be maintained or restored.

Kriging Interpolation

The estimated dataset could be mapped in Figure 4. At Site A (very deep peat, 8.10-15.00 m) there were several areas with peat depths of only 3.50-5.50 m deep, and about 10 m of peat depths were also found at Site B (deep peat, 3.10-8.00 m). Site C (shallow peat) displayed the most diverse peat depths, where about 25% of the Site C was mineral soil with peat depths of less than 0.50 cm, the true peatlands if the peat depth was more than 0.50 cm. At Site C, the interpolated map showed an increasing trend with improving distance to the Southeast because, in the Northwest, the Kumpeh River was found, which forms deep peat hydrology. The direction variation of the peats aligned with the position perpendicular to the Kumpeh River and the peat depths illustrated an anisotropic pattern aligned with the distance from the river.

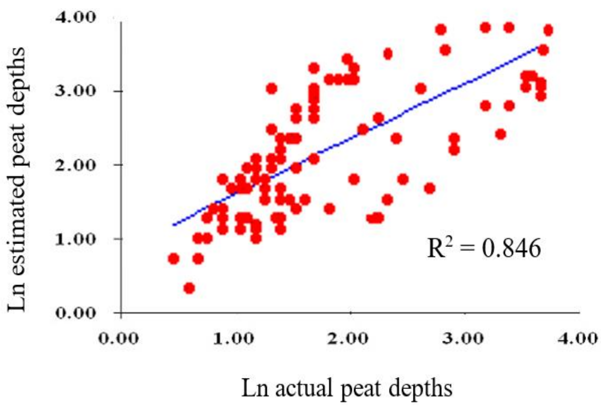

Figure 3. Estimated dataset was validated with the actual dataset (log-transformed data, n = 160)

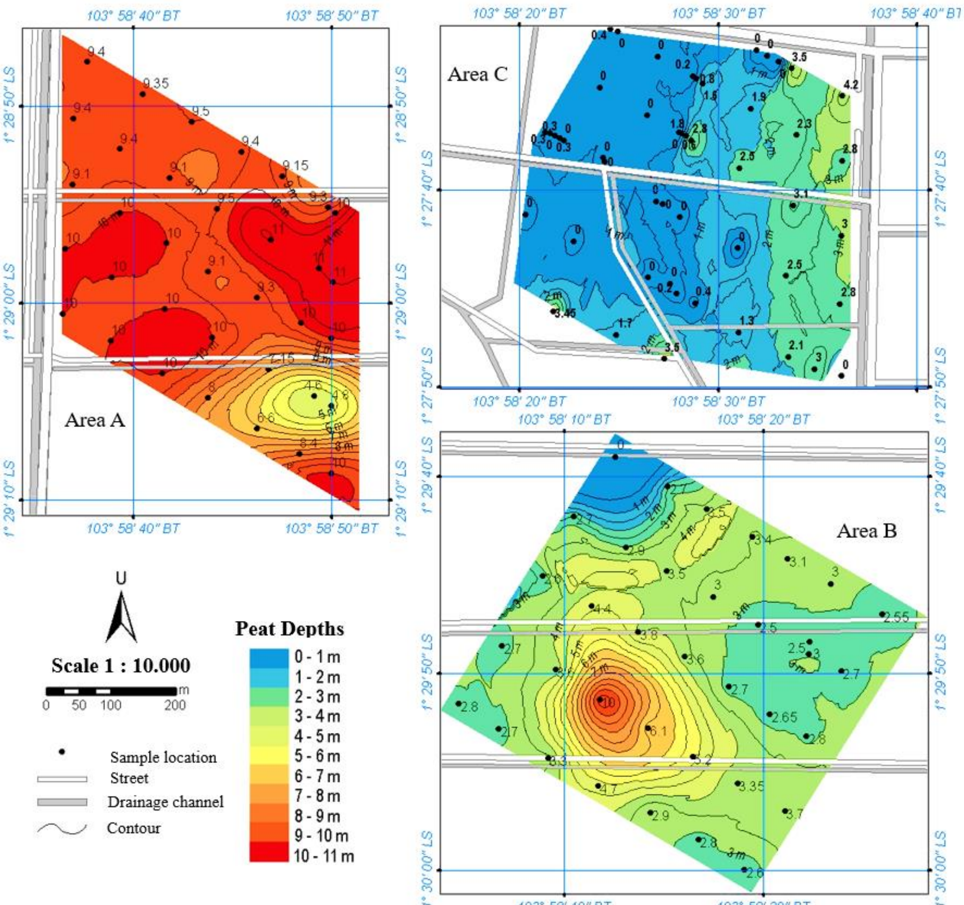

Figure 4. Kriging interpolation map for peat depths

Map of Standard Deviation

A map of the standard deviation of the actual peat depths was presented in Figure 5. The magnitude of the standard deviation depended on the distance of the sampling points. The closer the sampling points were taken, the smaller the standard deviation was calculated. If the sampling points were far from each other, thus the standard deviation would be greater.

The standard deviation of Site A was smaller when compared to Site B and Site C. There was a tendency to conclude that the thinner the peat layer, the greater their standard deviation. The reason was as followed; even though the tools, personnel, and sampling methods were not different, there would be differences in standard deviation due to differences in layer roughness between mineral soils and peatlands.

Long-term pressure from the peat mass above was the reason why the topography of the bottom layer of peat at Sites A and B tends to be smoother (more even). Because Site C was close to the surface and the peat mass was under less strain, the terrain beneath the peat tends to be rocky. This also explains why the contours of the peat depth (Figure 4) in Sites C and B appeared heavier and more irregular than in Site A (Figure 5).

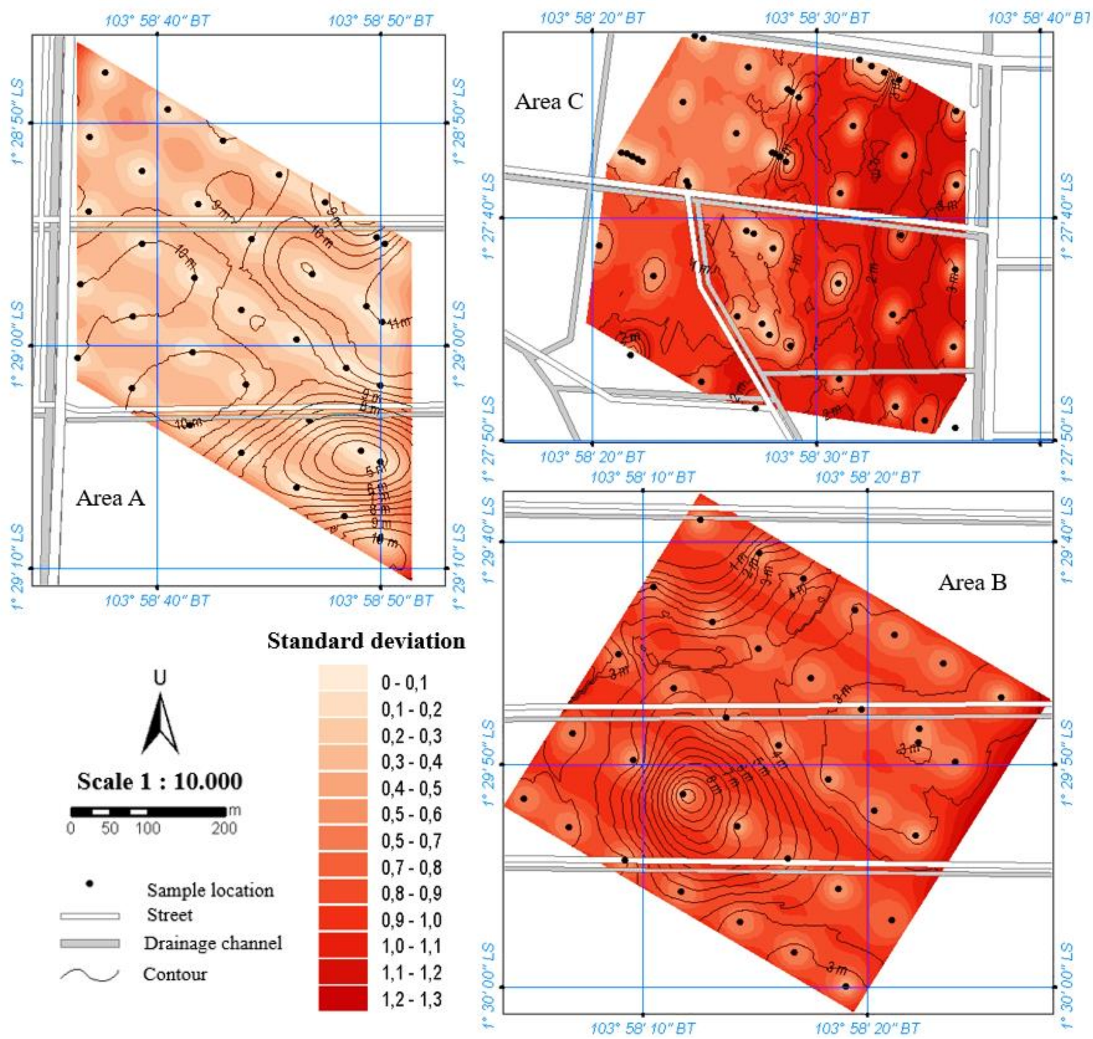

Figure 5. Map of the standard deviation of the actual peat depths

DISCUSSION

Map Benefits of Estimated Peat Depths

The main dynamic factors damaging peatlands include drainage, land clearing, illegal logging, and fires. Mapping peatlands is challenging since field measurement data is limited. This is relevant with other workers (Zuhdi et al., 2019). Only with the availability of a base map can an approximate map of peat depth be produced; if this is not present, then field measurement data is also not available and only a few maps of peat depth estimates are produced. The similar finding was also performed by Abijith & Saravanan (2021).

Estimated peat depth maps are a great resource for the general public as well as industry and government. This was stated by other workers (Junedi et al. 2017). Maps showing the depth of peat are mostly used by the government to manage peatlands holistically, such as when awarding concession permissions. Governmental Regulation No. 71/2014 states that if the peat depth is less than 3 m, then peatlands may be used for agriculture and plantations; if the peat depth is greater than 3 m, then peatlands must be maintained or restored. Peatland mapping is critical for broad agricultural management, as previous studies have explained (Jamali et al., 2021).

Maps with predicted peat depths can serve as a primary source of information for the industry when operating the plantation and forestry industries together. Byg et al. (2023) discovered in their research that industrial operations on peatlands devoid of mapping will result in major environmental issues that are hard to manage; Junedi et al. (2017) and Armanto (2019c) corroborated this claim. Maps showing predicted peat depths are helpful for the general population as a basic reference to determine which areas can be recovered and which ones can be managed. Maps should be used to manage any fishing activity.

Maps with estimated peat depths can be used to quantify the amount of carbon stored in peatlands, reduce carbon emissions into the atmosphere, and guarantee that the environmental services provided by peatlands operate as best they can. The public will have access to maps showing anticipated peat depths to increase knowledge and comprehension of the entire amount of carbon and peat resources. Lázaro-Lobo & Ervin (2021) gave examples of how to use maps to manage environmental aspects.

CONCLUSSION

Lastly, the following conclusions can be summed up based on the evaluation and discussion of the study findings the interpolated dataset of peat depths validated their actual dataset performed an excellent relationship (indicated by a positive correlation coefficient, r = 0.920) and a coefficient of determination (r^2 = 0.847). It indicated that the interpolated dataset can be utilized to make maps by kriging. The very deep peat (the Site A) and the deep peat (the Site B) show a tendency for a strong autocorrelation of the data distribution of peat depths. Autocorrelation tended to be anisotropic towards the river on the shallow peat (the Site C). A good interpolator of peat depth variability can be generated using the kriging method.

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