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Modeling Soil Erodibility Index with NDSI on Various Meso-Landforms in Smallholder Coffee Plantation at Kletek Sub Watershed

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Abstract

The Kletek sub-watershed, located on the southern slopes of Mount Kawi, exhibits volcanic landforms shaped by ongoing volcanic activity. The area's topography is highly varied, with 56.81% of the terrain consisting of slopes greater than 15%, making it prone to erosion. Dominant soil types, Inceptisol and Andisol, show medium to high susceptibility to erosion, as indicated by their soil erodibility index. Mesolandform studies have been instrumental in evaluating soil development and agricultural land monitoring, highlighting the need for effective erosion mitigation. Agriculture in the region focuses on robust coffee cultivation, essential for the local economy. Erosion control measures are crucial, using the soil erodibility method based on the Normalized Difference Soil Index (NDSI) derived from Sentinel 2A imagery. Key factors such as soil texture, organic matter, structure, and permeability determine soil erodibility and influence NDSI values. Statistical analyses, including MAPE (Mean Absolute Percentage Error) and ANOVA tests, confirm the model's accuracy, with MAPE showing 7% reliability. ANOVA further reveals a significant correlation between soil erodibility and landform types, indicating varying levels of erodibility across the sub-watershed. These results emphasize the importance of mitigation erosion control to sustain agricultural productivity, particularly in coffee cultivation.

Keywords: mitigation erosion, NDSI, smallholder coffee plantation, soil erodibility

Introduction

The Kletek sub-watershed is a tributary area of the main river that crosses the Brantas watershed and flows in the South Slope area of Gunung Kawi. The sub-watershed area is part of the watershed area, which is divided based on the contour lines of the highest elevations surrounding the tributary streams (Sajadi et al., 2022). The Kletek Sub-watershed area is on the southern slope of Mount Kawi and has various landform types because this area is a volcanic area due to the volcanic activity of Mount Kawi-Butak. Landform types consist of shape patterns and terrain that show particular variations in the size, scale, and shape of geomorphic features (MacMillan & Shary, 2009; Mokarram & Sathyamoorthy, 2018). The various characteristics of landforms in the southern part of Mount Kawi can be classified up to the size of the mesolandform, namely <1000 Ha, as an effort to monitor the land. The classification of meso-relief as mesolandform involves identifying and categorizing landforms based on their geometric and physical properties (Borisevich, 2016).

Land characteristics in the Kletek sub-watershed have diverse's topography, and 56.81% is dominated by rather steep to steep slopes (>15%), and the majority of farmers there cultivate robusta coffee plants based on people's coffee plantations. Because the land conditions in the Kletek sub-watershed are diverse and there is management of annual crops (I. Meya et al., 2020), erosion mitigation efforts are needed through soil sensitivity (Fiantis et al., 2019; Toohey et al., 2018). The unique composition of volcanic soils contributes to their fertility but also necessitates specific management practices to prevent erosion, especially on sloped terrains where coffee is often cultivated (Ricci et al., 2020; Santoso et al., 2019).

The general study used to analyze is the erodibility value of soil with the equation (Wischmeier & Smith, 1978) i.e. (100 K = 1.292 [2.1$M^{1.14}$ (10^{-4}) (12-a) + 3.25 (b-2) + 2.5 (c-3)]), where K = soil erodibility; M = (% silt + % very fine sand) × (100 - % clay); a = Percentage of organic matter (% C- organic × 1.724); b = Soil structure class; c = Soil permeability class code. Soils with high clay content tend to have lower erodibility due to their cohesive properties, while sandy soils are more susceptible to erosion (Ibeje, 2016). Higher levels of organic matter improve soil structure and increase water retention, thereby reducing erodibility (Karlen & Cambardella, 2020; Seitz et al., 2019). While the loss of organic matter due to land-use changes can increase soil erodibility (Arunrat et al., 2020; Ramesh et al., 2019). Conservation tillage can reduce soil disturbance and enhance organic matter, leading to lower erodibility (Borrelli et al., 2017; Mohammed et al., 2020). Soil erodibility refers to the susceptibility of the soil to the release and transport of erosion, which reflects the strength of the soil's resistance to erosion (Sholikah et al., 2024; Sholikah et al., 2024; Zhu et al., 2022). Understanding soil erodibility is essential for predicting erosion rates and implementing effective soil conservation strategies (Bonetti et al., 2019; Fokeng et al., 2020).

Mitigation erosion can be supports the United Nation Sustainable Development Goals (SDGs) is through mitigating climate change and land use change, which significantly impact agricultural productivity and ecosystem stability. The global dynamics of soil erosion is critical for decision-making to achieve the SDGs program, as it enables forecasting of erosion trends and implementation of effective soil conservation (Borrelli et al., 2020). These practices are critical for maintaining agricultural productivity and ensuring food security, which directly aligns with SDG 2 (Zero Hunger). Furthermore, the integration of agroecological practices, which promote sustainable land use and soil conservation, is essential for smallholder farmers to effectively combat soil erosion (Tibasiima et al., 2022). The application of soil conservation services (SCS) is another important aspect of erosion mitigation that supports the SDGs. SCS plays an important role in improving soil fertility, enhancing water quality and increasing carbon sequestration, which collectively contribute to climate resilience (Singh et al., 2024). The positive correlation between SCS and SDG 15 (Life on Land) suggests that effective soil management practices can lead to significant improvements in soil health and biodiversity (Yin et al., 2022). The use of innovative technologies to monitor soil erosion dynamics informs policy and prioritizes erosion mitigation areas (G. Chen et al., 2024) will maintain water sustainability supporting SDG 6 (Clean Water and Sanitation).

As technology develops, satellites are used to take satellite imagery, which can process data spatially to analyze objects or phenomena on the Earth's surface (Dziob et al., 2020; Fu et al., 2020). One of the uses of remote sensing is the use of NDSI to examine the spectral condition of the land (Sholikah et al., 2024). The research gap based on previous research is that there is still no integration between soil erodibility index modeling using spatial data in the form of NDSI on smallholder coffee plantations based on the condition of land characteristics in the form of mesolandform. NDSI is a form of spectral transformation that normalizes the ground cover factor through a combination of bands in aerial photos, namely near-infrared and green. NDSI is capable of spectral analysis of soil with dense vegetation cover. The NDSI formula developed is NDSI=(B8-B3)/(B8+B3), where B8 is near-infrared, and B3 is green (Deng et al., 2015). Utilization of NDSI can be used to estimate the amount of erosion. NDSI has been frequently used to estimate soil erosion as well as to evaluate soil erosion status and assess soil properties (Xu et al., 2019).

This research aims to assess soil erodibility within the Kletek Sub-watershed by utilizing the Normalized Difference Soil Index (NDSI) across various landforms, focusing on mesolandform plots as distinct unit areas. The NDSI, an index derived from remote sensing data, has proven to be a reliable tool for identifying soil properties linked to erodibility, offering a quantifiable method for evaluating soil susceptibility to erosion. By examining the relationship between NDSI values and erodibility across different landforms, this study intends to provide critical insights into the spatial variability of soil vulnerability, which is essential for sustainable land management practices. The results of this analysis are expected to offer valuable information for the management of local coffee plantations, as soil erosion can significantly impact agricultural productivity. Moreover, the findings will contribute to improving watershed management strategies, ensuring the long-term stability of agricultural landscapes in the region.

Materials and Methods

Study area location

The research was conducted in the Kletek sub-watershed, which includes the sub-districts, namely Sumberpucung sub- district, Wonosari sub-district, Ngajum sub-district, and Kromengan sub-district, which are part of Malang Regency and Selorejo sub-district in Blitar Regency (Figure 1). The Kletek Sub-watershed area has many coffee plantations, especially those managed by local communities.

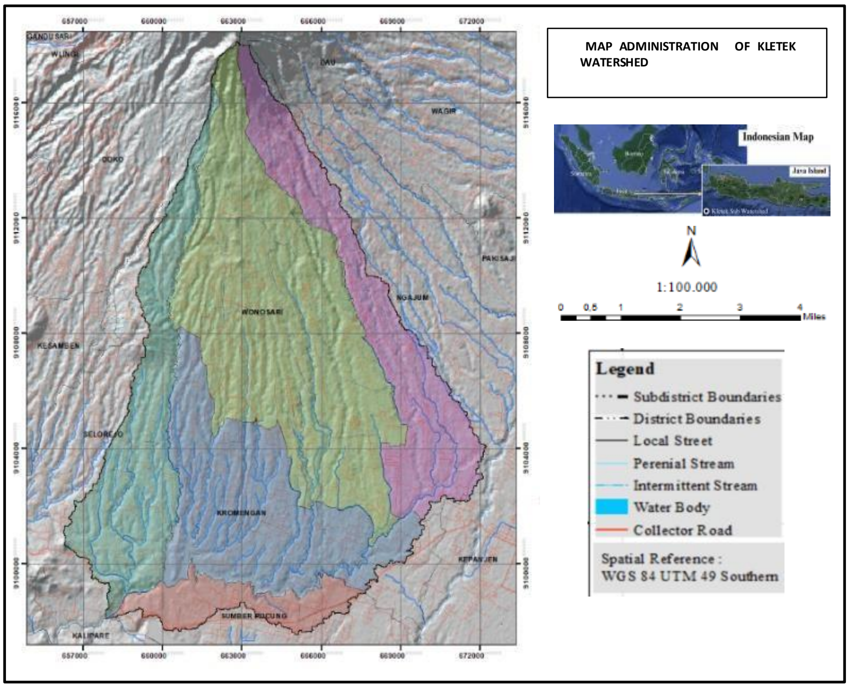


Figure 1. Research location in Kletek sub-watershed

Field Experimental Design

The research was carried out using a survey method, which was divided into several stages, including data preparation, image data processing, and data analysis. Mesolandform distribution is created as a land unit created with the limiting factors of Vegetation, Slope, Curvature, and TPI (Figure 2.). Determining observation points used stratified random sampling because there were differences in mesolandform, age, and phase of coffee plants, accessibility to land, and coffee land area of more than 1 Ha. Stratified random sampling is a sampling method by dividing the population into subgroups and determining points based on characteristics (Berndt, 2020). Stratified random sampling involves dividing the entire population into homogeneous groups called strata (singular or stratum) (Zhao et al., 2019).

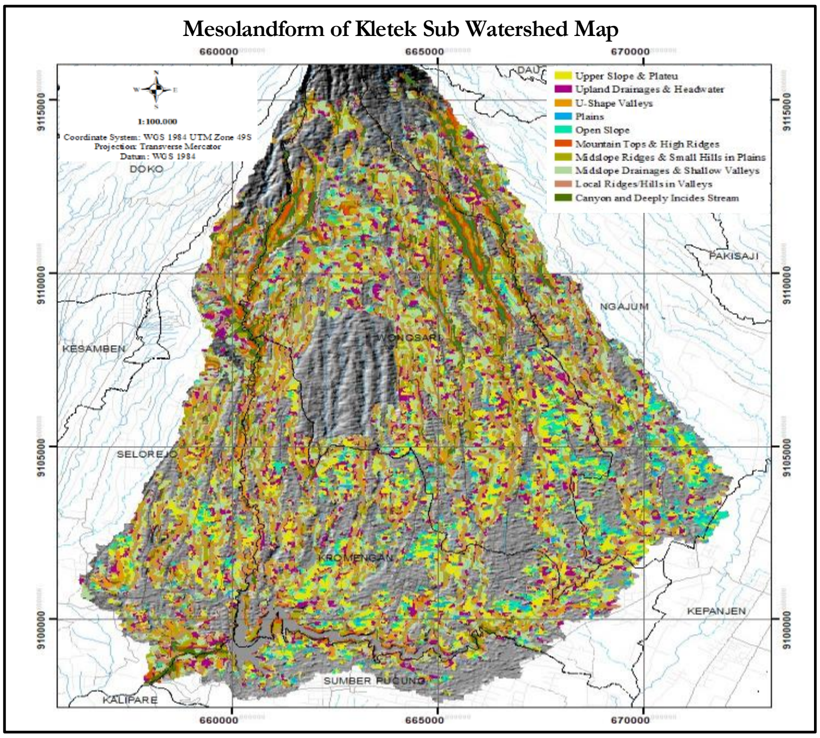


Figure 2. Mesolandform Map

Radiometric correction

Before processing spatial data, pre-processing is carried out to correct the aerial images used with semi-automatic classification in QGIS 3.24. To produce "smooth" spectral that accurately record ground conditions and minimize temporal noise due to sensor-to-sensor differences in atmospheric correction, display geometry, or bandpass approaches (Claverie et al., 2018).

Remote sensing and geographic information system analysis

The basic data used in this research is using Sentinel-2A image photos by transforming the bands into ground spectral. The soil index modeling used is the Normalized Difference Soil Index (NDSI). The NDSI formula developed is NDSI=(B8-B3)/(B8+B3), where B8 is near-infrared, and B3 is green. The results of the band transformation with the equation gave satisfactory results with a maximum NDSI value of 0.43 and a minimum of -0.14, which shows that soil spectral can be obtained (Vibhute et al., 2017). Spatial data processing uses QGIS 3.34 to calculate spectral values according to mathematical equations from band combinations for transformation into index form (Michael et al., 2024). The creation of erodibility maps can be done using GIS in visualizing soil characteristics that affect erosion in terms of soil conditions (Barbosa et al., 2024).

Statistical analysis

Processing Statistics using Microsoft Excel 2016 for analysis using correlation and regression methods to determine the relationship between erodibility values and mesolandform distribution. There are 10 types of mesolandform found in the Kletek sub-watershed, which are considered as treatments and 3 replications were taken for each type of mesolandform. Then a validation test was carried out with MAPE values to assess the NDSI created. The MAPE value <10% means highly accurate forecasting; 10-20% means good forecasting; 20-50% means reasonable forecasting; and >50% inaccurate forecasting (Chicco et al., 2021).

Result and Discussion

Erodibility in the Kletek Sub-watershed

Soil type is a determining factor in the erodibility value because it is a characteristic of soil properties (Raj et al., 2023; Shafii et al., 2023). Soil classification systems categorize soils based on their physical and chemical properties, such as texture, structure, organic matter content, and moisture retention capacity. These properties significantly affect how easily soil particles can be detached and transported by erosive forces such as water and wind. The classification of soils into categories based on their erodibility can help predict erosion rates and inform management practices. Soils with high clay content typically exhibit greater cohesion and resistance to erosion compared to sandy soils, which are more prone to being washed or blown away (Fox et al., 2022; Zhang et al., 2018). Soil classification is essential for developing targeted erosion control measures (Borrelli et al., 2021).

The level of erodibility of a type of soil is influenced by various soil parameters that are conditioned during the formation and development of the soil (Delgado et al., 2023). Erodibility data was obtained from sub-order classification soil type maps whose values were identified from the literature. The types of soil in the Kletek sub-watershed have the Inceptisols and Andisols soil orders. The following is the erodibility value based on several studies conducted in Table 1 and Figure 3.

Table 1. Erodibility values for soil order types

Land Sub Order	Erodibility Value	Source
Andic Eutrudepts	0.22	(Pambudi & Moersidik, 2019)
Aquic Eutrudepts	0.10	(Olumuyiwa, 2019)
Typic Epiaquepts	0.16	(Pambudi & Moersidik, 2019)
Typic Eutrudepts	0.24	(Pambudi & Moersidik, 2019)
Typic Happudands	0.21	(Pambudi & Moersidik, 2019)
Vitric Hapludands	0.15	(Wondrade, 2023)

Digital Soil Mapping at Kletek Sub-Watershed

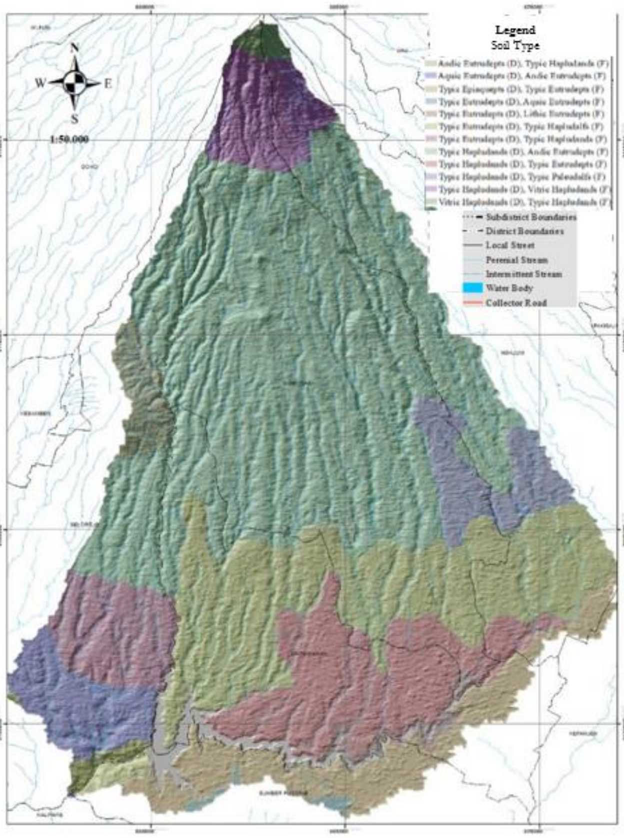


Figure 3. Kletek sub-watershed soil map unit

Modeling NDSI to Predict Erodibility

Soil index values using NDSI (Normalized Difference Soil Index) were obtained by converting NIR (Near InfraRed) and green digital data from Sentinel 2A imagery. NDSI can represent soil erosion values and can be used to analyze the occurrence of soil reflectance values (Xu et al., 2019). NDSI can be used to detect soil index values on land with dense vegetation, open ground, and under the forest canopy, but the index value will be smaller in areas that have dense vegetation (Lv & Pomeroy, 2019; Madasa et al., 2021). This has something to do with erodibility, when the soil is in dense vegetation it will have a low erodibility value. The range of different NDSI values is influenced by the results of the transformation of the spectral values by the soil surface conditions on each land (Van der Schaaf & van Hateren, 1996; Zhou et al., 2022). The following is a display of the NDSI shown in Figure 4.

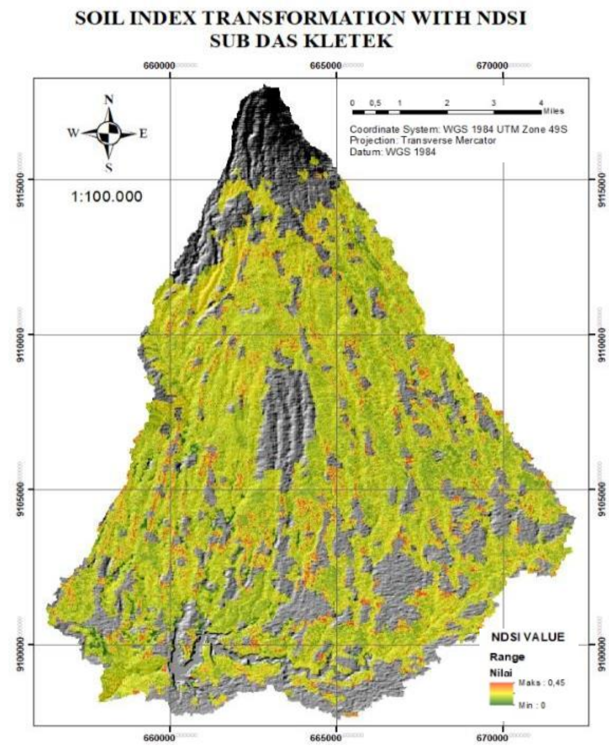
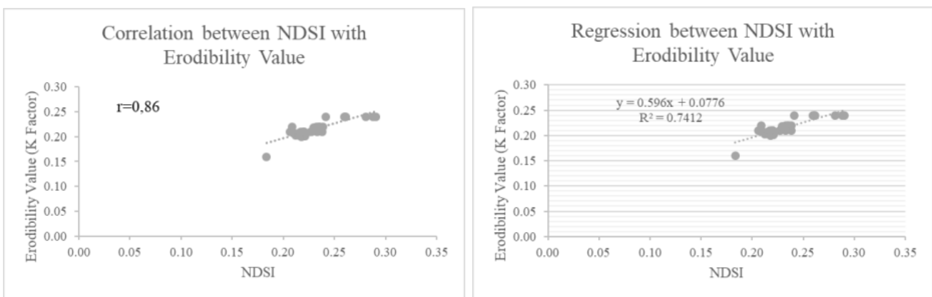


Figure 4. Transformation soil index use NDSI

To form the model equation, a correlation test was carried out and a regression equation was created to determine the factors that influence the erodibility value. NDSI has a close relationship with soil erodibility and is directly proportional, this is shown by the correlation coefficient (r) of 0.86. The soil is classified as good, as evidenced by the coefficient of determination (R^2) of 0.74, where the role of NDSI in predicting erodibility is 74%. The equation used to obtain the distribution of soil erodibility is $\hat{Y}=(0.596\times NDSI) + 0.0776$, where 0.596 indicates the influence of NDSI in predicting soil erodibility, while 0.0776 indicates the value of the erodibility distribution when NDSI is 0. The influence of NDSI in predicting soil erodibility is presented in Figure. 5.



(a) (b)

Figure 5. Relationship between NDSI and soil erodibility (a=correlation; b=regression)

NDSI or Normalized Difference Soil Index is an index used to identify areas where soil is the dominant background material or to represent differences in reflectance values in soil areas (Viscarra Rossel et al., 2022). NDSI images have a range of values between -1 and 1. NDSI values close to -1 indicate surface cover by water, NDSI values close to 0 indicate soil cover by plants, NDSI values closer to 1 indicate a higher level of soil openness, so the greater the NDSI value means the lower the soil cover (Demattê et al., 2018). The correlation test between NDSI index and erodibility value was conducted using the K-USLE method.

NDSI in predicting soil erodibility in each type of landform has a high level of accuracy. This is proven by the results of the validation test using the paired t-test that the calculated t value <t table ($-4.21 < 2.04$), this value shows that the NDSI soil erodibility value used with the soil erodibility data value and soil type does not have a significant difference. Based on the results of the model feasibility analysis using the MAPE method, a value of 7% was obtained, which shows that this model is classified as highly accurate forecasting.

Erodibility value in Mesolandform

The various types of mesolandforms found in the Kletek Sub-watershed have special characteristics or characteristics for each type. The Canyon and Deeply Incides Stream has the shape of a deep valley and is associated with a river flow, steep walls (slope >30%), slope direction parallel to the river and *plan curvature* conditions in the form of *convergent* (concave), *divergent* (convex), and *level* (straight). The character and elements of the landform will influence its erodibility value. The shape of the land will influence the thickness of the soil solum formed during the soil genesis process, usually on sloping land the soil solum is thinner or shallower than on flat land (L. Chen et al., 2023; Fazlollahi et al., 2016). There is a strong relationship between land use, soil properties and landform components, and erodibility (Vanini & Amini, 2017).

In the distribution of erodibility values in the Kletek sub-watershed, one of the soil types found was the Typic Eutrudepts sub-order soil type, which is located on the upper slopes to the middle slopes and has a clayey texture with low clay content. Coarse textured soils (high percentage of very fine sand and dust) have higher erodibility values than finer textured soils (Li et al., 2023). The cohesion ability of sand particles is low and difficult to compact so that the bearing capacity is not met. This makes it easy for the erodibility value of this soil type to be categorized as medium. Then Aquic Eutrudepts is located on the lower slopes, dominated by mesolandform types which have slopes between 8-15% and convergent curvature forms such as Midslope Drainage and Shallow Valley (8-15%), Upland Drainage and Headwater (8-15%), plain (<8%), and open slope (<15%) have a low erodibility value, namely 0.16. The low erodibility value is caused by the nature of Aquic Eutrudepts which have a clayey texture and are quite light (Olumuyiwa, 2019). The higher clay content on concave slopes is convergent or a reservoir for the flow of soil material, and together with low slope slopes generally promotes the deposition of eroded soil particles (Ogban et al., 2022).

Conclusion

The analysis of soil erodibility using the Normalized Difference Soil Index (NDSI) across various landforms has demonstrated the method's effectiveness in identifying erodibility values. The K-factor approach, based on soil type, was successfully utilized for this purpose. The derived soil erodibility model, formulated as $\hat{Y} = (0.596 \times NDSI) + 0.0776$, provides a reliable tool for assessing soil vulnerability. The accuracy of the NDSI-based forecasting model is confirmed by a calculated t value of -4.21, which is less than the critical t value of 2.04, indicating significant statistical validity. Additionally, the application of the Mean Absolute Percentage Error (MAPE) method resulted in a highly reliable value of 7%, further validating the model's precision. These findings underscore the potential of NDSI as a highly accurate method for forecasting soil erodibility, which is critical for effective erosion management and sustainable land use practices.

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