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ARTICLE

Enhancing Traceability and Sustainability in Smallholder Oil Palm Plantations Through Gap Analysis and Machine Learning

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Abstract

The European Union Deforestation Regulation (EUDR) requires all products entering the EU market to comply with deforestation-free requirements by using a traceability system that tracks products back to their plantation of origin. However, ensuring traceability for fresh fruit bunches (FFB) supplied by independent smallholders (ISHs) presents challenges. These challenges arise from the segregation of internal and external FFB trucks at weighbridges, where only the FFB weight is recorded, without identifying its source. To address this, a new segregation system was introduced, based on the level of sustainability implementation in plantations. This study aimed to develop an FFB traceability system using a bottom-up approach, starting from ISH' plantations and extending to crude palm oil (CPO) production at the palm oil mill (POM). The initial phase involved evaluating the sustainability levels of 318 palm oil plantations owned by ISHs in Rokan Hulu Regency. The research defined sustainability variables and parameters, then conducted a sustainability evaluation using a novel method combining gap analysis and machine learning-based cluster analysis. The cluster analysis classified the 318 plantations into three categories: 22 trusted plantations, 116 potential plantations, and 180 low-potential plantations. 102 plantations out of 138 trusted plantations and potential plantations succeeded in obtaining RSPO certificates. FFB transportation from 102 ISH plantations and legally compliant company-owned plantations will be segregated from FFB undocumented plantations transportation at weighbridges to produce traceable high-quality CPO and untraceable standard-quality CPO.

Keywords: Deforestation, Independent smallholder, Sustainability, Traceability

1. Introduction

The Roundtable Sustainable Palm Oil (RSPO) certification is a requirement for planters and industrial supply chain participants to export crude palm oil (CPO) derivative products to the EU. However, the RSPO's PalmTrace platform cannot guarantee full traceability of palm oil back to independent smallholders' (ISHs') plantations. While PalmTrace tracks fresh fruit bunches (FFB) from certified plantations, it does not cover FFB sourced from independent smallholders. Consequently, the RSPO can ensure the sustainability of CPO production but cannot fully address deforestation-related issues in the supply chain (Goggin & Murphy, 2018; Purnomo et al., 2019).

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Deforestation caused by the expansion of palm oil plantations and other agricultural commodities intensifies climate change. In response, the European Union Parliament approved the European Union Deforestation Regulation (EUDR) to close gaps in sustainability regulations for agricultural commodities (Berning & Sotirov, 2023). Under the EUDR, palm oil suppliers must demonstrate that their CPO is derived from a deforestation-free FFB supply chain. This involves verifying the legality of plantations through accurate location data, maps, and ownership documentation.

EUDR has significant implications for independent smallholders, who play a critical role in supplying FFB to Indonesia's palm oil agroindustry. According to Erman (2017), Indonesian ISHs own 6.72 million hectares of oil palm plantations, accounting for 41 % of the total plantation area, and are key FFB suppliers. Palm oil mills (POMs) rely on these farmers for 40–60 % of their FFB supply. Large-capacity POMs classify trucks from ISHs as external FFB, while company-owned trucks are identified as internal FFB. At weighbridges, officers record only the weight of external FFB, without identifying its origin. This lack of traceability creates challenges for POMs in identifying the source of external FFB, as it often passes through multiple intermediaries before arriving at the mill. Unidentified plantations are a significant barrier to developing a traceability system for ISH plantations. Ensuring compliance with the EUDR is particularly difficult because much of the FFB supplied to POMs comes from undocumented ISHs and large, illegal plantations (Astuti et al., 2022). Further complicating the situation, many ISHs lack ownership documents or permits, making it difficult to formally record their land. This documentation gap contributes to conflicts between farmers and the government, impeding the sustainability of ISH plantations (Hutabarat, 2017). Moreover, the widespread practice of burning land to establish or expand plantations (Naylor et al., 2019) exacerbates deforestation and undermines environmental sustainability.

The RSPO and the EUDR have highlighted the importance of addressing sustainability concerns in the palm oil industry. As a result, changes in regulations and markets in developed countries will continue to exert pressure on the industry. To address this situation, traceability systems should not focus solely on data regarding the legality of palm oil plantations. Instead, a more comprehensive traceability system should examine data from sustainability variables in the economic, environmental, and social dimensions. By providing comprehensive data of sustainability of independent smallholder plantations, a strong and sustainable supply chain can be built that is capable of adapting to changes in export destination countries.

The European Forest Institute (EFI) designed a Terpercaya Platform capable of tracing ISH plantations using a top-down approach by identifying POM IDs, Supplier IDs, STDB, and Plantation IDs (European Forest Institute (EFI), 2022). In addition to plantation identification, it is necessary to conduct data analysis on ISH plantations. The evaluation aims to distinguish legal plantations implementing sustainability practices from undocumented plantations with low levels of sustainability implementation.

Data analysis is a highly effective means of evaluating enhancements to business models, decision-making processes, and even product offerings (Braschler et al., 2019). However, the task of assessing the level of implementation of sustainability in oil palm plantations through data analysis is a complex undertaking. The data regarding sustainability implementation in oil palm plantations encompasses numerous attributes and must reflect three dimensions of sustainability, namely economic, social, and environmental. Researchers have developed various methods to analyze this data, such as the multi-dimensional scaling method developed by (Saragih et al., (2020). The research conducted by Safriyana et al. (2020) employs a spatial intelligent decision support system. The field of biodiversity, as outlined by Scott et al. (1993) employs a gap analysis approach to illustrate biodiversity in areas that are intensively managed.

Machine learning (ML) automates conventional data analysis methods, forming a core aspect of data science and artificial intelligence (AI) (Jordan & Mitchell, 2015). By utilizing ML, computer systems can enhance their capabilities through experience. Researchers have created supervised ML for prediction and classification, as well as unsupervised ML for clustering. ML has become a preferred method for many researchers studying production factors in oil palm plantations. Several studies on oil palm plantations have leveraged ML, such as predicting the number of harvests by classifying the anthesis stage of oil palm female flowers (Yousefi et al., 2020); developing a palm harvest grading system based on palm fruit texture using machine learning and deep learning (Alfatni, 2014; Alfatni et al., 2013), based on color features (Septiarini et al., 2020), identifying maturity and predicting FFB harvest time (Sinambela et al., 2020) designing a *smart crane grabber* (Harsawardana et al., 2020).

The integration of machine learning with other advanced technologies in research on palm oil plantations has led to the automation of complex tasks such as tree identification, disease identification, and mapping. Researchers have utilized data from drones and machine learning to detect and count the number of trees: (Cenggoro et al., 2019; Li, 2017; Liu, 2021; Mubin et al., 2019; Zhang & Sakurai, 2020; Zortea et al., 2018); as well as map palm oil plantation areas: (Agustin, 2020; Bonet, 2020; Dong, 2020; Puttinaovarat, 2019; Shaharum et al., 2019; Shaharum et al., 2020).

Moreover, researchers have successfully used machine learning to detect Genoderma, a disease that affects palm trees, by obtaining features through remote sensing (Grinn-Gofroń, 2021; Hashim, 2018; Hashim et al., 2021; Husin, 2020; Kresnawaty, 2020; Yarak, 2021) and (Santoso, 2017). This approach has been found to be more effective and efficient than traditional laboratory test methods and manual methods, resulting in significant reductions in resources and costs (Tee, 2021).

To address economic problems, research that concentrates solely on production factors has been conducted. From a sustainability standpoint, the use of AI in palm oil plantations should extend beyond the economic dimension to encompass social and environmental aspects as well. However, the integration of AI in the context of sustainability is a rare occurrence in agricultural domains, as the value of data work is often underestimated in various socio-technical settings (Sambasivan et al., 2021). The urgent need to tackle climate change has prompted us to utilize AI in addressing sustainability challenges within the agricultural sector.

The study of sustainability implementation in ISH plantations using machine learning involves high-stakes AI work, including its application to more complex domains like social and environmental issues (Sambasivan et al., 2021). It is essential to exercise caution and ensure data quality in high-stakes AI applications. Hence, adopting a data-centric approach is a critical task in building machine-learning models. In the perspective of data science and AI, cluster analysis is a method of big data analysis. Traditional data processing methods tend to be slow and unproductive. On the other hand, big data can be efficiently and rapidly processed, analyzed, and contrasted (Wen et al., 2023).

The objective of this research is to classify ISH plantations based on their legality and level of sustainability implementation using a data-centric approach. The evaluation of sustainability implementation levels was conducted using the gap analysis method, while the ISH plantations were grouped using the machine learning-based cluster analysis method. This method produced three distinct categories of plantations: trusted plantations with a high level of sustainability implementation, potential plantations with a medium level of sustainability implementation, and low-potential plantations with a low level of sustainability implementation, as outlined by Falgenti & Hambali (2022).

2. Material and method

This research is comprised of three distinct phases. The first phase involves identifying sustainability variables and parameters in each dimension by conducting observations and focus group discussions with Indonesian Palm Oil Farmers Union (SPKS) administrators. The second phase entails conducting a gap analysis to assess the implementation of sustainability in independent smallholder palm oil plantations. During this stage, the data for each variable is compared with the relevant parameters. If the data corresponds to the expected value of the parameter, then the variable being assessed is equal to 1; if it does not match, then the variable being assessed is equal to 0. Afterward, the gap in each dimension is calculated, which indicates the extent to which sustainability has been implemented in palm oil plantations. The larger the gap, the lower the level of sustainability implementation. The third phase involves building a model of the sustainability of independent palm oil plantations using machine learning clustering techniques and k-means algorithm. The k-means algorithm is applied after determining the optimal number of clusters using the elbow technique. This algorithm groups plantations based on the results of the gap analysis, allowing for an evaluation of the level of plantation sustainability. The three research stages are depicted in Fig. 1.

2.1. Data

The data regarding the implementation of sustainability in independent smallholder plantations was obtained from a diagnostic analysis survey carried out by the SPKS in Tambusai Sub-district, Rokan Hulu Regency, Riau Province. The survey was conducted in preparation for obtaining an RSPO certificate, and the data collected consisted of 250 farmers' data and 320 plantation data (Uwin, 2016). In 2022, 102 out of 320 independent smallholder plantations successfully obtained RSPO certification.

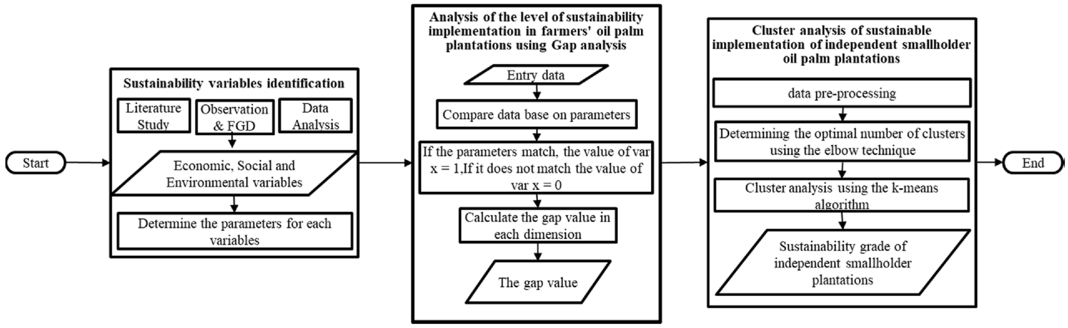


Fig. 1. Research stages.

Through FGD with SPKS administrators, 15 sustainability variables were identified and verified, comprising five variables each in the economic, social, and environmental dimensions. Five variables were selected from each of the three dimensions, and these are listed in Table 1.

The implementation of plantation sustainability was evaluated in palm oil plantations under the guidance of the SPKS in Tambusai District, Rokan Hulu Regency, Riau Province on 2–16 November 2023.

2.2. Data processing methods

2.2.1. Gap analysis

Gap analysis is a formal method that involves comparing expectations of a particular situation with actual reality. This technique has been employed in various research studies to assess the success and failure of different systems. For instance (Scott et al., 1993), utilized gap analysis to evaluate biodiversity in managed areas. Similarly (Hawari & Heeks, 2010), used the design-reality gap model to investigate the success and failure of information systems in the context of fit and misfit. The basis for developing this model was derived from earlier research conducted by (Leavitt, 1965; Venkatraman, 1989). In the present study, gap analysis is utilized to assess the expectations of sustainability implementation in comparison to the actual reality in 320 independent smallholder gardens located in Tambusai sub-district, Rokan Hulu district, and Riau Province. The analysis of the gap between expectations and reality is depicted in Fig. 2.

Table 1. Sustainability variables in oil palm plantations.

No	Dimension	Variables
1	Economic	Plantation area (E1) FFB buyer (E2) Truck ownership (E3) Palm oil seeds (E4) SKT ownership (E5)
2	Social	Farmer education (S1) Social security membership (S2) Number of family (S3) Distance to nearest hospital (S4) Availability of sanitation facilities at home (S5)
3	Environmental	Nutrient deficiency (L1) Land clearing method (L2) Palm tree disc (L3) Status of plantation before palm oil planting (L4) Distance from house to plantation (L5)

2.2.2. Cluster analysis

Cluster analysis is a well-established method for solving complex problems by grouping data. This method has been widely utilized in both computer science and statistics. It operates by creating groups of numerical data points that exhibit a high degree of similarity when compared to data points in other groups. Cluster analysis is a natural way to group datasets and is particularly useful for unlabeled data with multidimensional distributions. As an alternative to classification, which requires data labelling (Garcia-Dias et al., 2019). Cluster analysis is a suitable method for grouping palm oil plantations that are not easily classified based on the level of sustainability implementation. It is essential to

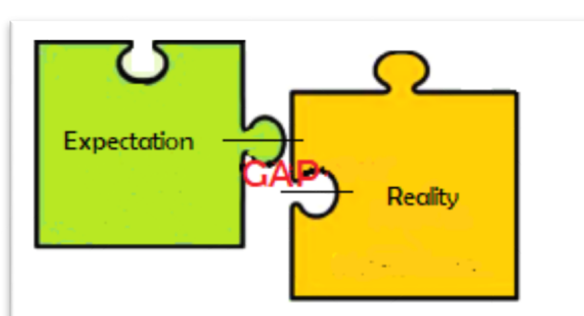


Fig. 2. Gap analysis.

note that all categorical data must be encoded using numerical data before conducting a cluster analysis. Finally, gap analysis produces a numerical value output that makes it easier to carry out a cluster analysis of the data.

This study applied the k-means algorithm to cluster the data. The k-means algorithm operates by determining the initial number of groups and selecting a random pattern, represented as *K*, as the starting point for the centroid. The k-means algorithm then repeatedly clusters the data to generate a cluster database. The number of iterations required to reach the cluster centroid is influenced by the number of clusters to be formed. The k-means algorithm offers simplicity and efficiency, with straightforward techniques that can produce optimal clusters (Sardar & Ansari, 2018). However, the k-means clustering algorithm has several limitations, including the following: 1) The number of clusters must be specified as an input. 2) It always creates data groups, even when there are no data groups in the observational data. If k-means produces two groups of data from the observation data, it divides the observation data into two groups of data, even when the observation data exhibit similarities. 3) K-means does not function optimally when the data are not linearly separable. 4) K-means performance may not be optimal when the clusters have different scales, shapes, or the amount of data observed is unbalanced (Garcia-Dias et al., 2019).

Determining the optimal number of clusters is a crucial step before conducting cluster analysis using the k-means algorithm. In this research, the WSS sensitivity analysis with the elbow method (Kuraria et al., 2018) is employed to determine the optimal number of clusters. The elbow method involves examining the percentage of comparison results at a specific point where the number of clusters begins to level off. The results are presented in a graph, which serves as a source of information. The optimal number of clusters is determined by comparing the number of clusters at each level, starting with the first, second, third, and so on. The cluster value that forms an elbow in the graph or experiences the greatest decrease is considered the optimal value.

3. Result

The findings of the exploratory data analysis (EDA) unveiled that a significant number of farmers had inadequate records. Notably, numerous farmers failed to respond to several survey questions, with the answer column merely stating "don't know". The analysis of the sustainability implementation survey data from 320 plantations across three continuous dimensions was conducted. It was discovered that two of the plantations were immature palm oil plantations and, therefore, were not included in the analysis. As a result, only 318 plantations were analyzed. The EDA results did not reveal any discernible patterns in the data. In light of this, it is more appropriate to adopt a data-centric approach prior to implementing an algorithm-centric approach for dealing with data that lack any discernible patterns.

3.1. Determining sustainability parameters

Gap analysis is a data-centric approach that examines the disparity between the actual value of sustainability variables in palm oil plantations and the expectation value based on RSPO standard. This approach is used to establish the point of differentiation between the actual and expected values of each sustainability variable.

The sustainability parameter of variable EI holds particular importance when considering plantation areas spanning at least 2 ha. This is based on the premise that land areas of 2 ha or more can yield sufficient produce to meet the needs of farming families, while also allowing for savings to support the education of future generations until they reach college. The sustainability parameters for variable E2 are contingent upon the buyer being cooperative or the POM. This decision was made due to the shorter logistics processes associated with cooperative buyers and POM supply chains, which result in higher quality due to less frequent loading and unloading. The sustainability parameter for variable E3 involves the presence of one or more trucks, enabling farmers to directly send FFB to POM. This direct delivery reduces the time required for TBS delivery. The sustainability parameter of variable E4 pertains to the use of palm oil seeds from a trusted nursery center. This parameter was chosen because seeds from these centers are of higher quality than those from other sources, such as fake seeds or seeds from neighbors with unclear origins. The sustainability parameter for variable E5 is the minimum number of independent farmers who possess land declaration letters (SKT) from subdistricts. This variable was chosen because SKT is a letter explaining how farmers control their land for palm oil plantations. The local government will not issue an SKT if the plantation is located in a forest area or is illegal.

The sustainability parameters for variable S1 include a farmer's education, which should be at least a high school education. This parameter was chosen because farmers with a high school education have the ability to carry out profitability analysis. By possessing this expertise, farmers can calculate the production cost of palm oil and the profits they obtain from each harvest. The sustainability parameters for variable S2 include being a registered participant in an insurance. This parameter was established to ensure that farmers can seek medical treatment without incurring significant expenses. If farmers do not have a social security membership, they may be required to sell their FFB to cover medical costs, which could negatively impact their ability to purchase fertilizers or maintain their palm oil plantations. The sustainability parameter for variable S3 is the number of family dependents, which should be fewer than or equal to five. This parameter was chosen because farmers with many family dependents require higher expenditures, which may lead to neglecting plantation maintenance or hiring additional workers. The sustainability parameter for variable S4 is the distance to the nearest hospital, which should be less than 10 km. This parameter was chosen to ensure that if a family member falls ill, they can receive prompt medical attention, reducing the risk of not receiving treatment. The sustainability parameter for variable S5 is a farmer's house with complete sanitation. Good sanitation is crucial for family health, and complete sanitation significantly reduces the risk of contracting diseases. By maintaining optimal sanitation, families can stay healthy, allowing them to provide proper care for their palm oil plantations.

The environmental dimension requires sustainability parameters for variables L1, L2, L3, L4, and L5. For variable L1, the plantation lacks only one nutrient among P, K, N, Mg, and Boron, and the more nutrients that are lacking, the lower the plant's growth and development ability, which leads to lower productivity. Consequently, farmers need more fertilizer to produce optimal palm fruit. For variable L2, the method of clearing land is essential, as burning the land risks causing fire disasters and environmental damage. Burning the land releases carbon, which pollutes the air, whereas clearing the land by cutting is more environmentally friendly. For variable L3, having discs around the palm oil tree is a critical to keeping the tree free from weeds. For variable L4, the status of the plantation before planting must not be a conservation forest, protected forest, or limited production forest. Finally, for variable L5, the distance from the house to the plantation must be $\leq$ 5 km. The farther the plantation is from home, the more challenging it is for farmers to allocate time to controlling the plantation, and plantations far from home are more likely to experience FFB theft, especially when FFB prices are high.

3.2. Gap analysis

The evaluation of the implementation of sustainability in ISH plantations is conducted through the utilization of the gap analysis method, which is based on predetermined sustainability parameters. The 15 variables, designated as E1 − L5, encompass both categorical and numerical data types. In order to facilitate the analysis process, categorical data were transformed into numerical data, with values of 0 and 1 assigned to each variable. The assessment process involves comparing the values of each variable to the established sustainability parameters, with a value of 1 indicating a match and a value of 0 indicating a discrepancy. The primary objective of this approach is to simplify the process of building the plantation cluster model by converting the categorical data into numerical values. To carry out the gap analysis, Microsoft Excel formulas were employed, which automatically determine the suitability value of each sustainability variable and generate results in the form of 0s and 1s. Table 2 provides a visual representation of the formulas utilized to assess the gap for each variable.

The evaluation of sustainability implementation in each plantation was carried out based on 15 sustainability variables and parameters. The output value for sustainability implementation was determined using the formula in Microsoft Excel, as shown in Table 2. The next step involved assessing the gap between the value obtained (reality) and the previously agreed expectation value. Table 3 provides an overview of the results of the sustainability implementation assessment in 320 plantations and the gaps in each dimension.

The gap value in each dimension was calculated using the formula dimensional gap = expectation − reality. The reality value ranged from 0 to 5, while the expectation value for each sustainability dimension was 5. A value of 5 indicates that all variables in the dimensions assessed are in line with expectations. For example, in Table 3, row 1 of the plantation with block id 30301, the gap between expectations and reality for the economic dimension can be calculated as 5 - 1 = 4, for the social dimension as 5 - 2 = 3, and for the environmental dimension as 5 - 4 = 1. The results of the gap analysis for each variable in the top 20 palm oil plantations owned by independent farmers in the Tambusai sub-district are presented in Table 3.

Table 2. Microsoft Excel formula and determining sustainability values in plantations.

No	Variables	Formula	Description
1	E1	=IF(petani!BP2≥2;1;0)	If the area of the farmers' plantation is ≥2 ha, the value E1 is 1. If the plantation area <2 then the value E1 is 0
2	E2	=IF(petani!AK2="Pabrik/mill (tanpa perantara)";1;0)	If the FFB is sent through cooperative to the POM, then the value E2 is 1. If the FFB is sent via an intermediary then the value of the variable E2 is 0
3	E3	=IF(petani!AA2=0;0;1)	If the farmer has one or more trucks, then the value of E3 is 1. If the farmer does not have a truck then the value of the E3 variable is 0
4	E4	=IF(OR(petani!CB2="PPKS Marihat"; petani!CB2="Sucfindo");1;0)	If the farmer's seeds come from a trusted nursery center then the value of E4 is 1, if the bibs come from other than the nursery center then the value of E4 is 0
5	E5	=IF(OR(petani!BW2="Ya"; petani!BX2= "Ya"; petani!BY2="Ya"; petani!BZ2="Ya");"1";"0")	If the farmer has a land purchase letter, SKT from the village or sub-district head, then the value of the E5 is 1. If he does not have an SKT then the value of E5 is 0
6	S1	=IF(OR(petani!I2="SD"; petani!I2= "SMP");"0";"1")	If the education of the farmer who owns the plantation is elementary or middle school, the value S1 is 0. If the farmer's education is high school or tertiary then the value S1 is 1
7	S2	=IF(OR(petani!AH2="");0;1)	If the farmer does not have a social security membership, then the value of S2 is 0. If the farmer has a social security card then the value S2 is 1
8	S3	=IF(OR(petani!L2≤5);1;0)	If the number of dependents in the farmer's family is <5, then the value S3 is 1. If the number of dependents in the farmer's family is more than 5 then the value is 0
9	S4	=IF(OR(petani!AG2="Di atas 10 km");0;1)	If the distance from the farmer's house to the hospital is greater than 10 km, then the value S4 is 0. If the distance is ≤10 km then the value S4 is 1
10	S5	=IF(petani!Y3="Ya";1;0)	If the farmer's house has complete sanitation, then the value S5 is 1. If the farmer's house does not have complete sanitation then the value S5 is 0
11	L1	=IF(OR(petani!AI2="K";petani!AI2="N"; petani!AI2="Mg"; petani!AI11="Boron";petani!AI11="P");1;0)	If the land lacks only one nutrient among P, K, N, Mg and Boron, then the value of the L1 variable in the plantation is 1. If more than one nutrient is lacking then the value of that variable is 0
12	L2	=IF(petani!BU2="Tebang dan imas (tanpa dibakar)";1;0)	If a farmer opens a plantation using environmentally friendly methods by cutting it down, the value of L2 is 1. If not by cutting then the value is 0
13	L3	=IF(petani!DT2="Ya";1;0)	If each palm tree had a disc, then the value of L3 is 1. If it does not have a disc then the value is 0
14	L4	=IF(petani!DU2="Ya";1;0)	If the status of the plantation before planting is known to not be a conservation forest, protected forest and limited production forest, then the value of L4 variable for the is 1. If it is known to be a prohibited forest then the value of L4 is 0
15	L5	=IF(petani!BO2<5;1;0)	If the distance from the house to the garden is <5 km, the value of L5 is 1. If the distance to the plantation is ≥5 then the value od L5 is 0

The results of the gap analysis for sustainable implementation on ISH plantations in the Tambusai Sub-district indicate that the economic dimension has the highest gap with a value of 3 out of a maximum of 5, while the environmental dimension has a gap of 2.62 out of 5. The social dimension has the lowest gap, with a value of 2.5 out of 5, indicating that it has a relatively good score equal to the average score. The large gap values in the economic and environmental dimensions suggest that the implementation of sustainability by ISHs on these plantations is relatively low in these areas. Following the collection of data on the gap between reality and expectations, a cluster analysis was conducted on the implementation of the three dimensions of sustainability in ISH plantations.

3.3. Cluster analysis

The following stage necessitates the processing of data from the gap analysis to construct a cluster model for fostering sustainability in ISH plantations. To achieve this, the k-means algorithm was implemented to analyze the gap values across the economic, social, and environmental dimensions of 318 ISH plantations. The data analysis was

Table 3. Assessment of sustainability implementation and gap analysis.

Blok Id	E1	E2	E3	E4	E5	real	exp	Eco GAP	S1	S2	S3	S4	S5	real	exp	Soc GAP	L1	L2	L3	L4	L5	real	exp	Env GAP
30301	0	0	0	0	1	1	5	4	0	1	1	0	0	2	5	3	1	1	0	1	1	4	5	1
205301	0	1	0	0	1	2	5	3	1	0	1	0	0	2	5	3	1	0	0	0	0	1	5	4
107501	0	0	0	0	1	1	5	4	1	1	1	0	1	4	5	1	1	0	1	1	1	4	5	1
107601	0	1	0	0	1	2	5	3	1	1	1	0	1	4	5	1	1	0	1	1	1	4	5	1
406701	0	1	1	0	1	3	5	2	0	1	0	1	0	2	5	3	1	0	1	0	1	3	5	2
406702	1	1	1	0	1	4	5	1	0	1	1	1	0	3	5	2	1	0	1	0	1	3	5	2
406703	0	1	1	1	1	4	5	1	0	1	1	1	0	3	5	2	1	1	1	0	1	4	5	1
206901	0	1	0	0	1	2	5	3	1	0	1	1	0	3	5	2	0	0	1	1	1	3	5	2
304601	1	1	0	0	1	3	5	2	1	1	1	0	1	4	5	1	1	0	1	0	1	3	5	2
304602	1	1	0	0	1	3	5	2	1	1	1	1	1	5	5	0	1	0	1	0	1	3	5	2
109601	1	0	0	1	0	2	5	3	1	1	1	0	1	4	5	1	1	0	0	0	0	1	5	4
205701	0	0	0	0	1	1	5	4	1	1	0	0	1	3	5	2	0	0	1	1	1	3	5	2
303501	1	1	0	1	1	4	5	1	1	1	0	1	1	4	5	1	0	0	0	0	0	0	5	5
30401	0	0	0	0	1	1	5	4	1	1	1	1	1	5	5	0	1	1	0	0	0	2	5	3
304201	1	1	0	0	1	3	5	2	1	1	1	0	1	4	5	1	1	0	0	0	0	1	5	4
304101	0	1	0	0	1	2	5	3	1	1	1	0	1	4	5	1	1	0	0	0	0	1	5	4
10601	0	0	0	0	1	1	5	4	1	1	1	1	0	4	5	1	0	0	0	0	0	0	5	5
106601	0	1	0	1	1	3	5	2	0	1	1	0	1	3	5	2	1	0	0	0	1	2	5	3
206101	0	1	0	0	1	2	5	3	1	1	1	0	1	4	5	1	1	0	1	1	0	3	5	2

conducted using the R Studio tool. Fig. 3 showcases the data analyzing the gaps in the economic, social, and environmental dimensions for 318 oil palm plantations in Tambusai.

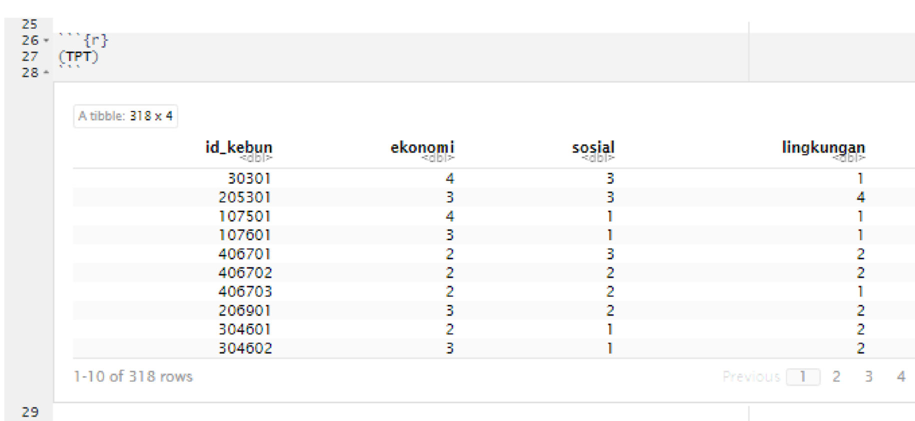
3.3.1. Determining the optimal number of clusters

The optimal number of clusters is determined using the fviz_nbclust function from the factoextra package in R Studio. This is done by examining the elbow fractures on the WSS curve, which is a key criterion for determining the number of clusters formed. According to the WSS criteria, the optimal number of clusters produced from three-dimensional gap data presents several options, as illustrated in Fig. 4. It is evident from the figure that there are four elbows specifically located in clusters 2, 3, 4, and 6. The cluster formation experiment was selected at fractures 2, 4, and 6. The WSS sensitivity analysis in this study was not to determine the optimal cluster but aimed to see which clusters have the potential to produce small centroid values in each dimension. Small centroid values indicate that the s in the cluster have low gap values and high levels of sustainability implementation.

3.3.2. K-mean clustering

Based on the optimal number of clusters (k value), the results of the WSS criteria and k-means algorithm are applied to the three-dimensional sustainability gap analysis data. The k-means clustering algorithm uses the k-means package in RStudio. The results for centroids 2, 4, and 6 are shown in Table 4.

The k-means algorithm generates multiple centroid values for each cluster. In evaluating the six clusters, the difference between anticipated and



```
25
26 ```{r}
27 (TPT)
28 ```
```

A tibble: 318 x 4

id_kebun	ekonomi	sosial	lingkungan
<dbl>	<dbl>	<dbl>	<dbl>
30301	4	3	1
205301	3	3	4
107501	4	1	1
107601	3	1	1
406701	2	3	2
406702	2	2	2
406703	2	2	1
206901	3	2	2
304601	2	1	2
304602	3	1	2

1-10 of 318 rows Previous 1 2 3 4

Fig. 3. Sustainability gap in independent smallholder plantations.

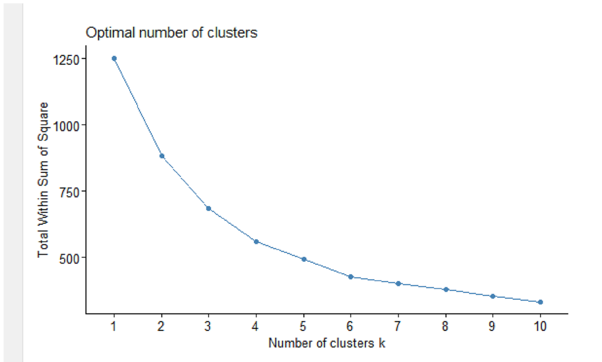


Fig. 4. Optimal number of clusters based on WSS criteria.

actual values in each dimension exhibited the lowest gap value, with a centroid value below two. This finding suggests that the gap between expectations and reality in the economic, social, and environmental dimensions of the 6th cluster was negligible, nearly zero. A centroid value of zero implies that there is no disparity between anticipated and actual outcomes, which could also be referred to as absolute sustainability. Although absolute sustainability is unattainable, a centroid value close to zero indicates that plantations are implementing exceptionally high levels of sustainability.

3.3.3. Level of implementation of palm oil plantation sustainability

Employing the centroid value as a basis, the plantations were categorized into three classifications of sustainability implementation: trusted, potential, and low-potential. The sixth cluster, comprising twenty-two plantations, demonstrates a high level of sustainability. A summary of the level of sustainability plantation outcomes is presented in Table 5.

Data on twenty-two oil palm plantations as grade A with a high level of sustainability implementation are hereinafter referred to as trusted plantations. These plantations are trusted plantations of FFB suppliers to produce traceable CPO. FFB from this trusted plantation was sent separately and processed together with the company's internal FFB to produce traceable high-quality CPO.

Table 5. Sustainability implementation level of ISH plantations.

No	Cluster/Number of Plantation	Implementation Level
1	Cluster 1 = 43	Low-potential → Grade C
2	Cluster 2 = 84	Low-potential → Grade C
3	Clsster 3 = 53	Low-potential → Grade C
4	Cluster 4 = 63	Potential → Grade B
5	Cluster 5 = 53	Potential → Grade B
6	Cluster 6 = 22	Trusted → Grade A

4. Discussion

Gap analysis combined with cluster analysis is a new method for analyzing sustainability in oil palm plantations. This method automates the process of grouping plantations based on variables from three dimensions of sustainability. An important part of the gap analysis method is determining the gap parameters for each variable. Different parameter determinations produce different outputs.

The results of cluster analysis using the k-mean algorithm are that there are 22 trusted plantations owned by farmers who implement high sustainability practices, 116 potential plantations are plantations owned by farmers who implement medium sustainability practices and low-potential plantations owned by farmers who implement low sustainability practices are 180 plantations. Twenty-two trusted plantations out of 318 plantations are plantations that have a centroid value between 1 and 2. These plantations have a centroid value closest to zero, namely plantations that implement absolute sustainability practices. An absolute value is impossible to achieve, but a value close to zero indicates that farmers and plantations have implemented best practices sustainability. Even though the gap analysis found that the level of gap in the implementation of each sustainability dimension was high, 22 ISH plantations were found to have a low gap value, meaning that the plantation implemented sustainability close to the absolute value.

Table 4. Centroid values of three different clusters.

Number of clusters	Two cluster			Four cluster			Six cluster		
Centroid/Dimension	E	S	L	E	S	L	E	S	L
Centroid 1	3,03	2,65	3,46	2,78	3,92	1,46	2,34	1,35	3,67
Centroid 2	2,98	2,59	1,44	3,08	3,69	3,49	3,03	3,70	3,50
Centroid 3				3,58	1,88	1,60	3,98	3,25	1,36
Centroid 4				2,47	1,48	3,15	3,86	1,70	2,59
Centroid 5							2,73	2,34	1,51
Centroid 6							1,87	1,04	1,32

The results of this research show that very few independent farmers implement sustainable practices. This is not much different from the results of research (Safriyana et al., 2020) which found that around 13 % of independent smallholder plantations had potential competitiveness. Only the gap in the social dimension has a fairly good value equal to the average value, while the gap in the economic and environmental dimensions is quite high. This finding is in accordance with the research results of Saragih et al. (2020) which states that the sustainability index for non-certified and non-partner ISHs is only 46.65, which is in the less sustainable category.

This study adopts a bottom-up approach to building a traceability system for CPO production, as proposed by Falgenti & Hambali (2022). The development of the traceability system begins with identifying plantations and evaluating their sustainability implementation levels. Only trusted plantations are included in the traceability system. This approach differs from the top-down method employed by EFI, which begins by identifying refineries, POMs, transportation networks, and finally independent smallholder plantations. EFI's Terpercaya Platform is designed to identify only legal plantations. The POMs eligible to join this platform are private mills that do not accept Fresh Fruit Bunches (FFB) from independent smallholders. Public POMs may participate in the trusted platform if they can ensure that smallholder plantations supplying FFB are free from deforestation. This means that POMs must reject FFB supplies from independent smallholders lacking legal documentation.

Restricting FFB acceptance from independent smallholders disrupts the harmonious relationship between smallholders and POMs. Further risks include protests and resistance from the smallholders. The segregation of FFB trucks and CPO production, as proposed by Falgenti & Hambali (2022), can maintain the harmonious relationship between ISHs and POMs. ISHs owning plantations with legal documentation, as well as those without such documents who deliver their FFB through intermediaries, can supply FFB for the production of two types of CPO. Twenty-two ISH plantations within the cluster of trusted plantations will be part of the source for traceable high-quality CPO. Meanwhile, FFB from 180 less potential plantations will serve as a source for non-traceable standard-quality CPO.

Separately, SPKS has provided training and guidance to these 250 smallholders. After undergoing this process, SPKS registered 320 ISH plantations with the RSPO. In July 2022, 102 smallholder plantations obtained RSPO certification. Most of the ISHs certified by RSPO are owners of trusted and potential plantations. These RSPO-certified ISHs have formed the Tambusai Independent Oil Palm Farmers Association (PPSTS) Cooperative (Sabarudin, 2022).

The twenty-two trusted plantations are part of the 102 ISH plantations that have obtained RSPO certification. Potential plantations that have received RSPO certification can serve as FFB sources for producing traceable, high-quality CPO after being registered with the electronic cultivated plantation registration certificate (eSTDB)service and obtaining STDB documents. The central government requires eSTDB registration for oil palm plantations owned by independent smallholders with SKTs and land areas of less than 4 ha.

Segregating FFB at POM weighbridges based on the level of sustainability implementation, replacing the previous segregation model based on FFB sources (internal and external). Only independent smallholders who own trusted plantations with a high level of sustainability implementation are prioritized as FFB suppliers to produce traceable high-quality CPO. Consequently, not all ISH plantations are included in the CPO production traceability system. Plantations belonging to ISHs who are members of cooperatives are given priority in the traceability system due to the ease of identifying cooperative members' plantations in greater detail.

FFB trucks from 102 trusted, RSPO-certified plantations are prioritized for weighing at weighbridges, ensuring efficiency in the process. Additionally, CPO production from these certified plantations is kept separate from that of plantations lacking legal documentation. This capability transforms the FFB supply chain into a smart supply chain that can separate the production time of traceable high-quality CPO from non-traceable standard-quality CPO. Traceable high-quality CPO can be applied to make clean products from deforestation for customers in developed countries. By leveraging smart supply chains, these deforestation-free products enhance customer trust and eliminate the need for “Palm Oil Free” labeling.

5. Conclusions

The clustering results show that only 7%, or 22 out of 318 smallholder plantation blocks in Tambusai District, Riau Province, fall into the category of high sustainability implementation. Through intensive guidance and mentoring, the Indonesian Oil Palm Smallholders Union (SPKS) successfully obtained RSPO certification for 102 of its member plantations. These findings demonstrate that sustained and targeted support for independent smallholders can significantly improve their adoption of sustainable practices.

Grouping plantations based on sustainability implementation is a crucial first step in developing a traceability system for CPO derivatives. This system enables the origin of CPO production to be traced back to ISH plantations. We propose that the FFB supply at the POM be segregated based on the level of sustainability implementation in the plantations, replacing the previous method of segregation based solely on internal and external FFB supplies. The level of sustainability implementation in ISH plantations can now be identified at weighbridges. The inclusion of 22 plantations in the trusted group—part of the 102 plantations that have obtained RSPO certification—not only ensures their legality but also highlights their high level of sustainability implementation.

The next step involves digitalization by building a service platform that records activities ranging from harvesting, FFB transportation, segregation, weighbridge scheduling, to CPO production. Digitalization also facilitates due diligence assessments in the supply chain, as importers must verify that CPO derivative products originate from a sustainable FFB supply chain. This strengthens the resilience of the FFB supply chain against changing regulations and growing consumer demand for environmentally friendly products in developed countries.

Ethical information

This research did not require ethical approval.

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Conflicts of interest

The authors declare that there is no con interest regarding the publication of this paper.

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