Machine Learning-Based Hierarchical Clustering for Priority CCUS Zones in Indonesia

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ABSTRAK

Indonesia's upstream oil and gas industry is facing significant challenges due to climate change, alongside the global shift toward clean energy transition to reduce CO_2 emissions and achieve the Net Zero Emission target by 2060. One of the key strategies in this effort is the implementation of Carbon Capture, Utilization, and Storage (CCUS).The adoption of the CCUS program is an integral part of SKK Migas' strategic plan to reach a production target of 1 million barrels of oil per day (BOPD) and 12 billion standard cubic feet of natural gas per day (BSCFD) by 2030. This study applies machine learning-based hierarchical clustering to analyze and classify CCUS project zones in Indonesia, utilizing data from the IEA CCUS Projects Database 2024. The methodology includes data collection, pre-processing, and clustering using a hierarchical algorithm to group projects with similar characteristics in CCUS implementation. The clustering process, interpreted through a dendrogram, considers key factors such as Announced Capacity (Mt CO_2/yr) and Estimated Capacity by IEA (Mt CO_2/yr). The Silhouette Coefficient after applying hierarchical clustering is 0.746, indicating well-defined cluster separation. The findings of this study provide valuable insights into the relationships among CCUS projects in Indonesia, categorizing them into priority zones. Additionally, this research supports strategic decision-making regarding CCUS project development, contributing to the achievement of the Net Zero Emission target and long-term energy security.

Keywords: CCUS, Hierarchical Clustering, Machine Learning, Carbon Storage, Indonesia

Industri hulu migas di Indonesia tengah menghadapi tantangan besar akibat perubahan iklim, seiring dengan pergeseran global menuju transisi energi bersih untuk mengurangi emisi CO_2 dalam mencapai target *Net Zero Emission* pada 2060 dengan menerapakan *Carbon Capture, Utilization, and Storage (CCUS).* Penerapan program *CCUS* ini menjadi bagian dari rencana strategis SKK Migas untuk pencapaian target produksi minyak sebesar 1 juta BOPD dan gas alam sebesar 12 BSCFD pada tahun 2030. Dalam Studi ini diterapakn *hierarchical clustering* berbasis *machine learning* dalam menganalisis dan mengklasifikasikan zona proyek CCUS di Indonesia menggunakan data dari *IEA CCUS Projects Database* 2024.Metodologi yang digunakan meliputi *collection data, pre-processing data*, dan *clustering* menggunakan *algoritma hierarchical clustering* guna mengklasifikasn proyek dengan karakteristik serupa dalam penerapan *CCUS*. Proses *clustering* dengan interpretasi *dendrogram* dengam faktor-faktor utama: *Announced capacity (Mt CO_2/yr)* dan *Estimated capacity by IEA (Mt CO_2/yr)* dengan *Silhouette Coefficient* setelah menerapkan *hierarchical clustering* adalah 0,746, menunjukkan pemisahan cluster yang baik. Hasil penelitian ini memberikan wawasan dalam memahami hubungan antar proyek *CCUS* di indonesia yang dikategorikan ke dalam zona prioritas. Selain itu, membantu dalam pengambilan keputusan strategis terkait pengembangan proyek *CCUS* dalam berkontribusi terhadap pencapaian target *Net Zero* Emission serta ketahanan energi jangka panjang.

Kata kunci: CCUS, Hierarchical Clustering, Machine Learning, Carbon Storage, Indonesia

1. INTRODUCTION

The upstream oil and gas industry in Indonesia is facing significant challenges due to climate change, in line with the global shift toward clean energy transition aimed at reducing CO_2 emissions and achieving Net Zero Emissions by 2060 through the implementation of Carbon Capture, Utilization, and Storage (CCUS) (Putri et al., 2024 ; Soesanto et al., 2025). CCUS technology captures CO_2 from major emission sources, repurposes it for industrial use, or stores it permanently underground to prevent its release into the atmosphere. The application of this technology plays a crucial role in carbon emission reduction efforts, both nationally and globally. Worldwide, CCUS adoption has become a key focus in transitioning to clean energy, particularly in countries still reliant on fossil fuels (Kemen. ESDM, 2023; Putri et al., 2024, (Vishal et al., 2024).

Indonesia, as one of Southeast Asia's largest oil and gas producers, has taken strategic steps in implementing CCUS. Through SKK Migas, the government has integrated CCUS into the Indonesia Oil and Gas 4.0 Strategic Plan (Renstra IOG 4.0) as part of its climate change mitigation efforts, formulating various policies to reduce carbon emissions (Laporan Keberlanjutan, 2022). The upstream oil and gas industry actively contributes to carbon emission reduction efforts, particularly through CCUS implementation. This initiative aligns with SKK Migas' strategic plan to achieve a production target of 1 million barrels of oil per day (BOPD) and 12 billion standard cubic feet per day (BSCFD) of natural gas by 2030 to strengthen national energy security (Reforminer, n.d; Kemen. ESDM, 2021; Kemen. ESDM, 2023).

In this effort, the implementation of Carbon Capture, Utilization, and Storage (CCUS) serves as a strategic solution to support sustainable production by utilizing CO_2 injection as an Enhanced Oil Recovery (EOR) method, as illustrated in **Fig 1**. This technique aims to improve oil recovery factors (Migas & Profile, n.d.). CO_2-EOR has the potential to increase domestic oil production, create job opportunities, and support environmental protection efforts. The method involves injecting CO_2 into mature oil fields, where the gas interacts with oil, facilitating its extraction from the reservoir and enabling it to flow toward production wells. Once the oil is processed, the CO_2 is separated using surface equipment and reinjected in a closed-loop system throughout the EOR operation (Policy, 2012).

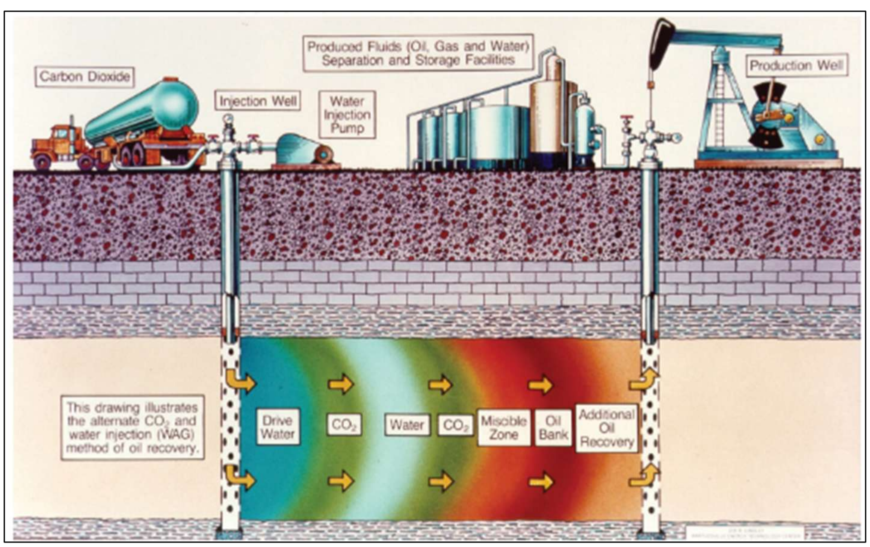

Fig 1. CO_2 injection and oil recovery process
(Department of Energy, National Energy Technology Laboratory, 2010)

Enhanced oil recovery through CO_2 flooding (by injection) has been well developed and has the potential to significantly increase oil production while providing economic benefits. This method can enhance additional oil recovery in the range of 7% to 23%. However, to maximize CO_2 storage in the EOR process, oil reservoirs may need to meet additional criteria (Goel et al., 2019). As a result, the government has started implementing CCUS. Although CCUS implementation has not been fully realized in Indonesia, several studies have been conducted to analyze its potential, challenges, environmental impacts, and contributions to the sustainable energy industry in Indonesia. CCUS aims to capture up to 85% of CO_2 emissions from the power generation and industrial sectors before being stored underground at depths of up to 700 meters (Adisaputro & Bastian, 2017; Anggraini et al., 2022; Prasetyo & Windarta, 2022; Putri et al., 2024).

2. MATERIALS AND METHODS

2.1. Material *(Literature Review)*

a. CCS/CCUS

Carbon Capture, Utilization, and Storage (CCUS) technology is one of the key pillars in accelerating greenhouse gas emission reduction and achieving global carbon neutrality. As a promising decarbonization technology, CCUS is used to capture CO_2 from flue gases or the atmosphere, then transport it for reuse or permanent storage (S. Chen et al., 2022). Carbon Capture, Utilization, and Storage (CCUS), also known as Carbon Capture, Utilization, and Sequestration, is an innovative technology for climate change mitigation. This technology works by capturing CO_2 emissions from various sources, such as fossil fuel power plants and industrial processes, and then either reusing or storing them to prevent their release into the atmosphere (*Carbon Capture, Utilization and Storage (CCUS)*, 2019).

CCS/CCUS plays a crucial role in addressing two major challenges of today: (i) climate change and (ii) energy security. According to a report by the International Energy Agency (IEA), there is significant potential to store up to 360 gigatons (Gt) of CO_2 through enhanced oil recovery (EOR) applications (Tontiwachwuthikul, 2017).

The technology of Carbon Capture, Utilization, and Storage (CCUS) has become a crucial element in climate change mitigation policies, particularly for reducing emissions from the industrial sector and fossil-based energy production to limit global warming to 1.5°C. According to the 2021 report by the International Energy Agency (IEA), the global CO_2 capture capacity in the heavy industry sector needs to reach 375 megatons (Mt) per year by 2030. However, over the past decade, the number of active or developing CCUS projects has stagnated. In 2020, the globally installed CO_2 capture capacity was approximately 40 Mt per year, with most of this capacity utilized for enhanced oil recovery (EOR) applications. Consequently, governments, researchers, and intergovernmental organizations have called for a significant acceleration in the scaling and implementation of CCUS. However, CCUS projects have had a mixed history, with several high-profile technical failures, public opposition, and cost overruns hindering their deployment. As a result, an increasing number of studies are focusing on documenting and addressing the various challenges affecting the implementation of CCUS (Storrs et al., 2023).

b. CO_2 – EOR

CO_2-EOR encompasses several specific methods of oil production that involve injecting CO_2 into oil-bearing formations through injection wells (Water, n.d.). CO_2-EOR is a displacement process in which CO_2 is injected into deep subsurface reservoir rocks through injection wells to drive oil toward production wells. The CO_2 produced along with reservoir fluids is separated at the surface and is typically reinjected or recycled back into the reservoir. This cycle continues throughout the operation (Núñez-lópez & Moskal, 2019).

The key technologies in CO_2-EOR (**Fig. 1**) include:

- Continuous CO_2 injection;
- Continuous CO_2 injection followed by water injection;
- Water-Alternating-Gas (WAG) injection, the most common CO_2-EOR method, in which fresh water or produced water (wastewater from oil fields) is alternately injected with CO_2;
- WAG followed by gas injection, a method in which a cheaper gas, such as nitrogen, is injected after the CO_2 injection cycle.

c. Machine learning

Machine Learning (ML) is a branch of Artificial Intelligence (AI) that studies computer algorithms enabling programs to automatically improve through experience. The advantages of ML include ease in identifying trends and patterns, minimal human intervention (automation), continuous performance improvement, and high efficiency in handling high-dimensional and diverse data types. However, its application is sometimes limited by factors such as ethics, lack of physical constraints, data availability and quality, implementation errors, and limitations in result interpretation (Hassanien, 2020; Yongliang et al., 2021; Swaminathan & Parente, 2023). **Fig 2** illustrates various types of Machine Learning (ML) along with their application areas. ML is categorized into three main types:Supervised learning

- **Supervised Learning**

Supervised learning, the most commonly used type, involves a known relationship between input and output data, meaning the data is already labeled.

- **Unsupervised learning**

If a dataset contains only input data without labels, unsupervised learning can be used to identify patterns, structures, trends, or clusters within the data.

- **Reinforcement learning**

Reinforcement learning enables an agent to learn through interaction with the environment using a trial-and-error approach, receiving feedback based on its actions and experiences.

The application of each ML type involves selecting appropriate algorithms.

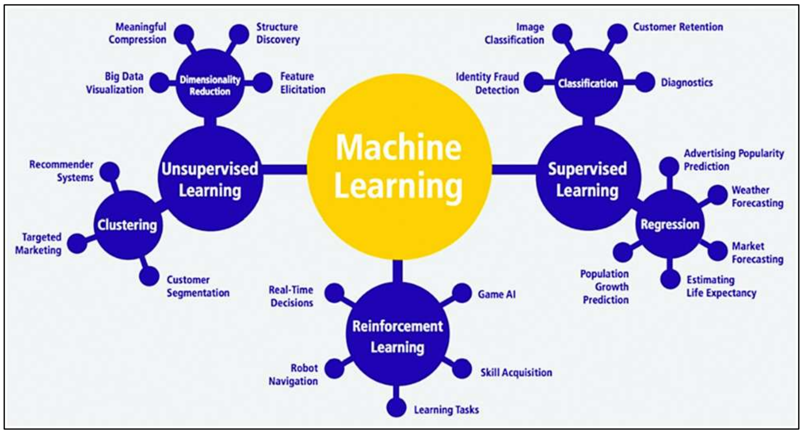

Fig 2. Types and applications of ML (Yongliang et al., 2021)

d. Hierarchical Clustering

This algorithm divides clusters into a hierarchical tree structure to build a classification system. Similar to k-means clustering, hierarchical clustering uses distance-based methods to determine the proximity between clusters. In general, there are two main types of hierarchical clustering (Rahmawati et al., n.d.; Zeng et al., 2020; Xu et al., 2021; Kumarahadi et al., 2023), Namely:

1) **Agglomerative hierarchical clustering (additive hierarchical clustering)**

In this method, each data point is initially treated as an individual cluster. For example, if there are 10 data points in a dataset, the hierarchical clustering process begins with 10 separate clusters. Subsequently, using a distance function such as the Euclidean distance, the closest pair of clusters is merged. This merging process continues iteratively until only a single main cluster remains (Z. Chen & Msezane, 2020; Li et al., 2022; Kumarahadi et al., 2023; Jáñez-martino et al., 2023).

2) **Divisive hierarchical clustering**

This method operates by dividing a large group into smaller clusters. If there are 10 data points, all points initially belong to a single cluster. Subsequently, the data point with the farthest distance is separated from the main cluster, and this process continues until each cluster contains only a single data point (Yamada et al., 2020; Manuel et al., 2023).

A dendrogram is used to represent the hierarchical relationships among objects and is the result of the hierarchical clustering process. This tool helps determine the optimal number of clusters and understand the overall data structure. For example, a dendrogram can be created to illustrate hierarchical clustering. In **Fig 3**, the distance between wells 1 and 2 is 0.2 (as shown on the y-axis), while the distance between wells 3 and 4 is 0.5. Finally, the merged clusters, (1,2) and (3,4), have a distance of 1.1 (Harb et al., 2022; Labbé et al., 2023).

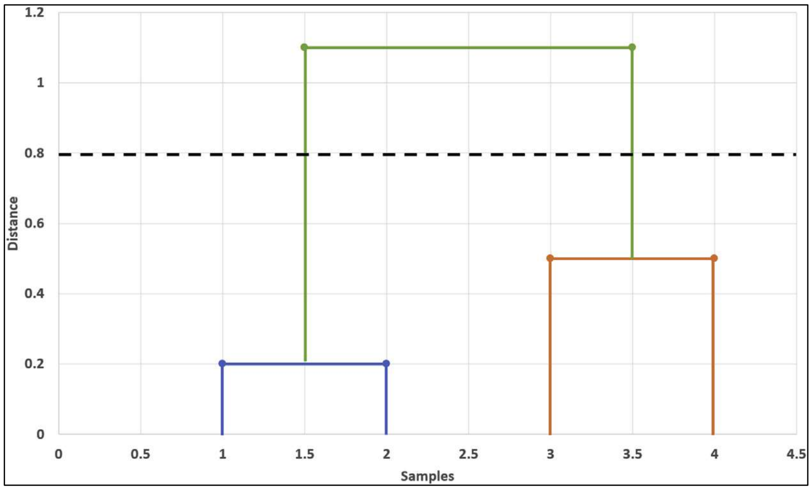

Fig. 3. A dendrogram illustration

e. Silhouette Coefficient

Another approach to evaluating clustering quality is silhouette analysis, which can be applied to various clustering algorithms. The silhouette coefficient ranges from -1 to 1, where higher values indicate more cohesive clusters. Specifically, a coefficient close to +1 suggests that a sample is well-separated from neighboring clusters. A value of 0 indicates that the sample is on or very close to the boundary between two adjacent clusters, while a negative value implies a possible misclassification of the sample into a cluster (Rousseeuw, 1987). To compute the silhouette coefficient, two key aspects must be considered: cluster cohesion (a) and cluster separation (b). Cluster cohesion measures the average distance between a sample and all other data points within the same cluster, whereas cluster separation refers to the average distance between the sample and the points in the nearest cluster. The silhouette coefficient is obtained by dividing the difference between cluster separation and cohesion by the maximum of the two values (Rousseeuw, 1987).

2.2. Methods

In this study, a machine learning-based hierarchical clustering method was applied to group CCUS projects in Indonesia using data from the IEA CCUS Projects Database 2024, with a global dataset of 844 projects, which was filtered specifically for analyzing Indonesian projects. The analytical process includes data collection, pre-processing, and the application of the hierarchical clustering algorithm, considering the key factors:

- **Announced capacity (Mt CO_2/yr)**

The announced or actual capture, transport, and/or storage CO_2 capacity, in Mt CO_2 per year. When the capture capacity is announced as a range or multiple values are available, the announced capacity is entered accordingly.

- **Estimated capacity by IEA (Mt CO_2/yr)**

The estimated capture capacity based on other plant details (e.g., fuel production capacity) or potential deployment plans. See conversion factors for further assumptions.

This approach facilitates the identification of priority zones for CCUS implementation. The methodology follows these steps:

a. Data Collection

Research data was obtained from the IEA CCUS Projects Database 2024, which was used for further processing before the preprocessing stage.

b. Data Preprocessing

The collected data underwent a cleaning process to remove irrelevant attributes for model building. Additionally, a completeness check was conducted before classifying the Indonesian projects for post-processing. The results are presented in **Table 1**.

c. Post-processing hierarchical clustering

The post-processing stage is the final step for interpreting results. This study applied hierarchical clustering using a dendrogram and evaluated cluster separation using the Silhouette Coefficient after clustering.

Table 1. Indonsia Project CCUS

Project name	ID	Country	Partners	Project type	Announcement	FID	Operation	Suspension /decommissioning	Project Status	Project phase	Announced capacity (Mt CO2/yr)	Estimated capacity by IEA (Mt CO2/yr)	Sector	Fate of carbon	Part of CCUS hub	Region
Abadi CCS/CCUS	227	Indonesia	Inpex Masela 65%, Shell (trying to find a buye...	Full chain	2018	NaN	2027	NaN	Planned	NaN	2.41	2.41	Natural gas processing/LNG	Unknown/unspecified	NaN	Other Asia Pacific
Arun CCS	37	Indonesia	Carbon Aceh, PEMA (JV)	Storage	2022	NaN	2029	NaN	Planned	NaN	NaN	NaN	Storage	Dedicated storage	Arun CCS	Other Asia Pacific
Balikpapan Refinery	43	Indonesia	Pertamina, Air Liquide	Full chain	2022	NaN	2030	NaN	Planned	NaN	1.4	1.4	Other fuel transformation	Mixed	Kutai Basin CCUS hub	Other Asia Pacific
Banggai ammonia plant Central Sulawesi	342	Indonesia	JOGMEC, Mitsubishi, PT Panca Amara Utama, ITB,...	Full chain	2021	NaN	NaN	NaN	Planned	NaN	NaN	NaN	Hydrogen or ammonia	Unknown/unspecified	NaN	Other Asia Pacific
CCS Sakakemang	353	Indonesia	Repsol, Petronas, MOECO	Full chain	2021	2024	2028	NaN	Planned	NaN	0.5	0.5	Natural gas processing/LNG	Dedicated storage	NaN	Other Asia Pacific
Central Sumatera Basin CCUS hub	761	Indonesia	Pertamina, Mitsui	Storage	2022	NaN	2030	NaN	Planned	NaN	NaN	NaN	Storage	Dedicated storage	Central Sumatera Basin CCUS hub	Other Asia Pacific
East Kalimantan CCUS hub	947	Indonesia	Kaltim Parna Industry, ITB	Storage	2022	NaN	2030	NaN	Planned	NaN	1	1	Storage	Dedicated storage	East Kalimantan CCUS hub	Other Asia Pacific
Gas power CCUS MoU	857	Indonesia	GE Vernova, CARBONCO, BP, PLN Nusantara (Jawa 1)	Capture	2023	NaN	NaN	NaN	Planned	NaN	NaN	NaN	Power and heat	Dedicated storage	NaN	Other Asia Pacific
Gemah field EOR	764	Indonesia	Petrochina (Daqing Petroleum Services), PT Gem...	Storage	2022	2025	2031	NaN	Planned	1	NaN	NaN	Storage	EOR	NaN	Other Asia Pacific
Gundih CCUS EGR	187	Indonesia	Pertamina, ITB, JGC, J-Power, JANUS (supported...	Full chain	2020	NaN	2030	NaN	Planned	NaN	0.3	0.3	Natural gas processing/LNG	EOR	NaN	Other Asia Pacific
JSA Pertamina Chevron East Kalimantan	948	Indonesia	Pertamina, Chevron	Storage	2023	NaN	NaN	NaN	Planned	NaN	NaN	NaN	Storage	Unknown/unspecified	NaN	Other Asia Pacific
Kutai Basin CCUS hub	765	Indonesia	Pertamina	Storage	2022	NaN	2030	NaN	Planned	NaN	NaN	NaN	Storage	Dedicated storage	Kutai Basin CCUS hub	Other Asia Pacific
Nagoya port cluster (capture sources under eva...	858	Japan-Indonesia	BP, Chubu Electric	T&S	2023	NaN	NaN	NaN	Planned	NaN	NaN	NaN	T&S	Unknown/unspecified	Nagoya port cluster	Other Asia Pacific
Ramba CCUS/EOR	760	Indonesia	Pertamina	Full chain	2022	NaN	2032	NaN	Planned	NaN	NaN	NaN	Natural gas processing/LNG	EOR	NaN	Other Asia Pacific
Sukowati CO2-EOR (Jambaran Tiung Biru gas proc...	230	Indonesia	Pertamina, Lemigas, JAPEX (supported by METI),...	Full chain	2020	2024	2025	NaN	Planned	NaN	0.47 - 0.93	0.93	Natural gas processing/LNG	EOR	NaN	Other Asia Pacific
Sunda Asri Basin CCUS hub	762	Indonesia	Pertamina, ExxonMobil	Storage	2022	NaN	2030	NaN	Planned	NaN	NaN	NaN	Storage	Dedicated storage	Sunda Asri Basin CCUS hub	Other Asia Pacific
Tambak Lorok Gas-Fired Power Plant	998	Indonesia	JERA, JGC Holdings, PLN	Full Chain	2023	NaN	NaN	NaN	Planned	NaN	NaN	NaN	Power and heat	Unknown/unspecified	NaN	Other Asia Pacific
Tangguh CCUS hub	860	Indonesia	BP	Storage	2023	NaN	NaN	NaN	Planned	2	NaN	NaN	Storage	Dedicated storage	Tangguh CCUS hub	Other Asia Pacific
Tangguh LNG EGR	388	Indonesia	BP (Mitsubishi, Inpex, JX Nippon, KG Mitsu...	Full chain	2021	2024	2027	NaN	Planned	1	2.5 - 3.3	3.3	Natural gas processing/LNG	EOR	Tangguh CCUS hub	Other Asia Pacific
West Java sea rig-to-CCS JSA	1022	Indonesia	Pertamina, KNOC	Storage	2024	NaN	NaN	NaN	Planned	NaN	NaN	NaN	Storage	Dedicated storage	NaN	Other Asia Pacific

3. RESULTS AND DISCUSSION

The results obtained from the hierarchical clustering process using the dendrogram in Figure 4 represent the analysis for grouping CCUS projects in Indonesia based on similarities in data, including project type, operation, and sector, with the main factors being Announced Capacity (Mt CO_2/yr) and Estimated Capacity by IEA (Mt CO_2/yr). As a result, CCUS projects with similar characteristics will be grouped together earlier, while those that are more different will merge at a higher level in the hierarchy. By examining the dendrogram structure, it is possible to determine the optimal number of clusters and understand the relationships between projects, which can be utilized for more effective CCUS strategy planning. This contributes to the national strategic project that can be implemented to support Net Zero Emission and National Energy Security.

Based on **Fig 4**, the dendrogram shows that there are 15 CCUS projects in Indonesia, each with different distances between them. A smaller distance between projects indicates a higher similarity, allowing them to be grouped together before merging into a larger cluster. For example, the Abadi CCS/CCUS field, with participating interests of INPEX (65%), Pertamina (20%), and Petronas (15%), and Tangguh LNG EGR, operated by BP with participating interests of BP Berau Ltd (40.22%), Mitsubishi INPEX (16.30%), CNOOC Muturi Limited (13.90%), Nippon Oil Exploration (Berau) Ltd (12.23%), KG Mitsui (10.00%), and LNG Japan (7.35%), have a small distance and share similarities in implementation, particularly in full-chain and natural gas processing (LNG), before merging into a larger cluster.

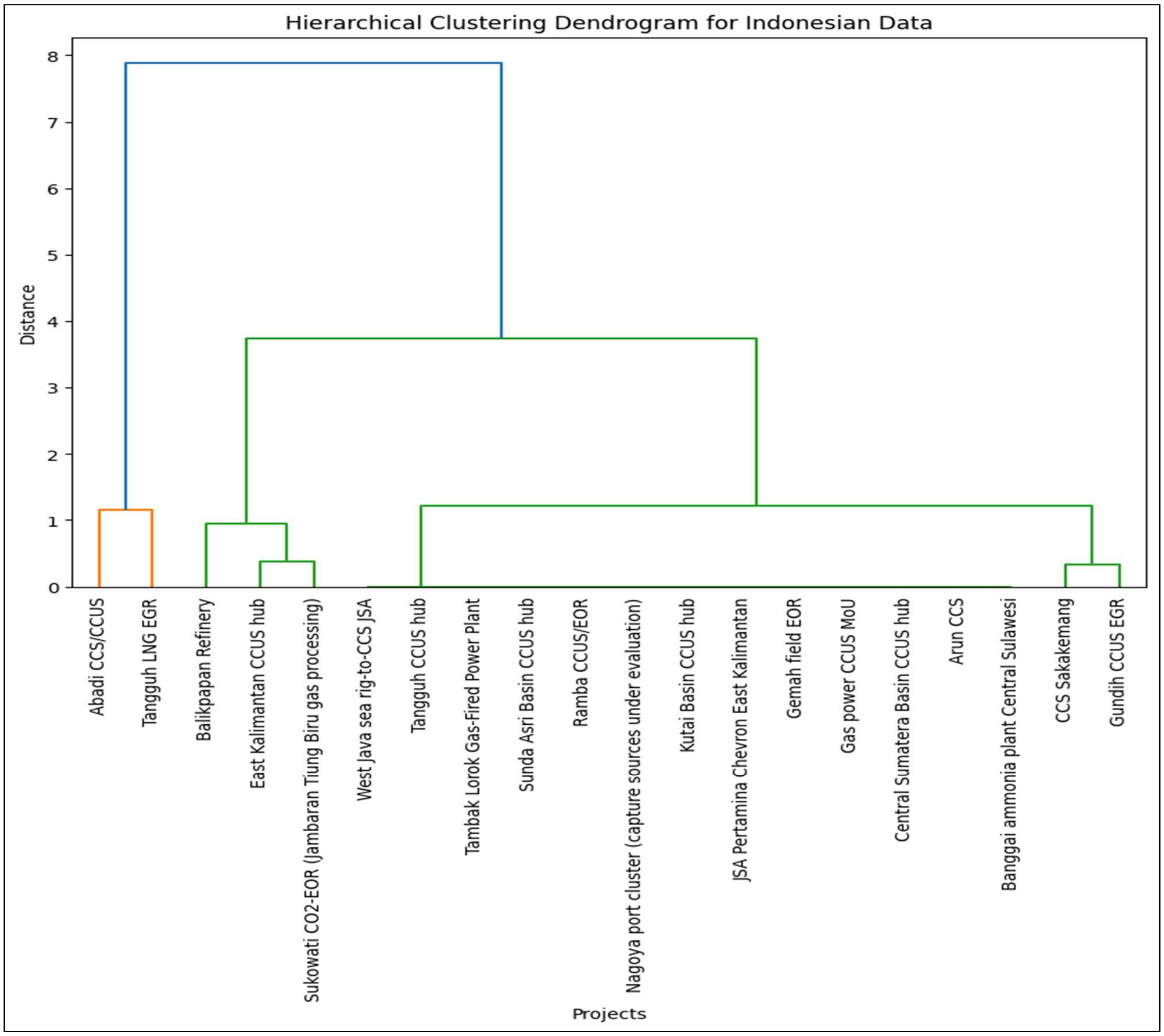

Fig. 4. A dendrogram Results to for Priority CCUS Zones in Indonesia

The results of the Hierarchical Clustering application indicate that the obtained Silhouette Coefficient (**Fig. 5**) is 0.746, as marked by the red dashed line, indicating good cluster separation. The Silhouette Coefficient value approaching 1 suggests that the data points are well assigned to their respective clusters. Additionally, **Fig 6** presents an overview of the national strategic projects for 2023 before the year 2030.

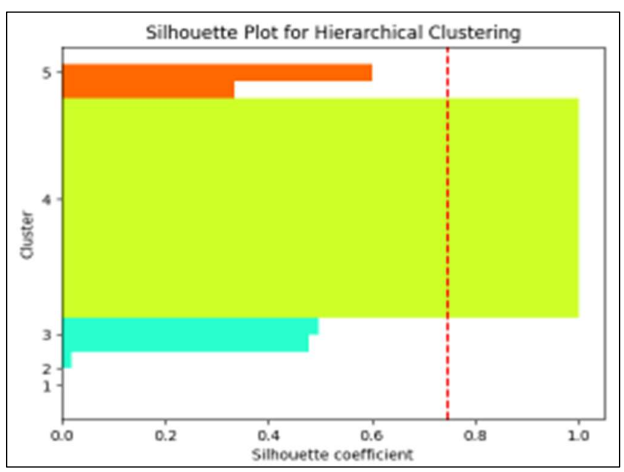

Fig. 5. Silhouette Coefficient

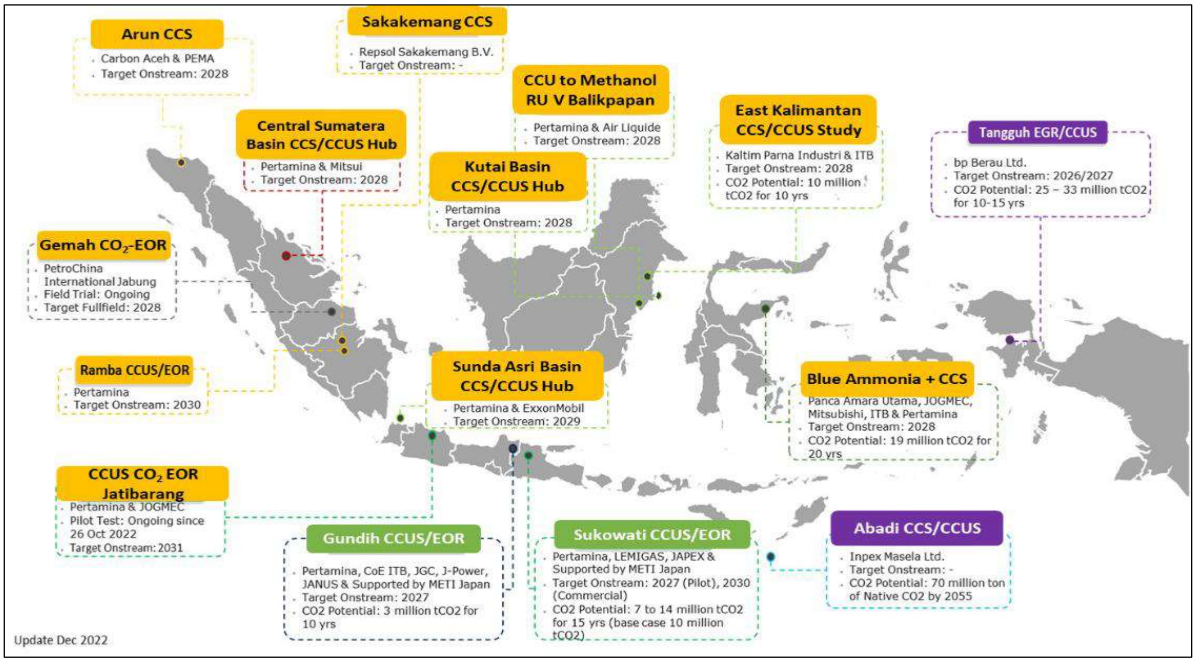

Fig 6. CCS/CCUS Project Locations in Indonesia (Kemen. ESDM, 2023)

Based on **Fig 6**, there are 15 CCS/CCUS projects in Indonesia that are still in the study or preparation stage, but most are targeted to be operational before 2030.

The implementation of Carbon Capture and Storage (CCS) and Carbon Capture, Utilization, and Storage (CCUS) in Indonesia is governed by several key regulations. These include the Minister of Energy and Mineral Resources Regulation No. 16 of 2024 concerning the administration of carbon storage activities within carbon storage permit areas, as part of broader CCS initiatives, and Regulation No. 2 of 2023 concerning the administration of CCS and CCUS in upstream oil and gas business activities. Furthermore, Presidential Regulation No. 14 of 2024 on the Implementation of Carbon Capture and Storage Activities (hereinafter referred to as Presidential Regulation 14/2024) serves as the primary legal foundation for CCS activities in Indonesia. This regulation provides a comprehensive legal framework for both the government and oil and gas companies operating in the upstream sector, outlining the licensing mechanisms, involved stakeholders, and investment regulations necessary to support CCS implementation. The linkage between CCS implementation and upstream oil and gas activities, as stipulated in Article 4, paragraph (1) of Presidential Regulation 14/2024, as well as the allowance for CCS implementation outside the upstream oil and gas sector, as set forth in Article 9, underscores the importance of strict compliance with the provisions of the regulation when undertaking carbon storage initiatives.

Between 2030 and 2035, the combined potential of CCS and CCUS technologies is estimated to reach 25.5 million to 68.2 million tons of CO_2. Currently, several CCS/CCUS projects are being conducted as pilot projects, such as those carried out by Pertamina in Gundih (**Fig 7**) and Sukowati (**Fig 8**), as well as the ongoing CO_2 Enhanced Gas Recovery (EGR) project in the Tangguh Field (**Fig 9**) by BP Tangguh. Additionally, there are several other potential projects, including initiatives led by Panca Amara Utama, JOGMEC, Mitsubishi, and ITB; CCS research in Sakakemang by Repsol; CCS/CCUS projects in the Abadi Field by Inpex; and blue ammonia production with CO_2 storage conducted by Toyo Engineering Corporation, Pupuk Kalimantan Timur, and Pertamina Hulu Indonesia.

These technologies also contribute to increasing oil and gas production through Enhanced Oil Recovery (EOR) and Enhanced Gas Recovery (EGR) methods. EOR is a technique used to enhance oil production by injecting external energy, while EGR involves the injection of CO_2 gas into reservoirs experiencing production decline to optimize oil and gas recovery.

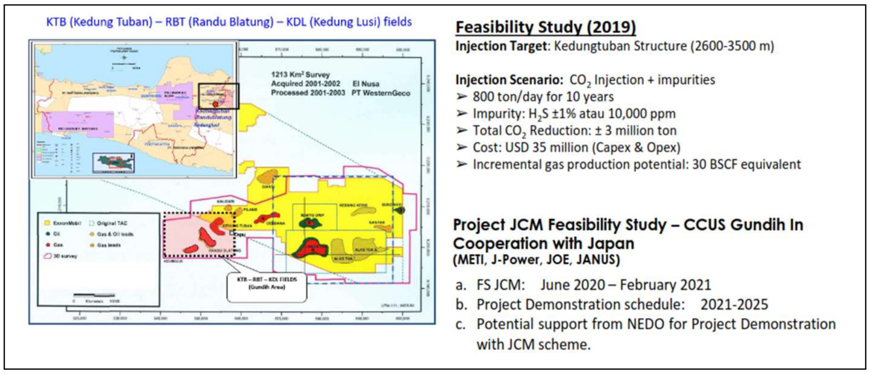

Fig 7. Gundih Co_2 – EOR Project (Wibowo, 2020)

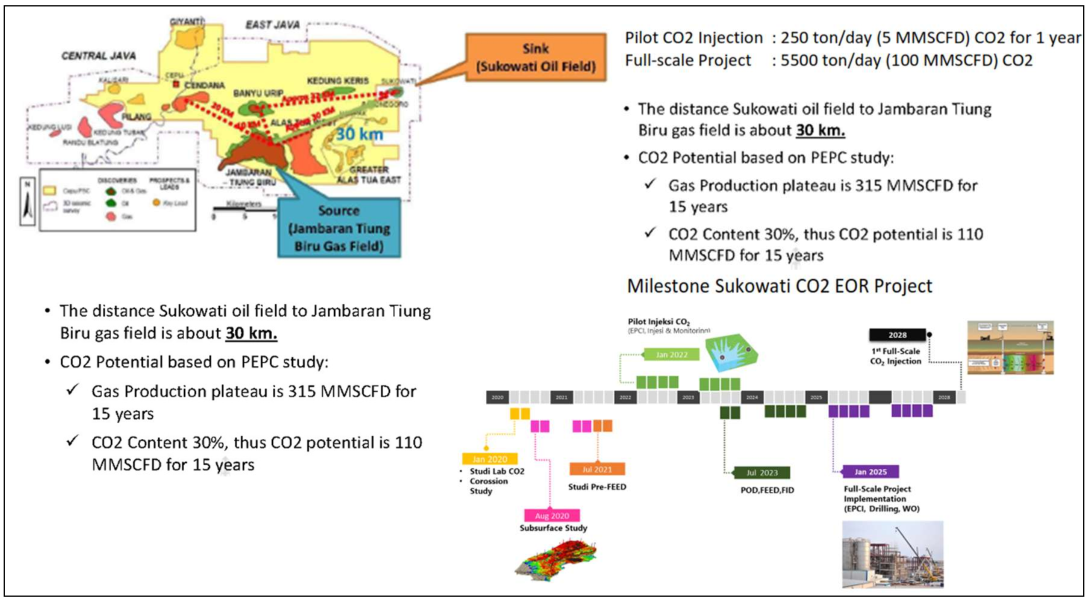

Fig 8. Sukowati Co_2 – EOR Project (Wibowo, 2020)

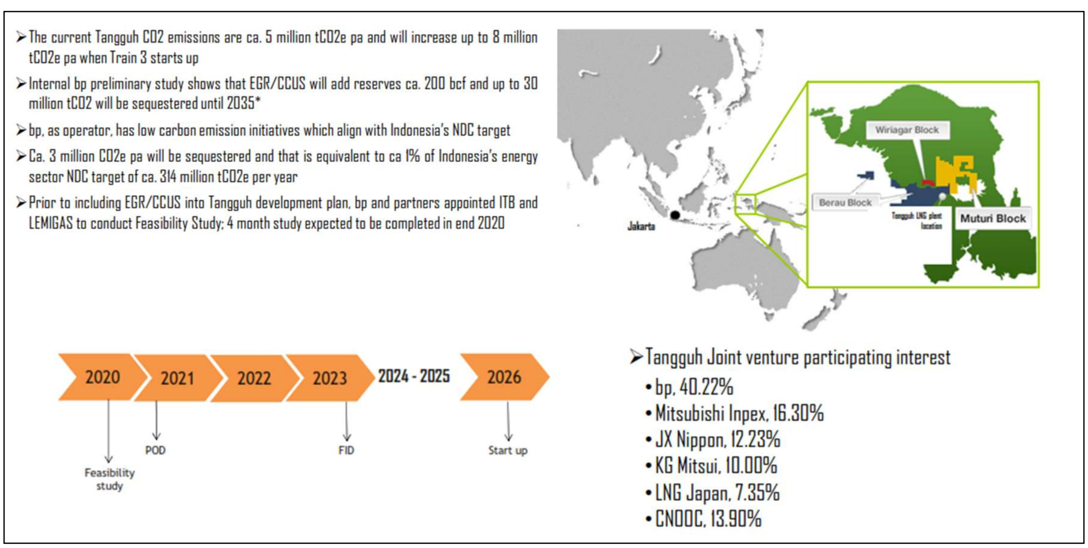

Fig 9. Tangguh Co_2 – EOR Project (Wibowo, 2020)

4. CONCLUSION

In this study, the clustering process was conducted using dendrogram interpretation with two main factors: Announced Capacity (Mt CO_2/yr) and Estimated Capacity by IEA (Mt CO_2/yr). The Silhouette Coefficient after applying hierarchical clustering was 0.746, indicating a well-separated clustering. This method was used to identify priority zones for CCUS (Carbon Capture, Utilization, and Storage) projects in Indonesia, aligning with global initiatives in energy conservation and efforts to achieve net-zero carbon emissions to mitigate global warming.

This study also discusses the challenges and opportunities Indonesia faces in achieving net-zero emissions while providing insights into the interconnections among CCUS projects categorized into priority zones. The results of this analysis support strategic decision-making in CCUS project development, contributing to the achievement of Net Zero Emission targets and national energy security. Additionally, ongoing projects and Indonesia's significant CO_2 storage potential offer promising solutions for reducing greenhouse gas emissions, particularly from the oil and gas energy sector.

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