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Carbon Trading Potential in the Forest Sector: Analysis at the Province Level in Indonesia

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ABSTRACT: Forests play a vital role in mitigating climate change by absorbing and storing carbon. Indonesia's forests have significant potential in the carbon market, offering opportunities to fund forestry projects. However, the sector has yet to fully utilize this potential. This study explores the current state and prospects of Indonesia's forestry carbon market and estimates its 2022 carbon trading value across 34 provinces using the K-Medoids method. Results indicate that Papua and Kalimantan Islands are key contributors due to their extensive, preserved primary forests. In particular, Papua's forests are highlighted as a strategic asset in Indonesia's climate change mitigation efforts through carbon trading.

Keywords*:* carbon market, carbon sink, climate change, financial instruments, forestry sector

ABSTRAK: *Hutan merupakan ekosistem yang memberikan berbagai jasa penting bagi umat manusia, khususnya dalam mitigasi perubahan iklim. Hutan di Indonesia sebagai penyerap dan penyimpan karbon mempunyai potensi pasar yang besar, dimana pasar karbon memberikan peluang untuk mendanai proyek-proyek sektor kehutanan. Namun sektor kehutanan di Indonesia belum mampu memanfaatkan pasar karbon secara maksimal. Penelitian ini bertujuan untuk mendeskripsikan kondisi dan potensi pasar karbon sektor kehutanan, serta memperkirakan nilai perdagangan karbon sektor kehutanan untuk 34 provinsi di Indonesia pada tahun 2022. Metode yang digunakan adalah K-Medoids dan menghitung nilai perdagangan karbon. Hasil studi menunjukkan bahwa wilayah di Pulau Papua dan Pulau Kalimantan merupakan penyumbang potensi utama perdagangan karbon di Indonesia. Kedua pulau ini mempunyai kawasan hutan primer luas yang masih terjaga. Kawasan hutan di Provinsi Papua merupakan aset strategis bagi Indonesia dalam upaya mitigasi perubahan iklim melalui perdagangan karbon.*

Kata Kunci: *pasar karbon, penyerap karbon, perubahan iklim, instrumen keuangan, sektor kehutanan*

INTRODUCTION

Since the 20th century, the world economy has grown quickly, industrialization has accelerated, population increase, excessive energy usage, irrational land use, and widespread deforestation have all contributed to the significant effects of global warming (Ali et al., 2022; Raihan et al., 2021; Zhao et al., 2023; Wang et al., 2017). The primary cause of global warming is greenhouse gas emissions brought on by human activity (Miswa & Kartiasih, 2025). Countries or regions are at risk of climate change because greenhouse gas emissions have detrimental externalities (Shao et al., 2016; Hassan et al., 2022). Human survival as well as social, human health, economic, and ecologically sustainable development will be seriously threatened by climate change (Isfat & Raihan, 2022; Kartiasih & Setiawan, 2020; Pribadi & Kartiasih, 2020; Vale, 2016). It takes teamwork and global shared governance to preserve the planet's natural ecosystem, lower atmospheric carbon dioxide (CO2) concentrations, and achieve green and sustainable economic development (Lin and Ge, 2019; Ge et al., 2023).

The concentration of greenhouse gases in the atmosphere can be decreased in two primary ways. One strategy is to lower carbon emissions through energy conservation and the advancement of renewable energy. The alternative is to develop carbon sequestration technologies to fix CO2 in the atmosphere and lower carbon concentrations by increasing carbon sinks (Zhao et al., 2019; Zhao et al., 2021). One of the most reliable carbon sinks is forests (Zhao et al., 2023).

A feature of the natural world, forests play a crucial role in the carbon cycle and are inexpensive to offset carbon emissions (Kindermann et al., 2008). Lowering emissions from Reducing Emissions Deforestation and Forest Degradation (REDD), including REDD+ a reduction in emissions achieved by preserving forest carbon reserves in conjunction with sustainable forest management. The importance of forests in reducing climate change has been acknowledged by the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol (KP). The Land Use, Land-Use Change, and Forestry (LULUCF) sector's emissions and removals serve as evidence of this.

According to the Food and Agriculture Organization of the United Nations (2020), Indonesia is one of the eight nations with the largest woods worldwide. Indonesia's forests have a significant impact on the planet (Simonson et al., 2021). The total estimated area of Indonesia's forests is 125,795,306 hectares. One of the lungs of the globe is our nation. Building carbon capture, utilization, and storage (CCUS) facilities is a top priority for Indonesia as part of its climate action program. Indonesia is aggressively deploying cutting-edge carbon capture and storage (CCS) technology in recognition of the need to lower emissions. This study provides a thorough evaluation of Indonesia's forest potential, taking into account policy frameworks, CO2 emission profiles, and prospects for carbon trading in the forestry industry. Indonesia aims to reduce carbon emissions by 29% by 2030 and achieve net zero emissions by 2050 (Ramadhan et al., 2024; Susantoro et al., 2023). The government is considerably outperforming its targets, with 15 CCUS projects set to begin by 2026.

Among the ten nations that produce the most carbon worldwide is Indonesia. In 2022, Indonesia's carbon emissions increased by 18.3%, the biggest increase among the nations. Land conversion, high levels of deforestation in Indonesia, and the use of fossil fuels—particularly coal—all contribute to the rise in emissions (Global Carbon Budget, 2023). In addition, Indonesia must contend with unequal regional economic growth and carbon emissions due to its large territory. More developed regions like Java and Sumatera have higher emissions, while less developed areas like Papua and Maluku show lower emissions (Rum et al., 2024). It is critical to acknowledge the significant regional differences in Indonesia's carbon emissions. Research has indicated that variations in economic development across Indonesia's western, central, and eastern regions significantly influence the distribution and intensity of carbon emissions, with the western and central regions contributing higher emissions from industrial and urban activities, while the eastern region shows higher sequestration potential due to extensive natural land cover (Hasanah & Wu, 2023; Rum et al., 2024). To create effective policies that strike a balance between environmental preservation and economic growth, policymakers must have a thorough understanding of these regional variations. Development plans and carbon reduction goals can be matched to help Indonesia move toward a more sustainable and just future.

In general, carbon emissions and economic growth rates are generally lower in Indonesia's eastern areas, as seen in provinces like East Nusa Tenggara, which have per capita carbon footprints as low as 2 t CO_2e/capita (Rum et al., 2024). Moderate economic growth and carbon emissions are produced in central Indonesia, with exceptions such as East Kalimantan, which reports a notably high per capita carbon footprint of 13.84 t CO_2e/capita due to extensive infrastructure projects and industrial activities. Conversely, the western regions, such as Jakarta and Riau, with higher per capita carbon footprints of 9.93 t CO_2e/capita and 7.94 t CO_2e/capita, respectively, are experiencing faster economic growth despite their larger carbon emissions (Rum et al., 2024). While the western portion of Indonesia has a small forest area and a bigger population, the eastern region is defined by a wider forest area and a smaller population. The western region's economy is consequently more developed and vibrant. Each region should have a distinct policymaking process as a result of these variations. It is essential to take into account the distinctive carbon features of each location in order to solve the issue of regional diversity.

Examining the flow of carbon emissions brought on by cross-regional trade is one strategy to slow down global warming. According to a study by Wu et al. (2022), China's carbon emissions are realized within the framework of international trade, and the country produces more carbon dioxide than it consumes. Trade can be a means of transferring carbon emissions between two nations or areas. For instance, because the majority of goods are produced in developing nations (like China and India), which have significantly higher carbon emissions, developed nations (like the United States), which account for the majority of the ultimate consumption of goods traded, may actually be net importers of carbon emissions.

Study by Indrajaya et al. (2016) found that if the carbon price were set at the average 2015 pricing in the EU Emissions Trading Scheme, a REDD+ carbon credit system could raise carbon stocks per hectare by 15.8% in the case of privately managed forests and by 22% in the case of government-managed forests. However, the interesting thing is that neither the amount of carbon stored nor the anticipated value of the land is raised, even when carbon credits are granted for carbon stored in end-use wood products.

The policymaking procedure ought to vary depending on the region due to these distinctions. It is imperative to take into account the distinct features of every region concerning carbon trading in the forestry industry in order to tackle the problem of regional diversity. As a result, it is crucial to conduct focused analysis of the carbon trade flow in the forestry industry. This analysis could offer a theoretical foundation for comprehending the regional disparity in carbon emissions and the consequences it has for the nation's sustainable economic growth. Therefore, the aim of this research is to group provinces based on their carbon trading potential and socio-economic conditions and estimate the value of carbon trading from 34 provinces in Indonesia in 2022.

This study contributes to the literature. First, this study fills the literature gap regarding the potential for carbon trading in Indonesia, broken down by province. Previous studies examined the potential for carbon trading in Indonesia and on the island of Kalimantan (Indrajaya et al., 2016). Second, this study maps regions and also groups regions (provinces) based on carbon trading potential, which has never been done before. This is important to do to provide new insights so that we can provide unique policy recommendations for each region. Third, the estimated carbon trading value in this study for 34 provinces in Indonesia has also never been found in previous studies. This estimated value can be a future reference for both the government and business people in carrying out carbon trading as an effort to reduce the impact of climate change.

METHODS

This study uses data on forest area, Gross Regional Domestic Product (GRDP), Human Development Index (HDI), deforestation, and investment realization by province in Indonesia. The data used is 2022 data covering 34 provinces in Indonesia sourced from the BPS-Statistics Indonesia. According to research conducted by Santosa et al. (2023), forests have the ability to absorb carbon emissions of 51.1 tons of carbon dioxide equivalent ($CO2e$) per year. This value will be used to calculate the total carbon credits generated by forests in absorbing carbon emissions in a particular region. The daily price of carbon is obtained from the IDX Carbon website (https://idxcarbon.co.id/id/data-daily). The daily price of carbon is used as a conversion factor to calculate the estimated value of carbon trading, which is IDR 58,800.

In general, the stages carried out in the research are as follows and the flow can be seen in Figure 1. Data was collected from the official website of the BPS-Statistics Indonesia to obtain data on forest area, Gross Regional Domestic Product (GRDP), Human Development Index (HDI), deforestation, investment realization by province in Indonesia in 2022. Standardize data on all variables using the robust scaling method. Scaled values will have a range of 0-1. The use of median and interquartile range (IQR) is used because it is robust to outliers. The advantage of robust scaling over standardization in general is that the scaled values have a sufficient range so that the distance between outliers and other values remains largely intact. Detecting Multicollinearity and Variable Reduction. Multicollinearity can be detected using the value of the correlation and Variance Inflation Factor (VIF). The correlation used is Pearson correlation with multicollinearity occurring when the correlation is above 0.8. The VIF value is the increase in variance of the estimated parameters between dependent variables. If the VIF value is more than 10, then the estimated parameters are not good, so the variable reduction is needed. This aims to avoid multicollinearity that causes instability because clustering algorithms are based on distance or covariance matrices. In addition, dimensionality reduction is useful to improve the performance of the clustering algorithm.

Cluster Analysis Non-Hierarchical Method (K-Medoids) aims to group individuals or objects into groups with similar characteristics, so that differences in characteristics between groups can be analyzed in detail. Members within a group are homogeneous, while between groups are heterogeneous. Generally, there are two methods used in cluster analysis: hierarchical and non-hierarchical methods (Firnanda & Wijayanto, 2023). Hierarchical methods are used to group observations in a structured manner based on similar traits, especially when the desired number of groups is unknown. This can be done through merging (agglomerative) or splitting (divisive). Meanwhile, non-hierarchical methods are used to group observations in an unstructured manner when the desired number of groups is predetermined. A variation of the K-Means technique called Medoids, or Partitioning Around Medoids (PAM), was created to address K-Means' sensitivity to outliers. K-Medoids is more resilient to extreme values since it employs medoids as cluster centers rather than the mean. According to Bahri & Midyanti (2023), clusters are created depending on the proximity of medoids and non-medoid items. Medoids are more resilient to outliers since they are positioned at the cluster center. Similar to K-Means, K-Medoids works well with big data sets. To guarantee balance, the data must be normalized before computing the distance. The K-Medoids algorithm's steps are as follows (Han et al., 2022): (1) Find out how many clusters there are (k); (2) Choose k initial medoids at random from the n data; (3) use Euclidean Distance to calculate the object's distance to each medoid and determine the overall closest distance for the first medoid; (4) choose new medoids at random and compute the object's distance to each new medoid. Determine the new medoids' total closest distance. (5) Determine the total deviation (S); (6) If S is less than zero, replace the object with the updated data to create k new medoids; (7) If not, repeat steps three through seven until the medoids stop changing, establishing the final cluster with its members.

Evaluation of Cluster Results (Internal Validity Test) with Silhouette Coefficient, Index Connectivity and Dunn Index. Silhouette coefficient is a method to evaluate the quality of a cluster by looking at the closeness of objects within a cluster as well as between clusters (Pramesthy et al., 2024; Widiyasari et al., 2023). The silhouette coefficient value ranges from -1 to 1, where values close to 1 indicate good clustering, while values close to -1 indicate poor clustering (Silhouettes, 1987). The following are the steps to calculate the silhouette coefficient value: (i) Calculate the average distance of a data with all other data in a cluster; (ii) Calculate the average distance of a data with all data in other clusters; (iii) Calculate the minimum value; (iv) Calculate the silhouette coefficient value using Eq:

$$s(i) = \frac{b(i) - a(i)}{[a(i), b(i)]}$$

In this case, the average distance between i and every other observation in the same cluster is denoted by a(i), and the average distance between i and the observation in the closest cluster is denoted by b(i).

Connectivity index is an evaluation method used to measure how well a cluster is internally connected. Connectivity index values range from 0 to infinity, where the smaller the Connectivity index value, the better the cluster formed. The Connectivity index takes into account the relationship between each data point and its neighbors in the cluster. The Connectivity index evaluates how well the points in a cluster are connected to each other. The higher the connectivity index value, the better the points are internally connected within the cluster, which indicates that the cluster is more dense and well-structured. Therefore, in clustering model selection, we tend to choose a model with a lower Connectivity index value (Firnanda and Wijayanto, 2021).

$$Conn\ (C) = \sum_{i=1}^{N} \sum_{j=1}^{L} x_{i,nni(j)}$$

Where L is a parameter that determines the number of neighbors that contribute to the connectivity measure

The Dunn index is a cluster validity method that compares the smallest distance between two different observations between two clusters with the largest intracluster distance. The larger the Dunn index value, the better the number of clusters formed. Dunn's index is susceptible to outliers and noise (Firnanda and Wijayanto, 2021).

$$C = \frac{d_{min}}{d_{max}}$$

Where d_{min} is the smallest distance between observations in different clusters, and d_{max} is the largest distance in each data cluster.

To calculate the total carbon credits from each province in Indonesia, the following equation was used. Total Carbon Credit = Forest area (Ha) x Conversion factor (51.1 tons CO2e/Ha). The total carbon credit of each province was calculated by multiplying the forest area in the province by the carbon conversion factor. The conversion factor used is 51.1 tons of CO2e per hectare, which is an estimate of the amount of carbon dioxide (CO2e) sequestered by one hectare of forest. With this equation, we can find out how much carbon is sequestered by forests in a province, which is then converted into tradable carbon credits.

To calculate the estimated carbon trading value of each province in Indonesia, the following equation was used. Estimated Carbon Trade (IDR) = Total Carbon Credits (tons CO2e) x Carbon Price (IDR 58,800/ton CO2e). Carbon trading value is calculated by multiplying the total carbon credits (in tons of CO2e) by the market price of carbon (in Rupiah per ton of CO2e). In this study, the carbon price used is IDR 58,800 per ton CO2e, which is the estimated value of the carbon price in the national or international carbon market.

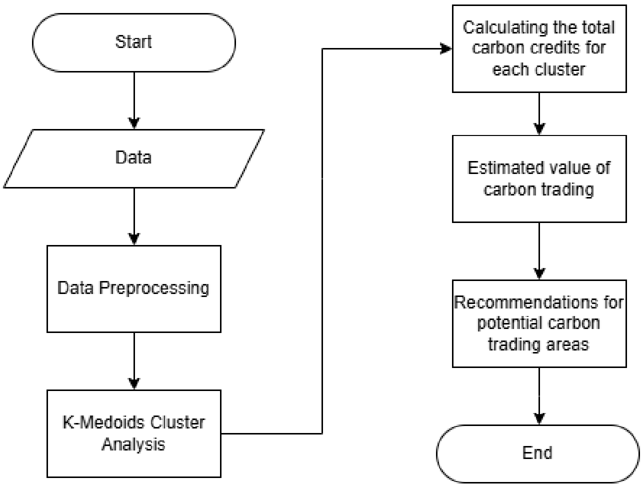

Figure 1. Research flow chart

RESULTS AND DISCUSSIONS

Indonesia's provinces have varying forest areas, with the smallest forest area of 1,100 hectares in DKI Jakarta, and the largest forest area of 253,221,900 hectares in Papua (see Table 1). This imbalance has implications for carbon dioxide emission levels and regional economic growth. Provinces with larger forest areas, such as Papua, tend to have higher carbon sequestration capacity, thus contributing positively to climate mitigation. In contrast, provinces with smaller forest areas, such as DKI Jakarta, face challenges in balancing urban development with environmental sustainability. Deforestation rates varying from -0.83% to 18.52% illustrate the dynamics of forest management, where negative numbers can indicate reforestation or forest recovery, while high positive numbers reflect serious threats to environmental sustainability.

Table 1. Descriptive statistics

Variables	Mean	Std. dev.	Minimum	Maximum
Forest (ha)	2822626	4631249.76	1100	253221900
GRDP (billion rupiah)	563117	782590.65	47570	3188539
HDI	71.97	3.90	61.39	81.65
Deforestation (percent)	1.69	3.79	-0.83	18.52
Investment (billion rupiah)	16258	22571.84	611	89224

Provincial GRDPs in Indonesia range from IDR47,570 billion to IDR3,188,539 billion, indicating a significant difference in the level of economic prosperity of the regions. Regions with higher GRDP may have better infrastructure and more diverse economic activities. Meanwhile, realized investment ranges from Rp611 billion to Rp89,224 billion, reflecting the level of attention and economic priority given to each region depending on its economic potential and efforts to manage natural resources sustainably. On the social side, the Human Development Index (HDI) of Indonesian provinces has a minimum value of 61.39 and a maximum of 81.65, indicating disparities in human well-being, which includes aspects of education, health, and living standards. Regions with a low HDI may face challenges in access to basic services, while those with a high HDI are likely to have better social conditions.

Data Preprocessing

Before proceeding to the next stage, it is necessary to check for missing values in the dataset. Missing values refer to empty or missing values in one or more columns of data. This step is important to ensure that each row of data has complete values and there is no significant loss of information before further analysis. After checking, it was found that there was no empty data, so we could proceed to the next stage. However, when checking for outliers, it was found that almost all variables had outliers.

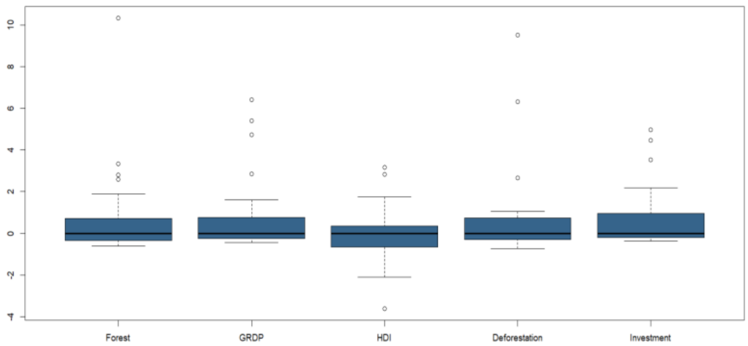

Figure 2. Outlier detection

After checking for missing data, continue with multicollinearity testing. To determine the presence or absence of multicollinearity in the model, it can be seen by the variance inflation factor (VIF) value. According to Ghozali (2016), the decision-making criteria related to the multicollinearity test are when the VIF value > 10, it can be said that multicollinearity occurs. In addition, it can also be seen from the correlation of each independent variable, if it is more than 0.8, multicollinearity occurs. This can be handled by replacing or removing variables that have a high correlation value.

Table 2. VIF value

Variables	VIF
Forest	1.46
GRDP	10.52
HDI	2.63
Deforestation	1.61
Investment	11.22

Figure 3. Pearson correlation all variables

Based on the multicollinearity test results by looking at the VIF value in Table 2, it is found that 2 variables have VIF values of more than 10, namely the GRDP and Investment variables. In addition, there is a high correlation between the GRDP variable and the Investment variable as shown in Figure 3. Thus, the Investment variable will be excluded from the data.

Table 3. VIF value

Variables	VIF
Forest	1.46
GRDP	1.49
HDI	2.49
Deforestation	1.55

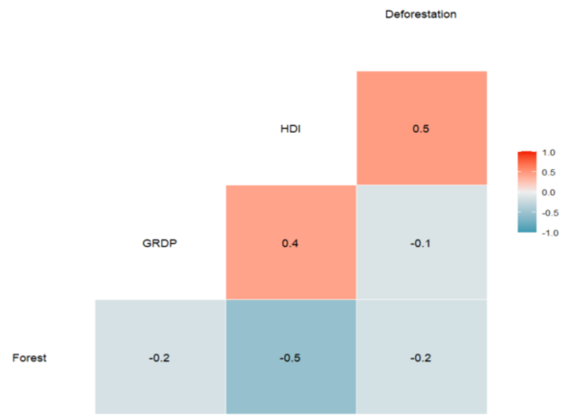

Figure 4. Pearson correlation excluding investment

After the investment variable is removed from the data, it can be seen that in Table 3 there are no variables that have a VIF value of more than 10. In addition, based on Figure 4, it can be seen that the correlation between independent variables is no more than 0.8. This means that the data no longer contains multicollinearity problems and can proceed to the next stage.

The data format/structure is changed by standardizing the data using Robscale. Robscale is a combined function of standard normalization and robust normalization methods that use median and mad instead of mean and standard deviation. This method can adjust well to data that is not normally distributed and has many outliers. In addition, this transformation was chosen because it is able to produce higher silhouette scores, showing effective cluster separation and a good fit.

Clustering Stages

In this research, a clustering method will be used to group data or objects into several clusters with the non-hierarchical K-Medoids method. With the following stages. To determine the optimum number of k clusters, it will be seen based on the Elbow graph. The optimum k cluster value will be obtained from the Elbow graph, when the slope of the line has not moved down sharply (sloping).

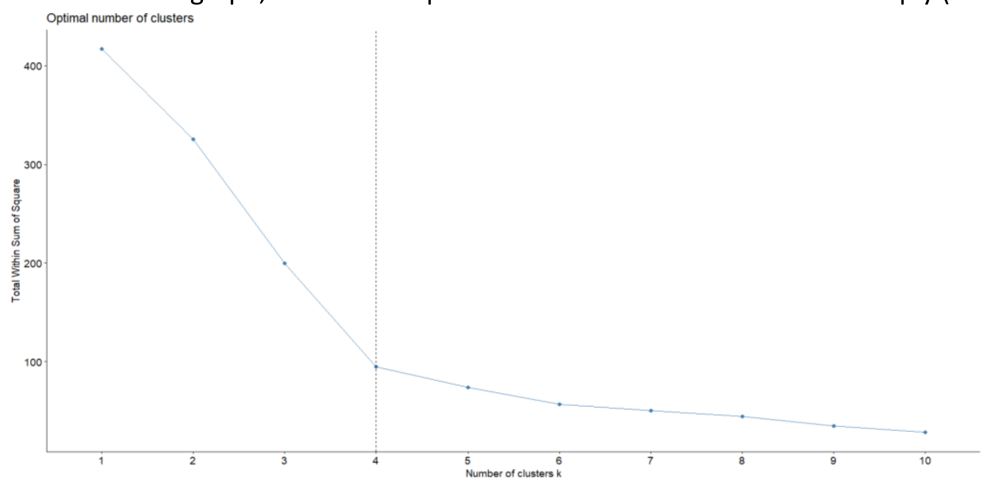

Figure 5. Elbow Chart for K-Medoids clustering

Based on Figure 5, it is obtained that the optimum number of clusters is 4 clusters. Then the formation of clusters with the K-Medoids method with the number of 4 clusters obtained results as in Figure 6.

Indonesia's 34 provinces are grouped into 4 groups based on the clusterization results (see Figure 6). Cluster 1 consists of 27 provinces, including Aceh, North Sumatera, West Sumatera, Riau, Jambi, South Sumatera, Bengkulu, Lampung, Bangka Belitung Islands, North Kalimantan, West Kalimantan, Central Kalimantan, South Kalimantan, East Kalimantan, North Sulawesi, Central Sulawesi, South Sulawesi, Southeast Sulawesi, Gorontalo, West Sulawesi, Bali, West Nusa Tenggara, East Nusa Tenggara, Maluku, North Maluku, and West Papua. Cluster 2 comprises Riau Islands Province and DI Yogyakarta Province. Cluster 3 includes DKI Jakarta and the major Java provinces, namely West Java, Central Java, and East Java. Lastly, Cluster 4 is represented solely by Papua Province. The label of the clusterization results is used for profiling. The purpose of the profiling stage is to identify each cluster's regional categorization. The mean value of each variable compared to the cluster label derived using the following information is used to determine the regional category.

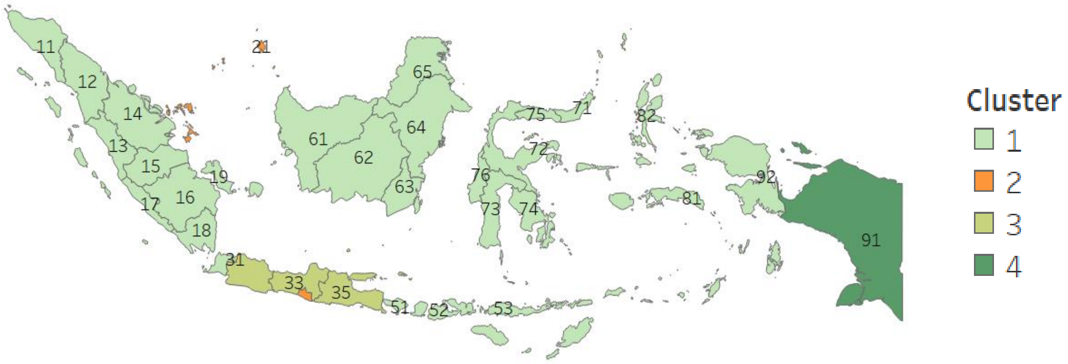

Figure 6. Clustering result of provinces based on carbon trading potential (K-Medoids)
Source: Author
Note: Aceh (11), North Sumatera (12), West Sumatera (13), Riau (14), Jambi (15), South Sumatera (16), Bengkulu (17), Lampung (18), Bangka Belitung Islands (19), Riau Islands (21), DKI Jakarta (31), West Java (32), Central Java (33), DI Yogyakarta (34), East Java (35), Banten (36), Bali (51), West Nusa Tenggara (52), East Nusa Tenggara (53), West Kalimantan (61), Central Kalimantan (62), South Kalimantan (63), East Kalimantan (64), North Kalimantan (65), North Sulawesi (71), Central Sulawesi (72), South Sulawesi (73), Southeast Sulawesi (74), Gorontalo (75), West Sulawesi (76), Maluku (81), North Maluku (82), West Papua (91), Papua (92)

The K-Medoids cluster analysis revealed a clear geographical grouping of provinces based on the forest area and deforestation. According to the results, there were four regional clusters of provinces, as seen in Figure 6, with cluster characteristics (refer to Table 4). Cluster 1 and Cluster 4 have high carbon trading potential due to their large forest area, with values of IDR 7534.26 billion and IDR 76,084.21 billion, respectively. Cluster 1 excels due to good economic and social factors, such as high GRDP (315,060.4 billion Rupiah), HDI (71.41), and low deforestation rate (0.97%). In contrast, Cluster 4 faces challenges with lower GRDP (262,519.8 billion Rupiah), the lowest HDI (61.39), and moderate deforestation (0.32%). Meanwhile, Cluster 2 and Cluster 3 show lower carbon trading potential due to small forest areas, having carbon trading potential worth IDR 518.31 billion and IDR 1952.82 billion, respectively. Cluster 2 has the highest HDI (78.55) but high deforestation (15.5%), while Cluster 3 stands out with the highest GRDP (2,475,562.8 billion Rupiah) and no deforestation (-0.03%).

Table 4. K-Medoids cluster composition, socioeconomic characteristics, and estimated carbon trading in Indonesia, 2022

Description	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Forest (ha)	2507507	172500	649925	25321900
GRDP (billion rupiah)	315060.4	237280.6	2475562.8	262519.8
HDI	71.41	78.55	75.08	61.39
Deforestation (percent)	0.97	15.5	-0.03	0.32
Estimated Carbon Trading (billion rupiah)	7534.26	518.31	1952.82	76084.21
Number of provinces	27	2	4	1

Source: own preparation
Note: The value of each cell in the table is the average value

Cluster 1 - High Carbon Trading Potential with Good Economic and Social Factors
Cluster 1 includes 27 provinces with high carbon trading potential and good socio-economic factors, including resource-rich regions like East Kalimantan and South Sumatera, where industrial activities drive emissions but also support economic growth. Conversely, provinces like Bali and Nusa Tenggara focus on tourism and agriculture, which contribute less to emissions but still require sustainable practices to protect their ecosystems. These regions leverage their economic strength and infrastructure for integrating carbon trading policies, with the potential to improve environmental outcomes through robust governance (Idris et al., 2023).
Cluster 2 - Low Carbon Trading Potential with Good Economic and Social Factors

Cluster 2, comprising the Riau Islands and DI Yogyakarta, shows low carbon trading potential but strong socio-economic factors. These provinces, characterized by service-driven economies, show minimal industrial emissions. However, limited natural resources for carbon sequestration reduce their contribution to carbon trading. Despite their low carbon trading potential, these provinces are well-positioned to adopt sustainability measures due to their strong socio-economic foundations and capacity for innovation. Such provinces could focus on urban greening and renewable energy initiatives, aligning sustainability with economic priorities (Faradila & Aqilla, 2022).

Cluster 3 - Low Carbon Trading Potential with Excellent Economic and Social Factors

Cluster 3 includes industrial and urban centers such as DKI Jakarta and major provinces in Java, namely West Java, Central Java, and East Java. It shows high carbon trading potential with excellent economic and social infrastructure. These regions are major industrial centers with high emissions but have the capacity to effectively adopt mitigation strategies, such as transitioning to renewable energy. Despite their high emissions, the economic and social advantages of these clusters make them ready to balance carbon trading with sustainable development. Improved institutional frameworks and market mechanisms will be key to optimizing carbon trading outcomes (Rahmawati et al., 2024).

Cluster 4 - High Carbon Trading Potential with Weak Economic and Social Factors

Cluster 4 is only represented by Papua Province, which offers high carbon trading potential but lacks economic and social support. Papua has extensive forests that serve as a carbon sink, but deforestation threatens this potential. Sustainable land management and investment in local development are essential to enable carbon trading while maintaining their ecological value (Mulia et al., 2014).

Evaluation of Cluster Results (Internal Validity Test)

The internal validity test is used to determine the best number of clusters and the best model to use. The smaller the Connectivity value and the greater the Dunn and Silhouette values, the better the model. From Table 5, it can be seen that the smallest connectivity value is at cluster number 3, but with the largest Dunn and Silhouette values at cluster number 4, so it can be said that cluster 4 is the optimal number of clusters for clustering.

Table 5. Internal validity test value of K-Medoids model evaluation

Number of Clusters	Connectivity	Dunn	Silhouette
3	10.2821	0.1263	0.5121
4	13.2111	0.2748	0.5498
5	26.4250	0.1326	0.2673

Estimated Value of Carbon Trading

The estimated value of carbon trading was calculated to see the potential of each province in Indonesia. Before estimating the value of carbon trading, the total carbon credit of each province was first calculated by multiplying the forest area with a conversion factor of 51.1 tons CO_2e/ha. From the results of this calculation, it is continued by calculating the estimated value of carbon trading by multiplying the total carbon credits from each province with the daily price of carbon in Indonesia, which is IDR 58,800. Thus, the 34 provinces estimated carbon trading value were obtained as shown in Figure 7.

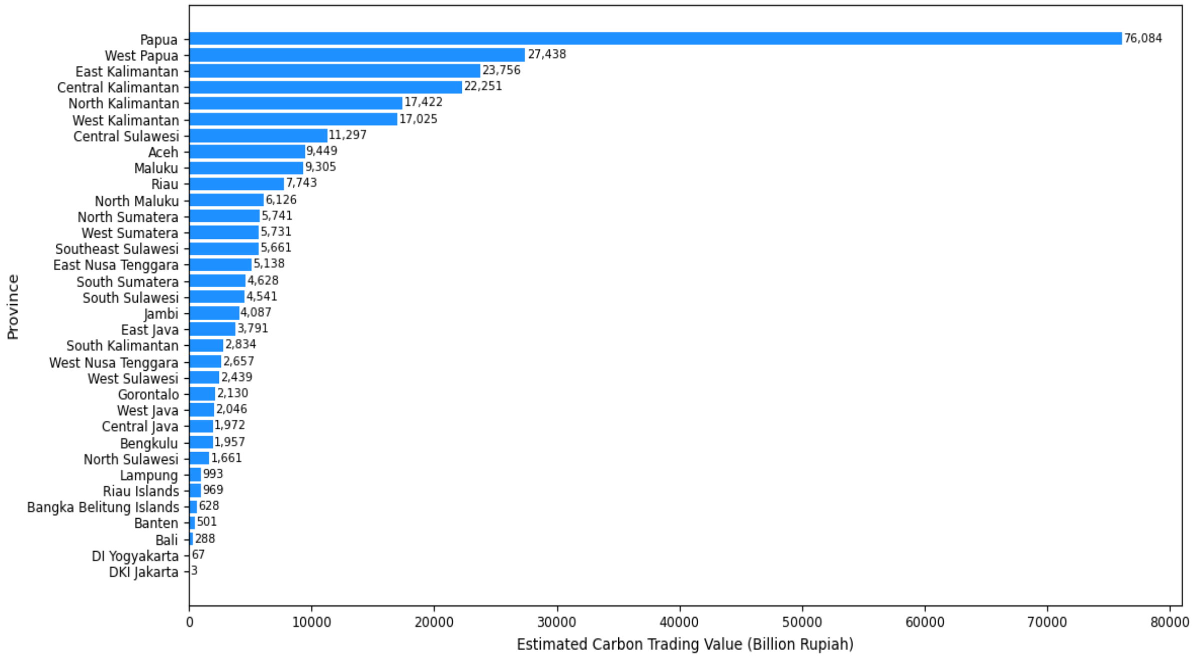

Figure 7. Estimated carbon trading value by province in Indonesia (billion rupiah)

It can be seen from Figure 7 that Papua Island and Kalimantan Island are the main contributors to Indonesia's carbon trading potential. Papua was the highest contributor to carbon trading with IDR 76,084 billion, followed by West Papua with IDR 27,438 billion and East Kalimantan with IDR 23,756 billion. This reflects the great potential of the region, especially in relation to its vast forest and land ecosystems. Other provinces, such as Jambi, South Sulawesi, South Sumatera, and East Nusa Tenggara, showed moderate contributions, ranging from IDR 4,087 to 5,138 billion. In contrast, provinces such as DKI Jakarta, DI Yogyakarta, Bali, and Banten have the lowest estimated values, indicating limited carbon contributions from urban areas and areas with smaller natural ecosystems. Overall, this graph highlights the large disparity in carbon trading potential between provinces in Indonesia, which seems to correlate with the extent and quality of natural resources in each region.

Papua holds the highest potential for carbon trading in Indonesia due to its extensive forest cover, low industrial emissions, and alignment with national and international environmental policies. According to data from the BPS-Statistics Indonesia, the forest area in Papua Province reached 29,368,482 hectares in 2022 (BPS, 2022). This forest area acts as a significant natural carbon sink, absorbing large amounts of carbon dioxide from the atmosphere. In addition, Papua also has relatively low emission levels compared to other regions due to the lack of industrialization and massive land conversion. This makes the region's carbon sequestration potential even greater. According to Indonesia's Enhanced Nationally Determined Contribution (NDC) document, the forestry sector in Papua is one of the main focuses for emission reduction, with a national target of achieving emission reductions of 31.89% by its own efforts and 43.20% with international assistance by 2030 (UNFCCC, 2022).

In the aspect of economic growth, Papua shows significant variations. In the first quarter of 2022, Papua's economy grew by 13.33% compared to the same period in the previous year (year-on-year). However, in the third quarter of 2022, economic growth slowed down to 5.78% (year-on-year). This variation reflects the dependence of Papua's economy on sectors such as mining and agriculture. The implementation of a carbon trading mechanism could be an opportunity to promote more sustainable economic growth in the region (UNFCCC, 2022). The carbon trading program is expected to be an instrument for more environmentally friendly economic diversification, while improving the welfare of local communities through forest conservation-based programs.

In comparison, areas on the island of Kalimantan also show great potential for carbon trading. However, the region's potential is affected by factors such as deforestation rates and land use policies. Provinces such as East Kalimantan and Central Kalimantan reflect the importance of forest conservation and management in Kalimantan to support carbon trading in Indonesia. The Indonesian government has committed to reducing emissions from deforestation and forest degradation, which directly affects Kalimantan's role in carbon trading. Based on the clustering results, all provinces in Kalimantan Island are classified as areas with high potential for carbon trading, supported by good economic and social factors.

CONCLUSION AND POLICY RECOMMENDATION

Conclusion

This study uses the K-Medoids clustering method to group provinces in Indonesia based on carbon trading potential by considering the variables of forest area, GRDP, HDI, and deforestation. The results show that there are four clusters with different characteristics. Cluster 1, which consists of 27 provinces, has high carbon trading potential with good economic and social support. Cluster 2, which includes two provinces, shows low carbon potential but is supported by good economic and social factors. Cluster 3 consists of four provinces with moderately high carbon potential, supported by excellent economic and social factors. Meanwhile, Cluster 4 includes only one province with high carbon potential but less economic and social support. Overall, the results of this study show that carbon trading potential in Indonesia varies widely between provinces and is strongly influenced by economic and social factors in each region. In the face of variations in potential between provinces, Indonesia needs to develop management strategies and policies tailored to the conditions of each region. Provinces with the highest carbon potential may require stricter forest protection and incentives to reduce deforestation, while provinces with low potential require support to improve forest management efficiency.

To maximize the potential and government policy in implementing one type of carbon trading, namely Reducing Emissions from Deforestation and Forest Degradation (REDD+), in areas based on high potential with good carrying capacity, it is necessary to group provinces to focus and map potential carbon trading areas by considering supporting factors. Establishing investment areas in the form of carbon forests requires management and maintenance by both government and private industries to obtain carbon certificates that can be converted and used in carbon trading types of cap-and-trade and cap-and-tax, where carbon certificate buying and selling transactions are carried out.

Policy Recommendations

Strengthening Economic and Social Support in Cluster 4 (Papua)

Papua's high carbon trading potential requires tailored investment to address its limited infrastructure and social support. The government should prioritize building roads, renewable energy facilities, clean water systems, and healthcare centers to improve access and productivity. Education programs must focus on environmental awareness, vocational skills for sustainable industries, and cultural alignment, including teacher training and scholarships for Papuan youth. Health interventions, such as mobile clinics and maternal health services, are essential to enhance the workforce's participation in carbon programs. Additionally, community-led initiatives, such as participatory forest management and training in carbon measurement and conservation, can empower local populations to take ownership of sustainable practices and carbon market engagement.

Facility Improvement for Cluster 1 (27 Provinces)

Provinces in Cluster 1 need enhanced access to carbon markets and adoption of low-carbon technologies to unlock their carbon trading potential. A digital marketplace should be developed to connect producers with buyers, ensuring transparency and inclusivity. Providing financial incentives such as tax breaks and grants can motivate private companies to adopt low-carbon technologies like carbon capture, bioenergy systems, and solar energy projects. Regional training workshops and public-private partnerships can further facilitate technology adoption and increase participation in carbon markets. The government should also streamline regulatory requirements to encourage investment in sustainable initiatives.

To foster sustainable carbon trading nationwide, Indonesia needs robust policy and regulatory frameworks. Enforceable laws mandating carbon offset obligations for industries, coupled with penalties for non-compliance, will enhance accountability. Establishing a national carbon registry ensures transparency and monitors compliance with emission reduction targets. Fiscal incentives such as tax credits for emission reductions and grants for renewable energy projects should reward industries showing strong commitments to sustainability. Creating platforms for cross-sector collaboration and international partnerships can further bolster Indonesia's carbon trading ecosystem.

Optimizing Potential in Cluster 3 (Java and DKI Jakarta)

With strong economic and social conditions, Cluster 3 should focus on improving the efficiency of land use and advanced technology deployment. Policymakers can incentivize green initiatives through fiscal measures such as reduced tariffs for environmentally friendly projects and grants for innovative carbon reduction technologies. Establishing partnerships between the government and private sector for co-financing sustainable infrastructure projects is critical. Investments in vertical urban farming, reforestation of urban spaces, and smart energy grids will optimize the region's carbon potential while creating economic opportunities.

Economic Diversification in Cluster 2 (Riau Islands and DI Yogyakarta)

For provinces in cluster 2, where carbon trading potential is low but economic and social conditions are favorable, economic diversification is key. The government should integrate environmental considerations into economic sectors like ecotourism, sustainable agriculture, and renewable energy. Providing support for ecotourism businesses and promoting sustainable practices in agriculture can reduce carbon emissions while creating new income streams. Investments in wind and solar power, along with public awareness campaigns on sustainable development, can enhance regional contributions to low-carbon goals. Policies encouraging collaboration between local governments and industries can amplify these efforts.

Strengthening the National Policy and Incentive Framework

Nationally, there is a need to strengthen the policy framework that supports carbon trading, including the development of a transparent and accessible domestic carbon market. The government should establish a digital carbon trading platform, enabling equitable access for small-scale producers and corporations alike. Platforms like the IDX Carbon could be leveraged to standardize transactions, improve traceability, and ensure credibility. Providing real-time data and performance analytics would enhance decision-making for participants. This system should include training modules for stakeholders, ensuring all participants understand the trading process and the environmental benefits of their contributions. The government also needs to provide incentives for provinces and sectors that demonstrate a strong commitment to climate change mitigation and forest conservation, and encourage cross-provincial and cross-sector collaboration to achieve sustainable carbon trading goals. The contemporary world's quest for development often stands at the crossroads of economic progress and socio-environmental conservation. The proposed airport project in Northern Bali, seemingly a lucrative venture promising economic growth, also brings to the fore several socio-environmental challenges. This paper delves into the multifaceted impacts of the project, segregating them into positive and negative dimensions, while discussing potential mitigation strategies and the overall implications for Bali's future (Table 1 and Figure 2). The planned relocation site spanning 16 hectares, envisioned as a hub for artists and farmers, carries the potential to become a beacon for sustainable living. The community gains a unique identity by preserving and integrating the Balinese culture, setting a precedent for other developmental projects.

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