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Spatio-Temporal Analysis of Carbon Monoxide (CO) Distribution According to Deforestation in West Kalimantan, Indonesia

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Abstract: Carbon monoxide (CO) is a harmful air pollutant primarily produced through biomass burning, including forest fires and deforestation activities. West Kalimantan Province, which has undergone massive land cover change, is a crucial area for examining the link between deforestation and the increase in atmospheric CO concentrations. This study aims to analyze the spatial and temporal relationship between CO distribution and deforestation throughout 2024. CO data were obtained from Sentinel-5P satellite imagery, while deforestation detection was carried out using the Normalized Burn Ratio (NBR) and the Normalized Difference Vegetation Index (NDVI), derived from Sentinel-2A imagery. The NBR index was used to detect areas affected by fire or land conversion, while the NDVI reflects vegetation health conditions. The analysis results show that regions with increased NBR and decreased NDVI tend to have high CO concentrations. The Pearson correlation between NBR and CO indicates a very strong positive relationship ($r = 1.00$), while the correlation between NDVI and CO shows a weak to moderate negative relationship, with correlation values varying from –0.35 to –0.68 across the study area. However, the dominance of cloud cover in most Sentinel-2A imagery in West Kalimantan potentially affects the quality and representativeness of the resulting vegetation data. This study highlights that deforestation significantly contributes to the decline in air quality, demonstrating that satellite-based remote sensing is an effective tool for air pollution monitoring and supporting environmental mitigation policies.

Keywords : Carbon Monoxide; Deforestation; NBR; Sentinel-5P; Google Earth Engine

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Introduction

Carbon monoxide (CO) is a toxic, colorless, and odorless gas that can have serious impacts on human health and environmental quality. One of the main sources of CO emissions in the atmosphere is biomass burning, including forest fires and deforestation, which commonly occur in tropical regions such as Indonesia. Land cover changes resulting from agricultural expansion, infrastructure development, and mining activities have led to large-scale forest loss, which not only reduces biodiversity but also increases greenhouse gas emissions and air pollutants (Margono et al., 2014; Mathew et al., 2024).

West Kalimantan Province is one of the regions in Indonesia that has recorded a high deforestation rate over the past two decades (Wegscheider et al., 2018). Between 1990 and 2015, West Kalimantan contributed approximately 21% of total emissions from deforestation across Kalimantan, and its share increased to around 38% during the 2013–2015 period (Wegscheider et al., 2018). Land-clearing activities, whether through burning, peat drainage, or forest conversion for agricultural and industrial expansion, have been identified as major contributors to greenhouse gas and air pollutant emissions. According to the Jurisdictional Emissions Reduction Program report, the historical average emissions from deforestation and degradation in West Kalimantan reached about 30.46 Mt CO_2e per year, of which 28.61 Mt CO_2e per year originated from deforestation alone. These processes are often accompanied by increased CO emissions, especially during dry seasons when burning intensity escalates (Park et al., 2020). Therefore, continuous monitoring of CO emissions associated with deforestation is essential to support evidence-based policymaking in air quality management and climate change mitigation.

Advancements in satellite remote sensing technology have enabled efficient and large-scale monitoring of atmospheric pollutants. The Sentinel-5P satellite, equipped with the TROPOMI sensor, provides daily global data on CO concentrations with high spatial resolution (Keppens et al., 2024). Meanwhile, deforestation detection can be carried out using vegetation indices such as the Normalized Burn Ratio (NBR), which is sensitive to biomass changes due to fire or vegetation loss (Singh et al., 2025), and the Normalized Difference Vegetation Index (NDVI), which is widely used to assess vegetation density and health. A decline in NDVI values may indicate vegetation stress or land cover loss, making it an important indicator for detecting non-fire deforestation patterns.

Although numerous studies have explored deforestation and CO emission patterns separately, few have integrated both parameters to analyze their spatial-temporal relationship, particularly in tropical regions with complex land use such as West Kalimantan. Previous research has often focused on large-scale fire events, overlooking the contribution of gradual deforestation processes to CO variability. Moreover, comparative studies employing multiple vegetation indices (e.g., NBR and NDVI) alongside atmospheric CO concentration data remain limited. This gap highlights the need for integrated analyses that combine vegetation dynamics and atmospheric pollution to better understand the environmental impacts of land cover change.

The integration of CO data from Sentinel-5P with vegetation indices from Sentinel-2A provides an opportunity for comprehensive spatial and statistical analysis to better understand the relationship between deforestation and air quality degradation (Fadhilah et al., 2022). This study aims to examine the spatial-temporal relationship between CO distribution and deforestation in West Kalimantan throughout 2024. The analysis is conducted using statistical correlation approaches to assess the strength of the relationship between CO and vegetation indices (NBR and NDVI). This approach is a robust method to address the identified research gap, as it quantitatively evaluates the degree and direction of association between vegetation loss and atmospheric CO concentration. Through this correlation-based framework, it is possible to identify deforestation patterns that contribute most significantly to CO variability, even in areas where in situ emission data are scarce. Hence, the use of statistical correlation not only strengthens the empirical linkage between deforestation and air quality degradation but also provides a valuable foundation for subsequent modeling and policy-oriented studies in tropical environments.

Methodology

Study Location

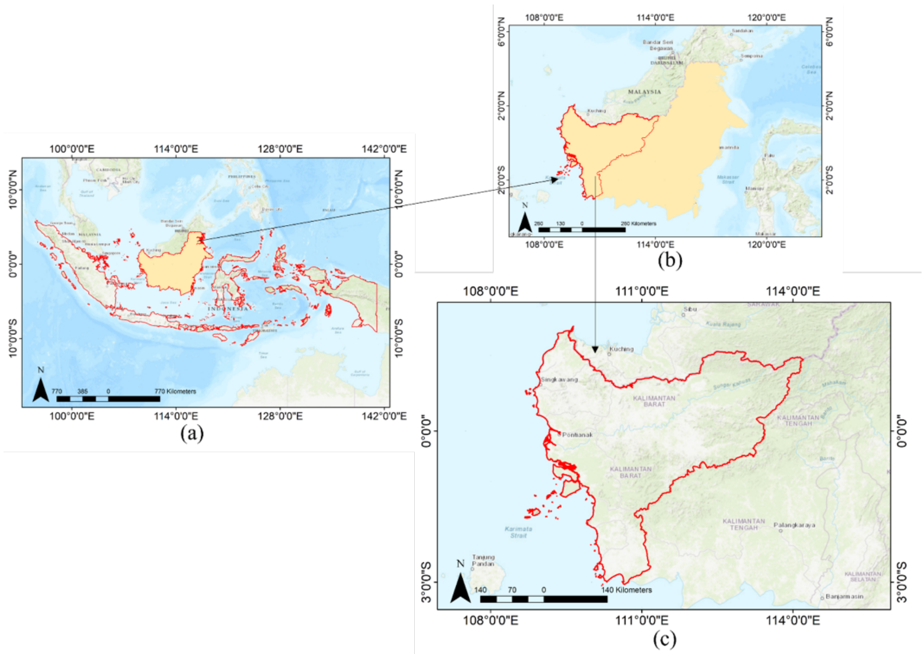

Figure 1. Study Area (a) Indonesia Country (b) Kalimantan Island (c) West Kalimantan Province

The study was conducted in West Kalimantan Province, Indonesia, which consists of 14 regencies and cities (Fig. 1). Located in the western part of Borneo Island, the province covers an area of approximately 147,307 km² and had a population of around 5.70 million in 2024 (about 2% of Indonesia's total population) (BPS, 2024). West Kalimantan is rich in natural resources, especially in bauxite and gold, making mining one of its major economic activities. However, extensive mining and land-use changes have also contributed to environmental degradation, including forest loss and air pollution.

Data and Equipment

This study employed multiple datasets to analyze the spatial and temporal distribution of CO concentrations in West Kalimantan Province. CO data were acquired from the Sentinel-5P satellite using the OFFL CO (Offline Carbon Monoxide) product, covering the period from 1 January to 31 December 2024. This timeframe was selected to capture monthly trends and seasonal variations in CO levels throughout the year. To identify areas affected by forest and land fires, the NBR index was derived from Sentinel-2A imagery for the same period. The NBR is a widely used spectral index for detecting burn scars and assessing post-fire conditions, which are potential sources of elevated CO emissions, particularly during the dry season. In addition, the NDVI was also extracted from Sentinel-2A imagery to assess vegetation health and monitor the extent of vegetation degradation. NDVI is especially useful in detecting gradual changes in green biomass and serves as a complementary indicator to NBR, particularly in non-burned areas of deforestation. Administrative boundary shapefiles for West Kalimantan were utilized to support spatial mapping and analysis at the regency level. The province is also characterized by intensive mining activities, particularly bauxite and gold extraction, which are concentrated in several regencies. These activities were taken into account due to their potential contribution to atmospheric CO emissions and environmental degradation. All data processing and analysis were conducted using the Google Earth Engine (GEE) Platform, which enables scalable, cloud-based processing of large satellite datasets. The Sentinel-5P carbon monoxide (CO) data were accessed from the COPERNICUS/S5P/OFFL/L3_CO collection, which provides Level-3 CO column density information derived from the TROPOMI sensor. Meanwhile, the Sentinel-2A imagery used for vegetation indices (NDVI and NBR) analysis was retrieved from the COPERNICUS/S2 collection, containing surface reflectance data with 10–20 m spatial resolution. Both datasets were filtered by date and region of interest (West Kalimantan Province) to match the 2024 observation period. The final map layout and visualization were performed using ArcGIS software for presentation and spatial interpretation purposes.

Data Processing

To analyze the temporal CO data from Sentinel-5P imagery throughout 2024, the relevant data were first extracted using GEE. The data were then carefully examined and clipped to match the administrative boundaries of West Kalimantan Province, ensuring that the analysis results accurately represent the specific study area. To enhance the accuracy of the annual CO concentration calculation, the median function was used, which is effective in reducing noise and minimizing the influence of outliers in satellite data. Subsequently, a correlation test was conducted using statistical methods to determine the relationship between the level of deforestation (represented by NBR and NDVI) and CO concentration.

Normalized Burn Ratio (NBR) is a spectral index algorithm designed to detect burned areas and assess fire severity by analyzing changes in vegetation reflectance before and after a fire event (Gracia & Caselles, 1991). The algorithm compares the Near-Infrared (NIR) and Shortwave Infrared (SWIR) spectral bands. Healthy vegetation reflects strongly in the NIR region but weakly in the SWIR region, while burned or stressed vegetation shows the opposite pattern and low reflectance in NIR and high reflectance in SWIR. These spectral changes make NBR effective for identifying burned regions. Below is NBR formula (Keeley, 2009; Alcaras et al., 2022).

$$NBR = \frac{(NIR-SWIR)}{(NIR+SWIR)} \quad (1)$$

For Sentinel-2A imagery, the NBR indeks utilizes Band 8, which represents the Near-Infrared (NIR) region with a wavelength of approximately 0.842 µm, and Band 12, which corresponds to the Shortwave Infrared

(SWIR) region with a wavelength of about 2.190 µm. These two spectral bands are chosen because of their strong sensitivity to vegetation and burned surface characteristics, allowing for a clear distinction between healthy vegetation and areas affected by fire or vegetation loss. High NBR values indicate healthy vegetation, while low or negative values correspond to burned or bare areas (Mohammad et al., 2023).

Normalized Difference Vegetation Index (NDVI) is a spectral index algorithm widely used to assess vegetation health, density, and coverage (Sultana et al., 2023). It is based on the principle that healthy green vegetation strongly absorbs visible light (particularly in the red region) for photosynthesis, while it reflects a large portion of near-infrared (NIR) radiation due to the internal structure of plant leaves. The NDVI formula is expressed below (Rouse et al., 1973).

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \tag{2}$$

For Sentinel-2A imagery, NDVI is calculated using Band 8 for the Near-Infrared (NIR) region with a wavelength of approximately 0.842 µm and Band 4 for the RED region with a wavelength of about 0.665 µm. The resulting NDVI values range from -1 to +1, where higher values indicate dense and healthy vegetation, while lower or negative values correspond to sparse vegetation, bare soil, or non-vegetated surfaces such as water or urban areas (Mohammad et al., 2023).

In this analysis, the Pearson correlation coefficient was used as a statistical measure. This coefficient is a unitless value that indicates the degree of linear relationship between two variables, ranging from -1 to 1. A value close to 1 indicates a strong positive correlation, while a value close to -1 indicates a strong negative correlation. The interpretation classification of Pearson correlation coefficient values is presented in Table 1 (Benesty et al., 2009).

Table 1. Pearson Correlation Strength Classification

Coefficient Interval	Correlation
0.00-0.10	Neglected correlation
0.10-0.39	Weak correlation
0.40-0.69	Medium correlation
0.70-0.89	Strong correlation
0.90-1.00	Very strong correlation

The mathematical model of the Pearson correlation coefficient can be seen as follows (Heidemann et al., 2023).

$$r = \frac{n\,(\sum XY)-(\sum X)-(\sum Y)}{\sqrt{[n(\sum X^2)-(\sum X)^2][n(\sum Y^2)-(\sum Y)^2]}} \tag{3}$$

where,

r = represents Pearson's correlation coefficient
n = is the number of variables
X = the observed value of the first variable (for example, the concentration of CO)
Y = the observed value of the second variable (for example, the concentration of NDVI)
ΣXY = the summation of the product of X and Y values
ΣX and ΣY = the summation of all X and Y values, respectively
ΣX^2 and ΣY^2 = the summation of the squares of X and Y values, respectively

The correlation coefficient (r) is used to determine the extent to which changes in one variable are associated with changes in another variable. It is commonly applied in statistical analysis to evaluate relationships among environmental parameters, such as the relationship between CO concentration, NDVI values, and NBR values.

Result and Discussion

Distribution of Carbon Monoxide in West Kalimantan

Analyzing the spatial and temporal distribution of carbon monoxide (CO) is essential to understanding atmospheric dynamics and emission sources in West Kalimantan. Figure 2 illustrates the monthly fluctuations of median CO concentrations across West Kalimantan throughout 2024. The recorded CO concentration ranged from 0.026 mol/m² to 0.033 mol/m². These values were derived from satellite image processing using monthly median values, which are considered more reliable in representing the general atmospheric conditions, as they effectively reduce the influence of extreme values or data noise, especially common in remote sensing datasets. A temporal analysis of the CO concentration distribution in West Kalimantan during 2024 reveals that the lowest concentration occurred in July, while peak levels were observed between September and October. The decrease in CO concentrations from January to July is likely associated with meteorological conditions during the rainy season, during which increased precipitation and shifts in wind circulation patterns facilitate the vertical and horizontal dispersion of atmospheric pollutants (Mohamed et al., 2025). Moreover, high humidity levels and frequent rainfall events further inhibit the formation and release of CO emissions from biomass burning activities.

In contrast, the surge in CO concentrations observed from August to October is strongly linked to the peak of the dry season, historically characterized by reduced rainfall, lower relative humidity, and more stable atmospheric conditions. These factors promote the accumulation of pollutants in the lower troposphere due to diminished vertical mixing (Mohamed et al., 2025). Additionally, the dry season in Kalimantan is commonly associated with an increase in land-clearing activities through biomass burning and the occurrence of forest and peatland fires, which significantly contribute to elevated CO emissions into the atmosphere (Hanami et al., 2025). The strong relationship between anthropogenic activities and CO variability is primarily attributed to land-use and land-cover (LULC) changes that alter the natural carbon balance. Large-scale conversion of forested areas into agricultural or plantation lands increases the frequency of open burning for land preparation, releasing substantial amounts of CO from incomplete combustion of organic matter. Furthermore, the loss of vegetation cover reduces the capacity of the ecosystem to absorb atmospheric CO, thereby amplifying its concentration during active burning periods. These findings are consistent with previous studies conducted in Sumatra, which reported a seasonal increase in CO and aerosol optical depth during the dry season as a result of intensified biomass burning (Hanami et al., 2025). Therefore, the CO concentration dynamics observed in West Kalimantan throughout 2024 can be interpreted as a reflection of the complex interplay between seasonal climatic variability and anthropogenic activities, particularly those related to land cover change and forest fire events.

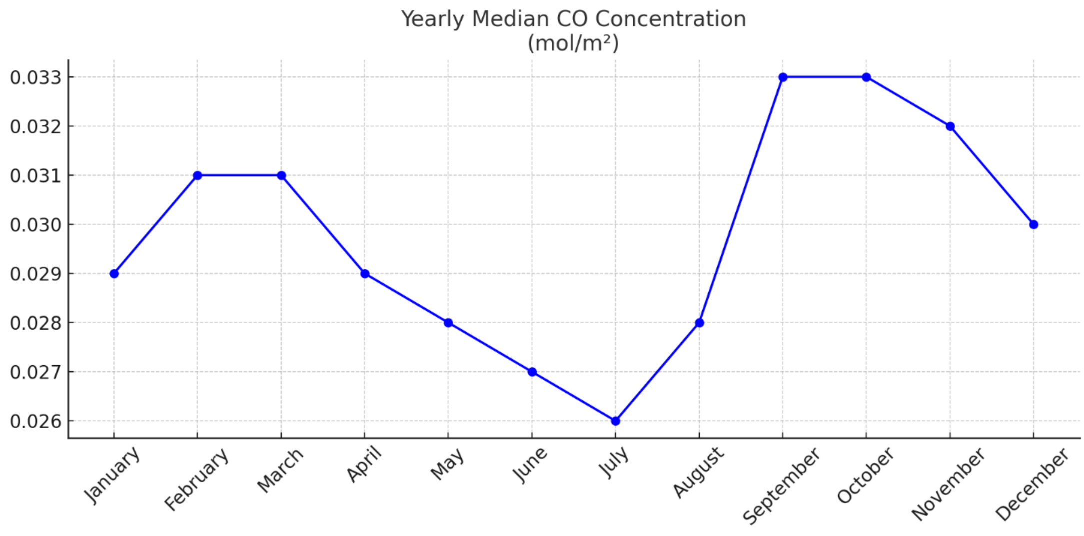

Figure 2. Monthly Median CO concentration 2025

The spatial and temporal distribution of CO concentrations in West Kalimantan throughout 2024 demonstrates a pattern strongly associated with seasonal dynamics and anthropogenic activities. Elevated CO concentrations observed from January to April, particularly in the western and coastal regions, are most likely attributed to increased emissions from motor vehicles and industrial activities in densely populated urban and coastal areas. This observation is consistent with previous studies, which have indicated that urban and coastal zones tend to exhibit higher CO emissions due to intense transportation activity and fossil fuel combustion (Patarasuk et al., 2016; Perez-Martinez et al., 2020).

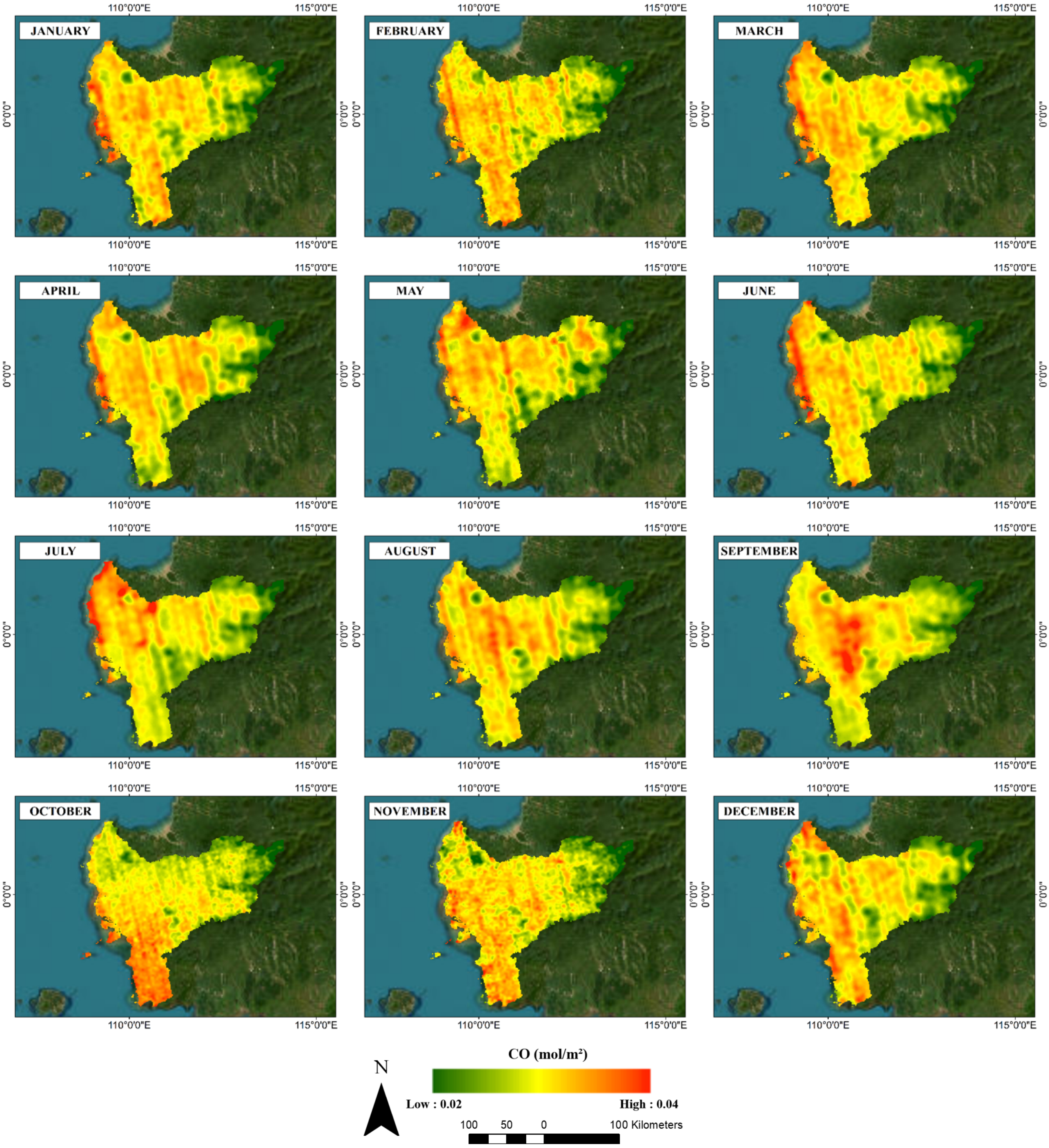

Figure 3. Spatial distribution of Carbon Monoxide 2024 in West Kalimantan

Significant increases in CO concentration during July and September can be linked to the dry season, which often intensifies the occurrence of forest and land fires—commonly referred to as karhutla—one of the primary sources of CO emissions in tropical regions (Roman-Cuesta et al., 2016; Mills et al., 2023). Biomass burning releases substantial amounts of CO into the atmosphere, particularly in regions with dense vegetation cover such as Kalimantan. This finding aligns with reports from the Global Fire Emissions Database (GFED), which indicate that CO emission peaks in Indonesia typically occur during the dry season, especially as a result of peatland and forest fires (Saharjo & Novita, 2021). Furthermore, recent climate change impacts, such as prolonged dry periods and rising surface temperatures, have exacerbated fire susceptibility by lowering soil and vegetation moisture content. These conditions not only extend the duration of the fire season but also intensify combustion processes, leading to greater CO emissions during the dry season (Wang et al., 2024).

Fluctuations in CO concentration observed in August and October suggest variability in both the intensity and spatial distribution of emission sources. The decline in concentration in some areas may reflect a reduction in burning activities or the onset of rainfall that helps suppress fire intensity. Meanwhile, the continued presence of hotspots along the coastal and central regions indicates that emission sources remained spatially active despite a general decline in concentration.

Toward the end of the year, in November and December, although CO concentrations remained elevated in the western and southern parts of the region, a noticeable decrease in the northern areas is likely influenced by seasonal shifts in wind direction and increased rainfall, both of which can suppress land fire activity and accelerate the atmospheric deposition of pollutants (He et al., 2024). Overall, the observed pattern underscores the significant role of the dry season in amplifying CO emissions and highlights the urgent need for stricter control of land-burning activities as a critical strategy for mitigating air pollution in tropical regions.

Distribution of Carbon Monoxide in District West Kalimantan Provincies

The spatial and temporal distribution of CO concentrations in West Kalimantan throughout 2024 demonstrates a pattern strongly associated with seasonal dynamics and anthropogenic activities. Elevated CO concentrations observed from January to April, particularly in the western and coastal regions, are most likely attributed to increased emissions from motor vehicles and industrial activities in densely populated urban and coastal areas. This observation is consistent with previous studies, which have indicated that urban and coastal zones tend to exhibit higher CO emissions due to intense transportation activity and fossil fuel combustion (Patarasuk et al., 2016; Perez-Martinez et al., 2020). Significant increases in CO concentration during July and September can be linked to the dry season, which often intensifies the occurrence of forest and land fires, commonly referred to as karhutlaone of the primary sources of CO emissions in tropical regions (Roman-Cuesta et al., 2016; Mills et al., 2023). Biomass burning releases substantial amounts of CO into the atmosphere, particularly in regions with dense vegetation cover such as Kalimantan. This finding aligns with reports from the Global Fire Emissions Database (GFED), which indicate that CO emission peaks in Indonesia typically occur during the dry season, especially as a result of peatland and forest fires (Saharjo & Novita, 2021). Fluctuations in CO concentration observed in August and October suggest variability in both the intensity and spatial distribution of emission sources. The decline in concentration in some areas may reflect a reduction in burning activities or the onset of rainfall that helps suppress fire intensity.

Rainfall also plays a crucial role in reducing atmospheric CO levels through wet deposition and enhanced vertical mixing. During precipitation events, CO and other trace gases are scavenged and diluted within rain droplets, while convective processes associated with rainfall promote the dispersion of pollutants, thereby lowering surface-level CO concentrations (Jacob & Winner, 2009; He et al., 2024). Meanwhile, the continued presence of hotspots along the coastal and central regions indicates that emission sources remained spatially active despite a general decline in concentration. Toward the end of the year, in November and December, although CO concentrations remained elevated in the western and southern parts of the region, a noticeable decrease in the northern areas is likely influenced by seasonal shifts in wind direction and increased rainfall, both of which can suppress land fire activity and accelerate the atmospheric deposition of pollutants (He et al., 2024). Overall, the observed pattern underscores the significant role of the dry season in amplifying CO emissions and highlights the urgent need for stricter control of land-burning activities as a critical strategy for mitigating air pollution in tropical regions.

Table 2. CO Concentration values were calculated for each District in West Kalimantan Provincies

District	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nop	Dec
Bengkayang	0.029	0.031	0.032	0.029	0.029	0.027	0.028	0.028	0.034	0.033	0.032	0.030
Kapuas Hulu	0.028	0.030	0.030	0.028	0.028	0.026	0.026	0.027	0.032	0.032	0.031	0.029

District	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nop	Dec
Kayong Utara	0.03	0.032	0.032	0.030	0.029	0.027	0.027	0.028	0.034	0.036	0.034	0.031
Ketapang	0.029	0.032	0.032	0.029	0.028	0.027	0.026	0.028	0.034	0.036	0.033	0.03
Kota Pontianak	0.031	0.034	0.035	0.031	0.029	0.029	0.027	0.028	0.035	0.035	0.035	0.03
Kubu Raya	0.030	0.032	0.032	0.030	0.029	0.028	0.027	0.028	0.034	0.035	0.034	0.031
Landak	0.029	0.032	0.031	0.030	0.029	0.027	0.027	0.028	0.034	0.033	0.032	0.03
Melawi	0.029	0.031	0.031	0.029	0.028	0.026	0.026	0.028	0.033	0.034	0.033	0.029
Pontianak	0.030	0.033	0.033	0.030	0.029	0.029	0.029	0.029	0.035	0.034	0.033	0.031
Sambas	0.029	0.032	0.033	0.030	0.029	0.028	0.028	0.028	0.033	0.033	0.032	0.031
Sanggau	0.030	0.032	0.032	0.030	0.029	0.027	0.027	0.029	0.036	0.034	0.033	0.03
Sengkadau	0.029	0.031	0.031	0.030	0.029	0.027	0.026	0.029	0.035	0.034	0.033	0.03
Singkawang	0.031	0.032	0.033	0.030	0.030	0.029	0.029	0.029	0.034	0.034	0.032	0.032
Sintang	0.028	0.030	0.031	0.029	0.028	0.026	0.026	0.027	0.033	0.033	0.032	0.029

Relationship between CO and Deforestation

Deforestation and CO concentrations are closely linked through complex environmental processes. The reduction of forest cover can disrupt the balance of the carbon cycle, often leading to elevated atmospheric CO levels due to biomass burning and the decreased capacity of vegetation to absorb carbon. In this study, the relationship between deforestation and CO distribution was analyzed using satellite-based vegetation indices, namely the NDVI and NBR, both derived from Sentinel-2A imagery. The NDVI was employed to detect vegetation greenness levels, while the NBR was used to identify areas affected by forest fires or extreme land cover changes. The extraction of NDVI and NBR values was conducted periodically to observe the dynamics of deforestation over a defined time period.

By performing correlation analysis between the vegetation indices and CO concentration data, this study aims to assess the extent to which forest cover changes, particularly those caused by fire and land conversion, affect atmospheric CO levels. To establish a foundation for interpreting the spatial relationship between vegetation cover dynamics and CO concentrations, Figure 4 presents the monthly NDVI maps across the study area. These visualizations depict the spatial variability in vegetation greenness and highlight areas of potential degradation, providing essential contextual information for the subsequent correlation analysis. In this study, the NDVI values were classified within a range of –1 to 0.199 (non-vegetation), 0.2 to 0.5 (low vegetation), and 0.501 to 1.0 (high vegetation) (Hashim et al., 2019). This classification enables a clearer differentiation of vegetation conditions and facilitates the identification of areas experiencing ecological stress or land-cover change throughout the observation period.The following section presents the correlation between CO concentration and NDVI for each region.

Table 3. Relationship between CO and NDVI

Month	Correlation	Description
January	-0.2718	Weak negative correlation
Februari	0.3187	Weak correlation
March	0.0224	Neglected correlation
April	0.0260	Neglected correlation
May	-0.0243	Neglected negative correlation
June	0.1469	Weak correlation
July	-0.2169	Weak negative correlation
August	0.0017	Neglected correlation
September	-0.0295	Neglected negative correlation
October	0.1093	Weak correlation

Month	Correlation	Description
Nopember	-0.3536	Weak negative correlation
December	0.6896	Medium correlation

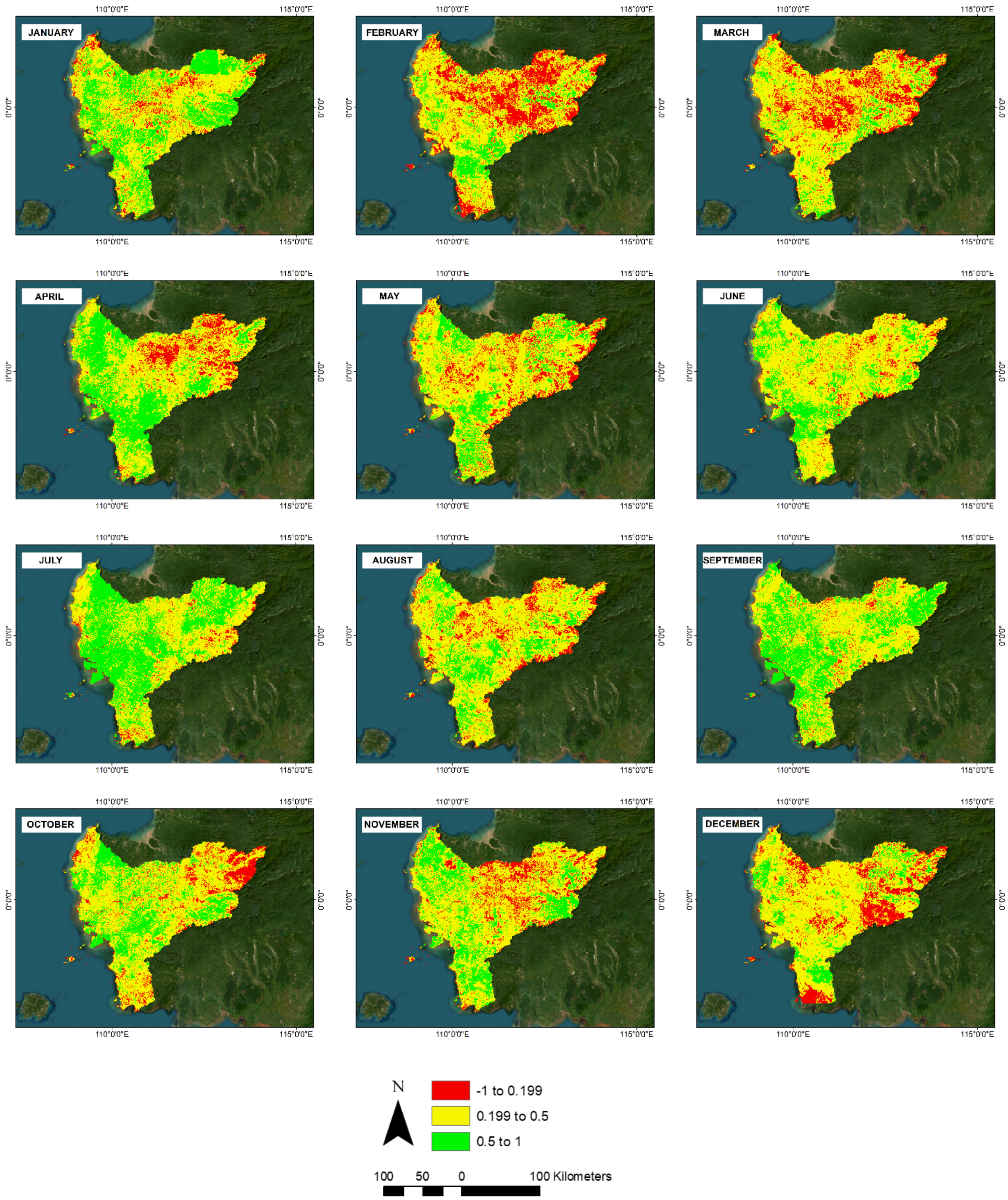

Figure 4. Spatial distribution of NDVI Algorithm 2024 in West Kalimantan

A correlation analysis between NDVI and CO concentration was conducted to examine the relationship between vegetation greenness and air pollution levels. The results indicate that most months exhibit weak correlations, both positive and negative, suggesting limited influence of vegetation on CO concentration during those periods. The highest correlation was observed in December, with a value of 0.6896, classified as a medium correlation. This suggests that increased vegetation in December had a relatively significant effect in reducing CO concentrations. Conversely, months such as March, April, and August showed very low correlation values or nearly no relationship (negligible correlation), indicating that vegetation had little impact on CO variability during those times. Weak negative correlations were observed in November (-0.3536), January (-0.2718), and July (-0.2169), reflecting a tendency for CO levels to decrease as vegetation increased, although the relationship was not strong. These findings are consistent with previous studies, which have emphasized the important role of vegetation in absorbing and filtering air pollutants such as CO through processes like photosynthesis and dry deposition, thereby improving air quality in both urban and rural environments (Fadhilah et al., 2022; Mandal et al., 2023).

In addition to NDVI, the analysis also incorporates the Normalized Burn Ratio (NBR) to identify areas affected by fire and severe land-cover disturbances. The NBR maps provide complementary information by emphasizing burn severity and post-fire vegetation conditions that are not fully captured by NDVI alone. By integrating both NDVI and NBR visualizations, the spatial patterns of vegetation loss, degradation, and fire-affected areas can be more accurately characterized, thereby strengthening the interpretation of how these landscape changes relate to fluctuations in CO concentration. In this study, the NBR values were classified within a range of < 0.1 (healthy), -0.101 to 0.099 (nonburned vegetation), 0.100 to 0.269 (low severity), 0.270 to 0.439 (moderate-low severity), 0.440 to 0.659 (moderate-high severity), dan >0.660 (high severity) (Ponomarev et al., 2022).

The following section presents the correlation between CO concentration and NBR for each region.

Table 4. Relationship between CO and NBR

Month	**Correlation**	**Description**
January	1	Very strong correlation
Februari	1	Very strong correlation
March	1	Very strong correlation
April	1	Very strong correlation
May	1	Very strong correlation
June	1	Very strong correlation
July	1	Very strong correlation
August	1	Very strong correlation
September	1	Very strong correlation
October	1	Very strong correlation
Nopember	1	Very strong correlation
December	1	Very strong correlation

The results of the correlation analysis between CO concentration and the NBR index in West Kalimantan Province showed a perfect correlation value of 1.0 for every month throughout the annual observation period. This value represents a perfect positive linear relationship between the two variables, indicating that any increase in CO concentration is consistently accompanied by an increase in NBR values, and vice versa. Conceptually, this positive association is plausible, as CO emissions are often a result of biomass burning, which also directly impacts vegetation conditions as captured by the NBR index. The NBR itself is a satellite-based spectral index commonly used to detect and assess the severity of forest fires, where lower values indicate burned or degraded areas (Escuin et al., 2008; Liu et al., 2025).

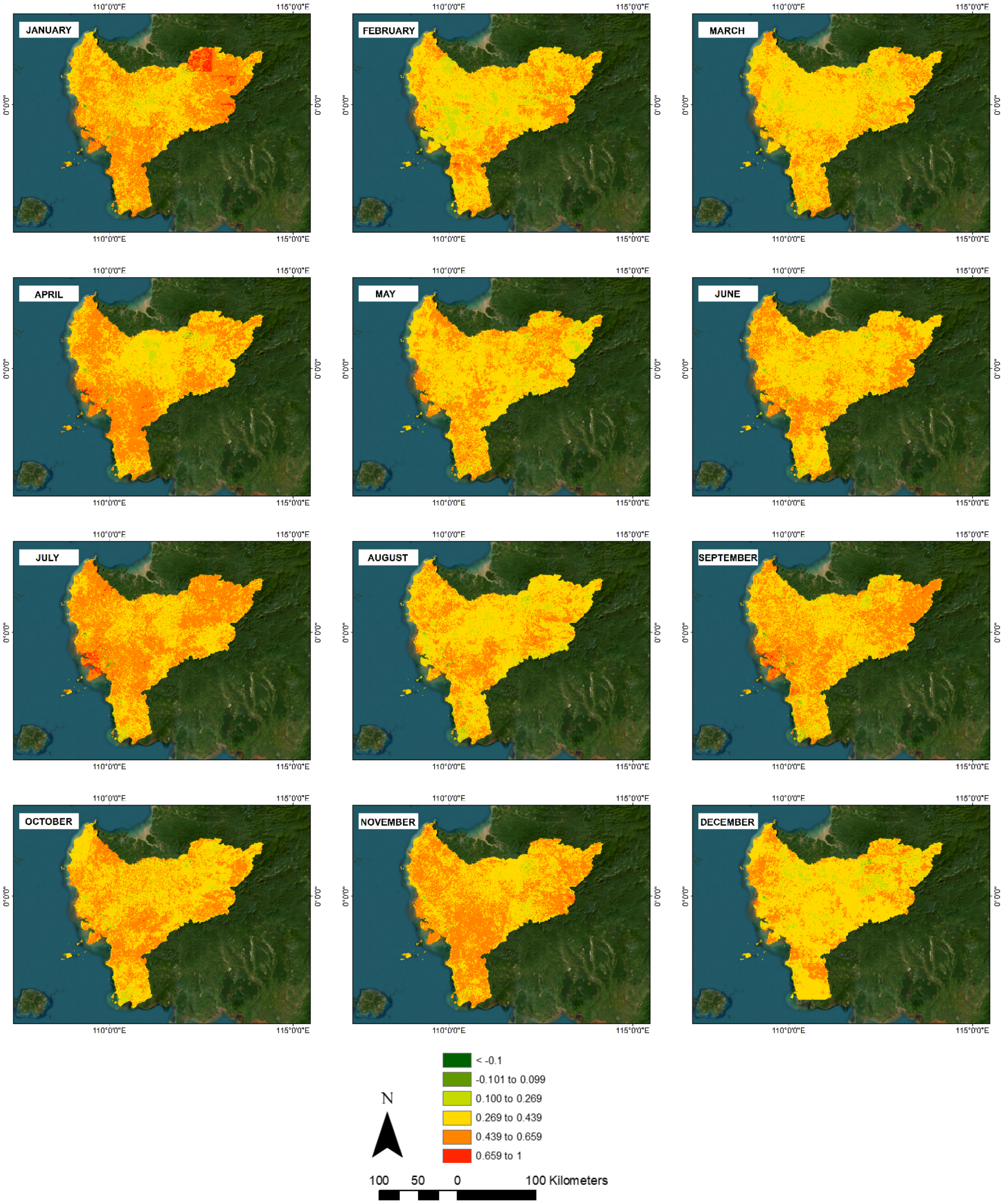

Figure 5. Spatial distribution of NBR lgorithm 2024 in West Kalimantan

Although the theoretical relationship between CO and NBR can be justified, the presence of a perfect correlation across all months raises concerns regarding possible distortions in data quality or distribution. Such consistently high correlation values suggest a lack of variability in the data, both in terms of magnitude and spatial distribution. A critical factor in this context is the high level of cloud cover in Sentinel-2A optical imagery over West Kalimantan. This region is known for its persistent humidity and high annual rainfall, leading to most satellite scenes being affected by cloud cover and cloud shadows that obscure surface information (Shrestha et al., 2019). When a large number of cloud-covered pixels are not effectively masked, or when only a small cloud-free portion of the area is used for analysis, the resulting values may not accurately represent the true spatial conditions.

The influence of high cloud cover may result in invalid or overly homogeneous NBR values, particularly if cloud masking and atmospheric correction procedures are not comprehensively applied. Under such conditions, the correlation between NBR and CO becomes biased, as it is based on limited and non-representative data. Consequently, the observed correlation does not reflect an actual on-ground relationship but rather stems from technical limitations in satellite data acquisition and preprocessing. Therefore, this correlation should be interpreted with caution and ideally supported by additional approaches such as field validation, spatial modeling, or the integration of complementary datasets, such as cloud-free Sentinel-1 radar imagery or MODIS data with higher temporal resolution. Overall, the statistical analysis suggests a very strong relationship between CO concentration and the NBR index in West Kalimantan, this finding should not be immediately interpreted as a causal or empirical link without accounting for technical factors affecting data integrity. The validity of the observed relationship heavily depends on the quality and representativeness of the data used, as well as the effectiveness of preprocessing methods in eliminating atmospheric and cloud-related distortions.

Conclusions

This study successfully identified significant spatial and temporal correlations between deforestation activities and increased CO concentrations in West Kalimantan Province during 2024. By utilizing Sentinel-5P and Sentinel-2A satellite imagery, the research demonstrates that satellite-based remote sensing is an effective approach for monitoring air quality dynamics associated with large-scale and continuous land cover changes. The statistical analysis revealed a very strong positive correlation between CO concentrations and NBR values throughout the observation period. This indicates that biomass burning, resulting from forest fires or land conversion, is the primary contributor to CO emissions in the study area. In contrast, the correlation between CO and the NDVI tended to be weak, suggesting that vegetation degradation does contribute to increasing CO levels, though not as significantly as fire-related activities. Nevertheless, the consistently perfect correlation between CO and NBR observed throughout the year suggests potential limitations in data quality and variability, particularly due to the high cloud cover in optical imagery within tropical regions. Therefore, interpretation of these correlation results must be approached with caution, taking into account technical factors such as the effectiveness of cloud masking and the accuracy of data preprocessing. Overall, this research provides a relevant scientific contribution to the understanding of the impact of deforestation on air quality degradation. The findings have important implications for the development of environmental mitigation policies, particularly in forest fire management and land cover regulation..

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