Contemporary Mathematics and Applications
Vol. 7, No. 2, 2025, pp. 64-78

Pattern-Based Identification of Priority Sectors for Greenhouse Gas Emission Control in Indonesia Using Self-Organizing Map

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Abstract. Indonesia is one of the countries that ratified the Paris Agreement, a legally binding international treaty under the United Nations Framework Convention on Climate Change (UNFCCC) regarding greenhouse gas emissions. In line with this commitment, Indonesia is expected to prioritize emission control in sectors that contribute significantly to national emission levels. This study applies the Self-Organizing Map (SOM), a type of neural network, to cluster emission data by sector based on similarity patterns, aiming to identify priority sectors for emission control in Indonesia. The results indicate that the highest-emitting sectors are: Processes for Carbon Dioxide (CO_2), Transport for Methane (CH_4), Processes for F-Gases, and Agriculture for Nitrous Oxide (N_2O). These findings can inform government efforts to prioritize emission control policies in the Processes, Transport, and Agriculture sectors, tailored to each dominant gas type. Such recommendations are essential to support data-driven decision-making, improve national emission control strategies, and strengthen Indonesia's position in meeting its Nationally Determined Contributions (NDCs) under the Paris Agreement. Model validation using Quantization Error (QE) produced values of 0.0218 for CO_2, 0.0207 for CH_4, 0.0040 for F-Gases, and 0.0171 for N_2O. These low values indicate high mapping accuracy and confirm that SOM is effective in capturing the distribution patterns of emission data, thus providing a scientific basis for designing more targeted mitigation strategies.

Keywords: *artificial neural network; self organizing map; paris agreement; greenhouse gas emission; quantization error*

1 Introduction

Climate change is a global challenge that requires serious attention from all countries, including Indonesia. One of the largest sources and causes of global climate change is the high emissions of gases that become greenhouse gases and result in global warming [1]. The increase in greenhouse gas emissions can lead to environmental pollution caused by energy derived from fossil fuel combustion in transportation, as well as other harmful substances from industrial, household, and other activities [2]. Greenhouse gases in the atmosphere, besides carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), and F-Gases [3]. Realizing this urgency, Indonesia has committed to reducing greenhouse gas emissions through the Paris Agreement.

Received: June 12, 2025
Accepted: July 7, 2025

The Paris Agreement is an international treaty that is legally binding under the United Nations Framework Convention on Climate Change (UNFCCC) regarding the mitigation, adaptation, and financing of greenhouse gas emissions [4]. Indonesia has ratified the Paris Agreement based on Law Number 16 of 2016 concerning the Ratification of the Paris Agreement to the United Nations Framework Convention on Climate Change and was enacted on October 25, 2016. The ratification is one of the government's efforts to guarantee every citizen a quality living environment [5]. In the Paris Agreement, Indonesia targets a 29% reduction in emissions by 2030 through its own efforts, and up to 41% with international support [6].

Related to the Sustainable Development Goals (SDGs), one of Indonesia's objectives is to prioritize development strategies related to the environment, namely clean energy and efforts to address climate change [7]. Nevertheless, until now, Indonesia is still striving to achieve that target while facing various challenges. Moreover, Indonesia ranked ninth as the country with the highest carbon emissions in the world in 2020, amounting to 590 MtCO2 Eq [8]. Based on this, there is a need for immediate efforts to control gas emissions to mitigate the adverse effects of emissions on both society and the ecosystem.

A study on sectors contributing to gas emissions can be conducted to help the government focus on the sectors with the highest gas emissions. This way, more attention can be given to controlling gas emission levels. To support targeted mitigation efforts, it is not only important to quantify total emissions but also to uncover patterns of emissions across sectors and gas types. Identifying sectors with consistent emission behaviors regardless of magnitude can offer strategic advantages in designing long-term control policies. This requires a method capable of uncovering underlying structures within high-dimensional, sector-based datasets.

One of the methods that can be used is the Self Organizing Map (SOM), which can perform mapping that is quite valid and unbiased. SOM can map feature-based datasets through self-organization rules. The main advantage of SOM is its ability to reduce the dimensions of complex data into a two-dimensional representation that is easy to interpret [9]. In the context of gas emissions, SOM can help identify emission patterns and provide new insights to develop more effective emission control strategies. This research aims to apply SOM in the analysis of gas emission data in Indonesia based on the contributions of relevant sectors. Thus, it can provide a clearer picture of the priorities for gas emission control in Indonesia and support the implementation of climate change mitigation policies more strategically.

2 Literature Review

2.1 Self Organizing Map

Self Organizing Map (SOM) is a network discovered by Kohonen and is classified as one type of neural network. Neural network is a learning model that resembles the neuron system in living beings. Neural networks consist of a set of input and output units that are interconnected, with each connection between units having its own weight [10]. SOM is one of the networks widely used to divide input patterns into several groups. In terms of how it modifies weights, SOM is classified as one of the methods of the Neural Network approach that uses unsupervised learning. That means, unsupervised learning does not require a target; during the learning process, inputs that are almost the same are grouped into certain clusters that produce output [11]. SOM can be chosen as a data analysis tool option due to its ability to reveal non-linear structures and hidden patterns in the data [12].

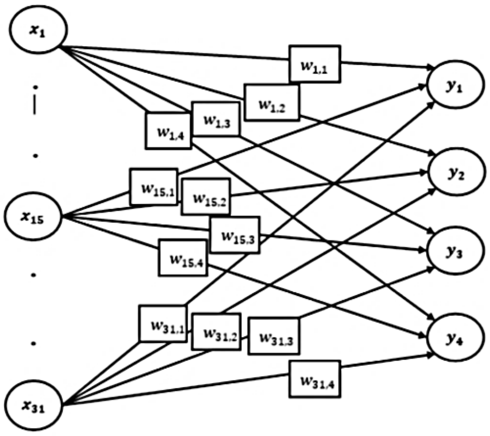

Figure 1. Structure of SOM

x	:	input used in learning $x = x_1,\ x_2, \dots, x_n$
α	:	*learning rate*
σ	:	neighborhood radius
x_1	:	neuron/vector *input*
w_{ij}	:	bias neuron *output* j-th
Y_i	:	neuron/vector *output* i-th.

Here are the steps explained for the operation *Self Organizing Map* [11]:

Step 0 : Starting with weight initialization w_{ij}, *learning rate* (α), grid size, neighborhood radius (σ), and number of iterations.

Step 1 : As long as the stop condition is false, perform Step 2 to 8.
Step 2 : For each input vector x_1, perform Step 3 to 5.
Step 3 : For each index j $(j = 1, 2, \dots, m)$, calculate the Euclidean distance:

$$D(j) = \sum_i \left(w_{ij} - x_i\right)^2 \quad (1)$$

Step 4 : Find the winning unit (index j), which is the unit with the minimum distance $D(j)$.
Step 5 : Calculate all the new w_{ij} values with the j value from Step 4, namely:

$$w_{ij}(new) = w_{ij}(old) + \alpha\left(x_i - w_{ij}(old)\right) \quad (2)$$

Step 6 : Update the learning rate value.

$$\alpha(new) = 0{,}5\ \alpha\ (old) \quad (3)$$

Step 7 : Reducing the radius of the surrounding function when the time required (*epoch*).

Step 8 : Test the stopping condition. Iteration stops when there is a difference between w_{ij} at the current moment and w_{ij} in the previous iteration. If the change in w_{ij} is minimal, then the iteration can be stopped.

2.2 *Quantization Error*

Quantization error (QE) is a metric used to assess the quality of data representation in the quantization process or algorithms such as Self-Organizing Map (SOM). QE measures how close the model's representation is to the original data by calculating the average distance between each input data and the winning neuron or Best Matching Unit (BMU) [13].

The QE value is directly correlated with the SOM's ability to detect very fine-scale visual changes in high-resolution images, even down to the pixel level [14]. As reported in a previous SOM-based study, a QE value of 0.354 was considered to provide a sufficiently good topological representation, therefore a lower QE value indicates better data representation because the input data vectors tend to be closer to the corresponding SOM unit [15]. The equation for the quantization error is shown below [16]:

$$QE = \frac{1}{N}\sum_{i=1}^{N} \|x_i - w_{BMU}\| \tag{4}$$

where

QE : quantization error
N : number of data
x_i : i-th data vector
w_{BMU} : weight vector of the BMU for the data x_i
$\|x_i - w_{BMU}\|$: the distance between the data and the BMU weight

2.3 Greenhouse Gases

Greenhouse gases (GHGs) are gases contained in the atmosphere, both natural and from human activities (anthropogenic), that absorb and re-emit infrared radiation [17]. Some of the solar radiation in the form of short waves received by the Earth's surface is re-emitted back into the atmosphere in the form of long-wave radiation (infrared radiation). This long-wave radiation emitted by GHGs present in the lower atmosphere layer, close to the Earth's surface, is absorbed and causes a warming effect known as the greenhouse effect.

According to the United Nations Framework Convention on Climate Change (UNFCCC), there are 6 types of gases classified as GHGs, namely carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). Then there is the category of F-Gases which includes sulfur hexafluoride (SF_6), perfluorocarbons (PFCs), and hydrofluorocarbons (HFCs) [18]. Of all these types of gases, the main greenhouse gases (GHGs) are CO_2, CH_4, and N_2O. Among these three types of gases, CO_2 is the most abundant in the atmosphere, while the others are less so. Although the concentration of CH_4, and N_2O gases is low, their global warming potential is higher. Here are the global warming potential capabilities of several types of GHGs:

Table 1. Classification of greenhouse gases and their types

Greenhouse Gases	Chemical Formula	Global Warming Potential Value	Lifetime in the Atmosfere
Carbon dioxide	CO2	1	Dozens to thousands of years
Methane	CH4	24	12,2 years
Dinitrogen oxide	N2O	298	120 years

F-Gases themselves are a group of greenhouse gases primarily produced from industrial activities and various manufacturing processes. These gases do not occur naturally in the atmosphere but are instead by-products of the production or use of certain materials.

2.4 Related Studies

A study in Salvador-Bahia applied the Self-Organizing Map (SOM) algorithm to cluster atmospheric pollutants and meteorological factors. The resulting maps revealed hidden emission patterns and source characteristics, demonstrating SOM's effectiveness in handling complex environmental data and supporting its application in emission pattern analysis [19]

In comparison, several studies have employed alternative clustering methods such as K-Means to analyze greenhouse gas emissions. One such application focused on grouping countries based on similarities in methane (CH_4) emission patterns. These clusters were used to help identify global mitigation priorities [20]. However, SOM has demonstrated superior clustering performance in various environmental contexts. For instance, a study on industrial potential across Indonesian provinces found that SOM produced more well-separated and meaningful clusters than K-Means, highlighting its ability to capture non-linear relationships in high-dimensional datasets [21].

At the local level, a sectoral emission study conducted at Terminal Mangkang and Terminal Penggaron quantified GHG emissions from vehicle activity using the Tier 2 method. The analysis identified major CO_2 sources from both moving and idle vehicles, and proposed mitigation through policy and behavioral changes. While informative, this study was confined to specific transport-related activities and did not address national-scale, sector-based contributions across multiple types of greenhouse gases [22].

Beyond methodological considerations, several studies emphasize the importance of identifying dominant emission-contributing sectors to guide effective environmental policy. One review chapter highlighted power generation, cement production, and transportation as major contributors to global warming, while also noting that international efforts to reduce emissions remain constrained by implementation gaps. This underscores the urgency for accurate sectoral identification to support more targeted and impactful mitigation strategies [23].

Building upon these previous studies, the present research adopts a SOM-based visualization approach to identify dominant emission sectors for each type of greenhouse gas (CO_2, CH_4, N_2O, and F-Gases) in Indonesia. Unlike conventional approaches that emphasize total emission volume, this study focuses on analyzing emission patterns across sectors to identify recurring and distinguishable trends. These patterns reflect not only the magnitude but also the consistency and uniqueness of sectoral emission behaviors over time. Understanding these patterns is critical for prioritizing sectors in emission control policies, as it provides a more stable and representative basis for long-term planning. By leveraging the Self-Organizing Map (SOM), this research emphasizes pattern-based mapping to support more nuanced, data-driven climate strategies in Indonesia.

3 Research Methodology

The data used in this study consist of greenhouse gas emission statistics obtained from the EDGAR (Emissions Database for Global Atmospheric Research), published by the European Commission Joint Research Centre (JRC). Each gas type includes sectoral emission values which are organized and preprocessed for training.

To ensure consistent scaling and fair treatment across all variables, input data were normalized per sector using the Min-Max Scaler prior to SOM training. Normalization is a crucial step in unsupervised learning tasks to prevent variables with larger magnitudes from dominating the distance calculations, especially in models like SOM that rely heavily on Euclidean distance. By rescaling all input values to a standard [0,1] range, this step ensures that the SOM model captures the underlying emission patterns rather than absolute values, which may vary significantly between sectors and gases.

In this study, the SOM model was configured using specific parameter values designed to optimize the balance between learning stability, convergence speed, and interpretability. Initial node weights were randomly assigned to avoid bias and allow the map to self-organize entirely based on the training data. The learning rate was set to 0.3, providing moderate adaptability—fast enough for meaningful updates in early training stages, yet stable enough to prevent erratic weight changes. A neighborhood radius of 1.0 was chosen to define the local region around the Best Matching Unit (BMU) that adjusts during each iteration, thereby promoting spatial coherence across the SOM grid.

The SOM grid was set to 4×4 neurons, providing a two-dimensional representation with 16 nodes. This grid size offers a reasonable compromise between resolution and generalization—large enough to capture distinct sectoral emission profiles, yet compact enough to prevent overfragmentation or the formation of empty nodes. The training was conducted over 400 iterations, which allowed the SOM to adjust sufficiently while avoiding overfitting or excessive computation. These settings were selected based on best practices in SOM modeling, particularly for structured environmental datasets with moderate dimensionality.

In line with the study's primary objective of identifying dominant emission patterns across sectors, the output analysis focuses on three key elements:

a. SOM visualization, which provides spatial insights into clustering patterns.
b. Average sectoral weight comparisons, to identify which sectors consistently occupy dominant regions of the map.
c. Quantization Error (QE), which serves as a quantitative measure of model accuracy in preserving the topological structure of input data.

As elaborated in Section 2.2, this study adopts a QE threshold of 0.3 as the benchmark for reliable topological representation, in accordance with previous SOM-based applications. All model development, training, and visualization processes were implemented using Python in Google

Colaboratory, employing the MiniSom library for SOM computation. This open-source framework offers flexible configuration and reproducible results, ensuring transparency and accessibility in the research workflow.

4 Result and Discussion

4.1 Carbon Dioxide (CO_2)

The Self-Organizing Map (SOM) training results on CO_2 emission data reveal clear sectoral distinctions, both visually and numerically. These distinctions are evident in the average SOM weight values per sector, as presented in Table 2, and further visualized through the weight vector distribution across the SOM grid in Figure 2.

Table 2. Average SOM weight values for CO_2

Name of Sector	Average SOM Weight Values
Processes	0.6825
Industrial Combustion	0.6044
Agriculture	0.5535
Transport	0.5399
Buildings	0.5315
Waste	0.5237
Power Industry	0.5185
Fuel Exploitation	0.4623

Based on the average SOM weight vectors for each sector, the Processes sector ranks highest with a value of 0.6825, indicating strong and consistent CO_2 emission patterns. This aligns with its typical role in high-emission activities such as cement manufacturing and chemical processing. The Industrial Combustion sector follows with an average weight of 0.6044, reflecting the energy-intensive nature of industrial operations that rely heavily on fossil fuels. The Agriculture sector holds the third-highest value at 0.5535, which may reflect consistent yet moderate emissions from activities such as crop cultivation and livestock management. Next, Transport (0.5399) and Buildings (0.5315) show comparable weight levels, indicating steady but slightly more variable emissions due to factors like vehicle usage and electricity demand in urban environments. Meanwhile, the Waste sector has an average weight of 0.5237, which could be attributed to relatively localized or irregular emission sources such as landfills and wastewater treatment. At the lower end, Power Industry (0.5185) and Fuel Exploitation (0.4623) register the smallest average weights, possibly indicating more scattered or less consistent emission patterns within these sectors, or differences in reporting and monitoring intensity.

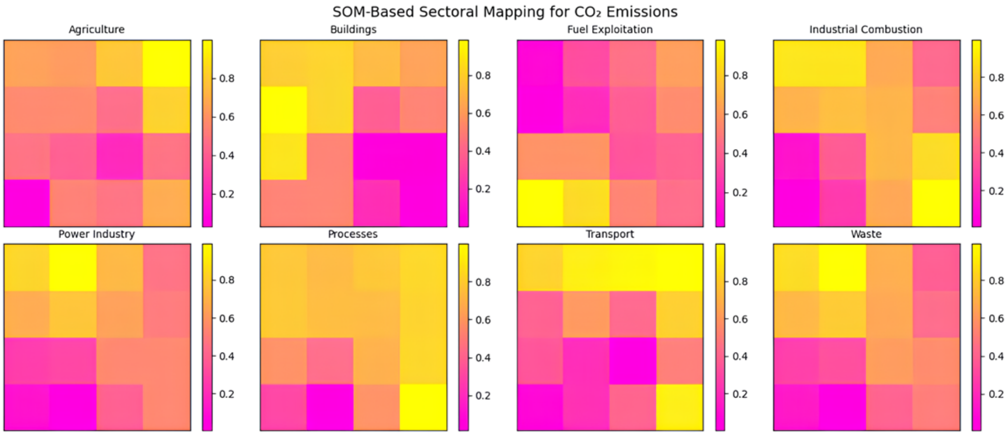

Figure 2. SOM based sectoral mapping for CO_2 emissions

These weight values are consistent with the SOM visualization, where brighter color intensities appear in the regions corresponding to the Processes, Industrial Combustion, and Agriculture sectors. The clustering observed in the SOM grid reflects meaningful differentiation, with these sectors forming more defined and densely activated areas, signifying stronger learned patterns. In contrast, darker regions associated with Fuel Exploitation and Power Industry further validate their relatively weaker emission signals within the dataset.

The reliability of the SOM model is affirmed through the calculated Quantization Error (QE) of 0.0218, indicating minimal average distance between each data point and its best-matching unit (BMU). This value is substantially lower than those reported in several prior studies (e.g., QE ≈ 0.35 for certain environmental datasets), signifying excellent topological preservation and accurate mapping performance. These findings highlight the SOM model's ability to capture and differentiate CO_2 emission patterns across sectors with high precision. The Processes, Industrial Combustion, and Agriculture sectors emerge as dominant contributors, aligning with known high-emission activities in industrial and agricultural domains. These sectors exhibit strong and structured emission profiles, effectively visualized through SOM clustering. The model's exceptionally low Quantization Error supports the robustness of these results, confirming SOM's value as a reliable analytical tool for informing targeted emission reduction strategies in CO_2-intensive sectors.

4.2 Methane (CH_4)

The Self-Organizing Map (SOM) training results on CH_4 emission data reveal clear distinctions are evident in the average SOM weight values per sector, as presented in Table 3, and further visualized through the weight vector distribution across the SOM grid in Figure 3.

Name of Sector	Average SOM Weight Values
Transport	0.6033
Waste	0.5780
Processes	0.5598
Agriculture	0.4916
Power Industry	0.4723
Buildings	0.4484
Industrial Combustion	0.4467
Fuel Exploitation	0.4205

Table 3. Average SOM weight values for CH_4

The Transport sector emerges with the highest average SOM weight vector at 0.6033, indicating relatively strong and consistent CH_4 emission patterns. This may be attributed to methane released during fuel combustion in land-based transportation, which exhibits repeated and measurable emission characteristics. The Waste sector follows closely with a weight of 0.5780, likely reflecting the continuous contribution of methane from landfill decomposition and wastewater processing—sources known for producing predictable and long-term emissions. The Processes sector ranks third with 0.5598, consistent with methane generation from specific industrial chemical reactions and treatment systems. Other sectors such as Agriculture (0.4916) and Power Industry (0.4723) present moderate weights, suggesting regular but less dominant methane emissions across regions and time. At the lower end, Buildings (0.4484), Industrial Combustion (0.4467), and Fuel Exploitation (0.4205) show the smallest average weights. These may reflect more diffuse or irregular methane sources, possibly due to variation in fuel handling, usage patterns, or system efficiencies.

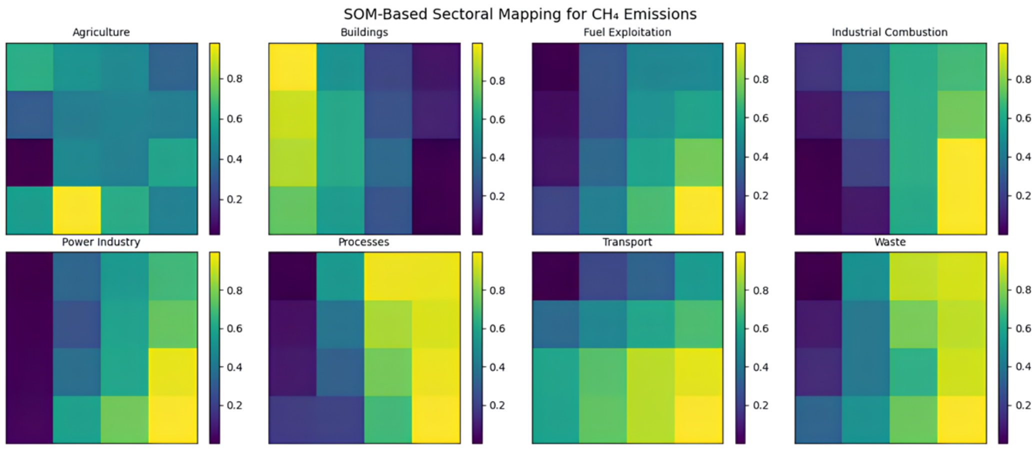

Figure 2. SOM based sectoral mapping for CH_4 emissions

The SOM visualization confirms these distinctions, with Transport, Waste, and Processes sectors appearing in the brightest regions of the map grid. These high-intensity zones visually indicate stronger activation and greater consistency of learned emission patterns for these sectors. In contrast, darker grid regions corresponding to lower-weight sectors validate their relatively weaker or less stable methane emission signatures.

The calculated Quantization Error (QE) is 0.0207, demonstrating high-quality mapping performance and minimal deviation between actual data vectors and their best-matching units (BMUs). Considering that QE values up to 0.35 are generally acceptable in environmental studies, this notably low QE confirms that the SOM model offers excellent topological preservation and accurate clustering for sectoral CH_4 emissions. These findings validate the SOM model's effectiveness in identifying and differentiating sectoral CH_4 emission patterns. With the Transport, Waste, and Processes sectors consistently emerging as dominant contributors, the results emphasize the importance of directing methane mitigation strategies toward these key sources. The relatively high and stable weights associated with these sectors suggest persistent and structured emission behaviors, which are well captured by the SOM's topological learning. The model's low Quantization Error further confirms its reliability in representing CH_4 emission structures, reinforcing its value as a decision-support tool in policy planning and emission control frameworks.

4.3 F-Gases

The Self-Organizing Map (SOM) training results for F-Gases emissions reveal a sector-specific pattern concentrated solely in the Processes sector, which is the only contributor to this gas type in the dataset. Unlike other greenhouse gases that span multiple emission sectors, the F-Gases dataset consists of a single-dimensional input vector, simplifying the SOM training process while still enabling meaningful interpretation.

Based on the SOM training, the average weight vector for the Processes sector is 0.5142. This moderate-to-high value reflects a stable and consistently recognized emission pattern throughout the dataset. Although only one sector is involved, the weight value suggests that emissions from the Processes sector are not only prominent but also regularly distributed across spatial or temporal dimensions in the input data.

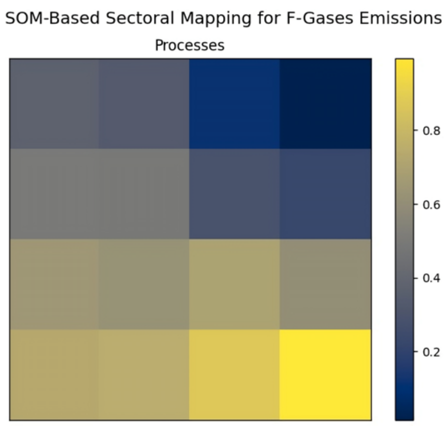

Figure 4. SOM based sectoral mapping for f-gases emissions

The SOM visualization supports this result, showing a clear gradient across the map. Brighter areas correspond to higher activation levels, which visually represent the strength and structure of the emission signal from the Processes sector. Despite the input being one-dimensional, the trained map still captures variation in the magnitude of emissions, revealing a meaningful internal differentiation even within a single-sector context.

The reliability of the SOM model is affirmed through the Quantization Error (QE) of 0.0040, indicating extremely low deviation between the original input vector and its Best Matching Unit (BMU). This value is significantly below commonly reported QE thresholds (e.g., ≈0.35), and even lower than most multi-sector mappings demonstrating excellent mapping precision despite the model's simplified structure. These findings confirm that the Processes sector plays a central role in F-Gases emissions, consistent with its association with industrial activities such as refrigeration, chemical manufacturing, and the use of synthetic gases like HFCs, PFCs, and SF_6. The strong and consistent SOM response, combined with a very low QE, reinforces the conclusion that mitigation strategies for F-Gases should be directly targeted at industrial process control and efficiency improvements.

4.4 Nitrous Oxide (N_2O)

The Self-Organizing Map (SOM) training results on N_2O emission data reveal meaningful sectoral differentiation, observable through both the average weight values per sector and the corresponding visual distribution across the map. These distinctions are evident in the average SOM weight values processes sector, as presented in Table 4, and further visualized through the weight vector distribution across the SOM grid in Figure 5.

Table 4. Average SOM weight values for N_2O

Name of Sector	Average SOM Weight Values
Agriculture	0.6469
Waste	0.6277
Power Industry	0.5841
Processes	0.5582
Transport	0.4966
Industrial Combustion	0.4948
Fuel Exploitation	0.4825
Buildings	0.3785

The Agriculture sector exhibits the highest average SOM weight at 0.6496, indicating that this sector contributes the most distinguishable and consistent nitrous oxide (N_2O) emission pattern in the dataset. This is consistent with Agriculture's dominant role in N_2O emissions due to extensive fertilizer use and livestock waste management. The Waste sector follows with a weight of 0.6277, highlighting the contribution of landfills and wastewater systems to methane and nitrous oxide emissions. The Power Industry, with an average weight of 0.5814, likely reflects emissions from fossil-fuel combustion and nitrogen-based compounds generated during energy production. Mid-weight sectors include Processes (0.5582), Transport (0.4966), Industrial Combustion (0.4948), and Fuel Exploitation (0.4825). These suggest moderately consistent but less dominant N_2O emissions, possibly due to variability in operation scale or technology usage. The Buildings sector has the lowest average weight at 0.3785, indicating limited or highly dispersed N_2O emission signals, potentially from indirect sources such as energy consumption patterns.

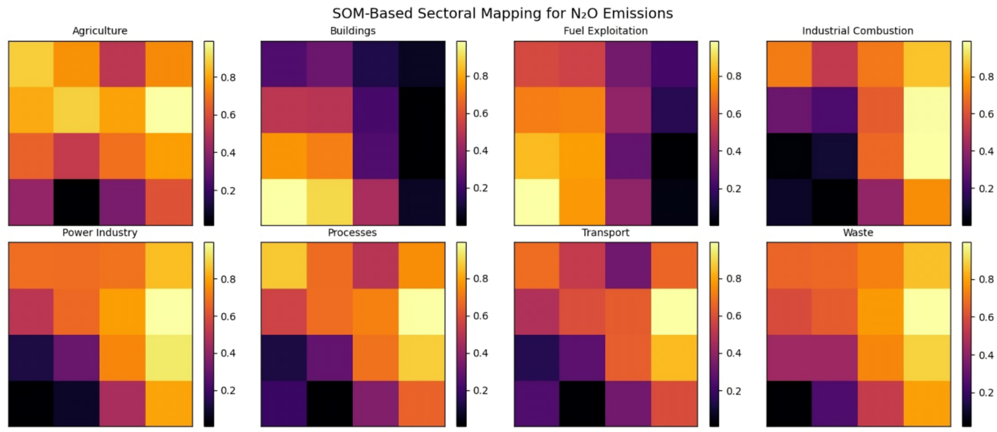

Figure 5. SOM based sectoral mapping for N_2O emissions

The SOM visualization aligns with these weight values. Neurons associated with Agriculture, Waste, and Power Industry appear in brighter, more activated regions of the SOM grid, signifying strong and consistent emission signals captured by the model. The clustering around these sectors confirms the SOM's ability to differentiate dominant patterns from the background variability of other sectors. In contrast, darker and more diffused areas correspond to lower-weight sectors like Buildings and Fuel Exploitation, reinforcing the interpretation that these sectors contribute weaker or more scattered N_2O signals in the dataset.

The quality of the SOM model is confirmed by the Quantization Error (QE) of 0.0171, which is far below the acceptable threshold often cited in environmental applications (QE ≈ 0.35). This low QE indicates high topological accuracy and minimal deviation between each data point and its Best Matching Unit (BMU), ensuring that the model has reliably captured the structural emission patterns present in the N_2O dataset. These findings validate the SOM model's effectiveness in capturing and distinguishing sectoral N_2O emission structures. With Agriculture, Waste, and Power Industry emerging as dominant contributors, the results suggest that targeted mitigation policies should prioritize these sectors in order to address N_2O emissions more effectively. The model's strong mapping accuracy further reinforces its potential as a decision-support tool in emission monitoring and control strategies.

4.5 Comparative Validation and Pattern Summary of SOM Across Gas Types

In addition to evaluating emission patterns within each gas type, this subsection presents a cross-gas comparative summary, as shown in Table 5. The comparison includes Quantization Error (QE) values as indicators of model accuracy, the most dominant sector per gas based on SOM weight distribution, and the corresponding average weight values. By consolidating these metrics, the analysis highlights key differences in emission structure and clustering consistency across CO_2, CH_4, F-Gases, and N_2O. These insights provide a clearer foundation for recommending sector-specific mitigation strategies aligned with each gas's unique emission behavior.

Table 5. Quantization error, dominant sector, and average SOM weight by gas type

Gas Name	Dominant Sector	Average Weight	QE Value
CO_2	Processes	0.6825	0.0221
CH_4	Transport	0.6033	0.0206
N_2O	Agriculture	0.6289	0.0171
F-Gases	Processes	0.0040	0.0051

Table 5 presents a comparative summary of SOM results across the three major greenhouse gases with multi-sectoral input: CO_2, CH_4, and N_2O. The table includes Quantization Error (QE) values, the most dominant emission sector per gas, and the corresponding average weight values. Among these gases, N_2O exhibits the lowest QE (0.0171), indicating highly distinct and consistent emission patterns across sectors. Its dominant sector, Agriculture, holds an average weight of 0.6289, reflecting strong, concentrated emission behavior—likely due to fertilizer usage and soil processes that produce predictable outputs. On the other hand, CO_2 has the highest QE (0.0218), suggesting more diffuse emission behavior. Although Processes emerges as the dominant sector (avg. weight 0.6825), the relatively higher QE implies that CO_2 emissions are more evenly distributed across other sectors, such as Transport and Buildings, which may reduce clustering clarity. CH_4 falls in the middle, with a QE of 0.0207. Its dominant sector, Transport, has a moderate average weight (0.6033), indicating a balanced emission pattern influenced by multiple sectors—particularly combustion-related activities. This dual-sector relevance is reflected in CH_4's visual and numerical SOM outputs. For comparison, F-Gases have a QE of 0.0040, but due to their single-sector input, this value is not directly comparable. The low QE simply reflects reduced dimensionality rather than stronger model performance. Collectively, these differences reinforce the importance of interpreting SOM results with consideration for data structure, and emphasize that emission control strategies must be gas-specific, as sectoral emission behaviors vary substantially by gas type.

Among the three multi-sector gases, N_2O has the lowest QE, indicating more distinct and consistent sectoral patterns, while CO_2 has the highest, suggesting more dispersed emission behavior. These differences likely reflect the nature of each gas's sectoral distribution: CO_2 is emitted broadly across sectors, whereas N_2O is typically associated with more specific sources. The F-Gases model shows an exceptionally low QE. However, this result is not directly comparable due to its one-dimensional input (a single emission sector). The reduced complexity inherently produces a lower error, but does not imply better clustering performance. As such, dimensional context is essential when interpreting QE values in cross-gas comparisons. Overall, the SOM demonstrates reliable performance across all gas types, with QE values well below the 0.3 threshold discussed in Section 2.2, confirming the model's suitability for identifying sectoral emission patterns.

5 Conclusion

This study applied the Self-Organizing Map (SOM) to classify greenhouse gas (GHG) emission patterns in Indonesia by sector and gas type. The results showed that the most dominant sectors vary by gas: Processes for CO_2 and F-Gases, Transport for CH_4, and Agriculture for N_2O. The SOM model successfully produced meaningful clusters with low Quantization Error (QE) across all gases—ranging from 0.0171 to 0.0218—which are well below the 0.3 threshold commonly used in environmental studies. This confirms that sectoral emission structures were effectively captured.

These findings highlight the need for gas-specific emission control strategies rather than uniform measures, and provide data-driven support for national climate mitigation policies. While SOM proved effective in mapping emission patterns, its reliance on unsupervised learning and manual interpretation requires cautious application in dynamic policy contexts.

Future research should explore hybrid approaches by combining SOM with supervised methods, applying the model to more complex datasets, and integrating policy-relevant indicators to strengthen the alignment between emission pattern analysis and strategic decision-making.

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