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Assessing the relative contribution of various anthropogenic sources to atmospheric methane in Rivers State, Nigeria: A multi-criteria decision analysis approach

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Abstract
Methane is a significant greenhouse gas, with a global warming potential many times greater than carbon dioxide over a 20-year period. Its release from sources like landfills, agriculture, and the energy sector exacerbates climate change, making it crucial to monitor and reduce methane emissions to mitigate global warming and achieve climate goals. This research utilized the Multi-Criteria Decision Analysis (MCDA) method, specifically the Analytic Hierarchy Process (AHP), to analyze the sources of atmospheric methane in Rivers State, Nigeria. It addressed the challenge of assessing the contributions of various anthropogenic sources such as fossil fuels, landfills, agriculture, wetlands, and oceans to atmospheric methane emissions. By incorporating expert opinions, literature reviews, and surveys, the study constructed a hierarchical model to prioritize these sources based on their impact. Findings identified fossil fuels and landfills as the main contributors. The study demonstrated MCDA's effectiveness in environmental analysis and provided a replicable framework for similar assessments in other regions, contributing to targeted emission mitigation and policy formulation efforts.

Keywords: Atmospheric methane, Multi-Criteria Decision Analysis (MCDA), Analytic Hierarchy Process (AHP), Anthropogenic methane sources, Emissions mitigation.

1. Introduction

Methane is a potent greenhouse gas (GHG) that significantly contributes to climate change (Carranza *et al*., 2018; Lorente *et al*., 2021; Ogbowuokara *et al*., 2023). It has a global warming potential (GWP) that is much higher than that of carbon dioxide (Thakur & Solanki, 2022). Methane emissions have a short atmospheric lifetime, but they have a strong warming effect during that time (Mar *et al*., 2022). Methane is released into the atmosphere through various sources, including natural processes, human activities, and industrial processes (Dlugokencky *et al*., 2011). Agricultural activities also contribute to methane emissions (Li *et al*., 2022). Methane oxidizes to form ground-level ozone (O_3) that is itself a greenhouse gas and a pollutant that impair health and damage vegetation (Heimann *et al*., 2020; Sarofim *et al*., 2017).

Methane, being over 25 times more effective than carbon dioxide at trapping heat in the atmosphere over a 100-year period, has profound implications for global warming (Bodunde, 2023). Research has consistently shown that even minor fluctuations in atmospheric methane source contributions can lead to substantial changes in global temperatures. These temperature variations, in turn, affect sea levels, weather patterns, and biodiversity (Dean *et al*., 2018). Nisbet *et al*. (2019) examined the rapid rise in atmospheric methane levels during the period 2014-2017, observing growth rates not seen since the 1980s. According to the authors, the implications of this surge were significant; they suggested that if such growth rates continued in the subsequent decades, the goals of the Paris Agreement could have been potentially jeopardized.

Numerous studies in the past have developed various methodologies to determine the different sources' relative contributions to atmospheric methane levels. Ozkaya *et al*. (2007) developed a neural network model to predict methane fractions in landfill gas from bioreactors, using data from the Odayeri Sanitary Landfill in Istanbul, Turkey. The model used various leachate parameters as inputs and highlighted the efficiencies of anaerobic conversion, with a focus on optimizing the neural network's architecture and discussing its potential improvements.

Wilson *et al*. (2016) assessed atmospheric methane concentrations over the Amazon Basin using a 3-D model, emission models, and observations from biweekly flights, finding that the region significantly contributed to global methane emissions and suggesting that factors like temperature variations might have impacted microbial emission rates. Another study by Allen (2016) explored new analytical methods for attributing past methane emissions to specific sources, using high-resolution methane measurements and chemical mass balance methods to enhance the understanding and quantification of historical methane emission sources.

The study by Jones *et al*. (2021) focused on investigating diffuse methane emissions in Indianapolis, USA, using a network of solar-tracking FTIR spectrometers and an innovative inversion method. This approach, combining a Lagrangian transport model with Bayesian inversion, revealed that the city's diffuse methane emissions were significantly higher than bottom-up estimates, accounting for about half of the total urban emissions. Naus *et al*. (2023) analyzed methane emissions from Algeria's largest gas field, Hassi R'Mel, and the oil-production area Hassi Messaoud in 2020. Using high-resolution Sentinel-2 and TROPOMI data, they identified superemitters and diffuse area sources, revealing significant discrepancies between actual emissions and national reporting, and emphasizing the need for targeted mitigation efforts in both oil and gas production sectors.

Xia *et al*. (2023) embarked on a detailed assessment of methane emissions from eight significant municipal solid waste landfills in southeast Michigan, USA. By leveraging advanced mobile monitoring techniques, their study aimed to capture the spatial and temporal fluctuations in methane levels. Results revealed pronounced methane concentrations on the downwind sides of the landfills, peaking at 38 ppm in mornings. Feng *et al*. (2022) investigated the record-breaking global atmospheric methane growth rates for 2020 and 2021, the highest since 1983. The study identified a strong correlation between tropical methane emissions and groundwater, hinting at microbial sources playing an influential role. The study concluded that the majority of the methane rise in 2020 and 2021 was due to enhanced emissions. Zimmermann *et al*. (2018) employed the EMAC atmospheric chemistry-general circulation model to investigate the global budget and trends of atmospheric methane from 1997 to 2014. Drawing from data sources such as AGAGE, NOAA 15 surface stations, and CARIBIC flights, the study observed a transient decline in methane increase between 1997-1999, followed by stagnation until 2006, and a sudden rise post-2006. The research identified the necessity for an additional emission of 28.3 Tg/y methane between 2007-2013 to account for observed growth, suggesting major contributions from tropical wetlands (62.6%) and North American shale gas emissions (37.4%).

Roberts *et al*. (2022) emphasized the importance of monitoring methane especially in regions with industrial activities, due to its significant impact on climate change. While the TROPOspheric Monitoring Instrument (TROPOMI) on the Sentinal-5P satellite provides daily global methane measurements, cloud cover often limits data accuracy. To address this limitation, the study introduced a statistical model utilizing nitrogen dioxide data from TROPOMI to predict methane columns. This approach increased the observed coverage of the Permian basin from 16% to 88% in 2019.

Nickl *et al*. (2020) investigated methane emissions from coal mining in the Upper Silesian Coal Basin, Poland. Using the CoMet 1.0 campaign's measurements from May-June 2018, they found the basin emits about 502 kt of methane annually from ventilation shafts. Using the MECO(n) model, they were able to accurately forecast methane emissions and patterns up to four days. The study underscored the significance of precise models and measurements in understanding methane's role in climate change. Moreover, Toha and Rahman (2023) conducted a study comparing a predictive model with physical measurements for estimating methane emissions at two landfill sites in Dhaka. They concluded that the predictive model was more effective for this purpose.

Lunt *et al*. (2019) and Nisbet *et al*. (2022) used aircraft campaigns and satellites to infer atmospheric methane emissions from Africa and concluded that in-situ measurements were scarce in Africa. Lunt *et al*. (2019) also found that linear emissions trend accounted for around one-third of the global emissions growth rate during the period 2010 and 2016. Consequently, Nisbet *et al*. (2022) informs that there is currently no methane data in Africa and that in order to balance the global methane budget isotropically, understanding African emissions is critically important. It follows therefore that predictive research on atmospheric methane source contributions is lacking in Africa. Also, the Global Methane Assessment of the United Nations Environment Programme and Climate and Clean Air Coalition (2021) maintains that methane inventory does not exist in Nigeria.

The estimation of the relative contributions of various sources to atmospheric methane involves a diverse array of modeling approaches tailored to specific contexts. Previous research in methane emissions estimation has predominantly utilized statistical regression and machine learning techniques. Key examples include linear univariate and multiple regression equations (Barros *et al*., 2011), random forests (Mosher *et al*., 2015), linear mixed models (Niu *et al*., 2018), probabilistic time series models (Rehman *et al*., 2021), and predictive models using nitrogen dioxide data (Roberts *et al*., 2022). Additionally, remote sensing methods like Raman lidar technology (Veselovskii *et al*., 2019) and atmospheric chemistry-general circulation models (Zimmermann *et al*., 2018) have been instrumental. Machine learning models (Mehrdad *et al*., 2021), including artificial neural networks, adaptive neuro-fuzzy inference system, and support vector regression and decision tree methods (Li *et al*., 2020), modified grey radial basis function neural network model (Yang *et al*., 2020), 3-D modeling approach (Heimann *et al*., 2020), detailed site-level methane emission estimation model (Cardoso-Saldana & Allen, 2020), as well as Monte Carlo simulations (De Faria *et al*., 2015), have also been applied.

Fiehn *et al*. (2023) focused on quantifying and analyzing the isotopic signatures of methane emissions in the Upper Silesian Coal Basin, using airborne and ground-based sampling during the CoMet campaign. This comprehensive analysis enabled differentiation between fossil and biogenic methane sources in the region, revealing significant variations in isotopic signatures among different coal mine shafts and highlighting the importance of δ2H-CH_4 observations in methane source apportionment.

Zhang *et al*. (2023) conducted an in-depth analysis of methane emissions from coal mining in Shanxi Province, China. The research divided the region into different zones, monitored methane emissions from various types of coal mines, and predicted future emissions based on coal production and emission factors, highlighting the significant contribution of these mines to the region's total methane emissions.

Moreover, numerous studies prior to ours have also applied Multi-Criteria Decision Analysis (MCDA) methods in the context of environmental research, exploring various aspects and challenges in this field. Huang *et al*. (2011) conducted a comprehensive review of over 300 papers published between 2000 and 2009 on the application of Multi-criteria Decision Analysis (MCDA) in environmental projects. This review classified the papers based on environmental application areas, decision types, and MCDA methods used, finding a significant increase in the use of MCDA tools across various environmental contexts over the decade.

Mustajoki and Marttunen (2017) analyzed 23 multi-criteria decision analysis software tools to determine their suitability for environmental planning processes. The research focused on assessing the features of these tools, how they address environmental problem-solving needs, and their utility in aiding practitioners with systematic analysis. It also aimed at identifying optimal software for environmental cases and highlighting innovative software development solutions. While the study by Ogonowski (2022) closely aligns with our research in its use of multicriteria decision-making methods, it did not apply these methods in an environmental context, specifically for assessing the relative contributions of various sources to atmospheric methane.

Despite the extensive application of Multi-Criteria Decision Analysis (MCDA) in environmental studies, a notable gap identified is that none of these studies have specifically used MCDA to assess the relative contributions of various sources to atmospheric methane. To the best of the authors' knowledge, this study represents the first comprehensive effort to analyze the relative contributions of various sources to atmospheric methane in Rivers State, Nigeria.

There are numerous Multi-Criteria Decision Analysis (MCDA) methods available that can be used for ranking, comparing, and selecting the most significant contributor to atmospheric methane in Rivers State, Nigeria based on selected criteria (Abdullah & Adawiyah, 2014; Taherdoost & Madanchian, 2023; Wątróbski, *et al*., 2019). These methods include, but are not limited to, the Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE), and Elimination and Choice Expressing Reality (ELECTRE). Among these, our study has chosen to use the Analytic Hierarchy Process (AHP), as developed by Saaty (1977), for its robust and well-established framework in handling complex decision-making processes.

This paper introduces a novel method for assessing the relative contributions of different sources to atmospheric methane levels in Rivers State, Nigeria. The popularity of the Analytic Hierarchy Process (AHP) methodology stems from its straightforward approach to determining criterion weights and its ability to incorporate diverse data types. This method is particularly advantageous in scenarios where defining exact relationships between numerous evaluation criteria is impractical or impossible (Chen *et al*., 2013). The Analytic Hierarchy Process (AHP) is adept at handling incomplete or inconsistent data through the use of matrix algebra. This involves employing eigenvalue-based methods or similar computational techniques to generate weights, overall scores, and consistency measures, as explained by Ishizaka and Lusti (2006). This capability makes AHP a robust tool for multi-criteria decision-making even in scenarios with challenging data quality.

However, AHP has limitations, particularly in handling the uncertainty and imprecision associated with decision-makers' perceptions. It provides qualitative sensitivity measures by ranking input factors in order of importance but does not quantify the extent to which one factor is more important than another (Chen *et al*., 2013). Further limitations of the method include its reliance on subjective judgments, potentially introducing bias. The method can be unwieldy when dealing with numerous criteria or alternatives. Additionally, maintaining consistency in pairwise comparisons is often difficult, particularly in more complex scenarios where multiple factors interact in nuanced ways (Hontoria & Munier, 2021).

Assessing the relative contributions of different sources to atmospheric methane is of paramount importance, especially in regions experiencing rapid industrial and agricultural growth. Rivers State, Nigeria, a region characterized by its bustling urban centres, extensive agricultural activities, and significant fossil fuel reserves, stands at the forefront of such areas where changes in methane concentrations can have pronounced environmental impacts. Rivers State, located in the southern part of Nigeria, occupies a prominent position in the Niger Delta region. It is bounded to the north by Imo, Abia and Anambra States, to the east by Akwa Ibom State, to the west by Bayelsa and Delta states, and to the south by the Atlantic Ocean. It is geographically positioned at coordinates 4°45′N 6°50′E. The state covers an area of approximately 11,077 square kilometres. Rivers State is crisscrossed by several rivers and creeks, the most prominent being the River Niger and its tributary, the River Benue. This intricate network of water bodies has given the state its name and plays a significant role in its economic and socio-cultural life (Akintola *et al*., 2021).

Assessing the relative contributions of different sources to atmospheric methane in Rivers State, Nigeria, is a multifaceted task that requires a multi-criteria approach. This complexity arises because a single factor cannot adequately measure these contributions. Multi Criteria Decision Analysis (MCDA) is an effective tool for this purpose. MCDA methods are designed to assess the importance of various criteria in decision-making processes, particularly when there are multiple alternatives to consider. These methods offer structured algorithms for ranking decision options and identifying the most suitable one (Labib *et al*., 1997). In recent years, MCDA has gained popularity for its effectiveness in addressing complex decision-making scenarios in various fields, including environmental studies (Bottero *et al*., 2011; Hill *et al*., 2005; Huang *et al*., 2011).

In this paper, we will utilize the Multi Criteria Decision Analysis (MCDA) method to evaluate the varying contributions of different sources to atmospheric methane in Rivers State, Nigeria. Specifically, the Analytic Hierarchy Process (AHP), developed by Saaty (1977), will be employed to determine weighting factors. AHP is particularly suited for complex problems where multiple criteria are involved and is effective in measuring and analyzing preferences. This method's application is well-documented in relevant literature (Gompf *et al*., 2021; Ogonowski, 2022; Wolnowska & Konicki, 2019), underlining its suitability for our analysis.

The aim of this paper is to demonstrate the application of the Analytic Hierarchy Process (AHP), a multicriteria decision-making method, in evaluating the relative contributions of various sources to atmospheric methane in Rivers State, Nigeria.

2. Methods

2.1 System sketch and dynamics analysis

The methodology initiated with a system sketch, identifying key variables and scenarios reflective of the dynamic nature of atmospheric methane production sources. This step was crucial in understanding the different factors influencing methane emissions.

The selected variables were then used for the initial characterization of the system and its dynamics. Also, at the level of the system structural analysis, the variables were evaluated from their impact relationships with the use of relative values (0-3 scale), based on theory, literature, information, and expert experience. The Cause is the row variable’s influence on the column variable, while the Effect is the column variable’s potential change due to the row variable. To determine the variables that were highly active and that influence other variables or are in turn influenced by other variables, a cause-effect plot and relationships diagram were constructed. As a result, a positive and negative feedback loops were also constructed to show the degree of stability of the system.

2.2 Methane predictive index (MPI)

Our study adopted a structured approach using Multi-Criteria Decision Analysis (MCDA) to systematically evaluate multiple factors influencing atmospheric methane sources. This method, informed by in-depth reviews of key literature such as Keeney and Raiffa (1993), Malczewski and Rinner (2015), Persson (2014), and Scholz and Tietje (2002), enabled a sequential analysis of various conditions contributing to methane emission sources.

2.3 Atmospheric methane source modeling

We also formulated the model objective, identified and structured the hierarchy of the criteria, assigned weights to the criteria, and standardized the range of the criteria using utility. We then aggregated criteria utility and criteria weights into a single resulting atmospheric methane predictive index, which corresponds to the model objective. Lastly, we undertook model result evaluation and presentation. This entire workflow is illustrated in Figure 1.

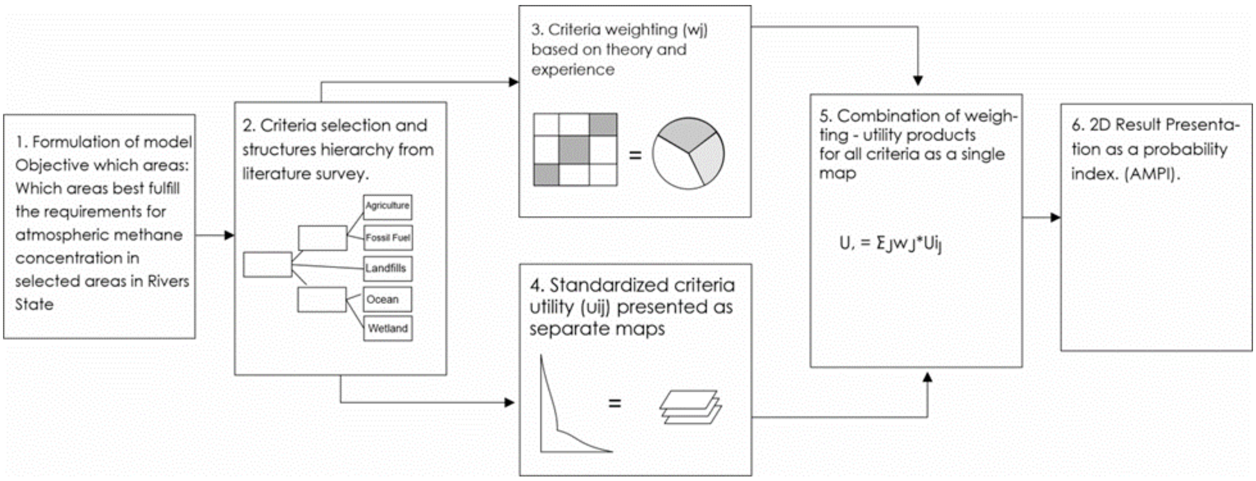

Figure 1 - Workflow of atmospheric Methane Predictive Index (MPI). Adapted from Keeney and Raiffa (1993), Malczewski and Rinner (2015), Persson (2014), and Scholz and Tietje (2002).

2.4 Criteria identification

We scoured information from diverse sources such as conceptual reasoning, knowledge, expert judgment, literature (journals and books), and surveys. We extensively consulted scientific databases like PubMed, ScienceDirect, Scopus, and Google Scholar for relevant journals and books. We utilized information acknowledging Rivers State, Nigeria, as a major crude oil and gas production zone, known for its open landfills, mangrove swamps, flood plains, and oceanic proximity. These factors contributed to our understanding of methane emissions. We reinforced this knowledge with studies like Aregbe (2016) and Anosike *et al*. (2016), highlighting the significant methane production from the fossil fuel sector in the Niger Delta. Additionally, we referred to reports by World Bank (2023), Obanijesu and Macaulay (2009), Thomas *et al*. (2014), and Kirschke *et al*. (2013) for insights on methane emissions from various sources, including urban areas and wetlands. Reay *et al*. (2018) was also consulted for information on oceanic methane emissions. From the literature, we identified several criteria known to be involved in the emission of atmospheric methane and then excluded those criteria perceived to have an insignificant impact on the process and retained agriculture, fossil fuel, ocean, wetland, and landfills. In this work, the ocean was assigned an order of 1, while agriculture, landfills, wetlands, and fossil fuel were assigned successively higher orders. To facilitate further modeling, criteria were parameterized, organized into a hierarchy, and weighted after selection and exclusion.

2.5 Weighting procedure

We set up pairwise comparison matrices using the Analytical Hierarchical Process (AHP) methodology (Saaty, 2008, 2001, 1977). The objective of this methodological approach was to pinpoint and focus on the key factor contributing most significantly to atmospheric methane emissions. Five factors were identified. For each factor, weights (w) were assessed based on their respective relative importance. Weights (w) were assigned to each factor according to their importance to the question or issue being considered (pairwise matrix comparisons). This assignment relied on multiple pathways, such as expert judgment and actual data. The central question revolved around the general importance of each factor. The analysis pinpointed the most dominant scenario, identifying it as the key contributor to the atmospheric methane levels within the system. When there are evaluation criteria or objectives, decision-makers must conduct pairwise comparisons, with scores determined by the investigator's subjective evaluation of each factor's importance.

Subsequently, we derived criteria weights from the pairwise comparison matrix. The eigenvector from this matrix approximates the Eigen Vector (and Eigen Value) of a reciprocal matrix. The Eigen Vector calculation involved 1) summing each column of the reciprocal matrix of the pairwise comparison matrix and 2) dividing each matrix value by its column's sum. We then normalized the relative weight so that each column's sum equaled 1. The normalized principal Eigen Vector was acquired by averaging the values across the rows.

Table 1 - The rating scale used in AHP weighting (Adapted from Saaty, 2008, 2001, 1994, 1990, 1980 & 1977).

Relative Importance score	Definition	Explanation
1	Equally important	Two factors contribute equally to the objective.
3	Moderately more important	Experience and judgment slightly favour one criteria over another.
5	Essential or strongly more important	Experience and judgment strongly favour one criteria over another.
7	Demonstrated importance or Very strongly more important	One criteria is favoured very strongly over another; its dominance demonstrated in practice.
9	Absolute importance or Extremely more important	The evidence favouring one criteria is overwhelming.
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When compromise is needed.
Reciprocal of above rationals	The Members of each pairwise comparisons have reciprocal values	By definition.
Ratios arising from the scale	-	If consistency were to be forced by obtaining n numerical values to span the matrix.

First, Consistency Indexes (C.I.) were calculated for the weighting matrix and a random matrix using Equation 1. Following this, Consistency Ratios (C.R.) were then computed using Equation 2 to ensure consistency in the weighting process.

The C.I is given by:

$$C.I = \frac{\lambda_{max} - n}{n-1} \tag{1}$$

In which

λ_{max} = Principal eigenvalues (i.e., the product of the matrix and the unadjusted weight vectors), and

n = number of rows or columns in the weighting matrix.

$$C.R = \frac{C.I\ of\ matrix}{C.I\ of\ "random\ matrix"} \tag{2}$$

2.6 Criteria quantification and standardization

Empirical data were used to quantify and standardize the criteria. However, when these were not available, especially in the case of the ocean, theoretically derived data or conceptual information were utilized. The observed criteria determined the effect on the atmospheric methane source contributions. How did the changes impact the question, as defined in the scenarios? In other words, how did the changes influence the atmospheric methane source contributions in Rivers State? To make these indirectly comparable, single criterion utility functions standardized all originally dissimilar criteria into a common 0-1 utility range.

2.7 *Multi-criteria decision analysis (MCDA)*

Following the standardization process, a score of '0' signified no fulfillment, whereas '1' represented optimal fulfillment of individual model criteria pertinent to methane prerequisites. Predictive modeling was thus advanced, utilizing MCDA through the equation:

$$\sum_i w_i \times u_i = Total\ "utility" \tag{3}$$

Here, the "utility," u_i is a unit-less likelihood measure, spanning from 0 (minimum) to 1 (maximum). Each parameter received a weight (w) based on its relevance. Parameters were evaluated in pair-wise or matrix comparisons, encapsulated as scenarios, culminating in the derived "utility". This utility gauged the parameter's influence on specific site conditions, assuming values within the 0-1 range. Numerous scenarios were analysed to ascertain their respective utilities. The scenario with the highest utility pinpointed the parameter with the highest potential for methane emission, hence serving as the optimal choice for climatic amelioration.

Saaty (2008, 1977) recognized that AHP, while robust, might entertain inconsistencies due to redundancies. To address this, an inconsistency assessment metric was introduced. The inconsistency ratio (CR) gauges the logical consistency in pair-wise comparisons (CI) against a random consistency index (RI), with RI defined as the average CI of randomly generated matrices. The corresponding algorithms for CR and CI are:

$$CR = \frac{CI}{RI} \tag{4}$$

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{5}$$

Where λ_{max} represents the maximum eigenvalue of the judgement matrix and n denotes the comparison matrix's size, which for this study is 5. In the context of the Poisson distribution, λ signifies the mean number of events in a predefined temporal or spatial interval, ranging between 0.0 and 1.0. The value of 0 indicates that there is no gain in the use of the independent variable to predict the dependent variable. That is, the independent variable does not predict the dependent variable in any way. The random index of 0.9999 was used for five factors of the normalized matrix.

2.8 Model reliability

Assessing the reliability of a model is crucial to ensure that the results and predictions it yields are consistent and dependable. In this study, the reliability of the model was determined using the cause-effect matrix with a Consistency Index (CI) and Consistency Ratio (CR) for validation. The model is reliable when it has a CR of less than 0.1. This recommendation aligns with the conditions set forth by Saaty (1977). The model is not reliable and cannot be relied upon if the values of CR is greater than 0.1. Through this rigorous testing process, we aimed to ensure that the model's outputs are both accurate and trustworthy for the purposes of our research.

2.9 Result validation and verification

Establishing the credibility of a model's outcomes is paramount for any scientific investigation. To affirm the robustness and accuracy of our model's results, a multi-faceted approach was undertaken. First, outcomes were meticulously juxtaposed against established literature, drawing comparisons with findings from previous research in the domain. This helped to discern patterns, consistencies, and potential deviations. Additionally, to further enhance the validation process, the model's outcomes were compared to data gleaned from various surveys. These surveys, conducted over diverse intervals, provided a real-world check on the model's predictions. By aligning the method's results with both historical literature and contemporary survey data, we aimed to ensure a comprehensive validation and verification process, thereby bolstering confidence in the method's applicability and precision.

3. Results and Discussion

The parameter interactions and their influence on each other are presented in Table 2, employing a Relative Impact Scale of 0-3. The cause-and-effect dynamics are shown in Figure 2, and the system's stability was evaluated through feedback loops in Figure 3.

Table 2- Variable interactions and their influence on each other.

Variables	AG	FF	LF	OC	WE	SUMS
Agriculture (AG)	-	1	2	2	3	8
Fossil Fuel (FF)	3	-	2	3	3	11
Landfills (LF)	2	0	-	1	2	5
Ocean (OC)	2	0	0	-	2	4
Wetland (WE)	1	0	2	1	-	4
SUMS	8	1	6	7	10	32

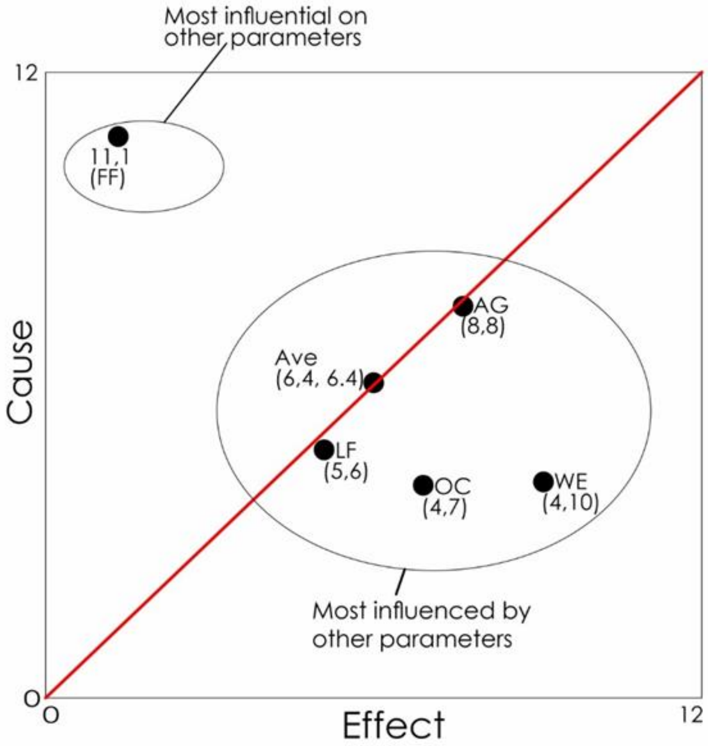

Figure 2 - Cause and effect plot.

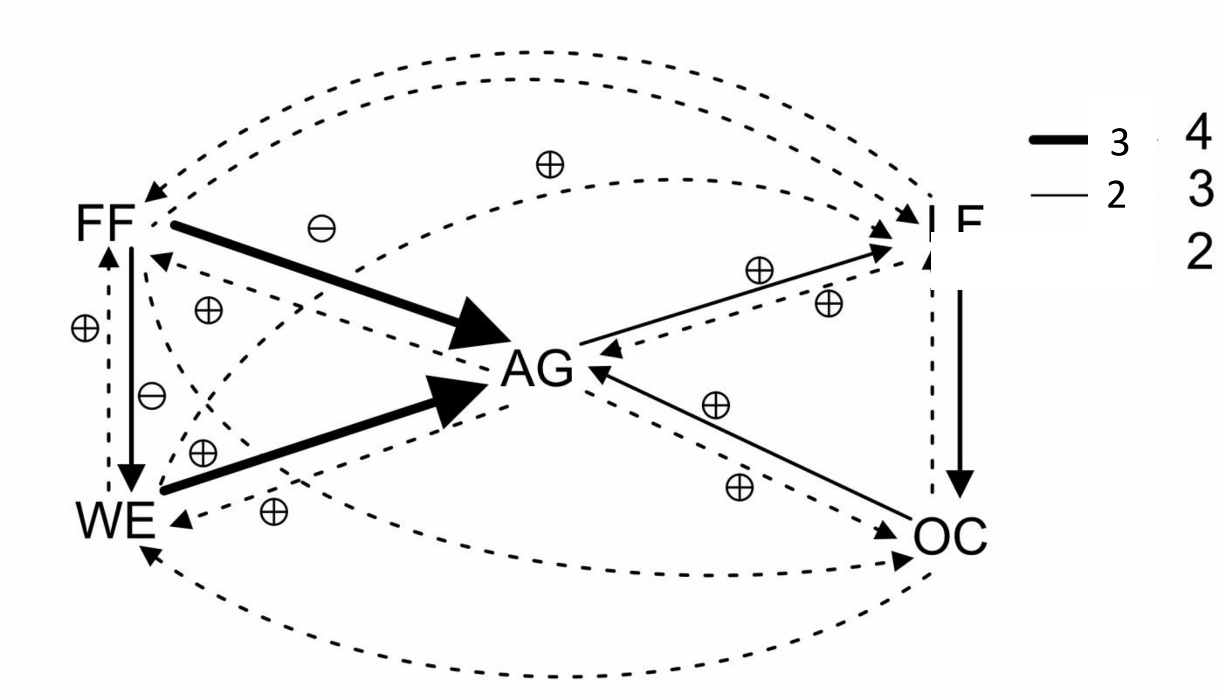

Figure 3 - Feedback loop plot.

Table 3 shows pairwise comparisons to determine the relative importance of different factors influencing atmospheric methane levels.

Table 3 - Matrix of pair-wise comparisons for selected variables.

Factors Name	AG	FF	LF	OC	WE
Agriculture (AG)	0	0.1429	5	0.2	3
Fossil Fuel (FF)	7	0	0.33	5	3

Landfills (LF)	0.2	3	0	3	3
Ocean (OC)	5	0.2	0.33	0	3
Wetland (WE)	0.33	0.33	0.33	0.2	0
SUMS	12.53	3.6729	5.99	8.4	12

Table 4 shows the results from the calculation of normalized matrix and eigenvector.

Table 4 - Normalized matrix and eigenvector calculation.

Factors Name	AG	FF	LF	OC	WE
Agriculture (AG)	0	0.0389	0.8347	0.0238	0.25
Fossil Fuel (FF)	0.5587	0	0.0551	0.5952	0.25
Landfills (LF)	0.0160	0.8167	0	0.3571	0.25
Ocean (OC)	0.3990	0.0545	0.0551	0	0.25
Wetland (WE)	0.0263	0.0898	0.0551	0.0238	0

Table 5 displays the eigenvector values (sums) derived from the normalized matrix, which represent the relative importance or weight of each variable in relation to atmospheric methane source contributions.

Table 5 - Normalized matrix eigenvector calculation with total utility values.

Factors Name	Sums	Weights (%)
Agriculture (AG)	1.1474	22.94
Fossil Fuel (FF)	1.459	29.18
Landfills (LF)	1.4398	28.79
Ocean (OC)	0.7589	15.17
Wetland (WE)	0.195	3.9
Total	5.0	99.98

Table 6 provides the values of the Random Index (RI) across different matrix sizes.

Table 6 - Value of the random index (RI).

Random Consistency Index	Matrix Size				
	1	2	3	4	5
RI	1	0.9999	1	0.4642	1

The Consistency Index (CI) was determined using the formula:

$$CI = \frac{29.18 - 5}{5} = 0.0604$$

Subsequently, the Consistency Ratio (CR) was computed as:

$$CR = \frac{CI}{RI} = \frac{0.0604}{0.9999} = 0.0604$$

In this study, all weighting matrices had a CR value of less than 0.1, which aligns with the recommended conditions set forth by Saaty (1977).

The variables' interactions and their influence on each other are presented in Table 2. This table revealed the intricate interactions among the variables, with fossil fuels showing the highest impact sum of 11, indicating its significant influence on other variables. The cause-and-effect dynamics were further illustrated in Figure 2, and the system's stability was evaluated through feedback loops in Figure 3, where we noted that negative feedback loops tend to stabilize the system, while positive feedback loops, primarily driven by fossil fuels, tend to destabilize it.

In Table 3, we conducted pair-wise comparisons for atmospheric methane source contributions, highlighting the relative importance of each variable. Fossil fuels were found to be significantly more influential than agriculture in affecting atmospheric methane. The matrix entries represent the relative importance of one variable compared with another in influencing atmospheric methane ratio. For example, under the AG column and FF row, a value of 7 suggests that fossil fuels are 7 times more influential than agriculture. This was further quantified in the Normalized Matrix and Eigenvector Calculation (Table 4), where normalized values or eigenvectors represented the relative importance of each variable. The values in this matrix are derived from normalizing the original matrix. These normalized values, or eigenvectors, represent the relative importance or weight of each variable in relation to atmospheric methane source contributions, as calculated through the analytic hierarchy process (AHP).

The calculated eigenvectors, as displayed in Table 5, provided a clearer understanding of how each variable contributes to the overall atmospheric methane ratio, with fossil fuel having the highest weight of 29.18%. The table displays the eigenvector values (sums) derived from the normalized matrix, which represent the relative importance or weight of each variable in relation to atmospheric methane source contributions. The percentages (weights) are calculated by normalizing the eigenvector values to add up to 100% (approximately, due to rounding errors). This provides a clearer understanding of how each factor contributes to the overall atmospheric methane source contributions.

We also included the Random Index (RI) in Table 6, which assists in evaluating the consistency of the pair-wise comparisons. The normalized principal eigenvector indicated the predominance of Fossil Fuel (FF), followed closely by Landfills (LF) and Agriculture (AG), as shown in Table 5. The RI, based on the random consistency index, affirmed the validity of our judgments in the decision-making process. Table 6 provides values of the Random Index (RI) across different matrix sizes. The RI values serve as benchmarks for determining the consistency of pair-wise comparisons in the Analytic Hierarchy Process (AHP). These values assist in evaluating the quality and reliability of the judgments made during the decision-making process.

The normalized principal eigenvector indicates that Fossil Fuel (FF) has the highest weight (29.18%), followed by Landfills LF (28.7%), Agriculture AG (22.94%), Ocean OC (15.17%) and Wetland WE (3.9%) as shown in Table 5. The RI is based on the random consistency index as displayed in Table 6.

In this study, all weighting matrices had a CR value of less than 0.1, which aligns with the recommended conditions set forth by Saaty (1977).

In this research, we predicted the factors that influence the atmospheric methane source contributions in selected areas of Rivers State by using the factors of agriculture, fossil fuel, landfills, ocean, and wetland, and then applying the Analytic Hierarchy Process (AHP) method. Our study indicated that fossil fuel, with a weight of 29.18%, is the most influential factor for the emission of atmospheric methane, followed closely by landfills and agriculture. The negligible difference in weights between fossil fuel and landfills highlighted the importance of landfills as point sources. The high impact of fossil fuel, as seen in the cause-effect matrix, reaffirms its significant role. The Consistency Index (CI) and Consistency Ratio (CR) values suggest a high level of consistency and reliability in our findings.

Therefore, the MCDA (Multi-Criteria Decision Analysis) method, as demonstrated in this study, can effectively evaluate atmospheric methane source contributions variability in diverse settings. This evaluation is advantageous for swift decision-making, as it does not require a site visit and relies on environmental, social, and economic information sources. The establishment of a spatial database, as envisaged in this study, could evaluate atmospheric methane source contributions using a combination of theory, expert experience, literature, and survey results, thereby creating a robust and foundational database for future research and policy-making.

4. Conclusion

The aim of this study was to investigate the potential of multi-criteria decision analysis in assessing the sources and variability of atmospheric methane source contributions. Through meticulous research, our findings underscore the efficacy of utilizing multi-criteria decision analysis for a comprehensive and expeditious assessment, determination, and prediction of these sources. Our empirical findings shed light on a number of salient conclusions. Specifically, fossil fuels emerged as a predominant contributor, accounting for a substantial 29.18% of the emissions, thereby asserting its critical role in the methane mixing ratio. Landfills, with a weight of 28.79%, were closely aligned, suggesting their near-equal significance in this context. Agriculture, oceans, and wetlands followed, contributing 22.94%, 15.17%, and 3.9% respectively. Therefore, this empirical study has effectively shown that utilizing multi-criteria decision analysis offers a rigorous and systematic approach for the expeditious assessment, determination, and estimation of atmospheric methane source contributions. This study also offers a novel and efficient means to predict and understand the dynamics of atmospheric methane concentrations.

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