Methane Emission in Michigan's Power Plant Sector

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ABSTRACT

Methane, which is one of the component from greenhouse gas, is estimated to have a global warming effect that is 80 times greater than that of carbon dioxide over a 20-year period, making it a significant contributor to global warming. Our research examines various factors that lead to the change of methane emissions level. By understanding these contributing factors, the study aims to come up with comprehensive suggestions for government regulations. These regulations would be potentially helpful in reducing methane emissions, and thus addressing a critical aspect of climate change mitigation.(1, 2).

1 Introduction

Climate change is increasingly becoming a serious problem that has the potential to destroy the stability and health of ecosystems worldwide. Rising global temperatures are affecting weather patterns, sea levels, and biological cycles. As these changes take place, the focus on environmental pollutants, especially greenhouse gases emission, has been intensified. Reducing emissions of these gases is essential for slowing the rate of global warming and preserving a healthier environment for the future generations. Greenhouse gases (GHGs) are gases in Earth's atmosphere that trap heat, which plays a crucial role in controlling global temperatures. According to a report of Environmental Protection Agency in 2023 (3). Methane, which is the second most abundant GHG other than carbon dioxide (CO_2), accounts for about 16 percent of global emissions. Moreover, Methane is over 28 times more potent than carbon dioxide at trapping heat in the atmosphere over a 100-year period (4). Because methane is a powerful greenhouse gas with a shorter atmospheric lifetime as opposed to that of carbon dioxide, it can alter atmospheric composition more readily than changes in CO_2 emissions.

Thus, reducing methane emissions is crucial and can substantial reduce the atmospheric warming potential.

To come up with a solution to address the above problem, our research project will be focused on identified the crucial factors that is related to methane emissions level, specifically from Michigan's power plant sector as our choice of interest. This sector-specific approach not only addresses a critical source of emissions but also serves as a potential reference for similar industrial regions.

2 Background

2.1 Literature Review and Methodological Framework

The background of our research draws valuable sources and inference from the Environmental Protection Agency. These studies emphasize the disproportionate impact of methane on climate change in the short term and the substantial climate benefits achievable through targeted methane reduction efforts.

The dataset is also adopted from the Environmental Protection Agency. Extensive emissions data is specifically filtered to include only Michigan's power plants, focusing on variables such as fuel types, operational practices, and emission control technologies. "Methane emissions" in this context refer to methane released during power generation and fuel processing. To analyze this data, we deploy the STAN model from the r packages using Markov Chain Monte Carlo (MCMC) methods. This sophisticated statistical framework allows for a strong probabilistic inference by simulating the distribution of possible methane emission outcomes based on the observed data.

2.2 Objective and Implications

This research aims to identify and implement effective strategies for reducing methane emissions within Michigan's power plant sector. By providing a detailed analysis of the factors influencing emissions, the project seeks to offer actionable insights for policymakers and industry leaders. The ultimate goal is to contribute to broader climate change mitigation efforts, yielding significant environmental and public health benefits through improved air quality. This project not only help us understand more of the sector-specific methane management but also equips useful information necessary to enact meaningful changes for government.

3 Data

3.1 Data Collection

We collect the 'Fuel' dataset from the United States Environmental Protection Agency (EPA), a national website that collect most of the environmental data in United States. This dataset provides an huge matrix of information, detailed across 271,087 rows and 16 columns, including a comprehensive scope of greenhouse gas (GHG) data and ancillary information essential for understanding the emission of energy sources in U.S. This dataset collect from reports of greenhouse gas (GHG) data and other relevant information from large GHG emission sources, fuel and industrial gas suppliers, which covers a substantial 85-90 percent of the United States' greenhouse gas emissions. In this case, it is not a simple random sample because we are directly focus on data of large methane emissions.

3.2 Data Cleaning

The data cleaning stage of our analysis was critical for ensuring the integrity and precision of the results. Because of the extremely large data, We want to focusing on a specific region most relevant to us and we filter the dataset rows to include only Michigan as the state variable. This allows us to narrow our analysis to find some unique pattern of GHG emission and have better understanding of the region we are currently living. Next, we directed our attention to refining the dataset. Entries reporting zero methane emissions were removed because our analysis want to focus on influential emission sources only.

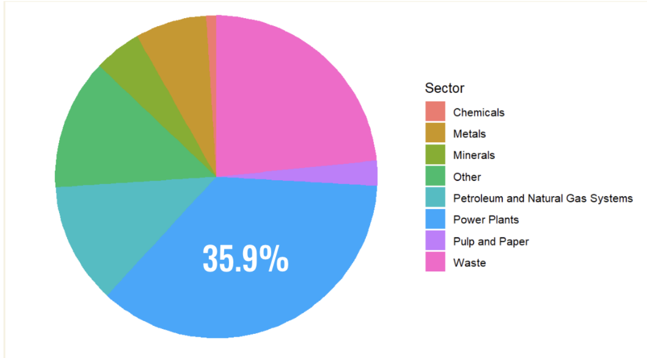

Figure 1. Pie chart of sectors in Michigan data

After this, we continue to narrow our date size by selecting attributes essential for our analytical framework. Removing all unrelated variables, we have attributes such as the year, sector, fuel type, methane emissions, and industry type.

Lastly, after examine the percentage of each sector in the dataset, we decided to concentrate on the 'Power Plant' sector only because we have about 36 % of those sectors classified as power plant (Figure 1). By doing so, we are able to focus on a key area of interest in the context of greenhouse gas emissions, facilitating a more detailed and sector-specific analysis.

3.3 Data Exploration

After the data cleaning process, our refined dataset consisting of 2,337 observations and 4 primary variables: Year, Fuel Type, Methane Emissions, and Industry Type. The 'year' variable consists of years

```
     Year         Fuel.Type     Methane.emissions   Industry.Type
 Min.   :2011   Min.   :1.000   Min.   :    0.025   Length:2337
 1st Qu.:2013   1st Qu.:2.000   1st Qu.:    1.500   Class :character
 Median :2016   Median :2.000   Median :   14.750   Mode  :character
 Mean   :2016   Mean   :2.184   Mean   :  502.587
 3rd Qu.:2019   3rd Qu.:2.000   3rd Qu.:  135.500
 Max.   :2022   Max.   :4.000   Max.   :24111.750
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Figure 2. Data Summary

that ranges from 2011 and 2022, The 'Fuel Type' variable, which means the energy provided to the process, consists of 4 kinds of different fuel categories, respectively Natural Gas, Coal, Petroleum Products and Other. This variable allows for a comparative analysis across different fuel sources, examining their relative contributions to overall methane emissions. The 'Industry.Type' variable means the different types of industries examined in the dataset. The 'Methane Emissions' variable, measured in metric tons, shows a direct quantitative measurement of the actual emission level. (Figure 2)

3.4 Data Visualization

The line graph (figure 3) shows the emissions for four fuel types—coal, natural gas, petroleum products, and other from 2011 to 2022. There is a dominant trend of emissions from coal, which shows a significant decline around 2016 before rising again. Natural gas emissions are lower than coal but appear relatively constant, with minor fluctuations around 2016. Two possible reason might be possible for this pattern: climate and

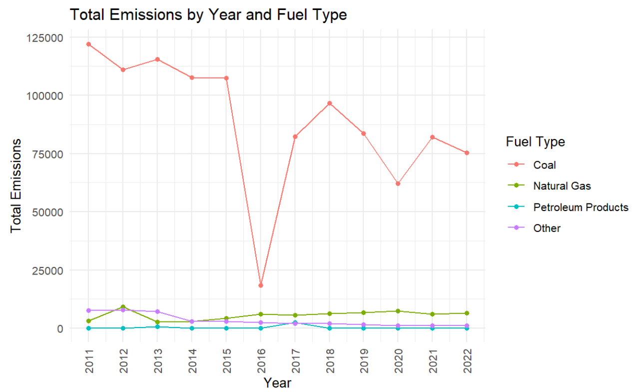

Figure 3. Total Emissions by Year and Fuel Type

increased shift to natural gas as resource. It is reported that 2016 had a relatively warmer winter than the other years, thus coal combustion, as a electricity source have lower demand (5). Another possible reason is that a new policy is proposed in 2016 in terms of sustainability, which encourage the power plants to use natural gas instead of coal in producing energy (6). In this case, the reduction in coal emissions around 2016 might indicate a closure of decrease of coal plants or the transition to cleaner energy sources, which is a positive development given the focus on methane as a potent greenhouse gas.

The bubble chart (figure 4) presents the frequency of occurrences (n) between fuel type and industry type (labeled C, CD, D). The size of the bubbles represents the frequency of occurrences, and the color intensity corresponds to the value of n, with darker shades indicating higher frequencies. The largest bubble is

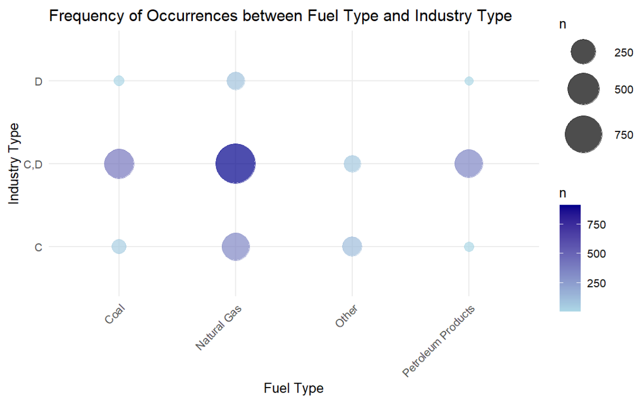

Figure 4. Frequency of Occurrences between Fuel Type and Industry Type

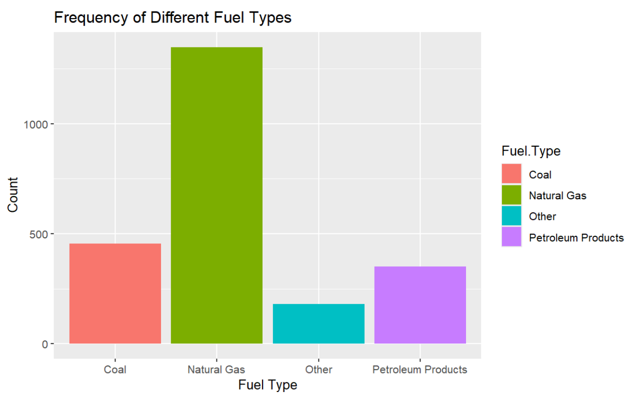

Figure 5. Frequency of Different Fuel Types

in the 'Natural Gas' column for industry type D, suggesting that this industry uses natural gas most frequently. This is relevant because if natural gas is not properly managed, it can lead to significant methane emissions. Therefore, industry D using natural gas predominantly could be a focal point for methane mitigation efforts.

The bar chart (figure 5) shows the count of occurrences for different fuel types in all rows of our dataset. Natural gas has the highest count, followed by coal, other, and petroleum products. The high use of natural gas might signals a significant potential for emissions.

However, comparing figure 5 with the line graph we got in figure 3, although coal has fewer counts, it consistently has significantly higher methane emissions. In contrast, natural gas, even with the highest count in figure 5,has notably lower emissions than coal produces. This indirectly demonstrates the significant environmental impact of coal. Therefore, our initial understanding before dive into the model is that seemingly we can use more natural gas instead of coal to reduce the emissions .

4 Method

In this research, we applied a comprehensive statistical approach using the Bayesian inference framework facilitated by the STAN software. Our primary analysis involved constructing a hierarchical model to assess the impact of various factors, such as fuel type and industry classification, on methane emissions from Michigan's power plant sector. The Bayesian model included fixed effects for year, fuel type, and industry type, with methane emissions as the response variable. We modeled the log of methane emissions to stabilize variance and normalize the residuals. To conduct the analysis, We employed Markov Chain

Monte Carlo (MCMC) simulations using the Rstan package, which estimate the posterior distributions of the model parameters scientifically.

4.1 Model Setup

4.1.1 Prior and Likelihood Selection

In our statistical model, we choose Gaussian priors to offer a neutral starting point that doesn't impose strong assumptions on the data. This aligns with the Bayesian approach where priors should be set without bias. The log transformation of methane emissions addresses the right skewness in the data, ensuring that the variance remains stable across the range of values. The use of an inverse gamma distribution for the standard deviation further supports this by handling the positive skewness typically present in such environmental data. These choices in priors and likelihood functions form a well-founded structure for our Bayesian inference model.

Priors

The priors for the model parameters are defined as follows:

- α (intercept) prior: $\alpha \sim \mathcal{N}(0, 1)$
- β_1 (coefficient for Year) prior: $\beta_1 \sim \mathcal{N}(0, 1)$
- β_2 (coefficient for scaled FuelType) prior: $\beta_2 \sim \mathcal{N}(0, 1)$
- β_3 (coefficient for scaled IndustryType) prior: $\beta_3 \sim \mathcal{N}(0, 1)$
- σ (standard deviation of emissions) prior: $\sigma \sim \text{Inv-Gamma}(0.5, 10)$

Likelihood

The likelihood function, representing the probability of the data given the parameters, is specified as:

$$
\begin{aligned}
&\log(\text{MethaneEmissions}) \\
&\sim \mathcal{N}(\\
&\quad \alpha + \beta_1 \times \text{Year}+ \\
&\quad \beta_2 \times \text{scaled\_FuelType}+ \\
&\quad \beta_3 \times \text{scaled\_IndustryType}, \sigma)
\end{aligned}
$$

4.1.2 Parameter Selection

To ensure that the parameter choice of prior is accurate, we apply a sensitivity analyses for our choice of parameter. By varying the standard deviations of the priors assigned to the model coefficients and rerunning the MCMC simulations, we assessed the impact of these priors on the posterior outcomes.

The sensitivity analysis result revealed that the parameters were robust to changes in the prior distributions of the model coefficients. Altering the standard deviations of the priors for the regression coefficients ($\beta 1$, $\beta 2$, $\beta 3$) produced results that were consistent with the original model estimates, indicating that the

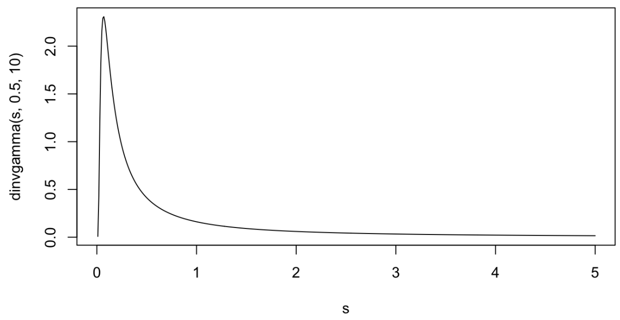

Figure 6. Inverse-Gamma Distribution

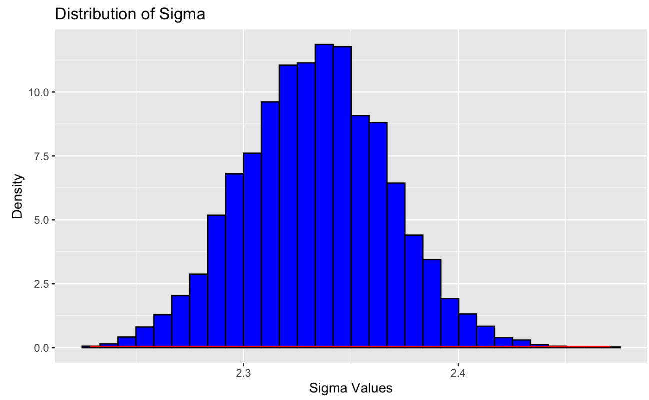

Figure 7. Sigma Distribution

findings are not overly sensitive to the choice of priors (Table 1).

For the parameter choice of inverse gamma prior, we adopted parameters α =0.5 and β =10 for the variance, sigma. The actual distribution of this plot shows that this prior favors smaller sigma values, reflecting our expectation of low variability in the emissions data, while still allowing for flexibility as shown by the long tail.(Figure 6) The histogram of sigma values from the model output clusters around a narrow range, which fits well with our chosen prior parameters. (Figure 7)

Our combined graphical and statistical evidence supports our choice of prior, ensuring it is grounded in both our data and initial understanding. This thoughtful selection aids in generating reliable Bayesian inferences about emissions.

Table 1. Sensitivity Analysis of Posterior Estimates for Beta Coefficients

Standard Deviation	Parameter	Mean	95% CI
0.5	β_1	0.03575	(-0.05973, 0.13066)
0.5	β_2	1.73641	(1.62944, 1.84163)
0.5	β_3	0.93010	(0.73001, 1.12465)
1.0	$\beta_{1.1}$	0.03590	(-0.05935, 0.13354)
1.0	$\beta_{2.1}$	1.75075	(1.64482, 1.85428)
1.0	$\beta_{3.1}$	0.95403	(0.75211, 1.15281)
2.0	$\beta_{1.2}$	0.03658	(-0.05737, 0.13339)
2.0	$\beta_{2.2}$	1.75528	(1.65355, 1.85566)
2.0	$\beta_{3.2}$	0.96434	(0.76009, 1.16355)

4.1.3 Ordinal Encoding

We convert categorical data into numerical values to fit our model properly. Each fuel type, such as 'Coal' or 'Natural Gas', is assigned a specific number, like 1, 2, or 3. This numerical assignment also applies to industry types. By doing this, we transform the categorical variables into a structured numerical format that our model can understand and work with. This step is essential for the model to interpret the different categories accurately and produce reliable results.

4.2 Model Summary

The model converged well, with trace plots indicating good mixing across the four chains and no divergent transitions(Figure 8). The posterior distributions for the parameters were symmetric and centered around the means, suggesting reliable estimates. Specifically, the average effect size for the Year was estimated with a posterior mean of $\beta1$, the Fuel Type effect was $\beta2$, and the Industry Type effect was $\beta3$. The interval plots suggest that the coefficients are likely to be different from zero (Figure 10), indicating a significant influence of these factors on methane emissions. The model also indicated a standard deviation (sigma) for the log of methane emissions, with the posterior mean suggesting variability in the emission data. The pairwise correlations between parameters indicate a satisfactory level of independence among them. This independence supports the validity of the model's conclusions regarding the significance of the predictors (Figure 9).

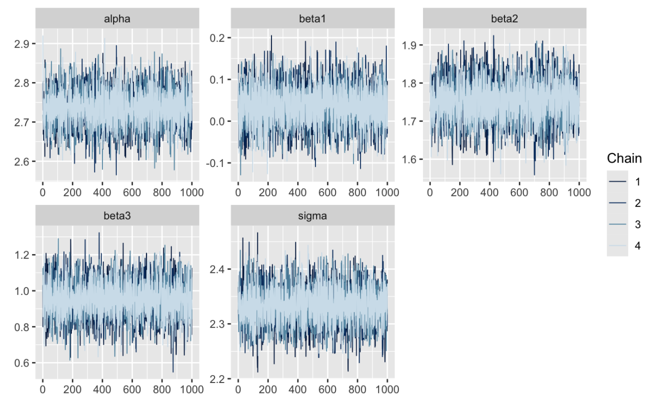

Figure 8. Trace Plot of MCMC Model

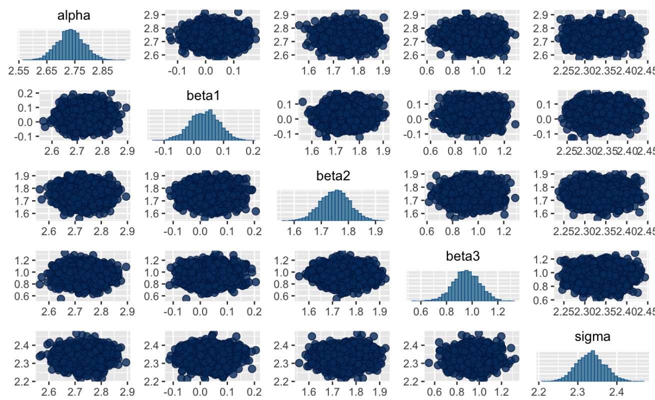

Figure 9. Pairwise Correlation Plot for Parameters

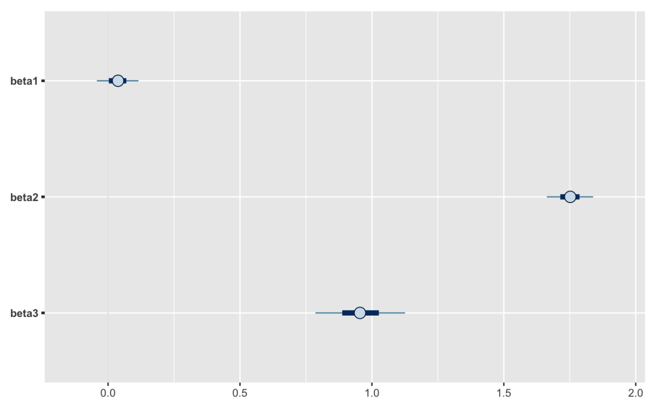

Figure 10. Interval Plot of Parameters

4.3 Inference

In our research, the analysis of methane emissions from different fuel types within Michigan's power plant sector yielded significant findings. The beta coefficient for Fuel Type (β_2) stood at 1.75, with a 95% credible interval ranging from 1.65 to 1.85, highlighting a notable effect where lower numeric values of Fuel Type, corresponding to less carbon-intensive fuels, are associated with decreased log

Table 2. Posterior Summary Statistics of Model Parameters.

Parameter	Mean	SD	2.5%	97.5%	N_Eff	Rhat
alpha	2.74	0.05	2.64	2.83	5448	1
beta1	0.04	0.05	-0.06	0.13	5443	1
beta2	1.75	0.05	1.65	1.85	4748	1
beta3	0.96	0.10	0.75	1.15	5319	1
sigma	2.33	0.04	2.27	2.40	5244	1
lp	-3156.93	1.62	-3160.84	-3154.81	1933	1

methane emissions. This points to a clear pathway for policy interventions: there is a compelling case for incentivizing the transition away from coal (numerically coded as 4, representing the most carbon-intensive fuel) towards less carbon-intensive alternatives such as petroleum products (coded as 1). Such a shift could have a pronounced impact on reducing methane emissions from the sector, aligning with environmental sustainability goals.

Regarding the influence of Industry Type, the positive beta coefficient (β_3) of 0.96, with a 95% credible interval from 0.75 to 1.15, implies that stationary combustion plants (coded as 3) are associated with higher log methane emissions compared to electricity generation-only facilities (coded as 1). The policy implication is straightforward: there is an urgent need to impose more rigorous methane emission control measures on stationary combustion plants. This could involve enhancing the efficiency of combustion processes and adopting advanced methane capture and utilization technologies to mitigate emissions. The Year variable (β_1) showed a smaller effect size with a mean of 0.04 and a 95% credible interval from -0.06 to 0.13, suggesting a gradual impact of time on methane emissions. Although the Year's influence appears to be more modest, it nevertheless underscores the importance of ongoing improvements in regulatory frameworks and technological advancements to continue reducing emissions over time.(Figure 8, Table 2)

5 Conclusion

Our inferential analysis has proved a strong relationship between fuel types and methane emissions within Michigan's power plant sector, which highlights the possible paths for government intervention. The data points towards a decisive impact of carbon-intensive fuels on the state's methane output, suggesting that policy-driven shifts towards cleaner fuels could significantly dampen emissions.

We suggest the implementation of incentives for energy sources with lower carbon footprints and the establishment of stringent emission regulations for stationary combustion plants. Such measures could not only reduce methane emissions but also catalyze industry-wide adoption of cleaner practices.

Furthermore, our study emphasizes the necessity for continuous refinement of emission-related policies. A combination of incentives, such as tax breaks for green energy adoption, alongside the reinforcement of penalties for high-emission activities, could encourage compliance and progressive industry transformation.

To ensure the efficacy of these interventions, ongoing improvement in emission monitoring and verification is paramount. This will facilitate informed decision-making and help in tracking the progress of implemented policies.

In essence, our research highlights the critical need for a strategic and multi-faceted approach to environmental policy. While Michigan has made strides in addressing methane emissions, our findings advocate for an enhanced and sustained effort. Government initiatives that reflect our study's insights could not only advance Michigan's environmental stewardship but also inspire broader national policies to counteract climate change.

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