Exploring the Determinants of Biogas Generation Potential in California

Web address for GitHub repository

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Background

Rationale of the study

The transition to cleaner and renewable sources of energy requires more work to scale already existing gains, for example in the area of biogas utilization, while also seeking out new opportunities. Biogas is a form of renewable energy produced by anaerobic decomposition or thermochemical conversion of biomass such as agricultural waste, manure, municipal waste sewage, green waste and food waste. Biogas is composed mostly of methane, alongside carbon dioxide, water vapor and other gases. Similar to natural gas, biogas can be burned directly as a fuel or treated to remove the CO2 and other gases before for being used in the form of biomethane.

Utilizing biogas as an energy source helps to transform harmful gases from decomposing waste into positive use. Methane is a powerful greenhouse gas that traps heat in the atmosphere, with a global warming potential estimated to be over 25 times as potent as that of Carbon Dioxide.Transforming waste into biogas therefore reduces greenhouse gas emissions and the risk of pollution to waterways. The
[UNECE](https://unece.org/challenge#:~:text=Methane%20is%20a%20powerful%20greenhouses,gr
estimates that over a 20 year period, this ratio increases to 84-86 times. However, stored biogas limits the amount of methane released into the atmosphere and reduces dependence on fossil fuels. When stored , biogas serves as a renewable and reliable baseload power source and can even be used to rapidly meet peak power demands. When biogas is used for energy generation in place of fossil fuels, it enables even more emission reductions, sometimes resulting in carbon negative systems. According to the [Environmental and Energy Study Institute,
EESI](https://www.eesi.org/papers/view/fact-sheet-biogasconverting-waste-to-energy)
,the reduction of methane emissions derived from tapping all the potential biogas in the United States would be equal to the annual emissions of 800,000 to 11 million passenger vehicles.

Unfortunately, despite the various benefits offered by biogas energy, the United States currently only has 2,200 operating biogas systems. The EESI estimates this current capacity to be less than 20% of the total potential. It is on this basis that this study attempts to examine the factors contributing to biogas generation potential, particularly in

California. California was selected because of its status as a leading state in biogas generation potential based on estimates by the National Renewable Energy Laboratory (NREL). According to the [American Biogas Council](chrome-extension://efaidnbmnnnibpcajpcglclefindmkaj/viewer.html?pdfurl=https%3A
California can power nearly 200,000 homes if this biogas is utilized appropriately. The results of our analysis for California can provide the basis for further analysis across several other US states.

Research Questions

The analysis conducted was done based on two research questions:

1. Is biogas generation potential correlated with population density across California counties?

2. What additional factors must be considered in determining biogas generation potential?

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Dataset Information

the datasets used include the following:

1. Methane Generation Potential The NREL's dataset on methane generation potential covers data for the entire United States of America. It particularly providing information for Methane generation potential across all states in metric tons from sources which include landfills, industrial organic waste, animal manure, and wastewater . All of these individual sources were aggregated to estimate total methane generation potential by state. The dataset contained estimates for 2009 to 2012, being the latest available data we could find online.

2. Population data Population data was pulled from the latest available the Social Vulnerability Index data compiled by the Center for Disease Control (CDC) and Agency for Toxic Substance and Diseace Reegistry (ATSDR). This dataset also includes details on impoverished populations and spans from 2017-2018. Since the SDI offers data that helps to effectly plan towards meeting the needs of improverished populations, this dataset also helps to dds another dimension to our analysis as it enables the exploration of impacts on socially vulnerable people.

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Exploratory Analysis

The two datasets were wrangled and joined both datasets to have a unified dataframe that captured data on methane generation potential, population and poverty levels by county. An initial exploration of the data was done to provide a visual assessment of spatial data and determine the emergence of any any trends.

1.1 Simple feature collection with 6 features and 14 fields

1.2 Geometry type: MULTIPOLYGON

1.3 Dimension: XY

1.4 Bounding box: xmin: -122.7851 ymin: 37.45447 xmax: -119.5423 ymax: 40.15203

1.5 Geodetic CRS: WGS 84

1.6 ObjectID NAME STATE_NAME FIPS OWCH4t AMCH4t WWTPCH4t

1.7 1 184 Alameda California 06001 5700.695190 0.367359 10461.687700

1.8 2 185 Alpine California 06003 6.483819 0.000000 6.667176

1.9 3 186 Amador California 06005 156.310667 3.826180 624.136548

1.10 4 187 Butte California 06007 817.909133 20.460013 1210.759120

1.11 5 188 Calaveras California 06009 97.664105 11.663426 200.148617

1.12 6 189 Colusa California 06011 72.199705 2.057210 104.007942

1.13 LFGCH4t TotalCH4t COUNTY LOCATION E_TOTPOP E_POV

1.14 1 49311 65473.75020 Alameda Alameda County, California 1643700 170884

1.15 2 0 13.15099 Alpine Alpine County, California 1146 227

1.16 3 0 784.27340 Amador Amador County, California 37829 3323

1.17 4 0 2049.12827 Butte Butte County, California 227075 44410

1.18 5 0 309.47615 Calaveras Calaveras County, California 45235 5242

1.19 6 0 178.26486 Colusa Colusa County, California 21464 2929

1.20 E_MINRTY geometry

1.21 1 1120309 MULTIPOLYGON (((-122.313 37...

1.22 2 468 MULTIPOLYGON (((-120.0726 3...

1.23 3 8066 MULTIPOLYGON (((-121.0276 3...

shaded yellow, Los Angeles, has the highest methane (CH4) generation potential. The density of impoverished population appears to be similarly distributed.

```
![](FDR_Final_files/figure-latex/unnamed-chunk-3-1.pdf)<!-- -->
```

The total Methane generation potential is greatest at the most densely populated areas. This trend appears to continue with wastewater derived methane.

```
![](FDR_Final_files/figure-latex/unnamed-chunk-4-1.pdf)<!-- -->
```

Industrial Organic waste, like wastewater, is highly correlated with population.With landfill-based methane, some counties in central CA, which do not appear to have a high population, have comparatively high methane generation potential. There may be some non-population related factors in play.

```
![](FDR_Final_files/figure-latex/unnamed-chunk-5-1.pdf)<!-- -->
```

The trend with animal-manure derived CH4 however substantially differs from the previous cases. Population does not appear to be a decisive factor.

```
![](FDR_Final_files/figure-latex/unnamed-chunk-6-1.pdf)<!-- -->
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Analysis

Question 1: What factors affect biogas generation potential in different counties of

1.27

1.28 Pearson's product-moment correlation

1.29

1.30 data: svi_sf_join$TotalCH4tandsvi_s f_j oin$E_TOTPOP

1.31 t = 10.655, df = 56, p-value = 4.365e-15

1.32 alternative hypothesis: true correlation is not equal to 0

1.33 95 percent confidence interval:

1.34 0.7101412 0.8887681

1.35 sample estimates:

1.36 cor

1.37 0.818333

1.38

1.39 Call:

1.40 lm(formula = svi_sf_join$TotalCH4t\ svi_s f_j oin$**E_TOTPOP)**

1.41

1.42 Residuals:

1.43 Min 1Q Median 3Q Max

1.44 -34706 -8182 -6090 -3565 76153

1.45

1.46 Coefficients:

1.47 Estimate Std. Error t value Pr(>|t|)

1.48 (Intercept) 5.836e+03 2.956e+03 1.974 0.0533 .

1.49 svi_sf_join$E_TOTPOP 1.962e-02 1.841e-03 10.655 4.36e-15 ***

1.50 —

1.51 Signif. codes: 0 '' *0.001* '' *0.01* '' 0.05 '.' 0.1 ' ' 1

1.52

1.53 Residual standard error: 20430 on 56 degrees of freedom

1.54 Multiple R-squared: 0.6697, Adjusted R-squared: 0.6638

1.55 F-statistic: 113.5 on 1 and 56 DF, p-value: 4.365e-15

`![](FDR_Final_files/figure-latex/unnamed-chunk-7-1.pdf)<!-- --> ![](FDR_Final_files/figu`

1.56

1.57 Pearson's product-moment correlation

1.58

1.59 data: svi_sf_join$OWCH4tandsvi_sf_join$E_TOTPOP

1.60 t = 82.353, df = 56, p-value < 2.2e-16

1.61 alternative hypothesis: true correlation is not equal to 0

1.62 95 percent confidence interval:

1.63 0.9930490 0.9975794

1.64 sample estimates:

1.65 cor

1.66 0.9958969

Call:
lm(formula = svi_sf_join$OWCH4t\ svi_{s}f_{j}oin$E_TOTPOP)

Residuals:
Min 1Q Median 3Q Max
-1801.49 -77.14 28.39 100.93 1809.74

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) -4.289e+01 7.117e+01 -0.603 0.549
svi_sf_join$E_TOTPOP 3.650e-03 4.432e-05 82.353 <2e-16 ***
—
Signif. codes: 0 ‘’ *0.001* ’’ *0.01* ” 0.05 ‘.’ 0.1 ’ ’ 1

Residual standard error: 491.8 on 56 degrees of freedom
Multiple R-squared: 0.9918, Adjusted R-squared: 0.9917
F-statistic: 6782 on 1 and 56 DF, p-value: < 2.2e-16

1.85

1.86 Pearson's product-moment correlation

1.87

1.88 data: svi_sf_join$AMCH4tandsvi_s f_j oin$E_TOTPOP

1.89 t = -0.02427, df = 56, p-value = 0.9807

1.90 alternative hypothesis: true correlation is not equal to 0

1.91 95 percent confidence interval:

1.92 -0.2613200 0.2552665

1.93 sample estimates:

1.94 cor

1.95 -0.003243157

Call:

lm(formula = svi_sf_join$AMCH4t\ svi_s f_j oin$E_TOTPOP)

Residuals:

Min 1Q Median 3Q Max

-5569 -5558 -5523 -3877 76775

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 5.569e+03 2.053e+03 2.712 0.00885 **

svi_sf_join$E_TOTPOP -3.103e-05 1.279e-03 -0.024 0.98072

—

Signif. codes: 0 ‘’ *0.001* ’’ *0.01* ” 0.05 ‘.’ 0.1 ’ ’ 1

Residual standard error: 14190 on 56 degrees of freedom

Multiple R-squared: 1.052e-05, Adjusted R-squared: -0.01785

F-statistic: 0.000589 on 1 and 56 DF, p-value: 0.9807

1.114

1.115 Pearson's product-moment correlation

1.116

1.117 data: svi_sf_join$WWTPCH4tandsvi_sf_join$E_TOTPOP

1.118 t = 57.684, df = 56, p-value $< 2.2e-16$

1.119 alternative hypothesis: true correlation is not equal to 0

1.120 95 percent confidence interval:

1.121 0.9859425 0.9950932

1.122 sample estimates:

1.123 cor

1.124 0.9916898

Call:

lm(formula = svi_sf_join$WWTPCH4t\ svi_s f_j oin$E_TOTPOP)

Residuals:

Min 1Q Median 3Q Max

-6663.5 -147.9 65.7 168.0 3785.4

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) -1.466e+02 1.637e+02 -0.895 0.375

svi_sf_join$E_TOTPOP 5.882e-03 1.020e-04 57.684 <2e-16 ***

—

Signif. codes: 0 ‘’ *0.001 ” 0.01 ”* 0.05 ‘.’ 0.1 ’ ’ 1

Residual standard error: 1131 on 56 degrees of freedom

Multiple R-squared: 0.9834, Adjusted R-squared: 0.9832

F-statistic: 3327 on 1 and 56 DF, p-value: < 2.2e-16

1.143

1.144 Pearson's product-moment correlation

1.145

1.146 data: svi_sf_join$LFGCH4tandsvi_sf_join$**E_TOTPOP**

1.147 t = 9.6217, df = 56, p-value = 1.815e-13

1.148 alternative hypothesis: true correlation is not equal to 0

1.149 95 percent confidence interval:

1.150 0.6670743 0.8702275

1.151 sample estimates:

1.152 cor

1.153 0.7893612

1.154

1.155 Call:

1.156 lm(formula = svi_sf_join$LFGCH4t\ svi_sf_join$**E_TOTPOP)**

1.157

1.158 Residuals:

1.159 Min 1Q Median 3Q Max

1.160 -31207 -3285 -1030 -501 46121

1.161

1.162 Coefficients:

1.163 Estimate Std. Error t value Pr(>|t|)

1.164 (Intercept) 4.564e+02 1.688e+03 0.270 0.788

1.165 svi_sf_join$E_TOTPOP 1.012e-02 1.052e-03 9.622 1.81e-13 ***

1.166 —

1.167 Signif. codes: 0 ‘’ *0.001 ’’ 0.01 ’’* 0.05 ‘.’ 0.1 ’ ’ 1

1.168

1.169 Residual standard error: 11670 on 56 degrees of freedom

1.170 Multiple R-squared: 0.6231, Adjusted R-squared: 0.6164

1.171 F-statistic: 92.58 on 1 and 56 DF, p-value: 1.815e-13

`![](FDR_Final_files/figure-latex/unnamed-chunk-7-6.pdf)<!-- -->`

1.172

1.173 Pearson's product-moment correlation

1.174

1.175 data: svi_sf_join$TotalCH4tandsvi_s f_j oin$**E_POV**

1.176 t = 11.12, df = 56, p-value = 8.476e-16

1.177 alternative hypothesis: true correlation is not equal to 0

1.178 95 percent confidence interval:

1.179 0.7271725 0.8959424

1.180 sample estimates:

1.181 cor

1.182 0.8296405

Call:

lm(formula = svi_sf_join$TotalCH4t\ svi_s f_j oin$**E_POV)**

Residuals:

Min 1Q Median 3Q Max

-23578 -8007 -6799 -4377 74610

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 6.684e+03 2.834e+03 2.358 0.0219 *

svi_sf_join$E_POV 1.310e-01 1.178e-02 11.120 8.48e-16 ***

—

Signif. codes: 0 '' *0.001* '' *0.01* '' 0.05 '.' 0.1 ' ' 1

Residual standard error: 19840 on 56 degrees of freedom

Multiple R-squared: 0.6883, Adjusted R-squared: 0.6827

F-statistic: 123.7 on 1 and 56 DF, p-value: 8.476e-16

1.201

1.202 Pearson's product-moment correlation

1.203

1.204 data: svi_sf_join$LFGCH4tandsvi_sf_join$E_POV

1.205 t = 9.3128, df = 56, p-value = 5.653e-13

1.206 alternative hypothesis: true correlation is not equal to 0

1.207 95 percent confidence interval:

1.208 0.6526255 0.8638755

1.209 sample estimates:

1.210 cor

1.211 0.7795177

Call:

lm(formula = svi_sf_join$LFGCH4t\ svi_sf_join$E_POV)

Residuals:

Min 1Q Median 3Q Max

-24928 -3488 -1556 -1095 47103

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 1.059e+03 1.700e+03 0.623 0.536

svi_sf_join$E_POV 6.581e-02 7.067e-03 9.313 5.65e-13 ***

—

Signif. codes: 0 ‘’ *0.001* ’’ *0.01* ” 0.05 ‘.’ 0.1 ’ ’ 1

Residual standard error: 11900 on 56 degrees of freedom

Multiple R-squared: 0.6076, Adjusted R-squared: 0.6006

F-statistic: 86.73 on 1 and 56 DF, p-value: 5.653e-13

1.230

1.231 Pearson's product-moment correlation

1.232

1.233 data: svi_sf_join$WWTPCH4tandsvi_{s}f_{j}oin$**E_POV**

1.234 t = 30.671, df = 56, p-value < 2.2e-16

1.235 alternative hypothesis: true correlation is not equal to 0

1.236 95 percent confidence interval:

1.237 0.9521271 0.9831025

1.238 sample estimates:

1.239 cor

1.240 0.9715012

Call:

lm(formula = svi_sf_join$WWTPCH4t\ svi_s f_j oin$E_POV)

Residuals:

Min 1Q Median 3Q Max

-8111.2 -525.9 -266.3 200.7 8372.5

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 2.329e+02 2.977e+02 0.782 0.437

svi_sf_join$E_POV 3.795e-02 1.237e-03 30.671 <2e-16 *

—

Signif. codes: 0 ‘’ *0.001* ’’ *0.01* ” 0.05 ‘.’ 0.1 ’ ’ 1

Residual standard error: 2084 on 56 degrees of freedom

Multiple R-squared: 0.9438, Adjusted R-squared: 0.9428

F-statistic: 940.7 on 1 and 56 DF, p-value: < 2.2e-16

1.259

1.260 Pearson's product-moment correlation

1.261

1.262 data: svi_sf_join$OWCH4tandsvi_sf_join$**E_POV**

1.263 t = 34.256, df = 56, p-value < 2.2e-16

1.264 alternative hypothesis: true correlation is not equal to 0

1.265 95 percent confidence interval:

1.266 0.9612260 0.9863552

1.267 sample estimates:

1.268 cor

1.269 0.9769612

Call:
lm(formula = svi_sf_join$OWCH4t\ svi_s f_j oin$E_POV)

Residuals:
Min 1Q Median 3Q Max
-2379.5 -363.1 -195.7 96.0 4351.1

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.895e+02 1.656e+02 1.144 0.257
svi_sf_join$E_POV 2.359e-02 6.885e-04 34.256 <2e-16 ***
—
Signif. codes: 0 '' *0.001* '' *0.01* '' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1160 on 56 degrees of freedom
Multiple R-squared: 0.9545, Adjusted R-squared: 0.9536
F-statistic: 1174 on 1 and 56 DF, p-value: < 2.2e-16

1.288

1.289 Pearson's product-moment correlation

1.290

1.291 data: svi_sf_join$AMCH4tandsvi_{s}f_{j}oin$**E_POV**

1.292 t = 0.43506, df = 56, p-value = 0.6652

1.293 alternative hypothesis: true correlation is not equal to 0

1.294 95 percent confidence interval:

1.295 -0.2033043 0.3116628

1.296 sample estimates:

1.297 cor

1.298 0.05803922

Call:

lm(formula = svi_sf_join$AMCH4t\ svi_s f_j oin$E_POV)

Residuals:

Min 1Q Median 3Q Max

-10228 -5295 -5206 -3608 76704

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 5.202e+03 2.023e+03 2.572 0.0128 *

svi_sf_join$E_POV 3.658e-03 8.408e-03 0.435 0.6652

—

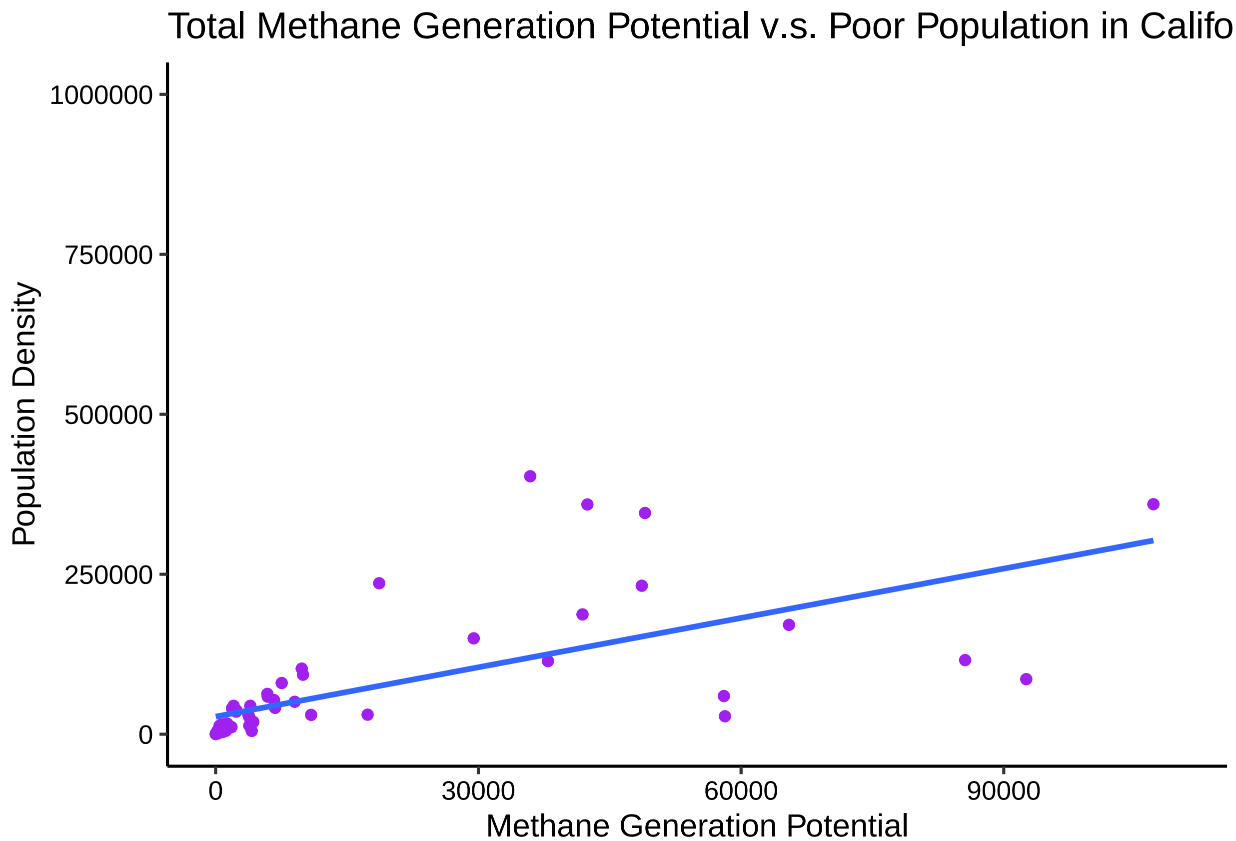
Signif. codes: 0 ‘’ *0.001* ’’ *0.01* ” 0.05 ‘.’ 0.1 ’ ’ 1

Residual standard error: 14160 on 56 degrees of freedom

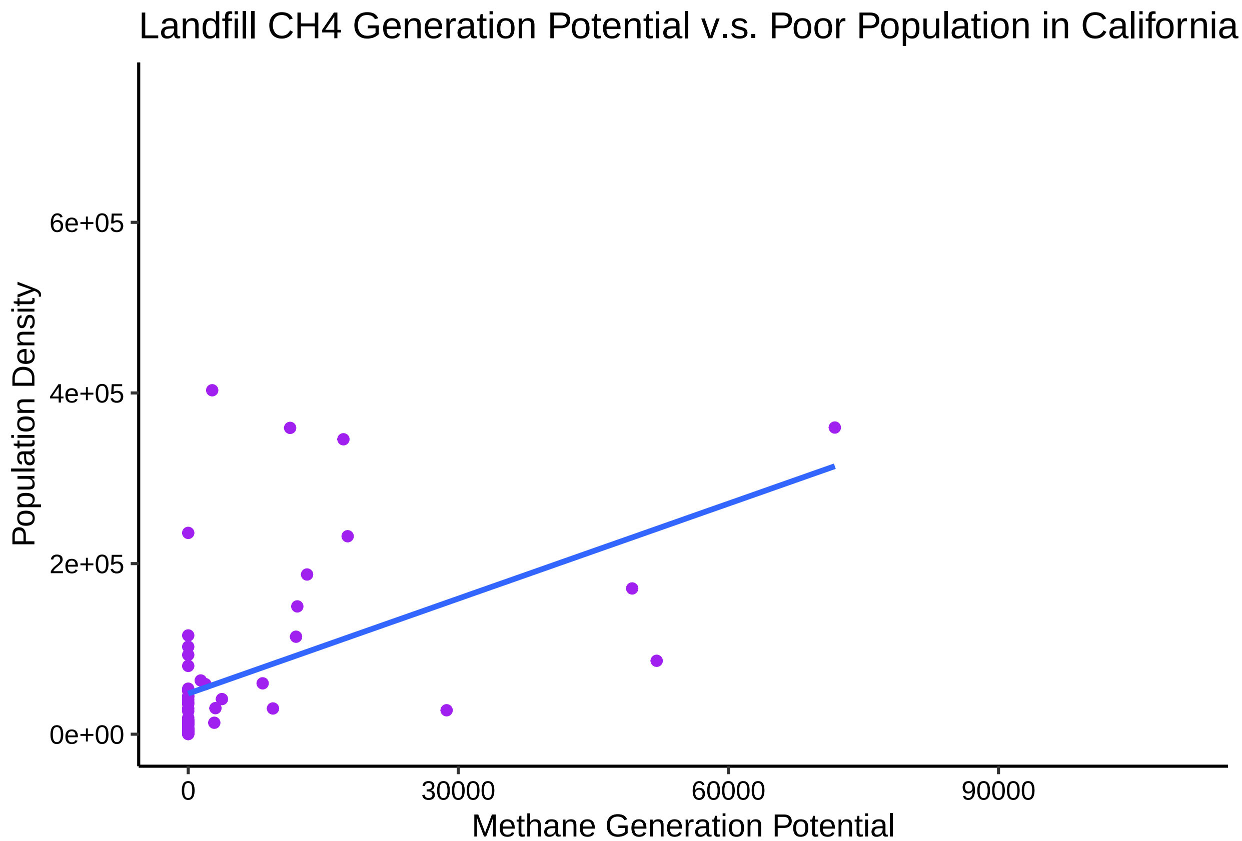
Multiple R-squared: 0.003369, Adjusted R-squared: -0.01443

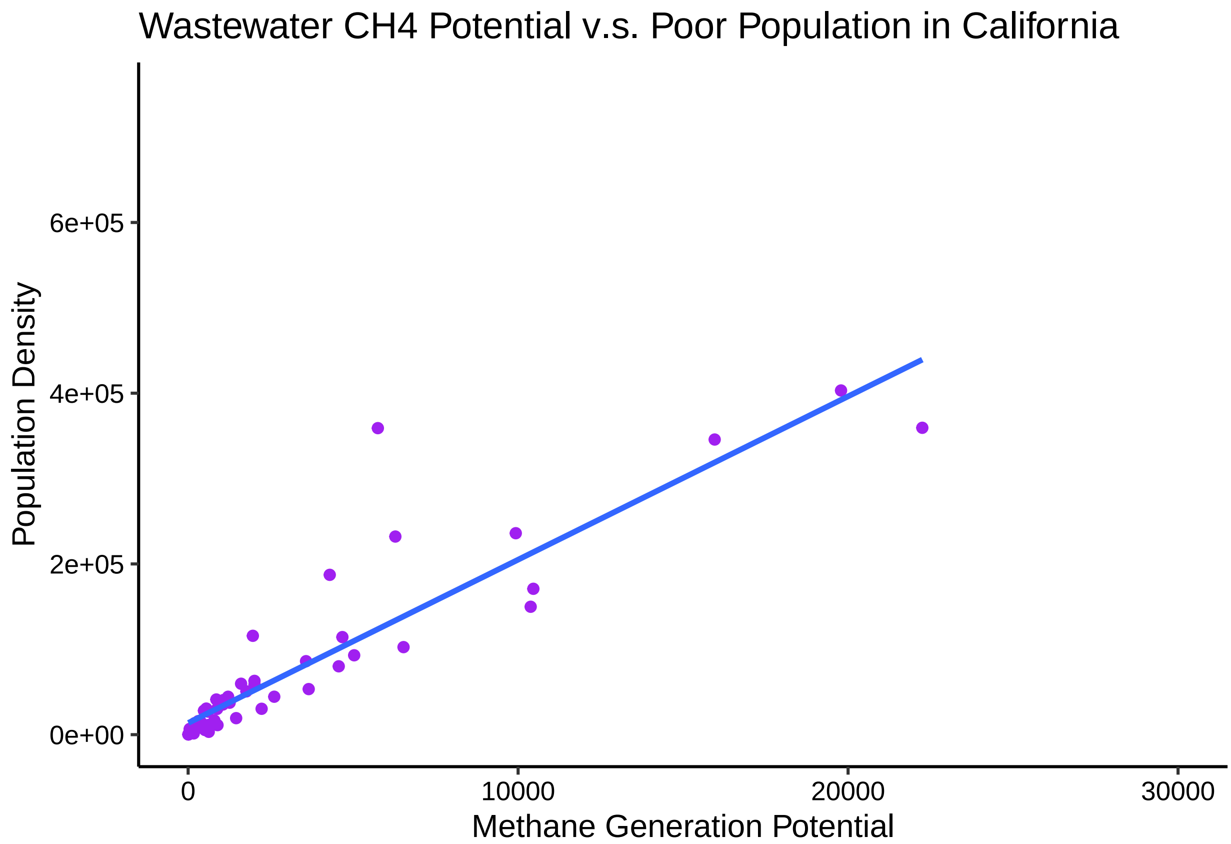
F-statistic: 0.1893 on 1 and 56 DF, p-value: 0.6652

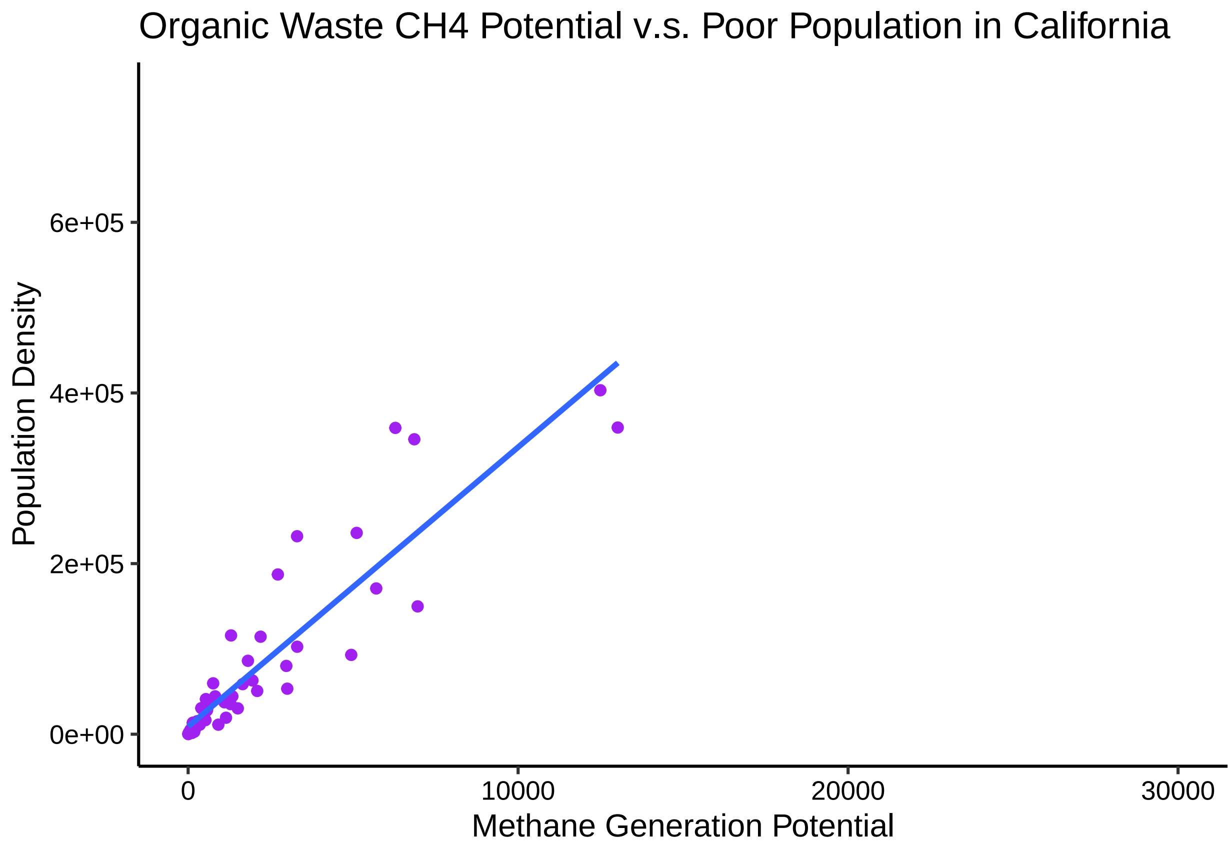
“‘

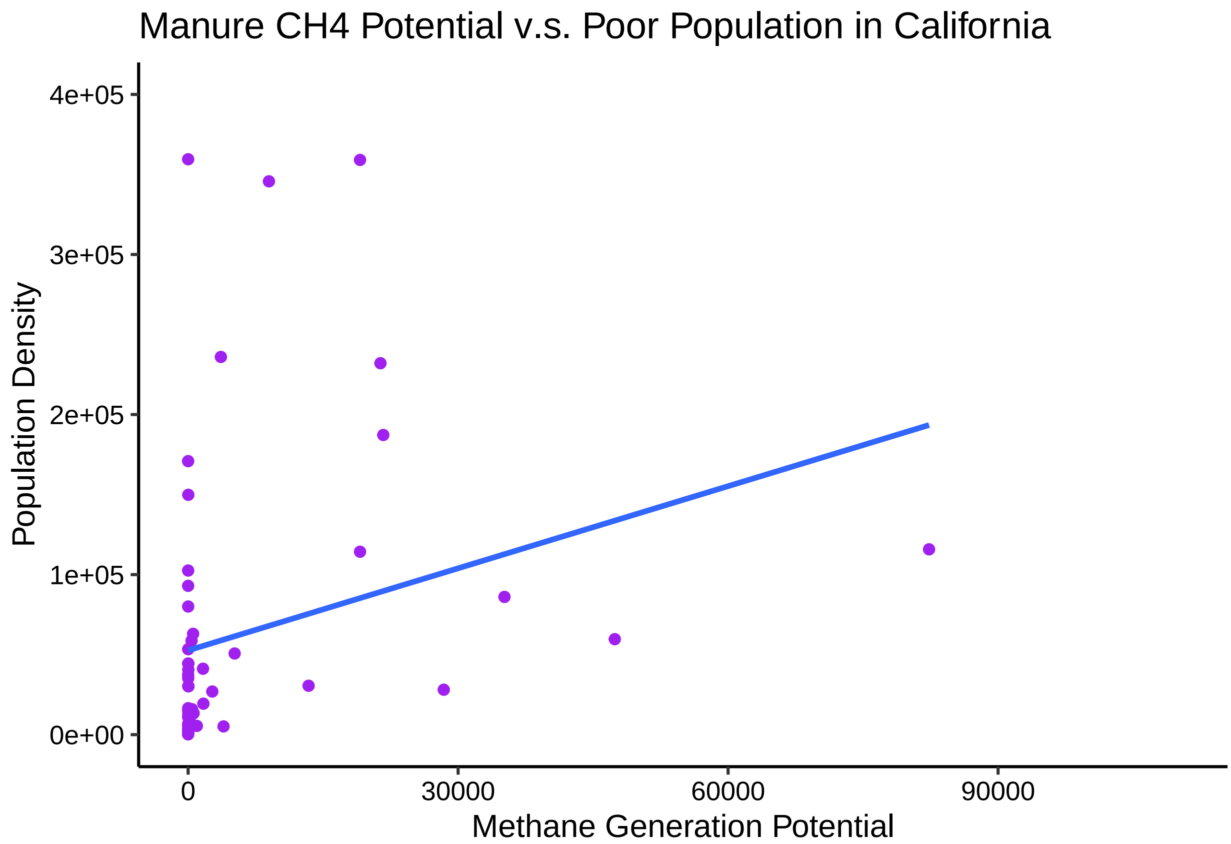


Total Methane Generation Potential v.s. Poor Population in Califor
1000000
750000
500000
250000
0
Population Density
0
30000
60000
90000
Methane Generation Potential


Landfill CH4 Generation Potential v.s. Poor Population in California
Population Density
6e+05
4e+05
2e+05
0e+00
0
30000
60000
90000
Methane Generation Potential


Wastewater CH4 Potential v.s. Poor Population in California
Population Density
6e+05
4e+05
2e+05
0e+00
0
10000
20000
30000
Methane Generation Potential


Organic Waste CH4 Potential v.s. Poor Population in California
Population Density
6e+05
4e+05
2e+05
0e+00
0
10000
20000
30000
Methane Generation Potential


Manure CH4 Potential v.s. Poor Population in California
Population Density
4e+05
3e+05
2e+05
1e+05
0e+00
0
30000
60000
90000
Methane Generation Potential

2 Conclusion

The null hypothesis to our research question is that there is no correlation between population density and biogas generation potential. We ran a correlation test to test the strength and direction between California population and the total biogas generation potential. We also ran a simple linear regression model to investigate whether these two variables involves a linear relationship. By looking at the residual plots, we can tell that the regression model fits our data but has outliers that disrupt the model accuracy. The p-value is 4.22e-15, indicating that the result is statistically significant. The multiple R-squared is 0.67, meaning that the independent variables can expalin 67% of the variations in biogas generation potential. Therefore, we are confident in rejecting the null hypothesis. Now we can say the total biogas generation potential in california does have a linear relationship with the population density. However, we still want to know how and what different sources is correlated with population. Subsequently, we ran the same test for each individual biogas sources. Based on the results from running correlation test and linear regression model for each of the biogas generation sources: Organic waste, Animal manure, Wastewater, and Landfill. We found out the the organic waste and wastewater contributes to the highest correlation to the population density, while Animal manure and landfill are less correlated.

Overall, the analysis conducted show that biogas generation potential across counties in California is positively correlated with the population density. This implies that the higher the population in a specific area, the higher the biogas generation potential. However, the analysis also recognises that generation potential and correlation with population density varies according to the biomass source across counties. As such, results show that animal based methane appeared to be less correlated with population. Assumptions that best explain this result are that more animals will contribute to animal-based biomass and that human habitation is often less where animal population is dense. Results of our analysis also show that the potential of landfill-based biogas was not limited to densely or sparsely populated areas, while organic waste and waste water represented the most significant sources of biogas generation potential across California.

Future analysis can focus on improving the model presented in this report by eliminating some outliers and using more recent datasets. This study made use of older data sets because those were the ones most recently made available on open and credible data portals. Other areas of future analysis include exploring the level and process of utilization of California's biogas generation potential, as well as how utilization can be scaled. For example, the potential of leveraging the biogas generation potential by enabling counties with lower generation potentials to tap into the resources for those with higher generation.This also includes scoping the potential to utilize biogas energy for base load power or peaking, using various analyses including a cost-benefit analysis.

3 References

<add references here if relevant, otherwise delete this section>