

# Sprint#02: Ways towards A Net-Zero Society, Take NYC as an Example

2023-04-21

## 1. Research Questions

Nowadays, the issue of environmental protection and energy consumption is becoming increasingly important. A potential solution to create sustainable cities is through the implementation of Net-Zero cities. These cities provide numerous benefits, such as reduced greenhouse gas emissions, enhanced economic development, and improved quality of life. However, achieving this status is a complex task due to challenges like existing infrastructure, resistance to change, lack of funding, regulatory barriers, and technical challenges.

To aid cities with high energy usage, such as New York City, in realizing the Net-Zero vision, we aim to examine the key factors that influence building energy use intensity. Our research will involve developing a basic model by analyzing the relationships between building energy use intensity and resource consumption such as water, electricity, and gas. We will then expand the model by incorporating additional factors like income level, demographic data, and health conditions to build an improved model. By investigating the coefficients of the improved model, we can determine how these factors impact building energy use intensity and provide recommendations based on our findings. We believe that this research will be valuable for achieving sustainable urban development.

## 2. Data Source

- 2016 LL33 Data Disclosure for CY2015 reporting, Government of New York City. <https://www.nyc.gov/site/buildings/codes/benchmarking.page>
- 2010 Shapefiles of NYC census blocks, United States Census Bureau. <https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html>
- 2023 Shapefiles of NYC Tax Lot (BBL), NYC Open Data. <https://www.nyc.gov/site/planning/data-maps/open-data.page#pluto>

## 3. Research Procedure #01 Basic Model: Benchmarking Data Exploration

**3.1 Load and check benchmarking data** The purpose of this section is to understand the dataset that we are going to use as the input of building energy consumption intensity - 2015 building energy consumption benchmarking data collected under NYC Local Law 84/133 Energy Benchmarking, which requires owners and managers of buildings larger than 50,000 square (25,000 after 2016) to report their building's energy usage to the City of New York on a yearly basis.

The column representing the energy consumption intensity is Site\_EUI, and there are many factors impacting this value, like Water, electricity, building age, etc. . .

```
library(tidyverse)
```

```
# Load raw data
```

```
file_path <- file.path(dirname(rstudioapi::getSourceEditorContext()$path), "dataset/NYCBuildingEnergyUse")
raw_data <- read_csv(file_path)
```

```
# Understanding the raw-dataset
```

```
# view the first few rows of the dataset
head(raw_data)
```

```
## # A tibble: 6 x 57
##   Record_~1 Order   BBL Corep~2 BBLs_~3 Repor~4 Prope~5 Paren~6 Paren~7 Stree~8
##   <dbl> <dbl> <dbl> <chr>   <chr>   <chr>   <chr>   <chr>   <chr>   <dbl>
## 1  1261451     6 1.00e9 <NA>   <NA>   1000005 1 NY P~ Not Ap~ Not Ap~     1
## 2  4292967     7 1.00e9 <NA>   <NA>   1000007 4 NY P~ Not Ap~ Not Ap~    115
## 3  2712342     8 1.00e9 <NA>   <NA>   1000006 Cushma~ Not Ap~ Not Ap~    125
## 4      NA 11986 1.00e9 <NA>   <NA>   <NA>   <NA>   <NA>   <NA>     6
## 5  2792771     9 1.00e9 <NA>   <NA>   1087700 Whiteh~ Not Ap~ Not Ap~    39
## 6  2897761    10 1.00e9 <NA>   <NA>   1000018 Wolfso~ Not Ap~ Not Ap~    34
## # ... with 47 more variables: Street_Name <chr>, Zip_Code <dbl>, Borough <chr>,
## #   DOF_Benchmarking_Submission_Status <chr>, Primary_Property_Type <chr>,
## #   List_of_All_Property_Use_Types_at_Property <chr>,
## #   Largest_Property_Use_Type <chr>,
## #   Largest_Property_Use_Type_Gross_Floor_Area_sqft <dbl>,
## #   '2nd_Largest_Property_Use_Type' <chr>,
## #   '2nd_Largest_Property_Use_Type_Gross_Floor_Area_sqft' <chr>, ...
```

```
# get summary statistics for each column
# summary(raw_data)
```

```
# get information about the structure of the dataset
# str(raw_data)
```

### 3.2 Process missing values (not completed in this sprint) Checking and removing missing values

```
# 0. Check for missing values in each column
# raw_data %>%
#   summarize_all(funs(sum(is.na(.))))
# 1. Removing missing values:
# data_clean <- na.omit(data)

#2.use mean imputation to replace missing values with the mean of non-missing values:
#library(missForest)
#data_imputed <- missForest(data)$ximp

#3.Using prediction models:
#library(mice)
#data_imputed <- mice(data, method = "pmm", m = 5, maxit = 50)
#This code uses the mice() function to perform multiple imputation using predictive mean matching (meth
```

### 3.3 Rename colums to make better legibility Rename columns to increase legibility and convenience

```
# Pre-processing
my_data <- raw_data %>%
  filter(DOF_Benchmarking_Submission_Status == "In Compliance") %>% # filter valid Benchmarking Submiss
  select(Record_Number,
```

```

    Site_EUI_kBtu_per_sqft,
    Weather_Normalized_Site_Electricity_Intensity_kWh_per_sqft,
    Weather_Normalized_Site_Natural_Gas_Intensity_therms_per_sqft,
    Total_GHG_Emissions_Metric_Tons_CO2e, # use net value
    Direct_GHG_Emissions_Metric_Tons_CO2e, # new
    Indirect_GHG_Emissions_Metric_Tons_CO2e, # new
    Municipally_Supplied_Potable_Water_Indoor_Intensity_gal_per_sqft,
# new added
    Year_Built,
    ENERGY_STAR_Score,
    Property_GFA_Self_reported_sqft
  ) %>%

  # change totoal value to net value

#my_data <- my_data %>%
  #mutate(Total_GHG_Emissions_Metric_Tons_CO2e_per_sqft = Total_GHG_Emissions_Metric_Tons_CO2e / Proper
  #mutate
  #mutate

na.omit() %>% # quit properties with missing values

rename(Record = Record_Number, # rename as the column names are too long
  EUI = Site_EUI_kBtu_per_sqft,
  EI = Weather_Normalized_Site_Electricity_Intensity_kWh_per_sqft,
  NGI = Weather_Normalized_Site_Natural_Gas_Intensity_therms_per_sqft,
  GHG = Total_GHG_Emissions_Metric_Tons_CO2e,
  WI = Municipally_Supplied_Potable_Water_Indoor_Intensity_gal_per_sqft,
  ES = ENERGY_STAR_Score, # new
  YB = Year_Built, # new
  # add sqrt-GHG
)

```

**3.4 Building linear models of EUI and basic factors like electricity usage, water usage, etc.**  
The R-squared value ranges from 0 to 1, with higher values indicating a better fit between the model and the data.

```
# Fit in linear model with different X variables
```

```
# electricity
model_EI <- lm(EUI ~ EI, data = my_data)
summary(model_EI)$r.squared
```

```
## [1] 0.01281571
```

```
# natural gas
model_NGI <- lm(EUI ~ NGI, data = my_data)
summary(model_NGI)$r.squared
```

```
## [1] 0.9412754
```

```
# change ghg to net value
# green house gas
model_GHG <- lm(EUI ~ GHG, data = my_data)
summary(model_GHG)$r.squared
```

```
## [1] 0.6015779
```

```
# water
model_WI <- lm(EUI ~ WI, data = my_data)
summary(model_WI)$r.squared
```

```
## [1] 6.950044e-07
```

```
# energy start
model_ES <- lm(EUI ~ ES, data = my_data)
summary(model_ES)$r.squared
```

```
## [1] 0.002490211
```

```
# building age
model_YB <- lm(EUI ~ YB, data = my_data)
summary(model_YB)$r.squared
```

```
## [1] 0.03301956
```

**3.5 Building linear models of Log(EUI) and basic factors to reduce impact of outliers** Modeling with basic single factors

```
# Fit in linear model with different X variables use log-y
model_EI <- lm(log(EUI) ~ EI, data = my_data)
summary(model_EI)$r.squared
```

```
## [1] 0.116978
```

```
model_NGI <- lm(log(EUI) ~ NGI, data = my_data)
summary(model_NGI)$r.squared
```

```
## [1] 0.06232492
```

```
# change ghg to net value
model_GHG <- lm(log(EUI) ~ GHG, data = my_data)
summary(model_GHG)$r.squared
```

```
## [1] 0.1913264
```

```
model_WI <- lm(log(EUI)~ WI, data = my_data)
summary(model_WI)$r.squared
```

```
## [1] 0.001520737
```

```
model_ES <- lm(log(EUI)~ ES, data = my_data)
summary(model_ES)$r.squared
```

```
## [1] 0.3326592
```

```
model_YB <- lm(log(EUI)~ YB, data = my_data)
summary(model_YB)$r.squared
```

```
## [1] 0.0485802
```

### 3.6 Build OLS models Modeling with multiple variables

```
# use OLS with y
```

```
model_ols_y <- lm(EUI ~ EI + NGI + GHG , data = my_data)
summary(model_ols_y)
```

```
##
## Call:
## lm(formula = EUI ~ EI + NGI + GHG, data = my_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -35421    -29     -19     -9  103449
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.665e+01  2.542e+01   0.655   0.513
## EI           2.394e+00  6.360e-02  37.645 <2e-16 ***
## NGI          8.542e+01  2.878e-01 296.838 <2e-16 ***
## GHG          4.942e-02  6.322e-04  78.174 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1712 on 4550 degrees of freedom
## Multiple R-squared:  0.9804, Adjusted R-squared:  0.9804
## F-statistic: 7.601e+04 on 3 and 4550 DF, p-value: < 2.2e-16
```

```
# use Ols with log-y
```

```
model_ols_logy <- lm(log(EUI) ~ EI + NGI + GHG, data = my_data) # ghg net value
summary(model_ols_logy)
```

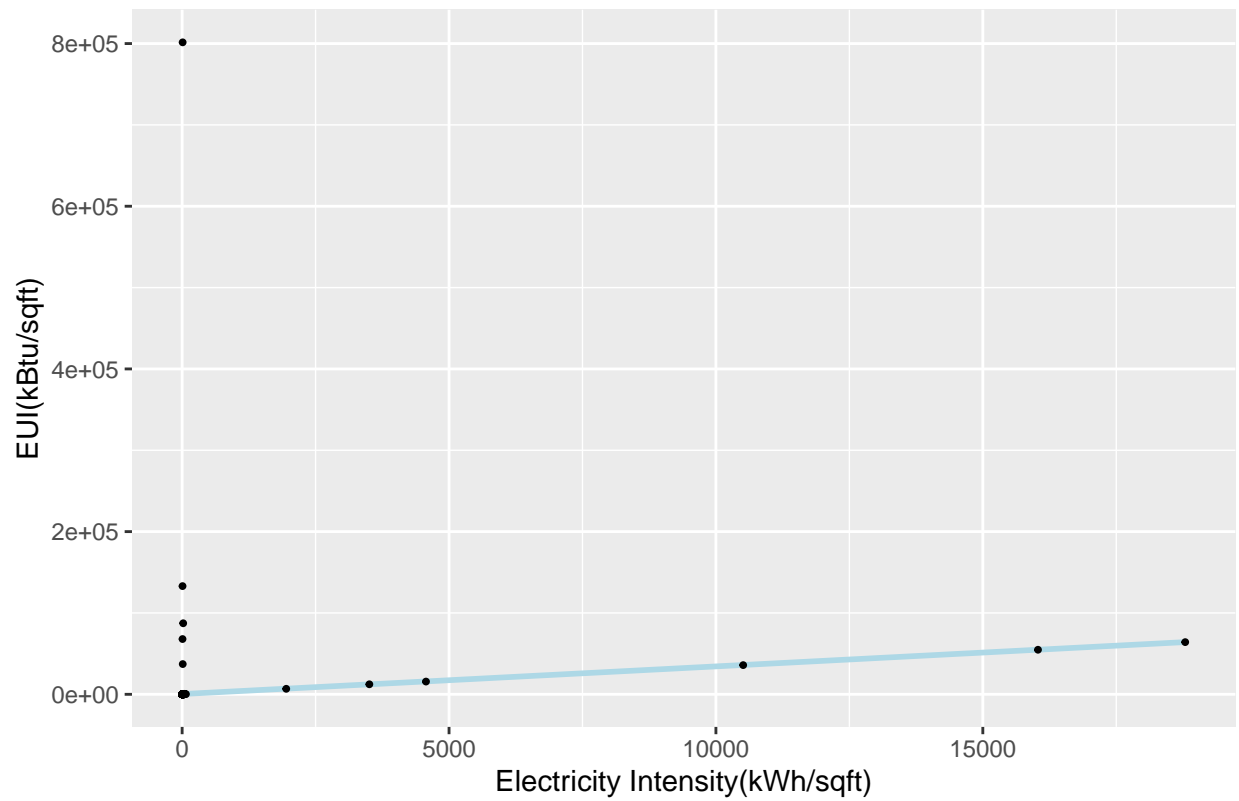
```
##
```

```
## Call:
## lm(formula = log(EUI) ~ EI + NGI + GHG, data = my_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -4.3743 -0.1576  0.0318  0.2283  5.1528
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.374e+00  6.967e-03  627.846  <2e-16 ***
## EI           3.765e-04  1.743e-05   21.602  <2e-16 ***
## NGI          -8.170e-05  7.886e-05   -1.036    0.3
## GHG           4.090e-06  1.733e-07   23.606  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4693 on 4550 degrees of freedom
## Multiple R-squared:  0.2689, Adjusted R-squared:  0.2684
## F-statistic: 557.8 on 3 and 4550 DF,  p-value: < 2.2e-16
```

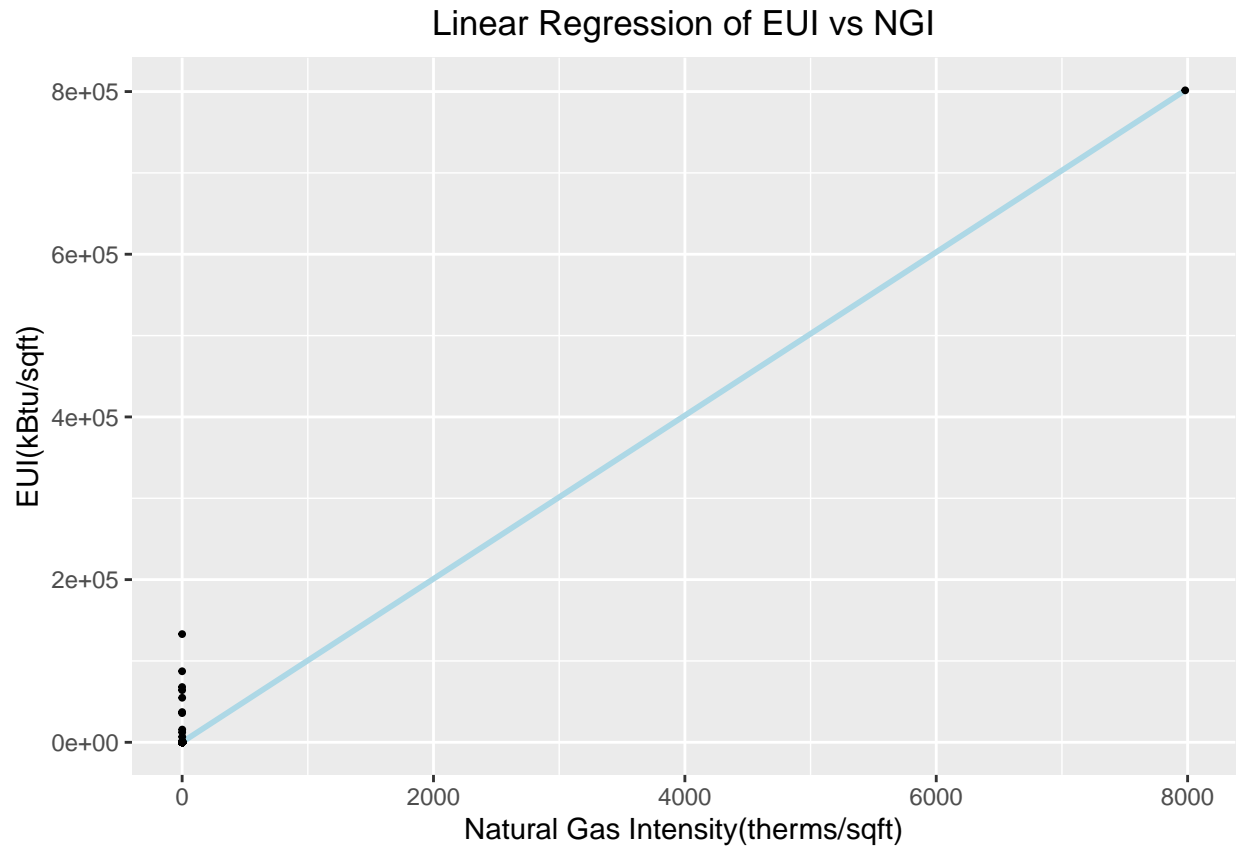
### 3.7 Some visualizations Plots for basic factors modeling

```
# Create a scatterplot with regression line
ggplot(data = my_data, aes(x = EI, y = EUI)) +
  geom_smooth(method = "lm", se = FALSE, color = "lightblue") +
  geom_point(size = 0.7) +
  labs(x = "Electricity Intensity(kWh/sqft)", y = "EUI(kBtu/sqft)", title = "Linear Regression of EUI v
  theme(plot.title = element_text(hjust = 0.5)) # make title in the middle
```

# Linear Regression of EUI vs EI



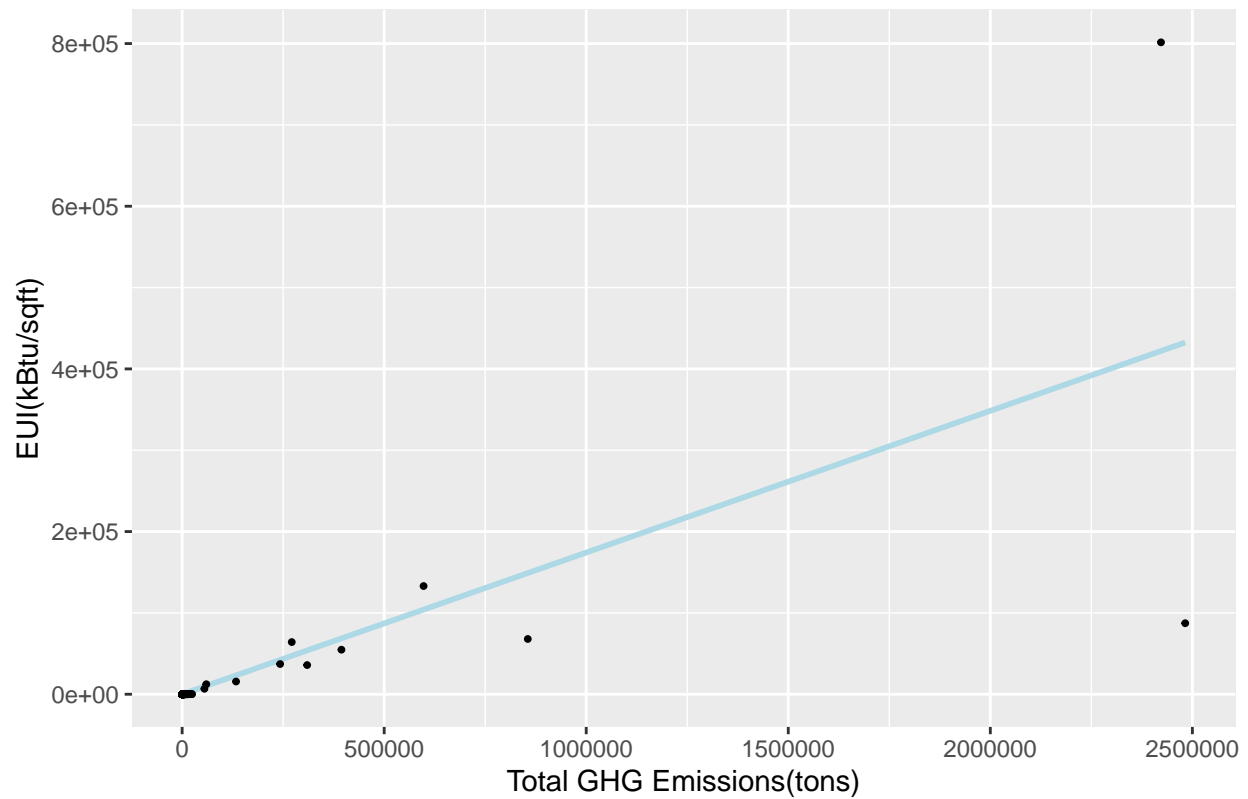
```
ggplot(data = my_data, aes(x = NGI, y = EUI)) +
  geom_smooth(method = "lm", se = FALSE, color = "lightblue") +
  geom_point(size = 0.7) +
  labs(x = "Natural Gas Intensity(therms/sqft)", y = "EUI(kBtu/sqft)", title = "Linear Regression of EUI vs EI")
theme(plot.title = element_text(hjust = 0.5))
```



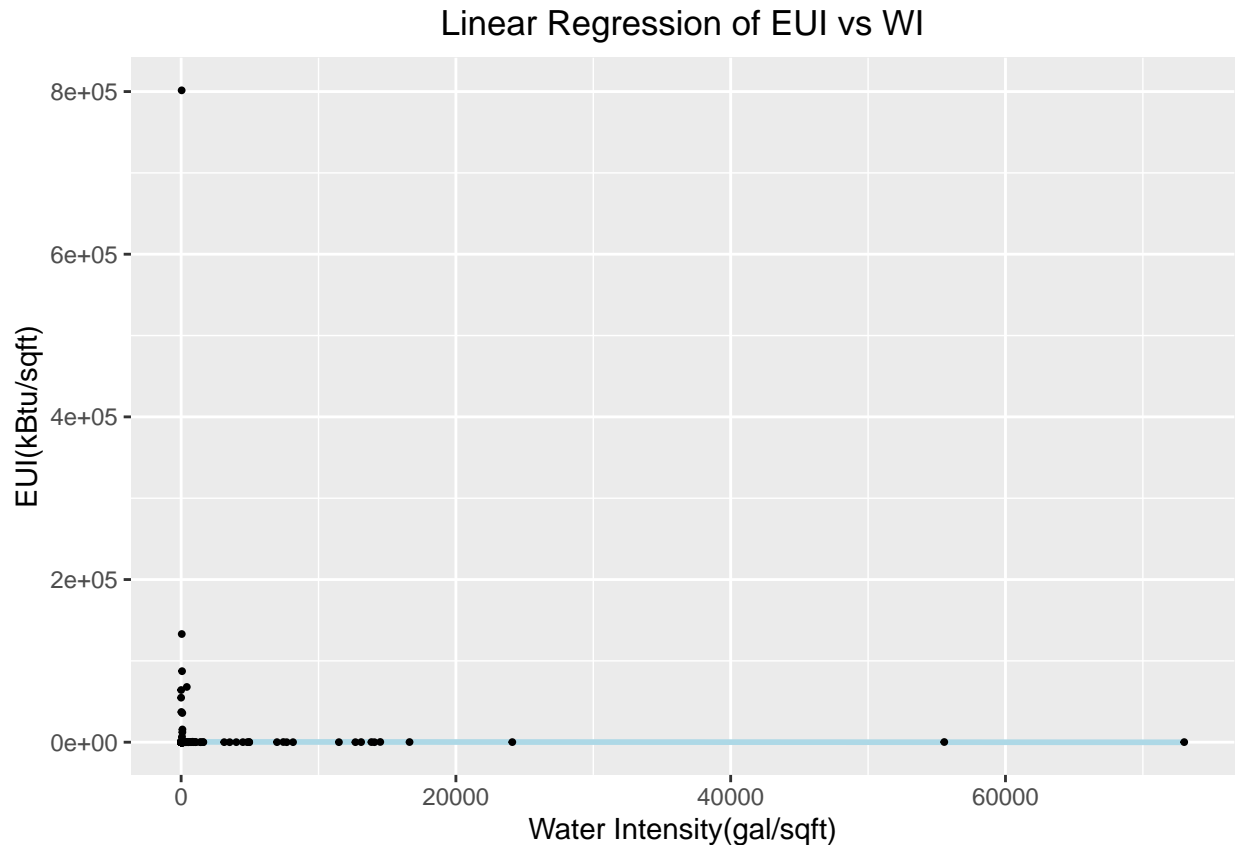
```
ggplot(data = my_data, aes(x = GHG, y = EUI)) +  
  geom_smooth(method = "lm", se = FALSE, color = "lightblue") +  
  geom_point(size = 0.7) +  
  labs(x = "Total GHG Emissions(tons)", y = "EUI(kBtu/sqft)", title = "Linear Regression of EUI vs GHG") +  
  theme(plot.title = element_text(hjust = 0.5))
```



Linear Regression of EUI vs GHG



```
ggplot(data = my_data, aes(x = WI, y = EUI)) +  
  geom_smooth(method = "lm", se = FALSE, color = "lightblue") +  
  geom_point(size = 0.7) +  
  labs(x = "Water Intensity(gal/sqft)", y = "EUI(kBtu/sqft)", title = "Linear Regression of EUI vs WI")  
  theme(plot.title = element_text(hjust = 0.5))
```



#### 4. Research Procedure #02 Improved Model: Joining Census data (Spatial join completed, waiting for joining census data)

**4.1: Spatial Join** The purpose of the spatial join operation is to join the data from American Community Survey(ACS) collected by Census Bureau to the 2015 building energy consumption benchmarking data collected under NYC Local Law 84/133 Energy Benchmarking.

**4.1.1 shapefile importing and visualization** Import the .shp files to and visualize the polygons in Arcgis Pro

**4.1.2 spatial join using Tax Lot data and Census block data** Spatial join with options: - Target features: Tax Lot data - Join features: Census block data - Join operation: One to one - Match option: Within - Fields to join: GeoId (the only required feature for joining ACS data)

This generate a new Tax Lot data table with a new column of the Census Block it belongs to. This means we have BBL number and Census Block geoID in each row.

**4.1.3 join building energy data** Join the geoID data to the building energy dataset using the field of BBL. This results in a new building energy use data table with a new column of Census Block geoID information it belongs to.

```
# load benchmarking table
BR <- read.csv(file = paste0(file.path(dirname(rstudioapi::getSourceEditorContext()$path)),
                             "/dataset/NYC_Building_Energy_with_GEOID/table.csv"),
               header=TRUE) %>%
data.frame()
```

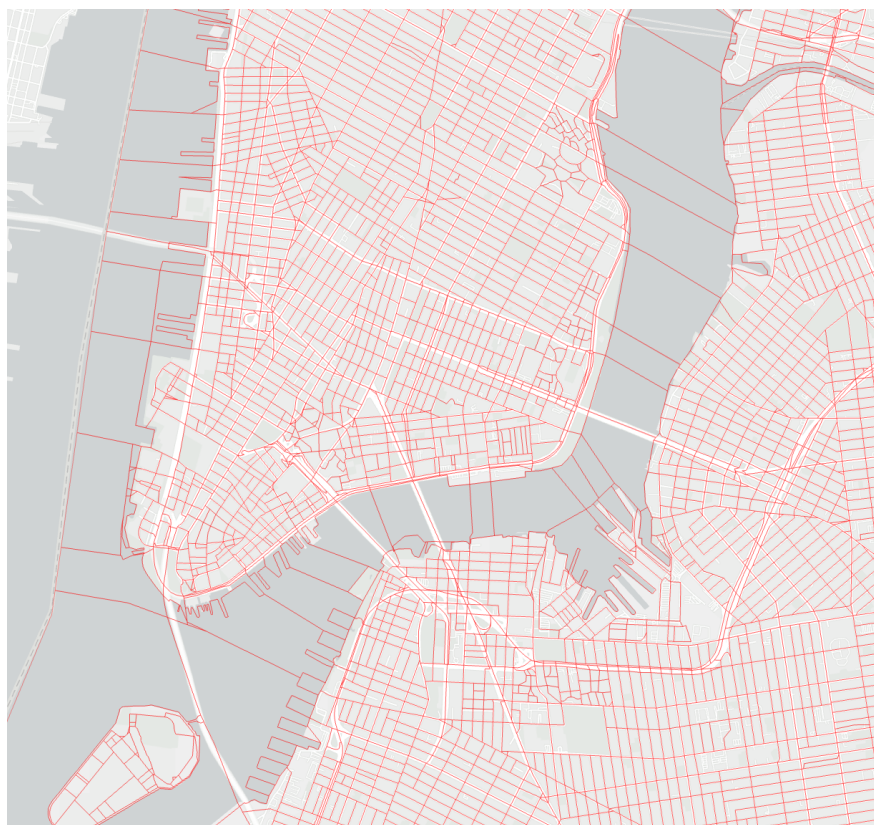


Figure 1: census block boundaries

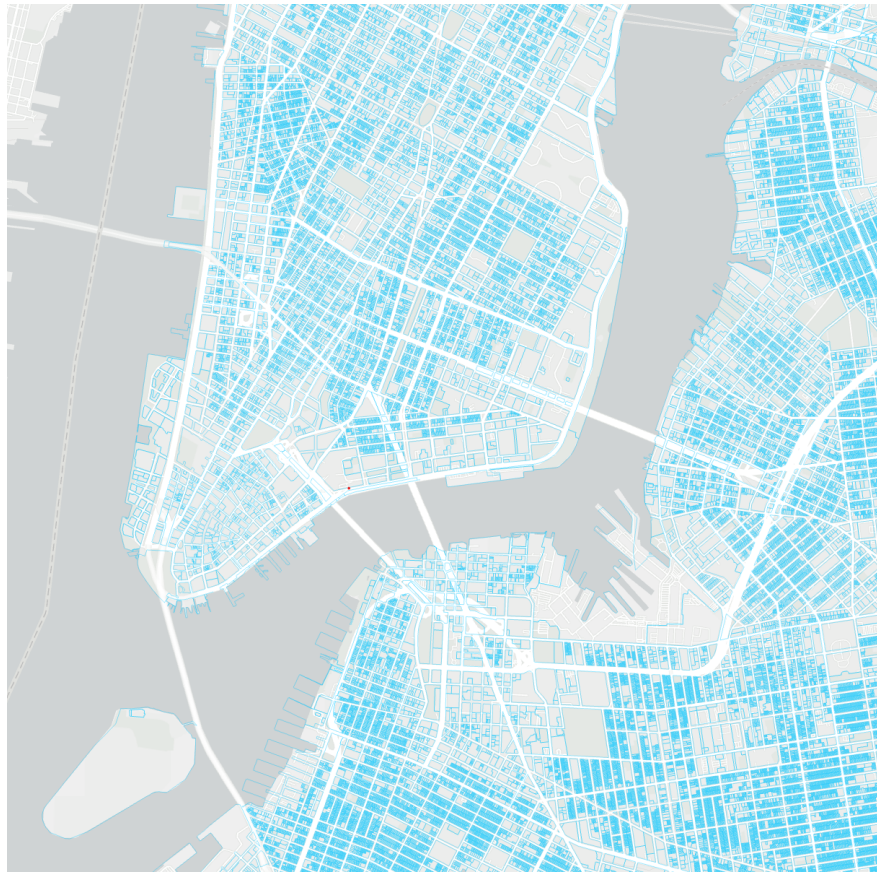


Figure 2: tax lot boundaries

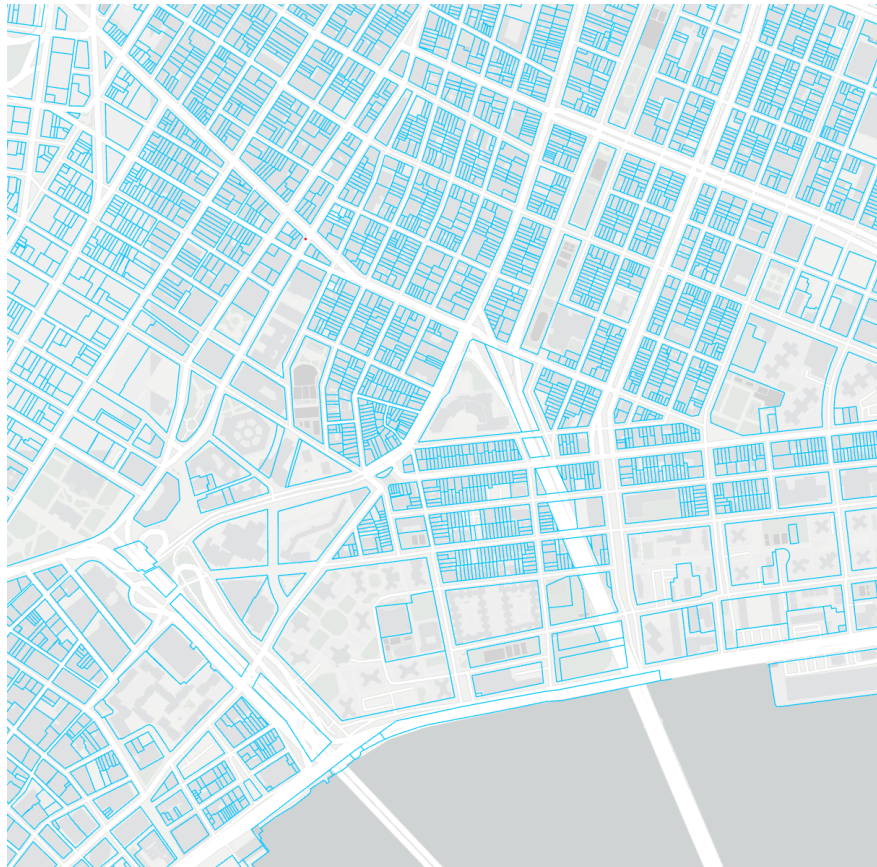


Figure 3: tax lot boundaries zoomed





Figure 4: overlay

```
head(BR)
```

```
##      OID_ Record_Number Order_      BBL Coreported_BBL_Status BBLs_Coreported
## 1      NA              NA 12515 2034327503
## 2      NA          2666985   6733 2036000004
## 3      NA          2639029   6751 2036720001
## 4      NA              NA 12519 2036040001
## 5      NA          2682362   6722 2035630005
## 6      NA          4402905   5381 2023090001
##      Reported_BINs      Property_Name
## 1
## 2          2092718      731-755 White Plains Road
## 3          2022645      1921-1965 Lafayette Park Lane
## 4
## 5 2116665;2819754;2819749      Gold - 669 White Plains Rd
## 6          2093995  Carnegie Management: 112 Lincoln Ave
##      Parent_Property_Id      Parent_Property_Name
## 1
## 2 Not Applicable: Standalone Property Not Applicable: Standalone Property
## 3 Not Applicable: Standalone Property Not Applicable: Standalone Property
## 4
## 5 Not Applicable: Standalone Property Not Applicable: Standalone Property
## 6 Not Applicable: Standalone Property Not Applicable: Standalone Property
##      Street_Number      Street_Name Zip_Code Borough
## 1          329 ADMIRAL LANE      10473   Bronx
## 2          1850 LAFAYETTE AVENUE      10473   Bronx
## 3          1965 LAFAYETTE AVENUE      10473   Bronx
## 4          700 WHITE PLAINS ROAD      10473   Bronx
## 5          669 WHITE PLAINS ROAD      10473   Bronx
## 6          112 LINCOLN AVENUE      10454   Bronx
##      DOF_Benchmarking_Submission_Status Primary_Property_Type
## 1              In Violation
## 2              In Compliance      Multifamily Housing
## 3              In Compliance      Multifamily Housing
## 4              In Violation
## 5              In Compliance      Multifamily Housing
## 6              In Compliance      Multifamily Housing
##      List_of_All_Property_Use_Types_at_Property
## 1
## 2 Medical Office, Multifamily Housing, Retail Store, Supermarket/Grocery Store
## 3      Multifamily Housing
## 4
## 5      Multifamily Housing, Office, Parking
## 6      Multifamily Housing
##      Largest_Property_Use_Type Largest_Property_Use_Type_Gross_Floor_Area_sqft
## 1      NA
## 2      Multifamily Housing      606627
## 3      Multifamily Housing      400933
## 4      NA
## 5      Multifamily Housing      50604
## 6      Multifamily Housing      90000
##      X2nd_Largest_Property_Use_Type
## 1
```

##	2	Medical Office		
##	3	Not Available		
##	4			
##	5	Parking		
##	6	Not Available		
##	X2nd_Largest_Property_Use_Type_Gross_Floor_Area_sqft			
##	1			
##	2		36180	
##	3		Not Available	
##	4			
##	5		8635	
##	6		Not Available	
##	X3rd_Largest_Property_Use_Type			
##	1			
##	2	Supermarket/Grocery Store		
##	3	Not Available		
##	4			
##	5	Office		
##	6	Not Available		
##	X3rd_Largest_Property_Use_Type_Gross_Floor_Area_sqft Year_Built			
##	1			NA
##	2		9638	1977
##	3		Not Available	1969
##	4			NA
##	5		334	2009
##	6		Not Available	1920
##	Number_of_Buildings_Self_reported Occupancy Metered_Areas_Energy			
##	1	NA	NA	
##	2	0	100	Whole Building
##	3	1	100	Whole Building
##	4	NA	NA	
##	5	1	100	Whole Building
##	6	1	100	Whole Building
##	Metered_Areas_Water ENERGY_STAR_Score Site_EUI_kBtu_per_sqft			
##	1		NA	NA
##	2	Not Available	94	70.9
##	3	Not Available	61	89.0
##	4		NA	NA
##	5	Not Available	NA	78.1
##	6	Not Available	74	46.2
##	Weather_Normalized_Site_EUI_kBtu_per_sqft			
##	1		NA	
##	2		70.9	
##	3		NA	
##	4		NA	
##	5		79.0	
##	6		46.1	
##	Weather_Normalized_Site_Electricity_Intensity_kWh_per_sqft			
##	1		NA	
##	2		3.1	
##	3		4.6	
##	4		NA	
##	5		7.4	
##	6		7.0	



##	Weather_Normalized_Site_Natural_Gas_Intensity_therms_per_sqft		
## 1			NA
## 2			0.6
## 3			0.6
## 4			NA
## 5			0.5
## 6			0.2
##	Source_EUI_kBtu_per_sqft Weather_Normalized_Source_EUI_kBtu_per_sqft		
## 1	NA		NA
## 2	97.6		96.5
## 3	126.6		NA
## 4	NA		NA
## 5	135.7		136.0
## 6	98.5		98.3
##	Fuel_Oil_1_Use__kBtu Fuel_Oil_2_Use__kBtu Fuel_Oil_4_Use__kBtu		
## 1			
## 2	Not Available	Not Available	Not Available
## 3	Not Available	4124640.6	Not Available
## 4			
## 5	Not Available	Not Available	Not Available
## 6	Not Available	Not Available	Not Available
##	Fuel_Oil_5_6_Use__kBtu Diesel_2_Use_kBtu District_Steam_Use_kBtu		
## 1			
## 2	Not Available	Not Available	Not Available
## 3	Not Available	Not Available	Not Available
## 4			
## 5	Not Available	Not Available	Not Available
## 6	Not Available	Not Available	Not Available
##	District_Hot_Water_Use_kBtu District_Chilled_Water_Use_kBtu		
## 1			
## 2	Not Available		Not Available
## 3	Not Available		Not Available
## 4			
## 5	Not Available		Not Available
## 6	Not Available		Not Available
##	Natural_Gas_Use_kBtu Weather_Normalized_Site_Natural_Gas_Use_therms		
## 1	NA		NA
## 2	39383800		396617.5
## 3	25111336		255164.1
## 4	NA		NA
## 5	2669935		27288.8
## 6	2008800		19935.2
##	Electricity_Use_Grid_Purchase_kBtu Weather_Normalized_Site_Electricity_kWh		
## 1	NA		NA
## 2	7284016		2042628.6
## 3	6438830		1845628.4
## 4	NA		NA
## 5	1308722		379132.1
## 6	2151972		630706.9
##	Total_GHG_Emissions_Metric_Tons_CO2e Direct_GHG_Emissions_Metric_Tons_CO2e		
## 1	NA		NA
## 2	2696.0		2091.9
## 3	2173.9		1639.9
## 4	NA		NA

## 5	250.4	141.8
## 6	285.2	106.7
##	Indirect_GHG_Emissions_Metric_Tons_CO2e	DOF_Property_Floor_Area_sqft
## 1	NA	110952
## 2	604.1	1021752
## 3	534.0	400932
## 4	NA	78347
## 5	108.5	58234
## 6	178.5	89275
##	Property_GFA_Self_reported_sqft	Water_Use_All_Water_Sources_kgal
## 1	NA	NA
## 2	657996	NA
## 3	400933	NA
## 4	NA	NA
## 5	50938	3821
## 6	90000	NA
##	Municipally_Supplied_Potable_Water_Indoor_Intensity_gal_per_sqft	
## 1		NA
## 2		NA
## 3		NA
## 4		NA
## 5		75.01
## 6		NA
##	Release_Date	DEP_Provided_Water_Use_kgal
## 1		NA
## 2	6/17/2016 11:59	NA
## 3	5/27/2016 10:47	NA
## 4		NA
## 5	7/31/2016 17:10	3821
## 6	4/27/2016 10:08	NA
##	Automatic_Water_Benchmarking_Eligible	Reported_Water_Method
## 1		BBL_1
## 2		2034327503
## 3		2036000004
## 4		2036720001
## 5	Eligible	2036040001
## 6		ABS 2035630005
##		2023090001
##	GEOID10	Shape_Length
## 1	3.6005e+14	1545.1905
## 2	3.6005e+14	125824.45
## 3	3.6005e+14	4510.0241
## 4	3.6005e+14	167236.53
## 5	3.6005e+14	1533.9754
## 6	3.6005e+14	113607.34
##		Shape_Area
## 1	3.6005e+14	812.9707
## 2	3.6005e+14	41278.00
## 3	3.6005e+14	1014.5318
## 4	3.6005e+14	61452.82
## 5	3.6005e+14	846.4841
## 6	3.6005e+14	23530.14

#### 4.2 Join ACS dataset to building energy dataset using the BR above (Next Step)

5. Research Procedure #03 Intepret Coefficients: Exploring the coefficients of the improved model (Next Step)
6. Research Procedure #04 Validate Model: Use the model to predict building energy use intensity of benchmarking data collected in 2017 and check the accuracy (Next Step)
7. Conclusion and Suggestions (Next Step)