DATA 607 Fall 2021 Final Project-Energy Forecast

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10/31/2021

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.6     v dplyr   1.0.7
## v tidyr   1.1.4     v stringr 1.4.0
## v readr   2.0.1     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

## Loading required package: airports

## Loading required package: cherryblossom

## Loading required package: usdata

##
## Attaching package: 'RCurl'

## The following object is masked from 'package:tidyr':
##
##     complete
```

Energy and Carbon Emissions data upload

Use the US Energy Information Administration (EIA) at www.eia.gov.international to collect following

Collect data on a world and regional level

Pair down the time series data for the review at the global level

1) Population dataset
2) GDP
3) Carbon Emissions data
4) Energy production and demand
5) Energy use per capita

6) Energy use per GDP

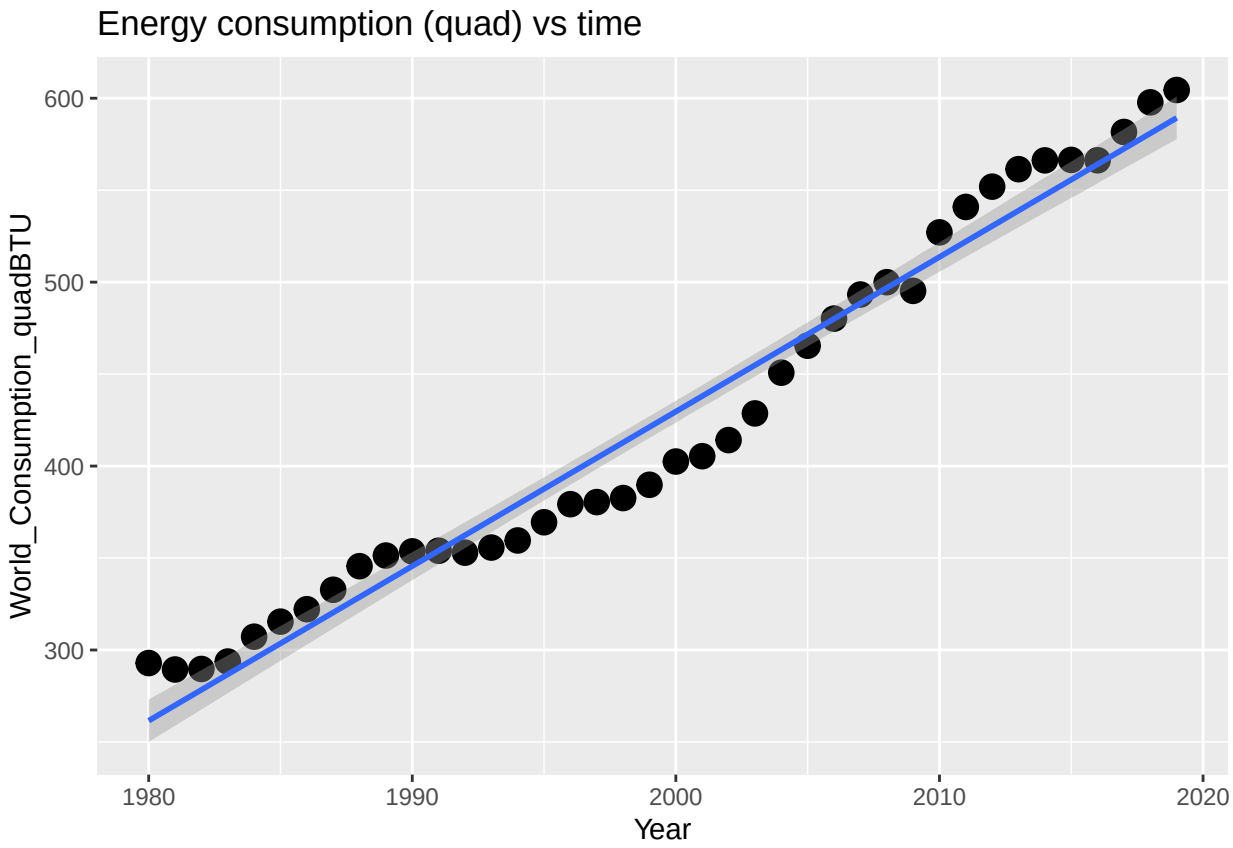
Subset the data and rename to clean up the variable names. Create a data frame with import global varialbes in time series (aprpox 40 year of annual data) Look at the glimpse of the dataset to see basic structure

```
URL<-"https://raw.githubusercontent.com/schmalmr/607Finalproject/main/EIAdata607FinalProject_Energy.csv

df<-read.csv(URL)


dfglobal<-select(df,Year, World_Consumption_quadBTU, World_GDP_USDB, World_consume_Coa._quadBTU, World_

dfglobal<-rename(dfglobal, gobal_zero_CO2_energy= World_consume_Nuclear..renewables_quadBTU)
dfglobal<-rename(dfglobal, global_population =World_pop)
dfglobal<-rename(dfglobal, global_CO2_fuels=Fossil_fuel_industry_emissions_GtCO2)
dfglobal<-rename(dfglobal, MBTU_per_GPD_Billions=World_1000BTU_GDPBUSD)
dfglobal<-rename(dfglobal, MBTU_per_person=World_MMBtu_person)
dfglobal<-rename(dfglobal, global_energy_use_quad_BTU= World_Consumption_quadBTU)
dfglobal<-rename(dfglobal, global_Coal_use_quad_BTU=World_consume_Coa._quadBTU)
dfglobal<-rename(dfglobal, global_NGAS_use_quad_BTU=World_consume_Natural.gas_quadBTU)
dfglobal<-rename(dfglobal, global_Oil_use_quad_BTU=World_consume_Petroleum_quadBTU)
dfglobal<-rename(dfglobal, global_fuelandlandland_use_GtCO2=Fossil.fuel_plus_landuse_emissions_GtCO2)
dfglobal<-rename(dfglobal, global_land_use_GtCO2=Land_use_emissions_GtCO2)

glimpse (dfglobal)
```

```
## Rows: 41
## Columns: 13
## $ Year                              <int> 1980, 1981, 1982, 1983, 1984, 1985, 1~
## $ global_energy_use_quad_BTU        <dbl> 292.8999, 289.4015, 289.6913, 293.731~
## $ World_GDP_USDB                    <dbl> 27745.48, 28640.20, 28776.47, 29593.0~
## $ global_Coal_use_quad_BTU          <dbl> 78.65628, 78.96407, 80.42250, 82.6310~
## $ global_NGAS_use_quad_BTU          <dbl> 53.86522, 53.89542, 54.05526, 55.1497~
## $ global_Oil_use_quad_BTU           <dbl> 132.0640, 126.8111, 123.9243, 122.215~
## $ gobal_zero_CO2_energy             <dbl> 28.31441, 29.73088, 31.28923, 33.7353~
## $ global_population                 <dbl> 4298127, 4377060, 4456830, 4537794, 4~
## $ MBTU_per_person                   <dbl> 68.14595, 66.11779, 64.99940, 64.7300~
## $ global_fuelandlandland_use_GtCO2  <dbl> 23636499800, 23341806580, 23109445670~
## $ global_land_use_GtCO2             <dbl> 4143886286, 4314896401, 4233685392, 4~
## $ global_CO2_fuels                  <dbl> 19492613520, 19026910180, 18875760280~
## $ MBTU_per_GPD_Billions             <dbl> 10.556672, 10.104733, 10.066950, 9.92~
```

```
ggplot(data=df, aes(x=Year, y=World_Consumption_quadBTU))+geom_point(size=4)+geom_smooth(method=lm)+ggt
```

```
## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 1 rows containing non-finite values (stat_smooth).

## Warning: Removed 1 rows containing missing values (geom_point).
```

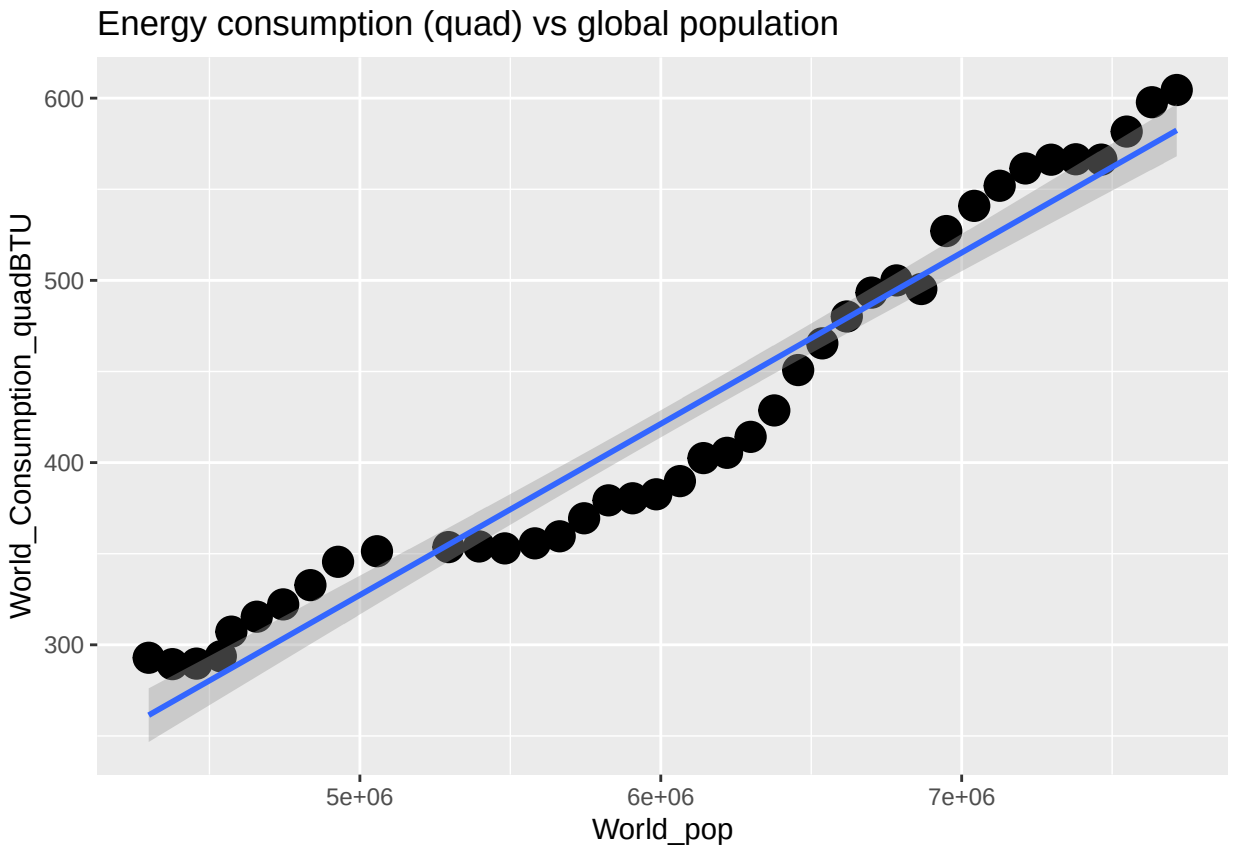



```
ggplot(data=df,aes(x=World_pop, y=World_Consumption_quadBTU))+geom_point(size=5)+geom_smooth(method=lm)+
```

```
## `geom_smooth()` using formula 'y ~ x'
```

```
## Warning: Removed 1 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```

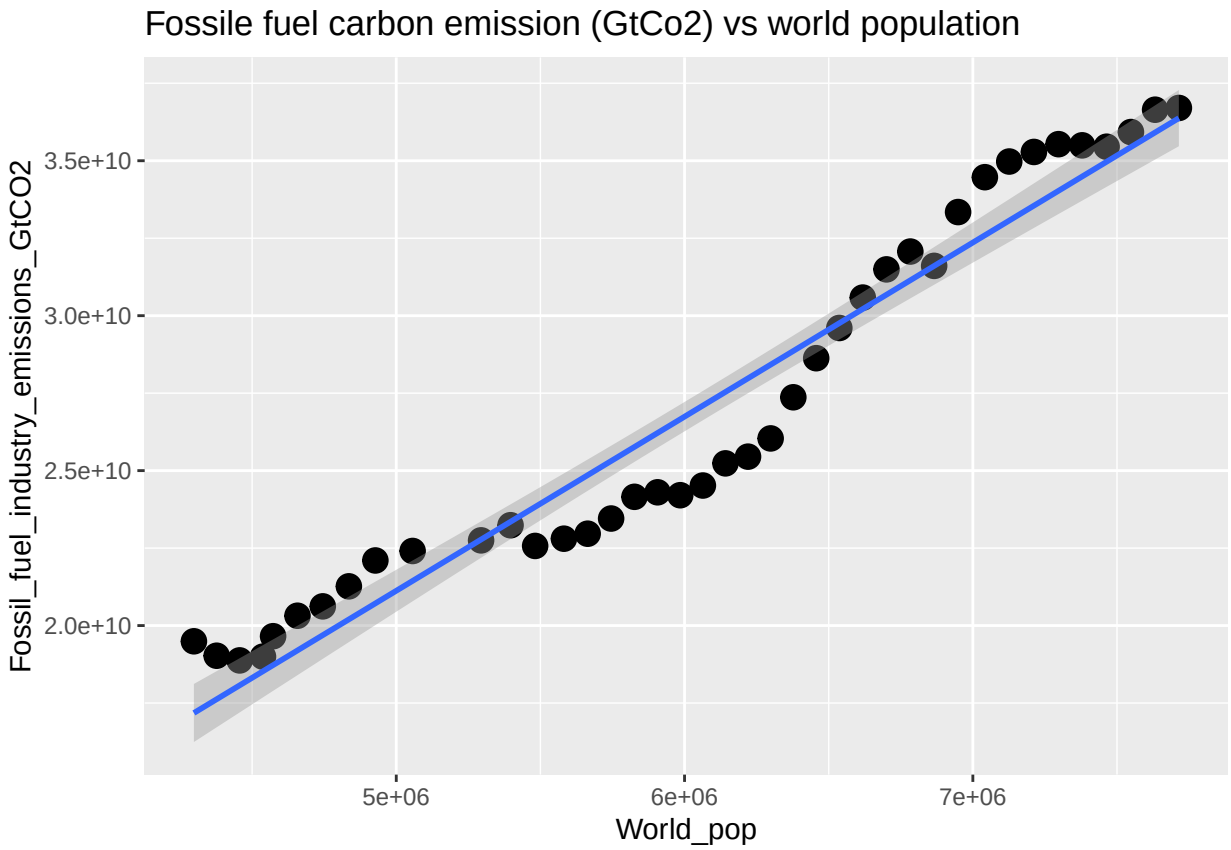



```
ggplot(data=df,aes(x=World_pop, y=Fossil_fuel_industry_emissions_GtCO2))+geom_point(size=4)+geom_smooth
```

```
## `geom_smooth()` using formula 'y ~ x'
```

```
## Warning: Removed 1 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```

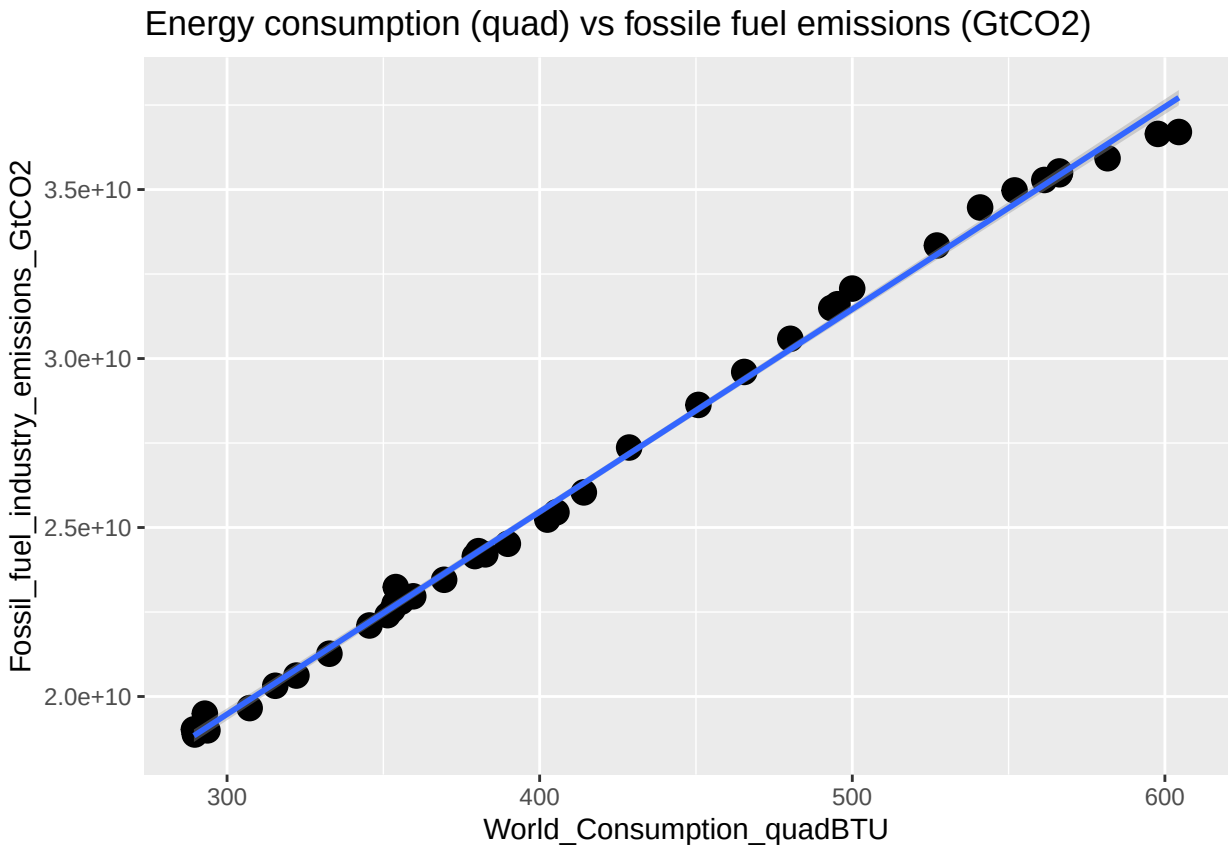



```
ggplot(data=df,aes(x=World_Consumption_quadBTU, y=Fossil_fuel_industry_emissions_GtCO2))+geom_point(siz
```

```
## `geom_smooth()` using formula 'y ~ x'
```

```
## Warning: Removed 1 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```

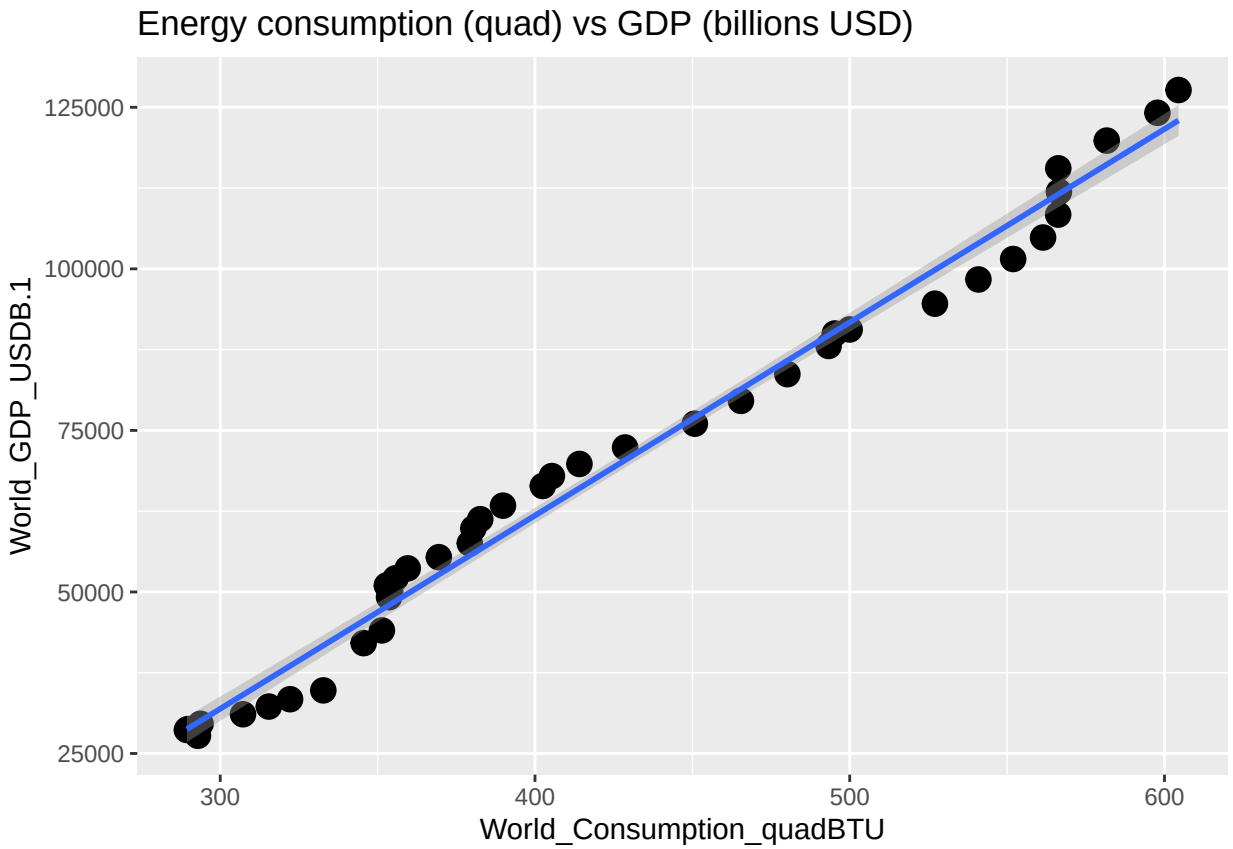



```
ggplot(data=df,aes(x=World_Consumption_quadBTU, y=World_GDP_USDB.1))+geom_point(size=4)+geom_smooth(metl
```

```
## `geom_smooth()` using formula 'y ~ x'
```

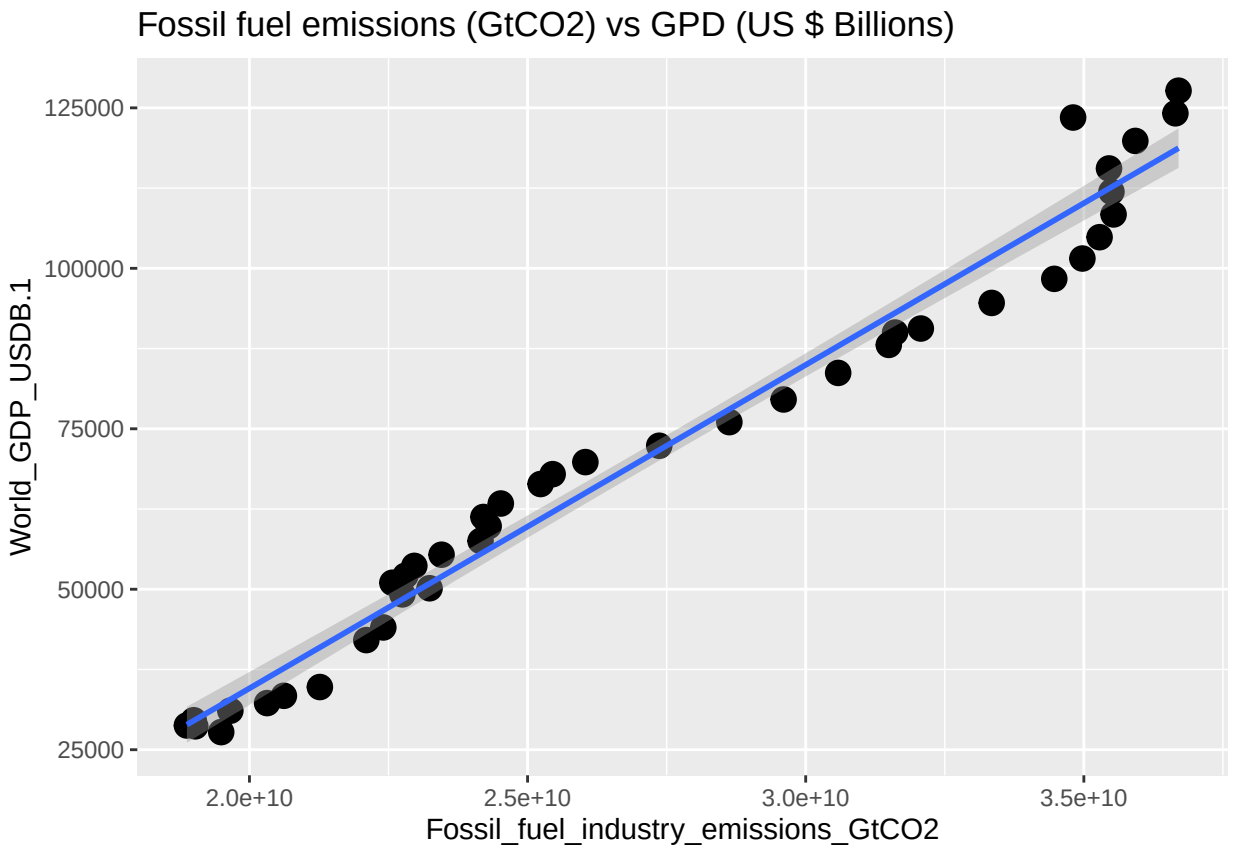
```
## Warning: Removed 1 rows containing non-finite values (stat_smooth).
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```




```
ggplot(data=df,aes(x=Fossil_fuel_industry_emissions_GtCO2, y=World_GDP_USDB.1))+geom_point(size=4)+geom_
```

```
## `geom_smooth()` using formula 'y ~ x'
```

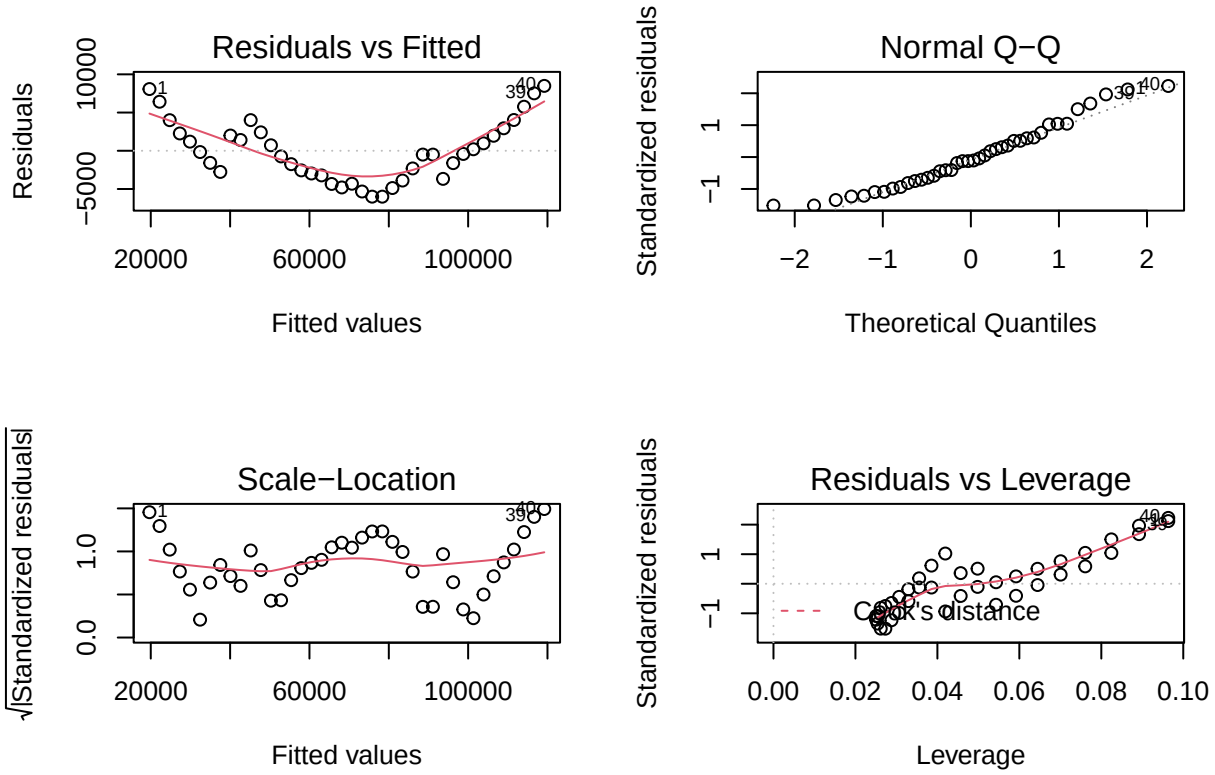


Evaluate linear model of GPD vs year

```
 m_gdp <- lm(World_GDP_USDB ~ Year, data = dfglobal)
summary(m_gdp)
```

```
##
## Call:
## lm(formula = World_GDP_USDB ~ Year, data = dfglobal)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6004.0 -3035.4  -457.7  2302.6  8486.9
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -5.033e+06  1.098e+05  -45.85   <2e-16 ***
## Year         2.552e+03  5.489e+01   46.49   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4008 on 38 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.9827, Adjusted R-squared:  0.9823
## F-statistic:  2161 on 1 and 38 DF,  p-value: < 2.2e-16
```

```
par(mfrow = c(2,2))
plot(m_gdp)
```



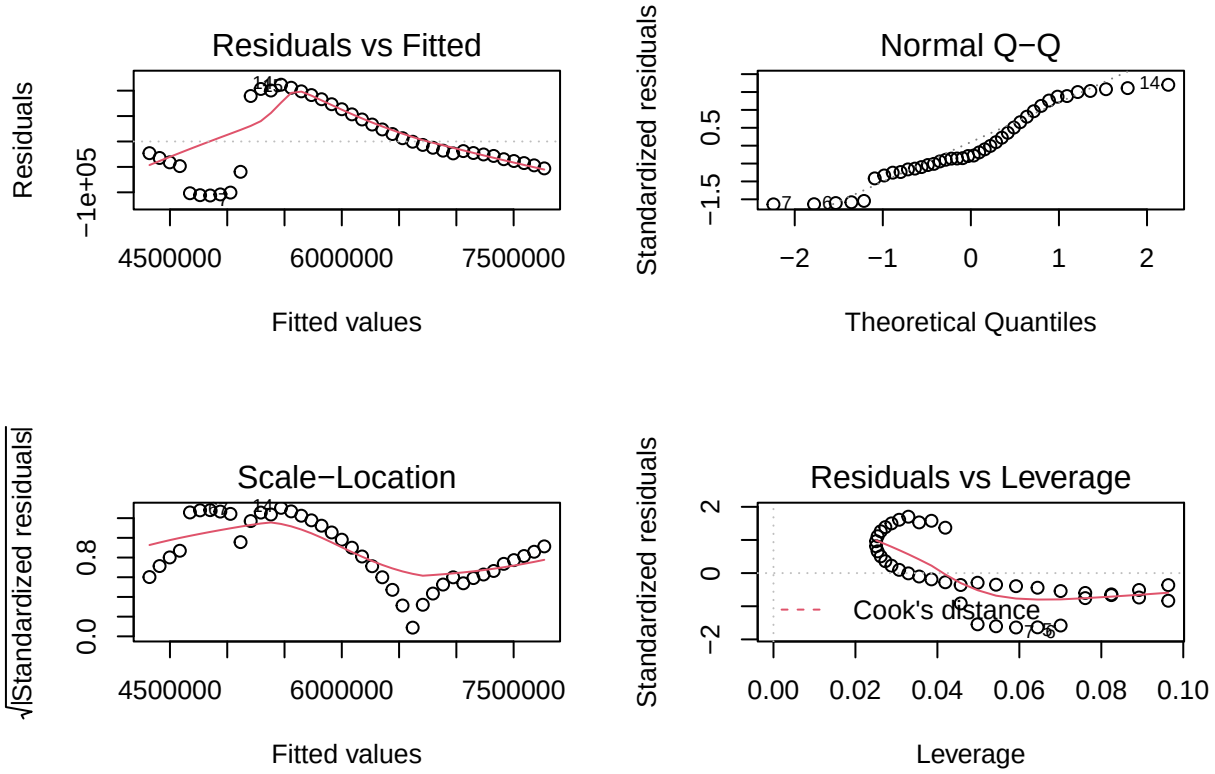
Evaluate linear model of global population over time

```
 m_population2 <- lm(global_population ~ Year, data = dfglobal)
summary(m_population2)
```

```
##
## Call:
## lm(formula = global_population ~ Year, data = dfglobal)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -106190  -41377  -18465   55885  111649
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.707e+08  1.827e+06  -93.39   <2e-16 ***
## Year         8.837e+04  9.138e+02   96.70   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 66720 on 38 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.996,  Adjusted R-squared:  0.9958
```

```
## F-statistic:  9351 on 1 and 38 DF,  p-value: < 2.2e-16
```

```
par(mfrow = c(2,2))
plot(m_population2)
```



Evalue Energy consumption total

Model is good with the GPD and the Population.

Population has a p value of 0.06 (just a bit higher than desired)

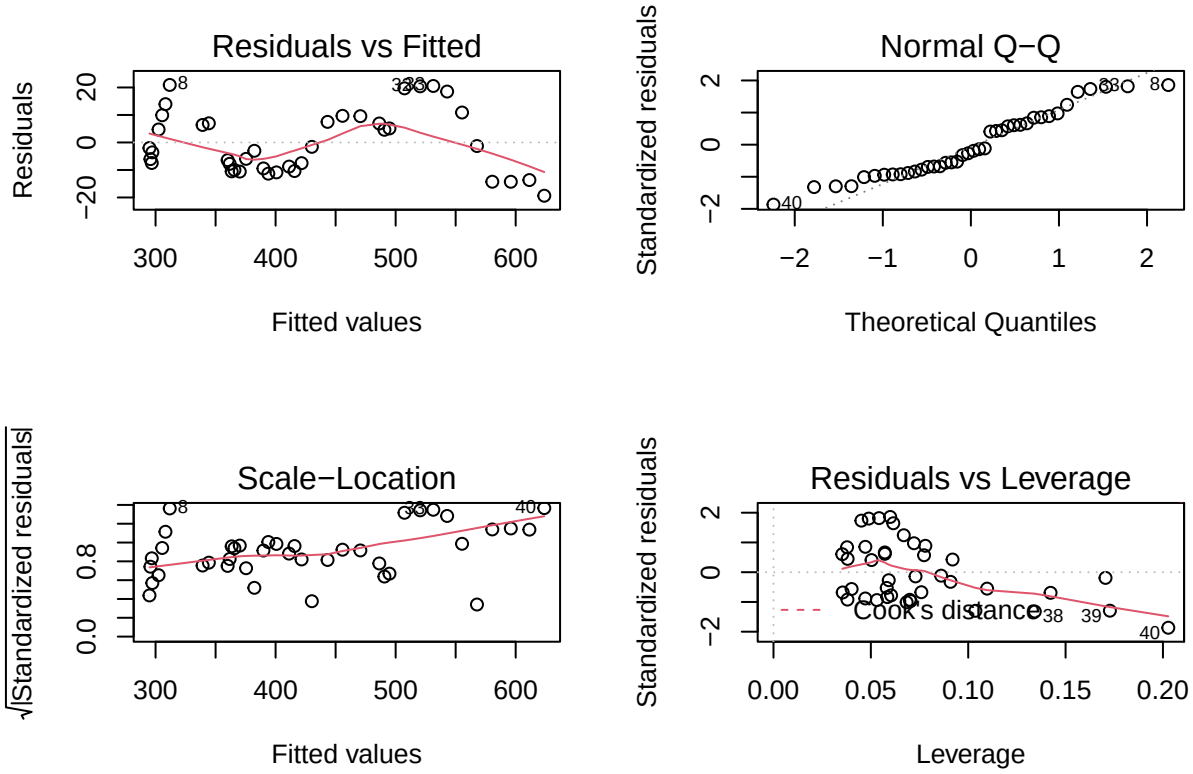
```
 m_energy <- lm(global_energy_use_quad_BTU ~World_GDP_USDB+global_population, data = dfglobal)
summary(m_energy)
```

Population retained as a variable in the model

```
##
## Call:
## lm(formula = global_energy_use_quad_BTU ~ World_GDP_USDB + global_population,
##     data = dfglobal)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -19.366  -9.582  -2.528   8.010  20.918
```

```
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)         2.735e+02  4.034e+01    6.78 5.58e-08 ***
## World_GDP_USDB      4.004e-03  3.736e-04   10.72 6.71e-13 ***
## global_population -2.086e-05  1.086e-05   -1.92   0.0626 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.62 on 37 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.9872, Adjusted R-squared:  0.9865
## F-statistic:  1424 on 2 and 37 DF,  p-value: < 2.2e-16
```

```
par(mfrow = c(2,2))
plot(m_energy)
```



Evaluate the Energy consumption not generating CO2

Correlation is most strong with the Global GDP

GDP calculated from model above can be used to estimate model Energy

consumption that is not generating CO2.

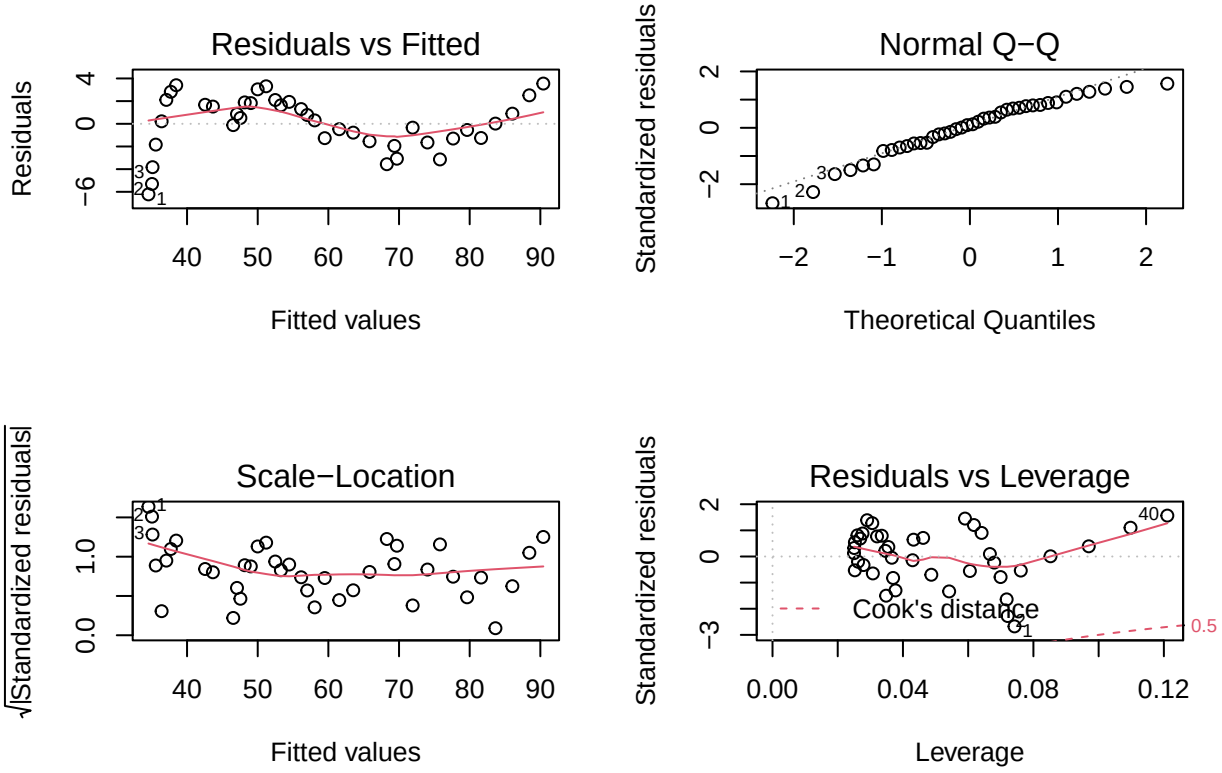
Assumption for ease of model: Nuclear, renewables and water

are net zero CO2 energy sources in this model All CO2 emissions are then attributed to fuel use.

```
 m_energyzero <- lm(gobal_zero_CO2_energy ~ World_GDP_USDB, data = dfglobal)
summary(m_energyzero)
```

```
##
## Call:
## lm(formula = gobal_zero_CO2_energy ~ World_GDP_USDB, data = dfglobal)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.2244 -1.3619  0.2599  1.8427  3.5481
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.902e+01  9.718e-01   19.58   <2e-16 ***
## World_GDP_USDB 5.592e-04  1.287e-05   43.46   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.418 on 38 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.9803, Adjusted R-squared:  0.9798
## F-statistic:  1889 on 1 and 38 DF,  p-value: < 2.2e-16
```

```
par(mfrow = c(2,2))
plot(m_energyzero)
```



Model of Carbon Emissions from Fuel over time

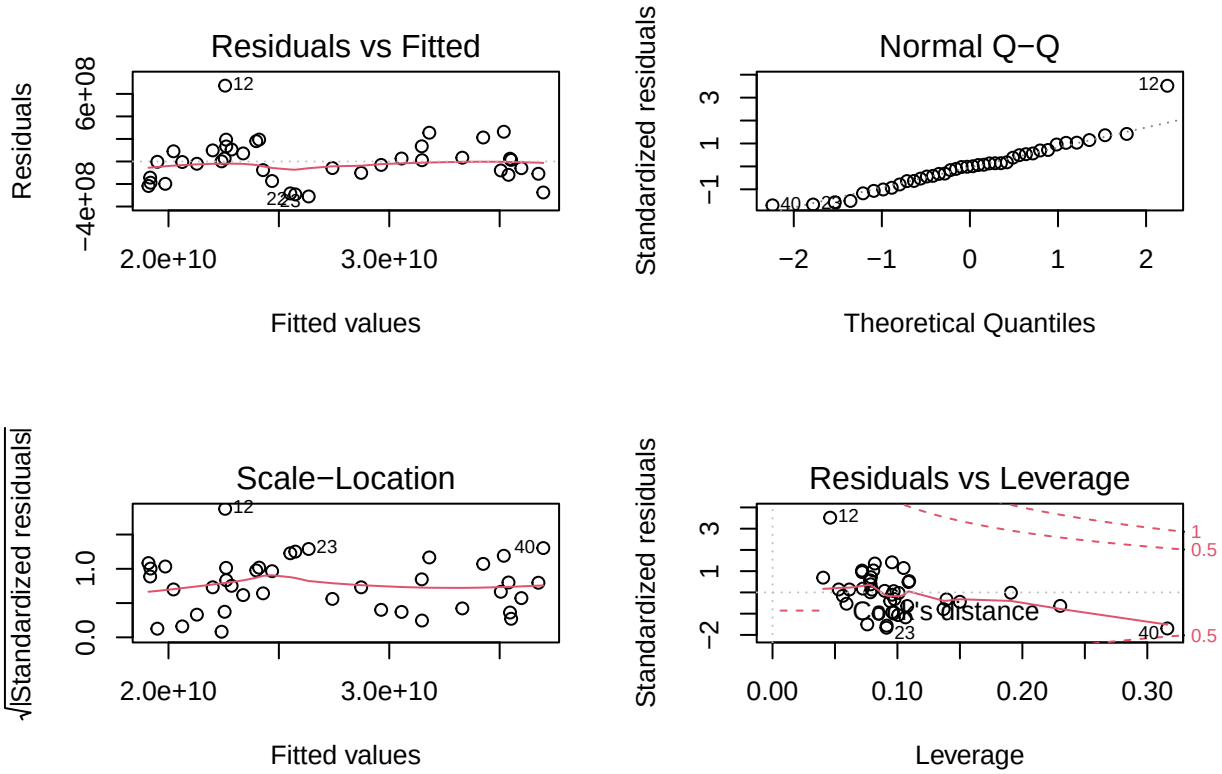
Key variables for the model are the global energy use, global zero CO2 energy and the global population

Note: For simplification the use of carbon capture technology is ignored and it is assumed later as a simple application of the technology to remove carbon from the atmosphere. It is actually a very challenging and difficult problem to solve economically and with efficent use of energy.

```
 m_co2 <- lm(global_CO2_fuels ~ global_energy_use_quad_BTU+gobal_zero_CO2_energy+global_population, data
summary(m_co2)
```

```
##
## Call:
## lm(formula = global_CO2_fuels ~ global_energy_use_quad_BTU +
##     gobal_zero_CO2_energy + global_population, data = dfglobal)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -310518436 -111468218    -777360  100461163  672995576
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 -1.130e+09  4.345e+08  -2.601   0.0134 *
## global_energy_use_quad_BTU  6.910e+07  1.591e+06  43.443  < 2e-16 ***
## gobal_zero_CO2_energy      -1.009e+08  1.151e+07  -8.766 1.86e-10 ***
## global_population           7.547e+02  1.716e+02   4.398 9.29e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 195900000 on 36 degrees of freedom
##   (1 observation deleted due to missingness)
## Multiple R-squared:  0.999,  Adjusted R-squared:  0.9989
## F-statistic: 1.216e+04 on 3 and 36 DF,  p-value: < 2.2e-16
```

```
par(mfrow = c(2,2))
plot(m_co2)
```



Modeling the future

The past 40 years provide a dataset used to establish a frame set of models

1) Models are noted to have some weaknesses in the models; however all of the models are very good at explaining the past. The R-squared values for the series of models is above 0.95 for all models (amazingly strong)
2) There are some indications of the residuals have a few outlyers in the models

- particually noted in the Carbon Emissions model (some trends in each of models)

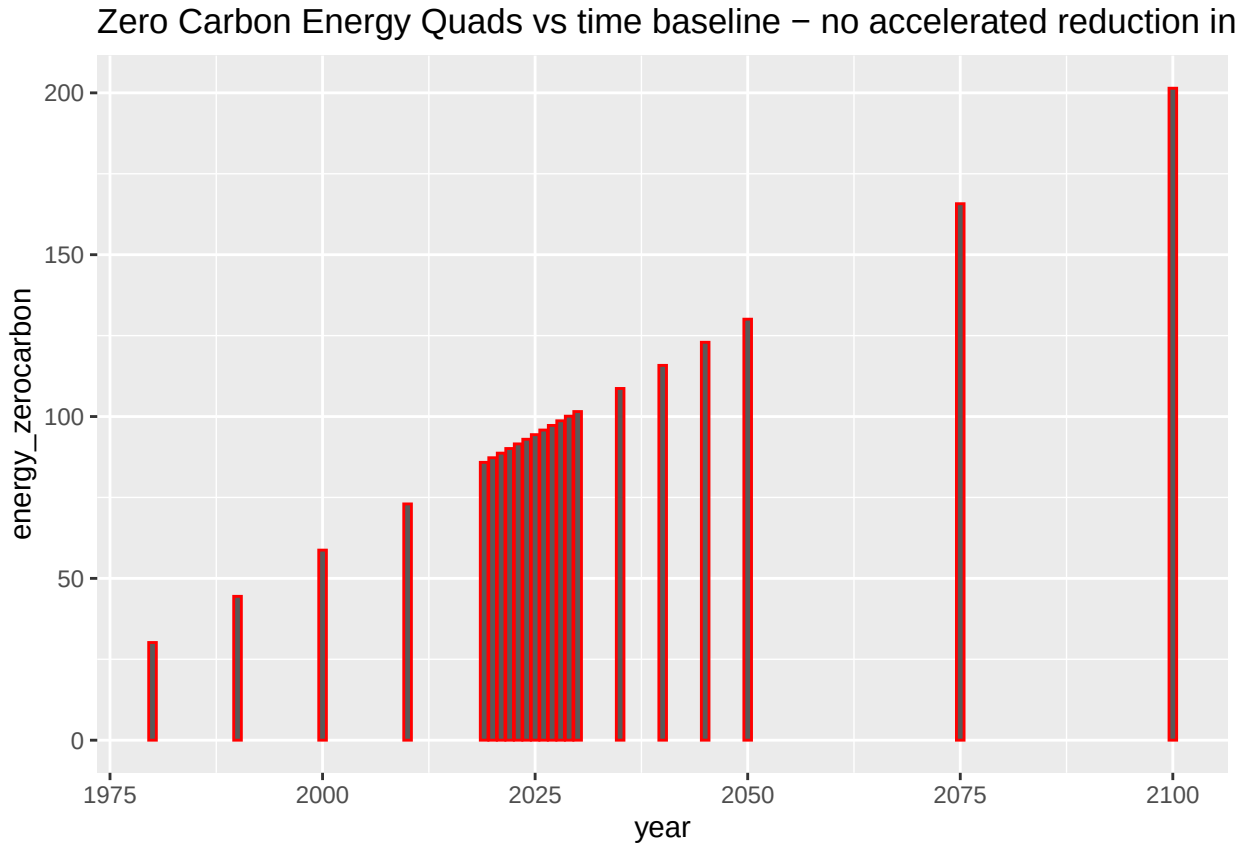
3) The Q-Q plots are pretty good for models except the population model over time which has more drift than others. Others do have some trends at the start and the tails of the plots.
4) Residuals are show good random variability for models except the
    - population model seems to have poor randomness - with a distinct line
    - GPD have drift in residuals up and down across the model
5) Major assumption for next step is to proceed to extrapolate the future with the current model.

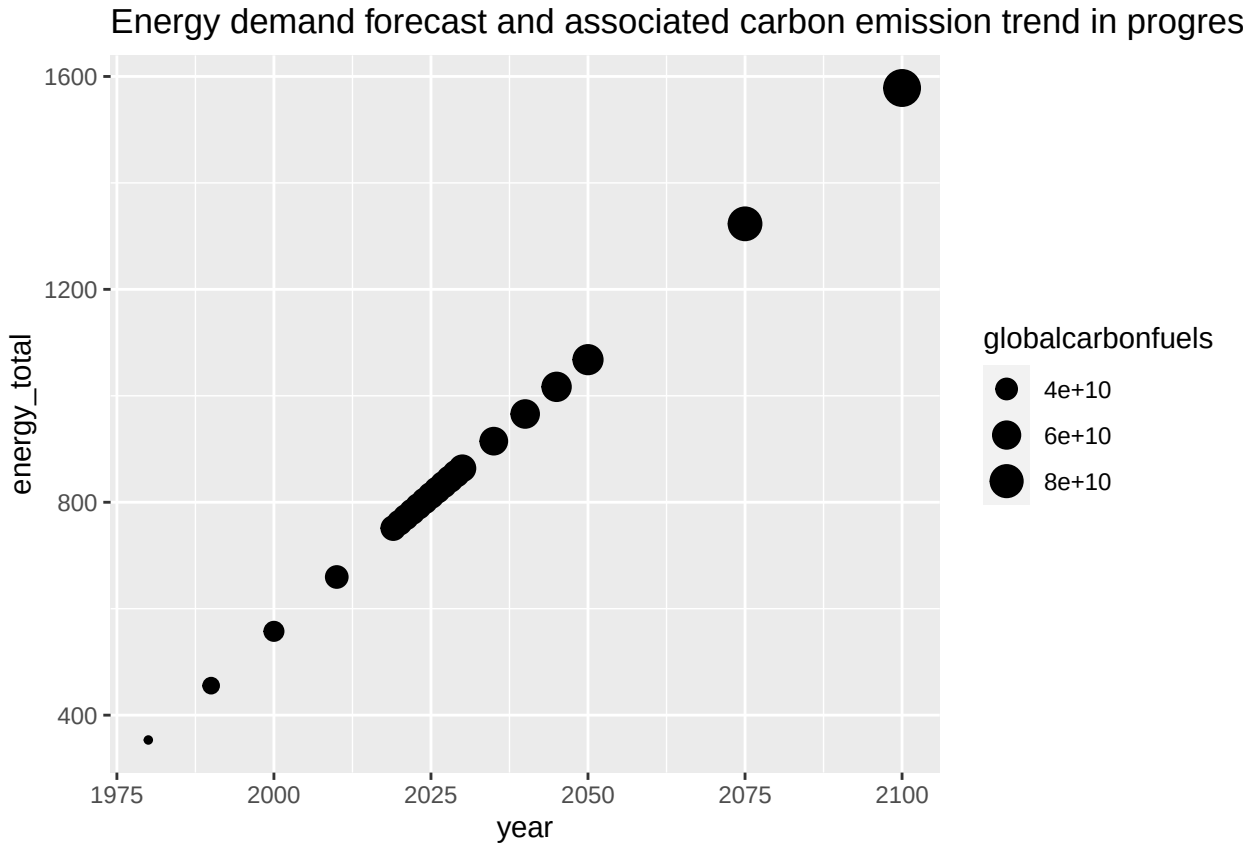
- Extrapolation out until 2050
- Note the use of an extrapolation is not recommended and error expected
- Extrapolation judged a risk to consider based the very strong R-squared for each of the individual models.

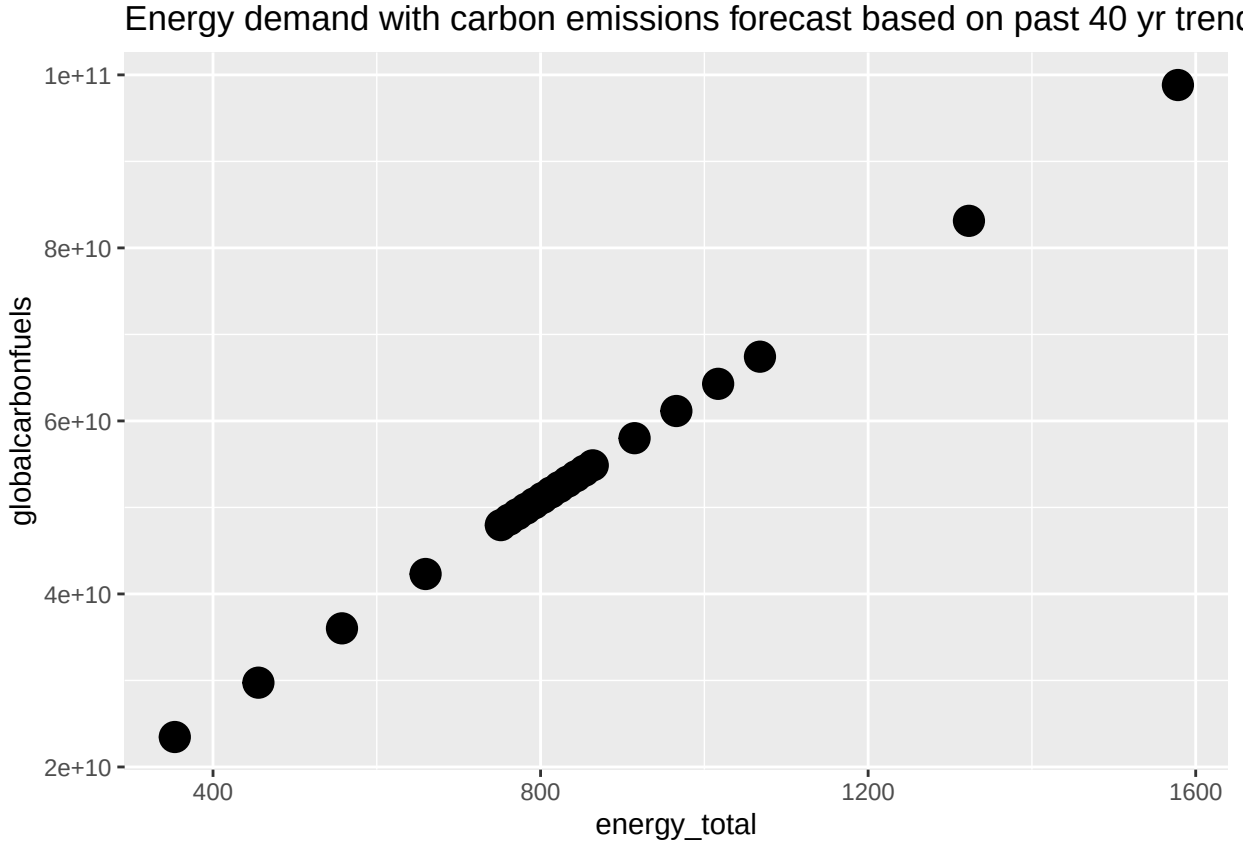
6) Create an incremental estimate to demonstrate the magnitude of the incremental renewable or zero carbon generating energy development is needed.
Placeholder globally without specific constraints on population or GDP

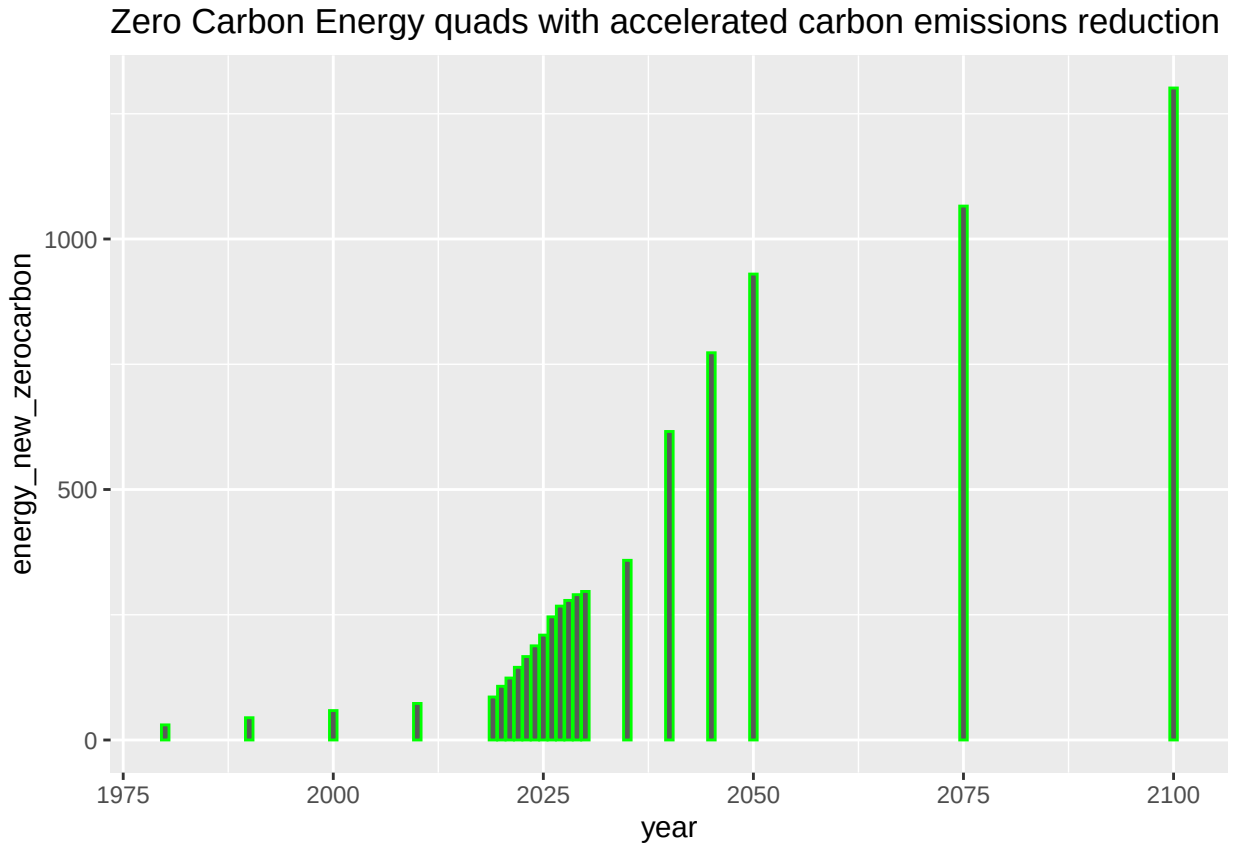
7) The appraoch is to show how much more is needed to just hold Carbon emissions flat or near constant. The later adjustments show how difficult or significant the energy transition needed is to achieve reductions on Carbon emissions.

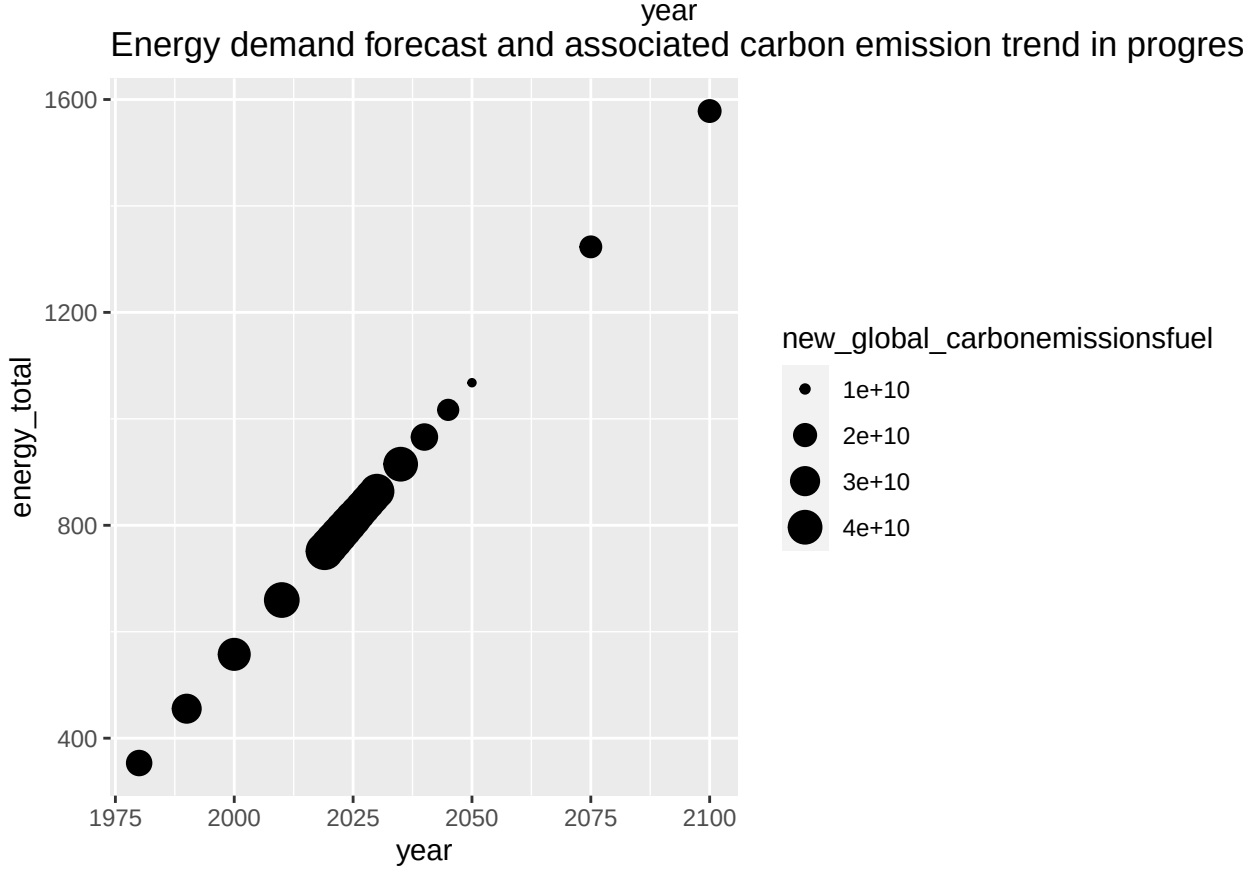
```
year <- c(1980,1990,2000,2010,2019, 2020, 2021,2022,2023,2024,2025,2026,2027,2028,2029,2030,2035,2040,2

df_model <- data.frame(year)

df_model<- df_model %>%mutate(GDP=(-5033000+2552*year),.after=year)
df_model<- df_model %>%mutate(population=(-170700000+88370*year),.after=GDP)
df_model<- df_model %>%mutate(energy_total=(273.5+0.004*(GDP)),.after=population)
df_model<- df_model %>%mutate(energy_zerocarbon=(19.02+0.0005592*(GDP)),.after=energy_total)
df_model<- df_model %>%mutate(globalcarbonfuels=(-1133000000+6.91E7*energy_total-100900000*energy_zeroca

df_model<- df_model %>%mutate(energywithcarbon=(energy_total-energy_zerocarbon),.after=energy_zerocarbo
df_model<- df_model %>%mutate(carbon_per_energy=(globalcarbonfuels/(energy_total-energy_zerocarbon)),.a

df_model$incremental_new_zero_carbonenergy <- c(0,0,0,0,0,20,35,55,75,95,115,150,170,180,190,195,250,50
df_model<-df_model %>% mutate(energy_new_zerocarbon=energy_zerocarbon+incremental_new_zero_carbonenergy
df_model<-df_model %>% mutate(energy_new_withcarbon=(energy_total-(energy_new_zerocarbon)))
df_model<-df_model %>% mutate(new_global_carbonemissionsfuel=(globalcarbonfuels+72000000*(energy_zeroca
```

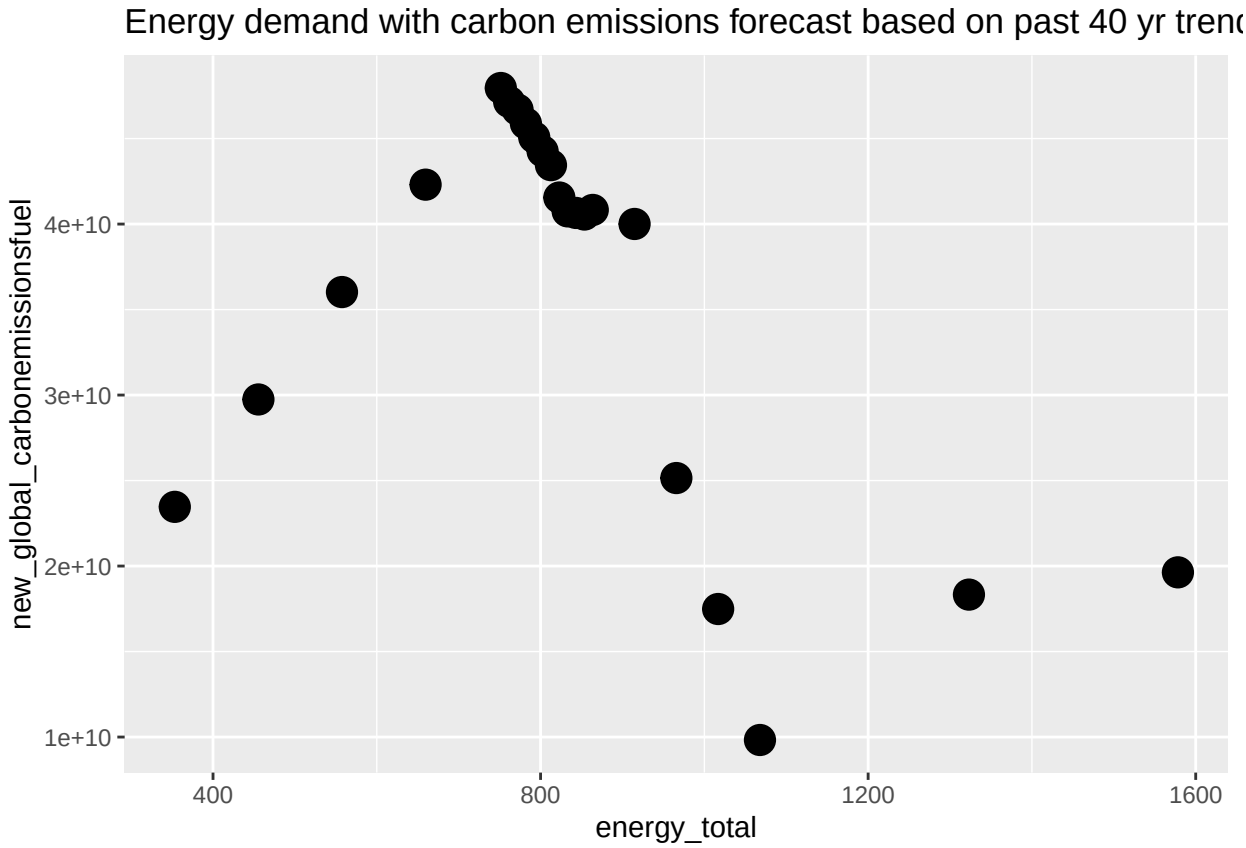


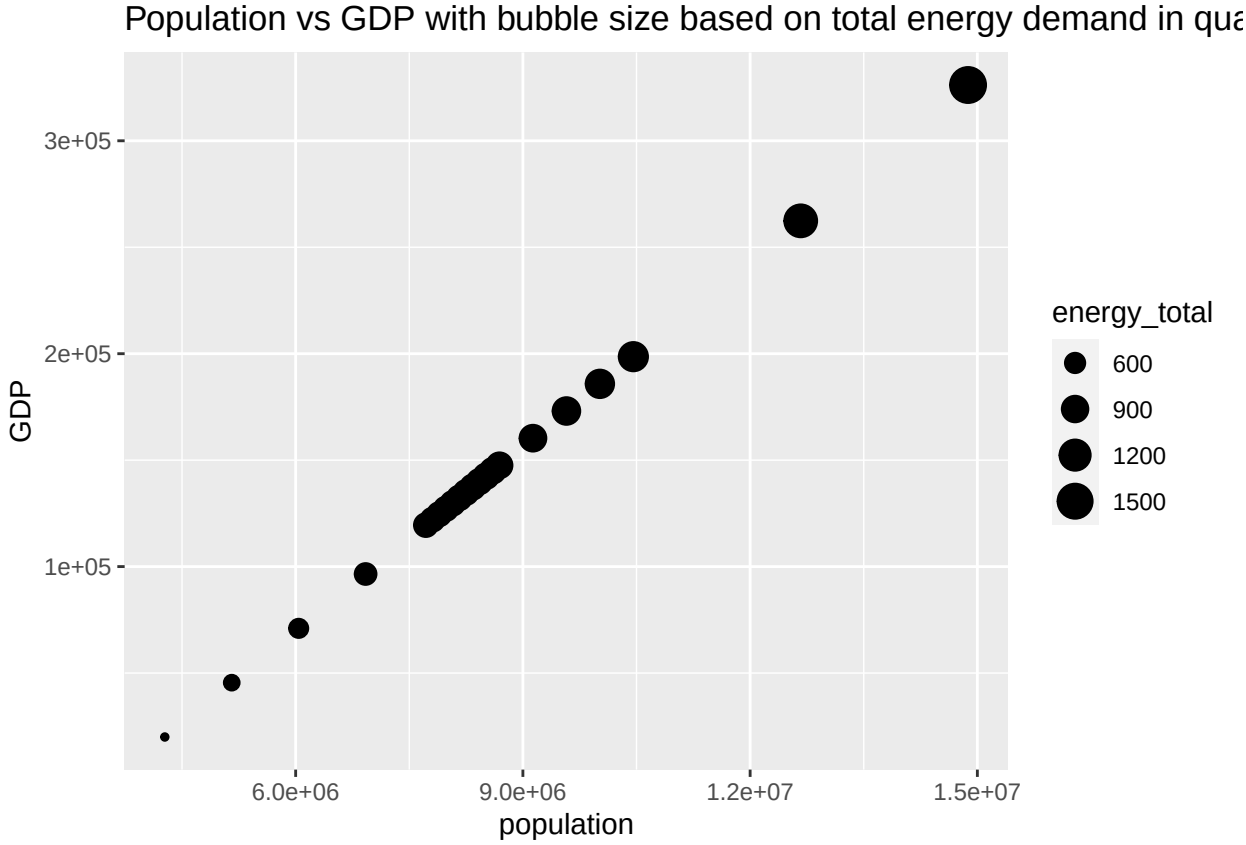

Energy demand forecast and associated carbon emission trend in progres
1600
1200
800
400
energy_total
1975
2000
2025
2050
2075
2100
year
globalcarbonfuels
4e+10
6e+10
8e+10


Energy demand with carbon emissions forecast based on past 40 yr trend
1e+11
8e+10
6e+10
4e+10
2e+10
globalcarbonfuels
400
800
1200
1600
energy_total


Zero Carbon Energy quads with accelerated carbon emissions reduction
energy_new_zerocarbon
1000
500
0
1975
2000
2025
2050
2075
2100
year


Energy demand forecast and associated carbon emission trend in progres
energy_total
1600
1200
800
400
1975
2000
2025
2050
2075
2100
year
new_global_carbonemissionsfuel
1e+10
2e+10
3e+10
4e+10





Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that

generated the plot.

Illustration of the impact energy shift away from fossil fuels

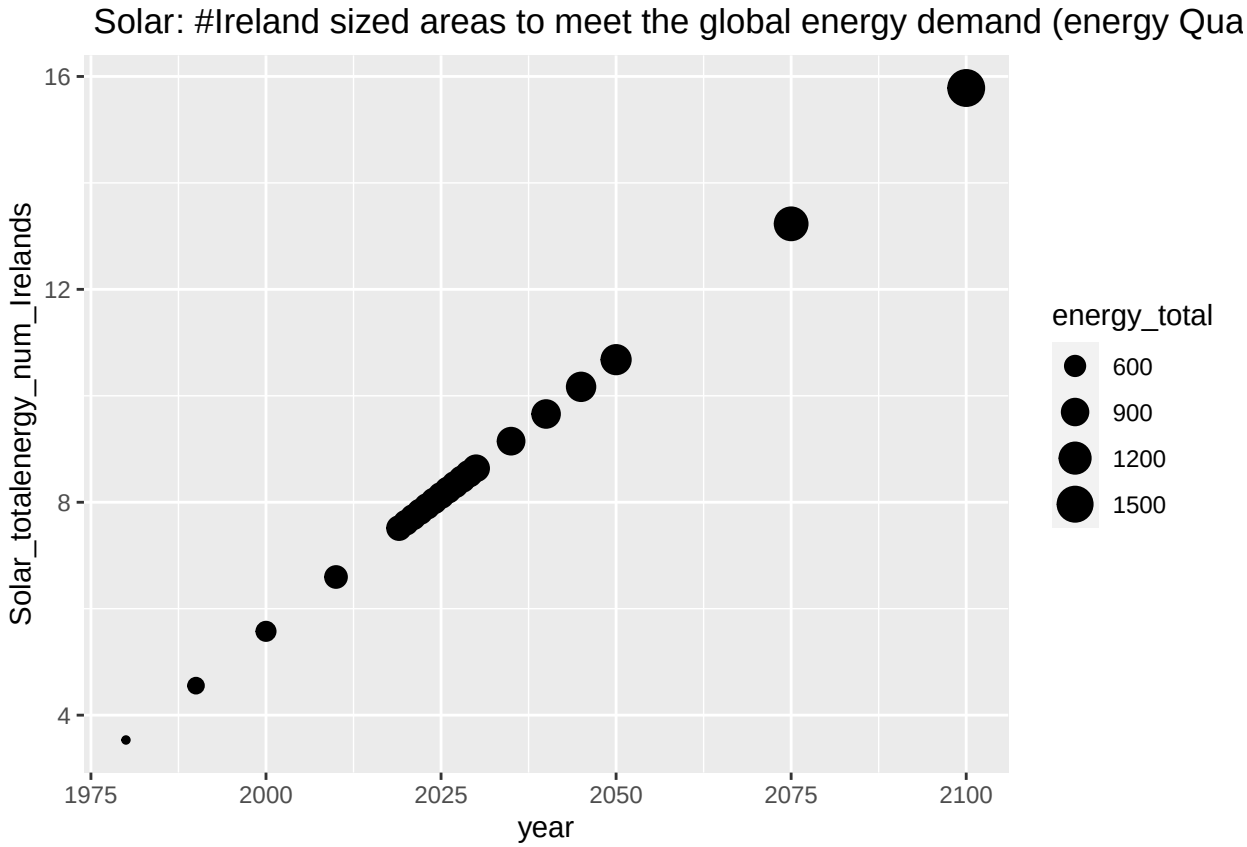
Assumptions for solar: 1) One square meter of solar cells generates 400 Kw hr per year and efficiency is 70% sunshine at 8 hr per day. 2) Therefore: 1 Quad= 10^15 BTU of energy or will require 755 Km2 of solar panels 3) Also 1 quad is approx equavlent to 183 million barrels of oil, 38.5 Million tons of coal or 980 billion cubic feet of natural gas. 4) How do we conceptualize the scale of the task? a) Two refinery locations at 250,000 BPD of oil processing is 1 Quad in a year (combined largest complex in the world that would exist today) b) Or appox 500 quad of energy would require a land area the size of Japan, Germany or a bit smaller than Spain. or approx 100 quad of energy would require a land area the size of Pannama or Ireland. c) or 1.2 Million wind turbines to generate 100 quads of energy which could fit into an area the scale of Delaware.

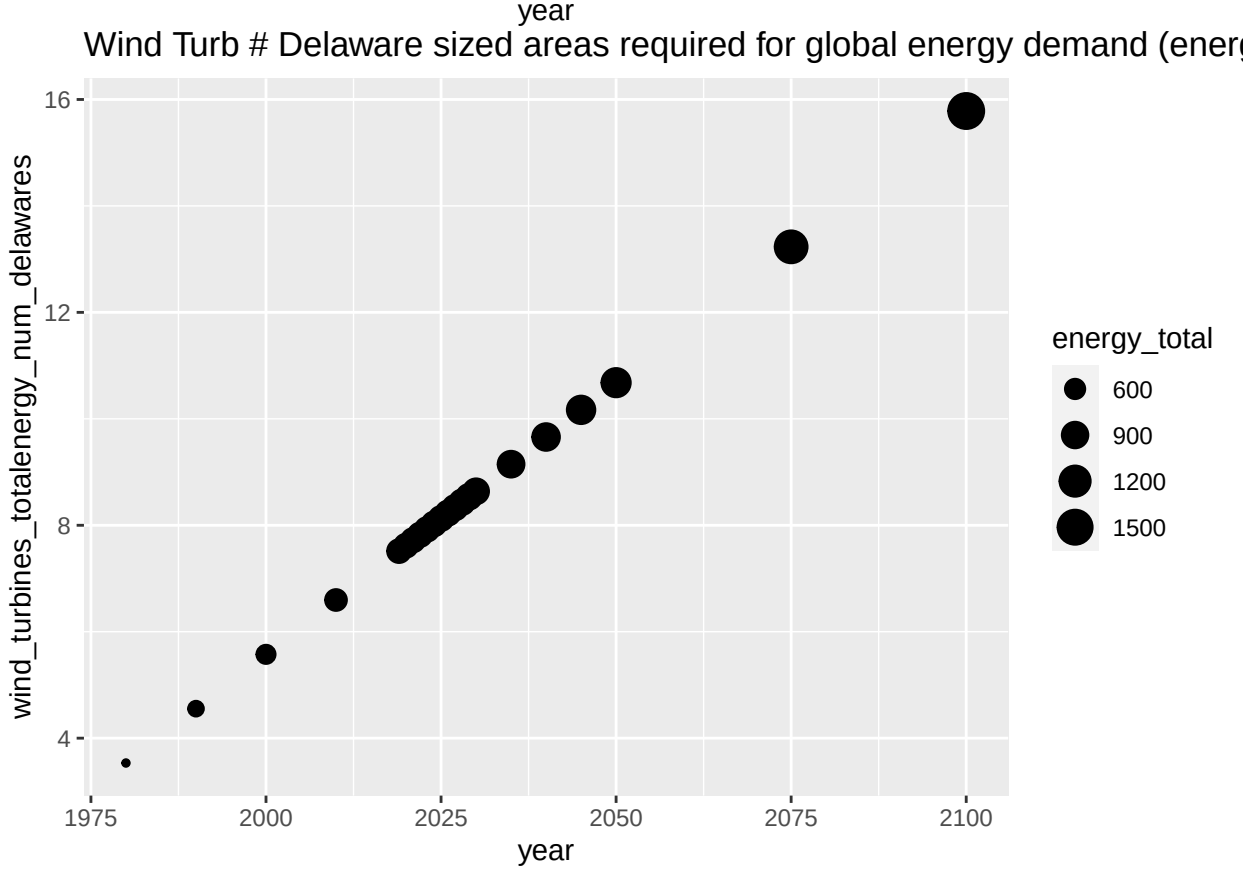
```
df_model<- df_model %>%mutate (Solar_total_energy_kmsquared=(energy_total*755),.after=year)
df_model<- df_model %>% mutate (Solar_totalenergy_num_Irelands=(Solar_total_energy_kmsquared/75500))

df_model<-df_model %>% mutate(Solar_renewable_energy_kmsquared=(energy_new_zerocarbon*755))
df_model<-df_model %>% mutate(Solar_renewable_num_Irelands=(Solar_renewable_energy_kmsquared/75500))

df_model<-df_model %>% mutate(wind_turbines_totalenergy=(energy_total/100*1200000))
df_model <-df_model %>% mutate(wind_turbines_totalenergy_num_delawares=(energy_total/100))
```

Plot relative measures of tasks scale to reduce CO2 Emissions with renewables

Renewable energy as solar or as wind turbines to supply total energy demand

Equivalent areas estimated to provide benchmark of the scale of the requirements


Solar: #Ireland sized areas to meet the global energy demand (energy Qua
Solar_totalenergy_num_Irelands
16
12
8
4
1975
2000
2025
2050
2075
2100
year
energy_total
600
900
1200
1500


Wind Turb # Delaware sized areas required for global energy demand (ener
wind_turbines_totalenergy_num_delawares
16
12
8
4
1975
2000
2025
2050
2075
2100
year
energy_total
600
900
1200
1500

Conclusions

~40 years of data from EIA provides good linear modules to represent the trend in energy demand, carbon emissions from fuel as it relates to GDP, Population (great R-squared correlations with multiple equation model to use in forecasting)

Model useful to drive understanding of task at hand to create a lower carbon future through forecasting into the future.

Future work/ improvements:

Evaluate model on regional basis and further utilize regional fuel mix.

Evaluate additional information on specific shifts in middle class, poverty, and urbanization related to energy use.

Evaluate more of the renewable mix sensitivity and include further economics (costs, benefits and non-linear growth potential)

Evaluate stronger means of developing forecast forward - extrapolation generally not recommended however based on strength of R-squared and p-values and the statistics is seems a good means of improving understanding.

References

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4. Hadley Wickham, Garret Grolemund.(2017) "R for Data Science" (OReilly)
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