Modern renewable energy consumption in R

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Overview:

In this project, a dataset include 5095 observations and 7 variables, The dataset is named “Modern renewable energy consumption”.

We see in this Project the rapid growth of renewable technologies in the World.

EDA DATA:

Data Understanding

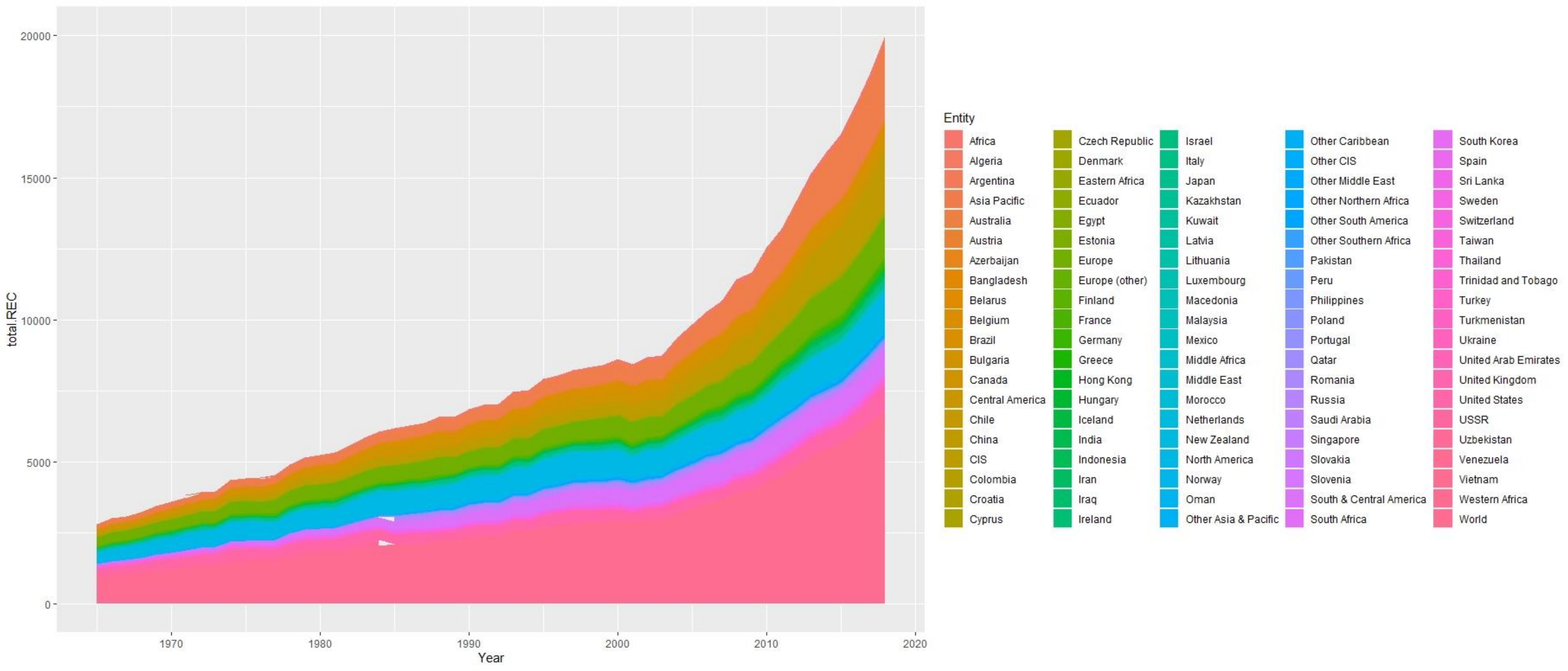
- In this project we looked at what share renewable technologies collectively accounted for in the energy mix.

- Globally we see that hydropower is by far the largest modern renewable source *[since traditional biomass is not included here]*. But we also see wind and solar power are both growing rapidly.

- The dataset have a 7 column. For understanding the dataset, Analysis and compare the data, 3 main columns by calculation added the dataset.

Data Understanding :

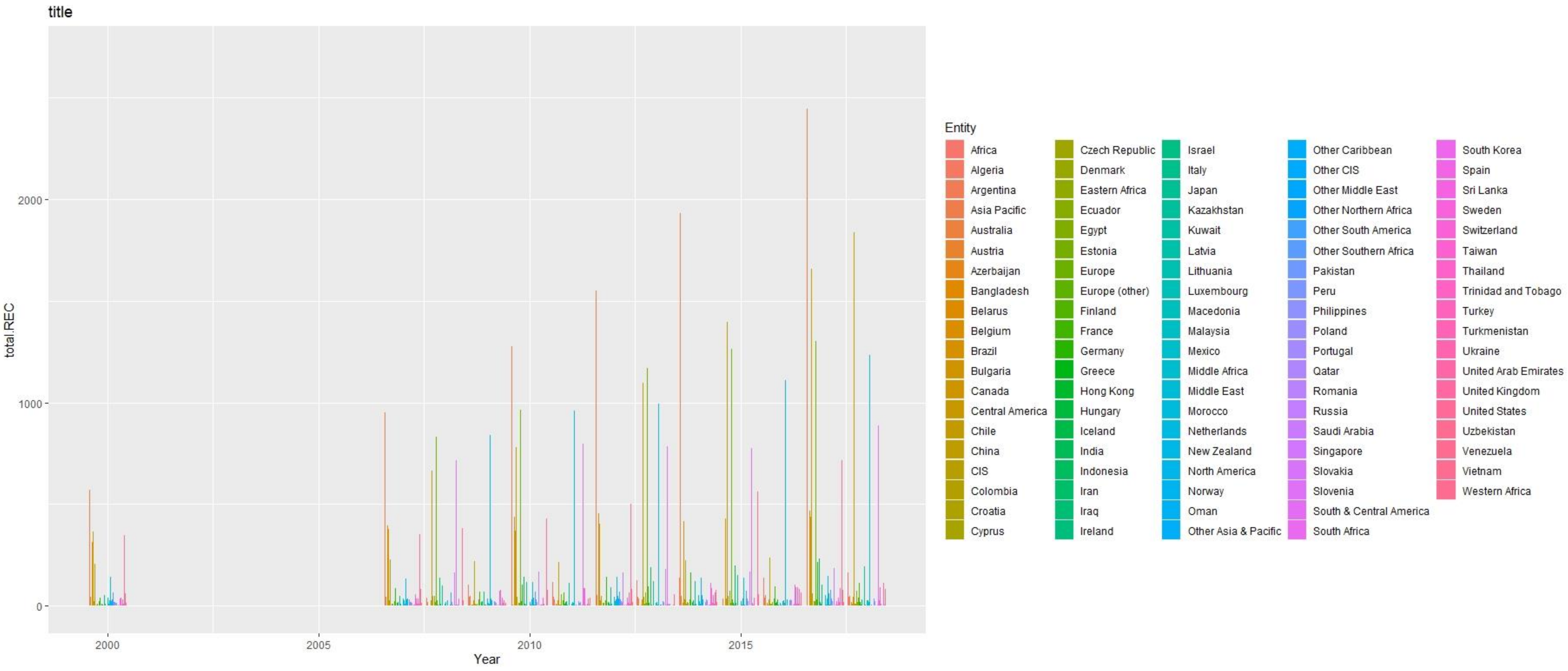
The chart shows this as a stacked area chart, which allows us to more readily see the breakdown of the renewable mix, and relative contribution of each.



Data Understanding:

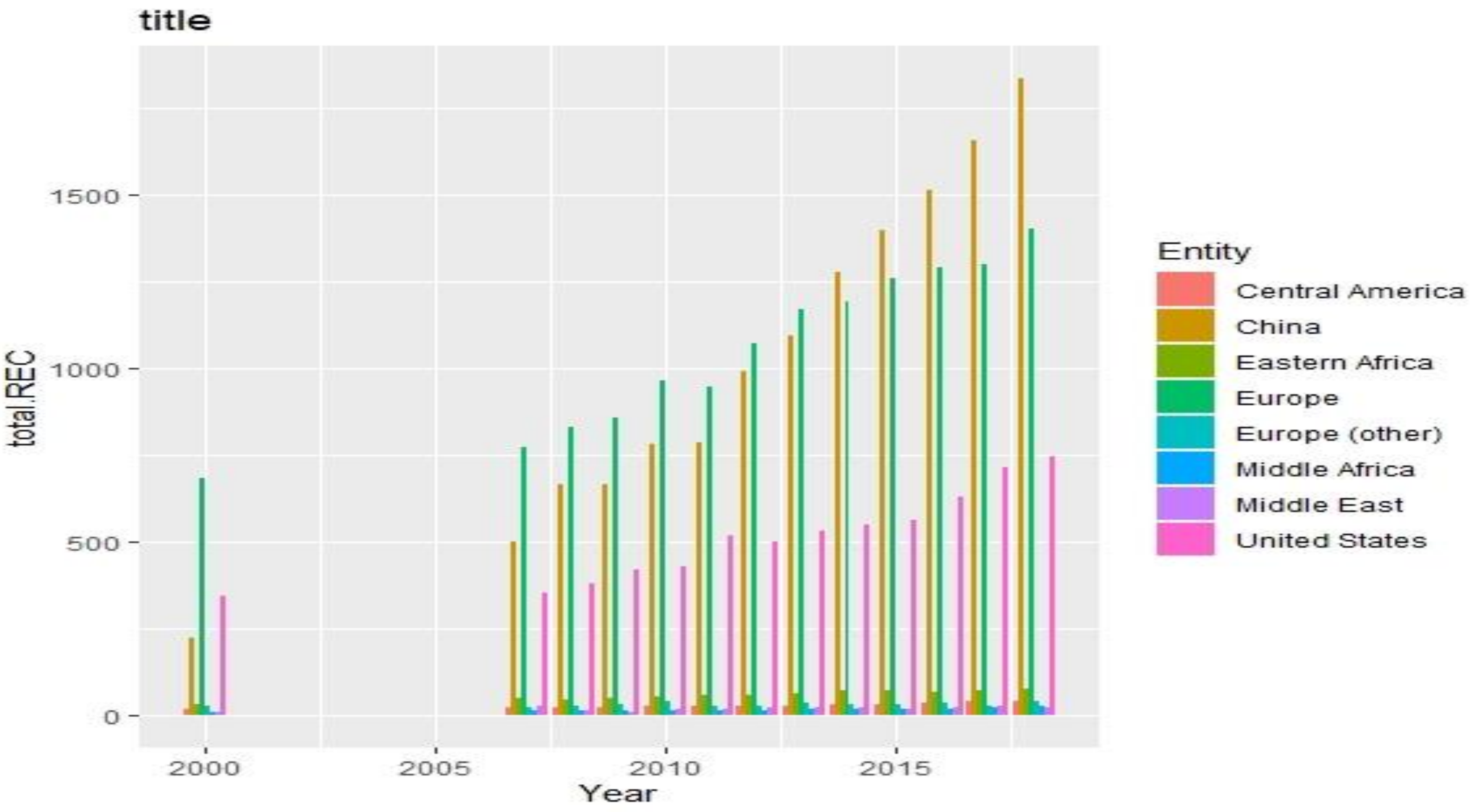
:

This Graph illustrated the Total Renewable Energy during the 1965 -2017. But the value before the 2007 is less, Therefore by using CUMSUM for cumulative the total consumption Renewable Energy during the 1965-2007, and after that the summation of that used this Graph. This is creating for visualization of data to understanding better.



Data Understanding:

This graph shows that 8 top consumer of Renewable Energy in the world.
To obtain this diagram, Filter, Subset and Full Joint commands have been used.



Data Understanding:

10 Top Consumption Renewable Energy

```
# A tibble: 1,089 x 8
# Groups:   Entity [99]
   Entity         Year Hydropower   Solar     Wind total.REC GROUPEntity$Entity
   <chr>         <int>      <dbl>   <dbl>    <dbl>     <dbl> <chr>
 1 World          2017      4065. 454.     1.13e+3     6232. World
 2 Asia Pacific   2017      1649. 227.     3.77e+2     2446. Asia Pacific
 3 China          2017      1165. 118.     2.95e+2     1657. China
 4 Europe         2017       585. 125.     3.84e+2     1302. Europe
 5 North Ameri~   2017       725.  82.5    2.97e+2     1204. North America
 6 South & Cen~   2017       720.   7.46   5.61e+1      860. South & Central A~
 7 United Stat~   2017       297.  78.1    2.57e+2      715. United States
 8 Brazil         2017       371.   0.832  4.24e+1      465. Brazil
 9 Canada         2017       397.   3.29   2.91e+1      439. Canada
10 CIS            2017       240.   0.767  5.98e-1      242. CIS
# ... with 1,079 more rows, and 1 more variable: Growth.rate <dbl>
> class(TOP.REC)
[1] "grouped_df" "tbl_df"     "tbl"        "data.frame"
```

Data Understanding:

Getting familiar with data for Data Understanding in EDA.
Data frame has a 5059 observation and 7 columns. The missing value can be seen in the dataset. The important column is Entity, Year , Hydropower, Solar and Wind, So by using slice the column of Code dropped at the dataset.

```
> typeof(REC)
[1] "list"
> # Compactly Display the Structure of an Arbitrary R Object
> str(REC)
'data.frame':   5095 obs. of  7 variables:
 $ Entity         : chr  "Africa" "Africa" "Africa" "Africa" ...
 $ Code           : chr  NA NA NA NA ...
 $ Year           : int  1965 1966 1967 1968 1969 1970 1971 1971 1971 1971 ...
 $ Hydropower     : num  14.3 15.6 16.2 18.6 21.6 ...
 $ Solar          : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Wind           : num  0 0 0 0 0 0 0 0 0 0 ...
 $ OtherRenewables: num  0 0 0 0 0 0 0.164 0.164 0.164 0.164 ...
> 
```

Data preparation:

For preparation the dataset 3 COLUMNS is add to dataset:

1. "total.REC"

```
REC$total.REC <- NA
REC$total.REC <- rowSums(REC[ ,c(3:6)], na.rm=TRUE)
```

2.GROUPEntity

```
NEWREC$GROUPEntity <- NEWREC %>% group_by(Entity)
```

3. cumulative REC consumption

```
NEWREC$cum_total <- cumsum(NEWREC$total.REC)
```

4. "Growth.rate“: Growth rate per annul

```
RECF <- NEWREC %>% group_by(Entity) %>% mutate(Growth.rate = (total.REC -
lag(total.REC))/lag(total.REC))
```

Data preparation:

Data preparation or Data cleaning is:

1) Handling duplicate data
2) Handling Missing Values
3) Handling outliers

❖ By using frequency in a dataset is observed
That data duplication exists in Africa.
This problem is solved by using the
Duplicated command.

❖ For handling Missing value in project is
Is used command in R.

❖ This project has outlier but this outlier it
is important for analysis of data. Because this
Outlier happened due to the rapid scientific progress
In this field recently.

```
> # since target is categorical variable, in uni-variate Analysis for summarizing I
> # will find frequency and for visualization I plot: pie chart or bar-chart
> tbl<-table(REC$ Entity)
> tbl

              Africa                 Algeria               Argentina            Asia Pacific
                  58                      54                      54                      54
           Australia                 Austria              Azerbaijan              Bangladesh
                  54                      54                      34                      54
             Belarus                 Belgium                  Brazil                Bulgaria
                  34                      54                      54                      54
              Canada         Central America                   Chile                   China
                  54                      54                      54                      54
                 CIS                Colombia                 Croatia                  Cyprus
                  54                      54                      29                      54
      Czech Republic                 Denmark          Eastern Africa                 Ecuador
                  54                      54                      54                      54
               Egypt                 Estonia                  Europe          Europe (other)
                  54                      34                      54                      54
             Finland                  France                 Germany                  Greece
                  54                      54                      54                      54
           Hong Kong                 Hungary                 Iceland                   India
                  54                      54                      54                      54
           Indonesia                    Iran                    Iraq                 Ireland
                  54                      54                      54                      54
              Israel                   Italy                   Japan              Kazakhstan
                  54                      54                      54                      34
              Kuwait                  Latvia               Lithuania              Luxembourg
                  54                      34                      34                      54
           Macedonia                Malaysia                  Mexico           Middle Africa
                  29                      54                      54                      54
         Middle East                 Morocco             Netherlands             New Zealand
                  54                      54                      54                      54
       North America                  Norway                    Oman     Other Asia & Pacific
                  54                      54                      54                      54
     Other Caribbean               Other CIS       Other Middle East    Other Northern Africa
                  54                      34                      54                      54
 Other South America    Other Southern Africa                Pakistan                    Peru
                  54                      54                      54                      54
         Philippines                  Poland                Portugal                   Qatar
                  54                      54                      54                      54
             Romania                  Russia            Saudi Arabia               Singapore
                  54                      34                      54                      54
            Slovakia                Slovenia South & Central America            South Africa
                  54                      29                      54                      54
         South Korea                   Spain               Sri Lanka                  Sweden
                  54                      54                      54                      54
         Switzerland                  Taiwan                Thailand     Trinidad and Tobago
                  54                      54                      54                      54
              Turkey            Turkmenistan                 Ukraine    United Arab Emirates
                  54                      34                      54                      54
      United Kingdom           United States                    USSR              Uzbekistan
                  54                      54                      20                      34
           Venezuela                 Vietnam          Western Africa                   World
                  54                      54                      54                      54
```

Univariate analysis:

Central tendency(mean, median,), five-number-summary, standard deviation, variance

	Hydropower	Solar	Wind	Other Renewable Energy	Total Of Renewable Energy
Mean	74.02	1.31	4.7	5.7	85.79
Median	6.03	0	0	0.042	7.53
Standard deviation	284.48	15.3	41.77	29.1	348.9
IQR	29.1	00.2	0.03	1.3	31.98

Hydropower	Solar	Wind	Other Renewable Energy	Total Of Renewable Energy
0.00000	0.000000e+00	0.000000e+00	0.0000	0.000000
0.81007	0.000000e+00	0.000000e+00	0.0000	1.204431
6.03100	0.000000e+00	0.000000e+00	0.0420	7.527449
29.93543	2.052632e-03	3.030303e-02	1.3099	33.187437
4193.10415	5.846309e+02	1.269953e+03	625.8054	6673.493806

Univariate analysis:

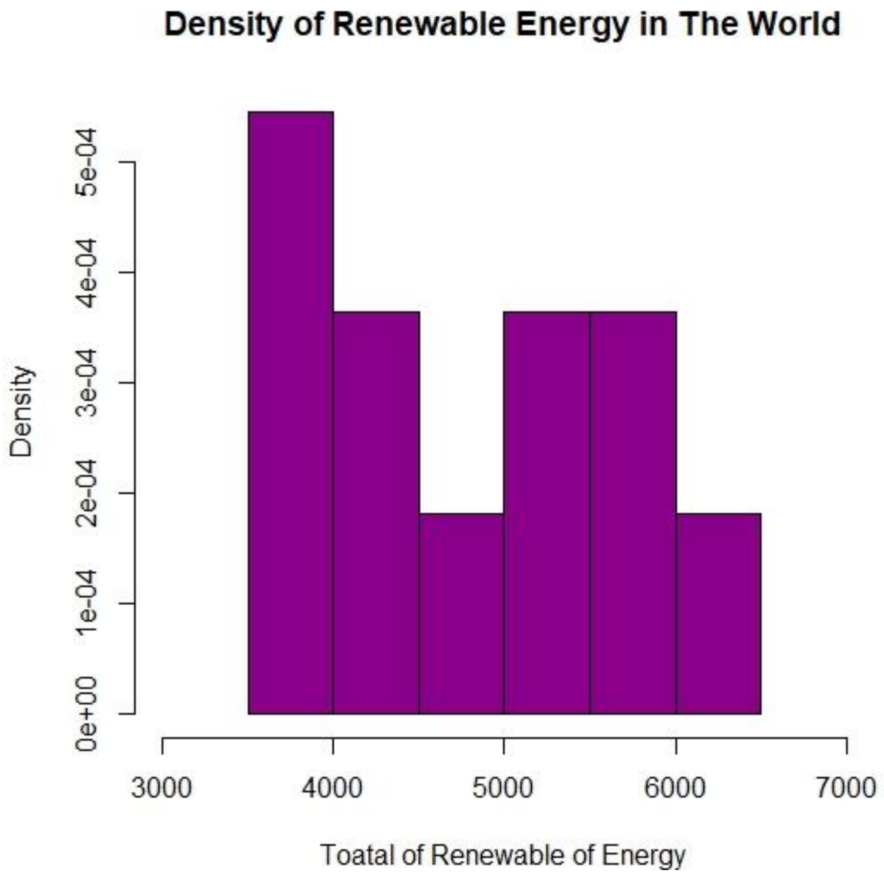
sapply(NUMdata, quantile, probs = seq(0, 1, 1/10), na.rm = TRUE)

For atain quartile is used 1/10 for porobs to get 10 quartile for dataset to accuaracy in distribution of data.

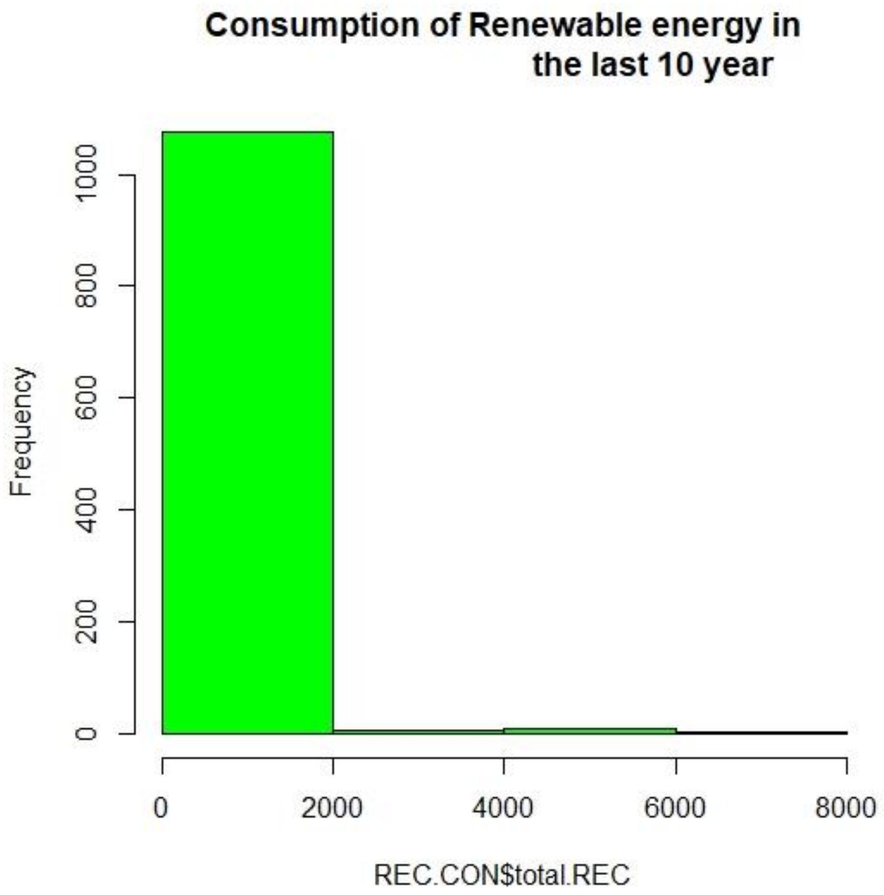
```
> sapply(NUMdata, quantile, probs = seq(0, 1, 1/10), na.rm = TRUE)
       Hydropower         Solar         Wind OtherRenewables    total.REC Rtotal.REC
0%       0.000000    0.00000000     0.000000        0.000000     0.000000      0.000
10%      0.000000    0.00000000     0.000000        0.000000     0.020040      0.020
20%      0.325420    0.00000000     0.000000        0.000000     0.600000      0.600
30%      1.480799    0.00000000     0.000000        0.000000     1.938000      1.940
40%      3.279117    0.00000000     0.000000        0.000000     3.911568      3.910
50%      6.031000    0.00000000     0.000000        0.042000     7.527449      7.530
60%     12.192727    0.00000000     0.000000        0.200792    14.405273     14.408
70%     21.542278    0.00015476     0.006000        0.685000    25.186939     25.184
80%     41.507005    0.00855600     0.122622        2.098000    47.478641     47.480
90%    141.900200    0.17390778     1.720150        8.137519   159.725955    159.730
100%  4193.104151  584.63091780  1269.953375      625.805362  6673.493806   6673.490
> 
```

Univariate analysis:

This diagram shows the consumption of renewable energy versus density.

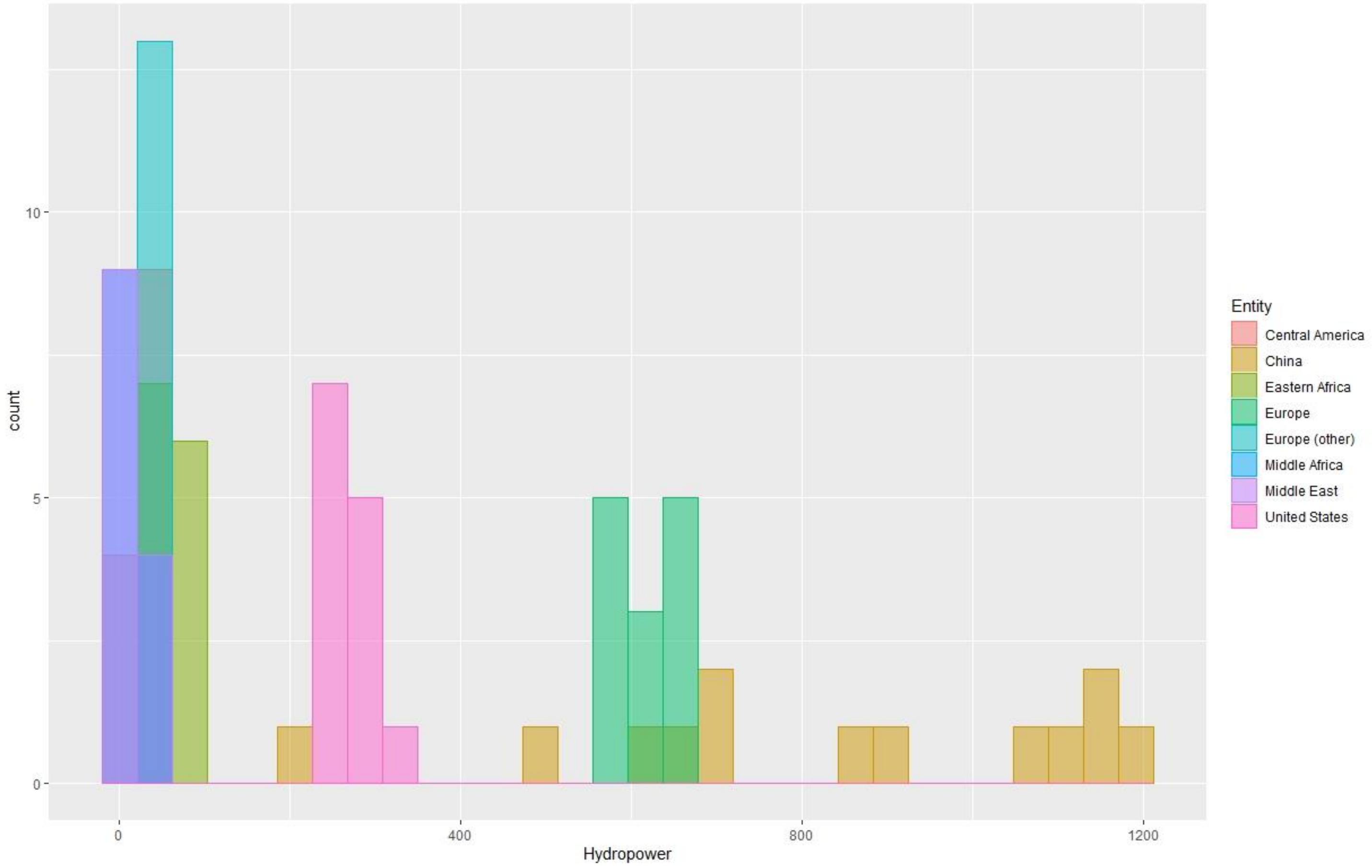


The distribution of “total.REC” shows us , we have mutated recently. Consumption of renewable of energy in the last 10 years has been divided into 4 bins. And this graph shows the jump in new energy consumption in recent years.



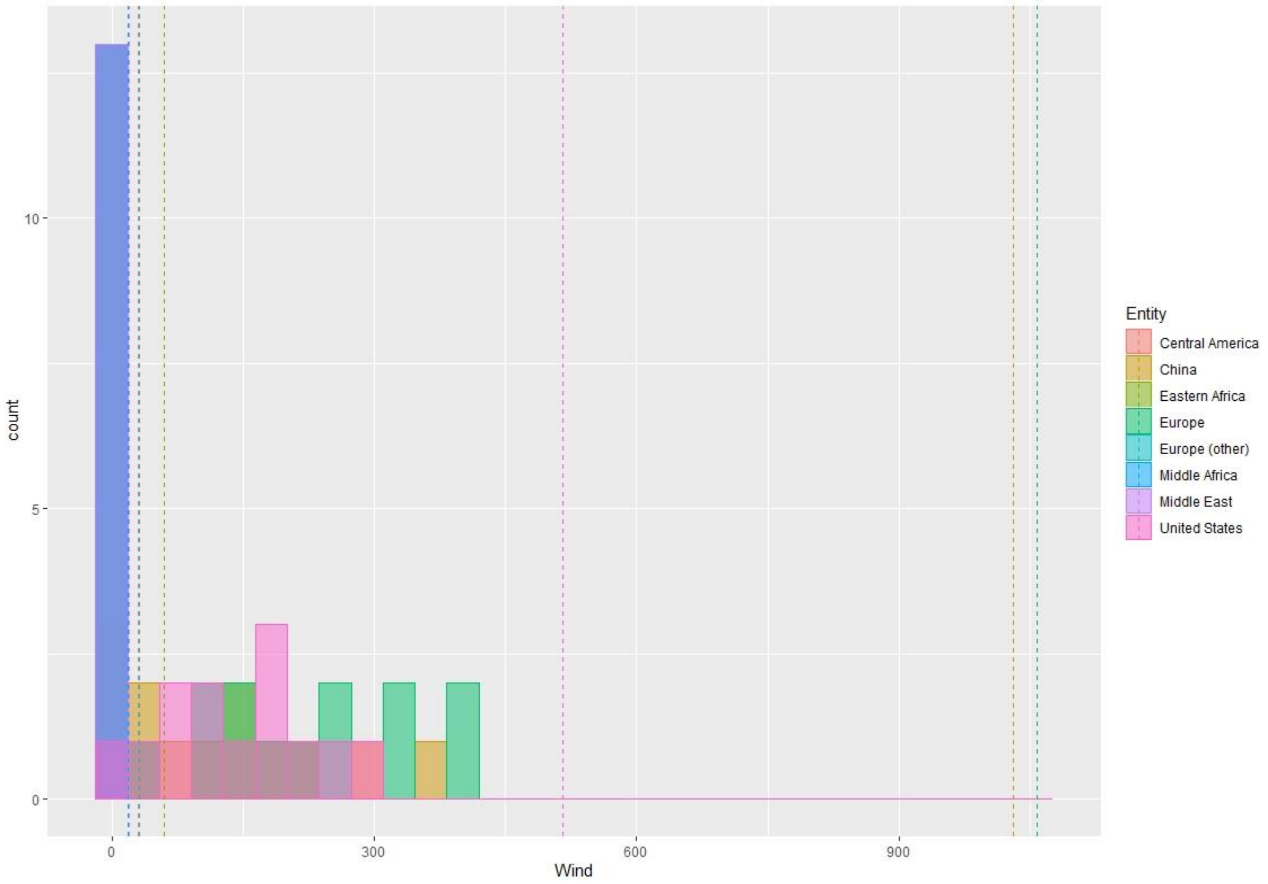
Analysis for Numerical columns:

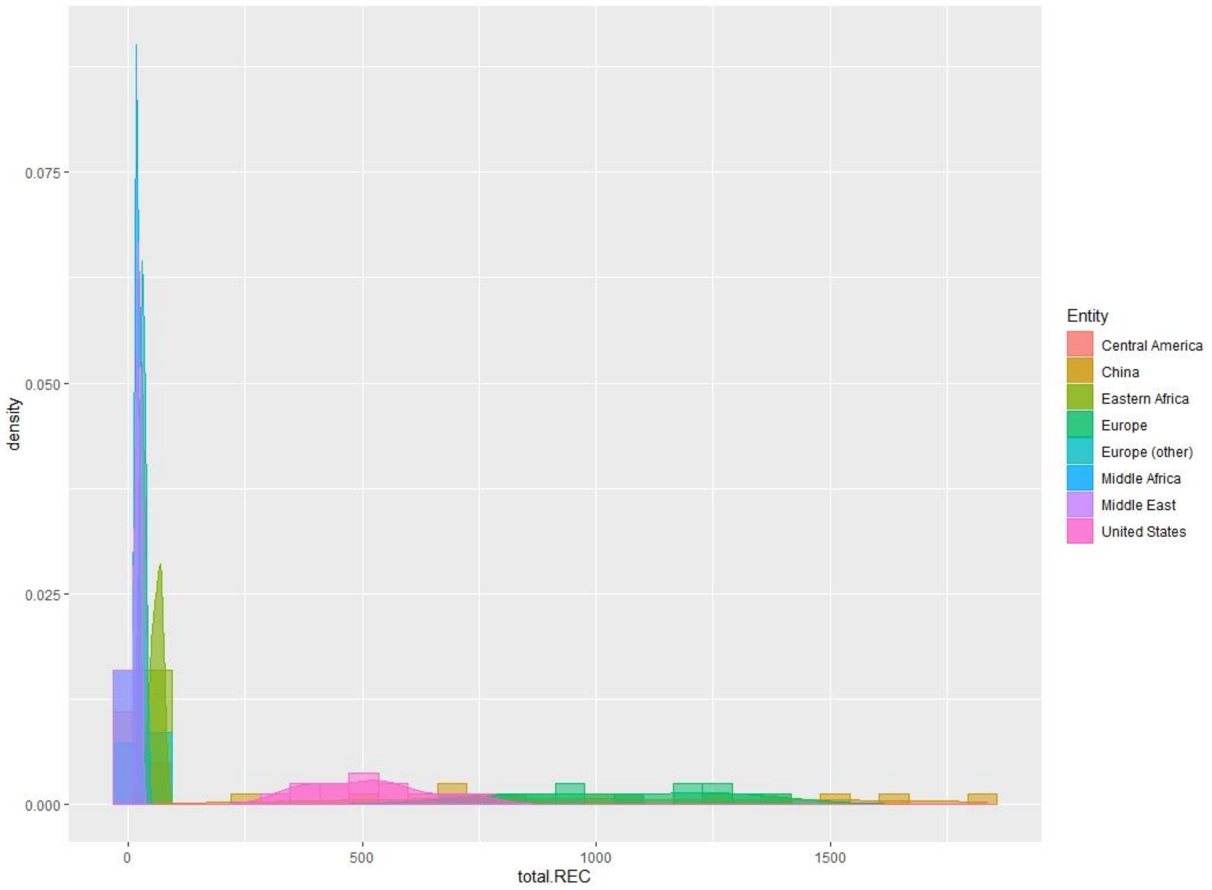
Analysis for continuous(Hydropower) Vs. count



Analysis for Numerical columns:

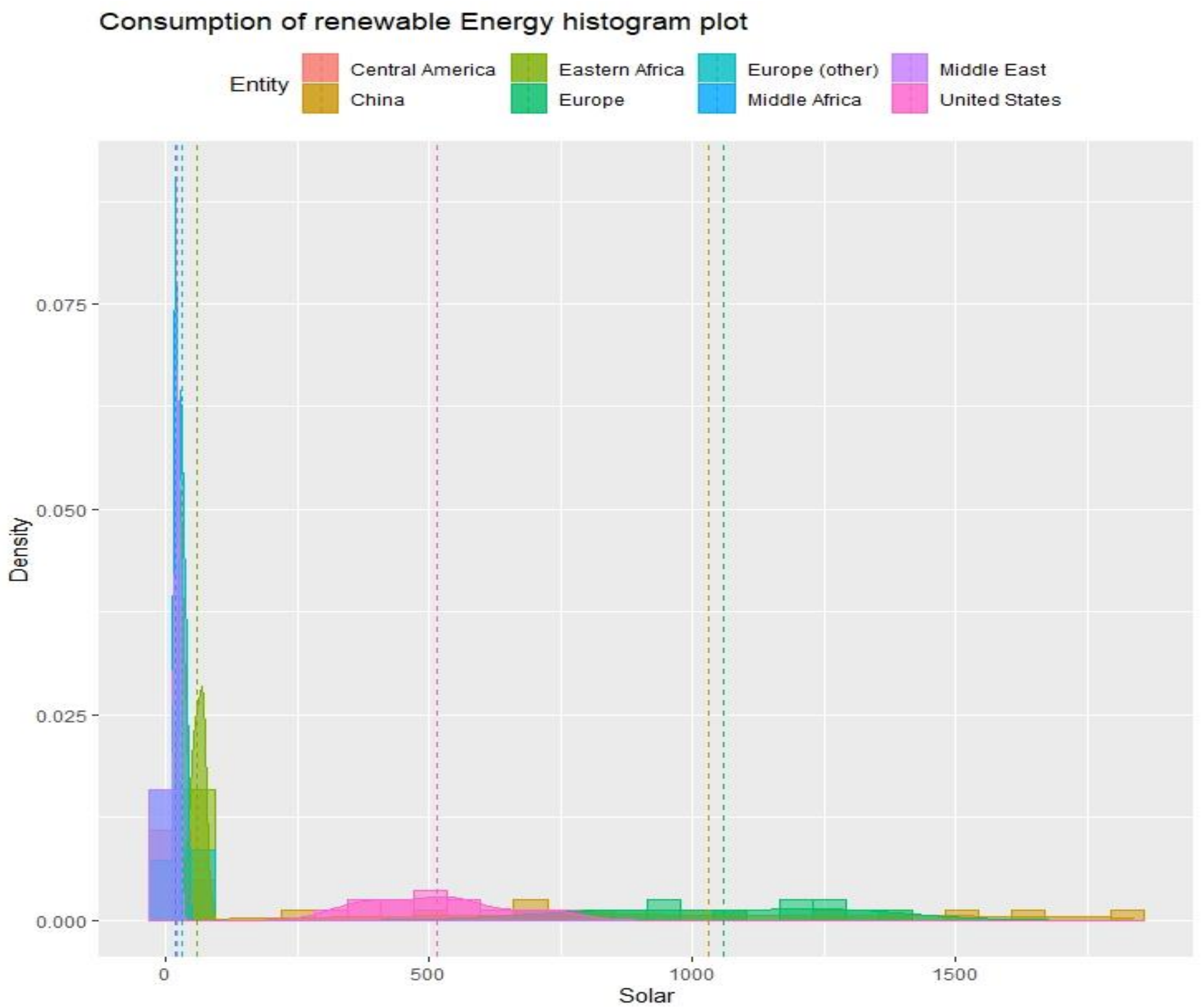
This graph shows , the total of renewable Energy versus density.





Analysis for Numerical columns:

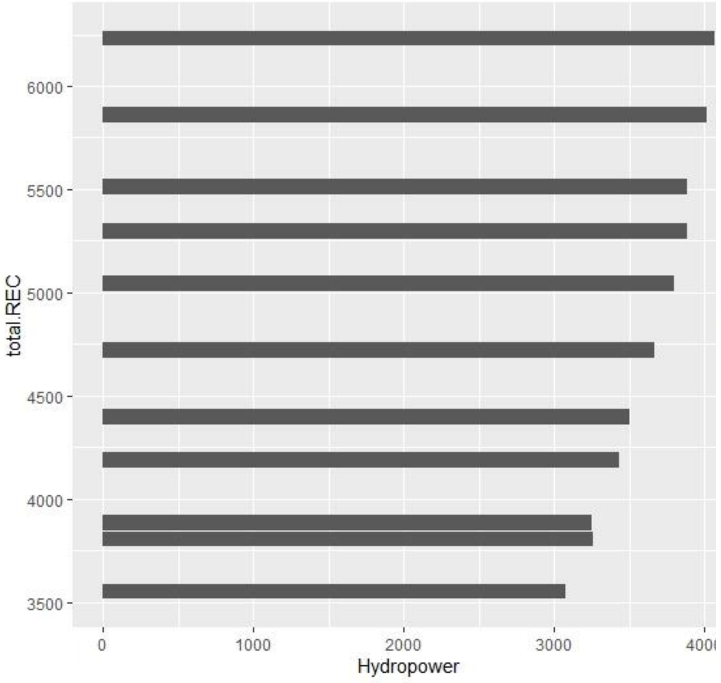
This graph shows , the Solar Energy versus density.

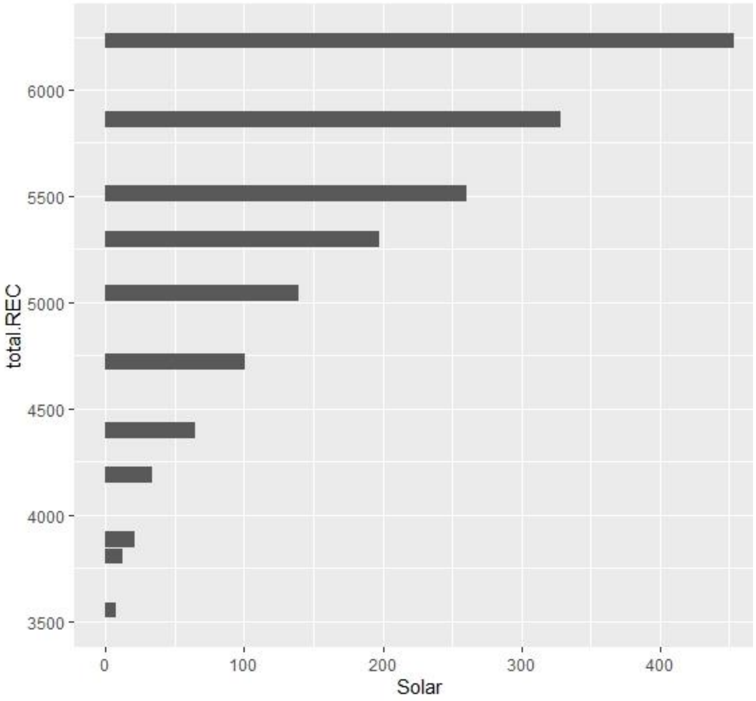


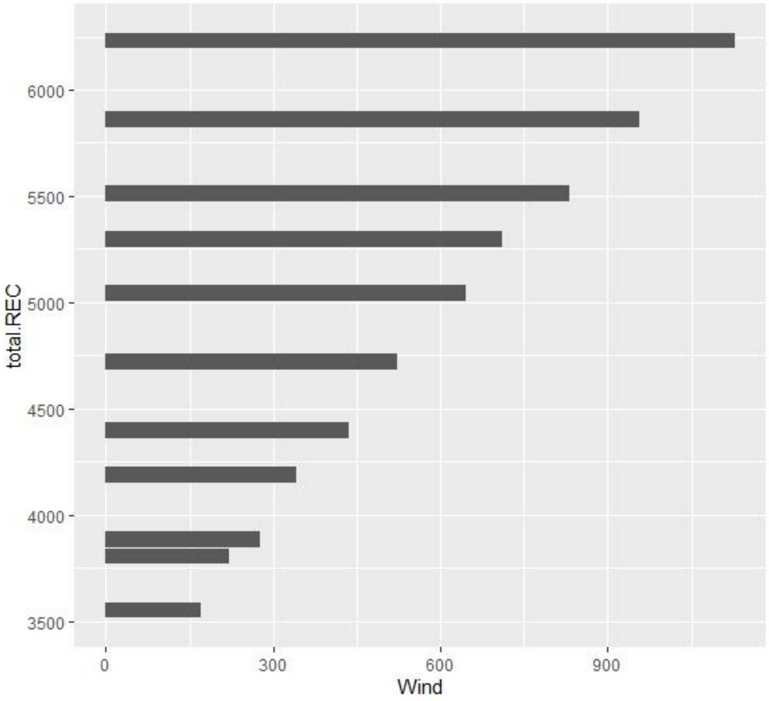
bi-variate Analysis for Numerical columns

The amount of Consumption Hydropower, Wind and Solar energy of the total of energy.

In charts shown here we look at the breakdown of renewable technologies by their individual components – hydropower, solar, wind, and others.

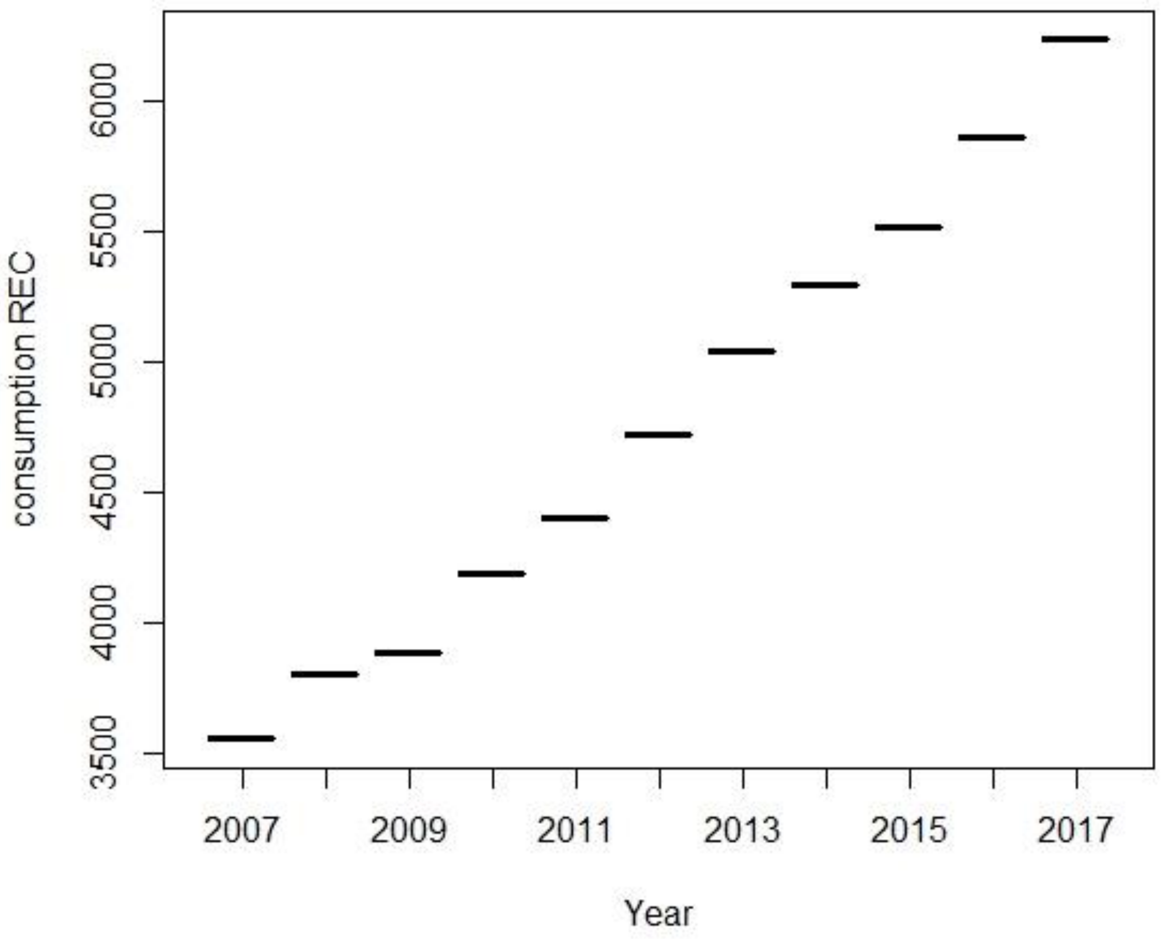






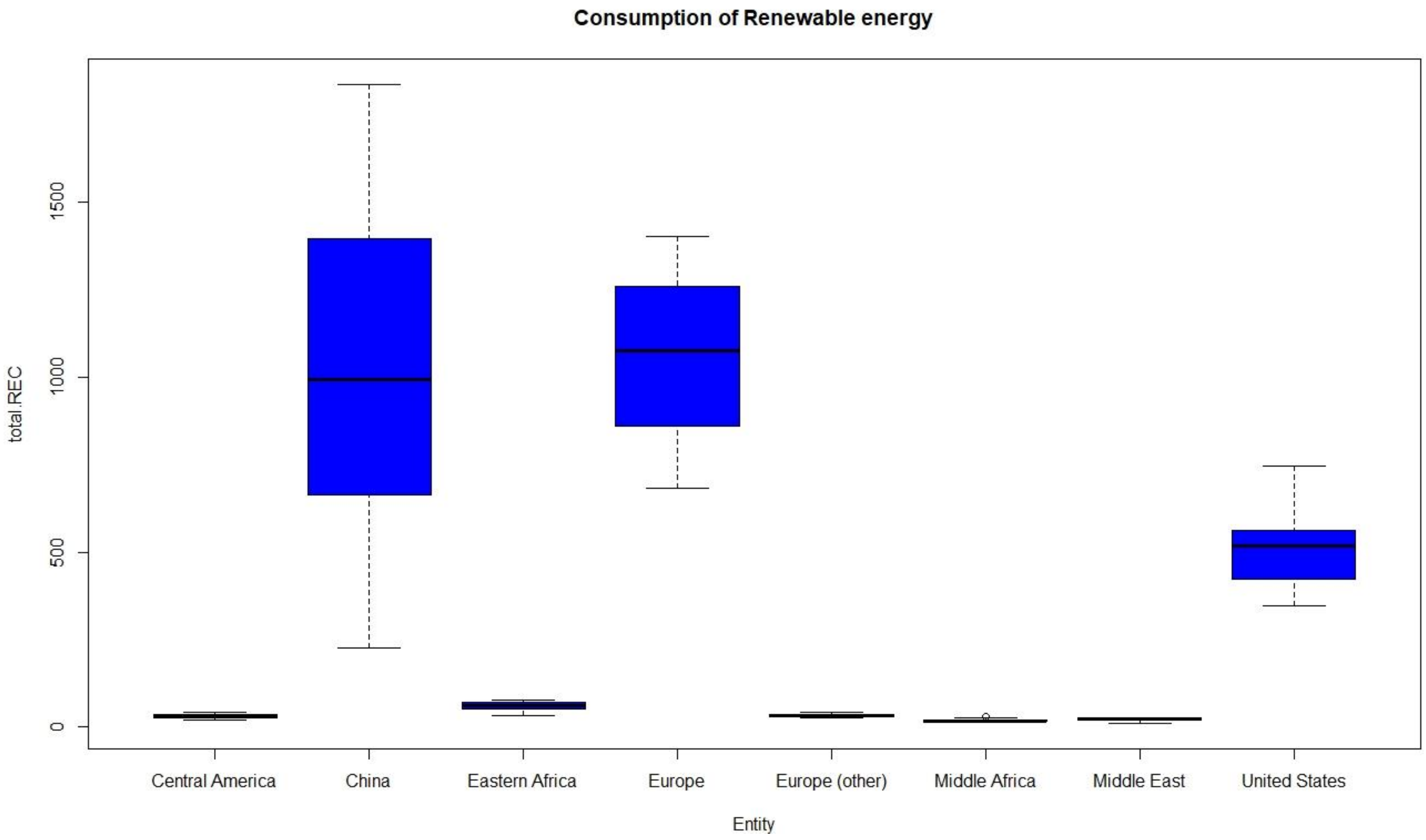
bi-variate Analysis for Numerical columns:

Consumption Renewable Energy during the 2007-2017 in the word.



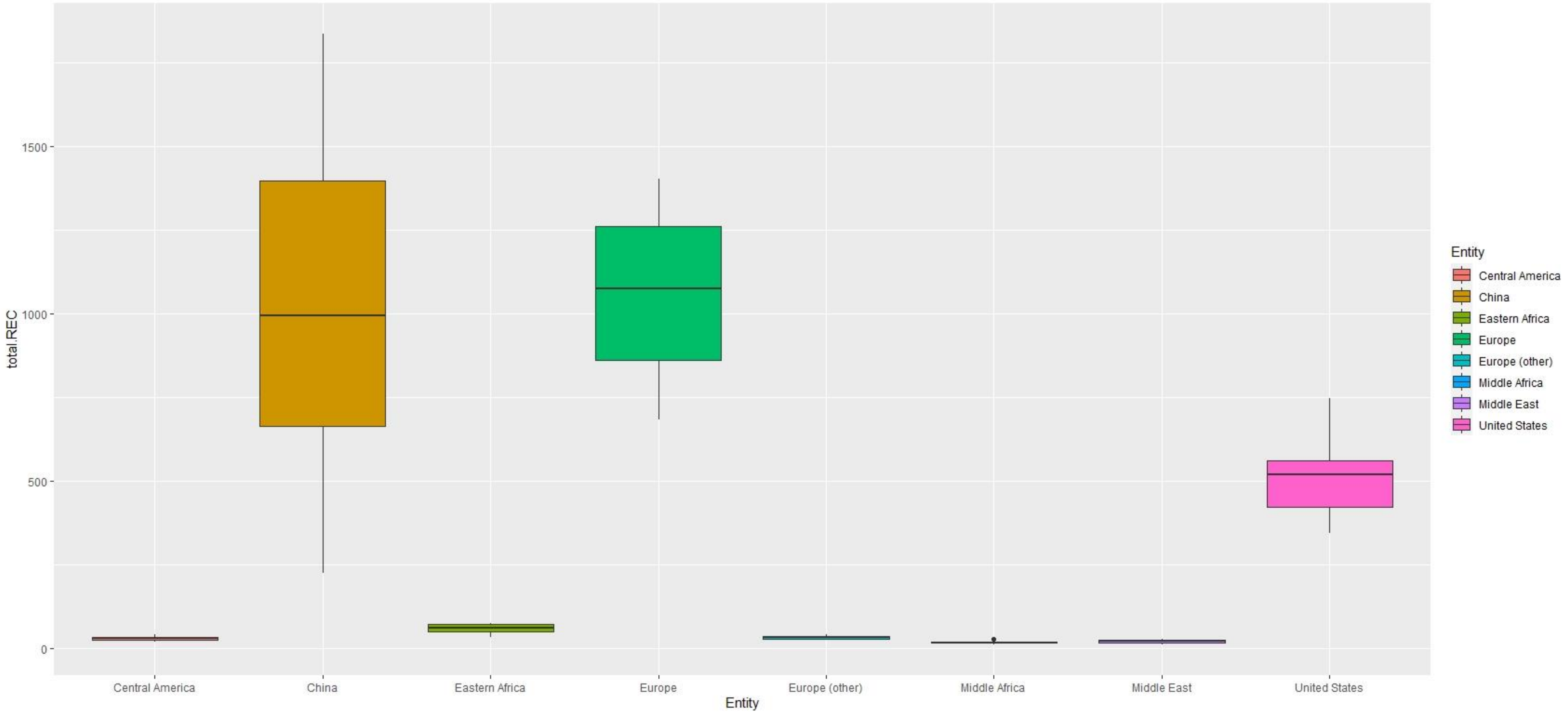
bi-variate Analysis for Numerical columns:

This graph illustrated the most consumption Of Renewable Energy in the world are China, Europe and United States.



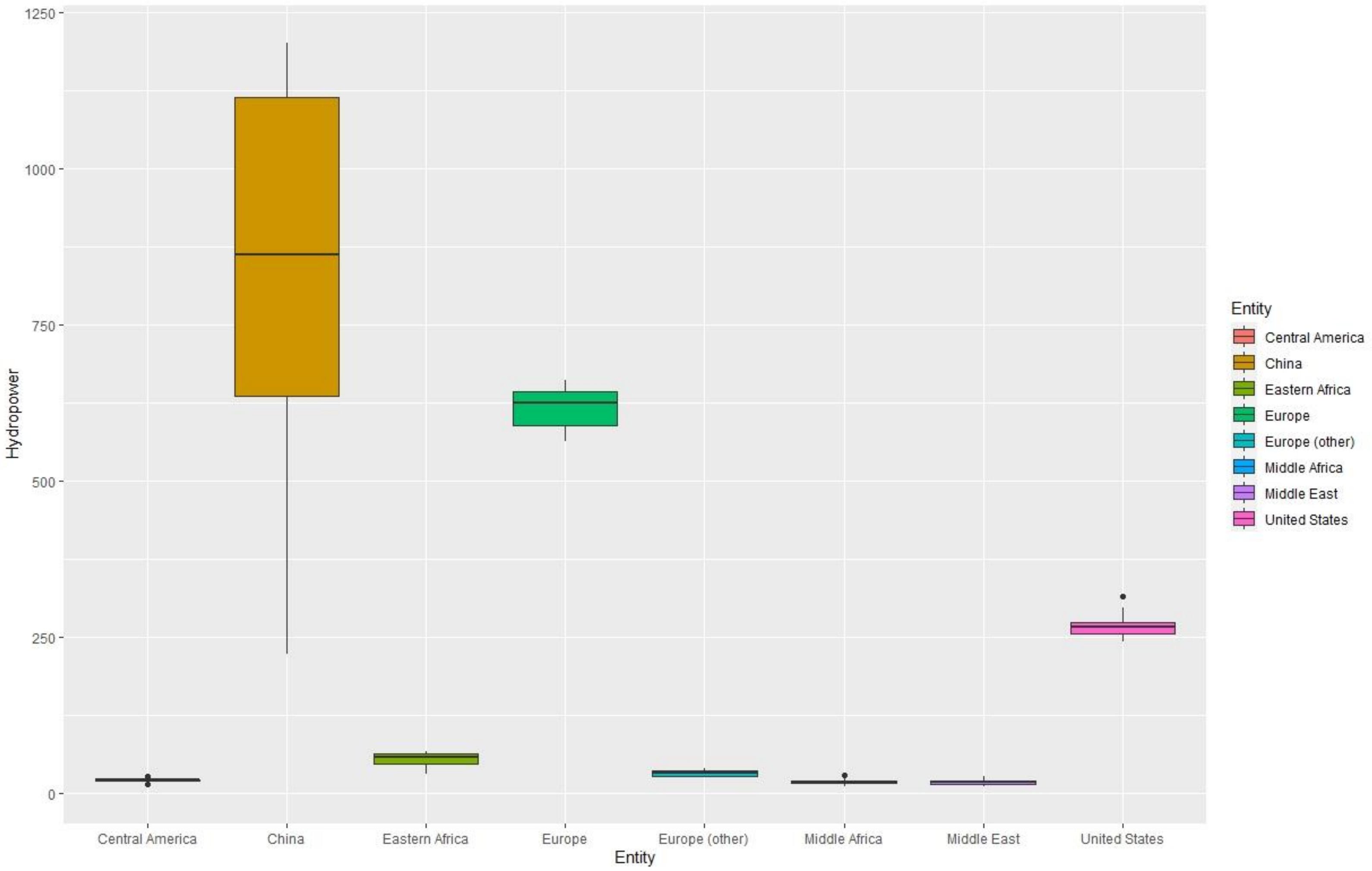
bi-variate Analysis for Numerical columns:

Bi-variate Analysis for continuous(total.REC) Vs. categorical (Entity)



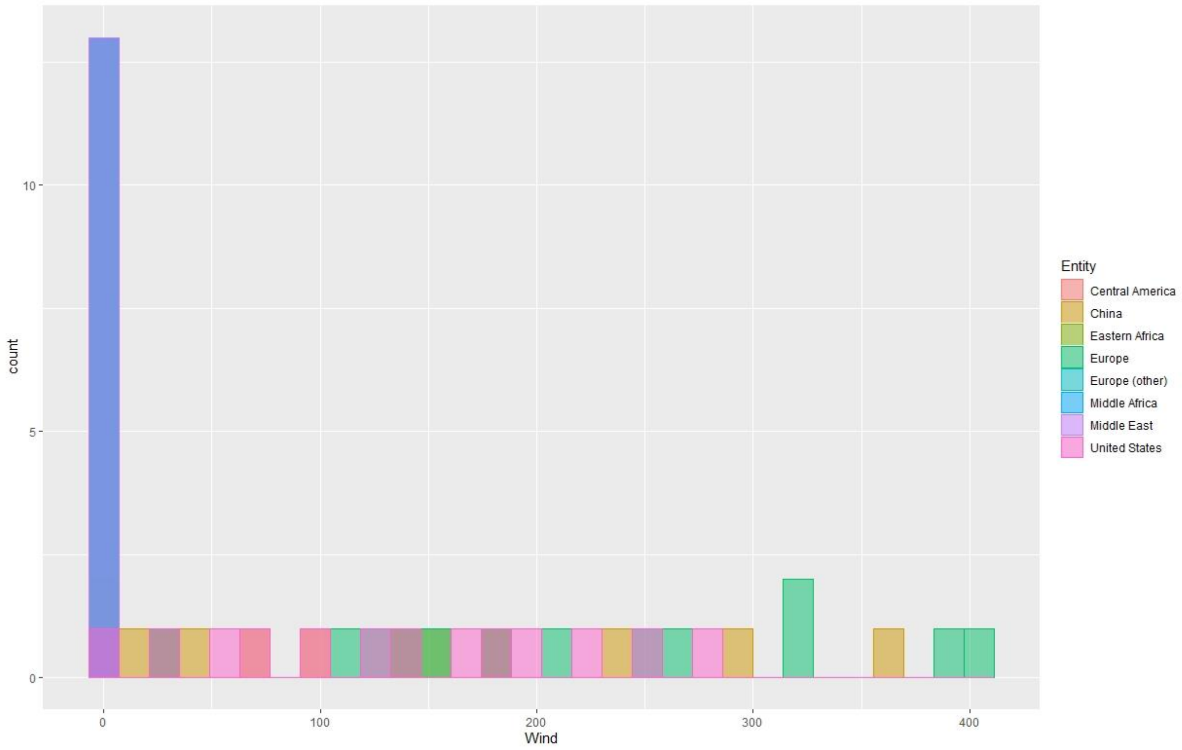
bi-variate Analysis for Numerical columns:

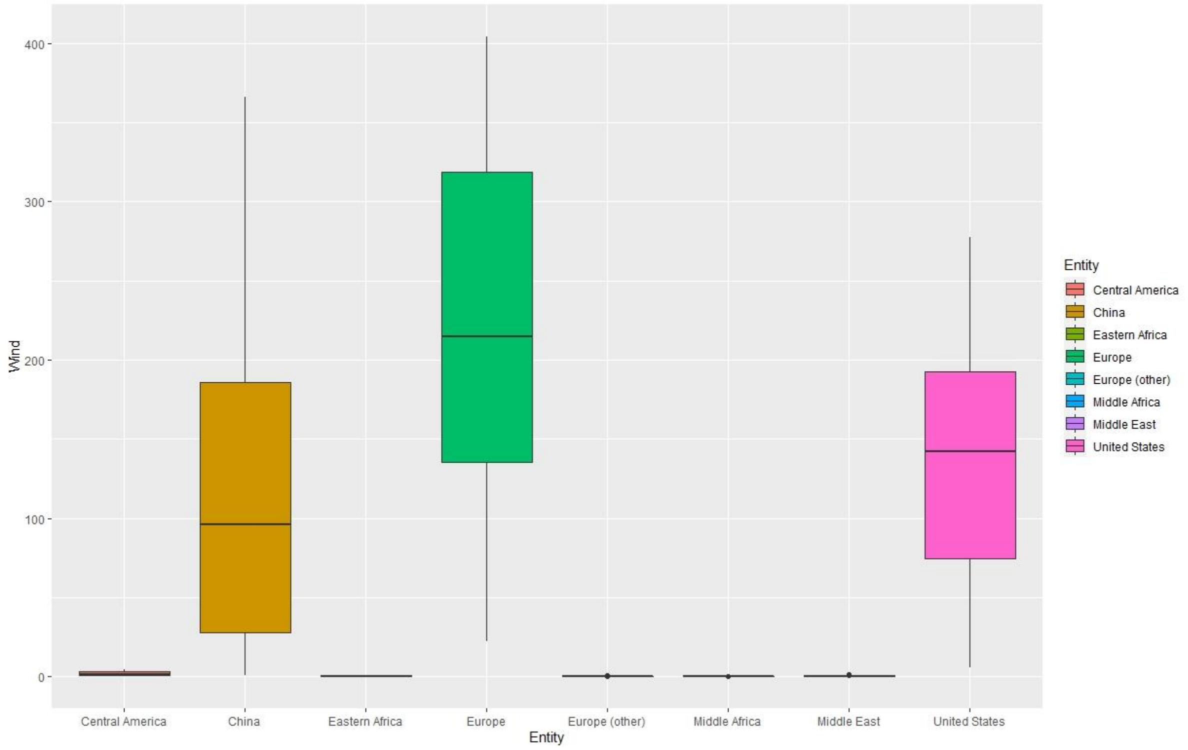
Bi-variate Analysis for continuous(Hydropower) Vs. categorical (Entity)



bi-variate Analysis for Numerical columns:

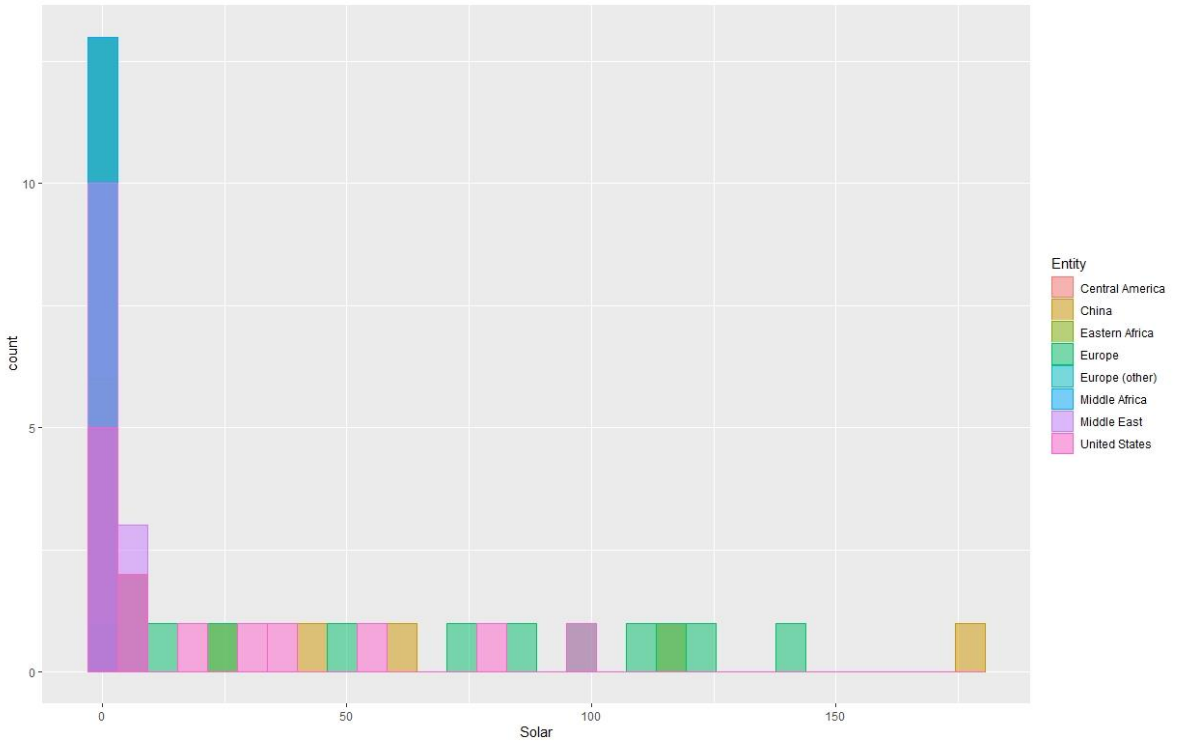
Bi-variate Analysis for continuous (Wind) Vs. categorical (Entity)

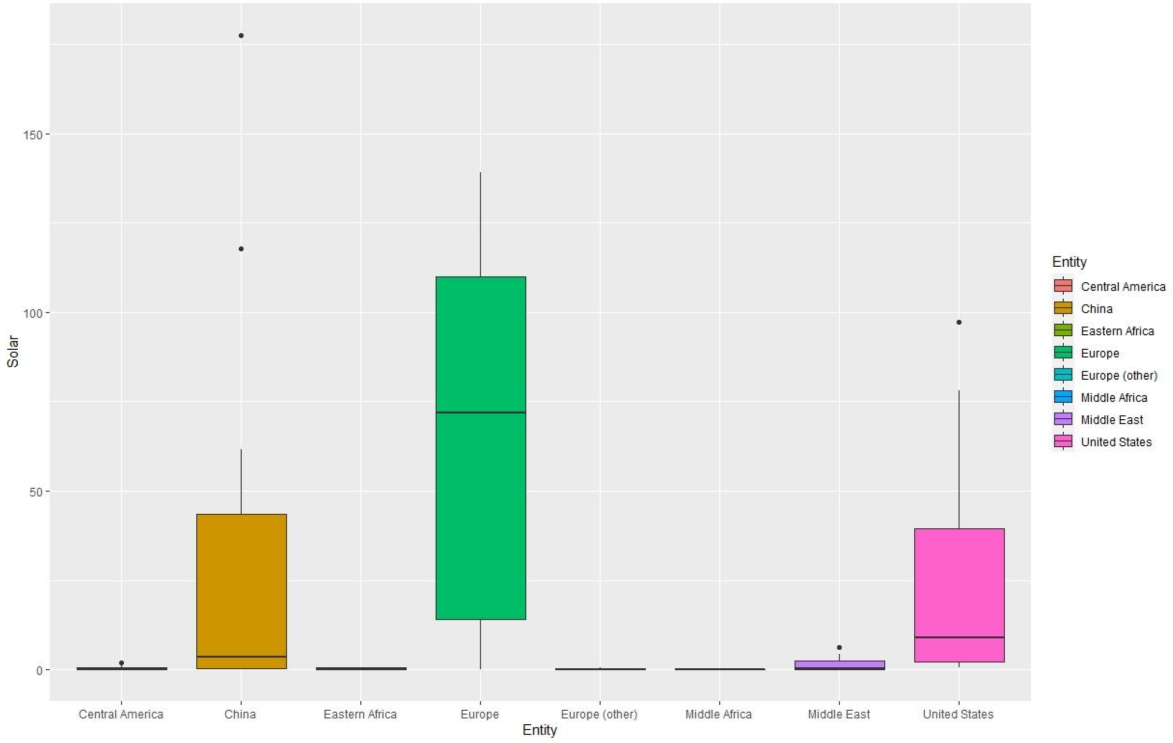




bi-variate Analysis for Numerical columns:

Bi-variate Analysis for continuous (Wind) Vs. categorical (Entity)





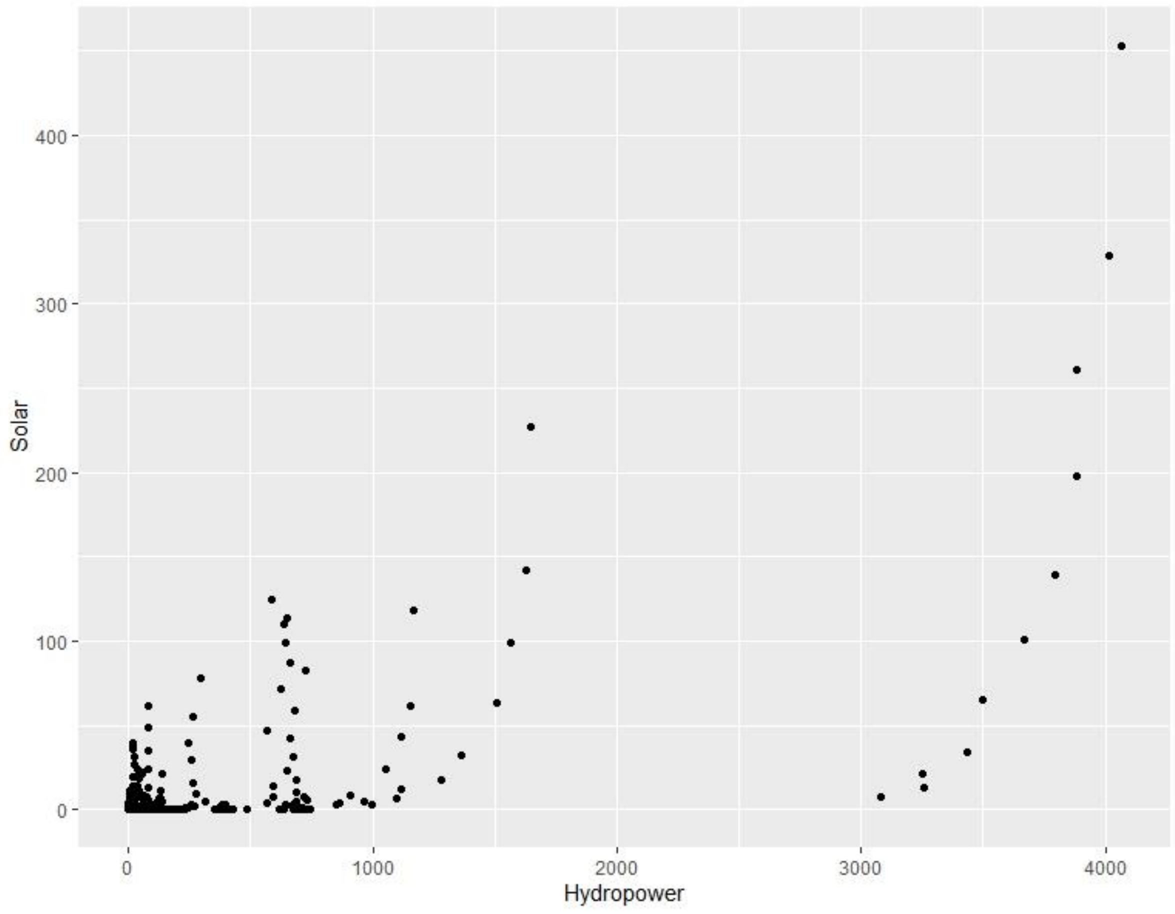
bi-variate Analysis for Numerical columns:

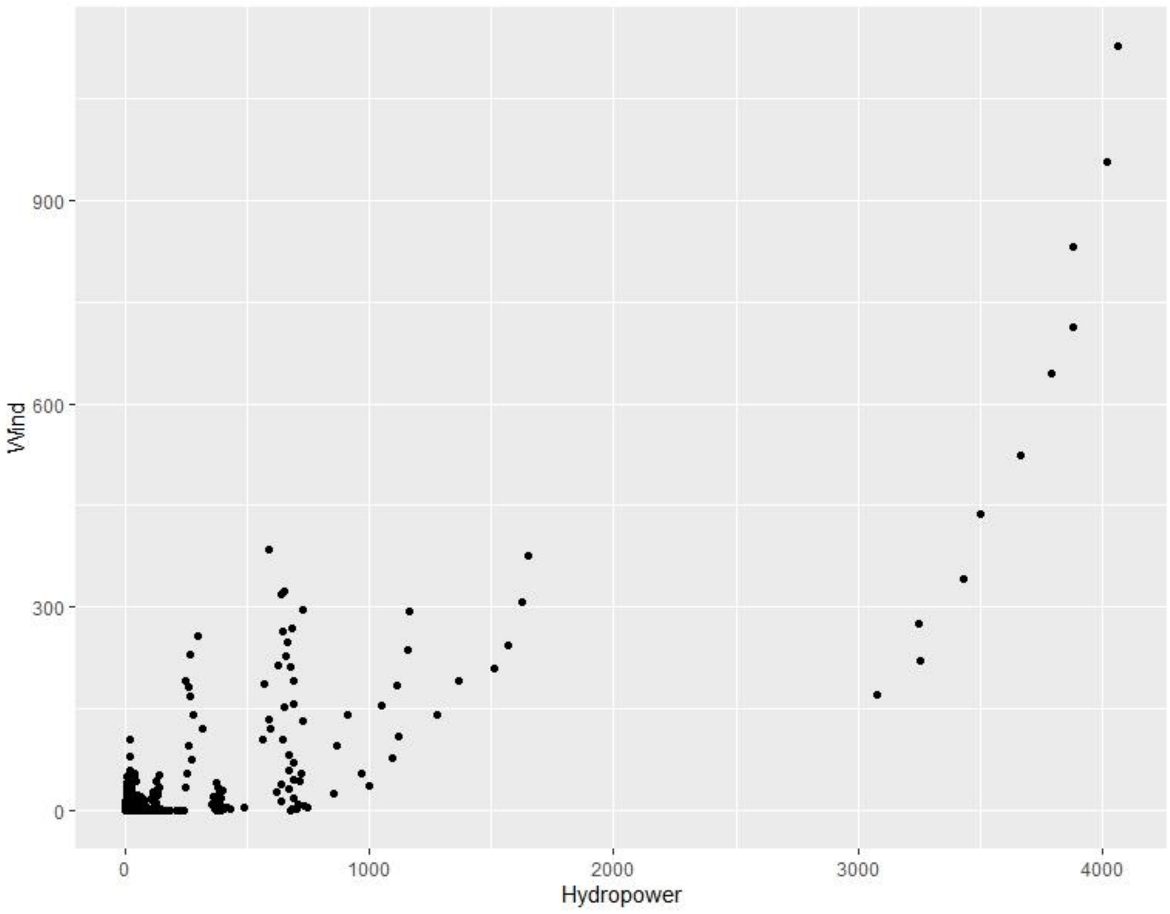
By using aggregation function compare the numerical variable is comfortable.

```
agg2 <- cbind(aggregate( total.REC ~ Entity , REC , min),
              aggregate( total.REC ~ Entity , REC  , max)[,2],
              aggregate( total.REC ~ Entity , REC  , mean)[,2])

names(agg2) <- c("total.REC","min_REC","max_REC","mean_REC")
agg2

write.table(agg2, file = "agg2.csv",
            sep = "\t", row.names = F)
```

bi-variate Analysis for Numerical columns:

using scatter plot for showing the relationship between solar versus Hydropower. And also relationship between Hydropower versus Solar .





bi-variate Analysis for Numerical columns:

Use aggregation Function for attain total consumption versus Entity, and also calculated min, max, mean for them

```
> agg2 <- cbind(aggregate( total.REC ~ Entity , REC , min),
+               aggregate( total.REC ~ Entity , REC  , max)[,2],
+               aggregate( total.REC ~ Entity , REC  , mean)[,2])
> names(agg2) <- c("total.REC","min_REC","max_REC","mean_REC")
> agg2
          total.REC      min_REC      max_REC     mean_REC
1            Africa  14.27880557 1.647168e+02 6.589835e+01
2           Algeria   0.05400000 7.557174e-01 3.221200e-01
3         Argentina   1.21091560 4.546722e+01 2.362641e+01
4      Asia Pacific 152.20159630 2.714488e+03 6.777371e+02
5         Australia   7.62904280 4.915484e+01 1.838341e+01
6           Austria  16.08300000 5.121165e+01 3.429335e+01
7        Azerbaijan   0.69826520 3.446800e+00 1.856208e+00
8        Bangladesh   0.00000000 1.307640e+00 6.283037e-01
9           Belarus   0.01600000 8.188784e-01 1.098908e-01
10          Belgium   0.13400000 1.715265e+01 2.792233e+00
11           Brazil  23.97524500 4.921938e+02 2.345469e+02
12         Bulgaria   1.30372300 8.766185e+00 3.312188e+00
13           Canada 117.12293880 4.385852e+02 2.979626e+02
14  Central America   1.21829100 4.209269e+01 1.434817e+01
15            Chile   3.57087520 3.868918e+01 1.625462e+01
16            China  19.38348840 1.836653e+03 3.433328e+02
17              CIS  85.32093640 2.473767e+02 1.879055e+02
18         Colombia   3.54394947 5.933623e+01 2.684201e+01
19          Croatia   3.80500000 9.937000e+00 6.650965e+00
20           Cyprus   0.00000000 4.638000e-01 5.425593e-02
21   Czech Republic   1.08275300 9.618473e+00 3.160531e+00
22          Denmark   0.01900000 2.191709e+01 4.914800e+00
23   Eastern Africa   6.13641138 7.570876e+01 3.031369e+01
24          Ecuador   0.34471320 2.124234e+01 5.738228e+00
25            Egypt   1.73240480 1.695809e+01 1.052231e+01
26          Estonia   0.00000000 2.048773e+00 4.342091e-01
27           Europe 305.52508640 1.403121e+03 6.392389e+02
28   Europe (other)   9.41572165 4.057329e+01 2.711962e+01
29          Finland   8.74545454 3.215866e+01 1.783236e+01
30           France  45.98265740 1.110707e+02 6.817898e+01
31          Germany  13.71347780 2.260910e+02 5.254236e+01
32           Greece   0.83084720 1.610984e+01 4.943902e+00
```

bi-variate Analysis for Numerical columns:

Test of independence: Anova

Perform the ANOVA test:

- One-way ANOVA

In the one-way ANOVA example, we are modeling crop total.REC as a function of the type of Entity used. First, we will use aov() to run the model, then we will use summary() to print the summary of the model.

```
one.way <- aov(total.REC~Entity, data = REC.ORGIN)
summary(one.way)
```

bi-variate Analysis for Numerical columns:

Test of independence: Anova

- ❖ Two-way ANOVA

In the two-way ANOVA example, we are modeling crop total.REC as a function of type of Entity and Year. First, we use aov() to run the model, then we use summary() to print the summary of the model.

```
two.way <- aov(total.REC~Entity + Year, data = REC.ORGIN)
summary(two.way)
```

- ❖ Adding interactions between variables

Sometimes you have reason to think that two of your independent variables have an interaction effect rather than an additive effect.

```
interaction <- aov(total.REC~Entity * Year, data =  REC.ORGIN)
summary(interaction
```

bi-variate Analysis for Numerical columns:

Test of independence: Anova

- ❖ Adding a Solaring variable

If you have grouped your experimental treatments in some way, or if you have a confounding variable that might affect the relationship you are interested in testing, you should include that element in the model as a Solaring variable. The simplest way to do this is just to add the variable into the

model with a '+'.

```
Solaring <- aov(total.REC~Entity + Year + Solar, data =  REC.ORGIN)
summary(Solaring)
```

- ❖ Find the best-fit model:

There are now four different ANOVA models to explain the data. How do you decide which one to use? Usually, you will want to use the 'best-fit' model -

the model that best explains the variation in the dependent variable.

bi-variate Analysis for Numerical columns:

Test of independence: Anova

```
install.packages("AICcmodavg")
library("AICcmodavg")

model.set <- list(one.way, two.way, interaction, Solaring)
model.names <- c("one.way", "two.way", "interaction", "Solaring")

aictab(model.set, modnames = model.names)
```

- Check for homoscedasticity

To check whether the model fits the assumption of homoscedasticity, look at the model diagnostic plots in R using the plot() function:

```
par(mfrow=c(2,2))
plot(two.way)
par(mfrow=c(1,1))
```

bi-variate Analysis for Numerical columns:

Test of independence: Anova