In [127…

```
import pandas as pd
import seaborn as sns
def output(filename):  ######## This function takes filename as argument and returns the contents of the file as
    df = pd.read_csv(filename)
    return df
df = output(r"World Bank Repository.csv")
```

In [128…

```
df.info() #### Dataframe information
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20216 entries, 0 to 20215
Data columns (total 65 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Country Name    20216 non-null  object 
 1   Country Code    20216 non-null  object 
 2   Indicator Name  20216 non-null  object 
 3   Indicator Code  20216 non-null  object 
 4   1960            3140 non-null   float64
 5   1961            4546 non-null   float64
 6   1962            4727 non-null   float64
 7   1963            4587 non-null   float64
 8   1964            4643 non-null   float64
 9   1965            4679 non-null   float64
 10  1966            4690 non-null   float64
 11  1967            4859 non-null   float64
 12  1968            4711 non-null   float64
 13  1969            4718 non-null   float64
 14  1970            5987 non-null   float64
 15  1971            7338 non-null   float64
 16  1972            7545 non-null   float64
 17  1973            7358 non-null   float64
 18  1974            7367 non-null   float64
 19  1975            7386 non-null   float64
 20  1976            7410 non-null   float64
 21  1977            7660 non-null   float64
 22  1978            7430 non-null   float64
 23  1979            7437 non-null   float64
 24  1980            7470 non-null   float64
 25  1981            7543 non-null   float64
 26  1982            7801 non-null   float64
 27  1983            7553 non-null   float64
 28  1984            7562 non-null   float64
 29  1985            7583 non-null   float64
 30  1986            7600 non-null   float64
 31  1987            7951 non-null   float64
 32  1988            7605 non-null   float64
 33  1989            7608 non-null   float64
 34  1990            11931 non-null  float64
 35  1991            10690 non-null  float64
 36  1992            11414 non-null  float64
 37  1993            11033 non-null  float64
 38  1994            11113 non-null  float64
 39  1995            11171 non-null  float64
 40  1996            11174 non-null  float64
 41  1997            11617 non-null  float64
 42  1998            11187 non-null  float64
 43  1999            11307 non-null  float64
 44  2000            13728 non-null  float64
 45  2001            11476 non-null  float64
 46  2002            12033 non-null  float64
 47  2003            11550 non-null  float64
 48  2004            11704 non-null  float64
 49  2005            12261 non-null  float64
 50  2006            11850 non-null  float64
 51  2007            12393 non-null  float64
 52  2008            12170 non-null  float64
 53  2009            11940 non-null  float64
 54  2010            14072 non-null  float64
 55  2011            11840 non-null  float64
 56  2012            12324 non-null  float64
 57  2013            10823 non-null  float64
 58  2014            10809 non-null  float64
 59  2015            10058 non-null  float64
 60  2016            9149 non-null   float64
 61  2017            8067 non-null   float64
 62  2018            7445 non-null   float64
 63  2019            3718 non-null   float64
 64  2020            2999 non-null   float64
dtypes: float64(61), object(4)
memory usage: 10.0+ MB
```

In [129…

```
df['Indicator Name'].value_counts()  ##### Returns the counts of all the Indicator names corresponding to each co
```

```
df['Indicator Name'].value_counts()  #### Returns the counts of all the indicator names corresponding to each co
```

Out[129…

```
Urban population (% of total population)                                              266
CO2 intensity (kg per kg of oil equivalent energy use)                                266
Renewable electricity output (% of total electricity output)                          266
Electricity production from renewable sources, excluding hydroelectric (kWh)          266
Electricity production from renewable sources, excluding hydroelectric (% of total)   266
                                                                                     ... 
GHG net emissions/removals by LUCF (Mt of CO2 equivalent)                             266
Droughts, floods, extreme temperatures (% of population, average 1990-2009)           266
Rural population living in areas where elevation is below 5 meters (% of total population)    266
Urban population living in areas where elevation is below 5 meters (% of total population)    266
Agricultural land (sq. km)                                                            266
Name: Indicator Name, Length: 76, dtype: int64
```

In [130…

```
df['Country Name'].value_counts()   #### Returns count of each country. The counts correspond to number of indica
```

Out[130…

```
Aruba                   76
Oman                    76
Malawi                  76
Malaysia                76
North America           76
                        ..
Guyana                  76
High income             76
Hong Kong SAR, China    76
Honduras                76
Zimbabwe                76
Name: Country Name, Length: 266, dtype: int64
```

In [131…

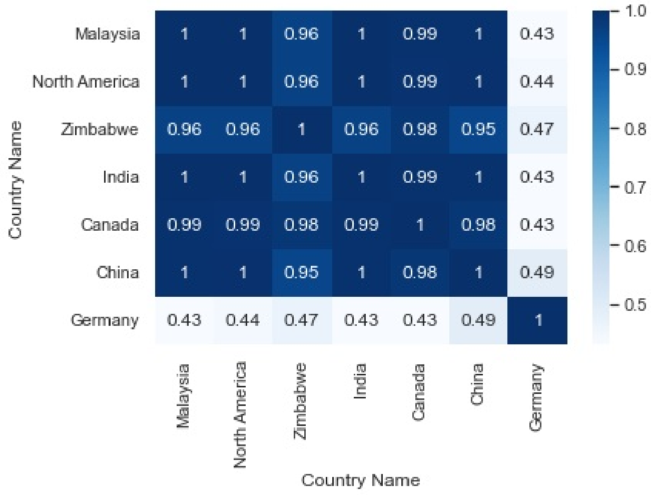
```
######## This cell contains code for analysis of the indicator total population
######## We clean the dataset by dropping all the nan values. For exploring the data analysis we take 7 countries
######## Correlation between each country is computed and a heatmap is plotted for visual understanding of the da
######## Also statistical analysis is done on the data which includes calculating mean, standard deviation, min, 
######## Also for each country data over the years 1990-2020 is plotted.

df_total_population = df.loc[df['Indicator Name'] == 'Population, total']
#print(df_total_population)
df_total_population = df_total_population.drop(columns=['Country Code', 'Indicator Name', 'Indicator Code','1960'
                                                       '1962','1963','1964','1965','1966','1967','1968','1969','1
                                                       '1972','1973','1974','1975','1976','1977','1978','1979','1
                                                       '1982','1983','1984','1985','1986','1987','1988','1989'])
df_total_population = df_total_population.dropna(how='any')
df_total_population = df_total_population.reset_index(drop=True)
df_total_population_t = df_total_population.set_index('Country Name').T
urban_x = df_total_population_t[['Malaysia','North America','Zimbabwe','India','Canada','China','Germany']].descr
print(urban_x)
df_total_population_t = df_total_population_t[['Malaysia','North America','Zimbabwe','India','Canada','China','Ge
corrurban = df_total_population_t.corr()
print(corrurban)
sns.heatmap(corrurban,cmap="Blues", annot=True)
df_total_population_t.plot()
```

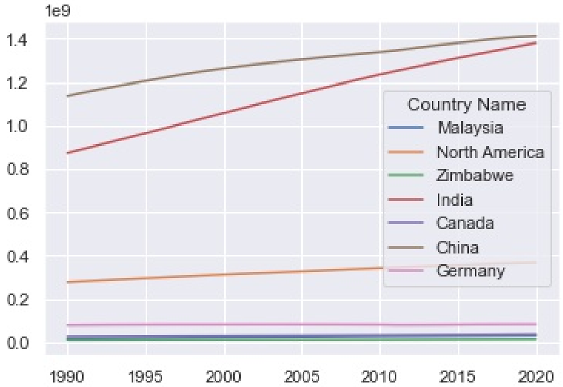
```
Country Name      Malaysia  North America      Zimbabwe         India  \
count         3.100000e+01   3.100000e+01  3.100000e+01  3.100000e+01   
mean          2.550357e+07   3.264777e+08  1.243139e+07  1.139727e+09   
std           4.417993e+06   2.765420e+07  1.193734e+06  1.563525e+08   
min           1.802982e+07   2.773735e+08  1.043241e+07  8.732778e+08   
25%           2.183872e+07   3.043468e+08  1.170017e+07  1.010192e+09   
50%           2.569062e+07   3.278245e+08  1.207670e+07  1.147610e+09   
75%           2.926856e+07   3.499323e+08  1.323276e+07  1.273311e+09   
max           3.236600e+07   3.675533e+08  1.486293e+07  1.380004e+09   

Country Name        Canada         China       Germany  
count         3.100000e+01  3.100000e+01  3.100000e+01  
mean          3.248361e+07  1.293987e+09  8.179689e+07  
std           3.025224e+06  8.113623e+07  9.361147e+05  
min           2.769114e+07  1.135185e+09  7.943303e+07  
25%           3.003056e+07  1.236005e+09  8.129736e+07  
50%           3.224375e+07  1.303720e+09  8.204720e+07  
75%           3.489859e+07  1.358715e+09  8.242294e+07  
max           3.800524e+07  1.410929e+09  8.324052e+07  
Country Name   Malaysia  North America  Zimbabwe     India    Canada  \
Country Name                                                           
Malaysia       1.000000       0.999596  0.961627  0.999971  0.993633   
North America  0.999596       1.000000  0.959984  0.999676  0.991500   
Zimbabwe       0.961627       0.959984  1.000000  0.961513  0.983263   
India          0.999971       0.999676  0.961513  1.000000  0.993439   
Canada         0.993633       0.991500  0.983263  0.993439  1.000000   
China          0.995066       0.997174  0.954490  0.995271  0.983655   
Germany        0.430826       0.442363  0.467788  0.431149  0.430465   
```

```
Country Name       China   Germany
Country Name
Malaysia       0.995066  0.430826
North America  0.997174  0.442363
Zimbabwe       0.954490  0.467788
India          0.995271  0.431149
Canada         0.983655  0.430465
China          1.000000  0.491620
Germany        0.491620  1.000000
```

Out[131…

```
<AxesSubplot:>
```





In [132…

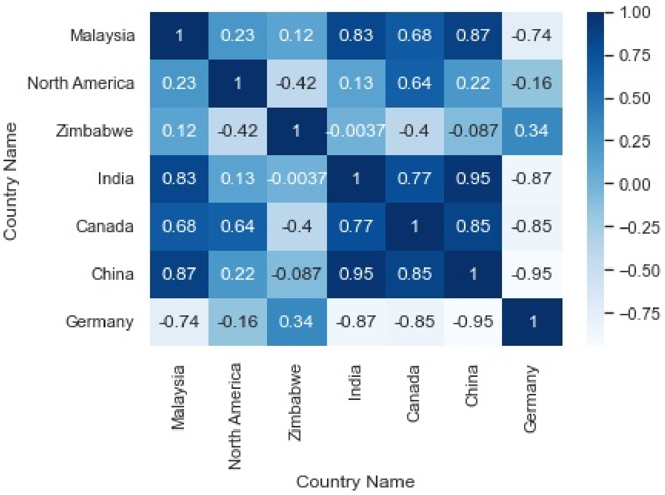
```
######## This cell contains code for analysis of the indicator CO2 emissions from liquid fuel
######## We clean the dataset by dropping all the nan values. For exploring the data analysis we take 7 countries
######## Correlation between each country is computed and a heatmap is plotted for visual understanding of the da
######## Also statistical analysis is done on the data which includes calculating mean, standard deviation, min,
######## Also for each country data over the years 1990-2020 is plotted.

df_primary = df.loc[df['Indicator Name'] == 'CO2 emissions from liquid fuel consumption (kt)']
df_primary = df_primary.drop(columns=['Country Code', 'Indicator Name', 'Indicator Code','1960','1961',
                                                        '1962','1963','1964','1965','1966','1967','1968','1969','1
                                                        '1972','1973','1974','1975','1976','1977','1978','1979','1
                                                        '1982','1983','1984','1985','1986','1987','1988','1989'])
df_primary = df_primary.reset_index(drop=True)
df_primary = df_primary.set_index('Country Name').T
primary_x = df_primary[['Malaysia','North America','Zimbabwe','India','Canada','China','Germany']].describe()
print(primary_x)
df_primary = df_primary[['Malaysia','North America','Zimbabwe','India','Canada','China','Germany']]
corrprimary = df_primary.corr()
print(corrprimary)
sns.heatmap(corrprimary,cmap="Blues", annot=True)
df_primary.plot()
```

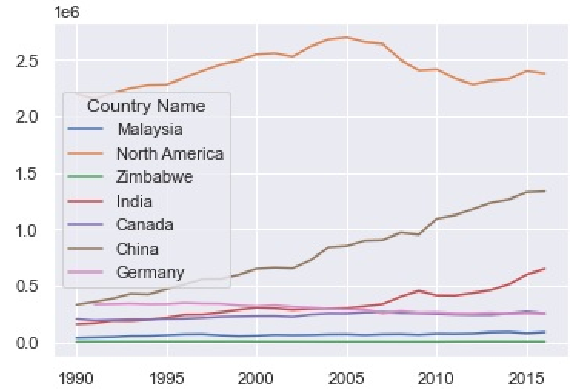
```
Country Name      Malaysia  North America     Zimbabwe          India  \
count            27.000000   2.700000e+01    27.000000      27.000000
mean          65494.113963   2.422063e+06  2987.925926  330472.892111
std           12752.110076   1.571670e+05   951.324381  127924.659584
min           38338.485000   2.154252e+06  1609.813000  158297.056000
25%           58129.284000   2.299957e+06  1947.177000  243881.169000
50%           65356.941000   2.404360e+06  3164.621000  298068.428000
75%           71906.203000   2.539368e+06  3712.837500  413382.743500
max           89628.814000   2.699517e+06  4726.763000  648956.324000

Country Name         Canada         China        Germany
count             27.000000  2.700000e+01      26.000000
```

```
mean          233901.903852  7.885055e+05  297676.623154
std            23377.788417  3.203081e+05   36218.041889
min           192418.491000  3.305617e+05  250800.798000
25%           211246.702500  5.347293e+05  258892.950250
50%           241970.662000  7.276941e+05  299872.592000
75%           252933.158500  1.032189e+06  334825.519250
max           269326.482000  1.336398e+06  346692.848000
Country Name   Malaysia  North America  Zimbabwe     India    Canada  \
Country Name
Malaysia       1.000000       0.230987  0.122466  0.830692  0.684361
North America  0.230987       1.000000 -0.419966  0.132174  0.636552
Zimbabwe       0.122466      -0.419966  1.000000 -0.003702 -0.398641
India          0.830692       0.132174 -0.003702  1.000000  0.771808
Canada         0.684361       0.636552 -0.398641  0.771808  1.000000
China          0.873394       0.222847 -0.087302  0.951990  0.847947
Germany       -0.742885      -0.162794  0.337677 -0.867276 -0.845153

Country Name      China   Germany
Country Name
Malaysia       0.873394 -0.742885
North America  0.222847 -0.162794
Zimbabwe      -0.087302  0.337677
India          0.951990 -0.867276
Canada         0.847947 -0.845153
China          1.000000 -0.947749
Germany       -0.947749  1.000000
```

Out[132…

```
<AxesSubplot:>
```





In [133…

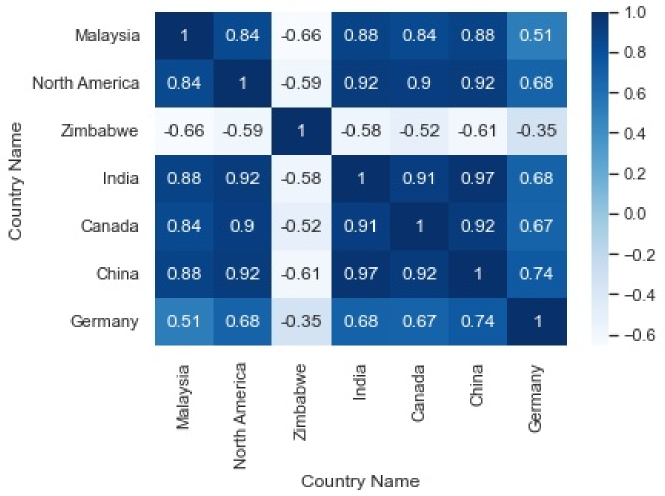
```
######## This cell contains code for analysis of the indicator cereal yield
######## We clean the dataset by dropping all the nan values. For exploring the data analysis we take 7 countries
######## Correlation between each country is computed and a heatmap is plotted for visual understanding of the da
######## Also statistical analysis is done on the data which includes calculating mean, standard deviation, min,
######## Also for each country data over the years 1990-2020 is plotted.

df_cereal = df.loc[df['Indicator Name'] == 'Cereal yield (kg per hectare)']
df_cereal = df_cereal.drop(columns=['Country Code', 'Indicator Name', 'Indicator Code','1960','1961',
                                                        '1962','1963','1964','1965','1966','1967','1968','1969','1
                                                        '1972','1973','1974','1975','1976','1977','1978','1979','1
                                                        '1982','1983','1984','1985','1986','1987','1988','1989'])
df_cereal = df_cereal.reset_index(drop=True)
df_cereal = df_cereal.set_index('Country Name').T
cereal_x = df_cereal[['Malaysia','North America','Zimbabwe','India','Canada','China','Germany']].describe()
print(cereal_x)
df_cereal = df_cereal[['Malaysia','North America','Zimbabwe','India','Canada','China','Germany']]
corrable = df_cereal.corr()
```

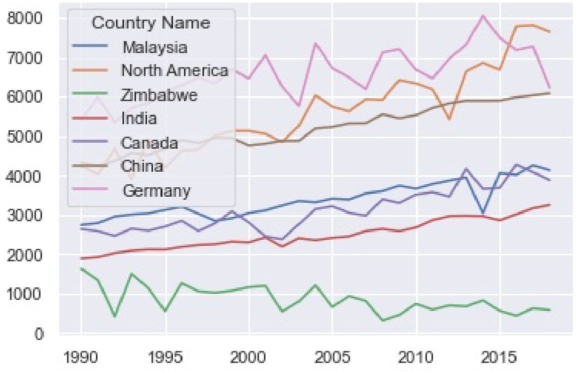
```
print(corrable)
sns.heatmap(corrable,cmap="Blues", annot=True)
df_cereal.plot()
```

```
Country Name     Malaysia  North America     Zimbabwe        India  \
count           29.000000      29.000000    29.000000    29.000000
mean          3381.155172    5607.826504   852.220690  2487.803448
std            441.217879    1099.653051   346.943967   381.724199
min           2740.300000    3895.818088   309.700000  1891.200000
25%           3031.900000    4846.748952   579.100000  2187.300000
50%           3314.900000    5423.214235   795.400000  2411.600000
75%           3734.700000    6332.699013  1134.600000  2856.700000
max           4250.800000    7809.845802  1625.400000  3247.900000

Country Name       Canada        China      Germany
count           29.000000    29.000000    29.000000
mean          3125.289655  5188.796552  6566.006897
std            549.679172   566.002563   658.786616
min           2375.400000  4237.300000  5335.600000
25%           2647.000000  4802.200000  6182.900000
50%           3046.300000  5189.800000  6484.900000
75%           3509.600000  5709.400000  7118.800000
max           4269.200000  6081.400000  8050.300000
Country Name   Malaysia  North America  Zimbabwe     India    Canada  \
Country Name
Malaysia       1.000000       0.838761 -0.656584  0.879272  0.839131
North America  0.838761       1.000000 -0.587419  0.917498  0.903837
Zimbabwe      -0.656584      -0.587419  1.000000 -0.583330 -0.515625
India          0.879272       0.917498 -0.583330  1.000000  0.907483
Canada         0.839131       0.903837 -0.515625  0.907483  1.000000
China          0.879621       0.916140 -0.607277  0.972279  0.924745
Germany        0.508269       0.675202 -0.350263  0.677918  0.671097

Country Name      China   Germany
Country Name
Malaysia       0.879621  0.508269
North America  0.916140  0.675202
Zimbabwe      -0.607277 -0.350263
India          0.972279  0.677918
Canada         0.924745  0.671097
China          1.000000  0.741049
Germany        0.741049  1.000000
```

Out[133…

```
<AxesSubplot:>
```





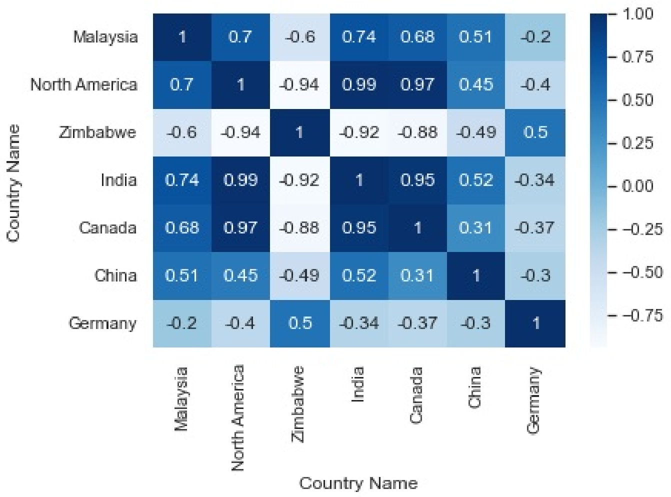
In [134…

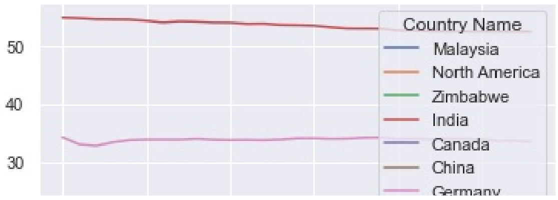
```
######## This cell contains code for analysis of the indicator agricultural land
```

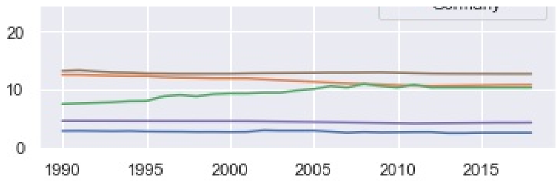
```
######## We clean the dataset by dropping all the nan values. For exploring the data analysis we take 6 countrie
######## Correlation between each country is computed and a heatmap is plotted for visual understanding of the da
######## Also statistical analysis is done on the data which includes calculating mean, standard deviation, min,
######## Also for each country data over the years 1990-2020 is plotted.

df_agri = df.loc[df['Indicator Name'] == 'Arable land (% of land area)']
df_agri = df_agri.drop(columns=['Country Code', 'Indicator Name', 'Indicator Code','1960','1961',
                                                       '1962','1963','1964','1965','1966','1967','1968','1969','1
                                                       '1972','1973','1974','1975','1976','1977','1978','1979','1
                                                       '1982','1983','1984','1985','1986','1987','1988','1989'])
df_agri = df_agri.reset_index(drop=True)
df_agri = df_agri.set_index('Country Name').T
agri_x = df_agri[['Malaysia','North America','Zimbabwe','India','Canada','China','Germany']].describe()
print(agri_x)
df_agri = df_agri[['Malaysia','North America','Zimbabwe','India','Canada','China','Germany']]
corragri = df_agri.corr()
print(corragri)
sns.heatmap(corragri,cmap="Blues", annot=True)
df_agri.plot()
```

```
Country Name   Malaysia  North America   Zimbabwe      India     Canada  \
count         29.000000      29.000000  29.000000  29.000000  29.000000
mean           2.682336      11.505436   9.518971  53.625161   4.426843
std            0.143528       0.673849   1.074593   0.818211   0.159827
min            2.443159      10.629996   7.522295  52.608814   4.158678
25%            2.571907      10.834506   8.788936  52.798173   4.292523
50%            2.669305      11.499907   9.822929  53.706961   4.455814
75%            2.819967      12.062575  10.339925  54.288155   4.577167
max            2.944757      12.526801  10.986170  54.977650   4.613974

Country Name      China    Germany
count         29.000000  29.000000
mean          12.828545  33.872078
std            0.161970   0.315017
min           12.678246  32.844499
25%           12.697844  33.814557
50%           12.800417  33.906711
75%           12.896634  34.040358
max           13.320891  34.288088
Country Name   Malaysia  North America  Zimbabwe     India    Canada  \
Country Name
Malaysia       1.000000       0.701816 -0.599460  0.743112  0.678719
North America  0.701816       1.000000 -0.942864  0.987991  0.973712
Zimbabwe      -0.599460      -0.942864  1.000000 -0.922235 -0.878506
India          0.743112       0.987991 -0.922235  1.000000  0.946749
Canada         0.678719       0.973712 -0.878506  0.946749  1.000000
China          0.513320       0.453493 -0.487961  0.520721  0.313210
Germany       -0.195522      -0.401337  0.502351 -0.339301 -0.374025

Country Name      China   Germany
Country Name
Malaysia       0.513320 -0.195522
North America  0.453493 -0.401337
Zimbabwe      -0.487961  0.502351
India          0.520721 -0.339301
Canada         0.313210 -0.374025
China          1.000000 -0.295918
Germany       -0.295918  1.000000
<AxesSubplot:>
```

Out[134…







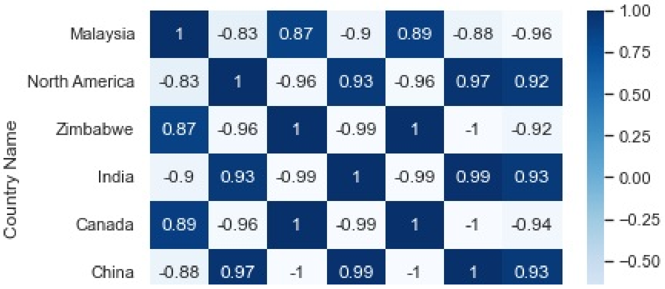
In [135…

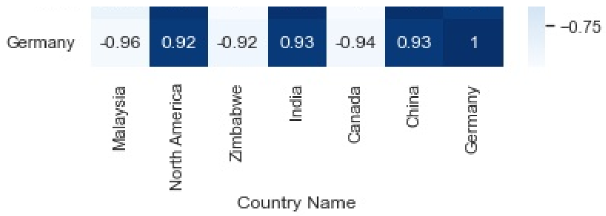
```
######## This cell contains code for analysis of the indicator forest area
######## We clean the dataset by dropping all the nan values. For exploring the data analysis we take 6 countries
######## Correlation between each country is computed and a heatmap is plotted for visual understanding of the da
######## Also statistical analysis is done on the data which includes calculating mean, standard deviation, min,
######## Also for each country data over the years 1990-2020 is plotted.

df_forest = df.loc[df['Indicator Name'] == 'Forest area (% of land area)']
df_forest = df_forest.drop(columns=['Country Code', 'Indicator Name', 'Indicator Code','1960','1961',
                                    '1962','1963','1964','1965','1966','1967','1968','1969','1
                                    '1972','1973','1974','1975','1976','1977','1978','1979','1
                                    '1982','1983','1984','1985','1986','1987','1988','1989'])
df_forest = df_forest.reset_index(drop=True)
df_forest = df_forest.set_index('Country Name').T
forest = df_forest[['Malaysia','North America','Zimbabwe','India','Canada','China','Germany']].describe()
print(forest)
df_forest = df_forest[['Malaysia','North America','Zimbabwe','India','Canada','China','Germany']]
corrM = df_forest.corr()
print(corrM)
sns.heatmap(corrM,cmap="Blues", annot=True)
df_forest.plot()
```

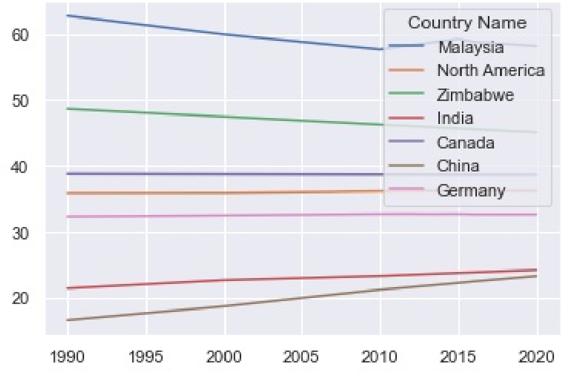
```
Country Name   Malaysia  North America   Zimbabwe      India     Canada  \
count         31.000000      31.000000  31.000000  31.000000  31.000000
mean          59.586058      36.082133  46.880264  22.994841  38.767558
std            1.495623       0.151534   1.082781   0.791334   0.046354
min           57.670522      35.902794  45.093912  21.504848  38.695513
25%           58.415918      35.928245  45.987088  22.426333  38.727954
50%           59.028671      36.060614  46.880264  23.053858  38.766226
75%           60.639591      36.251037  47.773439  23.598223  38.806114
max           62.756049      36.283851  48.666615  24.270228  38.845512

Country Name      China    Germany
count         31.000000  31.000000
mean          20.025744  32.595580
std            2.076112   0.123296
min           16.673325  32.366167
25%           18.253671  32.491011
50%           20.033048  32.634190
75%           21.799345  32.689584
max           23.340596  32.745166
Country Name   Malaysia  North America  Zimbabwe     India    Canada  \
Country Name
Malaysia       1.000000      -0.825949  0.874392 -0.896361  0.887899
North America -0.825949       1.000000 -0.959615  0.929465 -0.962718
Zimbabwe       0.874392      -0.959615  1.000000 -0.993997  0.999351
India         -0.896361       0.929465 -0.993997  1.000000 -0.994253
Canada         0.887899      -0.962718  0.999351 -0.994253  1.000000
China         -0.877715       0.967060 -0.999535  0.991384 -0.999535
Germany       -0.963847       0.919970 -0.922303  0.927419 -0.935336

Country Name      China   Germany
Country Name
Malaysia      -0.877715 -0.963847
North America  0.967060  0.919970
Zimbabwe      -0.999535 -0.922303
India          0.991384  0.927419
Canada        -0.999535 -0.935336
China          1.000000  0.928435
Germany        0.928435  1.000000
```

Out[135…

```
<AxesSubplot:>
```







In [136…

```
### This cell calculates the correlation of all 7 countries between arable land and forest land

df_agri.corrwith(df_forest, axis = 0)
```

Out[136…

```
Country Name
Malaysia         0.537099
North America   -0.969289
Zimbabwe        -0.905164
India           -0.974899
Canada           0.911196
China           -0.534498
Germany          0.454543
dtype: float64
```

In [137…

```
### This cell calculates the correlation of all 7 countries between total population and cereal yield

df_total_population_t.corrwith(df_cereal, axis = 0)
```

Out[137…

```
Country Name
Malaysia         0.886201
North America    0.928162
Zimbabwe        -0.598575
India            0.966196
Canada           0.899534
China            0.967947
Germany          0.249489
dtype: float64
```

In [138…

```
### This cell calculates the correlation of all 7 countries between Total Population and CO2 emissions from liqui

df_total_population_t.corrwith(df_primary, axis = 0)
```

Out[138…

```
Country Name
Malaysia         0.866558
North America    0.343515
Zimbabwe         0.077708
India            0.936917
Canada           0.862326
China            0.970058
Germany          0.098368
dtype: float64
```

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