Report_Governance_indicators_and_environmental_resources

November 30, 2020

1 Basic information

```
The dataset contains 4222 entries with 12 features each.
```

```
Country Code                                                      0
Country Name                                                      0
Year                                                              0
Control of Corruption: Estimate                                   0
Government Effectiveness: Estimate                                0
Political Stability and Absence of Violence/Terrorism: Estimate   0
Regulatory Quality: Estimate                                      0
Rule of Law: Estimate                                             0
Voice and Accountability: Estimate                                0
Capture fisheries production (metric tons)                      650
Forest area (% of land area)                                    706
CO2 emissions                                                   705
dtype: int64
```

```
We are dealing with 203 countries.
```

```
We have information on 21 different years.
```

2 Static Univariate analysis

In this part we will analyse the behavior of each variable individually, without its interaction with other variables.

We call it **"Static"**, as opposed to "Dynamic", because we will not look at the evolution of the variables over the years, but rather at the average value.

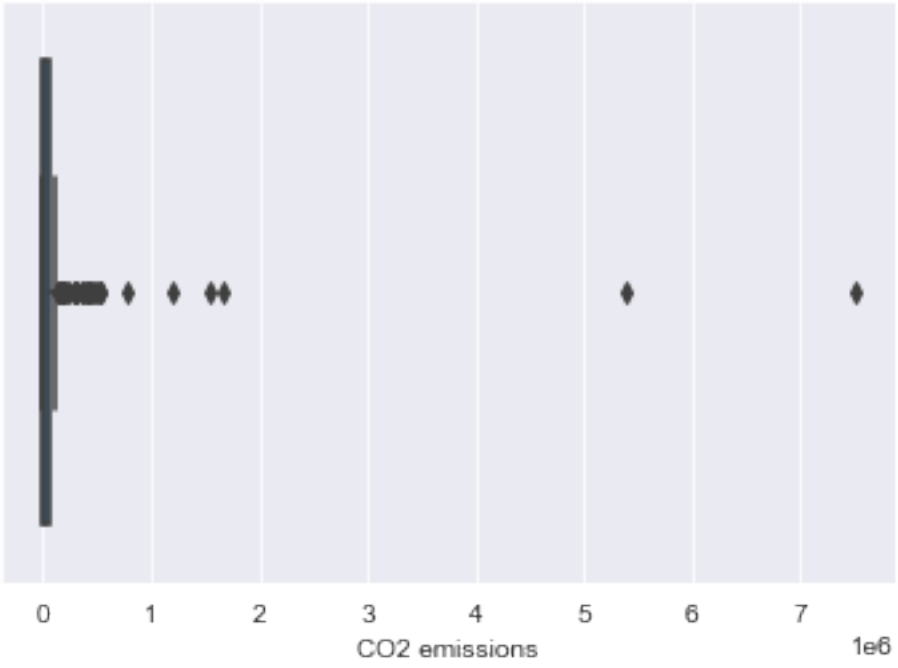
In the **Dynamic approach**, we will rather look at the evolution of the variables (environmental and political) for each country.

2.1 Environmental Variables

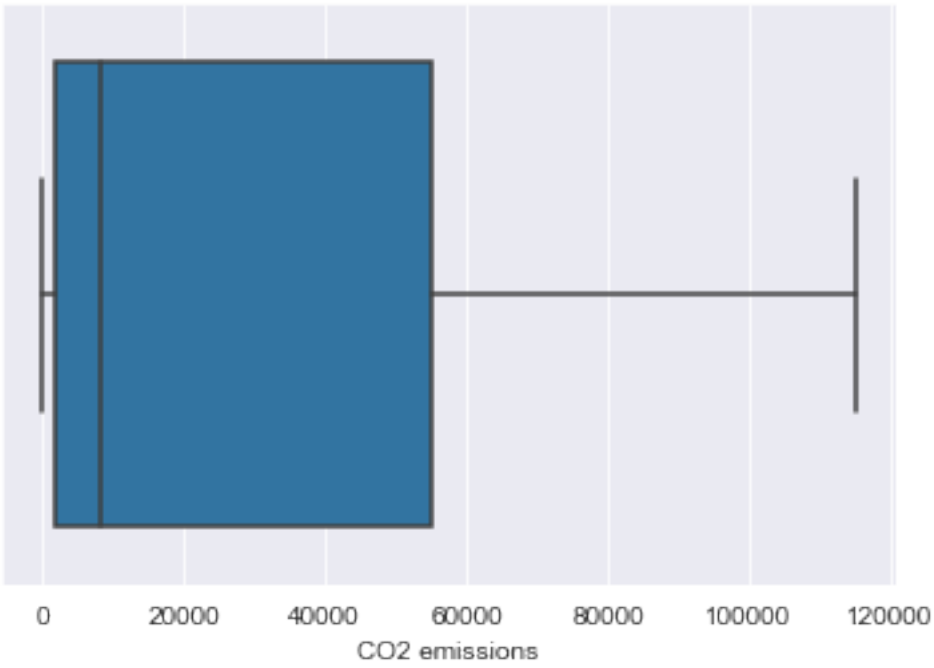
2.1.1 CO2

```
count       199.000
mean     148310.486
std      679530.903
min          10.215
25%        1823.518
50%        8106.311
75%       55077.525
max     7500366.726
Name: CO2 emissions, dtype: float64
```

50% of the countries have less than 8,106 kt of CO2 emissions (averaged over the years for each country).



We have few countries with very high emissions and the majority with low emissions.



Which are the countries with the most CO2 emissions ?

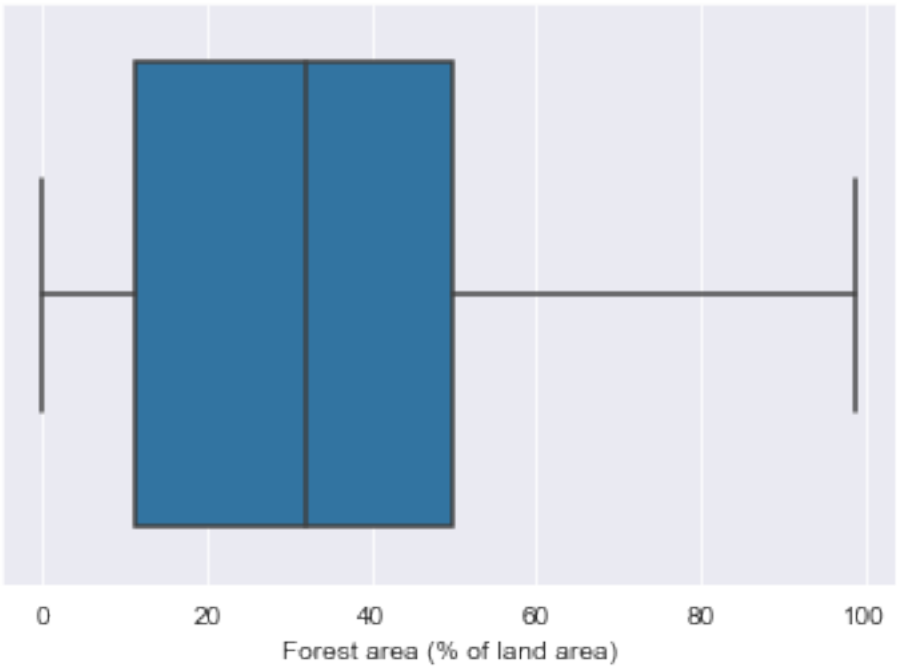
```
Country Code
CHN   7500366.726
USA   5390892.846
RUS   1665958.786
IND   1554369.590
JPN   1199997.636
DEU    774942.046
CAN    538200.177
KOR    524676.630
IRN    509718.093
GBR    494813.572
Name: CO2 emissions, dtype: float64
```

Which are the countries with the least CO2 emissions ?

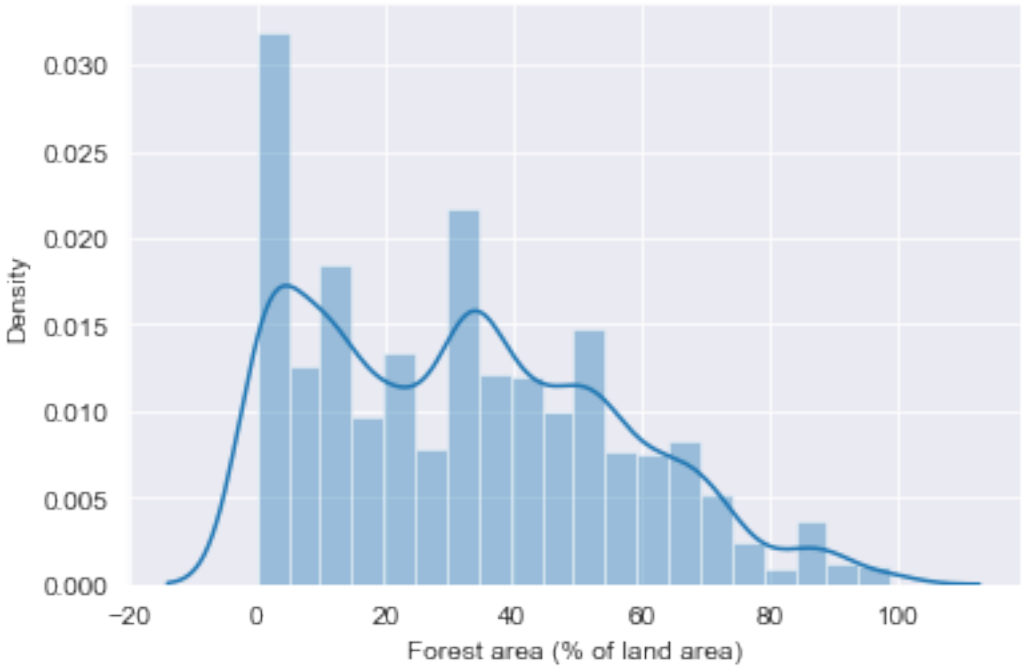
```
Country Code
TUV    10.215
NRU    44.004
LIE    56.472
KIR    57.100
STP    85.563
VUT   101.166
TON   117.082
```

```
FSM   129.917
MHL   130.178
COM   134.864
Name: CO2 emissions, dtype: float64
```

2.1.2 Forest Area

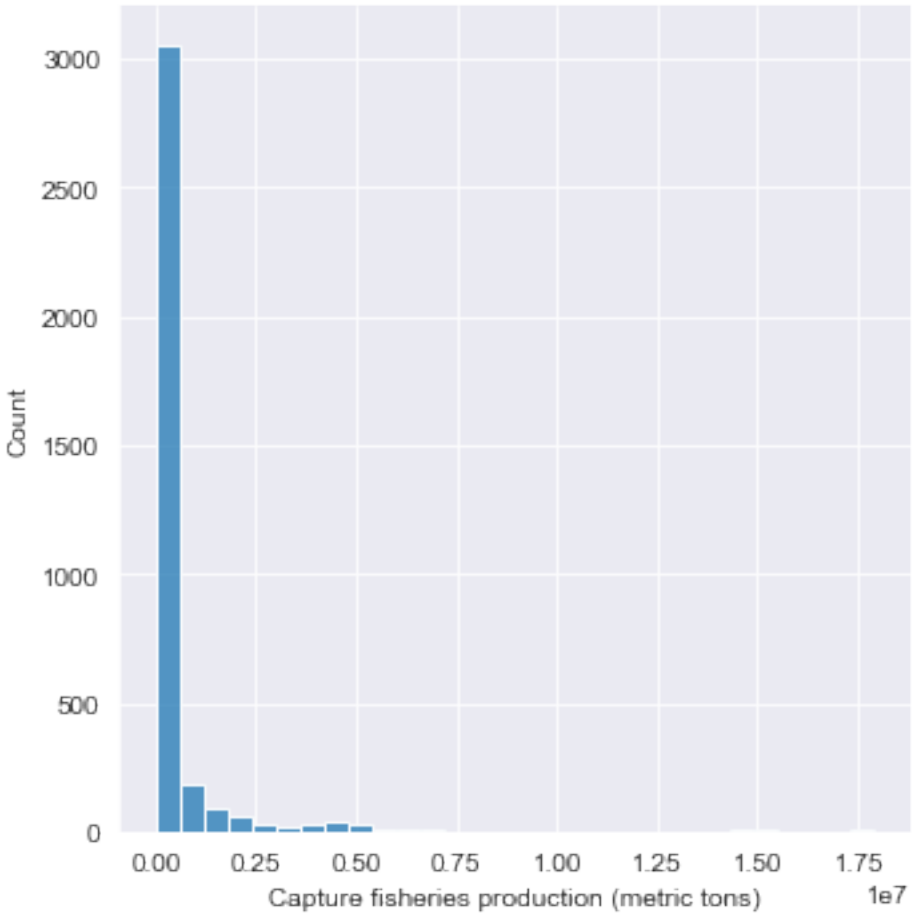


The mean foest area is 32% of the total land area, and 50% of countries have forest areas between 11% and 49%.

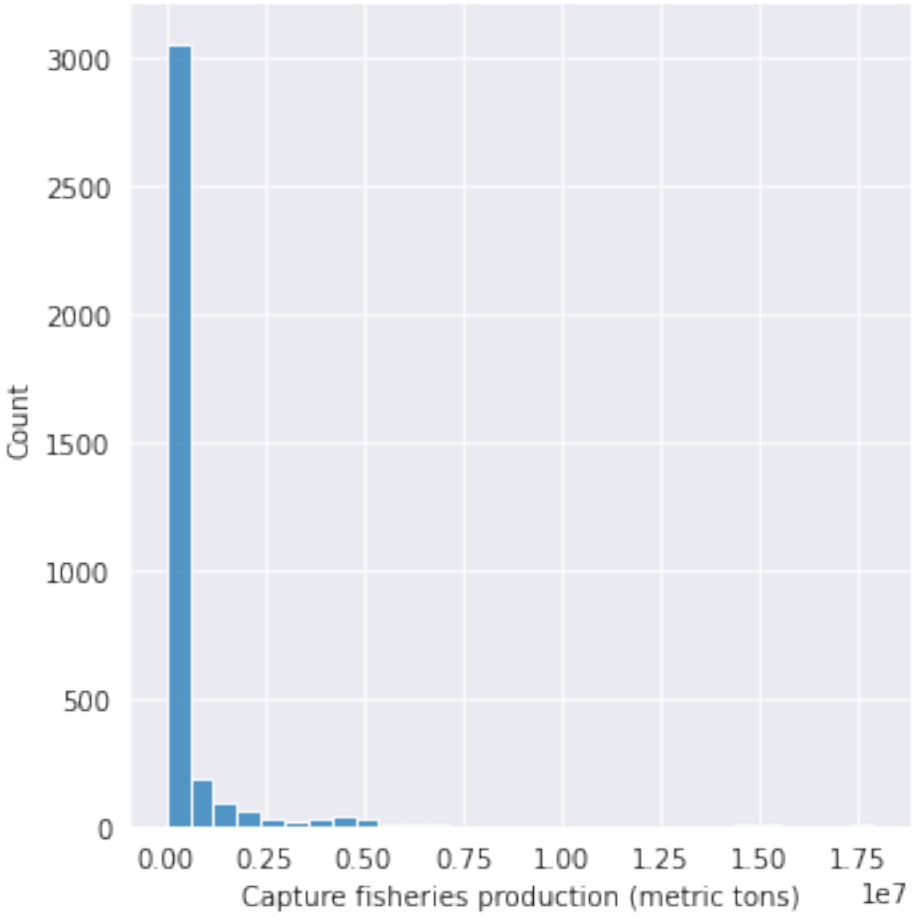


2.1.3 Fishing

```
<seaborn.axisgrid.FacetGrid at 0x236de124048>
```



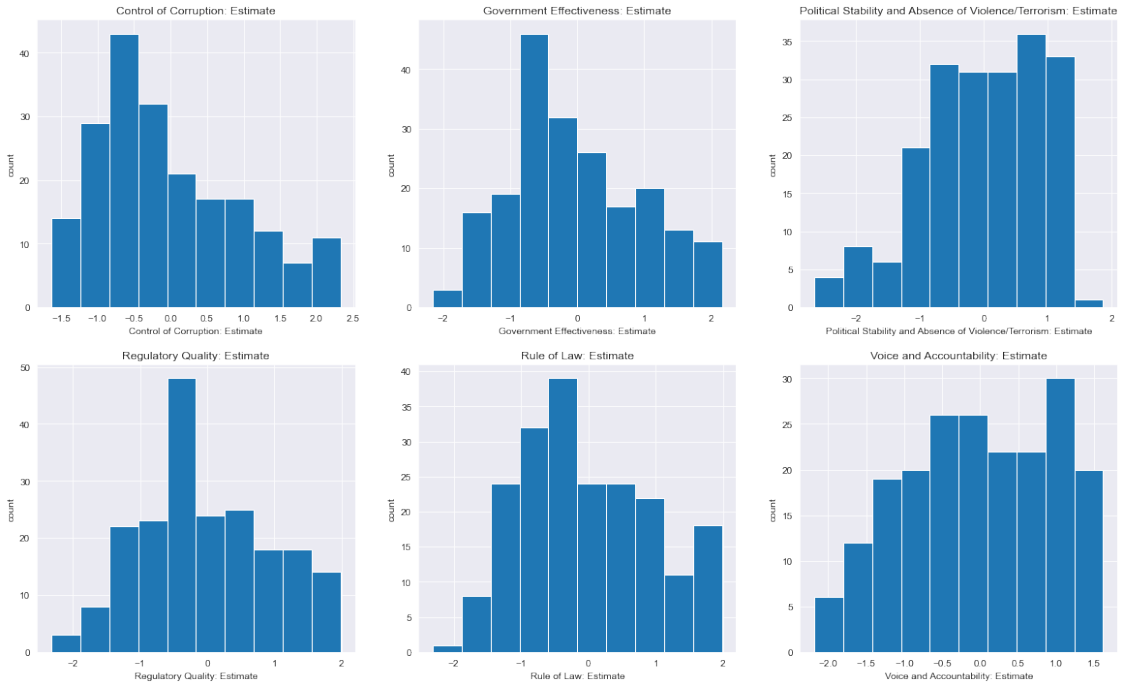

```
<AxesSubplot:xlabel='Capture fisheries production (metric tons)'>
```

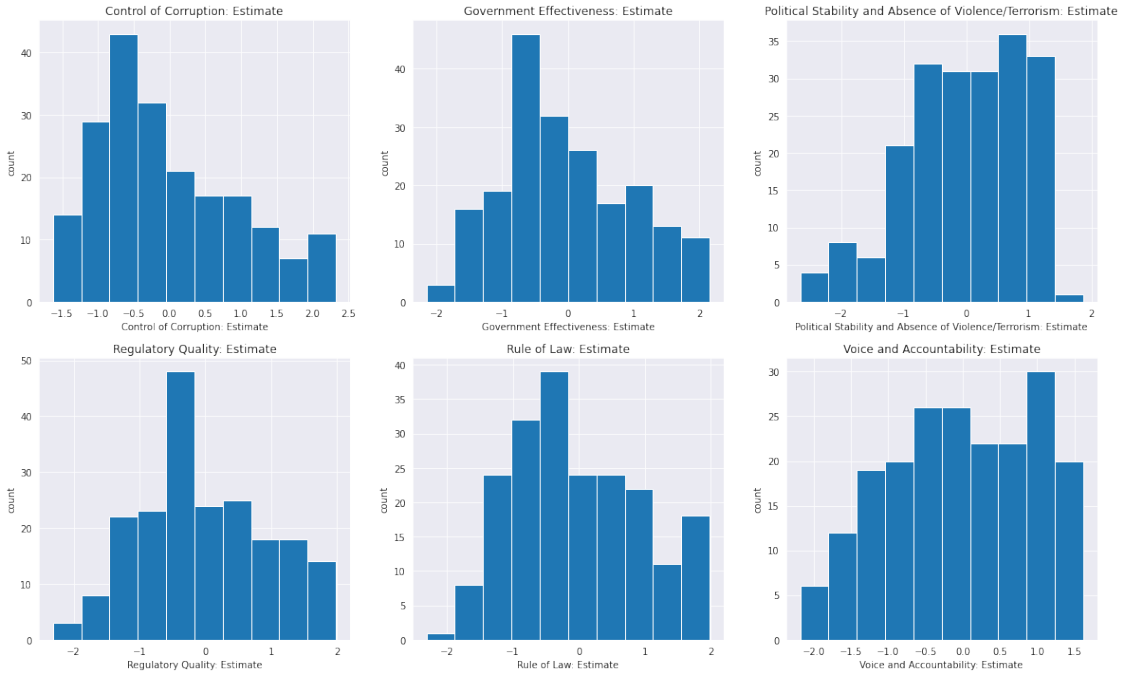


The vast majority of contries have a very low production of fish, which explains the many outliers on the boxplot.

2.2 Governance indicators

2.2.1 Overview





There doesn't seem to be many outliers for governance indicators. Political stabil-

ity appears to be skewed to the left which might indicate that more countries are polytically stable generally speaking.

2.3 Dimensionality reduction using PCA

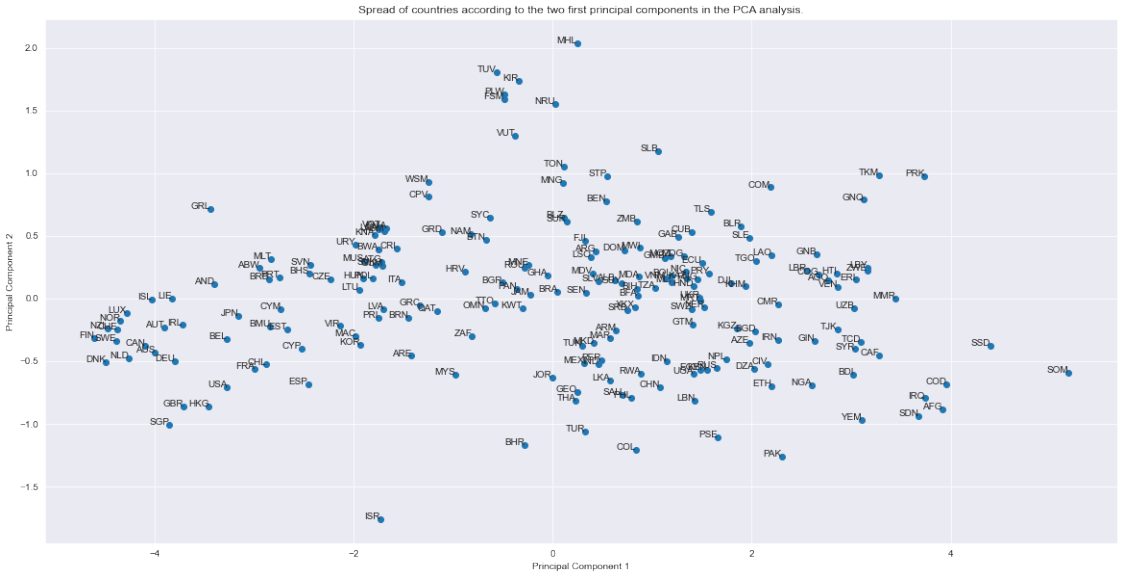
```
Explained variation by principal component 1: 0.8667045982586209

Explained variation by principal component 2: 0.06180012309177191

The 1st principal component for the political indicators is : [-0.42487826
-0.42305993 -0.35840434 -0.41415483 -0.43536935 -0.38855425]
The 2nd principal component for the political indicators is : [-0.12749172
-0.35505272  0.76775388 -0.41243727 -0.04670747  0.3097601 ]
```

We see that the first principal component in the Principal Components Analysis explains more than 86% of the variability and is a linear combination of all governance indicators with almost the same coefficient every time, which is due to the high correlation between these political variables as we will see in the bivariate analysis.

```
Text(0.5, 1.0, 'Spread of countries according to the two first principal
components in the PCA analysis.')
```

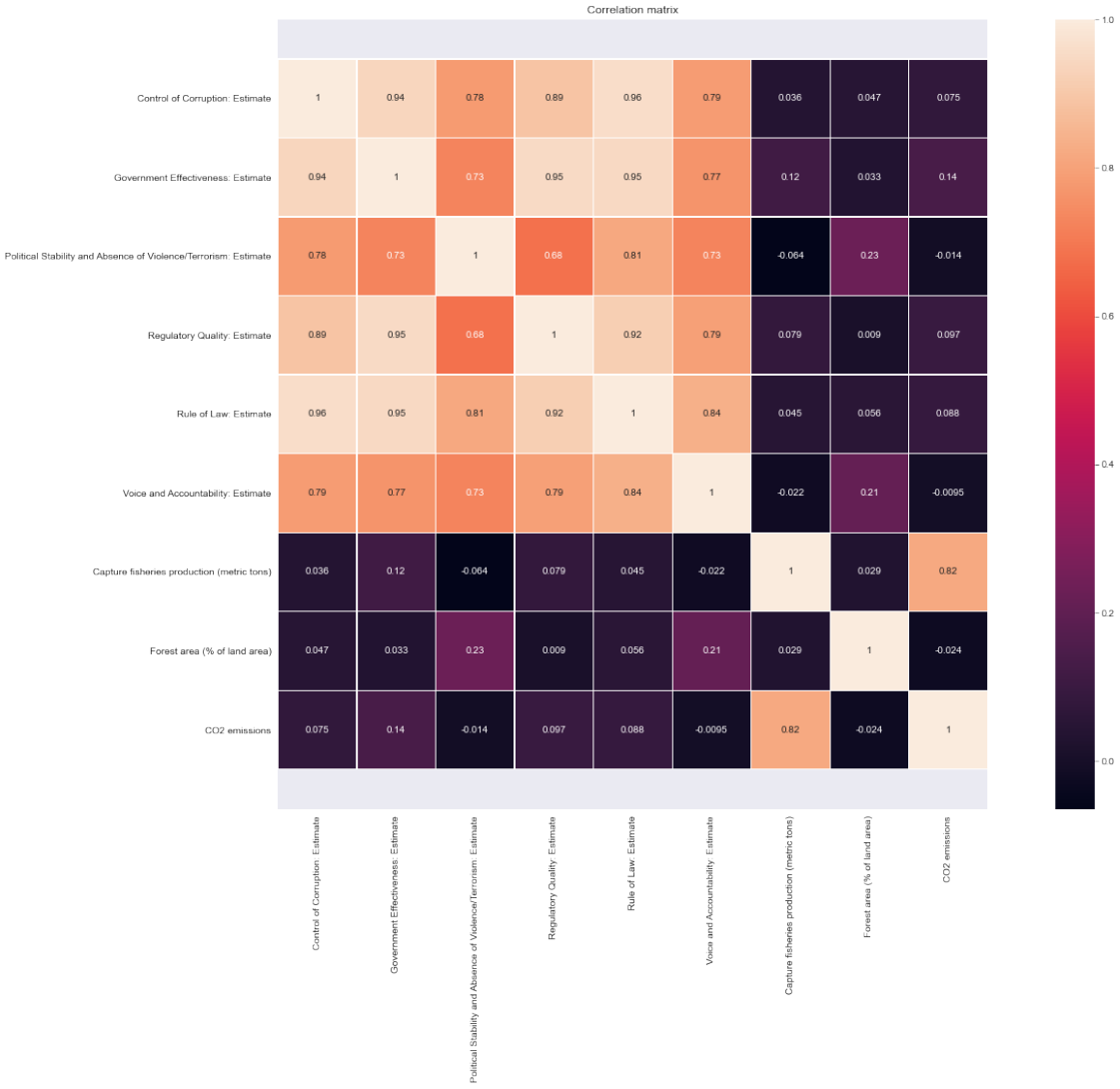


3 Static Bivariate Analysis

In this part, we will try to answer the following questions: - Does high Corruption equals high (or low) depletion of natural ressources ? - More generally, what is the link between the governance indicators and the environmental ones ?

Again, we will look at them in a **STATIC** way, meaning that we will ONLY look at the average value for each country of each variable and see if they correlate in any way.

3.1 Overall Correlation Analysis



We can notice several things:

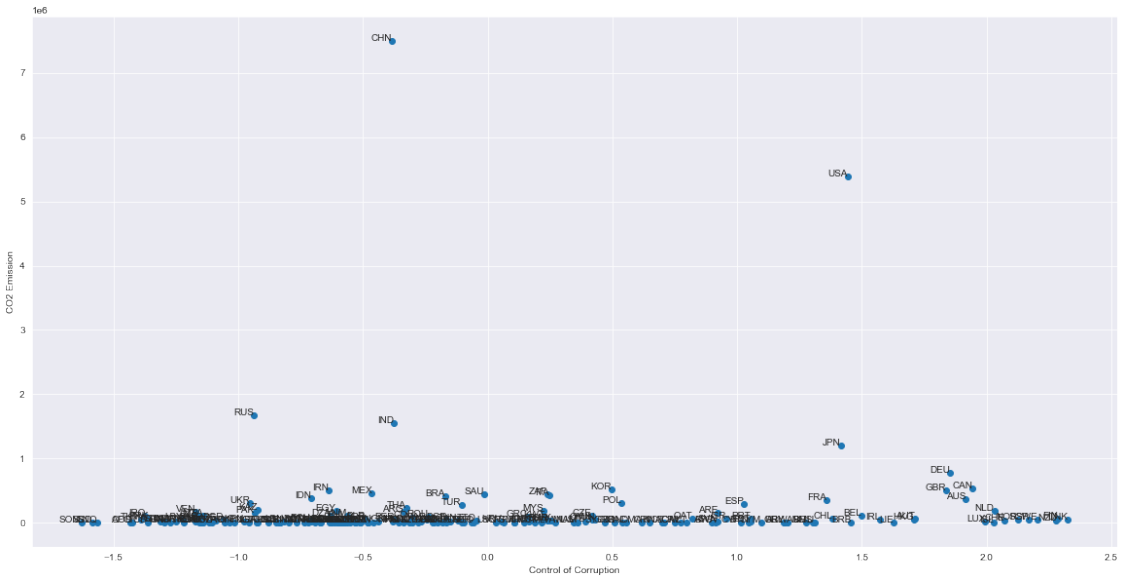
- Political factors are highly correlated between one another
- Environmental factors are not very correlated with the politcal factors, meaning : high political stability doesn't necessarily equal high (or low) impact on the depletion of natural ressources.

Now we will look at each individual interaction between a governance indicator and an environmental variable.

3.2 Control of Corruption

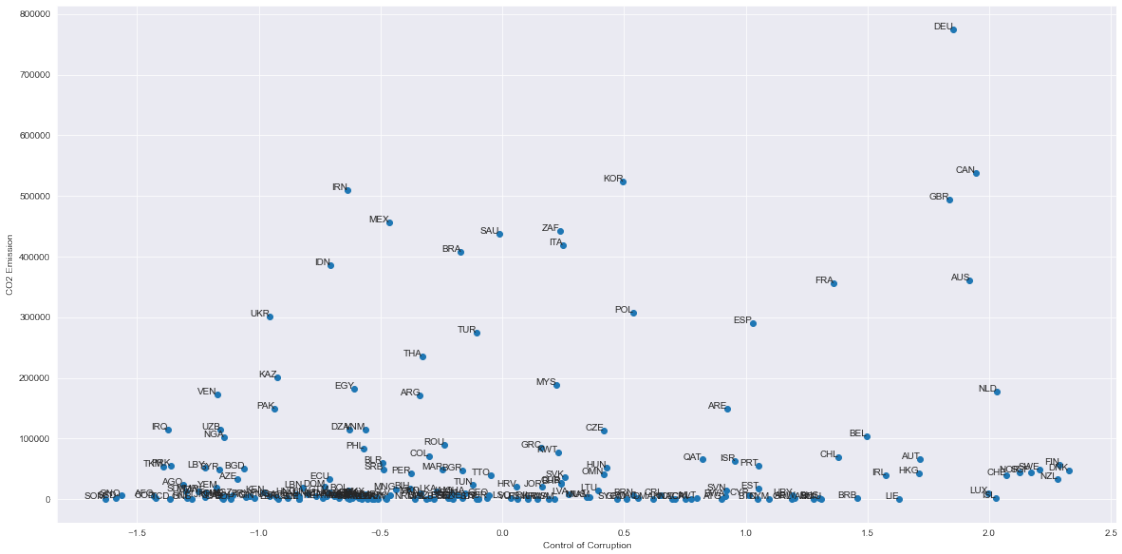
3.2.1 CO2

```
Text(0, 0.5, 'CO2 Emission')
```



We observe that outliers like China and the USA prevents us from looking at other countries. We decided to remove these outliers and show the graph again.

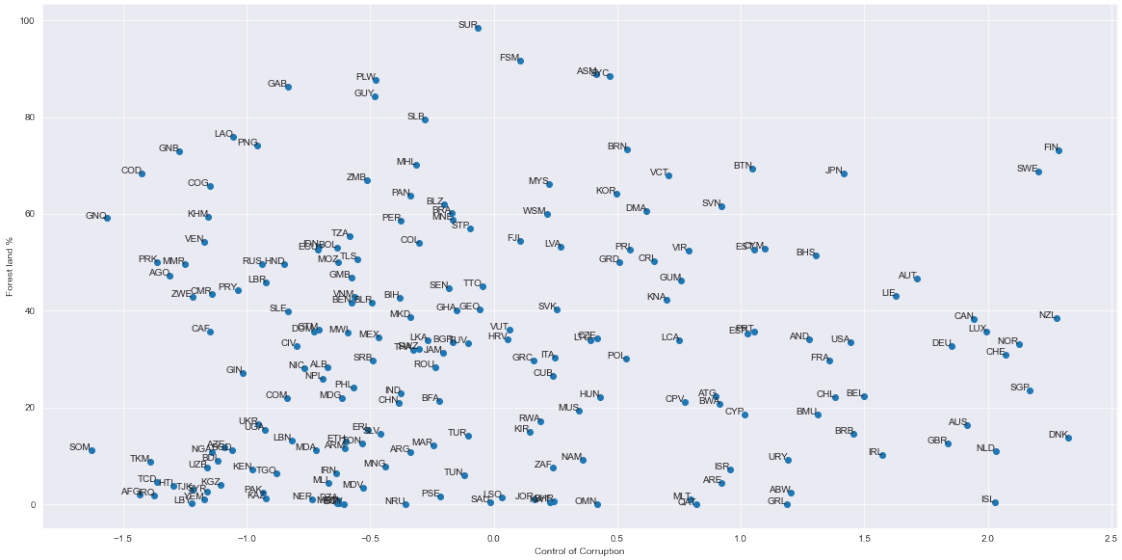
```
Text(0, 0.5, 'CO2 Emission')
```



We observe that Scandinavian countries have a low level of corruption and low Co2 emissions as well, whereas countries like India, Iran and Mexico are on the other end of the spectrum.

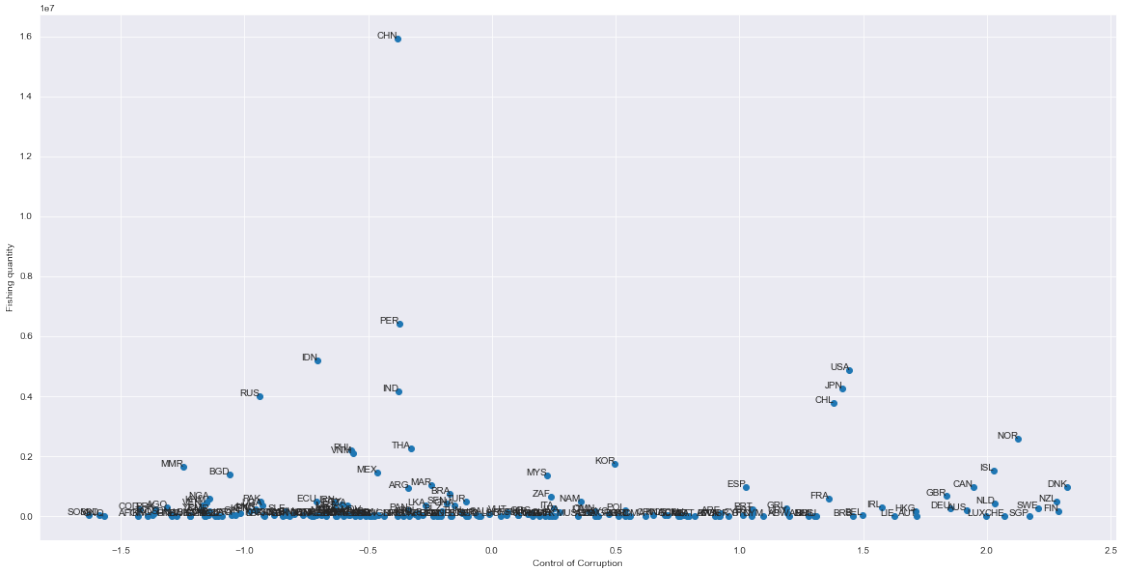
3.2.2 Forest

```
Text(0, 0.5, 'Forest land %')
```



3.2.3 Fishing

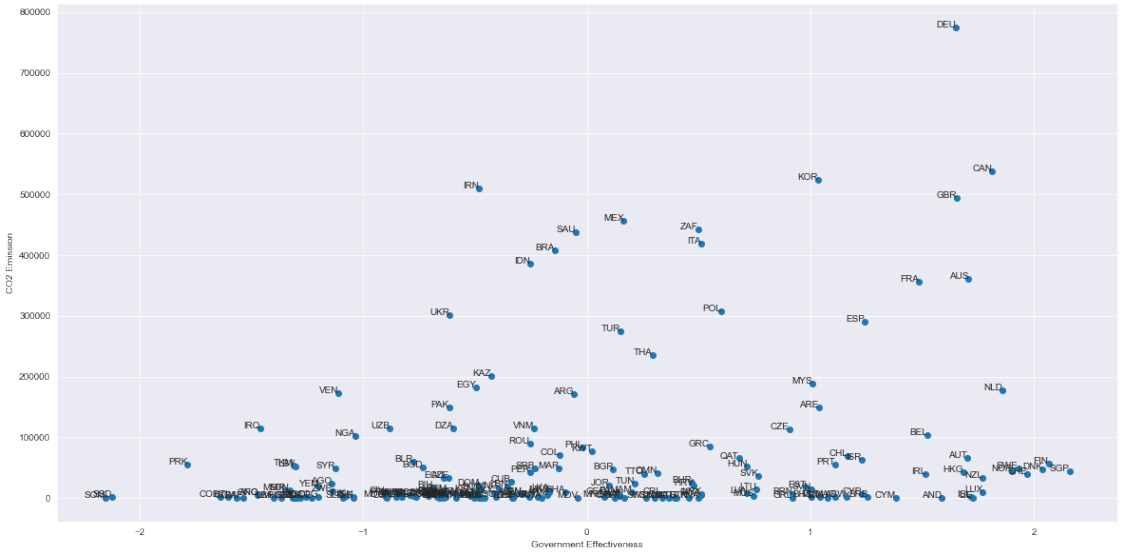
```
Text(0, 0.5, 'Fishing quantity')
```



3.3 Government effectiveness

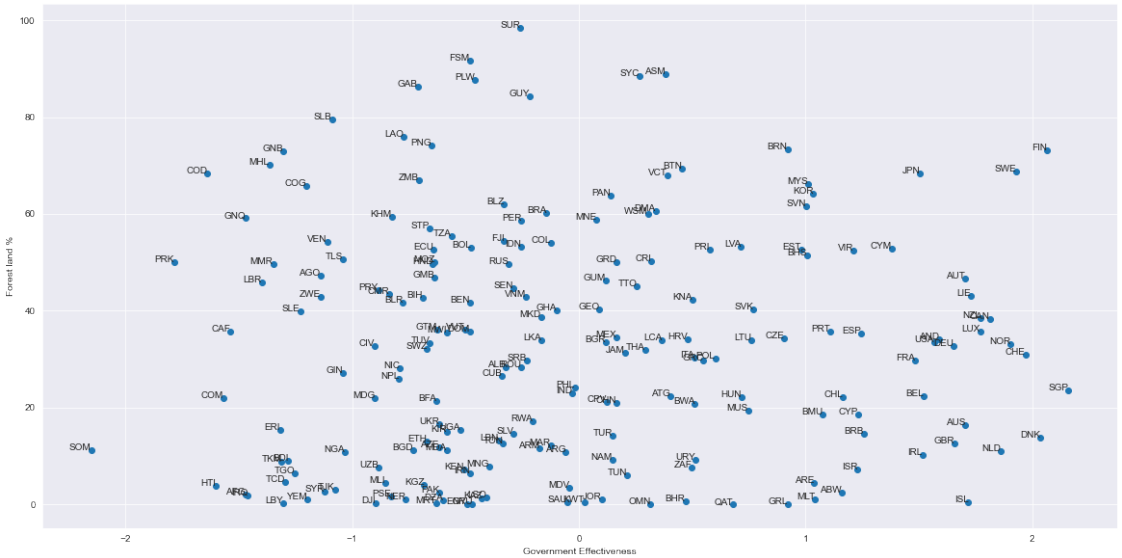
3.3.1 CO2

```
Text(0, 0.5, 'CO2 Emission')
```



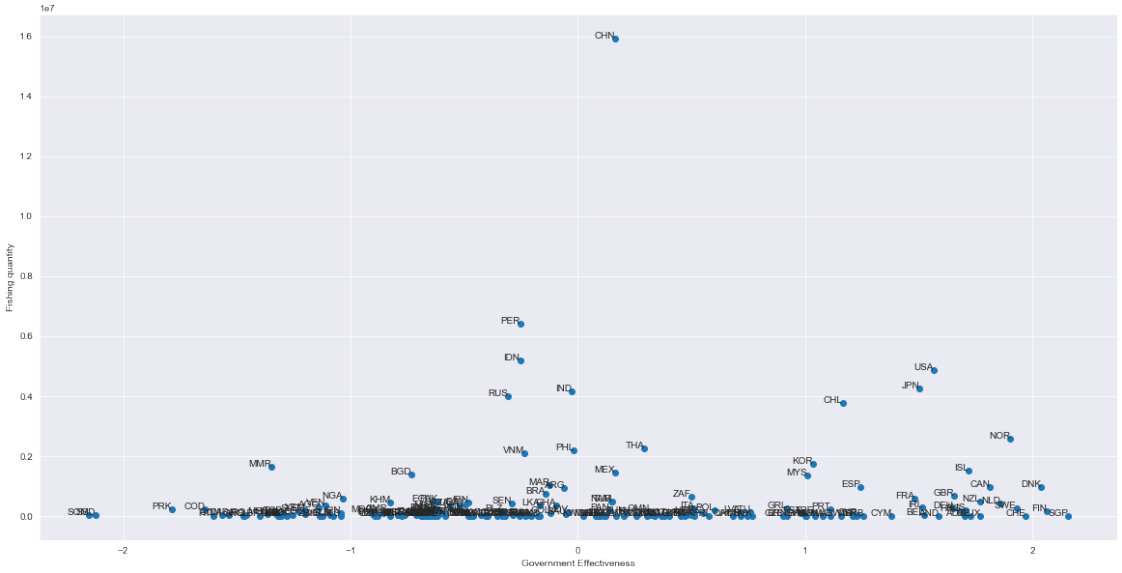
3.3.2 Forest

```
Text(0, 0.5, 'Forest land %')
```



3.3.3 Fishing

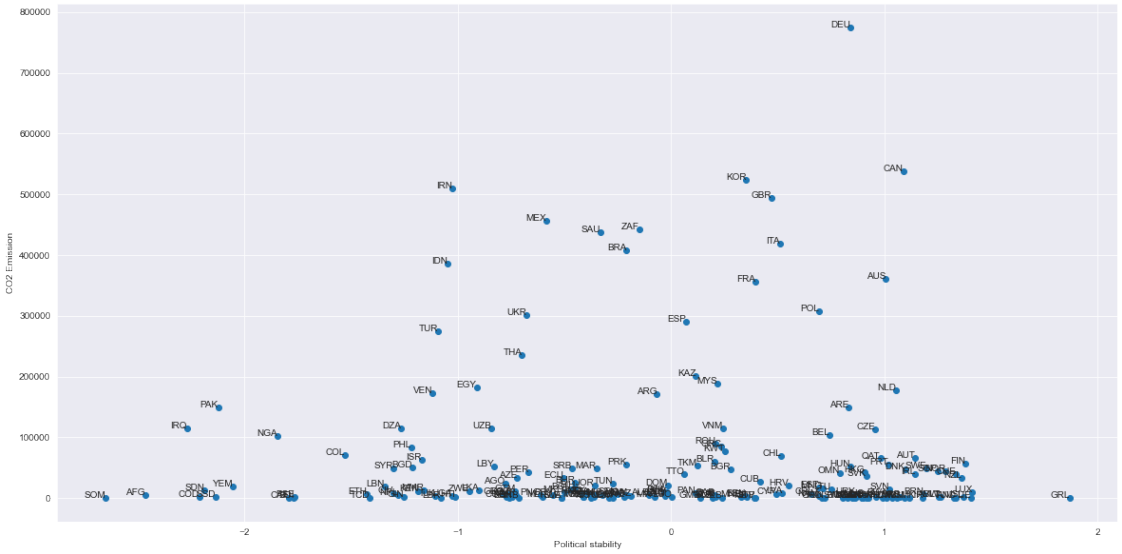
```
Text(0, 0.5, 'Fishing quantity')
```



3.4 Political stability

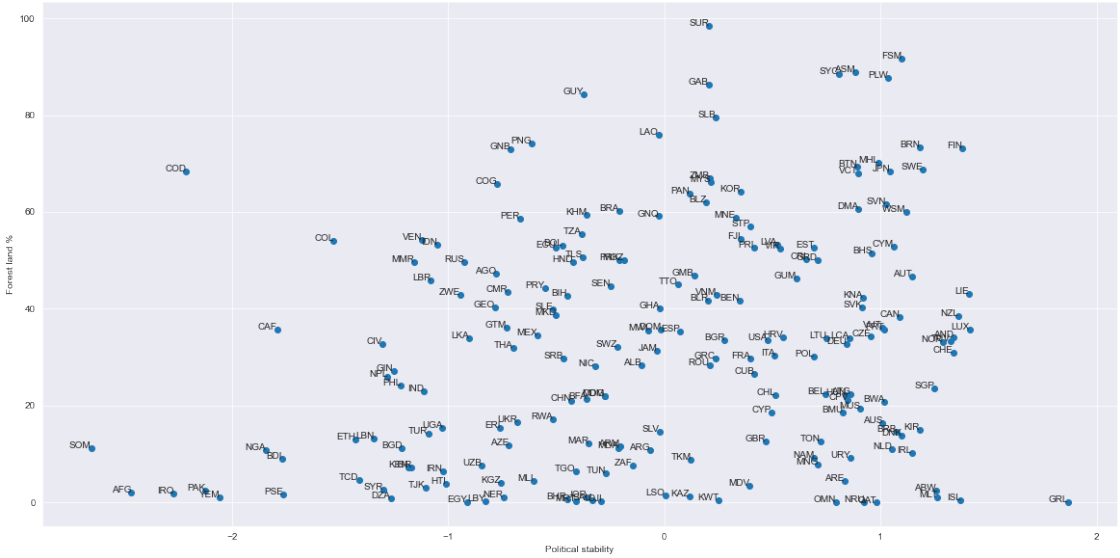
3.4.1 CO2

```
Text(0, 0.5, 'CO2 Emission')
```



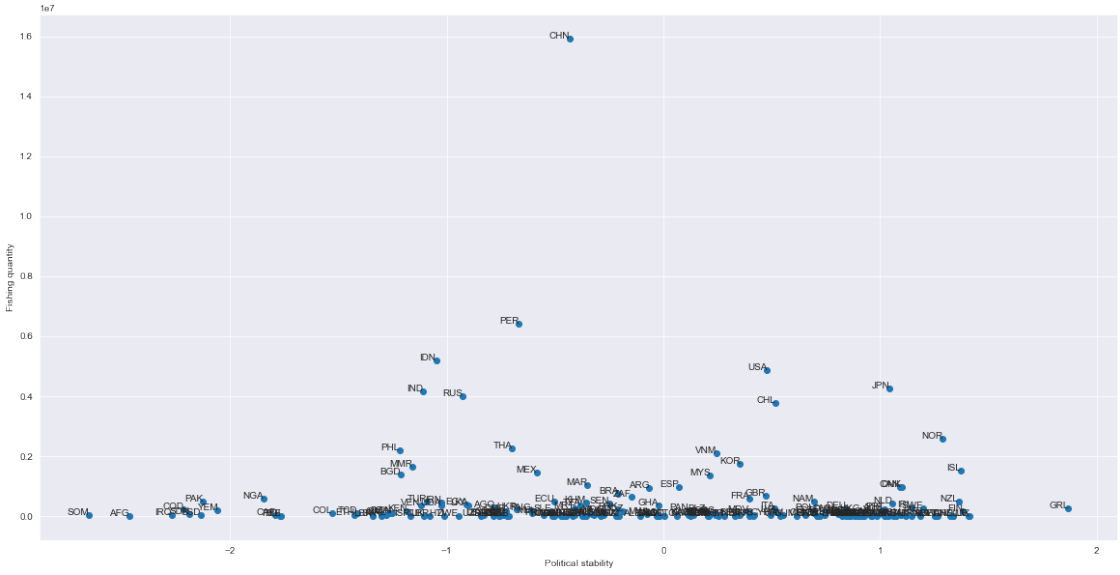
3.4.2 Forest

```
Text(0, 0.5, 'Forest land %')
```



3.4.3 Fishing

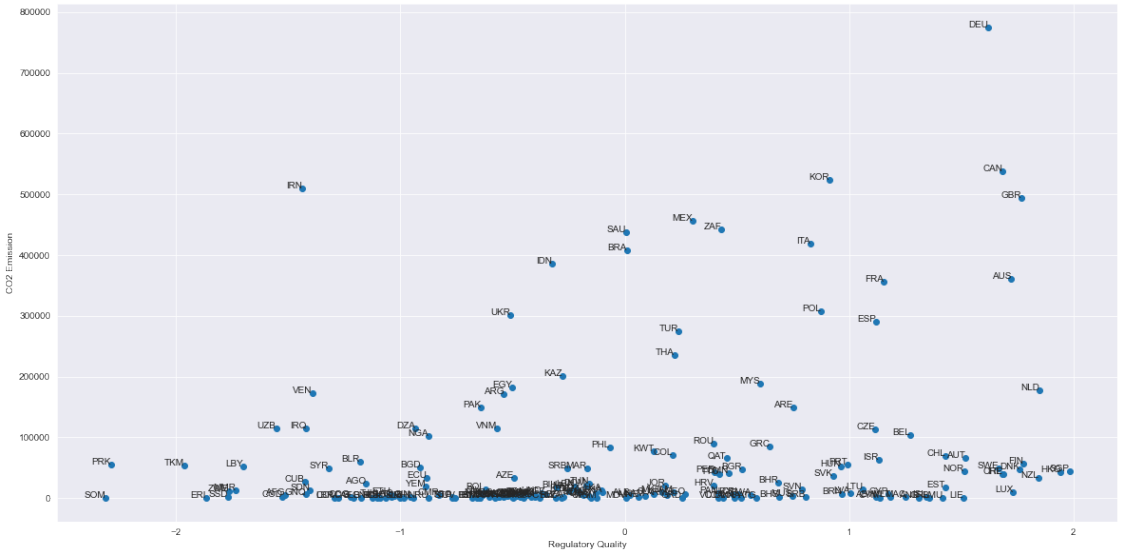
```
Text(0, 0.5, 'Fishing quantity')
```



3.5 Regulatory quality

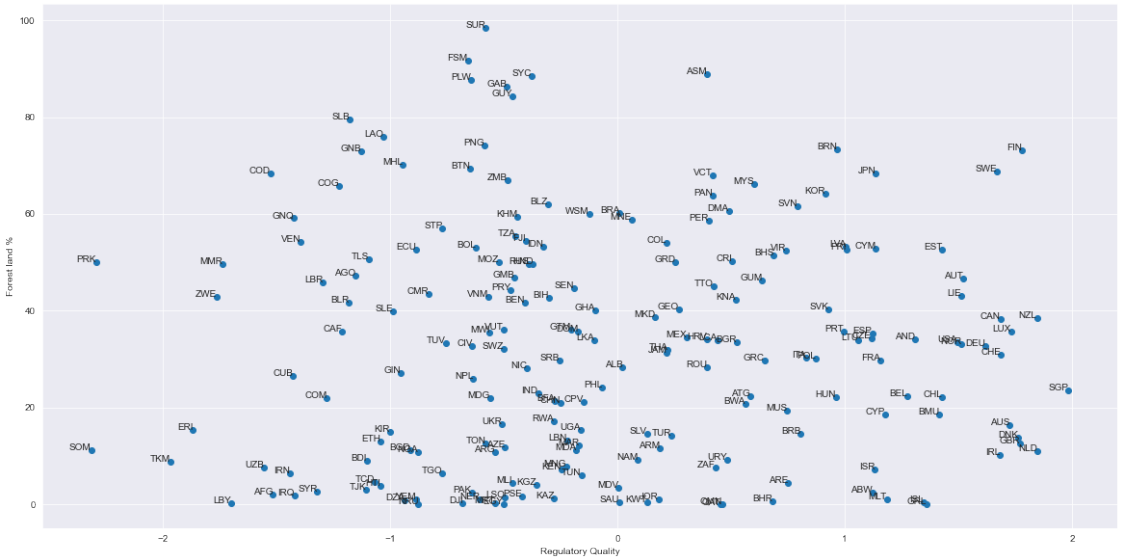
3.5.1 CO2

```
Text(0, 0.5, 'CO2 Emission')
```



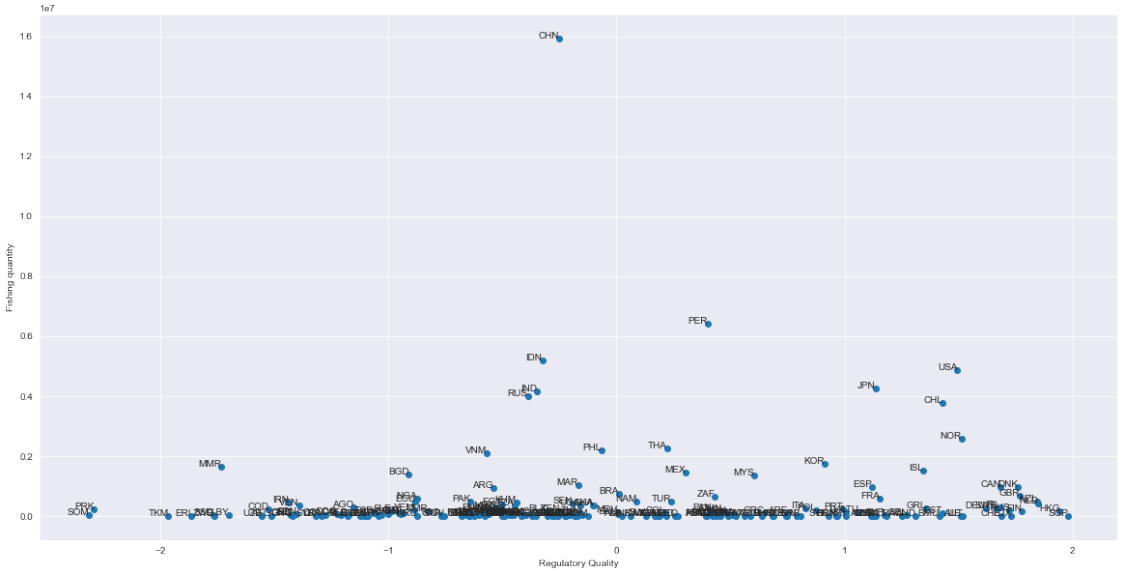
3.5.2 Forest

```
Text(0, 0.5, 'Forest land %')
```



3.5.3 Fishing

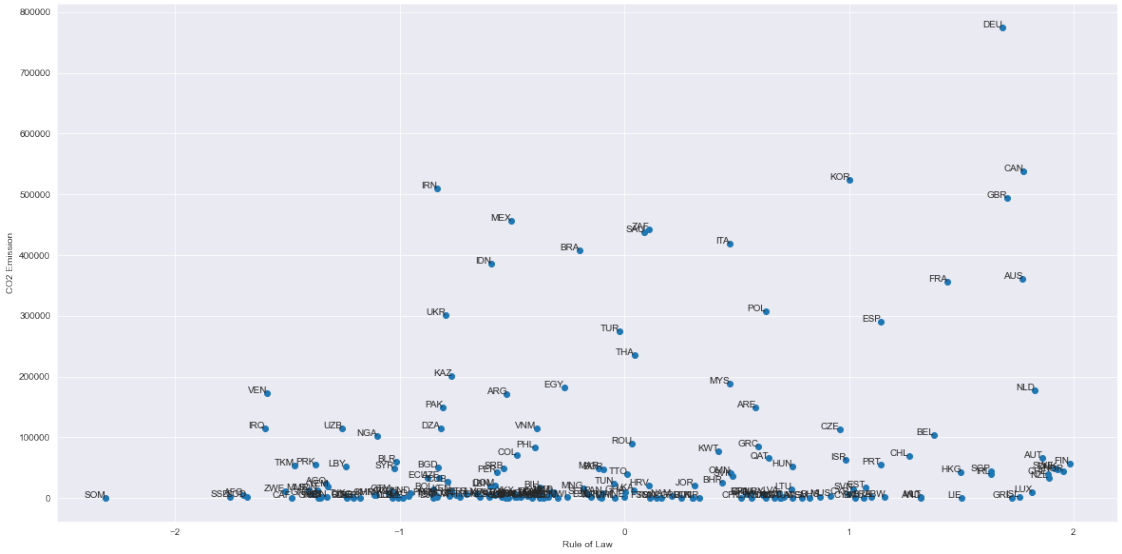
```
Text(0, 0.5, 'Fishing quantity')
```



3.6 Rule of Law

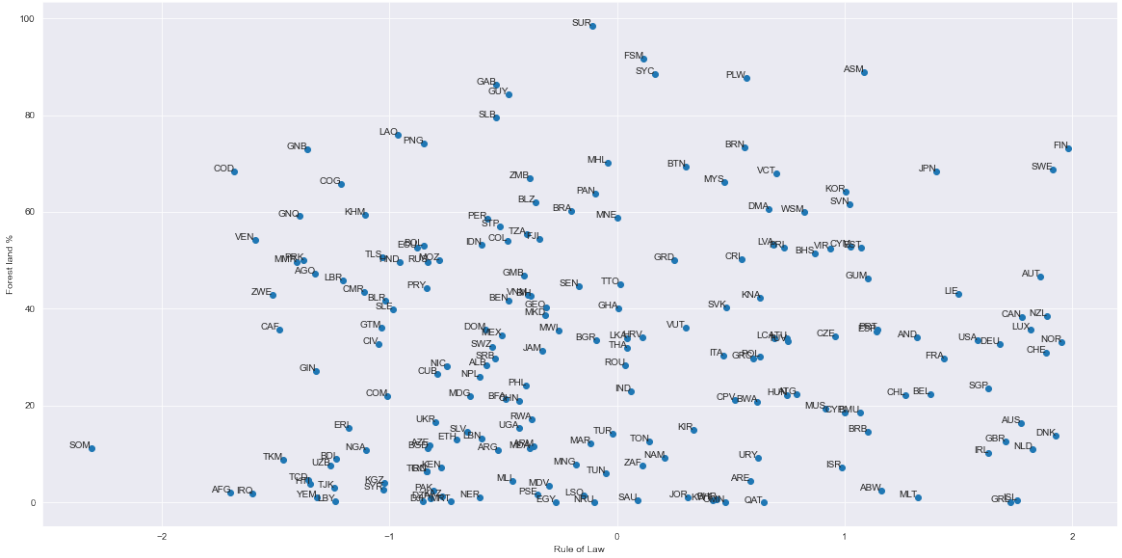
3.6.1 CO2

```
Text(0, 0.5, 'CO2 Emission')
```



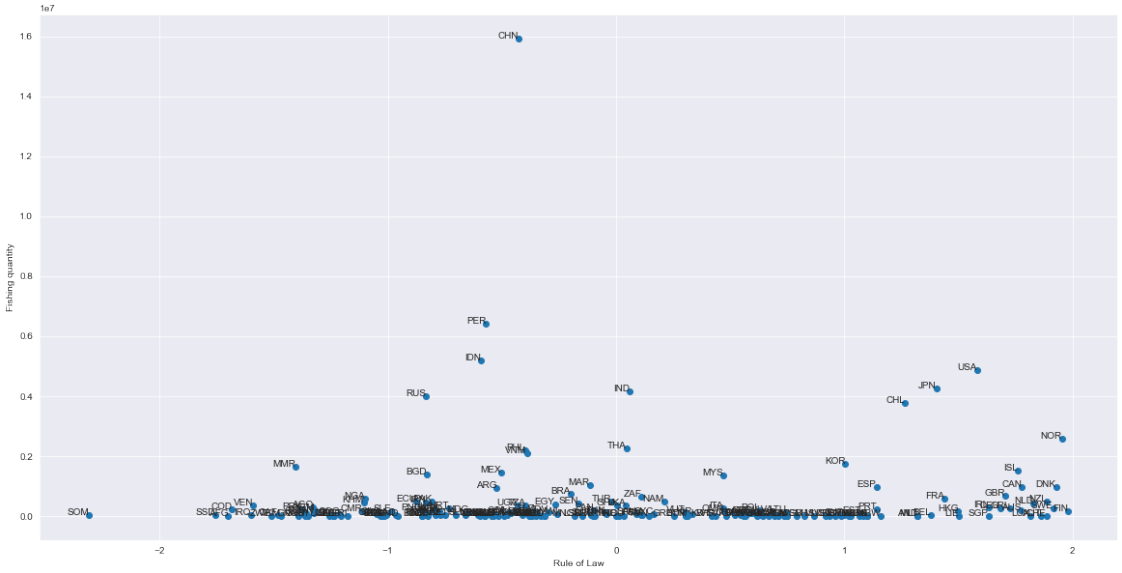
3.6.2 Forest

```
Text(0, 0.5, 'Forest land %')
```



3.6.3 Fishing

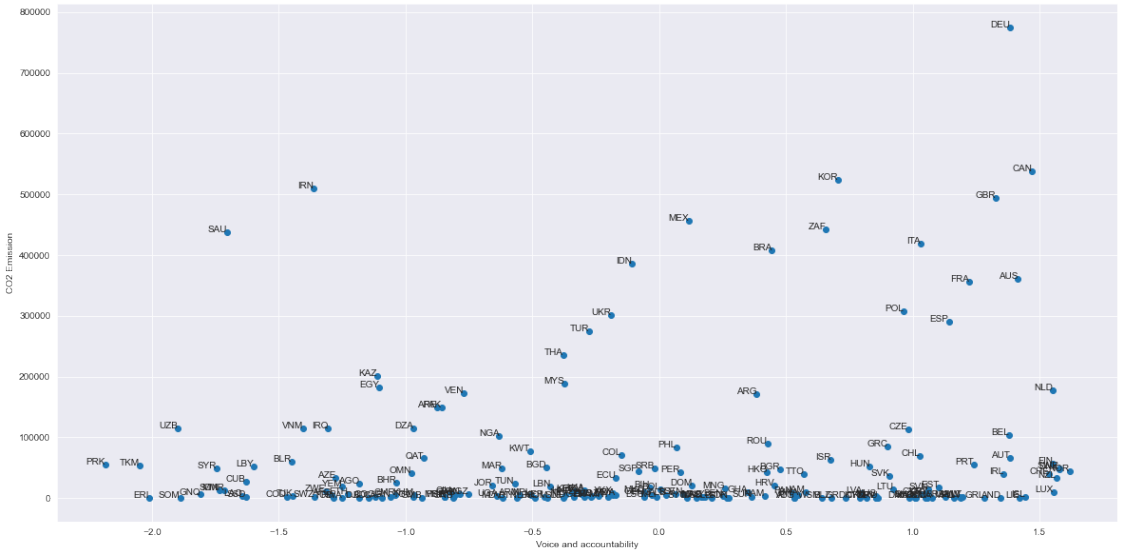
```
Text(0, 0.5, 'Fishing quantity')
```



3.7 Voice and accountability

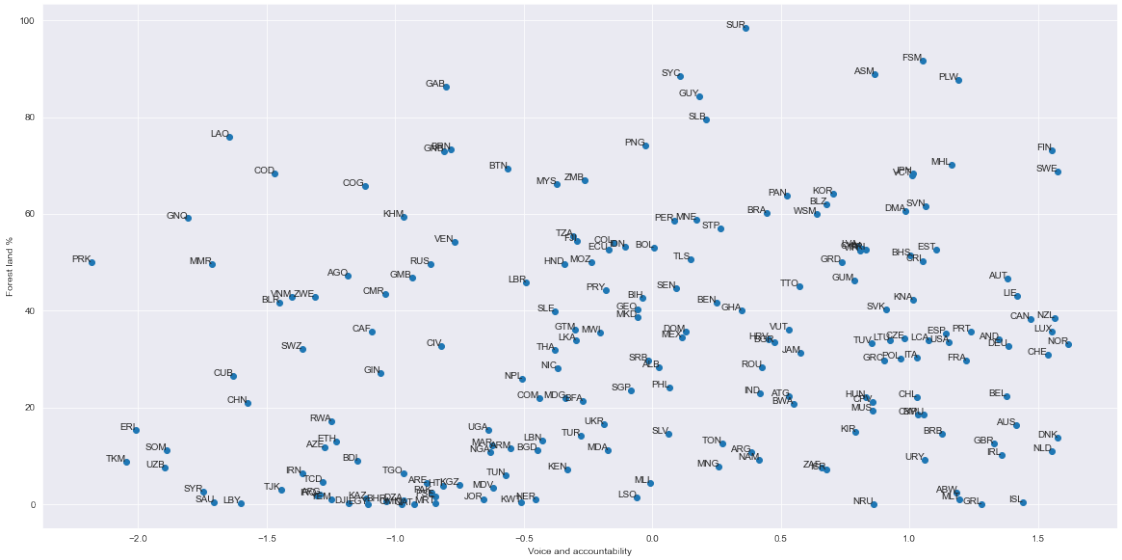
3.7.1 CO2

```
Text(0, 0.5, 'CO2 Emission')
```



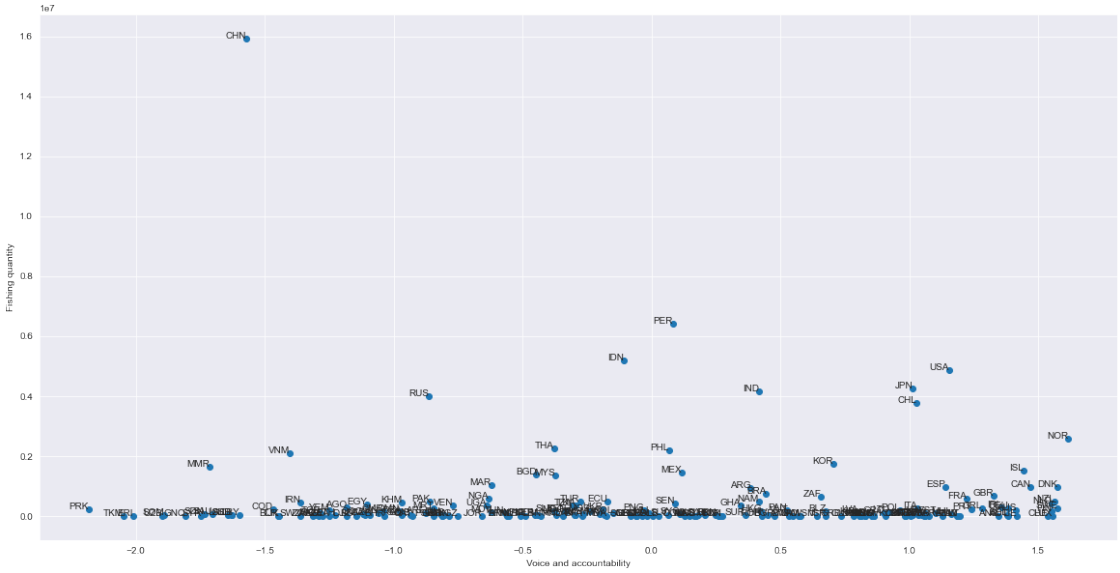
3.7.2 Forest

```
Text(0, 0.5, 'Forest land %')
```



3.7.3 Fishing

```
Text(0, 0.5, 'Fishing quantity')
```



4 Data Preparation for Dynamic Analysis

Since the STATIC analyses didn't show any significant correlation between the countries, we decided to rather look, for a given country, how the evolution of a political factors from one year to another (in %) influences the evolution of the environmental factors (in %).

4.1 Functions

Two steps:

- Dataframe with one row = country and one column = year, and value in cell = value of the variable
- Same dataframe but with percentage evolution

To build the "evolution" datasets, when we had missing years, we decided to conduct a linear interpolation on these missing years.

Note :

- Years are not incremented per 1 every time
- We have NaN in some columns

Example : in 2000 the forest was about 1,000 and in 2002 about 2,000. The year 2001 is missing. Therefore we assumed that the value of the year 2001 was about 1,500.

Overall we obtain ONE dataset for EACH variable (political & environmental). In each dataset:

- One row = One country
- One column = One year
- The value in the cell corresponding to one year equals the % evolution from the previous year.

4.2 Evolution CO2

The following code creates the "evolution" dataframe for the CO2 variable.

```
    1997   1998   1999   2000  2001  2002   2003   2004  2005   2006   2007  \
0 -0.058 -0.061 -0.129 -0.147 0.192 0.161  0.134 -0.245 0.448  0.243  0.378
1 -0.065 -0.070  0.362  0.266 0.121 0.108  0.145 -0.030 0.021 -0.084  0.008
2  0.051  0.049 -0.089 -0.098 0.012 0.012  0.019 -0.033 0.212 -0.058  0.082
3  0.040  0.039  0.034  0.032 0.007 0.007  0.007  0.048 0.026 -0.051 -0.013
4 -0.151 -0.177  0.153  0.133 0.164 0.141 -0.284  1.073 0.019  0.162  0.130

   2008   2009   2010   2011   2012   2013   2014   2015   2016  2017  2018  \
0 0.850  0.609  0.250  0.446 -0.121 -0.159 -0.064  0.067 -0.040 0.000 0.000
1 0.114  0.001  0.050  0.140 -0.060 -0.002  0.117 -0.159 -0.017 0.000 0.000
2 0.007  0.102 -0.018  0.017  0.073  0.034  0.081  0.053 -0.020 0.000 0.000
3 0.000 -0.041  0.000 -0.050 -0.007 -0.023 -0.031  0.008  0.008 0.000 0.000
4 0.022  0.081  0.046  0.053  0.117 -0.014  0.331 -0.229  0.003 0.000 0.000

   2019 Country Code
0 0.000          AFG
1 0.000          ALB
2 0.000          DZA
3 0.000          AND
4 0.000          AGO
```

4.3 Evolution Forest

```
    1997   1998   1999   2000   2001   2002   2003   2004   2005   2006  \
0  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
1 -0.003 -0.003 -0.003 -0.003  0.003  0.003  0.003  0.003  0.003 -0.002
2 -0.005 -0.005 -0.006 -0.006 -0.005 -0.005 -0.006 -0.006 -0.006  0.050
3  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
4 -0.002 -0.002 -0.002 -0.002 -0.002 -0.002 -0.002 -0.002 -0.002 -0.002

    2007   2008   2009   2010   2011   2012   2013   2014   2015   2016  \
0  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
1 -0.002 -0.002 -0.002 -0.002 -0.001 -0.001 -0.001 -0.001 -0.001 -0.001
2  0.047  0.045  0.043  0.041  0.004  0.004  0.004  0.004  0.004  0.004
3  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
4 -0.002 -0.002 -0.002 -0.002 -0.002 -0.002 -0.002 -0.002 -0.002 -0.002

  Country Code
```

```
0          AFG
1          ALB
2          DZA
3          AND
4          AGO
```

4.4 Evolution Fishing

```
    1997   1998   1999   2000   2001   2002   2003   2004   2005  2006   2007  \
0 -0.038 -0.040 -0.083 -0.091 -0.050 -0.053  0.000  0.111  0.000 0.000  0.000
1  0.131  0.116  0.120  0.107  0.049  0.047 -0.234  0.624  0.099 0.130 -0.042
2  0.063  0.059  0.113  0.101  0.094  0.086  0.049 -0.195  0.113 0.154  0.011
3    nan    nan    nan    nan    nan    nan    nan    nan    nan   nan    nan
4  0.092  0.084  0.234  0.189  0.034  0.033 -0.170  0.132 -0.156 0.114  0.357

    2008   2009   2010   2011  2012   2013   2014   2015   2016 Country Code
0  0.000  0.000  0.000  0.000 0.000  0.000  0.000  0.000  0.000          AFG
1 -0.009  0.083 -0.117 -0.064 0.793  0.043  0.007 -0.130  0.001          ALB
2 -0.058 -0.080 -0.269  0.089 0.037 -0.043 -0.032 -0.019 -0.010          DZA
3    nan    nan    nan    nan   nan    nan    nan    nan    nan          AND
4 -0.002 -0.111  0.140  0.103 0.094  0.088  0.086  0.120 -0.018          AGO
```

4.5 Evolution Corruption

```
    1997   1998   1999   2000   2001   2002   2003   2004   2005   2006  \
0  0.043  0.045 -0.048 -0.046  0.012  0.013 -0.069  0.004 -0.073  0.007
1 -0.078 -0.072  0.085  0.093 -0.007 -0.007  0.065  0.139 -0.124 -0.022
2 -0.278 -0.217 -0.032 -0.031  0.033  0.034  0.209  0.018  0.290 -0.081
3  0.023  0.022 -0.007 -0.007 -0.004 -0.004  0.020 -0.174  0.124 -0.015
4 -0.102 -0.093 -0.042 -0.040  0.111  0.125 -0.116  0.005  0.013  0.059

    2007   2008   2009   2010   2011   2012   2013   2014   2015   2016  \
0 -0.108 -0.032  0.063 -0.066  0.035  0.101 -0.012  0.057  0.009 -0.137
1  0.144  0.137  0.093  0.025 -0.301 -0.064  0.038  0.215  0.126  0.154
2 -0.074 -0.062  0.028  0.092 -0.038  0.076  0.059 -0.267 -0.076 -0.050
3  0.008  0.015  0.029 -0.013 -0.022 -0.009 -0.006 -0.028 -0.005  0.008
4 -0.057  0.004 -0.093  0.056 -0.014  0.056 -0.032 -0.102  0.034 -0.032

    2017   2018   2019 Country Code
0  0.006  0.014  0.064          AFG
1 -0.032 -0.248 -0.013          ALB
2  0.112 -0.047  0.013          DZA
3  0.011 -0.003 -0.004          AND
4  0.019  0.190  0.079          AGO
```

4.6 Evolution Government Effectiveness

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	\
0	0.009	0.009	-0.022	-0.022	0.149	0.175	0.310	0.174	-0.354	-0.181	
1	0.042	0.043	-0.098	-0.089	0.147	0.172	-0.009	0.227	-0.586	0.206	
2	0.119	0.135	-0.081	-0.075	0.190	0.235	-0.025	0.065	0.183	-0.011	
3	0.017	0.017	-0.005	-0.005	-0.008	-0.008	-0.009	0.081	-0.152	0.194	
4	-0.280	-0.219	-0.045	-0.043	0.076	0.083	0.066	-0.137	0.135	-0.204	

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	\
0	0.019	-0.066	0.008	0.020	0.004	0.061	-0.018	0.039	0.006	0.073	-0.088	
1	0.223	0.123	0.277	-0.096	0.264	-0.286	-0.183	0.730	1.120	0.290	5.313	
2	-0.197	-0.107	0.070	0.177	-0.177	0.057	-0.004	0.106	-0.049	-0.060	-0.109	
3	-0.023	0.019	0.002	-0.014	-0.009	0.018	0.005	0.116	0.040	0.041	0.041	
4	0.119	0.120	0.096	-0.164	-0.032	0.142	-0.236	0.081	0.110	-0.036	0.010	

	2018	2019	Country Code
0	-0.092	-0.005	AFG
1	0.370	-1.534	ALB
2	0.247	-0.163	DZA
3	0.004	-0.019	AND
4	-0.026	-0.062	AGO

4.7 Evolution Political Stability

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	\
0	-0.002	-0.002	-0.004	-0.004	0.083	0.090	-0.080	-0.045	0.098	-0.073	
1	-0.313	-0.238	0.004	0.004	0.226	0.292	-0.048	-0.387	-0.184	-0.002	
2	-0.027	-0.026	0.118	0.134	-0.070	-0.066	-0.074	0.225	0.327	-0.231	
3	0.006	0.006	-0.007	-0.007	0.049	0.047	0.143	-0.043	-0.012	-0.026	
4	-0.062	-0.059	0.060	0.064	0.113	0.127	0.362	-0.056	0.165	0.389	

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	\
0	-0.085	-0.116	-0.008	0.049	0.030	0.033	-0.042	0.043	-0.066	-0.039	-0.049	
1	0.600	0.848	-0.468	-3.232	-0.475	0.491	1.640	4.286	-0.288	-0.004	0.098	
2	-0.019	0.047	-0.094	-0.052	-0.080	0.026	0.093	0.010	0.084	-0.007	0.166	
3	-0.006	-0.002	-0.031	-0.014	0.019	-0.009	-0.005	0.002	0.081	0.016	0.006	
4	-0.229	0.455	0.043	0.349	-0.632	-0.054	-0.005	0.148	-0.503	0.369	-0.050	

	2018	2019	Country Code
0	0.017	0.037	AFG
1	-0.000	-0.687	ALB
2	0.097	-0.214	DZA
3	0.002	0.134	AND
4	0.045	0.017	AGO

4.8 Evolution Regulatory Quality

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
0	0.001	0.001	-0.005	-0.005	0.072	0.078	0.208	-0.053	-0.087	-0.019	-0.012
1	0.318	0.465	-0.235	-0.190	0.058	0.062	-0.992	0.630	-1.244	0.726	1.596
2	0.090	0.098	0.026	0.027	0.086	0.095	0.114	-0.052	0.295	-0.491	-0.088
3	0.014	0.013	-0.009	-0.010	0.076	0.070	-0.015	-0.016	-0.045	-0.008	0.020
4	-0.097	-0.088	-0.032	-0.031	0.093	0.103	0.172	-0.033	-0.005	0.099	0.096

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
0	0.039	-0.033	0.084	-0.005	0.226	-0.000	0.063	0.108	-0.331	-0.009
1	1.434	0.615	-0.037	0.015	-0.145	0.053	0.059	-0.159	0.013	0.180
2	-0.277	-0.351	-0.091	-0.016	-0.073	0.087	-0.100	0.085	0.001	-0.021
3	0.015	0.007	-0.012	0.162	-0.030	-0.001	-0.435	0.031	-0.045	0.385
4	-0.040	0.032	-0.004	-0.060	0.117	-0.087	0.062	0.080	-0.101	-0.043

	2018	2019	Country Code
0	0.156	0.009	AFG
1	0.204	0.022	ALB
2	-0.055	-0.032	DZA
3	-0.011	0.029	AND
4	0.162	-0.022	AGO

4.9 Evolution Rule of Law

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
0	0.014	0.014	-0.012	-0.012	0.030	0.031	0.070	-0.092	0.023	-0.123
1	-0.175	-0.149	-0.046	-0.044	0.122	0.139	0.051	0.049	-0.071	0.070
2	0.024	0.024	-0.022	-0.021	0.240	0.316	0.067	-0.057	-0.209	0.056
3	0.024	0.023	0.041	0.039	-0.023	-0.023	-0.132	0.113	-0.194	-0.113
4	-0.022	-0.021	0.011	0.011	0.014	0.014	0.059	0.017	0.046	0.089

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
0	0.018	-0.019	0.009	0.001	-0.028	0.134	0.028	0.095	-0.040	0.004	-0.048
1	0.056	0.089	0.150	0.186	-0.118	-0.143	0.004	0.348	0.029	-0.002	-0.222
2	-0.091	0.040	-0.070	0.011	-0.029	0.044	0.107	-0.122	-0.117	0.008	-0.008
3	0.366	0.011	0.024	-0.016	0.169	-0.000	0.001	0.165	-0.040	0.001	0.015
4	-0.050	-0.001	0.100	-0.028	-0.000	-0.003	0.001	0.118	0.032	-0.005	-0.016

	2018	2019	Country Code
0	-0.063	-0.027	AFG
1	0.023	-0.048	ALB
2	0.103	-0.052	DZA
3	0.003	-0.017	AND
4	0.051	-0.006	AGO

4.10 Evolution of Voice and accountability

```
    1997   1998   1999   2000   2001   2002   2003   2004   2005   2006  \
0 -0.034 -0.033  0.002  0.002  0.147  0.173  0.178 -0.022  0.065  0.013
1  0.201  0.252  0.132  0.152  0.486  0.944  9.626 -0.897 -0.493 19.668
2 -0.033 -0.032  0.054  0.057  0.029  0.030 -0.031  0.255  0.108 -0.281
3 -0.011 -0.011  0.002  0.002 -0.032 -0.033 -0.010  0.099 -0.022 -0.130
4  0.053  0.056 -0.016 -0.016  0.075  0.081 -0.027 -0.010  0.039 -0.014

    2007   2008   2009   2010   2011   2012   2013   2014   2015   2016  \
0  0.047 -0.105 -0.177 -0.021  0.049  0.051  0.022  0.084  0.016  0.071
1  0.489  0.548 -0.191 -0.125 -0.497 -0.646  1.216  1.940  0.093  0.088
2 -0.073  0.004 -0.060  0.015  0.018  0.098  0.014  0.087 -0.042 -0.016
3 -0.018  0.015 -0.002  0.001  0.027  0.054 -0.019 -0.171  0.024 -0.015
4  0.053  0.056 -0.006  0.005 -0.004  0.044 -0.035 -0.028 -0.028  0.032

    2017   2018   2019 Country Code
0  0.046 -0.003  0.005          AFG
1  0.190  0.021 -0.269          ALB
2 -0.047 -0.086 -0.057          DZA
3 -0.014 -0.078  0.065          AND
4  0.037  0.163  0.154          AGO
```

5 Dynamic Bivariate Analysis

Now, we want to see if the evolution of a political factor influences the evolution of an environmental factor.

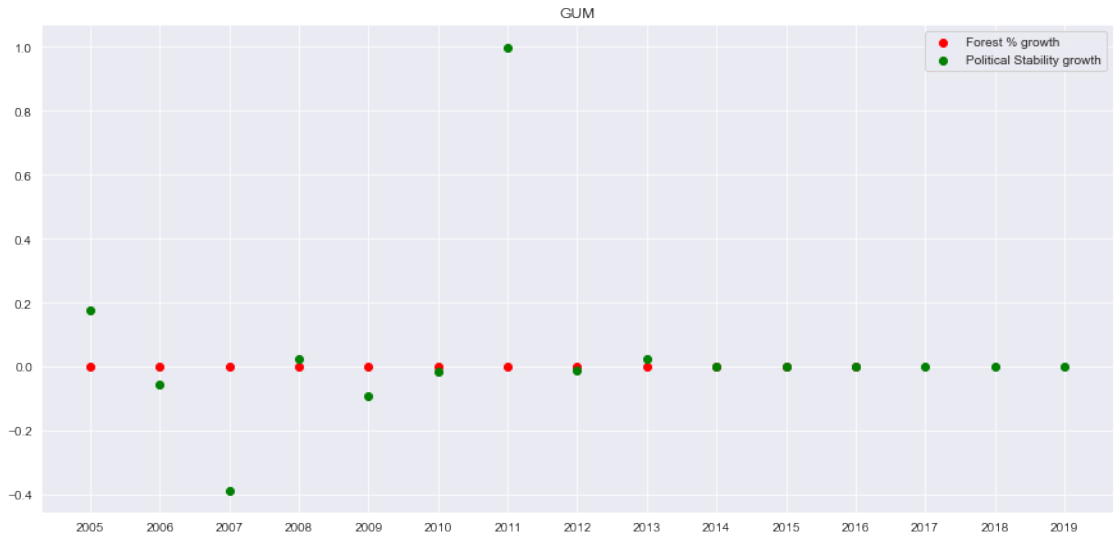
Example: does an increase in political instability lead to a decrease in forest area ?

To do so, and not to provide too much information, we will only focus on the most correlated variables, which are:

- Political Stability & Forest
- Voice and accountability & Forest
- Government Effectiveness & CO2
- Government Effectiveness & Fisheries

5.1 Political Stability & Forest

```
Text(0.5, 1.0, 'GUM')
```

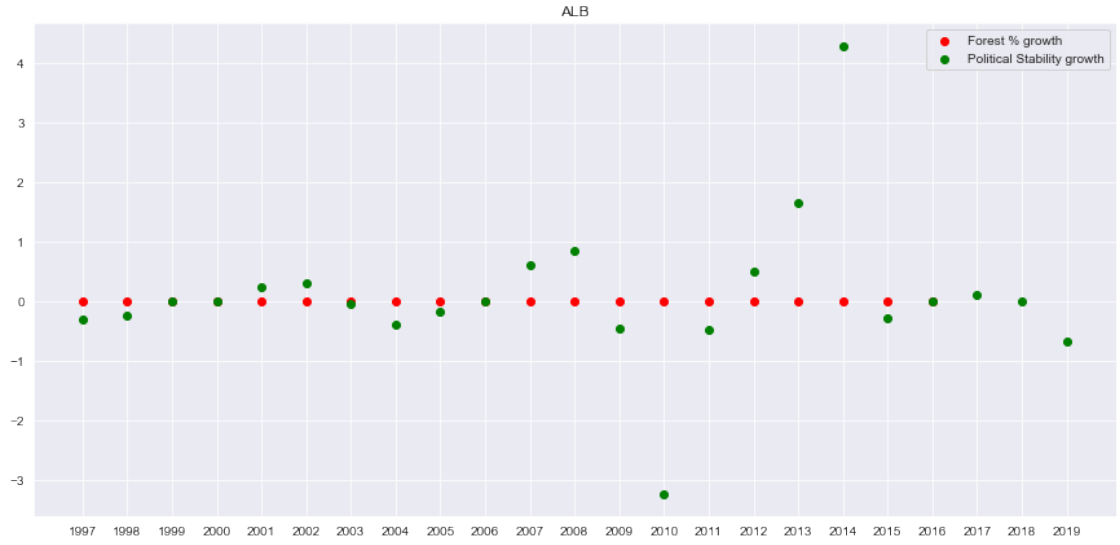


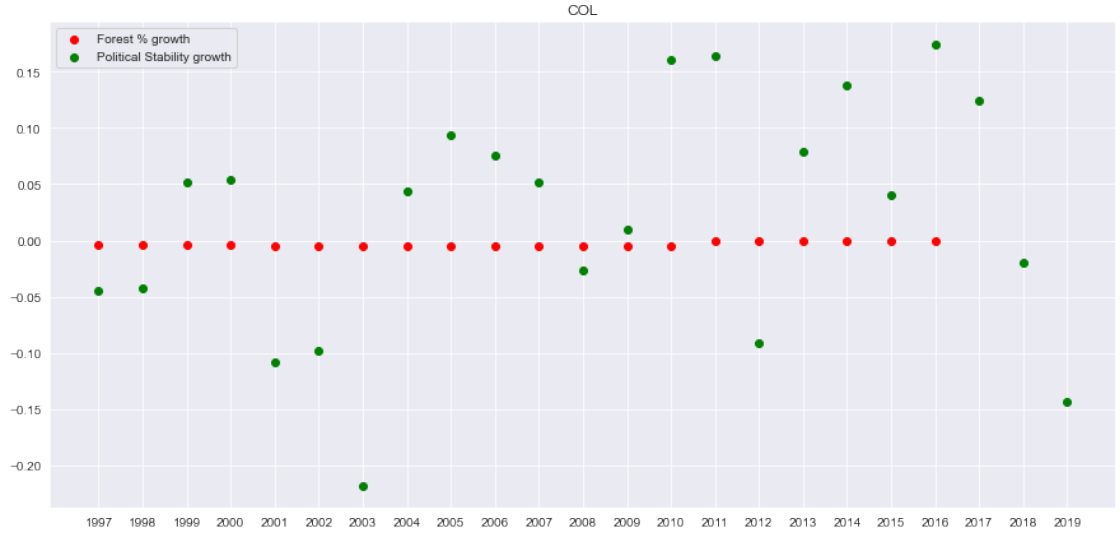
`Average correlation is : 0.00898548335332742`

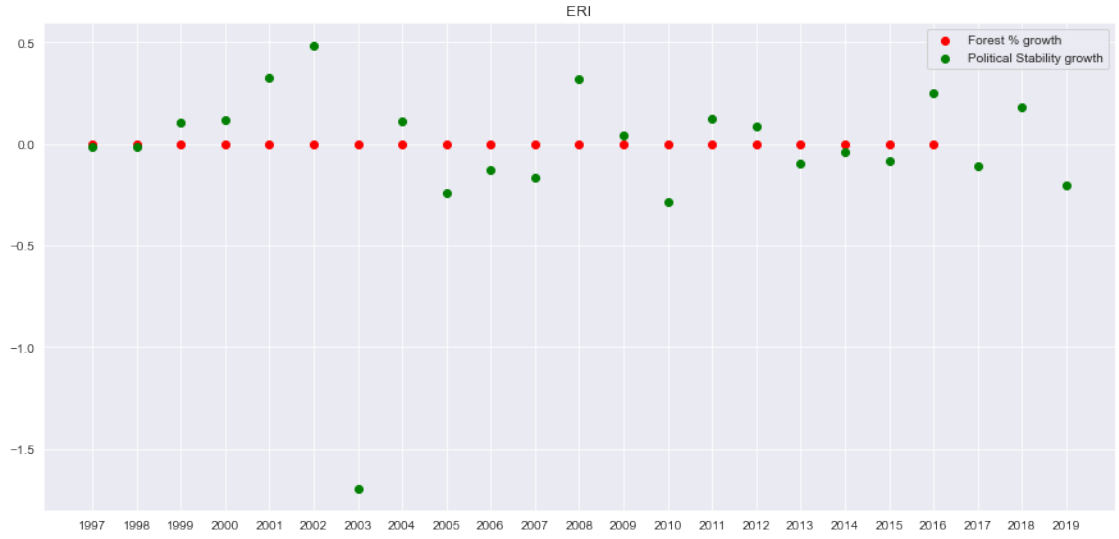
No overall correlation, so there is no identified link between the evolution of the political stability and the evolution of the forest land.

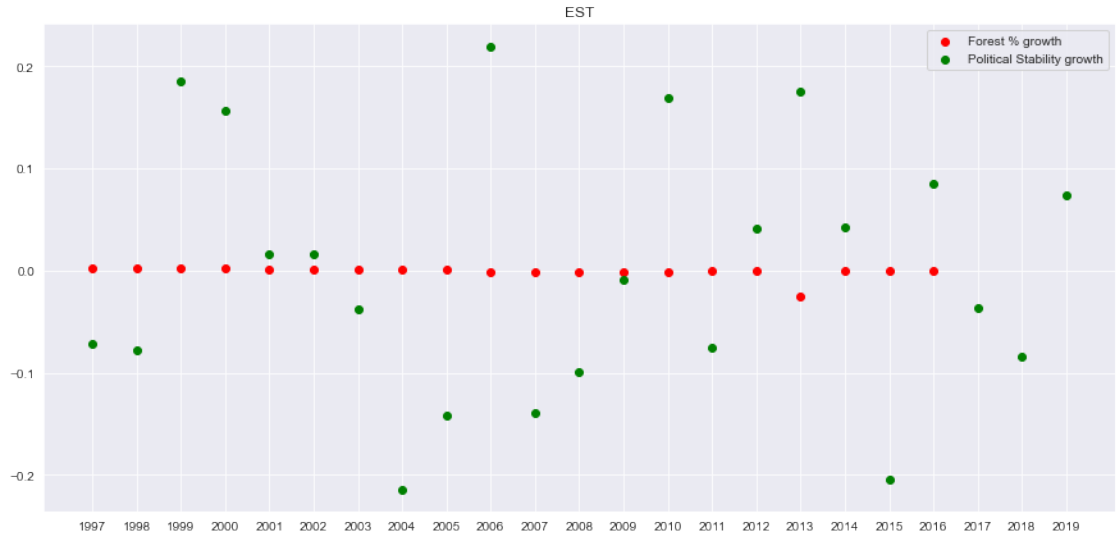
Maybe the average correlation is null but it works for some countries ?

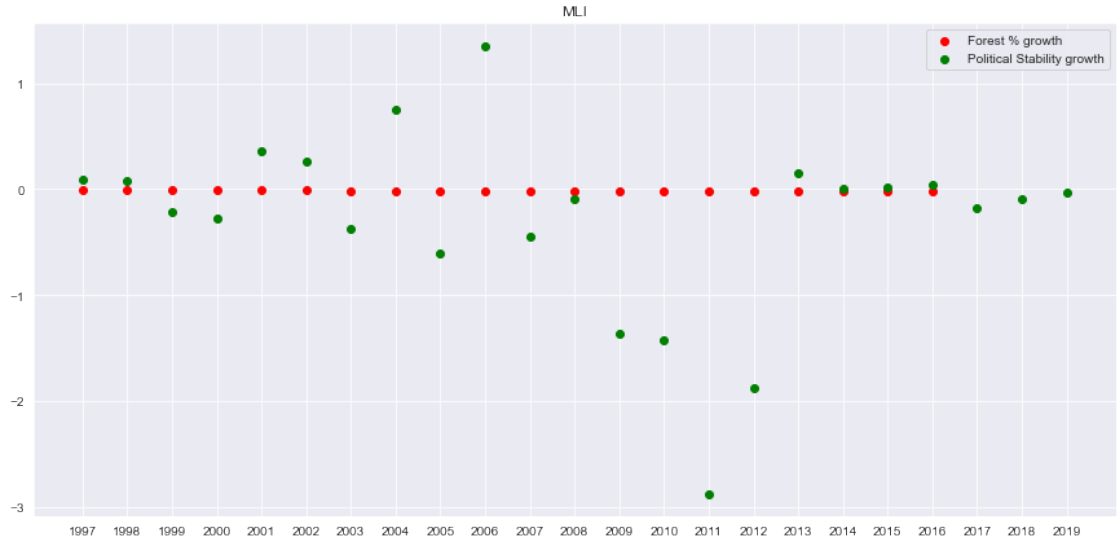
```
{'ALB': -0.44181907836237694,
 'COL': 0.48610548170252993,
 'ERI': -0.4336326638676377,
 'EST': 0.425237362249352,
 'MLI': 0.4756801884434646,
 'NPL': -0.5148176786146175,
 'NIC': 0.49034338837694613,
 'SAU': 0.42252399681269254,
 'SLE': 0.4406741556972522,
 'SWE': -0.5867551970873705,
 'THA': -0.5735656863151068,
 'USA': 0.5152340415645562}
```

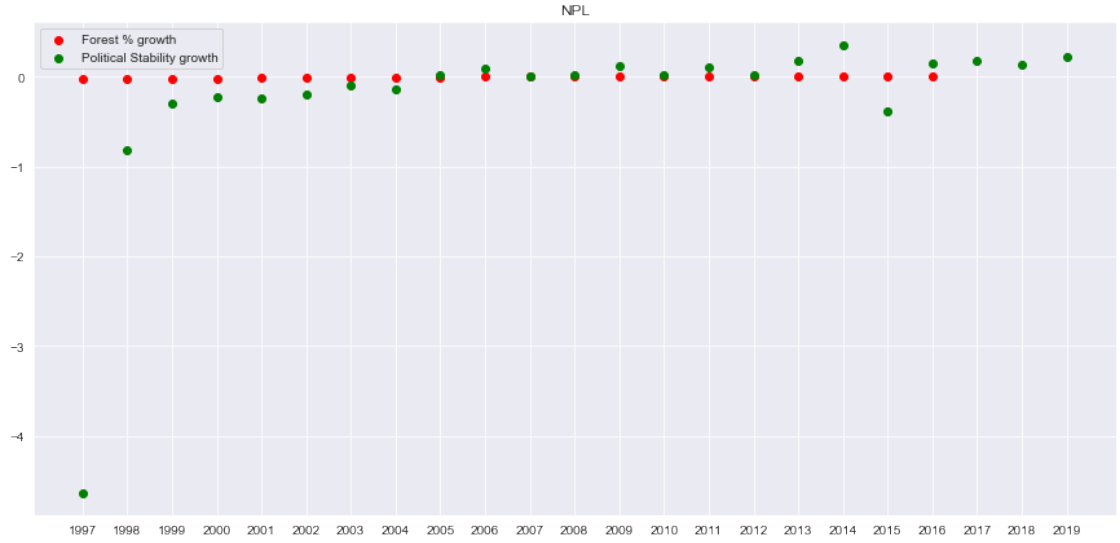

ALB
Forest % growth
Political Stability growth
4
3
2
1
0
−1
−2
−3
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

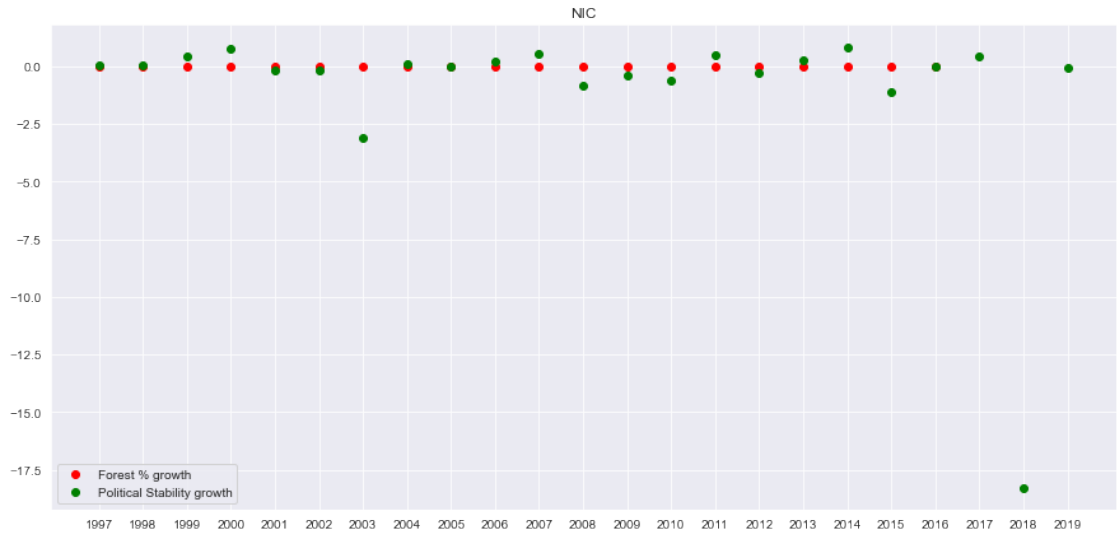

COL
Forest % growth
Political Stability growth
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

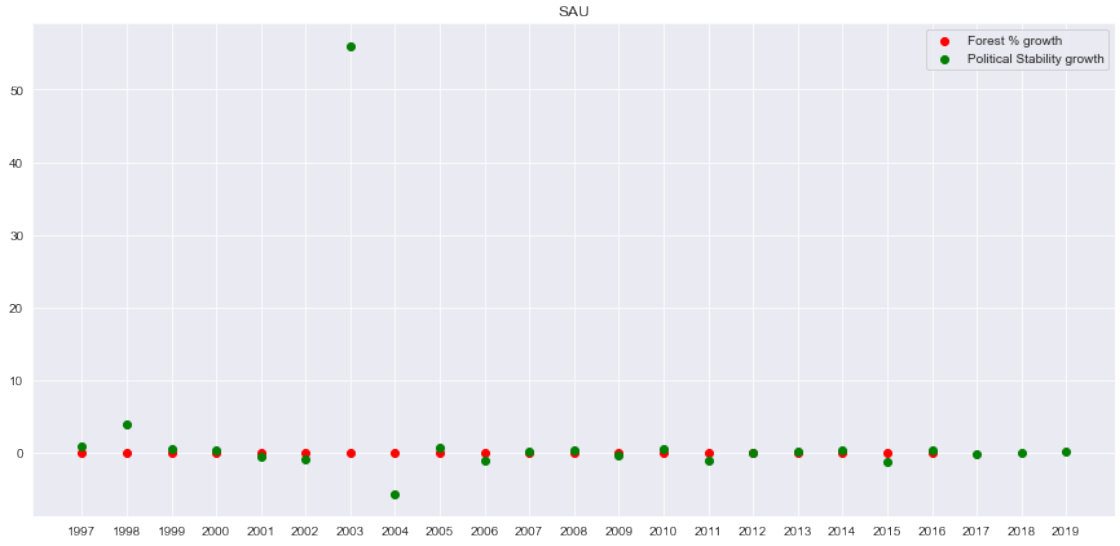

ERI
Forest % growth
Political Stability growth
0.5
0.0
−0.5
−1.0
−1.5
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

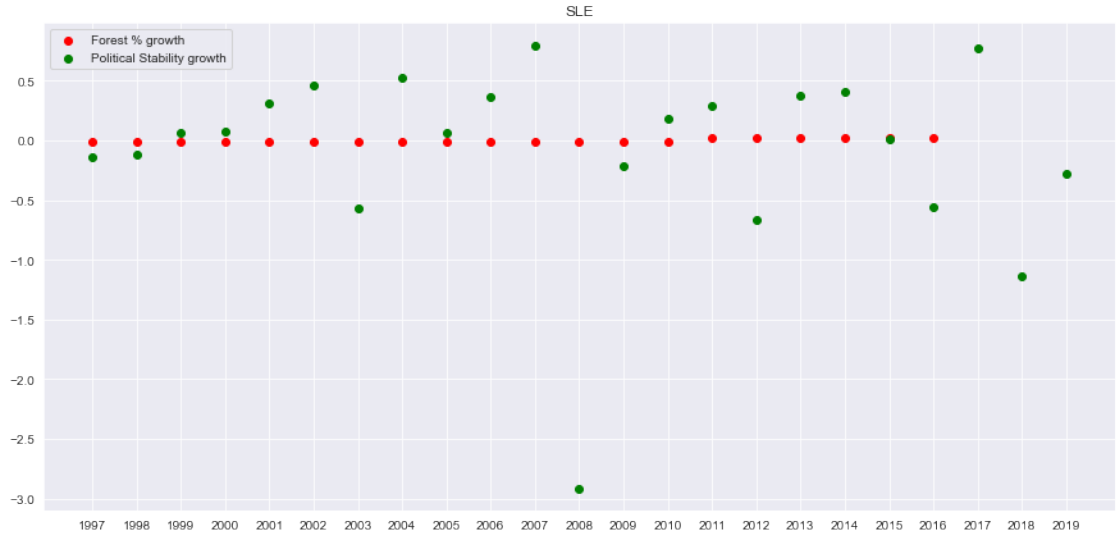

EST
Forest % growth
Political Stability growth
0.2
0.1
0.0
−0.1
−0.2
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

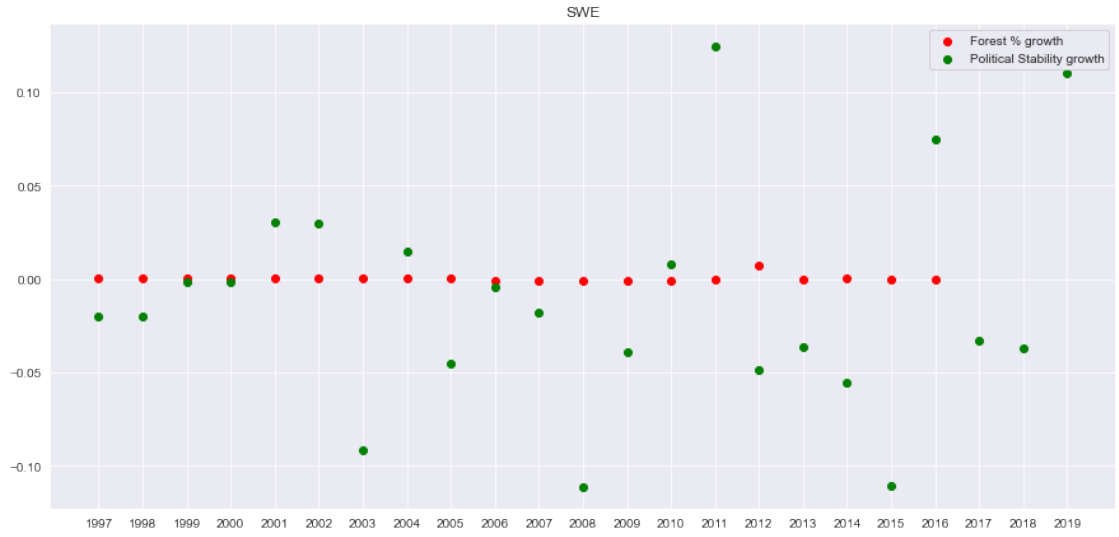

MLI
Forest % growth
Political Stability growth
1
0
−1
−2
−3
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

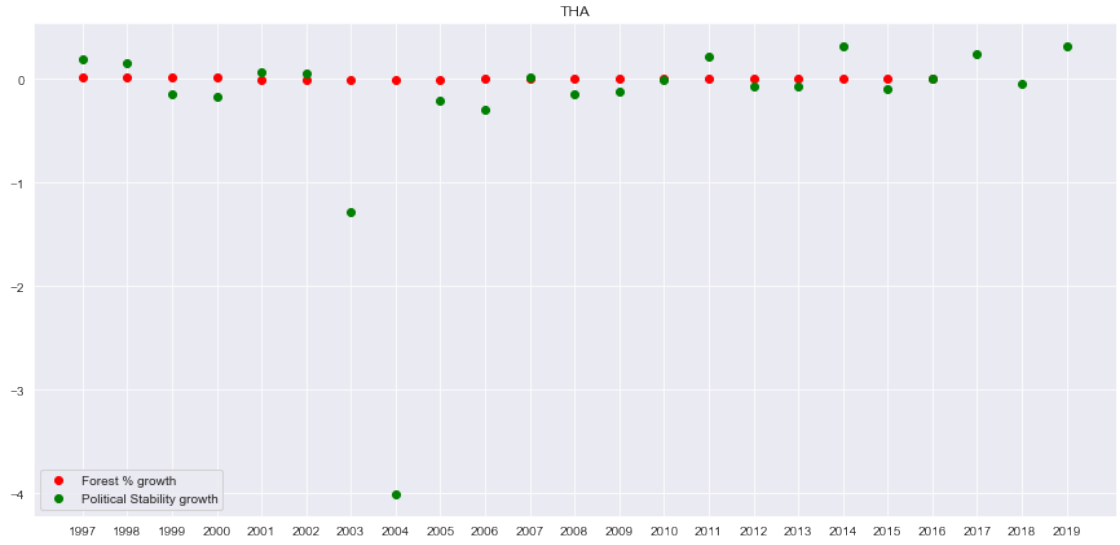

NPL
Forest % growth
Political Stability growth
0
−1
−2
−3
−4
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

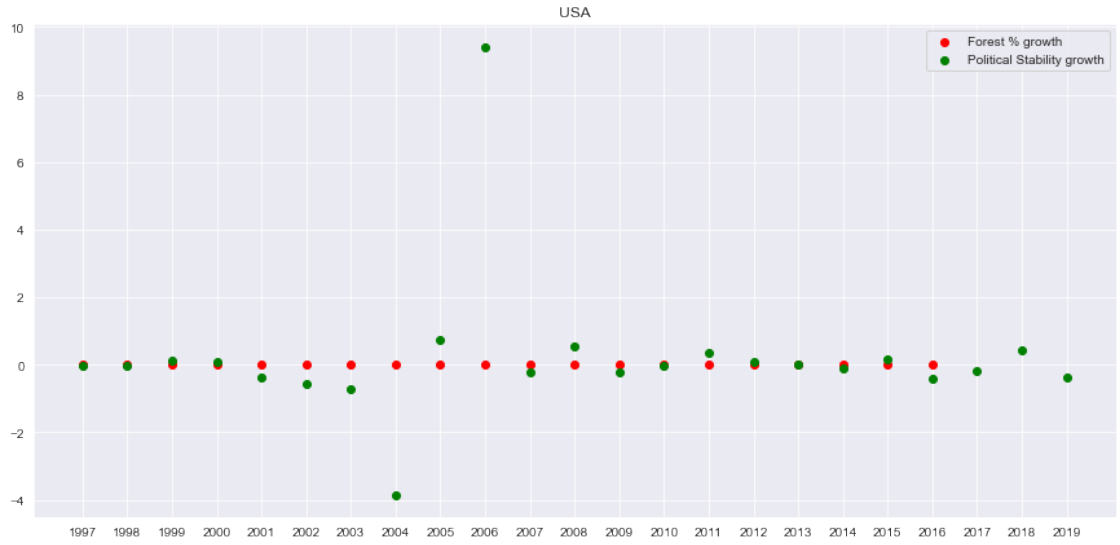

NIC
0.0
−2.5
−5.0
−7.5
−10.0
−12.5
−15.0
−17.5
Forest % growth
Political Stability growth
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019


SAU
Forest % growth
Political Stability growth
50
40
30
20
10
0
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019


SLE
Forest % growth
Political Stability growth
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

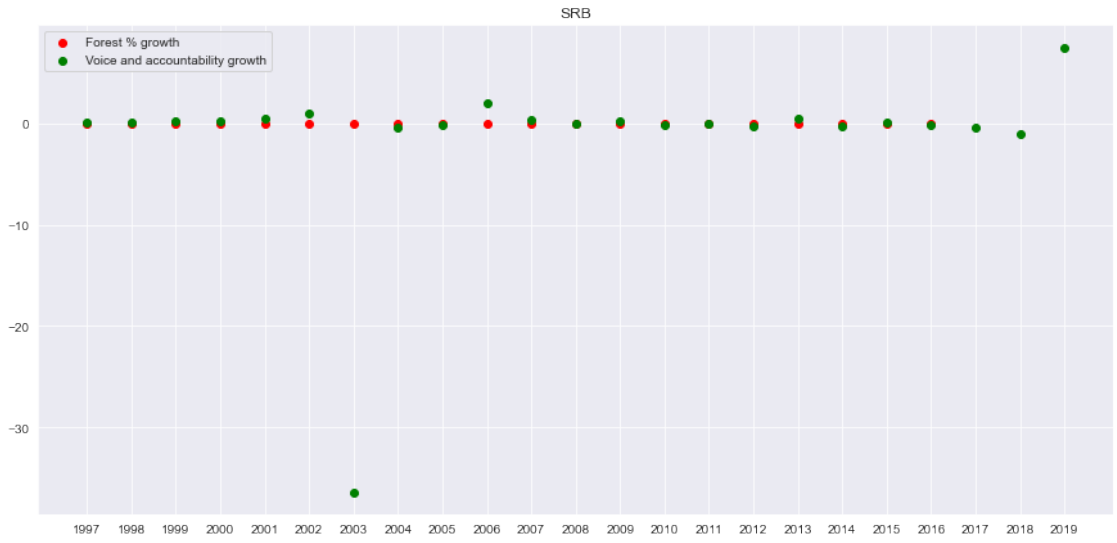

SWE
Forest % growth
Political Stability growth
0.10
0.05
0.00
−0.05
−0.10
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019





5.2 Voice and accountability & Forest

```
Text(0.5, 1.0, 'SRB')
```

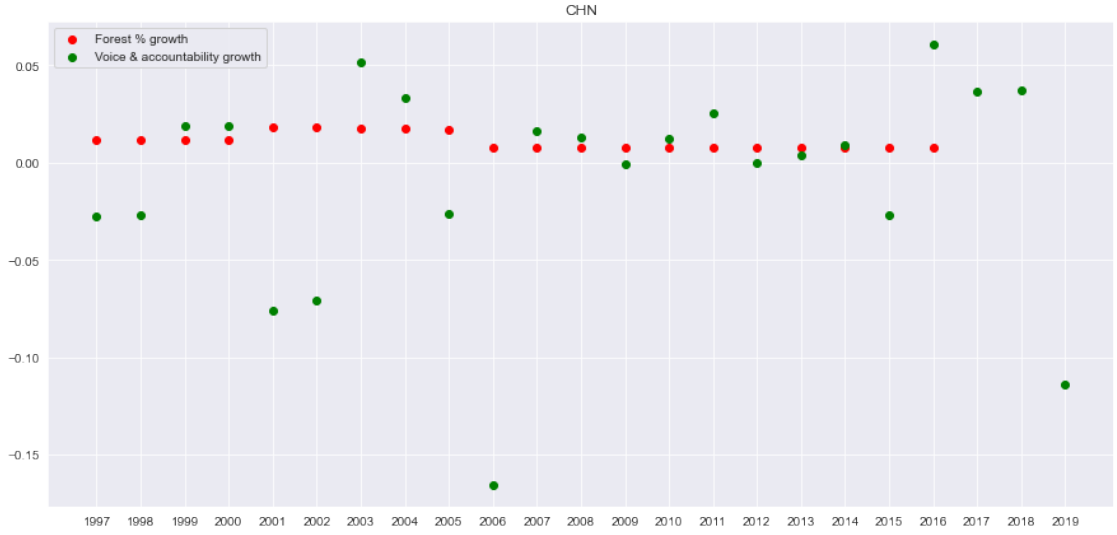


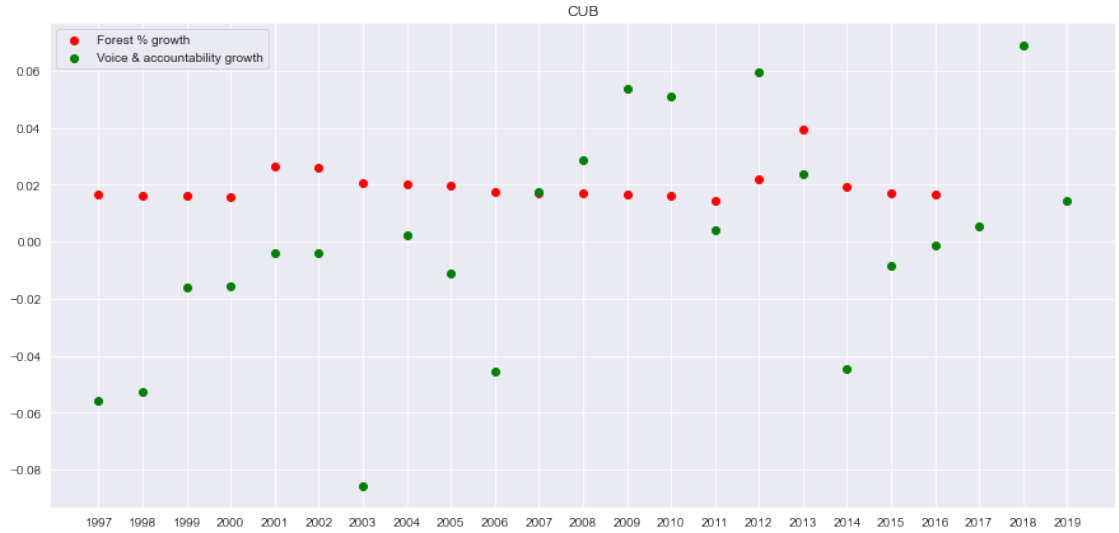

```
Average correlation is : -0.02409669377947286
```

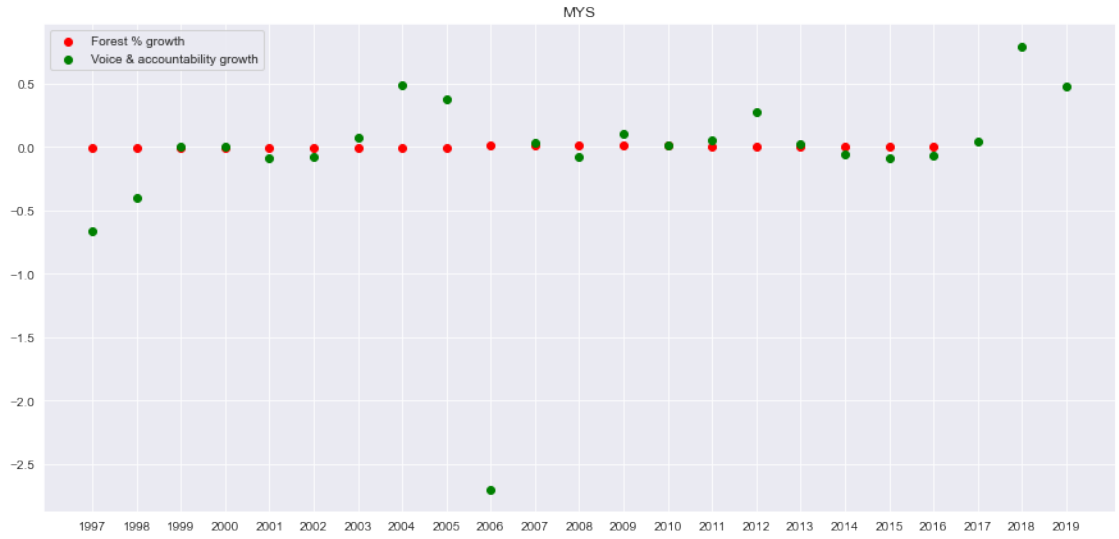
There is almost no correlation, we cannot identify a link between the evolution of the voice and accountability index with an evolution of the % of forest land.

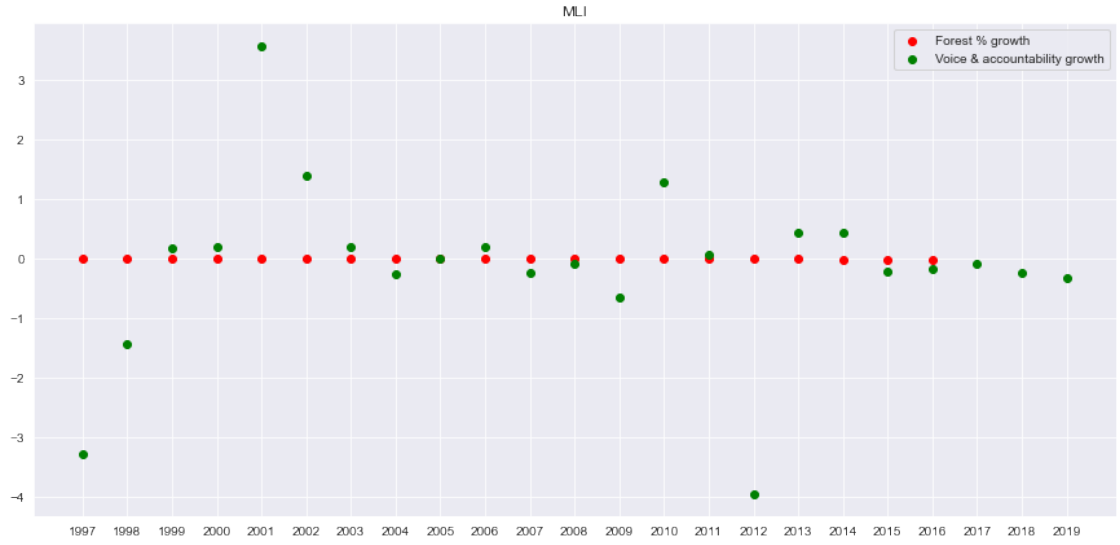
What about in some countries ?

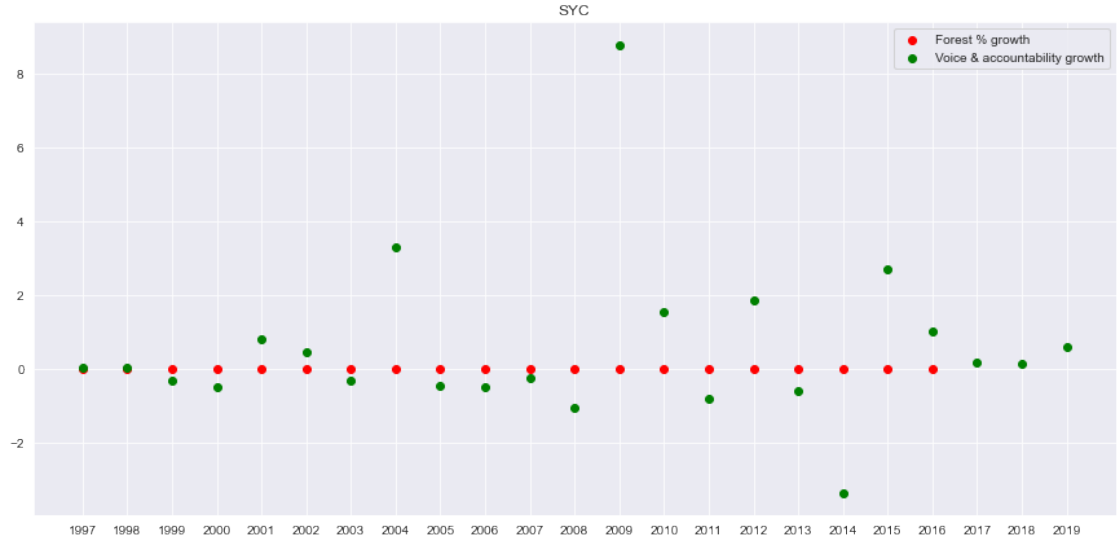
```
{'CHN': -0.6778900658079443,
 'CUB': 0.6592882120144723,
 'MYS': -0.7537255571237342,
 'MLI': 0.6619307037415794,
 'SYC': -0.6434622828498711,
 'THA': -0.8621561999634195,
 'GBR': -0.6558590191324177}
```

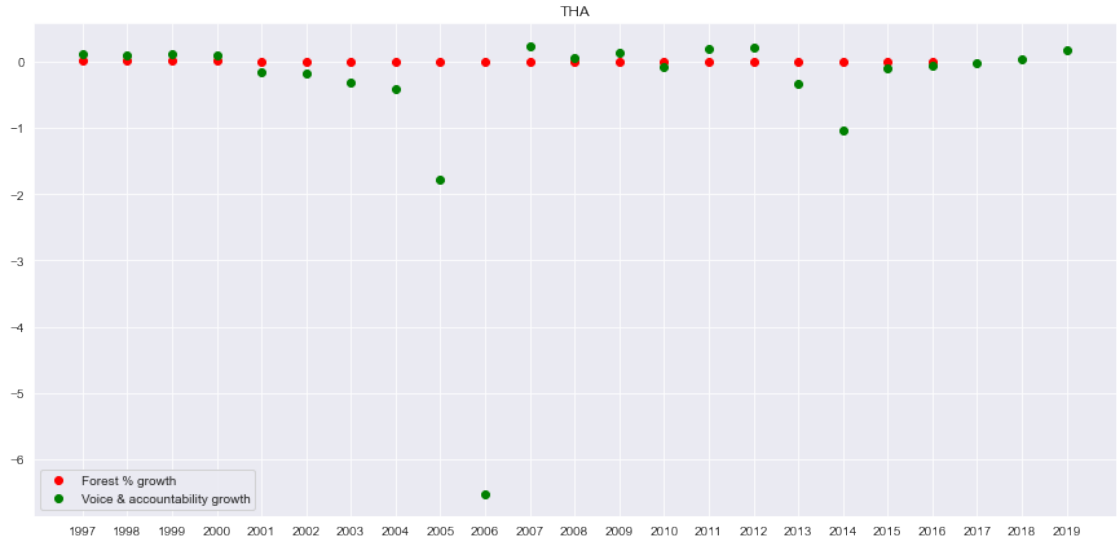


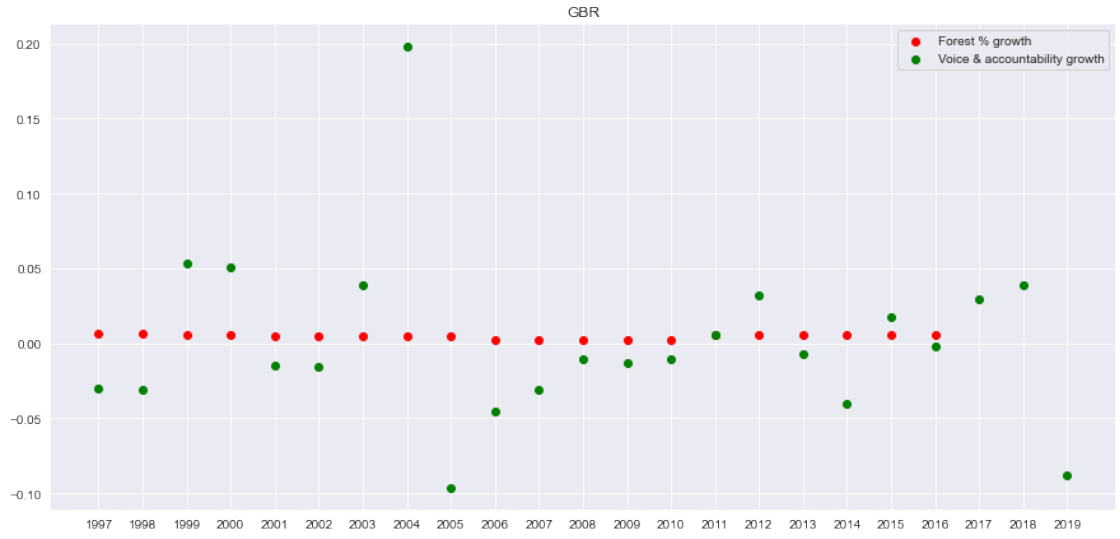

CUB
Forest % growth
Voice & accountability growth
0.06
0.04
0.02
0.00
−0.02
−0.04
−0.06
−0.08
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019


MYS
Forest % growth
Voice & accountability growth
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019


MLI
Forest % growth
Voice & accountability growth
3
2
1
0
−1
−2
−3
−4
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

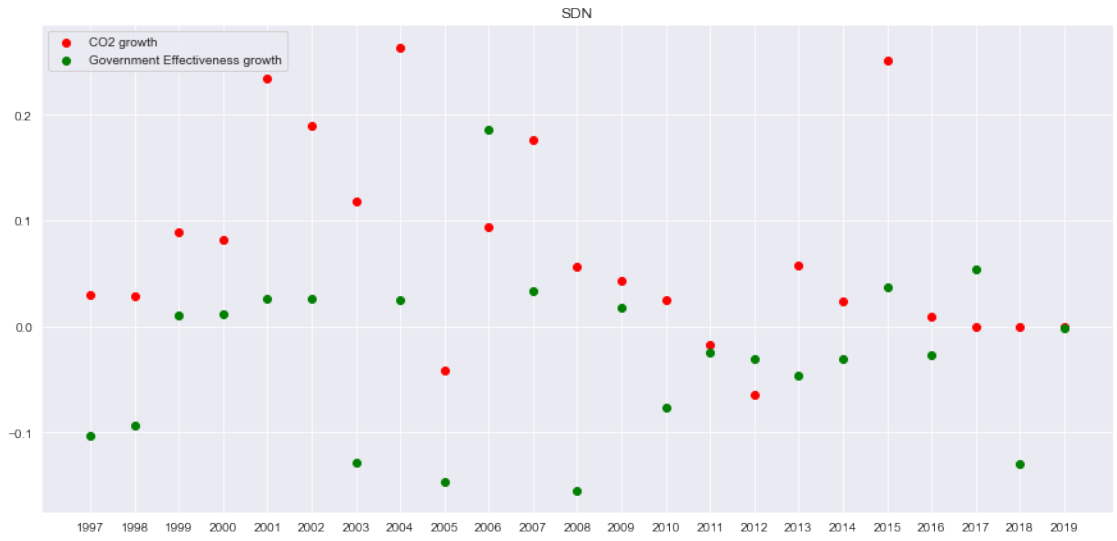

SYC
Forest % growth
Voice & accountability growth
8
6
4
2
0
−2
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019





5.3 Government Effectiveness & CO2

```
Text(0.5, 1.0, 'SDN')
```

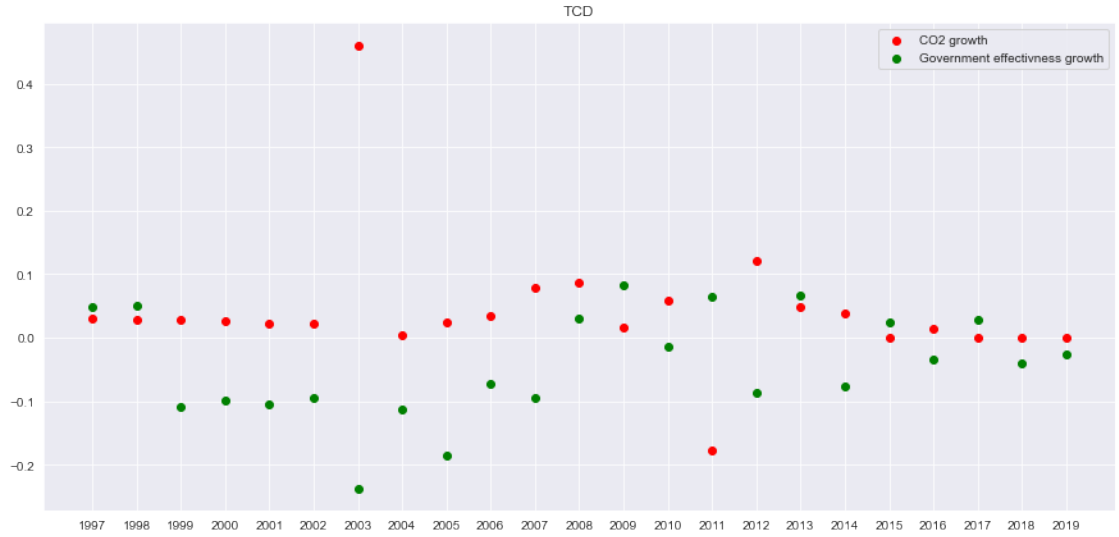


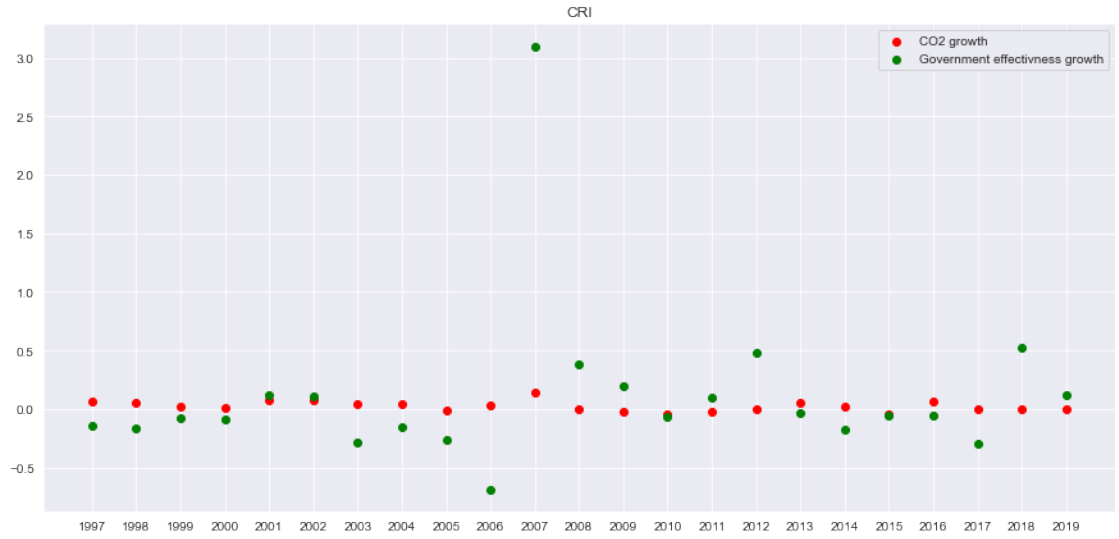
`Average correlation is : 0.042749899613488636`

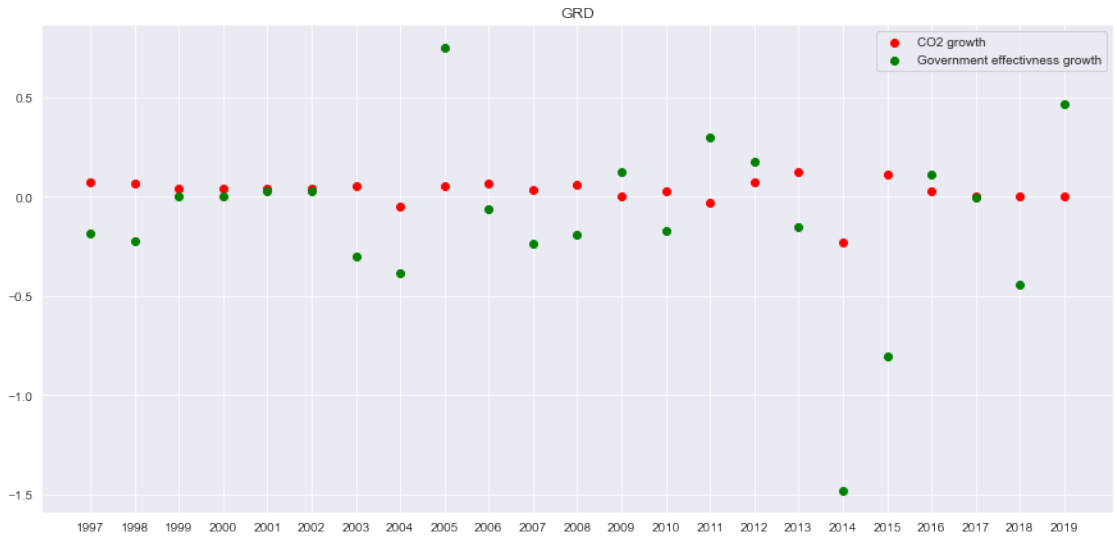
There is almost no correlation, we cannot link the evolution of government effectiveness with an evolution of CO2 emissions.

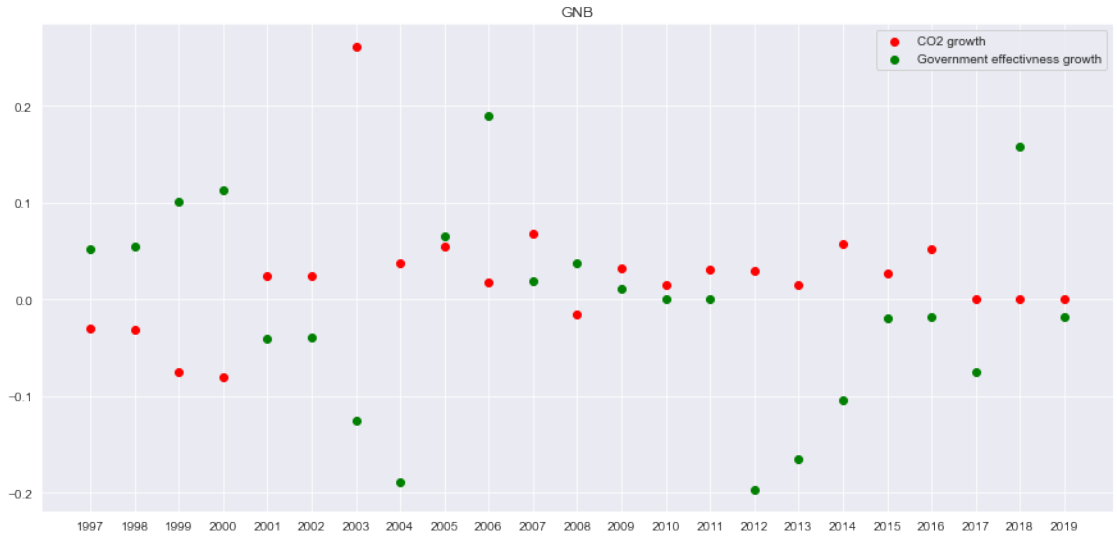
What about individual countries ?

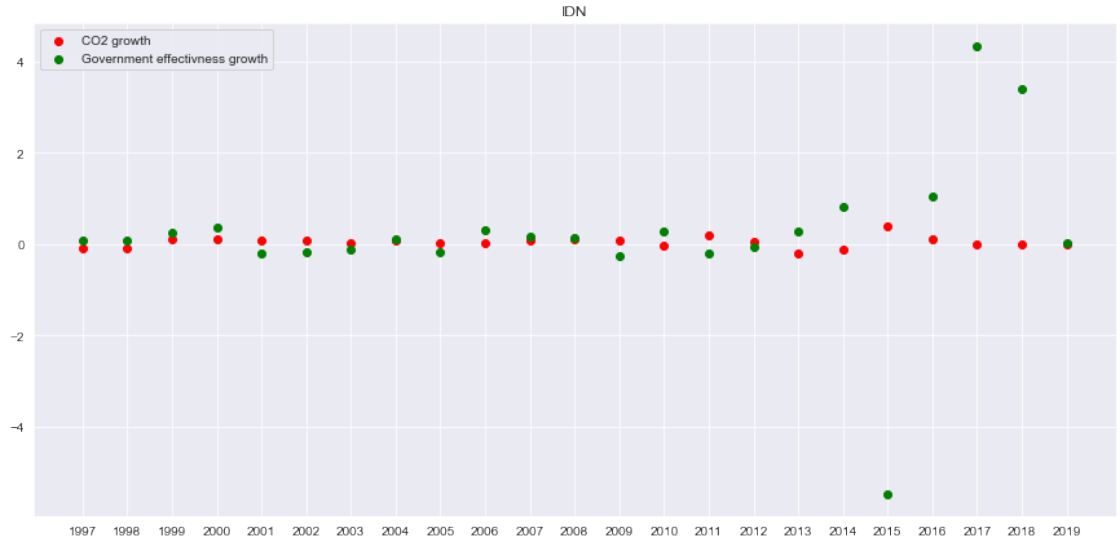
```
{'TCD': -0.5569659895808623,
 'CRI': 0.47226253882123714,
 'GRD': 0.45865892353372517,
 'GNB': -0.44761191668764866,
 'IDN': -0.5551081542863683,
 'IRQ': 0.4477571973471808,
 'ISR': 0.5096855411989489,
 'KOR': 0.6658000591509355,
 'NPL': 0.45620164169980004,
 'SEN': -0.4620040071014735,
 'SVN': 0.48146355647935607,
 'SYR': 0.46645241426981465,
 'TLS': 0.47717339840938133,
 'FSM': -0.5592567013512847,
 'ASM': 0.6841268502264699,
 'GUM': -0.5296793766050364}
```

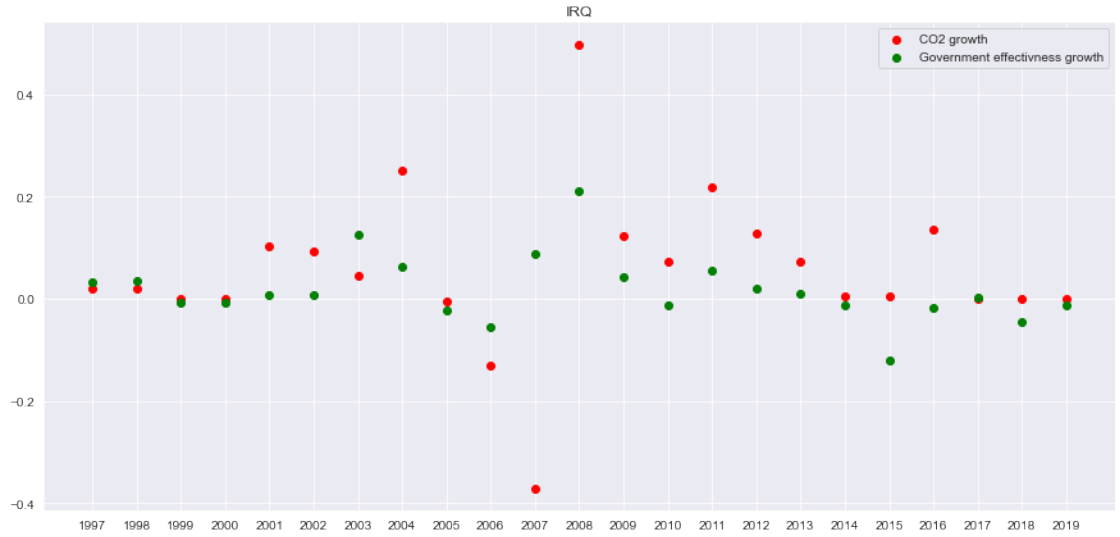

TCD
CO2 growth
Government effectivness growth
0.4
0.3
0.2
0.1
0.0
−0.1
−0.2
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

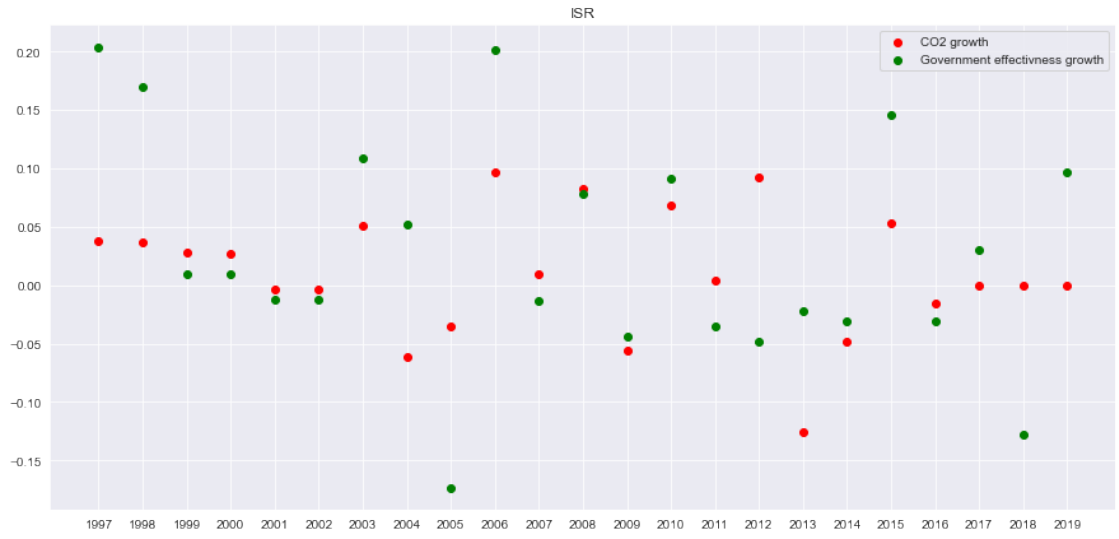

CRI
CO2 growth
Government effectivness growth
3.0
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

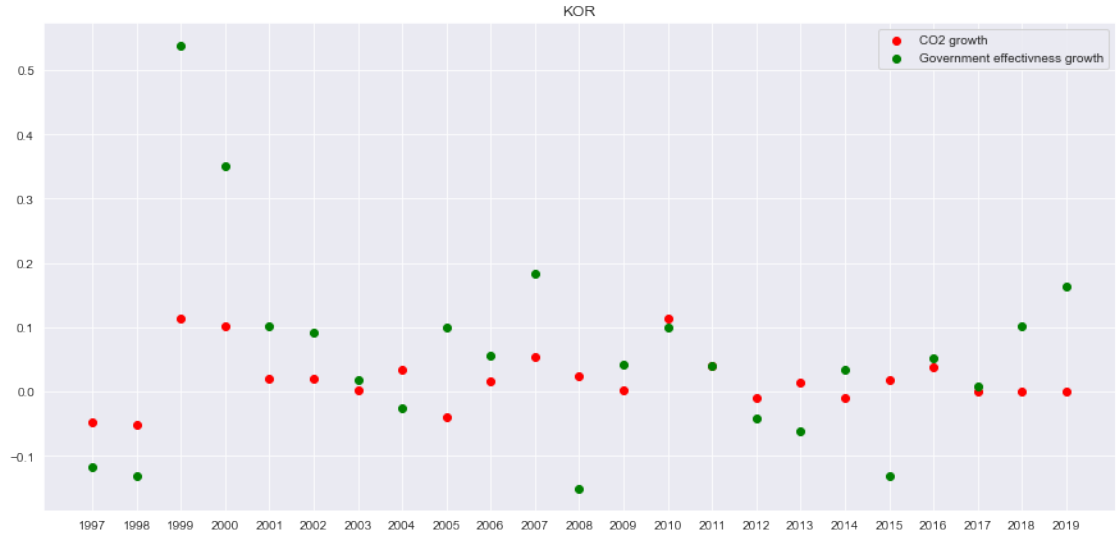

GRD
CO2 growth
Government effectivness growth
0.5
0.0
−0.5
−1.0
−1.5
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

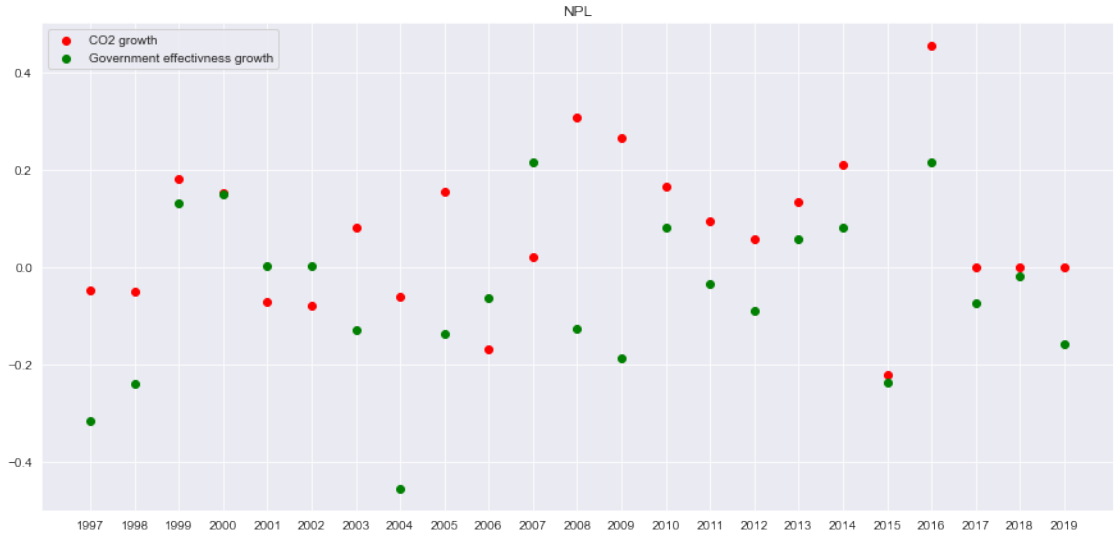

GNB
CO2 growth
Government effectivness growth
0.2
0.1
0.0
−0.1
−0.2
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

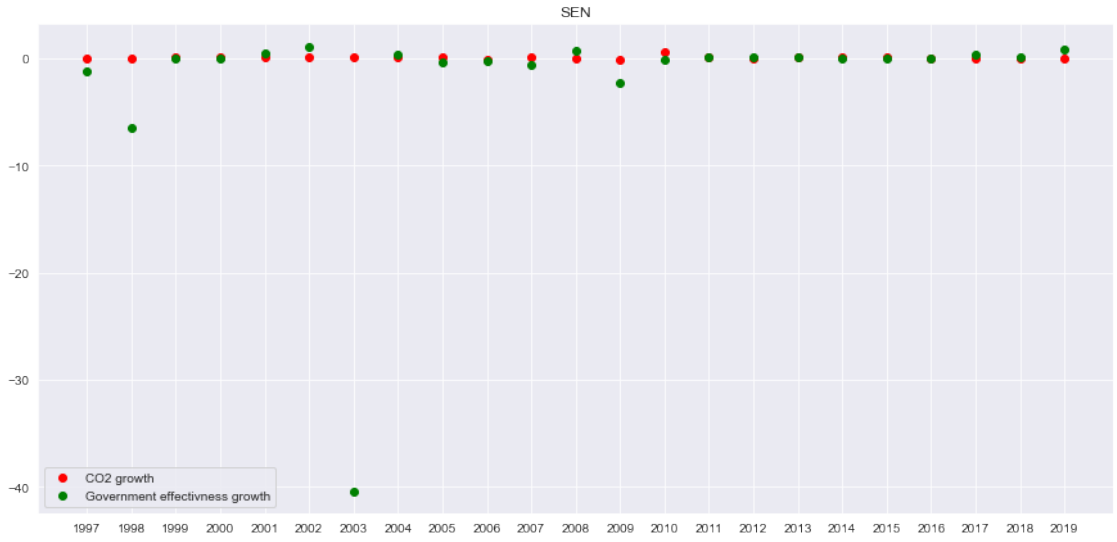

IDN
CO2 growth
Government effectivness growth
4
2
0
−2
−4
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

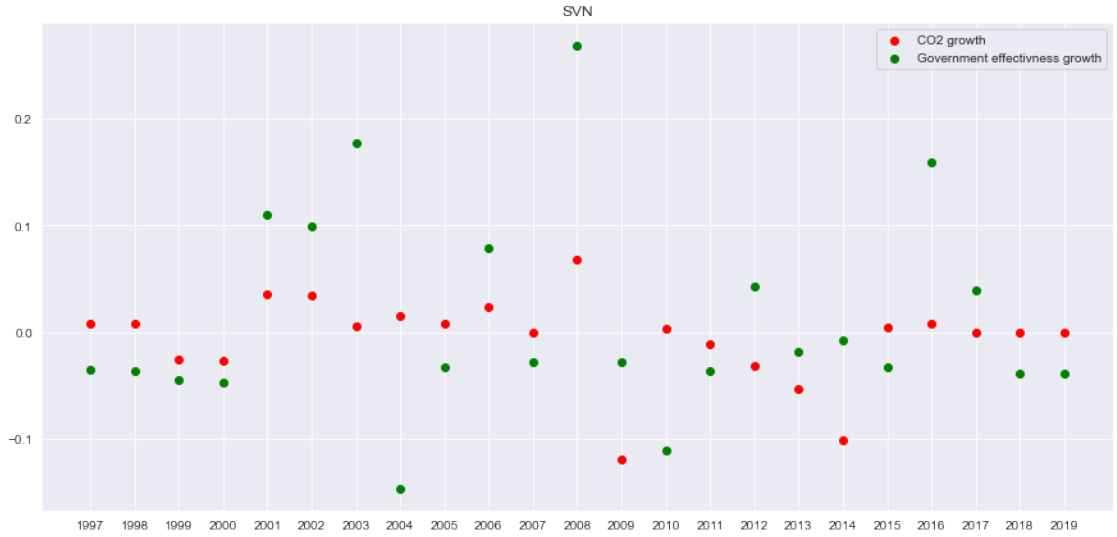

IRQ
CO2 growth
Government effectivness growth
0.4
0.2
0.0
−0.2
−0.4
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

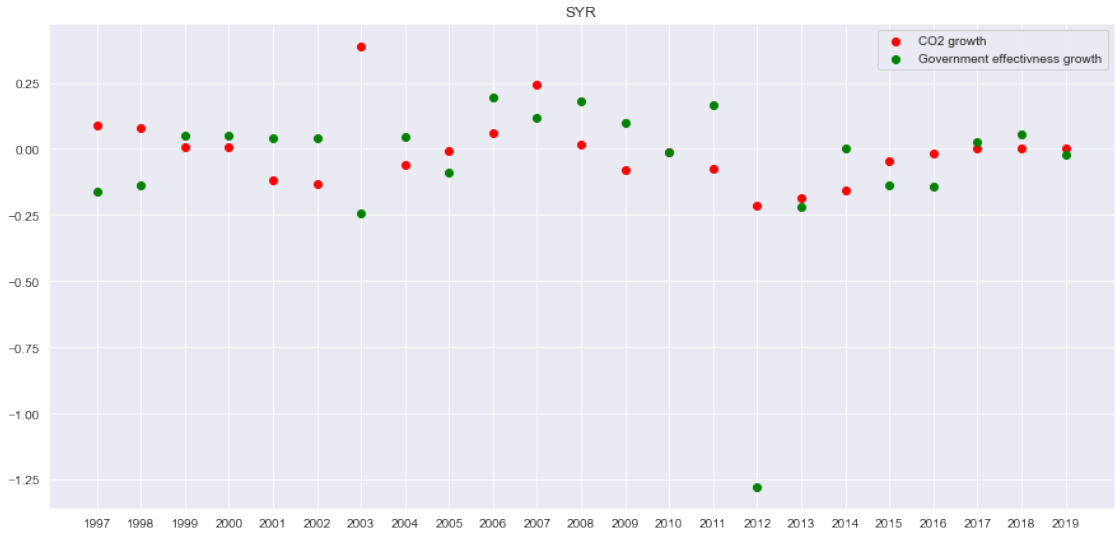

ISR
CO2 growth
Government effectivness growth
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

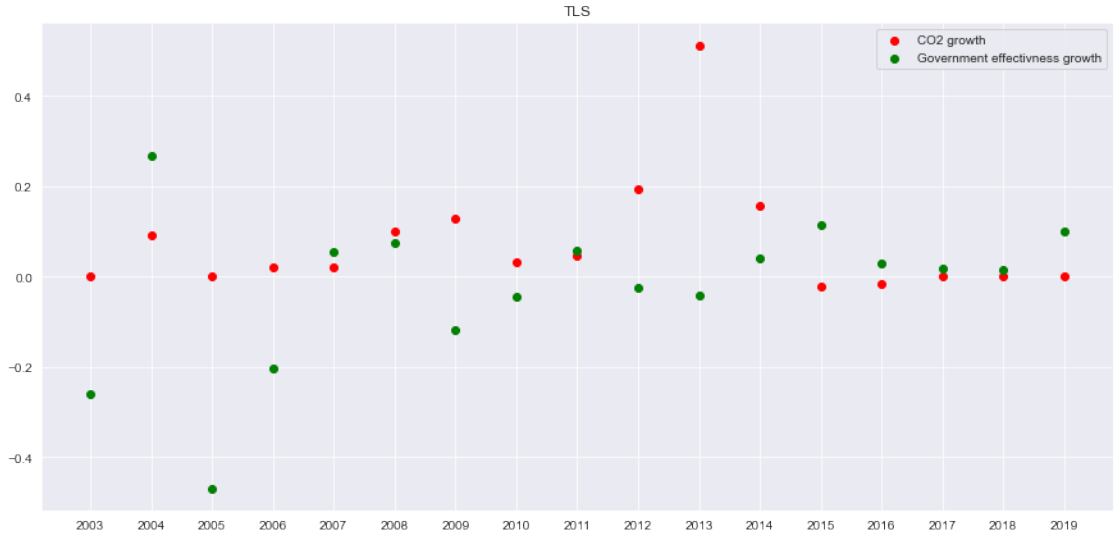

KOR
CO2 growth
Government effectivness growth
0.5
0.4
0.3
0.2
0.1
0.0
−0.1
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

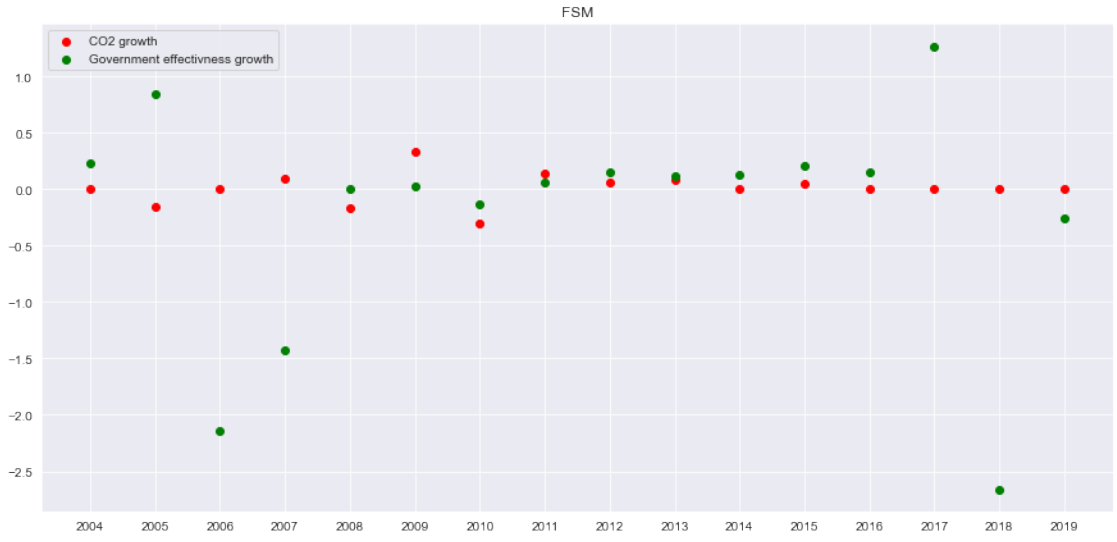

NPL
CO2 growth
Government effectivness growth
0.4
0.2
0.0
−0.2
−0.4
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019


SEN
0
−10
−20
−30
−40
CO2 growth
Government effectivness growth
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019


SVN
CO2 growth
Government effectivness growth
0.2
0.1
0.0
−0.1
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019


SYR
CO2 growth
Government effectivness growth
0.25
0.00
−0.25
−0.50
−0.75
−1.00
−1.25
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019

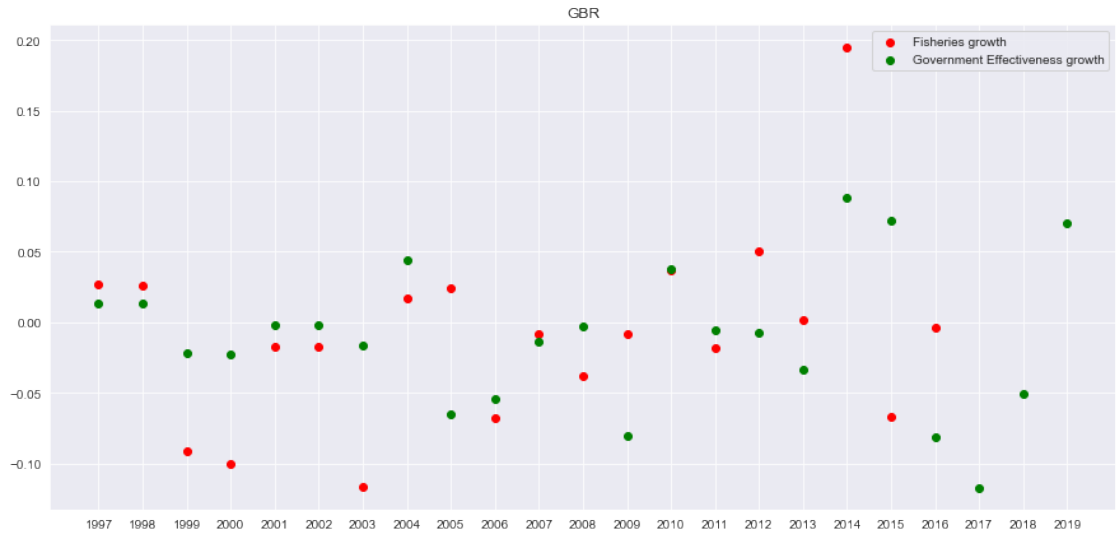




Look at Iraq !

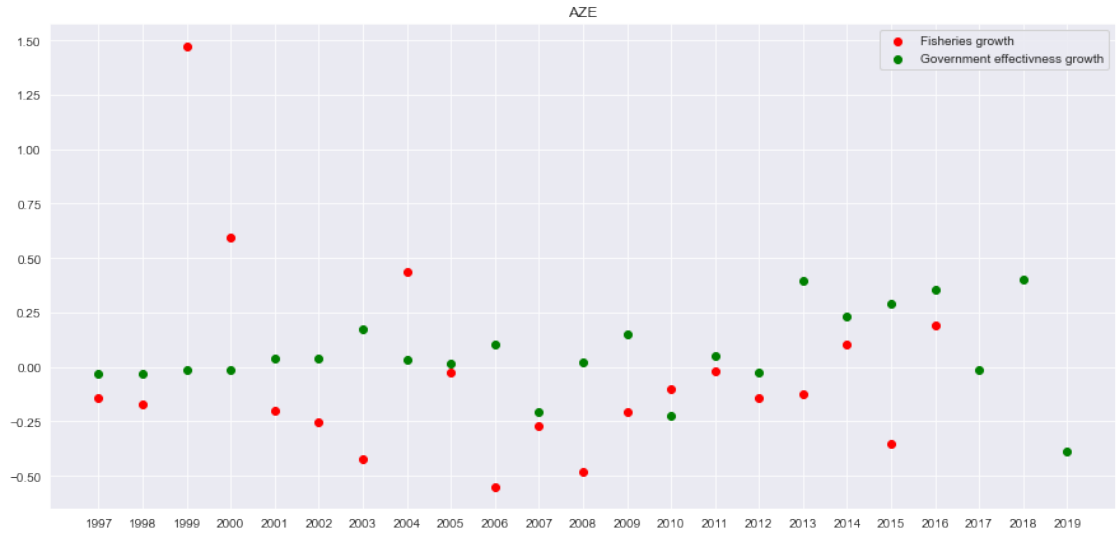
5.4 Government Effectiveness & Fisheries

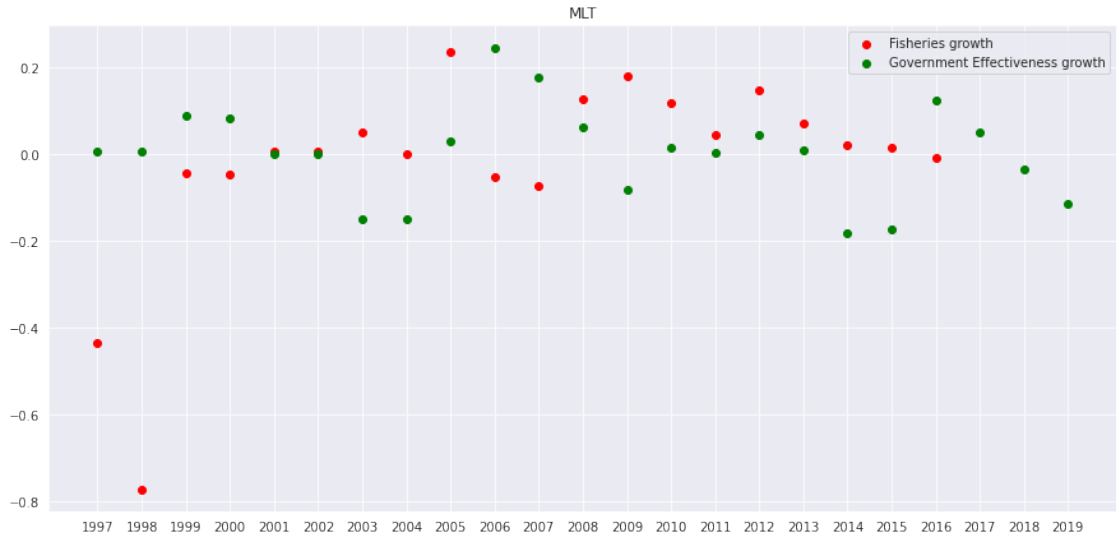
```
Text(0.5, 1.0, 'GBR')
```

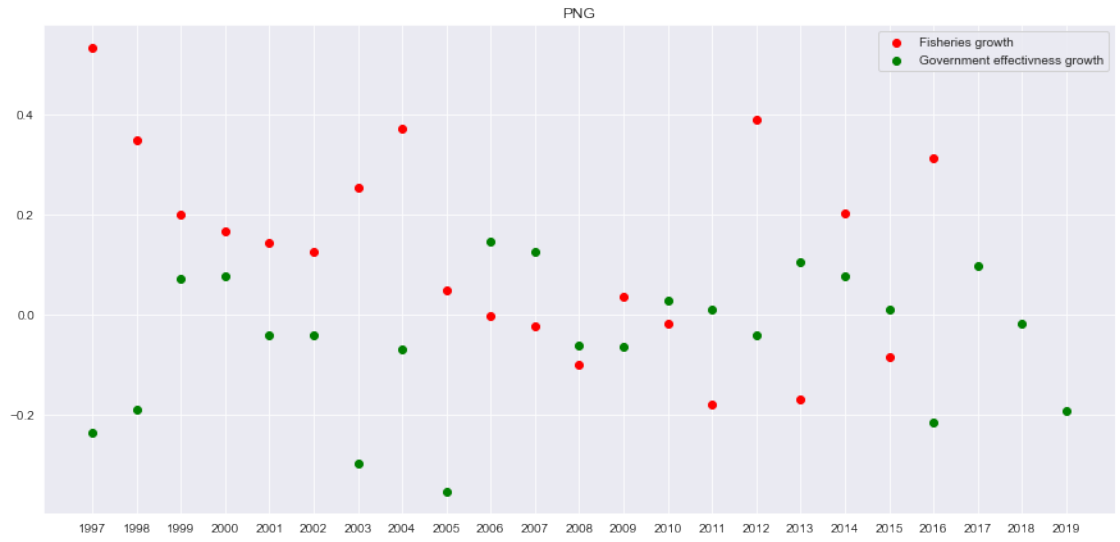


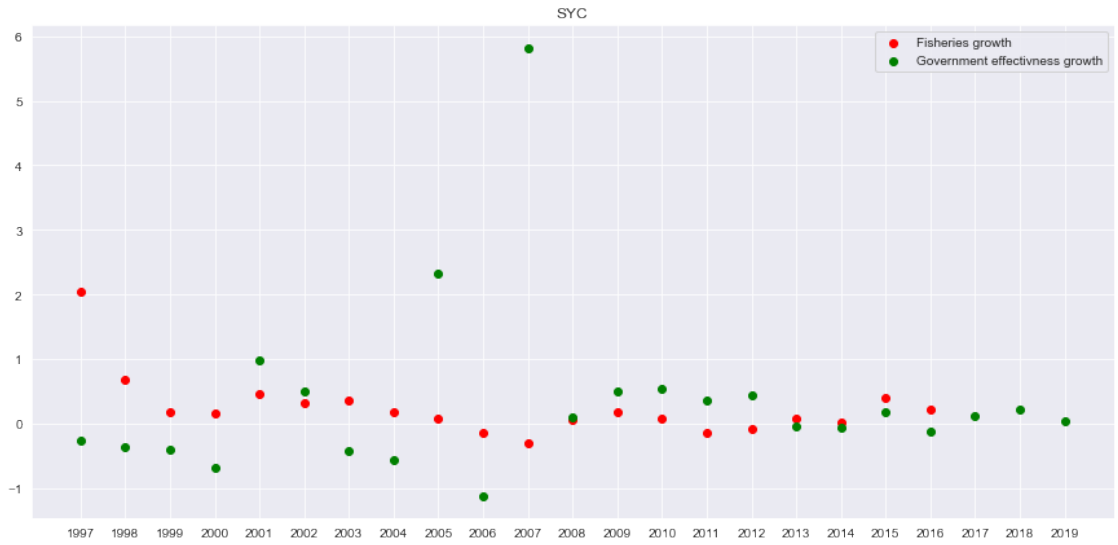

```
Average correlation is : -0.017907455698515175
```

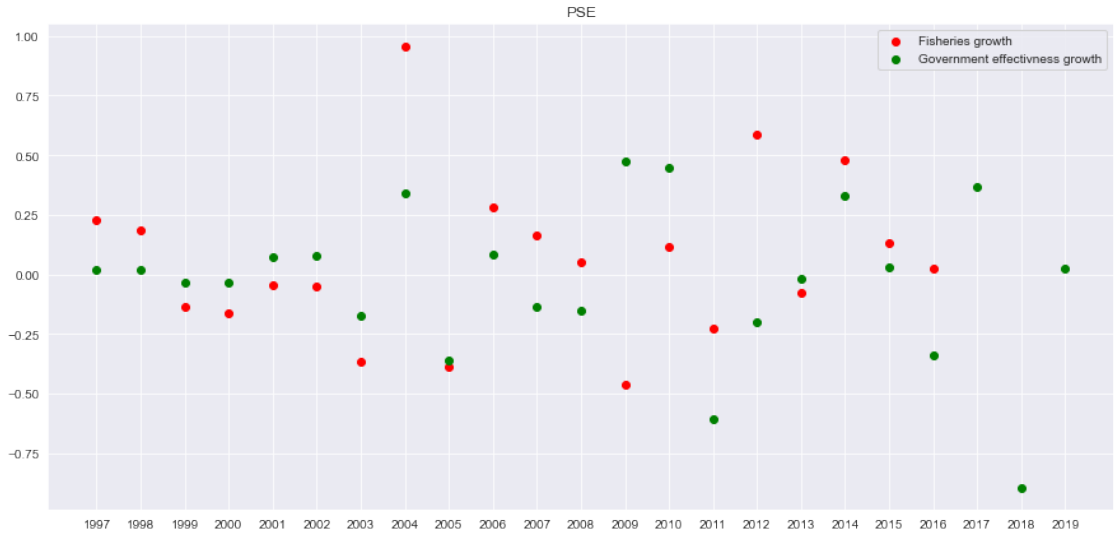
```
{'AZE': 0.6602307087592298,
 'MWI': 0.557196029727802,
 'PNG': -0.6783234515987618,
 'SYC': -0.5932642627141357,
 'PSE': 0.7145369218496881}
```




MLT
Fisheries growth
Government Effectiveness growth
0.2
0.0
−0.2
−0.4
−0.6
−0.8
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019


PNG
Fisheries growth
Government effectivness growth
0.4
0.2
0.0
−0.2
1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019





6 Cluster-based analysis on evolution data

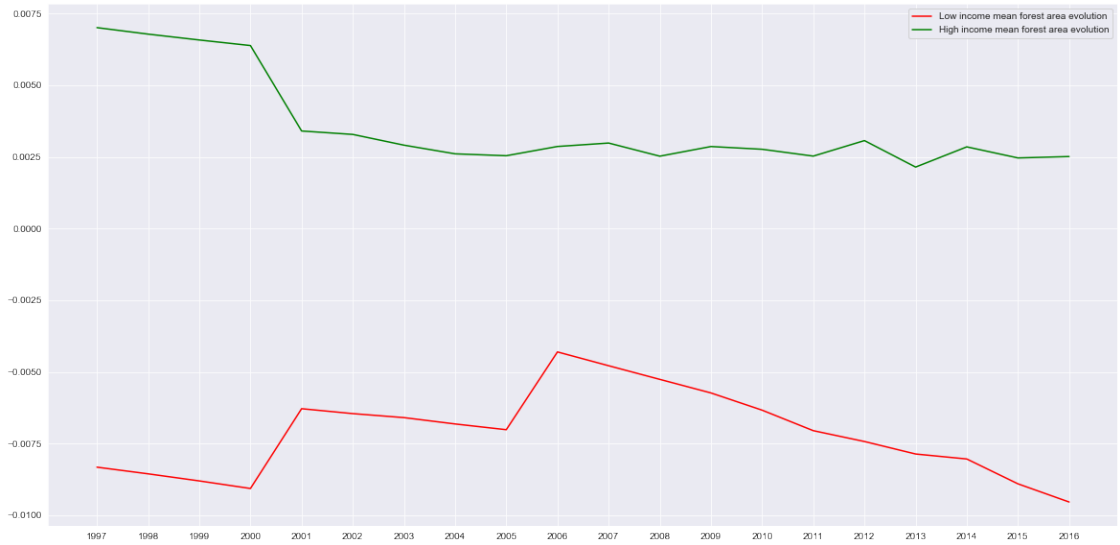
In this cluster-based analysis, we decided to consider evolution of two environmental variables (forest area and C02 emission) and two governance indicators (political stability and voice & accountability) that showed highest correlation in the previous analysis.

6.1 Univariate cluster-based analysis

6.1.1 Environmental variables

Forests

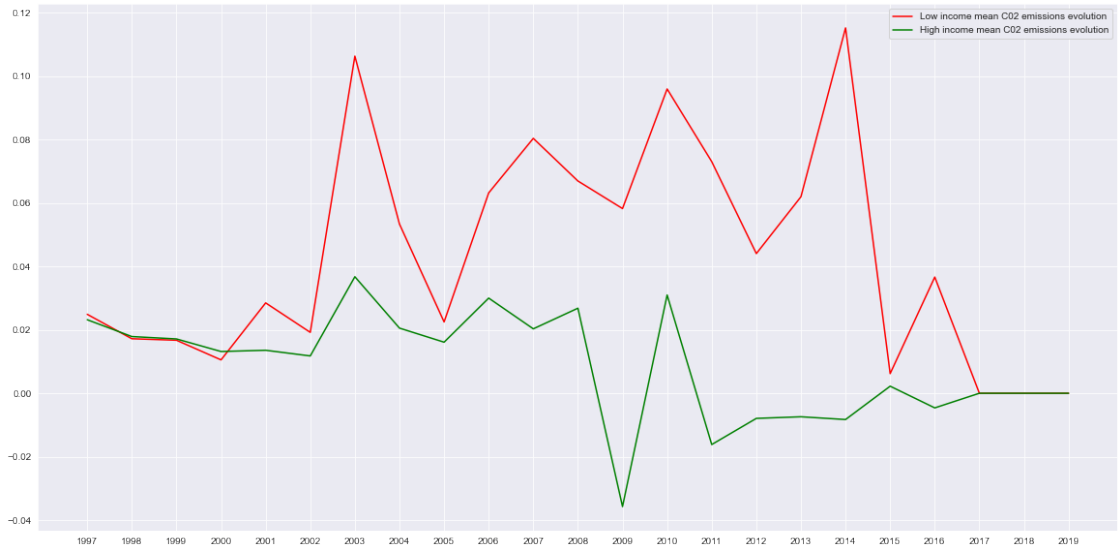
```
<matplotlib.legend.Legend at 0x236e5d61c88>
```



- **High income forest area evolution:** We see that evolution of forest area in high income countries is always above 0 (which means forests are expanding) and seems to be pretty stable since 2001.
- **Low income forest area evolution:** We see that evolution of forest area in low income countries is always below 0 (which means forests area is shrinking) and seems to only get worse since 2006.

CO2

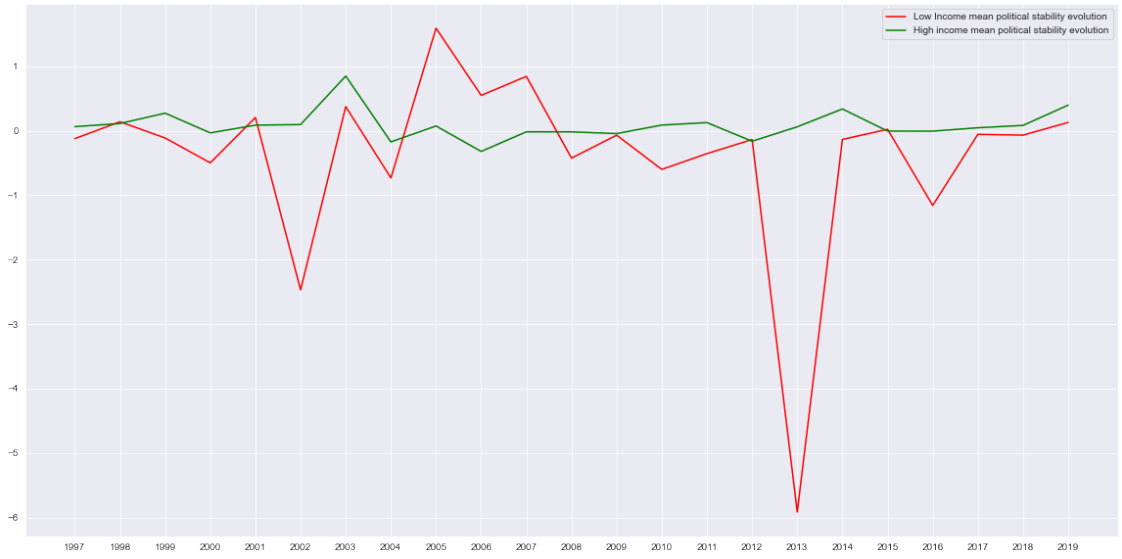
```
<matplotlib.legend.Legend at 0x236e3798808>
```



6.1.2 Governance Indicators

Political stability

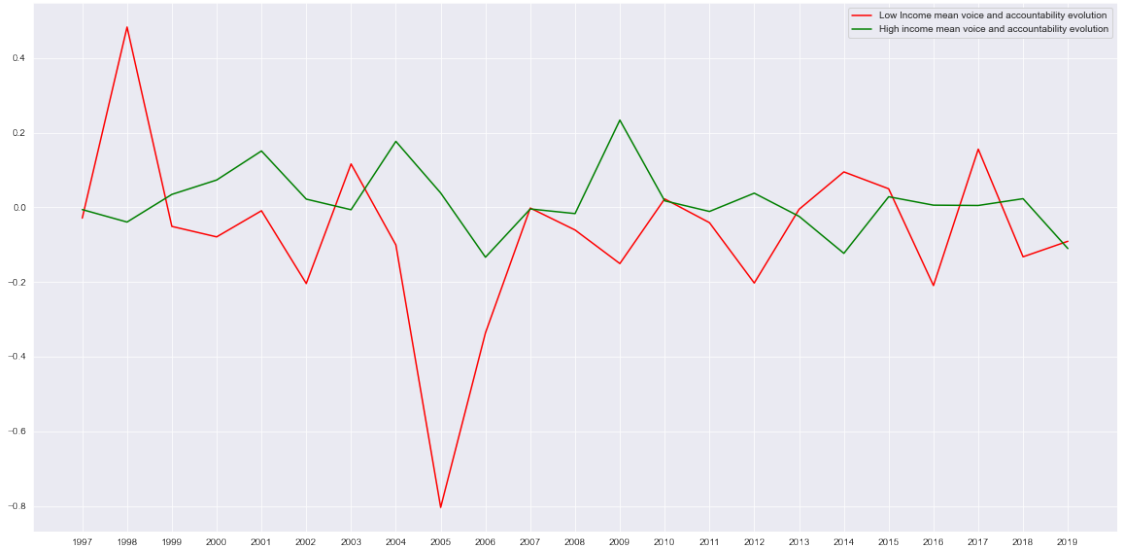
```
<matplotlib.legend.Legend at 0x236e37a5c48>
```



- **High income political stability evolution:** Seems to be pretty stable staying around 0.
- **Low income political stability evolution:** Seems to be fluctuating much more with a minimum in 2013 (why?).

Voice and accountability

```
<matplotlib.legend.Legend at 0x236e43dde88>
```



6.2 Correlation between average evolutions based on clusters

We now look at two pairs of correlations between average evolutions of env variables and governance indicators for both clusters of countries to see of we can observe any differences and try to come up with conclusions.

Forests and political stability:

```
Correlation between average forest evolution and average political stability
evolution:
- for high income countries is: 0.09105028424184024
- for low income countries is: 0.20902190421758896
```

We observe that correlation between forest area evolution and political stability on average is **much higher** for lower income countries, which might be due to the fact that political stability in higher income countries as well as forest area evolution are pretty stable.

C02 and voice & accountability:

```
Correlation between average co2 emissions evolution and average voice &
accountability evolution:
- for high income countries is: -0.22640621184968943
- for low income countries is: 0.10824765690940993
```

Relatively high negative correlation between co2 emissions evolutions and voice and accountability means that more accountability in high income countries leads to lower co2 emissions which makes sense, while it does not seem to make much difference for lower income countries.

7 Explanatory Models

After conducting a exploratory analysis on the variables, it is still difficult to determine if the evolution of one political variable influences the evolution of an environmental variable.

Therefore, in this part we will try to build a regression model that, given the variation of the political variables, tries to predict the variation of the environment variable (for a given year). If it succeeds, then there is a relation. If not, it doesn't seem to be a relation, or we do not have enough data to prove that there is a relation.

To do so, we will stay in the context of a given year, meaning we'll have the following dataset:

- 1 row = 1 country
- columns = political variables + environment variable (for the given year)
- Value in cell = the percentage evolution of the variable on that given year

The model will try to predict the % evolution of CO2 emissions.

7.1 Regression on CO2

In this part, the environment variable is the CO2 emission. We conducted a Linear Regression and a Random Forest on several years.

Linear Regression

- Very bad score on the training set (R2 around 0.03)
- The model cannot predict the evolution of CO2 based on the evolution of politcal factors

Random Forest

- Good R2 on the training set (around 0.7)
- But very bad R2 on the testing set (around -0.2)
- The model is overfitting
- The model cannot predict the evolution of CO2 based on the evolution of politcal factors

7.2 Regression on Forest

Here, we want to explain the evolution of the forest variable with the evolution of political factors.

Linear Regression

- R2 on training test of 0.02
- The model cannot predict correctly

Random Forest

- R2 on the training set of 0.74
- R2 on the testing set of -0.7
- Bad generalization
- The model cannot predict

7.3 Regression on Fishing

Here, we want to explain the evolution of the fishing variable with the evolution of political stability factors.

Linear Regression

- R2 of 0.004
- Cannot predict

Random Forest

- R2 on the training set of 0.64
- R2 on the testing set of -1.1
- Cannot predict

7.4 Conclusion

With the data that we have, we are not able to identify a relation between the evolution of political stability factors and the evolution of environmental variables.

8 Summary

In this report we considered six political indicators and three environmental variables:

Political Indicators	Environmental Variables
Control of Corruption: Estimate	Capture fisheries production (metric tons)
Government Effectiveness: Estimate	Forest area (% of land area)
Political Stability and Absence of Violence/Terrorism: Estimate	CO2 emissions
Regulatory Quality: Estimate	
Rule of Law: Estimate	
Voice and Accountability: Estimate	

Our work rests on five main pillars:

- Static Univariate analysis
- Static Bivariate Analysis
- Dynamic Bivariate Analysis
- Cluster-based analysis on evolution data
- Explanatory models

In the static univariate analysis, we explored each variable individually and performed a PCA on the political indicators. We found that the first component explained approx. 86% of the variance, hinting that the political indicators are highly correlated.

In the static bivariate analysis, we explored how all pairs constituted of one political indicator and one environmental variable behave. We found that the political indicators are highly correlated between them, as are the environmental variables between them. However, no political indicator is noticeably highly correlated with any of the environmental variables.

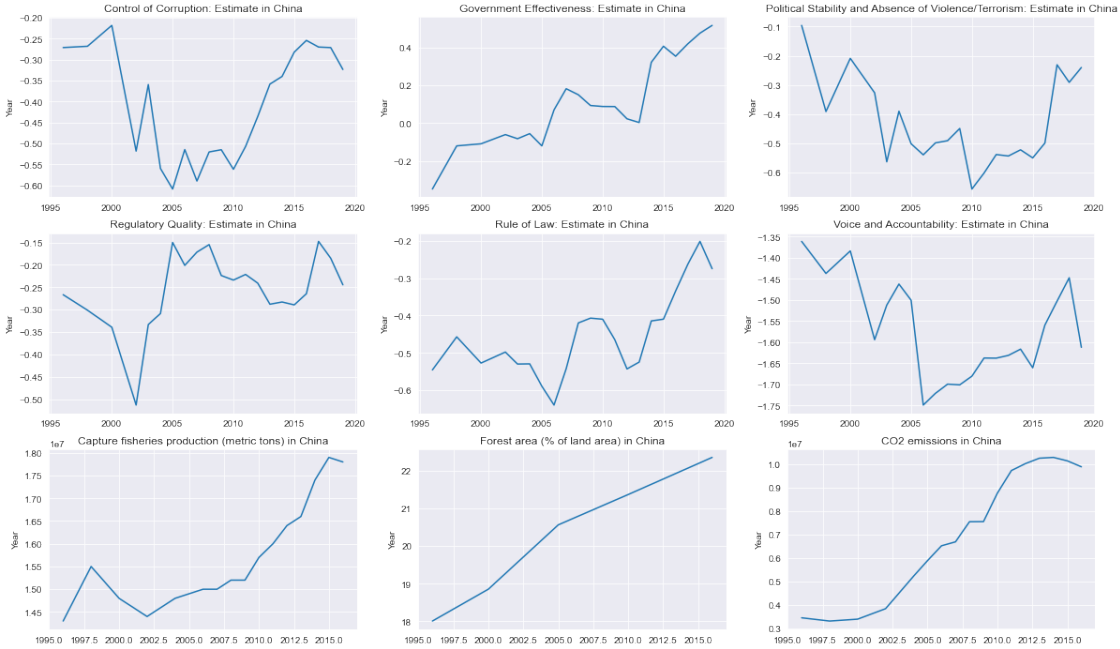
Then in the dynamic bivariate analysis and in the cluster-based analysis, we investigated the evolutions of the political indicators and how they influence the evolutions of the environmental variables. Also, we incorporated information about economic development and income level for each country. The correlation with an environmental variable may increase depending on the income level: higher for low-level income countries, which could be further explored.

Finally, we attempted to build predictive models of the evolution of each one of the environmental variables, using Linear Regression and RandomForest models. Unfortunately, they all delivered surprisingly low scores with weak metrics.

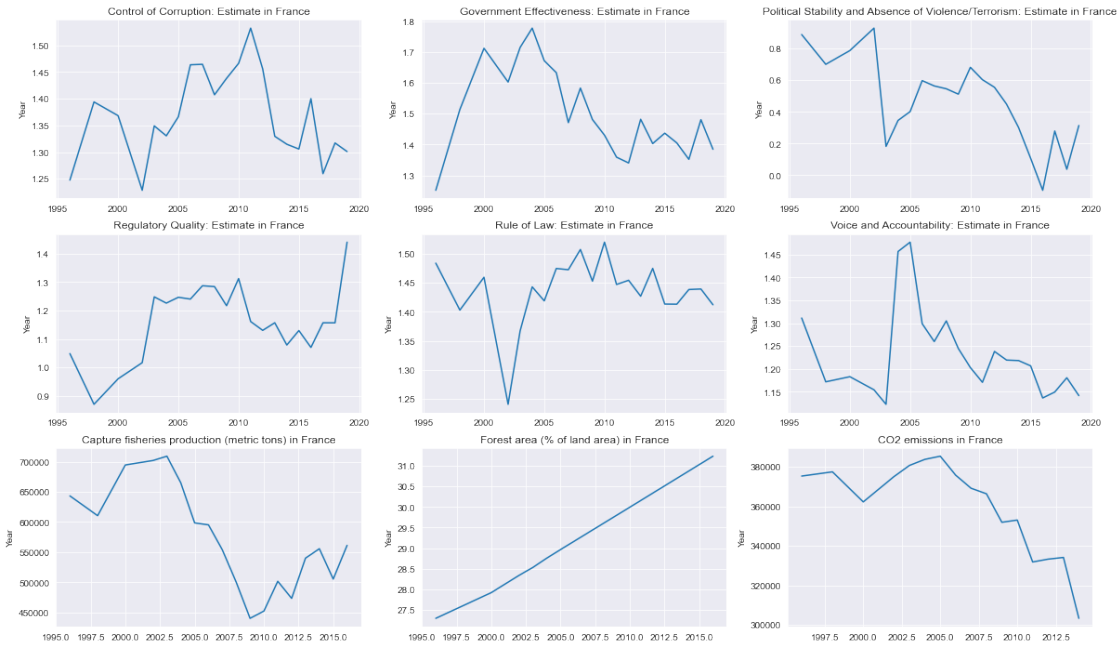
9 Appendix

9.1 Examples of analysis on individual countries

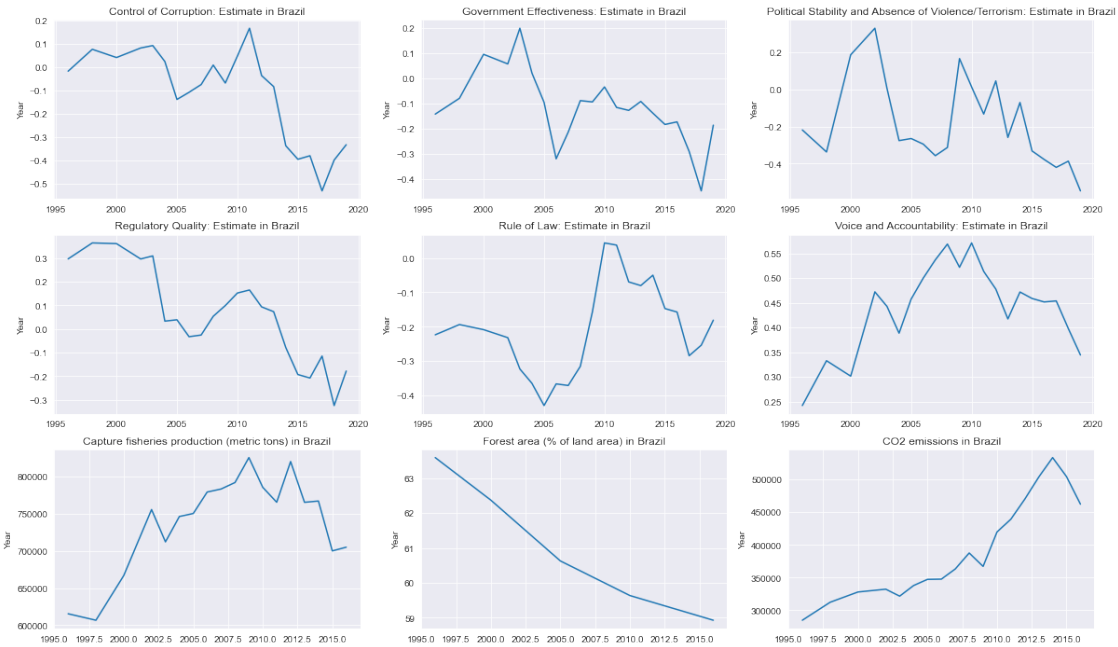
9.1.1 China



9.1.2 France



9.1.3 Brazil



9.1.4 South Africa