SDG 15: LIFE ON LAND

Life On Land from Economic Perspective

The status of Forest Area and respective contribution

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Abstract

The agenda of this report is to analyze specific data of Net Forest Area and link them with their economic effects and their economic outputs thus arriving at conclusions based on our objectives from an economic standpoint. In this report, various and diverse mathematical concepts that include Correlation, Regression, Hypothesis testing (One tailed or Two tailed based on the necessity of data and claim) etc. have been used to evaluate our results and lay a solid foundation to our claims and findings. Selected data is of total forest area and the GDP contribution of the forest land in the specific 49 countries listed in later sections that are ranked as high income, middle and low income. Their forest land loss or recovery have been analyzed and the net revenue generation have also been predicted for the last 5 years of this decade using inferential statistics in this report. In this pursuit of researching and analyzing and evaluating, attempts to successfully link the life on land to the life of our land that is economy have been made.

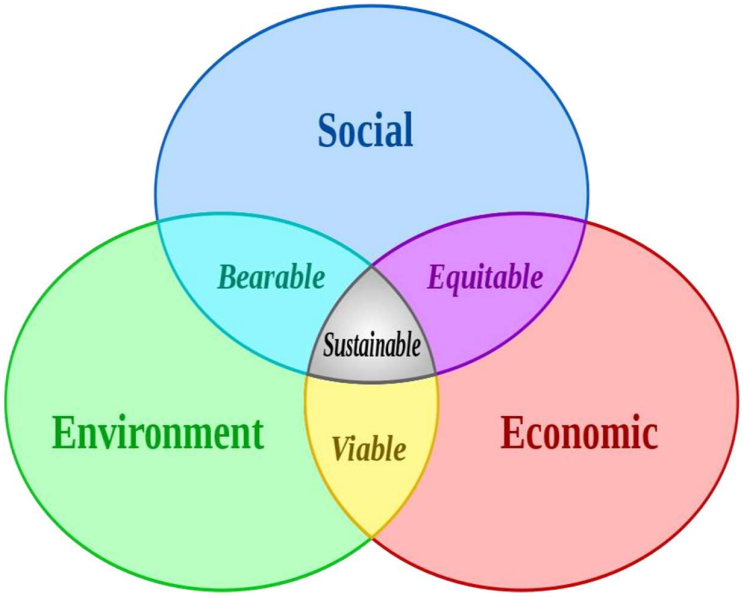
INTRODUCTION

As mankind sprints toward the exciting and breath-taking future the depletion in methods to manage pre-existing resource (from human resources to natural resources) is observed at a great extent which may hinder this great sprint to future, therefore the prominent authority of this world, UN decided lay down several goals based on the concept of Sustainable development.

What is Sustainable Development?

"Economic Development That is conducted without depletion of natural resources."

(according to Oxford Languages and Google)



(source wikipedia)

Figure 1: Sustainable Development

The term "sustainable development" can be defined in a variety of ways, but at its heart, it refers to a method of development that seeks to balance many, often conflicting needs against a recognition of our society's environmental, social, and economic constraints. Sustainability is a way of thinking about the future that balances environmental, sociological, and economic concerns in order to improve people's standard of life.

By gradually modifying the ways in which we produce and use technologies, sustainable development pushes us to protect and increase our resource base.

What are Sustainable Goals?

(source:un.org)

Figure 2: Sustainable Development Goals

The SDGs were adopted by 193 countries in 2015, and they have inspired people from all sectors, geographies, and cultures. To meet the targets by 2030, heroic and inventive efforts will be required, as well as a willingness to understand what works and the flexibility to adapt to new knowledge and shifting trends.

The 17 SDGs and their main target:

● **No Poverty:** To ensure the end of poverty everywhere considering all things together in its structure.

● **Zero Hunger:** To achieve food availability and improved nutrition along with advanced practical horticulture. Thus, ending hunger.

● **Good Health and Well-Being:** To ensure complete hygiene and advance security and comfort for everyone at any age.

● **Quality Education:** Ensuring thorough and fair standard training and deep-rooted schooling openings for all.

● **Gender Equality:** To ensure gender non-discrimination and women's entitlement to everything.

● **Clean Water and Sanitation:** Assuring practical conduct of water and its accessibility and decontamination for everyone and everything.

● **Affordable and Clean Energy:** To guarantee admittance for reasonable, dependable, feasible and modern energy for all.

● **Decent work and Economic growth:** To ensure advanced, supported, complete and feasible monetary growth, entire, beneficial business for all.

● **Industry, Innovation and Infrastructure:** Assembling strong foundations, advance global and maintainable industrialization and to motivate establishment.

● **Reduced Inequalities:** Diminishing imbalance within and amidst nations.

● **Sustainable cities and Communities:** Making suburban areas and population inclusive, protected, flexible and reasonable.

● **Responsible consumption and Production:** Guaranteeing manageable utilization and production ideas.

● **Climate Action:** Making a pressing move to engage in climate change and its effects.

● **Life below Water:** Monitoring and suitably utilizing the assets from waterbodies for manageable outcomes.

● **Life on Land:** Secure re-establish and advance reasonable utilization of environmental resources, economically oversee woodlands, battle desertification, and stop and converse land debasement and end biodiversity misfortune.

● **Justice, Peace and Strong Institutions:** To give admittance to integrity to all and construct effective, supervised and extensive establishments at all levels.

● **Association for the goals:** Reinforcement of the ways for usage and refresh the global union for reasonable turn of events.

SDG 15: Life On Land

(source:Wikipedia)

(Figure:3)

Goal 15 focuses on sustainable forest management, reducing and reversing land and surrounding ecosystems deterioration, effectively combating desertification, and halting biodiversity loss.

Terrestrial ecosystems provide a variety of goods, such as raw materials for construction, food, and a variety of ecosystem services, such as carbon capture, soil quality maintenance, biodiversity habitat provision, water quality maintenance, water flow regulation, and erosion control, all of which help to reduce the risk of natural disasters like floods and landslides, regulate climate, and maintain agricultural productivity. Climatic change adaptation and mitigation efforts are considerably aided by maintaining certain ecosystems.

Protecting, restoring, and promoting the protection and sustainable need for terrestrial as well as other ecosystems are all necessary for preserving varied types of life on land. All of these initiatives are aimed at benefits of land-based habitats, such as sustainable livelihoods, are enjoyed for future generations.

Literature Survey

Forest ecosystems are critical component of the world's biodiversity. That is why the area covered by forests is one of the indicators of Sustainable Development Goal 15 "Life on land". According to FRA 2020, forests currently cover up to 30.8 percent of the global land area (FAO, 2020). The total forest area is 4.06 billion hectares, or approximately 0.5 ha per person, but forests are unequally distributed around the world. Forest area as a proportion of total land area, which serves as SDG Indicator 15.1.1, decreased from 32.5 percent to 30.8 percent in the three decades between 1990 and 2020. This represents a net loss of 178 million hectares of forest, an area about the size of Libya. However, the average rate of net forest loss declined by roughly 40 percent between 1990–2000 and 2010–2020 (from 7.84 million hectares per year to 4.74 million hectares per year), the result of reduced forest area loss in some countries and forest gains in others (FAO, 2020). Forest loss is primarily caused by agricultural expansion, while an increase in forest area may occur through natural expansion of forests, e.g. on abandoned agricultural land, or through reforestation (including through assisted natural regeneration) or afforestation.

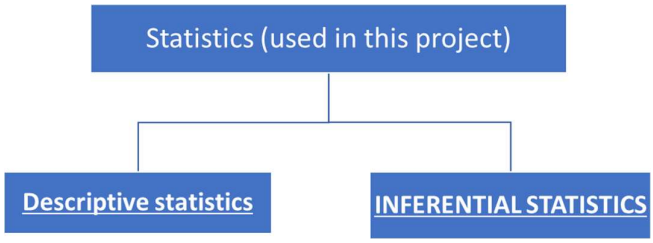
Objectives & Problem Statements

Objective: Collect data, study and analyze the amount of forest area recovered naturally or artificially (afforestation and reforestation) and the respective GDP contribution by those lands on the basis of the previous 3 decade's data.

- **PS1:** Find the linear relationship between no. of new flora originated in the previous decades and their GDP contribution with their respective years and conclude the correlation strength for both the variables on a scale of -1 to 1, all the while also finding out rate of gain/loss of forests of the selected 49 countries.
- **PS2:** Find out the rate (per year) of GDP Contribution of Forest Area of a country and then predict the net revenue generated that would be generated in every country by their green lands in the last five years of the current decade(2020-2030).
- **PS3:** To cross check the claim that the net forest area in the world has been approximately constant throughout the last 3 decades and also check whether there was a difference in the average percentage of forest land of the 49 countries between every progressive year for the last 3 decades (1991-2020).

Methodology

Statistics



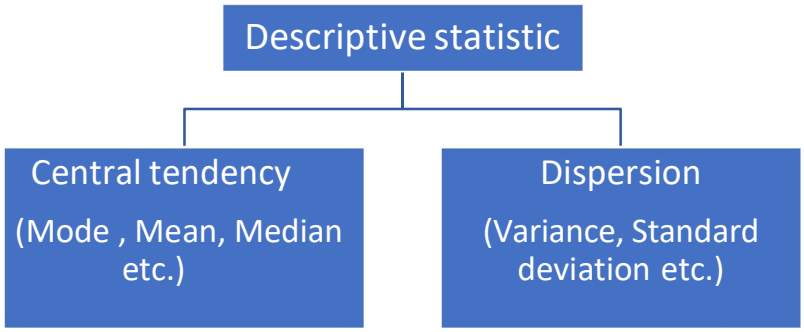
- **Descriptive statistics**

Descriptive statistics is used to mine out the basic information from the data give and it is packed with some features as follow:

Features:

1. Information of variables
2. Relation between variables

Descriptive statistic data is further can be classified into two types:



In this report there is use of:

Mean

Mean is outcome of sum of observations upon total number of observations.

$$\boldsymbol{Mean} = \overline{\chi} = \frac{\sum_i^n \chi_i}{n}$$

X_i refers to i^{th} observation and n is total number of observations.

1. **Standard Deviation**

Standard deviation can be calculated by doing square root of sum of square of observation upon total number of observations minus square of mean.

$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{N}}$$

σ : Population standard deviation
x : Datapoint value
μ : Population mean
N : Population size

- **INFERENTIAL STATISTICS:**

Inferential statistics are commonly employed for comparing the differences between treatment groups. The one which is used in report is mentioned below:

Hypothesis testing:

Hypothesis testing is a statistical reasoning that involves analyzing data from a sample to draw inferences about a population parameter or probability distribution. There are two attributes of hypothesis. First one is called null hypothesis and the other one is alternative hypothesis. In process, we first make a claim and if it is wrong then we reject the null hypothesis and accept the alternative hypothesis and vice-versa.

Test of Hypothesis concerning difference of means (Two Populations)

Step 1: Null Hypothesis H_0: $\mu_1 - \mu_2 = \delta$

Alternative Hypothesis: $\mu_1 - \mu_2 > \delta$ (Right tailed); $\mu_1 - \mu_2 < \delta$ (Left tailed); $\mu_1 - \mu_2 \neq \delta$ (Two tailed)

Level of Significance: α

Sample Size: Sample 1 - n_1 and Sample 2 – n_2

Step 2: Test Statistic

Case 1: If population variance is known: $z = \frac{\overline{X_1} - \overline{X_2} - \delta}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$

Where, σ_1^2 and σ_2^2 are population variances of sample 1 and sample 2 respectively.

Case 2: If population variance in unknown and n < 30: $t = \frac{\overline{X_1} - \overline{X_2} - \delta}{s_p\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$,

Where $s_p^2 = \frac{(n_1-1)s_1^2 + (n_2-1)s_2^2}{n_1+n_2-2}$; s_1^2 and s_2^2 are sample variances of sample 1 and 2 respectively.

Here, $s_p^2 = \frac{s_1^2 + s_2^2}{2}$ if $n_1 = n_2$

Step 3: Criteria of Rejection

Reject the null hypothesis if

Case 1: $z > z_\alpha$ (Right Tailed); $z < -z_\alpha$ (Left Tailed); $|z| > z_{\alpha/2}$ (Two Tailed)

Case 2: $t > t_{\alpha,n_1+n_2-2}$(Right Tailed); $t < -t_{\alpha,n_1+n_2-2}$ (Left Tailed); $|t| > t_{\alpha,n_1+n_2-2}$ (Two Tailed)

Step 4: Calculation

Step 5: Decision

Correlation:

Correlation is a statistical word that refers to the degree to which two variables move in lockstep. When two variables move in the same direction, it is said that they have a positive correlation. A negative correlation exists when they move in opposite directions.

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

r = correlation coefficient

x_i = values of the x-variable in a sample

$\bar{x}$ = mean of the values of the x-variable

y_i = values of the y-variable in a sample

$\bar{y}$ = mean of the values of the y-variable

If the correlation coefficient is close to zero, the correlation between two variables is deemed poor.

If the correlation coefficient is close to 1, the correlation between two variables is deemed good or high.

How to Calculate the Correlation Coefficient:

- **Step1:** Determine your data sets.
- **Step2**: Calculate the standardized value for your x variables.
- **(z(x))(i) = (x(i) - x̄) / s(x)**
- **Step3**: Calculate the standardized value for your y variables
- **(z(y))(i) = (y(i) - ȳ) / s(y)**
- **Step4:** Multiply and find the sum.
- (z(x))(i) * (z(y))(i)

- **Step5:** Divide the sum and determine the correlation coefficient.

REGRESSION:

A collection of statistical procedures for estimating connections between a dependent variable and one or more independent variables is known as regression analysis. It may be used to determine the strength of a relationship between variables and to predict how they will interact in the future.

Regression Analysis - Simple Linear Regression

Simple linear regression is a model that assesses the relationship between a dependent variable and an independent variable. The simple linear model is expressed using the following equation:

$$Y = a + bX + \epsilon$$

where,

- **Y – Dependent variable**

- **X – Independent (explanatory) variable**
- **a – Intercept**
- **b – Slope**
- **ϵ – Residual (error)**

$$b = \frac{[n(\sum \mathrm{xy}) - (\sum \mathrm{x})(\sum \mathrm{y})]}{[\mathrm{n}(\sum x^2) - (\sum \mathrm{x}^2)]}$$

Results and Discussions

Objective : Collect data and study and analyze the amount of forests recovered naturally or artificially (afforestation and reforestation) on the basis of the previous 3 decades of data.

Data Collection:

For this task, 49 countries were selected as shown below

um	Year	Switzerlar	Sweden	Austria	Germany	Finland	France	United Kir	Netherlan	Norway	Trinidad a	Australia	Korea, Re	Switzerlar	Romania	Singapore	Denmark	Puerto Ric	Paraguay	Brunei Da	Cyprus	Mexico
1	1991	29.289	68.414	45.797	32.382	72.006	26.520	11.555	10.271	33.211	47.080	17.400	67.836	29.289	27.763	22.456	12.632	37.341	63.656	78.065	17.550	36.20
2	1992	29.397	68.438	45.873	32.397	72.193	26.675	11.628	10.313	33.206	46.974	17.374	67.759	29.397	27.761	22.782	12.714	38.568	63.013	77.761	17.663	36.08
3	1993	29.505	68.463	45.948	32.413	72.381	26.831	11.701	10.355	33.201	46.869	17.347	67.681	29.505	27.759	23.109	12.809	39.794	62.370	77.457	17.777	35.97
4	1994	29.613	68.487	46.024	32.430	72.568	26.986	11.774	10.397	33.195	46.763	17.320	67.603	29.613	27.750	23.435	12.904	41.021	61.727	77.154	17.891	35.85
5	1995	29.721	68.511	46.100	32.446	72.755	27.142	11.846	10.439	33.190	46.658	17.293	67.525	29.721	27.751	23.761	12.998	42.248	61.084	76.850	18.004	35.74
6	1996	29.830	68.536	46.175	32.463	72.942	27.298	11.919	10.481	33.185	46.552	17.266	67.448	29.830	27.745	24.088	13.093	43.475	60.441	76.546	18.118	35.63
7	1997	29.938	68.560	46.251	32.482	73.130	27.453	11.992	10.523	33.180	46.447	17.239	67.370	29.938	27.741	24.414	13.188	44.702	59.798	76.243	18.232	35.51
8	1998	30.047	68.585	46.327	32.500	73.317	27.609	12.065	10.565	33.175	46.342	17.212	67.292	30.047	27.732	24.741	13.282	45.929	59.156	75.939	18.345	35.40
9	1999	30.156	68.609	46.402	32.519	73.504	27.764	12.137	10.607	33.169	46.236	17.185	67.214	30.156	27.729	25.067	13.377	47.155	58.513	75.636	18.459	35.29
10	2000	30.265	68.633	46.478	32.538	73.691	27.920	12.210	10.649	33.164	46.131	17.158	67.137	30.265	27.713	25.393	13.472	48.382	57.870	75.332	18.573	35.17
11	2001	30.363	68.611	46.508	32.558	73.624	28.126	12.254	10.690	33.161	46.048	17.129	66.850	30.363	27.778	25.502	13.507	49.085	57.009	75.009	18.586	35.10
12	2002	30.461	68.589	46.539	32.578	73.558	28.333	12.297	10.732	33.158	45.965	17.099	66.724	30.461	27.824	25.420	13.542	49.787	56.147	74.687	18.599	35.02
13	2003	30.560	68.568	46.569	32.598	73.491	28.524	12.340	10.773	33.155	45.883	17.070	66.625	30.560	27.879	25.082	13.577	50.489	55.286	74.364	18.612	34.95
14	2004	30.658	68.546	46.599	32.617	73.424	28.746	12.384	10.814	33.152	45.800	17.040	66.519	30.658	27.937	25.115	13.612	51.192	54.425	74.042	18.626	34.88
15	2005	30.757	68.524	46.630	32.634	73.357	28.953	12.427	10.856	33.149	45.717	17.011	66.407	30.757	28.005	25.220	13.647	51.894	53.564	73.719	18.639	34.80
16	2006	30.855	68.502	46.660	32.654	73.406	29.160	12.471	10.897	33.146	45.635	16.981	66.294	30.855	28.069	25.144	13.682	52.596	52.703	73.397	18.652	34.73
17	2007	30.953	68.480	46.691	32.674	73.344	29.366	12.514	10.939	33.143	45.552	16.951	66.175	30.953	28.145	25.212	13.717	53.299	51.842	73.074	18.666	34.65
18	2008	31.051	68.458	46.722	32.694	73.323	29.573	12.557	10.980	33.140	45.469	16.922	66.036	31.051	28.209	25.136	13.752	54.001	50.980	72.751	18.679	34.58
19	2009	31.149	68.436	46.752	32.711	73.256	29.779	12.601	11.031	33.137	45.387	16.892	65.896	31.149	28.254	25.240	13.787	54.703	50.119	72.429	18.692	34.51
20	2010	31.246	68.414	46.786	32.731	73.189	29.986	12.644	11.073	33.134	45.304	16.863	65.710	31.246	28.320	25.271	13.823	55.406	49.258	72.106	18.706	34.43
21	2011	31.333	68.369	46.836	32.738	73.301	30.138	12.724	11.025	33.155	45.221	16.955	65.614	31.333	28.641	24.839	14.003	55.461	48.215	72.106	18.703	34.37
22	2012	31.420	68.827	46.883	32.745	73.411	30.291	12.803	10.973	33.177	45.139	17.048	65.430	31.420	28.995	24.409	15.044	55.515	47.173	72.106	18.700	34.31
23	2013	31.507	68.781	46.940	32.719	73.521	30.443	12.882	10.932	33.209	45.056	17.140	65.250	31.507	29.329	24.016	15.235	55.570	46.130	72.106	18.697	34.24
24	2014	31.594	68.740	46.988	32.723	73.631	30.595	12.962	10.880	33.232	44.973	17.232	65.144	31.594	29.658	23.590	15.426	55.625	45.087	72.106	18.694	34.18
25	2015	31.681	68.695	47.033	32.732	73.736	30.747	13.041	10.835	33.246	44.891	17.325	65.032	31.681	29.994	23.232	15.617	55.680	44.045	72.106	18.692	34.12
26	2016	31.768	68.695	47.077	32.685	73.736	30.900	13.057	10.863	33.271	44.809	17.425	64.879	31.768	30.116	22.970	15.617	55.735	43.627	72.106	18.681	34.05
27	2017	31.855	68.695	47.120	32.685	73.733	31.052	13.078	10.891	33.295	44.727	17.423	64.783	31.855	30.116	22.722	15.640	55.790	42.638	72.106	18.679	33.99
28	2018	31.942	68.695	47.164	32.684	73.733	31.204	13.115	10.919	33.317	44.645	17.421	64.674	31.942	30.116	22.468	15.664	55.846	41.935	72.106	18.676	33.92
29	2019	32.029	68.695	47.207	32.684	73.733	31.357	13.153	10.947	33.339	44.563	17.421	64.571	32.029	30.116	22.214	15.688	55.901	41.232	72.106	18.674	33.85
30	2020	32.116	68.695	47.251	32.684	73.733	31.500	13.186	10.974	33.360	44.481	17.421	64.469	32.116	30.116	21.951	15.711	55.956	40.539	72.106	18.672	33.79

Table 1:

Percentage of Area of forest land in all different 49 countries in the last 3 decades (1991-2020).

ium	Year	Switzerlar	Sweden	Austria	Germany	Finland	France	United Kir	Netherlan	Norway	Trinidad a	Australia	Korea, Re	Switzerlar	Romania	Singapore	Denmark	Puerto Ric	Paraguay	Brunei Da	Cyprus	Mexico
1	1991	1.979	3.231	2.811	1.102	4.825	2.614	1.281	3.900	2.911	2.477	3.172	6.824	1.979	18.871	0.250	3.030	1.392	16.001	1.022	6.191	6.49
2	1992	1.809	3.069	2.453	1.005	4.278	2.593	1.271	3.638	2.628	2.536	3.044	6.608	1.809	19.039	0.197	2.792	1.213	14.949	0.965	5.724	5.99
3	1993	1.656	2.892	2.204	0.962	4.373	2.296	1.282	3.186	2.609	2.515	3.253	5.915	1.656	20.991	0.173	2.692	1.114	16.719	1.077	5.613	5.10
4	1994	1.519	2.900	2.372	0.976	4.186	2.401	1.325	3.213	2.604	2.222	3.338	5.658	1.519	19.885	0.173	2.601	0.930	18.164	1.199	5.068	4.61
5	1995	1.398	2.889	2.159	0.995	3.797	2.445	1.263	3.104	2.590	2.313	3.012	5.329	1.398	18.163	0.145	2.852	0.747	18.444	1.162	4.776	4.42
6	1996	1.218	2.554	1.982	1.042	3.449	2.404	1.098	2.877	2.227	2.085	3.381	4.961	1.218	17.539	0.150	2.793	0.829	18.365	1.122	4.578	4.86
7	1997	1.244	2.470	1.905	1.031	3.423	2.344	0.970	2.968	2.062	2.167	3.232	4.475	1.244	17.511	0.133	2.637	0.967	16.428	1.227	3.920	4.45
8	1998	1.170	2.311	1.793	0.975	2.899	2.362	0.966	2.557	2.264	2.058	3.031	4.226	1.170	14.379	0.111	2.145	0.807	14.801	1.410	4.335	4.15
9	1999	1.090	2.130	1.722	0.958	2.886	2.236	0.877	2.330	2.052	1.936	3.052	4.250	1.090	12.649	0.111	1.941	0.581	14.005	1.235	3.899	3.68
10	2000	1.052	1.943	1.647	0.995	2.954	2.098	0.851	2.299	1.823	1.357	3.115	3.858	1.052	10.854	0.092	2.152	0.660	12.857	1.024	3.647	3.32
11	2001	0.919	1.945	1.671	1.083	2.764	2.107	0.782	2.225	1.589	1.286	3.502	3.566	0.919	13.150	0.082	2.340	0.588	11.373	1.135	3.861	3.40
12	2002	0.931	1.900	1.563	0.900	2.672	2.011	0.916	2.078	1.521	1.398	3.949	3.207	0.931	11.342	0.071	1.781	0.534	11.010	1.094	3.788	3.27
13	2003	0.835	1.859	1.492	0.832	2.536	1.850	0.873	2.060	1.308	0.948	2.889	2.965	0.835	11.914	0.061	1.611	0.563	13.009	1.222	3.353	3.38
14	2004	0.931	1.828	1.476	0.951	2.380	1.823	0.760	1.866	1.386	0.761	3.064	2.958	0.931	12.706	0.056	1.623	0.627	13.933	1.127	3.083	3.33
15	2005	0.814	1.254	1.259	0.727	2.278	1.680	0.545	1.858	1.403	0.484	2.888	2.620	0.814	8.486	0.055	1.146	0.595	12.714	0.947	2.739	3.07
16	2006	0.750	1.362	1.303	0.738	2.001	1.518	0.596	1.946	1.404	0.567	2.734	2.497	0.750	7.821	0.049	1.165	0.591	11.794	0.706	2.276	3.07
17	2007	0.769	1.578	1.416	0.779	2.380	1.613	0.563	1.817	1.240	0.372	2.208	2.283	0.769	5.502	0.043	1.174	0.481	12.710	0.690	2.024	3.18
18	2008	0.779	1.567	1.342	0.838	2.205	1.515	0.676	1.635	1.128	0.366	2.344	2.142	0.779	6.302	0.041	0.858	0.554	13.703	0.636	2.093	3.16
19	2009	0.717	1.437	1.147	0.695	2.254	1.323	0.681	1.553	1.300	0.595	2.302	2.241	0.717	6.116	0.041	0.834	0.588	10.250	0.909	1.989	3.24
20	2010	0.658	1.649	1.267	0.804	2.419	1.604	0.602	1.779	1.569	0.520	2.206	2.144	0.658	4.997	0.036	1.202	0.836	13.321	0.733	2.063	3.21
21	2011	0.671	1.670	1.402	0.910	2.321	1.650	0.690	1.579	1.345	0.457	2.292	2.209	0.671	6.253	0.035	1.312	0.792	14.125	0.575	2.151	3.08
22	2012	0.629	1.547	1.349	0.848	2.314	1.632	0.637	1.660	1.128	0.639	2.268	2.186	0.629	4.684	0.033	1.655	0.804	10.371	0.655	2.007	3.17
23	2013	0.656	1.467	1.255	0.943	2.367	1.459	0.638	1.791	1.315	0.723	2.286	2.099	0.656	5.382	0.034	1.302	0.826	13.185	0.685	2.041	3.13
24	2014	0.701	1.443	1.201	0.905	2.398	1.556	0.747	1.738	1.443	0.737	2.221	2.057	0.701	4.713	0.035	1.382	0.846	12.099	0.863	1.850	3.13
25	2015	0.619	1.450	1.130	0.685	2.254	1.606	0.634	1.724	1.538	1.054	2.376	2.004	0.619	4.187	0.033	0.958	0.827	9.773	1.102	1.874	3.19
26	2016	0.651	1.399	1.110	0.698	2.311	1.437	0.567	1.767	2.092	1.124	2.404	1.859	0.651	4.070	0.032	0.961	0.806	11.041	1.204	2.153	3.34
27	2017	0.623	1.444	1.211	0.852	2.316	1.542	0.593	1.856	1.976	1.240	2.702	1.851	0.623	4.313	0.031	1.305	0.819	10.527	1.086	1.858	3.38
28	2018	0.635	1.393	1.130	0.689	2.387	1.649	0.577	1.651	1.863	1.039	2.458	1.746	0.635	4.332	0.030	1.027	0.708	10.253	1.018	1.734	3.38
29	2019	0.631	1.392	1.072	0.779	2.456	1.522	0.612	1.636	1.930	1.159	2.117	1.668	0.631	4.124	0.032	1.222	0.686	10.000	0.986	1.809	3.39
30	2020	0.689	1.394	1.100	0.735	2.451	1.597	0.583	1.582	1.878	1.268	2.006	1.832	0.689	3.836	0.032	1.306	0.618	11.033	1.218	1.937	3.80

Mozambi	Burkina F	Togo	Sierra Leo	Gambia,
54.883	28.021	24.864	43.045	40.408
54.605	27.838	24.692	42.771	39.841
54.326	27.656	24.521	42.498	39.275
54.048	27.473	24.350	42.225	38.708
53.769	27.290	24.178	41.952	38.142
53.491	27.107	24.007	41.678	37.575
53.212	26.924	23.836	41.405	37.009
52.934	26.742	23.664	41.132	36.442
52.655	26.559	23.493	40.858	35.876
52.377	26.376	23.322	40.585	35.309
52.095	26.193	23.267	40.312	34.743
51.813	26.011	23.213	40.038	34.176
51.531	25.828	23.158	39.765	33.610
51.250	25.645	23.104	39.492	33.043
50.968	25.462	23.050	39.219	32.477
50.686	25.280	22.995	38.945	31.910
50.404	25.097	22.941	38.672	31.344
50.122	24.914	22.886	38.399	30.777
49.841	24.731	22.832	38.125	30.211
49.559	24.549	22.778	37.852	29.644
49.296	24.366	22.723	37.579	29.078
49.034	24.183	22.669	37.305	28.511
48.771	24.000	22.614	37.032	27.945
48.509	23.817	22.560	36.759	27.379
48.246	23.635	22.505	36.486	26.812
47.850	23.452	22.451	36.212	26.245
47.568	23.269	22.397	35.939	25.679
47.336	23.086	22.342	35.666	25.113
47.008	22.904	22.288	35.392	24.545
46.725	22.721	22.233	35.119	23.979

Table 2:

Percentage of GDP contributed by forest land of all different 49 countries in the last 3 decades(1991-2020).

7.862	13.772	24.034	6.841	7.656	14.356	15.247	15.682	11.812	18.338	27.333	19.662	24.259	40.489	22.842	15.792	37.093	48.598	58.666	31.581	29.899	35.508	18.26
7.818	7.263	21.329	6.806	6.920	14.572	14.984	14.822	25.557	19.107	26.670	19.521	26.580	33.939	23.310	12.965	35.139	48.005	63.831	33.159	34.121	34.324	16.55
8.292	7.557	19.307	6.778	6.590	13.787	15.416	14.160	25.709	18.908	26.882	17.880	18.237	29.870	22.198	12.729	27.585	47.170	59.945	34.077	30.847	31.372	17.39
8.416	6.110	19.474	8.722	6.461	13.661	15.463	14.406	27.483	19.260	26.389	17.286	19.610	27.428	22.753	12.462	34.346	40.732	52.699	31.169	33.928	37.218	20.16
8.038	6.692	19.597	5.012	6.486	12.949	15.693	12.167	32.543	18.925	24.457	17.138	19.145	27.183	23.422	11.529	28.050	42.023	51.925	30.731	23.555	35.059	18.51
8.504	6.549	19.325	4.768	6.435	11.680	16.855	12.972	38.477	18.014	25.417	16.672	18.322	27.759	23.196	10.850	22.365	53.381	51.165	32.329	19.495	37.548	17.39
8.048	5.870	17.895	4.685	6.315	11.101	14.461	12.544	32.237	16.449	24.345	16.092	18.968	25.772	24.484	10.915	28.199	42.422	54.029	30.233	20.815	38.345	20.11
8.378	5.103	17.159	4.750	6.427	13.312	12.450	12.065	32.433	14.747	24.379	18.083	19.001	25.781	25.303	9.468	26.800	44.539	49.062	35.414	21.162	39.005	21.16
8.265	6.581	16.065	4.646	6.021	10.842	10.458	12.137	31.698	15.194	22.989	19.613	18.979	25.434	25.169	7.934	29.023	47.635	45.485	35.003	22.561	38.069	21.49
8.069	5.752	14.676	4.750	6.293	8.599	10.033	11.904	27.423	13.941	21.609	15.679	18.118	24.535	25.617	7.173	30.056	44.107	44.666	36.576	17.186	40.705	20.98
7.894	5.876	13.983	4.801	6.732	8.011	8.788	11.295	22.969	13.303	21.621	15.995	18.621	23.241	24.198	6.686	29.974	43.843	42.341	40.182	16.451	40.295	21.74
7.524	5.566	13.301	5.475	6.683	8.985	10.191	10.840	18.919	13.448	19.537	16.320	18.272	23.029	23.063	5.823	30.123	43.334	38.692	41.367	15.836	37.903	21.63
7.313	5.503	12.349	6.167	6.868	9.306	9.795	11.038	18.440	13.151	19.581	15.185	17.474	22.542	22.865	5.488	28.462	42.841	37.285	41.196	16.159	32.286	20.78
6.934	4.904	12.917	5.665	6.438	9.271	9.327	11.198	20.030	13.984	17.815	14.336	17.561	21.808	23.083	5.728	26.444	41.903	38.680	37.372	15.846	22.897	23.31
6.854	4.256	11.641	4.651	6.016	8.262	9.165	11.488	19.798	13.518	17.620	13.127	16.734	19.300	22.960	6.172	26.331	40.848	41.174	39.281	18.063	53.814	22.28
6.603	3.861	10.626	4.370	5.750	8.610	8.095	10.501	17.644	13.361	16.809	12.974	15.625	18.727	21.608	6.046	25.079	40.638	42.524	39.745	17.707	55.772	15.58
6.706	3.779	10.246	4.417	4.847	9.987	7.457	10.446	18.428	13.607	16.750	13.717	15.858	18.655	21.800	6.993	23.236	34.934	42.265	37.095	19.097	54.673	16.82
7.161	3.753	10.169	4.568	4.495	9.969	7.425	11.565	19.215	14.516	16.791	14.482	16.001	20.413	22.500	7.090	19.690	38.005	45.185	38.775	18.436	54.590	15.98
7.404	4.084	9.636	4.477	3.793	9.219	8.072	12.552	17.864	14.540	16.744	15.290	16.387	19.168	22.717	6.669	18.633	36.721	45.883	34.785	18.793	46.549	16.36
6.828	3.344	9.325	4.116	3.612	10.090	8.967	11.466	11.733	13.749	17.027	13.929	17.270	18.378	23.282	6.982	26.922	38.431	41.447	35.821	20.233	51.946	17.48
7.100	3.151	9.178	4.342	3.229	11.453	8.174	12.501	10.307	14.096	17.192	13.512	16.697	19.568	25.129	7.330	29.699	36.705	41.250	33.647	20.043	51.196	16.07
6.725	2.926	9.114	4.168	3.048	9.794	7.695	12.020	11.258	13.096	16.845	13.374	16.657	19.221	23.710	6.514	28.964	35.421	44.331	33.681	19.470	54.900	16.83
6.668	2.994	8.943	4.507	2.945	9.113	6.676	13.985	13.414	12.473	17.148	13.357	16.724	17.964	23.832	5.613	27.811	38.367	41.240	32.235	19.327	50.045	17.54
6.804	3.361	8.643	4.326	2.850	8.873	6.557	13.455	13.341	12.272	16.792	13.337	16.826	17.699	23.745	5.867	28.696	34.958	38.520	33.429	17.839	50.648	17.52
7.046	3.873	8.387	4.319	2.786	8.287	6.868	14.056	14.079	10.996	16.175	13.493	17.209	16.992	23.817	5.530	29.221	30.681	36.057	32.417	17.239	50.396	18.47
6.935	3.840	8.057	4.891	2.601	8.463	6.142	16.272	12.628	10.205	16.364	13.479	17.193	16.320	23.215	5.732	29.277	31.544	34.699	35.263	18.088	46.126	17.59
6.780	3.554	7.464	4.601	2.385	8.598	6.039	13.449	11.137	10.183	16.558	13.157	16.693	15.345	22.926	5.393	28.658	28.547	33.779	35.817	18.899	48.613	20.52
6.864	3.394	7.043	4.420	2.248	7.512	5.776	11.107	11.428	9.650	15.970	12.808	16.499	14.682	22.856	5.133	26.761	29.012	31.112	37.662	18.648	45.096	22.32
6.746	3.496	7.144	4.402	2.187	7.240	6.401	11.983	11.558	8.820	16.677	12.713	16.802	13.956	21.973	4.868	24.614	28.898	33.521	36.915	19.486	42.594	24.18

Mozambi	Burkina F	Togo	Sierra Leo	Gambia,
34.437	29.793	32.824	36.745	18.159
30.126	28.810	35.263	35.887	17.326
33.439	30.231	44.144	40.302	17.206
30.522	32.948	34.923	37.395	19.231
31.649	33.217	37.763	39.955	21.359
30.937	36.379	40.837	45.210	17.946
30.264	33.739	42.192	57.396	20.580
27.223	36.564	34.964	59.402	19.204
22.937	27.252	36.933	59.866	24.012
19.095	24.914	30.562	55.014	24.532
18.248	26.920	33.930	45.136	25.426
22.800	26.372	33.154	46.214	24.125
22.706	25.961	28.379	46.357	26.748
22.384	23.381	31.112	48.486	31.503
22.767	26.771	36.550	49.391	32.091
23.903	25.229	33.643	50.294	25.600
23.766	21.839	29.140	52.176	23.566
26.415	27.314	38.902	53.654	29.776
27.476	23.205	30.930	55.261	31.734
26.846	24.143	28.739	52.943	35.193
25.752	23.044	29.875	54.593	27.202
24.915	23.756	42.524	50.592	27.394
23.504	23.641	37.515	47.983	26.222
23.935	23.694	25.685	51.793	22.459
22.916	22.633	24.374	58.652	22.209
22.855	21.715	20.758	58.209	21.861
25.044	20.586	20.639	60.611	21.002
24.568	20.997	20.440	58.934	19.872
24.211	18.376	19.755	58.154	20.016
25.577	18.398	18.777	59.487	20.554

High Income Countries: Index= 1-20

Middle Income Countries: Index= 21-38

Low Countries: Index= 39-49

Table 3:

1991-2000	2001-2010	2011-2020
41210028	40510303	40123639
41137361	40464584	40090561
41064693	40418865	40057482
40992026	40373146	40024403
40919359	40327427	39991325
40846691	40293288	39958246
40774024	40259148	39902853
40701357	40225009	39872546
40628690	40190869	39833985
40556022	40156730	39784128

Forest Area(in sqkm) of the Whole World in the last 3 decades(1991-2020).

Major Code:

```
import matplotlib.pyplot as plt
import pandas as pd
from scipy import stats
area=pd.read_csv('area.csv')
gdp=pd.read_csv('gdp.csv')
warudo=pd.read_csv('muda.csv')
df=pd.DataFrame(columns=['Country','Rate of Recovery/Loss(in %)','Rate of GDP Contribution','Intercept(GDP Plot)',
                         'Correlation Coefficient(GDP)','Correlation Coefficient(Area)','Prediction(2030)'])
df['Country']=gdp.columns[1:51]
dl=pd.DataFrame(columns=['Country','2026','2027','2028','2029','2030'])
dl['Country']=gdp.columns[1:51]
c=0
d=0
for i in range(len(gdp.iloc[3])-1):
    c=c+1
    slope, intercept, r_value, p_value, std_err = stats.linregress(gdp['Num'],gdp.iloc[:,c])
    slope1, intercept1, r_value1, p_value1, std_err1 = stats.linregress(area['Num'],area.iloc[:,c])
    df.iloc[d:d+1,1]=slope1
    df.iloc[d:d+1,2]=slope
    df.iloc[d:d+1,3]=intercept
    df.iloc[d:d+1,4]=r_value
    df.iloc[d:d+1,5]=r_value1
    df.iloc[d:d+1,6]=slope*40+intercept
    dl.iloc[d:d+1,1]=slope*36+intercept
    dl.iloc[d:d+1,2]=slope*37+intercept
    dl.iloc[d:d+1,3]=slope*38+intercept
    dl.iloc[d:d+1,4]=slope*39+intercept
    dl.iloc[d:d+1,5]=slope*40+intercept
    d=d+1
print('Rate of Recovery/Loss=> The percentage of forest area gained/lost per year on average')
print('Rate of GDP Contribution=>GDP contribution(in%) by the Forests in the last 3 decades for the selected countries')
print('Intercept= Of the GDP Plot')
print('Prediction2030=>Predicting GDP contribution for 2030 in percentage by different countries')
df=df.drop(0)
prophecy=dl.drop(0)
df
```

Inferential Statistics Results of the above Table 1 and Table 2:

Rate of Recovery/Loss=> The percentage of forest area gained/lost per year on average

Rate of GDP Contribution=>GDP contribution(in%) by the Forests in the last 3 decades for the selected countries

Intercept= GDP Plots of all the countries.

Prediction2030=>Predicting GDP contribution for 2030 in percentage by different countries

Correlation Coefficient(GDP)=> Correlation coefficient between Years(1991-2020) and GDP contribution of Forest Area of the country as specified

Correlation Coefficient(Area)=> Correlation coefficient between Years(1991-2020) and Percentage of Forest Area of the country as specified

Table 4:

Country	Rate of Recovery/ Loss(in %)	Rate of GDP Contribution	Intercept (GDP Plot)	Correlation Coefficient (GDP)	Correlation Coefficient (Area)	Prediction (2030)
Switzerland	0.097	-0.039	1.559	-0.893	0.999	0.009
Sweden	0.008	-0.060	2.845	-0.889	0.569	0.438
Austria	0.046	-0.048	2.302	-0.911	0.989	0.400
Germany	0.012	-0.011	1.050	-0.758	0.914	0.615
Finland	0.042	-0.070	3.895	-0.807	0.774	1.115
France	0.179	-0.041	2.511	-0.897	0.999	0.890
United Kingdom	0.056	-0.025	1.209	-0.875	0.996	0.192
Netherlands	0.024	-0.067	3.229	-0.878	0.876	0.562
Norway	0.004	-0.033	2.323	-0.579	0.536	0.984
Trinidad and Tobago	-0.088	-0.059	2.190	-0.717	-0.999	-0.158
Australia	0.000	-0.045	3.456	-0.792	0.000	1.663
Korea, Rep.	-0.123	-0.165	5.836	-0.931	-0.996	-0.774
Switzerland. 1	0.097	-0.039	1.559	-0.893	0.999	0.009
Romania	0.096	-0.630	19.896	-0.950	0.896	-5.288
Singapore	-0.031	-0.006	0.175	-0.892	-0.236	-0.070
Denmark	0.113	-0.068	2.786	-0.863	0.944	0.052
Puerto Rico	0.644	-0.010	0.914	-0.410	0.943	0.527
Paraguay	-0.829	-0.234	16.865	-0.800	-0.998	7.488
Brunei Darussalam	-0.227	-0.008	1.126	-0.326	-0.959	0.803
Cyprus	0.032	-0.146	5.409	-0.935	0.816	-0.426
Mexico	-0.081	-0.072	4.870	-0.716	-0.993	1.981
Peru	-0.056	-0.056	8.275	-0.784	-0.784	6.024
Russian Federation	0.019	-0.192	7.993	-0.786	0.956	0.309
China	0.229	-0.536	21.133	-0.962	1.000	-0.313
Brazil	-0.387	-0.067	6.121	-0.564	-0.988	3.430
Panama	-0.165	-0.194	7.935	-0.936	-0.995	0.180

Malaysia	-0.137	-0.193	13.122	-0.790	-0.861	5.419
Turkey	0.108	-0.364	15.491	-0.917	0.986	0.921
Dominica	-0.077	-0.005	12.714	-0.026	-0.762	12.525
Mongolia	-0.005	-0.697	30.549	-0.759	-0.992	2.684
Philippines	-0.080	-0.308	18.842	-0.919	-0.802	6.522
India	0.085	-0.405	26.236	-0.900	0.994	10.041
Indonesia	-0.444	-0.216	18.541	-0.870	-0.958	9.912
Cameroon	-0.150	-0.176	20.719	-0.674	-0.996	13.676
Vietnam	0.625	-0.635	31.845	-0.926	0.986	6.443
Pakistan	-0.054	-0.017	23.621	-0.148	-0.999	22.940
El Salvador	-0.217	-0.277	12.042	-0.838	-1.000	0.974
Uzbekistan	0.075	-0.172	30.404	-0.386	0.960	23.543
Burundi	0.053	-0.686	50.063	-0.912	0.345	22.605
Ethiopia	-0.162	-0.809	56.435	-0.867	-0.924	24.079
Niger	-0.019	0.100	33.954	0.280	-0.925	37.972
Haiti	-0.038	-0.332	25.796	-0.586	-0.856	12.524
Chad	-0.066	0.601	34.143	0.625	-0.981	58.190
Guinea	-0.147	0.035	18.751	0.120	-1.000	20.149
Mozambique	-0.280	-0.230	29.266	-0.514	-1.000	20.082
Burkina Faso	-0.183	-0.469	33.327	-0.848	-1.000	14.575
Togo	-0.082	-0.581	40.851	-0.715	-0.961	17.600
Sierra Leone	-0.273	0.598	41.595	0.704	-1.000	65.529
Gambia	-0.566	0.151	21.467	0.276	-1.000	27.497

Problem Statement 1: To Find the linear relationship between no. of new flora originated in the previous decades and their GDP contribution with their respective years and conclude the correlation strength for both the variables on a scale of -1 to 1, all the while also finding out rate of gain/loss of forests of every selected country.

Correlation for Area:

Correlation between Percentage of Forest Area and Years of the last 3 decade.

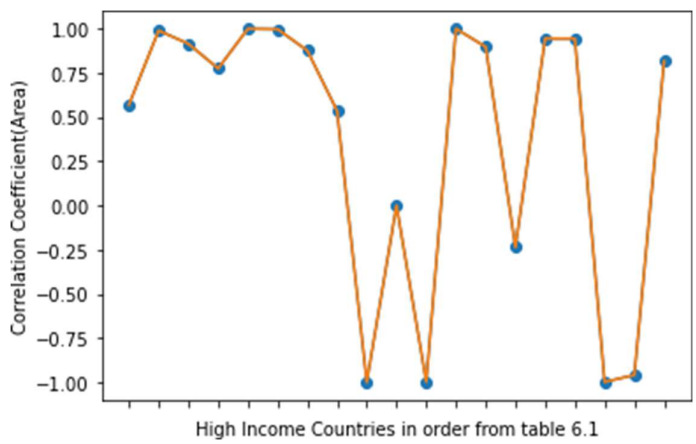
Table 5:

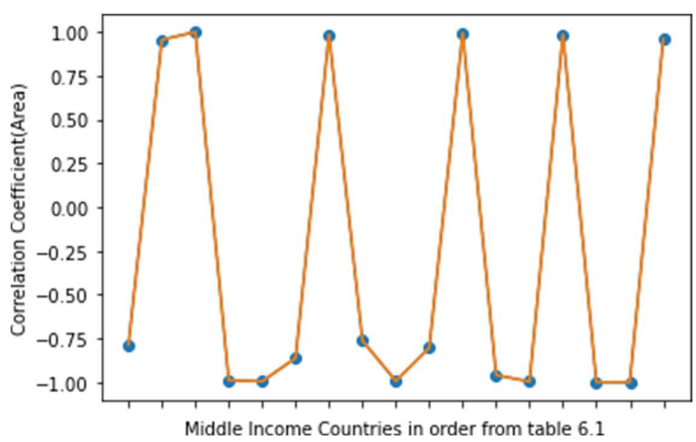
Country	Sign	Value	Remarks
Switzerland	+	0.999	positively and strongly related with time
Sweden	+	0.569	positively and strongly related with time
Austria	+	0.989	positively and strongly related with time
Germany	+	0.914	positively and strongly related with time
Finland	+	0.774	positively and strongly related with time

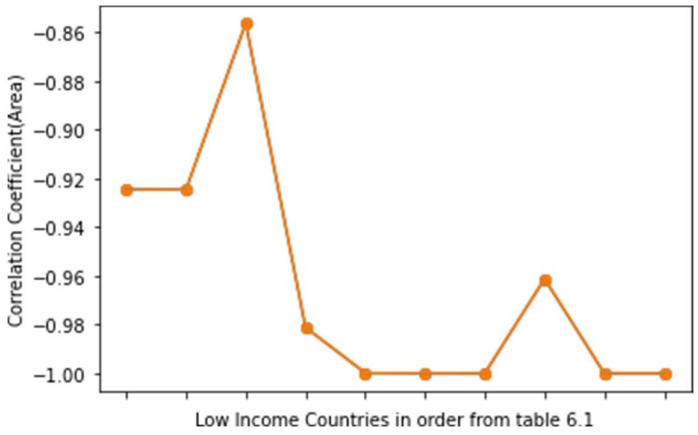
France	+	0.999	positively and strongly related with time
United Kingdom	+	0.996	positively and strongly related with time
Netherlands	+	0.876	positively and strongly related with time
Norway	+	0.536	positively and strongly related with time
Trinidad and Tobago	-	-0.999	negatively and strongly related with time
Australia	-	0.000	negatively and weakly related with time
Korea, Rep.	-	-0.996	negatively and strongly related with time
Switzerland.1	+	0.999	positively and strongly related with time
Romania	+	0.896	positively and strongly related with time
Singapore	-	-0.236	negatively and weakly related with time
Denmark	+	0.944	positively and strongly related with time
Puerto Rico	+	0.943	positively and strongly related with time
Paraguay	-	-0.998	negatively and strongly related with time
Brunei Darussalam	-	-0.959	negatively and strongly related with time
Cyprus	+	0.816	positively and strongly related with time
Mexico	-	-0.993	negatively and strongly related with time
Peru	-	-0.784	negatively and mildly related with time
Russian Federation	+	0.956	positively and strongly related with time
China	+	1.000	positively and strongly related with time
Brazil	-	-0.988	negatively and strongly related with time
Panama	-	-0.995	negatively and strongly related with time
Malaysia	-	-0.861	negatively and mildly related with time
Turkey	+	0.986	positively and strongly related with time

Dominica	-	-0.762	negatively and mildly related with time
Mongolia	-	-0.992	negatively and strongly related with time
Philippines	-	-0.802	negatively and mildly related with time
India	+	0.994	positively and strongly related with time
Indonesia	-	-0.958	negatively and strongly related with time
Cameroon	-	-0.996	negatively and strongly related with time
Vietnam	+	0.986	positively and strongly related with time
Pakistan	-	-0.999	negatively and strongly related with time
El Salvador	-	-1.000	negatively and strongly related with time
Uzbekistan	+	0.960	positively and strongly related with time
Burundi	+	0.345	positively and strongly related with time
Ethiopia	-	-0.924	negatively and strongly related with time
Niger	-	-0.925	negatively and strongly related with time
Haiti	-	-0.856	negatively and mildly related with time
Chad	-	-0.981	negatively and strongly related with time
Guinea	-	-1.000	negatively and strongly related with time
Mozambique	-	-1.000	negatively and strongly related with time
Burkina Faso	-	-1.000	negatively and strongly related with time
Togo	-	-0.961	negatively and strongly related with time
Sierra Leone	-	-1.000	negatively and strongly related with time
Gambia, The	-	-1.000	negatively and strongly related with time

```
def corr_area():
    k=0
    for i in df['Correlation Coefficient(Area)']:
        if i>=0.9:
            print('The Forest area of',df.iat[k,0], 'is positively and strongly related with time: ',i)
        elif 0.5<=i<0.9:
            print('The Forest area of',df.iat[k,0], 'is positively and mildly related with time',i)
        elif 0<i<0.5:
            print('The Forest area of',df.iat[k,0], 'is positively but weakly related with time',i)
        elif 0==i:
            print('The Forest area of',df.iat[k,0], 'is not related with time',i)
        if i<=-0.9:
            print('The Forest area of',df.iat[k,0], 'is negatively and strongly related with time',i)
        elif -0.5>=i>-0.9:
            print('The Forest area of',df.iat[k,0], 'is negatively and mildly related with time',i)
        elif 0>i>-0.5:
            print('The Forest area of',df.iat[k,0], 'is negatively and weakly related with time',i)
        k=k+1
corr_area()
```







Correlation for GDP:

Correlation between GDP Contribution by Forests and Years of the last 3 decade.

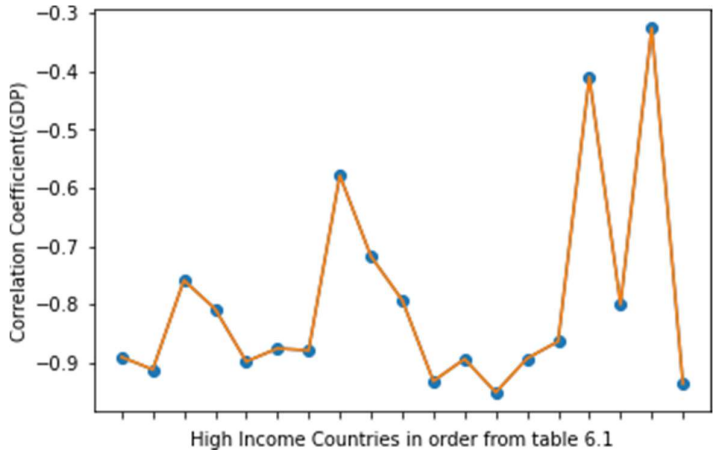
Table 6:

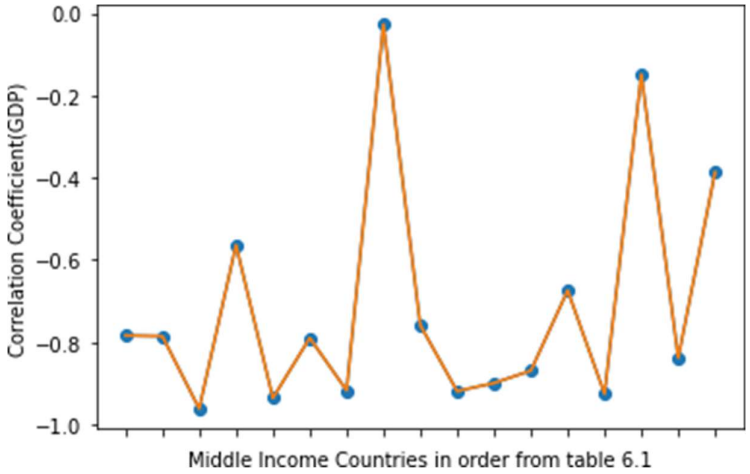
Country	Sign	Value	Remarks
Switzerland	-	-0.893	negatively and mildly related with time
Sweden	-	-0.889	negatively and mildly related with time
Austria	-	-0.911	negatively and strongly related with time
Germany	-	-0.758	negatively and mildly related with time
Finland	-	-0.807	negatively and mildly related with time
France	-	-0.897	negatively and mildly related with time
United Kingdom	-	-0.875	negatively and mildly related with time
Netherlands	-	-0.878	negatively and mildly related with time
Norway	-	-0.579	negatively and mildly related with time
Trinidad and Tobago	-	-0.717	negatively and mildly related with time
Australia	-	-0.792	negatively and mildly related with time
Korea, Rep.	-	-0.931	negatively and strongly related with time
Switzerland.1	-	-0.893	negatively and mildly related with time
Romania	-	-0.950	negatively and strongly related with time

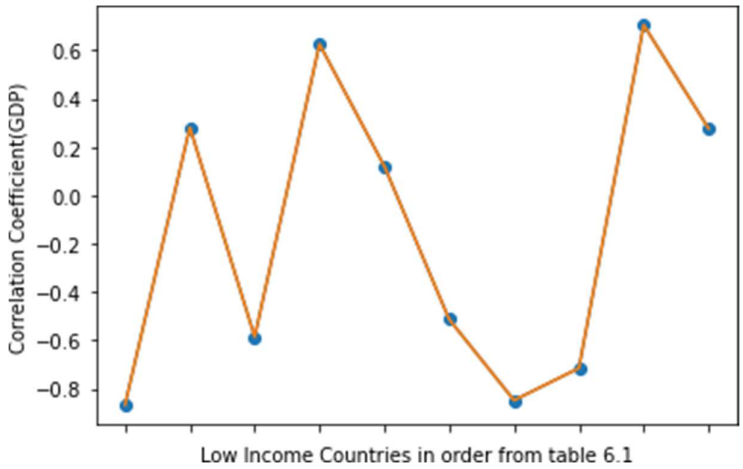
Singapore	-	-0.892	negatively and mildly related with time
Denmark	-	-0.863	negatively and mildly related with time
Puerto Rico	-	-0.410	negatively and mildly related with time
Paraguay	-	-0.800	negatively and mildly related with time
Brunei Darussalam	-	-0.326	negatively and weakly related with time
Cyprus	-	-0.935	negatively and strongly related with time
Mexico	-	-0.716	negatively and mildly related with time
Peru	-	-0.784	negatively and mildly related with time
Russian Federation	-	-0.786	negatively and mildly related with time
China	-	-0.962	negatively and strongly related with time
Brazil	-	-0.564	negatively and mildly related with time
Panama	-	-0.936	negatively and strongly related with time
Malaysia	-	-0.790	negatively and mildly related with time
Turkey	-	-0.917	negatively and strongly related with time
Dominica	-	-0.026	negatively and weakly related with time
Mongolia	-	-0.759	negatively and mildly related with time
Philippines	-	-0.919	negatively and strongly related with time
India	-	-0.900	negatively and mildly related with time
Indonesia	-	-0.870	negatively and mildly related with time
Cameroon	-	-0.674	negatively and mildly related with time
Vietnam	-	-0.926	negatively and strongly related with time
Pakistan	-	-0.148	negatively and weakly related with time
El Salvador	-	-0.838	negatively and mildly related with time

Uzbekistan	-	-0.386	negatively and weakly related with time
Burundi	-	-0.912	negatively and strongly related with time
Ethiopia	-	-0.867	negatively and mildly related with time
Niger	+	0.280	positively and strongly related with time
Haiti	-	-0.586	negatively and mildly related with time
Chad	+	0.625	positively and strongly related with time
Guinea	+	0.120	positively and strongly related with time
Mozambique	-	-0.514	negatively and mildly related with time
Burkina Faso	-	-0.848	negatively and mildly related with time
Togo	-	-0.715	negatively and mildly related with time
Sierra Leone	+	0.704	positively and strongly related with time
Gambia, The	+	0.276	positively and strongly related with time

```
def corr_gdp():
    k=0
    for i in df['Correlation Coefficient(GDP)']:
        if i>=0.9:
            print('The GDP contribution of Forests of',df.iat[k,0], 'is positively and strongly related with time',i)
        elif 0.5<=i<0.9:
            print('The GDP contribution of Forests of',df.iat[k,0], 'is positively and mildly related with time',i)
        elif 0<i<0.5:
            print('The GDP contribution of Forests of',df.iat[k,0], 'is positively but weakly related with time',i)
        elif 0==i:
            print('The GDP contribution of Forests of',df.iat[k,0], 'is not related with time',i)
        if i<=-0.9:
            print('The GDP contribution of Forests of',df.iat[k,0], 'is negatively and strongly related with time',i)
        elif -0.5>=i>-0.9:
            print('The GDP contribution of Forests of',df.iat[k,0], 'is negatively and mildly related with time',i)
        elif 0>i>-0.5:
            print('The GDP contribution of Forests of',df.iat[k,0], 'is negatively and weakly related with time',i)
        k=k+1
corr_gdp()
```


−0.3
−0.4
−0.5
−0.6
−0.7
−0.8
−0.9
Correlation Coefficient(GDP)
High Income Countries in order from table 6.1


0.0
−0.2
−0.4
−0.6
−0.8
−1.0
Correlation Coefficient(GDP)
Middle Income Countries in order from table 6.1


0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8
Correlation Coefficient(GDP)
Low Income Countries in order from table 6.1

Rate of Loss/Recovery:

Table 7:

Following is the status of Forest area of different countries(Per Year):

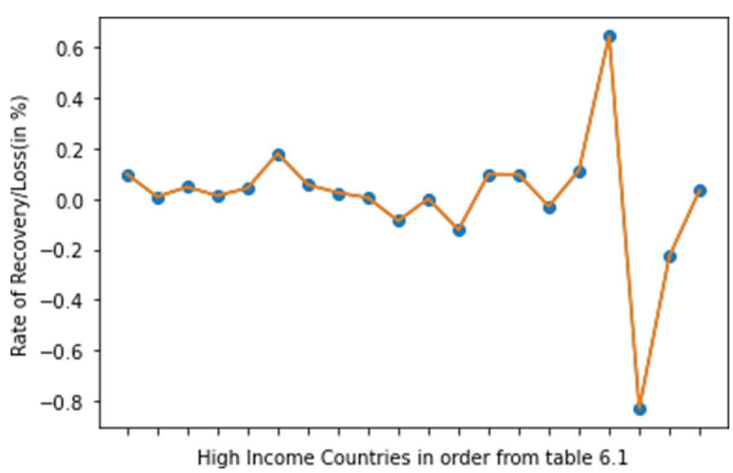
+ for increasing

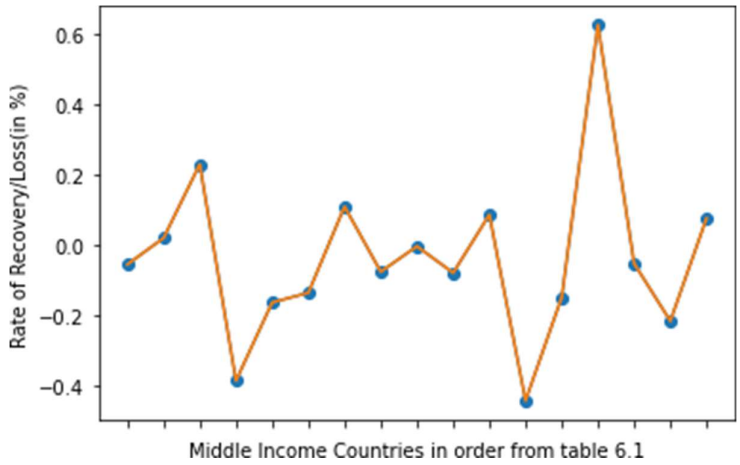
- for decreasing

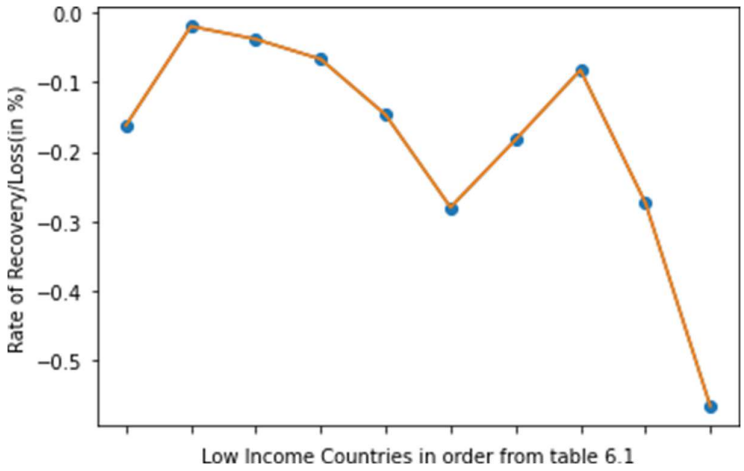
Country	Sign	Value
Switzerland	+	0.097
Sweden	+	0.008
Austria	+	0.046
Germany	+	0.012
Finland	+	0.042
France	+	0.179
United Kingdom	+	0.056
Netherlands	+	0.024
Norway	+	0.004
Trinidad and Tobago	-	-0.088
Australia	-	0.000
Korea, Rep.	-	-0.123
Switzerland.1	+	0.097
Romania	+	0.096
Singapore	-	-0.031
Denmark	+	0.113
Puerto Rico	+	0.644
Paraguay	-	-0.829
Brunei Darussalam	-	-0.227
Cyprus	+	0.032
Mexico	-	-0.081
Peru	-	-0.056
Russian Federation	+	0.019
China	+	0.229
Brazil	-	-0.387
Panama	-	-0.165
Malaysia	-	-0.137
Turkey	+	0.108
Dominica	-	-0.077
Mongolia	-	-0.005
Philippines	-	-0.080
India	+	0.085
Indonesia	-	-0.444

Cameroon	-	-0.150
Vietnam	+	0.625
Pakistan	-	-0.054
El Salvador	-	-0.217
Uzbekistan	+	0.075
Burundi	+	0.053
Ethiopia	-	-0.162
Niger	-	-0.019
Haiti	-	-0.038
Chad	-	-0.066
Guinea	-	-0.147
Mozambique	-	-0.280
Burkina Faso	-	-0.183
Togo	-	-0.082
Sierra Leone	-	-0.273
Gambia, The	-	-0.566

```
def rate_area():
    print('Following is the status of Forest area of different countries(Per Year): ')
    print('+ for increasing')
    print('- for decreasing')
    k=0
    for i in df['Rate of Recovery/Loss(in %)']:
        if i>0:
            print(df.iat[k,0],': Increasing(+) =>',df.iat[k,1])
        else:
            print(df.iat[k,0],': Decreasing(-) =>',df.iat[k,1])
        k=k+1
rate_area()
```







<u>Problem Statement 2</u>: Find out the rate of GDP contribution through forests for selected countries and predict how much revenue will be generated in the last five years of the current decade(2020-2030).

<u>Rate of GDP Contribution:</u>

<u>Table 8:</u>

Following is the rate of GDP contribution by Forest Area of different countries(per year):

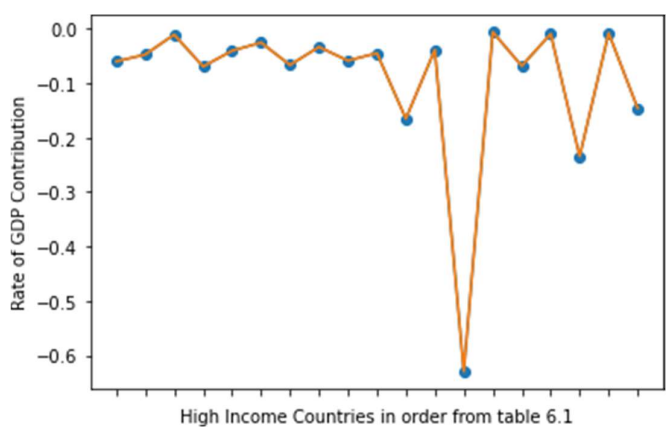
+ for increasing

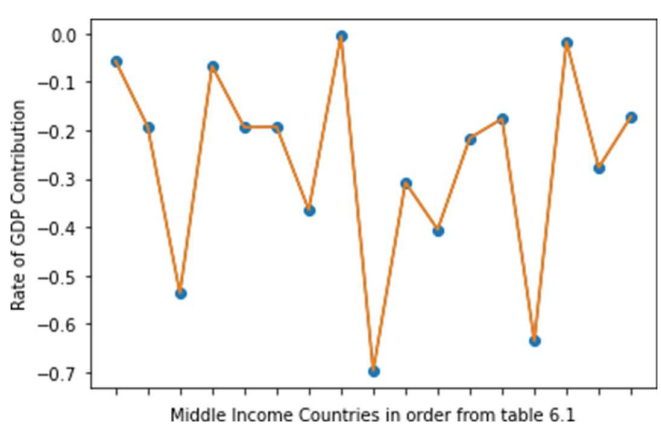
- for decreasing

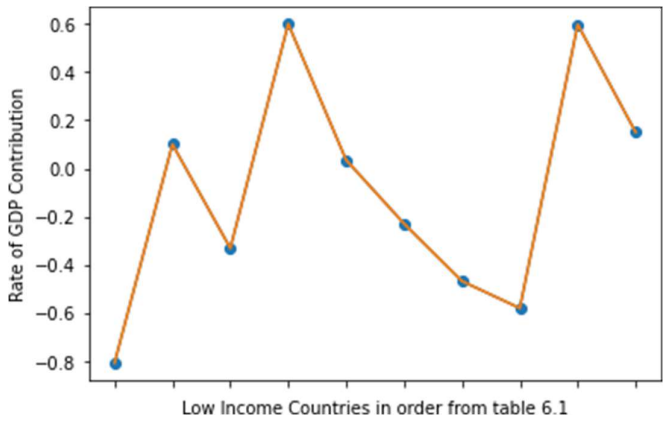
Country	Sign	Value
Switzerland	-	-0.039
Sweden	-	-0.060
Austria	-	-0.048
Germany	-	-0.011
Finland	-	-0.070
France	-	-0.041
United Kingdom	-	-0.025
Netherlands	-	-0.067
Norway	-	-0.033
Trinidad and Tobago	-	-0.059
Australia	-	-0.045
Korea, Rep.	-	-0.165
Switzerland.1	-	-0.039
Romania	-	-0.630
Singapore	-	-0.006
Denmark	-	-0.068
Puerto Rico	-	-0.010
Paraguay	-	-0.234
Brunei Darussalam	-	-0.008
Cyprus	-	-0.146
Mexico	-	-0.072
Peru	-	-0.056
Russian Federation	-	-0.192
China	-	-0.536
Brazil	-	-0.067
Panama	-	-0.194
Malaysia	-	-0.193
Turkey	-	-0.364
Dominica	-	-0.005
Mongolia	-	-0.697
Philippines	-	-0.308
India	-	-0.405
Indonesia	-	-0.216
Cameroon	-	-0.176
Vietnam	-	-0.635
Pakistan	-	-0.017
El Salvador	-	-0.277
Uzbekistan	-	-0.172
Burundi	-	-0.686
Ethiopia	-	-0.809
Niger	+	0.100

Haiti	-	-0.332
Chad	+	0.601
Guinea	+	0.035
Mozambique	-	-0.230
Burkina Faso	-	-0.469
Togo	-	-0.581
Sierra Leone	+	0.598
Gambia, The	+	0.151

```
def rate_gdp():
    print('Following is the rate of GDP contribution by Forest Area of different countries(per year): ')
    print('+ for increasing')
    print('- for decreasing')
    k=0
    for i in df['Rate of GDP Contribution']:
        if i>0:
            print(df.iat[k,0],': Increasing(+) =>',df.iat[k,2])
        else:
            print(df.iat[k,0],': Decreasing(-) =>',df.iat[k,2])
        k=k+1
rate_gdp()
```







Prediction: To predict the Revenue Generation through Forests in the last 5 years of decade 2020-2030.

Predicted Value=Slope × Year Order + intercept (All values in the result table above)

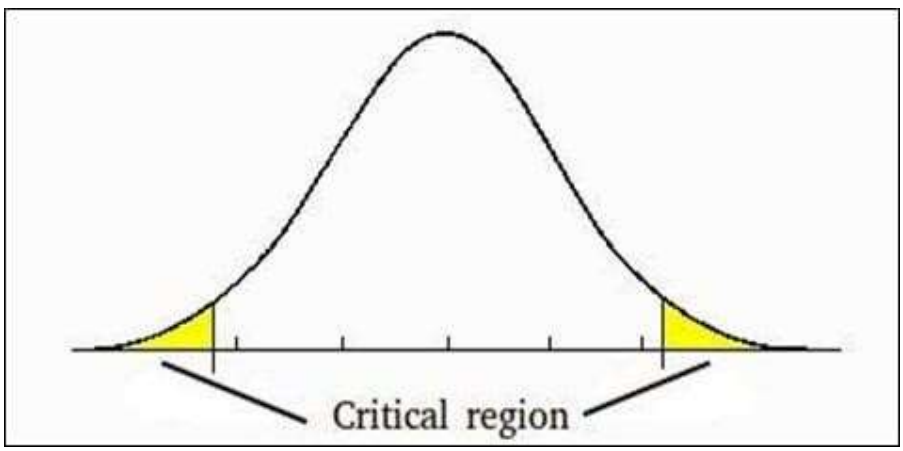
Table 9:

Country	2026	2027	2028	2029	2030
Switzerland	0.164	0.125	0.086	0.047	0.009
Sweden	0.679	0.618	0.558	0.498	0.438
Austria	0.590	0.542	0.495	0.447	0.400
Germany	0.658	0.647	0.636	0.626	0.615
Finland	1.393	1.324	1.254	1.185	1.115
France	1.052	1.011	0.971	0.930	0.890
United Kingdom	0.294	0.269	0.243	0.218	0.192
Netherlands	0.829	0.762	0.695	0.628	0.562
Norway	1.118	1.084	1.051	1.017	0.984
Trinidad and Tobago	0.077	0.018	-0.041	-0.099	-0.158
Australia	1.843	1.798	1.753	1.708	1.663
Korea, Rep.	-0.113	-0.278	-0.443	-0.609	-0.774
Switzerland.1	0.164	0.125	0.086	0.047	0.009
Romania	-2.769	-3.399	-4.029	-4.658	-5.288
Singapore	-0.045	-0.051	-0.057	-0.064	-0.070
Denmark	0.325	0.257	0.188	0.120	0.052
Puerto Rico	0.566	0.556	0.547	0.537	0.527
Paraguay	8.426	8.192	7.957	7.723	7.488
Brunei Darussalam	0.836	0.828	0.819	0.811	0.803
Cyprus	0.157	0.012	-0.134	-0.280	-0.426
Mexico	2.270	2.197	2.125	2.053	1.981
Peru	6.249	6.193	6.137	6.080	6.024
Russian Federation	1.077	0.885	0.693	0.501	0.309

China	1.832	1.296	0.760	0.223	-0.313
Brazil	3.699	3.631	3.564	3.497	3.430
Panama	0.955	0.761	0.568	0.374	0.180
Malaysia	6.189	5.996	5.804	5.611	5.419
Turkey	2.378	2.014	1.649	1.285	0.921
Dominica	12.544	12.540	12.535	12.530	12.525
Mongolia	5.470	4.773	4.077	3.380	2.684
Philippines	7.754	7.446	7.138	6.830	6.522
India	11.660	11.255	10.850	10.445	10.041
Indonesia	10.775	10.559	10.344	10.128	9.912
Cameroon	14.381	14.205	14.029	13.853	13.676
Vietnam	8.983	8.348	7.713	7.078	6.443
Pakistan	23.008	22.991	22.974	22.957	22.940
El Salvador	2.081	1.804	1.527	1.251	0.974
Uzbekistan	24.229	24.057	23.886	23.714	23.543
Burundi	25.351	24.665	23.978	23.292	22.605
Ethiopia	27.314	26.505	25.696	24.887	24.079
Niger	37.571	37.671	37.772	37.872	37.972
Haiti	13.852	13.520	13.188	12.856	12.524
Chad	55.785	56.386	56.988	57.589	58.190
Guinea	20.009	20.044	20.079	20.114	20.149
Mozambique	21.001	20.771	20.541	20.312	20.082
Burkina Faso	16.450	15.982	15.513	15.044	14.575
Togo	19.925	19.343	18.762	18.181	17.600
Sierra Leone	63.136	63.734	64.333	64.931	65.529
Gambia, The	26.894	27.044	27.195	27.346	27.497

```
import matplotlib.pyplot as plt
import pandas as pd
from scipy import stats
area=pd.read_csv('area.csv')
gdp=pd.read_csv('gdp.csv')
df=pd.DataFrame(columns=['Country','Rate of Recovery/Loss(in %)','Rate of GDP Contribution','Intercept(GDP Plot)',
                         'Correlation Coefficient(GDP)','Correlation Coefficient(Area)','Prediction(2030)'])
df['Country']=gdp.columns[1:51]
dl=pd.DataFrame(columns=['Country','2026','2027','2028','2029','2030','2041'])
dl['Country']=gdp.columns[1:51]
c=0
d=0
for i in range(len(gdp.iloc[3])-1):
    c=c+1
    slope, intercept, r_value, p_value, std_err = stats.linregress(gdp['Num'],gdp.iloc[:,c])
    slope1, intercept1, r_value1, p_value1, std_err1 = stats.linregress(area['Num'],area.iloc[:,c])
    df.iloc[d:d+1,1]=slope1
    df.iloc[d:d+1,2]=slope
    df.iloc[d:d+1,3]=intercept
    df.iloc[d:d+1,4]=r_value
    df.iloc[d:d+1,5]=r_value1
    df.iloc[d:d+1,6]=slope*40+intercept
    dl.iloc[d:d+1,1]=slope*36+intercept
    dl.iloc[d:d+1,2]=slope*37+intercept
    dl.iloc[d:d+1,3]=slope*38+intercept
    dl.iloc[d:d+1,4]=slope*39+intercept
    dl.iloc[d:d+1,5]=slope*40+intercept
    dl.iloc[d:d+1,6]=slope*51+intercept
    d=d+1
print('Rate of Recovery/Loss=> The percentage of forest area gained/lost per year on average')
print('Rate of GDP Contribution=>GDP contribution(in%) by the Forests in the last 3 decades for the selected countries')
print('Intercept= Of the GDP Plot')
print('Prediction2030=>Predicting GDP contribution for 2030 in percentage by different countries')
df=df.drop(0)
prophecy=dl.drop(0)
df
prophecy
```

Problem Statement 3: Check and cross verify whether the total global forest area has been constant for the last 3 decades.



Source=packtpub.com/book/big-data-and-business-intelligence/9781784390150/2/ch02lvl1sec16/one-tailed-and-two-tailed-tests

Figure:

Problem statement 3.1: To Claim that the average Forest area in the selected countries is approximately equal for every passing year from 1991-2020.

Null Hypothesis for all the cases:

H_o= μ1-μ2=0, where μ1 is the average Forest area in the selected countries one year, and μ2 is the average Forest area in the selected countries next year.

H_a= μ1≠μ2

Level of Significance for all the tests:

α= 0.005

Year	Null Hypothesis
1992	Accepted
1993	Accepted
1994	Accepted
1995	Accepted
1996	Accepted
1997	Accepted
1998	Accepted
1999	Accepted
2000	Accepted
2001	Accepted
2002	Accepted
2003	Accepted
2004	Accepted
2005	Accepted
2006	Accepted
2007	Accepted
2008	Accepted
2009	Accepted
2010	Accepted
2011	Accepted
2012	Accepted
2013	Accepted
2014	Accepted
2015	Accepted
2016	Accepted
2017	Accepted
2018	Accepted
2019	Accepted
2020	Accepted

```
from scipy import stats
p=pd.DataFrame(columns=['Year','Null Hypothesis'])
p['Year']=area['Year']
l=-1
for i in range(30):
    if l==-1:
        y=area.iloc[l+1,2:51]
    else:
        y=area.iloc[l,2:51]
    x=area.iloc[l+1,2:51]
    def ttest(x,y,clmdiff,q):
        n1=len(x)
        n2=len(y)
        x1=x.mean()
        x2=y.mean()
        s1=x.std()
        s2=y.std()
        a=(s1**2)/n1
        b=(s2**2)/n2
        dfree=((a+b)**2)/((a**2)/(n1-1)+(b**2)/(n2-1))
        Tc=((x1-x2)-clmdiff)/((a+b)**0.5)
        T=stats.t.ppf(q,dfree)
        if T<Tc<(T*-1):
            p.iat[i,1]='Accepted'
        else:
            p.iat[i,1]='Rejected'
    ttest(x,y,0,0.005)
    l=l+1
p=p.drop(0)
p
```

Problem Statement 3.2: To Claim that the average Global Forest area is approximately equal for every passing decade from 1991-2020.

We will use Two Tailed Test to verify our claim.

Since our value of sample size(n) is smaller than 30 in both data sets, we will be using T distribution table in our python code

H_o= μ1-μ2=0, where μ1 is the average Global Forest area(in sqkm) , and μ2 is the average Forest area in the selected countries next year.

H_a= μ1≠μ2

α= 0.005

1. Hypothesis test for the decades 1991-2000 and 2001:2010:

- Sample size for the data is: n1=10

- Sample size for the data is: n2=10
- Mean of the first decade data is: μ1=40883025.02
- Mean of the second decade data is: μ2= 40321936.84
- Standard Deviation for the first decade data is: σ1= 220011.06
- Standard Deviation for the next decade data is: σ2= 118560.0
- The degree of freedom is: 14
- The T value for degree of freedom 14 at significance level 0.005 is: 2.98
- Critical T_c value is: 7.1

Since $T>T_c$

The null hypothesis is REJECTED and it is evident that there is a significant difference between the Forest Area of Decades 1991-2000 and 2001-2010.

2. Hypothesis test for the decades 2001-2010 and 2011:2020:

- Sample size for the data is: n1=10
- Sample size for the data is: n2=10
- Mean of the first decade data is: μ1= 40321936.84
- Mean of the second decade data is: μ2= 39963916.73
- Standard Deviation for the first decade data is: σ1= 118560.0
- Standard Deviation for the next decade data is: σ2= 113543.93
- The degree of freedom is: 18
- The T value for degree of freedom 18 at significance level 0.005 is: 2.88
- Critical T value is: 6.9

Since $T>T_c$

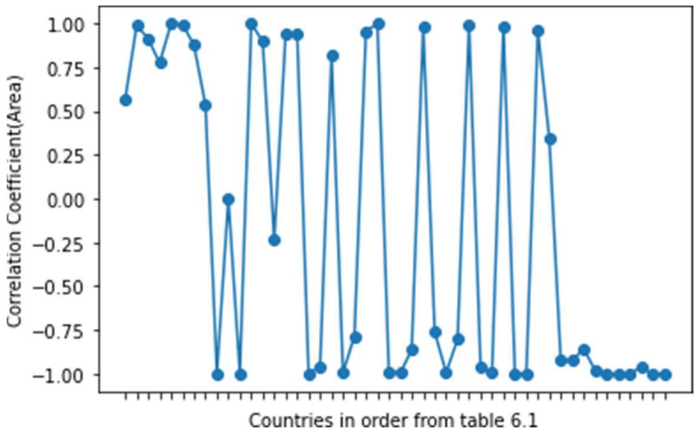
The null hypothesis is REJECTED which proves that there is a significant difference between the Forest Area of Decades 2001-2010 and 2011-2020.

```
def ttest(x,y,clmdiff,q):
    n1=len(x)
    print('Sample size for the data is: ',round(n1,2))
    n2=len(y)
    print('Sample size for the data is: ',round(n2,2))
    x1=x.mean()
    print("Mean of the first dataset is: ",round(x1,2))
    x2=y.mean()
    print("Mean of the second dataset is: ",round(x2,2))
    s1=x.std()
    print('Standard Deviation for the data is: ',round(s1,2))
    s2=y.std()
    print('Standard Deviation for the data is: ',round(s2,2))
    a=(s1**2)/n1
    b=(s2**2)/n2
    dfree=((a+b)**2)/((a**2)/(n1-1)+(b**2)/(n2-1))
    print('The degree of freedom is:',round(dfree,0))
    Tc=((x1-x2)-clmdiff)/((a+b)**0.5)
    T=stats.t.ppf(q,dfree)
    print('The T value for this data is', round(T,2))
    print('Critical T value is: ',round(Tc,2))
    if T<Tc<(T*-1):
        print('The null hypothesis is ACCEPTED')
    else:
        print('The null hypothesis is REJECTED')
ttest(warudo['1991-2000'],warudo['2001-2010'],0,0.005)
```

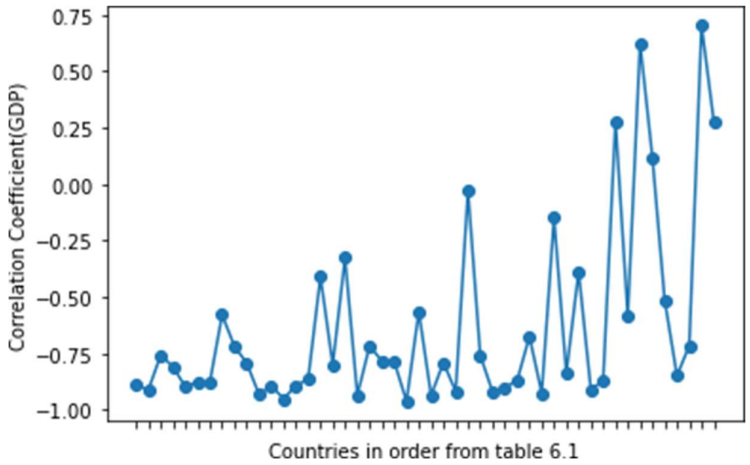
Conclusion

Analyzing Forest Area and Respective GDP Contribution

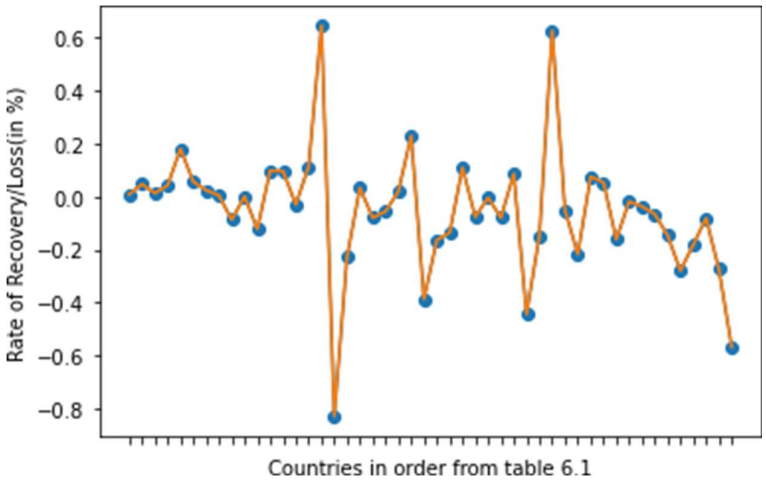
Problem Statement 1:



The following graph clearly shows that the Forest Areas of high income countries have high and positive correlation with time which is a good indication, meanwhile Forest Areas of low and middle income countries on average show frequent high but negative correlation with time which is not a good sign.

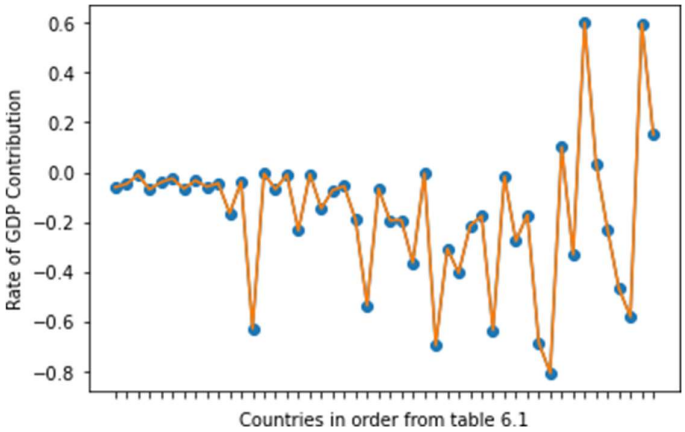


We unanimously conclude from the above graph that High Income First World Countries are getting less dependent on Forest Products and services as time passes but on the contrary countries with low income seems to use their resources more efficiently with time as we can see the graph rising for the variable GDP Contribution.



The above graph clearly shows that the value of rate of recovery/loss of forest land is random among all the countries regardless of the Income Status. Although the net tree area of low-income countries do slightly portray frequent net deforestation case.

Problem statement 2:



The above graph helps us in understanding and concluding that high Income Countries have less GDP contribution growth as they already have other advanced method of extracting and utilizing resources while low and middle income countries still depend on the forest and agriculture to fill a major portion of their GDP income. As they are developing countries, they tend to exploit their natural resources more thus resulting in have a net growth in GDP contribution. The poorer the country, the more it depends on its Forest and Agriculture.

Prediction: From the prediction table, we can analyse that all the countries are depending less and less on their primitive resources whether developed, developing, or underdeveloped , each passing year, every country, progresses a little bit further and utilising their current resources more efficiently and diversly.

Problem statement 3:

Problem statement 3.1: The null hypothesis for the change in combined average forest land of the 49 countries for each progressive year in decades 1991-2020 was accepted in all the cases demonstrating that all though there is a

specific rate of forest land on average, it is not at a significant level. This proves that forest land in terms of percentage is almost constant for two adjacent years in recent history.

Problem statement 3.2: The null hypothesis that the average forest area was constant through the last 3 decades was rejected when the area was in square kilometers, which suggest there may not be a huge or even a significant loss of Forest Area in terms of Percentage but in square kilometers, we can notice the slight loss of Green land every year which is small but drastic enough to change the very face of earth over long time. These results beg more of our attention to the sensitive issue of deforestation and climate change.

References

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https://data.worldbank.org/

http://www.efi.int/files/attachments/publications/ir_06.pdf

https://wedocs.unep.org/bitstream/handle/20.500.11822/32472/WF20EN.pdf?sequence=1&isAllowed=y

https://www.unep.org/resources/state-worlds-forests-forests-biodiversity-and-people#:~:text=The%20State%20of%20the%20World's%20Forests%202020%20assesses%20progress%20to,conservation%20and%20sustainable%20development%20outcomes.

Appendices

```
import matplotlib.pyplot as plt
import pandas as pd
from scipy import stats
area=pd.read_csv('area.csv')
gdp=pd.read_csv('gdp.csv')
warudo=pd.read_csv('muda.csv')
df=pd.DataFrame(columns=['Country','Rate of Recovery/Loss(in %)','Rate of GDP Contribution','Intercept(GDP Plot)',
                         'Correlation Coefficient(GDP)','Correlation Coefficient(Area)','Prediction(2030)'])
df['Country']=gdp.columns[1:51]
dl=pd.DataFrame(columns=['Country','2026','2027','2028','2029','2030'])
dl['Country']=gdp.columns[1:51]
c=0
d=0
for i in range(len(gdp.iloc[3])-1):
    c=c+1
    slope, intercept, r_value, p_value, std_err = stats.linregress(gdp['Num'],gdp.iloc[:,c])
    slope1, intercept1, r_value1, p_value1, std_err1 = stats.linregress(area['Num'],area.iloc[:,c])
    df.iloc[d:d+1,1]=slope1
    df.iloc[d:d+1,2]=slope
    df.iloc[d:d+1,3]=intercept
    df.iloc[d:d+1,4]=r_value
    df.iloc[d:d+1,5]=r_value1
    df.iloc[d:d+1,6]=slope*40+intercept
    dl.iloc[d:d+1,1]=slope*36+intercept
    dl.iloc[d:d+1,2]=slope*37+intercept
    dl.iloc[d:d+1,3]=slope*38+intercept
    dl.iloc[d:d+1,4]=slope*39+intercept
    dl.iloc[d:d+1,5]=slope*40+intercept
    d=d+1
print('Rate of Recovery/Loss=> The percentage of forest area gained/lost per year on average')
print('Rate of GDP Contribution=>GDP contribution(in%) by the Forests in the last 3 decades for the selected countries')
print('Intercept= Of the GDP Plot')
print('Prediction2030=>Predicting GDP contribution for 2030 in percentage by different countries')
df=df.drop(0)
prophecy=dl.drop(0)
df
```

```
Rate of Recovery/Loss=> The percentage of forest area gained/lost per year on average
Rate of GDP Contribution=>GDP contribution(in%) by the Forests in the last 3 decades for the selected countries
Intercept= Of the GDP Plot
Prediction2030=>Predicting GDP contribution for 2030 in percentage by different countries
```

Out[32]:

	Country	Rate of Recovery/Loss(in %)	Rate of GDP Contribution	Intercept(GDP Plot)	Correlation Coefficient(GDP)	Correlation Coefficient(Area)	Prediction(2030)
1	Switzerland	0.097478	-0.038751	1.558753	-0.893002	0.999088	0.00872
2	Sweden	0.00774	-0.060178	2.844995	-0.889487	0.56943	0.437879
3	Austria	0.046192	-0.047554	2.301939	-0.911118	0.988706	0.39977
4	Germany	0.012219	-0.010872	1.049611	-0.758111	0.913992	0.614735
5	Finland	0.041587	-0.069502	3.895143	-0.807213	0.774427	1.115062
6	France	0.179257	-0.040534	2.511239	-0.897386	0.998761	0.889899
7	United Kingdom	0.055786	-0.025427	1.209327	-0.874889	0.996284	0.192261
8	Netherlands	0.0236	-0.066693	3.229447	-0.87825	0.875653	0.561744

```
In [19]: prophecy
```

Out[19]:

	Country	2026	2027	2028	2029	2030
1	Switzerland	0.163724	0.124973	0.086222	0.047471	0.00872
2	Sweden	0.67859	0.618412	0.558235	0.498057	0.437879
3	Austria	0.589987	0.542433	0.494879	0.447325	0.39977
4	Germany	0.658223	0.647351	0.636479	0.625607	0.614735
5	Finland	1.39307	1.323568	1.254066	1.184564	1.115062
6	France	1.052033	1.0115	0.970966	0.930433	0.889899
7	United Kingdom	0.293968	0.268541	0.243114	0.217688	0.192261
8	Netherlands	0.828514	0.761822	0.695129	0.628436	0.561744
9	Norway	1.117747	1.084262	1.050778	1.017293	0.983808
10	Trinidad and Tobago	0.076776	0.018074	-0.040628	-0.09933	-0.158032
11	Australia	1.842725	1.797901	1.753078	1.708254	1.66343
12	Korea, Rep.	0.11289	0.278133	0.443376	0.608618	0.773861

```
In [65]: area
```

Out[65]:

	Num	Year	Switzerland	Sweden	Austria	Germany	Finland	France	United Kingdom	Netherlands	...	Niger	Haiti	Chad	Guinea	N
0	1	1991	29.289079	68.413998	45.797009	32.381634	72.006176	26.519543	11.555409	10.270942	...	1.486785	13.885813	5.314724	29.469722	
1	2	1992	29.397050	68.438368	45.872657	32.397101	72.193414	26.675141	11.628157	10.312915	...	1.438083	13.877576	5.284784	29.328504	
2	3	1993	29.505022	68.462738	45.948305	32.413497	72.380653	26.830738	11.700905	10.354887	...	1.389382	13.869340	5.254844	29.187286	
3	4	1994	29.612993	68.487108	46.023953	32.429893	72.567891	26.986336	11.773654	10.396860	...	1.340681	13.861103	5.224905	29.046069	
4	5	1995	29.720964	68.511478	46.099600	32.446290	72.755130	27.141934	11.846402	10.438833	...	1.291979	13.852866	5.194965	28.904851	
5	6	1996	29.829690	68.535848	46.175248	32.462689	72.942368	27.297531	11.919150	10.480806	...	1.243278	13.844630	5.165025	28.763633	
6	7	1997	29.938422	68.560218	46.250896	32.481879	73.129607	27.453129	11.991898	10.522778	...	1.194576	13.836393	5.135086	28.622416	
7	8	1998	30.047159	68.584588	46.326544	32.500143	73.316846	27.608727	12.064647	10.564751	...	1.145875	13.828157	5.105146	28.481198	
8	9	1999	30.155901	68.608958	46.402192	32.519342	73.504084	27.764324	12.137395	10.606724	...	1.097174	13.819920	5.075206	28.339980	
9	10	2000	30.264649	68.633328	46.477840	32.537613	73.691323	27.919871	12.210143	10.648697	...	1.048472	13.811684	5.045267	28.198763	

```
In [66]: gdp
```

Out[66]:

	Num	Year	Switzerland	Sweden	Austria	Germany	Finland	France	United Kingdom	Netherlands	...	Niger	Haiti	Chad	Guinea	Moza
0	1	1991	1.978570	3.230720	2.811282	1.101526	4.825142	2.614351	1.281073	3.900485	...	31.580852	29.898800	35.507749	18.260911	34
1	2	1992	1.809351	3.069367	2.453335	1.005429	4.278031	2.592789	1.270528	3.638321	...	33.159410	34.120608	34.324439	16.555936	30
2	3	1993	1.655551	2.891642	2.204441	0.961568	4.372987	2.295733	1.281820	3.185939	...	34.077093	30.847043	31.371895	17.394535	33
3	4	1994	1.519239	2.900370	2.371546	0.975540	4.186272	2.400694	1.325110	3.212752	...	31.169294	33.928258	37.218270	20.168439	30
4	5	1995	1.397567	2.889122	2.158596	0.995456	3.797096	2.444772	1.262968	3.104261	...	30.730581	23.555397	35.058695	18.518747	31
5	6	1996	1.218411	2.553932	1.982471	1.042168	3.449154	2.404282	1.098452	2.877330	...	32.328700	19.495361	37.547919	17.399407	30
6	7	1997	1.243784	2.470071	1.905483	1.031385	3.423069	2.344256	0.969677	2.967923	...	30.232525	20.814661	38.344664	20.117364	30
7	8	1998	1.170302	2.311342	1.793344	0.975318	2.899381	2.362460	0.965524	2.556969	...	35.413781	21.162473	39.004947	21.164099	27
8	9	1999	1.089984	2.130189	1.722217	0.958397	2.886161	2.236261	0.876609	2.329667	...	35.002595	22.561071	38.068801	21.495465	22
9	10	2000	1.051535	1.942860	1.647300	0.994789	2.953636	2.098358	0.850706	2.298637	...	36.575560	17.185517	40.705094	20.981831	19

```
In [45]: rta=pd.DataFrame(columns=['Country','Sign','Value'])
         rta['Country']=df['Country']
         def rate_area():
             print('Following is the status of Forest area of different countries(Per Year): ')
             print('+ for increasing')
             print('- for decreasing')
             k=0
             for i in range(49):
                 if df.iat[k,1]>0:
                     rta.iat[k,1]='+'
                     rta.iat[k,2]=df.iat[k,1]
                 else:
                     rta.iat[k,1]='-'
                     rta.iat[k,2]=df.iat[k,1]
                 k=k+1
             return rta
         rate_area()
```

```
Following is the status of Forest area of different countries(Per Year):
+ for increasing
- for decreasing
```

Out[45]:

	Country	Sign	Value
1	Switzerland	+	0.097478
2	Sweden	+	0.00774
3	Austria	+	0.046192
4	Germany	+	0.012219
5	Finland	+	0.041587
6	France	+	0.179257
7	United Kingdom	+	0.055786
8	Netherlands	+	0.0236
9	Norway	+	0.003753

```
In [59]: corra=pd.DataFrame(columns=['Country','Sign','Value','Remarks'])
         corra['Country']=df['Country']
         def corr_area():
             k=0
             for i in range(49):
                 if df.iat[k,5]>0:
                     corra.iat[k,1]='+'
                     corra.iat[k,2]=df.iat[k,5]
                     corra.iat[k,3]='positively and strongly related with time'
                 elif 0.5<=df.iat[k,5]<0.9:
                     corra.iat[k,1]='+'
                     corra.iat[k,2]=df.iat[k,5]
                     corra.iat[k,3]='positively and mildly related with time'
                 elif 0<df.iat[k,5]<0.5:
                     corra.iat[k,1]='+'
                     corra.iat[k,2]=df.iat[k,5]
                     corra.iat[k,3]='positively but weakly related with time'
                 elif 0==df.iat[k,5]:
                     corra.iat[k,1]='+'
                     corra.iat[k,2]=df.iat[k,5]
                     corra.iat[k,3]='not related with time'
                 if df.iat[k,5]<=-0.9:
                     corra.iat[k,1]='-'
                     corra.iat[k,2]=df.iat[k,5]
                     corra.iat[k,3]='negatively and strongly related with time'
                 elif -0.5>=df.iat[k,5]>-0.9:
                     corra.iat[k,1]='-'
                     corra.iat[k,2]=df.iat[k,5]
                     corra.iat[k,3]='negatively and mildly related with time'
                 elif 0>df.iat[k,5]>-0.5:
                     corra.iat[k,1]='-'
                     corra.iat[k,2]=df.iat[k,5]
                     corra.iat[k,3]='negatively and weakly related with time'
                 k=k+1
             return corra
         corr_area()
```

Out[59]:

	Country	Sign	Value	Remarks
1	Switzerland	+	0.999088	positively and strongly related with time
2	Sweden	+	0.56943	positively and strongly related with time
3	Austria	+	0.988706	positively and strongly related with time
4	Germany	+	0.913992	positively and strongly related with time
5	Finland	+	0.774427	positively and strongly related with time
6	France	+	0.998761	positively and strongly related with time
7	United Kingdom	+	0.996284	positively and strongly related with time
8	Netherlands	+	0.875653	positively and strongly related with time
9	Norway	+	0.53592	positively and strongly related with time
10	Trinidad and Tobago	-	-0.998612	negatively and strongly related with time
11	Australia	-	-0.000336	negatively and weakly related with time

In [62]:

```
corrg=pd.DataFrame(columns=['Country','Sign','Value','Remarks'])
corrg['Country']=df['Country']
def corr_gdp():
    k=0
    for i in range(49):
        if df.iat[k,4]>0:
            corrg.iat[k,1]='+'
            corrg.iat[k,2]=df.iat[k,4]
            corrg.iat[k,3]='positively and strongly related with time'
        elif 0.4<=df.iat[k,4]<0.9:
            corrg.iat[k,1]='+'
            corrg.iat[k,2]=df.iat[k,4]
            corrg.iat[k,3]='positively and mildly related with time'
        elif 0<df.iat[k,4]<0.4:
            corrg.iat[k,1]='+'
            corrg.iat[k,2]=df.iat[k,4]
            corrg.iat[k,3]='positively but weakly related with time'
        elif 0==df.iat[k,4]:
            corrg.iat[k,1]='+'
            corrg.iat[k,2]=df.iat[k,4]
            corrg.iat[k,3]='not related with time'
        if df.iat[k,4]<=-0.9:
            corrg.iat[k,1]='-'
            corrg.iat[k,2]=df.iat[k,4]
            corrg.iat[k,3]='negatively and strongly related with time'
        elif -0.4>=df.iat[k,4]>-0.9:
            corrg.iat[k,1]='-'
            corrg.iat[k,2]=df.iat[k,4]
            corrg.iat[k,3]='negatively and mildly related with time'
        elif 0>df.iat[k,4]>-0.4:
            corrg.iat[k,1]='-'
            corrg.iat[k,2]=df.iat[k,4]
            corrg.iat[k,3]='negatively and weakly related with time'
        k=k+1
    return corrg
corr_gdp()
```

Out[62]:

	Country	Sign	Value	Remarks
1	Switzerland	-	-0.893002	negatively and mildly related with time
2	Sweden	-	-0.889487	negatively and mildly related with time
3	Austria	-	-0.911118	negatively and strongly related with time
4	Germany	-	-0.758111	negatively and mildly related with time
5	Finland	-	-0.807213	negatively and mildly related with time
6	France	-	-0.897386	negatively and mildly related with time
7	United Kingdom	-	-0.874889	negatively and mildly related with time
8	Netherlands	-	-0.87825	negatively and mildly related with time
9	Norway	-	-0.57869	negatively and mildly related with time
10	Trinidad and Tobago	-	-0.717299	negatively and mildly related with time
11	Australia	-	-0.79207	negatively and mildly related with time

In [50]:

```
rtg=pd.DataFrame(columns=['Country','Sign','Value'])
rtg['Country']=df['Country']
def rate_gd():
    print('Following is the status of Forest area of different countries(Per Year): ')
    print('+ for increasing')
    print('- for decreasing')
    k=0
    for i in range(49):
        if df.iat[k,2]>0:
            rtg.iat[k,1]='+'
            rtg.iat[k,2]=df.iat[k,2]
        else:
            rtg.iat[k,1]='-'
            rtg.iat[k,2]=df.iat[k,2]
        k=k+1
    return rtg
rate_gd()
```

2	Sweden	-	-0.060178
3	Austria	-	-0.047554
4	Germany	-	-0.010872
5	Finland	-	-0.069502
6	France	-	-0.040534
7	United Kingdom	-	-0.025427
8	Netherlands	-	-0.066693
9	Norway	-	-0.033485
10	Trinidad and Tobago	-	-0.058702
11	Australia	-	-0.044824
12	Korea, Rep.	-	-0.165243
13	Switzerland.1	-	-0.038751
14	Romania	-	-0.628586

```
In [14]: df.to_csv(r'C:\Users\Manish Pratap Singh\Desktop\file4.csv', index=False)
```

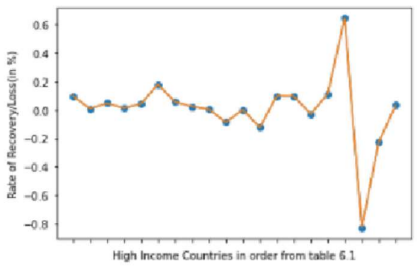
```
In [19]: prophecy.to_csv(r'C:\Users\Manish Pratap Singh\Desktop\file5.csv', index=False)
```

```
In [63]: corra.to_csv(r'C:\Users\Manish Pratap Singh\Desktop\corra.csv', index=False)
         corrg.to_csv(r'C:\Users\Manish Pratap Singh\Desktop\corrg.csv', index=False)
         rta.to_csv(r'C:\Users\Manish Pratap Singh\Desktop\rta.csv', index=False)
         rtg.to_csv(r'C:\Users\Manish Pratap Singh\Desktop\rtg.csv', index=False)
```

```
In [61]: y=df.iloc[:20,1]
         x=df.iloc[:20,0]
         plot=plt.plot(x,y)
         plot=plt.scatter(x,y)
         plot=plt.plot(x,y)
         plt.xlabel('High Income Countries in order from table 6.1')
         plt.ylabel('Rate of Recovery/Loss(in %)')
         plt.xticks(x,'')

         plot
         print('Please refer country name from from tabel 6.1 in numeral order')
```

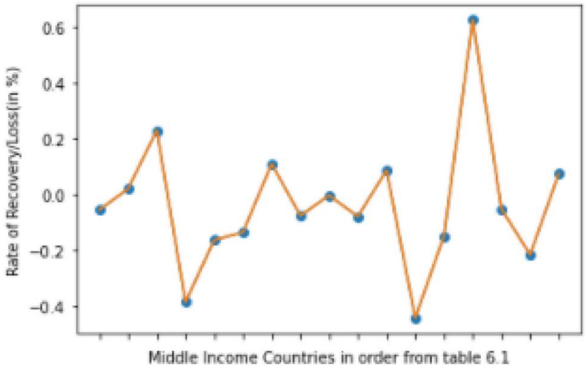
```
Please refer country name from from tabel 6.1 in numeral order
```




```
y=df.iloc[21:38,1]
x=df.iloc[21:38,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Middle Income Countries in order from table 6.1')
plt.ylabel('Rate of Recovery/Loss(in %)')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

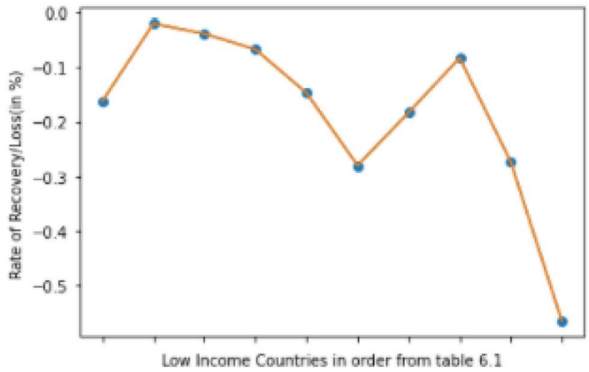
```
Please refer country name from from tabel 6.1 in numeral order
```



```
y=df.iloc[39:49,1]
x=df.iloc[39:49,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Low Income Countries in order from table 6.1')
plt.ylabel('Rate of Recovery/Loss(in %)')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

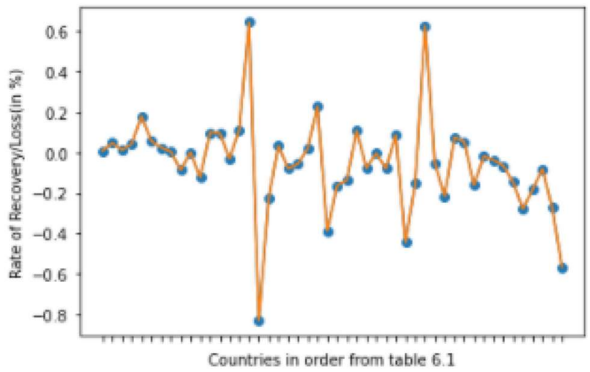
```
Please refer country name from from tabel 6.1 in numeral order
```



```
y=df.iloc[1:49,1]
x=df.iloc[1:49,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Countries in order from table 6.1')
plt.ylabel('Rate of Recovery/Loss(in %)')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

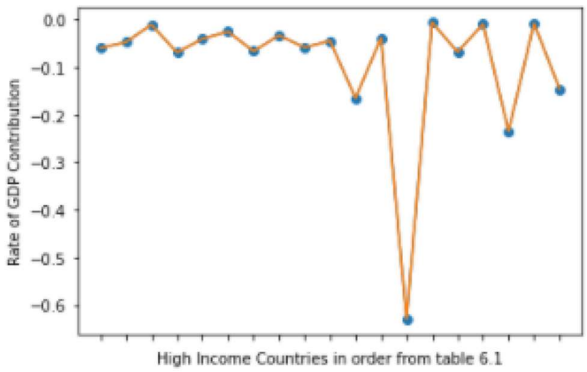
```
Please refer country name from from tabel 6.1 in numeral order
```



```
y=df.iloc[1:20,2]
x=df.iloc[1:20,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('High Income Countries in order from table 6.1')
plt.ylabel('Rate of GDP Contribution')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

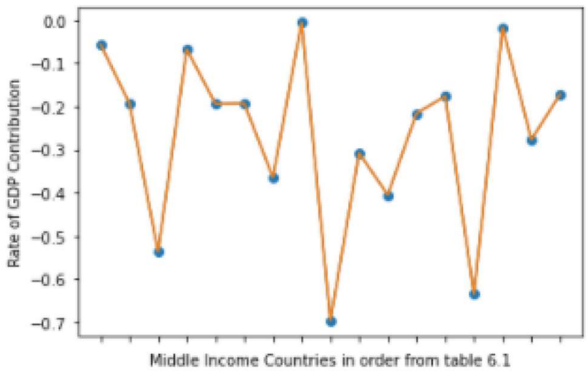
```
Please refer country name from from tabel 6.1 in numeral order
```



```
y=df.iloc[21:38,2]
x=df.iloc[21:38,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Middle Income Countries in order from table 6.1')
plt.ylabel('Rate of GDP Contribution')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

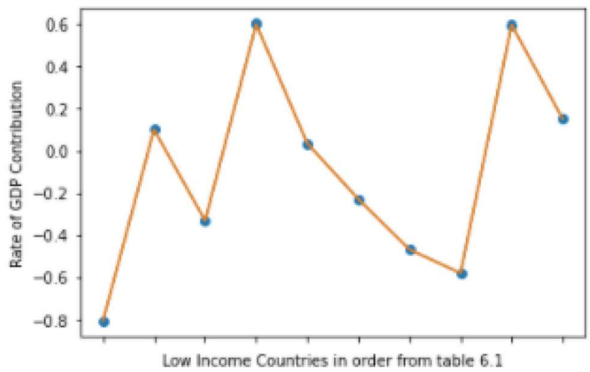
```
Please refer country name from from tabel 6.1 in numeral order
```



```
y=df.iloc[39:49,2]
x=df.iloc[39:49,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Low Income Countries in order from table 6.1')
plt.ylabel('Rate of GDP Contribution')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

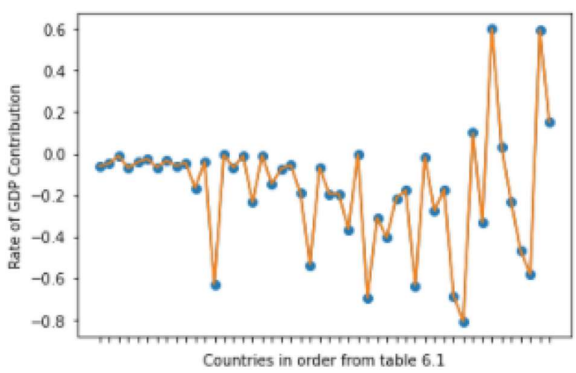
```
Please refer country name from from tabel 6.1 in numeral order
```




```
y=df.iloc[1:49,2]
x=df.iloc[1:49,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Countries in order from table 6.1')
plt.ylabel('Rate of GDP Contribution')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

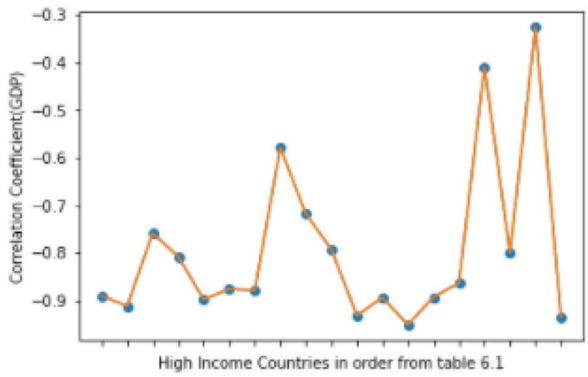
```
Please refer country name from from tabel 6.1 in numeral order
```



```
y=df.iloc[1:20,4]
x=df.iloc[1:20,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('High Income Countries in order from table 6.1')
plt.ylabel('Correlation Coefficient(GDP)')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

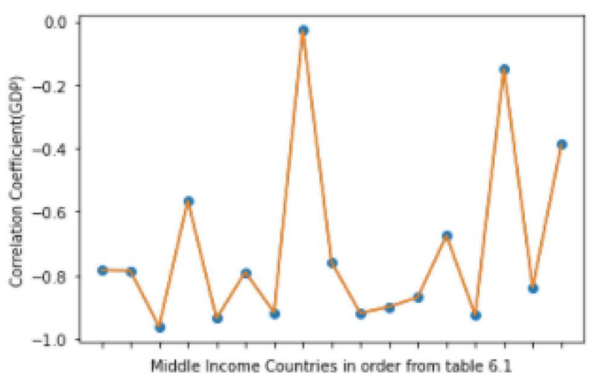
```
Please refer country name from from tabel 6.1 in numeral order
```



```
y=df.iloc[21:38,4]
x=df.iloc[21:38,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Middle Income Countries in order from table 6.1')
plt.ylabel('Correlation Coefficient(GDP)')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

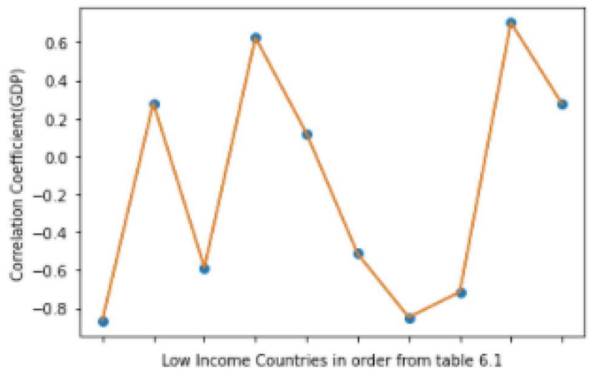
```
Please refer country name from from tabel 6.1 in numeral order
```



```
y=df.iloc[39:49,4]
x=df.iloc[39:49,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Low Income Countries in order from table 6.1')
plt.ylabel('Correlation Coefficient(GDP)')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

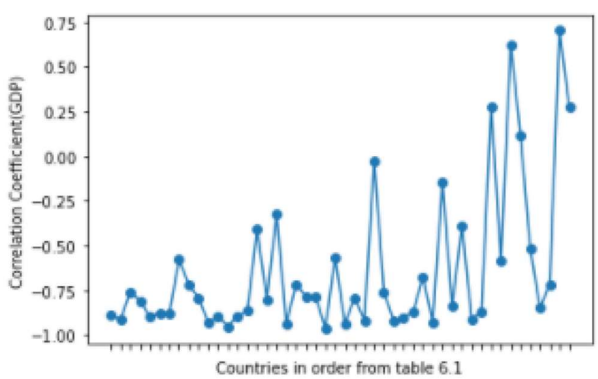
```
Please refer country name from from tabel 6.1 in numeral order
```



```
y=df.iloc[1:49,4]
x=df.iloc[1:49,0]
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Countries in order from table 6.1')
plt.ylabel('Correlation Coefficient(GDP)')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

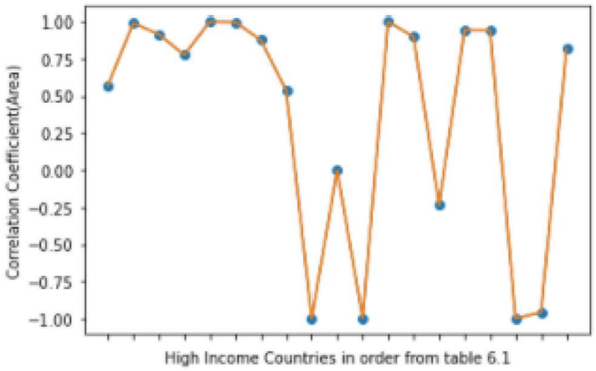
```
Please refer country name from from tabel 6.1 in numeral order
```



```
y=df.iloc[1:20,5]
x=df.iloc[1:20,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('High Income Countries in order from table 6.1')
plt.ylabel('Correlation Coefficient(Area)')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

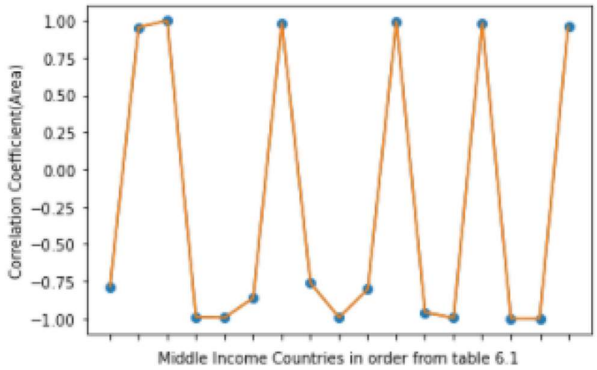
```
Please refer country name from from tabel 6.1 in numeral order
```



```
y=df.iloc[21:38,5]
x=df.iloc[21:38,0]
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Middle Income Countries in order from table 6.1')
plt.ylabel('Correlation Coefficient(Area)')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

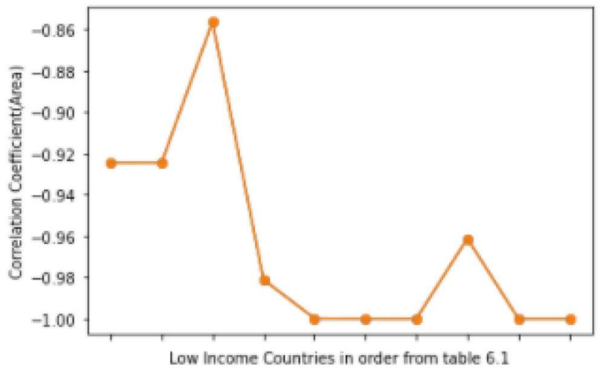
```
Please refer country name from from tabel 6.1 in numeral order
```



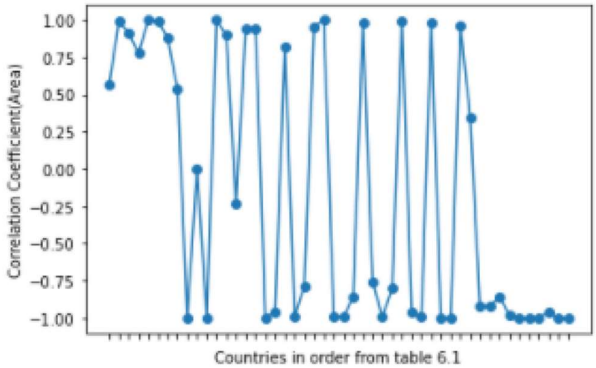
```
y=df.iloc[39:49,5]
x=df.iloc[39:49,0]
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Low Income Countries in order from table 6.1')
plt.ylabel('Correlation Coefficient(Area)')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

```
Please refer country name from from tabel 6.1 in numeral order
```




```
y=df.iloc[1:49,5]
x=df.iloc[1:49,0]
plot=plt.scatter(x,y)
plot=plt.plot(x,y)
plt.xlabel('Countries in order from table 6.1')
plt.ylabel('Correlation Coefficient(Area)')
plt.xticks(x,'')

plot
print('Please refer country name from from tabel 6.1 in numeral order')
```

```
Please refer country name from from tabel 6.1 in numeral order
```