Team Enterpeneurs:

EDA Analysis of HPZ-competition-Land Cover Data

Abstract:

- This Land cover data set is based on Data Source gathered from https://www.fao.org/faostat/en/#data/LC.
- Data of 244 Countries was selected.

Description of Columns:

Column Name	Column Description
Domain	Land Cover
Area	the country name
Element	MODIS land cover types based on the Land Cover Classification System
Item	Artificial surfaces (including urban and associated areas)', 'Herbaceous crops', 'Woody crops', 'Multiple or layered crops', 'Grassland', 'Tree-covered areas', 'Mangroves', 'Shrub-covered areas', 'Shrubs and/or herbaceous vegetation, aquatic or regularly flooded', 'Sparsely natural vegetated areas', 'Terrestrial barren land', 'Permanent snow and glaciers', 'Inland water bodies', 'Coastal water bodies and intertidal areas'
Year	2001 to 2018
Unit	1000 ha
Value	Hactres of covered land
Flag Description	"Calculated Data", "Data not available" and "Aggregate, may include official, semi-official, estimated or calculated data"

Methodolgy:

> First of all whole data was explored. Redundent Data was removed to simplify the analysis. There were 28% Missing values in Values columns.Distribution of data is right skewed due to:
> i.e Land Cover is different in variou countries oand largely depend on the Area of Country.
> We Divide our EDA into two parts.

- Part 1 is EDA on whole data
- Part 2 is EDA on Subcontinent Countries only

Part 1:EDA on whole dataset

Step 1: Import Necessary Libraries

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.ticker as ticker
```

Step 2: Import the Data

```
# Open file
df=pd.read_csv('land_cover_data_11-30-2021.csv')
df.head()
```

	Domain Code	Domain	Area Code (ISO3)	Area	Element Code	Element	Item Code	Item	Year Code	Year	Unit	Value	Flag	De
0	LC	Land Cover	AFG	Afghanistan	5007	Area from MODIS	6970	Artificial surfaces (including urban and assoc...	2001	2001	1000 ha	88.1603	FC	Ca dat
1	LC	Land Cover	AFG	Afghanistan	5007	Area from MODIS	6970	Artificial surfaces (including urban and assoc...	2002	2002	1000 ha	88.1818	FC	Ca dat
2	LC	Land Cover	AFG	Afghanistan	5007	Area from MODIS	6970	Artificial surfaces (including urban and assoc...	2003	2003	1000 ha	88.2247	FC	Ca dat
3	LC	Land Cover	AFG	Afghanistan	5007	Area from MODIS	6970	Artificial surfaces (including urban and assoc...	2004	2004	1000 ha	88.2462	FC	Ca dat
4	LC	Land Cover	AFG	Afghanistan	5007	Area from MODIS	6970	Artificial surfaces (including urban and assoc...	2005	2005	1000 ha	88.3106	FC	Ca dat

Step 3: View The Data Structure

```
rows,columns=df.shape
print("number of columns: ",columns)
print("number of rows: ",rows)
```

```
number of columns:  14
number of rows:  60760
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 60760 entries, 0 to 60759
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Domain Code       60760 non-null  object 
 1   Domain            60760 non-null  object 
 2   Area Code (ISO3)  60760 non-null  object 
 3   Area              60760 non-null  object 
 4   Element Code      60760 non-null  int64  
 5   Element           60760 non-null  object 
 6   Item Code         60760 non-null  int64  
 7   Item              60760 non-null  object 
 8   Year Code         60760 non-null  int64  
 9   Year              60760 non-null  int64  
 10  Unit              60760 non-null  object 
 11  Value             43400 non-null  float64
 12  Flag              60760 non-null  object 
 13  Flag Description  60760 non-null  object 
dtypes: float64(1), int64(4), object(9)
memory usage: 6.5+ MB
```

```
#get unique values count for each column
c=list(df.columns.values)
for i in c:
  print( i,":", df[ i ].nunique())
```

```
Domain Code : 1
Domain : 1
Area Code (ISO3) : 244
Area : 244
Element Code : 1
Element : 1
Item Code : 14
Item : 14
Year Code : 18
Year : 18
Unit : 1
Value : 18961
Flag : 2
Flag Description : 2
continent : 7
```

Step 4: Find the Null Values

```
#check missing values
df.isnull().sum()
```

```
Domain Code             0
Domain                  0
Area Code (ISO3)        0
Area                    0
Element Code            0
Element                 0
Item Code               0
Item                    0
Year Code               0
Year                    0
Unit                    0
Value               17360
Flag                    0
Flag Description        0
dtype: int64
```

```
#percentage of missing values
df.isnull().sum()/df.shape[0]*100
```

```
Domain Code          0.000000
Domain               0.000000
Area Code (ISO3)     0.000000
Area                 0.000000
Element Code         0.000000
Element              0.000000
Item Code            0.000000
Item                 0.000000
Year Code            0.000000
Year                 0.000000
Unit                 0.000000
Value               28.571429
Flag                 0.000000
Flag Description     0.000000
dtype: float64
```

> **Result interpreted**
>
> - No Column has missing values except Value column
> - Missing values in Value column account for 28%
> - Now we are going to remove na values

Step 5: Handling the missing data

```
df = df[df["Flag Description"] != "Data not available"]
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 43472 entries, 0 to 60741
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Domain Code       43472 non-null  object 
 1   Domain            43472 non-null  object 
 2   Area Code (ISO3)  43472 non-null  object 
 3   Area              43472 non-null  object 
 4   Element Code      43472 non-null  int64  
 5   Element           43472 non-null  object 
 6   Item Code         43472 non-null  int64  
 7   Item              43472 non-null  object 
 8   Year Code         43472 non-null  int64  
 9   Year              43472 non-null  int64  
 10  Unit              43472 non-null  object 
 11  Value             43400 non-null  float64
 12  Flag              43472 non-null  object 
 13  Flag Description  43472 non-null  object 
dtypes: float64(1), int64(4), object(9)
memory usage: 5.0+ MB
```

```
df["Value"] = df.groupby('Area')['Value'].transform(lambda x: x.fillna(x.mean()))
```

```
#percentage of missing values
df.isnull().sum()/df.shape[0]*100
```

```
Domain Code         0.0
Domain              0.0
Area Code (ISO3)    0.0
Area                0.0
Element Code        0.0
Element             0.0
Item Code           0.0
Item                0.0
Year Code           0.0
Year                0.0
Unit                0.0
Value               0.0
Flag                0.0
Flag Description    0.0
dtype: float64
```

> **Result interpreted**
>
> - No Column has missing values Now

Step 6: Features Engineering

> We are going to do following steps for feature engineering
>
> - Create a ssperate column for Continent
> - Create seperate dataframes for each item and each continent

```
#Adding a new column of Continent
import pycountry_convert as pc
def country_to_continent(country_name):
    country_alpha2 = pc.country_name_to_country_alpha2(country_name)
    country_continent_code = pc.country_alpha2_to_continent_code(country_alpha2)
    country_continent_name = pc.convert_continent_code_to_continent_name(country_continent_code)
    return country_continent_name

continent=[]
for i in df['Area']:

   if i=='Chagos Archipelago':
       continent.append('Africa')

   elif i=='Western Sahara':
       continent.append('Africa')
   elif i=='Channel Islands'  :
       continent.append('Europe')
   elif i=='China, Hong Kong SAR'  :
       continent.append('Asia')
   elif i=='China, Macao SAR'  :
       continent.append('Asia')
   elif i=='China, mainland'  :
       continent.append('Asia')
   elif i=='China, Taiwan Province of'  :
       continent.append('Asia')
   elif i=='French Guyana'  :
       continent.append('South America')
   elif i=='French Southern Territories'  :
       continent.append('Antarctica')
   elif i=='Heard and McDonald Islands'  :
       continent.append('Antarctica')
   elif i=='Holy See'  :
       continent.append('Europe')
   elif i=='Iran (Islamic Republic of)'  :
       continent.append('Europe')
   elif i=='Johnston Island'  :
       continent.append('Oceania')
   elif i=='Micronesia (Federated States of)'  :
       continent.append('Oceania')
   elif i=='Midway Island'  :
       continent.append('North America')
   elif i=='Netherlands Antilles (former)'  :
       continent.append('Europe')
   elif i=='Pitcairn'  :
       continent.append('Oceania')
   elif i=='Wake Island'  :
       continent.append('Oceania')
   elif i=='Wallis and Futuna Islands'  :
       continent.append('Oceania')
   elif i=='Republic of Korea'  :
       continent.append('Asia')
   elif i=='Serbia and Montenegro'  :
       continent.append('Europe')
   elif i=='Sudan (former)'  :
       continent.append('Asia')
   elif i=='Timor-Leste'  :
       continent.append('Asia')
   elif i=='Venezuela (Bolivarian Republic of)'  :
       continent.append('South America')
   elif i=='Antarctica' :
       continent.append('Antarctica')
   elif i=='Bolivia (Plurinational State of)' :
       continent.append('South America')
   else:
      continent.append(country_to_continent(i))

df["continent"]=continent


#create a new data frame with selected columns
# Domain code,Domain,element code,element, unit are left because have only 1 value
df=df[['Area Code (ISO3)','Area','Item Code','Item','Year','Value','continent']]


df['continent'].value_counts()
```

```
Africa           10420
Asia              9342
Europe            8950
North America     6660
Oceania           4860
South America     2700
Antarctica         540
Name: continent, dtype: int64
```

```
#Create dataframe based on continents
df_a=df.loc[df['continent']=='Asia']
df_e=df.loc[df['continent']=='Europe']
df_an=df.loc[df['continent']=='Antarctica']
df_aus=df.loc[df['continent']=='Australia']
df_o=df.loc[df['continent']=='Oceania']
df_s=df.loc[df['continent']=='South America']
df_an=df.loc[df['continent']=='North America']
```

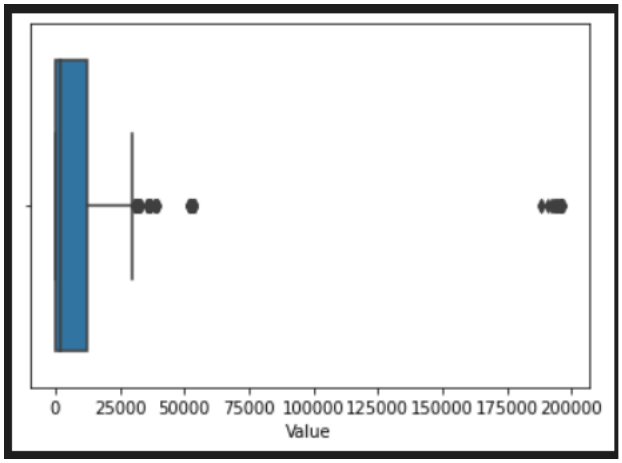
```
df['Item'].value_counts()
```

```
Artificial surfaces (including urban and associated areas)          4340
Herbaceous crops                                                    4340
Grassland                                                           4340
Tree-covered areas                                                  4340
Mangroves                                                           4340
Shrub-covered areas                                                 4340
Shrubs and/or herbaceous vegetation, aquatic or regularly flooded   4340
Terrestrial barren land                                             4340
Permanent snow and glaciers                                         4340
Inland water bodies                                                 4340
Woody crops                                                           18
Multiple or layered crops                                             18
Sparsely natural vegetated areas                                      18
Coastal water bodies and intertidal areas                             18
Name: Item, dtype: int64
```

```
#create dataframebased on item
Artif=df.loc[df['Item']== 'Artificial surfaces (including urban and associated areas)' ]
Grass=df.loc[df['Item']== 'Grassland']
Tree=df.loc[df['Item']== 'Tree-covered areas']
shrub=df.loc[df['Item']== 'Shrub-covered areas']
flooded=df.loc[df['Item']== 'Shrubs and/or herbaceous vegetation, aquatic or regularly flooded']
terrestrial=df.loc[df['Item']== 'Terrestrial barren land']
snow=df.loc[df['Item']== 'Permanent snow and glaciers']
inland=df.loc[df['Item']== 'Inland water bodies']
```

Step 7: Outlier Detection

```
sns.boxplot(df["Value"])
```

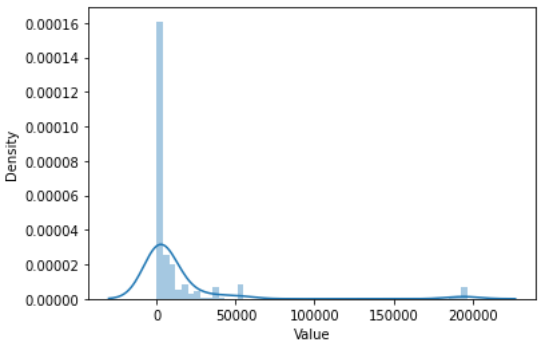


```
df.head()
```

	Domain Code	Domain	Area Code (ISO3)	Area	Element Code	Element	Item Code	Item	Year Code	Year	Unit	Value	Flag	De
0	LC	Land Cover	AFG	Afghanistan	5007	Area from MODIS	6970	Artificial surfaces (including urban and assoc...	2001	2001	1000 ha	88.1603	FC	Ca dat
1	LC	Land Cover	AFG	Afghanistan	5007	Area from MODIS	6970	Artificial surfaces (including urban and assoc...	2002	2002	1000 ha	88.1818	FC	Ca dat
2	LC	Land Cover	AFG	Afghanistan	5007	Area from MODIS	6970	Artificial surfaces (including urban and assoc...	2003	2003	1000 ha	88.2247	FC	Ca dat
3	LC	Land Cover	AFG	Afghanistan	5007	Area from MODIS	6970	Artificial surfaces (including urban and assoc...	2004	2004	1000 ha	88.2462	FC	Ca dat
4	LC	Land Cover	AFG	Afghanistan	5007	Area from MODIS	6970	Artificial surfaces (including urban and assoc...	2005	2005	1000 ha	88.3106	FC	Ca dat

Step 8: Checking the Normalization

```
sns.distplot(df_selected["Value"])
```



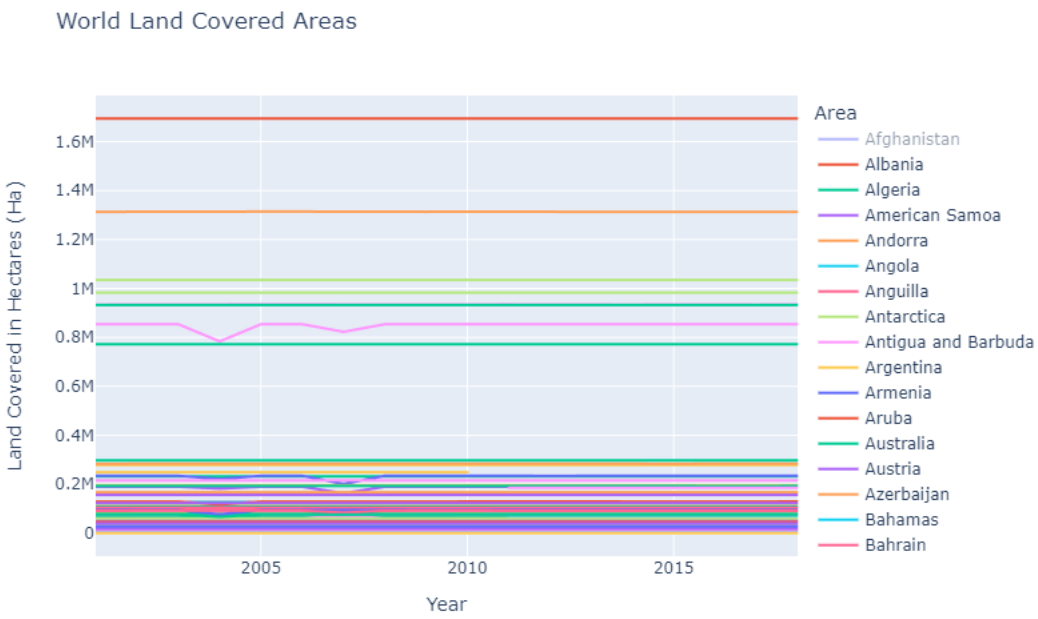
Interpretation

> Data is right skewed for every type of Land Cover

Step-9 Data Visualization

Visualization of World land coverage over the years(2001-2018)

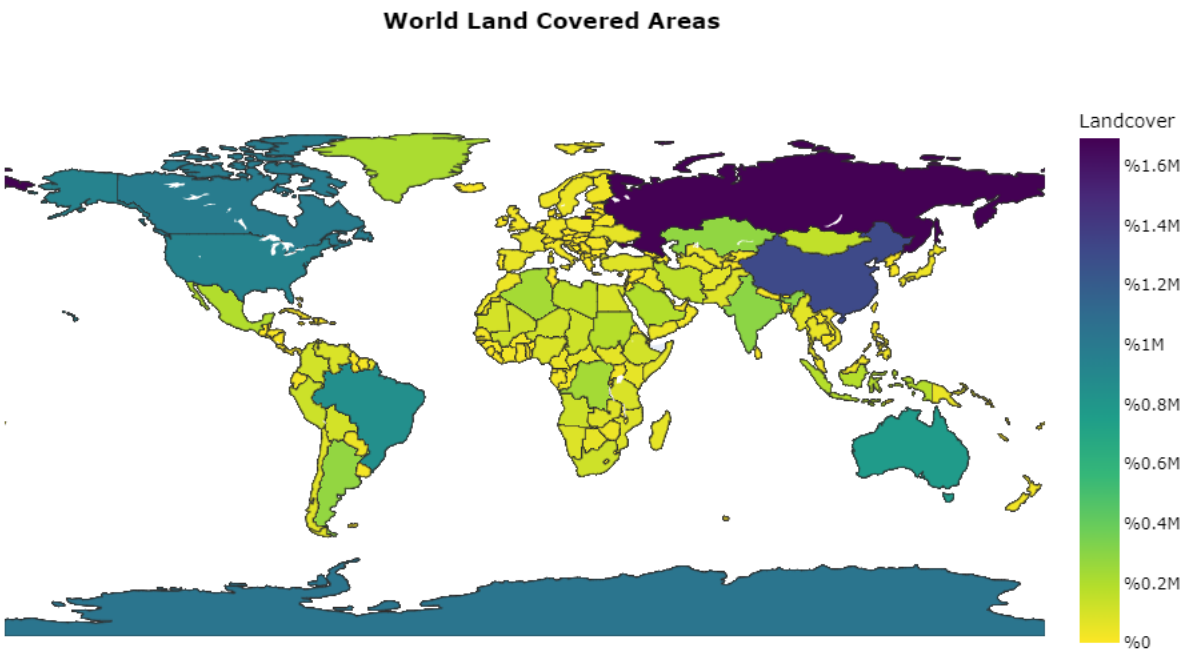
```
# Visualization of World land coverage over the years(2001-2018)

import plotly.express as px
fig = px.line(df1, x="Year",
              y="Value",
              labels={
                     "Value" : "Land Covered in Hectares (Ha)"
                 },
              color='Area',
              title='World Land Covered Areas')
fig.show()
```



The World Land Coverage plot shows the land coverage of world countries over the years. Over the years there is not much significant change in the land coverage. The world top land covered territories are Russian Federation, China, Antarctica, Canada,China, mainland.

Land Coverage on a World Map

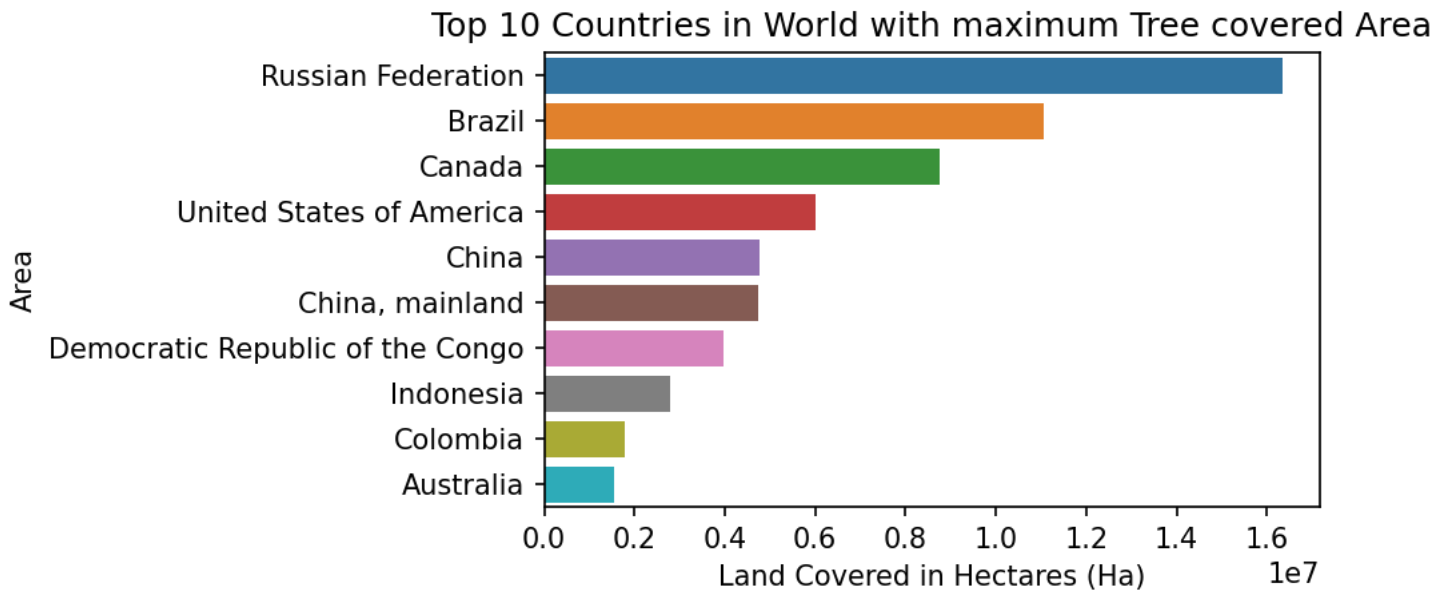
```
# Create the layout of the chart
title = '<b>World Land Covered Areas</b>'
layout2 = go.Layout(title = {'text' : title,
                             'x':0.5, 'xanchor': 'center'},
                    font = {"color" : 'black'},
                    width=980, height=600, plot_bgcolor="white", paper_bgcolor="white",
                    geo=dict(showframe=False, showcoastlines=False, projection_type='equirectangular'
                            )
                   )

# Create the figure
fig2 = go.Figure(layout = layout2)


# Create the Choropleth map tracing
trace2 = go.Choropleth(
    locations = df1['Area Code (ISO3)'],
    z = df1['Value'],
    text = df1['Area'],
    colorscale = 'Viridis',
    #color_continuous_scale="RdYlGn",
    autocolorscale=False,
    reversescale=True,
    marker_line_color='#2E2E2E',
    marker_line_width=0.5,
    colorbar_tickprefix = '%',
    colorbar_title = 'Landcover',
)

fig2.add_trace(trace2)
fig2.show()
```



The world map shows the land coverage of the countries. The color bar shows the land coverage in hectares. The regions with purple color being the top land covered and the regions with the yellowish color being the least land covered.

Top 10 Countries in world with maximum Tree covered Area

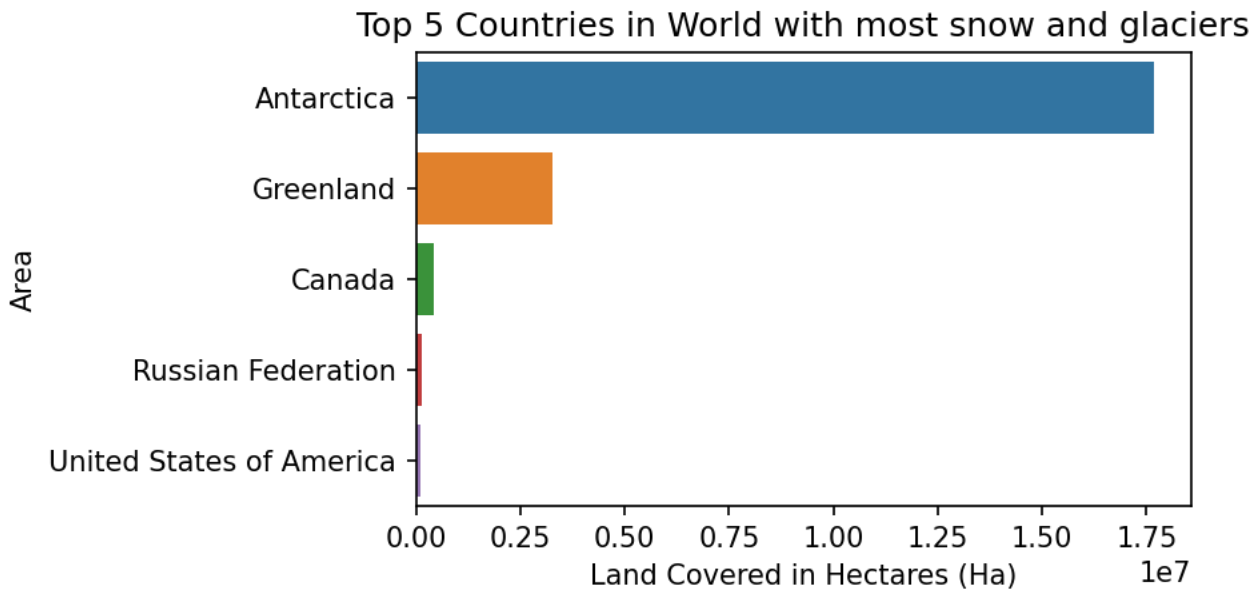
```
s=Tree.groupby(["Area"]).sum().sort_values(by="Value", ascending=False).head(10)
plt.figure(figsize=(5,3), dpi=150, linewidth=2)
pl=sns.barplot(x='Value',y=s.index,data=s).set(title='Top 10 Countries in World with maximum Tree covered Area')
plt.xlabel("Land Covered in Hectares (Ha)")
```



Out of the top world countries Russian Federation have maximum land covered by Trees.

Top 5 countries in world with snow and glaciers

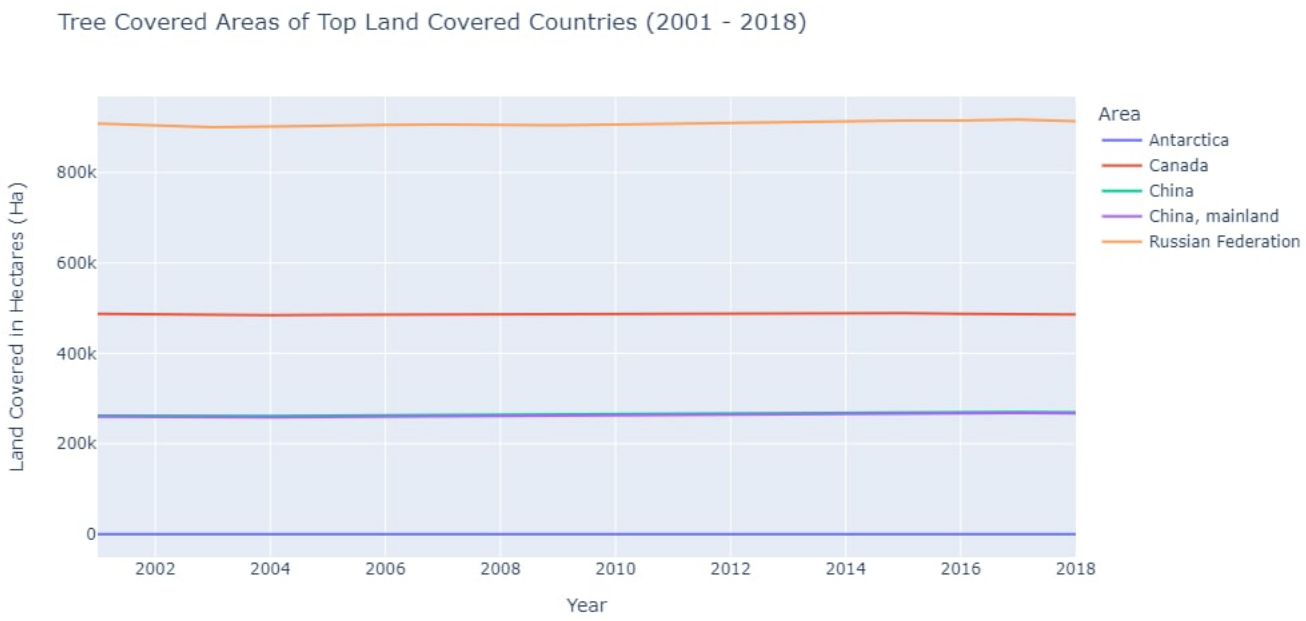
```
s=snow.groupby(["Area"]).sum().sort_values(by="Value", ascending=False).head(5)
plt.figure(figsize=(5,3), dpi=150, linewidth=2)
pl=sns.barplot(x='Value',y=s.index,data=s).set(title='Top 5 Countries in World with most snow and glaciers')
plt.xlabel("Land Covered in Hectares (Ha)")
```



Out of the world top five countries/regions, Antarctica have maximum land covered by Snow and Glaciers.

Tree Covered Areas of Top Land Covered Countries (2001 - 2018)

```
fig = px.line(landcover, x="Year", y="Value",color='Area',
                          labels={
                     "Value" : "Land Covered in Hectares (Ha)"
                 },
              title='Tree Covered Areas of Top Land Covered Countries (2001 - 2018')
fig.show()
```



Part-2: EDA on Subcontinent

Land Coverage from Subcontinent
In this section subcontinent countries will be examined. the list of countries are as follows:

- Bangladesh,
- India,
- Pakistan

Feature Selection and Data Insights

```
# Selecting Subcontinents countries
df_selected = df_land[df_land["Area"].isin(["India", "Pakistan", "Bangladesh"])]
df_selected.head()
```

	Area Code (ISO3)	Area	Item	Year	Value	continent
4284	BGD	Bangladesh	Artificial surfaces (including urban and assoc...	2001	97.5194	Asia
4285	BGD	Bangladesh	Artificial surfaces (including urban and assoc...	2002	97.6053	Asia
4286	BGD	Bangladesh	Artificial surfaces (including urban and assoc...	2003	98.0132	Asia
4287	BGD	Bangladesh	Artificial surfaces (including urban and assoc...	2004	98.6142	Asia
4288	BGD	Bangladesh	Artificial surfaces (including urban and assoc...	2005	98.6786	Asia

```
# Shape of selected subcontinents countries dataframe
df_selected.shape
```

OutPut:

```
(540, 6)
```

```
# Summary Statistics of selected subcontinents countries dataframe
df_selected.describe()
```

OutPut:

	Year	Value
count	540.000000	540.000000
mean	2009.500000	13002.479985
std	5.192938	35663.518492
min	2001.000000	0.000000
25%	2005.000000	248.236625
50%	2009.500000	1060.199200
75%	2014.000000	9115.342125
max	2018.000000	196808.100200

Selecting the important features and combining them based on Land Coverage Value

```
dfsouth = df_selected.groupby(["Area", "Area Code (ISO3)", "Year"])["Value"].sum().reset_index()
dfsouth.head()
```

	Area	Area Code (ISO3)	Year	Value
0	Bangladesh	BGD	2001	14039.9652
1	Bangladesh	BGD	2002	14040.0295
2	Bangladesh	BGD	2003	14040.0297
3	Bangladesh	BGD	2004	14040.0726
4	Bangladesh	BGD	2005	14040.1798

Checking the different Land Types in the Subcontient

```
df_selected["Item"].unique()
```

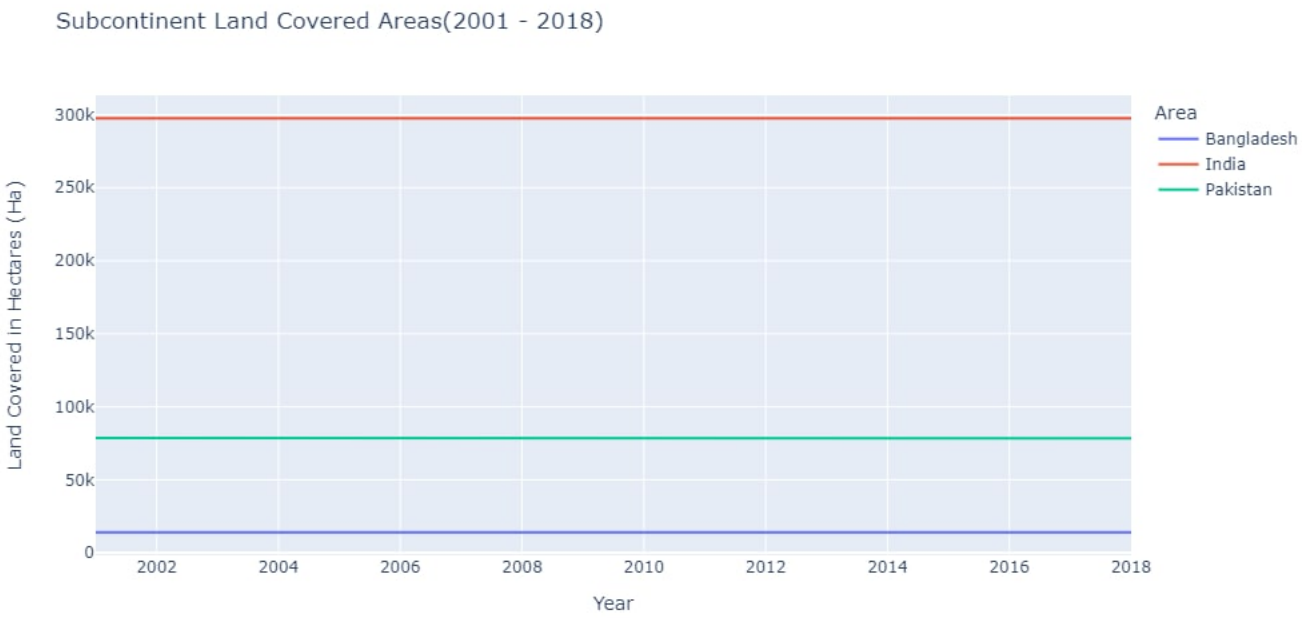
The different land types are:

array(['Artificial surfaces (including urban and associated areas)',
'Herbaceous crops', 'Grassland', 'Tree-covered areas', 'Mangroves',
'Shrub-covered areas',
'Shrubs and/or herbaceous vegetation, aquatic or regularly flooded',
'Terrestrial barren land', 'Permanent snow and glaciers',
'Inland water bodies'], dtype=object)

Visualizing Subcontinents Countries Land Coverage and Percent Changes Over the Time

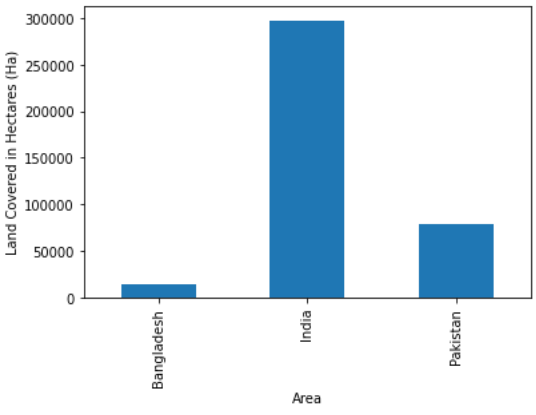
Subcontinent Countries Land Coverage over the years

```
fig = px.line(dfsouth, x="Year", y="Value",
              labels={
                     "Value" : "Land Covered in Hectares (Ha)"
                 },
              color='Area', title='South Asia Land Covered Areas(2001 - 2018)')
fig.show()
```



Land Coverage by Subcontinent Countries (Combine)

```
dfsouth[dfsouth["Year"] == 2018].groupby('Area').Value.sum().plot(kind='bar')
plt.ylabel("Land Covered in Hectares (Ha)")
```



Study the Percent Change in the Forest Land in Subcontinent

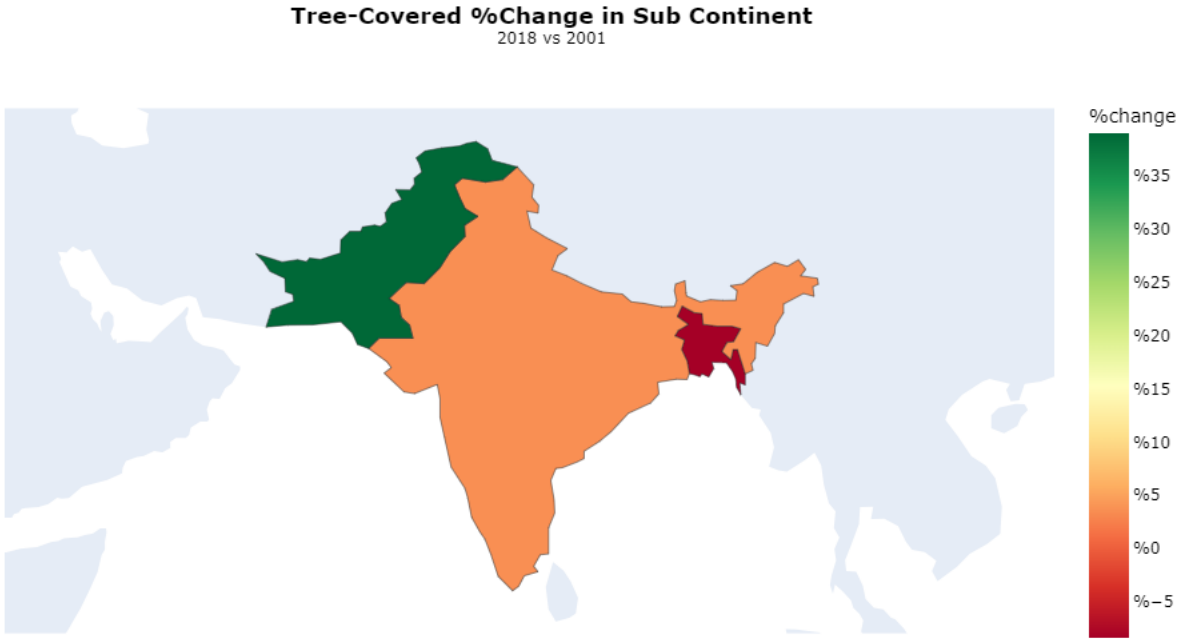
```
# === Covered Forest Land ===

# Filter only tree-covered areas & Group
landcover = df_selected[df_selected["Item"] == "Tree-covered areas"]
landcover = landcover.groupby(["Area Code (ISO3)","Area","Year"])["Value"].sum().reset_index()

# Select only the base year (2001) and reference year (2018)
# and compute the percent change between them
landcover = landcover[(landcover["Year"] == 2001) | (landcover["Year"] == 2018)].reset_index()
landcover = landcover.pivot(index=["Area Code (ISO3)","Area"], columns = "Year", values="Value").reset_index()
landcover["%change"] = ((landcover[2018] - landcover[2001])/ landcover[2001])*100
```

```
landcover.head()
```

	Year	Area Code (ISO3)	Area	2001	2018	%change
0		BGD	Bangladesh	3830.6184	3509.2658	-8.389053
1		IND	India	51981.7658	53830.9687	3.557407
2		PAK	Pakistan	1390.9796	1934.3237	39.061975

Visualizing the Percent Change in a Map for clear Understanding

```
# Create the layout of the chart
title = '<b>Tree-Covered %Change in South Asia</b><br><sup>2018 vs 2001</sup>'
layout1 = go.Layout(title = {'text' : title,
                             'x':0.5, 'xanchor': 'center'},
                    font = {"color" : 'black'},
                    width=980, height=600, plot_bgcolor="white", paper_bgcolor="white",
                    geo=dict(showframe=False, showcoastlines=False, projection_type='equirectangular'
                            )
                   )

# Create the figure
fig1 = go.Figure(layout = layout1)

# Create the Choropleth map tracing
trace1 = go.Choropleth(
    locations = landcover['Area Code (ISO3)'],
    z = landcover['%change'],
    text = landcover['Area'],
    colorscale = 'RdYlGn',
    autocolorscale=False,
    reversescale=False,
    marker_line_color='#2E2E2E',
    marker_line_width=0.5,
    colorbar_tickprefix = '%',
    colorbar_title = '%change',
)

fig1.add_trace(trace1)

fig1.show()
```



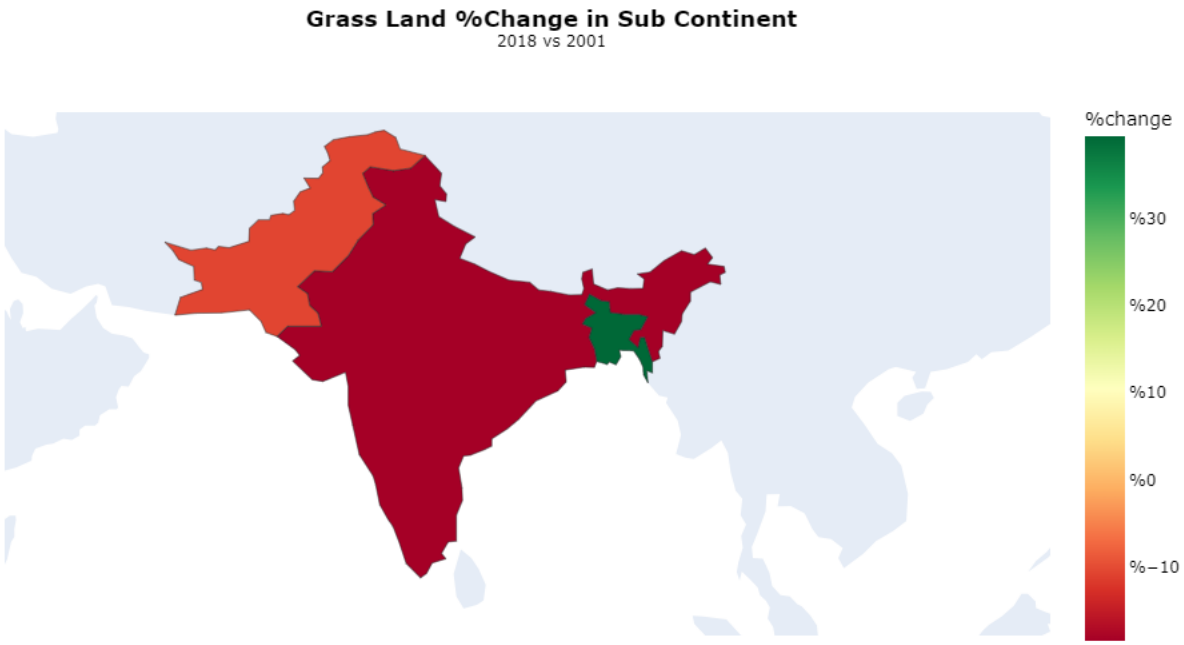
Study the Percent Change in the Grass Land in Subcontinent

```
# === Covered Grass Land ===

# Filter only tree-covered areas & Group
landcover = df_selected[df_selected["Item"] == "Grassland"]
landcover = landcover.groupby(["Area Code (ISO3)","Area","Year"])["Value"].sum().reset_index()

# Select only the base year (2001) and reference year (2018)
# and compute the percent change between them
landcover = landcover[(landcover["Year"] == 2001) | (landcover["Year"] == 2018)].reset_index()
landcover = landcover.pivot(index=["Area Code (ISO3)","Area"], columns = "Year", values="Value").reset_index()
landcover["%change"] = ((landcover[2018] - landcover[2001])/ landcover[2001])*100

landcover.head()
```

Year	Area Code (ISO3)	Area	2001	2018	%change
0	BGD	Bangladesh	254.5208	354.9381	39.453475
1	IND	India	29504.1907	24067.3845	-18.427234
2	PAK	Pakistan	9232.9547	8248.6588	-10.660682

Visualizing the Percent Change in a Map for clear Understanding

```
# Create the layout of the chart
title = '<b>Grass Land %Change in Sub Continent</b><br><sup>2018 vs 2001</sup>'
layout1 = go.Layout(title = {'text' : title,
                             'x':0.5, 'xanchor': 'center'},
                    font = {"color" : 'black'},
                    width=980, height=600, plot_bgcolor="white", paper_bgcolor="white",
                    geo=dict(showframe=False, showcoastlines=False, projection_type='equirectangular'
                            )
                   )

# Create the figure
fig1 = go.Figure(layout = layout1)

# Create the Choropleth map tracing
trace1 = go.Choropleth(
    locations = landcover['Area Code (ISO3)'],
    z = landcover['%change'],
    text = landcover['Area'],
    colorscale = 'RdYlGn',
    autocolorscale=False,
    reversescale=False,
    marker_line_color='#2E2E2E',
    marker_line_width=0.5,
    colorbar_tickprefix = '%',
    colorbar_title = '%change',
)

fig1.add_trace(trace1)

fig1.show()
```



Conclusion

> This has been an extensive examination of the global Land Coverage over 18 years period. Globally, Russian Federation, China are among the countries with most land covered. In Land Coverage, Russian Federation, Brazil, Canada have the most forest land which are vital to life on Earth. Land Snow and Glaciers, which helps to reduce water scarcity are particularly in majority in Antarctica, Greenland, Canada.
>
> In subcontinent (India, Pakistan, Bangladesh) there is a change in Forest land and grassland. As compared to 2001, India have 3.55%, Pakistan have 39.06% increase in forest land on the other hand Bangladesh have 8.38% decrease in forest land in 2018. When it comes to grass covered land as

> compared to 2001, India have 18.42%, Pakistan have 10.42% descrease in 2018 on the other hand Bangladesh have 39.45% increase in 2018.
>
> Bangladesh should have to take measure to increase the number of forests because they are vital to life on earth and have positive impact on the environment.