CleanWaterAndSanitationAnalysis

August 5, 2024

1 Description

- The objective of this project is to analyze drinking water and sanitation data to identify key challenges and propose actionable solutions. The datasets consists of Analysis of "Drinking water", "Sanitation" and "Hygiene" by 'Service level' aligned with SDG Goal 6 : "Clean Water and Sanitation" ## Names of columns with their meanings

1. **Basic service** : refer to drinking water from an improved water source, provided collection time is not more than/**within** 30 minutes for a round trip, including queuing.
2. **Limited service** : Drinking water from an improved source, for which collection time **exceeds** 30 minutes for a round trip, including queuing.
3. **Open defecation** : refers to the practice of defecating in the open, such as in fields, forests, bushes, or by bodies of water, rather than using a toilet.
4. **Surface water** : Drinking water directly from a river, dam, lake, pond, stream, canal or irrigation canal.
5. **Unimproved** : Drinking water from an improved source, for which collection time exceeds 30 minutes for a round trip, including queuing.
6. **No handwashing facility** : refers to the absence of a designated place or infrastructure for individuals to wash their hands.It means there is no provision for people to clean their hands using soap and water or other sanitizing methods.
7. **Safely managed service** : mean having an improved water source (such as a pipe, borehole, or protected well) near one's home. The water should be available throughout the day and free from faecal and priority chemical contamination.

- Categorized by following **REGIONS** :
  - Australia and New Zealand
  - Central and Southern Asia
  - Eastern and South-Eastern Asia
  - Europe and Northern America
  - Latin America and the Caribbean
  - Northern Africa and Western Asia
  - Oceania
  - Sub-Saharan Africa
- of 23 years (2000-2022)
- **Source** of Datasets used : https://washdata.org/data/household#!/table?geo0=region&geo1=sdg

2 Step 1 : Importing python libraries like Numpy, Pandas, Seaborn, Sci-kit learn

[211]:
```
import pandas as pd
import numpy as np
import matplotlib.pylab as plt
import seaborn as sns
plt.style.use('ggplot') #using style-sheet for matplotlib and seaborn style␣
↪plots
pd.set_option('display.max_columns',200) #To "Expand the number of columns"␣
↪that are shown when we display a different data frame in our notebook
```

3 Step 2 : Load the Datasets

[212]:
```
df1 = pd.read_csv('Drinking water (Analysis by Service level) by SDG Regions,␣
↪23 years.csv')
```

4 Step 3 : Exploratory Data Analysis (EDA)

EDA is a step in Data Analysis Process , in which a number of techniques are used to, better understand the dataset, being used. ## 3.1) In this step, we will perform following operations to understand schema of datasets : 1. **head()** : Displays first 5 rows of dataset ,or head(n)–> first "n" number of rows 2. **tail()** : Displays last 5 rows of dataset, or tail(n)–>last "n" number of rows 3. **.shape** : Display "order" of dataset as (number_of_columns, number_of_rows) #it is an attribute so don't require () 4. **.columns** : Display array of all columns present with their names 5. **.describe()** : Give "Descriptive analysis/Statistical summary" of "numerical data" present in dataset 6. **.unique()** : returns array of unique values in given column 7. **.info()** : provides column names, their data-types, memory usage, count, Non-Null 8. **.dtypes** : provides data-type of each column

4.1 3.2) In this step, we will perform following operations:

4.1.1 Data Cleaning

1. **To find the number of DUPLICATE rows** : .duplicated().sum()
2. **To find DUPLICATE rows** : df.loc[df.duplicated()]
3. **Dropping the DUPLICATE rows** and reseting index :
   - using loc : df = df.loc[~df.duplicated()].reset_index(drop=True).copy()
4. **Dropping unnecessary columns** *(which are not required for analysis)* :
   - .drop(['column_name'],axis=1) or
   - By SUBSETTING the columns
5. **Dropping DUPLICATES in "specific columns"** using loc :
   - df.loc[df.duplicated(subset=['column_name1','column_name2'])].head(10)
6. **Removing NULL Values** : Displaying number of null values in "every column" in dataset
   - .isna().sum()
   - .isnull().sum()
7. **Renaming column names** :

- df = df.rename(columns = {“old_col_name1” :“new_col_name1”, “old_col_name2” : “new_col_name2”, })

8. **Replacing number of zero values** :
   - df[‘col_name’]=df[‘col_name’].replace(0,df[‘col_name’].mean()/median())

5 3.1) Understanding Dataset

[213]:
```
df1.head()
```

[213]:
```
  Type                     Region Residence Type    Service Type  Year  \
0  sdg  Australia and New Zealand          total  Drinking water  2000
1  sdg  Australia and New Zealand          rural  Drinking water  2000
2  sdg  Australia and New Zealand          total  Drinking water  2001
3  sdg  Australia and New Zealand          rural  Drinking water  2001
4  sdg  Australia and New Zealand          total  Drinking water  2002

   Coverage    Population   Service level
0  99.76079  2.281851e+07  At least basic
1  99.20040  3.508827e+06  At least basic
2  99.75979  2.308214e+07  At least basic
3  99.19829  3.572236e+06  At least basic
4  99.76071  2.336838e+07  At least basic
```

[214]:
```
df1.tail(7)
```

[214]:
```
      Type              Region Residence Type    Service Type  Year  Coverage  \
2627  sdg  Sub-Saharan Africa          urban  Drinking water  2020   5.22820
2628  sdg  Sub-Saharan Africa          total  Drinking water  2021  15.39112
2629  sdg  Sub-Saharan Africa          rural  Drinking water  2021  22.99280
2630  sdg  Sub-Saharan Africa          urban  Drinking water  2021   4.92702
2631  sdg  Sub-Saharan Africa          total  Drinking water  2022  14.92553
2632  sdg  Sub-Saharan Africa          rural  Drinking water  2022  22.44654
2633  sdg  Sub-Saharan Africa          urban  Drinking water  2022   4.72997

        Population Service level
2627  2.413971e+07    Unimproved
2628  1.751415e+08    Unimproved
2629  1.513195e+08    Unimproved
2630  2.364091e+07    Unimproved
2631  1.741461e+08    Unimproved
2632  1.500443e+08    Unimproved
2633  2.357014e+07    Unimproved
```

[215]:
```
df1.sample(10) #returns random 10 rows
```

[215]:
```
      Type                           Region Residence Type    Service Type  \
7     sdg         Australia and New Zealand          rural  Drinking water
```

```
639   sdg         Central and Southern Asia          total  Drinking water
1775  sdg       Europe and Northern America          urban  Drinking water
956   sdg  Northern Africa and Western Asia          urban  Drinking water
857   sdg   Latin America and the Caribbean          urban  Drinking water
32    sdg         Australia and New Zealand          total  Drinking water
2170  sdg         Central and Southern Asia          rural  Drinking water
1940  sdg  Northern Africa and Western Asia          urban  Drinking water
590   sdg         Australia and New Zealand          urban  Drinking water
1186  sdg         Central and Southern Asia          urban  Drinking water

      Year  Coverage    Population           Service level
7     2003  99.26952  3.611604e+06          At least basic
639   2006   3.68285  6.250441e+07         Limited service
1775  2012   0.03515  2.902704e+05           Surface water
956   2019   3.04420  1.009225e+07         Limited service
857   2009   0.30184  1.380338e+06         Limited service
32    2016  99.97482  2.885652e+07          At least basic
2170  2006  11.80057  1.368470e+08              Unimproved
1940  2021   0.06019  2.067767e+05           Surface water
590   2012   0.00000  0.000000e+00         Limited service
1186  2019  66.46423  4.931283e+08  Safely managed service
```

[216]:
```
df1.describe()
```

[216]:
```
              Year     Coverage    Population
count  2634.000000  2634.000000  2.634000e+03
mean   2011.025057    20.956720  1.234508e+08
std       6.633832    28.295861  2.548160e+08
min    2000.000000     0.000000  0.000000e+00
25%    2005.000000     1.167235  2.431691e+06
50%    2011.000000     6.533270  1.963503e+07
75%    2017.000000    31.438005  1.175108e+08
max    2022.000000   100.000000  1.840461e+09
```

[217]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2634 entries, 0 to 2633
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Type            2634 non-null   object
 1   Region          2634 non-null   object
 2   Residence Type  2634 non-null   object
 3   Service Type    2634 non-null   object
 4   Year            2634 non-null   int64
 5   Coverage        2634 non-null   float64
 6   Population      2634 non-null   float64
```

```
 7   Service level   2634 non-null   object
dtypes: float64(2), int64(1), object(5)
memory usage: 164.8+ KB
```

[218]:
```
df1.dtypes
```

[218]:
```
Type              object
Region            object
Residence Type    object
Service Type      object
Year               int64
Coverage         float64
Population       float64
Service level     object
dtype: object
```

[219]:
```
df1.columns
```

[219]:
```
Index(['Type', 'Region', 'Residence Type', 'Service Type', 'Year', 'Coverage',
       'Population', 'Service level'],
      dtype='object')
```

[220]:
```
df1['Service level'].unique()
```

[220]:
```
array(['At least basic', 'Basic service', 'Limited service',
       'Safely managed service', 'Surface water', 'Unimproved'],
      dtype=object)
```

[221]:
```
df1['Service Type'].unique()
```

[221]:
```
array(['Drinking water'], dtype=object)
```

[222]:
```
df1.shape #Shape before dropping duplicates
```

[222]:
```
(2634, 8)
```

6 3.2) Data Cleaning

6.0.1 3.2.1 Finding DUPLICATE number of rows

[223]:
```
df1.duplicated().sum()
```

[223]:
```
np.int64(0)
```

6.0.2 3.2.2 Finding DUPLICATE rows

[224]:
```
df1.loc[df1.duplicated()]
```

[224]:
```
Empty DataFrame
Columns: [Type, Region, Residence Type, Service Type, Year, Coverage,
Population, Service level]
Index: []
```

[225]:
```
df1 = df1.loc[~df1.duplicated()].reset_index(drop=True).copy()
df1
```

[225]:

	Type	Region	Residence Type	Service Type	Year	Coverage	Population	Service level
0	sdg	Australia and New Zealand	total	Drinking water	2000	99.76079	2.281851e+07	At least basic
1	sdg	Australia and New Zealand	rural	Drinking water	2000	99.20040	3.508827e+06	At least basic
2	sdg	Australia and New Zealand	total	Drinking water	2001	99.75979	2.308214e+07	At least basic
3	sdg	Australia and New Zealand	rural	Drinking water	2001	99.19829	3.572236e+06	At least basic
4	sdg	Australia and New Zealand	total	Drinking water	2002	99.76071	2.336838e+07	At least basic
…	…	…	…	…	…	…	…	…
2629	sdg	Sub-Saharan Africa	rural	Drinking water	2021	22.99280	1.513195e+08	Unimproved
2630	sdg	Sub-Saharan Africa	urban	Drinking water	2021	4.92702	2.364091e+07	Unimproved
2631	sdg	Sub-Saharan Africa	total	Drinking water	2022	14.92553	1.741461e+08	Unimproved
2632	sdg	Sub-Saharan Africa	rural	Drinking water	2022	22.44654	1.500443e+08	Unimproved
2633	sdg	Sub-Saharan Africa	urban	Drinking water	2022	4.72997	2.357014e+07	Unimproved

[2634 rows x 8 columns]

We have **no duplicate rows** in our dataset, therfore no need for dropping the duplicate rows (#step 3.2.3)

6.0.3 3.2.4 Dropping unneccessary columns

[226]:
```
df1.head()
```

[226]:

	Type	Region	Residence Type	Service Type	Year	Coverage	Population	Service level
0	sdg	Australia and New Zealand	total	Drinking water	2000	99.76079	2.281851e+07	At least basic
1	sdg	Australia and New Zealand	rural	Drinking water	2000	99.20040	3.508827e+06	At least basic
2	sdg	Australia and New Zealand	total	Drinking water	2001	99.75979	2.308214e+07	At least basic
3	sdg	Australia and New Zealand	rural	Drinking water	2001	99.19829	3.572236e+06	At least basic

```
4  sdg  Australia and New Zealand          total  Drinking water  2002

   Coverage    Population   Service level
0  99.76079  2.281851e+07  At least basic
1  99.20040  3.508827e+06  At least basic
2  99.75979  2.308214e+07  At least basic
3  99.19829  3.572236e+06  At least basic
4  99.76071  2.336838e+07  At least basic
```

[227]:
```
df1.columns
```

[227]:
```
Index(['Type', 'Region', 'Residence Type', 'Service Type', 'Year', 'Coverage',
       'Population', 'Service level'],
      dtype='object')
```

[228]:
```
# By subsetting the Dataset
df1 = df1[[ #'Type',
    'Region', 'Residence Type', 'Service Type', 'Year', 'Coverage',
       'Population', 'Service level']].copy() #commenting out not-required␣
 ↪column name and "reassigning" dataframe
df1
```

[228]:
```
                         Region Residence Type    Service Type  Year  \
0     Australia and New Zealand          total  Drinking water  2000
1     Australia and New Zealand          rural  Drinking water  2000
2     Australia and New Zealand          total  Drinking water  2001
3     Australia and New Zealand          rural  Drinking water  2001
4     Australia and New Zealand          total  Drinking water  2002
…                           …              …               …   …
2629         Sub-Saharan Africa          rural  Drinking water  2021
2630         Sub-Saharan Africa          urban  Drinking water  2021
2631         Sub-Saharan Africa          total  Drinking water  2022
2632         Sub-Saharan Africa          rural  Drinking water  2022
2633         Sub-Saharan Africa          urban  Drinking water  2022

      Coverage    Population   Service level
0     99.76079  2.281851e+07  At least basic
1     99.20040  3.508827e+06  At least basic
2     99.75979  2.308214e+07  At least basic
3     99.19829  3.572236e+06  At least basic
4     99.76071  2.336838e+07  At least basic
…        …           …              …
2629  22.99280  1.513195e+08      Unimproved
2630   4.92702  2.364091e+07      Unimproved
2631  14.92553  1.741461e+08      Unimproved
2632  22.44654  1.500443e+08      Unimproved
2633   4.72997  2.357014e+07      Unimproved
```

```
[2634 rows x 7 columns]
```

6.0.4 3.2.6 Removing NULL values

[229]:
```
df1.isna().sum()
```

[229]:
```
Region            0
Residence Type    0
Service Type      0
Year              0
Coverage          0
Population        0
Service level     0
dtype: int64
```

[230]:
```
df1.isnull().sum()
```

[230]:
```
Region            0
Residence Type    0
Service Type      0
Year              0
Coverage          0
Population        0
Service level     0
dtype: int64
```

Hence, we can see, we have **no null values** in our dataset to remove

6.0.5 3.2.7 Renaming column names

[231]:
```
df1.dtypes
```

[231]:
```
Region             object
Residence Type     object
Service Type       object
Year                int64
Coverage          float64
Population        float64
Service level      object
dtype: object
```

We dont need to perform step #3.2.7 Renaming column names, because their "names" convey the true meaning of type of "values" contained in them.

6.0.6 3.2.8 Checking the number of Zero values in dataset

[232]:
```
df1.columns
```

[232]:
```
Index(['Region', 'Residence Type', 'Service Type', 'Year', 'Coverage',
       'Population', 'Service level'],
      dtype='object')
```

[233]:
```
print("No of zero values in Region :",df1[df1["Region"]==0].shape[0])
```

```
No of zero values in Region : 0
```

[234]:
```
print("No of zero values in Residence Type :",df1[df1["Residence Type"]==0].
↪shape[0])
```

```
No of zero values in Residence Type : 0
```

[235]:
```
print("No of zero values in Service Type :",df1[df1["Service Type"]==0].
↪shape[0])
```

```
No of zero values in Service Type : 0
```

[236]:
```
print("No of zero values in Year :",df1[df1["Year"]==0].shape[0])
```

```
No of zero values in Year : 0
```

[237]:
```
print("No of zero values in Coverage :",df1[df1["Coverage"]==0].shape[0])
```

```
No of zero values in Coverage : 123
```

[238]:
```
print("No of zero values in Population :",df1[df1["Population"]==0].shape[0])
```

```
No of zero values in Population : 123
```

[239]:
```
print("No of zero values in Service level :",df1[df1["Service level"]==0].
↪shape[0])
```

```
No of zero values in Service level : 0
```

[240]:
```
#Lets check if is there any need to replace zero values of columns
df1[df1['Coverage']==0]
```

[240]:

	Region	Residence Type	Service Type	Year	\
552	Australia and New Zealand	total	Drinking water	2000	
553	Australia and New Zealand	rural	Drinking water	2000	
554	Australia and New Zealand	urban	Drinking water	2000	
555	Australia and New Zealand	total	Drinking water	2001	
556	Australia and New Zealand	rural	Drinking water	2001	
…	…	…	…	…	
2137	Australia and New Zealand	rural	Drinking water	2018	
2140	Australia and New Zealand	rural	Drinking water	2019	

```
2143  Australia and New Zealand          rural  Drinking water  2020
2146  Australia and New Zealand          rural  Drinking water  2021
2149  Australia and New Zealand          rural  Drinking water  2022

      Coverage  Population    Service level
552        0.0         0.0  Limited service
553        0.0         0.0  Limited service
554        0.0         0.0  Limited service
555        0.0         0.0  Limited service
556        0.0         0.0  Limited service
…          …           …               …
2137       0.0         0.0       Unimproved
2140       0.0         0.0       Unimproved
2143       0.0         0.0       Unimproved
2146       0.0         0.0       Unimproved
2149       0.0         0.0       Unimproved

[123 rows x 7 columns]
```

Here, we can see that ,"Coverage" of "Drinking water" and "Population" is 0 for "Australia and New Zealand" mainly - Australia is a dry continent with insufficient water and fertile soil, so coverage justifies being 0, also there is extremely low population(only reseachers, and scientists) to be considered in "Population" - New Zealand is a mountaineous country situated in southeast of Australia, hence it also justifies why "Coverage" and "Population" is 0 here.

Conclusion : We don't need to replace zero values present in "Coverage" and "Population" columns ,because it will disrupt the other parameters

6.0.7 More Refining our dataset

[241]:
```
dw_total =df1[df1["Residence Type"]=="total"]
dw_total #total means "National" data(combined of all rural and urban places)
```

[241]:
```
                        Region Residence Type    Service Type  Year  \
0     Australia and New Zealand          total  Drinking water  2000
2     Australia and New Zealand          total  Drinking water  2001
4     Australia and New Zealand          total  Drinking water  2002
6     Australia and New Zealand          total  Drinking water  2003
8     Australia and New Zealand          total  Drinking water  2004
…                           …              …               …   …
2619         Sub-Saharan Africa          total  Drinking water  2018
2622         Sub-Saharan Africa          total  Drinking water  2019
2625         Sub-Saharan Africa          total  Drinking water  2020
2628         Sub-Saharan Africa          total  Drinking water  2021
2631         Sub-Saharan Africa          total  Drinking water  2022

      Coverage    Population   Service level
```

```
0     99.76079  2.281851e+07  At least basic
2     99.75979  2.308214e+07  At least basic
4     99.76071  2.336838e+07  At least basic
6     99.77938  2.366661e+07  At least basic
8     99.79777  2.395792e+07  At least basic
…        …           …              …
2619  17.10086  1.800256e+08      Unimproved
2622  16.53103  1.786471e+08      Unimproved
2625  15.98120  1.772729e+08      Unimproved
2628  15.39112  1.751415e+08      Unimproved
2631  14.92553  1.741461e+08      Unimproved

[874 rows x 7 columns]
```

[242]:
```
dw_total.columns
```

[242]:
```
Index(['Region', 'Residence Type', 'Service Type', 'Year', 'Coverage',
       'Population', 'Service level'],
      dtype='object')
```

[243]:
```
#Dropping unnecessary columns in dw_total dataframe
dw_total = dw_total[['Region', #'Residence Type', 'Service Type',
                     'Year', 'Coverage', #'Population',
                     'Service level']].copy()
dw_total.head()
```

[243]:
```
                      Region  Year  Coverage   Service level
0  Australia and New Zealand  2000  99.76079  At least basic
2  Australia and New Zealand  2001  99.75979  At least basic
4  Australia and New Zealand  2002  99.76071  At least basic
6  Australia and New Zealand  2003  99.77938  At least basic
8  Australia and New Zealand  2004  99.79777  At least basic
```

[244]:
```
#Creating pivot table named "dw_ServiceLevel" from existing "dw_total",␣
 ↪redefining columns according to "Service level", and resetting index
dw_ServiceLevel = pd.pivot_table(dw_total, values = 'Coverage',␣
 ↪index=['Region','Year'], columns = 'Service level').reset_index()
dw_ServiceLevel.head()
```

[244]:
```
Service level                    Region  Year  At least basic  Basic service  \
0              Australia and New Zealand  2000        99.76079            NaN
1              Australia and New Zealand  2001        99.75979            NaN
2              Australia and New Zealand  2002        99.76071            NaN
3              Australia and New Zealand  2003        99.77938            NaN
4              Australia and New Zealand  2004        99.79777            NaN

Service level  Limited service  Safely managed service  Surface water  \
```

```
0                         0.0                     NaN        0.03932
1                         0.0                     NaN        0.03968
2                         0.0                     NaN        0.03936
3                         0.0                     NaN        0.03901
4                         0.0                     NaN        0.03869

Service level  Unimproved
0                 0.19989
1                 0.20053
2                 0.19994
3                 0.18161
4                 0.16355
```

[245]:
```
#Dropping "At least basic" column and reassigning values of it to "Basic␣
 ↪service" column at the place of "null values"
dw_ServiceLevel.loc[dw_ServiceLevel['Basic service'].isnull(), 'Basic service']␣
 ↪= dw_ServiceLevel['At least basic']
dw_ServiceLevel = dw_ServiceLevel.drop(['At least basic'], axis = 1)
dw_Final  = dw_ServiceLevel
dw_Final.head()
```

[245]:
```
Service level                    Region  Year  Basic service  \
0              Australia and New Zealand  2000       99.76079
1              Australia and New Zealand  2001       99.75979
2              Australia and New Zealand  2002       99.76071
3              Australia and New Zealand  2003       99.77938
4              Australia and New Zealand  2004       99.79777

Service level  Limited service  Safely managed service  Surface water  \
0                         0.0                     NaN        0.03932
1                         0.0                     NaN        0.03968
2                         0.0                     NaN        0.03936
3                         0.0                     NaN        0.03901
4                         0.0                     NaN        0.03869

Service level  Unimproved
0                 0.19989
1                 0.20053
2                 0.19994
3                 0.18161
4                 0.16355
```

[246]:
```
dw_Final['Region'].unique()
```

[246]:
```
array(['Australia and New Zealand', 'Central and Southern Asia',
       'Eastern and South-Eastern Asia', 'Europe and Northern America',
       'Latin America and the Caribbean',
```

```
       'Northern Africa and Western Asia', 'Oceania',
       'Sub-Saharan Africa'], dtype=object)
```

[247]:
```
dw_Final_aus = dw_Final[dw_Final['Region'] == 'Australia and New Zealand']
dw_Final_csa = dw_Final[dw_Final['Region'] == 'Central and Southern Asia']
dw_Final_lac = dw_Final[dw_Final['Region'] == 'Latin America and the Caribbean']
dw_Final_nawa = dw_Final[dw_Final['Region'] == 'Northern Africa and Western␣
 ↪Asia']
dw_Final_oce = dw_Final[dw_Final['Region'] == 'Oceania']
dw_Final_ssa = dw_Final[dw_Final['Region'] == 'Sub-Saharan Africa']
```

[248]:
```
dw_Final_aus
```

[248]:
```
Service level                    Region  Year  Basic service  \
0              Australia and New Zealand  2000       99.76079
1              Australia and New Zealand  2001       99.75979
2              Australia and New Zealand  2002       99.76071
3              Australia and New Zealand  2003       99.77938
4              Australia and New Zealand  2004       99.79777
5              Australia and New Zealand  2005       99.81587
6              Australia and New Zealand  2006       99.83373
7              Australia and New Zealand  2007       99.85137
8              Australia and New Zealand  2008       99.86885
9              Australia and New Zealand  2009       99.88627
10             Australia and New Zealand  2010       99.90241
11             Australia and New Zealand  2011       99.90966
12             Australia and New Zealand  2012       99.91689
13             Australia and New Zealand  2013       99.92419
14             Australia and New Zealand  2014       99.96769
15             Australia and New Zealand  2015       99.97485
16             Australia and New Zealand  2016       99.97482
17             Australia and New Zealand  2017       99.97480
18             Australia and New Zealand  2018       99.97478
19             Australia and New Zealand  2019       99.97479
20             Australia and New Zealand  2020       99.97479
21             Australia and New Zealand  2021       99.97477
22             Australia and New Zealand  2022       99.97474

Service level  Limited service  Safely managed service  Surface water  \
0                         0.0                     NaN        0.03932
1                         0.0                     NaN        0.03968
2                         0.0                     NaN        0.03936
3                         0.0                     NaN        0.03901
4                         0.0                     NaN        0.03869
5                         0.0                     NaN        0.03839
6                         0.0                     NaN        0.03812
7                         0.0                     NaN        0.03786
```

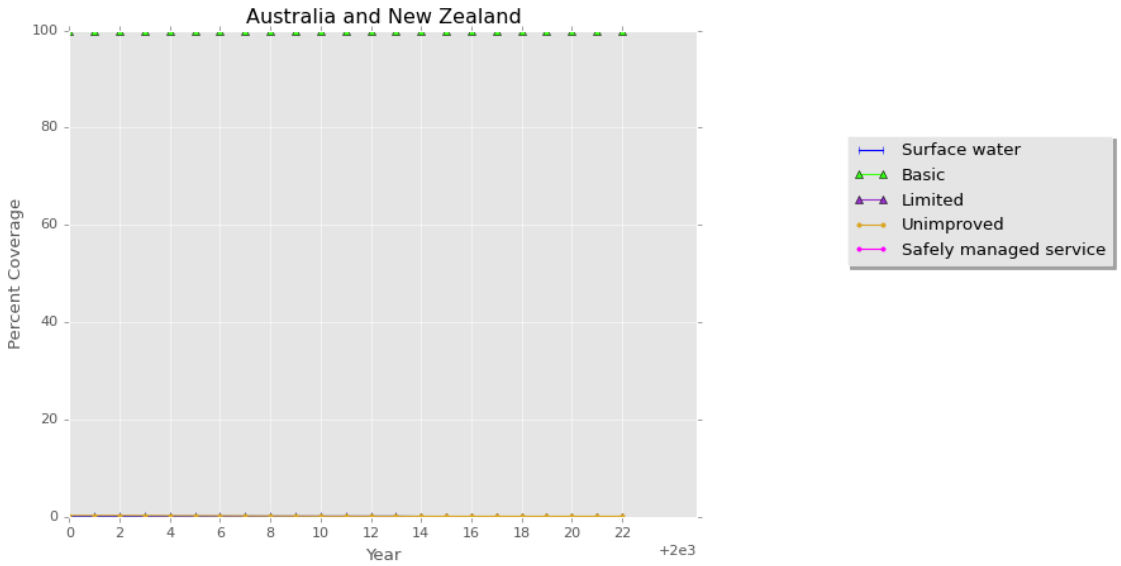
8	0.0	NaN	0.03763
9	0.0	NaN	0.03738
10	0.0	NaN	0.03712
11	0.0	NaN	0.03684
12	0.0	NaN	0.03661
13	0.0	NaN	0.03638
14	0.0	NaN	0.00000
15	0.0	NaN	0.00000
16	0.0	NaN	0.00000
17	0.0	NaN	0.00000
18	0.0	NaN	0.00000
19	0.0	NaN	0.00000
20	0.0	NaN	0.00000
21	0.0	NaN	0.00000
22	0.0	NaN	0.00000

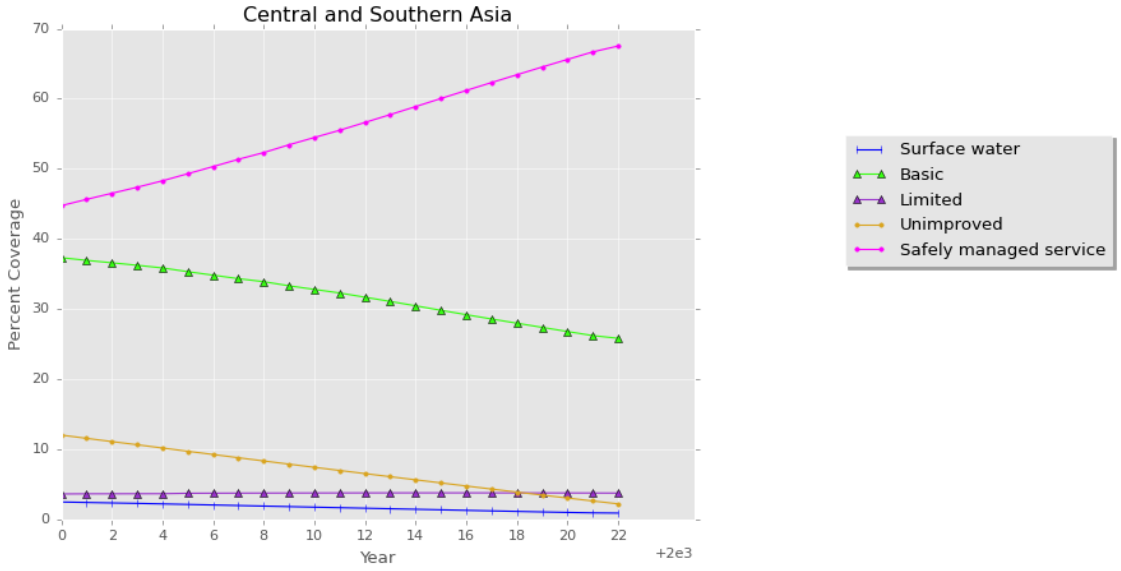
Service level	Unimproved
0	0.19989
1	0.20053
2	0.19994
3	0.18161
4	0.16355
5	0.14574
6	0.12815
7	0.11076
8	0.09352
9	0.07635
10	0.06047
11	0.05350
12	0.04649
13	0.03943
14	0.03231
15	0.02515
16	0.02518
17	0.02520
18	0.02522
19	0.02521
20	0.02521
21	0.02523
22	0.02526

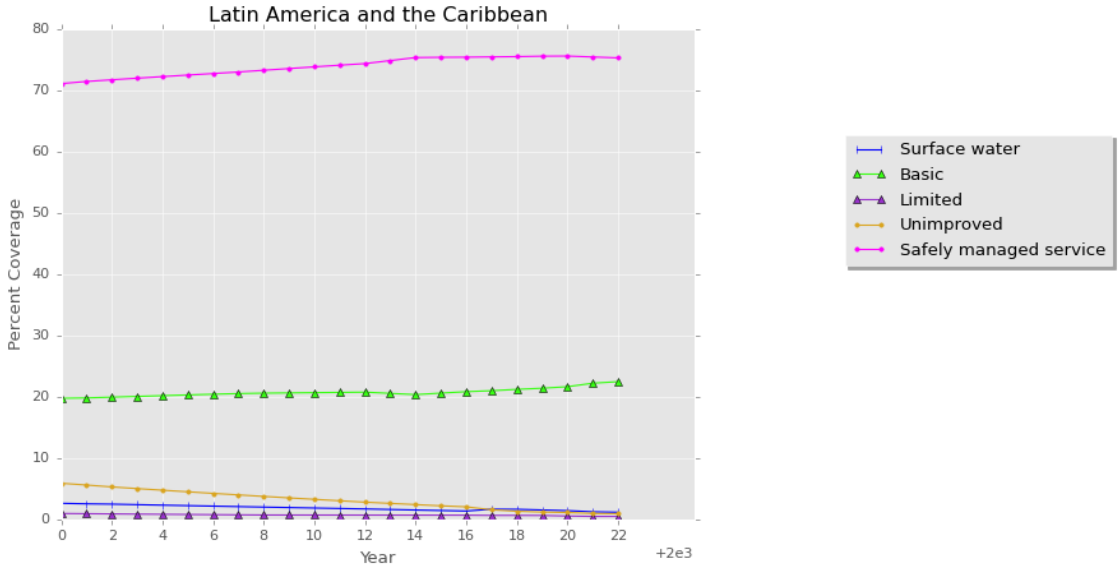
7 Step 4 : Data Visualization

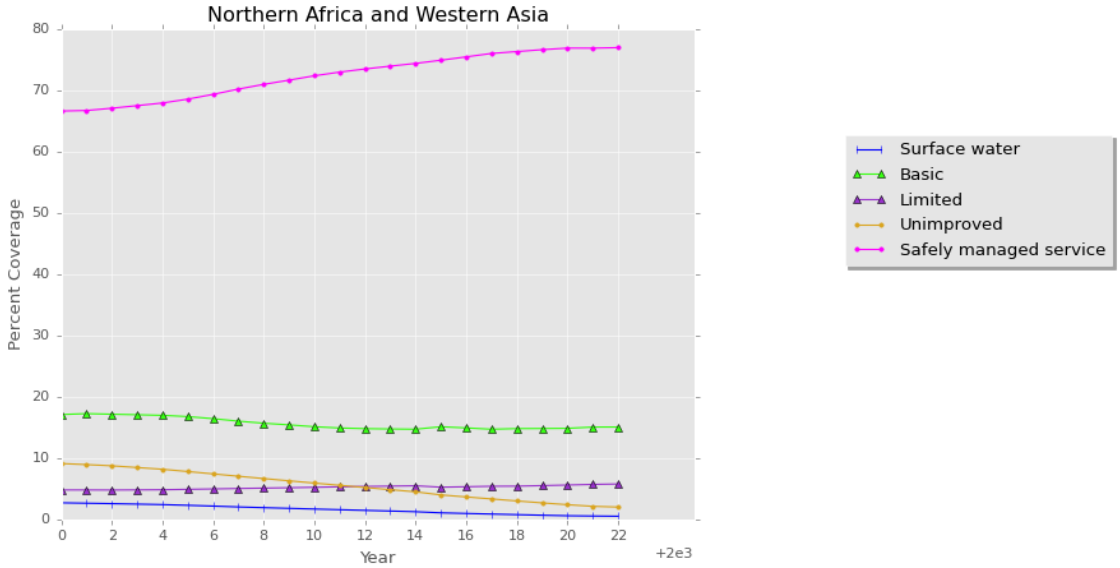
7.0.1 4.1) Progress on "Surface water", "Basic surface","Limited service","Unimproved","Safely managed service" over the years (2000-2022) by regions

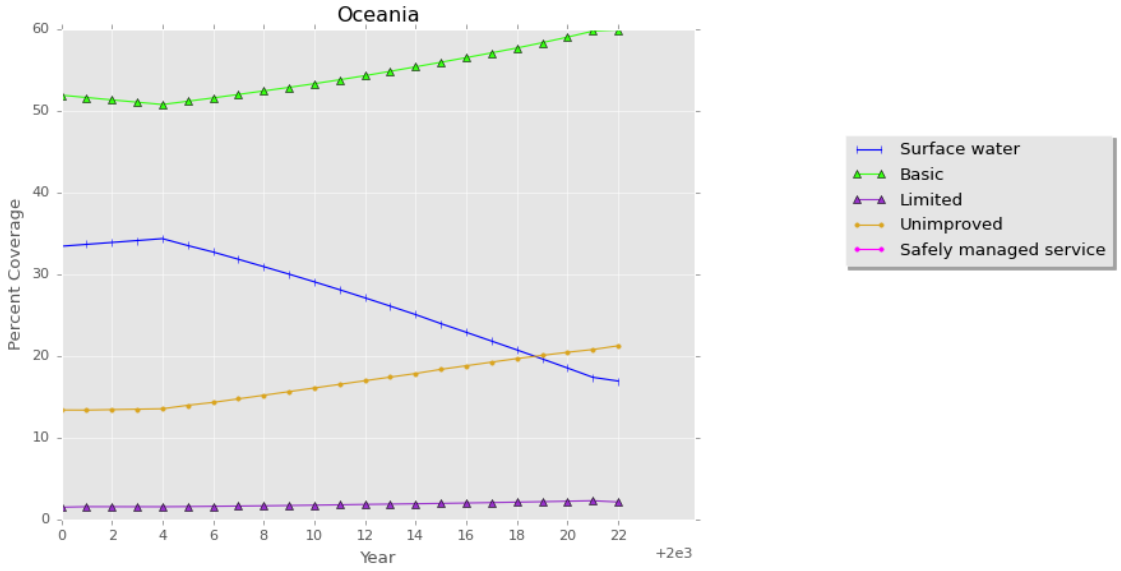
[249]:
```
import matplotlib.pyplot as plt
from matplotlib import pyplot
sdg_regions = [dw_Final_aus, dw_Final_csa, dw_Final_lac, dw_Final_nawa,␣
 ↪dw_Final_oce, dw_Final_ssa]
sdg_region_title = ['Australia and New Zealand',
                    'Central and Southern Asia',
                    'Latin America and the Caribbean',
                    'Northern Africa and Western Asia',
                    'Oceania',
                    'Sub-Saharan Africa']
index = 0
for region in sdg_regions:
        title = sdg_region_title[index]

        plt.plot(region['Year'], region['Surface water'], fillstyle = 'full',␣
 ↪color = '#0000FF', marker = '|', label = "Surface water")
        plt.plot(region['Year'], region['Basic service'], fillstyle =␣
 ↪'full',color = '#39FF14', marker = '^', label = "Basic")
        plt.plot(region['Year'], region['Limited service'], fillstyle =␣
 ↪'full',color = '#9932CC', marker = '^', label = 'Limited')
        plt.plot(region['Year'], region['Unimproved'],fillstyle = 'full', color␣
 ↪= '#DAA520', marker ='.', label = 'Unimproved')
        plt.plot(region['Year'], region['Safely managed service'], fillstyle =␣
 ↪'full',color = '#FF00FF', marker = '.', label = "Safely managed service")

        plt.legend(loc='upper center', bbox_to_anchor=(1.45, 0.8), shadow=True,␣
 ↪ncol=1)
        plt.xticks(range(2000,2023,2))
        plt.xlabel('Year')
        plt.ylabel('Percent Coverage')
        plt.title(title)
        plt.show()

        image_title =  'Plot of Water Service Levels Across the world'

        index += 1
```

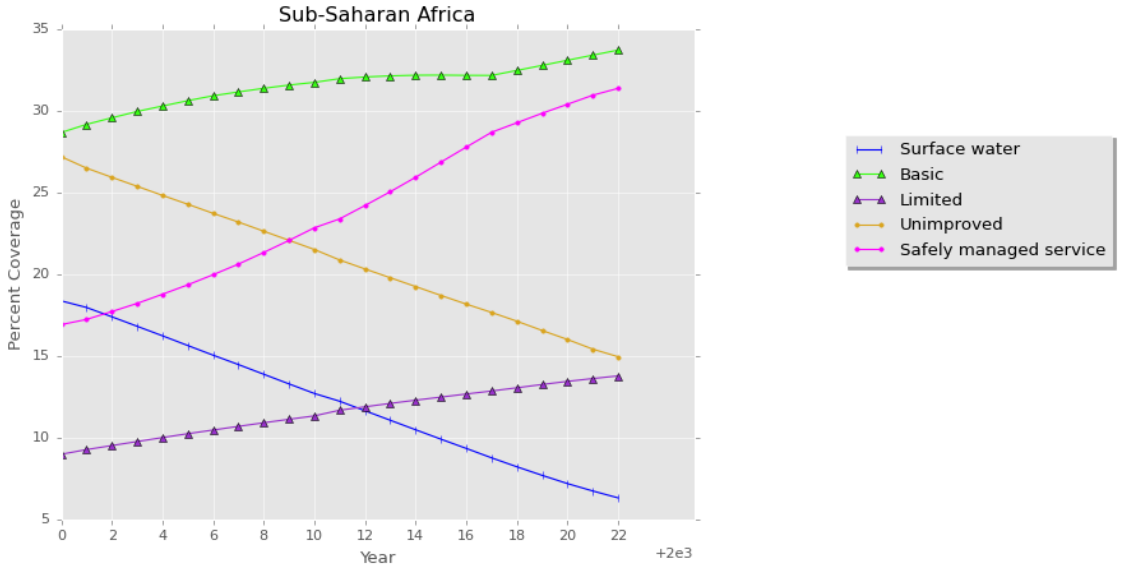

Australia and New Zealand
Percent Coverage
Year
+2e3
Surface water
Basic
Limited
Unimproved
Safely managed service


Central and Southern Asia
Percent Coverage
Year
+2e3
Surface water
Basic
Limited
Unimproved
Safely managed service


Latin America and the Caribbean
Percent Coverage
Year
+2e3
Surface water
Basic
Limited
Unimproved
Safely managed service


Northern Africa and Western Asia
Percent Coverage
Year
+2e3
Surface water
Basic
Limited
Unimproved
Safely managed service

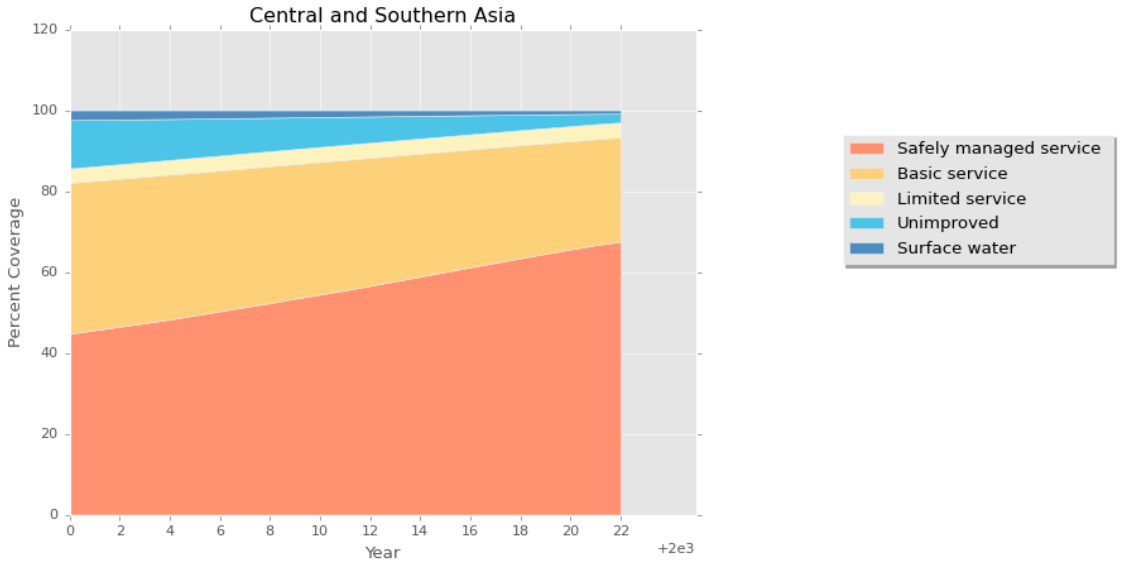


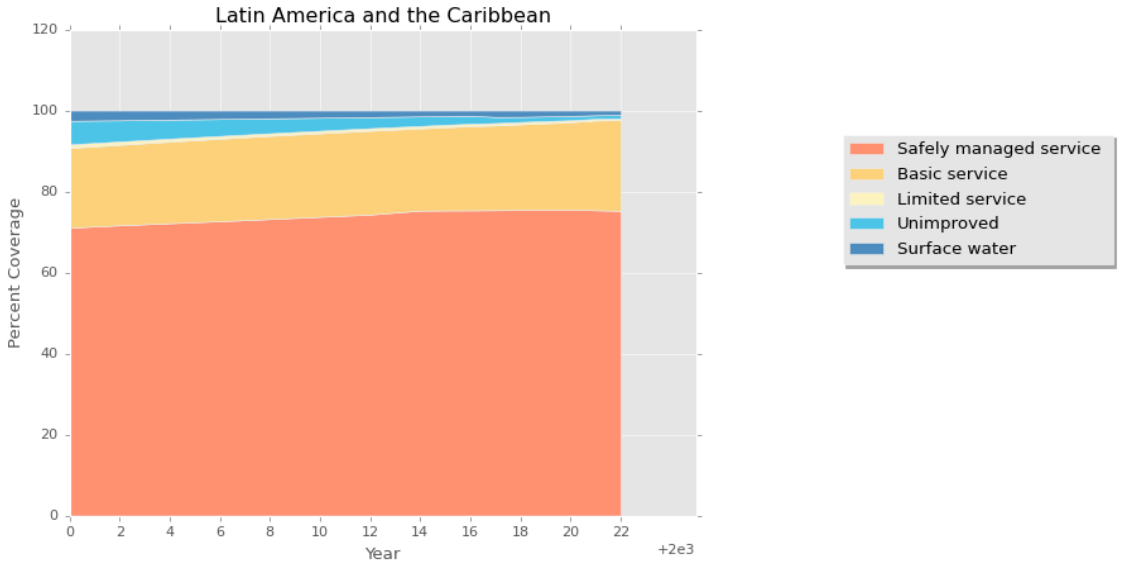


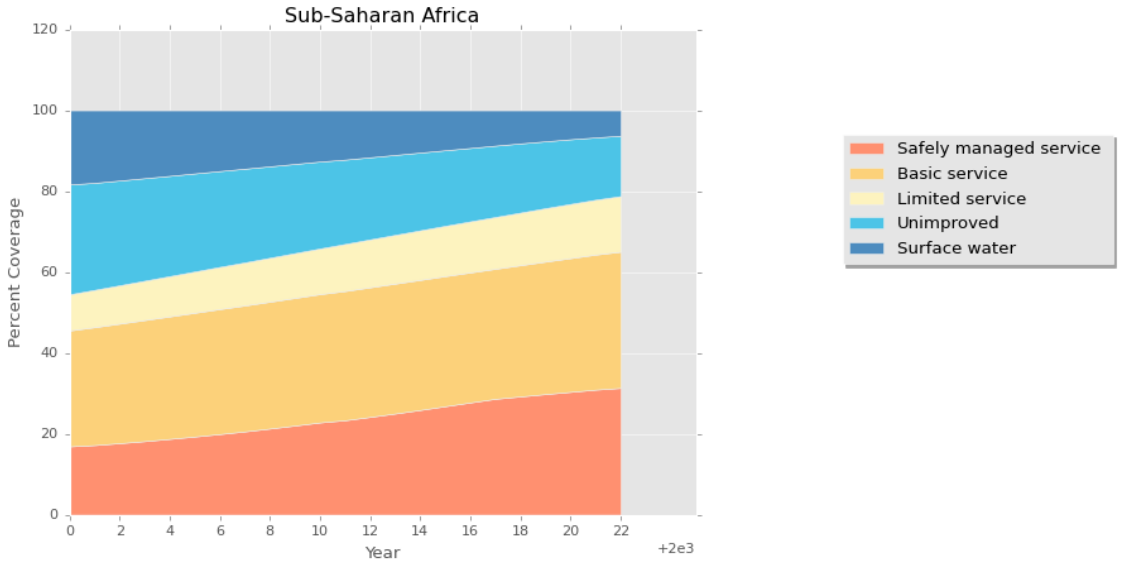
[250]:
```
import numpy as np
```

[251]:
```
from matplotlib import pyplot
sdg_regions = [dw_Final_csa, dw_Final_lac, dw_Final_ssa]
sdg_region_title = ['Central and Southern Asia',
                    'Latin America and the Caribbean',
                    'Sub-Saharan Africa']
index = 0
for region in sdg_regions:
```

```
    title = sdg_region_title[index]
    x = region['Year']
    y1 = region['Safely managed service']
    y2 = region['Basic service']
    y3 = region['Limited service']
    y4 = region['Unimproved']
    y5 = region['Surface water']

    y = np.vstack([y1,y2,y3,y4,y5])

    labels = ["Safely managed service ", "Basic service", "Limited service",␣
↪"Unimproved",
         "Surface water"]
    colors=['#FF9070','#FCD17A','#FDF3BF', '#4CC4E7','#4D8CBF']
    fig, ax = plt.subplots()
    ax.stackplot(x,y1,y2,y3,y4,y5, labels=labels, colors=colors)
    plt.legend(loc='upper center', bbox_to_anchor=(1.45, 0.8), shadow=True,␣
↪ncol=1)
    plt.xticks(range(2000,2023,2))
    plt.xlabel('Year')
    plt.ylabel('Percent Coverage')
    plt.title(title)
    plt.show()
    index += 1
```

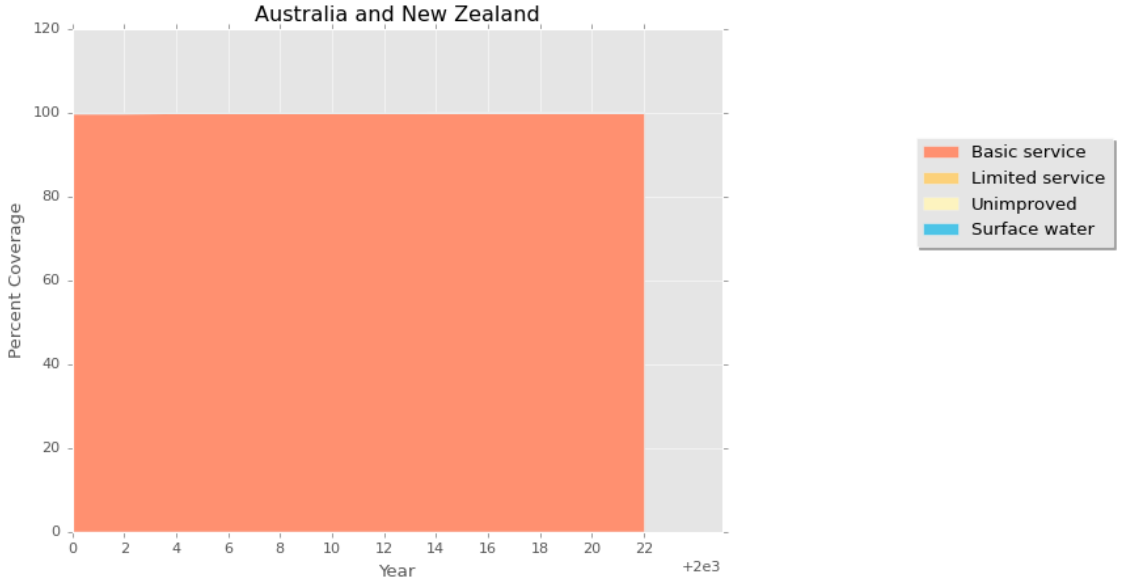


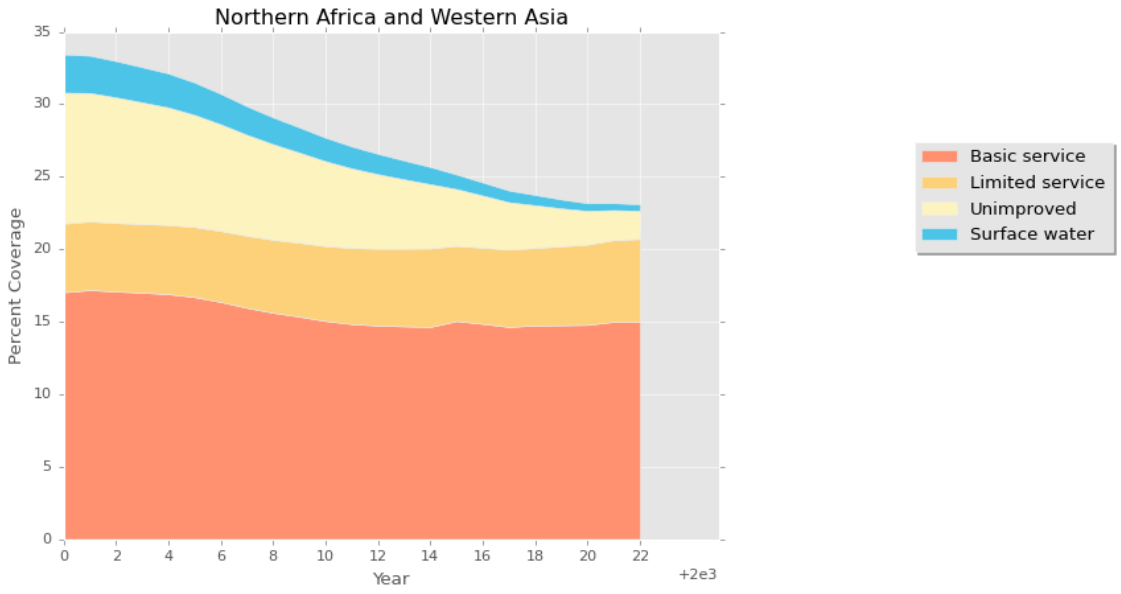


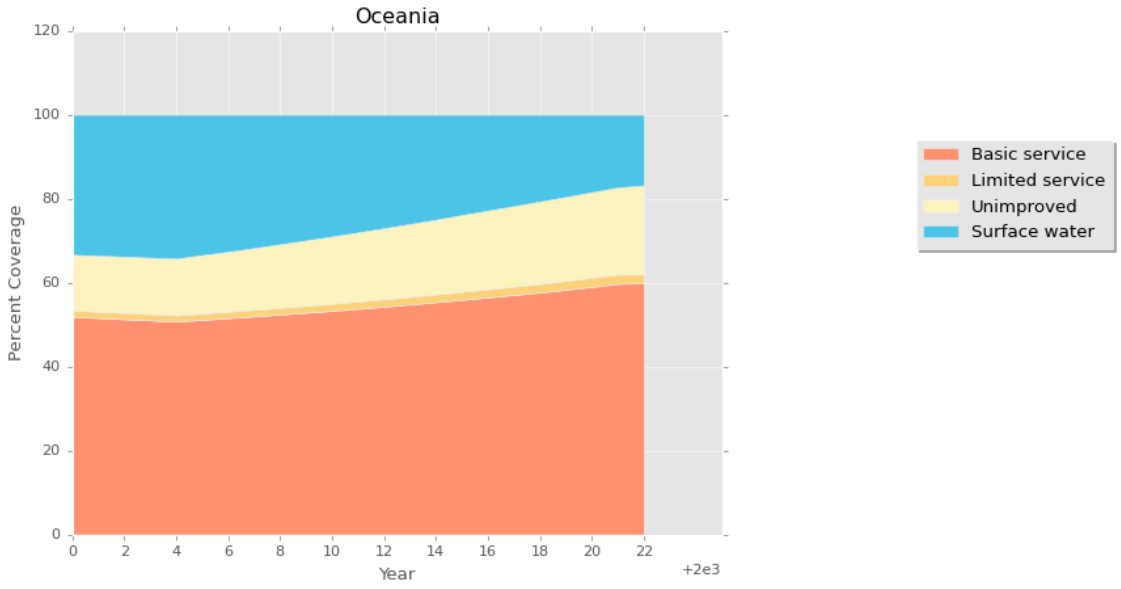


[252]:
```
from matplotlib import pyplot
sdg_regions = [dw_Final_aus,dw_Final_nawa, dw_Final_oce]
sdg_region_title = ['Australia and New Zealand',
                    'Northern Africa and Western Asia',
                    'Oceania']
index = 0
for region in sdg_regions:
    title = sdg_region_title[index]
    x = region['Year']
```

```
    y2 = region['Basic service']
    y3 = region['Limited service']
    y4 = region['Unimproved']
    y5 = region['Surface water']
    colors=['#FF9070','#FCD17A','#FDF3BF', '#4CC4E7','#4D8CBF']

    y = np.vstack([y2,y3,y4,y5])

    labels = ["Basic service", "Limited service", "Unimproved", "Surface water"]
    fig, ax = plt.subplots()
    ax.stackplot(x,y2,y3,y4,y5, labels=labels, colors=colors)
    plt.legend(loc='upper center', bbox_to_anchor=(1.45, 0.8), shadow=True,␣
↪ncol=1)
    plt.xticks(range(2000,2023,2))
    plt.xlabel('Year')
    plt.ylabel('Percent Coverage')
    plt.title(title)
    plt.show()
    index += 1
```





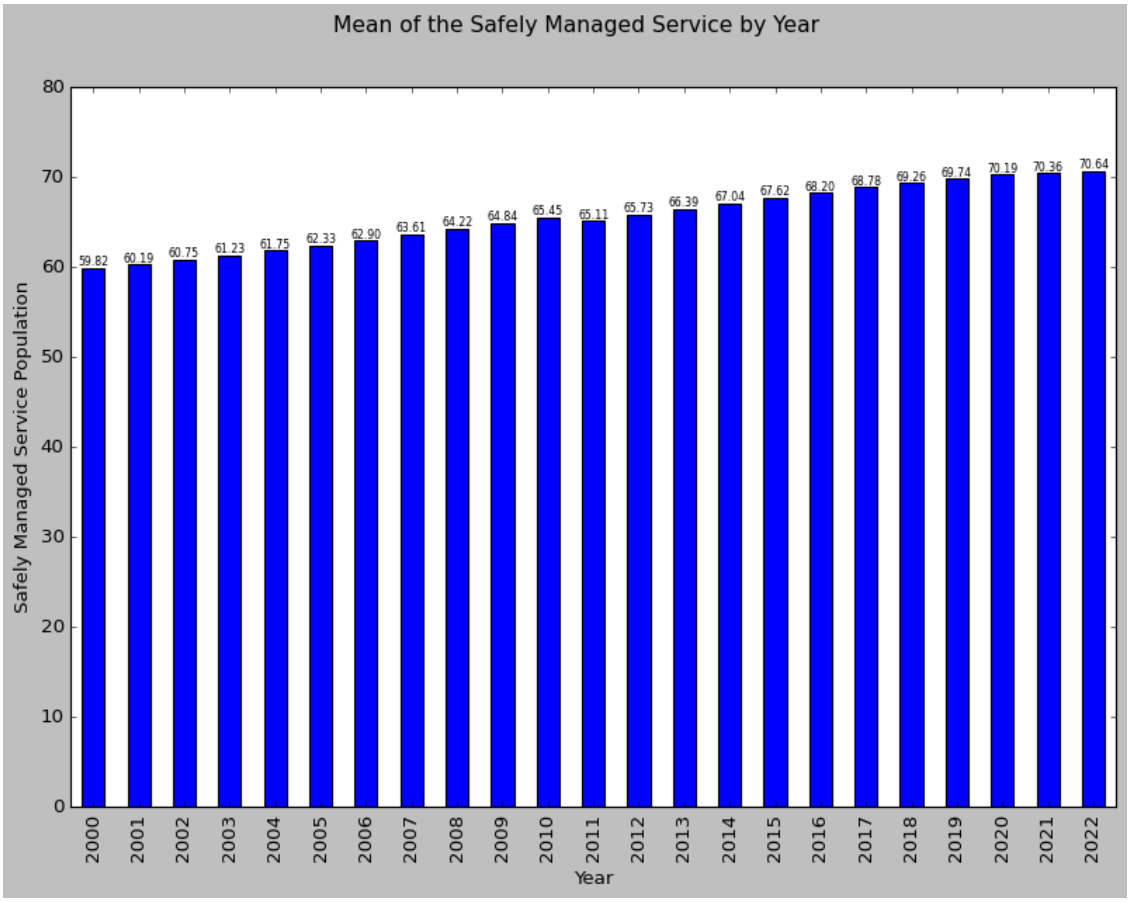


7.0.2 4.2) Mean and Medians of different water services by "Year"

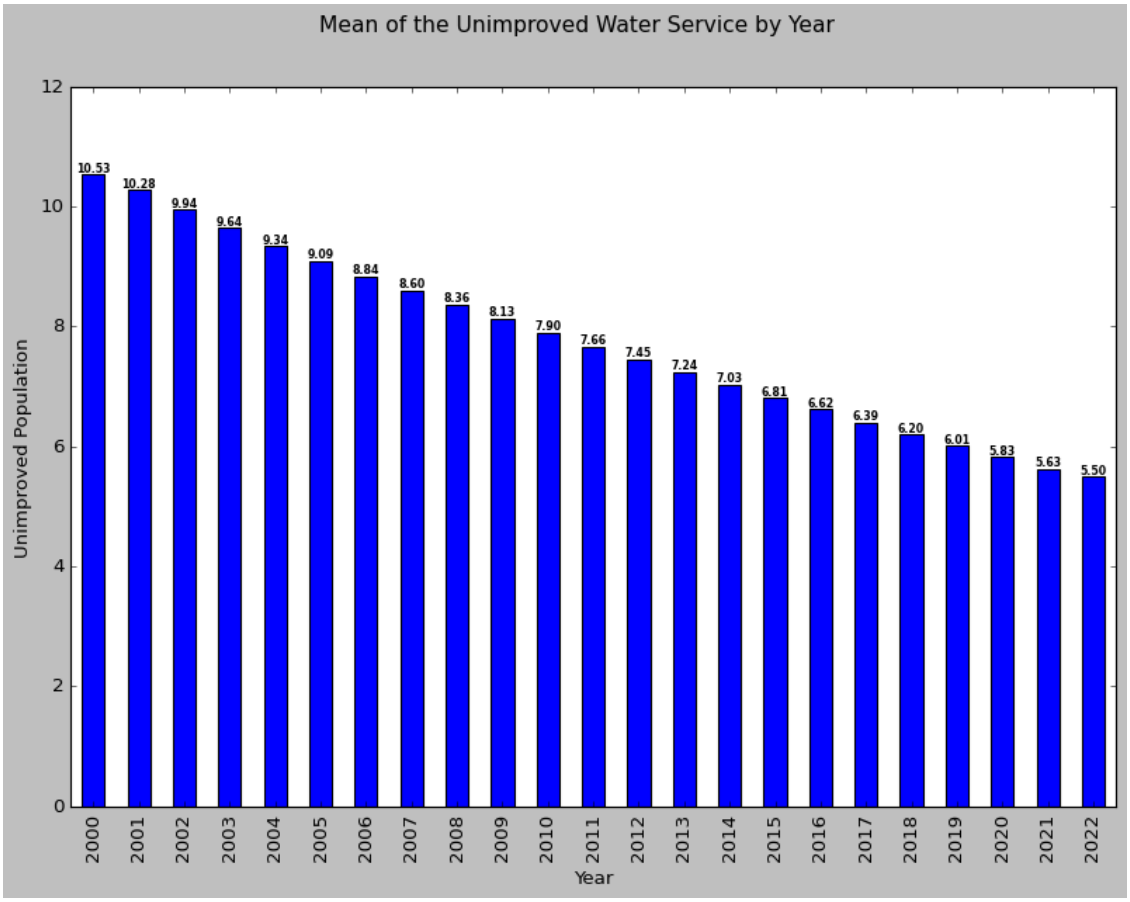
[253]:
```
plt.style.use('classic')
mean_safely_managed = dw_Final.groupby('Year')['Safely managed service'].mean()
dw_Final.groupby('Year')['Safely managed service'].mean().plot(kind='bar',␣
 ↪figsize=(12, 8))
for i, value in enumerate(mean_safely_managed):
```

```
    plt.text(i, value, f"{value:.2f}", ha='center', va='bottom',fontsize=7)
plt.suptitle('Mean of the Safely Managed Service by Year', fontsize=14)
plt.ylabel('Safely Managed Service Population')
plt.xlabel('Year')
```

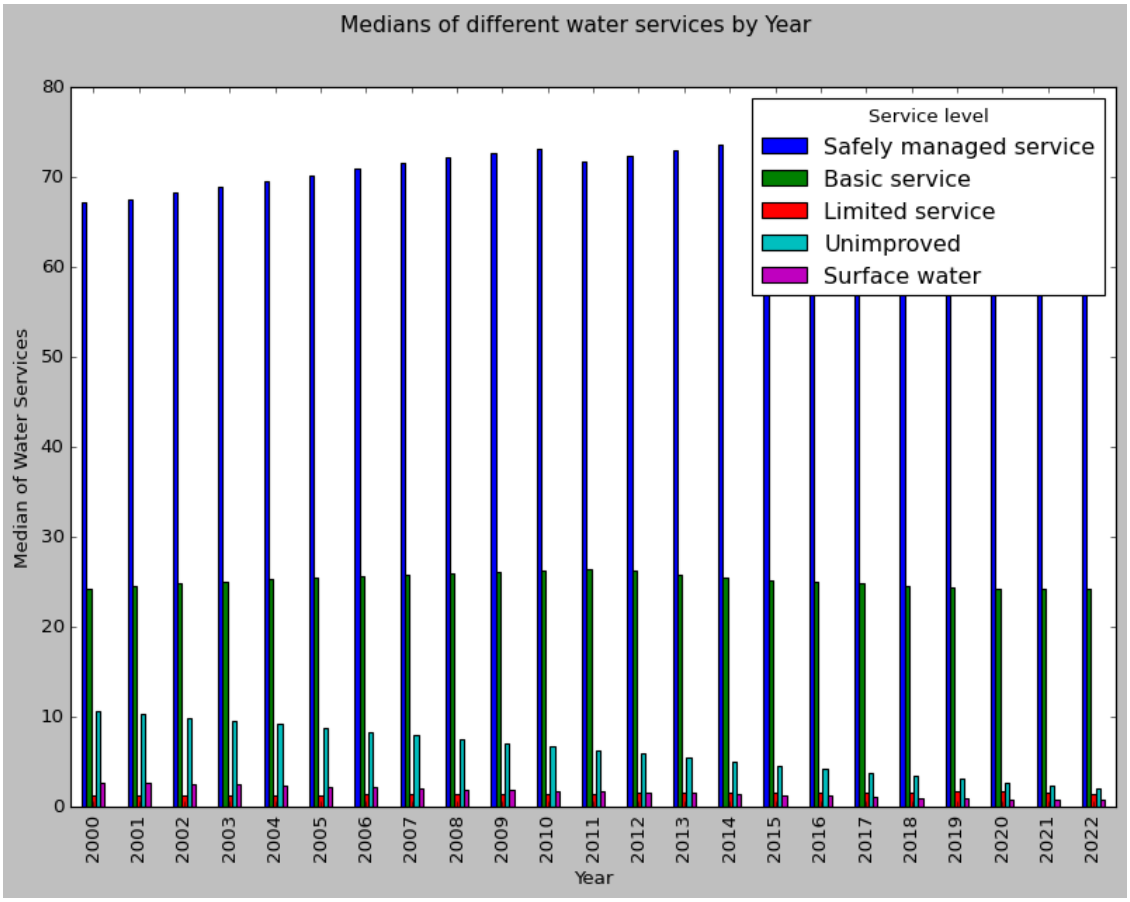
[253]: Text(0.5, 0, 'Year')



[254]:
```
mean_unimproved = dw_Final.groupby('Year')['Unimproved'].mean()
for i, value in enumerate(mean_unimproved):
    plt.text(i, value, f"{value:.2f}", ha='center',␣
 ↪va='bottom',fontsize=7,fontweight='bold')
dw_Final.groupby('Year')['Unimproved'].mean().plot(kind='bar', figsize=(12, 8))
plt.suptitle('Mean of the Unimproved Water Service by Year', fontsize=14)
plt.ylabel('Unimproved Population')
plt.xlabel('Year')
plt.show()
```



[255]:
```
dw_Final.groupby('Year')[['Safely managed service', 'Basic service', 'Limited␣
 ↪service','Unimproved', 'Surface water']].median().plot(kind='bar',␣
 ↪figsize=(12, 8))
plt.suptitle('Medians of different water services by Year', fontsize=14)
plt.ylabel('Median of Water Services')
plt.xlabel('Year')
plt.show()
```



[256]:
```
dw_Final.columns=['Region','Year','Basic Water','Limited Water','Safely Managed␣
↪Water','Surface water','Unimproved water']
```

7.0.3 4.3) Data Cleaning and Analysis on Sanitation and Hygiene practices

- Transforming Hygiene and Sanitation data to merge them to Drinking Water and look at the trends

[257]:
```
import pandas as pd
hygiene = pd.read_csv("Hygiene_by_Regions(2000-2022).csv")
sanitation=pd.read_csv("Sanitation_by_Regions(2000-2022).csv")
```

[258]:
```
hygiene.columns
```

[258]:
```
Index(['Unnamed: 0', 'Region', 'Year', 'Basic Hygiene', 'Limited Hygiene',
       'No handwashing facility'],
      dtype='object')
```

[259]:
```
hygiene = hygiene[[#'Unnamed: 0',
    'Region', 'Year', 'Basic Hygiene', 'Limited Hygiene',
       'No handwashing facility']].copy()
hygiene.head()
```

[259]:

	Region	Year	Basic Hygiene	Limited Hygiene	No handwashing facility
0	Central and Southern Asia	2010	178.89795	107.61639	13.48567
1	Central and Southern Asia	2011	180.64756	106.15612	13.19632
2	Central and Southern Asia	2012	182.54004	104.81504	12.64492
3	Central and Southern Asia	2013	184.46369	103.26237	12.27392
4	Central and Southern Asia	2014	186.36567	101.92441	11.70989

[260]:
```
sanitation.columns
```

[260]:
```
Index(['Unnamed: 0', 'Region', 'Year', 'Basic Sanitation',
       'Limited Sanitation', 'Open Defecation', 'Safely Managed Sanitation',
       'Unimproved Sanitation'],
      dtype='object')
```

[261]:
```
sanitation = sanitation[[#'Unnamed: 0',
    'Region', 'Year', 'Basic Sanitation',
       'Limited Sanitation', 'Open Defecation', 'Safely Managed Sanitation',
       'Unimproved Sanitation']].copy()
sanitation.head()
```

[261]:

	Region	Year	Basic Sanitation	Limited Sanitation	Open Defecation	Safely Managed Sanitation	Unimproved Sanitation
0	Australia and New Zealand	2000	6.42874	0.0	0.0	93.56357	0.00769
1	Australia and New Zealand	2001	6.32666	0.0	0.0	93.66607	0.00728
2	Australia and New Zealand	2002	6.22457	0.0	0.0	93.76857	0.00686
3	Australia and New Zealand	2003	6.12248	0.0	0.0	93.87108	0.00644
4	Australia and New Zealand	2004	6.02040	0.0	0.0	93.97358	0.00602

7.0.4 Merging sanitation and water data on Year and Region columns

[262]:
```
newdf=pd.merge(sanitation, dw_Final, how='left', left_on=['Year','Region'],␣
↪right_on = ['Year', 'Region'])
```

[263]:
```
masterdf=pd.merge(newdf, hygiene, how='left', left_on=['Year',␣
↪'Region'],right_on=['Year', 'Region'])
```

[264]:
```
masterdf.head()
```

[264]:

	Region	Year	Basic Sanitation	Limited Sanitation	Open Defecation	Safely Managed Sanitation	Unimproved Sanitation	Basic Water	Limited Water	Safely Managed Water	Surface water	Unimproved water	Basic Hygiene	Limited Hygiene	No handwashing facility
0	Australia and New Zealand	2000	6.42874	0.0	0.0	93.56357	0.00769	99.76079	0.0	NaN	0.03932	0.19989	NaN	NaN	NaN
1	Australia and New Zealand	2001	6.32666	0.0	0.0	93.66607	0.00728	99.75979	0.0	NaN	0.03968	0.20053	NaN	NaN	NaN
2	Australia and New Zealand	2002	6.22457	0.0	0.0	93.76857	0.00686	99.76071	0.0	NaN	0.03936	0.19994	NaN	NaN	NaN
3	Australia and New Zealand	2003	6.12248	0.0	0.0	93.87108	0.00644	99.77938	0.0	NaN	0.03901	0.18161	NaN	NaN	NaN
4	Australia and New Zealand	2004	6.02040	0.0	0.0	93.97358	0.00602	99.79777	0.0	NaN	0.03869	0.16355	NaN	NaN	NaN

[265]:
```
masterdf.shape
```

[265]:
```
(184, 15)
```

[266]:
```
masterdf.isnull().sum()
```

[266]:
```
Region                          0
Year                            0
Basic Sanitation                0
Limited Sanitation              0
```

```
Open Defecation                0
Safely Managed Sanitation      0
Unimproved Sanitation          0
Basic Water                    0
Limited Water                  0
Safely Managed Water          46
Surface water                  0
Unimproved water               0
Basic Hygiene                118
Limited Hygiene              122
No handwashing facility      103
dtype: int64
```

7.0.5 Handling Missing values

[267]:
```
masterdf['Safely Managed Water'].fillna(0)
masterdf['Basic Hygiene'].fillna(0)
masterdf['Limited Hygiene'].fillna(0)
masterdf['No handwashing facility'].fillna(0)
masterdf.isnull().sum()
```

[267]:
```
Region                         0
Year                           0
Basic Sanitation               0
Limited Sanitation             0
Open Defecation                0
Safely Managed Sanitation      0
Unimproved Sanitation          0
Basic Water                    0
Limited Water                  0
Safely Managed Water          46
Surface water                  0
Unimproved water               0
Basic Hygiene                118
Limited Hygiene              122
No handwashing facility      103
dtype: int64
```

[268]:
```
masterdf.sample(5)
```

[268]:

	Region	Year	Basic Sanitation	\
16	Australia and New Zealand	2016	4.79538	
93	Latin America and the Caribbean	2001	95.90218	
44	Central and Southern Asia	2021	80.90621	
54	Eastern and South-Eastern Asia	2008	107.61502	
135	Northern Africa and Western Asia	2020	82.44524	

```
     Limited Sanitation  Open Defecation  Safely Managed Sanitation  \
16              0.00000          0.00000                   95.20355
93             14.45326         40.22690                   62.95101
44             35.57699         28.74743                  145.65910
54             15.15380         14.21905                  111.83549
135             9.50724          7.75824                  177.48969

     Unimproved Sanitation  Basic Water  Limited Water  Safely Managed Water  \
16                 0.00107     99.97482        0.00000                   NaN
93                36.08405     19.75033        0.86230              71.37896
44                 9.11028     26.17805        3.70627              66.67643
54                51.17665     13.42152        1.03042              73.85641
135               22.79960     14.78617        5.53644              76.82320

     Surface water  Unimproved water  Basic Hygiene  Limited Hygiene  \
16         0.00000           0.02518            NaN              NaN
93         2.47128           5.53712            NaN              NaN
44         0.87123           2.56802     226.76649         62.68975
54         2.19803           9.49362            NaN              NaN
135        0.52675           2.32745     158.88217         22.13427

     No handwashing facility
16                       NaN
93                       NaN
44                  10.54377
54                  15.18874
135                  2.70490
```

[269]:
```
masterdf['Region'].unique()
```

[269]:
```
array(['Australia and New Zealand', 'Central and Southern Asia',
       'Eastern and South-Eastern Asia', 'Europe and Northern America',
       'Latin America and the Caribbean',
       'Northern Africa and Western Asia', 'Oceania',
       'Sub-Saharan Africa'], dtype=object)
```

[270]:
```
masterdf.columns
```

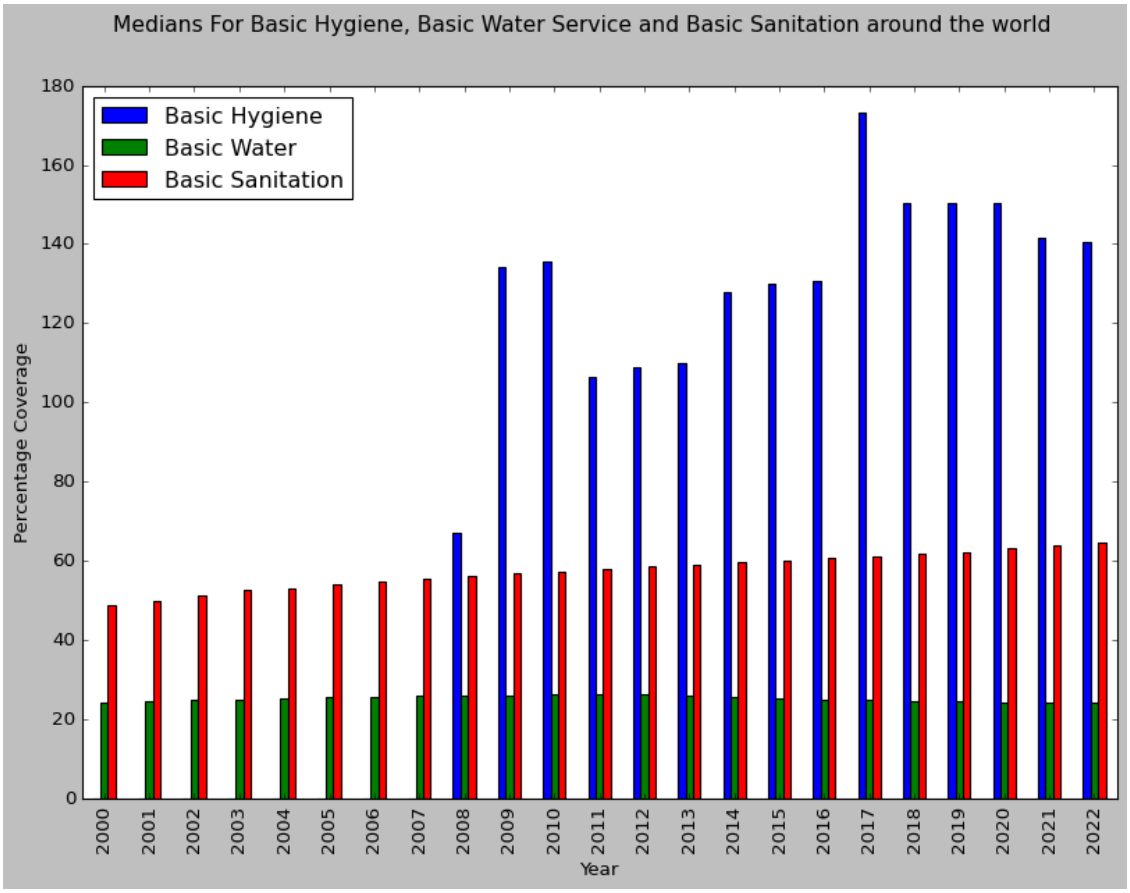
[270]:
```
Index(['Region', 'Year', 'Basic Sanitation', 'Limited Sanitation',
       'Open Defecation', 'Safely Managed Sanitation', 'Unimproved Sanitation',
       'Basic Water', 'Limited Water', 'Safely Managed Water', 'Surface water',
       'Unimproved water', 'Basic Hygiene', 'Limited Hygiene',
       'No handwashing facility'],
      dtype='object')
```

7.0.6 4.4) Data Visualization on Basic

- Following plot demonstrates the Median Percentage Coverages for

1. “Basic Hygiene”,
2. “Basic Water Service” and
3. “Basic Sanitation” #around the world in given years. We are aiming to find trends that are present

[271]:
```
plt.style.use('classic')
masterdf.groupby('Year')[['Basic Hygiene', 'Basic Water','Basic Sanitation']].
 ↪median().plot(kind='bar', figsize=(12, 8))
plt.suptitle('Medians For Basic Hygiene, Basic Water Service and Basic␣
 ↪Sanitation around the world', fontsize=14)
plt.ylabel('Percentage Coverage')
plt.xlabel('Year')
plt.show()
```

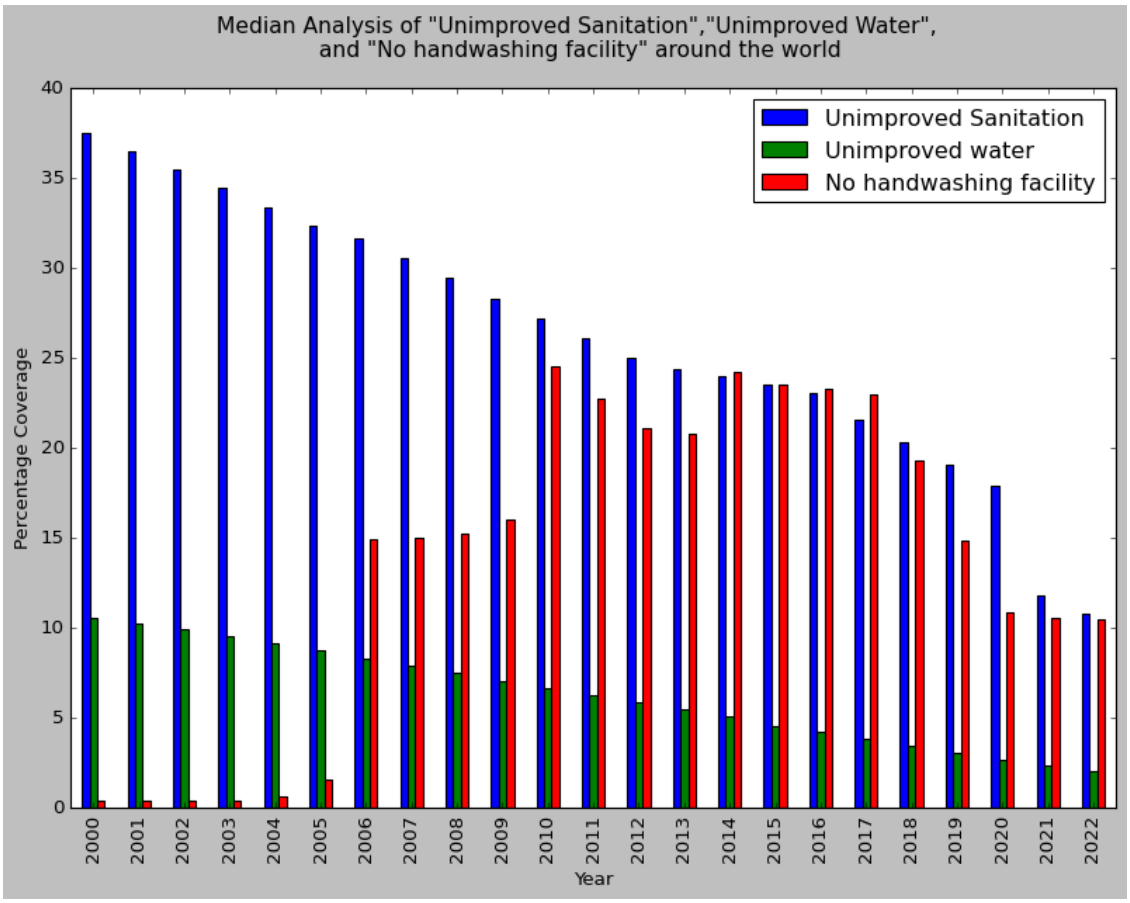


7.1 4.5) Data Visualization on Unimproved

- Following plot demonstrates the Median Percentage Coverages for
  1. “Unimproved Sanitation”,
  2. “Unimproved Water” and
  3. “No Handwashing Facility” #around the world in given years.We are aiming to find

trends that are present.

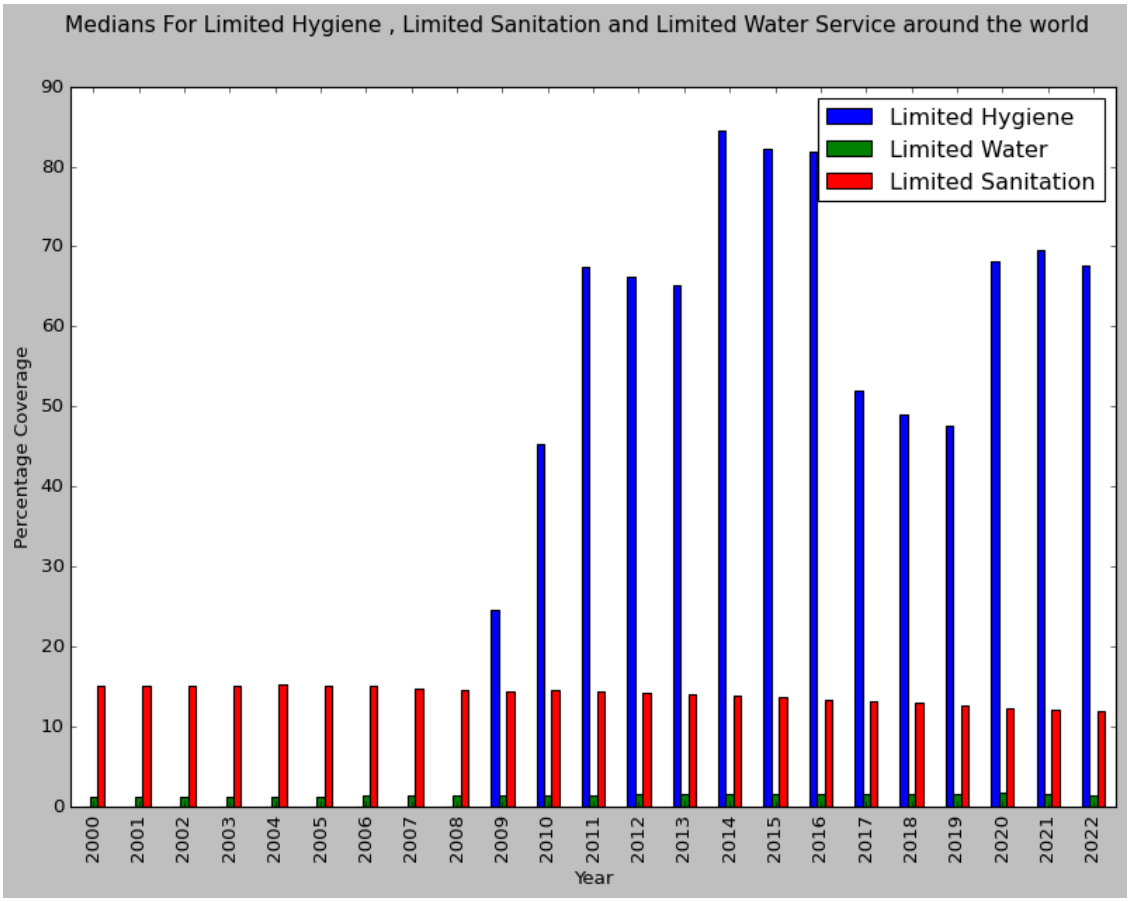
[272]:
```
masterdf.groupby('Year')[['Unimproved Sanitation','Unimproved water', 'No␣
↪handwashing facility']].median().plot(kind='bar', figsize=(12, 8))
plt.suptitle('Median Analysis of "Unimproved Sanitation","Unimproved Water",\n␣
↪and "No handwashing facility" around the world', fontsize=14)
plt.ylabel('Percentage Coverage')
plt.xlabel('Year')
plt.show()
```



7.1.1 4.6) Data Visualization on Limited

- Following plot demonstrates the Median Percentage Coverages for
  1. “Limited Hygiene”,
  2. “Limited Water Service” and
  3. “Limited Sanitation” #around the world in given years. We are aiming to find trends that are present.

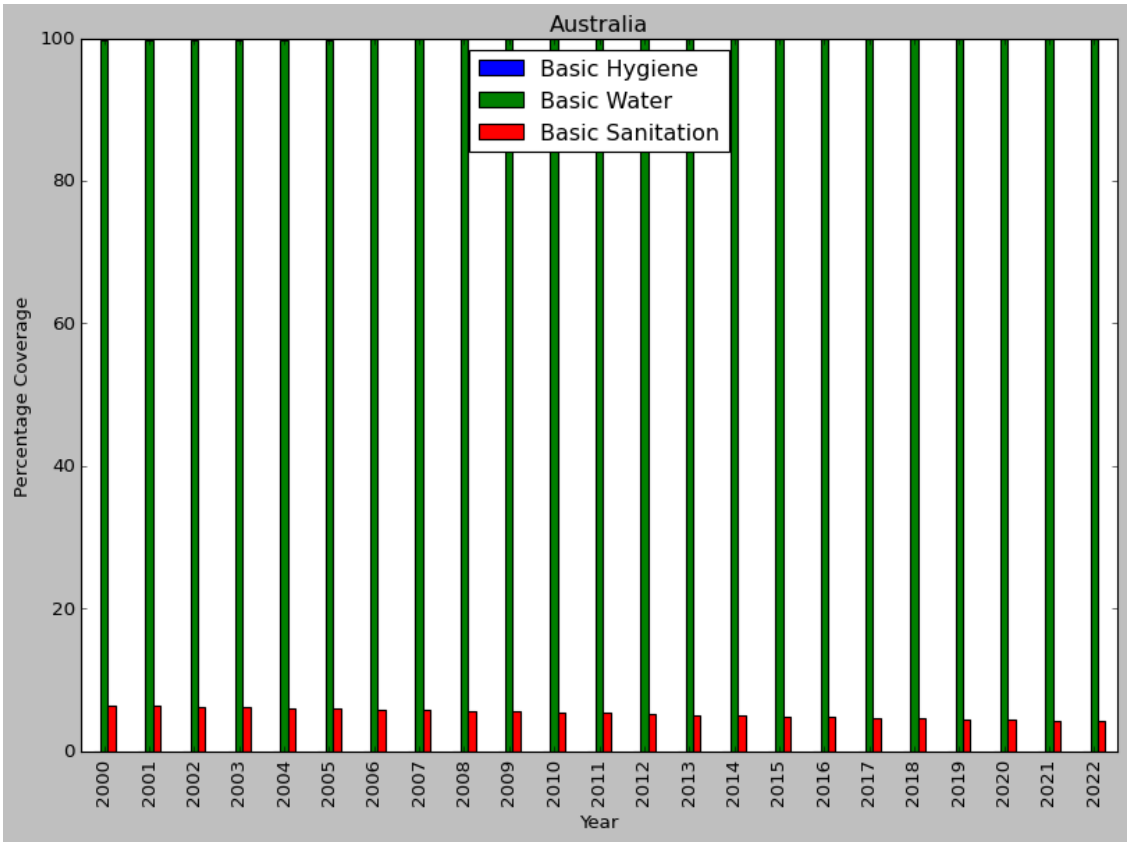
[273]:
```
masterdf.groupby('Year')[['Limited Hygiene', 'Limited Water','Limited␣
 ↪Sanitation']].median().plot(kind='bar', figsize=(12, 8))
plt.suptitle('Medians For Limited Hygiene , Limited Sanitation and Limited␣
 ↪Water Service around the world', fontsize=14)
plt.ylabel('Percentage Coverage')
plt.xlabel('Year')
plt.show()
```

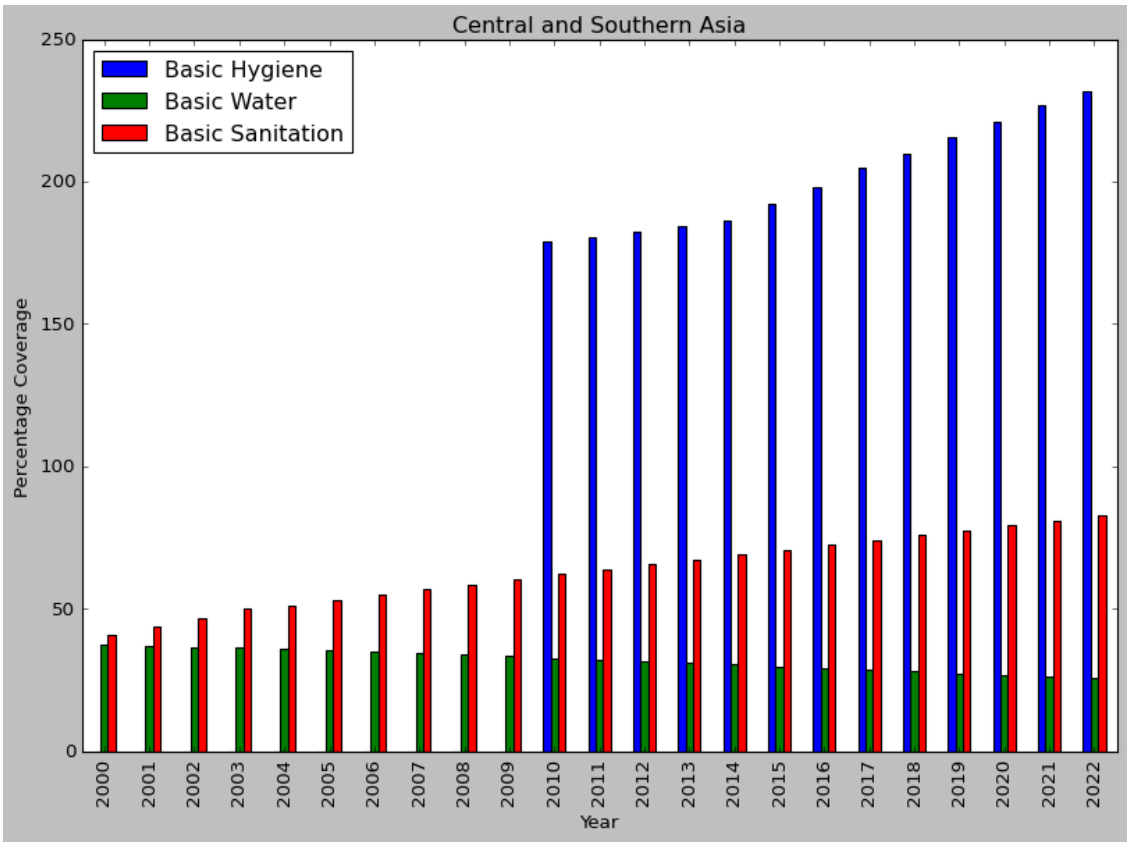


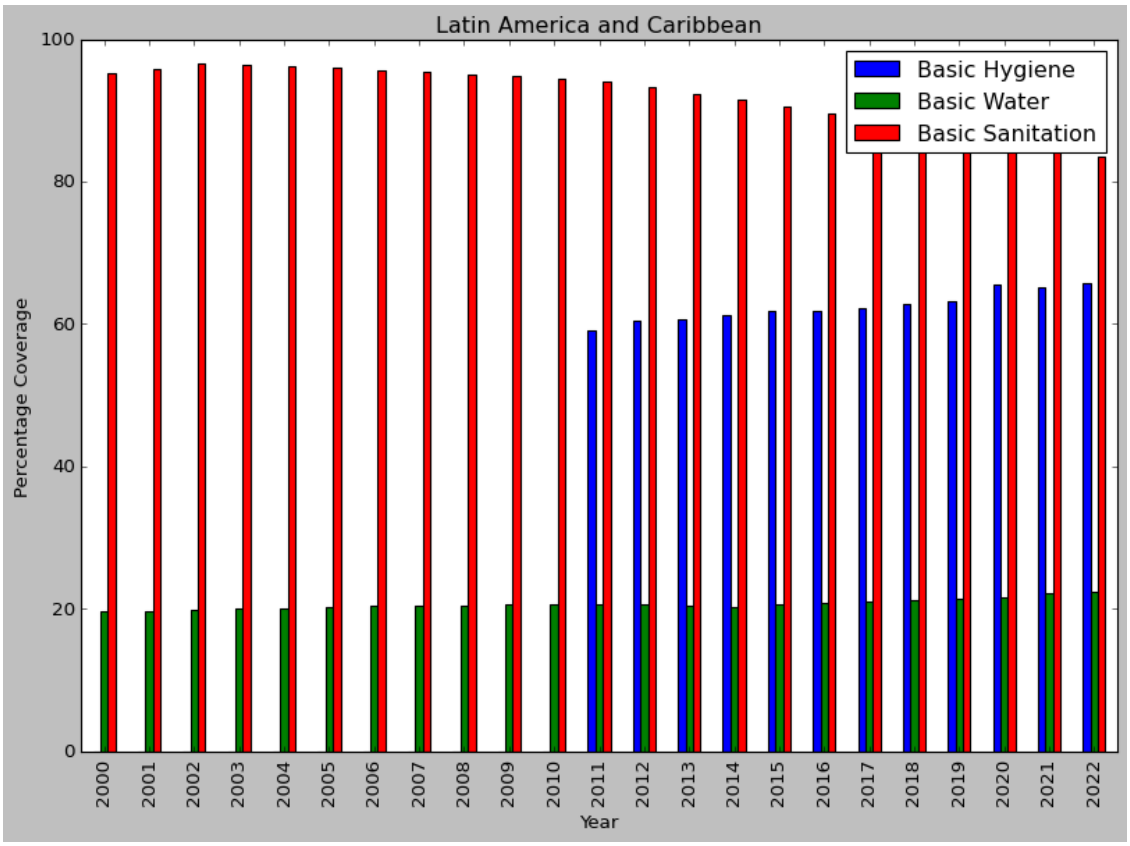
7.1.2 4.7) Data Visualization of "Basic Water", "Basic Sanitation" and "Basic Hygiene" services around different REGIONS

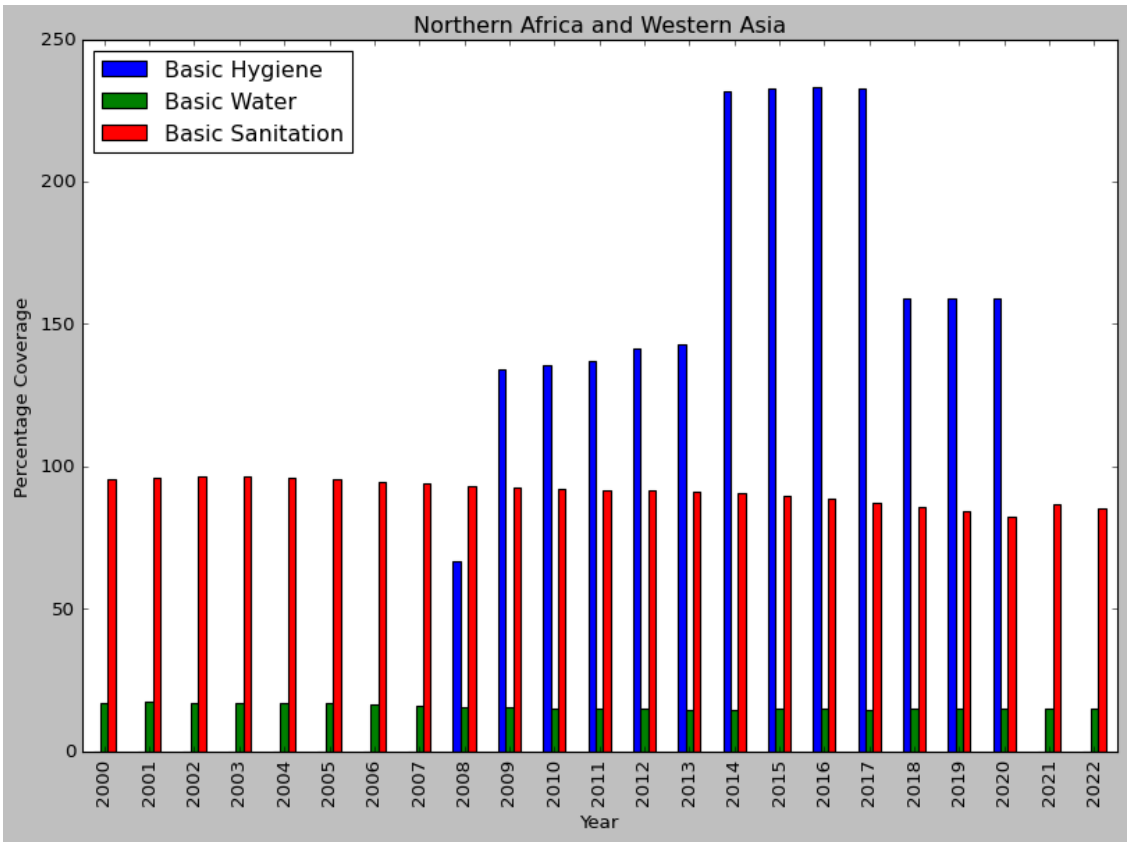
[274]:
```
masterdf_aus = masterdf[masterdf['Region'] == 'Australia and New Zealand']
masterdf_csa = masterdf[masterdf['Region'] == 'Central and Southern Asia']
masterdf_lac = masterdf[masterdf['Region'] == 'Latin America and the Caribbean']
masterdf_nawa = masterdf[masterdf['Region'] == 'Northern Africa and Western␣
 ↪Asia']
masterdf_oce = masterdf[masterdf['Region'] == 'Oceania']
masterdf_ssa = masterdf[masterdf['Region'] == 'Sub-Saharan Africa']
```

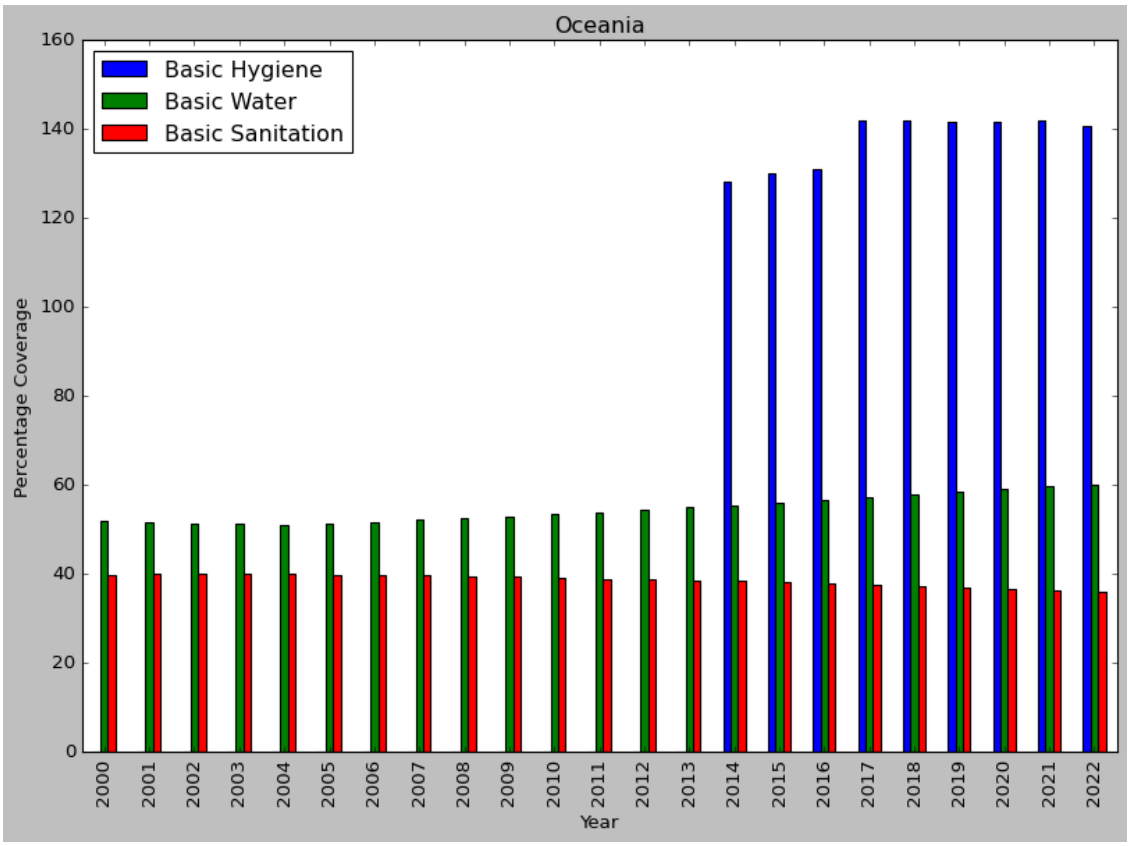
[275]:
```
from matplotlib import pyplot
sdg_regions = [masterdf_aus, masterdf_csa,␣
 ↪masterdf_lac,masterdf_nawa,masterdf_oce,masterdf_ssa]
sdg_region_title = ['Australia',
                    'Central and Southern Asia','Latin America and␣
 ↪Caribbean','Northern Africa and Western Asia','Oceania',
                    'Sub-Saharan Africa']
index = 0
for region in sdg_regions:
    title = sdg_region_title[index]
    region.groupby('Year')[['Basic Hygiene', 'Basic Water','Basic Sanitation']].
 ↪max().plot(kind='bar', figsize=(12, 8))
    plt.ylabel('Percentage Coverage')
    plt.title(title)
    plt.xlabel('Year')
    index += 1
```

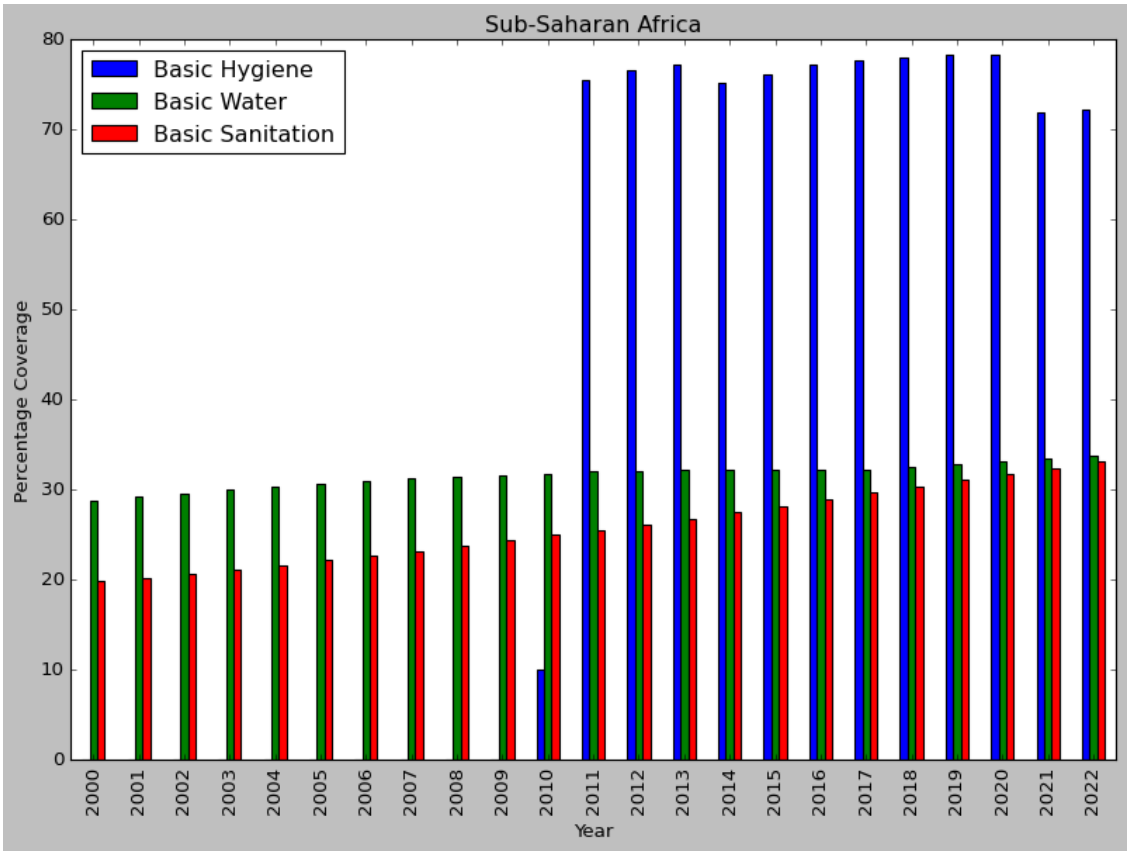



Central and Southern Asia
Basic Hygiene
Basic Water
Basic Sanitation
Percentage Coverage
Year
0
50
100
150
200
250
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022


Latin America and Caribbean
Basic Hygiene
Basic Water
Basic Sanitation
Percentage Coverage
Year
0
20
40
60
80
100
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022


Northern Africa and Western Asia
Basic Hygiene
Basic Water
Basic Sanitation
Percentage Coverage
Year
0
50
100
150
200
250
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022

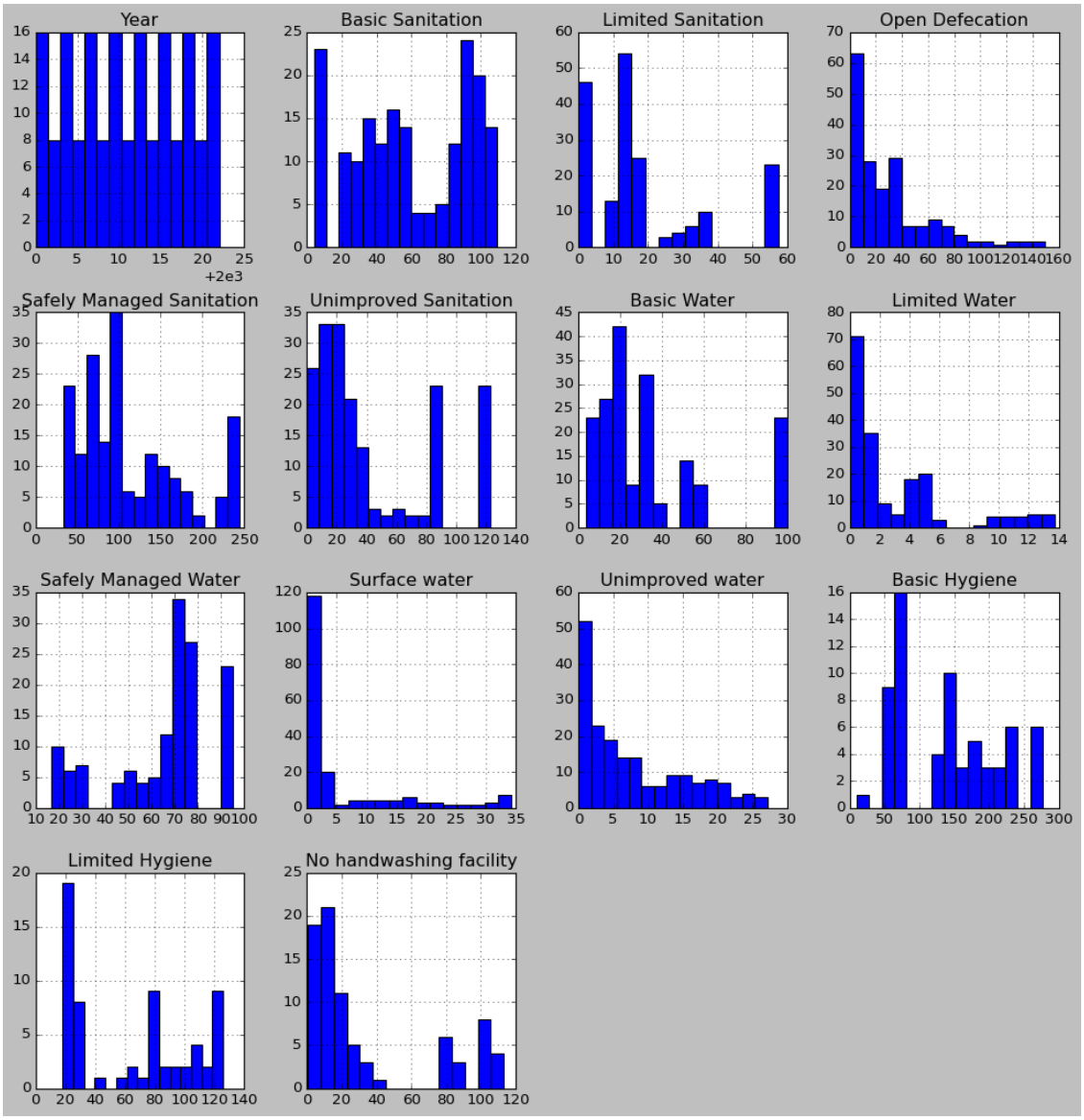

Oceania
Basic Hygiene
Basic Water
Basic Sanitation
Percentage Coverage
Year
0
20
40
60
80
100
120
140
160
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022



7.1.3 4.8) Histograms

- **Histograms** are commonly used for data visualization because they provide a clear representation of the distribution of continuous data.
- By grouping data into intervals (bins) and showing the frequency or percentage of observations in each bin, histograms reveal patterns, identify outliers, and help us understand central tendencies. - They allow quick comparisons between different groups and provide essential insights for data analysis.

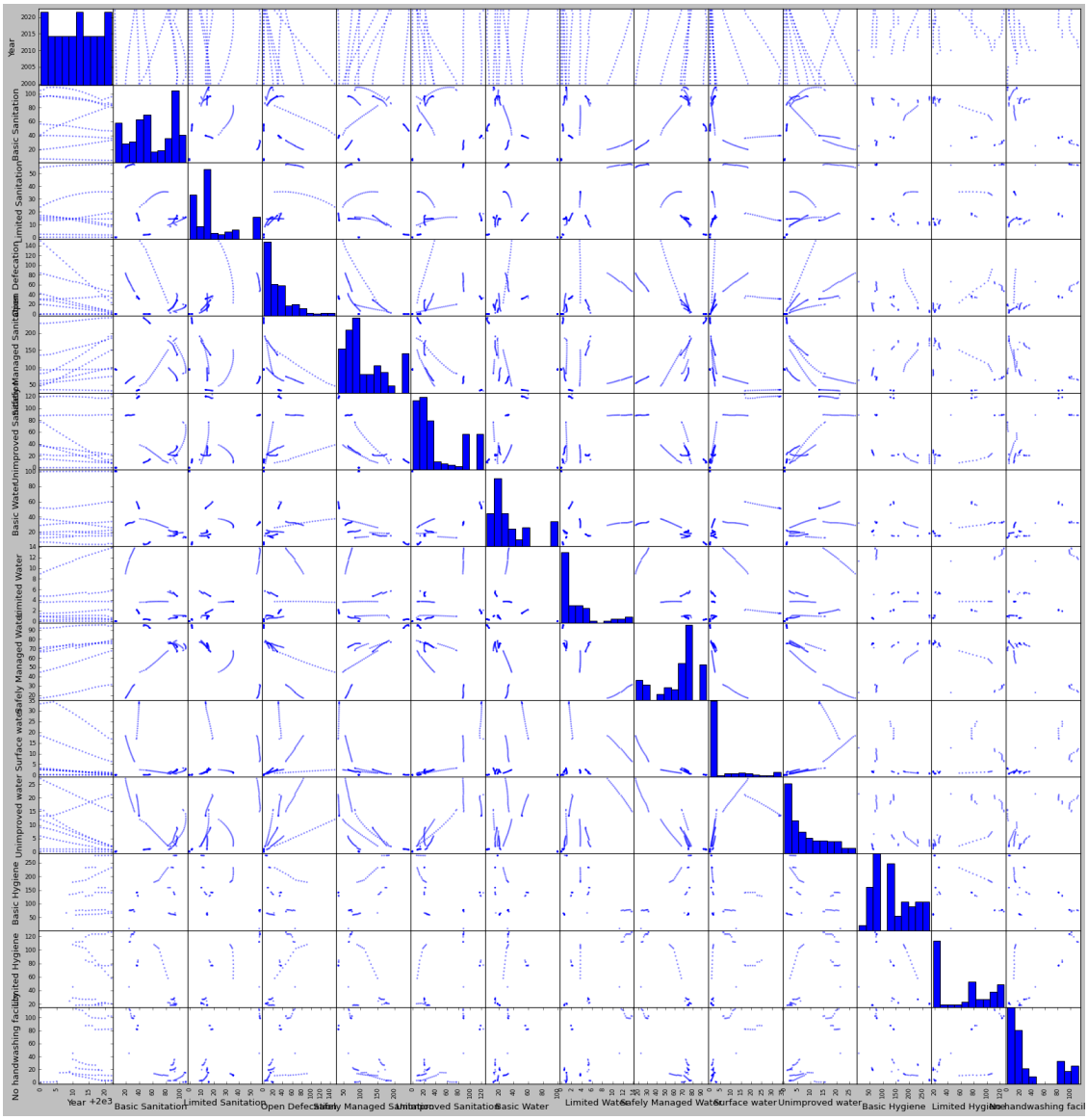
[276]:
```
#Histogram of each category
plt.style.use('classic')
masterdf.hist(bins=15, figsize=(15,15))
plt.show()
```



7.1.4 4.9) Scatter Plots

- **Scatter plots** are widely used for data visualization because they effectively display the relationship between two continuous variables.
- Each data point is represented as a dot, and the position of these dots reveals patterns such as correlations, clusters, or outliers.
- Scatter plots allow quick visual assessment of data distribution and help identify trends, making them essential for exploratory analysis and understanding relationships in data.
- Scatterplots are useful for many reasons: like **correlation matrices**, it allows us to quickly understand a relationship between two categories

[277]:
```
#Scatter plot matrix
from pandas.plotting import scatter_matrix
scatter_matrix(masterdf, figsize=(25,25));
plt.show()
```



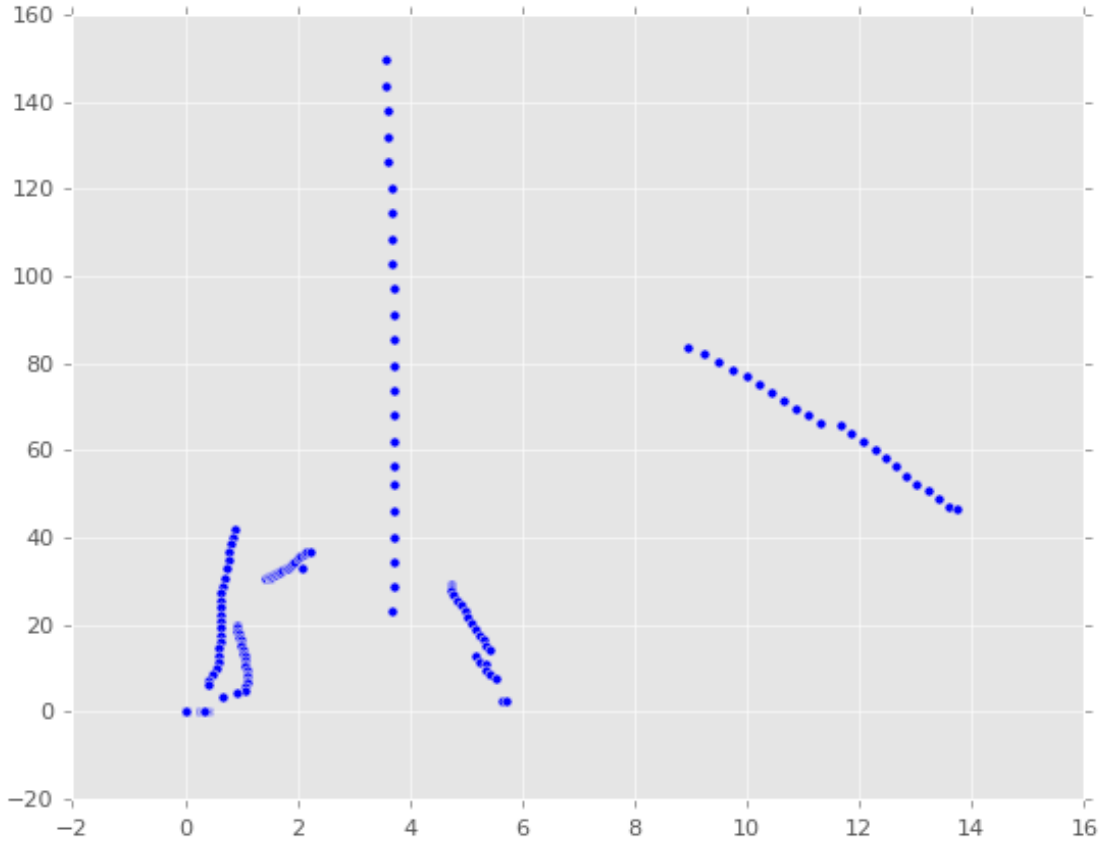
[278]:
```
masterdf.columns
```

[278]:
```
Index(['Region', 'Year', 'Basic Sanitation', 'Limited Sanitation',
       'Open Defecation', 'Safely Managed Sanitation', 'Unimproved Sanitation',
       'Basic Water', 'Limited Water', 'Safely Managed Water', 'Surface water',
       'Unimproved water', 'Basic Hygiene', 'Limited Hygiene',
       'No handwashing facility'],
```

```
      dtype='object')
```

[284]:
```
plt.scatter(x=masterdf['Limited Water'],y=masterdf['Open Defecation']) #␣
 ↪Relation of x with y will be linear or not
```

[284]:
```
<matplotlib.collections.PathCollection at 0x1b8d8327e30>
```



7.1.5 4.10) Pairplot

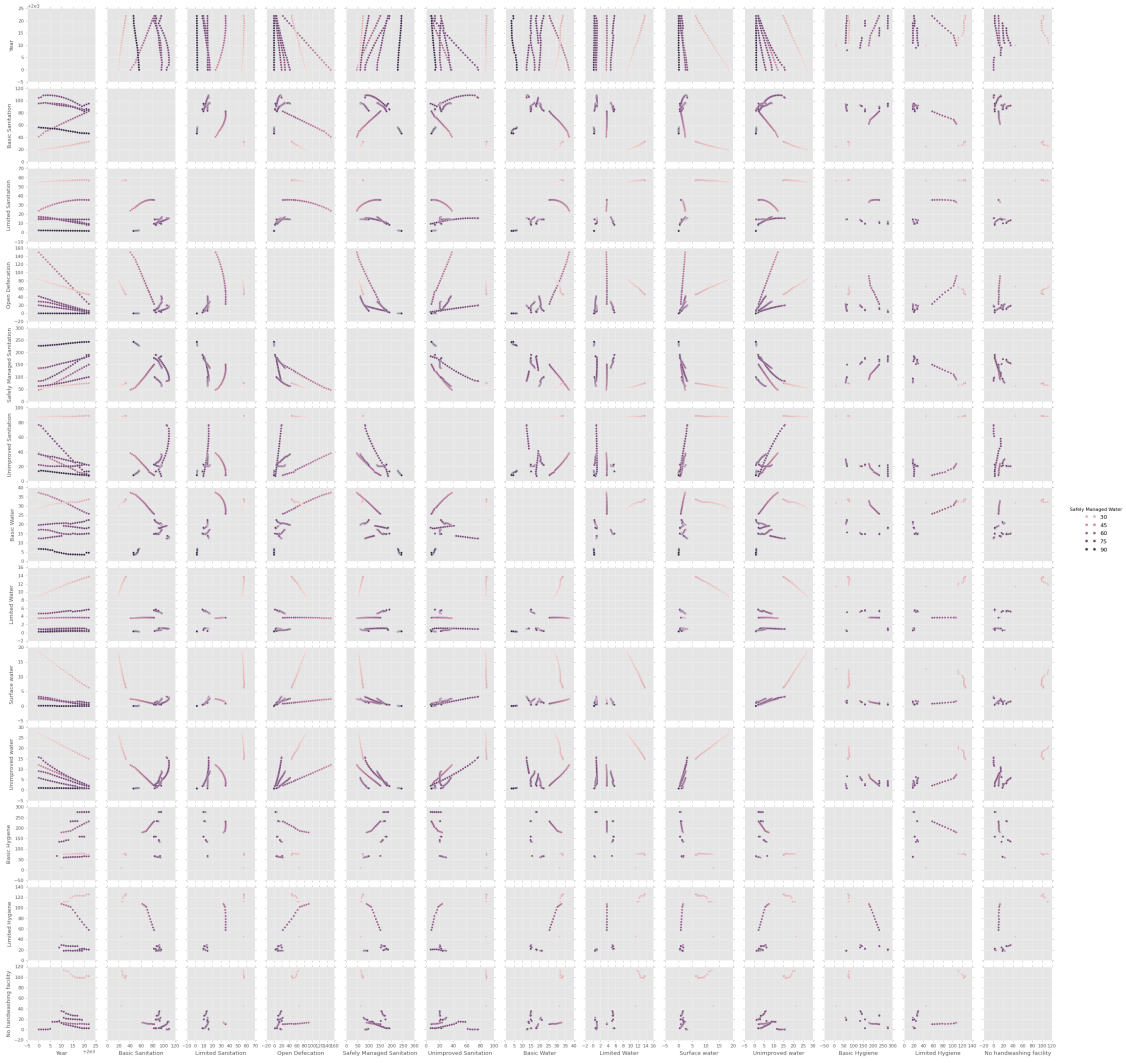
- **Pair plots** provide a comprehensive view of feature interactions in a dataset.
- By displaying scatter plots for pairs of variables, they reveal relationships, clusters, and outliers.
- Pair plots inspire hypotheses and help us understand how features influence each other.
- sns.pairplot() is a great way to create scatterplots between all of our categories

[280]:
```
masterdf.columns
```

[280]:
```
Index(['Region', 'Year', 'Basic Sanitation', 'Limited Sanitation',
       'Open Defecation', 'Safely Managed Sanitation', 'Unimproved Sanitation',
       'Basic Water', 'Limited Water', 'Safely Managed Water', 'Surface water',
```

```
       'Unimproved water', 'Basic Hygiene', 'Limited Hygiene',
       'No handwashing facility'],
      dtype='object')
```

[281]:
```
plt.style.use("ggplot")
sns.pairplot(data=masterdf,hue="Safely Managed Water")
plt.show()
```



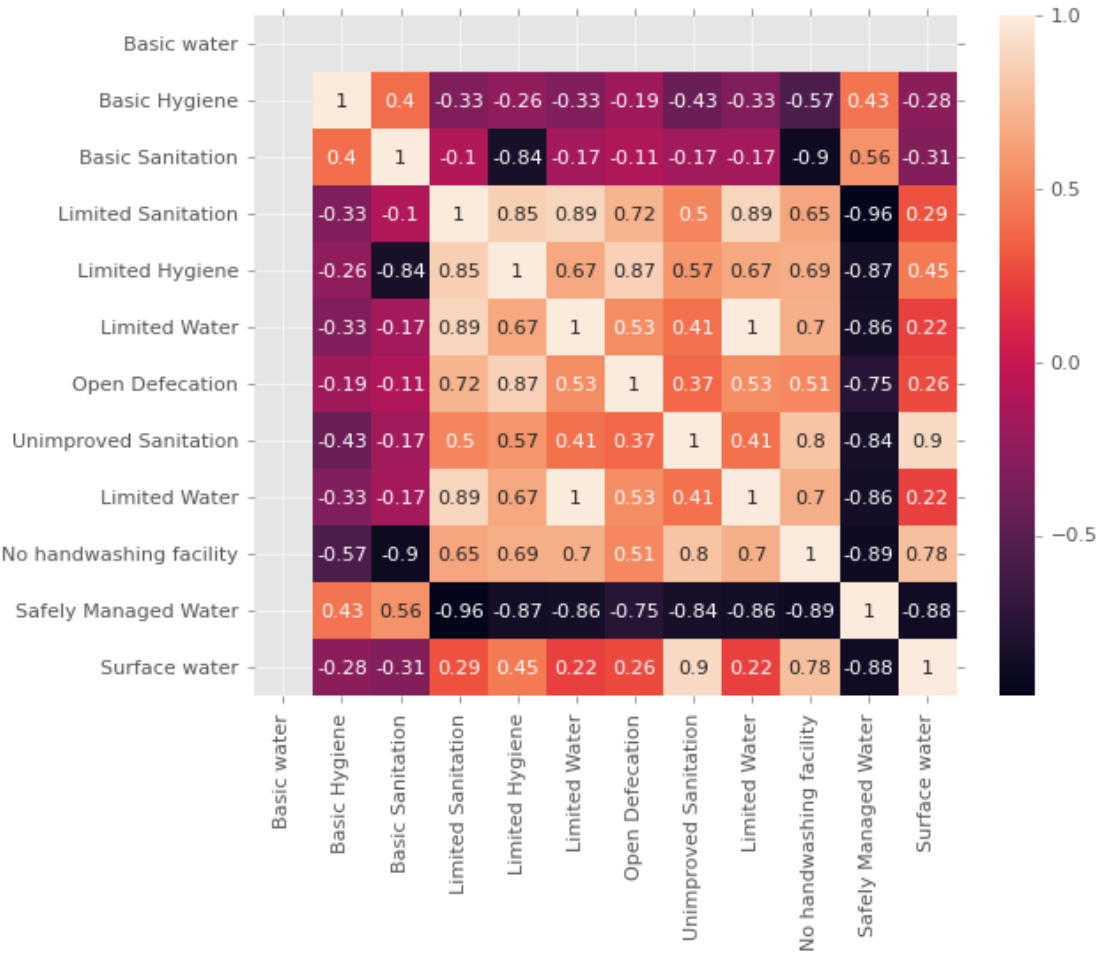
7.1.6 5) Analyzing relationship between variables

Correlation analysis - Correlation analysis in Data Analysis is a statistical technique used to measure the strength and direction of the relationship between two or more variables in a dataset. - It helps data analysts to understand how changes in one variable are associated with changes in another. - By calculating correlation coefficients, such as Pearson's correlation coefficient for continuous variables or rank-based correlations for non-linear or ordinal data, data scientists can

identify patterns and dependencies in the data. - This analysis is valuable for feature selection, identifying potential predictor variables, and gaining insights into the interactions between different aspects of the dataset, facilitating better decision-making and predictive modeling.

[282]:
```
# Correlations provide evidence of association, not causation.
# Positive r values indicate positive association between the variables, and␣
 ↪negative r values indicate negative associations.
from pandas import DataFrame
import seaborn as sns

df = DataFrame(masterdf,columns=['Basic water','Basic Hygiene','Basic␣
 ↪Sanitation','Limited Sanitation',
                          'Limited Hygiene','Limited Water', 'Open␣
 ↪Defecation','Unimproved Sanitation','Limited Water','No handwashing␣
 ↪facility','Safely Managed Water','Surface water'])

corrMatrix = df.corr()
sns.heatmap(corrMatrix, annot=True)
```

[282]: <Axes: >



Deinitions of Terms used above

1. **Basic Water**: According to UNICEF, basic water refers to access to an improved water source **within a *30-minute* walk from home**. This can include piped water, public taps, boreholes, protected wells, and rainwater collection systems.
2. **Basic Hygiene**: UNICEF defines basic hygiene as the availability of a handwashing facility with soap and water within the household or **within a *30-minute* walk from home**.
3. **Basic Sanitation**: According to the World Health Organization (WHO), basic sanitation refers to the use of improved sanitation facilities, such as flush toilets, pit latrines, and composting toilets, that are not shared with other households.
4. **Limited Sanitation**: The WHO defines limited sanitation as the use of sanitation facilities that are shared with other households, or the use of unimproved sanitation facilities, such as open pits or bucket toilets.
5. **Limited Hygiene**: UNICEF defines limited hygiene as the availability of a handwashing facility without soap, or the lack of a handwashing facility within the household or **within a *30-minute* walk from home**.
6. **Limited Water**: According to UNICEF, limited water refers to access to an improved water source that is **more than *30 minutes* away from home**, or the use of unimproved water sources, such as surface water or unprotected wells.
7. **Open Defecation**: The WHO defines open defecation as the practice of defecating in the open, without using a toilet or other sanitation facility.
8. **Unimproved Sanitation**: According to the WHO, unimproved sanitation refers to the use of sanitation facilities that do not meet the standards for improved sanitation, such as open pits, bucket toilets, or hanging toilets.
9. **No Handwashing Facility**: UNICEF defines no handwashing facility as the lack of a handwashing facility with soap and water within the household or **within a *30-minute* walk from home**.
10. **Safely Managed Water**: According to the WHO, safely managed water refers to access to an improved water source that is located on premises, is available when needed, and is free from contamination.
11. **Surface Water**: The WHO defines surface water as water that is collected from the surface of the earth, such as from rivers, lakes, or ponds, without any treatment or protection.

7.2 Conclusions:

7.2.1 Following are closely related

1. **Limited Water & Limited Sanitation**(0.89) : People with limited water access tends to practice shared sanitation facilities or use of unimproved sanitation facilities like open pits or bucket toilets.

2. **Limited Sanitation & Limited Hygiene**(0.85) : People with limited sanitation facilities are likely to follow less hygienic practices like handwashing without SOAP or within a 30-min walk from home.

3. **Limited Hygiene & Open defecation**(0.87) : means people who are less hygienic tends to defecate on open grounds, farms, etc (especially in rural areas and less developed regions),

without using toilets for same.

4. **Surface Water & Unimproved Sanitation**(0.90) : People who collect unfiltered or not-well-treated water from surface sources like rivers, ponds, or lakes,etc are more tilted to practice unimproved sanitation facilities like open pits, hanging toilets,or bucket toilets on open grounds.
5. **Unimproved Sanitation & No handwashing facility**(0.80) : People who are not equiped with good sanitation facilities, lacks the proper handwashing facility(like with soap) or water access 30-min walk from home.