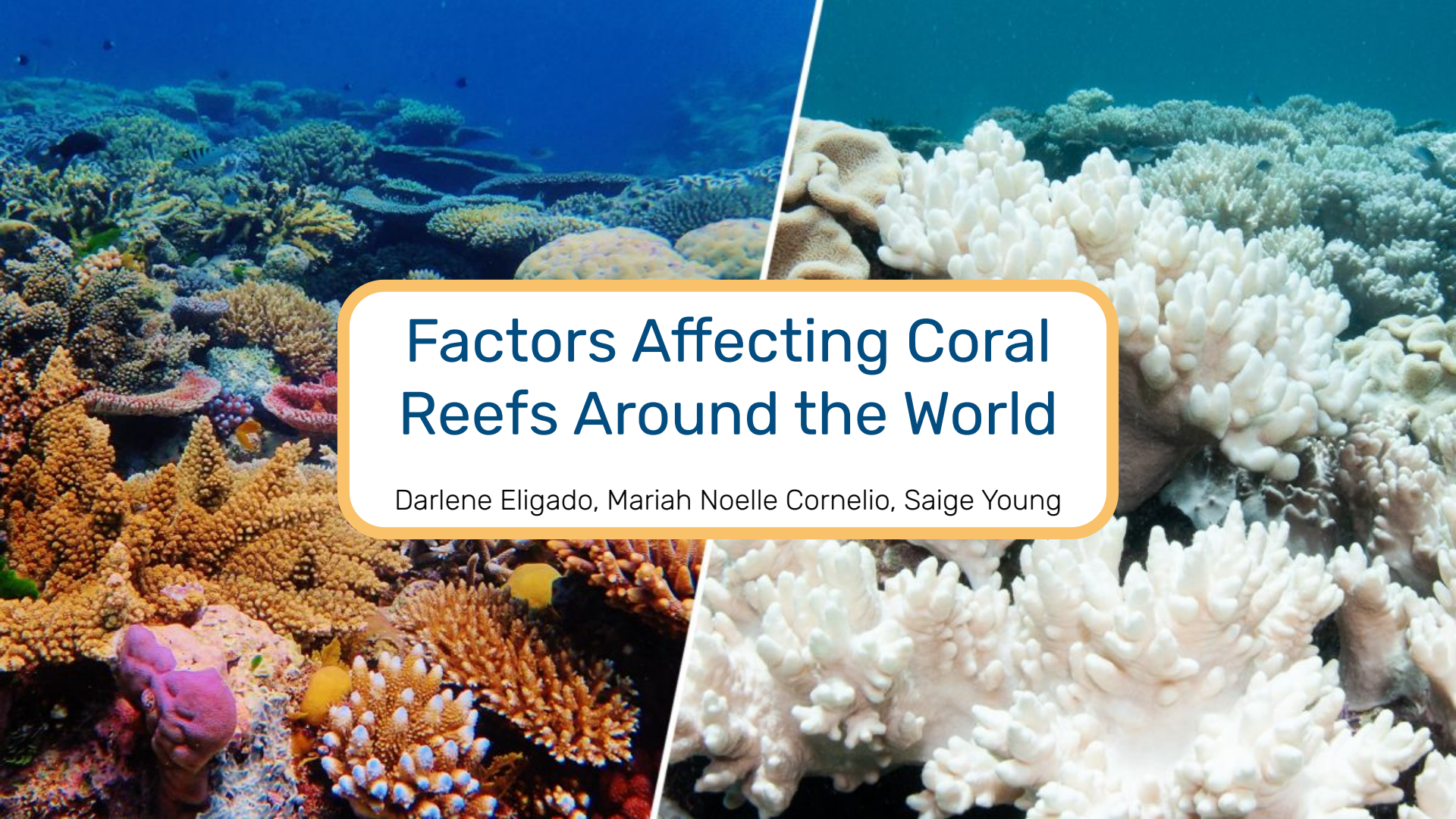

Factors Affecting Coral Reefs Around the World

Darlene Eligado, Mariah Noelle Cornelio, Saige Young

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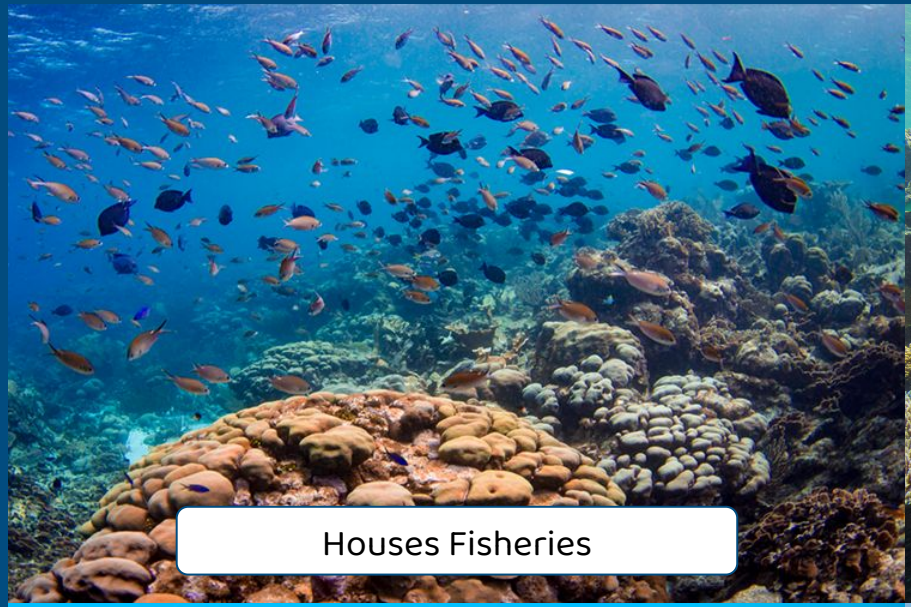
Background



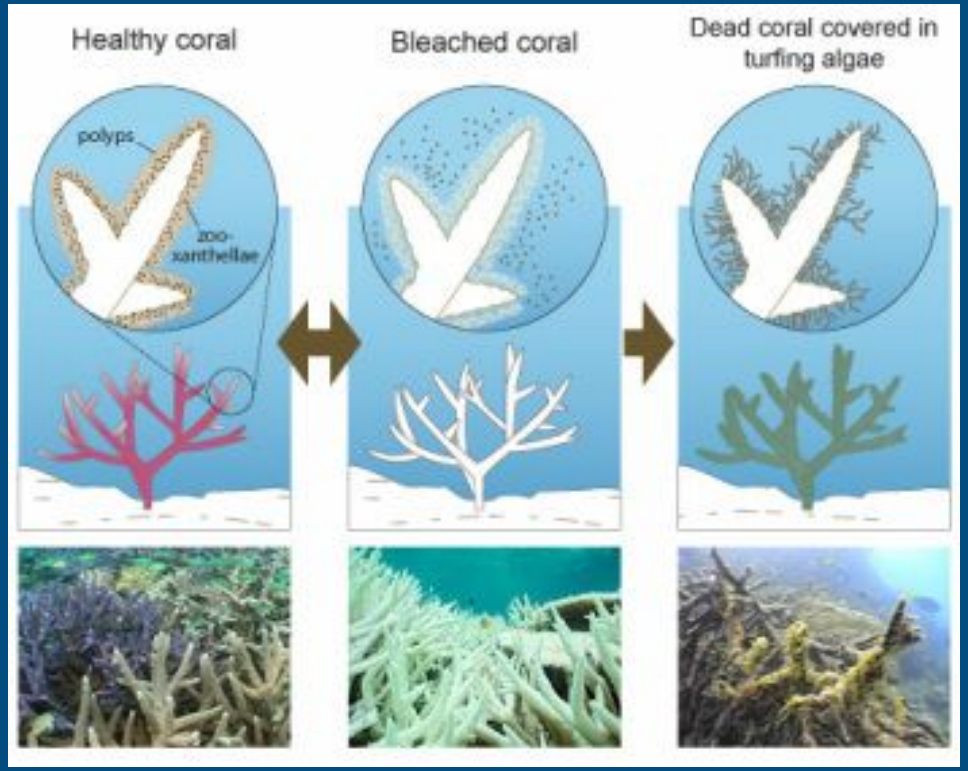
Houses Fisheries

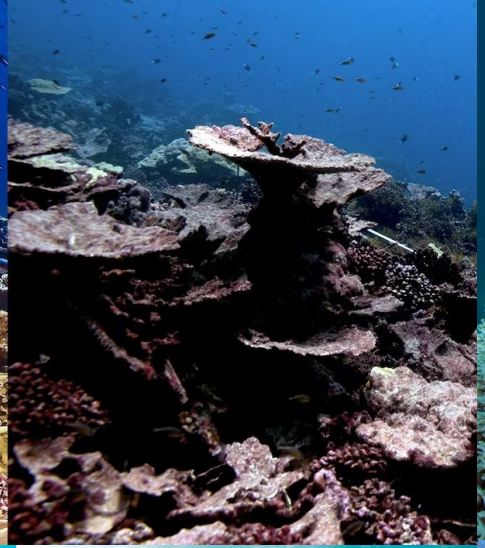
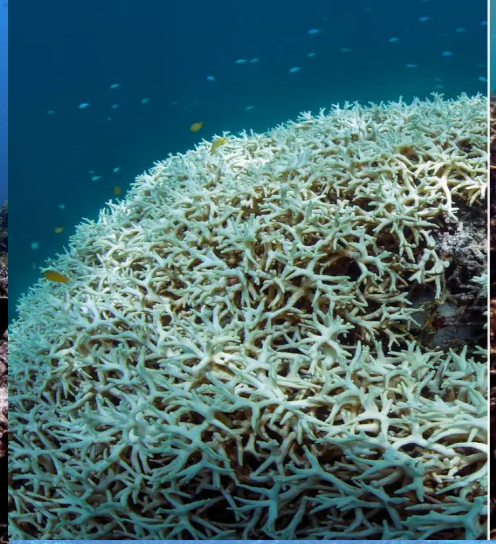
Tourism

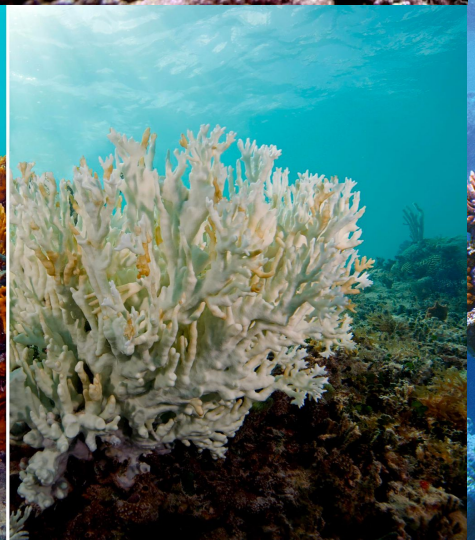
Medicinal Properties

Coastline Protection

Comparison of Zooxanthellae in Healthy vs Bleached Corals



Objective:

Show how various factors such as the rise of Earth's temperatures affect coral reefs on a global scale

Our Dataset

Publisher: Biological & Chemical Oceanography Data Management Office

Title: "Global Bleaching and Environmental Data"

PI: Robert van Woesik

Project: Take data of bleaching events of coral reefs globally every 52 weeks (one year). Began in 1980. Last sample was taken in 2022.

02

Data Understanding

import and display columns

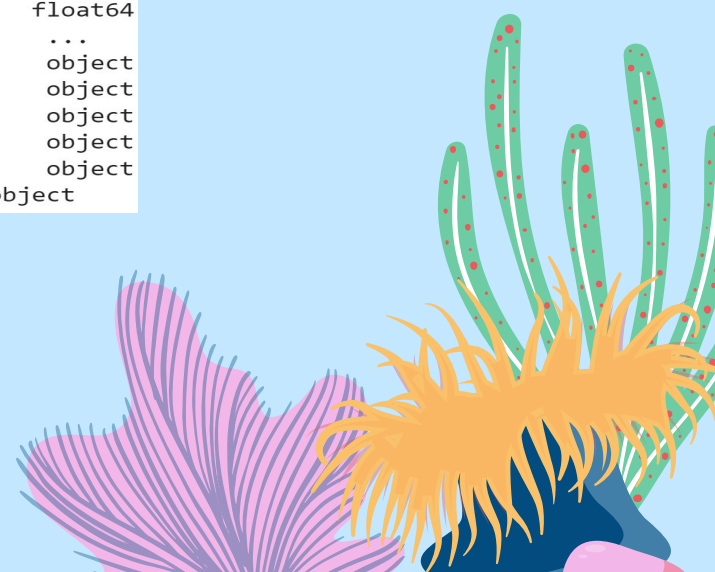
```
## display all columns and column types ##
df.columns
```

```
Index(['Site_ID', 'Sample_ID', 'Data_Source', 'Latitude_Degrees',
       'Longitude_Degrees', 'Ocean_Name', 'Reef_ID', 'Realm_Name',
       'Ecoregion_Name', 'Country_Name', 'State_Island_Province_Name',
       'City_Town_Name', 'Site_Name', 'Distance_to_Shore', 'Exposure',
       'Turbidity', 'Cyclone_Frequency', 'Date_Day', 'Date_Month', 'Date_Year',
       'Depth_m', 'Substrate_Name', 'Percent_Cover', 'Bleaching_Level',
       'Percent_Bleaching', 'ClimSST', 'Temperature_Kelvin',
       'Temperature_Mean', 'Temperature_Minimum', 'Temperature_Maximum',
       'Temperature_Kelvin_Standard_Deviation', 'Windspeed', 'SSTA',
       'SSTA_Standard_Deviation', 'SSTA_Mean', 'SSTA_Minimum', 'SSTA_Maximum',
       'SSTA_Frequency', 'SSTA_Frequency_Standard_Deviation',
       'SSTA_FrequencyMax', 'SSTA_FrequencyMean', 'SSTA_DHW',
       'SSTA_DHW_Standard_Deviation', 'SSTA_DHWMax', 'SSTA_DHWMean', 'TSA',
       'TSA_Standard_Deviation', 'TSA_Minimum', 'TSA_Maximum', 'TSA_Mean',
       'TSA_Frequency', 'TSA_Frequency_Standard_Deviation', 'TSA_FrequencyMax',
       'TSA_FrequencyMean', 'TSA_DHW', 'TSA_DHW_Standard_Deviation',
       'TSA_DHWMax', 'TSA_DHWMean', 'Date', 'Site_Comments', 'Sample_Comments',
       'Bleaching_Comments'],
      dtype='object')
```

```
columns_and_types = df.dtypes
columns_and_types
```

```
Site_ID                 int64
Sample_ID               int64
Data_Source            object
Latitude_Degrees      float64
Longitude_Degrees     float64
                          ...
TSA_DHWMean            object
Date                   object
Site_Comments          object
Sample_Comments        object
Bleaching_Comments     object
Length: 62, dtype: object
```

```
df=pd.read_csv("global_bleaching_environmental.csv")
df.shape #41361 rows and 62 columns
```



display first and last five rows

```
df.head(5)
```

	Site_ID	Sample_ID	Data_Source	Latitude_Degrees	Longitude_Degrees	Ocean_Name	Reef_ID	Realm_Name	Ecoregion_Name	Country_Name	...	TSA_FrequencyMax	TSA_FrequencyMean	TSA_DHW	TSA_DHW_Standard_Deviation	TSA_DHWMax	TSA_DHWMean	Date	Site_Comments	Sample_Comments	Bleaching_Comments
0	2501	10324336	Donner	23.163	-82.5260	Atlantic	nd	Tropical Atlantic	Cuba and Cayman Islands	Cuba	...	5	0	0	0.74	7.25	0.18	2005-09-15	nd	nd	nd
1	3467	10324754	Donner	-17.575	-149.7833	Pacific	nd	Eastern Indo-Pacific	Society Islands French Polynesia	French Polynesia	...	4	0	0.26	0.67	4.65	0.19	1991-03-15	The bleaching does not appear to have gained ...	The bleaching does not appear to have gained ...	nd
2	1794	10323866	Donner	18.369	-64.5640	Atlantic	nd	Tropical Atlantic	Hispaniola Puerto Rico and Lesser Antilles	United Kingdom	...	7	0	0	1.04	11.66	0.26	2006-01-15	nd	nd	nd
3	8647	10328028	Donner	17.760	-64.5680	Atlantic	nd	Tropical Atlantic	Hispaniola Puerto Rico and Lesser Antilles	United States	...	4	0	0	0.75	5.64	0.2	2006-04-15	nd	nd	nd
4	8648	10328029	Donner	17.769	-64.5830	Atlantic	nd	Tropical Atlantic	Hispaniola Puerto Rico and Lesser Antilles	United States	...	5	0	0	0.92	6.89	0.25	2006-04-15	nd	nd	nd

```
df.tail(5)
```

	Site_ID	Sample_ID	Data_Source	Latitude_Degrees	Longitude_Degrees	Ocean_Name	Reef_ID	Realm_Name	Ecoregion_Name	Country_Name	...	TSA_FrequencyMax	TSA_FrequencyMean	TSA_DHW	TSA_DHW_Standard_Deviation	TSA_DHWMax	TSA_DHWMean	Date	Site_Comments	Sample_Comments	Bleaching_Comments
41356	15446	10310562	Reef_Check	-8.3651	116.0844	Pacific	116.5.3.9E.8.21.54.4S	Central Indo-Pacific	Lesser Sunda Islands and Savu Sea	Indonesia	...	8	1	2.09	1.49	9	0.63	2019-05-28	nd	nd	nd
41357	15456	10310527	Reef_Check	-8.3473	116.0503	Pacific	116.3.1.1E.8.20.50.2S	Central Indo-Pacific	Lesser Sunda Islands and Savu Sea	Indonesia	...	8	1	2	1.29	8.01	0.65	2019-05-16	nd	nd	nd
41358	15456	10310527	Reef_Check	-8.3473	116.0503	Pacific	116.3.1.1E.8.20.50.2S	Central Indo-Pacific	Lesser Sunda Islands and Savu Sea	Indonesia	...	8	1	2	1.29	8.01	0.65	2019-05-16	nd	nd	nd
41359	15457	10310536	Reef_Check	-8.3445	116.0629	Pacific	116.3.46.548E.8.20.40.236S	Central Indo-Pacific	Lesser Sunda Islands and Savu Sea	Indonesia	...	8	1	2	1.29	8.01	0.65	2019-05-29	nd	nd	nd
41360	15457	10310536	Reef_Check	-8.3445	116.0629	Pacific	116.3.46.548E.8.20.40.236S	Central Indo-Pacific	Lesser Sunda Islands and Savu Sea	Indonesia	...	8	1	2	1.29	8.01	0.65	2019-05-29	nd	nd	nd

identify missing values

```
## identify any missing values in the dataset ##
df.isnull().sum()
```

```
Site_ID               0
Sample_ID             0
Data_Source           0
Latitude_Degrees      0
Longitude_Degrees     0
                     ..
TSA_DHWMean           0
Date                  0
Site_Comments         0
Sample_Comments       0
Bleaching_Comments    0
Length: 62, dtype: int64
```

```
# in this case, our missing values are called "nd", so it is best to remove the columns we do
# not need first and then filter out the missing values from those selected columns.
```

03

Data Cleaning

removing null values

```
## removing the rows we do not need ##
remove_columns=["Site_ID","Data_Source","Reef_ID",
                "City_Town_Name","Site_Name","Date_Day","Date_Month","Substrate_Name",
                "Temperature_Minimum","Temperature_Maximum","Temperature_Kelvin_Standard_Deviation",
                "SSTA_Standard_Deviation","SSTA_Minimum","SSTA_Maximum","SSTA_Frequency_Standard_Deviation",
                "SSTA_FrequencyMax","SSTA_DHW_Standard_Deviation","SSTA_DHWMax","TSA_Standard_Deviation",
                "TSA_Maximum","TSA_Frequency_Standard_Deviation","TSA_FrequencyMax","TSA_DHW_Standard_Deviation",
                "Date","Site_Comments","Sample_Comments","Bleaching_Comments"]

df=df.drop(columns=remove_columns)
```

```
## changing "nd" to "NA" and removing those null values to reduce the dataset ##
df.replace("nd", None, inplace=True)
df.dropna(inplace=True)
```

more data cleaning

```
## remove any duplicate rows ##
df.drop_duplicates(inplace=True)
```

```
## removing outliers or setting a threshold ##
df=df[df["Date_Year"]>2013] #takes data obtained in the last 10 years
```

```
# convert data types to desired type
df["Cyclone_Frequency"] = df["Cyclone_Frequency"].astype(int)
df["Temperature_Kelvin"] = pd.to_numeric(df["Temperature_Kelvin"])
df["Percent_Bleaching"] = pd.to_numeric(df["Percent_Bleaching"])
df["SSTA"] = pd.to_numeric(df["SSTA"])
df["SSTA_Frequency"] = pd.to_numeric(df["SSTA_Frequency"])
df["TSA"] = pd.to_numeric(df["TSA"])
df["TSA_Frequency"] = pd.to_numeric(df["TSA_Frequency"])
df["Distance_to_Shore"] = pd.to_numeric(df["Distance_to_Shore"])
df["Turbidity"] = pd.to_numeric(df["Turbidity"])
df["Depth_m"] = pd.to_numeric(df["Depth_m"])
df["ClimSST"] = pd.to_numeric(df["ClimSST"])
df["Windspeed"] = pd.to_numeric(df["Windspeed"])
df["SSTA_DHW"] = pd.to_numeric(df["SSTA_DHW"])
df["TSA_DHW"] = pd.to_numeric(df["TSA_DHW"])

df["Temperature_Kelvin"] = df["Temperature_Kelvin"].astype(int)
df["Percent_Bleaching"] = df["Percent_Bleaching"].astype(int)
df["Windspeed"] = df["Windspeed"].astype(int)
```

```
Sample_ID                      int64
Latitude_Degrees             float64
Longitude_Degrees            float64
Ocean_Name                    object
Realm_Name                    object
Ecoregion_Name                object
Country_Name                  object
State_Island_Province_Name    object
Distance_to_Shore             object
Exposure                      object
Turbidity                     object
Cyclone_Frequency            float64
Date_Year                      int64
Depth_m                       object
Percent_Cover                 object
Bleaching_Level               object
Percent_Bleaching             object
ClimSST                       object
Temperature_Kelvin            object
Temperature_Mean              object
Windspeed                     object
SSTA                          object
SSTA_Mean                     object
SSTA_Frequency                object
SSTA_FrequencyMean            object
...
TSA_FrequencyMean             object
TSA_DHW                       object
TSA_DHWMax                    object
TSA_DHWMean                   object
dtype: object
```

```
Sample_ID                      int64
Latitude_Degrees             float64
Longitude_Degrees            float64
Ocean_Name                    object
Realm_Name                    object
Ecoregion_Name                object
Country_Name                  object
State_Island_Province_Name    object
Distance_to_Shore             float64
Exposure                      object
Turbidity                     float64
Cyclone_Frequency               int64
Date_Year                       int64
Depth_m                       float64
Percent_Cover                 object
Bleaching_Level               object
Percent_Bleaching               int64
ClimSST                       float64
Temperature_Kelvin              int64
Temperature_Mean              object
Windspeed                       int64
SSTA                          float64
SSTA_Mean                     object
SSTA_Frequency                float64
SSTA_FrequencyMean            object
...
TSA_FrequencyMean             object
TSA_DHW                       float64
TSA_DHWMax                    object
TSA_DHWMean                   object
dtype: object
```

final results

```
### check shape of dataframe ##
df.shape
```

```
(7690, 35)
```

We were able to reduce our dataset to 7690 rows and 35 columns as opposed to our beginning 41361 rows and 62 columns.

04

Data Preprocessing

oop

```python
# create an OOP to change Kelvin to Celsius ##
class Convert:
    def __init__(self, dataframe, kelvin_column):
        self.dataframe=dataframe
        self.kelvin_column=kelvin_column

    def KelvintoCelsius(self, kelvin_temp):
        return kelvin_temp - 273

    def convert_column(self):
        self.dataframe[self.kelvin_column]=self.dataframe[self.kelvin_column].apply(self.KelvintoCelsius)
        return self.dataframe
```

applying the oop

```
df["Temperature_Kelvin"].head(3) # before conversion
```

```
6991    297
6992    297
6993    297
Name: Temperature_Kelvin, dtype: int64
```

```
column_to_convert = Convert(df, "Temperature_Kelvin")
df = column_to_convert.convert_column()
```

```
df["Temperature_Kelvin"].head(3) # after conversion
```

```
6991    24
6992    24
6993    24
Name: Temperature_Kelvin, dtype: int64
```

aggregating data

Use a loop/lambda to categorize percent evel bleaching where 0 is “No Bleaching”, 1-30 is “Low Bleaching”, 31-60 is “Moderate Bleaching”, and 61-100 is “Severe Bleaching”

```
df["Bleaching_Status"]=df["Percent_Bleaching"].apply(lambda x:"No Bleaching" if x == 0 else("Low Bleaching" if 1 <= x <= 30 else("Moderate Bleaching" if 31 <= x <= 60 else
...    "Severe Bleaching")))
```

```
df["Bleaching_Status"].tail(3) # check to see if it worked
```

```
35037    Severe Bleaching
35038    Severe Bleaching
35039    Severe Bleaching
Name: Bleaching_Status, dtype: object
```

Make a new csv of bleaching status by country - note that this csv will be used later on to help with data visualization.

```
# make a new csv of bleaching status by country

bleaching_status_by_country=df.groupby(["Country_Name", "Bleaching_Status"]).size().reset_index(name="Count")
bleaching_status_by_country
# bleaching_status_by_country.to_csv("bleaching_status_by_country.csv", index=False)
```

	Country_Name	Bleaching_Status	Count
0	Australia	Low Bleaching	417
1	Australia	Moderate Bleaching	46
2	Australia	No Bleaching	113
3	Australia	Severe Bleaching	14
4	Bahamas	Low Bleaching	12
...	...	...	...
76	Turks and Caicos	No Bleaching	4
77	United Arab Emirates	Moderate Bleaching	2
78	United Arab Emirates	No Bleaching	2
79	United States	Low Bleaching	40
80	United States	No Bleaching	90

81 rows × 3 columns

Group by country and find the SSTA mean location

```
SSTA_mean_country=df.groupby("Country_Name")["SSTA"].mean().reset_index()
SSTA_mean_country
# SSTA_mean_country.to_csv("SSTA_mean_country.csv", index=False)
```

	Country_Name	SSTA
0	Australia	0.466847
1	Bahamas	0.504167
2	Belize	-0.122500
3	Brunei	-0.605000
4	Colombia	-0.100526
5	Dominica	0.493200
6	Dominican Republic	0.290833
7	East Timor	0.278889
8	Egypt	0.527738
9	Fiji	0.001358
10	France	0.536573
11	French Polynesia	0.338419
12	Grenada	0.387931
13	Haiti	0.187727
14	Honduras	1.277500
15	Indonesia	0.162386
16	Iran	-0.066667
17	Jamaica	0.158942
18	Japan	0.183125
19	Madagascar	0.394000
20	Malaysia	0.193809
21	Maldives	0.344849
22	Martinique	0.140000
23	Netherlands Antilles	0.280000
24	Oman	0.814130
25	Philippines	0.141161
26	Saint Kitts and Nevis	0.353158
27	Saint Lucia	-0.135000
28	Sao Tome & Principe	0.309412
29	Taiwan	0.852961
30	Thailand	0.408298
31	Trinidad and Tobago	0.171216
32	Turks and Caicos	0.630000
33	United Arab Emirates	1.475000
34	United States	0.536923

Group by country and find the SSTA_frequency

```
SSTA_frequency_country=df.groupby("Country_Name")["SSTA_Frequency"].size().reset_index(name="Count")
SSTA_frequency_country
# SSTA_frequency_country.to_csv("SSTA_frequency_country.csv", index=False)
```

	Country_Name	Count
0	Australia	590
1	Bahamas	24
2	Belize	16
3	Brunei	48
4	Colombia	38
5	Dominica	25
6	Dominican Republic	24
7	East Timor	18
8	Egypt	305
9	Fiji	162
10	France	213
11	French Polynesia	506
12	Grenada	58
13	Haiti	44
14	Honduras	8
15	Indonesia	943
16	Iran	18
17	Jamaica	208
18	Japan	32
19	Madagascar	20
20	Malaysia	2696
21	Maldives	332
22	Martinique	2
23	Netherlands Antilles	32
24	Oman	92
25	Philippines	310
26	Saint Kitts and Nevis	38
27	Saint Lucia	4

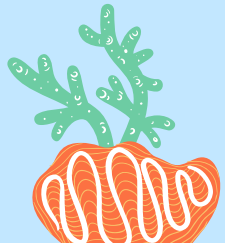
28	Sao Tome & Principe	34
29	Taiwan	466
30	Thailand	94
31	Trinidad and Tobago	148
32	Turks and Caicos	8
33	United Arab Emirates	4
34	United States	130

Group by location and find if the TSA value is positive or negative

```
df["Positive_TSA"] = df["TSA"].apply(lambda x: "Positive" if x >= 0 else "Negative")
TSA_by_country = df.groupby(["Country_Name", "Positive_TSA"]).size().unstack(fill_value=0)
TSA_by_country
# TSA_by_country.to_csv( "TSA_by_country.csv", index=False)
```

Positive_TSA Country_Name	Negative	Positive
Australia	533	57
Bahamas	10	14
Belize	12	4
Brunei	36	12
Colombia	28	10
Dominica	25	0
Dominican Republic	24	0
East Timor	2	16
Egypt	214	91
Fiji	130	32
France	197	16
French Polynesia	342	164
Grenada	44	14
Haiti	40	4
Honduras	8	0
Indonesia	631	312
Iran	18	0

Positive_TSA Country_Name	Negative	Positive
Jamaica	172	36
Japan	28	4
Madagascar	20	0
Malaysia	1877	819
Maldives	248	84
Martinique	2	0
Netherlands Antilles	22	10
Oman	86	6
Philippines	246	64
Saint Kitts and Nevis	38	0
Saint Lucia	4	0
Sao Tome & Principe	27	7
Taiwan	314	152
Thailand	72	22
Trinidad and Tobago	124	24
Turks and Caicos	2	6
United Arab Emirates	2	2
United States	110	20



05

Data Visualization

Objectives

1

Visualizing global bleaching events

2

What could be the best explanation for bleaching events?

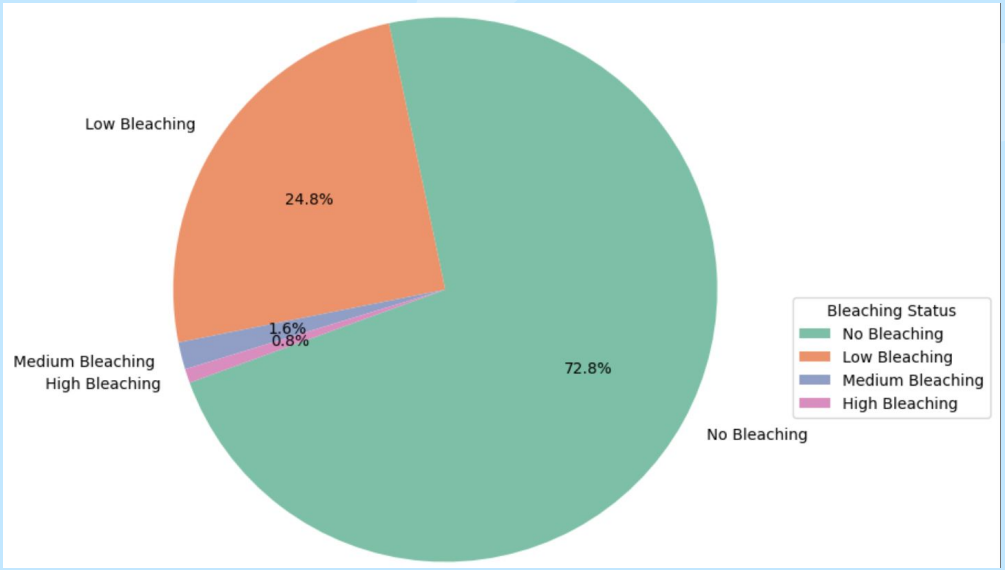
3

When did this begin and the differences between locations

OBJECTIVE 1

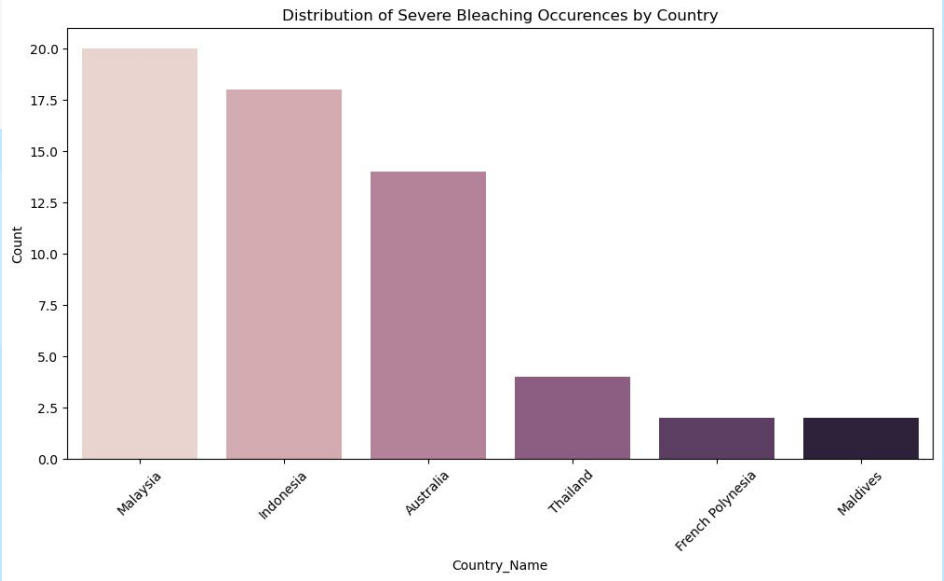
bleaching status frequency

```
bleaching_status_counts=df["Bleaching_Status"].value_counts()
plt.figure(figsize=(8,8))
plt.title("Bleaching Status Distribution Over the Past 10 Years")
plt.pie(bleaching_status_counts, labels=bleaching_status_counts.index,
        autopct="%1.1f%%", colors=sns.color_palette("Set2"), startangle=200)
plt.legend(bleaching_status_counts.index, title="Bleaching Status", bbox_to_anchor=(1, 0.5), loc="best")
plt.show()
```



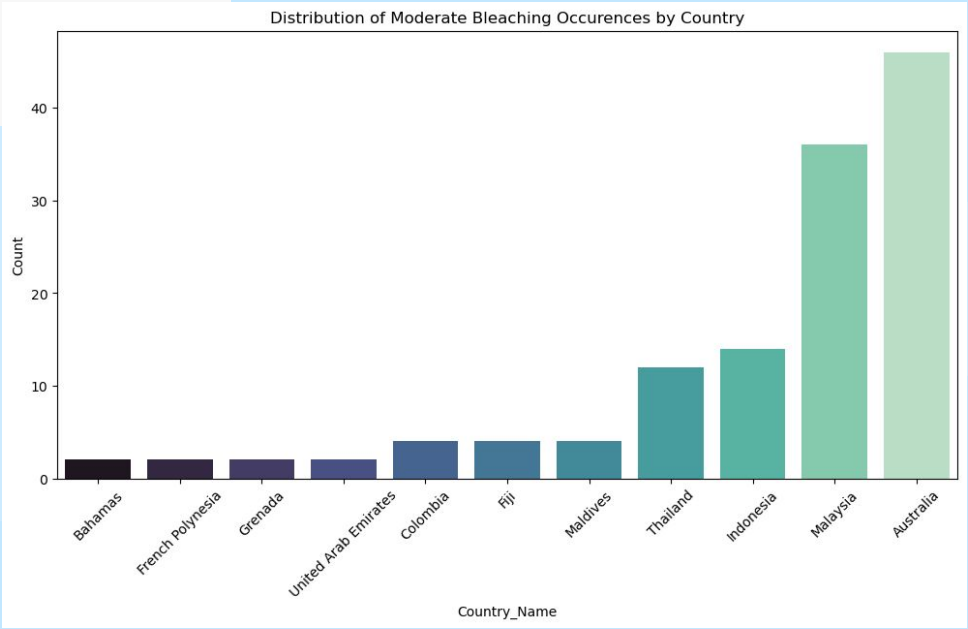
severe bleaching occurrences

```
# OBJECTIVE 1
# bar chart to show the frequency/count of each group by country (moderate and severe)
# Severe
bleach_location_df=pd.read_csv("bleaching_status_by_country.csv")
bleach_location_df=bleach_location_df[bleach_location_df["Bleaching_Status"].isin(["Severe Bleaching"])]
bleach_location_df=bleach_location_df.sort_values("Count", ascending=False)

color_palette=sns.cubehelix_palette()
plt.figure(figsize=(12,6))
sns.barplot(data=bleach_location_df, x="Country_Name", y="Count", palette=color_palette)
plt.xticks(rotation=45)
plt.title("Distribution of Severe Bleaching Occurences by Country")
plt.show()
```



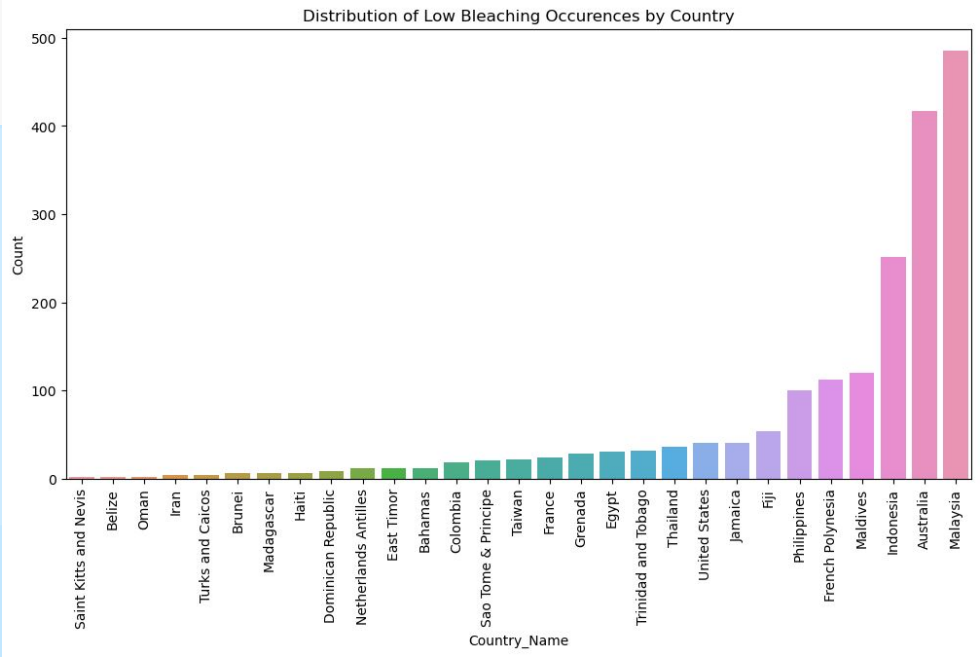
moderate bleaching occurrences

```
# Moderate

bleach_location_df=pd.read_csv("bleaching_status_by_country.csv")
bleach_location_df=bleach_location_df[bleach_location_df["Bleaching_Status"].isin(["Moderate Bleaching"])]
bleach_location_df=bleach_location_df.sort_values("Count", ascending=True)

plt.figure(figsize=(12,6))
sns.barplot(data=bleach_location_df, x="Country_Name", y="Count", palette="mako")
plt.xticks(rotation=45)
plt.title("Distribution of Moderate Bleaching Occurences by Country")
plt.show()
```



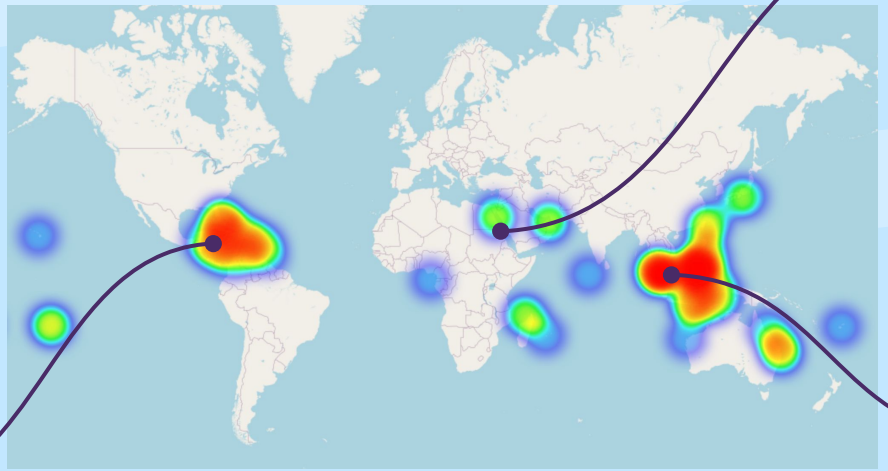
low bleaching occurences

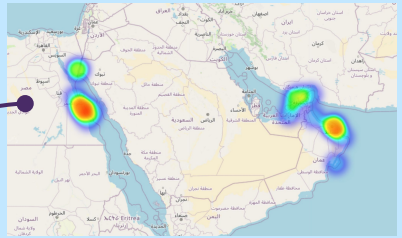
```
# Low

bleach_location_df=pd.read_csv("bleaching_status_by_country.csv")
bleach_location_df=bleach_location_df[bleach_location_df["Bleaching_Status"].isin(["Low Bleaching"])]
bleach_location_df=bleach_location_df.sort_values("Count", ascending=True)

plt.figure(figsize=(12,6))
sns.barplot(data=bleach_location_df, x="Country_Name", y="Count")
plt.xticks(rotation=90)
plt.title("Distribution of Low Bleaching Occurences by Country")
plt.show()
```



heatmap of percent bleaching by coordinates

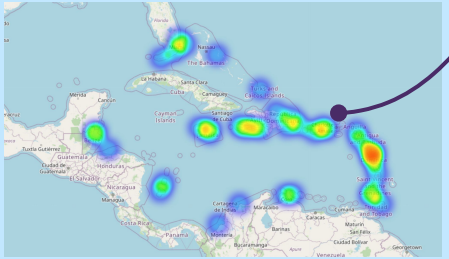
```
import folium
from folium.plugins import HeatMap

bleach_location=df[["Bleaching_Status", "Longitude_Degrees", "Latitude_Degrees"]]
m = folium.Map(location=[bleach_location["Latitude_Degrees"].mean(), bleach_location["Longitude_Degrees"].mean()], zoom_start=2)
heat_data = [[point[0], point[1], 1] for point in zip(bleach_location["Latitude_Degrees"], bleach_location["Longitude_Degrees"])]
HeatMap(heat_data).add_to(m)
# m.save("Bleach_Map_Locations.html")
```



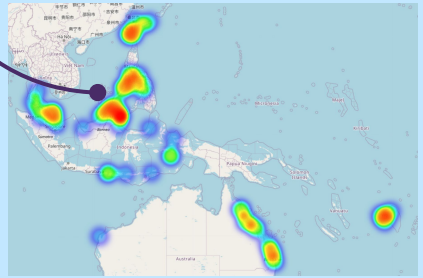


Africa

South America

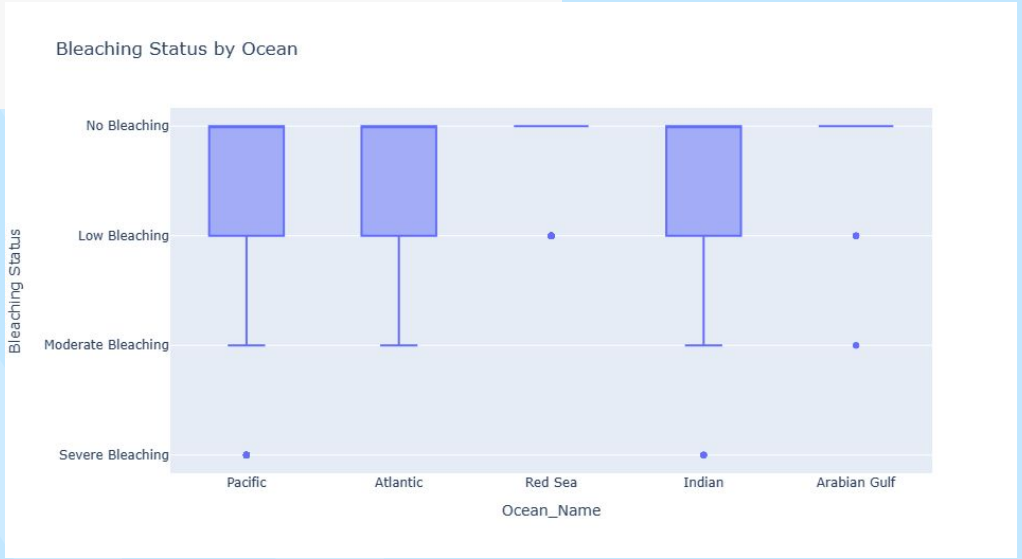


Malaysia/Indonesia



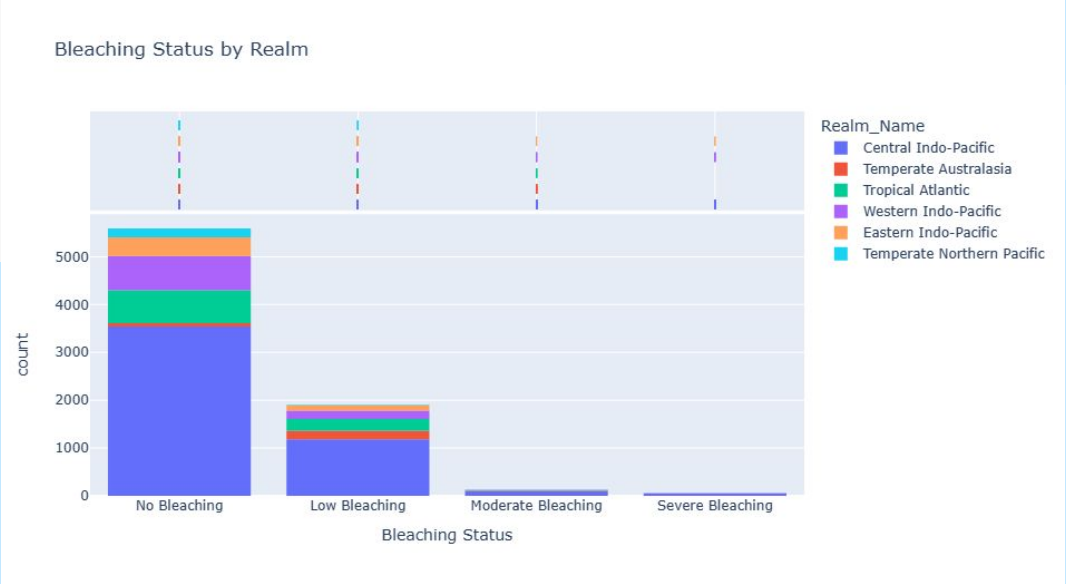
bleaching status by ocean name

```
# compare bleaching_status by ocean using box plot
df_ocean=df[["Ocean_Name", "Bleaching_Status"]]

fig=px.box(
    df_ocean,
    x="Ocean_Name",
    y="Bleaching_Status",
    category_orders={"Bleaching_Status": ["No Bleaching", "Low Bleaching", "Moderate Bleaching", "Severe Bleaching"]},
    title="Bleaching Status by Ocean",
    labels={"Bleaching_Status": "Bleaching Status"},
)

fig.show()
```

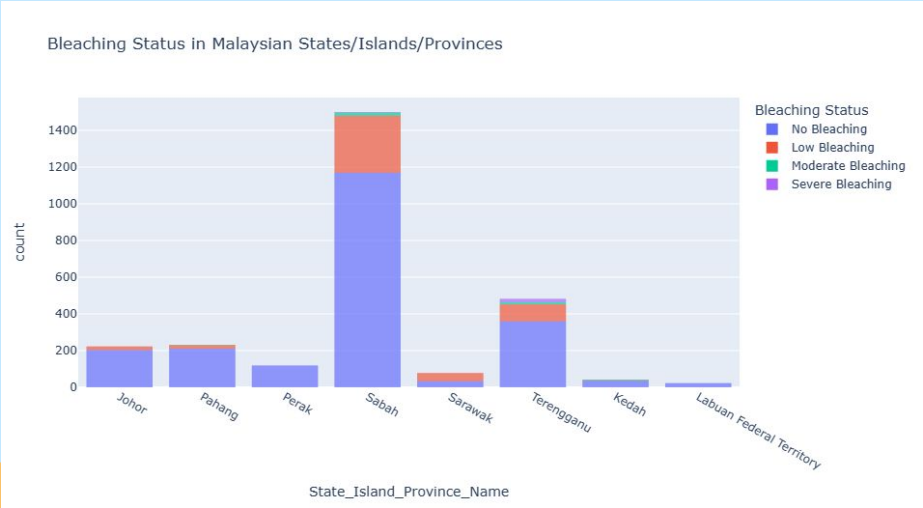


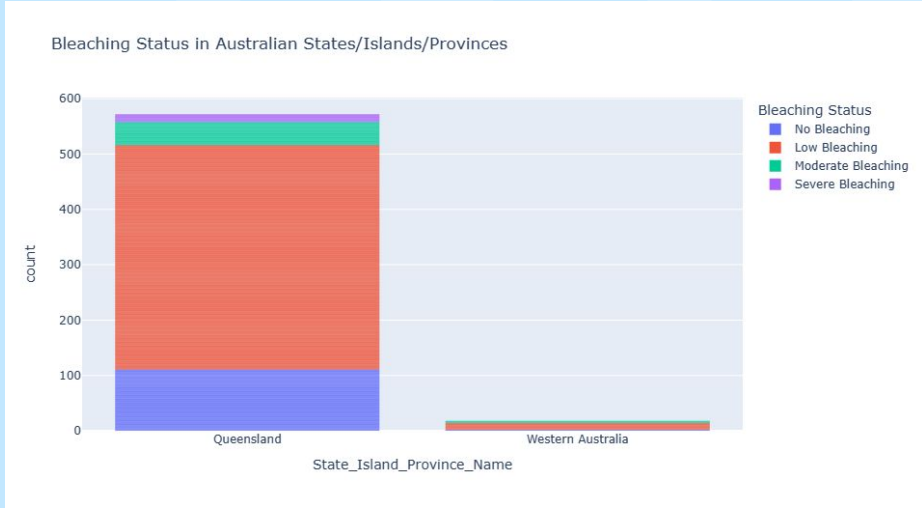
bleaching status by realm

```
# compare bleaching_status by Realm_Name using histogram density plot / bar graph

df_realm=df[["Realm_Name", "Bleaching_Status"]]
fig = px.histogram(
    df_realm,
    x="Bleaching_Status",
    color="Realm_Name",
    marginal="rug",
    title="Bleaching Status by Realm",
    labels={"Bleaching_Status": "Bleaching Status"},
)

fig.show()
```



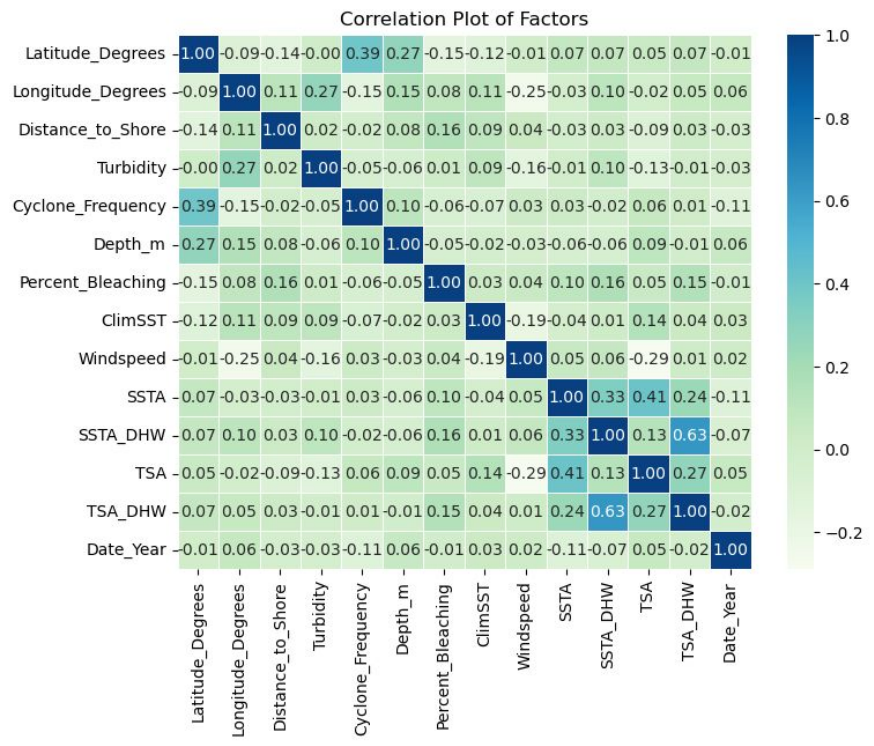
bleaching status in states/islands/provinces of malaysia and australia





OBJECTIVE 2

factors affecting bleaching events



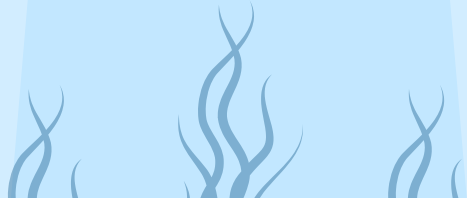

```
sns.pairplot(df, vars=["Distance_to_Shore", "Turbidity", "Depth_m", "Cyclone_Frequency", "ClimSST", "Windspeed", "Date_Year"],
             palette="crest",
             hue="Percent_Bleaching")
plt.legend(title="Percent Bleaching", bbox_to_anchor=(1.05, 0.5), loc='center left')
plt.suptitle("Pair Plot of Various Factors Affecting Bleaching Rates in Corals", size=20)
plt.tight_layout()
plt.subplots_adjust(top=0.90)
plt.show()
```

factors affecting bleaching events
code for pair plot

```
sns.pairplot(df, vars=["Distance_to_Shore", "Turbidity", "Depth_m", "Cyclone_Frequency", "ClimSST", "Windspeed", "Date_Year"],
             palette="crest",
             hue="Percent_Bleaching")
plt.legend(title="Percent Bleaching", bbox_to_anchor=(1.05, 0.5), loc='center left')
plt.suptitle("Pair Plot of Various Factors Affecting Bleaching Rates in Corals", size=20)
plt.tight_layout()
plt.subplots_adjust(top=0.90)
plt.show()
```


Pair Plot of Various Factors Affecting Bleaching Rates in Corals
Distance_to_Shore
Turbidity
Depth_m
Cyclone_Frequency
ClimSST
Windspeed
Date_Year
Percent_Bleaching
0
20
40
60
80
100
Percent Bleaching

OBJECTIVE 3



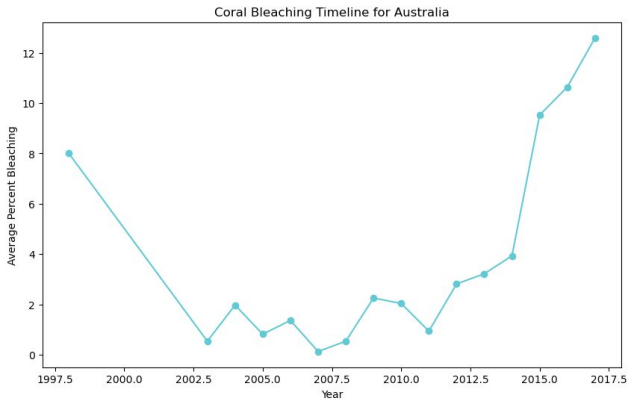
code for the timelines

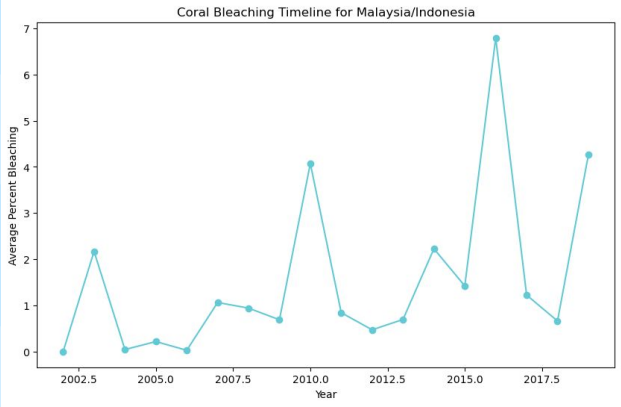
```
df=pd.read_csv("global_bleaching_environmental.csv")
remove_columns=["Site_ID","Data_Source","Reef_ID",
                "City_Town_Name","Site_Name","Date_Day","Date_Month","Substrate_Name",
                "Temperature_Minimum","Temperature_Maximum","Temperature_Kelvin_Standard_Deviation",
                "SSTA_Standard_Deviation","SSTA_Minimum","SSTA_Maximum","SSTA_Frequency_Standard_Deviation",
                "SSTA_FrequencyMax","SSTA_DHW_Standard_Deviation","SSTA_DHWMax","TSA_Standard_Deviation",
                "TSA_Maximum","TSA_Frequency_Standard_Deviation","TSA_FrequencyMax","TSA_DHW_Standard_Deviation",
                "Date","Site_Comments","Sample_Comments","Bleaching_Comments"]
df=df.drop(columns=remove_columns)
df.replace("nd", None, inplace=True)
df.dropna(inplace=True)
df.drop_duplicates(inplace=True)
df["Percent_Bleaching"] = pd.to_numeric(df["Percent_Bleaching"])
df["Percent_Bleaching"] = df["Percent_Bleaching"].astype(int)
```

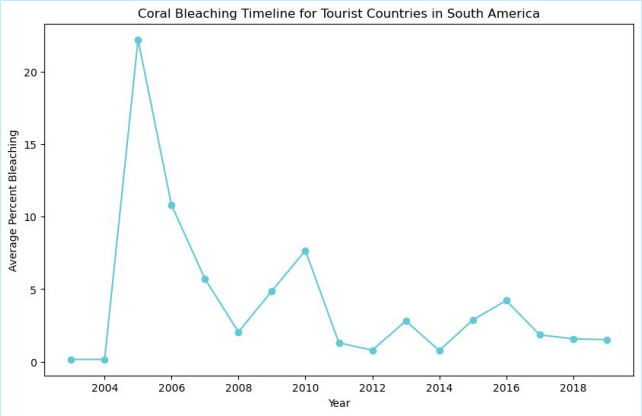
```
df_australia=df[df["Country_Name"]=="Australia"]
df_australia=df_australia[["Country_Name", "Date_Year", "Percent_Bleaching"]]

df_malayindo=df[df["Country_Name"].isin(["Malaysia", "Indonesia"])]
df_malayindo=df_malayindo[["Country_Name", "Date_Year", "Percent_Bleaching"]]

df_tourist_southam=df[df["Country_Name"].isin(["Bahamas", "Colombia", "Jamaica", "Maldives",
                                               "Turks and Caicos", "Trinidad and Tobago"])]
df_tourist_southam=df_tourist_southam[["Country_Name", "Date_Year", "Percent_Bleaching"]]
```

```
avg_bpy_tourist_southam=df_tourist_southam.groupby("Date_Year")["Percent_Bleaching"].mean().reset_index()
plt.figure(figsize=(10, 6))
plt.plot(avg_bpy_tourist_southam["Date_Year"], avg_bpy_tourist_southam["Percent_Bleaching"], marker='o', linestyle='-',
        color="#62C9D5")

plt.title("Coral Bleaching Timeline for Tourist Countries in South America")
plt.xlabel("Year")
plt.ylabel("Average Percent Bleaching")
plt.show()
```

timeline of coral percent bleaching averages







06

Conclusion

conclusion

- Cyclone frequency and wind speed of an area can also cause coral bleaching because it affects the sea surface temperature
- There are less coral bleaching events in tourist heavy places because better care is being done, such as cruise ships avoiding coral reefs
- Australia, Malaysia, and Indonesia are the top 3 countries in this dataset that suffer the most coral bleaching events
- Challenges during our project involved using lambda, and handling the “nd” values

Resources

Reef-World. “What Would Happen If There Were No Coral Reefs?” *The Reef-World Foundation*, 16 Mar. 2021, reef-world.org/blog/no-coral-reefs#:~:text=For%20these%20creatures%2C%20the%20reef,and%20other%20creatures%20would%20disappear.

US Department of Commerce, National Oceanic and Atmospheric Administration. “The Importance of Coral Reefs - Corals: NOAA’s National Ocean Service Education.” *Corals Tutorial*, National Ocean and Atmospheric Administration, 1 June 2013, oceanservice.noaa.gov/education/tutorial_corals/coral07_importance.html. Accessed 01 Dec. 2023.

US Department of Commerce, National Oceanic and Atmospheric Administration. “What Is Coral Bleaching?” *NOAA’s National Ocean Service*, NOAA, 15 Mar. 2010, oceanservice.noaa.gov/facts/coral_bleach.html#:~:text=When%20water%20is%20too%20warm,and%20are%20subject%20to%20mortality.

Van Woesik, R, Burkepile, D. 2022. Bleaching and environmental data for global coral reef sites from 1980-2022. Biological and Chemical Oceanography Data Management Office. Version 2.