Harvey_Project_Python

August 27, 2022

1 Background and Scope

Hurricane Harvey had a great impact and resulted in a lot of damage cost to the country. Let's find out the most affected areas.

1.1 Import the Data

Let us import dataset for the events held in 2017 and filter out the events with no data about property cost.

[ ]:
```
import pandas as pd
import numpy as np
import datetime
from matplotlib import pyplot as  plt
import geoplot
import geopandas
import plotly.graph_objects as go
```

[ ]:
```
df = pd.read_csv('StormEvents_2017_finalProject.csv')
df.dropna(subset='Property_Cost', inplace=True)
df.head()
```

[ ]:
```
   EpisodeID  Event_ID     State  Year  Month        Event_Type       CZ_Name  \
1     113459    679228   FLORIDA  2017  April           Tornado           LEE
2     113448    679268      OHIO  2017  April  Thunderstorm Wind        GREENE
3     113697    682042      OHIO  2017  April             Flood      CLERMONT
4     113683    682062  NEBRASKA  2017  April              Hail          CASS
5     114718    688082   INDIANA  2017  April       Flash Flood   SWITZERLAND

       Begin_Date_Time Timezone        End_Date_Time  …  Damage_Property  \
1  2017-04-06 09:30:00    EST-5  2017-04-06 09:40:00  …          110.00K
2  2017-04-05 17:49:00    EST-5  2017-04-05 17:53:00  …            1.00K
3  2017-04-16 17:59:00    EST-5  2017-04-16 19:00:00  …            5.00K
4  2017-04-15 15:50:00    CST-6  2017-04-15 15:50:00  …            0.00K
5  2017-04-29 09:15:00    EST-5  2017-04-29 11:15:00  …           10.00K

   Property_Cost  Damage_Crops  Crop_Cost Begin_Lat  Begin_Lon  End_Lat  \
1       110000.0         0.00K        0.0   26.5010   -81.9980  26.5339
```

```
2         1000.0         0.00K         0.0    39.8500   -83.9900  39.8500
3         5000.0         0.00K         0.0    39.1065   -84.2875  39.1061
4            0.0         0.00K         0.0    40.9800   -95.8900  40.9800
5        10000.0         0.00K         0.0    38.7500   -85.0700  38.7465

   End_Lon                                  Episode_Narrative  \
1 -81.8836  A line of thunderstorms developed along a pref…
2 -83.9900  Showers and thunderstorms developed ahead of a…
3 -84.2874  Thunderstorms with very heavy rain developed a…
4 -95.8900  An upper level storm system moved into Nebrask…
5 -85.0766  Thunderstorms trained along a warm front that …

                                      Event_Narrative
1  Emergency management reported and broadcast me…
2  An entire tree was uprooted in a yard on Dayto…
3        Garage of a home was flooded by high water.
4                                                NaN
5  A road was closed and water was reported in th…

[5 rows x 24 columns]
```

1.2 Two States Most Impacted by Harvey

Now, since Harvey impacted only Arkansas, Kentucky, Louisiana, Mississippi, North Carolina, Tennessee, and Texas, we shall filter out the remaining states from the table, i.e., events irrelevant from Harvey. We shall further filter out the events which didn't occur during Harvey or the irrelevant data as the Harvey's events occured between 17th of August and 3rd of September.

[ ]:
```
#('Arkansas', 'Kentucky', 'Louisiana', 'Mississippi', 'North Carolina',␣
 ↪'Tennessee', 'Texas')
df = df[(df['State'] == 'ARKANSAS') | (df['State'] == 'KENTUCKY') |␣
 ↪(df['State'] == 'Louisiana'.upper()) | (df['State'] == 'Mississippi'.
 ↪upper()) | (df['State'] == 'North Carolina'.upper()) | (df['State'] ==␣
 ↪'Tennessee'.upper()) | (df['State'] == 'TEXAS')]
df.head()
```

[ ]:
```
     EpisodeID  Event_ID           State  Year     Month   Event_Type  \
10      115066    690966        ARKANSAS  2017     April         Hail
113     115737    695622           TEXAS  2017       May         Hail
132     118165    710139  NORTH CAROLINA  2017      June  Flash Flood
152     115476    693428        KENTUCKY  2017      June  Flash Flood
156     121277    726031        ARKANSAS  2017  November      Drought

       CZ_Name      Begin_Date_Time Timezone        End_Date_Time  …  \
10    FRANKLIN  2017-04-26 07:57:00    CST-6  2017-04-26 07:57:00  …
113  HENDERSON  2017-05-03 14:06:00    CST-6  2017-05-03 14:06:00  …
132       WAKE  2017-06-16 19:32:00    EST-5  2017-06-16 19:32:00  …
```

```
152      KNOTT  2017-06-14 16:25:00    EST-5  2017-06-14 16:25:00  …
156  SEBASTIAN  2017-11-15 00:00:00    CST-6  2017-11-30 23:59:00  …

     Damage_Property  Property_Cost  Damage_Crops  Crop_Cost Begin_Lat  \
10             0.00K            0.0         0.00K        0.0   35.2971
113            1.00K         1000.0         0.00K        0.0   32.3256
132            0.00K            0.0         0.00K        0.0   35.8300
152            0.00K            0.0         0.00K        0.0   37.3300
156            0.00K            0.0         0.00K        0.0       NaN

     Begin_Lon  End_Lat  End_Lon  \
10    -94.0383  35.2971 -94.0383
113   -95.4287  32.3256 -95.4287
132   -78.7600  35.8296 -78.7614
152   -82.8800  37.3301 -82.8795
156        NaN      NaN      NaN

                                    Episode_Narrative  \
10   Severe thunderstorms developed along and ahead…
113  Storms developed ahead of a cold front during …
132  A few loosely organized multicell convective c…
152  Numerous thunderstorms developed this morning …
156  Unusually dry conditions occurred across much …

                                      Event_Narrative
10                                                NaN
113  Amateur radio reported quarter size hail near …
132  Locally heavy rainfall of 2 to 3 inches floode…
152  Broadcast media relayed a report and pictures …
156                                               NaN

[5 rows x 24 columns]
```

[ ]:
```python
begindate = datetime.datetime(2017,8,17,00,00,00)
enddate = datetime.datetime(2017,9,3, 23,59,59)
```

[ ]:
```python
df = df[(df['Begin_Date_Time']>=str(begindate)) &
 ↪(df['End_Date_Time']<=str(enddate))]
df.head()
```

[ ]:
```
       EpisodeID  Event_ID           State  Year      Month      Event_Type  \
33599     119753    723472           TEXAS  2017     August  Tropical Storm
34738     118750    713329     MISSISSIPPI  2017  September     Strong Wind
34813     120636    722605  NORTH CAROLINA  2017  September     Flash Flood
34814     120636    722608  NORTH CAROLINA  2017  September     Flash Flood
34815     120636    722610  NORTH CAROLINA  2017  September            Hail
```

```
         CZ_Name      Begin_Date_Time Timezone        End_Date_Time  …  \
33599  MONTGOMERY  2017-08-25 12:00:00    CST-6  2017-08-30 00:00:00  …
34738     LOWNDES  2017-09-01 01:00:00    CST-6  2017-09-01 01:00:00  …
34813        WAKE  2017-09-01 17:35:00    EST-5  2017-09-01 18:15:00  …
34814  CUMBERLAND  2017-09-01 19:20:00    EST-5  2017-09-01 21:25:00  …
34815         LEE  2017-09-01 15:20:00    EST-5  2017-09-01 15:20:00  …

       Damage_Property  Property_Cost  Damage_Crops  Crop_Cost Begin_Lat  \
33599            7.00B   7.000000e+09           NaN        NaN       NaN
34738            5.00K   5.000000e+03         0.00K        0.0       NaN
34813            0.00K   0.000000e+00         0.00K        0.0   35.9719
34814            0.00K   0.000000e+00         0.00K        0.0   35.0621
34815            0.00K   0.000000e+00         0.00K        0.0   35.4700

       Begin_Lon  End_Lat  End_Lon  \
33599        NaN      NaN      NaN
34738        NaN      NaN      NaN
34813   -78.5516  35.9425 -78.5543
34814   -79.0078  35.0258 -79.0006
34815   -79.1800  35.4700 -79.1800

                                        Episode_Narrative  \
33599  Harvey made landfall as a category 4 hurricane…
34738  The remnants of Hurricane Harvey moved across …
34813  The remnants of Harvey increased the southwest…
34814  The remnants of Harvey increased the southwest…
34815  The remnants of Harvey increased the southwest…

                                          Event_Narrative
33599  Tropical Storm Harvey brought heavy rains and …
34738  A tree was blown down on Military Road near th…
34813  Heavy rain resulted in flash flooding on the U…
34814  Heavy rain resulted in flash flooding of multi…
34815                                                NaN

[5 rows x 24 columns]
```

The type of events that took place in the time being are as follows. The events remaining correspond to urricane and hence don't need to be eliminated from the database.

[ ]:
```
event_cats = list(df['Event_Type'].unique())
print(event_cats)
```

```
['Tropical Storm', 'Strong Wind', 'Flash Flood', 'Hail', 'Thunderstorm Wind',
'High Wind', 'Heavy Rain', 'Heat', 'Flood', 'Tornado', 'Storm Surge/Tide',
'Lightning', 'Funnel Cloud', 'Hurricane']
```

The total cost to property for every state during the Hurricane Harvey is listed below sorted in descending order of the cost. Since the Harvey was most prominent and destructive event during the time, it will be the reason for most cost to property damage, i.e., no other event during that time was more destructive than Harvey.

[ ]:
```
groupeddf = df.groupby('State')['Property_Cost'].agg('sum', 'count')
sorteddf = groupeddf.sort_values(ascending=False )
print(sorteddf)
```

```
State
TEXAS             7.742727e+10
LOUISIANA         7.527700e+07
NORTH CAROLINA    1.233850e+07
MISSISSIPPI       9.150000e+05
TENNESSEE         5.040000e+05
KENTUCKY          4.350000e+05
ARKANSAS          6.100000e+04
Name: Property_Cost, dtype: float64
```

Hence, it the top 2 in the below table are the 2 most impacted states in order.

[ ]:
```
top_two = sorteddf[:2]
print(top_two)
```

```
State
TEXAS        7.742727e+10
LOUISIANA    7.527700e+07
Name: Property_Cost, dtype: float64
```

2 Table of Events for Two Most Impacted States

A few rows of events that include only the two most affected states are shown below.

[ ]:
```
harvey_top = df[(df['State'] == 'TEXAS') | (df['State'] == 'LOUISIANA')]
harvey_top.head()
```

[ ]:
```
       EpisodeID  Event_ID  State  Year   Month      Event_Type      CZ_Name  \
33599     119753    723472  TEXAS  2017  August  Tropical Storm   MONTGOMERY
34851     119753    723473  TEXAS  2017  August  Tropical Storm    FORT BEND
35115     119753    723449  TEXAS  2017  August  Tropical Storm    GALVESTON
35116     119753    723474  TEXAS  2017  August  Tropical Storm  SAN JACINTO
35580     119753    723475  TEXAS  2017  August  Tropical Storm       WALKER

           Begin_Date_Time Timezone        End_Date_Time  …  \
33599  2017-08-25 12:00:00    CST-6  2017-08-30 00:00:00  …
34851  2017-08-26 00:00:00    CST-6  2017-08-30 00:00:00  …
35115  2017-08-25 12:00:00    CST-6  2017-08-30 00:00:00  …
35116  2017-08-25 12:00:00    CST-6  2017-08-30 00:00:00  …
35580  2017-08-25 12:00:00    CST-6  2017-08-30 00:00:00  …
```

```
      Damage_Property  Property_Cost  Damage_Crops  Crop_Cost Begin_Lat  \
33599           7.00B   7.000000e+09           NaN        NaN       NaN
34851           8.00B   8.000000e+09           NaN        NaN       NaN
35115          10.00B   1.000000e+10           NaN        NaN       NaN
35116         350.00M   3.500000e+08           NaN        NaN       NaN
35580         600.00M   6.000000e+08           NaN        NaN       NaN

      Begin_Lon End_Lat  End_Lon  \
33599       NaN     NaN      NaN
34851       NaN     NaN      NaN
35115       NaN     NaN      NaN
35116       NaN     NaN      NaN
35580       NaN     NaN      NaN

                                      Episode_Narrative  \
33599  Harvey made landfall as a category 4 hurricane…
34851  Harvey made landfall as a category 4 hurricane…
35115  Harvey made landfall as a category 4 hurricane…
35116  Harvey made landfall as a category 4 hurricane…
35580  Harvey made landfall as a category 4 hurricane…

                                        Event_Narrative
33599  Tropical Storm Harvey brought heavy rains and …
34851  Harvey made landfall as a category 4 hurricane…
35115  Galveston County experienced catastrophic floo…
35116  Slow moving Tropical Storm Harvey produced ver…
35580  Slow moving Tropical Storm Harvey produced tor…

[5 rows x 24 columns]
```

3 Visualizations

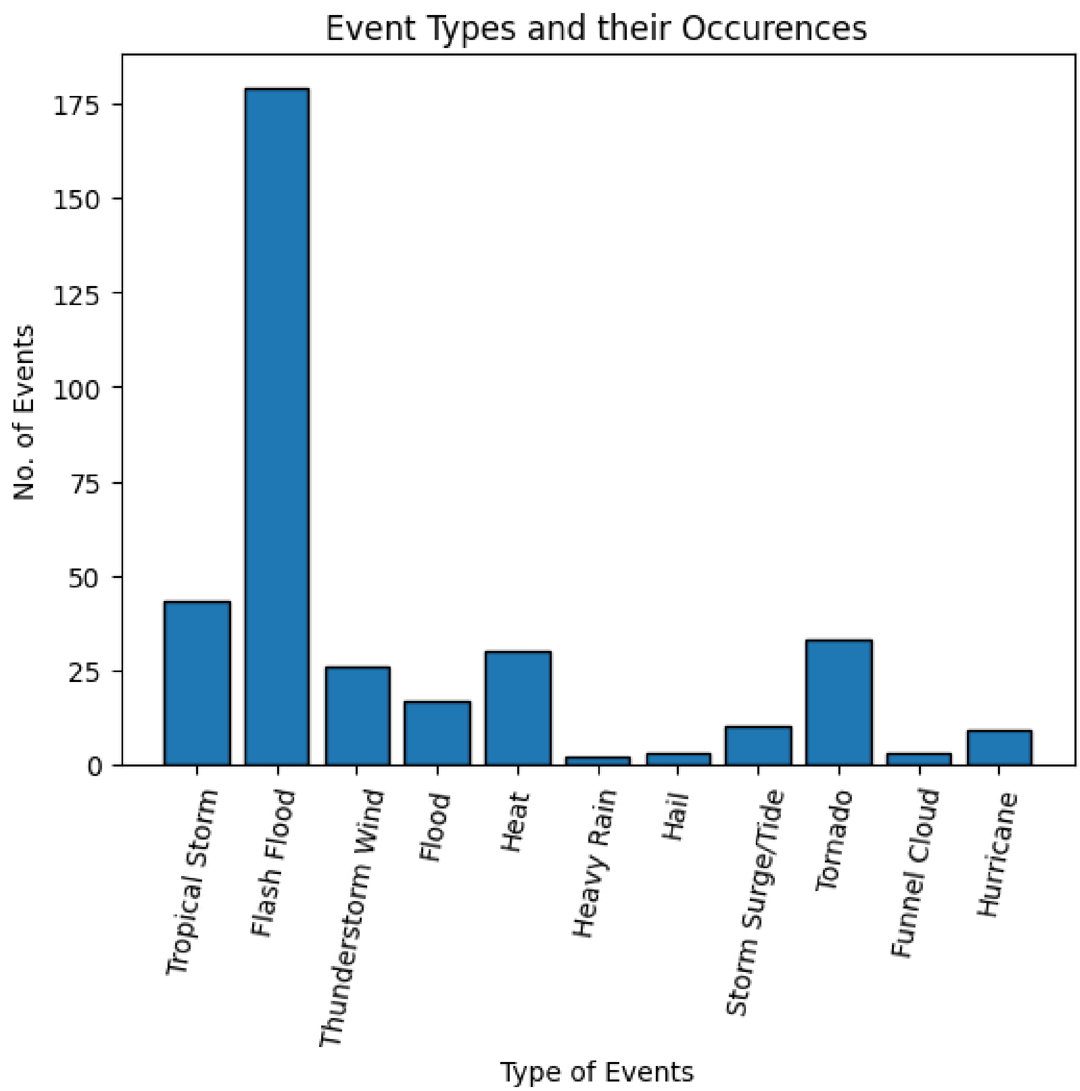
3.1 Figure of Event Types

A figure showing the type and number of occurances for events related to Harvey in the two states is shown below. Events with zero occurences have already been removed from the dataset.

[ ]:
```
event_cats = list(harvey_top['Event_Type'].unique())
event_cats_count = []
for event in event_cats:
    event_cats_count.append(harvey_top['Event_Type'].value_counts()[event])
```

[ ]:
```
plt.bar(event_cats, event_cats_count, edgecolor = 'black')
plt.title('Event Types and their Occurences')
plt.xlabel('Type of Events')
plt.ylabel('No. of Events')
```

```
plt.xticks(rotation=80) # Rotation of the bars names
plt.show()
```



3.2 Figure of Event Locations

Below are the locations of events in the two states. The size of marker depends upon the property cost of the event. ### Begin Locations

[ ]:
```
start_df = harvey_top[['State', 'Begin_Lat', 'Begin_Lon', 'Property_Cost']].
↪dropna().reset_index()
start_df.drop('index', axis=1, inplace=True)
```

```
start_df['Text'] = start_df['State'] + '<br>Property Cost ' +␣
↪(start_df['Property_Cost']).astype(str)
start_df.head()
```

```
[ ]:   State  Begin_Lat  Begin_Lon  Property_Cost  \
0  TEXAS    31.5285  -106.1346            0.0
1  TEXAS    31.7715  -106.5028            0.0
2  TEXAS    31.7839  -106.5205            0.0
3  TEXAS    29.7585   -93.9153    600000000.0
4  TEXAS    30.9235   -94.5992     85000000.0

                                Text
0          TEXAS<br>Property Cost 0.0
1          TEXAS<br>Property Cost 0.0
2          TEXAS<br>Property Cost 0.0
3  TEXAS<br>Property Cost 600000000.0
4   TEXAS<br>Property Cost 85000000.0
```

```
[ ]: top_two = list(start_df['State'].unique())
top_two
```

```
[ ]: ['TEXAS', 'LOUISIANA']
```

```
[ ]: colors = ['#E58606', '#5D69B1']
```

```
[ ]: fig = go.Figure()

for state in top_two:

    st = start_df[(start_df['State']) == state]


    fig.add_trace(go.Scattergeo(
        locationmode= 'USA-states',
        lon = st['Begin_Lon'],
        lat = st['Begin_Lat'],
        text = st['Text'],
        marker=dict(
            size = start_df['Property_Cost']/(10**8.6)+3, #6,
            color = colors[top_two.index(state)],
            line_color = 'rgb(40,40,40)',
            line_width = 0.2,
            sizemode = 'diameter'),
        name = state
    ))

fig.update_layout(
```

```
showlegend = True,
title = 'Events Began From these Locations<br>(Hover for details)',
geo = dict(scope = 'usa',
projection_type='albers usa',
landcolor = 'rgb(250,250,250)',
subunitcolor = "rgb(200, 200, 200)",
countrycolor = "rgb(217, 217, 217)",
countrywidth = 0.5,
subunitwidth = 0.5
)
)

fig.show()
```

3.2.1 End Locations

[ ]:
```
end_df = harvey_top[['State', 'End_Lat', 'End_Lon', 'Property_Cost']].dropna().
 ↪reset_index()
end_df.drop('index', axis=1, inplace=True)
end_df['Text'] = start_df['State'] + '<br>Property Cost ' +␣
 ↪(end_df['Property_Cost']).astype(str)
end_df.head()
```

[ ]:

	State	End_Lat	End_Lon	Property_Cost	Text
0	TEXAS	31.5183	-106.1176	0.0	TEXAS Property Cost 0.0
1	TEXAS	31.7715	-106.5028	0.0	TEXAS Property Cost 0.0
2	TEXAS	31.7573	-106.4989	0.0	TEXAS Property Cost 0.0
3	TEXAS	29.6142	-94.3451	600000000.0	TEXAS Property Cost 600000000.0
4	TEXAS	31.2083	-93.5815	85000000.0	TEXAS Property Cost 85000000.0

[ ]:
```
fig = go.Figure()

for state in top_two:

    st = end_df[(end_df['State']) == state]


    fig.add_trace(go.Scattergeo(
        locationmode= 'USA-states',
        lon = st['End_Lon'],
        lat = st['End_Lat'],
        text = st['Text'],
        marker=dict(
            size = end_df['Property_Cost']/(10**8.6)+3, #6,
            color = colors[top_two.index(state)],
            line_color = 'rgb(40,40,40)',
            line_width = 0.2,
```

```
            sizemode = 'diameter'),
        name = state
    ))

fig.update_layout(
showlegend = True,
title = 'Events Ended at These Locations<br>(Hover for details)',
geo = dict(scope = 'usa',
projection_type='albers usa',
landcolor = 'rgb(250,250,250)',
subunitcolor = "rgb(200, 200, 200)",
countrycolor = "rgb(217, 217, 217)",
countrywidth = 0.5,
subunitwidth = 0.5
)
)

fig.show()
```

4 Analysis

4.1 Three Counties with Most Events in Texas

Below are given the top 3 Counties in Texas which encountered the most number of events during Harvey.

[ ]:
```
state_1 = harvey_top[harvey_top['State'] == 'TEXAS']
state_1.head()
```

[ ]:
```
       EpisodeID  Event_ID  State  Year   Month      Event_Type      CZ_Name  \
33599     119753    723472  TEXAS  2017  August  Tropical Storm   MONTGOMERY
34851     119753    723473  TEXAS  2017  August  Tropical Storm    FORT BEND
35115     119753    723449  TEXAS  2017  August  Tropical Storm    GALVESTON
35116     119753    723474  TEXAS  2017  August  Tropical Storm  SAN JACINTO
35580     119753    723475  TEXAS  2017  August  Tropical Storm       WALKER

           Begin_Date_Time Timezone        End_Date_Time  …  \
33599  2017-08-25 12:00:00    CST-6  2017-08-30 00:00:00  …
34851  2017-08-26 00:00:00    CST-6  2017-08-30 00:00:00  …
35115  2017-08-25 12:00:00    CST-6  2017-08-30 00:00:00  …
35116  2017-08-25 12:00:00    CST-6  2017-08-30 00:00:00  …
35580  2017-08-25 12:00:00    CST-6  2017-08-30 00:00:00  …

       Damage_Property  Property_Cost  Damage_Crops  Crop_Cost Begin_Lat  \
33599            7.00B   7.000000e+09           NaN        NaN       NaN
34851            8.00B   8.000000e+09           NaN        NaN       NaN
35115           10.00B   1.000000e+10           NaN        NaN       NaN
```

```
35116          350.00M   3.500000e+08           NaN         NaN        NaN
35580          600.00M   6.000000e+08           NaN         NaN        NaN

       Begin_Lon End_Lat  End_Lon  \
33599        NaN     NaN      NaN
34851        NaN     NaN      NaN
35115        NaN     NaN      NaN
35116        NaN     NaN      NaN
35580        NaN     NaN      NaN

                                Episode_Narrative  \
33599  Harvey made landfall as a category 4 hurricane…
34851  Harvey made landfall as a category 4 hurricane…
35115  Harvey made landfall as a category 4 hurricane…
35116  Harvey made landfall as a category 4 hurricane…
35580  Harvey made landfall as a category 4 hurricane…

                                  Event_Narrative
33599  Tropical Storm Harvey brought heavy rains and …
34851  Harvey made landfall as a category 4 hurricane…
35115  Galveston County experienced catastrophic floo…
35116  Slow moving Tropical Storm Harvey produced ver…
35580  Slow moving Tropical Storm Harvey produced tor…

[5 rows x 24 columns]
```

[ ]:
```
county_top = state_1.groupby('CZ_Name').size()
county_top = county_top.sort_values(ascending= False)
county_top = county_top[:3]
county_top
```

[ ]:
```
CZ_Name
HARRIS       21
GALVESTON    17
FORT BEND    13
dtype: int64
```

4.2 Three Counties with Most Events in Louisiana

Below are given the top 3 Counties in Louisiana which encountered the most number of events during Harvey.

[ ]:
```
state_2 = harvey_top[harvey_top['State'] == 'LOUISIANA']
county_top2 = state_2.groupby('CZ_Name').size()
county_top2 = county_top2.sort_values(ascending= False)
county_top2 = county_top2[:3]
county_top2
```

```
[ ]: CZ_Name
     NATCHITOCHES    21
     SABINE          15
     RED RIVER        9
     dtype: int64
```

4.3 Three Counties with Highest Property Cost in Texas

The counties with most property cost in Texas are given below.

```
[ ]: county1_property = state_1.groupby('CZ_Name')['Property_Cost'].agg('sum',␣
      ↪'count')
     county1_property = county1_property.sort_values(ascending=False )
     county1_property = county1_property[:3]
     county1_property
```

```
[ ]: CZ_Name
     GALVESTON     2.000020e+10
     FORT BEND     1.600433e+10
     MONTGOMERY    1.400000e+10
     Name: Property_Cost, dtype: float64
```

4.4 Three Counties with Highest Property Cost in Louisiana

The counties with most property cost in Louisiana are given below.

```
[ ]: county2_property = state_2.groupby('CZ_Name')['Property_Cost'].agg('sum',␣
      ↪'count')
     county2_property = county2_property.sort_values(ascending=False )
     county2_property = county2_property[:3]
     county2_property
```

```
[ ]: CZ_Name
     CALCASIEU     60000000.0
     BEAUREGARD    15000000.0
     ACADIA          200000.0
     Name: Property_Cost, dtype: float64
```

5 Conclusions and Recommendations

The Most Affected states were Texas and Louisiana and hence the company should focus on these states firstly to send people to. However, the property cost to the counties in Texas was relatively muh higher than that to the Louisiana and can be seen that the property cost of Calcasieu of Louisiana was lower than Montgomery of Texas, which means the company should be prioritising Texas over. We may also note that there may be other counties in Texas too which had higher damage than Calcasieu of Louisiana which the company should look into too. It is also clearly visible from the plots that the events did most damage at the coastal regions and the most affected areas are not much far from each other.