PROJECT: ANALYSIS OF SUDAN CONFLICT(1997-2024)

Violent conflict in Africa has been the leading cause of deaths, injuries, destruction of homes, displacement of populations and and restriction on freedom of expressions. This project is interested exploring the roles of various conflict actors in Sudan conflict and how they impact on civilian fatalities. The dataset for the project is obatined from Armed Conflict Location Events Tracking Data (ACled at https://acleddata.com/curated-data-files/#regional (https://acleddata.com/curated-data-files/#regional)*).

The project seeks to identify the event_types related to violence and related actors. The project will identify the regions with the higest count of fatalities and will project the trends of violent accross time.

Business problem

Multilateral agencies and humanitarain organisations are providing aid in Sudan but needs to know prevalence of conflict in Sudan and national actors responsbile for violation of human rights. There is need for situational awareness about the pattern of conflcit and the categories of populations suffering from violence.

Data understanding

The dataset is large but focus is on fatalities, event-types, actors and locations at risk of violent conflict. The overal goal is estbalish a linear relationship between fatalities and violent events.

1: Importing the neccessary python libraries and loading the data

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import statistics
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots

df = pd.read_csv(r'C:\Users\pgaduel\Desktop\Gaduel_Phase3_Project\Sudan_1997-2024_Dec06.csv')
print(df.columns)
```

```
Index(['event_id_cnty', 'event_date', 'year', 'time_precision',
       'disorder_type', 'event_type', 'sub_event_type', 'actor1',
       'assoc_actor_1', 'inter1', 'actor2', 'assoc_actor_2', 'inter2',
       'interaction', 'civilian_targeting', 'iso', 'region', 'country',
       'admin1', 'admin2', 'admin3', 'location', 'latitude', 'longitude',
       'geo_precision', 'source', 'source_scale', 'notes', 'fatalities',
       'tags', 'timestamp'],
      dtype='object')
```

2: Data inspection, cleaning and preprocessing

In [2]:
```
#Inspecting the dataset

print("Shape of the data:", df.shape)
Rows,Cols=df.shape
df.head()
```

```
Shape of the data: (35057, 31)
```

Out[2]:

	event_id_cnty	event_date	year	time_precision	disorder_type	event_type	sub_event_type	actor1	assoc_actor_1	inte
0	SUD31794	12/6/2024	2024	1	Political violence	Battles	Armed clash	Military Forces of Sudan (2019-)	NaN	St forc
1	SUD31815	12/6/2024	2024	1	Political violence; Demonstrations	Protests	Excessive force against protesters	Protesters (Sudan)	NaN	Protest
2	SUD31831	12/6/2024	2024	1	Political violence	Explosions/Remote violence	Air/drone strike	Military Forces of Sudan (2019-)	NaN	St forc
3	SUD31839	12/6/2024	2024	1	Demonstrations	Protests	Peaceful protest	Protesters (Sudan)	NaN	Protest
4	SUD31842	12/6/2024	2024	2	Strategic developments	Strategic developments	Change to group/activity	Military Forces of Sudan (2019-)	NaN	St forc

5 rows × 31 columns

In [3]:
```
# Selecting certain columns
selected_columns = ['year','disorder_type', 'event_type' , 'actor1', 'inter1',  'location', 'fatalities', 'act

# Creating a new DataFrame with selected columns

df_selected = df[selected_columns]

df_selected.head(10)
```

Out[3]:

	year	disorder_type	event_type	actor1	inter1	location	fatalities	actor1	admin1	geo_precision	source_scal
0	2024	Political violence	Battles	Military Forces of Sudan (2019-)	State forces	El Fasher	0	Military Forces of Sudan (2019-)	North Darfur	1	New medi
1	2024	Political violence; Demonstrations	Protests	Protesters (Sudan)	Protesters	Malha	1	Protesters (Sudan)	North Darfur	1	New media Subnationa
2	2024	Political violence	Explosions/Remote violence	Military Forces of Sudan (2019-)	State forces	Khartoum North - Shambat	5	Military Forces of Sudan (2019-)	Khartoum	1	New media Nationa
3	2024	Demonstrations	Protests	Protesters (Sudan)	Protesters	Sunta	0	Protesters (Sudan)	South Darfur	1	Subnationa
4	2024	Strategic developments	Strategic developments	Military Forces of Sudan (2019-)	State forces	Al Sharif Wad El Obeid	0	Military Forces of Sudan (2019-)	Al Jazirah	1	New medi
5	2024	Political violence	Explosions/Remote violence	Military Forces of Sudan (2019-)	State forces	Um Talha	8	Military Forces of Sudan (2019-)	Al Jazirah	1	Internationa
6	2024	Strategic developments	Strategic developments	Military Forces of Sudan (2019-)	State forces	Um Algura	0	Military Forces of Sudan (2019-)	Al Jazirah	2	New medi
7	2024	Political violence	Explosions/Remote violence	Military Forces of Sudan (2019-)	State forces	Ombada	10	Military Forces of Sudan (2019-)	Khartoum	1	Nationa
8	2024	Political violence	Violence against civilians	Murle Ethnic Militia (South Sudan)	Identity militia	Yuai	1	Murle Ethnic Militia (South Sudan)	Jonglei	3	Nationa
9	2024	Political violence	Battles	Unidentified Communal Militia (South Sudan)	Identity militia	Cueibet	0	Unidentified Communal Militia (South Sudan)	Lakes	2	Nationa

In [4]:
```
print(df_selected.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35057 entries, 0 to 35056
Data columns (total 11 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   year           35057 non-null  int64 
 1   disorder_type  35057 non-null  object
 2   event_type     35057 non-null  object
 3   actor1         35057 non-null  object
 4   inter1         35057 non-null  object
 5   location       35057 non-null  object
 6   fatalities     35057 non-null  int64 
 7   actor1         35057 non-null  object
 8   admin1         35057 non-null  object
 9   geo_precision  35057 non-null  int64 
 10  source_scale   35057 non-null  object
dtypes: int64(3), object(8)
memory usage: 2.9+ MB
None
```

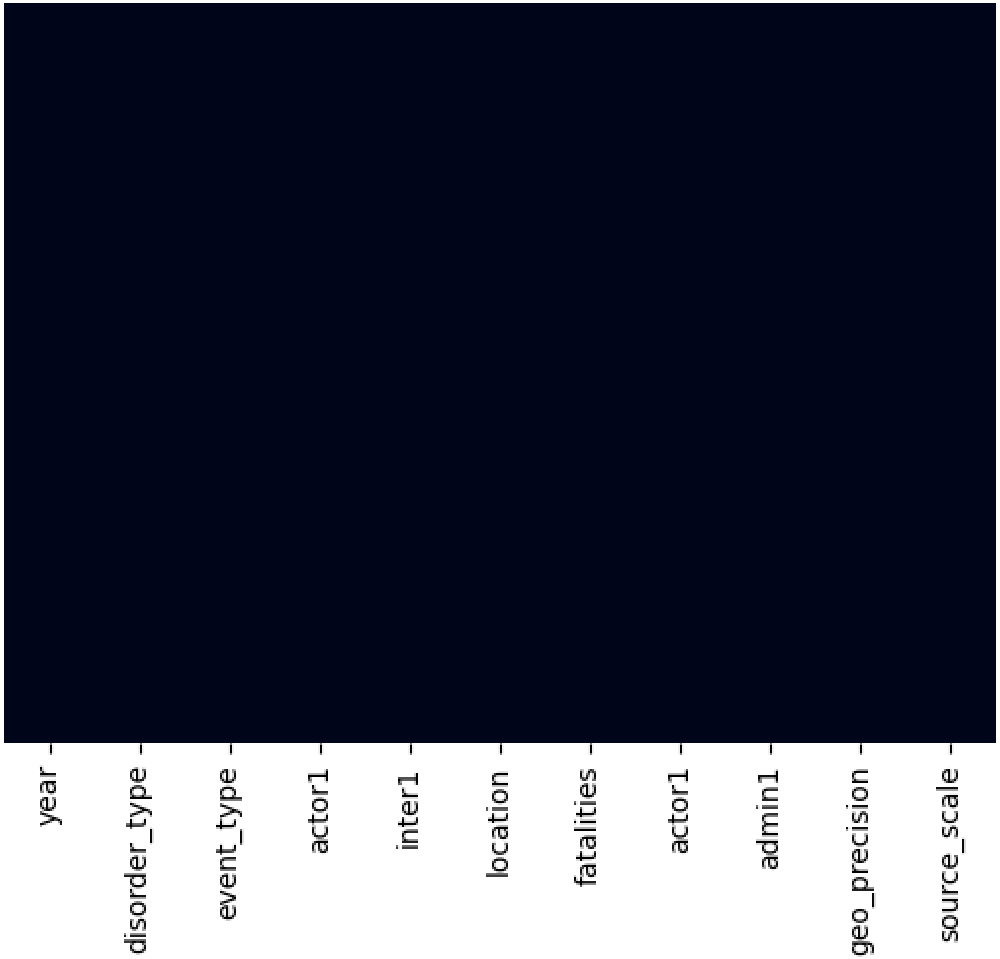
In [5]:
```
df_selected.shape
```

Out[5]:
```
(35057, 11)
```

the dataset has 35057 rows and 11 columns

In [6]:
```
#Visulising missing values through heatmap
sns.heatmap(df_selected.isnull(), yticklabels=False, cbar=False)
```

Out[6]: <Axes: >



The heatmap shows there are no missing or null values

3: Exppploratory data Analysis

Understanding the data and preparing the target Variables

The aim of this step is to map conflict in Sudan by type for example; disorder_type (e.g., "Protests", "Battles", etc.)

What is the most common source of violence in Sudan?

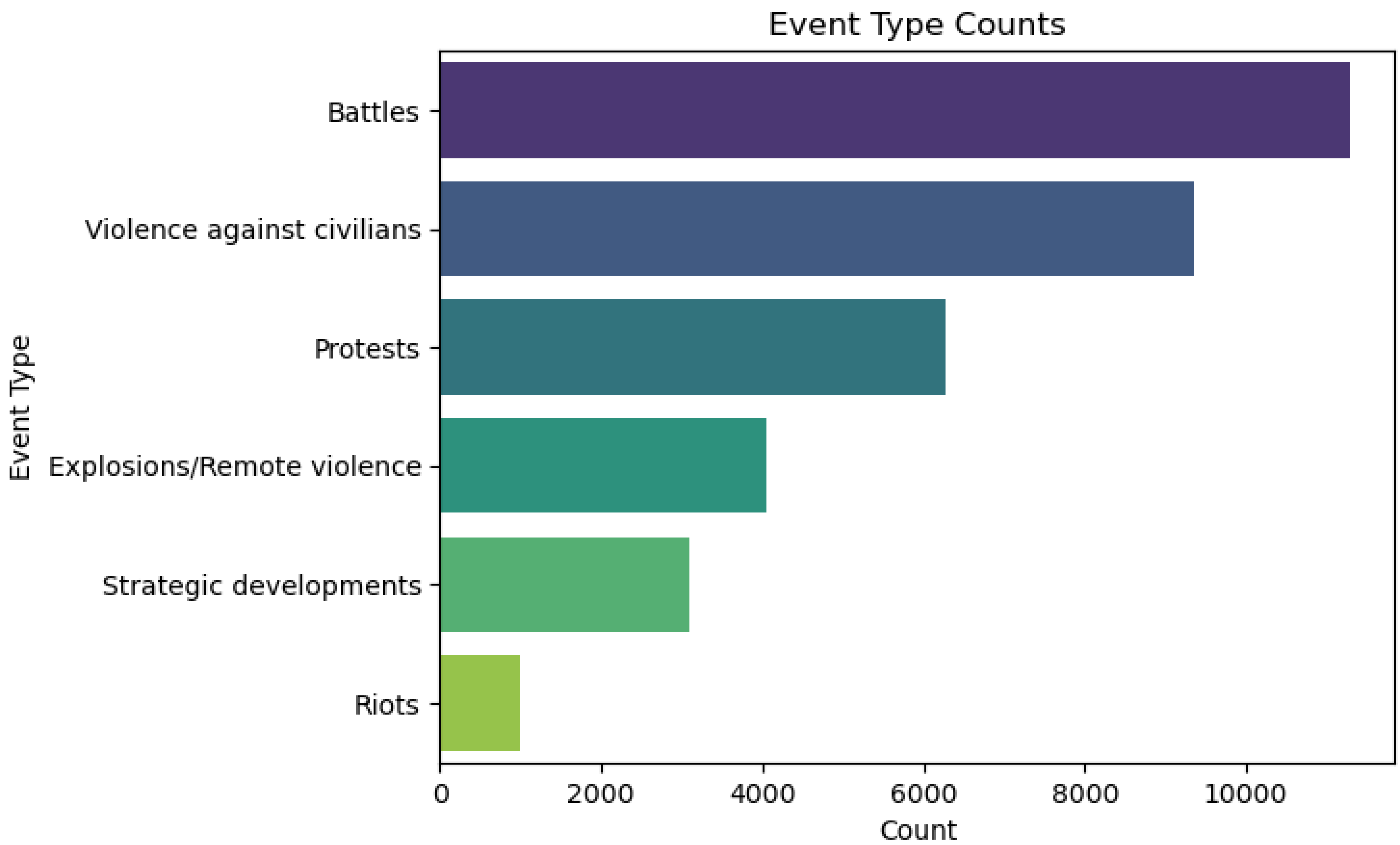
In [7]:
```
print(df_selected['event_type'].value_counts())
```

```
event_type
Battles                       11282
Violence against civilians     9355
Protests                       6282
Explosions/Remote violence     4058
Strategic developments         3086
Riots                           994
Name: count, dtype: int64
```

The battles are the most common violent events in Sudan

In [8]:
```
# Count occurrences of each 'event_type'

event_counts = df_selected['event_type'].value_counts()

# Create a barplot
sns.barplot(x=event_counts.values, y=event_counts.index, palette='viridis')

# Add titles and labels
plt.title('Event Type Counts')
plt.xlabel('Count')
plt.ylabel('Event Type')

# Display the plot
plt.show()
```

```
C:\Users\pgaduel\AppData\Local\Temp\ipykernel_29480\793652818.py:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` varia
ble to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=event_counts.values, y=event_counts.index, palette='viridis')
```



Battles are the leading types of violence, followed by violence against civilains.

Riots are the least common disorder types in Sudan.

In [9]:
```
import plotly.express as px

# Calculate the value counts of event types
event_type = df_selected["event_type"].value_counts()

# Create a pie chart using Plotly
fig = px.pie(event_type, values=event_type.values, names=event_type.index, title='Total Type of Event percenta
# Show the plot

fig.show()
```

The pie_chart shows the propportions of violent in Sudan by event percentage.

Battles constitute the largest proportion of violence.

In [10]:
```
# Group by event_type and sub_event_type and count the occurrences
sub_event = df.groupby(["event_type", "sub_event_type"])["event_date"].agg({'count'}).reset_index()

# Create a sunburst chart using Plotly
fig = px.sunburst(sub_event,
                  path=['event_type', 'sub_event_type'],
                  values='count',
                  width=600, # Width of map
                  height=600)

fig.update_traces(textinfo="label+percent parent")
fig.layout.update(title="<b> Event type and Sub event type percentage in Sudan (ACLED)<b>",
                  titlefont={'color':None, 'size': 15, 'family': 'San-Serif'})

fig.show()
```

Based on the sunburst chart, armed clashes constitute the largest source of sub_violent events.

Attacks , and peaceful protests are other major categories that trigger violence.

Who is responsible for most of violent counts in Sudan?

In [11]:
```
#Summary of events by actor_type1
actor_type1=df["inter1"].value_counts()
actor_type1
```

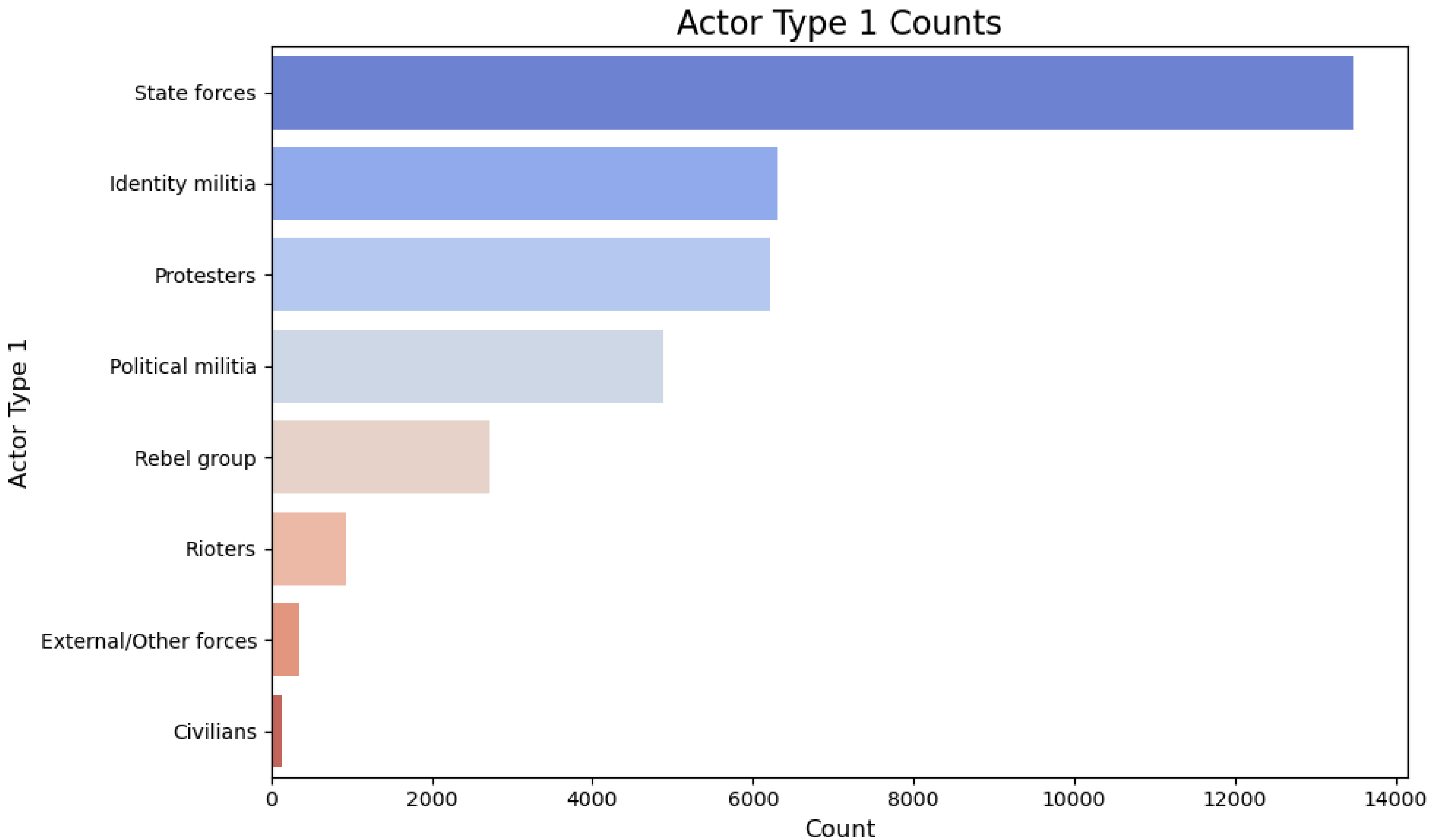
Out[11]:
```
inter1
State forces             13484
Identity militia          6309
Protesters                6218
Political militia         4889
Rebel group               2715
Rioters                    941
External/Other forces      360
Civilians                  141
Name: count, dtype: int64
```

the state forces are the leading perpertrators responsbile for violence in Sudan.

violence by civilians is the least.

In [12]:
```
# Count occurrences of each 'inter1' value
actor_type1 = df["inter1"].value_counts()

# Create a bar plot
plt.figure(figsize=(10, 6))
sns.barplot(x=actor_type1.values, y=actor_type1.index, palette='coolwarm')

# Add titles and labels
plt.title('Actor Type 1 Counts', fontsize=16)
plt.xlabel('Count', fontsize=12)
plt.ylabel('Actor Type 1', fontsize=12)

# Show the plot
plt.tight_layout()
plt.show()
```

```
C:\Users\pgaduel\AppData\Local\Temp\ipykernel_29480\2717016390.py:6: FutureWarning:



Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` varia
ble to `hue` and set `legend=False` for the same effect.
```



The bar chart shows that state forces are the leading source of violent conflict in Sudan.

In [13]:
```
# Create subplots
fig = make_subplots(rows=1, cols=2, specs=[[{'type':'domain'}, {'type':'domain'}]])

# Add pie charts to subplots
fig.add_trace(go.Pie(labels=actor_type1.index, values=actor_type1, name="Actor type1"), 1, 1)
#fig.add_trace(go.Pie(labels=actor_type2.index, values=actor_type2, name="Actor type2"), 1, 2)

# Update traces to create donut-like pie charts
fig.update_traces(hole=.6, hoverinfo="label+percent+name")

# Update layout with title and annotations
fig.update_layout(
    title="<b> Actor type involved in Sudan conflict<b>",
    titlefont={'color':None, 'size': 20, 'family': 'San-Serif'},
    height=600,
    width=1000,
    annotations=[
        dict(text='<b>instigator', x=0.16, y=0.5, font_size=20, showarrow=False),
        dict(text='<b>victim/hit back', x=0.88, y=0.5, font_size=20, showarrow=False)
    ]
)

# Show the plot
fig.show()
```

Based on the visualization of the instigators (Actor type1) involved in the Sudan conflict, several insights can be drawn:

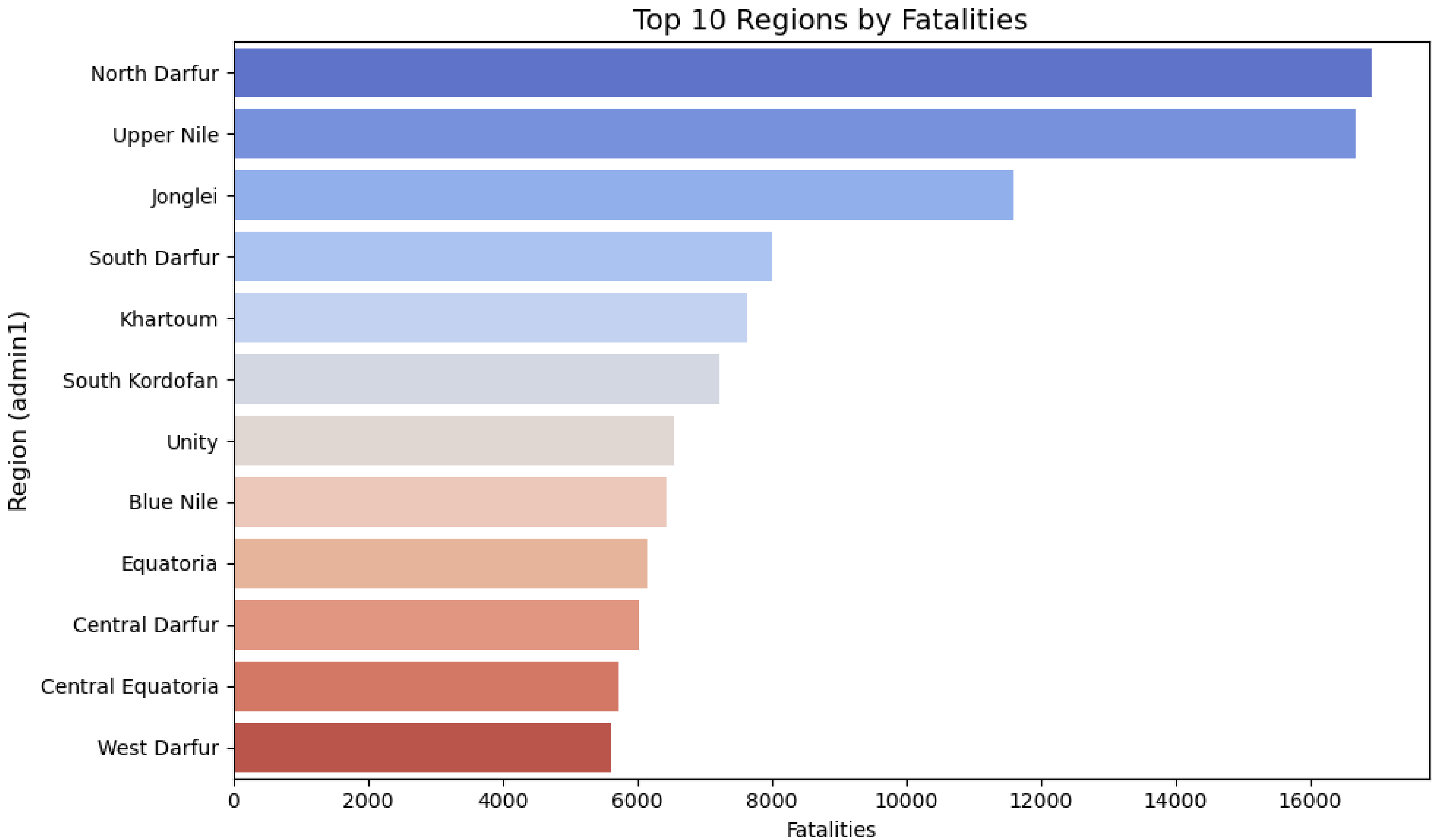
The state forces are the main dominant actors in Sudan conflict responsible for most fatalities.

The civilians are least perpertartors

What are the top 10 regions of Sudan with the higest count of fatalities?

In [14]:
```
# Grouping by 'admin1', summing, and sorting by 'fatalities'
df_grouped = df_selected.groupby('admin1').sum().sort_values(by='fatalities', ascending=False)

# Selecting the top 10 rows
top_10 = df_grouped.head(12).reset_index()

# Create a horizontal bar plot
plt.figure(figsize=(10, 6))
sns.barplot(data=top_10, x='fatalities', y='admin1', palette='coolwarm')

# Add titles and labels
plt.title('Top 10 Regions by Fatalities', fontsize=14)
plt.xlabel('Fatalities', fontsize=10)
plt.ylabel('Region (admin1)', fontsize=12)

# Show the plot
plt.tight_layout()
plt.show()
```

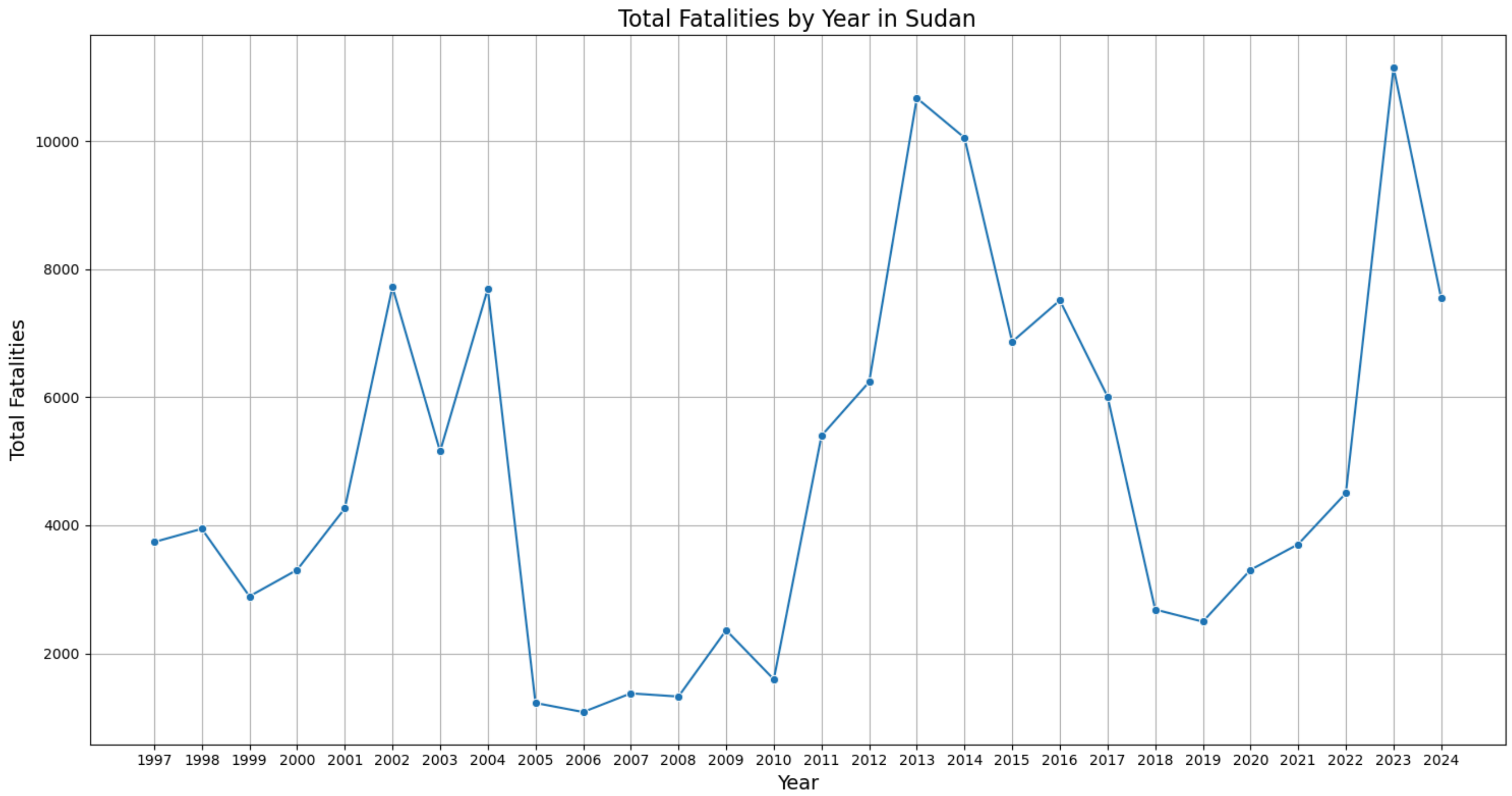
```
C:\Users\pgaduel\AppData\Local\Temp\ipykernel_29480\1969468016.py:9: FutureWarning:



Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` varia
ble to `hue` and set `legend=False` for the same effect.
```



According to the bar chart, North Darfur, and Upper Nile region has the higest count of fatalities in Sudan

Which particular period did Sudan recored the higest number of fatalities?

In [15]:
```
# Aggregate fatalities by year
fatalities_by_year = df_selected.groupby('year')['fatalities'].sum().reset_index()
# Create the plot using seaborn (Alternative, often preferred for aesthetics)
plt.figure(figsize=(15, 8))
sns.lineplot(x='year', y='fatalities', data=fatalities_by_year, marker='o') #using seaborn lineplot
plt.title('Total Fatalities by Year in Sudan', fontsize=16)
plt.xlabel('Year', fontsize=14)
plt.ylabel('Total Fatalities', fontsize=14)
plt.xticks(fatalities_by_year['year']) #Set x ticks to be the years
plt.grid(True)
plt.tight_layout()
plt.show()
```



Data Processing Feature engineering

In [16]:
```
from sklearn.feature_selection import (VarianceThreshold, SelectKBest, f_regression, mutual_info_regression,
    RFE, RFECV)
from sklearn.preprocessing import OneHotEncoder, StandardScaler, PolynomialFeatures
```

Hotencoding of categorical values in the dataset

In [17]:
```
df_encoded = pd.get_dummies(df_selected, dtype=int)
df_encoded.head(10)
```

Out[17]:

	year	fatalities	geo_precision	disorder_type_Demonstrations	disorder_type_Political violence	disorder_type_Political violence; Demonstrations	disorder_type_Strategic developments
0	2024	0	1	0	1	0	0
1	2024	1	1	0	0	1	0
2	2024	5	1	0	1	0	0
3	2024	0	1	1	0	0	0
4	2024	0	1	0	0	0	1
5	2024	8	1	0	1	0	0
6	2024	0	2	0	0	0	1
7	2024	10	1	0	1	0	0
8	2024	1	3	0	1	0	0
9	2024	0	2	0	1	0	0

10 rows × 4959 columns

Feature selection with filter method to remove redundant variables

In [18]:
```
df_encoded = pd.DataFrame(df_encoded)

# Define the list of columns to keep
selected_columns = [
    'year',
    'fatalities',
    'disorder_type_Demonstrations',
    'disorder_type_Political violence',
    'disorder_type_Political violence; Demonstrations',
    'disorder_type_Strategic developments',
    'event_type_Battles',
    'event_type_Explosions/Remote violence',
    'event_type_Protests'
]

# Create a new DataFrame with only the selected columns
selected_df = df_encoded[selected_columns]

print(selected_df)

#If you want to create a copy to ensure you are not modifying the original:
selected_df_copy = df_encoded[selected_columns].copy()
print("\nCopy of selected dataframe:")
selected_df_copy.head(10)
```

```
       year  fatalities  disorder_type_Demonstrations  \
0      2024           0                             0
1      2024           1                             0
2      2024           5                             0
3      2024           0                             1
4      2024           0                             0
...     ...         ...                           ...
35052  1997           0                             1
35053  1997           0                             0
35054  1997           7                             0
35055  1997           0                             0
35056  1997           0                             0

       disorder_type_Political violence  \
0                                     1
1                                     0
2                                     1
3                                     0
4                                     0
...                                 ...
35052                                 0
35053                                 0
35054                                 1
35055                                 1
35056                                 1

       disorder_type_Political violence; Demonstrations  \
0                                                     0
1                                                     1
2                                                     0
3                                                     0
4                                                     0
...                                                 ...
35052                                                 0
35053                                                 1
35054                                                 0
35055                                                 0
35056                                                 0

       disorder_type_Strategic developments  event_type_Battles  \
0                                         0                   1
1                                         0                   0
2                                         0                   0
```

```
3                                         0                   0
4                                         1                   0
...                                     ...                 ...
35052                                     0                   0
35053                                     0                   0
35054                                     0                   0
35055                                     0                   1
35056                                     0                   1

       event_type_Explosions/Remote violence  event_type_Protests
0                                          0                    0
1                                          0                    1
2                                          1                    0
3                                          0                    1
4                                          0                    0
...                                      ...                  ...
35052                                      0                    1
35053                                      0                    1
35054                                      0                    0
35055                                      0                    0
35056                                      0                    0

[35057 rows x 9 columns]

Copy of selected dataframe:
```

Out[18]:

	year	fatalities	disorder_type_Demonstrations	disorder_type_Political violence	disorder_type_Political violence; Demonstrations	disorder_type_Strategic developments	event_type_Batt
0	2024	0	0	1	0	0	
1	2024	1	0	0	1	0	
2	2024	5	0	1	0	0	
3	2024	0	1	0	0	0	
4	2024	0	0	0	0	1	
5	2024	8	0	1	0	0	
6	2024	0	0	0	0	1	
7	2024	10	0	1	0	0	
8	2024	1	0	1	0	0	
9	2024	0	0	1	0	0	

In [19]:

```
selected_df_copy.columns
```

Out[19]:

```
Index(['year', 'fatalities', 'disorder_type_Demonstrations',
       'disorder_type_Political violence',
       'disorder_type_Political violence; Demonstrations',
       'disorder_type_Strategic developments', 'event_type_Battles',
       'event_type_Explosions/Remote violence', 'event_type_Protests'],
      dtype='object')
```

df_encoded group by Year and counts

In [20]:
```
# Assuming 'year' is the column containing year information
grouped_df = selected_df_copy.groupby('year')

# Calculate summary statistics (e.g., mean, count) for each column in each group
summary_stats = grouped_df.agg(['mean', 'count'])

summary_stats.head(20)
```

Out[20]:

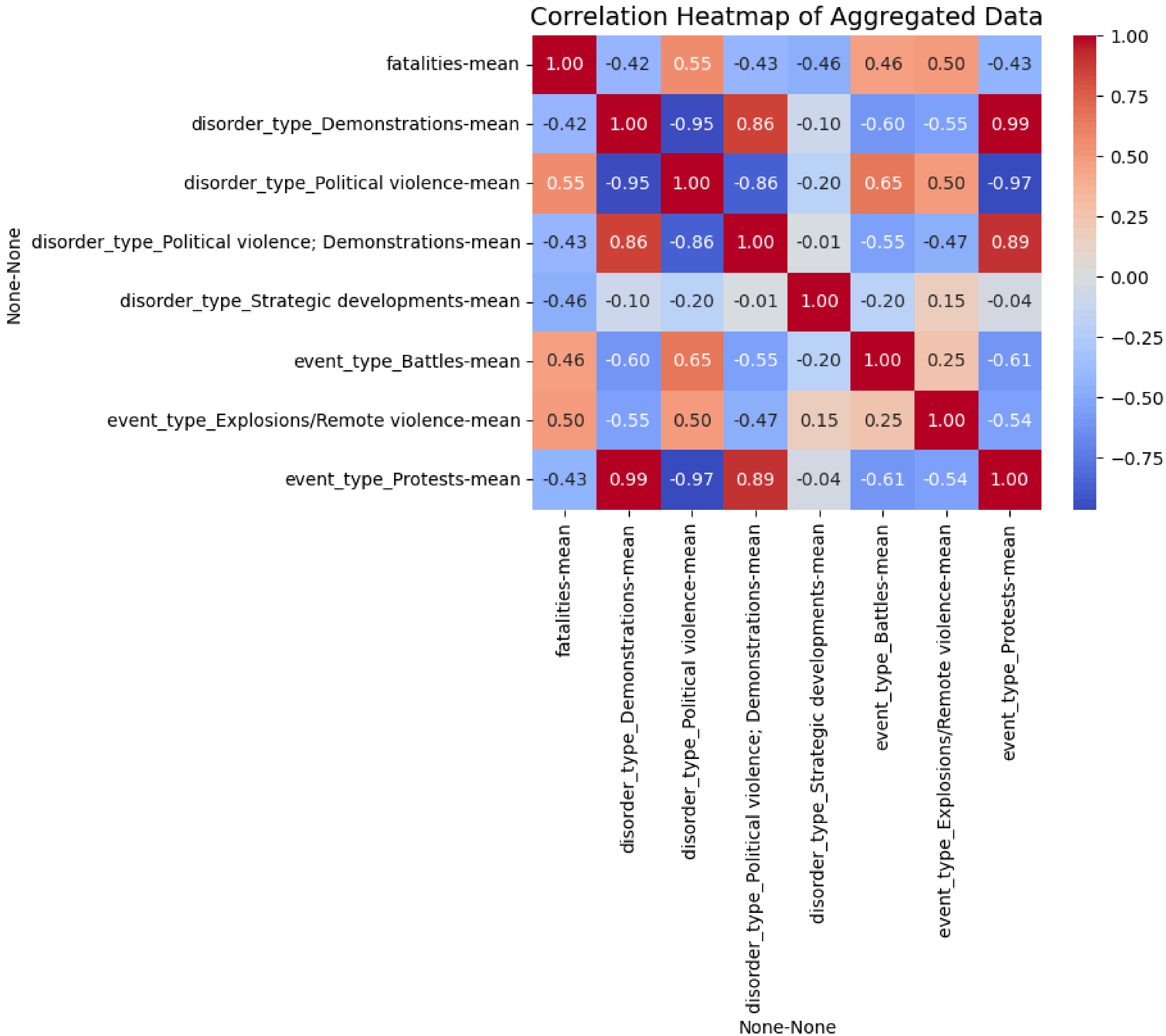
	fatalities		disorder_type_Demonstrations		disorder_type_Political violence		disorder_type_Political violence; Demonstrations		disorder_type_Strategic developments		event_typ
	mean	count	mean	count	mean	count	mean	count	mean	count	mean
year											
1997	17.073059	219	0.077626	219	0.872146	219	0.009132	219	0.041096	219	0.712329
1998	15.784000	250	0.048000	250	0.928000	250	0.000000	250	0.024000	250	0.740000
1999	13.641509	212	0.080189	212	0.896226	212	0.000000	212	0.023585	212	0.566038
2000	14.123932	234	0.076923	234	0.905983	234	0.008547	234	0.008547	234	0.500000
2001	19.035714	224	0.098214	224	0.879464	224	0.000000	224	0.022321	224	0.562500
2002	28.921348	267	0.056180	267	0.932584	267	0.000000	267	0.011236	267	0.486891
2003	30.862275	167	0.077844	167	0.892216	167	0.000000	167	0.029940	167	0.335329
2004	22.360465	344	0.008721	344	0.947674	344	0.000000	344	0.043605	344	0.313953
2005	5.133891	239	0.062762	239	0.903766	239	0.004184	239	0.029289	239	0.313808
2006	7.045455	154	0.038961	154	0.902597	154	0.000000	154	0.058442	154	0.318182
2007	12.185841	113	0.008850	113	0.938053	113	0.000000	113	0.053097	113	0.380531
2008	5.064885	262	0.019084	262	0.908397	262	0.003817	262	0.068702	262	0.488550
2009	8.850187	267	0.048689	267	0.928839	267	0.000000	267	0.022472	267	0.483146
2010	8.142857	196	0.076531	196	0.882653	196	0.005102	196	0.035714	196	0.581633
2011	16.262048	332	0.126506	332	0.822289	332	0.012048	332	0.039157	332	0.415663
2012	7.032694	887	0.149944	887	0.786922	887	0.005637	887	0.057497	887	0.254791
2013	7.892012	1352	0.106509	1352	0.830621	1352	0.008876	1352	0.053994	1352	0.317308
2014	4.922135	2042	0.113614	2042	0.791381	2042	0.009305	2042	0.085700	2042	0.376102
2015	3.318511	2069	0.086032	2069	0.877719	2069	0.006283	2069	0.029966	2069	0.342194
2016	3.310710	2269	0.085500	2269	0.835170	2269	0.016747	2269	0.062583	2269	0.305862

In [21]:
```
# Assuming 'year' is the column containing year information
grouped_df = selected_df_copy.groupby('year')

# Calculate summary statistics (e.g., mean, count) for each column in each group
summary_stats = grouped_df.agg(['mean'])

summary_stats.head(20)
```

Out[21]:

	fatalities	disorder_type_Demonstrations	disorder_type_Political violence	disorder_type_Political violence; Demonstrations	disorder_type_Strategic developments	event_type_Battle
	mean	mean	mean	mean	mean	mea
year						
1997	17.073059	0.077626	0.872146	0.009132	0.041096	0.71232
1998	15.784000	0.048000	0.928000	0.000000	0.024000	0.74000
1999	13.641509	0.080189	0.896226	0.000000	0.023585	0.56603
2000	14.123932	0.076923	0.905983	0.008547	0.008547	0.50000
2001	19.035714	0.098214	0.879464	0.000000	0.022321	0.56250
2002	28.921348	0.056180	0.932584	0.000000	0.011236	0.48689
2003	30.862275	0.077844	0.892216	0.000000	0.029940	0.33532
2004	22.360465	0.008721	0.947674	0.000000	0.043605	0.31395
2005	5.133891	0.062762	0.903766	0.004184	0.029289	0.31380
2006	7.045455	0.038961	0.902597	0.000000	0.058442	0.31818
2007	12.185841	0.008850	0.938053	0.000000	0.053097	0.38053
2008	5.064885	0.019084	0.908397	0.003817	0.068702	0.48855
2009	8.850187	0.048689	0.928839	0.000000	0.022472	0.48314
2010	8.142857	0.076531	0.882653	0.005102	0.035714	0.58163
2011	16.262048	0.126506	0.822289	0.012048	0.039157	0.41566
2012	7.032694	0.149944	0.786922	0.005637	0.057497	0.25479
2013	7.892012	0.106509	0.830621	0.008876	0.053994	0.31730
2014	4.922135	0.113614	0.791381	0.009305	0.085700	0.37610
2015	3.318511	0.086032	0.877719	0.006283	0.029966	0.34219
2016	3.310710	0.085500	0.835170	0.016747	0.062583	0.30586

In [22]:
```
# Calculate the correlation matrix
correlation_matrix = grouped_df.agg(['mean']).corr()

# Create the heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")

# Add a title
plt.title("Correlation Heatmap of Aggregated Data", fontsize=14)

# Show the plot
plt.show()
```


Correlation Heatmap of Aggregated Data
fatalities-mean
disorder_type_Demonstrations-mean
disorder_type_Political violence-mean
disorder_type_Political violence; Demonstrations-mean
disorder_type_Strategic developments-mean
event_type_Battles-mean
event_type_Explosions/Remote violence-mean
event_type_Protests-mean
None-None
None-None
1.00 -0.42 0.55 -0.43 -0.46 0.46 0.50 -0.43
-0.42 1.00 -0.95 0.86 -0.10 -0.60 -0.55 0.99
0.55 -0.95 1.00 -0.86 -0.20 0.65 0.50 -0.97
-0.43 0.86 -0.86 1.00 -0.01 -0.55 -0.47 0.89
-0.46 -0.10 -0.20 -0.01 1.00 -0.20 0.15 -0.04
0.46 -0.60 0.65 -0.55 -0.20 1.00 0.25 -0.61
0.50 -0.55 0.50 -0.47 0.15 0.25 1.00 -0.54
-0.43 0.99 -0.97 0.89 -0.04 -0.61 -0.54 1.00
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

Model Selection and training

In [24]:
```
#Feature selection
#from sklearn.feature_selection import SelectKBest, chi2, f_classif
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
import warnings
warnings.filterwarnings('ignore')
#from itertools import combinations
#from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression, Lasso
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.linear_model import Ridge
# Prepare data for modeling
X = summary_stats.drop(['fatalities'], axis=1)
y = summary_stats['fatalities']


# Split data FIRST

# Split into train, test, and validation sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,random_state=42)
```

In [25]:
```
# Scale X_train and X_val using StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

X_train = pd.DataFrame(X_train_scaled, columns=X.columns)
X_test =  pd.DataFrame(X_test_scaled, columns=X.columns)

X_train
```

Out[25]:

	disorder_type_Demonstrations	disorder_type_Political violence	disorder_type_Political violence; Demonstrations	disorder_type_Strategic developments	event_type_Battles	event_type_
	mean	mean	mean	mean	mean	
0	-0.062184	-0.196612	0.286997	0.672818	-0.144070	
1	3.277993	-3.175152	3.576348	-0.457802	-1.966187	
2	-0.826333	0.699569	-0.364326	0.303258	0.672871	
3	-0.361954	0.502407	-0.211786	-0.413948	1.349126	
4	0.231491	-0.230760	-0.148296	0.059643	-1.025399	
5	-0.592586	0.849702	-0.817324	-0.668633	2.499676	
6	-0.186671	0.477985	-0.817324	-0.705127	1.210126	
7	-0.526463	0.884811	-0.817324	-0.946141	0.660824	
8	-0.332384	0.606360	-0.817324	-0.677658	1.235828	
9	-0.119620	0.103915	0.236097	-0.016519	-0.571214	
10	1.672319	-1.353045	0.004685	-0.657606	-0.875389	
11	-0.358782	0.681081	0.197082	-1.004603	0.756059	
12	-0.089861	-0.676184	-0.303147	2.216778	0.258629	
13	2.008370	-1.911145	1.302940	-0.214909	-1.412596	
14	-0.285149	0.464616	-0.071596	-0.538920	-0.390411	
15	-0.791544	-0.373768	-0.761248	3.329403	-0.447921	
16	-0.238721	-0.035350	0.194538	0.706767	-0.151164	
17	-0.910104	1.000381	-0.817324	-0.242400	-0.595582	
18	-0.909065	0.926695	-0.817324	-0.036016	-0.111892	
19	0.042030	0.040102	0.612621	-0.339107	0.143342	
20	-0.289447	0.138749	1.170357	0.170208	-0.654370	
21	-0.351335	0.575642	-0.817324	-0.539486	-0.440285	

LINEAR REGRESSION AS BASELINE MODEL

In [27]:
```
# Create a LinearRegression model and fit it on scaled training data
regression = LinearRegression()
regression.fit(X_train, y_train)

# Calculate a baseline r-squared score on training data and validation

print("Train R^2:", r2_score((regression.predict(X_train)), y_train))
print("Test R^2:", r2_score((regression.predict(X_test)), y_test))
```

```
Train R^2: 0.4347308718794314
Test R^2: 0.3043523148504288
```

Observations: Train R^2 : (0.43)

The model explains 43% of the variance in the training dataset.

Test R^2: (0.30):

The model explains only 30 % of the variance in the test dataset. This indicates the model is not generalizing well to unseen data

Random Forest regressor as second model

In [32]:
```
# Create and train the Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor
rf_regressor = RandomForestRegressor(n_estimators=100, random_state=42)
rf_regressor.fit(X_train, y_train)
```

Out[32]:
```
RandomForestRegressor(random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [33]:

```
print("Train R^2:", r2_score((rf_regressor.predict(X_train)), y_train))
print("Test R^2:", r2_score((rf_regressor.predict(X_test)), y_test))
```

```
Train R^2: 0.8617894726016958
Test R^2: -0.33393212263004624
```

Training Set

Train R^2 (0.86):

This means that the model explains 86% of the variance in the target variable for the training data.

A high R^2 suggests that the model is fitting well in capturing patterns in the data effectively.

Test dataset

test R^2 -0.33

A negative R^2 indicates that the model performs worse than a simple baseline (e.g., predicting the mean of the target variable).

This suggests the model is overfitted or poorly generalized to unseen data.