In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
data = pd.read_csv('earthquake_data_tsunami.csv')
data
```

Out[2]:

	magnitude	cdi	mmi	sig	nst	dmin	gap	depth	latitude	longitude	Year
0	7.0	8	7	768	117	0.509	17.0	14.000	-9.7963	159.596	2022
1	6.9	4	4	735	99	2.229	34.0	25.000	-4.9559	100.738	2022
2	7.0	3	3	755	147	3.125	18.0	579.000	-20.0508	-178.346	2022
3	7.3	5	5	833	149	1.865	21.0	37.000	-19.2918	-172.129	2022
4	6.6	0	2	670	131	4.998	27.0	624.464	-25.5948	178.278	2022
...	...	...	...	...	...	...	...	...	...	...	...
777	7.7	0	8	912	427	0.000	0.0	60.000	13.0490	-88.660	2001
778	6.9	5	7	745	0	0.000	0.0	36.400	56.7744	-153.281	2001
779	7.1	0	7	776	372	0.000	0.0	103.000	-14.9280	167.170	2001
780	6.8	0	5	711	64	0.000	0.0	33.000	6.6310	126.899	2001
781	7.5	0	7	865	324	0.000	0.0	33.000	6.8980	126.579	2001

782 rows × 13 columns

In [8]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 782 entries, 0 to 781
Data columns (total 13 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   magnitude  782 non-null    float64
 1   cdi        782 non-null    int64  
 2   mmi        782 non-null    int64  
 3   sig        782 non-null    int64  
 4   nst        782 non-null    int64  
 5   dmin       782 non-null    float64
 6   gap        782 non-null    float64
 7   depth      782 non-null    float64
 8   latitude   782 non-null    float64
 9   longitude  782 non-null    float64
 10  Year       782 non-null    int64  
 11  Month      782 non-null    int64  
 12  tsunami    782 non-null    int64  
dtypes: float64(6), int64(7)
memory usage: 79.6 KB
```

In [9]:
```
data.describe()
```

Out[9]:

	magnitude	cdi	mmi	sig	nst	dmin	
count	782.000000	782.000000	782.000000	782.000000	782.000000	782.000000	782.00(
mean	6.941125	4.333760	5.964194	870.108696	230.250639	1.325757	25.038
std	0.445514	3.169939	1.462724	322.465367	250.188177	2.218805	24.22!
min	6.500000	0.000000	1.000000	650.000000	0.000000	0.000000	0.00(
25%	6.600000	0.000000	5.000000	691.000000	0.000000	0.000000	14.62!
50%	6.800000	5.000000	6.000000	754.000000	140.000000	0.000000	20.00(
75%	7.100000	7.000000	7.000000	909.750000	445.000000	1.863000	30.00(
max	9.100000	9.000000	9.000000	2910.000000	934.000000	17.654000	239.00(

In [10]:

```
data.isnull().sum()
```

Out[10]:

```
magnitude    0
cdi          0
mmi          0
sig          0
nst          0
dmin         0
gap          0
depth        0
latitude     0
longitude    0
Year         0
Month        0
tsunami      0
dtype: int64
```

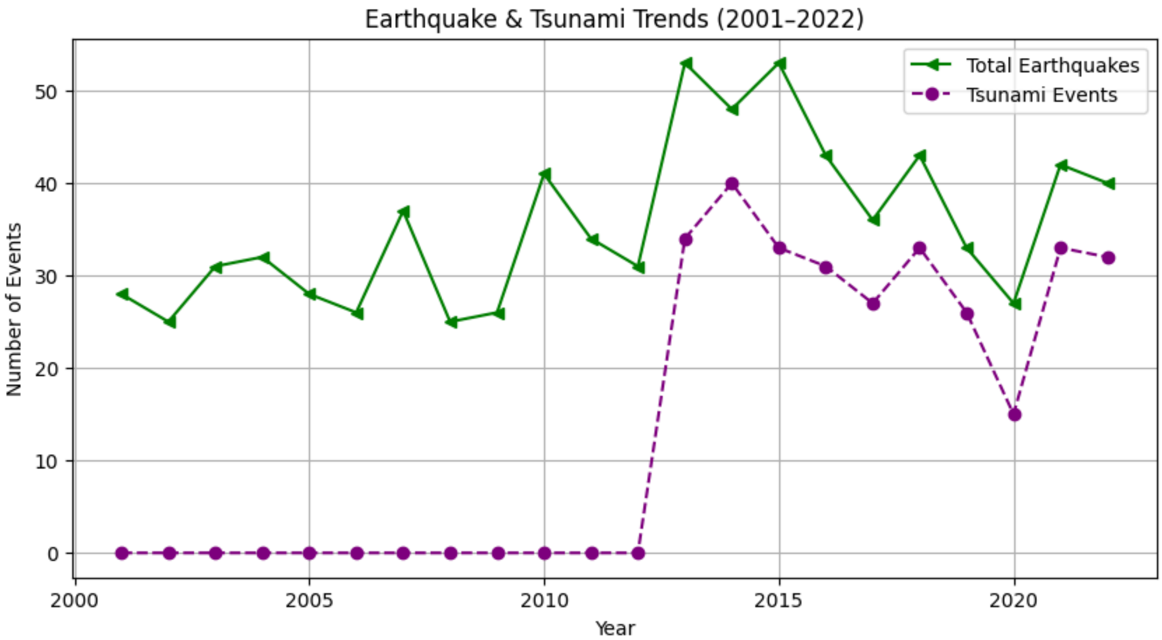
1) Time-Based Analysis:

** Explore how earthquake occurrences and tsunami events have changed over the 22-year period (2001–2022).

In [3]:

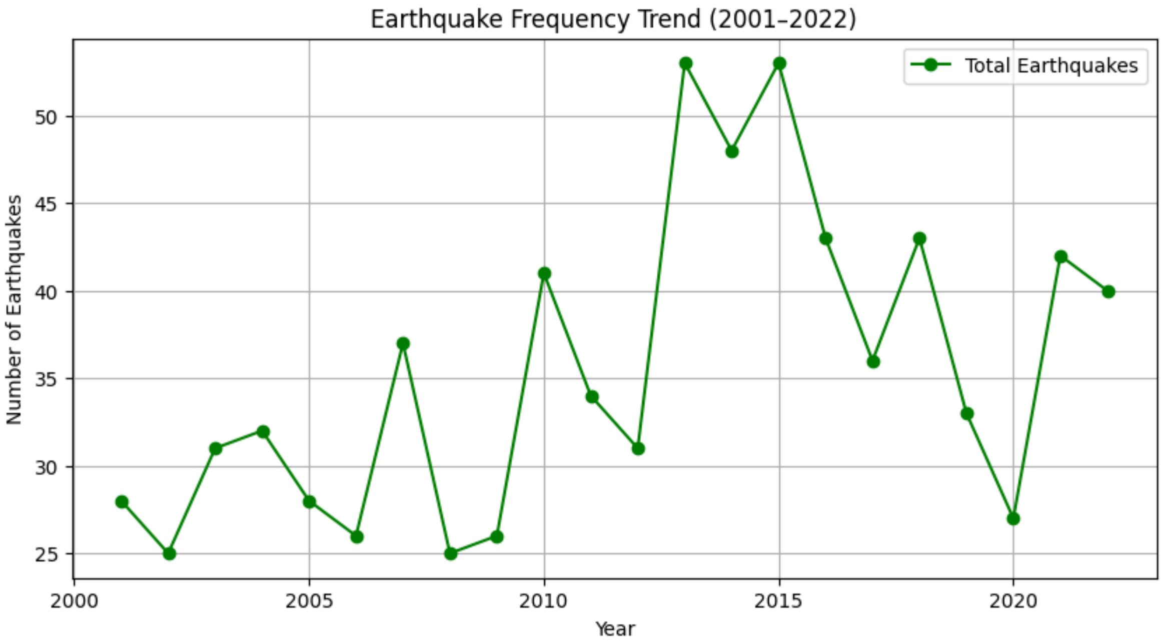
```
# Group earthquake counts per year
earthquake_count = data.groupby('Year').size()

# Group tsunami events per year (sum of 1s and 0s)
tsunami_count = data.groupby('Year')['tsunami'].sum()

# Plot directly using those grouped results
plt.figure(figsize=(10,5))
plt.plot(earthquake_count.index, earthquake_count.values,
         marker='<', linestyle='-', color='green', label='Total Earthquakes')

plt.plot(tsunami_count.index, tsunami_count.values,
         marker='o', linestyle='--', color='purple', label='Tsunami Events')

plt.title("Earthquake & Tsunami Trends (2001-2022)")
plt.xlabel("Year")
plt.ylabel("Number of Events")
```

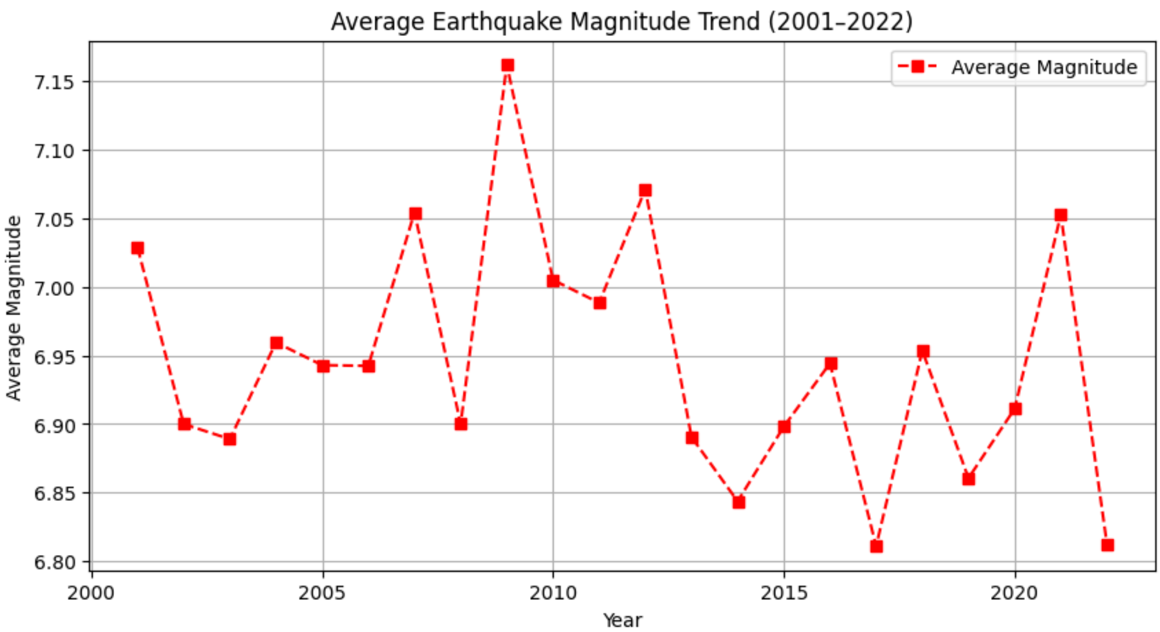
```
plt.legend()
plt.grid(True)
plt.show()
```



** Identify any trends in the frequency or magnitude of earthquakes over time.

In [13]:
```
# Group by year to calculate total earthquakes and average magnitude
yearly_data = data.groupby('Year').agg({
    'magnitude': 'mean'
}).reset_index()

# Add total earthquake count
yearly_data['Earthquake_Count'] = data.groupby('Year').size().values

# Plot 1: Earthquake Frequency Over Time
plt.figure(figsize=(10,5))
plt.plot(yearly_data['Year'], yearly_data['Earthquake_Count'], marker='o', color
plt.title("Earthquake Frequency Trend (2001–2022)")
plt.xlabel("Year")
plt.ylabel("Number of Earthquakes")
plt.legend()
plt.grid(True)
plt.show()

# Plot 2: Average Magnitude Over Time
plt.figure(figsize=(10,5))
plt.plot(yearly_data['Year'], yearly_data['magnitude'], marker='s', linestyle='-
plt.title("Average Earthquake Magnitude Trend (2001–2022)")
plt.xlabel("Year")
plt.ylabel("Average Magnitude")
plt.legend()
plt.grid(True)
plt.show()
```



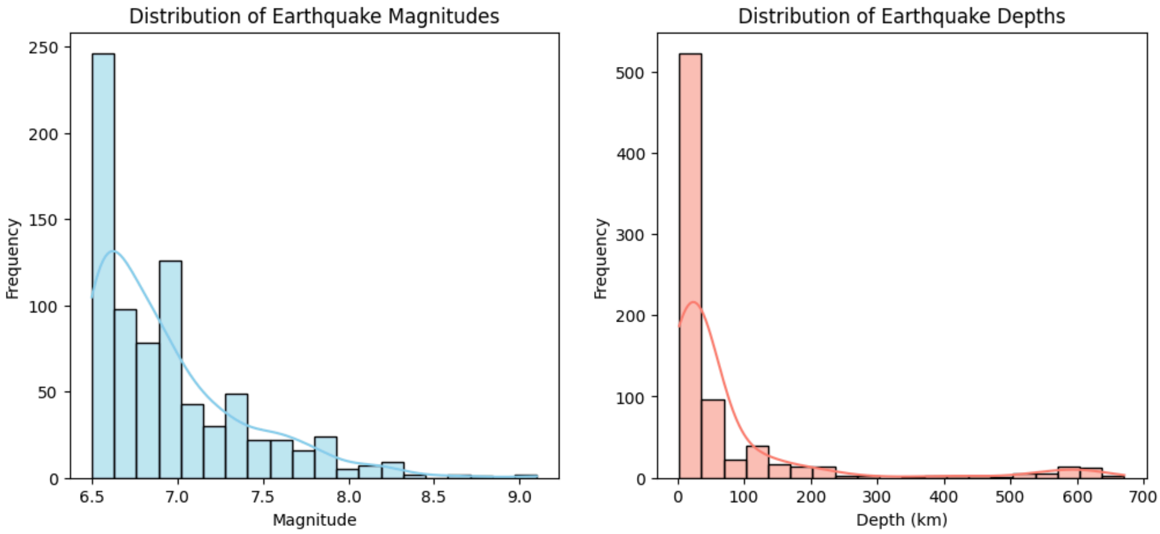


2) Magnitude and Depth Analysis:

** Analyze the distribution of earthquake magnitudes and depths.

In [4]:
```
# Plot the distribution of Magnitude and Depth
plt.figure(figsize=(12,5))

# Magnitude distribution
plt.subplot(1,2,1)
sns.histplot(data['magnitude'], bins=20, kde=True, color='skyblue')
plt.title('Distribution of Earthquake Magnitudes')
plt.xlabel('Magnitude')
plt.ylabel('Frequency')

# Depth distribution
plt.subplot(1,2,2)
sns.histplot(data['depth'], bins=20, kde=True, color='salmon')
```

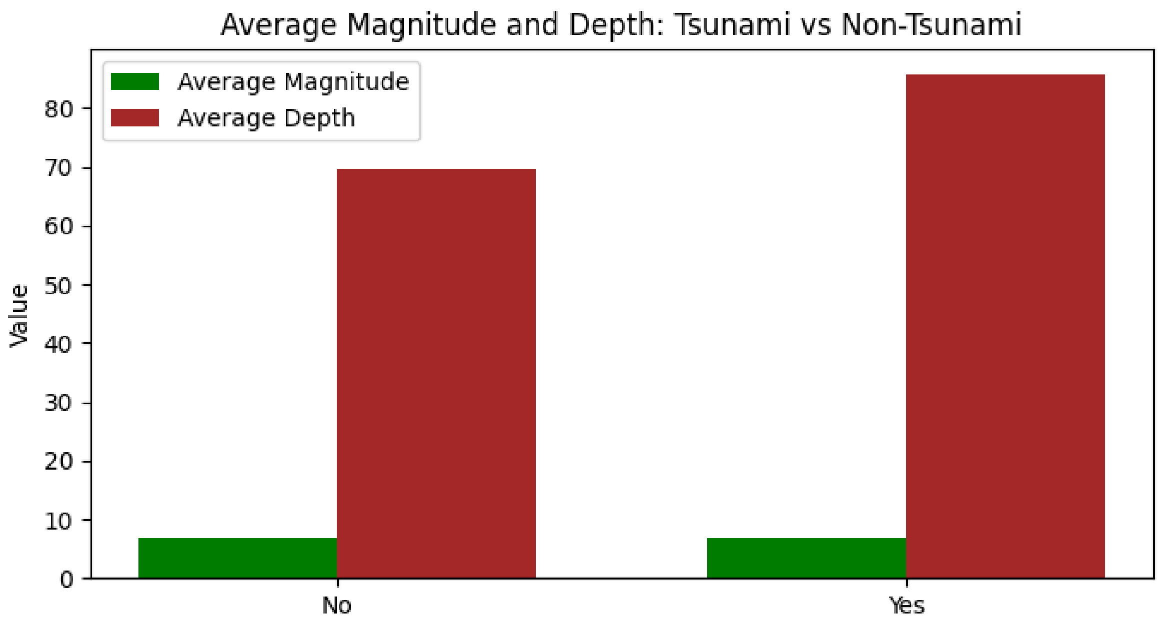
```
plt.title('Distribution of Earthquake Depths')
plt.xlabel('Depth (km)')
plt.ylabel('Frequency')

plt.show()
```



**Compare the average magnitude and depth of tsunami vs. non-tsunami events.

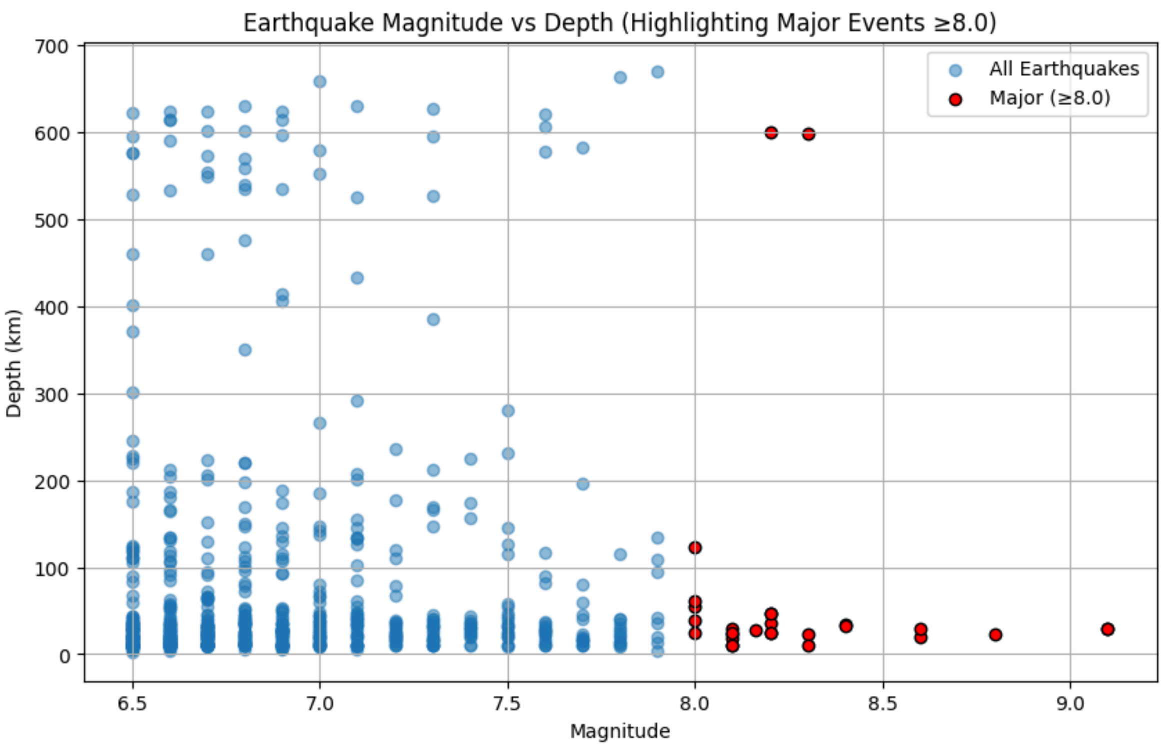
In [14]:

```
import matplotlib.pyplot as plt
import pandas as pd

# Group by tsunami (0 = No, 1 = Yes) and calculate mean
avg_stats = data.groupby('tsunami')[['magnitude','depth']].mean().reset_index()
avg_stats['Tsunami'] = avg_stats['tsunami'].map({0:'No', 1:'Yes'})

# Plotting
plt.figure(figsize=(8,4))
bar_width = 0.35
x = range(len(avg_stats))

# Average Magnitude
plt.bar(x, avg_stats['magnitude'], width=bar_width, label='Average Magnitude', c

# Average Depth
plt.bar([i + bar_width for i in x], avg_stats['depth'], width=bar_width, label='

# X-axis labels
plt.xticks([i + bar_width/2 for i in x], avg_stats['Tsunami'])
plt.ylabel('Value')
plt.title('Average Magnitude and Depth: Tsunami vs Non-Tsunami')
plt.legend()
plt.show()
```



** Highlight major earthquakes (≥8.0) and their characteristics.

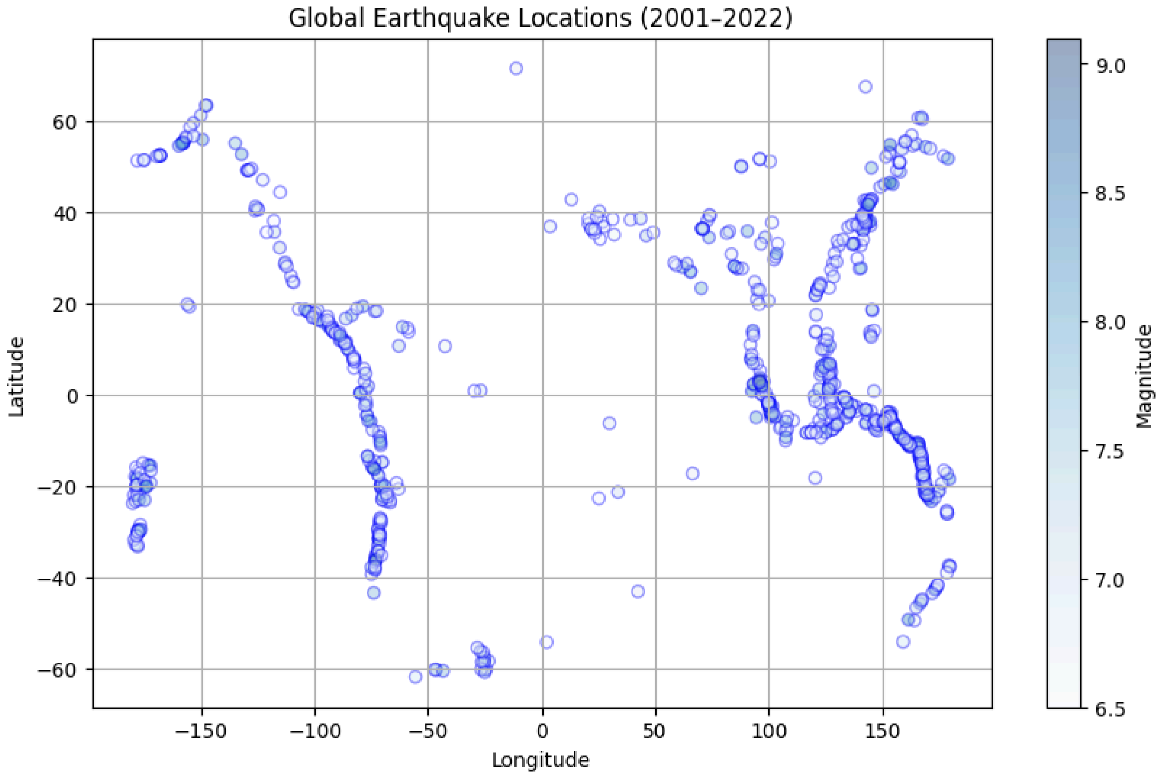
In [6]:
```
major_eq = data[data['magnitude'] >= 8.0]

plt.figure(figsize=(10,6))
plt.scatter(data['magnitude'], data['depth'], alpha=0.5, label='All Earthquakes'
plt.scatter(major_eq['magnitude'], major_eq['depth'], color='red', label='Major

plt.title("Earthquake Magnitude vs Depth (Highlighting Major Events ≥8.0)")
plt.xlabel("Magnitude")
plt.ylabel("Depth (km)")
plt.legend()
plt.grid(True)
plt.show()
```



3) Geographic Distribution Using 2D Plotting:

** Plot earthquake locations using latitude and longitude on a 2D scatter plot.

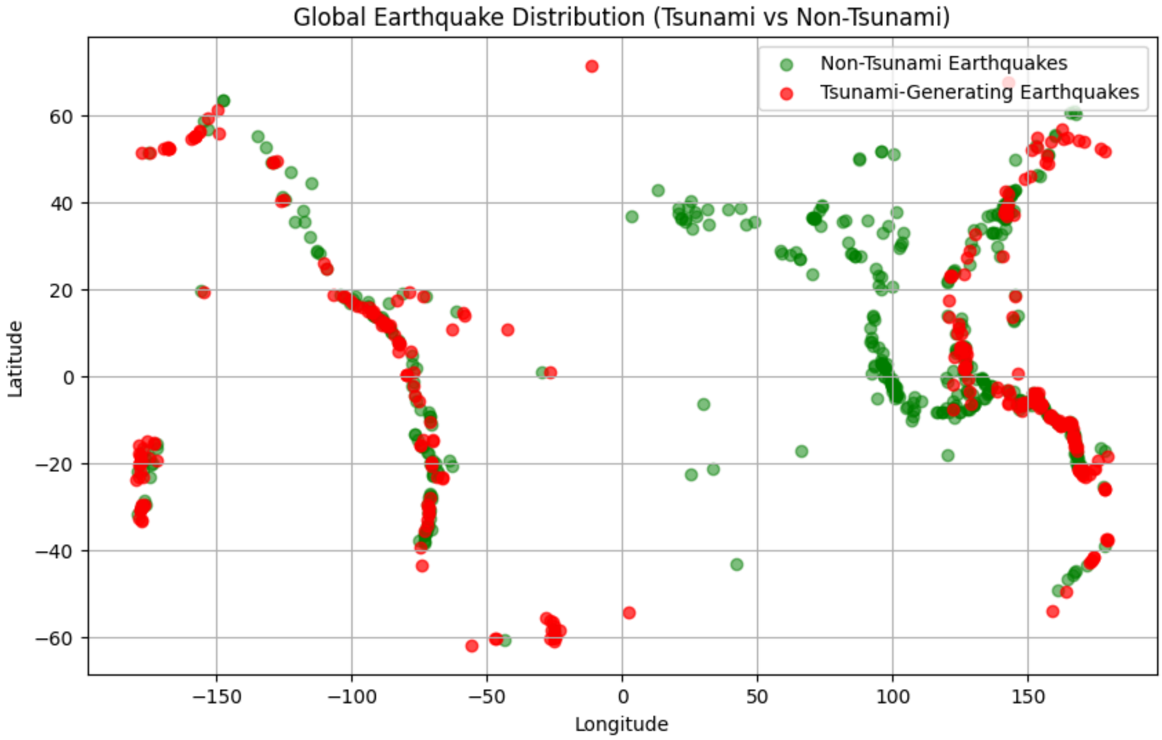
In [15]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(10,6))
plt.scatter(
    data['longitude'], data['latitude'],alpha=0.4,c=data['magnitude'],cmap='Blue
)
plt.title("Global Earthquake Locations (2001-2022)")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.colorbar(label='Magnitude')
plt.grid(True)
plt.show()
```



** Visually distinguish between tsunami and non-tsunami events.

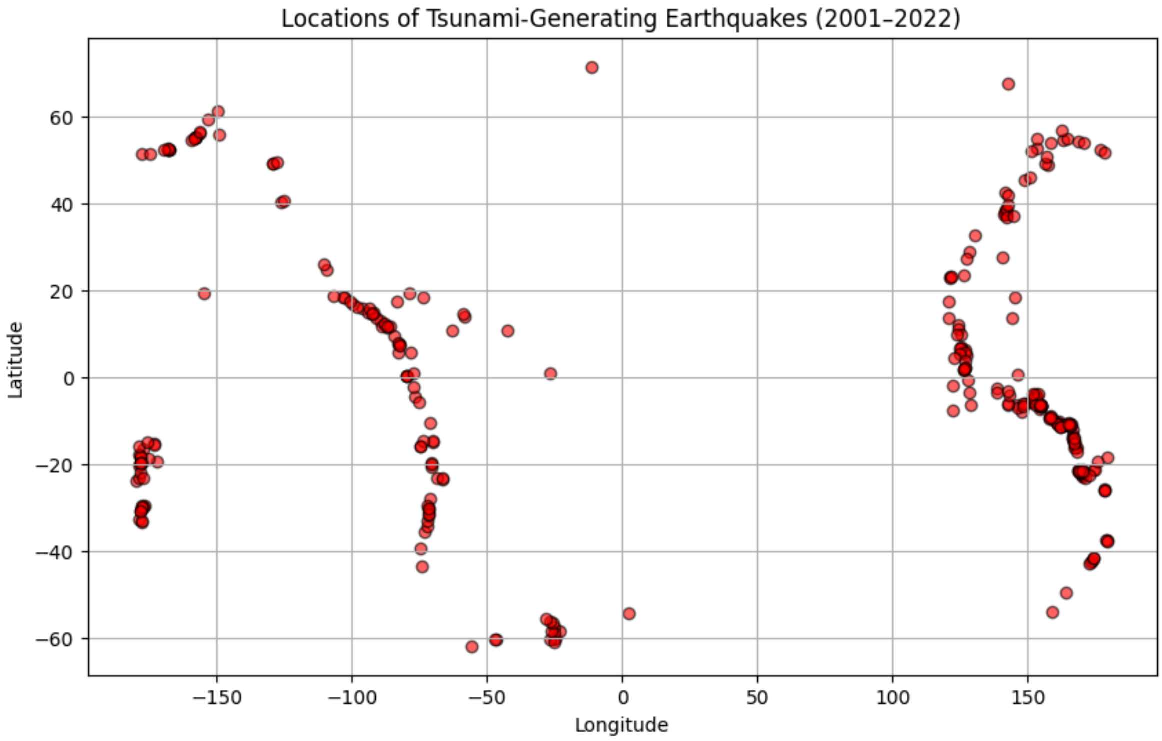
In [16]:
```
df = pd.DataFrame(data)
# Plot both groups
plt.figure(figsize=(10,6))

plt.scatter(df[data['tsunami'] == 0]['longitude'],
            df[data['tsunami'] == 0]['latitude'],
            color='green', alpha=0.5, label='Non-Tsunami Earthquakes')

plt.scatter(df[data['tsunami'] == 1]['longitude'],
            df[data['tsunami'] == 1]['latitude'],
```

```
            color='red', alpha=0.7, label='Tsunami-Generating Earthquakes')

plt.title("Global Earthquake Distribution (Tsunami vs Non-Tsunami)")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.legend()
plt.grid(True)
plt.show()
```



** Identify clusters or regions with higher concentration of tsunami events (without using map tiles or interactive maps).

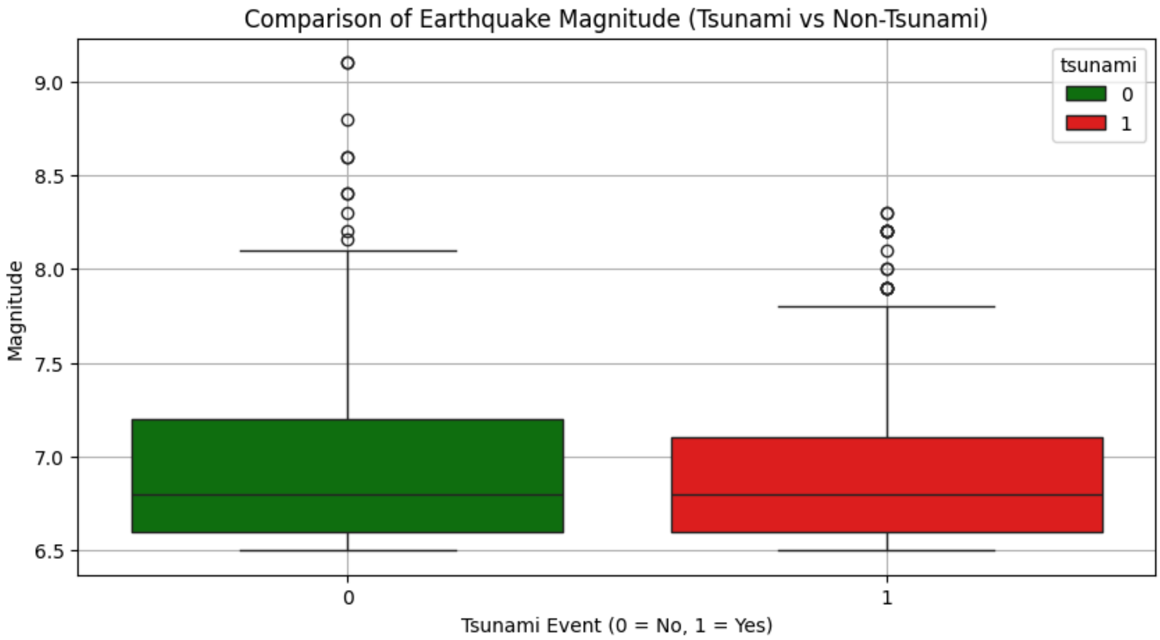
In [17]:
```
plt.figure(figsize=(10,6))
plt.scatter(
    data[data['tsunami'] == 1]['longitude'],   # filter directly for tsunami eve
    data[data['tsunami'] == 1]['latitude'],
    color='red', alpha=0.6, edgecolor='black'
)
plt.title("Locations of Tsunami-Generating Earthquakes (2001-2022)")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.grid(True)
plt.show()
```

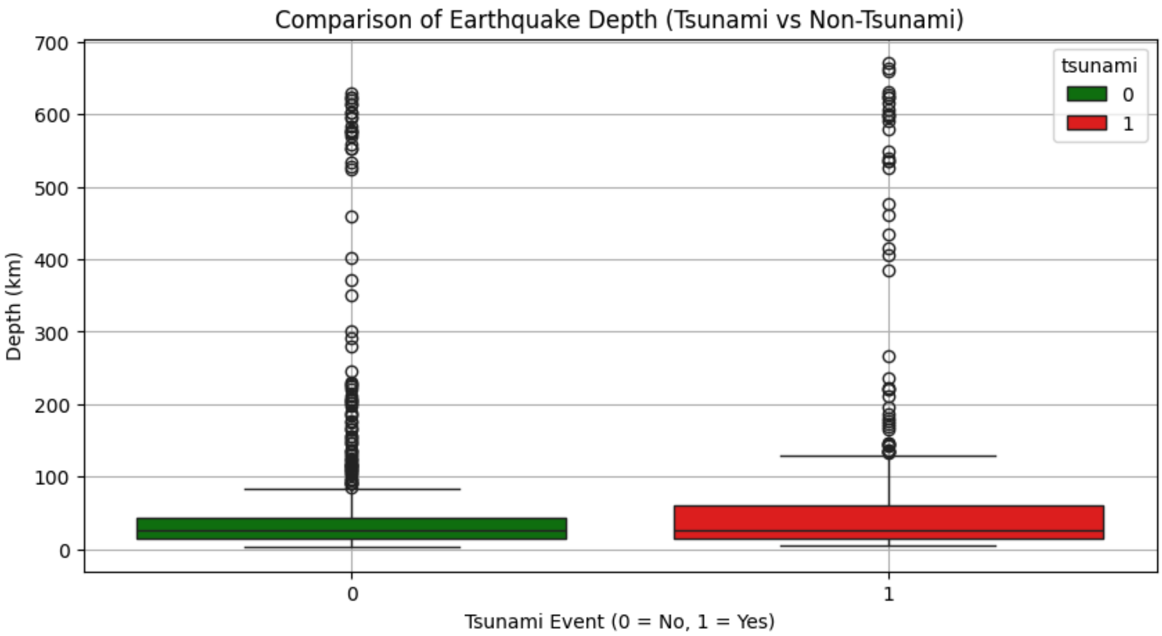


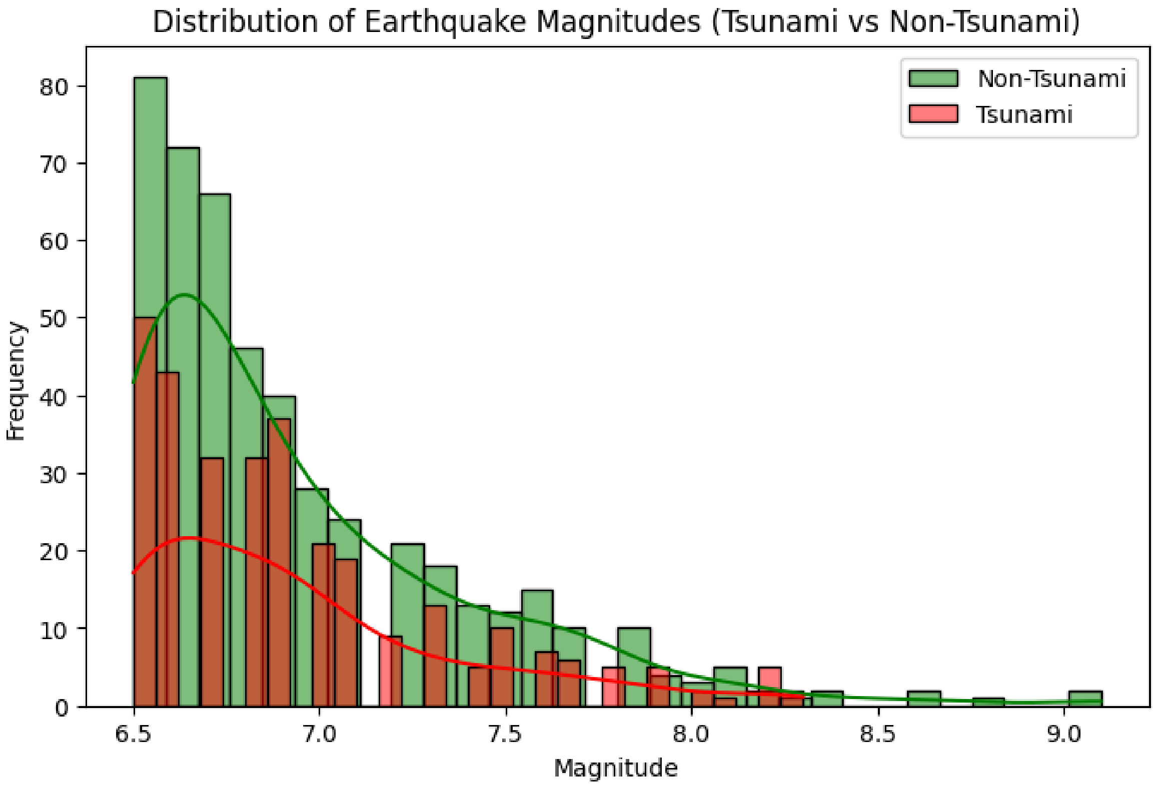
4) Statistical and Comparative Analysis:

** Use box plots, histograms, and bar chart to compare seismic features between tsunami and non-tsunami events.

In [18]:
```
plt.figure(figsize=(10,5))

# Boxplot for Magnitude
sns.boxplot(x='tsunami', y='magnitude',hue='tsunami', data=data, palette=['green
plt.title("Comparison of Earthquake Magnitude (Tsunami vs Non-Tsunami)")
plt.xlabel("Tsunami Event (0 = No, 1 = Yes)")
plt.ylabel("Magnitude")
plt.grid(True)
plt.show()


# Boxplot for Depth
plt.figure(figsize=(10,5))
sns.boxplot(x='tsunami', y='depth',hue='tsunami', data=data, palette=['green', '
plt.title("Comparison of Earthquake Depth (Tsunami vs Non-Tsunami)")
plt.xlabel("Tsunami Event (0 = No, 1 = Yes)")
plt.ylabel("Depth (km)")
plt.grid(True)
plt.show()

plt.figure(figsize=(8,5))
sns.histplot(data[data['tsunami']==0]['magnitude'], bins=30, color='green', labe
sns.histplot(data[data['tsunami']==1]['magnitude'], bins=30, color='red', label=
plt.title("Distribution of Earthquake Magnitudes (Tsunami vs Non-Tsunami)")
plt.xlabel("Magnitude")
plt.ylabel("Frequency")
plt.legend()
plt.show()
```

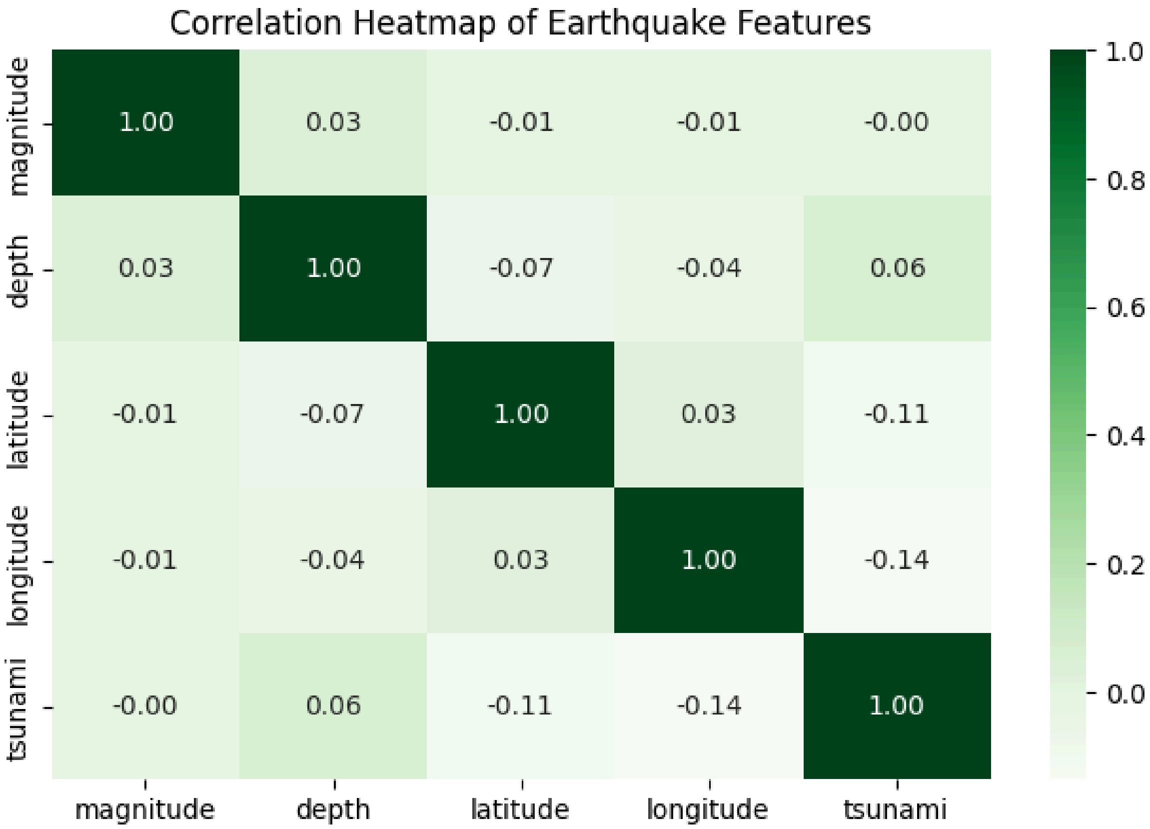

Comparison of Earthquake Magnitude (Tsunami vs Non-Tsunami)
tsunami
0
1
9.0
8.5
8.0
7.5
7.0
6.5
Magnitude
0
1
Tsunami Event (0 = No, 1 = Yes)


Comparison of Earthquake Depth (Tsunami vs Non-Tsunami)
tsunami
0
1
700
600
500
400
300
200
100
0
Depth (km)
0
1
Tsunami Event (0 = No, 1 = Yes)



** Analyze correlations between variables using heatmaps.

In [19]:
```
# Select only numeric columns for correlation
numeric_data = data[['magnitude', 'depth', 'latitude', 'longitude', 'tsunami']]

# Compute correlation matrix
corr = numeric_data.corr()

# Plot heatmap
plt.figure(figsize=(8,5))
sns.heatmap(corr, annot=True, cmap='Greens', fmt='.2f')

plt.title("Correlation Heatmap of Earthquake Features")
plt.show()
```



5) Insights and Observations:

1. Key Differences in Seismic Behavior (Tsunami vs Non-Tsunami)

Magnitude:

Tsunami-generating earthquakes generally have higher magnitudes, most often above 6.5, while non-tsunami earthquakes are more frequent in the 4.0–6.0 range. → This shows that energy release is a critical factor for tsunami generation.

Depth:

Tsunami events occur predominantly at shallow depths (≤70 km), whereas non-tsunami earthquakes can occur at any depth, often deeper than 100 km. → Shallow-focus quakes displace more ocean water, increasing tsunami likelihood.

2. Seismic Thresholds and Indicators of Tsunami Potential

| Indicator | Tsunami-Prone Range | Observation | ---------------------| -----------------------------------| -- | | **Magnitude Threshold**| ≥ **6.5** | Earthquakes above this magnitude often coincide with tsunami generation.
| **Depth Threshold** | ≤ **70 km** (shallow-focus) | Shallow earthquakes are more capable of displacing ocean water.
| **Location Factor** | **Subduction zones / coastal regions**| Undersea or near-shore faults

along plate boundaries are high-risk areas.
| **Energy Release** | High magnitude & low depth combination| These conditions produce sufficient vertical sea-floor movement to initiate tsunamis. |

In [ ]: