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	Month	tsunami
0	7.0	8	7	768	117	0.509	17.0	14.000	-9.7963	159.596	2022	11	1
1	6.9	4	4	735	99	2.229	34.0	25.000	-4.9559	100.738	2022	11	0
2	7.0	3	3	755	147	3.125	18.0	579.000	-20.0508	-178.346	2022	11	1
3	7.3	5	5	833	149	1.865	21.0	37.000	-19.2918	-172.129	2022	11	1
4	6.6	0	2	670	131	4.998	27.0	624.464	-25.5948	178.278	2022	11	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...
777	7.7	0	8	912	427	0.000	0.0	60.000	13.0490	-88.660	2001	1	0
778	6.9	5	7	745	0	0.000	0.0	36.400	56.7744	-153.281	2001	1	0
779	7.1	0	7	776	372	0.000	0.0	103.000	-14.9280	167.170	2001	1	0
780	6.8	0	5	711	64	0.000	0.0	33.000	6.6310	126.899	2001	1	0
781	7.5	0	7	865	324	0.000	0.0	33.000	6.8980	126.579	2001	1	0

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	gap	depth	latitude	longitud
count	782.000000	782.000000	782.000000	782.000000	782.000000	782.000000	782.000000	782.000000	782.000000	782.00000
mean	6.941125	4.333760	5.964194	870.108696	230.250639	1.325757	25.038990	75.883199	3.538100	52.60919
std	0.445514	3.169939	1.462724	322.465367	250.188177	2.218805	24.225067	137.277078	27.303429	117.89888
min	6.500000	0.000000	1.000000	650.000000	0.000000	0.000000	0.000000	2.700000	-61.848400	-179.96800
25%	6.600000	0.000000	5.000000	691.000000	0.000000	0.000000	14.625000	14.000000	-14.595600	-71.66805
50%	6.800000	5.000000	6.000000	754.000000	140.000000	0.000000	20.000000	26.295000	-2.572500	109.42600
75%	7.100000	7.000000	7.000000	909.750000	445.000000	1.863000	30.000000	49.750000	24.654500	148.94100
max	9.100000	9.000000	9.000000	2910.000000	934.000000	17.654000	239.000000	670.810000	71.631200	179.66200

In [10]:
```
data.isnull().sum()
```

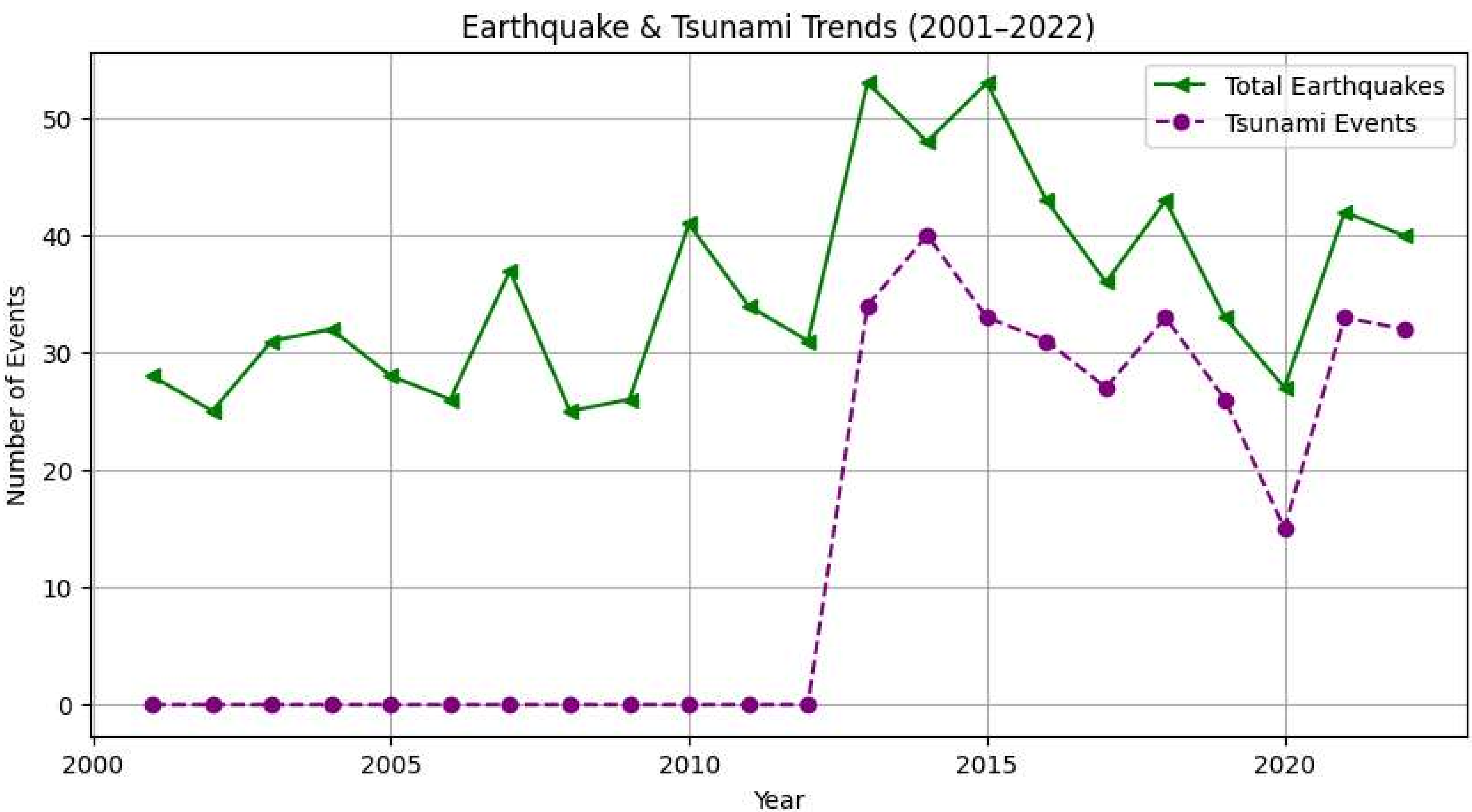
Out[10]:
```
magnitude    0
cdi          0
mmi          0
sig          0
nst          0
dmin         0
gap          0
depth        0
latitude     0
longitude    0
Year         0
Month        0
tsunami      0
dtype: int64
```

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")
```

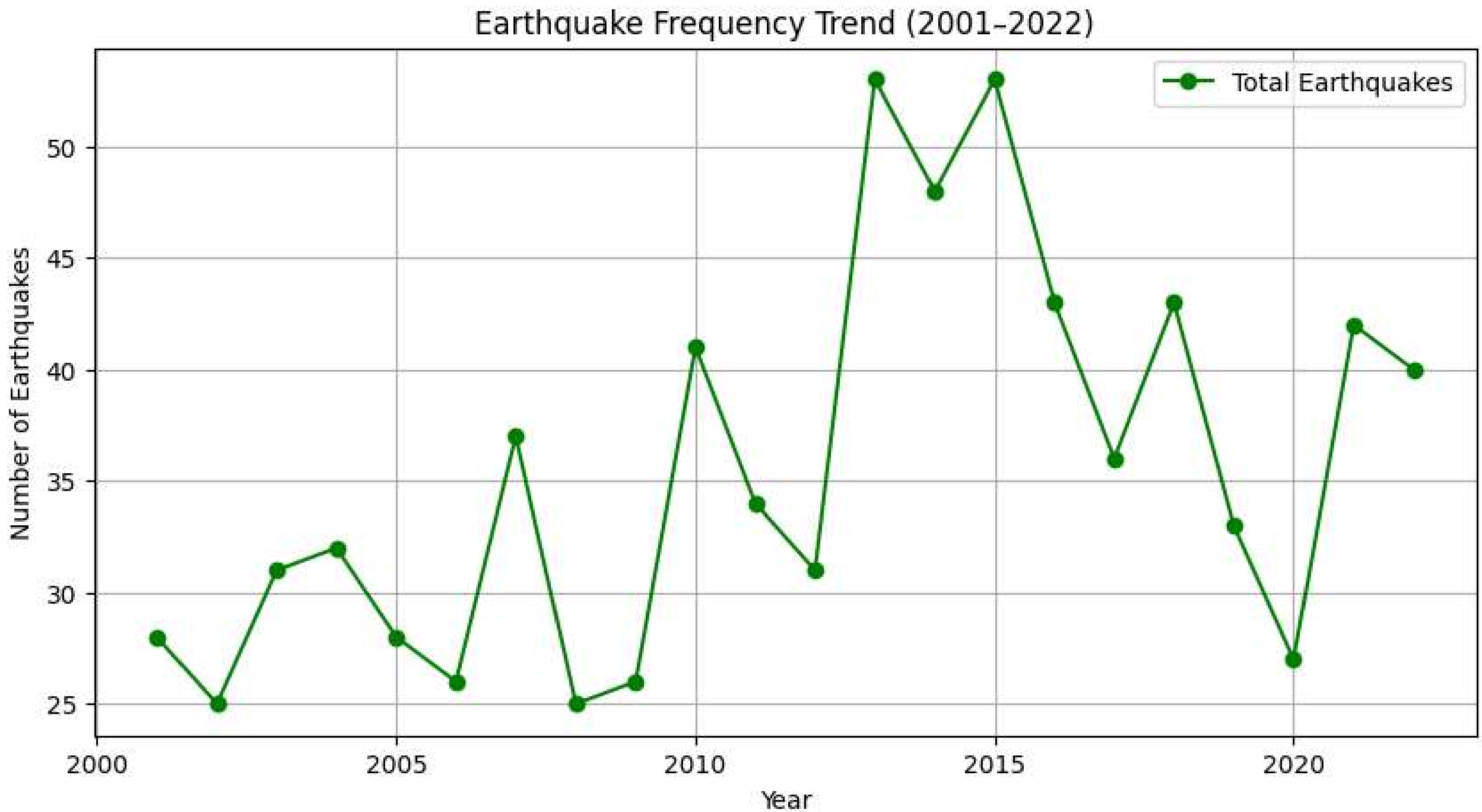
```
plt.legend()
plt.grid(True)
plt.show()
```



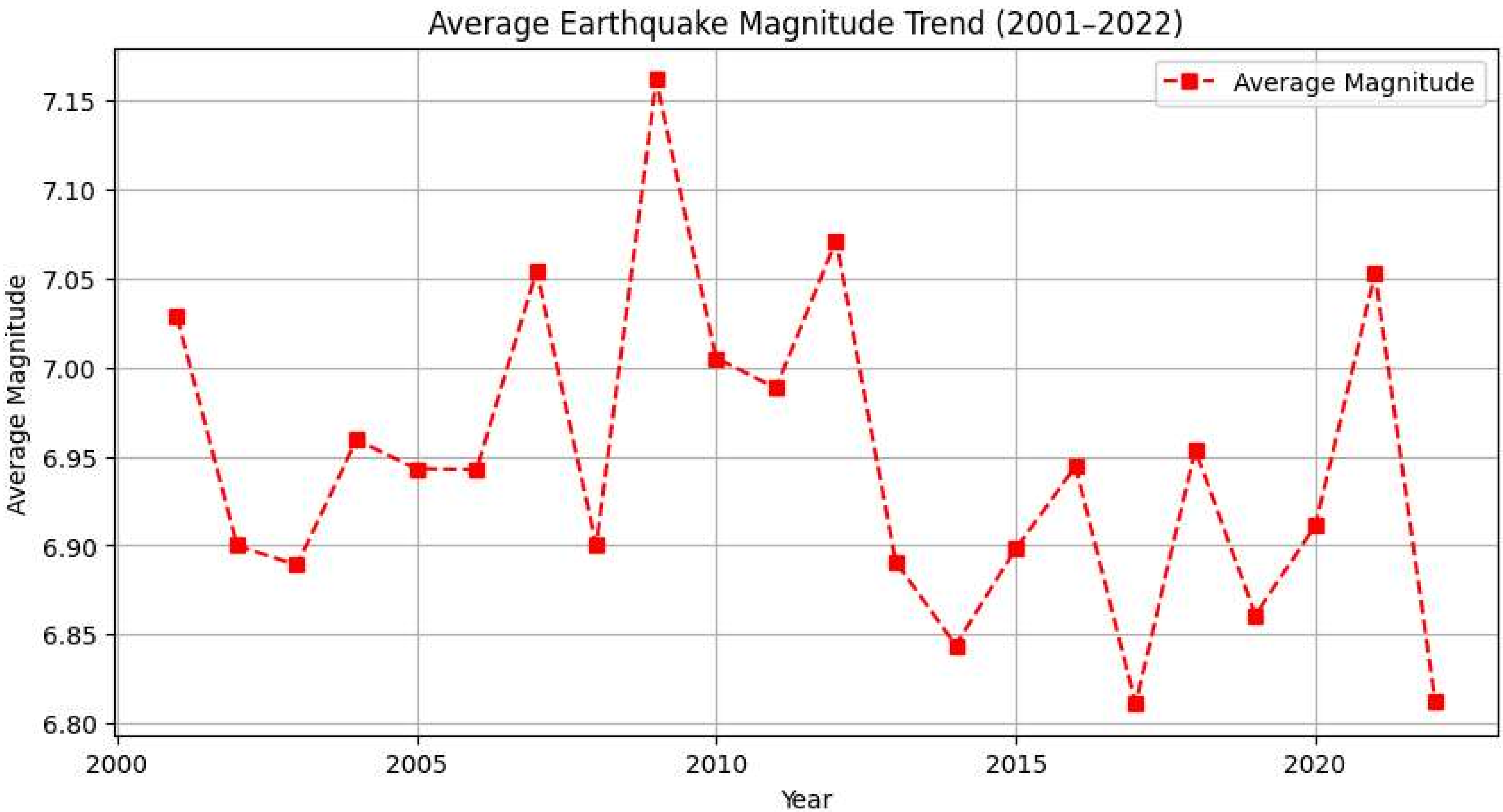
** Identify any trends in the frequency or magnitude of earthquakes over time.

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='green', label='Total Earthquakes')
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='--', color='red', label='Average Magn:
plt.title("Average Earthquake Magnitude Trend (2001–2022)")
plt.xlabel("Year")
plt.ylabel("Average Magnitude")
plt.legend()
plt.grid(True)
plt.show()
```



Earthquake Frequency Trend (2001–2022)
Total Earthquakes
Number of Earthquakes
Year
25
30
35
40
45
50
2000
2005
2010
2015
2020

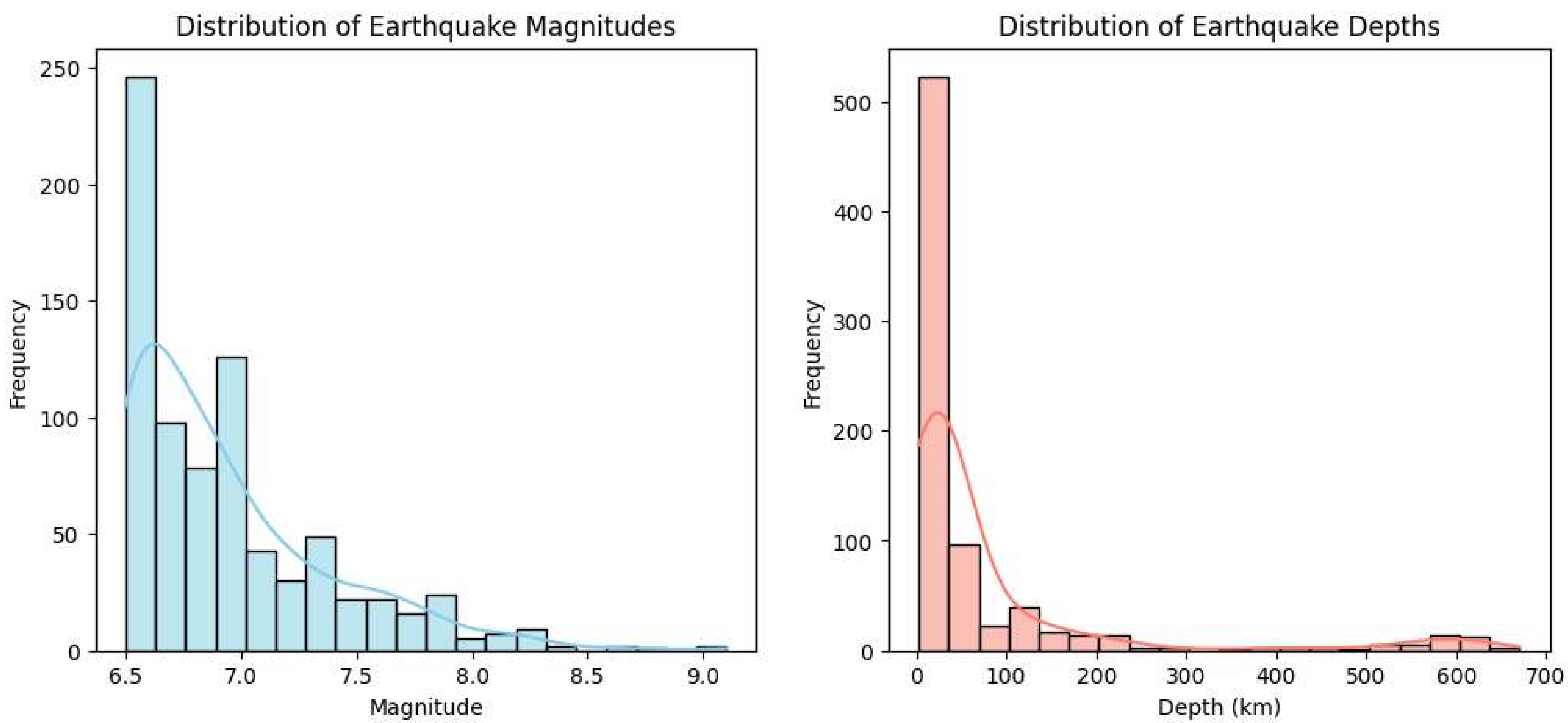


2) Magnitude and Depth Analysis:

** 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')
```

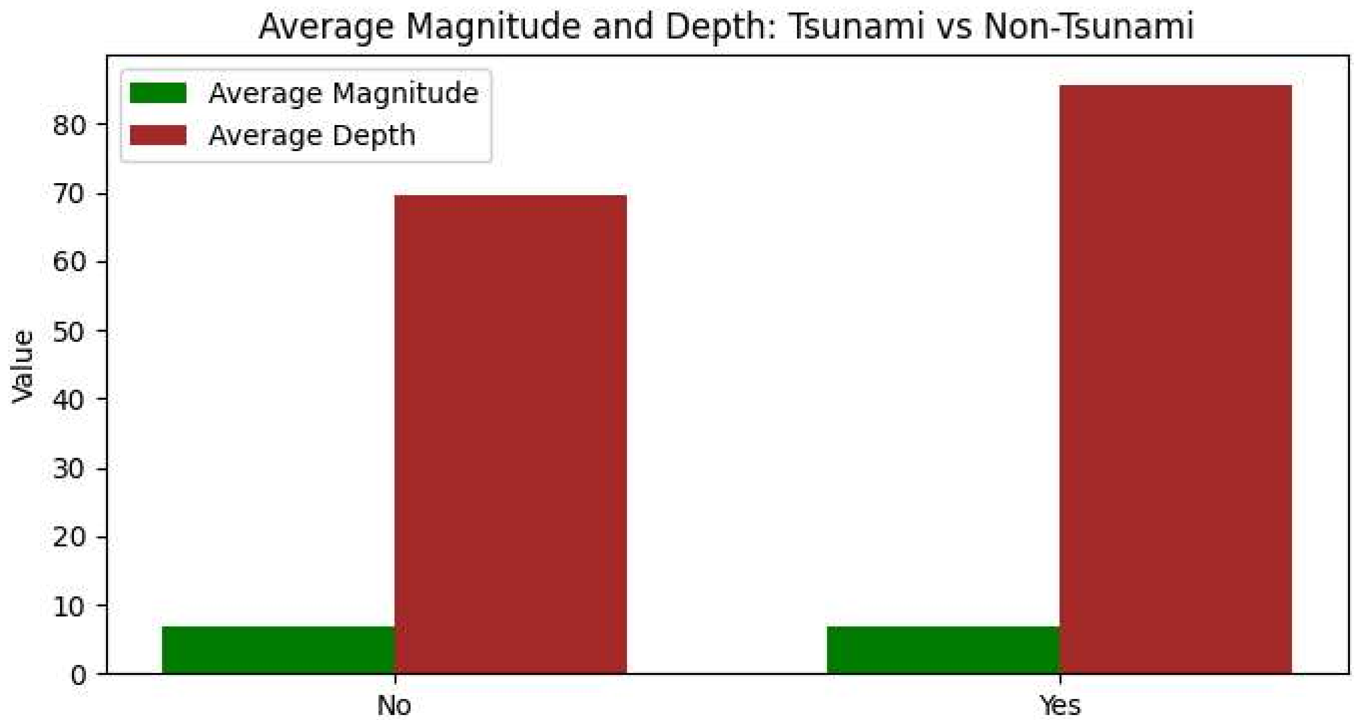
```
plt.xlabel('Magnitude')
plt.ylabel('Frequency')

# 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
```

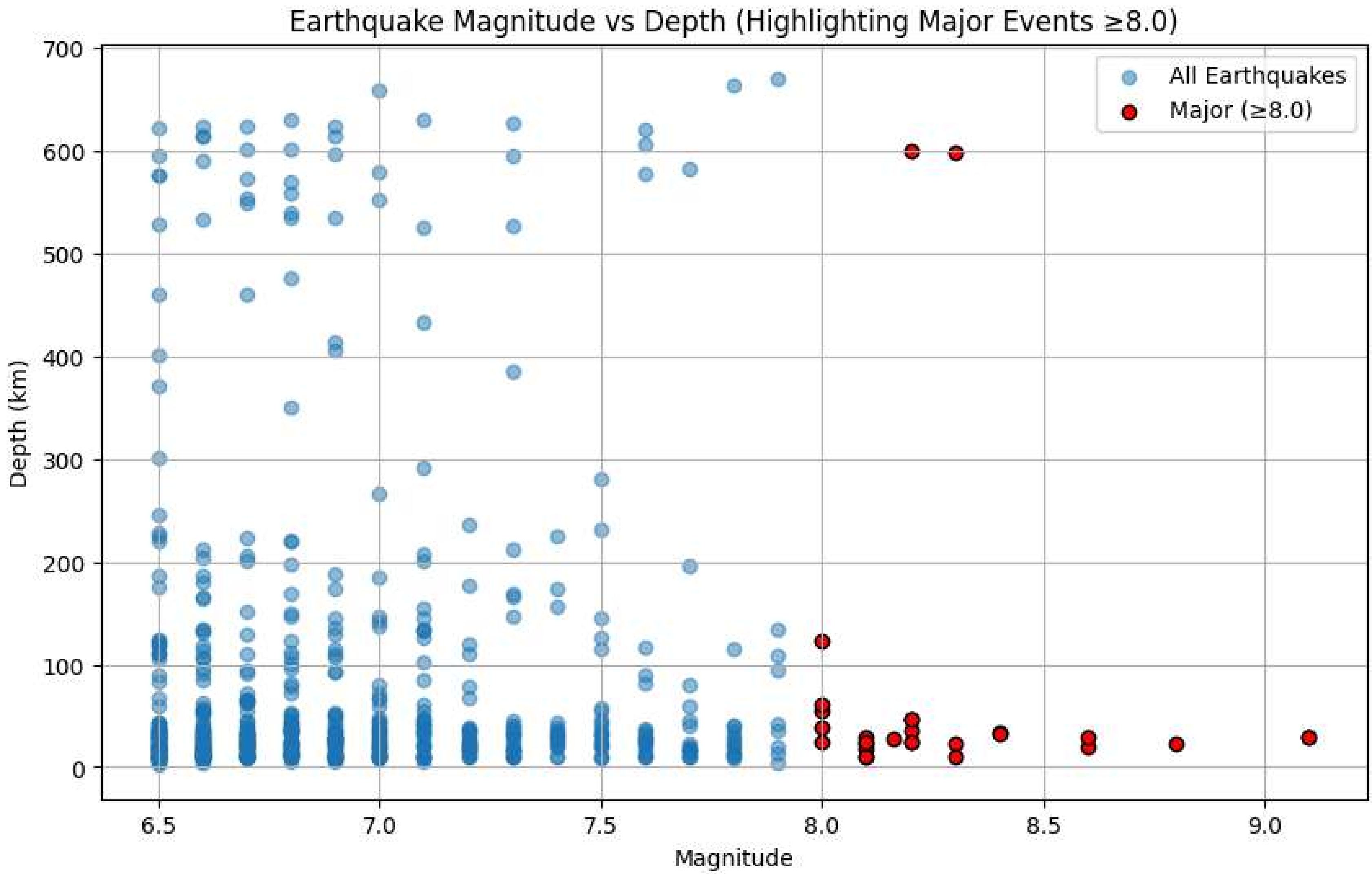
```python
# Group by tsunami (0 = No, 1 = Yes) and calculate mean
avg_stats = data.groupby('tsunami')[['magnitude','depth']].mean().reset_index()
avg_stats['Tsunami'] = avg_stats['tsunami'].map({0:'No', 1:'Yes'})

# 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', color='green')

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

# 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 (≥8.0)', edgecolor='black')

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()
```

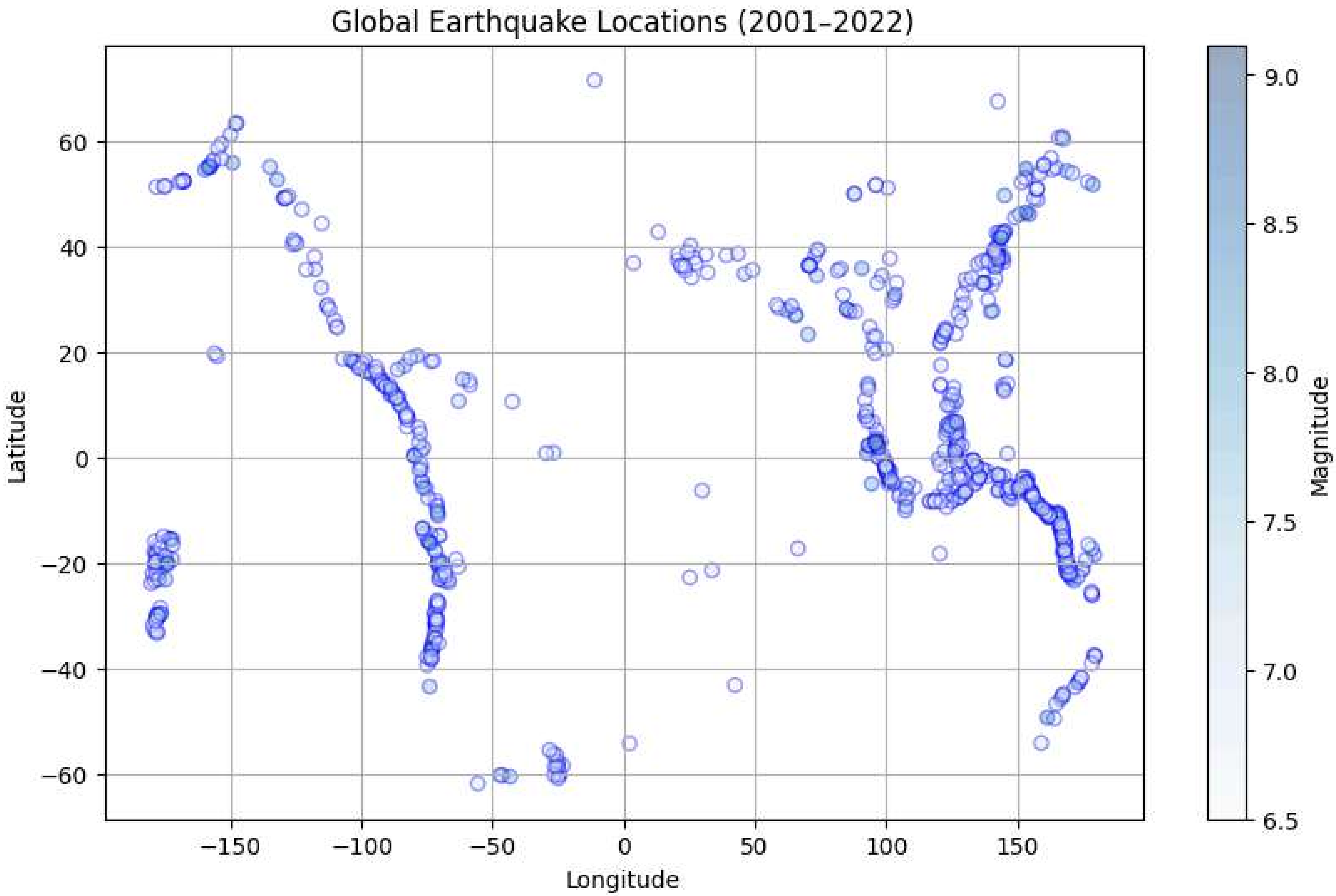


3) Geographic Distribution Using 2D Plotting:

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

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

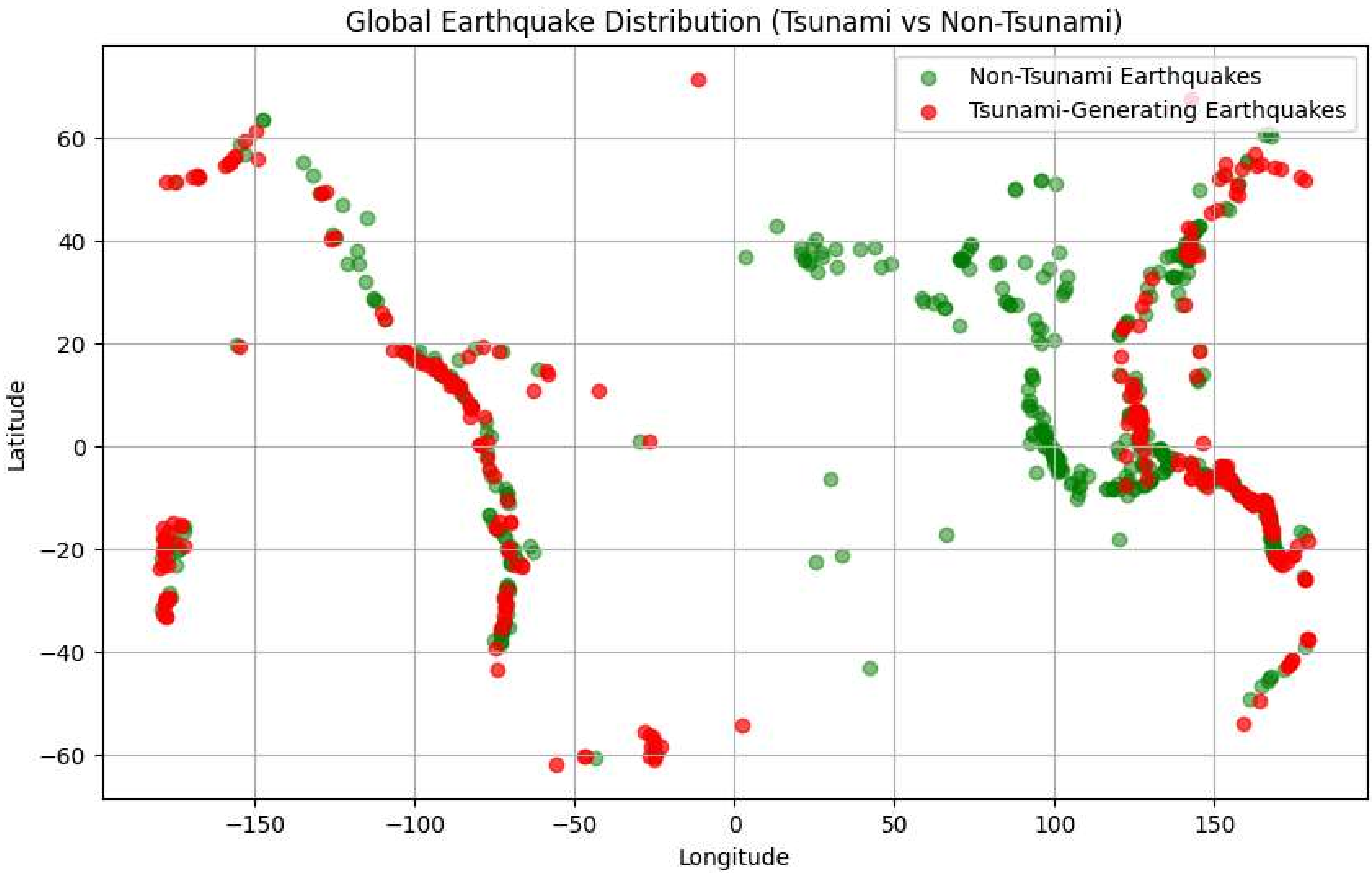
```
plt.figure(figsize=(10,6))
plt.scatter(
    data['longitude'], data['latitude'],alpha=0.4,c=data['magnitude'],cmap='Blues',edgecolor='b'
)
plt.title("Global Earthquake Locations (2001-2022)")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.colorbar(label='Magnitude')
plt.grid(True)
plt.show()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



** 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'],
```

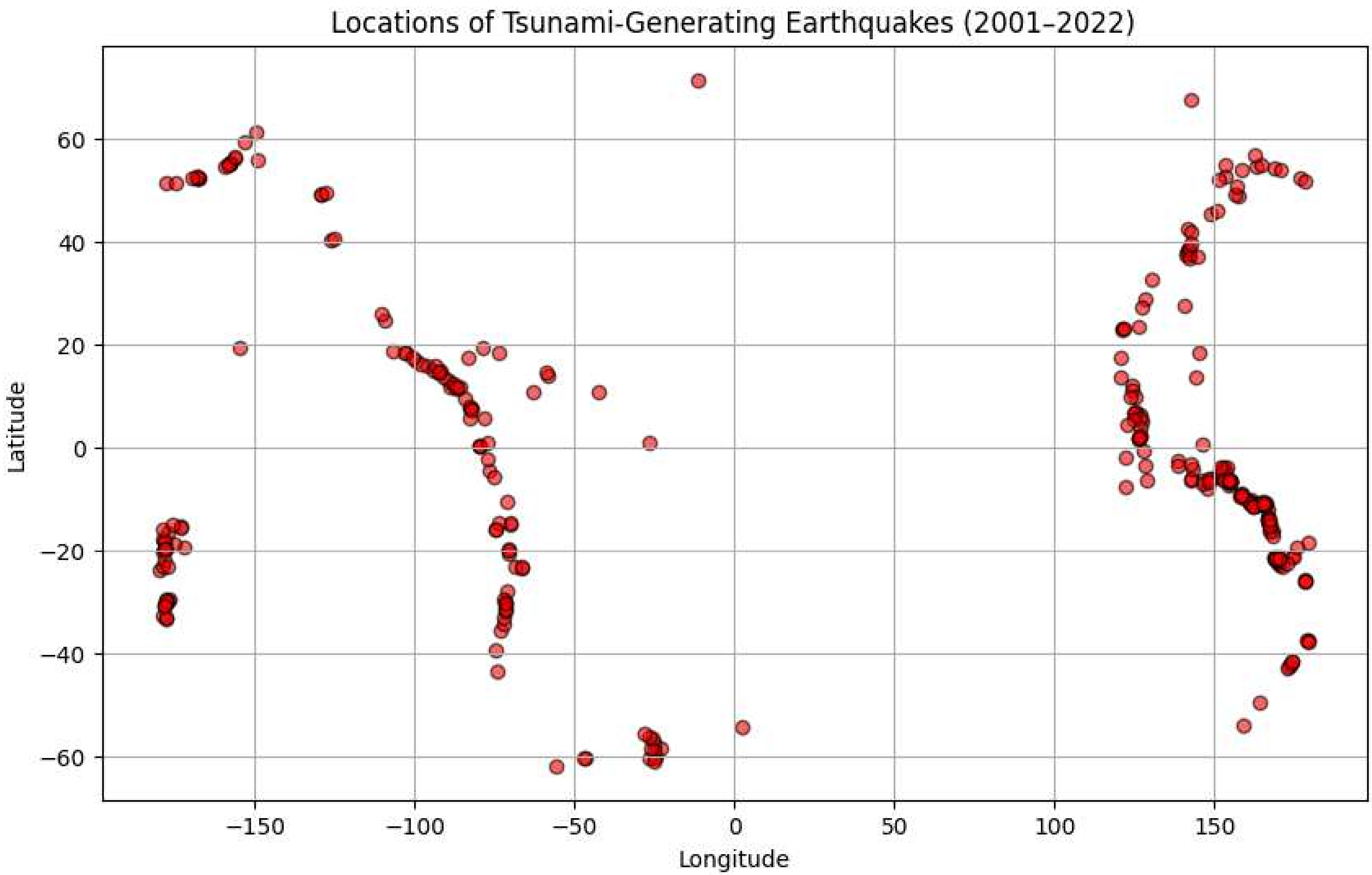
```
            color='green', alpha=0.5, label='Non-Tsunami Earthquakes')

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 events
    data[data['tsunami'] == 1]['latitude'],
```

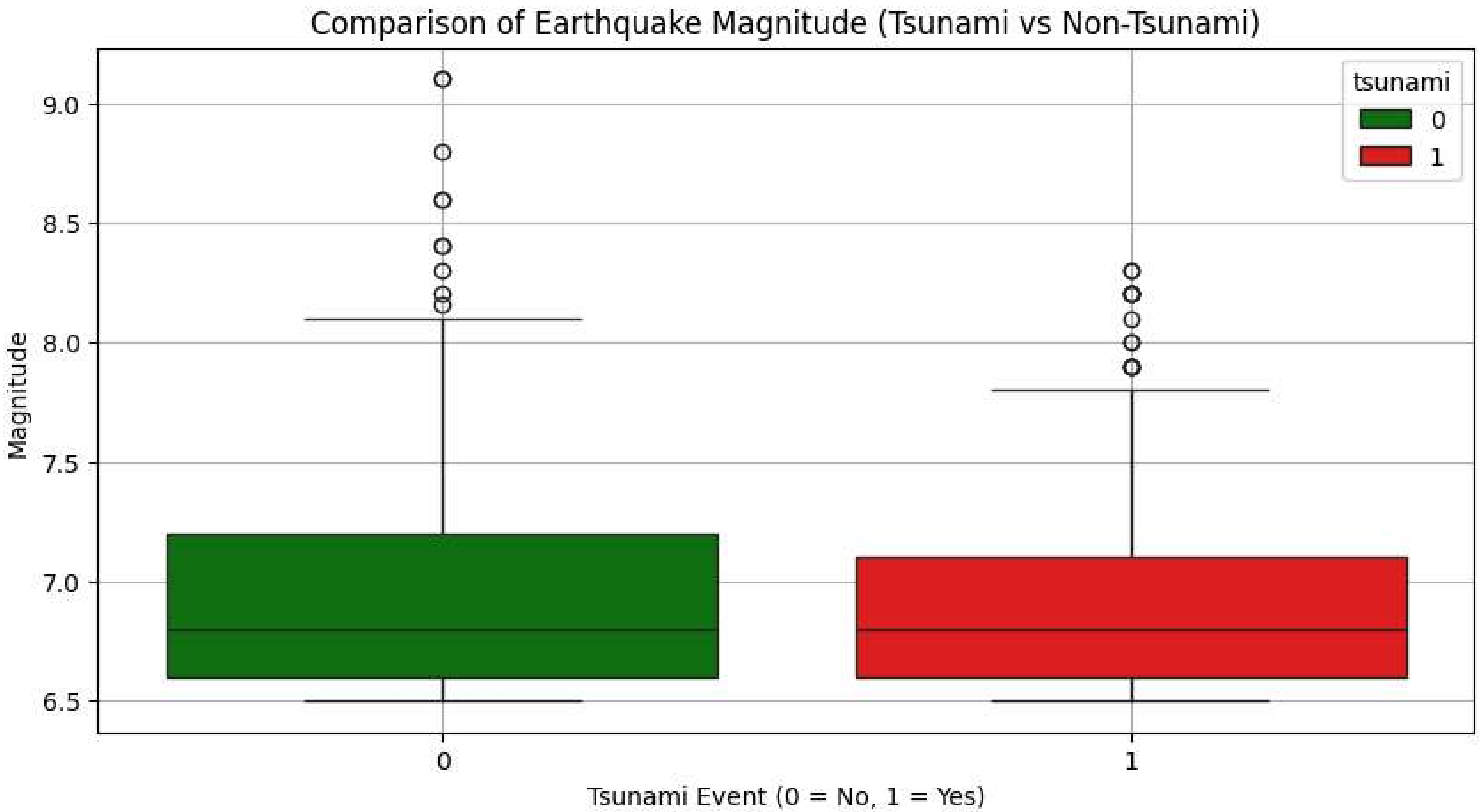
```
    color='red', alpha=0.6, edgecolor='black'
)
plt.title("Locations of Tsunami-Generating Earthquakes (2001–2022)")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.grid(True)
plt.show()
```

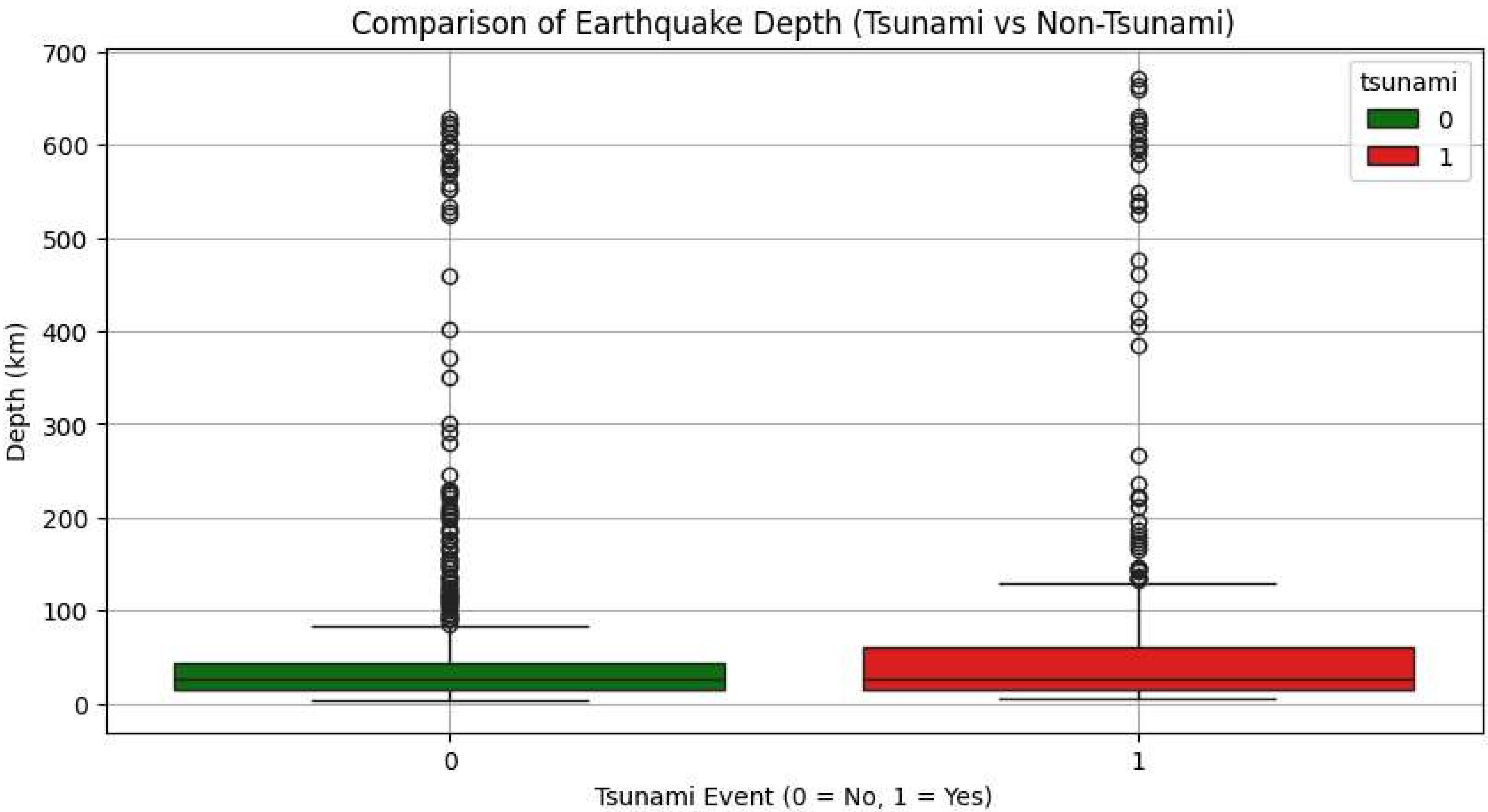


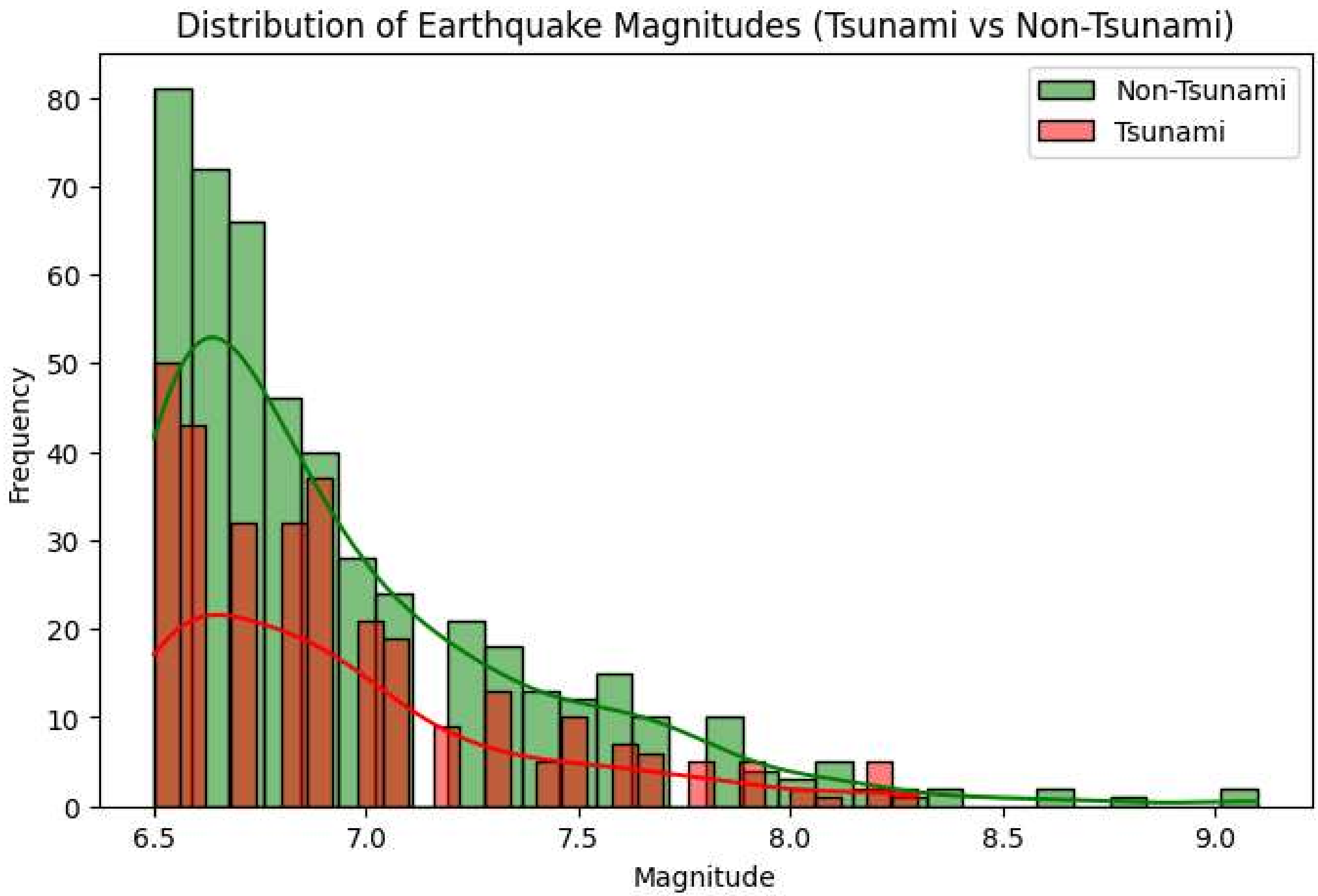
4) Statistical and Comparative Analysis:

** 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', 'red'])
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', 'red'])
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', label='Non-Tsunami', kde=True)
sns.histplot(data[data['tsunami']==1]['magnitude'], bins=30, color='red', label='Tsunami', kde=True)
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)
Magnitude
9.0
8.5
8.0
7.5
7.0
6.5
0
1
Tsunami Event (0 = No, 1 = Yes)
tsunami
0
1

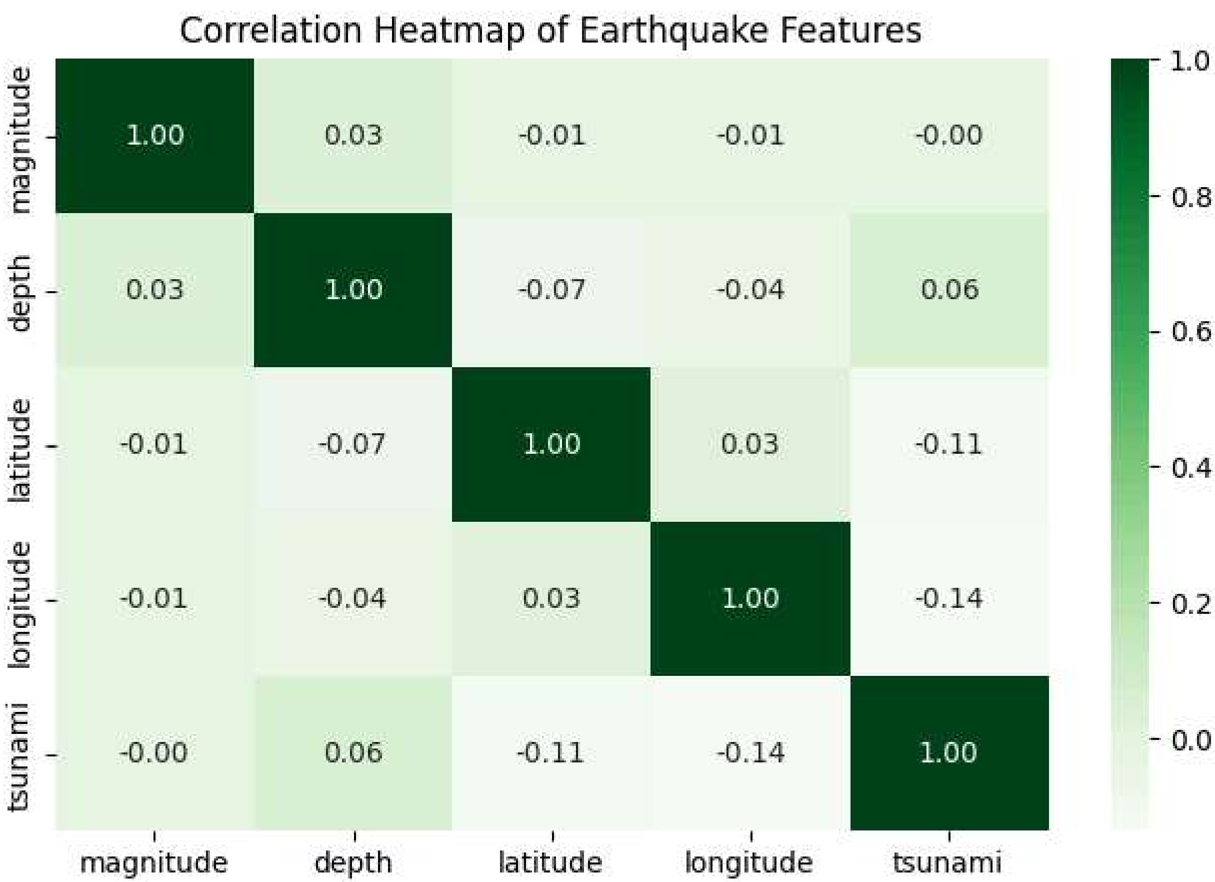

Comparison of Earthquake Depth (Tsunami vs Non-Tsunami)
Depth (km)
700
600
500
400
300
200
100
0
tsunami
0
1
Tsunami Event (0 = No, 1 = Yes)



** 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:

📊 Key Insights

Consistent Magnitude Range: Average earthquake magnitudes remained steady between 6.8 and 7.1, showing stable global seismic activity.

Dominance of Shallow Quakes: A majority of earthquakes occurred at depths below 300 km, leading to more intense shaking at the surface.

Tsunami-Generating Conditions: Powerful, shallow, and near-coastal earthquakes are the most likely to produce tsunamis.

Major Events (≥8.0): Though infrequent, these massive quakes are high-impact disasters, primarily recorded in the Pacific Ring of Fire (notably 2004 and 2011).

Fluctuating Annual Activity: The yearly earthquake count varied but showed no clear long-term increase over the two decades.

📁 Includes

Annual earthquake frequency and magnitude trends

Relationship between magnitude and depth

Overview of major (≥8.0) earthquakes

Comparative analysis of tsunami vs non-tsunami events

In [ ]:

```

```