Dataset Description

The US Arrests dataset contains crime statistics for the 50 U.S. states in 1973. It includes the number of arrests (per 100,000 residents) for:

- **Murder**
- **Assault**
- **Rape**

It also includes:

- **UrbanPop**: The percentage of the population living in urban areas.
- **City** column (which actually represents state names).

The aim is to explore the data for patterns in crime across states.

In [8]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load data with 'City' as the index
df = pd.read_csv("usarrest.csv", index_col="City")
df.head()
```

Out[8]:

City	Murder	Assault	UrbanPop	Rape
Alabama	13.2	236	58	21.2
Alaska	10.0	263	48	44.5
Arizona	8.1	294	80	31.0
Arkansas	8.8	190	50	19.5
California	9.0	276	91	40.6

In [9]:
```
df.info()
df.isnull().sum()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 50 entries, Alabama to Wyoming
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Murder    50 non-null     float64
 1   Assault   50 non-null     int64  
 2   UrbanPop  50 non-null     int64  
 3   Rape      50 non-null     float64
dtypes: float64(2), int64(2)
memory usage: 2.0+ KB
```

Out[9]:

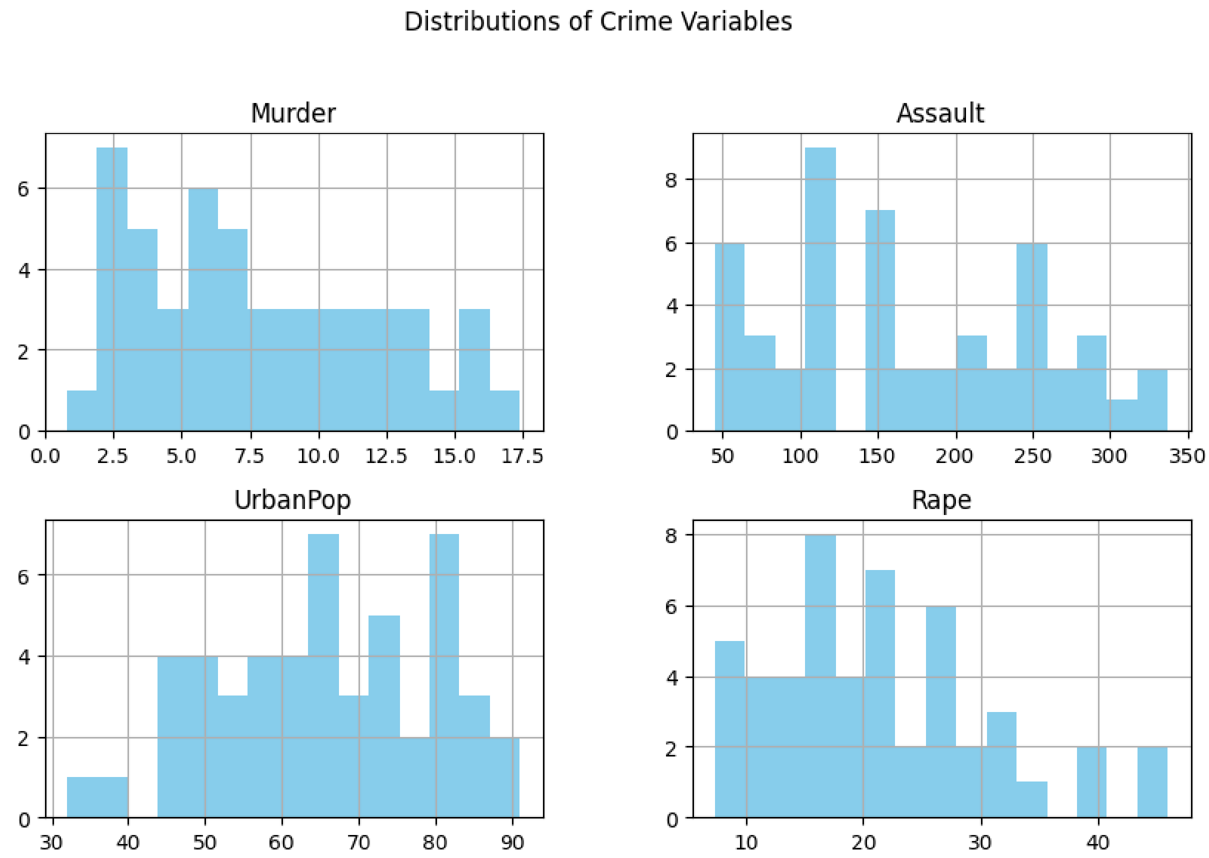
	Murder	Assault	UrbanPop	Rape
count	50.00000	50.000000	50.000000	50.000000
mean	7.78800	170.760000	65.540000	21.232000
std	4.35551	83.337661	14.474763	9.366385
min	0.80000	45.000000	32.000000	7.300000
25%	4.07500	109.000000	54.500000	15.075000
50%	7.25000	159.000000	66.000000	20.100000
75%	11.25000	249.000000	77.750000	26.175000
max	17.40000	337.000000	91.000000	46.000000

Data Cleaning

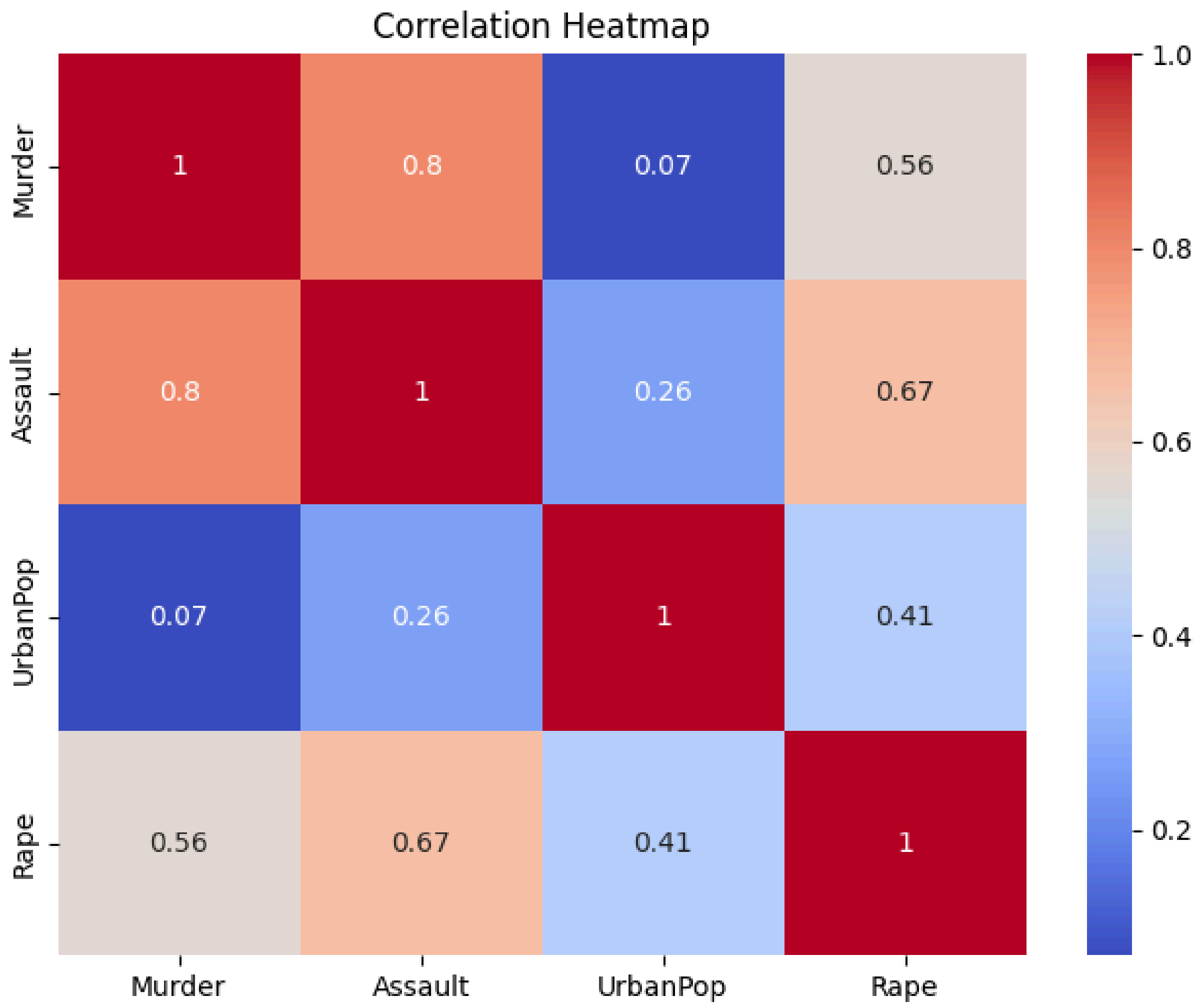
- No missing values detected in any column.
- Data types are already numeric and ready for analysis.
- Renamed the index to represent state names for clarity.

In [10]:

```
df.hist(figsize=(10, 6), bins=15, color='skyblue')
plt.suptitle("Distributions of Crime Variables", y=1.02)
plt.show()
```

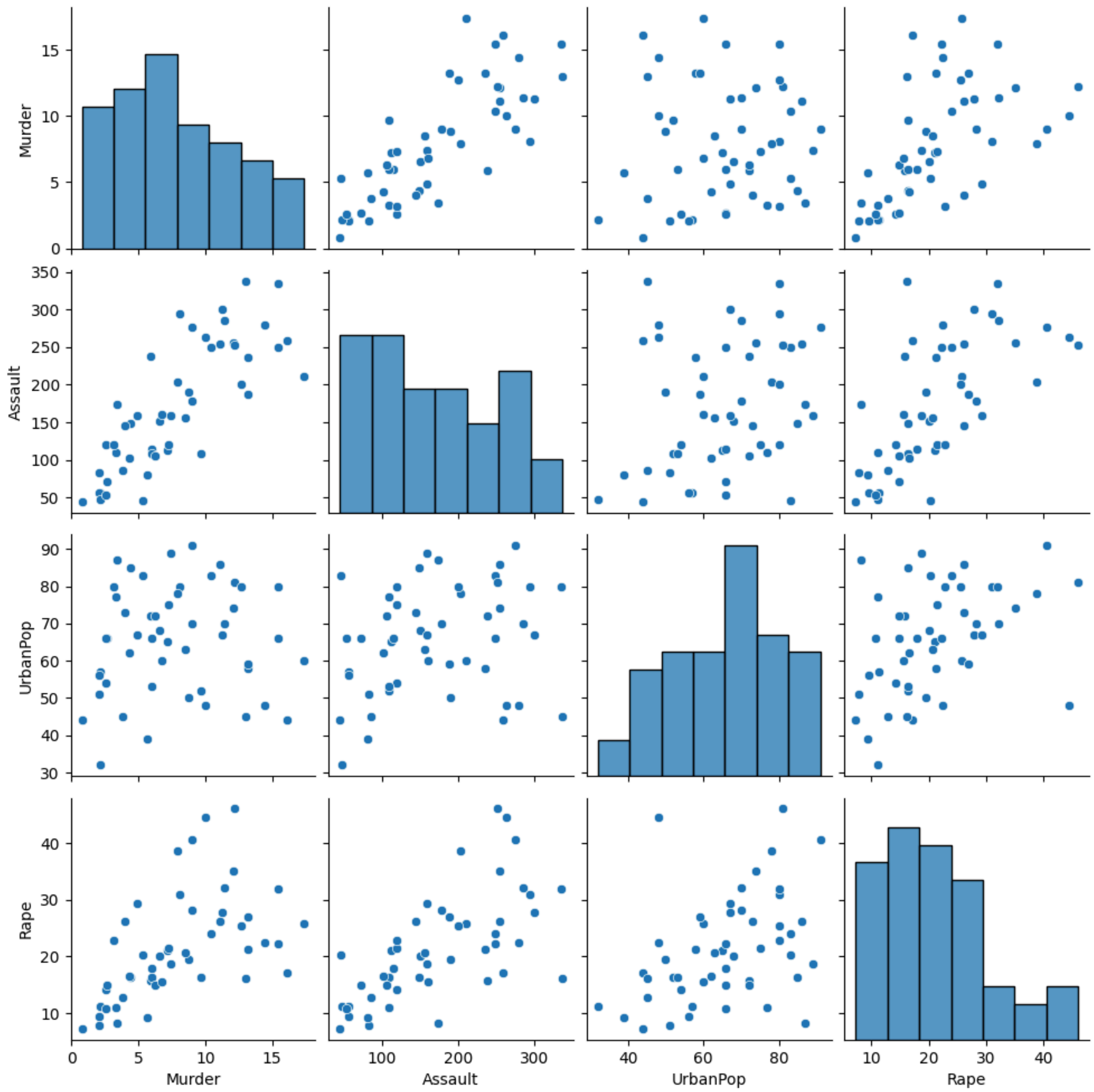


In [11]:
```
plt.figure(figsize=(8, 6))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```



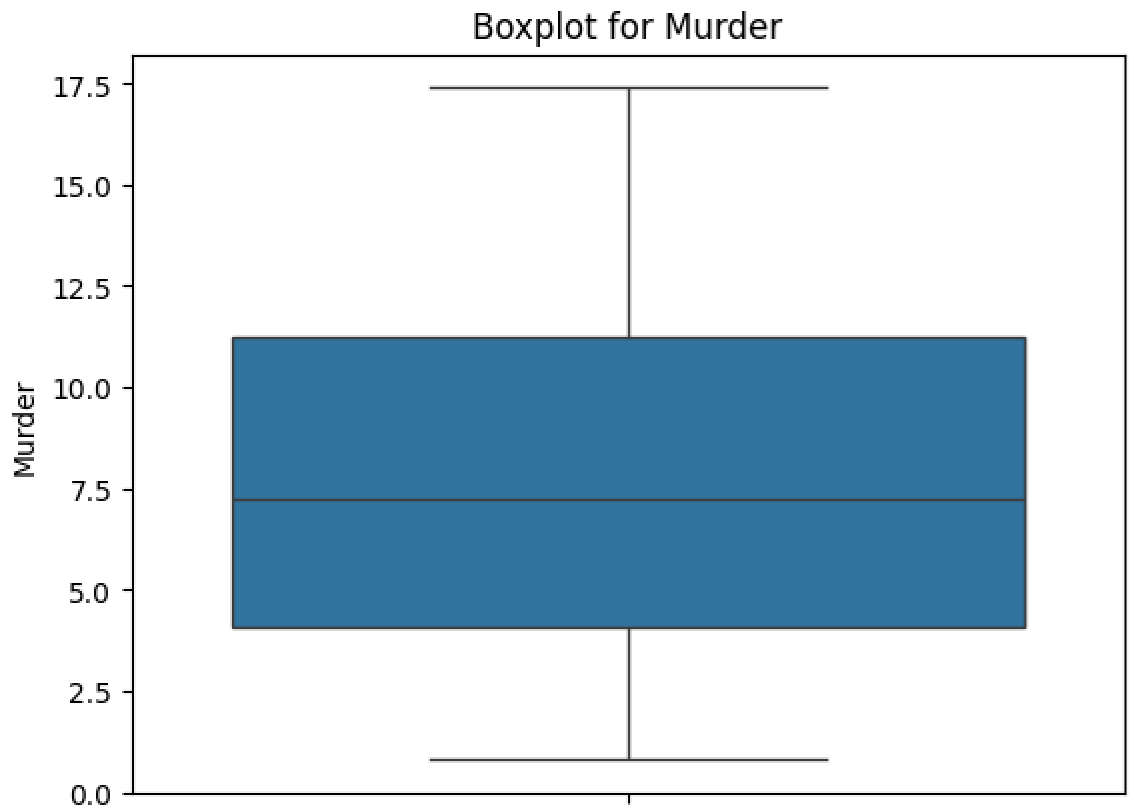
In [12]:
```
sns.pairplot(df)
```

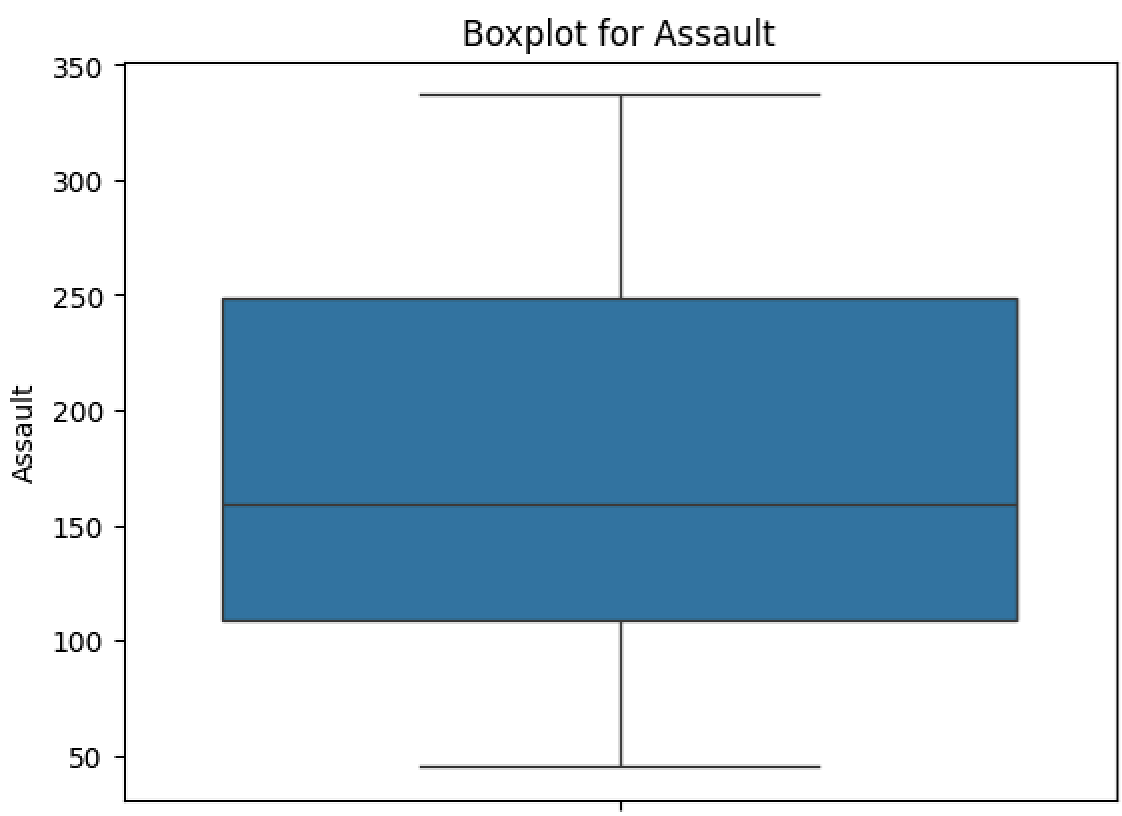
Out[12]: <seaborn.axisgrid.PairGrid at 0x178fd62e650>

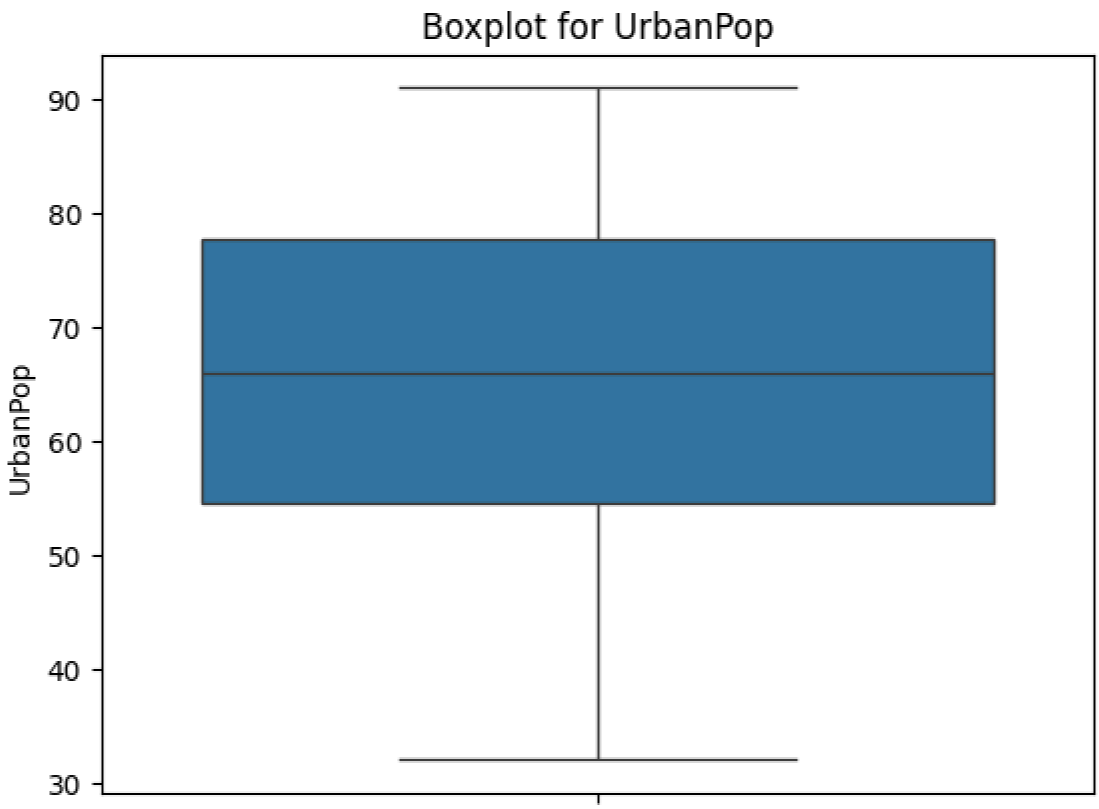


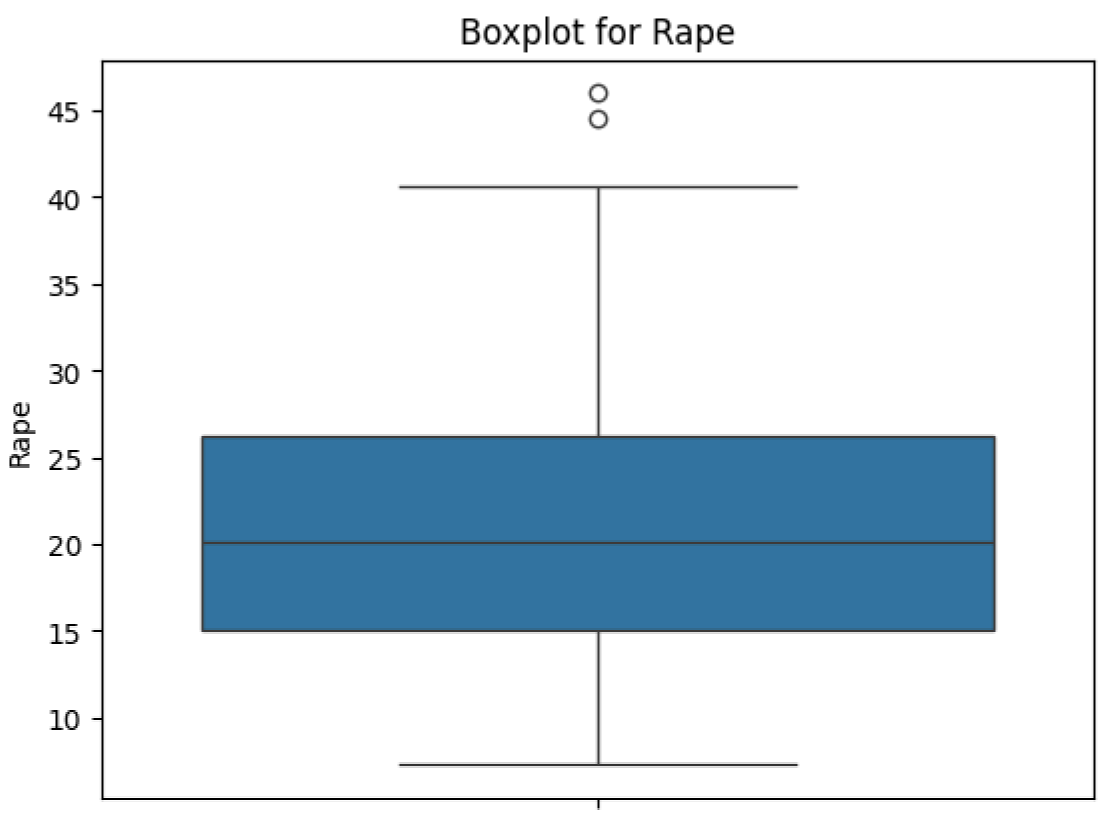
In [13]:

```
for col in df.columns:
    sns.boxplot(data=df, y=col)
    plt.title(f"Boxplot for {col}")
    plt.show()
```


Boxplot for Murder
Murder
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0


Boxplot for Assault
Assault
350
300
250
200
150
100
50





In [14]:
```
print("Top 5 States by Murder Rate:\n", df['Murder'].sort_values(ascending=False).h
print("\nTop 5 States by Assault Rate:\n", df['Assault'].sort_values(ascending=Fals
print("\nTop 5 States by Rape Rate:\n", df['Rape'].sort_values(ascending=False).hea
```

```
Top 5 States by Murder Rate:
 City
Georgia           17.4
Mississippi       16.1
Louisiana         15.4
Florida           15.4
South Carolina    14.4
Name: Murder, dtype: float64

Top 5 States by Assault Rate:
 City
North Carolina    337
Florida           335
Maryland          300
Arizona           294
New Mexico        285
Name: Assault, dtype: int64

Top 5 States by Rape Rate:
 City
Nevada        46.0
Alaska        44.5
California    40.6
Colorado      38.7
Michigan      35.1
Name: Rape, dtype: float64
```

Findings

- **Assault** and **Murder** are strongly correlated (states with higher murder rates tend to also have more assaults).
- **UrbanPop** does not have a strong correlation with crime — urbanisation alone doesn't explain violent crime rates.
- **Rape** has moderate correlation with Murder and Assault, suggesting partial co-occurrence in violent crime trends.
- **Georgia**, **Florida**, and **Mississippi** are consistently high in violent crime metrics.
- States with lower crime metrics tend to be in the Midwest or Northeast (e.g. Vermont, North Dakota).

Additional Observation

Some outliers are visible in the `Rape` and `Assault` variables. These may reflect reporting differences or genuine spikes in certain states.