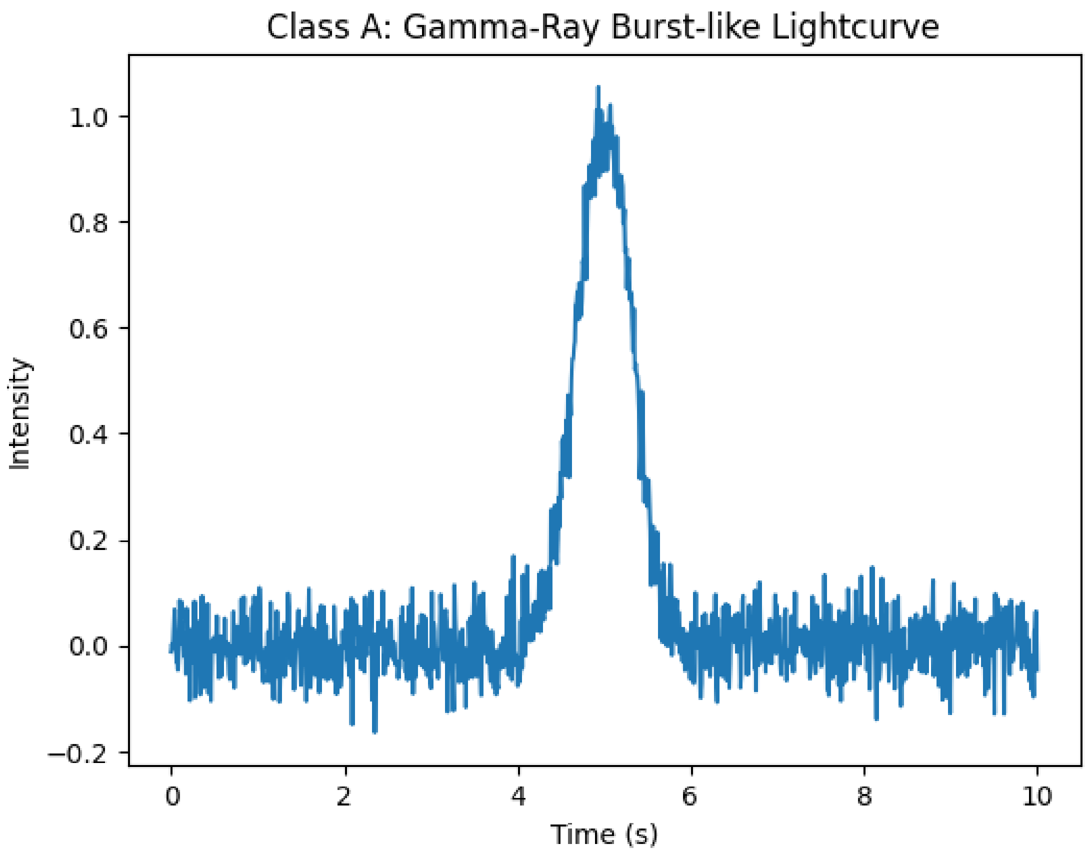
examples2

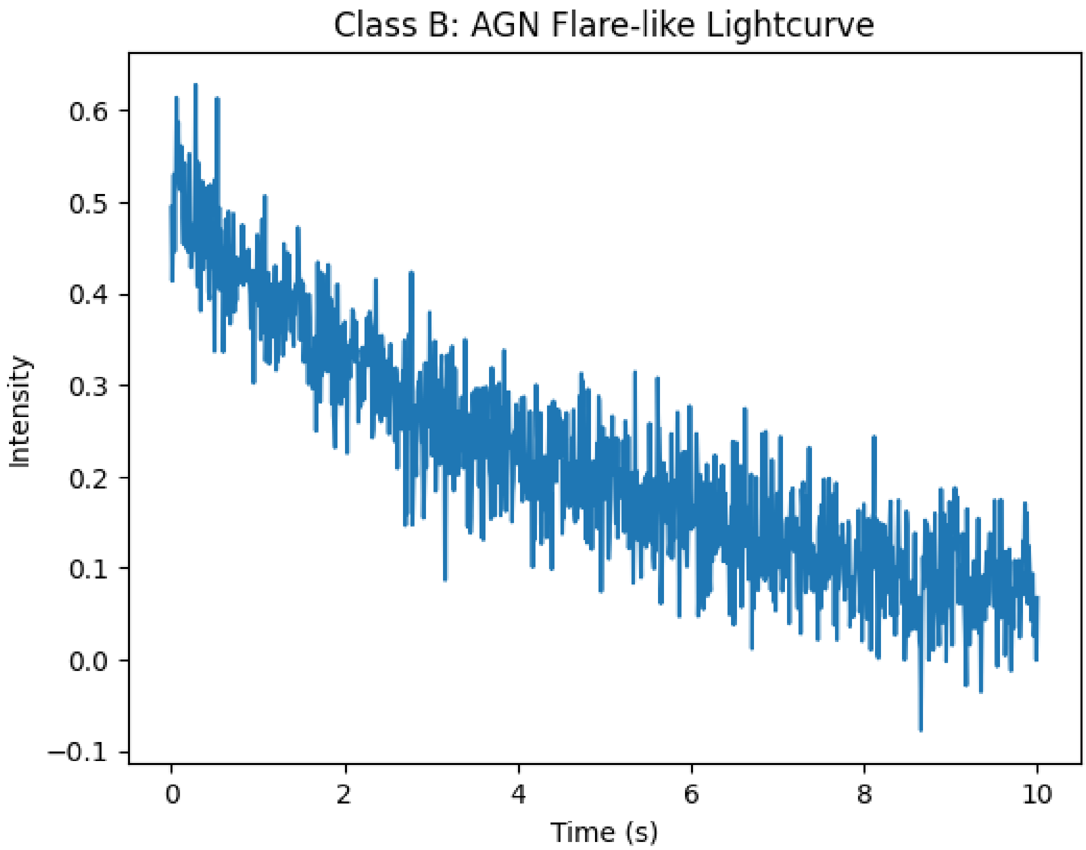
May 12, 2025

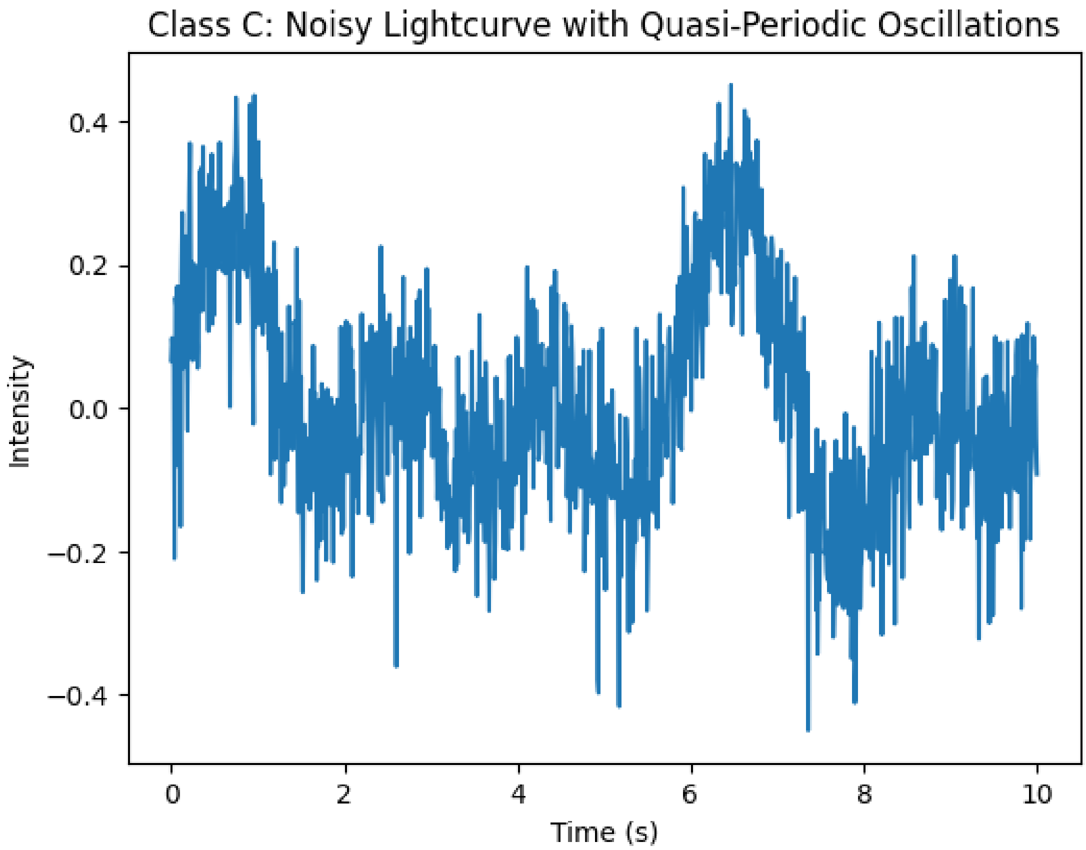
[54]:
```python
import numpy as np
import matplotlib.pyplot as plt
import chronoxtract as ct
import pandas as pd
```

[55]:
```python
# Parameters for GRB-like lightcurve
t = np.linspace(0, 10, 1000)  # Time axis
burst_intensity = np.exp(-((t - 5)**2) / 0.2)  # Gaussian pulse
noise = np.random.normal(0, 0.05, len(t))  # Small noise

class_a = burst_intensity + noise  # Short-duration burst with noise

plt.plot(t, class_a)
plt.title("Class A: Gamma-Ray Burst-like Lightcurve")
plt.xlabel("Time (s)")
plt.ylabel("Intensity")
plt.show()

# Parameters for AGN flare-like lightcurve
flare_intensity = 0.5 * np.exp(-t / 5)  # Slow decay (longer duration)
noise = np.random.normal(0, 0.05, len(t))  # Small noise

class_b = flare_intensity + noise  # Long-duration, low-intensity flare

plt.plot(t, class_b)
plt.title("Class B: AGN Flare-like Lightcurve")
plt.xlabel("Time (s)")
plt.ylabel("Intensity")
plt.show()


# Parameters for noisy oscillating lightcurve
frequencies = np.linspace(0.2, 0.5, 3)  # Three oscillations with different␣
↪frequencies
oscillation = 0.1*np.sum([np.sin(2 * np.pi * f * t) for f in frequencies],␣
↪axis=0)  # Sum of oscillations
noise = np.random.normal(0, 0.1, len(t))  # Noise to simulate irregularities
```

```
class_c = oscillation + noise  # Noisy, quasi-periodic oscillation

plt.plot(t, class_c)
plt.title("Class C: Noisy Lightcurve with Quasi-Periodic Oscillations")
plt.xlabel("Time (s)")
plt.ylabel("Intensity")
plt.show()
```




Class B: AGN Flare-like Lightcurve
Intensity
Time (s)
0.6
0.5
0.4
0.3
0.2
0.1
0.0
−0.1
0
2
4
6
8
10

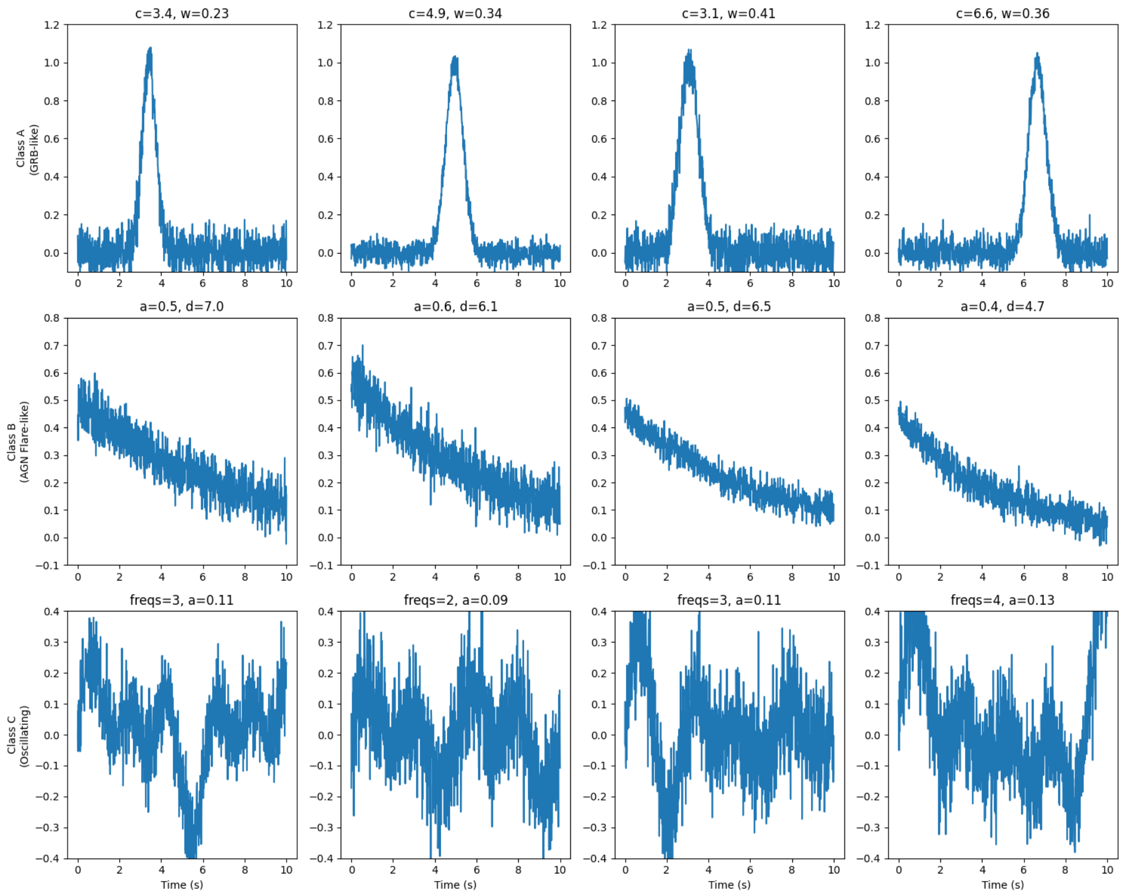


[59]:
```python
# Generate random lightcurves with different parameters for each class
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.gridspec import GridSpec

# Define functions to generate each class of lightcurves with random parameters
def generate_class_a(n_samples=10):
    """Generate Gamma-Ray Burst-like lightcurves with randomized parameters"""
    samples = []
    params = []

    for _ in range(n_samples):
        # Randomize parameters
        center = np.random.uniform(3, 7)  # Burst center position
        width = np.random.uniform(0.1, 0.5)  # Burst width
        noise_level = np.random.uniform(0.03, 0.08)  # Noise level

        # Generate lightcurve
        burst = np.exp(-((t - center)**2) / width)
```

```
        noise = np.random.normal(0, noise_level, len(t))
        lightcurve = burst + noise

        samples.append(lightcurve)
        params.append({'center': center, 'width': width, 'noise_level':␣
↪noise_level})

    return samples, params

def generate_class_b(n_samples=10):
    """Generate AGN Flare-like lightcurves with randomized parameters"""
    samples = []
    params = []

    for _ in range(n_samples):
        # Randomize parameters
        amplitude = np.random.uniform(0.3, 0.7)  # Flare amplitude
        decay = np.random.uniform(3, 8)  # Decay timescale
        noise_level = np.random.uniform(0.03, 0.08)  # Noise level

        # Generate lightcurve
        flare = amplitude * np.exp(-t / decay)
        noise = np.random.normal(0, noise_level, len(t))
        lightcurve = flare + noise

        samples.append(lightcurve)
        params.append({'amplitude': amplitude, 'decay': decay, 'noise_level':␣
↪noise_level})

    return samples, params

def generate_class_c(n_samples=10):
    """Generate Oscillating lightcurves with randomized parameters"""
    samples = []
    params = []

    for _ in range(n_samples):
        # Randomize parameters
        n_freqs = np.random.randint(2, 5)  # Number of component frequencies
        min_freq = np.random.uniform(0.1, 0.3)  # Min frequency
        max_freq = np.random.uniform(0.4, 0.7)  # Max frequency
        amplitude = np.random.uniform(0.08, 0.15)  # Oscillation amplitude
        noise_level = np.random.uniform(0.07, 0.12)  # Noise level

        # Generate lightcurve
        freqs = np.linspace(min_freq, max_freq, n_freqs)
```

```
        oscillation = amplitude * np.sum([np.sin(2 * np.pi * f * t) for f in␣
↪freqs], axis=0)
        noise = np.random.normal(0, noise_level, len(t))
        lightcurve = oscillation + noise

        samples.append(lightcurve)
        params.append({'n_freqs': n_freqs, 'min_freq': min_freq, 'max_freq':␣
↪max_freq,
                       'amplitude': amplitude, 'noise_level': noise_level})

    return samples, params

# Generate 10 samples of each class
n_samples = 100
class_a_samples, class_a_params = generate_class_a(n_samples)
class_b_samples, class_b_params = generate_class_b(n_samples)
class_c_samples, class_c_params = generate_class_c(n_samples)

# Plot a subset of samples for each class
fig = plt.figure(figsize=(15, 12))
gs = GridSpec(3, 4, figure=fig)

# Plot Class A samples
for i in range(4):
    ax = fig.add_subplot(gs[0, i])
    ax.plot(t, class_a_samples[i])
    if i == 0:
        ax.set_ylabel("Class A\n(GRB-like)")
    ax.set_title(f"c={class_a_params[i]['center']:.1f},␣
↪w={class_a_params[i]['width']:.2f}")
    ax.set_ylim(-0.1, 1.2)

# Plot Class B samples
for i in range(4):
    ax = fig.add_subplot(gs[1, i])
    ax.plot(t, class_b_samples[i])
    if i == 0:
        ax.set_ylabel("Class B\n(AGN Flare-like)")
    ax.set_title(f"a={class_b_params[i]['amplitude']:.1f},␣
↪d={class_b_params[i]['decay']:.1f}")
    ax.set_ylim(-0.1, 0.8)

# Plot Class C samples
for i in range(4):
    ax = fig.add_subplot(gs[2, i])
    ax.plot(t, class_c_samples[i])
    if i == 0:
```

```
        ax.set_ylabel("Class C\n(Oscillating)")
    ax.set_title(f"freqs={class_c_params[i]['n_freqs']},␣
↪a={class_c_params[i]['amplitude']:.2f}")
    ax.set_xlabel("Time (s)")
    ax.set_ylim(-0.4, 0.4)

plt.tight_layout()
plt.show()

# Create a dataset with features from all samples
all_samples = class_a_samples + class_b_samples + class_c_samples
all_features = []
class_labels = []

# Extract features from each sample
for i, sample in enumerate(all_samples):
    if i < n_samples:
        class_label = 'Class A'
    elif i < 2*n_samples:
        class_label = 'Class B'
    else:
        class_label = 'Class C'

    features = ct.time_series_summary(sample)
    all_features.append(features)
    class_labels.append(class_label)

# Create a DataFrame with all features
all_features_df = pd.DataFrame(all_features)
all_features_df['class'] = class_labels

print(f"Generated dataset with {len(all_features_df)} samples:")
print(all_features_df['class'].value_counts())
```




```
Generated dataset with 300 samples:
class
Class A    100
Class B    100
Class C    100
Name: count, dtype: int64
```

[60]:
```
all_features_df
```

[60]:

	mean	median	mode	variance	standard_deviation	skewness	\
0	0.086873	0.021329	0.042312	0.056288	0.237251	2.585912	
1	0.100850	0.010981	0.107280	0.063831	0.252647	2.439804	
2	0.112782	0.022337	-0.062249	0.072318	0.268921	2.109079	
3	0.106853	0.015539	0.064472	0.064987	0.254925	2.334392	
4	0.111485	0.019354	0.769504	0.072280	0.268850	2.174503	
..	…	…	…	…	…	…	
295	-0.002159	-0.005943	-0.121861	0.027234	0.165028	0.021960	
296	0.034571	0.024063	0.081179	0.029835	0.172728	0.105760	
297	0.021468	0.009937	-0.128631	0.028824	0.169776	0.578260	

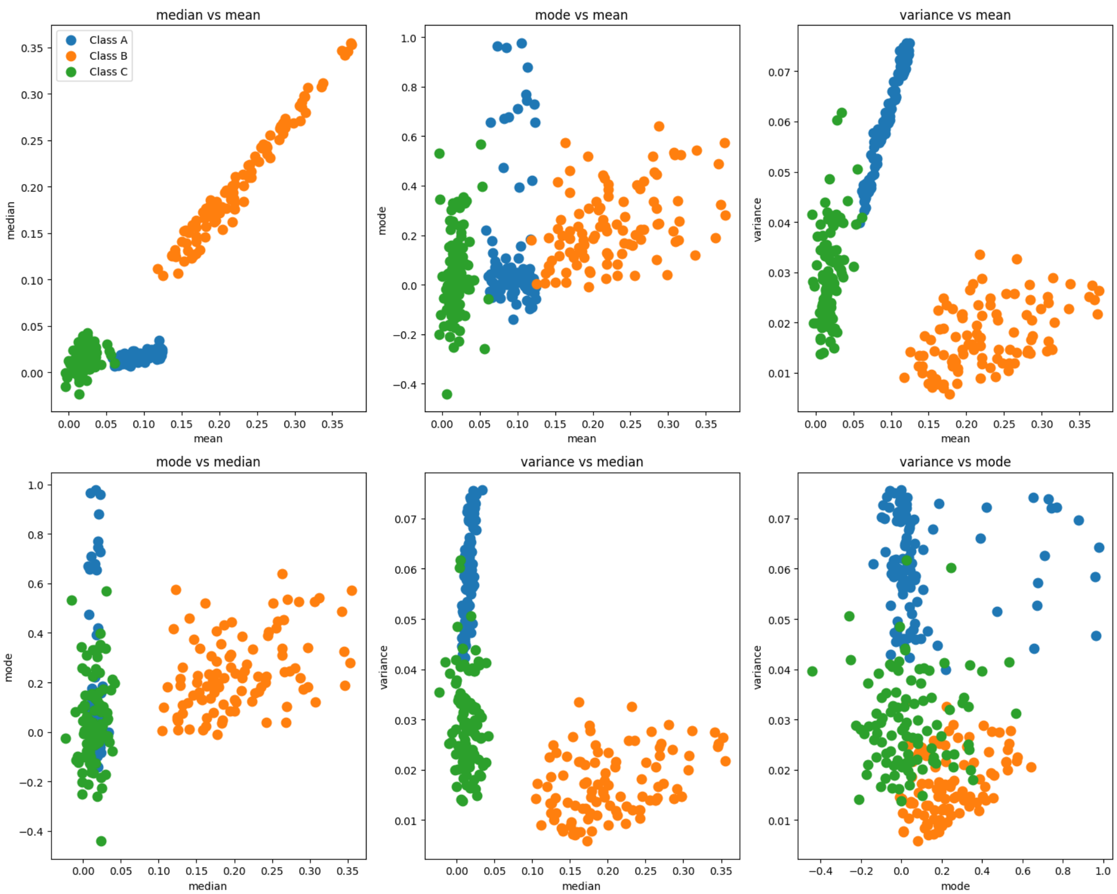
```
298  0.006398 -0.000160 -0.101442  0.016579            0.128759  0.196790
299  0.008051  0.007711  0.000752  0.020488            0.143138  0.180284

     kurtosis   minimum   maximum     range       q05       q25       q75  \
0    9.231607 -0.201090  1.079853  1.280943 -0.096049 -0.031876  0.079086
1    7.835348 -0.107344  1.034410  1.141754 -0.056648 -0.017836  0.050097
2    6.509705 -0.256986  1.068633  1.325619 -0.098311 -0.030311  0.098665
3    7.400740 -0.140057  1.051298  1.191355 -0.066741 -0.019775  0.071516
4    6.851488 -0.199573  1.181461  1.381035 -0.096257 -0.031723  0.102101
..        …         …         …         …         …         …         …
295  3.202984 -0.554220  0.568801  1.123020 -0.273385 -0.110709  0.112712
296  3.101203 -0.461804  0.495336  0.957140 -0.262075 -0.070035  0.141220
297  3.839999 -0.434514  0.603675  1.038189 -0.234962 -0.089122  0.114672
298  2.958526 -0.331164  0.455886  0.787050 -0.193978 -0.083117  0.083648
299  2.969128 -0.431030  0.446456  0.877486 -0.216715 -0.087734  0.095157

          q95         sum  absolute_energy    class
0    0.768546   86.872750        63.834965  Class A
1    0.832847  100.849840        74.001283  Class A
2    0.872939  112.781784        85.038146  Class A
3    0.835626  106.853235        76.404623  Class A
4    0.848314  111.484978        84.709365  Class A
..        …          …               …       …
295  0.269056   -2.158891        27.238744  Class C
296  0.343756   34.571479        31.030019  Class C
297  0.341295   21.467520        29.284741  Class C
298  0.238313    6.397857        16.619695  Class C
299  0.256435    8.051167        20.553196  Class C

[300 rows x 17 columns]
```

[68]:

```python
# Plot feature comparisons across classes
def plot_features(x_col, y_col):
    """Plot a specific feature comparison with classes colored differently"""
    plt.figure(figsize=(8, 6))
    colors = ['r', 'g', 'b']
    markers = ['o', 's', '^']

    # Group by class
    classes = all_features_df['class'].unique()

    for i, class_name in enumerate(classes):
        class_data = all_features_df[all_features_df['class'] == class_name]
        plt.scatter(
            class_data[x_col],
            class_data[y_col],
            color=colors[i],
```

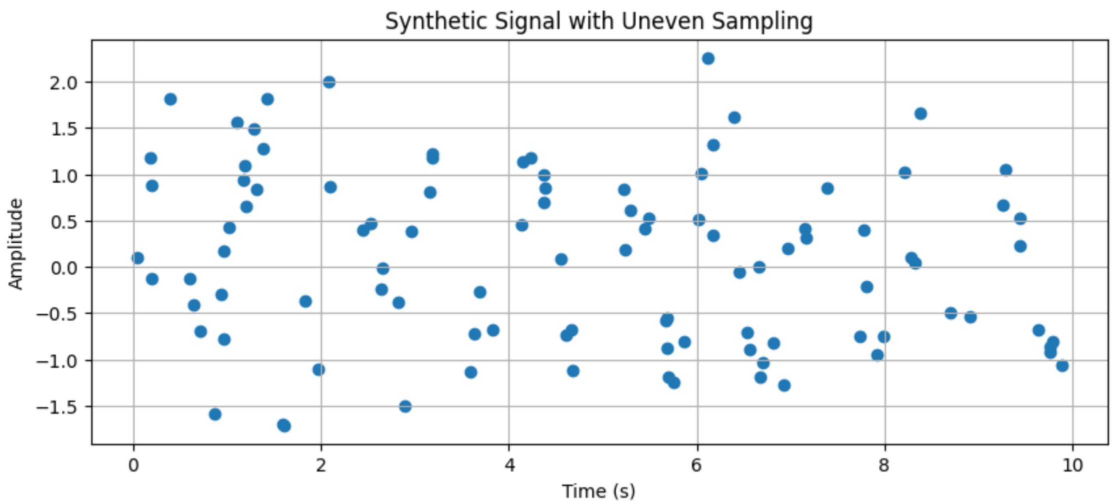
```
            marker=markers[i],
            s=100,
            label=class_name
        )

    plt.xlabel(x_col)
    plt.ylabel(y_col)
    plt.title(f"{y_col} vs {x_col}")
    plt.legend()
    plt.grid(True, alpha=0.3)
    plt.show()

# Create a matrix of plots for multiple feature combinations
plt.figure(figsize=(15, 12))

# Select key features to compare (adjust based on your actual feature names)
features = list(all_features_df.columns[:4])  # Using all feature columns
features = [col for col in features if col != 'class']  # Exclude class column␣
↪if it's in the first 4

# Use a simple counter to track subplot position
subplot_idx = 1

# Create a grid of subplots
for i, feat1 in enumerate(features):
    for j, feat2 in enumerate(features):
        if i >= j:  # Skip diagonal and lower triangle
            continue

        plt.subplot(2, 3, subplot_idx)
        subplot_idx += 1

        for k, class_name in enumerate(all_features_df['class'].unique()):
            class_data = all_features_df[all_features_df['class'] == class_name]
            plt.scatter(
                class_data[feat1],
                class_data[feat2],
                label=class_name if subplot_idx == 2 else None,  # Only show␣
↪legend on first plot
                s=80
            )

        plt.xlabel(feat1)
        plt.ylabel(feat2)
        plt.title(f"{feat2} vs {feat1}")

        if subplot_idx == 2:  # Show legend on first completed plot
```

```
            plt.legend()

plt.tight_layout()
plt.show()
```

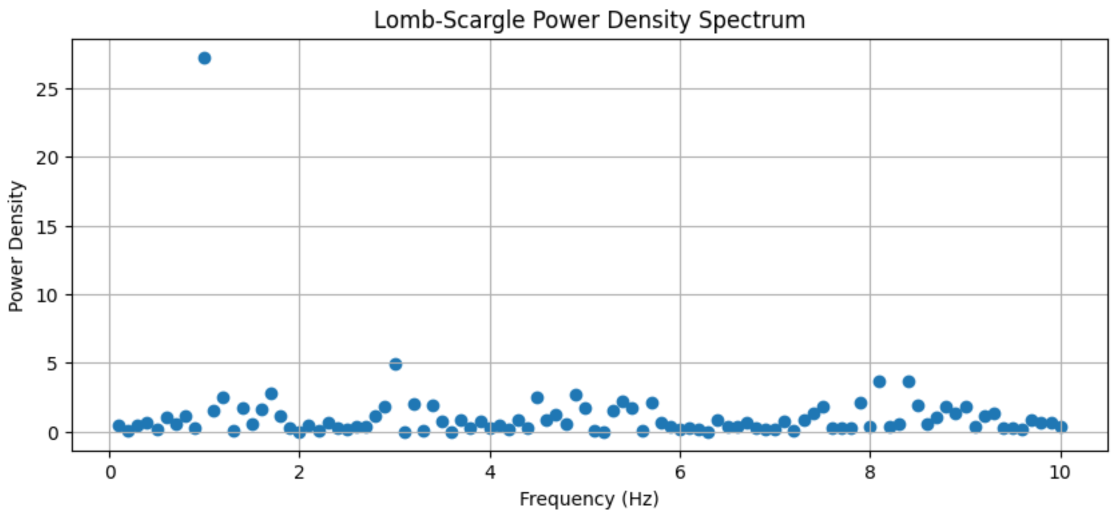


[71]:
```
# generate a synthetic signal with two frequencies and uneven sampling
np.random.seed(0)
time = np.sort(np.random.rand(100) * 10)  # unevenly spaced time points
signal = np.sin(2 * np.pi * 1 * time) + 0.5 * np.sin(2 * np.pi * 3 * time) + 0.
 ↪5 * np.random.normal(size=time.shape)
plt.figure(figsize=(10, 4))
plt.scatter(time, signal)
plt.title('Synthetic Signal with Uneven Sampling')
plt.xlabel('Time (s)')
plt.ylabel('Amplitude')
plt.grid()
plt.show()

print("Original frequencies: 1 and 3 Hz")
```

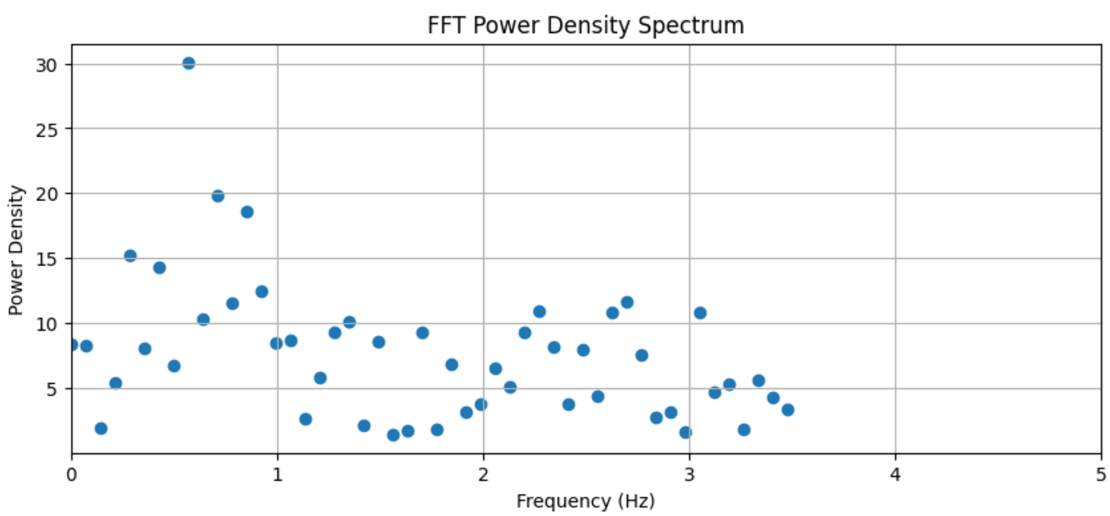
```
# Lomb-Scargle
ls_pds = ct.lomb_scargle_py(time, signal, freqs=np.linspace(0.1, 10, 100))
# Highest peak frequency
peak_freq = np.argmax(ls_pds)
print(f"Peak frequency (Lomb-Scargle): {np.linspace(0.1, 10, 100)[peak_freq]}␣
↪Hz")
plt.figure(figsize=(10, 4))
plt.scatter(np.linspace(0.1, 10, 100), ls_pds)
plt.title('Lomb-Scargle Power Density Spectrum')
plt.xlabel('Frequency (Hz)')
plt.ylabel('Power Density')
plt.grid()
plt.show()
# FFT
# Perform FFT on unevenly sampled data
fft_pds = ct.perform_fft_py(signal)
# Taking absolute value of FFT result
fft_pds = np.abs(fft_pds)
# Highest peak frequency
peak_freq = np.argmax(fft_pds)
print(f"Peak frequency (FFT): {np.abs(np.fft.fftfreq(len(signal),␣
↪d=(time[1]-time[0]))[peak_freq])} Hz")
plt.figure(figsize=(10, 4))
plt.scatter(np.fft.fftfreq(len(signal), d=(time[1]-time[0])), fft_pds)
plt.title('FFT Power Density Spectrum')
plt.xlabel('Frequency (Hz)')
plt.ylabel('Power Density')
plt.xlim(0, 5)  # Limit x-axis to positive frequencies
plt.grid()
plt.show()
```



```
Original frequencies: 1 and 3 Hz
Peak frequency (Lomb-Scargle): 1.0 Hz
```



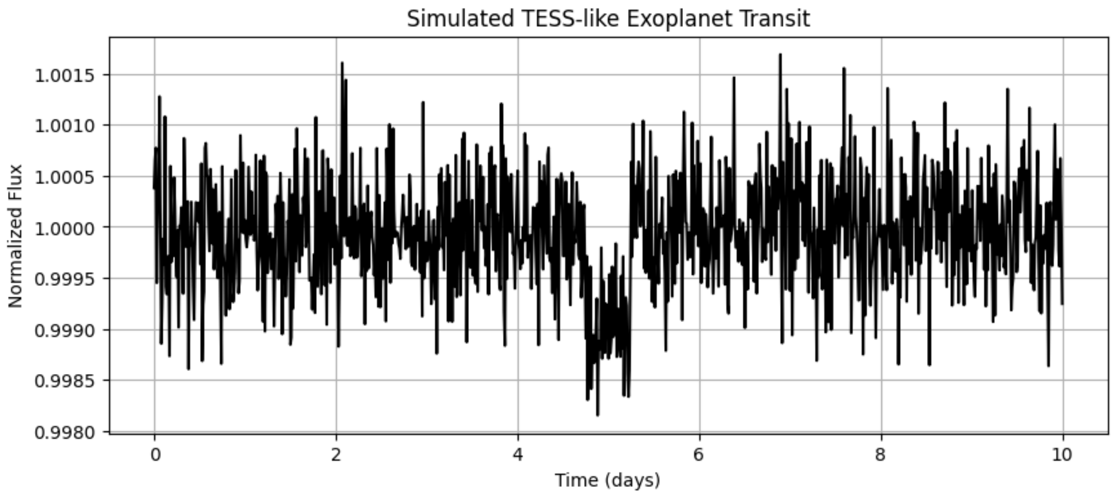

```
Peak frequency (FFT): 0.56760436765988 Hz
```

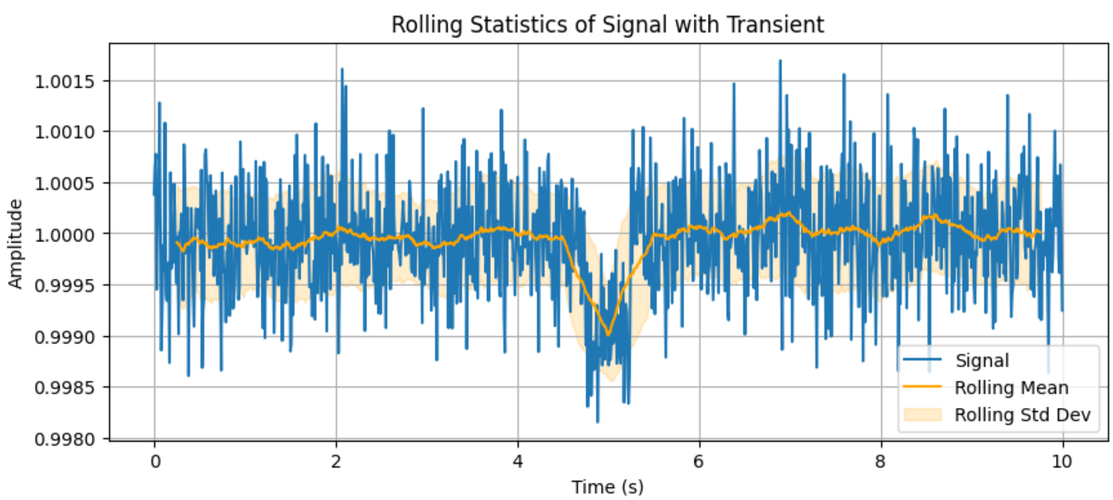


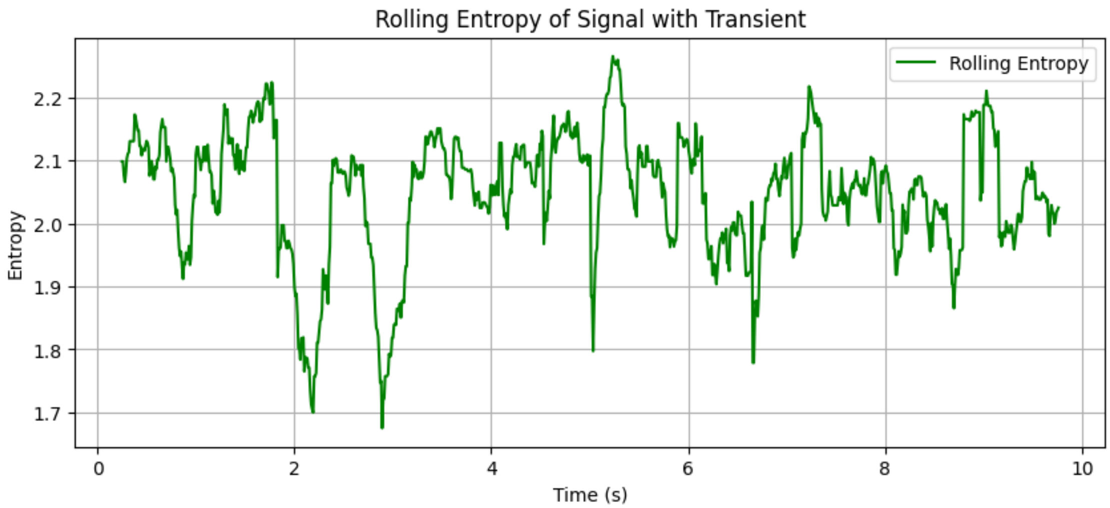
[84]:
```
# Injecting a sudden transient into the signal and plotting the rolling␣
↪statistics
# Create a new signal with a sudden transient
# Parameters
transit_time = 5.0             # Midpoint of the transit
```

```
transit_depth = 0.001          # Fractional decrease in brightness (~1%)
transit_duration = 0.5        # Duration of the transit
time = np.linspace(0, 10, 1000)

# Simulated stellar brightness (normalized around 1 with small noise)
signal = 1 + 0.0005 * np.random.normal(size=time.shape)

# Insert a transit: dip in brightness
in_transit = (time >= transit_time - transit_duration/2) & (time <=
 ↪transit_time + transit_duration/2)
signal[in_transit] -= transit_depth

# Plot
plt.figure(figsize=(10, 4))
plt.plot(time, signal, color='black')
plt.title('Simulated TESS-like Exoplanet Transit')
plt.xlabel('Time (days)')
plt.ylabel('Normalized Flux')
plt.grid(True)
plt.show()

transient_signal = signal

# Calculate rolling statistics on the transient_signal (not the previous signal)
window_size = 50
rolling_mean = ct.rolling_mean(transient_signal, window=window_size)
rolling_variance = ct.rolling_variance(transient_signal, window=window_size)
rolling_std = np.sqrt(rolling_variance)
rolling_entropy = ct.sliding_window_entropy(transient_signal,
 ↪window=window_size, bins=10)

# Create a properly aligned time array for the rolling statistics
# Assuming the rolling window returns values centered at each window
time_rolled = time[window_size//2:-window_size//2+1]

plt.figure(figsize=(10, 4))
plt.plot(time, transient_signal, label='Signal')
plt.plot(time_rolled, rolling_mean, label='Rolling Mean', color='orange')
plt.fill_between(time_rolled, rolling_mean - rolling_std, rolling_mean +
 ↪rolling_std, color='orange', alpha=0.2, label='Rolling Std Dev')
plt.title('Rolling Statistics of Signal with Transient')
plt.xlabel('Time (s)')
plt.ylabel('Amplitude')
plt.legend()
plt.grid()
plt.show()
```

```
# Plot rolling entropy with properly aligned time axis
plt.figure(figsize=(10, 4))
plt.plot(time_rolled, rolling_entropy, label='Rolling Entropy', color='green')
plt.title('Rolling Entropy of Signal with Transient')
plt.xlabel('Time (s)')
plt.ylabel('Entropy')
plt.legend()
plt.grid()
plt.show()
```






Rolling Entropy of Signal with Transient
Rolling Entropy
Entropy
Time (s)
2.2
2.1
2.0
1.9
1.8
1.7
0
2
4
6
8
10