In [1]:
```
>>> import numpy as np
>>> import pandas as pd
>>> import statsmodels.api as sm
>>> import matplotlib.pyplot as plt
>>> %matplotlib inline
```

In [2]:
```
>>> df = pd.read_csv('Electric_Production.csv')
>>> df.head()
```

Out[2]:

	DATE	Value
0	01-01-1985	72.5052
1	02-01-1985	70.6720
2	03-01-1985	62.4502
3	04-01-1985	57.4714
4	05-01-1985	55.3151

In [3]:
```
>>> df.columns = ['Date','Production']
>>> df.head()
```

Out[3]:

	Date	Production
0	01-01-1985	72.5052
1	02-01-1985	70.6720
2	03-01-1985	62.4502
3	04-01-1985	57.4714
4	05-01-1985	55.3151

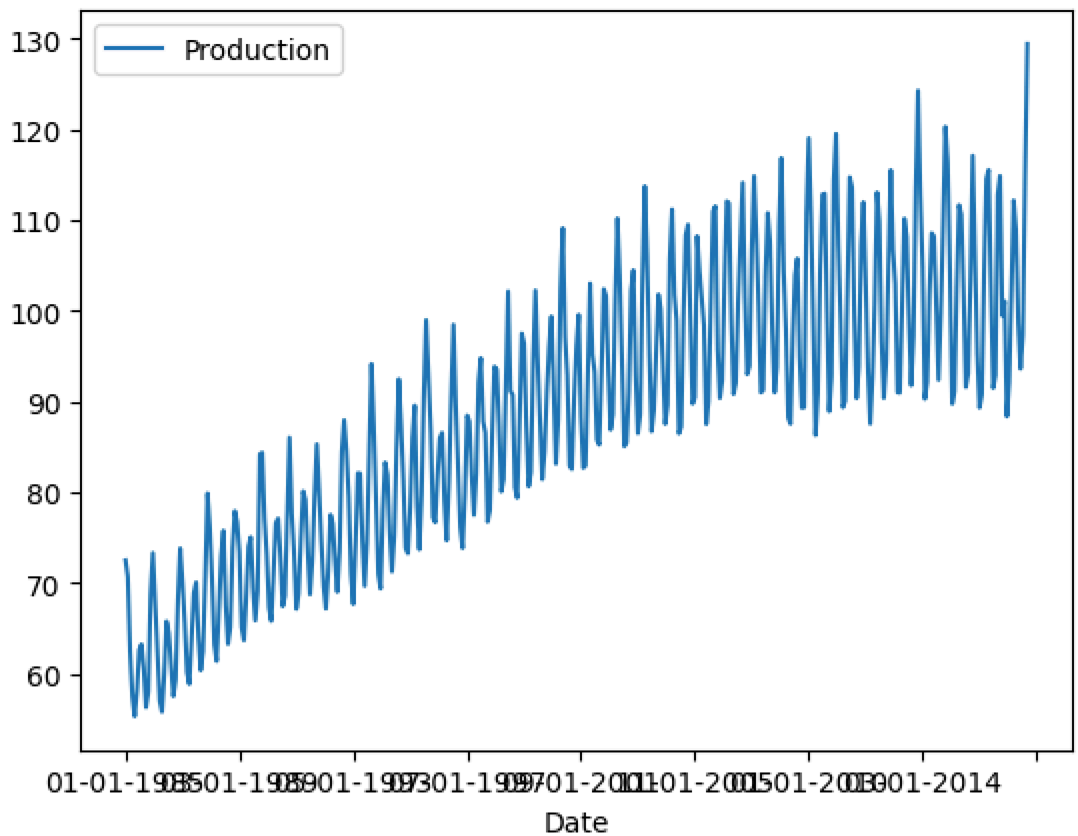
In [4]:
```
>>> df.set_index('Date',inplace=True)
>>> df.head()
```

Out[4]:

Date	Production
01-01-1985	72.5052
02-01-1985	70.6720
03-01-1985	62.4502
04-01-1985	57.4714
05-01-1985	55.3151

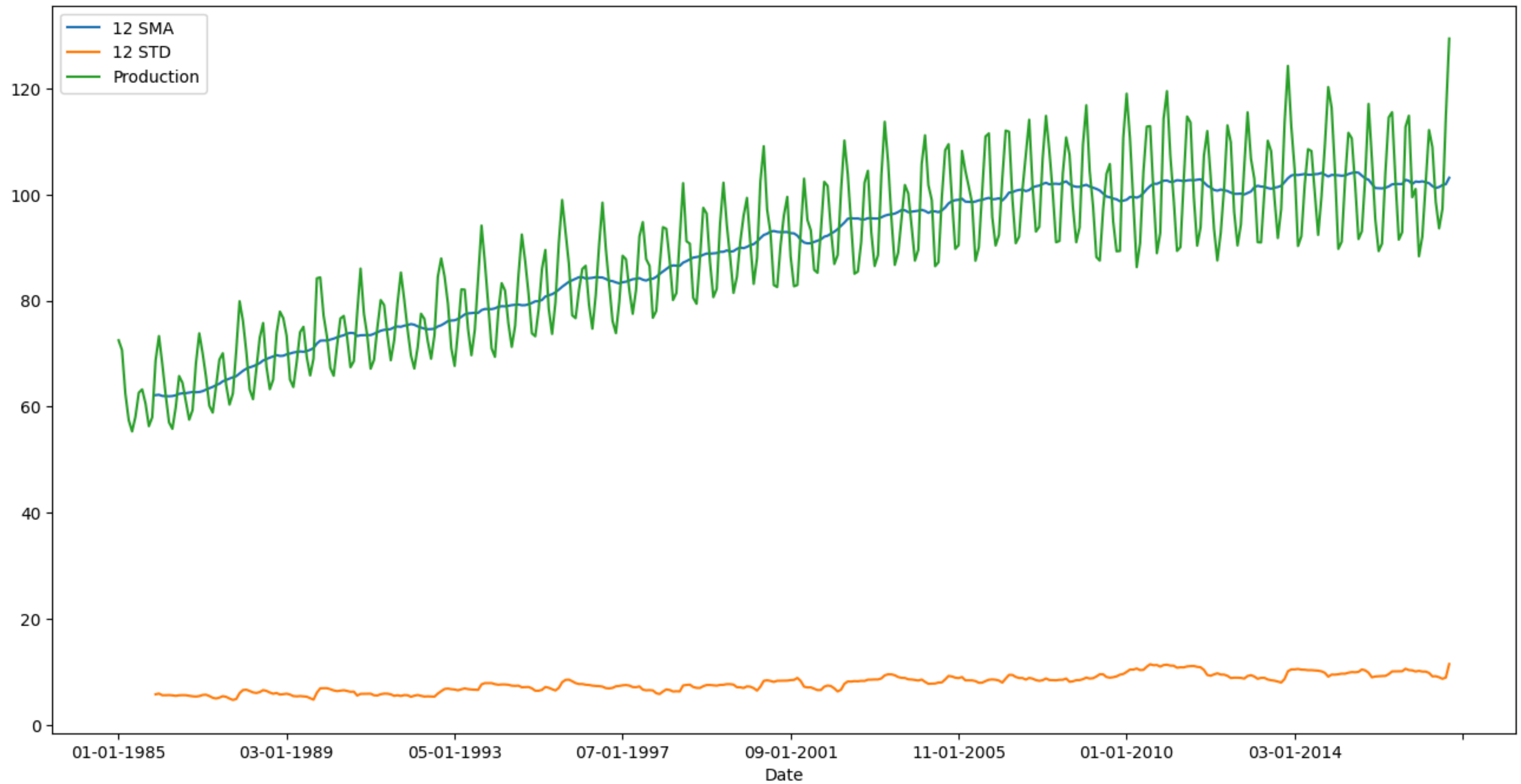
In [5]:
```
>>> df.plot()
```

Out[5]:
```
<Axes: xlabel='Date'>
```



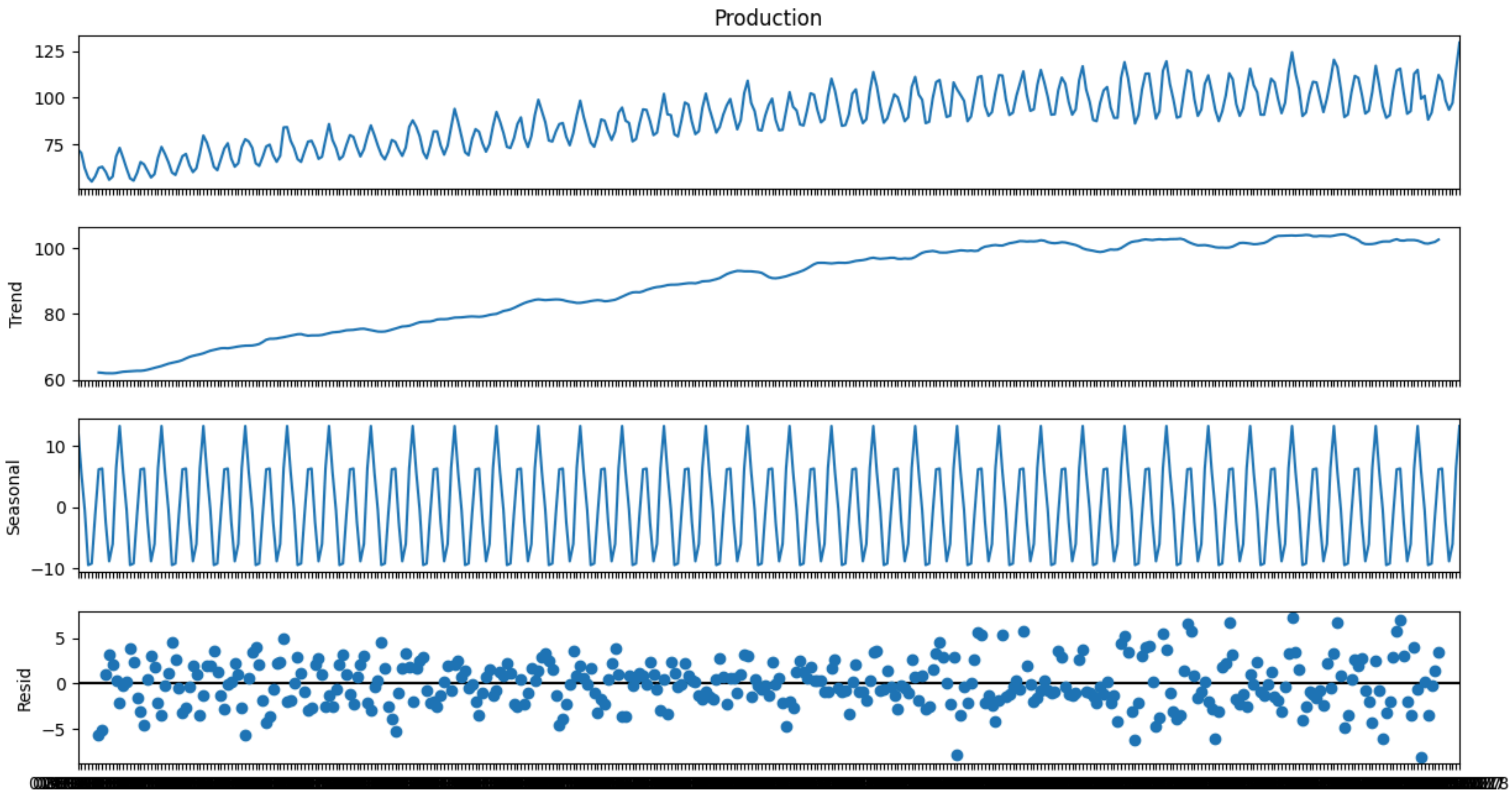
In [6]:
```
>>> df['Production'].rolling(12).mean().plot(label='12 SMA',figsize=(16,8))
>>> df['Production'].rolling(12).std().plot(label='12 STD')
>>> df['Production'].plot()
>>> plt.legend()
```

Out[6]: <matplotlib.legend.Legend at 0x21670e82b50>



In [7]:
```
>>> from statsmodels.tsa.seasonal import seasonal_decompose
```

In [8]:
```
>>> decomp = seasonal_decompose(df['Production'],period=12)
>>> fig = decomp.plot()
>>> fig.set_size_inches(14,7)
```



In [9]:
```
>>> from statsmodels.tsa.stattools import adfuller
```

In [10]:
```
>>> fuller_test = adfuller(df['Production'])
>>> fuller_test
```

Out[10]:
```
(-2.256990350047227,
 0.1862146911658738,
 15,
 381,
 {'1%': -3.4476305904172904,
  '5%': -2.869155980820355,
  '10%': -2.570827146203181},
 1840.8474501627156)
```

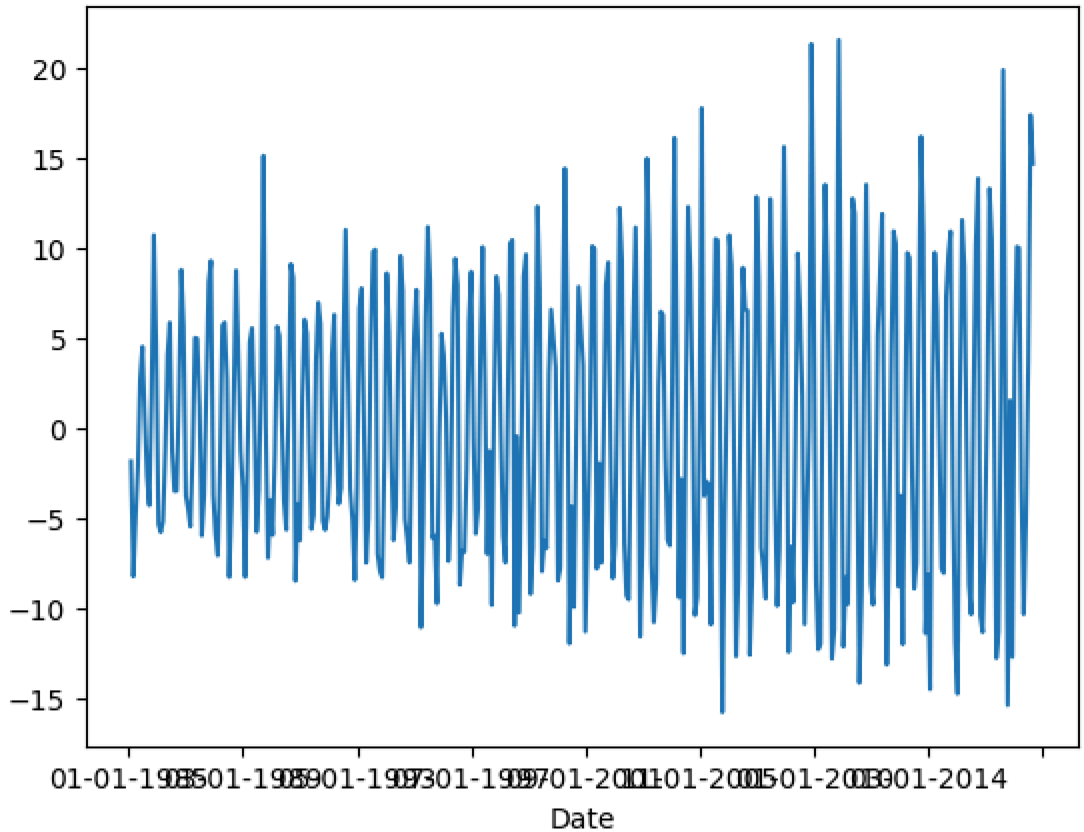
In [11]:
```
>>> def test_p_value(data):
        fuller_test = adfuller(data)
        print('P-value: ',fuller_test[1])
        if fuller_test[1] <= 0.05:
            print('Reject null hypothesis, data is stationary')
        else:
            print('Do not reject null hypothesis, data is not stationary')
```

In [12]:
```
>>> test_p_value(df['Production'])
```

```
P-value:  0.1862146911658738
Do not reject null hypothesis, data is not stationary
```

In [13]:
```
df['First_diff'] = df['Production'] - df['Production'].shift(1)
df['First_diff'].plot()
```

Out[13]: <Axes: xlabel='Date'>

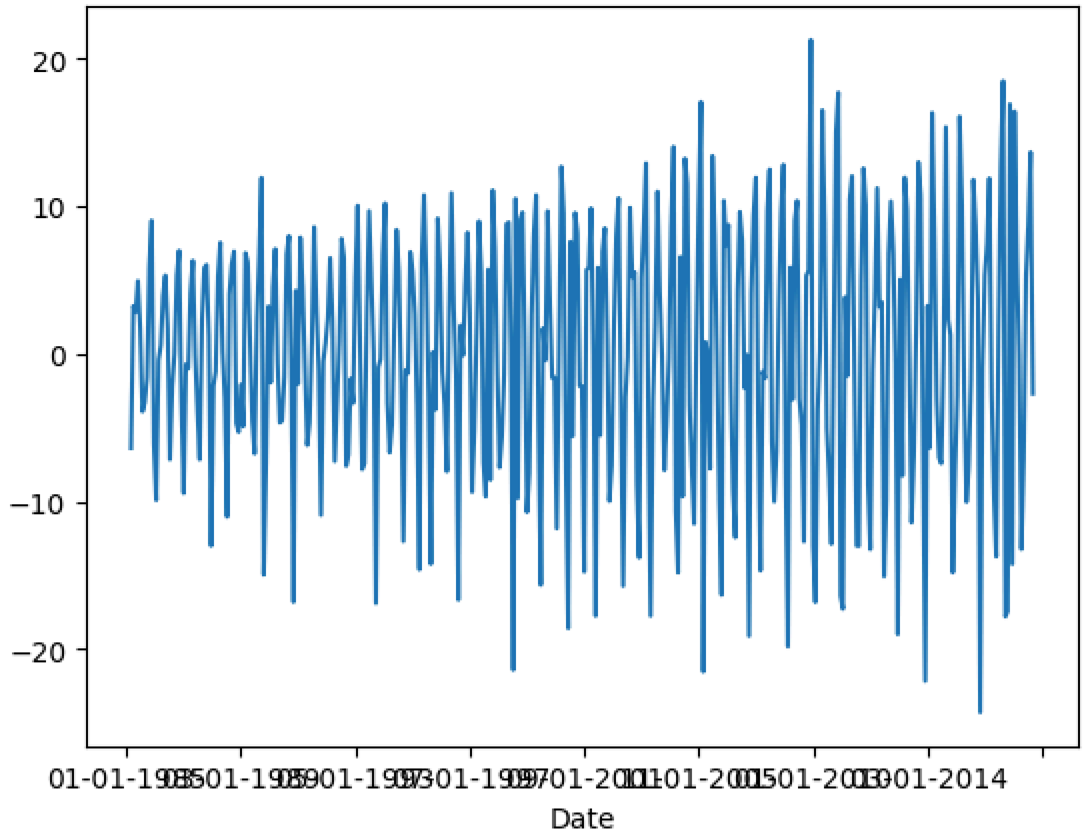


In [14]:
```
>>> test_p_value(df['First_diff'].dropna())
```

```
P-value:  4.0777865655397073e-10
Reject null hypothesis, data is stationary
```

In [15]:
```
>>> df['Second_diff'] = df['First_diff'] - df['First_diff'].shift(1)
>>> df['Second_diff'].plot()
```

Out[15]: <Axes: xlabel='Date'>

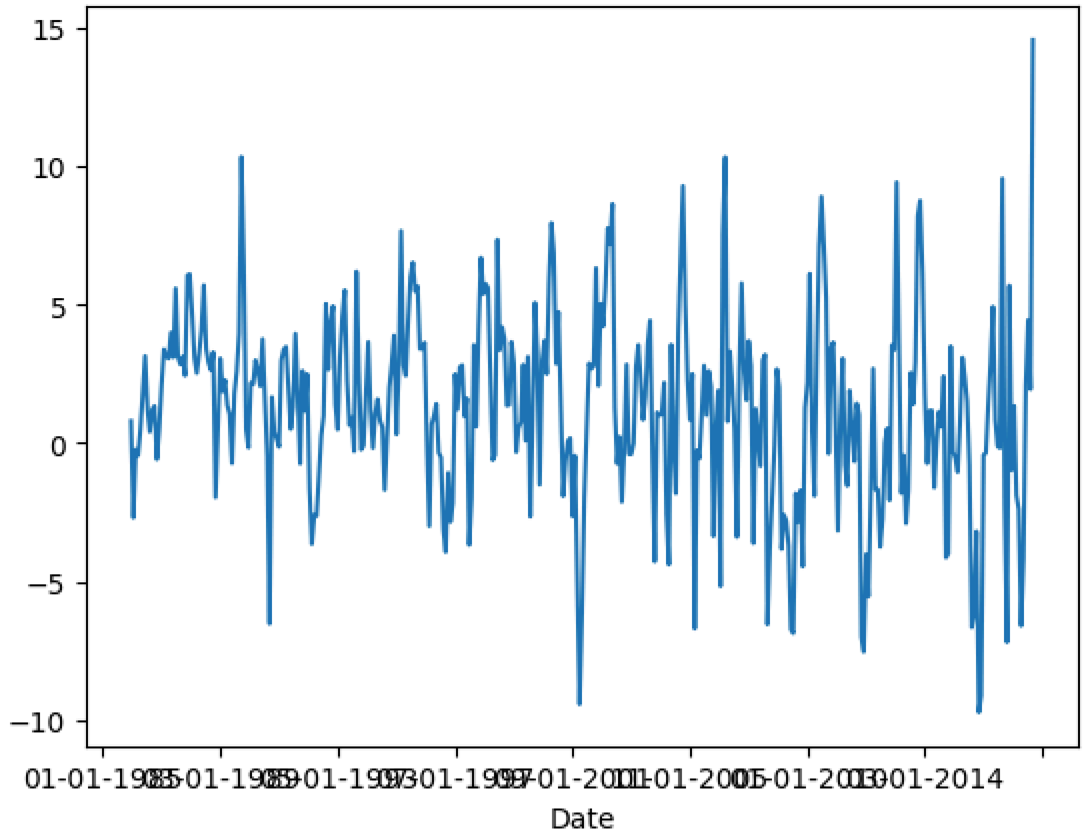


In [16]:
```
>>> test_p_value(df['Second_diff'].dropna())
```

```
P-value:  4.183693748002117e-17
Reject null hypothesis, data is stationary
```

In [17]:
```
>>> df['Seasonal_diff'] = df['Production'] - df['Production'].shift(12)
>>> df['Seasonal_diff'].plot()
```

Out[17]: <Axes: xlabel='Date'>

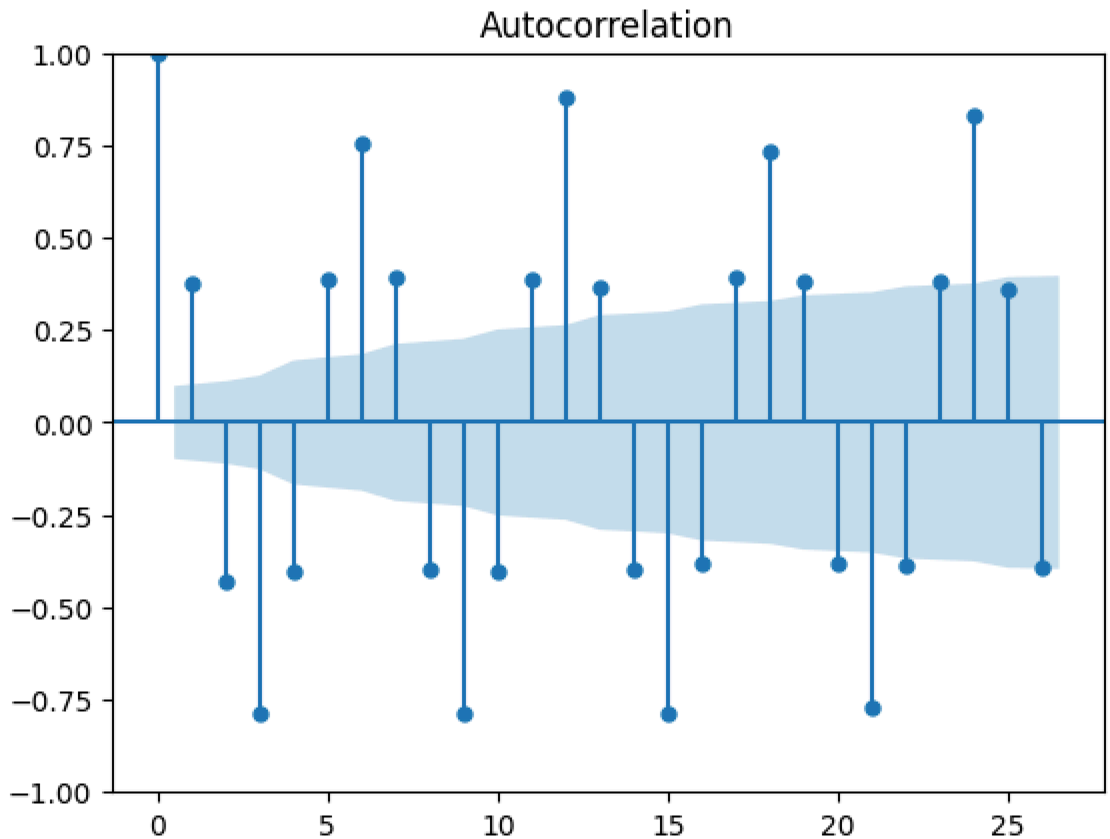


In [18]:
```
>>> test_p_value(df['Seasonal_diff'].dropna())
```

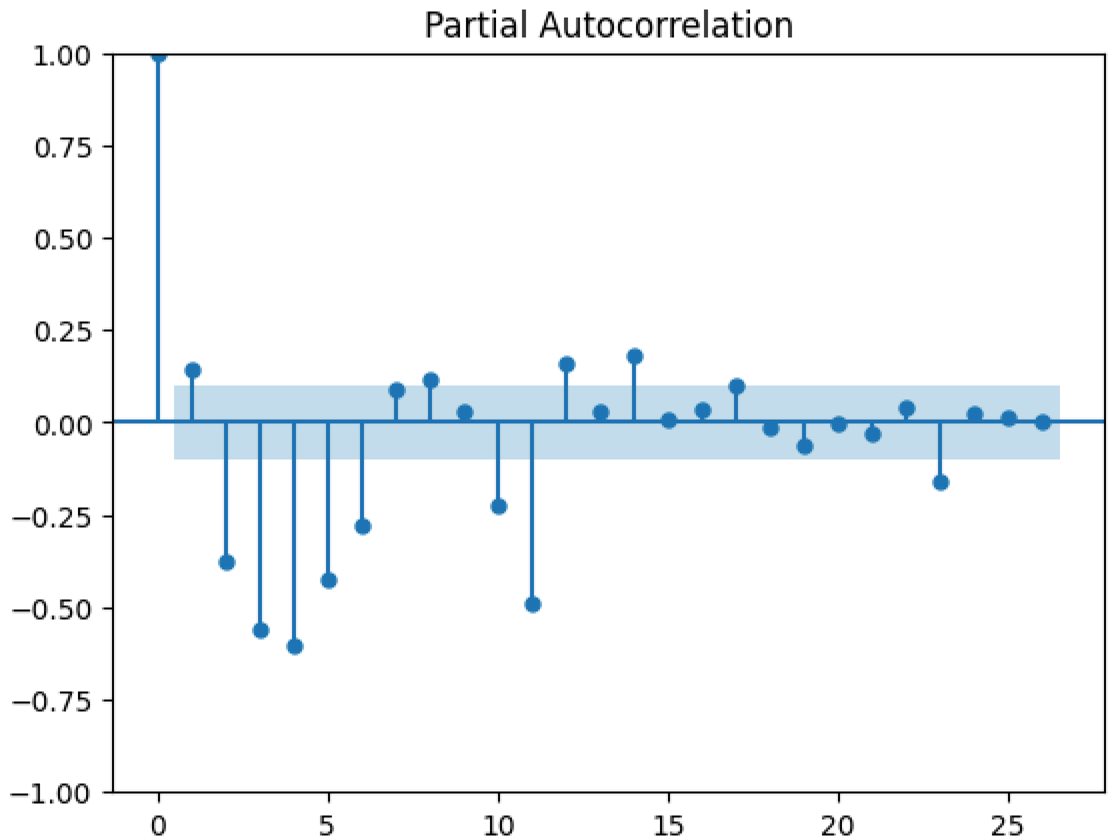
```
P-value:  8.812644938089026e-07
Reject null hypothesis, data is stationary
```

In [19]:
```
>>> from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

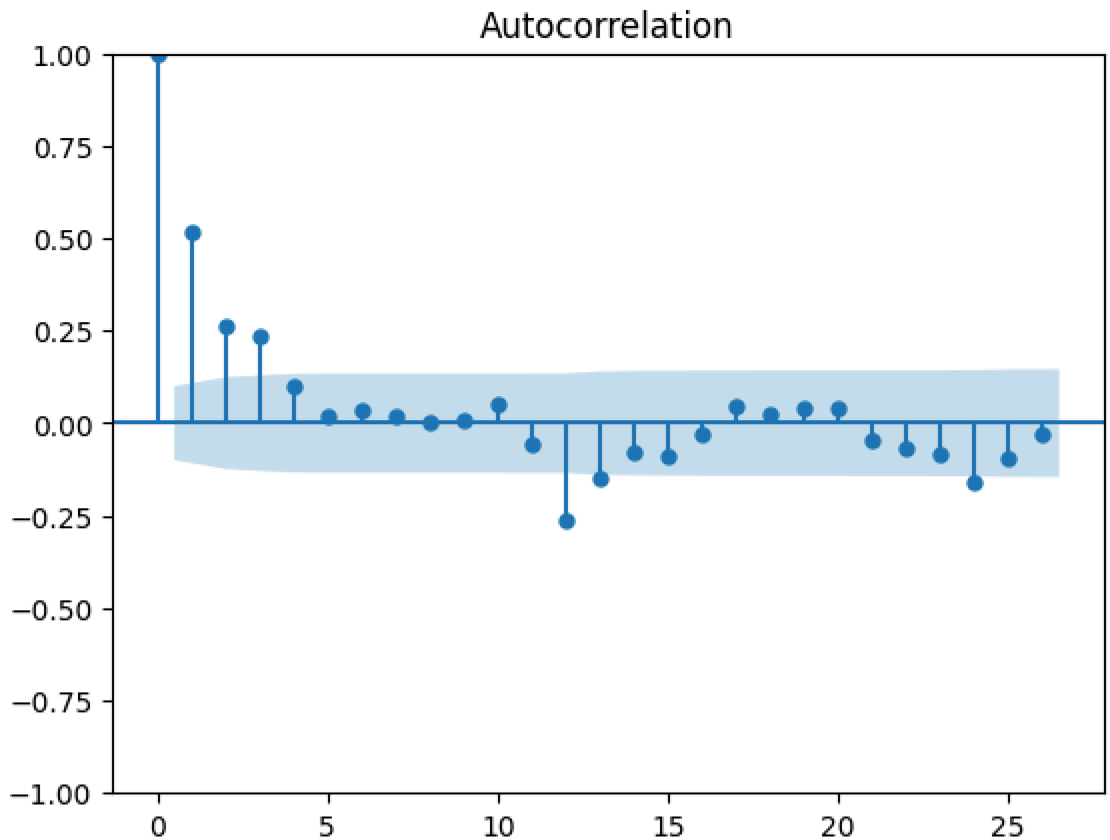
In [20]:
```
>>> first_diff = plot_acf(df['First_diff'].dropna())
```

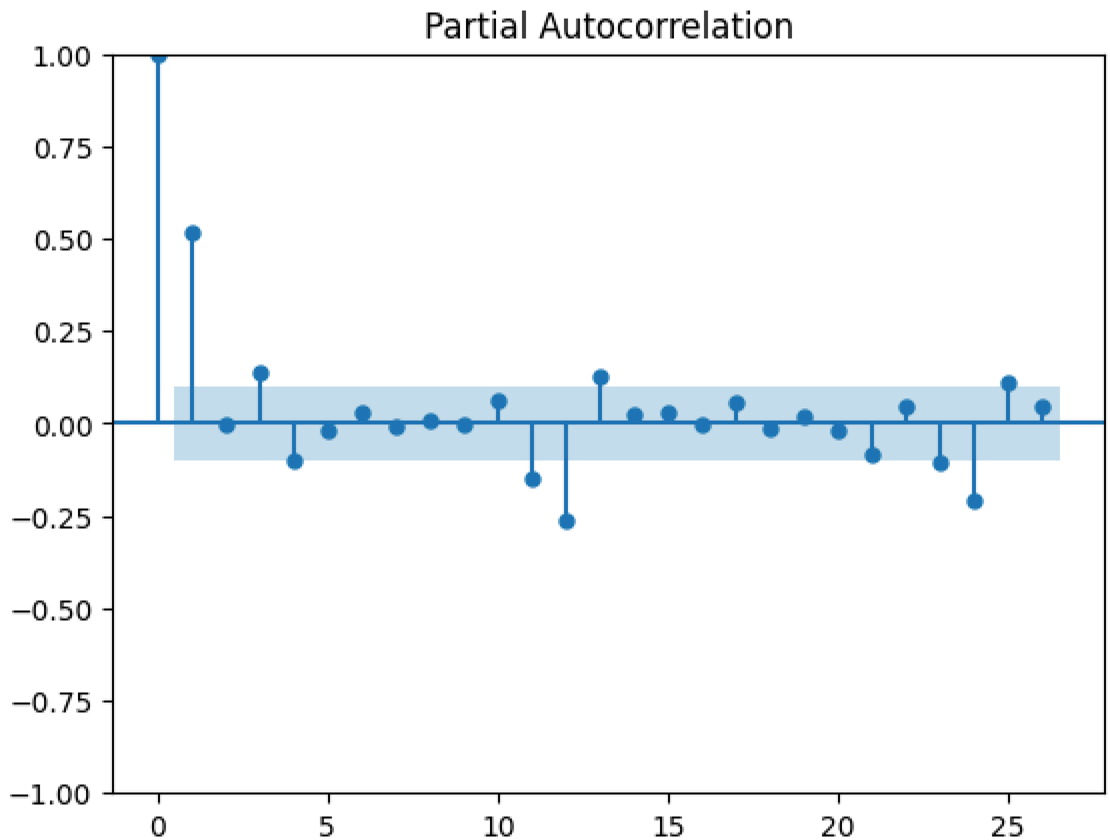


In [21]:
```
>>> sec_diff = plot_pacf(df['Second_diff'].dropna())
```



In [22]:
```
>>> p1 = plot_acf(df['Seasonal_diff'].dropna())
>>> p2 = plot_pacf(df['Seasonal_diff'].dropna())
```





In [23]:
```
>>> from statsmodels.tsa.arima_model import ARIMA
```

In [24]:
```
>>> model = sm.tsa.statespace.SARIMAX(df['Production'],order=(0,1,0),seasonal_order=(1,1,1,12))
```

```
C:\Users\Arka Pravo Dutta\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\tsa\base\tsa
_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
C:\Users\Arka Pravo Dutta\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\tsa\base\tsa
_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
```

In [25]:
```
>>> results = model.fit()
>>> results.summary()
```

Out[25]:

SARIMAX Results

Dep. Variable:	Production	**No. Observations:**	397
Model:	SARIMAX(0, 1, 0)x(1, 1, [1], 12)	**Log Likelihood**	-928.856
Date:	Sat, 25 May 2024	**AIC**	1863.712
Time:	20:47:52	**BIC**	1875.564
Sample:	01-01-1985	**HQIC**	1868.413
	- 01-01-2018		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.S.L12	0.0421	0.058	0.721	0.471	-0.072	0.157
ma.S.L12	-0.7790	0.041	-19.119	0.000	-0.859	-0.699
sigma2	7.1906	0.417	17.245	0.000	6.373	8.008

Ljung-Box (L1) (Q):	13.53	**Jarque-Bera (JB):**	30.47
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	2.86	**Skew:**	-0.04
Prob(H) (two-sided):	0.00	**Kurtosis:**	4.38

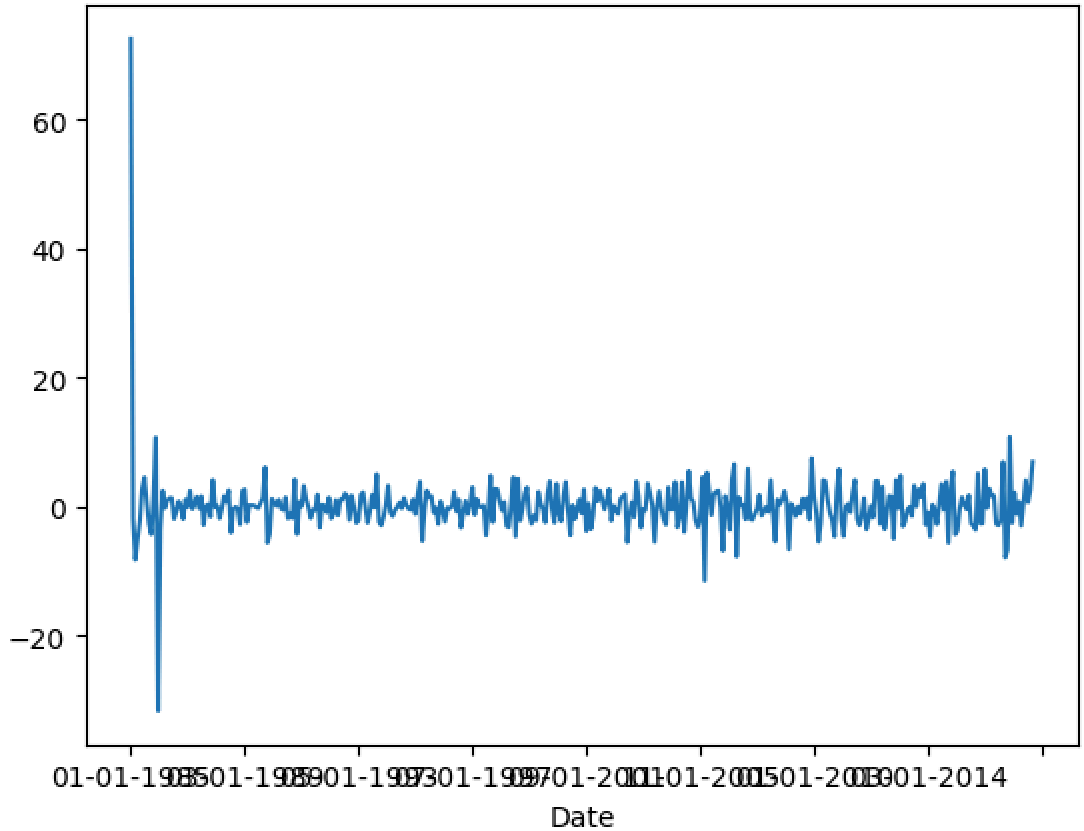
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [26]:
```
>>> results.resid
```

Out[26]:
```
Date
01-01-1985    72.505200
02-01-1985    -1.833200
03-01-1985    -8.221800
04-01-1985    -4.978800
05-01-1985    -2.156300
                ...
09-01-2017     0.529985
10-01-2017     4.057874
11-01-2017     0.690663
12-01-2017     2.477697
01-01-2018     6.953533
Length: 397, dtype: float64
```

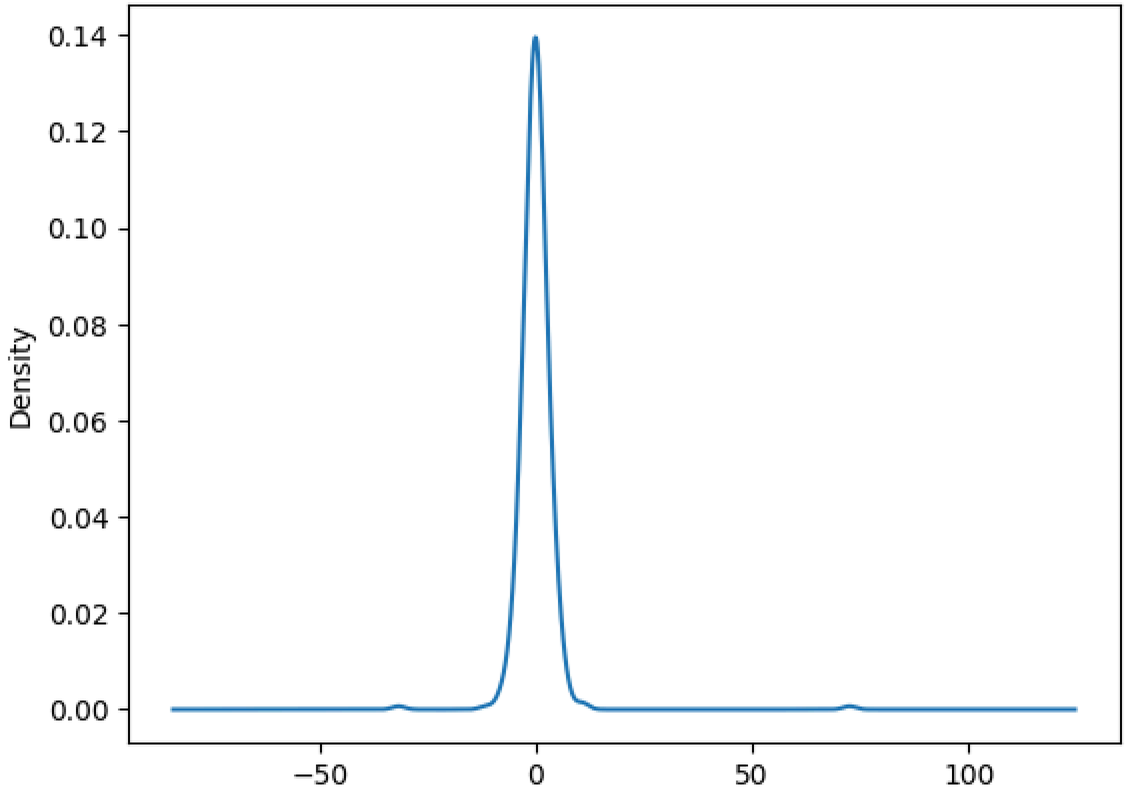
In [26]:
```
>>> results.resid.plot()
```

Out[26]: <Axes: xlabel='Date'>



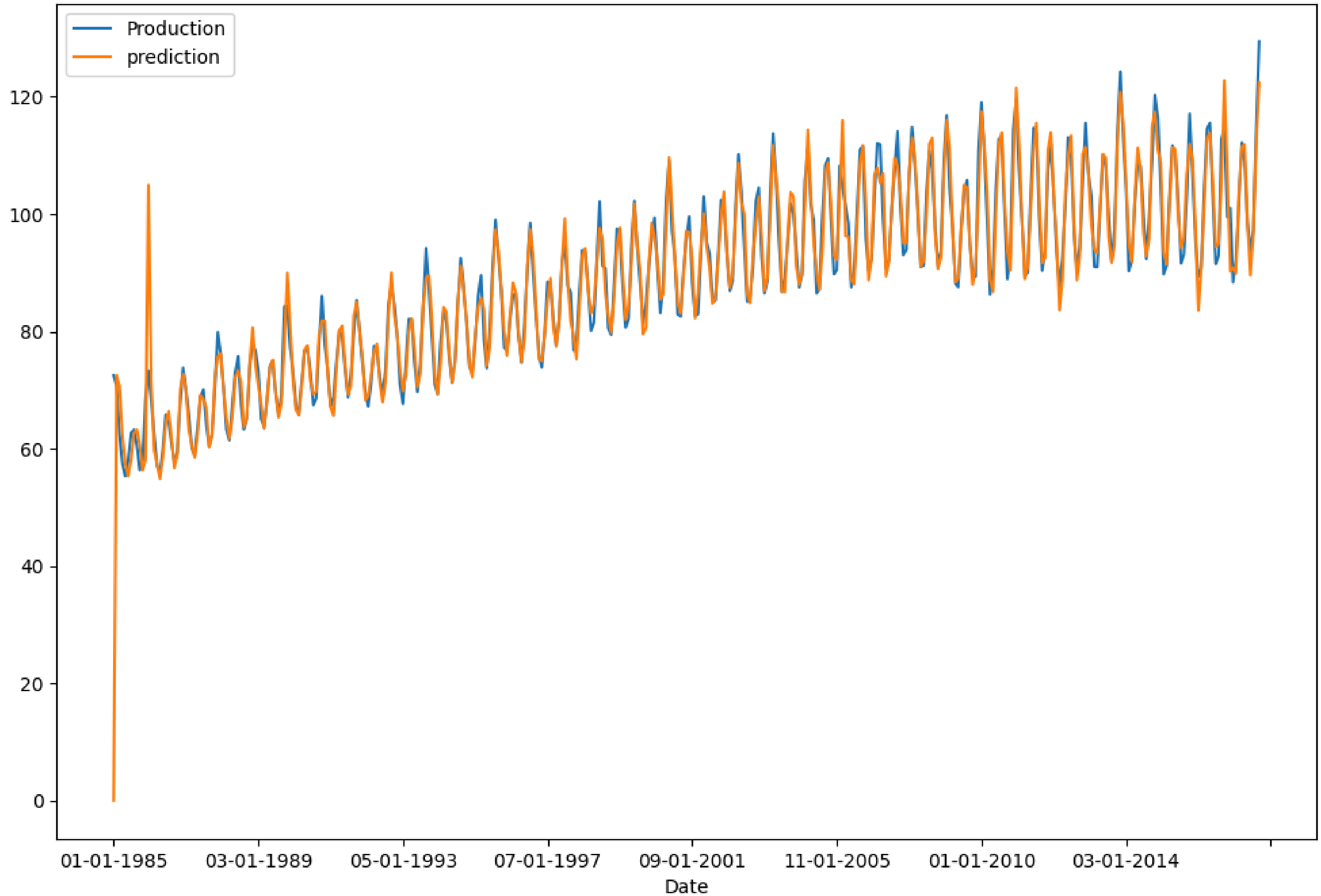
In [27]:
```
>>> results.resid.plot(kind='kde')
```

Out[27]: <Axes: ylabel='Density'>



In [28]:
```
>>> df['prediction'] = results.predict()
>>> df[['Production','prediction']].plot(figsize=(12,8))
```

Out[28]: <Axes: xlabel='Date'>



In [30]:
```
>>> from pandas.tseries.offsets import DateOffset
df.index = pd.to_datetime(df.index)
>>> extra_dates = [df.index[-1] + DateOffset(months=m) for m in range (1,24)]
```

In [31]:
```
>>> forecast_df = pd.DataFrame(index=extra_dates,columns=df.columns)
>>> forecast_df.head()
```

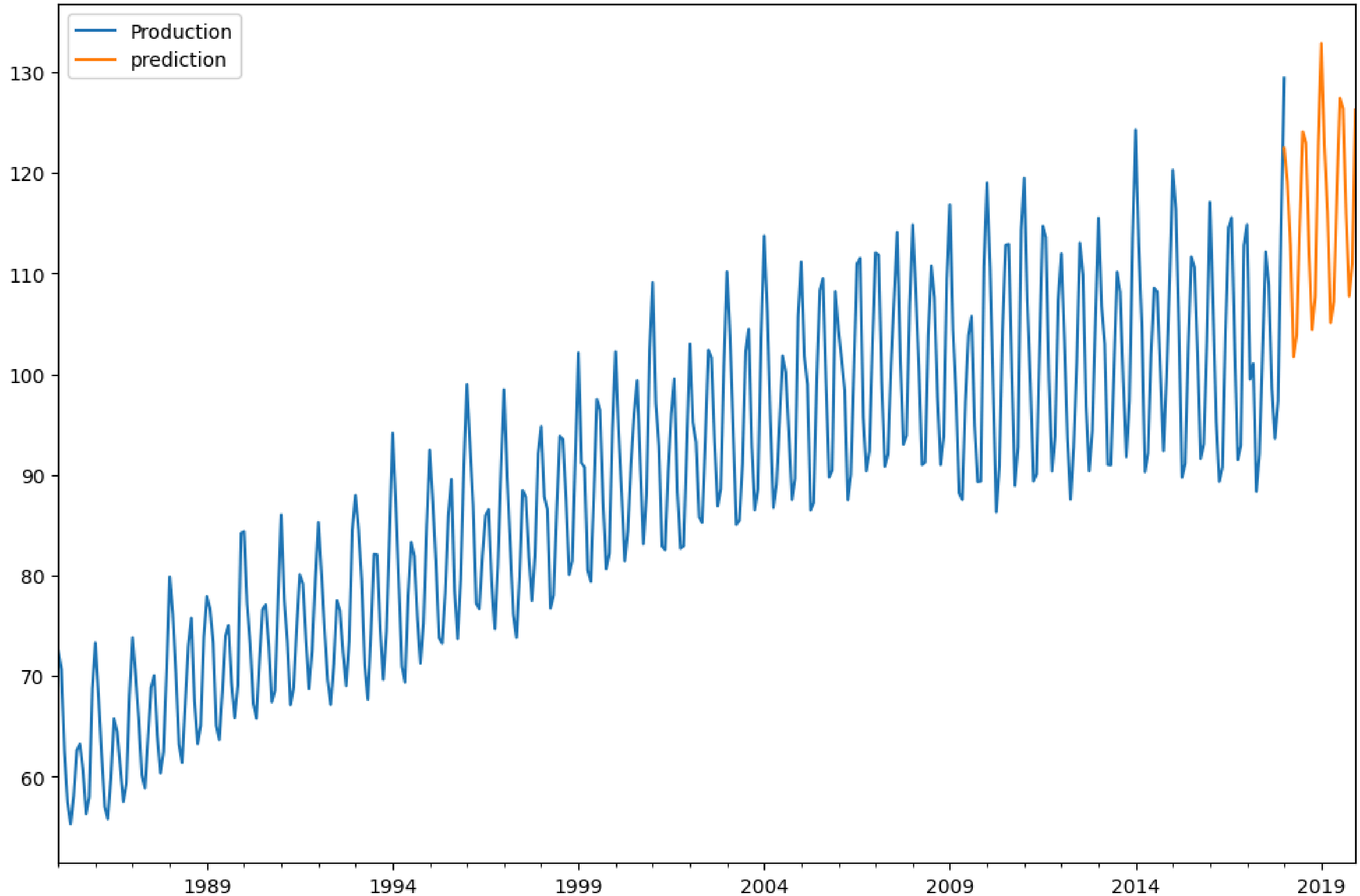
Out[31]:

	Production	First_diff	Second_diff	Seasonal_diff	prediction
2018-02-01	NaN	NaN	NaN	NaN	NaN
2018-03-01	NaN	NaN	NaN	NaN	NaN
2018-04-01	NaN	NaN	NaN	NaN	NaN
2018-05-01	NaN	NaN	NaN	NaN	NaN
2018-06-01	NaN	NaN	NaN	NaN	NaN

In [32]:
```
>>> final_df = pd.concat([df,forecast_df])
```

In [33]:
```
>>> final_df['prediction'] = results.predict(start=396, end=430)
>>> final_df[['Production','prediction']].plot(figsize=(12,8))
```

Out[33]: <Axes: >



In [34]:
```
# Calculate predictions
start_index=396
end_index=430
final_df['prediction'] = results.predict(start=start_index, end=end_index)

# Select and display the actual production and predictions for the specified range
forecasted_data = final_df.iloc[start_index:end_index + 1]  # Adding 1 to include the end_index
forecasted_data = forecasted_data[['Production', 'prediction']]
print(forecasted_data)
```

```
            Production  prediction
2018-01-01    129.4048  122.451267
2018-02-01         NaN  119.058512
2018-03-01         NaN  112.722705
2018-04-01         NaN  101.712003
2018-05-01         NaN  103.848850
2018-06-01         NaN  114.660887
2018-07-01         NaN  124.071660
2018-08-01         NaN  122.958026
2018-09-01         NaN  112.332041
2018-10-01         NaN  104.433611
2018-11-01         NaN  107.715500
2018-12-01         NaN  123.065460
2019-01-01         NaN  132.863193
2019-02-01         NaN  122.728247
2019-03-01         NaN  116.060079
2019-04-01         NaN  105.120015
2019-05-01         NaN  107.189817
2019-06-01         NaN  118.033017
2019-07-01         NaN  127.418929
2019-08-01         NaN  126.394187
2019-09-01         NaN  115.755127
2019-10-01         NaN  107.734602
2019-11-01         NaN  110.997932
2019-12-01         NaN  126.262104
```

In [35]:
```
from sklearn.metrics import mean_squared_error
rmse=np.sqrt(mean_squared_error(df['Production'],df['prediction']))
print(f'Root Mean Squared Error (RMSE): {rmse}')
```

```
Root Mean Squared Error (RMSE): 4.84601517137247
```

In [ ]: