In [ ]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import datetime
```

In [ ]:
```python
from meteostat import Point, Monthly

# Set time period
start = datetime.datetime(1970, 3, 1)
end = datetime.datetime(2022, 12, 31)

# Create Point for Madrid
location = Point(40.416775, -3.703790, 657)

# Get daily data for March 2023
df_madrid = Monthly(location, start, end)
df_madrid = df_madrid.fetch()
```

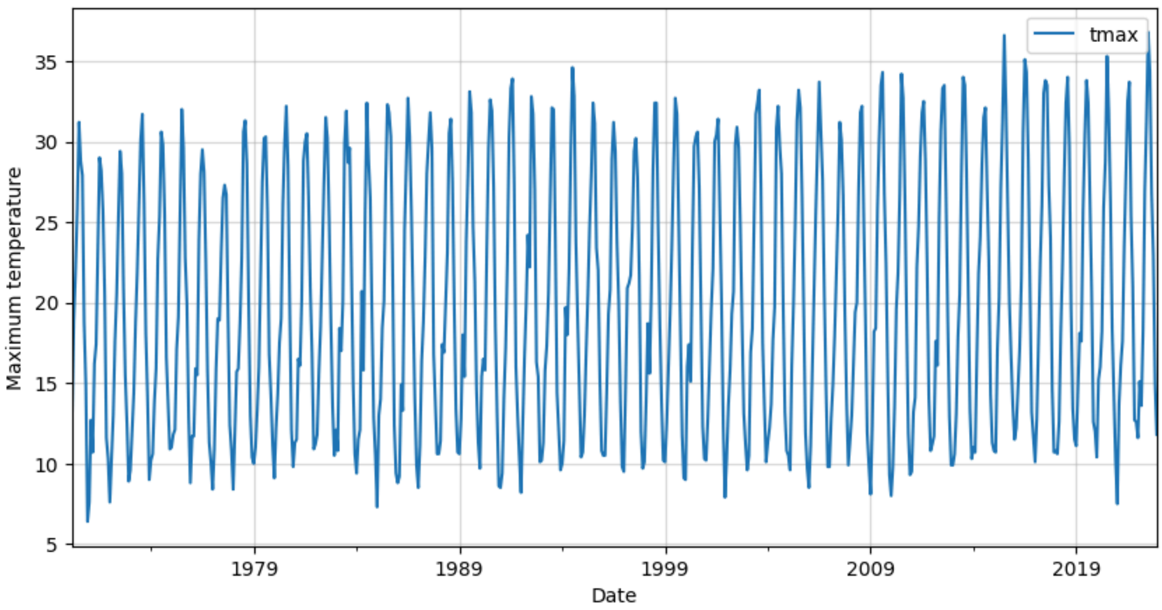
In [ ]:
```python
df_madrid
```

Out[ ]:

time	tavg	tmin	tmax	prcp	wspd	pres	tsun
1970-03-01	9.5	3.2	12.9	14.6	NaN	1016.0	NaN
1970-04-01	12.8	7.3	18.9	1.4	NaN	1021.0	NaN
1970-05-01	16.2	11.0	22.0	18.8	NaN	1016.0	NaN
1970-06-01	20.3	15.5	25.8	17.7	NaN	1016.0	NaN
1970-07-01	24.3	18.1	31.2	11.5	NaN	1016.0	NaN
...	...	...	...	...	...	...	...
2022-08-01	27.4	21.4	34.3	4.9	10.1	1013.8	NaN
2022-09-01	20.9	16.1	26.8	43.9	10.2	1014.6	NaN
2022-10-01	17.7	14.1	22.9	27.8	8.0	1019.8	NaN
2022-11-01	10.7	7.7	15.0	47.0	11.5	1020.1	NaN
2022-12-01	8.5	6.9	11.8	145.4	9.3	1017.1	NaN

634 rows × 7 columns

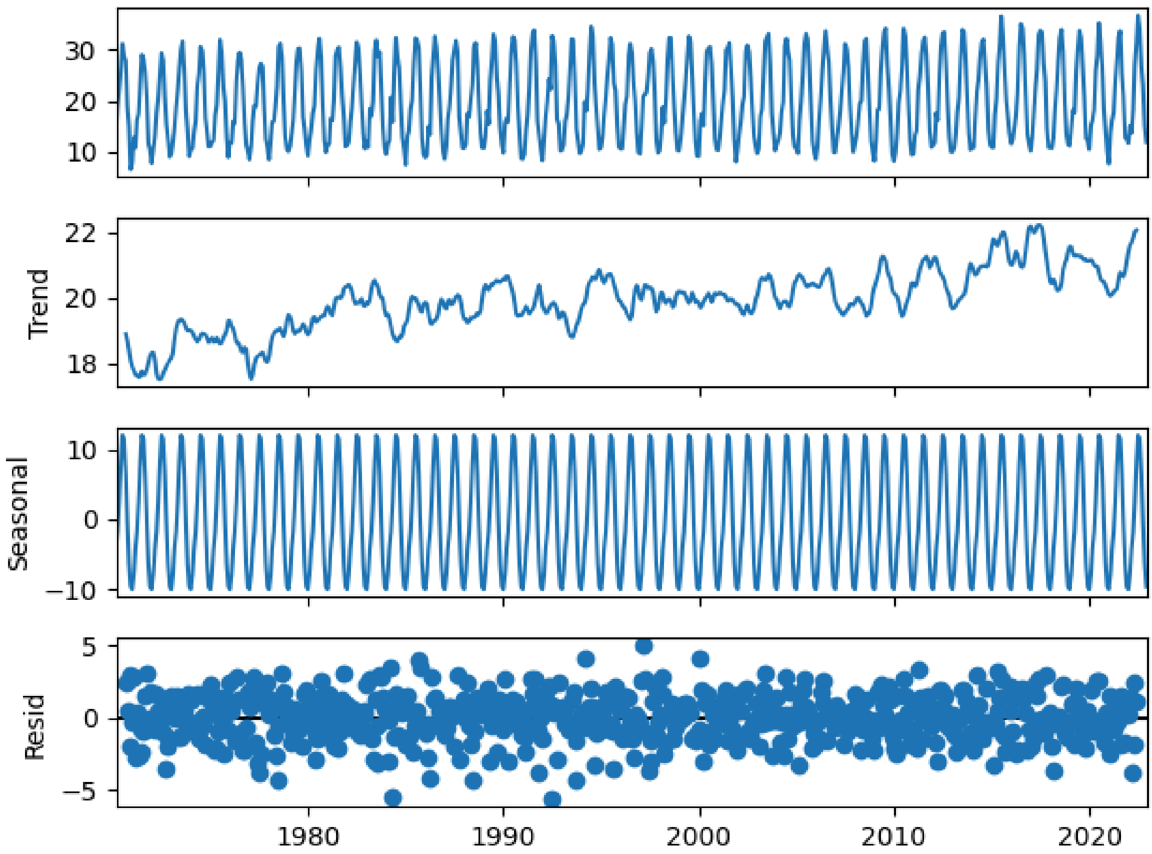
In [ ]:
```python
# Keep only the maximum temperature
df_temp_max = df_madrid[['tmax']]

# Visualize the data
df_temp_max.plot(figsize=(10,5))
plt.grid(alpha=0.5)
plt.xlabel('Date')
plt.ylabel('Maximum temperature')
plt.show()
```



In [ ]:
```
df_temp_max.isna().sum()
```

Out[ ]:
```
tmax    0
dtype: int64
```

In [ ]:
```
# Import statsmodels library
import statsmodels.api as sm

# Perform seasonal decomposition
decomposition = sm.tsa.seasonal_decompose(df_temp_max,
                                          model='additive',
                                          period=12)

# Extract the decomposed components
trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

# Plot the decomposed components
decomposition.plot()
plt.show()
```



Prophet

In [ ]:
```
df_temp_max
```

Out[ ]:

time	tmax
1970-03-01	12.9
1970-04-01	18.9
1970-05-01	22.0
1970-06-01	25.8
1970-07-01	31.2
...	...
2022-08-01	34.3
2022-09-01	26.8
2022-10-01	22.9
2022-11-01	15.0
2022-12-01	11.8

634 rows × 1 columns

In [ ]:
```
df_temp_max.reset_index(inplace=True)
df_temp_max
```

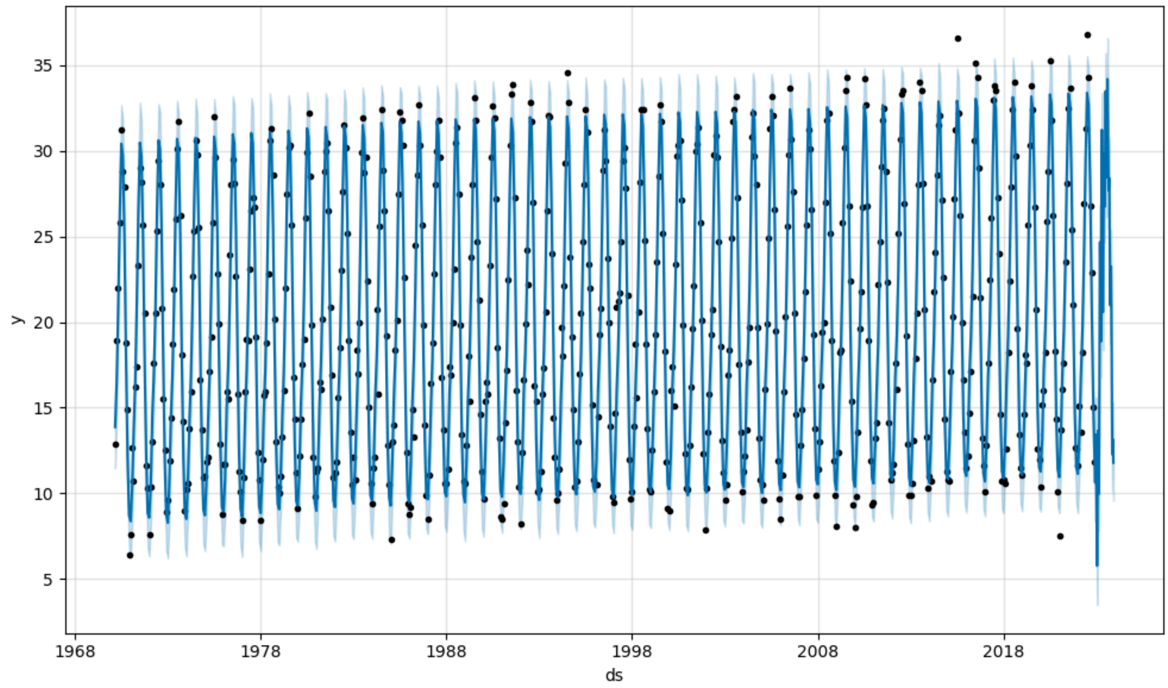
Out[ ]:

	time	tmax
0	1970-03-01	12.9
1	1970-04-01	18.9
2	1970-05-01	22.0
3	1970-06-01	25.8
4	1970-07-01	31.2
...	...	...
629	2022-08-01	34.3
630	2022-09-01	26.8
631	2022-10-01	22.9
632	2022-11-01	15.0
633	2022-12-01	11.8

634 rows × 2 columns

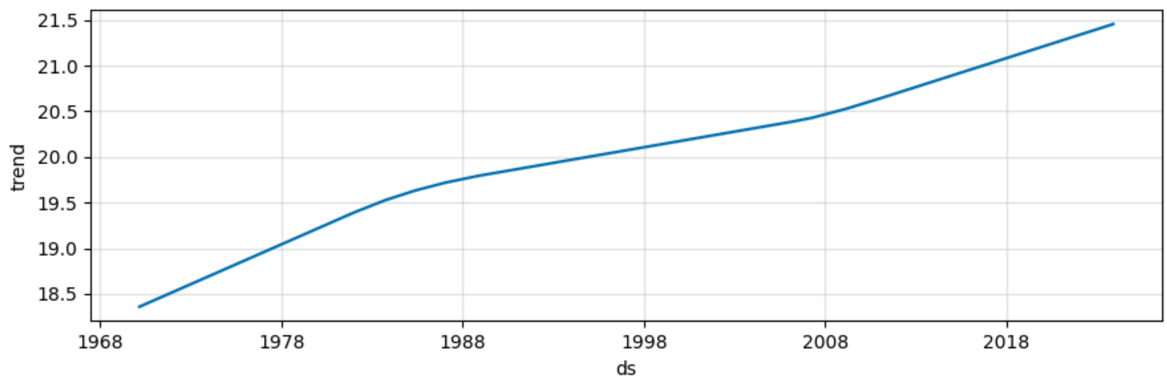
In [ ]:
```
from prophet import Prophet
import pandas as pd
import matplotlib.pyplot as plt

# Veriyi Prophet için uygun formata dönüştürme
df_prophet = df_temp_max.rename(columns={'time': 'ds', 'tmax': 'y'})

# Prophet modelini oluşturma
model = Prophet()
model.fit(df_prophet)

# Gelecekteki değerler için tahmin yapma
future = model.make_future_dataframe(periods=365)
forecast = model.predict(future)

# Bileşenleri görselleştirme
fig1 = model.plot(forecast)
plt.show()
```

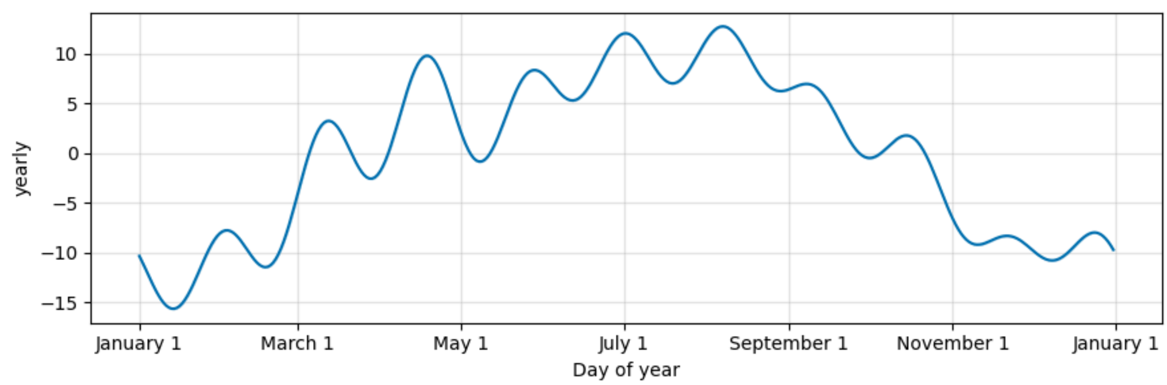
```
17:09:16 - cmdstanpy - INFO - Chain [1] start processing
17:09:17 - cmdstanpy - INFO - Chain [1] done processing
FutureWarning: The behavior of DatetimeProperties.to_pydatetime is deprecated, in
a future version this will return a Series containing python datetime objects ins
tead of an ndarray. To retain the old behavior, call `np.array` on the result
FutureWarning: The behavior of DatetimeProperties.to_pydatetime is deprecated, in
a future version this will return a Series containing python datetime objects ins
tead of an ndarray. To retain the old behavior, call `np.array` on the result
```



In [ ]:
```
fig2 = model.plot_components(forecast)
```

```
FutureWarning: The behavior of DatetimeProperties.to_pydatetime is deprecated, in a future version this will return a Series containing python datetime objects instead of an ndarray. To retain the old behavior, call `np.array` on the result
FutureWarning: The behavior of DatetimeProperties.to_pydatetime is deprecated, in a future version this will return a Series containing python datetime objects instead of an ndarray. To retain the old behavior, call `np.array` on the result
FutureWarning: The behavior of DatetimeProperties.to_pydatetime is deprecated, in a future version this will return a Series containing python datetime objects instead of an ndarray. To retain the old behavior, call `np.array` on the result
```





Check for stationarity

In [ ]:
```
df_temp_max=df_madrid[['tmax']]
```

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

# Perform Augmented Dickey-Fuller test
result = adfuller(df_temp_max)

# Extract and print the test statistics and p-value
test_statistic = result[0]
p_value = result[1]
print(f"Test statistics : {test_statistic}")
print(f"P value less 0.05 --> stationary  {p_value}")
```

```
Test statistics : -2.971872590243201
P value less 0.05 --> stationary  0.03760595188739098
```

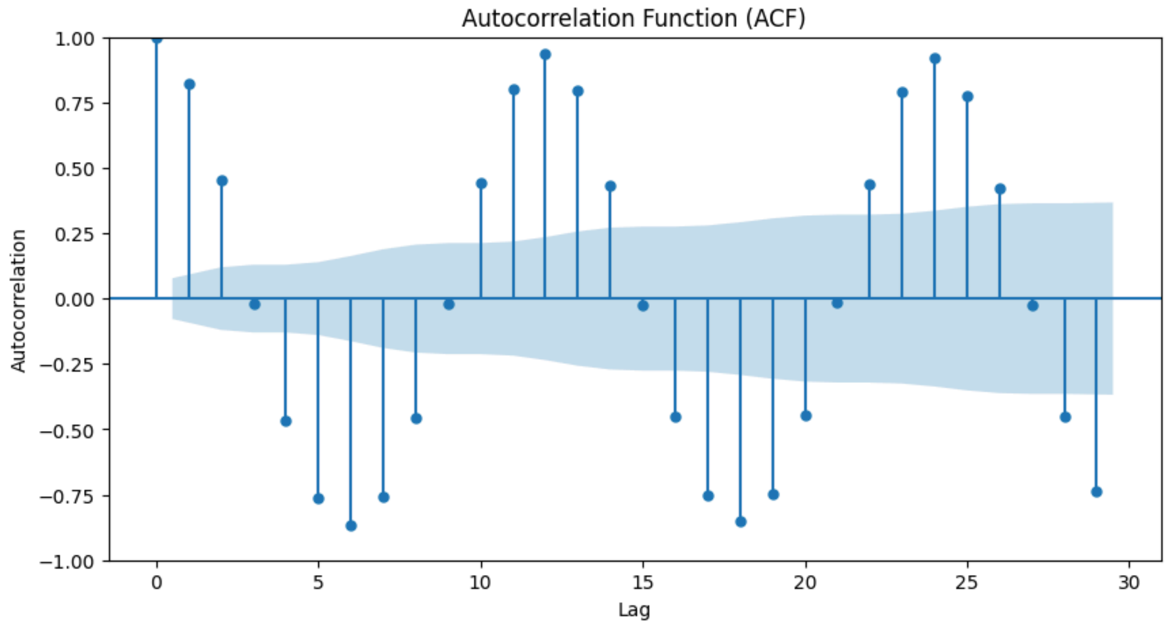
Kwiatkowski–Phillips–Schmidt–Shin (KPSS)

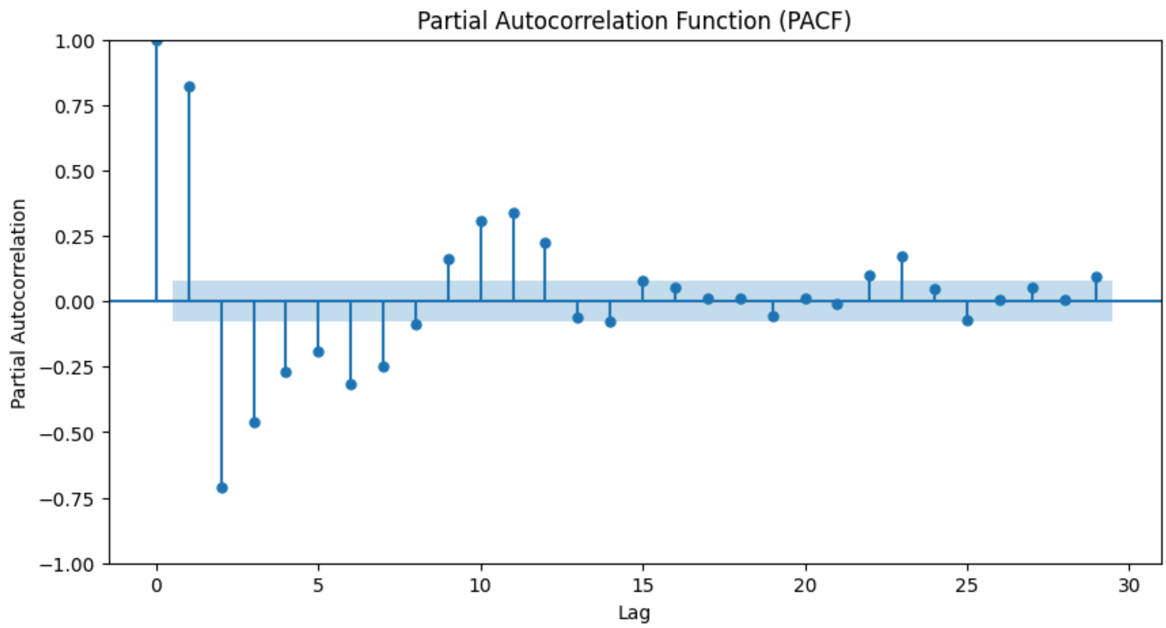
In [ ]:
```
from statsmodels.tsa.stattools import kpss

# Perform KPSS test
result = kpss(df_temp_max)

# Extract and print the test statistic and p-value
test_statistic = result[0]
p_value = result[1]
print(f"Test Statistic: {test_statistic}")
print(f"P-value bigger than 0.05 ---> stationary {p_value}")
```

```
Test Statistic: 0.23003042556646808
P-value bigger than 0.05 ---> stationary 0.1
```

```
InterpolationWarning: The test statistic is outside of the range of p-values avai
lable in the
look-up table. The actual p-value is greater than the p-value returned.
```

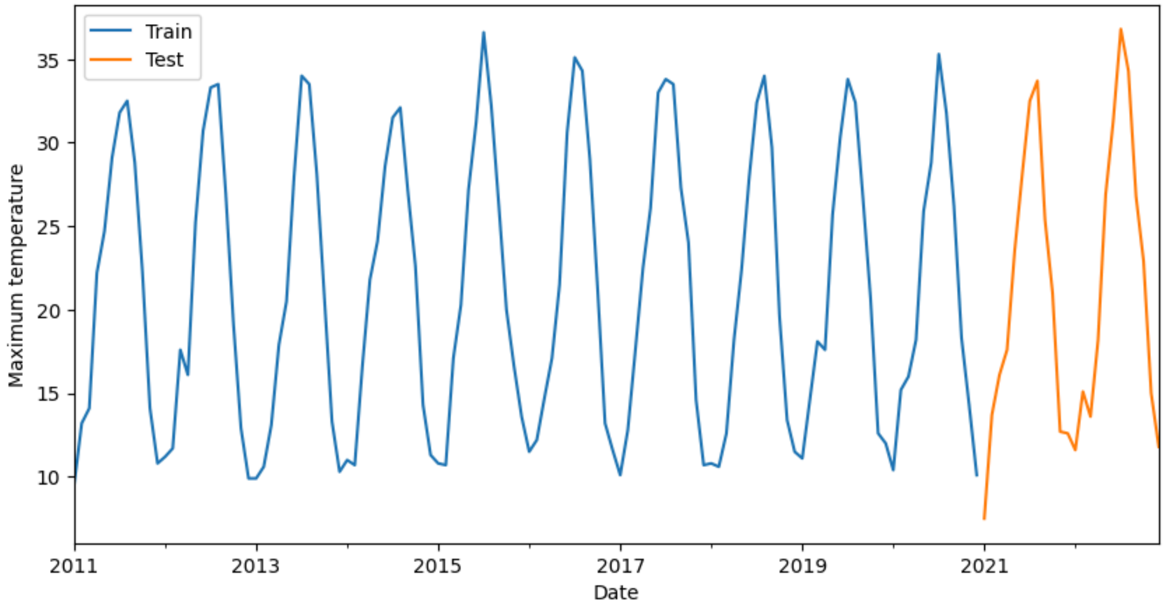
In [ ]:
```
# ACF PACF
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Plot ACF
fig, ax = plt.subplots(figsize=(10, 5))
plot_acf(df_temp_max, ax=ax)
plt.xlabel('Lag')
plt.ylabel('Autocorrelation')
plt.title('Autocorrelation Function (ACF)')
plt.show()

# Plot PACF
fig, ax = plt.subplots(figsize=(10, 5))
plot_pacf(df_temp_max, ax=ax)
plt.xlabel('Lag')
plt.ylabel('Partial Autocorrelation')
plt.title('Partial Autocorrelation Function (PACF)')
plt.show()
```





In [ ]:

```
# Split into training and testing
df_train = df_temp_max.loc[:'2020']
df_test = df_temp_max.loc['2021':]

# Plot the last 10 years of training data and the 2 of testing
ax = df_train[-120:].plot(figsize=(10, 5))
df_test.plot(ax=ax)
plt.legend(['Train', 'Test'])
plt.xlabel('Date')
plt.ylabel('Maximum temperature')
plt.show()
```



In [ ]:
```
df_temp_max
```

Out[ ]:

	tmax
time	
1970-03-01	12.9
1970-04-01	18.9
1970-05-01	22.0
1970-06-01	25.8
1970-07-01	31.2
...	...
2022-08-01	34.3
2022-09-01	26.8
2022-10-01	22.9
2022-11-01	15.0
2022-12-01	11.8

634 rows × 1 columns

model 찾기

In [ ]:
```
df_temp_max
```

Out[ ]:

	tmax
time	
1970-03-01	12.9
1970-04-01	18.9
1970-05-01	22.0
1970-06-01	25.8
1970-07-01	31.2
...	...
2022-08-01	34.3
2022-09-01	26.8
2022-10-01	22.9
2022-11-01	15.0
2022-12-01	11.8

634 rows × 1 columns

In [ ]:

```
df_train.reset_index(inplace=True)
```

In [ ]:

```
df_train
```

Out[ ]:

	time	tmax
0	1970-03-01	12.9
1	1970-04-01	18.9
2	1970-05-01	22.0
3	1970-06-01	25.8
4	1970-07-01	31.2
...	...	...
605	2020-08-01	31.8
606	2020-09-01	26.2
607	2020-10-01	18.3
608	2020-11-01	14.3
609	2020-12-01	10.1

610 rows × 2 columns

In [ ]:

```
df_train=df_train.rename(columns={"time":"Date","tmax":"y"})
```

In [ ]:

```
df_test.reset_index(inplace=True)
```

```
df_test=df_test.rename(columns={"time":"Date","tmax":"y"})
```

In [ ]:
```
'''from auto_ts import auto_timeseries
import pandas as pd
strf_time_format = "%Y-%m-%d"
# Veri çerçevesini yükleyin
# Örnek veride 'Date' sütunu ve 'y' sütunu olduğunu varsayıyoruz
data = df_train

# Veri çerçevesini kontrol edin
print(data.head())  # İlk birkaç satırı kontrol edin
print(data.columns)  # Sütun adlarını kontrol edin


model = auto_timeseries(score_type='rmse',
                        time_interval='M',
                        non_seasonal_pdq=None,
                        seasonality=False,
                        seasonal_period=12,
                        model_type=['best'],
                        verbose=2,
                        dask_xgboost_flag=0,
                        strf_time_format=strf_time_format)

# Modeli eğitme
model.fit(traindata=data, ts_column='Date', target='y')

# Gelecek veriler için tahmin yapma
# testdata, test seti veya ileriye yönelik tahminler için kullanılacak veriyi iç
testdata = df_test
predictions = model.predict(testdata, model='best')
print(predictions)'''
```

Out[ ]:
```
'from auto_ts import auto_timeseries\nimport pandas as pd\nstrf_time_format =
"%Y-%m-%d"\n# Veri çerçevesini yükleyin\n# Örnek veride \'Date\' sütunu ve \'y
\' sütunu olduğunu varsayıyoruz\ndata = df_train\n\n# Veri çerçevesini kontrol
edin\nprint(data.head())  # İlk birkaç satırı kontrol edin\nprint(data.columns)
# Sütun adlarını kontrol edin\n\n\nmodel = auto_timeseries(score_type=\'rmse\',
\n                        time_interval=\'M\', \n                        non_se
asonal_pdq=None, \n                        seasonality=False, \n
seasonal_period=12, \n                        model_type=[\'best\'], \n
verbose=2, \n                        dask_xgboost_flag=0,\n
strf_time_format=strf_time_format)\n\n# Modeli eğitme\nmodel.fit(traindata=dat
a, ts_column=\'Date\', target=\'y\')\n\n# Gelecek veriler için tahmin yapma\n#
testdata, test seti veya ileriye yönelik tahminler için kullanılacak veriyi içe
rir\ntestdata = df_test\npredictions = model.predict(testdata, model=\'best\')
\nprint(predictions)'
```

Model Manual Grid Search

In [ ]:
```
df_train = df_temp_max.loc[:'2020']
df_test = df_temp_max.loc['2021':]
```

In [ ]:
```
import itertools
import math

# Define the range of values for p, d, q, P, D, Q, and m
p_values = range(0, 3)  # Autoregressive order
```

```python
d_values = [0]          # Differencing order
q_values = range(0, 3)  # Moving average order
P_values = range(0, 2)  # Seasonal autoregressive order
D_values = range(0, 1)  # Seasonal differencing order
Q_values = range(0, 2)  # Seasonal moving average order
m_values = [12]         # Seasonal period

# Create all possible combinations of SARIMA parameters
param_combinations = list(itertools.product(p_values,
                                            d_values,
                                            q_values,
                                            P_values,
                                            D_values,
                                            Q_values,
                                            m_values))

# Initialize AIC with a large value
best_aic = float("inf")
best_params = None

# Perform grid search
for params in param_combinations:
    order = params[:3]
    seasonal_order = params[3:]

    try:
        model = sm.tsa.SARIMAX(df_train,
                               order=order,
                               seasonal_order=seasonal_order)
        result = model.fit(disp=False)
        aic = result.aic

        # Ensure the convergence of the model
        if not math.isinf(result.zvalues.mean()):
            print(order, seasonal_order, aic)

            if aic < best_aic:
                best_aic = aic
                best_params = params

        else:
            print(order, seasonal_order, 'not converged')

    except:
        continue

# Print the best parameters and AIC
print("Best Parameters:", best_params)
print("Best AIC:", best_aic)
```

```
(0, 0, 0) (0, 0, 0, 12) 5471.171017366447
(0, 0, 0) (0, 0, 1, 12) 4755.531108034635
(0, 0, 0) (1, 0, 0, 12) 2807.037567597904
```

```
UserWarning: Non-stationary starting seasonal autoregressive Using zeros as start
ing parameters.
```

```
(0, 0, 0) (1, 0, 1, 12) 2495.7206995950114
(0, 0, 1) (0, 0, 0, 12) 4738.463525441684
```

```
UserWarning: Non-invertible starting MA parameters found. Using zeros as starting
parameters.
UserWarning: Non-invertible starting MA parameters found. Using zeros as starting
parameters.
(0, 0, 1) (0, 0, 1, 12) 4158.49284580789
UserWarning: Non-invertible starting MA parameters found. Using zeros as starting
parameters.
(0, 0, 1) (1, 0, 0, 12) 2774.9066952418134
UserWarning: Non-invertible starting MA parameters found. Using zeros as starting
parameters.
UserWarning: Non-stationary starting seasonal autoregressive Using zeros as start
ing parameters.
(0, 0, 1) (1, 0, 1, 12) 2465.3748335252812
(0, 0, 2) (0, 0, 0, 12) 4243.9352354742205
UserWarning: Non-invertible starting MA parameters found. Using zeros as starting
parameters.
UserWarning: Non-invertible starting MA parameters found. Using zeros as starting
parameters.
(0, 0, 2) (0, 0, 1, 12) 3882.0060978979773
UserWarning: Non-invertible starting MA parameters found. Using zeros as starting
parameters.
(0, 0, 2) (1, 0, 0, 12) 2766.7676303568724
UserWarning: Non-invertible starting MA parameters found. Using zeros as starting
parameters.
UserWarning: Non-stationary starting seasonal autoregressive Using zeros as start
ing parameters.
(0, 0, 2) (1, 0, 1, 12) 2458.3402520327427
(1, 0, 0) (0, 0, 0, 12) 3608.6351931886247
(1, 0, 0) (0, 0, 1, 12) 3288.4677539389613
(1, 0, 0) (1, 0, 0, 12) 2768.1940545514626
UserWarning: Non-stationary starting seasonal autoregressive Using zeros as start
ing parameters.
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check mle
_retvals
(1, 0, 0) (1, 0, 1, 12) 2458.2712044309396
(1, 0, 1) (0, 0, 0, 12) 3435.3925302674907
(1, 0, 1) (0, 0, 1, 12) 3250.53675916754
(1, 0, 1) (1, 0, 0, 12) 2768.3590289410145
UserWarning: Non-stationary starting seasonal autoregressive Using zeros as start
ing parameters.
(1, 0, 1) (1, 0, 1, 12) 2463.9888775951167
(1, 0, 2) (0, 0, 0, 12) 3346.2318147637366
(1, 0, 2) (0, 0, 1, 12) 3200.8842293756384
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check mle
_retvals
UserWarning: Non-stationary starting seasonal autoregressive Using zeros as start
ing parameters.
(1, 0, 2) (1, 0, 0, 12) 2747.6207361308793
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check mle
_retvals
(1, 0, 2) (1, 0, 1, 12) 2442.5868704760833
(2, 0, 0) (0, 0, 0, 12) 3350.2113890997543
(2, 0, 0) (0, 0, 1, 12) 3225.0056253306097
(2, 0, 0) (1, 0, 0, 12) 2767.658132945013
```

```
UserWarning: Non-stationary starting seasonal autoregressive Using zeros as start
ing parameters.
ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check mle
_retvals
(2, 0, 0) (1, 0, 1, 12) 2457.3956266247887
(2, 0, 1) (0, 0, 0, 12) 3352.2113837840684
(2, 0, 1) (0, 0, 1, 12) 3220.6412732930767
(2, 0, 1) (1, 0, 0, 12) 2772.1172603439227
UserWarning: Non-stationary starting seasonal autoregressive Using zeros as start
ing parameters.
(2, 0, 1) (1, 0, 1, 12) 2440.5100267919584
(2, 0, 2) (0, 0, 0, 12) 3313.1117876447825
(2, 0, 2) (0, 0, 1, 12) 3188.8753722953247
(2, 0, 2) (1, 0, 0, 12) 2770.7681968285
UserWarning: Non-stationary starting seasonal autoregressive Using zeros as start
ing parameters.
(2, 0, 2) (1, 0, 1, 12) 2441.31983835827
Best Parameters: (2, 0, 1, 1, 0, 1, 12)
Best AIC: 2440.5100267919584
```

In [ ]:

```
model = sm.tsa.SARIMAX(df_train,
                       order=best_params[:3],
                       seasonal_order=best_params[3:])
result = model.fit(disp=False)

# Show the summary
result.summary()
```

```
UserWarning: Non-stationary starting seasonal autoregressive Using zeros as start
ing parameters.
```

Out[ ]:

SARIMAX Results

Dep. Variable:	tmax	**No. Observations:**	610
Model:	SARIMAX(2, 0, 1)x(1, 0, 1, 12)	**Log Likelihood**	-1214.255
Date:	Thu, 01 Aug 2024	**AIC**	2440.510
Time:	17:09:44	**BIC**	2466.991
Sample:	03-01-1970	**HQIC**	2450.811
	- 12-01-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	1.2328	0.031	39.785	0.000	1.172	1.294
ar.L2	-0.2357	0.032	-7.371	0.000	-0.298	-0.173
ma.L1	-0.9843	0.015	-65.662	0.000	-1.014	-0.955
ar.S.L12	0.9989	0.001	1604.986	0.000	0.998	1.000
ma.S.L12	-0.8517	0.027	-31.517	0.000	-0.905	-0.799
sigma2	2.9016	0.148	19.631	0.000	2.612	3.191

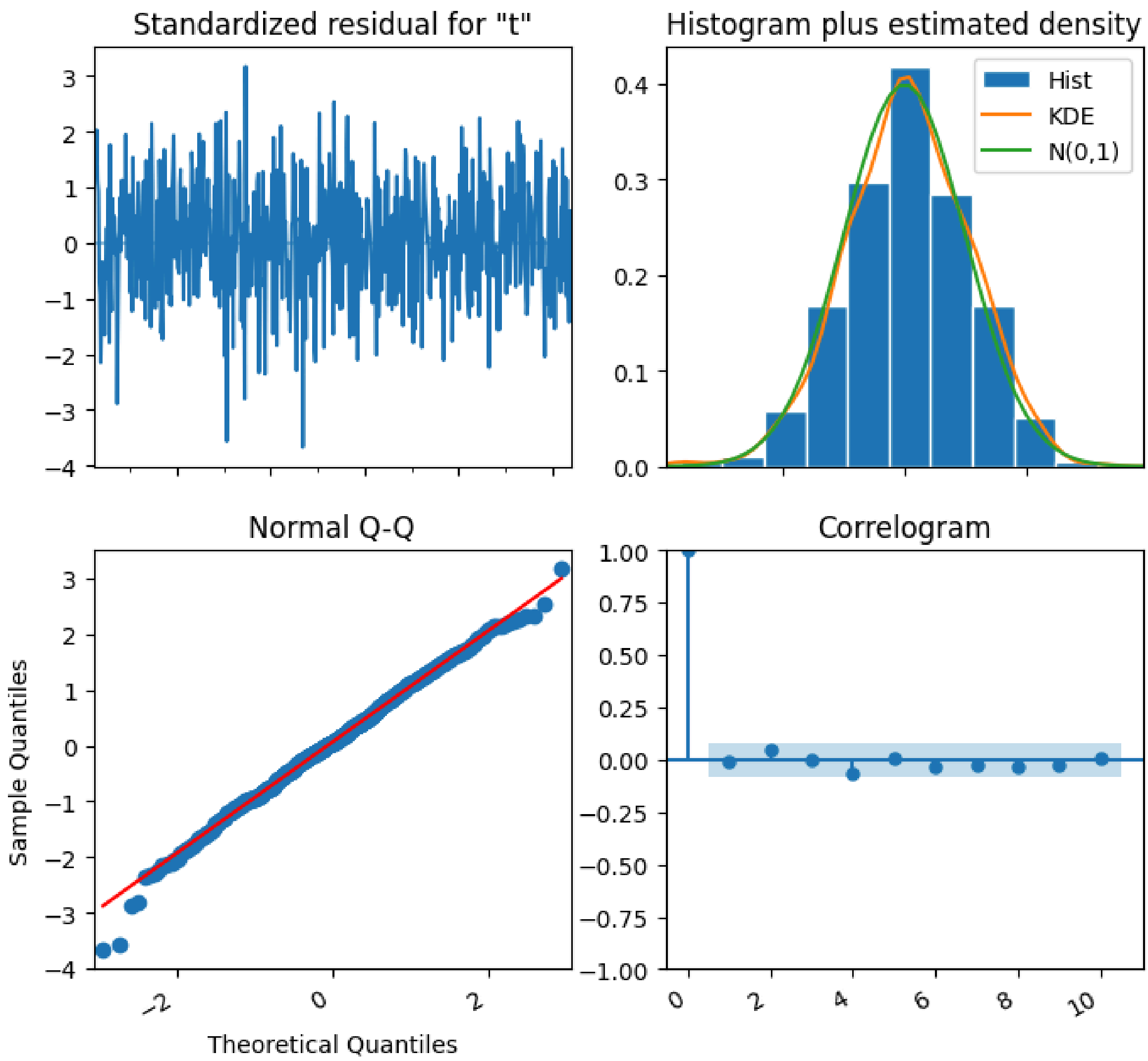
Ljung-Box (L1) (Q):	0.03	**Jarque-Bera (JB):**	3.77
Prob(Q):	0.87	**Prob(JB):**	0.15
Heteroskedasticity (H):	0.75	**Skew:**	-0.16
Prob(H) (two-sided):	0.04	**Kurtosis:**	3.21

Warnings:

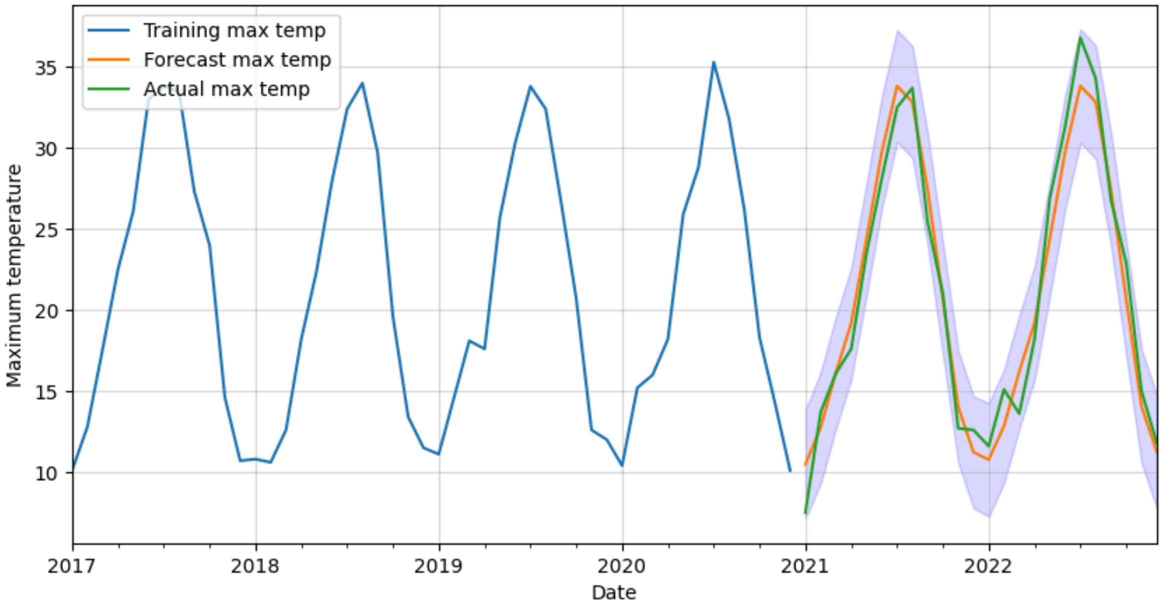
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [ ]:

```
# Display the model diagnostics
fig = result.plot_diagnostics(figsize=(8, 8))
fig.autofmt_xdate()
plt.show()
```



In [ ]:
```
# Get forecast and confidence intervals for two years
forecast = result.get_forecast(steps=24)
forecast_values = forecast.predicted_mean
confidence_intervals = forecast.conf_int()

# Plot forecast with training data
ax = df_train[-12*4:].plot(figsize=(10,5))
forecast_values.plot()
df_test.plot(ax=ax)
plt.fill_between(forecast_values.index,
                 confidence_intervals['lower tmax'],
                 confidence_intervals['upper tmax'],
                 color='blue',
                 alpha=0.15)
plt.legend(['Training max temp',
            'Forecast max temp',
            'Actual max temp'],
           loc='upper left')
plt.xlabel('Date')
plt.ylabel('Maximum temperature')
plt.grid(alpha=0.5)
plt.show()
```



In [ ]:
```python
# Predicted values and actual values
predicted_values = forecast_values.values
actual_values = df_test.values.flatten()

# Mean Absolute Error (MAE)
mae = np.mean(np.abs(predicted_values - actual_values))
print("MAE:", mae)

# Root Mean Squared Error (RMSE)
mse = np.mean((predicted_values - actual_values) ** 2)
rmse = np.sqrt(mse)
print("RMSE:", rmse)

# Mean Absolute Percentage Error (MAPE)
mape = np.mean(np.abs((predicted_values - actual_values) / actual_values)) * 100
print("MAPE:", mape)
```

```
MAE: 1.4569389654497853
RMSE: 1.658247956123041
MAPE: 8.32826951067223
```

AutoARIMA

In [ ]:
```python
from pmdarima.arima import auto_arima

# Build and fit the AutoARIMA model
model = auto_arima(df_train,
                   seasonal=True,
                   m=12,
                   suppress_warnings=True)
model.fit(df_train)

# Check the model summary
model.summary()
```

Out[ ]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	610
Model:	SARIMAX(0, 0, 2)x(1, 0, [1], 12)	**Log Likelihood**	-1216.861
Date:	Thu, 01 Aug 2024	**AIC**	2445.721
Time:	17:10:34	**BIC**	2472.202
Sample:	03-01-1970	**HQIC**	2456.022
	- 12-01-2020		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	0.0564	0.023	2.486	0.013	0.012	0.101
ma.L1	0.2375	0.038	6.226	0.000	0.163	0.312
ma.L2	0.1341	0.040	3.332	0.001	0.055	0.213
ar.S.L12	0.9974	0.001	903.685	0.000	0.995	1.000
ma.S.L12	-0.8335	0.026	-32.203	0.000	-0.884	-0.783
sigma2	2.9227	0.172	16.958	0.000	2.585	3.261

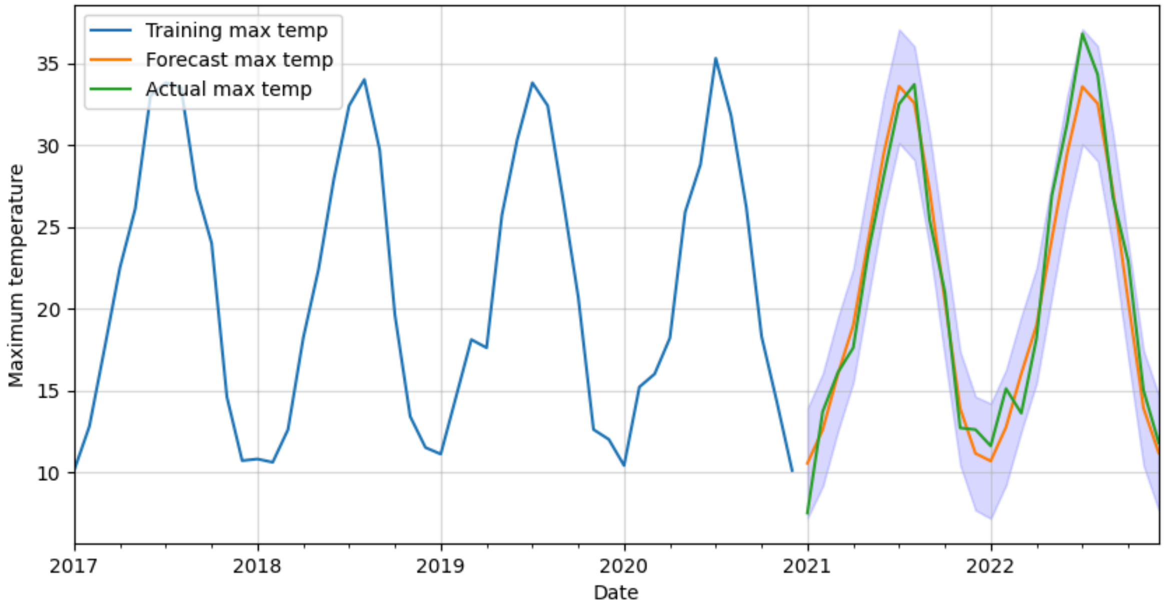
Ljung-Box (L1) (Q):	0.08	**Jarque-Bera (JB):**	4.88
Prob(Q):	0.78	**Prob(JB):**	0.09
Heteroskedasticity (H):	0.72	**Skew:**	-0.19
Prob(H) (two-sided):	0.02	**Kurtosis:**	3.23

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

In [ ]:

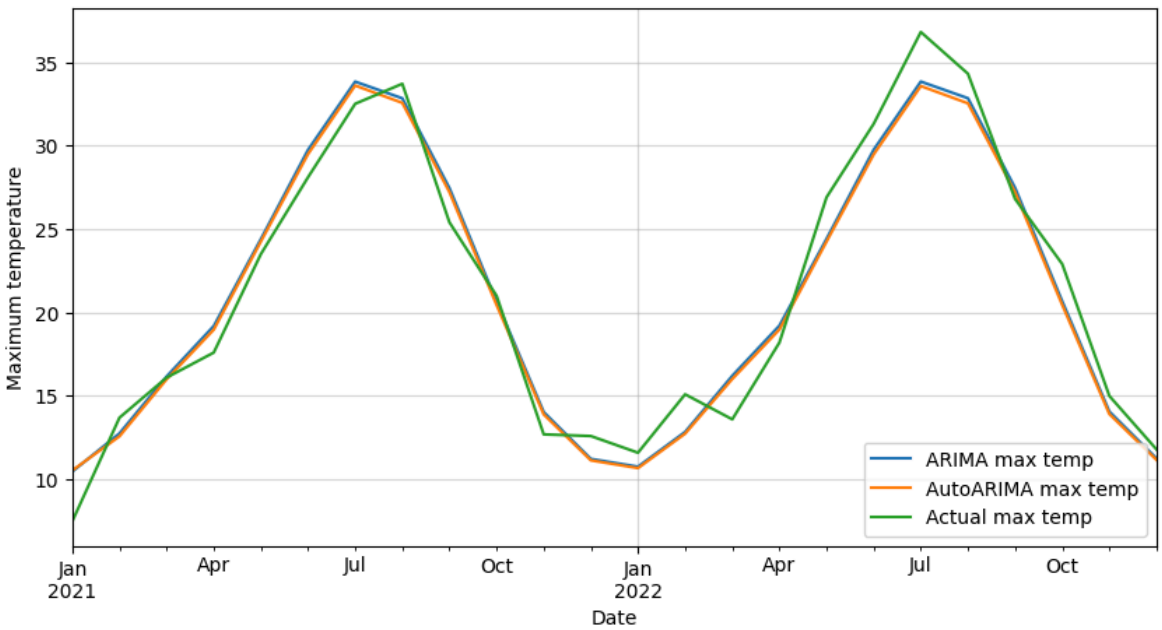
```
# Make predictions
forecast_auto, conf_int_auto = model.predict(n_periods=24,
                                              return_conf_int=True)

# Get forecast and confidence intervals for two years
forecast_values_auto = forecast_auto
confidence_intervals_auto = conf_int_auto

# Plot forecast with training data
ax = df_train[-12*4:].plot(figsize=(10,5))
forecast_auto.plot(ax=ax)
df_test.plot(ax=ax)
plt.fill_between(forecast_values_auto.index,
                 confidence_intervals_auto[:,[0]].flatten(),
                 confidence_intervals_auto[:,[1]].flatten(),
                 color='blue',
                 alpha=0.15)
plt.legend(['Training max temp',
```

```
             'Forecast max temp',
             'Actual max temp'],
            loc='upper left')
plt.xlabel('Date')
plt.ylabel('Maximum temperature')
plt.grid(alpha=0.5)
plt.show()
```



In [ ]:

```
# Plot both forecasts against actual data
ax = forecast_values.plot(figsize=(10,5))
forecast_auto.plot(ax=ax)
df_test.plot(ax=ax)

plt.legend(['ARIMA max temp',
            'AutoARIMA max temp',
            'Actual max temp'],
           loc='lower right')
plt.xlabel('Date')
plt.ylabel('Maximum temperature')
plt.grid(alpha=0.5)
plt.show()
```



Prophet Model

In [ ]:
```
df_train.reset_index(inplace=True)
df_train=df_train.rename(columns={"time":"Date","tmax":"y"})
df_test.reset_index(inplace=True)
df_test=df_test.rename(columns={"time":"Date","tmax":"y"})
```

In [ ]:
```
from prophet import Prophet
from sklearn.model_selection import ParameterGrid, TimeSeriesSplit
import pandas as pd
import numpy as np

# Veri çerçevesini yükleyin
data = df_train.copy()
data.rename(columns={'Date': 'ds', 'y': 'y'}, inplace=True)

# Hiperparametre aralıklarını belirleme
param_grid = {
    'changepoint_prior_scale': [0.001, 0.01, 0.1, 0.5],
    'seasonality_prior_scale': [0.1, 1.0, 10.0],
    'seasonality_mode': ['additive', 'multiplicative']
}

# Cross-validation split
tscv = TimeSeriesSplit(n_splits=3)

# En iyi hiperparametreleri bulmak için değişkenler
best_params = None
best_rmse = float('inf')

# Grid search
for params in ParameterGrid(param_grid):
    rmses = []
    for train_index, test_index in tscv.split(data):
        train_data = data.iloc[train_index]
        test_data = data.iloc[test_index]
```

```python
        model = Prophet(**params)
        model.fit(train_data)

        # Gelecekteki verileri tahmin et
        future = model.make_future_dataframe(periods=len(test_data), freq='ME')
        forecast = model.predict(future)

        # Sadece test verilerinin tahminlerini al
        forecast_test = forecast.iloc[-len(test_data):]

        # RMSE hesapla
        rmse = np.sqrt(np.mean((forecast_test['yhat'] - test_data['y'])**2))
        rmses.append(rmse)

    mean_rmse = np.mean(rmses)
    print(f"Params: {params}, RMSE: {mean_rmse}")

    if mean_rmse < best_rmse:
        best_rmse = mean_rmse
        best_params = params

print(f"En İyi Parametreler: {best_params}")
print(f"En İyi RMSE: {best_rmse}")
```

```
17:10:35 - cmdstanpy - INFO - Chain [1] start processing
17:10:35 - cmdstanpy - INFO - Chain [1] done processing
17:10:35 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation
not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:35 - cmdstanpy - INFO - Chain [1] start processing
17:10:35 - cmdstanpy - INFO - Chain [1] done processing
17:10:36 - cmdstanpy - INFO - Chain [1] start processing
17:10:36 - cmdstanpy - INFO - Chain [1] done processing
17:10:36 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation
not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:36 - cmdstanpy - INFO - Chain [1] start processing
17:10:36 - cmdstanpy - INFO - Chain [1] done processing
17:10:36 - cmdstanpy - INFO - Chain [1] start processing
17:10:36 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.001, 'seasonality_mode': 'additive', 'seaso
nality_prior_scale': 0.1}, RMSE: 2.350056174858796
17:10:37 - cmdstanpy - INFO - Chain [1] start processing
17:10:37 - cmdstanpy - INFO - Chain [1] done processing
17:10:37 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation
not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:37 - cmdstanpy - INFO - Chain [1] start processing
17:10:37 - cmdstanpy - INFO - Chain [1] done processing
17:10:38 - cmdstanpy - INFO - Chain [1] start processing
17:10:38 - cmdstanpy - INFO - Chain [1] done processing
17:10:38 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation
not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:38 - cmdstanpy - INFO - Chain [1] start processing
17:10:38 - cmdstanpy - INFO - Chain [1] done processing
17:10:38 - cmdstanpy - INFO - Chain [1] start processing
17:10:38 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.001, 'seasonality_mode': 'additive', 'seaso
nality_prior_scale': 1.0}, RMSE: 2.576582778137548
```

```
17:10:39 - cmdstanpy - INFO - Chain [1] start processing
17:10:39 - cmdstanpy - INFO - Chain [1] done processing
17:10:39 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation
not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:39 - cmdstanpy - INFO - Chain [1] start processing
17:10:39 - cmdstanpy - INFO - Chain [1] done processing
17:10:39 - cmdstanpy - INFO - Chain [1] start processing
17:10:39 - cmdstanpy - INFO - Chain [1] done processing
17:10:39 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation
not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:39 - cmdstanpy - INFO - Chain [1] start processing
17:10:40 - cmdstanpy - INFO - Chain [1] done processing
17:10:40 - cmdstanpy - INFO - Chain [1] start processing
17:10:40 - cmdstanpy - INFO - Chain [1] done processing
```

```
Params: {'changepoint_prior_scale': 0.001, 'seasonality_mode': 'additive', 'seaso
nality_prior_scale': 10.0}, RMSE: 2.5279135132999646
```

```
17:10:41 - cmdstanpy - INFO - Chain [1] start processing
17:10:41 - cmdstanpy - INFO - Chain [1] done processing
17:10:41 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation
not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:41 - cmdstanpy - INFO - Chain [1] start processing
17:10:41 - cmdstanpy - INFO - Chain [1] done processing
17:10:42 - cmdstanpy - INFO - Chain [1] start processing
17:10:42 - cmdstanpy - INFO - Chain [1] done processing
17:10:42 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation
not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:42 - cmdstanpy - INFO - Chain [1] start processing
17:10:42 - cmdstanpy - INFO - Chain [1] done processing
17:10:43 - cmdstanpy - INFO - Chain [1] start processing
17:10:43 - cmdstanpy - INFO - Chain [1] done processing
```

```
Params: {'changepoint_prior_scale': 0.001, 'seasonality_mode': 'multiplicative',
'seasonality_prior_scale': 0.1}, RMSE: 3.0187284284256806
```

```
17:10:43 - cmdstanpy - INFO - Chain [1] start processing
17:10:43 - cmdstanpy - INFO - Chain [1] done processing
17:10:43 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation
not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:43 - cmdstanpy - INFO - Chain [1] start processing
17:10:44 - cmdstanpy - INFO - Chain [1] done processing
17:10:44 - cmdstanpy - INFO - Chain [1] start processing
17:10:44 - cmdstanpy - INFO - Chain [1] done processing
17:10:44 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation
not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:44 - cmdstanpy - INFO - Chain [1] start processing
17:10:44 - cmdstanpy - INFO - Chain [1] done processing
17:10:45 - cmdstanpy - INFO - Chain [1] start processing
17:10:45 - cmdstanpy - INFO - Chain [1] done processing
17:10:45 - cmdstanpy - INFO - Chain [1] start processing
17:10:45 - cmdstanpy - INFO - Chain [1] done processing
17:10:45 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation
not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:45 - cmdstanpy - INFO - Chain [1] start processing
```

```
Params: {'changepoint_prior_scale': 0.001, 'seasonality_mode': 'multiplicative', 'seasonality_prior_scale': 1.0}, RMSE: 2.1784509152253633
```

```
17:10:45 - cmdstanpy - INFO - Chain [1] done processing
17:10:46 - cmdstanpy - INFO - Chain [1] start processing
17:10:46 - cmdstanpy - INFO - Chain [1] done processing
17:10:46 - cmdstanpy - ERROR - Chain [1] error: error during processing Operation not permitted
Optimization terminated abnormally. Falling back to Newton.
17:10:46 - cmdstanpy - INFO - Chain [1] start processing
17:10:46 - cmdstanpy - INFO - Chain [1] done processing
17:10:47 - cmdstanpy - INFO - Chain [1] start processing
17:10:47 - cmdstanpy - INFO - Chain [1] done processing
```

```
Params: {'changepoint_prior_scale': 0.001, 'seasonality_mode': 'multiplicative', 'seasonality_prior_scale': 10.0}, RMSE: 2.980188125157292
```

```
17:10:47 - cmdstanpy - INFO - Chain [1] start processing
17:10:47 - cmdstanpy - INFO - Chain [1] done processing
17:10:47 - cmdstanpy - INFO - Chain [1] start processing
17:10:47 - cmdstanpy - INFO - Chain [1] done processing
17:10:48 - cmdstanpy - INFO - Chain [1] start processing
17:10:48 - cmdstanpy - INFO - Chain [1] done processing
```

```
Params: {'changepoint_prior_scale': 0.01, 'seasonality_mode': 'additive', 'seasonality_prior_scale': 0.1}, RMSE: 1.944251592827598
```

```
17:10:48 - cmdstanpy - INFO - Chain [1] start processing
17:10:48 - cmdstanpy - INFO - Chain [1] done processing
17:10:49 - cmdstanpy - INFO - Chain [1] start processing
17:10:49 - cmdstanpy - INFO - Chain [1] done processing
17:10:49 - cmdstanpy - INFO - Chain [1] start processing
17:10:49 - cmdstanpy - INFO - Chain [1] done processing
```

```
Params: {'changepoint_prior_scale': 0.01, 'seasonality_mode': 'additive', 'seasonality_prior_scale': 1.0}, RMSE: 1.9594226130678418
```

```
17:10:50 - cmdstanpy - INFO - Chain [1] start processing
17:10:50 - cmdstanpy - INFO - Chain [1] done processing
17:10:50 - cmdstanpy - INFO - Chain [1] start processing
17:10:50 - cmdstanpy - INFO - Chain [1] done processing
17:10:50 - cmdstanpy - INFO - Chain [1] start processing
17:10:50 - cmdstanpy - INFO - Chain [1] done processing
```

```
Params: {'changepoint_prior_scale': 0.01, 'seasonality_mode': 'additive', 'seasonality_prior_scale': 10.0}, RMSE: 1.9623950222894742
```

```
17:10:51 - cmdstanpy - INFO - Chain [1] start processing
17:10:51 - cmdstanpy - INFO - Chain [1] done processing
17:10:51 - cmdstanpy - INFO - Chain [1] start processing
17:10:51 - cmdstanpy - INFO - Chain [1] done processing
17:10:52 - cmdstanpy - INFO - Chain [1] start processing
17:10:52 - cmdstanpy - INFO - Chain [1] done processing
```

```
Params: {'changepoint_prior_scale': 0.01, 'seasonality_mode': 'multiplicative', 'seasonality_prior_scale': 0.1}, RMSE: 1.8255388836803377
```

```
17:10:52 - cmdstanpy - INFO - Chain [1] start processing
17:10:52 - cmdstanpy - INFO - Chain [1] done processing
17:10:52 - cmdstanpy - INFO - Chain [1] start processing
17:10:53 - cmdstanpy - INFO - Chain [1] done processing
17:10:53 - cmdstanpy - INFO - Chain [1] start processing
17:10:53 - cmdstanpy - INFO - Chain [1] done processing
```

```
Params: {'changepoint_prior_scale': 0.01, 'seasonality_mode': 'multiplicative', 'seasonality_prior_scale': 1.0}, RMSE: 1.8290704866724372
```

```
17:10:53 - cmdstanpy - INFO - Chain [1] start processing
17:10:53 - cmdstanpy - INFO - Chain [1] done processing
17:10:54 - cmdstanpy - INFO - Chain [1] start processing
17:10:54 - cmdstanpy - INFO - Chain [1] done processing
17:10:54 - cmdstanpy - INFO - Chain [1] start processing
17:10:54 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.01, 'seasonality_mode': 'multiplicative', 
'seasonality_prior_scale': 10.0}, RMSE: 1.8317458745121875
17:10:55 - cmdstanpy - INFO - Chain [1] start processing
17:10:55 - cmdstanpy - INFO - Chain [1] done processing
17:10:55 - cmdstanpy - INFO - Chain [1] start processing
17:10:55 - cmdstanpy - INFO - Chain [1] done processing
17:10:55 - cmdstanpy - INFO - Chain [1] start processing
17:10:56 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.1, 'seasonality_mode': 'additive', 'seasona
lity_prior_scale': 0.1}, RMSE: 2.15874151816482
17:10:56 - cmdstanpy - INFO - Chain [1] start processing
17:10:56 - cmdstanpy - INFO - Chain [1] done processing
17:10:56 - cmdstanpy - INFO - Chain [1] start processing
17:10:56 - cmdstanpy - INFO - Chain [1] done processing
17:10:57 - cmdstanpy - INFO - Chain [1] start processing
17:10:57 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.1, 'seasonality_mode': 'additive', 'seasona
lity_prior_scale': 1.0}, RMSE: 2.218059662373664
17:10:57 - cmdstanpy - INFO - Chain [1] start processing
17:10:57 - cmdstanpy - INFO - Chain [1] done processing
17:10:58 - cmdstanpy - INFO - Chain [1] start processing
17:10:58 - cmdstanpy - INFO - Chain [1] done processing
17:10:58 - cmdstanpy - INFO - Chain [1] start processing
17:10:58 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.1, 'seasonality_mode': 'additive', 'seasona
lity_prior_scale': 10.0}, RMSE: 2.221205988640674
17:10:58 - cmdstanpy - INFO - Chain [1] start processing
17:10:58 - cmdstanpy - INFO - Chain [1] done processing
17:10:59 - cmdstanpy - INFO - Chain [1] start processing
17:10:59 - cmdstanpy - INFO - Chain [1] done processing
17:10:59 - cmdstanpy - INFO - Chain [1] start processing
17:10:59 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.1, 'seasonality_mode': 'multiplicative', 's
easonality_prior_scale': 0.1}, RMSE: 2.0715964470860033
17:11:00 - cmdstanpy - INFO - Chain [1] start processing
17:11:00 - cmdstanpy - INFO - Chain [1] done processing
17:11:00 - cmdstanpy - INFO - Chain [1] start processing
17:11:00 - cmdstanpy - INFO - Chain [1] done processing
17:11:00 - cmdstanpy - INFO - Chain [1] start processing
17:11:00 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.1, 'seasonality_mode': 'multiplicative', 's
easonality_prior_scale': 1.0}, RMSE: 2.154210248670977
17:11:01 - cmdstanpy - INFO - Chain [1] start processing
17:11:01 - cmdstanpy - INFO - Chain [1] done processing
17:11:01 - cmdstanpy - INFO - Chain [1] start processing
17:11:01 - cmdstanpy - INFO - Chain [1] done processing
17:11:02 - cmdstanpy - INFO - Chain [1] start processing
17:11:02 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.1, 'seasonality_mode': 'multiplicative', 's
easonality_prior_scale': 10.0}, RMSE: 2.1792044279873397
```

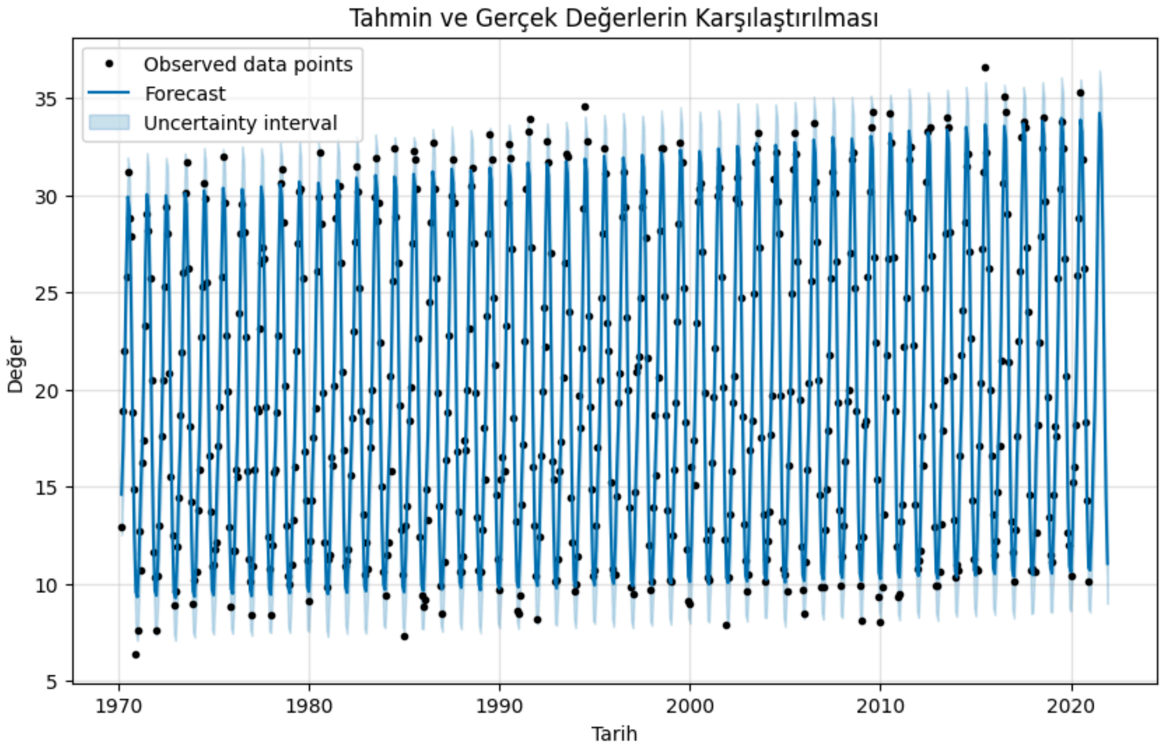
```
17:11:02 - cmdstanpy - INFO - Chain [1] start processing
17:11:02 - cmdstanpy - INFO - Chain [1] done processing
17:11:03 - cmdstanpy - INFO - Chain [1] start processing
17:11:03 - cmdstanpy - INFO - Chain [1] done processing
17:11:03 - cmdstanpy - INFO - Chain [1] start processing
17:11:03 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.5, 'seasonality_mode': 'additive', 'seasona
lity_prior_scale': 0.1}, RMSE: 2.2727486737750526
17:11:04 - cmdstanpy - INFO - Chain [1] start processing
17:11:04 - cmdstanpy - INFO - Chain [1] done processing
17:11:04 - cmdstanpy - INFO - Chain [1] start processing
17:11:04 - cmdstanpy - INFO - Chain [1] done processing
17:11:04 - cmdstanpy - INFO - Chain [1] start processing
17:11:04 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.5, 'seasonality_mode': 'additive', 'seasona
lity_prior_scale': 1.0}, RMSE: 2.348045432711578
17:11:05 - cmdstanpy - INFO - Chain [1] start processing
17:11:05 - cmdstanpy - INFO - Chain [1] done processing
17:11:05 - cmdstanpy - INFO - Chain [1] start processing
17:11:05 - cmdstanpy - INFO - Chain [1] done processing
17:11:06 - cmdstanpy - INFO - Chain [1] start processing
17:11:06 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.5, 'seasonality_mode': 'additive', 'seasona
lity_prior_scale': 10.0}, RMSE: 2.3726227737997276
17:11:06 - cmdstanpy - INFO - Chain [1] start processing
17:11:06 - cmdstanpy - INFO - Chain [1] done processing
17:11:07 - cmdstanpy - INFO - Chain [1] start processing
17:11:07 - cmdstanpy - INFO - Chain [1] done processing
17:11:07 - cmdstanpy - INFO - Chain [1] start processing
17:11:07 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.5, 'seasonality_mode': 'multiplicative', 's
easonality_prior_scale': 0.1}, RMSE: 2.0198924273104537
17:11:08 - cmdstanpy - INFO - Chain [1] start processing
17:11:08 - cmdstanpy - INFO - Chain [1] done processing
17:11:08 - cmdstanpy - INFO - Chain [1] start processing
17:11:08 - cmdstanpy - INFO - Chain [1] done processing
17:11:08 - cmdstanpy - INFO - Chain [1] start processing
17:11:08 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.5, 'seasonality_mode': 'multiplicative', 's
easonality_prior_scale': 1.0}, RMSE: 2.1345681820067255
17:11:09 - cmdstanpy - INFO - Chain [1] start processing
17:11:09 - cmdstanpy - INFO - Chain [1] done processing
17:11:09 - cmdstanpy - INFO - Chain [1] start processing
17:11:09 - cmdstanpy - INFO - Chain [1] done processing
17:11:10 - cmdstanpy - INFO - Chain [1] start processing
17:11:10 - cmdstanpy - INFO - Chain [1] done processing
Params: {'changepoint_prior_scale': 0.5, 'seasonality_mode': 'multiplicative', 's
easonality_prior_scale': 10.0}, RMSE: 2.1566723685903333
En İyi Parametreler: {'changepoint_prior_scale': 0.01, 'seasonality_mode': 'multi
plicative', 'seasonality_prior_scale': 0.1}
En İyi RMSE: 1.8255388836803377
```

In [ ]:

```python
import matplotlib.pyplot as plt
from prophet import Prophet

# En iyi parametrelerle Prophet modelini oluştur
best_model = Prophet(**best_params)
best_model.fit(data)
```

```python
# Gelecek veriler için tahmin yapma (örneğin, 12 ay ileriye dönük)
future = best_model.make_future_dataframe(periods=12, freq='ME')
forecast = best_model.predict(future)

# Tahminlerin ve gerçek verilerin grafiği
fig, ax = plt.subplots(figsize=(10, 6))
best_model.plot(forecast, ax=ax)
plt.title('Tahmin ve Gerçek Değerlerin Karşılaştırılması')
plt.xlabel('Tarih')
plt.ylabel('Değer')

# Legend'ı düzenleme
handles, labels = ax.get_legend_handles_labels()
labels[0] = "Observed data points"  # "Gerçek Veriler" yerine
labels[1] = "Forecast"  # "Tahmin"
labels[2] = "Uncertainty interval"  # "Güven Aralıkları"

ax.legend(handles, labels)
plt.show()
```

```
17:11:10 - cmdstanpy - INFO - Chain [1] start processing
17:11:10 - cmdstanpy - INFO - Chain [1] done processing
FutureWarning: The behavior of DatetimeProperties.to_pydatetime is deprecated, in
a future version this will return a Series containing python datetime objects ins
tead of an ndarray. To retain the old behavior, call `np.array` on the result
FutureWarning: The behavior of DatetimeProperties.to_pydatetime is deprecated, in
a future version this will return a Series containing python datetime objects ins
tead of an ndarray. To retain the old behavior, call `np.array` on the result
```

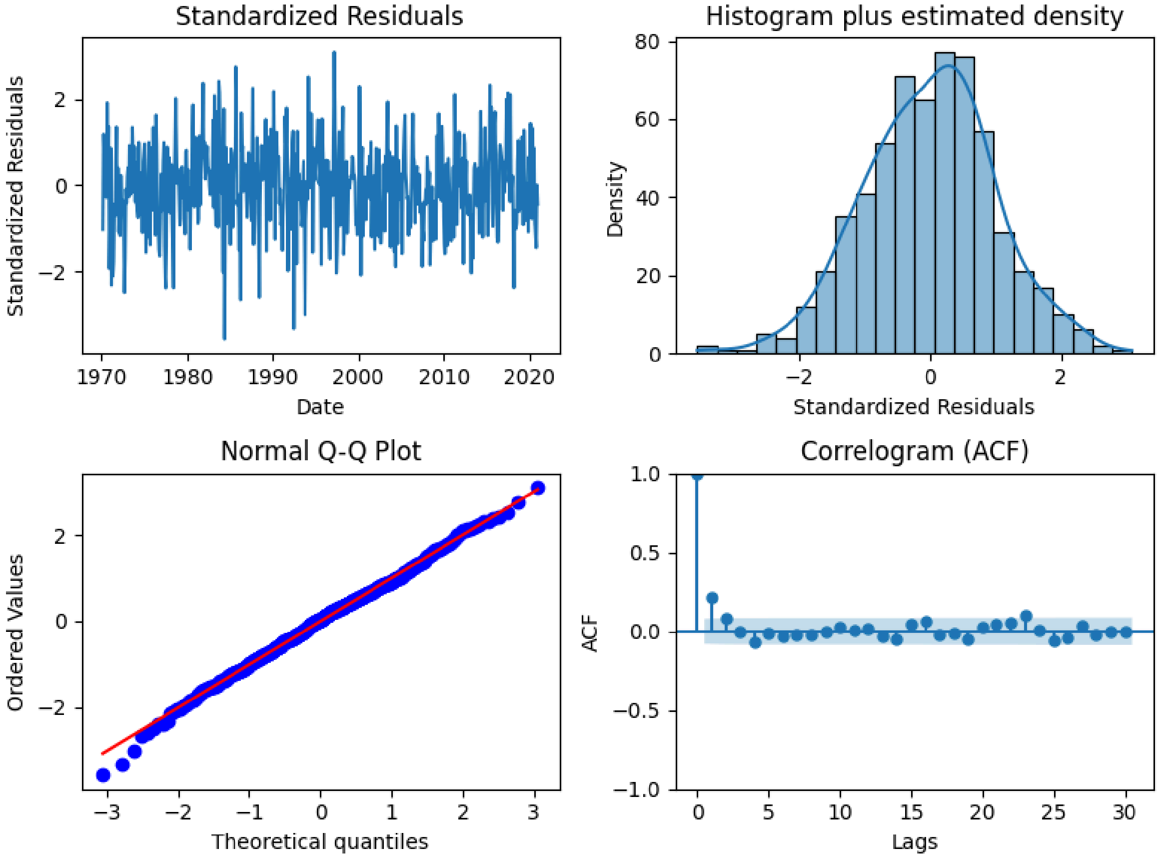


Prophet Model Diagnostic

In [ ]:
```python
# Artıkların hesaplanması
data['yhat'] = forecast['yhat'][:len(data)]
data['residuals'] = data['y'] - data['yhat']
```

In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
import scipy.stats as stats

# Standardized residuals
data['standardized_residuals'] = data['residuals'] / data['residuals'].std()

fig, axes = plt.subplots(2, 2, figsize=(8, 6))

# Standardized Residuals Plot
axes[0, 0].plot(data['ds'], data['standardized_residuals'])
axes[0, 0].set_title('Standardized Residuals')
axes[0, 0].set_xlabel('Date')
axes[0, 0].set_ylabel('Standardized Residuals')

# Histogram and Density Plot
sns.histplot(data['standardized_residuals'], kde=True, ax=axes[0, 1])
axes[0, 1].set_title('Histogram plus estimated density')
axes[0, 1].set_xlabel('Standardized Residuals')
axes[0, 1].set_ylabel('Density')

# Q-Q Plot
stats.probplot(data['standardized_residuals'], dist="norm", plot=axes[1, 0])
axes[1, 0].set_title('Normal Q-Q Plot')

# ACF Plot
sm.graphics.tsa.plot_acf(data['standardized_residuals'], lags=30, ax=axes[1, 1])
axes[1, 1].set_title('Correlogram (ACF)')
axes[1, 1].set_xlabel('Lags')
axes[1, 1].set_ylabel('ACF')

# Layout adjustment
plt.tight_layout()
plt.show()
```

```
FutureWarning: use_inf_as_na option is deprecated and will be removed in a future
version. Convert inf values to NaN before operating instead.
```



Standardized Residuals
Standardized Residuals
Date
Histogram plus estimated density
Density
Standardized Residuals
Normal Q-Q Plot
Ordered Values
Theoretical quantiles
Correlogram (ACF)
ACF
Lags