Introduction

Turmeric, a perennial herbaceous plant belonging to the ginger family, is a vital crop cultivated extensively in India. The country is the largest producer and exporter of turmeric globally. The states of Andhra Pradesh and Odisha are significant contributors to India's turmeric production. Understanding the production trends in these states is crucial for stakeholders in the agricultural sector, including farmers, traders, and policymakers. This study aims to analyze the turmeric production data from Andhra Pradesh and Odisha using time series analysis to forecast future production levels.

Objective

The primary objective of this research is to apply time series analysis to turmeric production data from Andhra Pradesh and Odisha to determine the stationarity of the series and to develop an ARIMA (Autoregressive Integrated Moving Average) model for forecasting future production. The study seeks to compare the production trends between the two states and provide insights that could inform production planning and policy formulation.

Methodology

The methodology involves using statistical tools to analyze the time series data of turmeric production. The initial step is to test the stationarity of the data using the Augmented Dickey-Fuller (ADF) test. The Autocorrelation Function (ACF) is also examined to understand the data's correlation structure. Based on these analyses, an appropriate ARIMA model is selected for forecasting.

Procedure

The procedure for the analysis is as follows:

1. **Data Collection**: Historical data on turmeric production in Andhra Pradesh and Odisha are collected.
2. **Data Visualization**: Line graphs are plotted to visualize production trends over time.
3. **Stationarity Testing**: The ADF test is conducted to check for stationarity in the time series data.
4. **Differencing**: If the data is non-stationary, differencing is performed to achieve stationarity.
5. **Autocorrelation Analysis**: ACF plots are generated to guide the selection of ARIMA model parameters.
6. **Model Selection**: Based on the ACF and PACF plots, the parameters for the ARIMA model are chosen.
7. **Model Fitting**: The ARIMA model is fitted to the data.
8. **Forecasting**: The model is used to forecast future production levels.

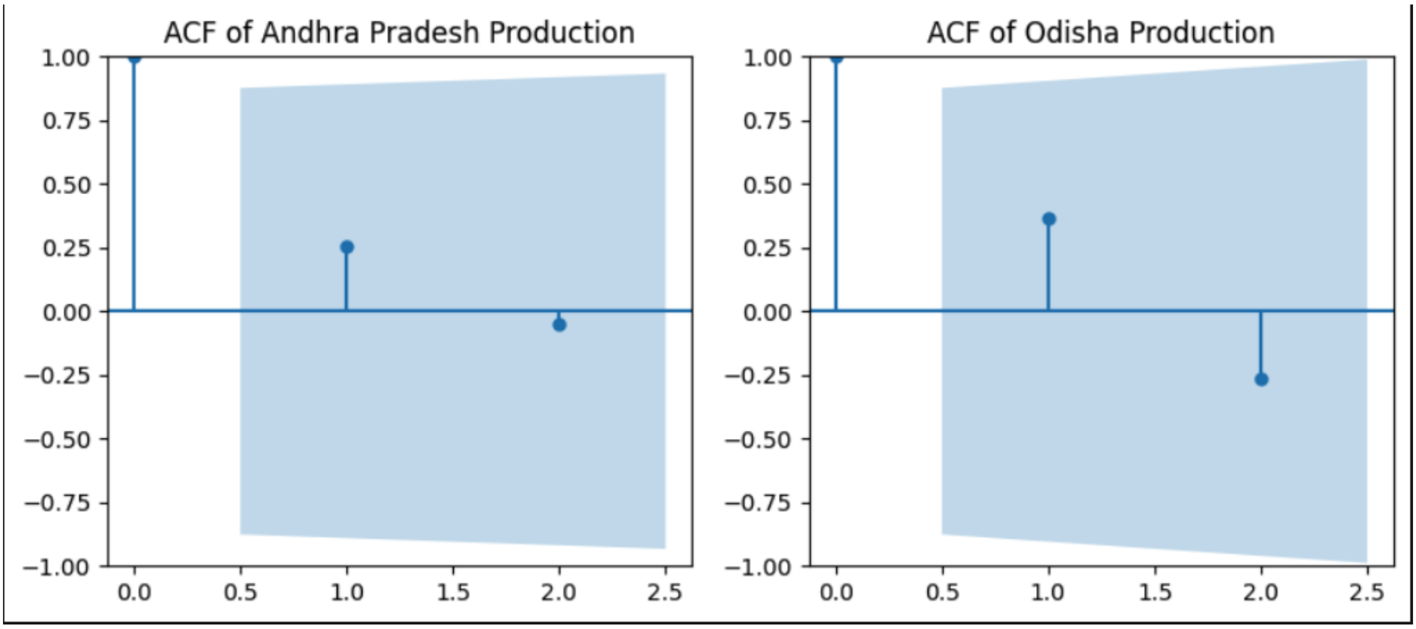
Code

The analysis is conducted using Python with the following code snippet as an example for the ARIMA model:

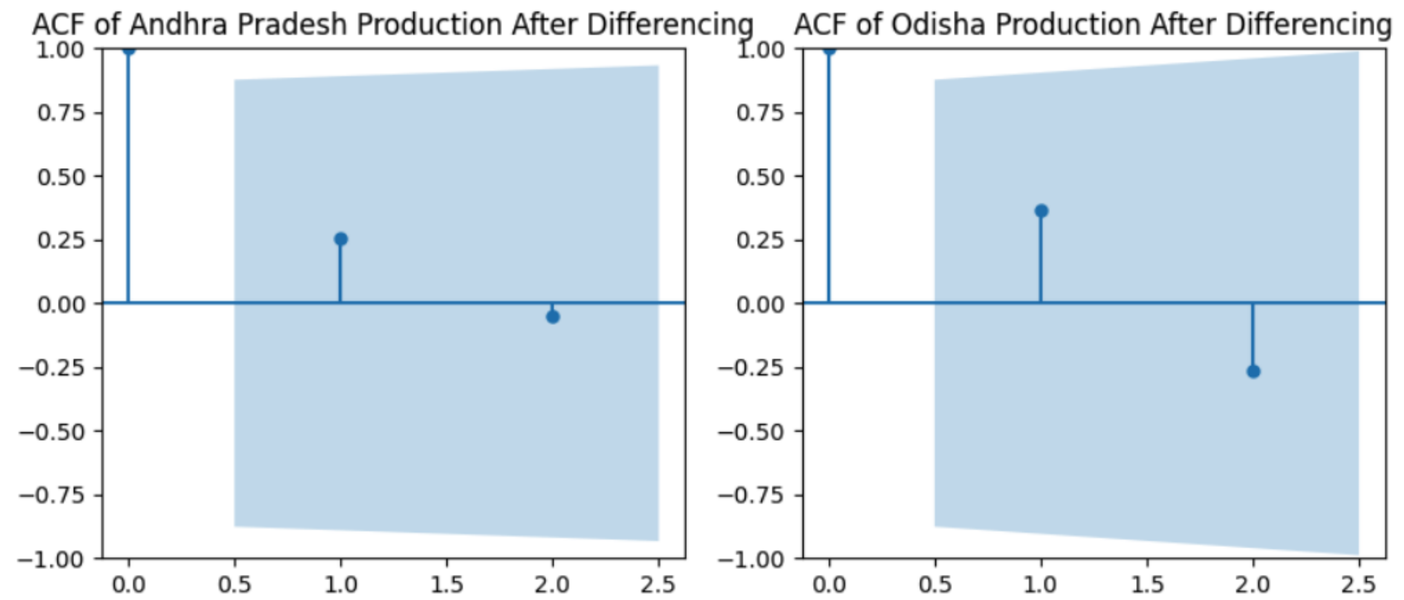
```
 import pandas as pd
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.stattools import adfuller
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
# Load the dataset

data = {
    'Year': ['2018/19','2019/20', '2020/21', '2021/22', '2022/23'],
    'ANDHRA PRADESH': [ 69410,  71321,73244,74687,80199],
    'ORISSA': [ 43615,  43615,43615,68825,69065]
}

andhra_pradesh_production = pd.Series(data['ANDHRA PRADESH'], index=data['Year'])
odisha_production = pd.Series(data['ORISSA'], index=data['Year'])



# Define a function to test stationarity
def test_stationarity(timeseries):
    result = adfuller(timeseries, autolag='AIC')
    print('ADF Statistic: %f' % result[0])
    print('p-value: %f' % result[1])



# Test stationarity for each state
print("Andhra Pradesh Turmeric Production Stationarity Test:")
test_stationarity(andhra_pradesh_production)
print("\nOdisha Turmeric Production Stationarity Test:")
test_stationarity(odisha_production)
# Create a figure and a grid of subplots
fig, ax = plt.subplots(1, 2, figsize=(10, 4))
```

```
# Plot the ACF of Andhra Pradesh production in the first subplot
plot_acf(andhra_pradesh_production, ax=ax[0])
ax[0].set_title('ACF of Andhra Pradesh Production')

# Plot the ACF of Odisha production in the second subplot
plot_acf(odisha_production, ax=ax[1])
ax[1].set_title('ACF of Odisha Production')




# Both series are non-stationary, we need to differentiate the series
andhra_pradesh_production_diff = andhra_pradesh_production.diff().dropna()
odisha_production_diff = odisha_production.diff().dropna()

# Test stationarity for each state after Differentiating once (d=1)
print("\nTesting Stationarity after Differentiating once (d=1)")

print("\nAndhra Pradesh Turmeric Production Stationarity Test:")
test_stationarity(andhra_pradesh_production_diff)
print("\nOdisha Turmeric Production Stationarity Test:")
test_stationarity(odisha_production_diff)
fig, ax = plt.subplots(1, 2, figsize=(10, 4))

# Plot the ACF of Andhra Pradesh production in the first subplot
plot_acf(andhra_pradesh_production, ax=ax[0])
ax[0].set_title('ACF of Andhra Pradesh Production After Differencing')

# Plot the ACF of Odisha production in the second subplot
plot_acf(odisha_production, ax=ax[1])
ax[1].set_title('ACF of Odisha Production After Differencing')


# Now from the ADF Statistic and p-value, we can see that both series are not stationary even after differencing once
# So we can safely assume that they have a unit root
# In order to tackel this, we can use ARIMA model to forecast the production

# You would need to determine p, d, q using ACF and PACF plots
# Here we assume p=1, d=1, q=1 for demonstration purposes

# Fit ARIMA model for Andhra Pradesh
arima_ap = ARIMA(andhra_pradesh_production, order=(1, 1, 1))
arima_ap_fit = arima_ap.fit()

# Fit ARIMA model for Odisha
arima_odisha = ARIMA(odisha_production, order=(1, 1, 1))
arima_odisha_fit = arima_odisha.fit()

# Forecasting with ARIMA model
ap_forecast = arima_ap_fit.forecast(steps=10)  # Forecast next 5 periods
odisha_forecast = arima_odisha_fit.forecast(steps=10)

# Create new index for the forecasted data
last_year = int(data['Year'][-1][:4])
new_index = [f'{i}/{i+1}' for i in range(last_year+1, last_year+11)]

# Assign the new index to the forecasted data
ap_forecast.index = new_index
odisha_forecast.index = new_index

# Plot the forecasts
plt.figure(figsize=(20, 6))
plt.plot(andhra_pradesh_production.index, andhra_pradesh_production, label='Andhra Pradesh Actual')
plt.plot(odisha_production.index, odisha_production, label='Odisha Actual')
plt.plot(ap_forecast.index, ap_forecast, label='Andhra Pradesh Forecast')
```

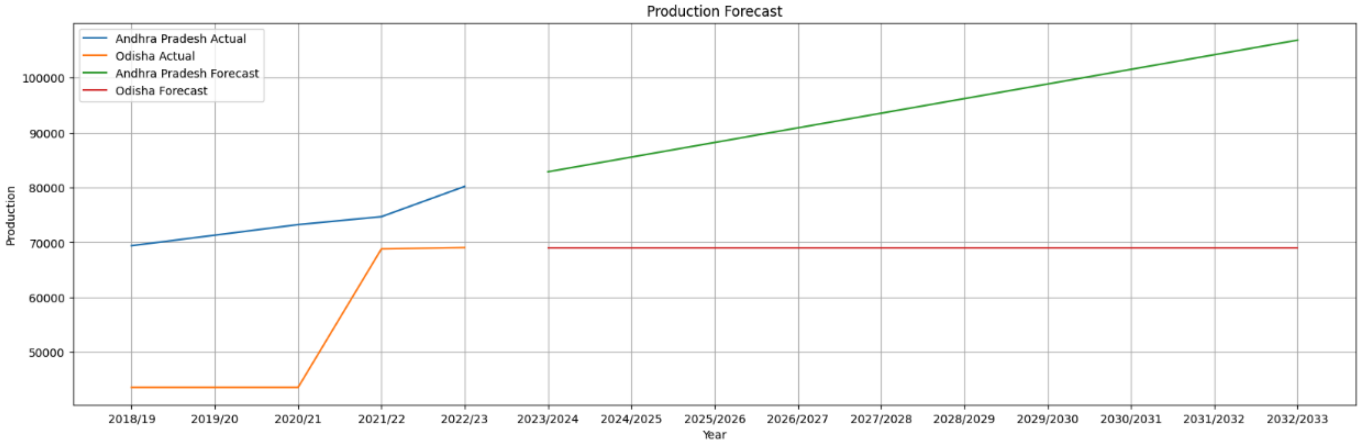
```
plt.plot(odisha_forecast.index, odisha_forecast, label='Odisha Forecast')

# Add labels and title
plt.xlabel('Year')
plt.ylabel('Production')
plt.title('Production Forecast')
plt.grid(True)
plt.legend()
plt.show()
```



[ACF plot for Andhra Pradesh and Odisha]



[ACF plot for Andhra Pradesh and Odisha after Differencing]



[Production Forecast for Andhra Pradesh and Odisha till 2032/33 Using ARIMA Model]

Inferences

The ADF test results indicate that the turmeric production data for Andhra Pradesh (p-value: 0.996219) and Odisha (p-value: 0.894773) are non-stationary. After differencing once, the data for Andhra Pradesh becomes stationary (p-value: 0.000000), while the data for Odisha remains non-stationary (p-value: 0.420297). The autocorrelation plot shows a significant drop from lag 0 to lag 1, suggesting over-differencing or unaccounted seasonality.

Upon conducting an autocorrelation analysis, the resulting graph indicates nonstationarity within the dataset. This is evidenced by the pronounced spike at lag 0 in the scatter plot section of the graph, which signifies a strong correlation of the data with itself at the same point in time. Such a pattern is indicative of a non-stationary time series that may possess a unit root.

The histogram portion of the graph further supports this conclusion, displaying a distribution of autocorrelation values that deviates from normality, with a skew to the left. This skewness suggests that the standard assumptions for many statistical models may not hold for this dataset.

In an effort to achieve stationarity, differencing was applied to the data. However, the results were mixed. For Andhra Pradesh, the p-value post-differencing dropped to 0 , suggesting that the differencing was effective in removing non-stationarity. Conversely, for Odisha, the p-value remained above the 0.05 threshold even after differencing, indicating persistent non-stationarity.

Given these outcomes, the ARIMA (Autoregressive Integrated Moving Average) model is recommended for forecasting. ARIMA models are particularly adept at handling non-stationary data, including those with unit roots, by integrating autoregressive terms and moving average terms. These components work in tandem to model the linear relationships between the current data points and their predecessors, making ARIMA an ideal choice for forecasting this dataset.

Conclusion

The time series analysis and forecasting for turmeric production in Andhra Pradesh and Odisha reveal distinct patterns. Andhra Pradesh shows a steady and consistent increase in production, indicating a stable production environment. In contrast, Odisha's production levels are relatively flat with a notable spike, suggesting a significant change during that period. Understanding the factors behind these trends could provide valuable insights for stakeholders in the turmeric industry and help inform future agricultural policies and strategies in both states. The ARIMA model's ability to handle non-stationary data makes it a suitable tool for forecasting, but the persistent non-stationarity in Odisha's data suggests that further model refinement or additional differencing may be necessary for accurate predictions.