扇形圖與時間序列模型

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1 安裝套件

[1]:
```
# pip install prophet
# pip install pmdarima
```

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.statespace.sarimax import SARIMAX
import pmdarima as pm
from prophet import Prophet
```

2 載入資料

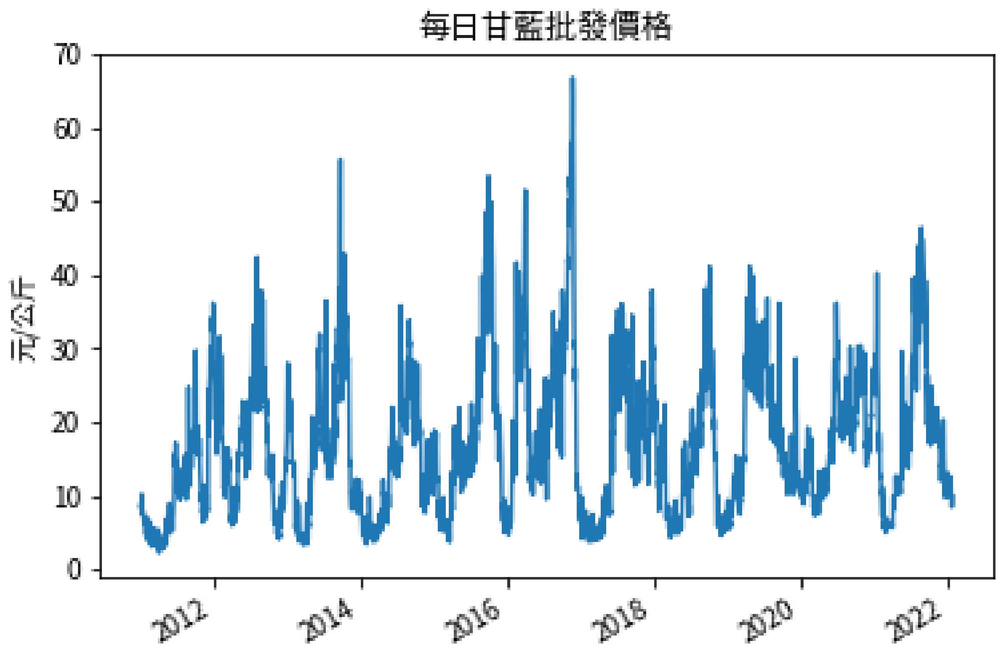
[3]:
```
df_c = pd.read_excel('cabbage.xlsx', index_col='date', parse_dates=True)
df_m = pd.read_csv('mvrs.csv', index_col='date', parse_dates=True)
cols = ['ObsTime', 'Temperature', 'Precp']
df_w = pd.read_csv('weather.csv', usecols=cols, index_col='ObsTime', parse_dates=True)
df_w.index.name = 'date'
```

3 檢視資料

3.1 甘藍

[4]:
```
display(df_c.head())
df_c.price.plot()
plt.title('每日甘藍批發價格')
plt.ylabel('元/公斤')
plt.xlabel('')
plt.show()
```

	price	quantity
date		
2011-01-01	8.645042	297507
2011-01-02	8.257309	272084
2011-01-04	9.171932	235652
2011-01-05	9.839765	203173
2011-01-06	10.080478	194846

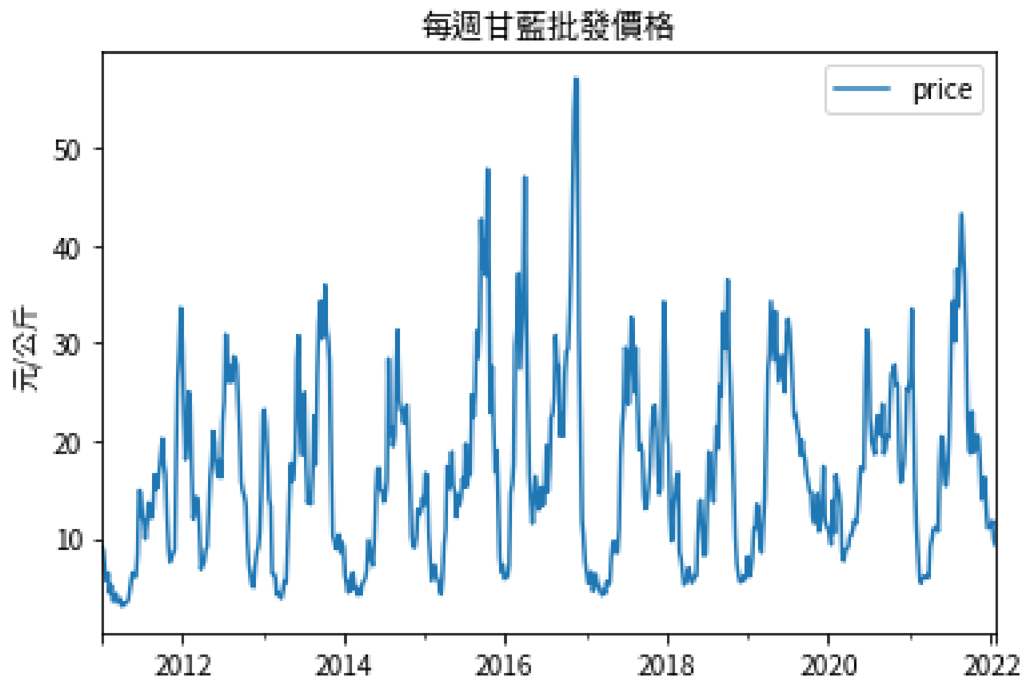


[5]:
```
df_c['pq'] = df_c.price * df_c.quantity
df_c = df_c.resample('W-Fri', label='right').sum()
df_c.price = df_c.pq / df_c.quantity
df_c = df_c.drop(columns=['quantity', 'pq'])
```

[6]:
```
display(df_c.head())
display(df_c.tail())
df_c.plot()
plt.title('每週甘藍批發價格')
plt.ylabel('元/公斤')
plt.xlabel('')
plt.show()
```

	price
date	
2011-01-07	9.229535
2011-01-14	8.637490
2011-01-21	6.727316
2011-01-28	5.659670
2011-02-04	6.425445

	price
date	
2021-12-31	11.118384
2022-01-07	11.310858
2022-01-14	11.804070
2022-01-21	9.820779
2022-01-28	9.356194



3.2 甘藍育苗

[8]:
```
df_m.head() # 千株
```

[8]:

	LA_num
date	
2011-01-05	6020.64
2011-01-15	5809.97
2011-01-25	6209.84
2011-02-05	4715.74
2011-02-15	4997.61

[9]:
```
df_m = df_m.resample('W-Fri', label='right').nearest()
df_m.head()
```

[9]:

	LA_num
date	
2011-01-07	6020.64
2011-01-14	5809.97
2011-01-21	6209.84
2011-01-28	6209.84
2011-02-04	4715.74

[10]:
```
df_m = df_m.shift(9)
display(df_m.head())
df_m.tail()
```

	LA_num
date	
2011-01-07	NaN
2011-01-14	NaN
2011-01-21	NaN
2011-01-28	NaN
2011-02-04	NaN

[10]:

	LA_num
date	
2021-12-03	6514.52
2021-12-10	6514.52
2021-12-17	6806.48
2021-12-24	7487.16
2021-12-31	7487.16

3.3 天氣

[11]:
```python
df_w.head() # 攝氏、毫米
```

[11]:

	Temperature	Precp
date		
2011-01-01	11.3	0.0
2011-01-02	14.1	0.0
2011-01-03	13.5	3.0
2011-01-04	13.1	0.1
2011-01-05	16.8	1.0

[12]:
```python
df_w = df_w.resample('W-Fri', label='right').mean()
display(df_w.head())
df_w.tail()
```

	Temperature	Precp
date		
2011-01-07	13.428571	0.714286
2011-01-14	13.442857	7.614286
2011-01-21	14.014286	1.000000
2011-01-28	15.071429	0.385714
2011-02-04	14.071429	0.985714

[12]:

	Temperature	Precp
date		
2021-12-03	19.185714	1.857143
2021-12-10	19.514286	2.785714
2021-12-17	20.514286	0.785714
2021-12-24	18.300000	3.428571
2021-12-31	15.700000	0.714286

3.4 合併

[13]:
```python
df = pd.concat([df_c, df_m, df_w], axis=1)
df = df['2011-03-11':'2021']
dfall = df.copy()
display(df.head())
df.tail()
```

	price	LA_num	Temperature	Precp
date				
2011-03-11	4.351267	6020.64	15.585714	8.000000
2011-03-18	3.421378	5809.97	17.071429	0.542857
2011-03-25	3.442451	6209.84	17.428571	0.128571
2011-04-01	3.818407	6209.84	16.357143	8.342857
2011-04-08	3.057363	4715.74	19.542857	0.428571

[13]:

	price	LA_num	Temperature	Precp
date				
2021-12-03	14.733079	6514.52	19.185714	1.857143
2021-12-10	16.248890	6514.52	19.514286	2.785714
2021-12-17	13.145006	6806.48	20.514286	0.785714
2021-12-24	11.053453	7487.16	18.300000	3.428571
2021-12-31	11.118384	7487.16	15.700000	0.714286

[14]:
```python
df['ln_price'] = np.log(df.price)
```

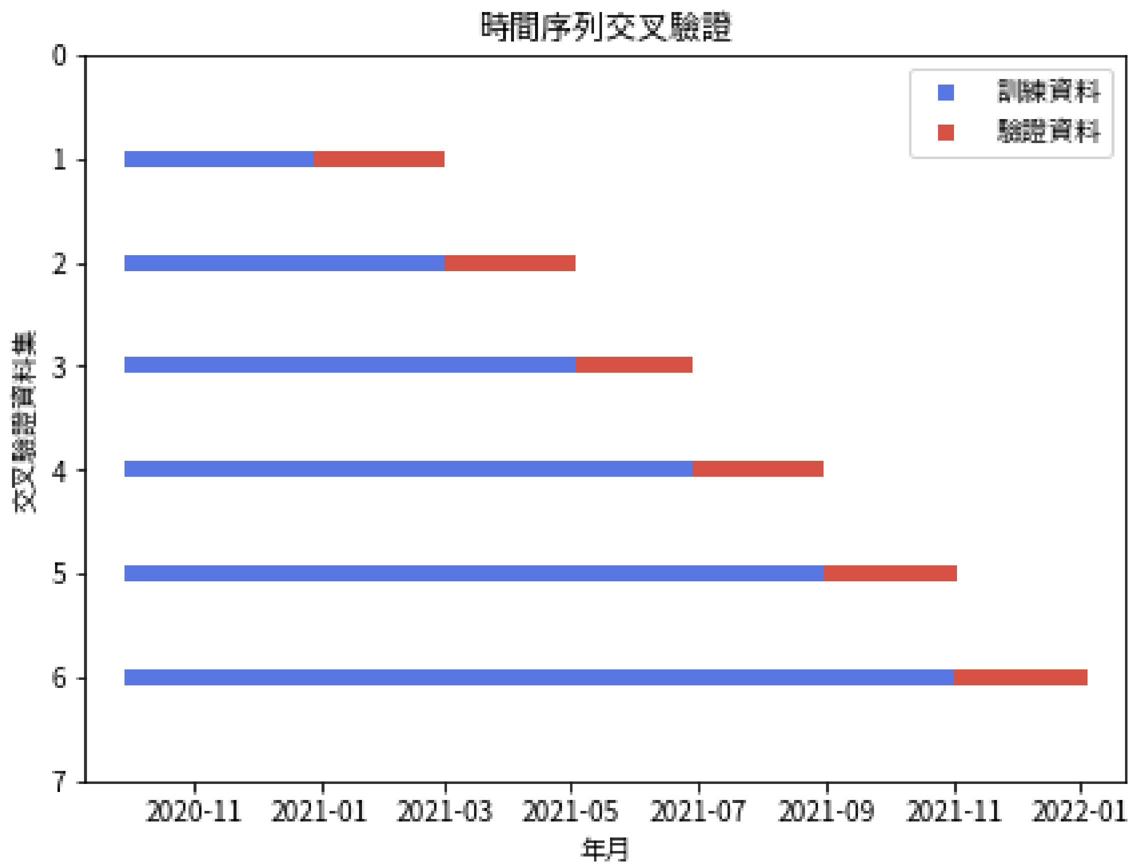
[15]:
```python
print(df.isna().sum())
```

```
price          0
LA_num         0
Temperature    0
Precp          0
ln_price       0
dtype: int64
```

4 切割資料

[16]:
```
tr_splits = ['2020-12', '2021-02', '2021-04',
             '2021-06', '2021-08', '2021-10', '2021-12']
va_splits = ['2021-01', '2021-03', '2021-05',
             '2021-07', '2021-09', '2021-11']
trs, vas = [], []

for i in range(6):
    trs.append(df[:tr_splits[i]])
    vas.append(df[va_splits[i]:tr_splits[i+1]])
```

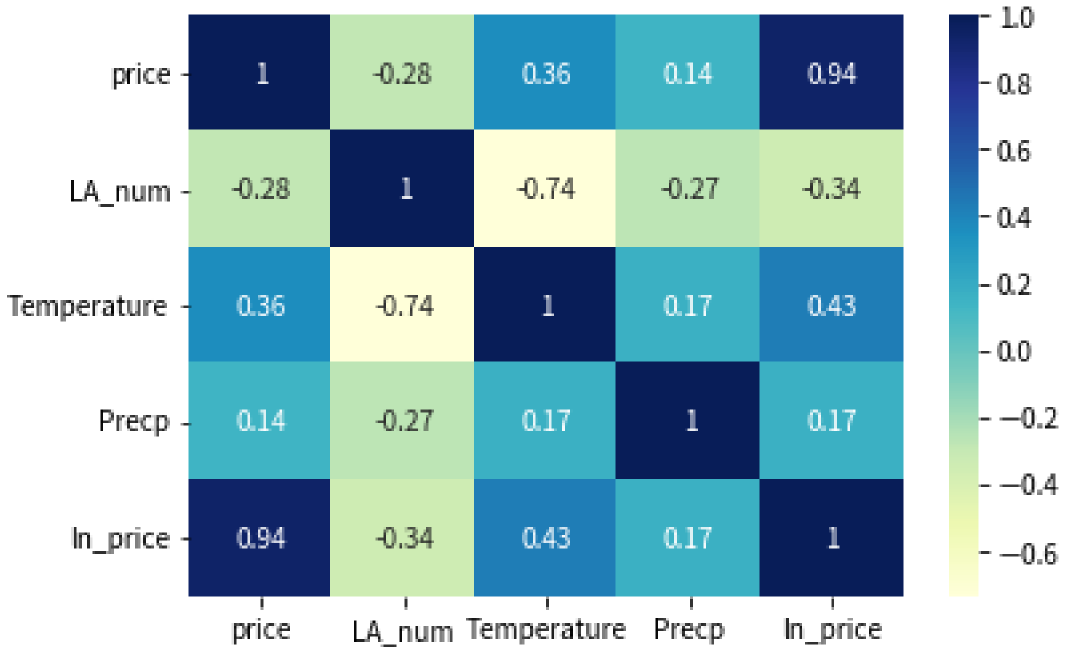
[17]:
```
fig, ax = plt.subplots(figsize=(7, 5))
for ii, (r, v) in enumerate(zip(trs, vas), 1):
    l1 = ax.scatter(r['2020-10':].index, [ii]*len(r['2020-10':]),
                    c=[plt.cm.coolwarm(.1)], marker='_', lw=6)
    l2 = ax.scatter(v.index, [ii]*len(v),
                    c=[plt.cm.coolwarm(.9)], marker='_', lw=6)
    ax.set(title='時間序列交叉驗證', ylim=[7, 0],
           xlabel='年月', ylabel='交叉驗證資料集',)
    ax.legend([l1, l2], ['訓練資料', '驗證資料'])
```



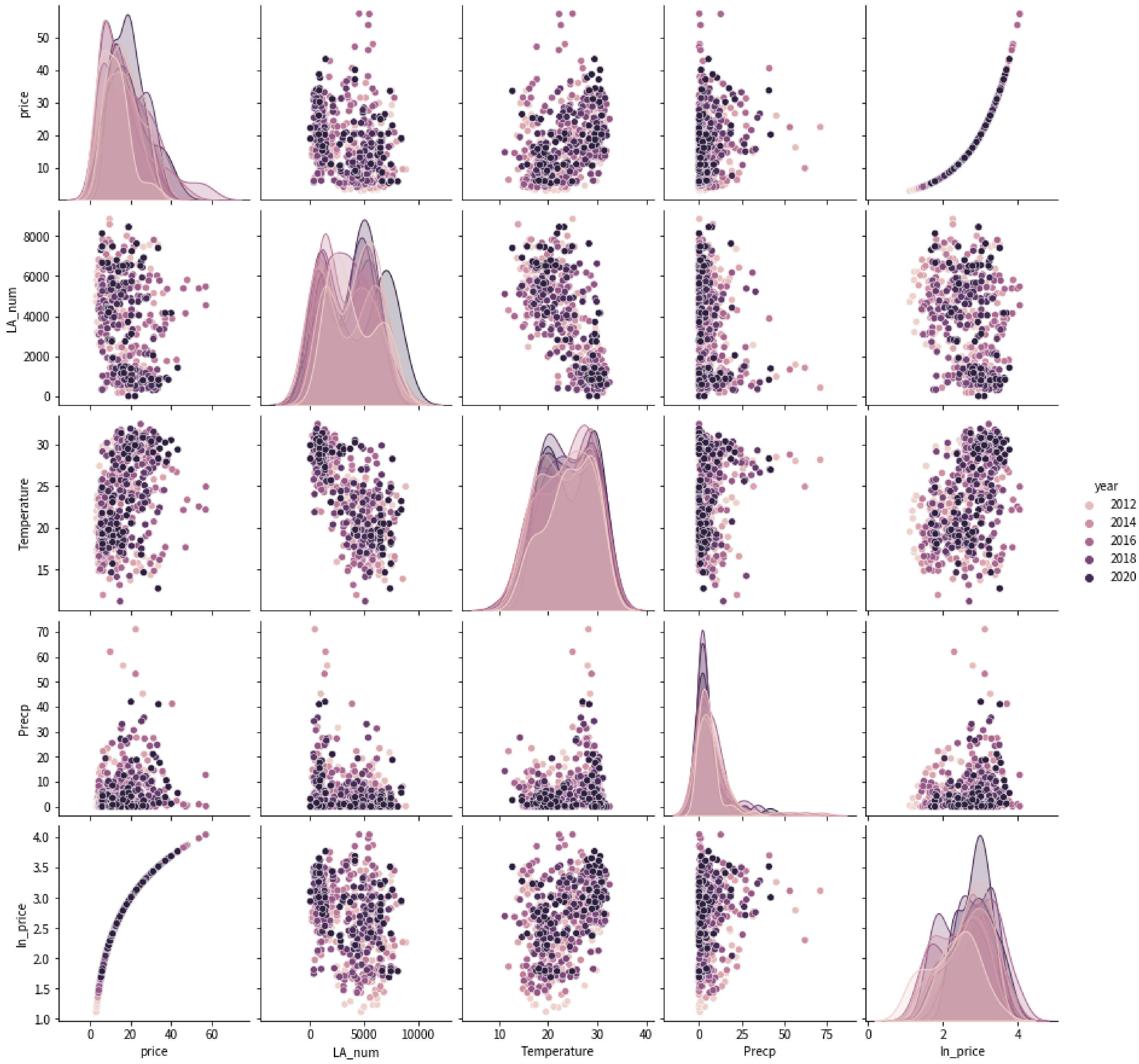
5 資料分析

5.1 Visualization

[18]:
```
import seaborn as sns
sns.heatmap(df.corr(), annot=True, cmap='YlGnBu')
plt.show()
```

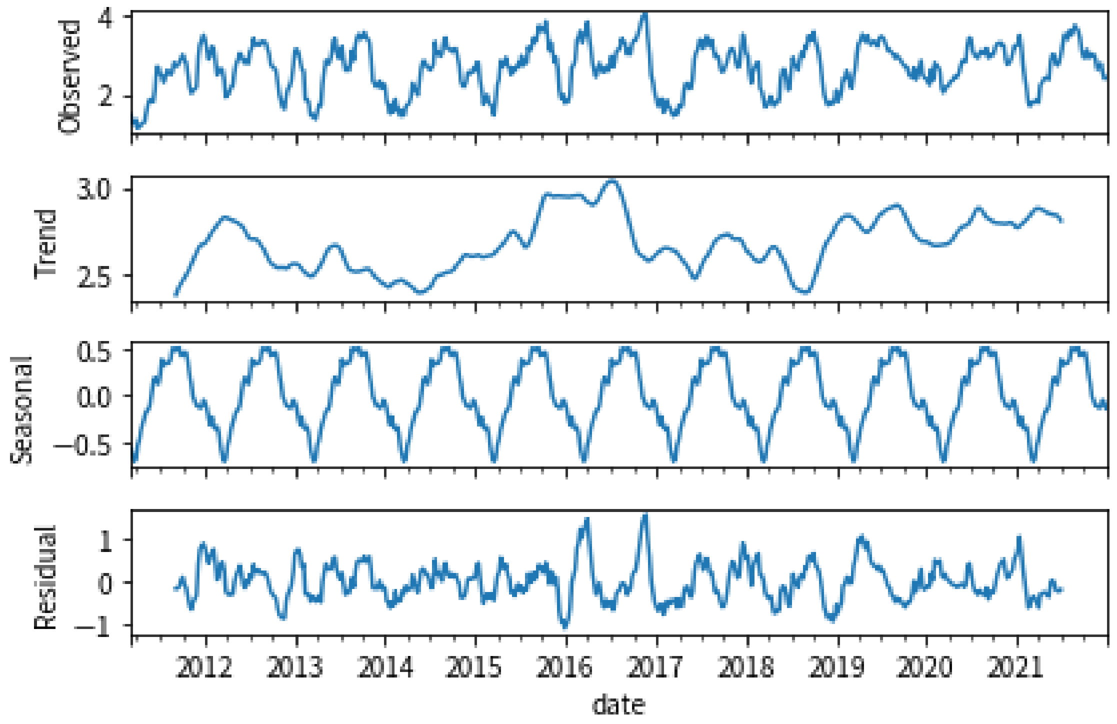


[19]:
```
df['year'] = df.index.year
sns.pairplot(df, hue='year')
plt.show()
```

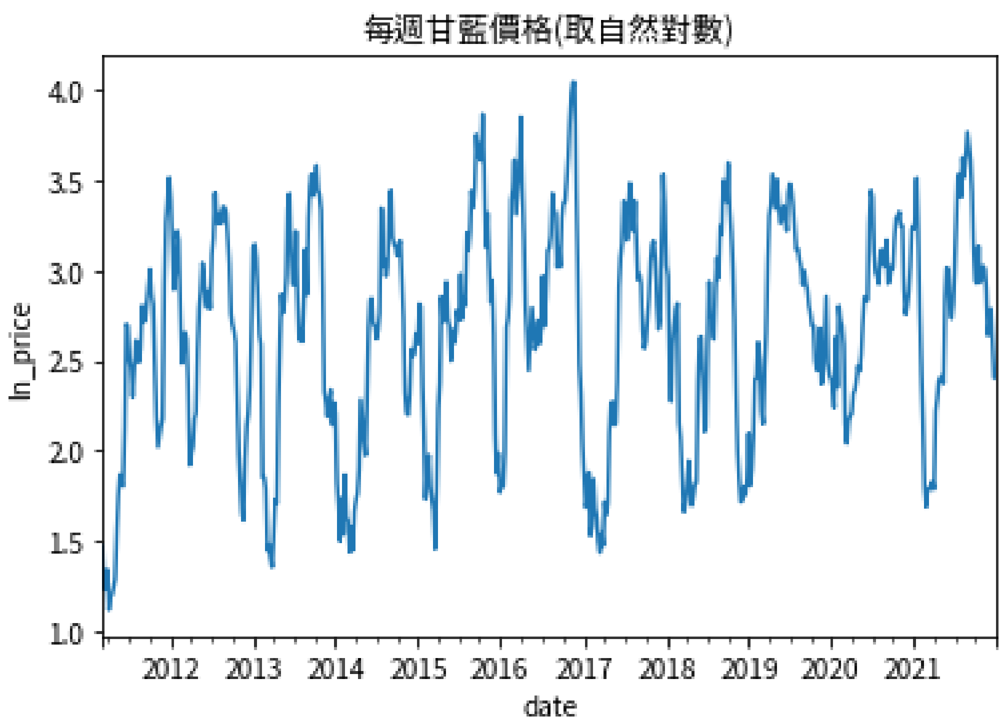


5.2 Decomposition

[20]:
```
decomp_results = seasonal_decompose(df.ln_price)
decomp_results.plot()
plt.show()
```



[21]:
```
df.ln_price.plot()
plt.title('每週甘藍價格（取自然對數）')
plt.ylabel('ln_price')
plt.show()
```



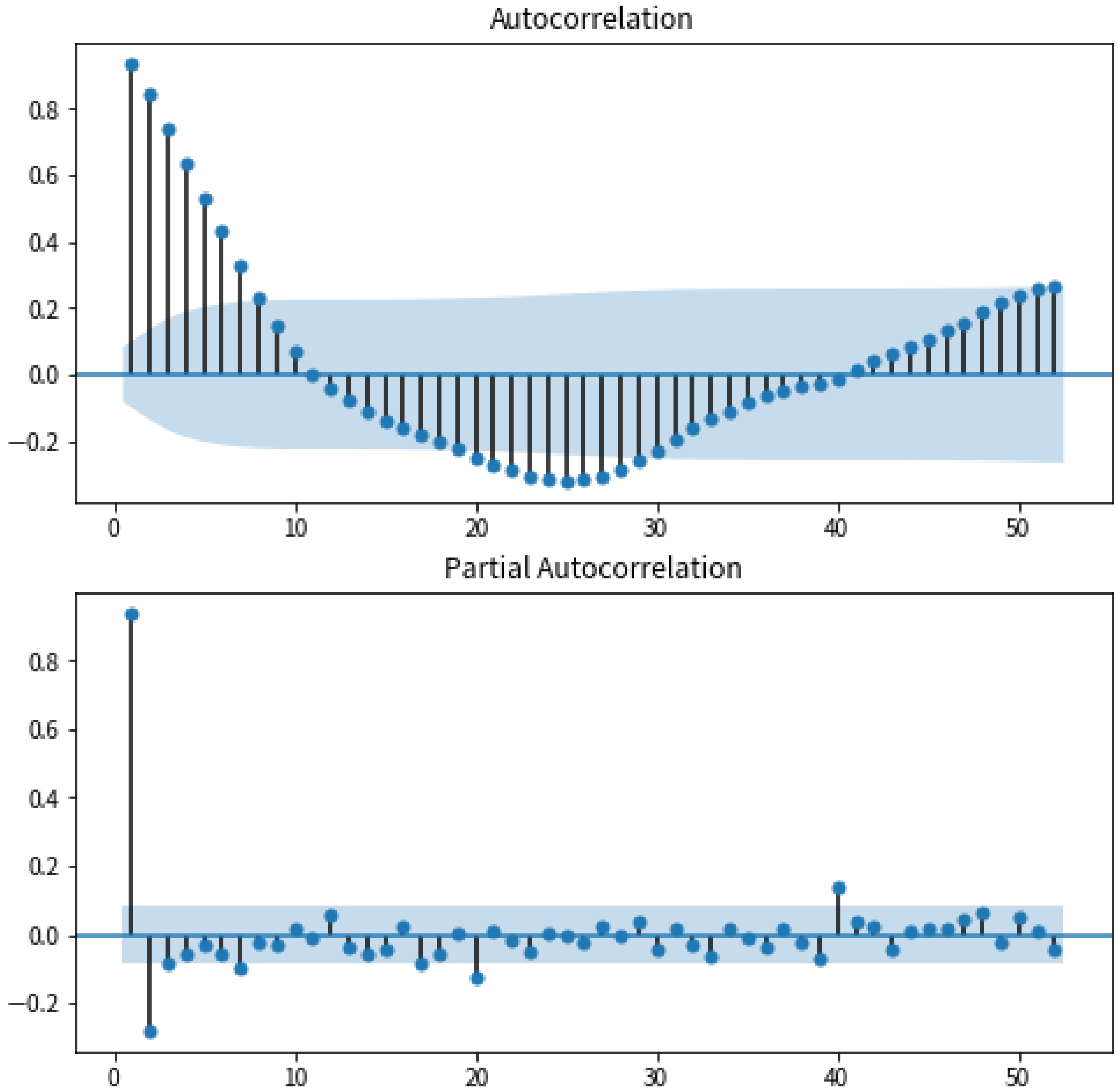
5.3 ADF TEST

[22]:
```
# print(adfuller(df.price))
print(adfuller(df.ln_price))
```

```
(-6.86993697048007, 1.524778106779821e-09, 6, 558, {'1%': -3.4421235439968862,
'5%': -2.866733577794069, '10%': -2.569536010842615}, -218.19823520770672)
```

5.4 ACF 與 PACF

[23]:
```
# Create figure
fig, (ax1, ax2) = plt.subplots(2,1, figsize=(8,8))

# Make ACF plot
plot_acf(df.ln_price, lags=52, zero=False, ax=ax1)

# Make PACF plot
plot_pacf(df.ln_price, lags=52, zero=False, ax=ax2, method='ywm')
plt.show()
```



6 模型

6.1 SARIMAX

$SARIMAX(p,d,q) \times (P,D,Q) : Seasonal + ARIMA + Exogenous$
$AR(p) : Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + u_t$
$MR(q) : Y_t = \theta_0 + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} + u_t$
$ARIMR(p,d,q) : (1 - \sum_{i=1}^{p} \beta_i L^i)(1-L)^d Y_t = (1 - \sum_{i=1}^{q} \theta_i L^i) u_t$, where L stands for Lag operator.

[24]:
```
%%capture
results = []
#for tr in trs:
    #result = pm.auto_arima(tr.ln_price, X=tr[['LA_num', 'Temperature', 'Precp']], seasonal=True, D=1, m=52)
    ##WEEK:  SARIMAX(3, 0, 0)x(2, 1, 0, 52)       ##MONTH: SARIMAX(2, 0, 0)x(2, 1, 0, 12)
for tr in trs:
    model = SARIMAX(tr.ln_price, exog=tr[['LA_num', 'Temperature', 'Precp']],
                    order=(3, 0, 0), seasonal_order=(2, 1, 0, 52))
    result = model.fit()
```

```
    results.append(result)
```

[25]:
```
print(results[-1].summary())
```

```
                               Statespace Model Results
================================================================================
Dep. Variable:                           ln_price   No. Observations:        556
Model:             SARIMAX(3, 0, 0)x(2, 1, 0, 52)   Log Likelihood       -15.036
Date:                            Fri,  4 Mar 2022   AIC                   48.073
Time:                                    01:37:33   BIC                   86.076
Sample:                                03-11-2011   HQIC                  62.980
                                     - 10-29-2021
Covariance Type:                              opg
===============================================================================
                  coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
LA_num       -9.42e-06   2.07e-05     -0.456      0.648   -4.99e-05    3.11e-05
Temperature    -0.0342      0.007     -4.897      0.000      -0.048      -0.020
Precp          -0.0003      0.002     -0.186      0.852      -0.003       0.003
ar.L1           1.0221      0.078     13.065      0.000       0.869       1.175
ar.L2          -0.0544      0.120     -0.454      0.649      -0.289       0.180
ar.L3          -0.1000      0.081     -1.238      0.216      -0.258       0.058
ar.S.L52       -0.6503      0.077     -8.436      0.000      -0.801      -0.499
ar.S.L104      -0.4360      0.074     -5.907      0.000      -0.581      -0.291
sigma2          0.0885      0.009      9.850      0.000       0.071       0.106
================================================================================
Ljung-Box (Q):                       47.67   Jarque-Bera (JB):                3.78
Prob(Q):                              0.19   Prob(JB):                        0.15
Heteroskedasticity (H):               0.80   Skew:                            0.21
Prob(H) (two-sided):                  0.16   Kurtosis:                        2.94
================================================================================

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

6.1.1 訓練資料

[26]:
```
def sarimax_forcast(tr, va=pd.DataFrame(), exo=['LA_num', 'Temperature', 'Precp'], ci=0.68):
    """
    Args:
      tr: Training Set
      va: Validation Set
      exo: Exog. List
      ci: Confidence Interval
    Returns:
      fcst: Forcast Dataframe
    """
    # model = SARIMAX(tr.ln_price, exog=tr[exo],
    #                 order=(3,0,0), seasonal_order=(2, 1, 0, 52))
    # result = model.fit()
    result = results[-1]

    preiods = len(va)
    if preiods == 0:
        predicted = result.get_prediction()
    else:
        predicted = result.get_forecast(steps=preiods, exog=va[exo])

    mean = pd.DataFrame({'predicted_mean':predicted.predicted_mean})
    conf = predicted.conf_int(alpha=1-ci)  # 68%
```

```python
    fcst = pd.concat([mean, conf], axis=1)
    return fcst
```

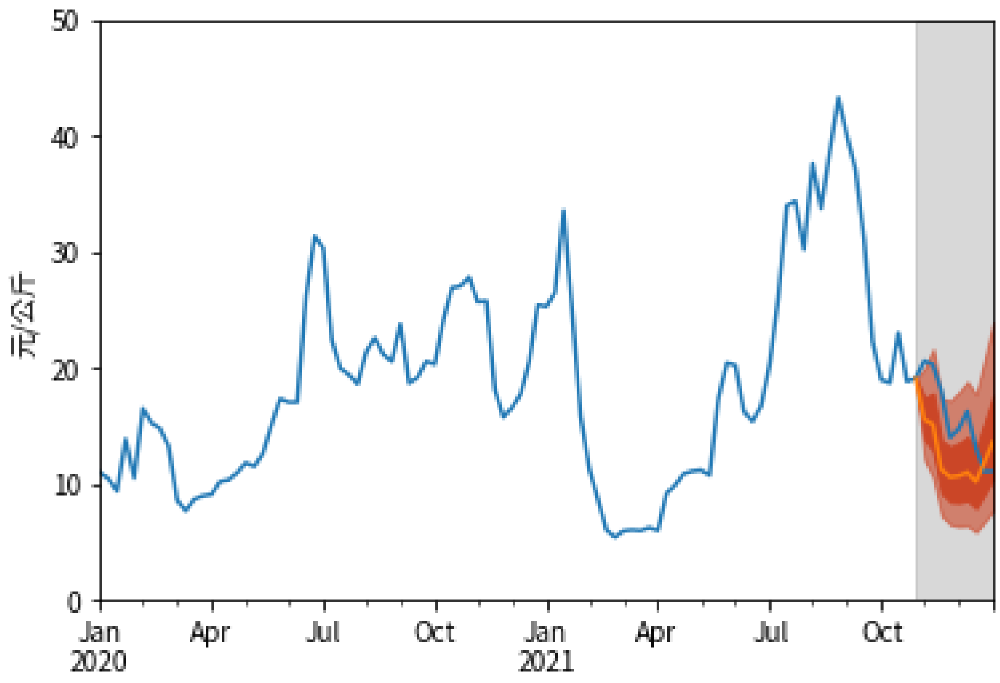
[27]:
```python
def connectpoint(tr):
    """
    Args:
      tr: Training Set
    Returns:
      lastp: Price of last date
      lastci: Price lower & upper Bound of last date
    """
    lastp = tr.price[-1:]
    lastci = tr[['price', 'price']][-1:]
    lastci.columns = ['lower price', 'upper price']
    lastci.index.name = 'ds'
    return lastp, lastci
```

[28]:
```python
def fanchart(tr, va, fcst30, fcst60, start='2020'):
    """
    Args:
      tr: Training Set
      va: Validation Set
      fcst30: DataFrame of 30% CI
      fcst60: DataFrame of 60% CI
      start: Start Time
    Returns:
      plt.show()
    """
    lastp, lastci = connectpoint(tr)

    yhat = fcst30.iloc[:, 0]

    point_est = np.exp(yhat)
    point_est = point_est.append(lastp).sort_index()

    fig, ax = plt.subplots()
    tr[start:].price.plot(ax=ax, legend=False)
    va.price.append(lastp).sort_index().plot(color='C0')

    point_est.plot()
    plt.axvspan(point_est.index.min(), point_est.index.max(), color='grey', alpha=0.3)

    conf30 = fcst30.iloc[:, 1:]
    conf60 = fcst60.iloc[:, 1:]
    confs = [conf30, conf60]

    for i, conf in enumerate(confs):
        conf = np.exp(conf)
        conf.columns = ['lower price', 'upper price']
        conf = conf.append(lastci).sort_index()
        plt.fill_between(conf.index, conf['lower price'], conf['upper price'],
                         color='xkcd:tomato red', alpha=(1-i/2.5), facecolor='black')

    ax.set_xlabel('')
    ax.set_ylabel('元/公斤')
    ax.set_ylim(0, 50)
    return plt.show()
```

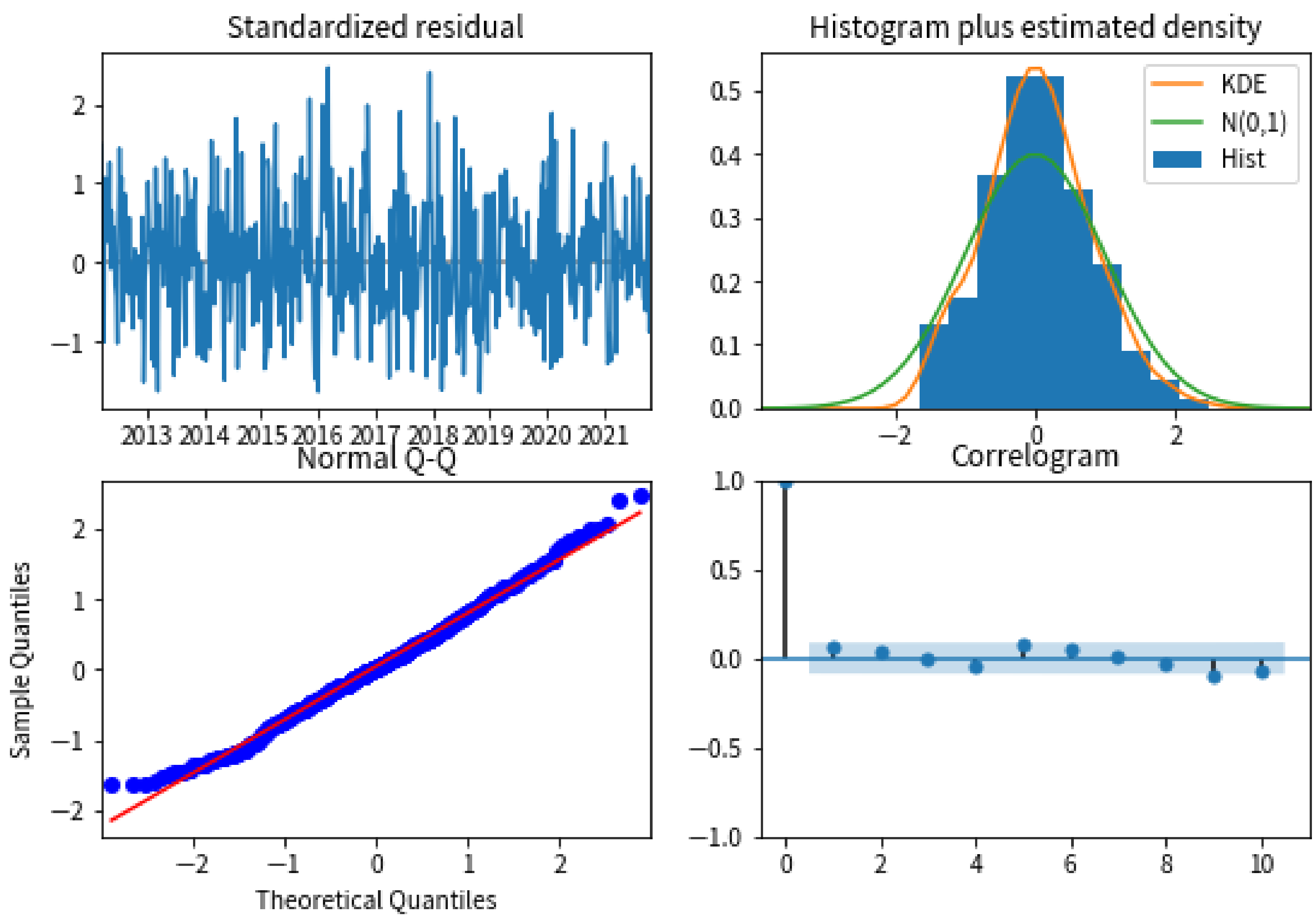
[ ]:
```python
# sarimax_forcast(trs[-1])
```

6.1.2 驗證資料

[29]:
```
fcst30 = sarimax_forcast(tr=trs[-1], va=vas[-1], ci=0.3)
fcst60 = sarimax_forcast(tr=trs[-1], va=vas[-1], ci=0.6)

fanchart(trs[-1], vas[-1], fcst30, fcst60)
```



[30]:
```
results[-1].plot_diagnostics(figsize=(9,6))
plt.show()
```



6.2 fbporphet

$y(t) = g(t) + s(t) + h(t) + e(t)$

$g(t)$: trend models non-periodic changes.

$s(t)$: seasonality presents periodic changes.

$h(t)$: effects of holidays with irregular schedules.

$e(t)$: covers idiosyncratic changes not accommodated by the model.

6.2.1 設定資料

[31]:
```python
def setdata(df):
    """
    Args:
      df: Source DataFrame
    Returns:
      df: Result DataFrame
    """
    df = df.reset_index()
    df.columns = ['ds', 'price', 'LA_num', 'Temperature', 'Precp', 'ln_price']
    df['y'] = df.ln_price
    return df
```

[32]:
```python
trps, vaps = [], []
for tr, va in zip(trs, vas):
    trps.append(setdata(tr))
    vaps.append(setdata(va))
```

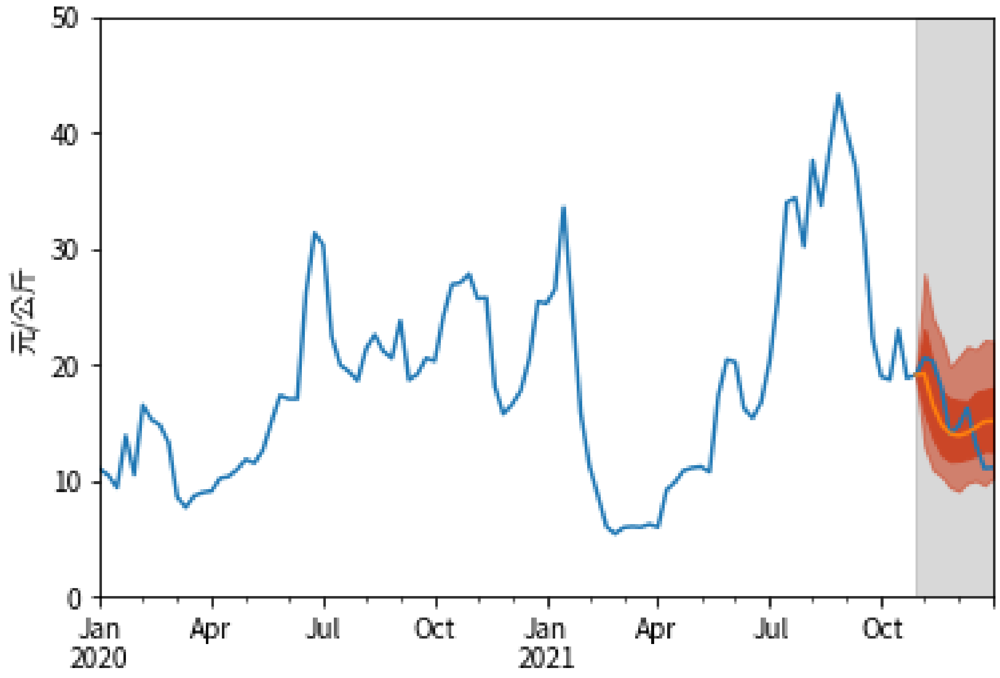
6.2.2 訓練資料

[33]:
```python
def prophet_forecast(tr, va=pd.DataFrame(), exo=['LA_num', 'Temperature', 'Precp'], ci=0.68):
    """
    Args:
      tr: Training Set
      va: Validation Set
      exo: Exog. List
      ci: Confidence Interval
    Returns:
      fcst: Forecast Dataframe
    """
    m = Prophet(seasonality_mode='multiplicative', interval_width=ci,
                yearly_seasonality=True, weekly_seasonality=False, daily_seasonality=False)
    for x in exo:
        m.add_regressor(x)
    cols = ['ds', 'y'] + exo
    m.fit(tr[cols])

    preiods = len(va)
    if preiods == 0:
        predict = m.make_future_dataframe(periods=preiods, freq='W-Fri', include_history=True)
        for x in exo:
            predict[x] = tr[[x]].reset_index(drop=True)
    else:
        predict = m.make_future_dataframe(periods=preiods, freq='W-Fri', include_history=False)
        for x in exo:
            predict[x] = va[[x]].reset_index(drop=True)
    fcst = m.predict(predict)
    fcst = fcst.set_index(fcst.ds, drop=True)
    return fcst[['yhat', 'yhat_lower', 'yhat_upper']]
```

[ ]:
```python
# prophet_forecast(trps[-1])
```

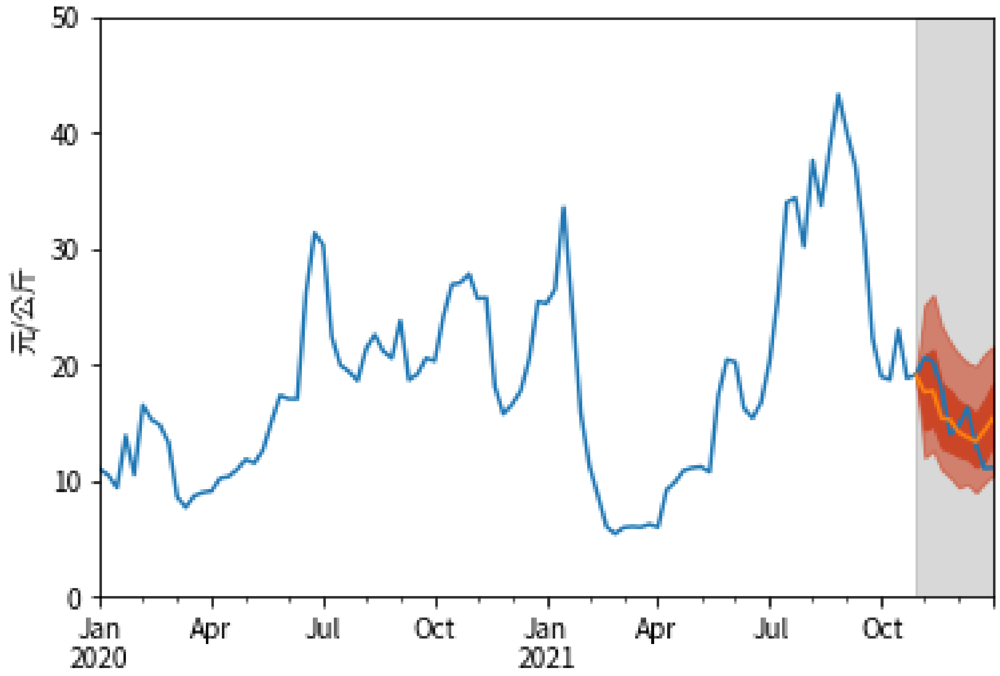
6.2.3 驗證資料 - 無外生變數

[34]:
```python
fcst30 = prophet_forecast(tr=trps[-1], va=vaps[-1], exo=[], ci=0.3)
fcst60 = prophet_forecast(tr=trps[-1], va=vaps[-1], exo=[], ci=0.6)

fanchart(trs[-1], vas[-1], fcst30, fcst60)
```



6.2.4 驗證資料

[35]:
```
fcst30 = prophet_forecast(tr=trps[-1], va=vaps[-1], ci=0.3)
fcst60 = prophet_forecast(tr=trps[-1], va=vaps[-1], ci=0.6)

fanchart(trs[-1], vas[-1], fcst30, fcst60)
```



7 評估

7.1 準備評估資料

7.1.1 訓練資料

[36]:
```
dfins = pd.DataFrame({'y_real': trs[-1].price,
                      'y_sarimax': np.exp(results[-1].get_prediction().predicted_mean),
                      'y_prophet': np.exp(prophet_forecast(trps[-1]).yhat)})
dfins.tail()
```

[36]:

	y_real	y_sarimax	y_prophet
2021-10-01	18.968285	22.790067	33.187853
2021-10-08	18.718567	16.033195	24.749402
2021-10-15	23.008165	17.930942	21.109855
2021-10-22	18.830983	24.478487	21.356169
2021-10-29	19.119969	16.749888	19.594124

7.1.2 驗證資料

[37]:
```
dfoos = pd.DataFrame({'y_real': vas[-1].price,
                      'y_sarimax': np.exp(sarimax_forcast(tr=trs[-1], va=vas[-1], ci=0.3).predicted_mean),
                      'y_prophet': np.exp(prophet_forecast(tr=trps[-1], va=vaps[-1]).yhat)})
dfoos.head()
```

[37]:

	y_real	y_sarimax	y_prophet
2021-11-05	20.615359	15.554690	17.644919
2021-11-12	20.288235	15.138622	17.752219
2021-11-19	18.010898	11.244562	15.407024
2021-11-26	14.008714	10.591525	15.251011
2021-12-03	14.733079	10.686173	14.177256

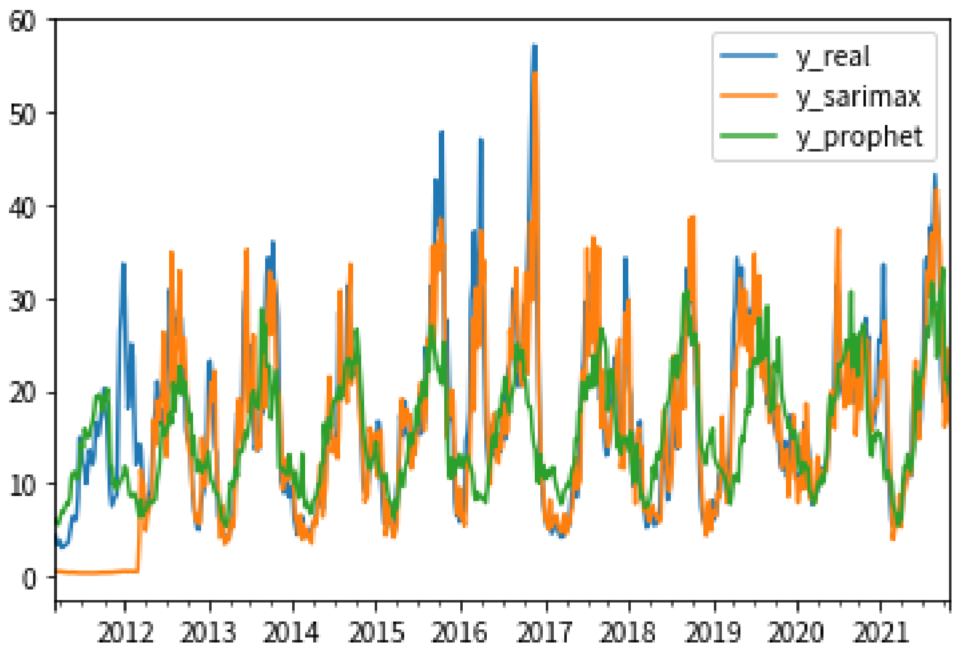
7.2 評估標準

[38]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error, mean_absolute_percentage_error
```

- $\text{MSE}(Y, \widehat{Y}) = \frac{1}{T}\sum_{t=1}^{T}(Y_t - \widehat{Y}_t)^2$
- $\text{MAE}(Y, \widehat{Y}) = \frac{1}{T}\sum_{t=1}^{T}|Y_t - \widehat{Y}_t|$
- $\text{MAPE}(Y, \widehat{Y}) = \frac{1}{T}\sum_{t=1}^{T}\frac{|Y_t - \widehat{Y}_t|}{max(u_t, |Y_t|)}$

7.3 訓練資料

[39]:
```
dfins.plot()
plt.show()
```



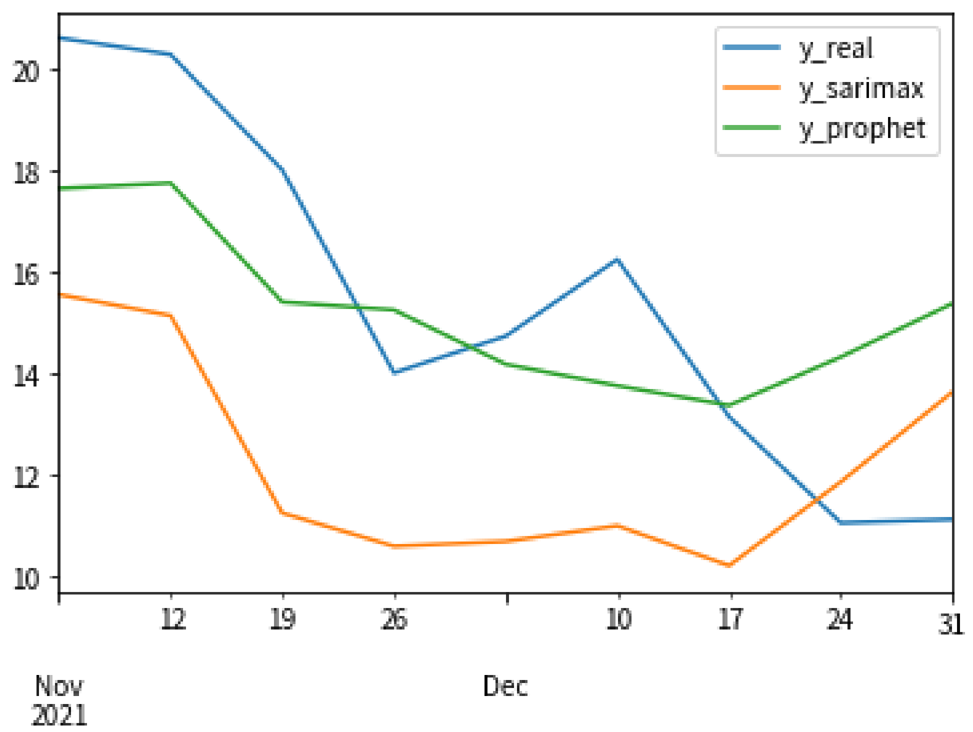
[40]:
```
mse = [mean_squared_error(dfins.y_real, dfins.y_sarimax),
       mean_squared_error(dfins.y_real, dfins.y_prophet)]
mae = [mean_absolute_error(dfins.y_real, dfins.y_sarimax),
       mean_absolute_error(dfins.y_real, dfins.y_prophet)]
mape = [mean_absolute_percentage_error(dfins.y_real, dfins.y_sarimax),
        mean_absolute_percentage_error(dfins.y_real, dfins.y_prophet)]
dfv_ins = pd.DataFrame({'MSE': mse,
                        'MAE': mae,
                        'MAPE': mape}, index=['SARIMAX', 'prophet'])
dfv_ins
```

[40]:

	MSE	MAE	MAPE
SARIMAX	38.315079	4.026199	0.256260
prophet	63.482737	5.554545	0.366049

7.4 驗證資料

[41]:
```
dfoos.plot()
plt.show()
```



[42]:
```
mse = [mean_squared_error(dfoos.y_real, dfoos.y_sarimax),
       mean_squared_error(dfoos.y_real, dfoos.y_prophet)]
rmse = [np.sqrt(mean_squared_error(dfoos.y_real, dfoos.y_sarimax)),
        np.sqrt(mean_squared_error(dfoos.y_real, dfoos.y_prophet))]
mae = [mean_absolute_error(dfoos.y_real, dfoos.y_sarimax),
       mean_absolute_error(dfoos.y_real, dfoos.y_prophet)]
mape = [mean_absolute_percentage_error(dfoos.y_real, dfoos.y_sarimax),
      mean_absolute_percentage_error(dfoos.y_real, dfoos.y_prophet)]
dfv_oos = pd.DataFrame({'MSE': mse,
                        'RMSE': rmse,
                        'MAE': mae,
                        'MAPE': mape}, index=['SARIMAX', 'prophet'])
dfv_oos
```

[42]:

	MSE	RMSE	MAE	MAPE
SARIMAX	18.794983	4.335318	3.994496	0.248816
prophet	6.550445	2.559384	2.238885	0.154340

[43]:
```
# log(Price)
mse = [mean_squared_error(np.log(dfoos.y_real), np.log(dfoos.y_sarimax)),
       mean_squared_error(np.log(dfoos.y_real), np.log(dfoos.y_prophet))]
rmse = [np.sqrt(mean_squared_error(np.log(dfoos.y_real), np.log(dfoos.y_sarimax))),
        np.sqrt(mean_squared_error(np.log(dfoos.y_real), np.log(dfoos.y_prophet)))]
mae = [mean_absolute_error(np.log(dfoos.y_real), np.log(dfoos.y_sarimax)),
       mean_absolute_error(np.log(dfoos.y_real), np.log(dfoos.y_prophet))]
mape = [mean_absolute_percentage_error(np.log(dfoos.y_real), np.log(dfoos.y_sarimax)),
      mean_absolute_percentage_error(np.log(dfoos.y_real), np.log(dfoos.y_prophet))]
dfv_oos = pd.DataFrame({'MSE': mse,
                        'RMSE': rmse,
                        'MAE': mae,
                        'MAPE': mape}, index=['SARIMAX', 'prophet'])
dfv_oos
```

[43]:

	MSE	RMSE	MAE	MAPE
SARIMAX	0.092360	0.303908	0.284876	0.103418
prophet	0.030591	0.174902	0.148365	0.056106

Lewis(1982)
MAPE < 10%：Highly accurate forcasting
10%< MAPE < 20%：Good forecasting
20%< MAPE < 50%：Reasonable forecasting
MAPE > 50%：Week and inaccurate forecasting

Those Lewis numbers are fairly arbitrary, you can't just say that a 20% error is good forecasting because some guy wrote it in a book 40 years ago.The acceptable margin or error completely depends on the problem domain. In some situations a model that gives a 20% error will be great, in others it will be unusable. I know its tempting to rely on general rules like the ones you posted because they feel 'objective', but they are ultimately arbitrary and can't override common sense and domain expertise.

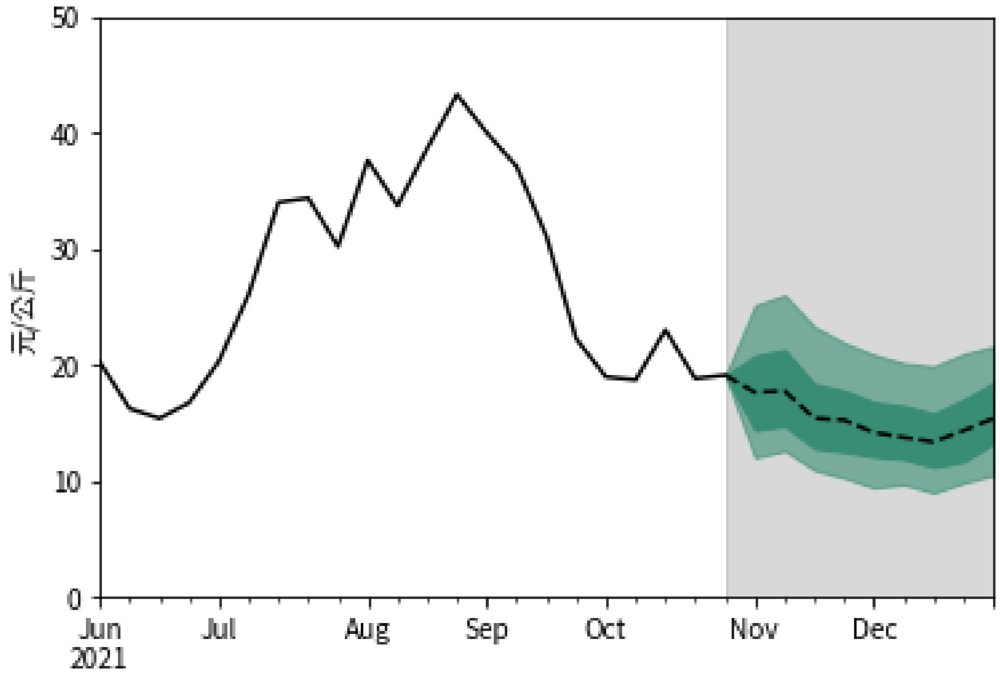
8 扇形圖

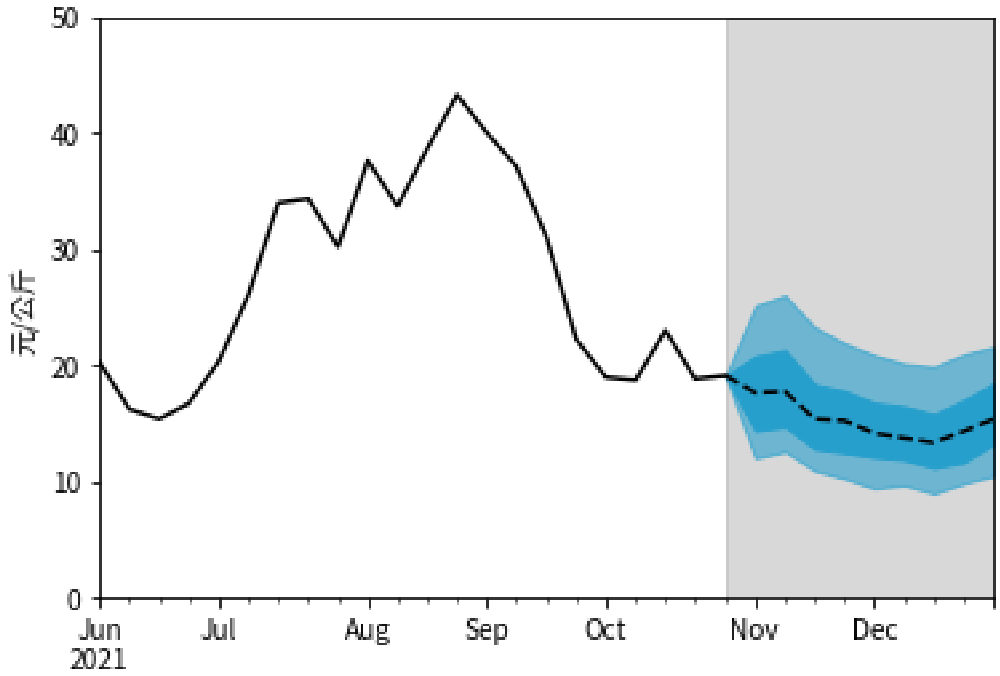
8.1 定義 fanchart function

[44]:
```python
def fanchart(tr, va, fcst30, fcst60, start='2020', color='#199370'):
    """
    Args:
      tr: Training Set
      va: Validation Set
      yhat: Forecasting Price
      lastp: Price of last date
      lastci: Confidence Interval of last date
    Returns:
      plt.show()
    """
    lastp, lastci = connectpoint(tr)

    yhat = fcst30.iloc[:, 0]

    point_est = np.exp(yhat)
    point_est = point_est.append(lastp).sort_index()

    fig, ax = plt.subplots()
    tr[start:].price.plot(ax=ax, legend=False, color='black')
    # va.price.append(lastp).sort_index().plot(color='C0')

    point_est.plot(color='black', linestyle='--')
    plt.axvspan(point_est.index.min(), point_est.index.max(), color='grey', alpha=0.3)

    conf30 = fcst30.iloc[:, 1:]
    conf60 = fcst60.iloc[:, 1:]
    confs = [conf30, conf60]

    for i, conf in enumerate(confs):
        conf = np.exp(conf)
        conf.columns = ['lower price', 'upper price']
        conf = conf.append(lastci).sort_index()
        plt.fill_between(conf.index, conf['lower price'], conf['upper price'],
                         color=color, alpha=(1-i/2.5), facecolor='black')

    ax.set_xlabel('')
    ax.set_ylabel('元/公斤')
    ax.set_ylim(0, 50)
    return plt.show()
```

8.2 繪製

[45]:
```
fanchart(trs[-1], vas[-1], fcst30, fcst60, start='2021-06')
fanchart(trs[-1], vas[-1], fcst30, fcst60, start='2021-06', color='#00adee')
```





9 TODO

9.1 Six Validation

[ ]:
```
```

9.2 Test Set

[ ]:
```
```