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

In [2]:
```
passengers = pd.read_excel('Airlines+Data.xlsx')
passengers
```

Out[2]:

	Month	Passengers
0	1995-01-01	112
1	1995-02-01	118
2	1995-03-01	132
3	1995-04-01	129
4	1995-05-01	121
...	...	...
91	2002-08-01	405
92	2002-09-01	355
93	2002-10-01	306
94	2002-11-01	271
95	2002-12-01	306

96 rows × 2 columns

In [3]:
```
passengers.head()
```

Out[3]:

	Month	Passengers
0	1995-01-01	112
1	1995-02-01	118
2	1995-03-01	132
3	1995-04-01	129
4	1995-05-01	121

Converting the 'Month' column into proper date time format

In [4]:
```
dates = pd.date_range(start='1949-01-01', freq='MS',periods=len(passengers))
dates
```

Out[4]:
```
DatetimeIndex(['1949-01-01', '1949-02-01', '1949-03-01', '1949-04-01',
               '1949-05-01', '1949-06-01', '1949-07-01', '1949-08-01',
               '1949-09-01', '1949-10-01', '1949-11-01', '1949-12-01',
               '1950-01-01', '1950-02-01', '1950-03-01', '1950-04-01',
               '1950-05-01', '1950-06-01', '1950-07-01', '1950-08-01',
               '1950-09-01', '1950-10-01', '1950-11-01', '1950-12-01',
               '1951-01-01', '1951-02-01', '1951-03-01', '1951-04-01',
               '1951-05-01', '1951-06-01', '1951-07-01', '1951-08-01',
               '1951-09-01', '1951-10-01', '1951-11-01', '1951-12-01',
               '1952-01-01', '1952-02-01', '1952-03-01', '1952-04-01',
               '1952-05-01', '1952-06-01', '1952-07-01', '1952-08-01',
               '1952-09-01', '1952-10-01', '1952-11-01', '1952-12-01',
               '1953-01-01', '1953-02-01', '1953-03-01', '1953-04-01',
               '1953-05-01', '1953-06-01', '1953-07-01', '1953-08-01',
               '1953-09-01', '1953-10-01', '1953-11-01', '1953-12-01',
               '1954-01-01', '1954-02-01', '1954-03-01', '1954-04-01',
               '1954-05-01', '1954-06-01', '1954-07-01', '1954-08-01',
               '1954-09-01', '1954-10-01', '1954-11-01', '1954-12-01',
               '1955-01-01', '1955-02-01', '1955-03-01', '1955-04-01',
               '1955-05-01', '1955-06-01', '1955-07-01', '1955-08-01',
               '1955-09-01', '1955-10-01', '1955-11-01', '1955-12-01',
               '1956-01-01', '1956-02-01', '1956-03-01', '1956-04-01',
               '1956-05-01', '1956-06-01', '1956-07-01', '1956-08-01',
               '1956-09-01', '1956-10-01', '1956-11-01', '1956-12-01'],
              dtype='datetime64[ns]', freq='MS')
```

In [5]:
```
passengers['Month'] = dates.month
passengers['Year'] = dates.year
```

In [6]:
```
passengers.head()
```

Out[6]:

	Month	Passengers	Year
0	1	112	1949
1	2	118	1949
2	3	132	1949
3	4	129	1949
4	5	121	1949

In [7]:
```
passengers.dtypes
```

Out[7]:
```
Month         int64
Passengers    int64
Year          int64
dtype: object
```

In [8]:
```
passengers.head()
```

Out[8]:

	Month	Passengers	Year
0	1	112	1949
1	2	118	1949
2	3	132	1949
3	4	129	1949
4	5	121	1949

In [9]:
```
import calendar
passengers['Month'] = passengers['Month'].apply(lambda x: calendar.month_abbr[x])
passengers.rename({'#Passengers':'Passengers'},axis=1,inplace=True)
passengers = passengers[['Month','Year','Passengers']]
```

In [10]:
```
passengers.head()
```

Out[10]:

	Month	Year	Passengers
0	Jan	1949	112
1	Feb	1949	118
2	Mar	1949	132
3	Apr	1949	129
4	May	1949	121

In [11]:
```
passengers['Date'] = dates
passengers.set_index('Date',inplace=True)
```

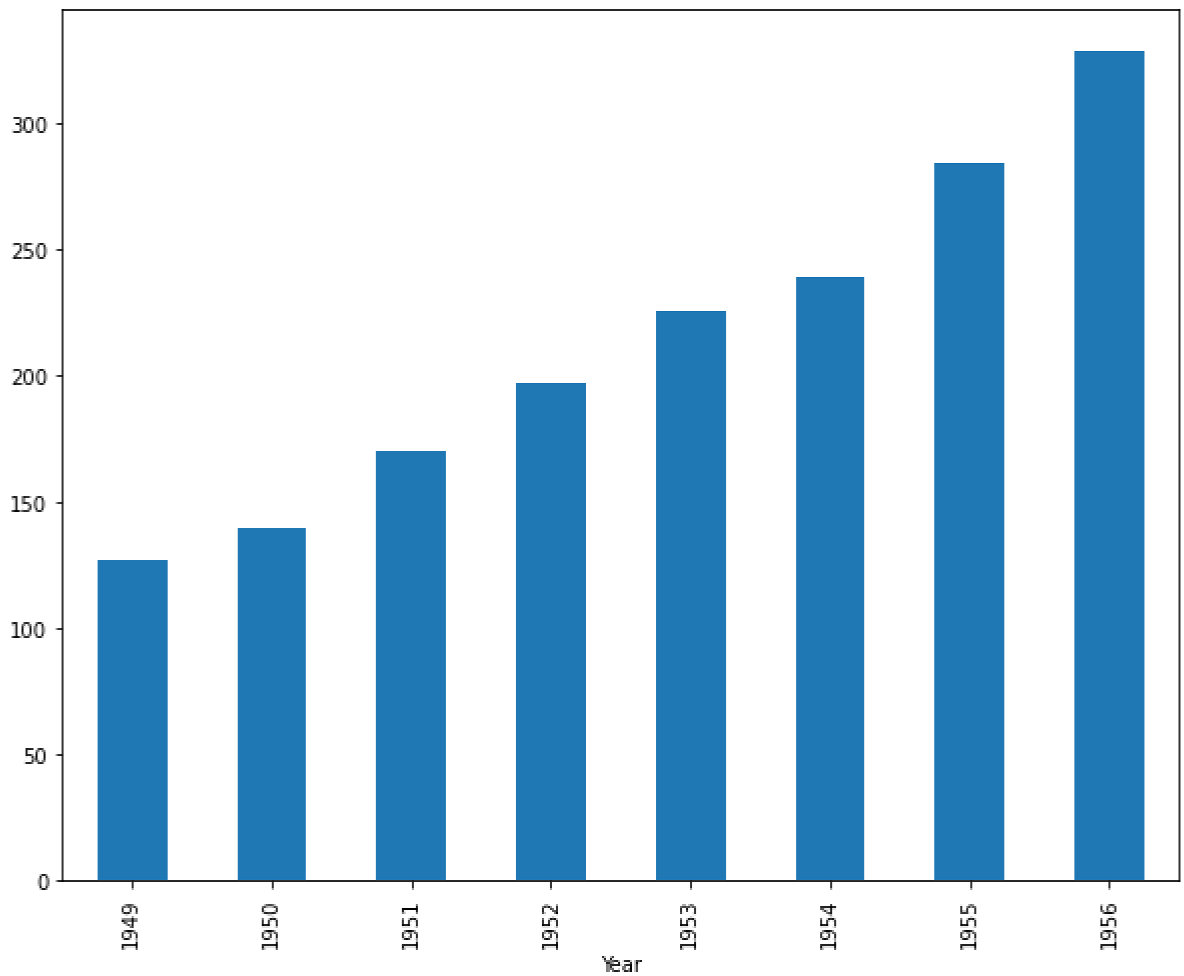
```
C:\Users\PRASHA~1\AppData\Local\Temp/ipykernel_3360/3979590641.py:1: SettingWit
hCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/sta
ble/user_guide/indexing.html#returning-a-view-versus-a-copy (https://pandas.pyd
ata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-c
opy)
  passengers['Date'] = dates
```

In [12]:
```
passengers.head()
```

Out[12]:

	Month	Year	Passengers
Date			
1949-01-01	Jan	1949	112
1949-02-01	Feb	1949	118
1949-03-01	Mar	1949	132
1949-04-01	Apr	1949	129
1949-05-01	May	1949	121

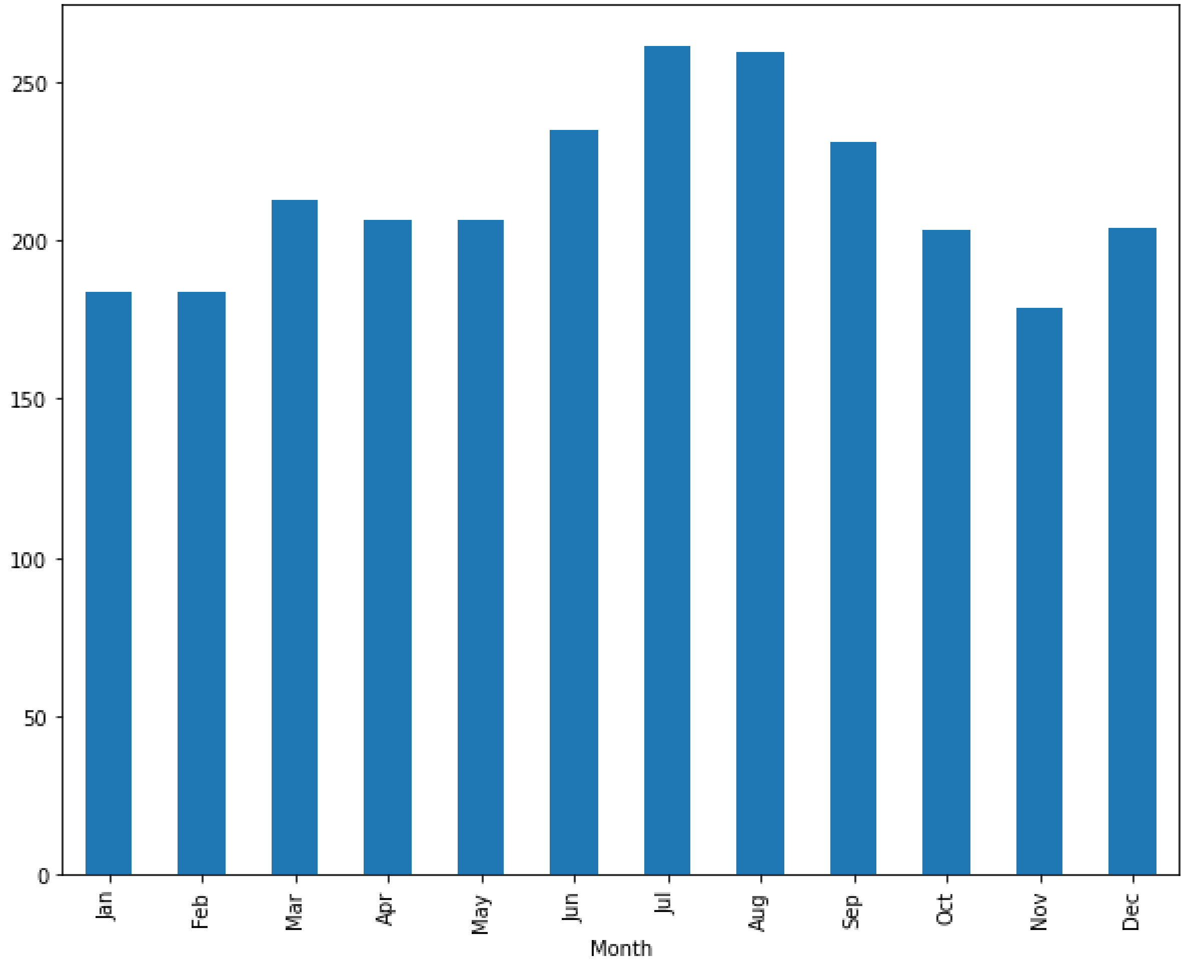
In [13]:
```
plt.figure(figsize=(10,8))
passengers.groupby('Year')['Passengers'].mean().plot(kind='bar')
plt.show()
```



In [14]:
```
print('From the above figure we can see that passengers are increasing with the i
```

```
From the above figure we can see that passengers are increasing with the increa
se in the year
```

In [15]:
```
plt.figure(figsize=(10,8))
passengers.groupby('Month')['Passengers'].mean().reindex(index=['Jan','Feb','Mar'
plt.show()
```



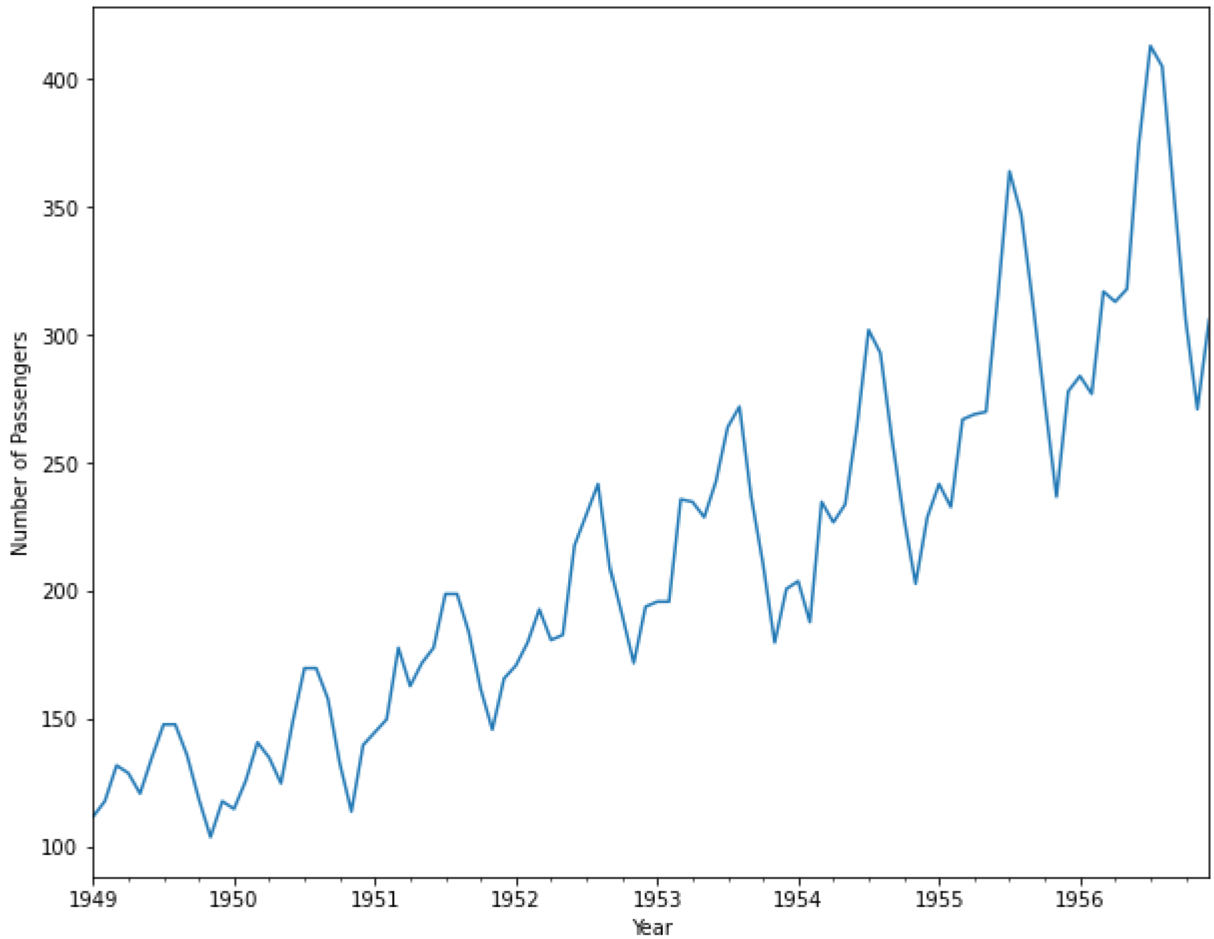
In [16]:
```
print('From the above figure we can see that more passengers can be seen between
```

```
From the above figure we can see that more passengers can be seen between month
s June to September.
```

Lets plot the data to see the trend and seasonality

In [17]:
```
passengers_count = passengers['Passengers']
```

In [18]:
```
plt.figure(figsize=(10,8))
passengers_count.plot()
plt.xlabel('Year')
plt.ylabel('Number of Passengers')
plt.show()
```

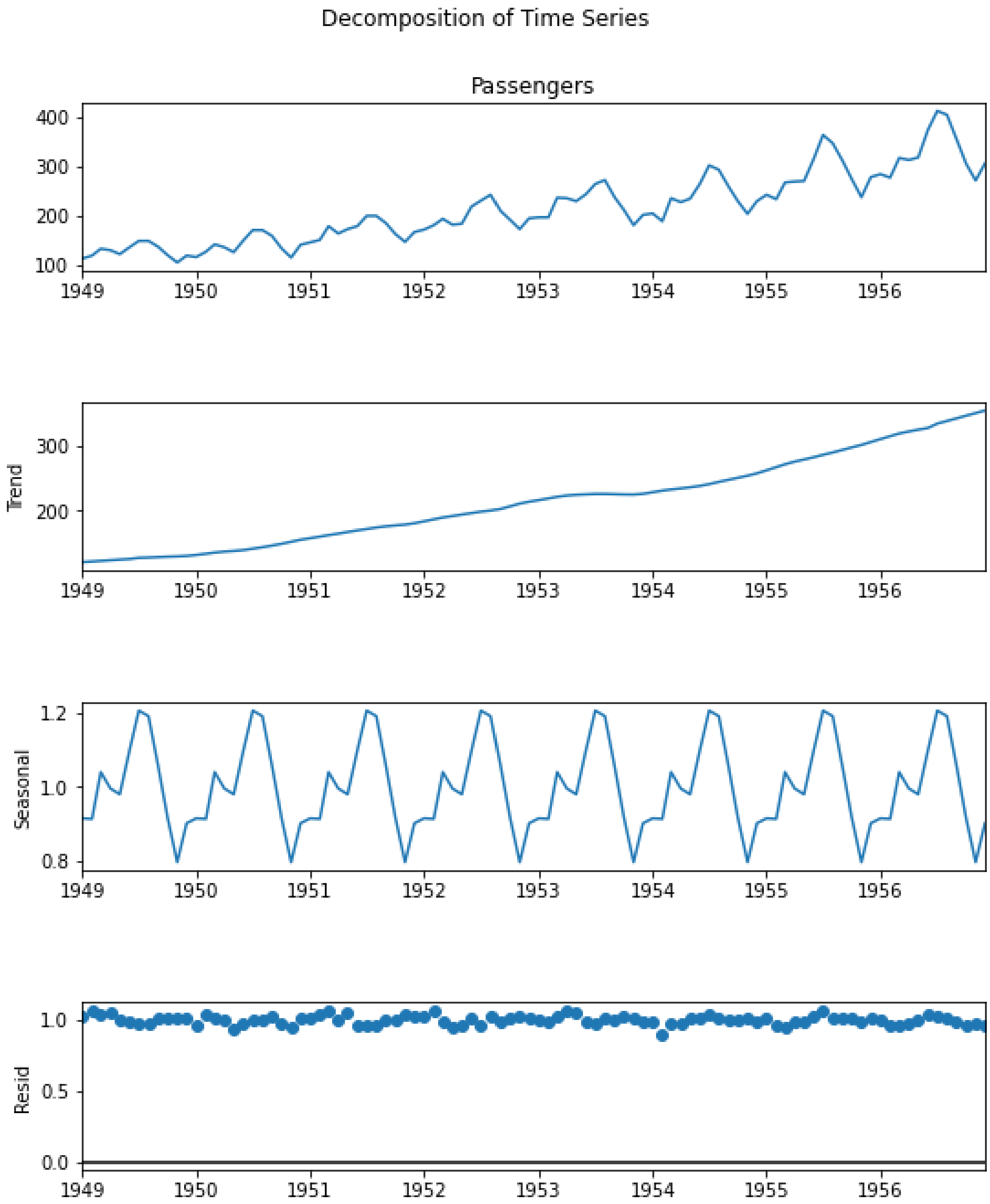


Now we start with time series decomposition of this data to understand underlying patterns such as trend, seasonality, cycle and irregular remainder

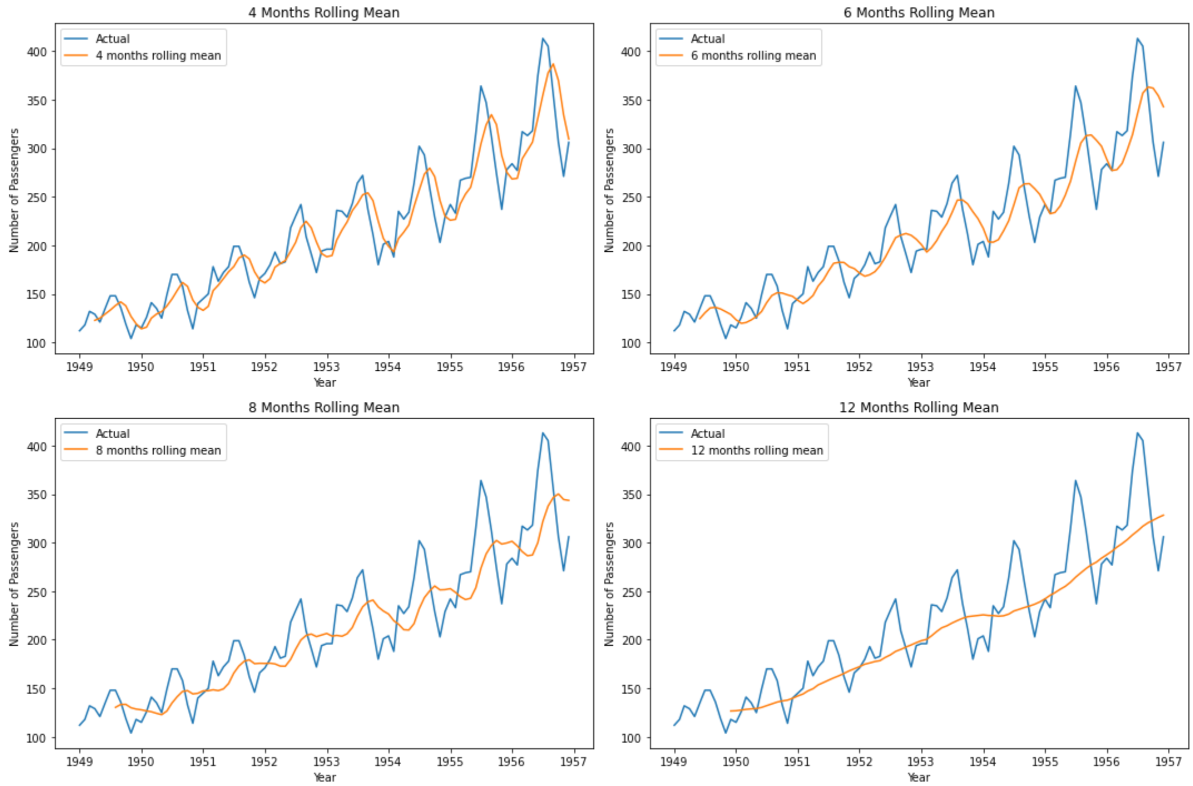
In [19]:
```
decompose = sm.tsa.seasonal_decompose(passengers_count,model='multiplicative',ext
```

In [20]:
```
fig = decompose.plot()
fig.set_figheight(10)
fig.set_figwidth(8)
fig.suptitle('Decomposition of Time Series')
```

Out[20]:
```
Text(0.5, 0.98, 'Decomposition of Time Series')
```



In [21]:
```
fig,axes = plt.subplots(2,2)
fig.set_figheight(10)
fig.set_figwidth(15)
axes[0][0].plot(passengers.index,passengers_count,label='Actual')
axes[0][0].plot(passengers.index,passengers_count.rolling(window=4).mean(),label=
axes[0][0].set_xlabel('Year')
axes[0][0].set_ylabel('Number of Passengers')
axes[0][0].set_title('4 Months Rolling Mean')
axes[0][0].legend(loc='best')


axes[0][1].plot(passengers.index,passengers_count,label='Actual')
axes[0][1].plot(passengers.index,passengers_count.rolling(window=6).mean(),label=
axes[0][1].set_xlabel('Year')
axes[0][1].set_ylabel('Number of Passengers')
axes[0][1].set_title('6 Months Rolling Mean')
axes[0][1].legend(loc='best')



axes[1][0].plot(passengers.index,passengers_count,label='Actual')
axes[1][0].plot(passengers.index,passengers_count.rolling(window=8).mean(),label=
axes[1][0].set_xlabel('Year')
axes[1][0].set_ylabel('Number of Passengers')
axes[1][0].set_title('8 Months Rolling Mean')
axes[1][0].legend(loc='best')


axes[1][1].plot(passengers.index,passengers_count,label='Actual')
axes[1][1].plot(passengers.index,passengers_count.rolling(window=12).mean(),label
axes[1][1].set_xlabel('Year')
axes[1][1].set_ylabel('Number of Passengers')
axes[1][1].set_title('12 Months Rolling Mean')
axes[1][1].legend(loc='best')

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



As we could see in the above plots, 12-month moving average could produce a wrinkle free curve as desired. This on some level is expected since we are using month-wise data for our analysis and there is expected monthly-seasonal effect in our data.

Seasonality

Let us see how many passengers travelled in flights on a month on month basis. We will plot a stacked annual plot to observe seasonality in our data.

In [22]:
```
passengers.head()
```

Out[22]:

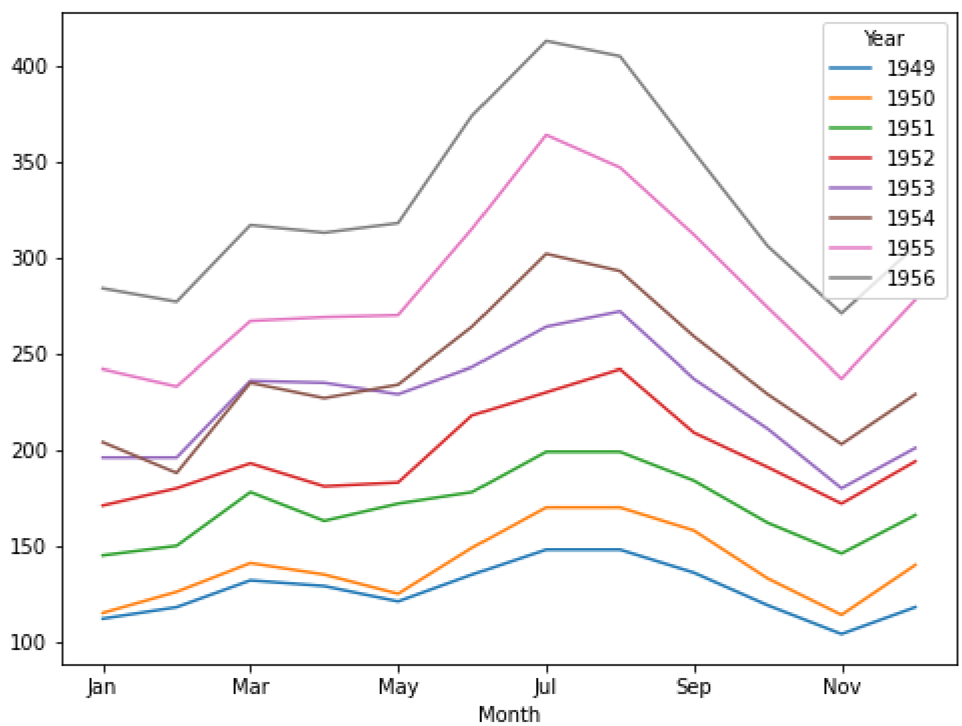
Date	Month	Year	Passengers
1949-01-01	Jan	1949	112
1949-02-01	Feb	1949	118
1949-03-01	Mar	1949	132
1949-04-01	Apr	1949	129
1949-05-01	May	1949	121

In [23]:
```
monthly = pd.pivot_table(data=passengers,values='Passengers',index='Month',columr
monthly = monthly.reindex(index=['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug',
monthly
```

Out[23]:

Year	1949	1950	1951	1952	1953	1954	1955	1956
Month								
Jan	112	115	145	171	196	204	242	284
Feb	118	126	150	180	196	188	233	277
Mar	132	141	178	193	236	235	267	317
Apr	129	135	163	181	235	227	269	313
May	121	125	172	183	229	234	270	318
Jun	135	149	178	218	243	264	315	374
Jul	148	170	199	230	264	302	364	413
Aug	148	170	199	242	272	293	347	405
Sep	136	158	184	209	237	259	312	355
Oct	119	133	162	191	211	229	274	306
Nov	104	114	146	172	180	203	237	271
Dec	118	140	166	194	201	229	278	306

In [24]:
```
monthly.plot(figsize=(8,6))
plt.show()
```

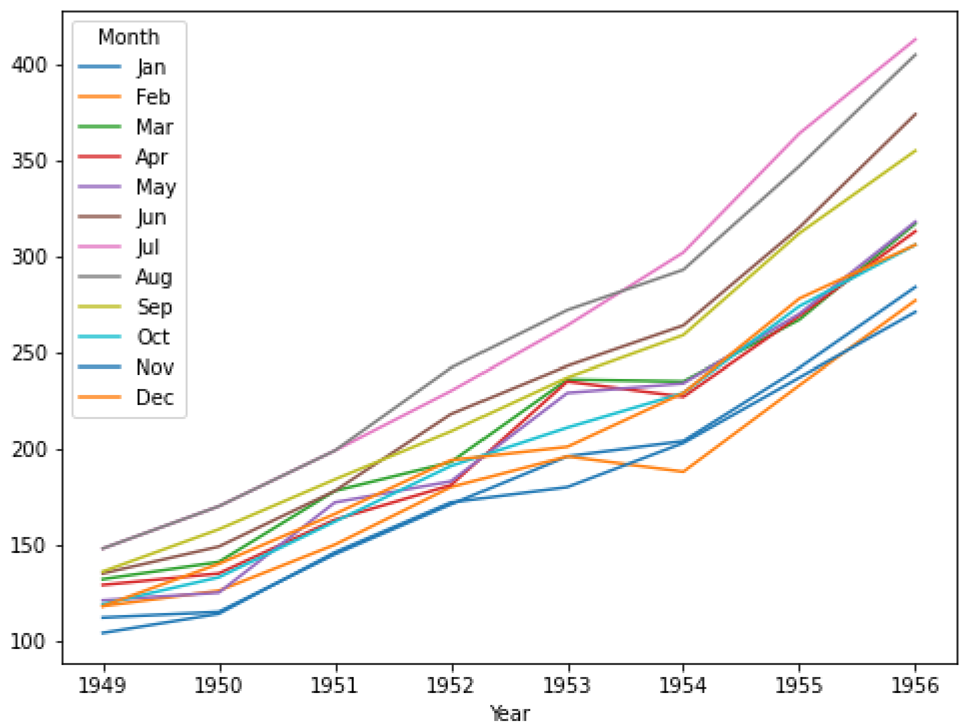


In [25]:
```
yearly = pd.pivot_table(data=passengers,values='Passengers',index='Year',columns=
yearly = yearly[['Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov
yearly
```

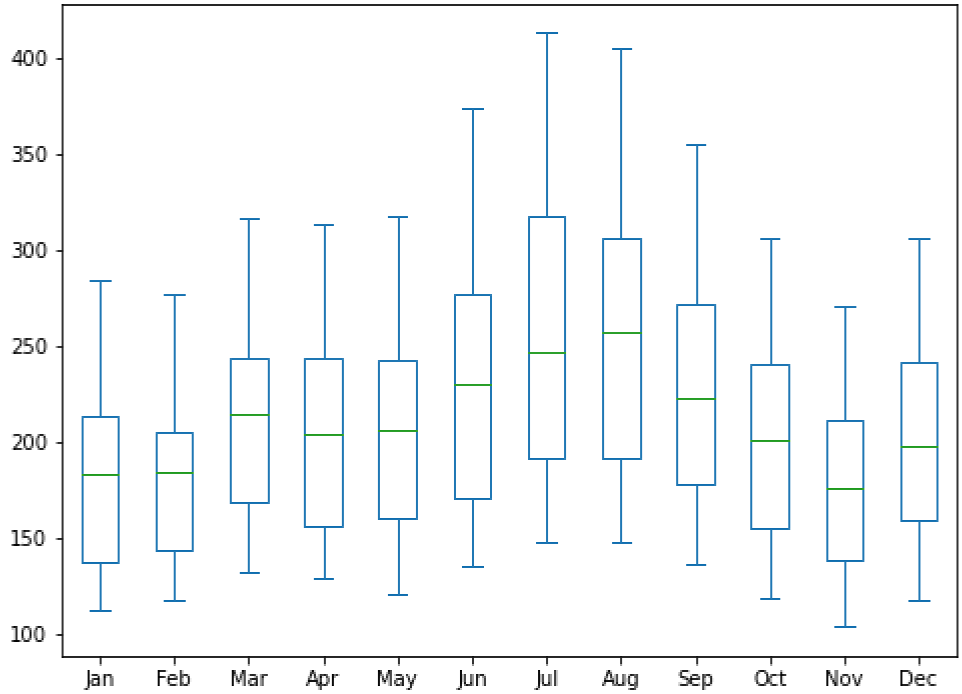
Out[25]:

Month Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1949	112	118	132	129	121	135	148	148	136	119	104	118
1950	115	126	141	135	125	149	170	170	158	133	114	140
1951	145	150	178	163	172	178	199	199	184	162	146	166
1952	171	180	193	181	183	218	230	242	209	191	172	194
1953	196	196	236	235	229	243	264	272	237	211	180	201
1954	204	188	235	227	234	264	302	293	259	229	203	229
1955	242	233	267	269	270	315	364	347	312	274	237	278
1956	284	277	317	313	318	374	413	405	355	306	271	306

In [26]:
```
yearly.plot(figsize=(8,6))
plt.show()
```



In [27]:
```
yearly.plot(kind='box',figsize=(8,6))
plt.show()
```



Important Inferences

The passengers are increasing without fail every year.

July and August are the peak months for passengers.

We can see a seasonal cycle of 12 months where the mean value of each month starts with a increasing trend in the beginning of the year and drops down towards the end of the year. We can see a seasonal effect with a cycle of 12 months.

ARIMA Modelling

Dickey-Fuller Test

In [28]:
```
# Perform Dickey-Fuller test:
from statsmodels.tsa.stattools import adfuller
adfuller(passengers_count)
```

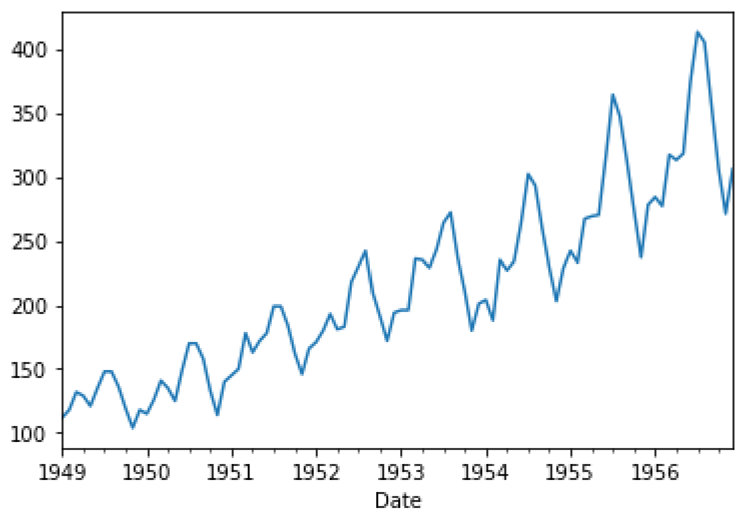
Out[28]:
```
(1.3402479596466985,
 0.9968250481137263,
 12,
 83,
 {'1%': -3.5117123057187376,
  '5%': -2.8970475206326833,
  '10%': -2.5857126912469153},
 626.0084713813505)
```

In [29]:
```
adfuller_results = pd.Series(adfuller(passengers_count)[:4],index=['T stats','p-v
for key,value in adfuller(passengers_count)[4].items():
    adfuller_results['Critical Value'+' '+ key] = value
print(adfuller_results)
```

```
T stats                      1.340248
p-value                      0.996825
lags used                   12.000000
Number of observations      83.000000
Critical Value 1%           -3.511712
Critical Value 5%           -2.897048
Critical Value 10%          -2.585713
dtype: float64
```

The p-value is greater than 0.05 (Coinfidence Interval 95%).

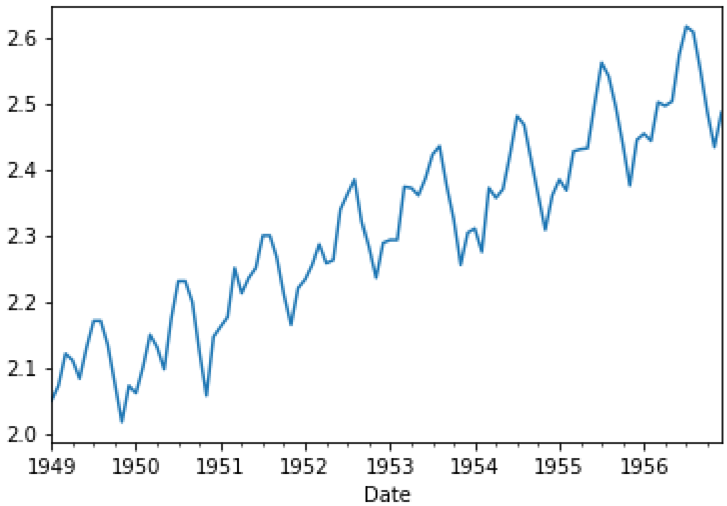
In [30]:
```
passengers_count.plot()
plt.show()
```



Let's do log transformation to convert the TS to stationary TS

In [31]:
```
passengers_log = np.log10(passengers_count)
```

In [32]:
```
passengers_log.plot()
plt.show()
```



In [33]:
```
# Perform Dickey-Fuller test:
from statsmodels.tsa.stattools import adfuller
adfuller(passengers_log)
adfuller_results = pd.Series(adfuller(passengers_log)[:4],index=['T stats','p-val
for key,value in adfuller(passengers_log)[4].items():
    adfuller_results['Critical Value (%s)'%key] = value
print(adfuller_results)
```

```
T stats                      -0.723027
p-value                       0.840695
lags used                    12.000000
Number of observations       83.000000
Critical Value (1%)          -3.511712
Critical Value (5%)          -2.897048
Critical Value (10%)         -2.585713
dtype: float64
```

The p-value is still greater than 0.05 (Coinfidence Interval 95%).

The log transformation has made variance stationary but mean is still increasing.

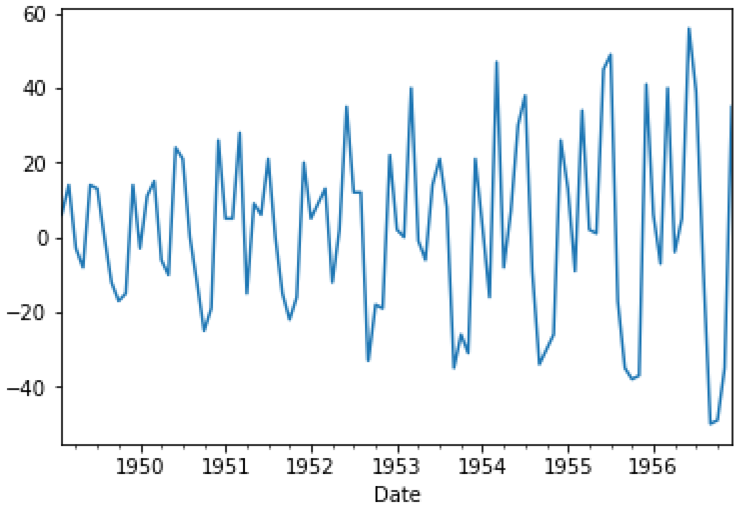
Let's try differencing by 1.

In [34]:
```
diff1 = passengers_count.diff(1)
diff1.head()
```

Out[34]:
```
Date
1949-01-01     NaN
1949-02-01     6.0
1949-03-01    14.0
1949-04-01    -3.0
1949-05-01    -8.0
Name: Passengers, dtype: float64
```

In [35]:
```
diff1.dropna(axis=0,inplace=True)
```

In [36]:
```
diff1.plot()
plt.show()
```



In [37]:
```
# Perform Dickey-Fuller test:
from statsmodels.tsa.stattools import adfuller
adfuller(diff1)
adfuller_results = pd.Series(adfuller(diff1)[:4],index=['T stats','p-value','lags
for key,value in adfuller(diff1)[4].items():
    adfuller_results['Critical Value (%s)'%key] = value
print(adfuller_results)
```

```
T stats                      -2.150002
p-value                       0.224889
lags used                    12.000000
Number of observations       82.000000
Critical Value (1%)          -3.512738
Critical Value (5%)          -2.897490
Critical Value (10%)         -2.585949
dtype: float64
```

The p-value is still greater than 0.05 (Coinfidence Interval 95%).

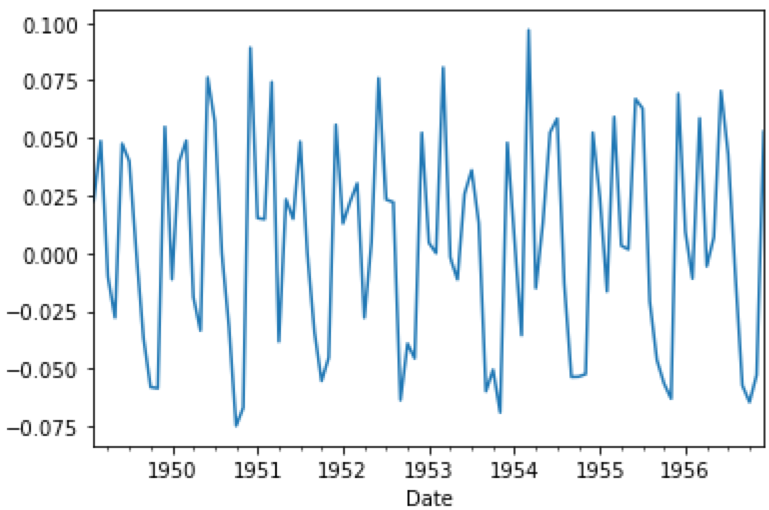
The differencing by 1 has made mean stationary but variance is changing.

Let's try differencing by 1 on the log transformation.

In [38]:
```
log_diff1 = passengers_log.diff(1)
log_diff1.head()
```

Out[38]:
```
Date
1949-01-01         NaN
1949-02-01    0.022664
1949-03-01    0.048692
1949-04-01   -0.009984
1949-05-01   -0.027804
Name: Passengers, dtype: float64
```

In [39]:
```
log_diff1.dropna(axis=0,inplace=True)
log_diff1.plot()
plt.show()
```



In [40]:
```
# Perform Dickey-Fuller test:
from statsmodels.tsa.stattools import adfuller
adfuller(log_diff1)
adfuller_results = pd.Series(adfuller(log_diff1)[:4],index=['T stats','p-value','
for key,value in adfuller(log_diff1)[4].items():
    adfuller_results['Critical Value (%s)'%key] = value
print(adfuller_results)
```

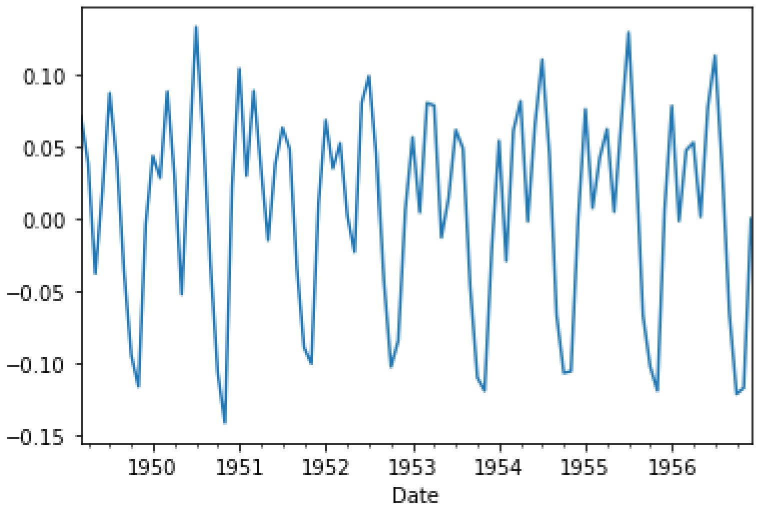
```
T stats                   -2.670823
p-value                    0.079225
lags used                 12.000000
Number of observations    82.000000
Critical Value (1%)       -3.512738
Critical Value (5%)       -2.897490
Critical Value (10%)      -2.585949
dtype: float64
```

p-value is still greateer than 0.05.

In [41]:
```
log_diff2 = passengers_log.diff(2)
log_diff2.head()
```

Out[41]:
```
Date
1949-01-01          NaN
1949-02-01          NaN
1949-03-01     0.071356
1949-04-01     0.038708
1949-05-01    -0.037789
Name: Passengers, dtype: float64
```

In [42]:
```
log_diff2.dropna(axis=0,inplace=True)
log_diff2.plot()
plt.show()
```



In [43]:
```
# Perform Dickey-Fuller test:
from statsmodels.tsa.stattools import adfuller
adfuller(log_diff2)
adfuller_results = pd.Series(adfuller(log_diff2)[:4],index=['T stats','p-value','
for key,value in adfuller(log_diff2)[4].items():
    adfuller_results['Critical Value (%s)'%key] = value
print(adfuller_results)
```

```
T stats                    -2.787629
p-value                     0.060063
lags used                  11.000000
Number of observations     82.000000
Critical Value (1%)        -3.512738
Critical Value (5%)        -2.897490
Critical Value (10%)       -2.585949
dtype: float64
```

p-value is less than 0.05. In this case we reject null hypothesis that TS is non stationary.

Iterate the process to find the best values for p, d, q and P, D, Q

In [44]:
```
import itertools
# Define the p, d and q parameters to take any value between 0 and 2
p = q = range(0, 3)
d = range(0,1)
# Generate all different combinations of p, d and q triplets
pdq = list(itertools.product(p, d, q))
pdq
```

Out[44]:
```
[(0, 0, 0),
 (0, 0, 1),
 (0, 0, 2),
 (1, 0, 0),
 (1, 0, 1),
 (1, 0, 2),
 (2, 0, 0),
 (2, 0, 1),
 (2, 0, 2)]
```

In [45]:
```
# Generate all different combinations of seasonal p, q and q triplets
D = range(0,3)
P = Q = range(0, 3)
seasonal_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(P, D, Q))]
seasonal_pdq
```

Out[45]:
```
[(0, 0, 0, 12),
 (0, 0, 1, 12),
 (0, 0, 2, 12),
 (0, 1, 0, 12),
 (0, 1, 1, 12),
 (0, 1, 2, 12),
 (0, 2, 0, 12),
 (0, 2, 1, 12),
 (0, 2, 2, 12),
 (1, 0, 0, 12),
 (1, 0, 1, 12),
 (1, 0, 2, 12),
 (1, 1, 0, 12),
 (1, 1, 1, 12),
 (1, 1, 2, 12),
 (1, 2, 0, 12),
 (1, 2, 1, 12),
 (1, 2, 2, 12),
 (2, 0, 0, 12),
 (2, 0, 1, 12),
 (2, 0, 2, 12),
 (2, 1, 0, 12),
 (2, 1, 1, 12),
 (2, 1, 2, 12),
 (2, 2, 0, 12),
 (2, 2, 1, 12),
 (2, 2, 2, 12)]
```

In [46]:
```
import sys
warnings.filterwarnings("ignore") # specify to ignore warning messages

best_aic = np.inf
best_pdq = None
best_seasonal_pdq = None
temp_model = None

for param in pdq:
    for param_seasonal in seasonal_pdq:

        try:
            temp_model = sm.tsa.statespace.SARIMAX(log_diff2,
                                                 order = param,
                                                 seasonal_order = param_seasonal,
                                                 enforce_stationarity=False,
                                                 enforce_invertibility=False)
            results = temp_model.fit()

           # print("SARIMAX{}x{}12 - AIC:{}".format(param, param_seasonal, result
            if results.aic < best_aic:
                best_aic = results.aic
                best_pdq = param
                best_seasonal_pdq = param_seasonal
        except:
            #print("Unexpected error:", sys.exc_info()[0])
            continue
print("Best SARIMAX{}x{}12 model - AIC:{}".format(best_pdq, best_seasonal_pdq, be
```

```
Best SARIMAX(1, 0, 1)x(1, 0, 1, 12)12 model - AIC:-401.1413191266139
```

Best SARIMAX(1, 0, 1)x(1, 0, 1, 12)12 model - AIC:-671.0386830029513 The best fit model is selected based on Akaike Information Criterion (AIC) , and Bayesian Information Criterion (BIC) values. The idea is to choose a model with minimum AIC and BIC values.

Predict sales on in-sample date using the best fit ARIMA model

The next step is to predict passengers for in-sample data and find out how close is the model prediction on the in-sample data to the actual truth.

In [47]:
```
sarima = sm.tsa.statespace.SARIMAX(log_diff2,order=(1,0,1),seasonal_order=(1,0,1,
sarima_results = sarima.fit()
print(sarima_results.summary())
```

```
                                      SARIMAX Results
==============================================================================
===========
Dep. Variable:                           Passengers   No. Observations:
94
Model:             SARIMAX(1, 0, 1)x(1, 0, 1, 12)   Log Likelihood
205.571
Date:                              Sun, 30 Jan 2022   AIC
-401.141
Time:                                      12:45:22   BIC
-389.231
Sample:                                  03-01-1949   HQIC
-396.366
                                       - 12-01-1956
Covariance Type:                                opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.3152      0.118     -2.673      0.008      -0.546      -0.084
ma.L1          1.0001     43.412      0.023      0.982     -84.086      86.086
ar.S.L12       0.9976      0.024     41.513      0.000       0.950       1.045
ma.S.L12      -0.6116      0.142     -4.299      0.000      -0.890      -0.333
sigma2         0.0003      0.013      0.023      0.982      -0.025       0.026
==============================================================================
====
Ljung-Box (L1) (Q):                   0.05   Jarque-Bera (JB):
0.00
Prob(Q):                              0.83   Prob(JB):
1.00
Heteroskedasticity (H):               0.33   Skew:                           -
0.01
Prob(H) (two-sided):                  0.00   Kurtosis:
3.02
==============================================================================
====

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

In [48]:
```
passengers_count.tail(15)
```

Out[48]:
```
Date
1955-10-01    274
1955-11-01    237
1955-12-01    278
1956-01-01    284
1956-02-01    277
1956-03-01    317
1956-04-01    313
1956-05-01    318
1956-06-01    374
1956-07-01    413
1956-08-01    405
1956-09-01    355
1956-10-01    306
1956-11-01    271
1956-12-01    306
Name: Passengers, dtype: int64
```

In [49]:
```
prediction = sarima_results.get_prediction(start=pd.to_datetime('1960-01-01'),ful
prediction.predicted_mean
```

Out[49]:
```
1960-01-01    0.069703
Freq: MS, dtype: float64
```

In [50]:
```
predicted_values = np.power(10,prediction.predicted_mean)
predicted_values
```

Out[50]:
```
1960-01-01    1.174095
Freq: MS, dtype: float64
```

In [51]:
```
actual = passengers_count['1960-01-01':]
actual
```

Out[51]:
```
Series([], Name: Passengers, dtype: int64)
```

In [52]:
```
# mean absolute percentage error
mape = np.mean(np.abs(actual - predicted_values)/actual)
mape
```

Out[52]:
```
nan
```

In [53]:
```
# mean square error
mse = np.mean((actual - predicted_values) ** 2)
mse
```

Out[53]:
```
nan
```

Forecast sales using the best fit ARIMA model

The next step is to foercast passengers for next 3 years i.e. for 1961, 1962, and 1963 through the above model.

In [54]:
```
# Get forecast 36 steps (3 years) ahead in future
n_steps = 36
pred_uc_99 = sarima_results.get_forecast(steps=36, alpha=0.01) # alpha=0.01 signi
pred_uc_95 = sarima_results.get_forecast(steps=36, alpha=0.05) # alpha=0.05 95% C

# Get confidence intervals 95% & 99% of the forecasts
pred_ci_99 = pred_uc_99.conf_int()
pred_ci_95 = pred_uc_95.conf_int()
pred_ci_99.head()
```

Out[54]:

	lower Passengers	upper Passengers
1957-01-01	0.034234	0.102566
1957-02-01	-0.038543	0.043521
1957-03-01	0.012618	0.095923
1957-04-01	0.015624	0.099040
1957-05-01	-0.045416	0.038007

In [55]:
```
pred_ci_95.head()
```

Out[55]:

	lower Passengers	upper Passengers
1957-01-01	0.034234	0.102566
1957-02-01	-0.038543	0.043521
1957-03-01	0.012618	0.095923
1957-04-01	0.015624	0.099040
1957-05-01	-0.045416	0.038007

In [56]:
```
n_steps = 36
idx = pd.date_range(passengers_count.index[-1], periods=n_steps, freq='MS')
fc_95 = pd.DataFrame(np.column_stack([np.power(10, pred_uc_95.predicted_mean), np
                     index=idx, columns=['forecast', 'lower_ci_95', 'upper_ci_95'
fc_99 = pd.DataFrame(np.column_stack([np.power(10, pred_ci_99)]),
                     index=idx, columns=['lower_ci_99', 'upper_ci_99'])
fc_95.head()
```

Out[56]:

	forecast	lower_ci_95	upper_ci_95
1956-12-01	1.170577	1.082017	1.266386
1957-01-01	1.005748	0.915076	1.105404
1957-02-01	1.133106	1.029481	1.247162
1957-03-01	1.141122	1.036630	1.256147
1957-04-01	0.991506	0.900708	1.091458

In [57]:
```
fc_99.head()
```

Out[57]:

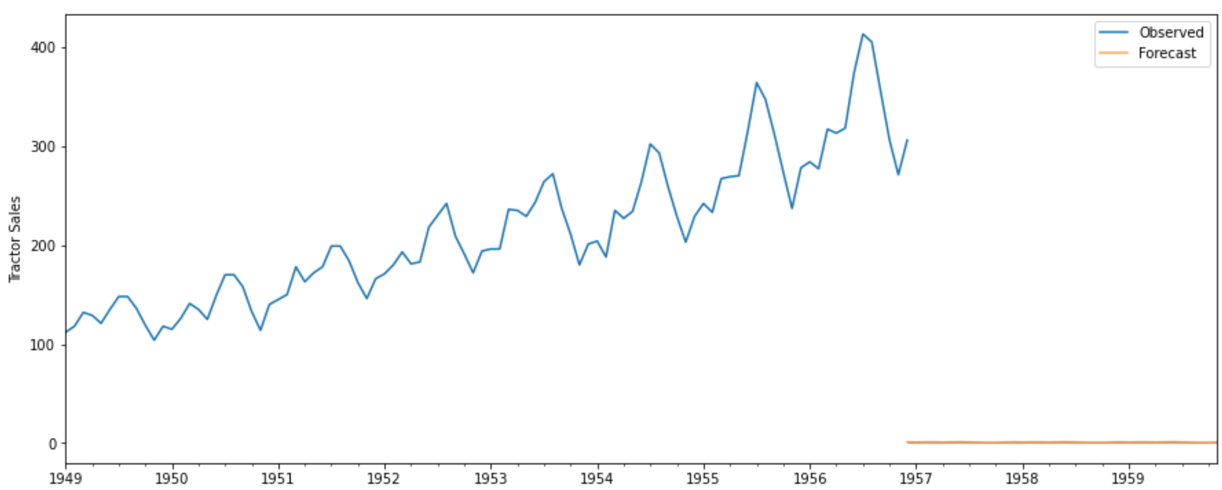
	lower_ci_99	upper_ci_99
1956-12-01	1.082017	1.266386
1957-01-01	0.915076	1.105404
1957-02-01	1.029481	1.247162
1957-03-01	1.036630	1.256147
1957-04-01	0.900708	1.091458

In [58]:
```
fc_all = fc_95.combine_first(fc_99)
fc_all = fc_all[['forecast', 'lower_ci_95', 'upper_ci_95', 'lower_ci_99', 'upper_
fc_all.head()
```

Out[58]:

	forecast	lower_ci_95	upper_ci_95	lower_ci_99	upper_ci_99
1956-12-01	1.170577	1.082017	1.266386	1.082017	1.266386
1957-01-01	1.005748	0.915076	1.105404	0.915076	1.105404
1957-02-01	1.133106	1.029481	1.247162	1.029481	1.247162
1957-03-01	1.141122	1.036630	1.256147	1.036630	1.256147
1957-04-01	0.991506	0.900708	1.091458	0.900708	1.091458

In [59]:
```
# plot the forecast along with the confidence band
axis = passengers_count.plot(label='Observed', figsize=(15, 6))
fc_all['forecast'].plot(ax=axis, label='Forecast', alpha=0.7)
#axis.fill_between(fc_all.index, fc_all['lower_ci_95'], fc_all['upper_ci_95'], co
axis.fill_between(fc_all.index, fc_all['lower_ci_99'], fc_all['upper_ci_99'], col
axis.set_xlabel('Years')
axis.set_ylabel('Tractor Sales')
plt.legend(loc='best')
plt.show()
```

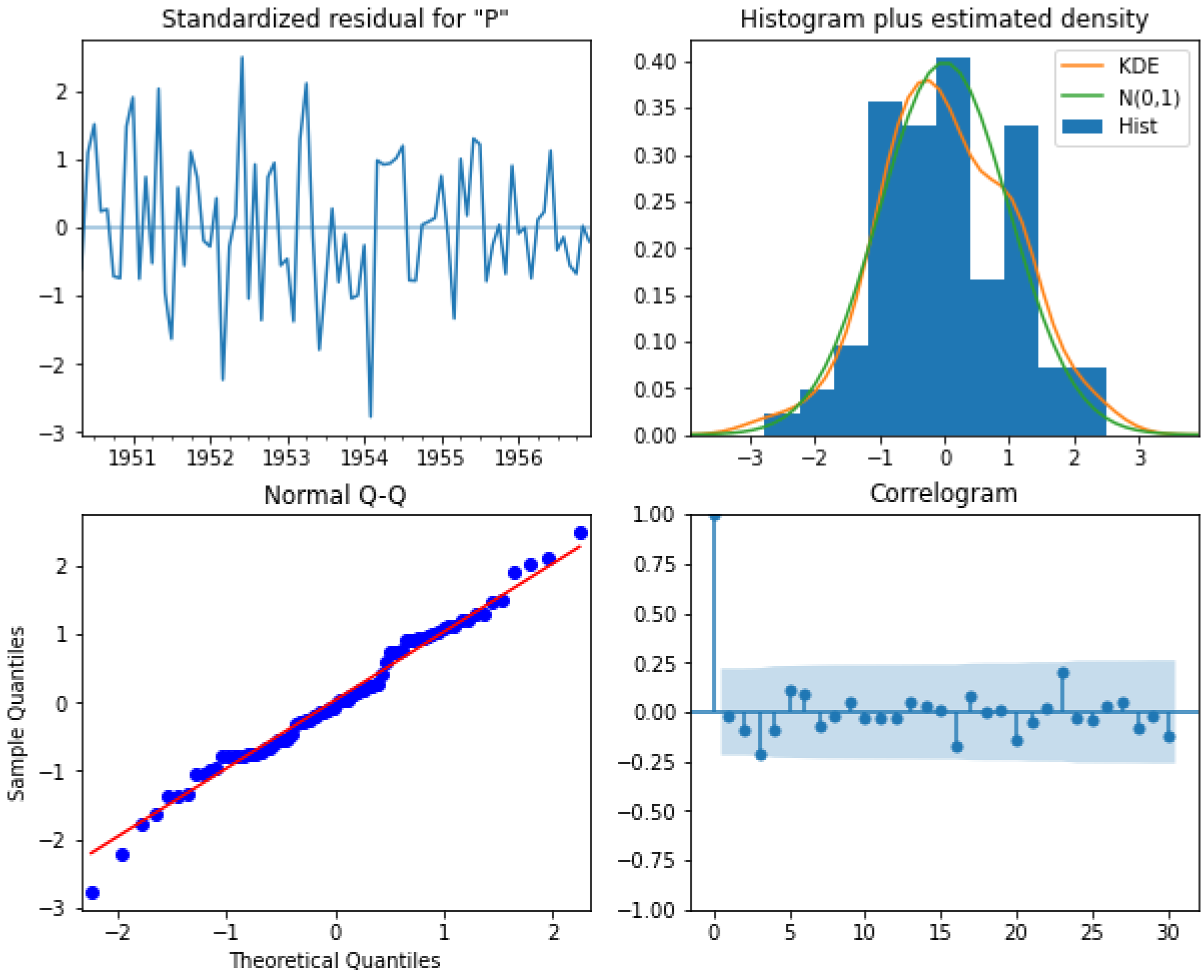


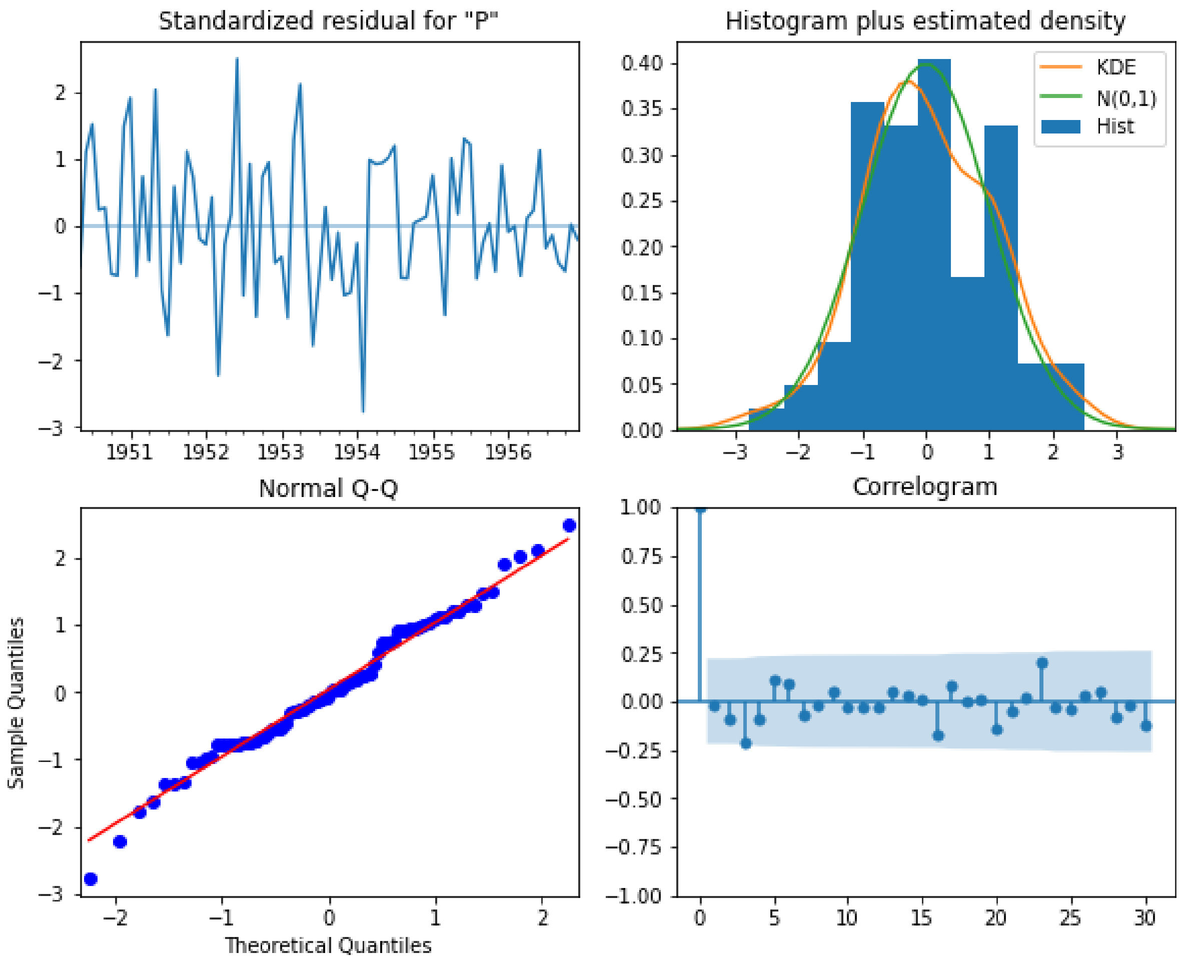
Diagnostics

1. Errors follows normality
2. Errors should not have auto correlation (ACF, no spikes beyond the limits)
3. Errors should not have any spikes (if the spikes are present, that particular time period, model didn't predict propoerly)

In [60]:
```
sarima_results.plot_diagnostics(lags=30,figsize=(10,8))
```

Out[60]:




Standardized residual for "P"
Histogram plus estimated density
KDE
N(0,1)
Hist
Normal Q-Q
Sample Quantiles
Theoretical Quantiles
Correlogram

In [ ]: