Climate change

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1 Analysing and predicting climate change in Texas, US

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Purpose: Analysing temperature to prectict climate change in Texas, US - Climate change and global warming have a direct impact on agriculture. Here I whow a brief analysis of temperature change and predict the tempeature in future in Texas, US.

Data: Downloaded from NOAA (National centers for environmental information) from 1920 until now.

To do: - Exploratory data analysis - Data summary - Group data by STATION - Missing values - Basic analysis of some specific features - Statistical analyses - Boxplot - Histplot - Stationarity - Autocorrelation - Seasonality - Prediction using fbprophet - ***Summary and suggestions for WorldCover.***

```
In [74]: import numpy as np
         import pandas as pd
         import zipfile
         import matplotlib.pyplot as plt
         import matplotlib.animation as animation
         import re
         import json
         import pickle
         import datetime
         import os
         import seaborn as sns
```

```
In [256]: import warnings
          warnings.filterwarnings('ignore')
```

```
In [5]: from statsmodels.graphics.tsaplots import plot_acf
```

2 Loading data

```
In [6]: data_dir = '/home/duc/Duc/Data/climate/'
```

```
In [7]: df = pd.read_csv(data_dir + 'request/data1.csv')
        # Converting temperature from Fahreneit to Celsius
        df['TMAX'] = (df['TMAX'] - 32)*(5/9)
        df['TMIN'] = (df['TMIN'] - 32)*(5/9)
```

```
In [8]: df.shape
```

```
Out[8]: (96682, 46)
```

```
In [9]: # df.head()
```

3 Exploratory data analysis

```
In [10]: df.columns
```

```
Out[10]: Index(['STATION', 'NAME', 'LATITUDE', 'LONGITUDE', 'ELEVATION', 'DATE', 'DAPR',
                'DAPR_ATTRIBUTES', 'DASF', 'DASF_ATTRIBUTES', 'MDPR', 'MDPR_ATTRIBUTES',
                'MDSF', 'MDSF_ATTRIBUTES', 'PRCP', 'PRCP_ATTRIBUTES', 'SNOW',
                'SNOW_ATTRIBUTES', 'SNWD', 'SNWD_ATTRIBUTES', 'TAVG', 'TAVG_ATTRIBUTES',
                'TMAX', 'TMAX_ATTRIBUTES', 'TMIN', 'TMIN_ATTRIBUTES', 'TOBS',
                'TOBS_ATTRIBUTES', 'WT01', 'WT01_ATTRIBUTES', 'WT03', 'WT03_ATTRIBUTES',
                'WT04', 'WT04_ATTRIBUTES', 'WT05', 'WT05_ATTRIBUTES', 'WT06',
                'WT06_ATTRIBUTES', 'WT07', 'WT07_ATTRIBUTES', 'WT10', 'WT10_ATTRIBUTES',
                'WT11', 'WT11_ATTRIBUTES', 'WT14', 'WT14_ATTRIBUTES'],
               dtype='object')
```

```
In [11]: pd.unique(df['STATION'])
```

```
Out[11]: array(['USC00416108', 'USC00416119', 'USR0000TLND', 'US1TXMRR002',
                'USC00416649', 'USC00419826', 'US1TXTI0001', 'USC00416114',
                'USC00417066', 'US1TXTI0003'], dtype=object)
```

```
In [12]: # Quick check information of the columns
         df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 96682 entries, 0 to 96681
Data columns (total 46 columns):
STATION            96682 non-null object
NAME               96682 non-null object
LATITUDE           96682 non-null float64
LONGITUDE          96682 non-null float64
ELEVATION          96682 non-null float64
DATE               96682 non-null object
DAPR               411 non-null float64
DAPR_ATTRIBUTES    411 non-null object
DASF               3 non-null float64
DASF_ATTRIBUTES    3 non-null object
MDPR               418 non-null float64
MDPR_ATTRIBUTES    418 non-null object
MDSF               3 non-null float64
MDSF_ATTRIBUTES    3 non-null object
PRCP               89571 non-null float64
```

```
PRCP_ATTRIBUTES    89571 non-null object
SNOW               87088 non-null float64
SNOW_ATTRIBUTES    87088 non-null object
SNWD               85645 non-null float64
SNWD_ATTRIBUTES    85645 non-null object
TAVG               6251 non-null float64
TAVG_ATTRIBUTES    6251 non-null object
TMAX               67745 non-null float64
TMAX_ATTRIBUTES    67745 non-null object
TMIN               67651 non-null float64
TMIN_ATTRIBUTES    67651 non-null object
TOBS               54079 non-null float64
TOBS_ATTRIBUTES    54079 non-null object
WT01               729 non-null float64
WT01_ATTRIBUTES    729 non-null object
WT03               1781 non-null float64
WT03_ATTRIBUTES    1781 non-null object
WT04               177 non-null float64
WT04_ATTRIBUTES    177 non-null object
WT05               128 non-null float64
WT05_ATTRIBUTES    128 non-null object
WT06               96 non-null float64
WT06_ATTRIBUTES    96 non-null object
WT07               4 non-null float64
WT07_ATTRIBUTES    4 non-null object
WT10               2 non-null float64
WT10_ATTRIBUTES    2 non-null object
WT11               99 non-null float64
WT11_ATTRIBUTES    99 non-null object
WT14               13 non-null float64
WT14_ATTRIBUTES    13 non-null object
dtypes: float64(23), object(23)
memory usage: 33.9+ MB
```

3.1 Missing values

```
In [13]: for station in pd.unique(df['STATION']):
             df_test = df[df.STATION == station]
             df_test = df_test.loc[:, ['TMIN', 'TMAX', 'SNOW']]
         #     df_test.head()
             print('STATION: ',station, 'length',df_test.shape[0], 'missing TMAX: ',  df_test[
         #     print('STATION: ',station, 'length',df_test.shape[0], 'missing SNOW: ',  df_tes
```

```
STATION:  USC00416108 length 35850 missing TMAX:  345
STATION:  USC00416119 length 19560 missing TMAX:  115
```

```
STATION:  USR0000TLND length 6251 missing TMAX:  0
STATION:  US1TXMRR002 length 500 missing TMAX:  500
STATION:  USC00416649 length 2495 missing TMAX:  37
STATION:  USC00419826 length 6149 missing TMAX:  6149
STATION:  US1TXTI0001 length 1365 missing TMAX:  1365
STATION:  USC00416114 length 546 missing TMAX:  546
STATION:  USC00417066 length 23472 missing TMAX:  19386
STATION:  US1TXTI0003 length 494 missing TMAX:  494
```

Many stationsbecause have NO temperature data such as US1TXMRR002, USC00419826, US1TXTI0001, USC00416114, and US1TXTI0003. We can confirm it by a boxplot

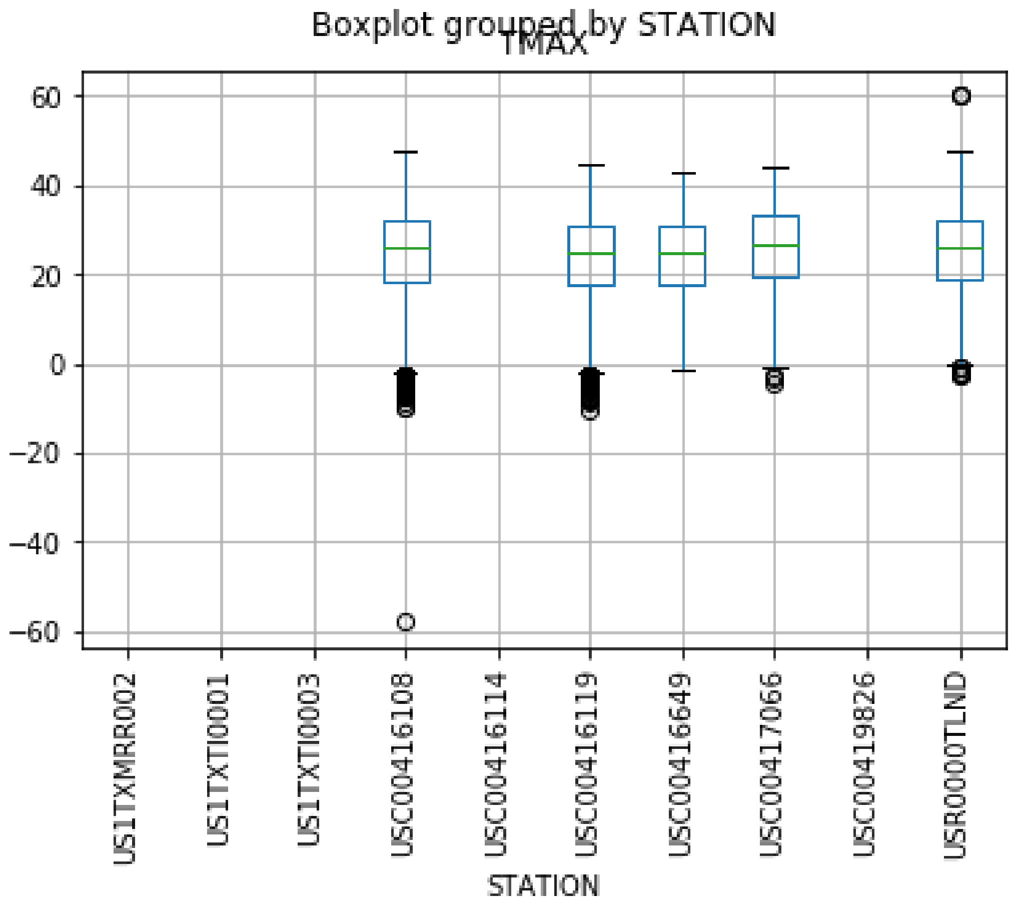
In [14]:
```
# If we want to check the missing values of each colummn we run these lines
# for col in df.columns:
#     print('Total missing rows of columns',col, ':',  df[col].isnull().sum())
```

In [15]:
```
df.loc[:, ['TMIN', 'TMAX']].describe()
```

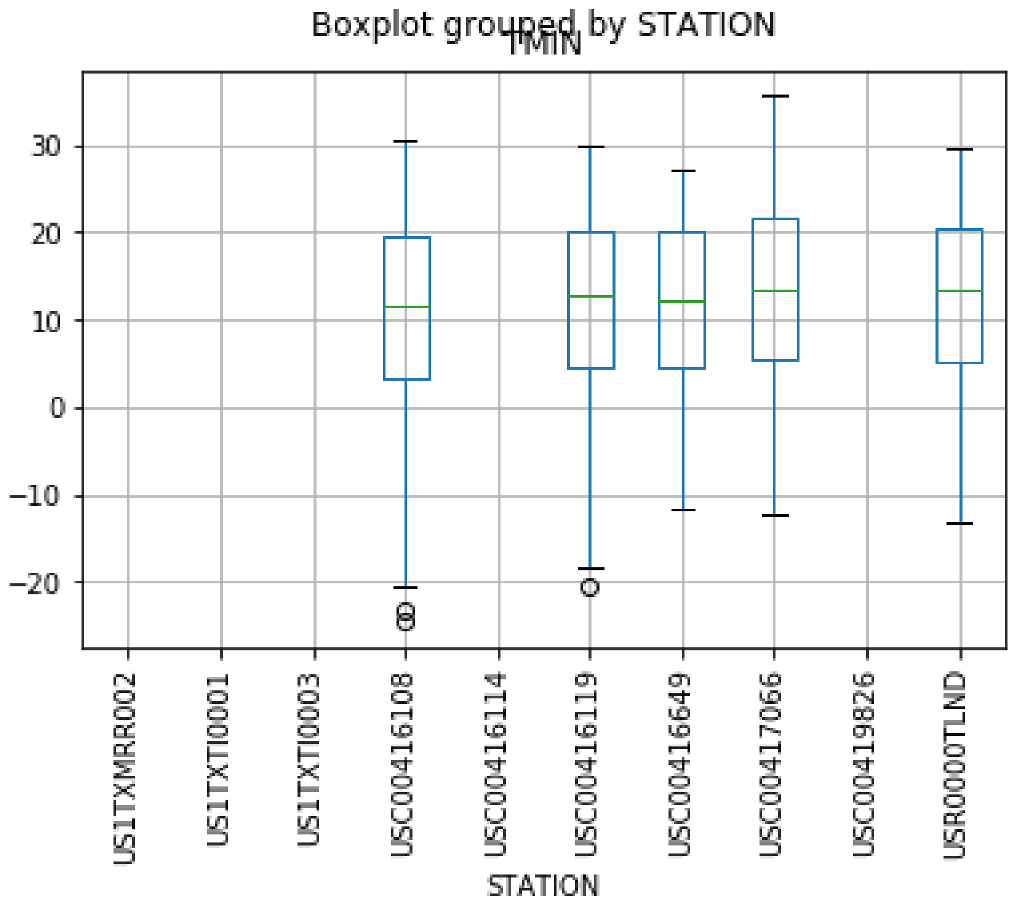
Out[15]:

	TMIN	TMAX
count	67651.000000	67745.000000
mean	11.309827	24.506450
std	9.070998	9.254719
min	-24.444444	-57.777778
25%	3.888889	18.333333
50%	12.222222	25.555556
75%	19.444444	32.222222
max	35.555556	60.000000

In [16]:
```
df.boxplot(rot = 90, by = 'STATION', column = ['TMAX'])
plt.show()
```

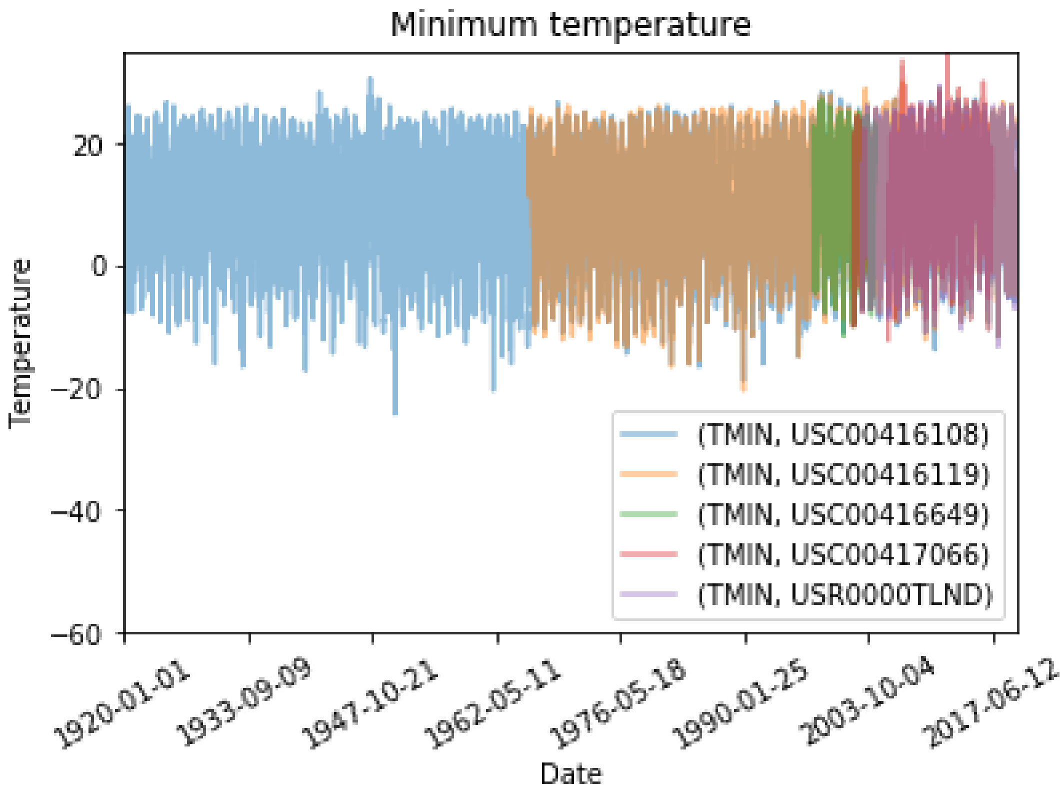



```
In [17]: df.boxplot(rot = 90, by = 'STATION', column = ['TMIN'])
         plt.show()
```

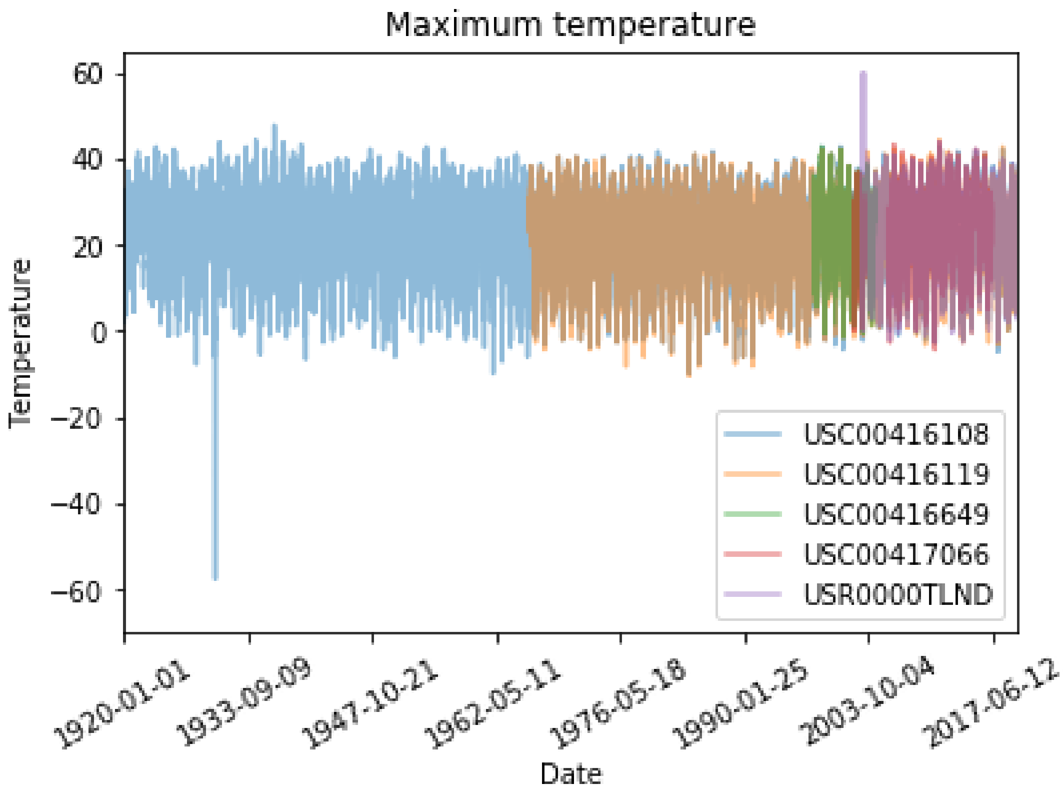



```
In [18]: df_group = df.pivot_table(index = 'DATE', columns = ['STATION'], values = ['TMAX', 'TI

In [19]: df_group.plot(alpha = 0.5, rot = 30, y = ['TMIN'])
         # plt.legend(loc = 'top right', ncol = 2)
         plt.title('Minimum temperature')
         plt.xlabel('Date')
         plt.ylabel('Temperature')
         plt.ylim(-60,35)
         plt.legend(loc = 'lower right')
         plt.show()
```




```
In [20]: df_group.plot(alpha = 0.5, rot = 30, y = 'TMAX')
         plt.title('Maximum temperature')
         plt.xlabel('Date')
         plt.ylabel('Temperature')
         plt.ylim(-70,65)
         # plt.xlim(2000,5000)
         plt.legend(loc = 'lower right')
         plt.show()
```



A boxplot of TMAX shows clear outliers of the stations USC00416108 and USR0000TLND. They were probably typos, we can remove or replace them by other values. It is reasonable to replacce it by the temperture of a day before

We observed that some stations have been newly installed that why, while some old ones have been removed. In addition, we see the temperature values of all stations are more or less the same. Therefore, by taking the average values from all stations, we might have a complete data of temperature for Texas

4 Temperature data

In [178]:
```
# Assuming temperature in Texas is the mean values of all available stations
df_Temp = pd.DataFrame(df_group['TMIN'].mean(axis = 1), columns = ['TMIN'])
df_Temp['TMAX'] = df_group['TMAX'].mean(axis = 1)
df_Temp = df_Temp.set_index(pd.DatetimeIndex(df_Temp.index))
# filling the missing data by the next values
df_Temp = df_Temp.fillna(method = 'bfill')
```

In [179]:
```
# df_Temp.info()
```

In [180]:
```
df_Temp.head()
```

Out[180]:
```
                TMIN       TMAX
DATE
```

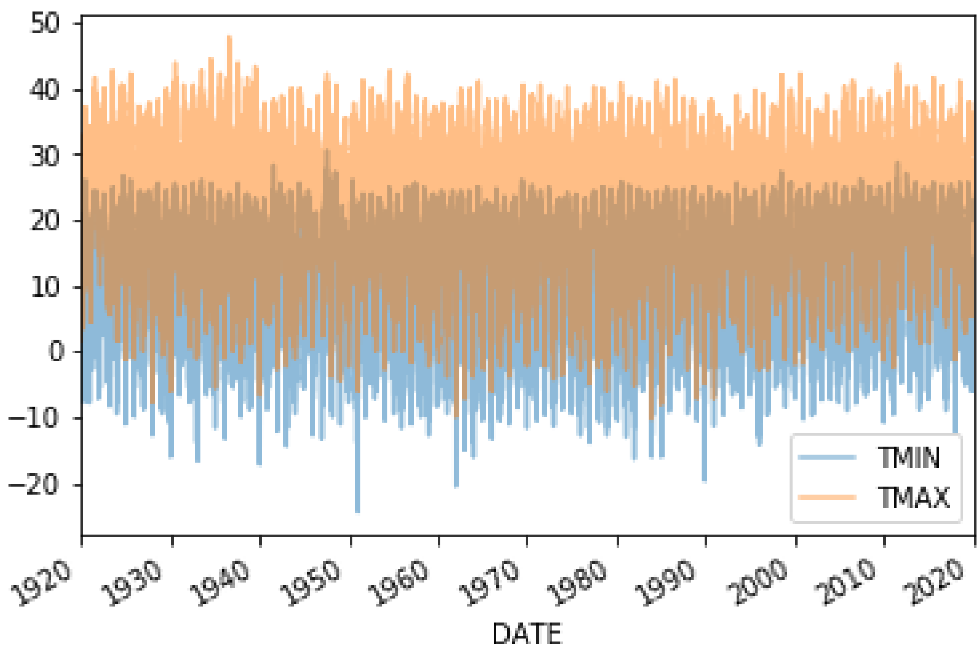
```
1920-01-01 -2.222222  10.000000
1920-01-02 -5.000000  11.111111
1920-01-03 -2.222222  12.777778
1920-01-04 -2.777778  13.888889
1920-01-05 -2.777778   6.111111
```

```
In [223]: # create final data for analysis
          df_final = df_Temp.copy()
```

```
In [224]: # df_final.shape
```

```
In [225]: # Replace the temperature which has the absolute value larger than 50 by the value o
          for idx in range(len(df_final['TMAX'])):
              if np.abs(df_final['TMAX'][idx]) > 50:
                  df_final['TMAX'][idx] = df_final['TMAX'][idx-1]
          df_final['Delta_T'] =  df_final['TMAX'] - df_final['TMIN']
```

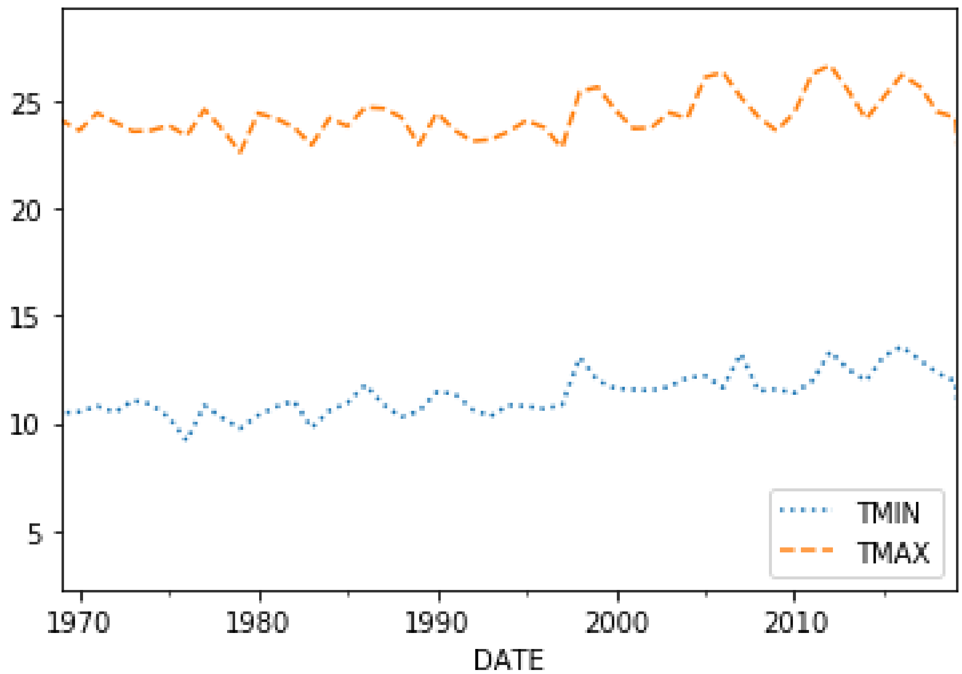
```
In [294]: df_final.plot(y = ['TMIN', 'TMAX'], rot = 30, alpha = 0.5)
          plt.legend(loc = 'lower right')
          plt.show()
```



5 Resampling data

It is often useful to resample our time series data to a lower or higher frequency. Resampling to a lower frequency (downsampling) usually involves an aggregation operation — for example, computing monthly mean temprature from daily data. We will focus here on downsampling, exploring how it can help us analyze our temperture data on various time scales.We can then apply an aggregation method such as mean(), median(), sum(), etc., to the data group for each time bin.

```
In [302]: # Resampling data of the last 50 years.
          weekly = df_final.loc[:, ['TMIN', 'TMAX']].resample('Y').mean()
          weekly.plot(style = [':', '--', '-'])
          plt.legend(loc = 'lower right')
          plt.xlim(datetime.date(1969,1,1), datetime.date(2019,1,1))
          plt.show()
```

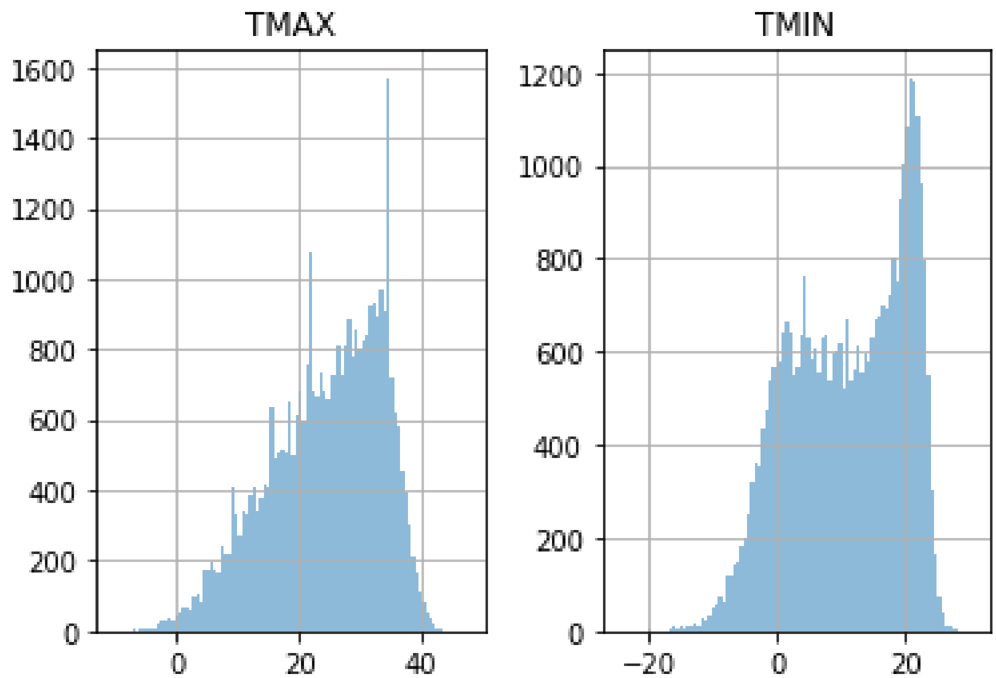


We observe a sligth increasing of both TMIN and TMAX over 100 years

6 Statistical analyses

6.1 Basic Statistics

```
In [233]: # Histogram plot
          df_final.loc[:, ['TMIN', 'TMAX']].hist(bins = 100, alpha = 0.5)
          plt.show()
```



We observe 2 peaks of TMIN. Therefore, we can conclude that the temperature during the night (TMIN) is very different from winter to summer. While the (almost) Gaussion distribution of temperature during the day (TMAX) suggests that changes gradually.

6.2 Stationarity

Stationarity is an important characteristic of time series. A time series is said to be stationary if its statistical properties do not change over time. In other words, it has constant mean and variance, and covariance is independent of time.

```
In [306]: from statsmodels.tsa.stattools import adfuller
          def adf_test(timeseries):
              #Perform Dickey-Fuller test:
              print ('Results of Dickey-Fuller Test:')
              dftest = adfuller(timeseries, autolag='AIC')
              dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used'
              for key,value in dftest[4].items():
                 dfoutput['Critical Value (%s)'%key] = value
              print (dfoutput)
```

```
In [307]: #apply adf test on the series
          adf_test(df_final['TMAX'])
```

```
Results of Dickey-Fuller Test:
Test Statistic                 -1.609061e+01
p-value                         5.258307e-29
```

```
#Lags Used                          5.300000e+01
Number of Observations Used     3.592900e+04
Critical Value (1%)            -3.430532e+00
Critical Value (5%)            -2.861620e+00
Critical Value (10%)           -2.566813e+00
dtype: float64
```

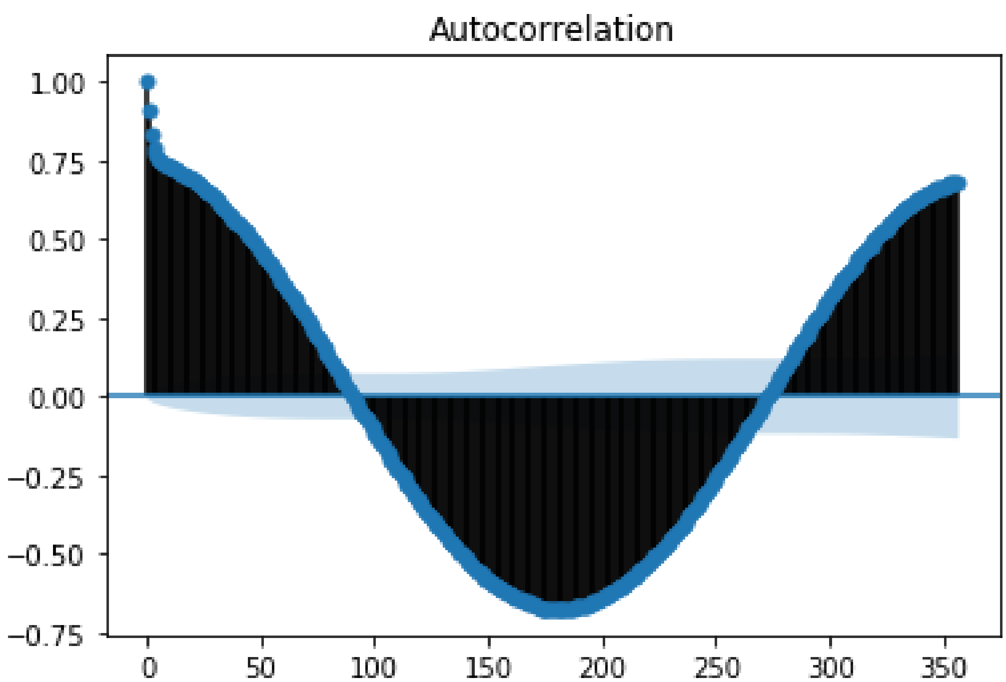
The test statistic is greater than the critical value at all levels, and p-values is very small. We, therefore, fail to reject the null hypothesis. That means means the series is NOT stationary. We can conclude that both TMIN and TMAX change over 100 years.

6.3 Autocorrelation

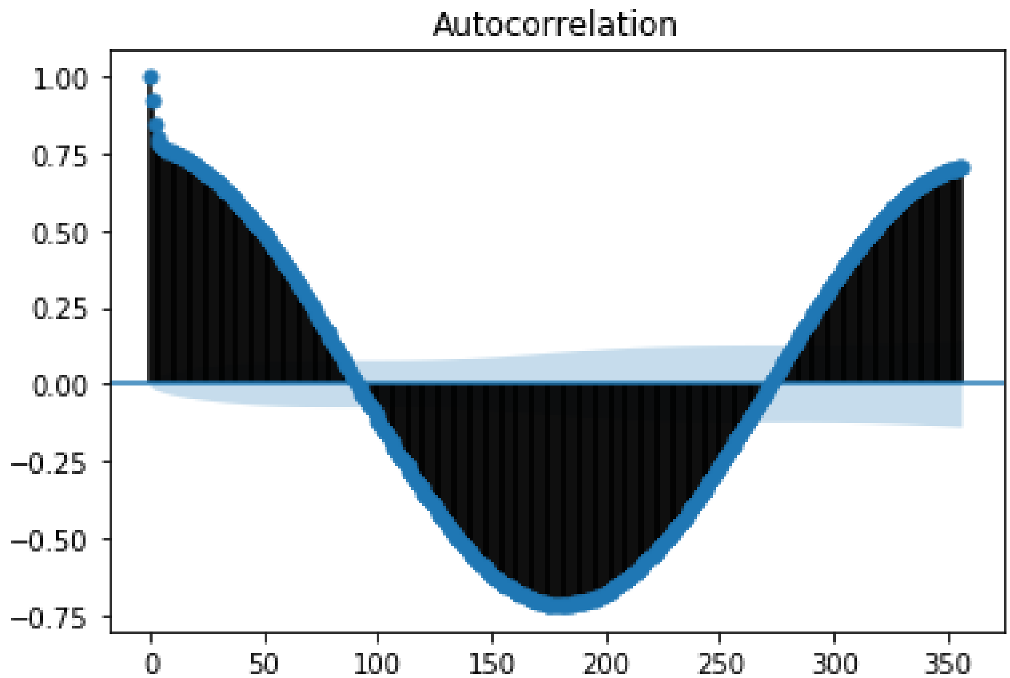
Informally, autocorrelation is the similarity between observations as a function of the time lag between them.

```
In [212]: # !pip3 install git+https://github.com/statsmodels/statsmodels.git
```

```
In [213]: plot_acf(df_final['TMAX'], lags = 356)
          plt.show()
```




```
In [214]: plot_acf(df_final['TMIN'], lags = 356)
          plt.show()
```



From the autocorrelation curve, we can see the correlation reduces with timelag, and we can also see the seasonality. Autocorrelation changes from postive to negative and then to postive again due to the temperature changes from winter to summer and again to winter.

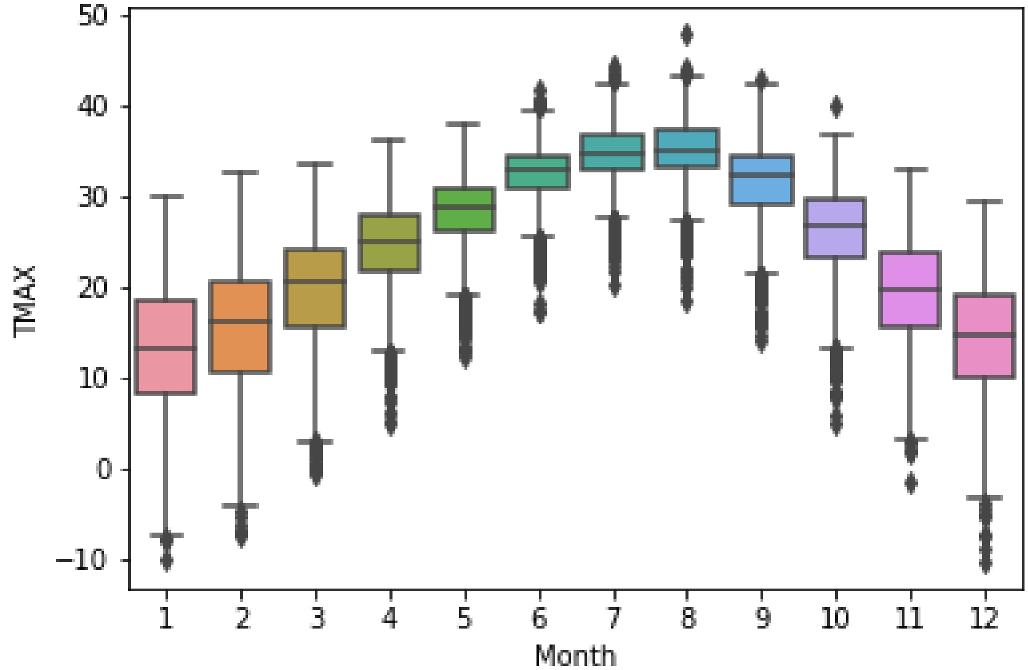
```
In [216]: # plot_acf(df_final['TMAX'], lags= df_Temp.shape[0]-1)
          # plt.show()
```

6.4 Seasonality

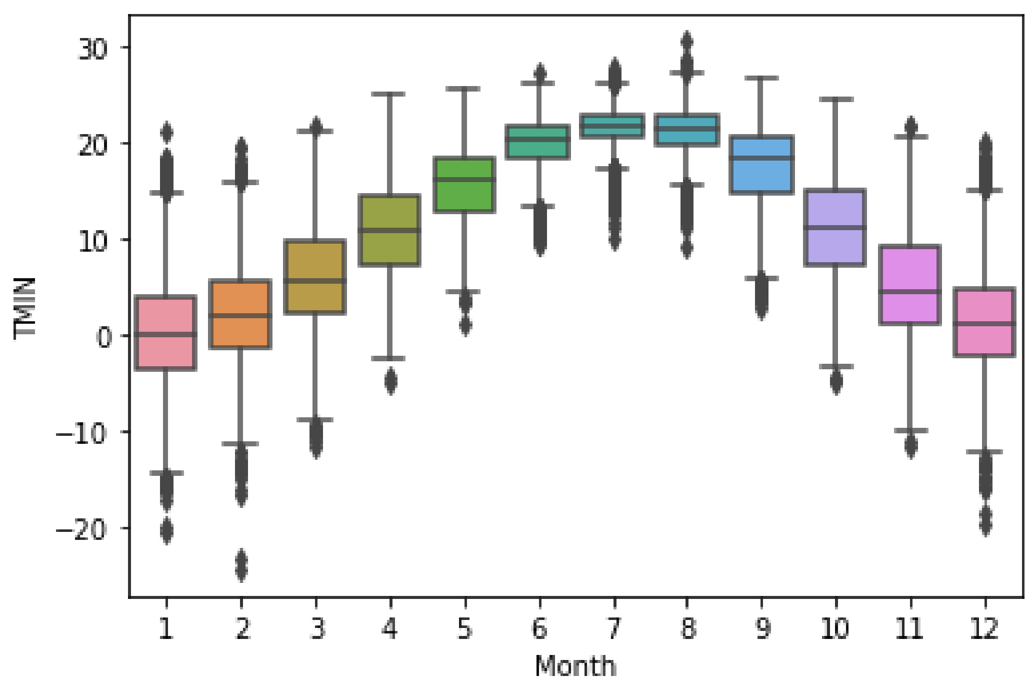
Seasonality refers to periodic fluctuations. For example, temperature is high during the day/summer and low during winter/night.

```
In [217]: # Add columns with year, month, and weekday name
          df_final['Year'] = df_final.index.year
          df_final['Month'] = df_final.index.month
          df_final['Weekday Name'] = df_final.index.weekday_name
```

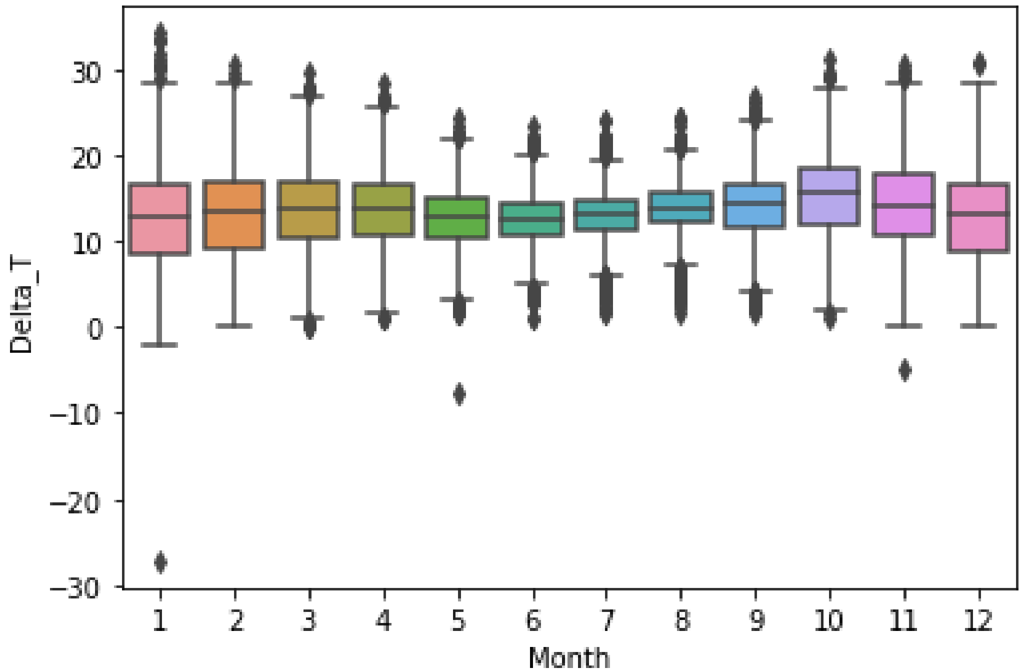
```
In [218]: sns.boxplot(data= df_final, x = 'Month', y = 'TMAX')
          plt.show()
```



In [219]:
```
sns.boxplot(data= df_final, x = 'Month', y = 'TMIN')
plt.show()
```



```
In [220]: sns.boxplot(data= df_final, x = 'Month', y = 'Delta_T')
          plt.show()
```



We observe a clear yearly seasonality. It is also intersting to mention that the temperature difference within a day of summer is smaller than that value of winter

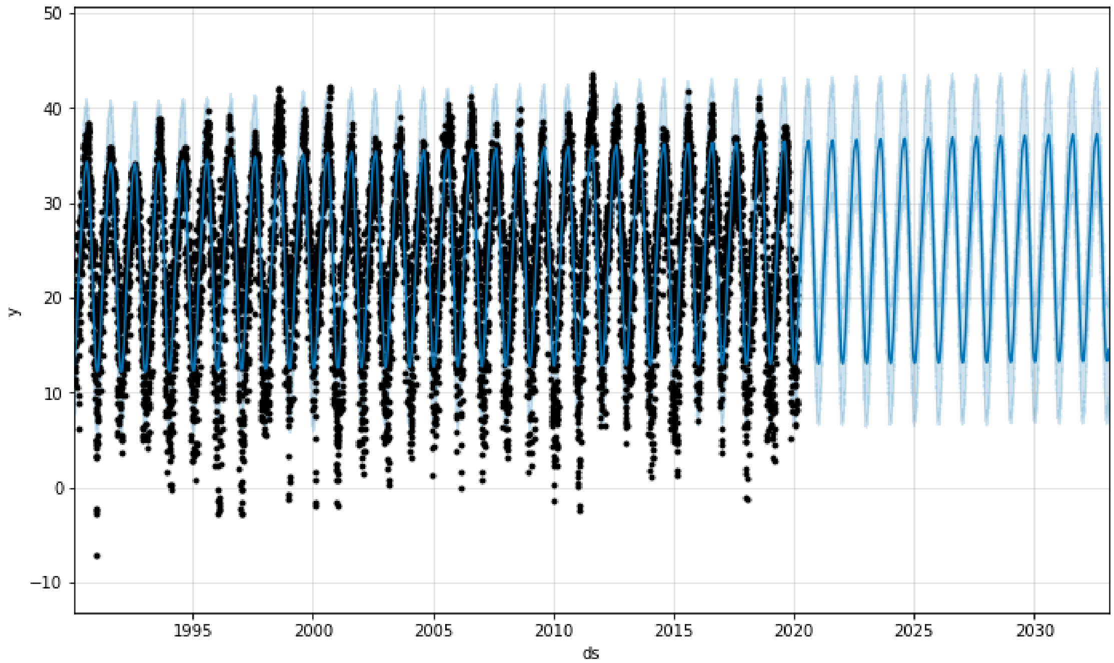
7 Predicting future temperature using fbprophet

```
In [280]: from fbprophet import Prophet
```

```
In [281]: def future_temperature(temp = 'TMAX'):
              df = pd.DataFrame({'ds': df_final.index,
                                 'y': df_final.loc[:, temp]})
              df = df.iloc[2000:, :]
              m = Prophet(daily_seasonality=False, weekly_seasonality = False, yearly_seasonali
                          growth = 'linear',
                          seasonality_mode = 'multiplicative')
              m.fit(df)
              future = m.make_future_dataframe(periods=365*15)
              forecast = m.predict(future)
              m.plot(forecast)
              plt.xlim([datetime.date(1990, 1, 26), datetime.date(2033, 2, 1)])
              plt.show()
```

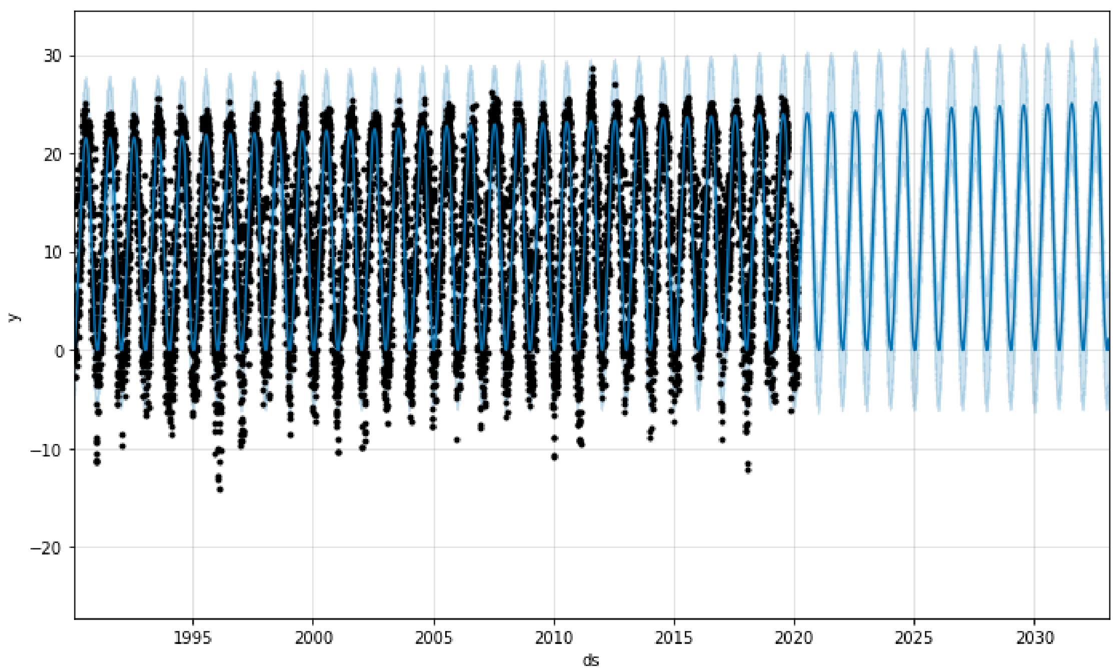
7.1 Maximum temperature

```
In [282]: future_temperature(temp = 'TMAX')
```



7.2 Minimum temperature

```
In [279]: future_temperature(temp = 'TMIN')
```



8 Summary and suggestions for WorlCover

- By analysing the maximum and the minimum temperature, we can conclude that the temperature increases gradually in Texas, US. That is because of the global warming.

- If a famer in Texas would like to by agricultural insurance I would suggest WorldCover to give them some discount. The temperature range in Texas , which is from -10 to 42, is very good for crops. From the prediction, in the next 15 years, it is even beter for crops.
- However, temperature is the only one condition to consider if the climate is good or not for agriculture.To have a full picture, we need to analyse data of wind, snow, rainfall, natural disasters, etc.