20240115_CO2_concentration_in_the_Atmosphere_Since_1958

February 18, 2024

1 CO2 concentration in the atmosphere since 1958

[1]:
```
%matplotlib inline
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit
import pandas as pd
import numpy as np
import datetime
```

The data has been loaded from the available from the Web site of the Scripps Institute.
The data selected contains the weekly frequency and has been downloaded from https://scrippsco2.ucsd.edu/data/atmospheric_co2/mlo.html on the 16th of January 2024.

[2]:
```
import os
os.chdir(os.getcwd())
data_url = "../Source/20240116_weekly_in_situ_co2_mlo.csv"
```

When opening the CSV file the below message is dispalyed and we can see that the data is loaded from the line 45 without any header.
We therefore skip the first 44 rows using `skiprows=44`. "——————————————————————————————-" " Atmospheric CO2 concentrations (ppm) derived from in situ air measurements " " at Mauna Loa, Observatory, Hawaii: Latitude 19.5°N Longitude 155.6°W Elevation 3397m " " " " Source: R. F. Keeling, S. J. Walker, S. C. Piper and A. F. Bollenbacher " " Scripps CO2 Program (http://scrippsco2.ucsd.edu) " " Scripps Institution of Oceanography (SIO) " " University of California " " La Jolla, California USA 92093-0244 " " " " Status of data and correspondence: " " " " These data are subject to revision based on recalibration of standard gases. Questions " " about the data should be directed to Dr. Ralph Keeling (rkeeling@ucsd.edu), Stephen Walker" " (sjwalker@ucsd.edu) and Stephen Piper (scpiper@ucsd.edu), Scripps CO2 Program. " " " " Baseline data in this file through 07-Jan-2024 from archive dated 08-Jan-2024 14:25:05 " " " "——————————————————————————————-" " " " Please cite as: " " " " C. D. Keeling, S. C. Piper, R. B. Bacastow, M. Wahlen, T. P. Whorf, M. Heimann, and " " H. A. Meijer, Exchanges of atmospheric CO2 and 13CO2 with the terrestrial biosphere and " " oceans from 1978 to 2000. I. Global aspects, SIO Reference Series, No. 01-06, Scripps " " Institution of Oceanography, San Diego, 88 pages, 2001. " " " " If it is necessary to cite a peer-reviewed article, please cite as: " " " " C. D. Keeling, S. C. Piper, R. B. Bacastow, M. Wahlen, T. P. Whorf, M. Heimann, and " " H. A. Meijer, Atmospheric CO2 and 13CO2 exchange with the terrestrial biosphere and " " oceans from 1978 to 2000: observations and carbon cycle implications, pages 83-113, " " in "A History of Atmospheric CO2 and its effects on Plants, Animals, and Ecosystems",

" " editors, Ehleringer, J.R., T. E. Cerling, M. D. Dearing, Springer Verlag, " " New York, 2005. " " " "——————————————————————————————-" " " " The data file below contains 2 columns indicaing the date and CO2 " " concentrations in micro-mol CO2 per mole (ppm), reported on the 2012 " " SIO manometric mole fraction scale. These weekly values have been " " adjusted to 12:00 hours at middle day of each weekly period as " " indicated by the date in the first column. " "——————————————————————————————-"

[3]:
```
raw_data = pd.read_csv(data_url, skiprows=44,header = None)
raw_data
```

[3]:
```
               0       1
0     1958-03-29  316.19
1     1958-04-05  317.31
2     1958-04-12  317.69
3     1958-04-19  317.58
4     1958-04-26  316.48
…            …       …
3353  2023-12-02  420.28
3354  2023-12-09  421.23
3355  2023-12-16  422.57
3356  2023-12-23  422.06
3357  2023-12-30  421.76

[3358 rows x 2 columns]
```

First we are checking if there are any data missing.

[4]:
```
raw_data[raw_data.isnull().any(axis=1)]
```

[4]:
```
Empty DataFrame
Columns: [0, 1]
Index: []
```

There isn't any missing data.
We are naming the columns to get it more readable.

[5]:
```
raw_data.columns = ["date","co2_concentration"]
raw_data
```

[5]:
```
            date  co2_concentration
0     1958-03-29             316.19
1     1958-04-05             317.31
2     1958-04-12             317.69
3     1958-04-19             317.58
4     1958-04-26             316.48
…            …                  …
3353  2023-12-02             420.28
3354  2023-12-09             421.23
3355  2023-12-16             422.57
```

```
3356   2023-12-23              422.06
3357   2023-12-30              421.76

[3358 rows x 2 columns]
```

[6]:
```
raw_data.dtypes
```

[6]:
```
date                     object
co2_concentration       float64
dtype: object
```

We can see that the data type of the column "data" is not defined as a period and we are updating it to be sure that it is going to be treated appropriately.

[7]:
```
raw_data.date = pd.to_datetime(raw_data.date,format='%Y-%m-%d')
raw_data.dtypes
```

[7]:
```
date                 datetime64[ns]
co2_concentration           float64
dtype: object
```

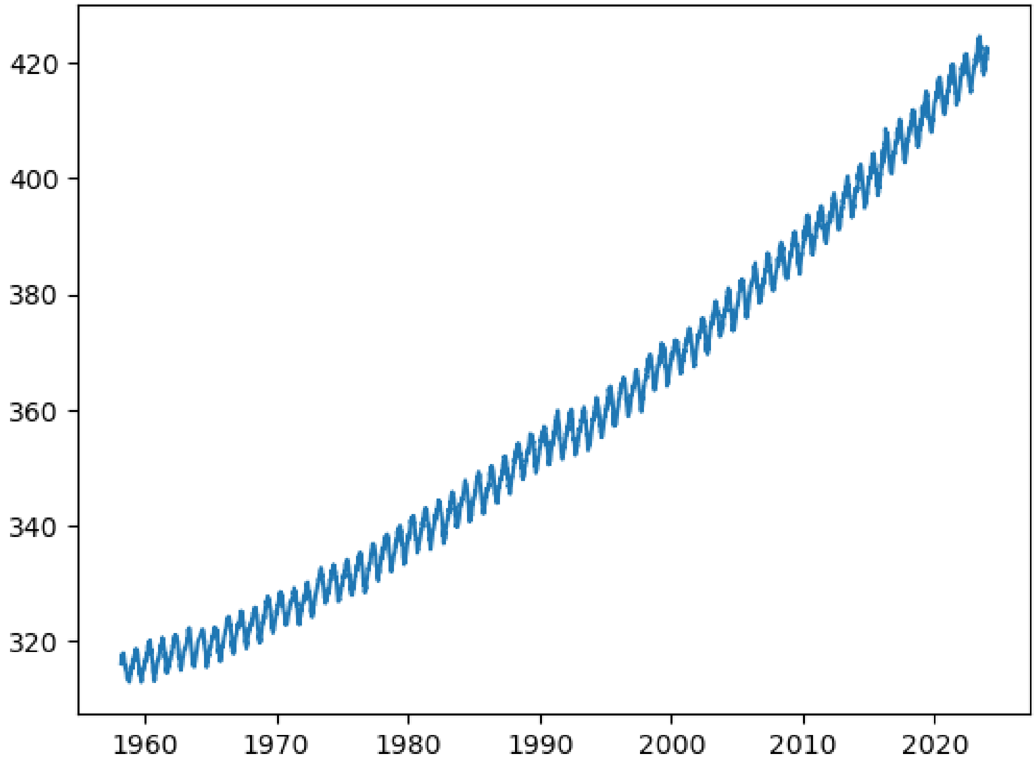
We now change the index and sort by date to make sure that it is effectively ordered correctly.

[8]:
```
raw_data["date_index"] = pd.to_datetime(raw_data.date,format='%Y-%m-%d')
sorted_data = raw_data.set_index("date_index").sort_index().
 ↪drop(['date'],axis=1)
sorted_data
```

[8]:
```
            co2_concentration
date_index
1958-03-29             316.19
1958-04-05             317.31
1958-04-12             317.69
1958-04-19             317.58
1958-04-26             316.48
…                        …
2023-12-02             420.28
2023-12-09             421.23
2023-12-16             422.57
2023-12-23             422.06
2023-12-30             421.76

[3358 rows x 1 columns]
```

We are now plotting all the values into a graph.

[9]:
```
fig, ax = plt.subplots()
ax.plot(sorted_data.index,sorted_data["co2_concentration"])
plt.show()
```

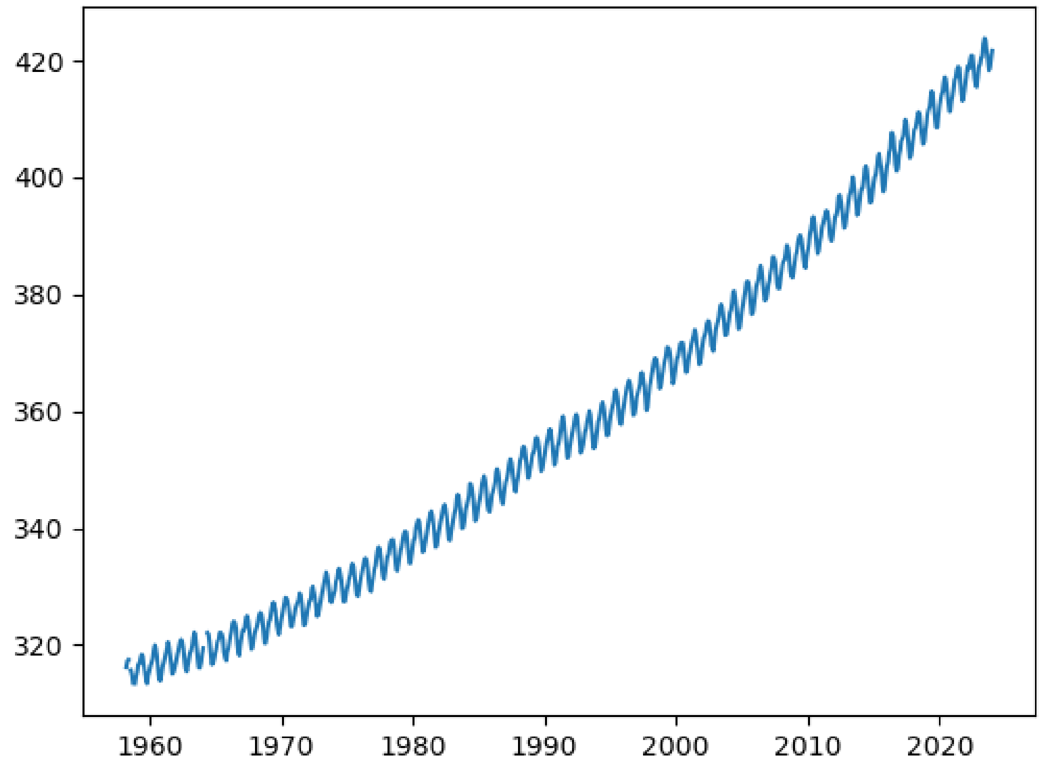


We are creating 2 new dataframes taking the average per month and average per year. We are plotting also those 2 new dataframes.

[10]:
```
sorted_data_bymonth = sorted_data.resample("M").mean()
sorted_data_bymonth
```

[10]:
```
            co2_concentration
date_index
1958-03-31           316.1900
1958-04-30           317.2650
1958-05-31           317.5000
1958-06-30                NaN
1958-07-31           315.6875
…                         …
2023-08-31           419.6225
2023-09-30           418.1920
2023-10-31           418.5975
2023-11-30           420.2200
2023-12-31           421.5800

[790 rows x 1 columns]
```

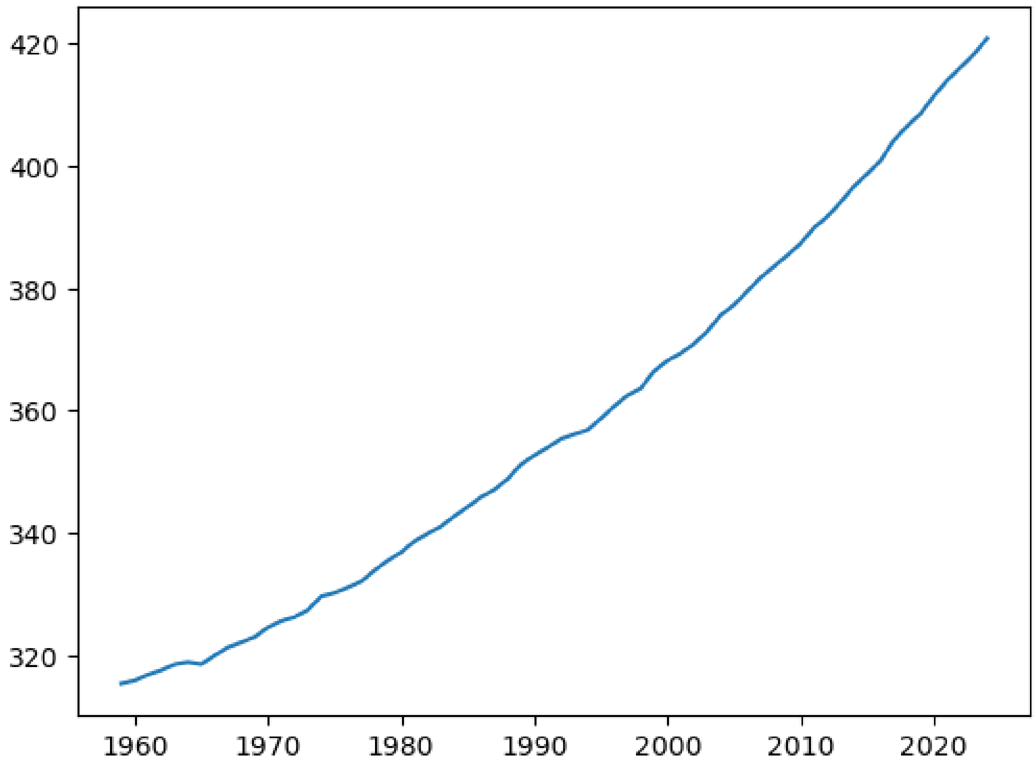
[11]:
```
fig, ax = plt.subplots()
ax.plot(sorted_data_bymonth.index,sorted_data_bymonth["co2_concentration"])
plt.show()
```



[12]:
```
sorted_data_byyear = sorted_data.resample("Y").mean()
sorted_data_byyear
```

[12]:
```
            co2_concentration
date_index
1958-12-31         315.474000
1959-12-31         315.945417
1960-12-31         316.898868
1961-12-31         317.634038
1962-12-31         318.597708
…                         …
2019-12-31         411.417500
2020-12-31         413.964902
2021-12-31         416.086346
2022-12-31         418.211569
2023-12-31         420.831346

[66 rows x 1 columns]
```

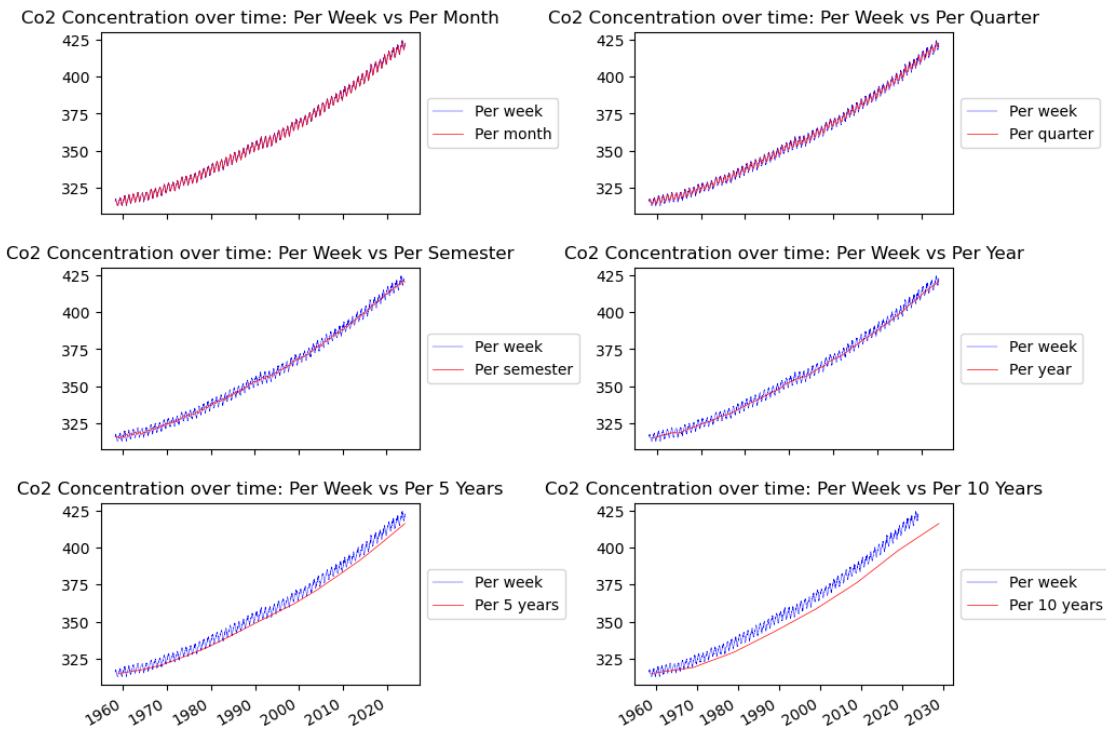
[13]:
```
fig, ax = plt.subplots()
ax.plot(sorted_data_byyear.index,sorted_data_byyear["co2_concentration"])
plt.show()
```



We can see that the result per month is very close to the curve obtained per week but also that when we look at the year we are leaving the frequency model and are approaching to a line. We are now comparing the result for multiple cases to see how the plots are evovling with different grouping.

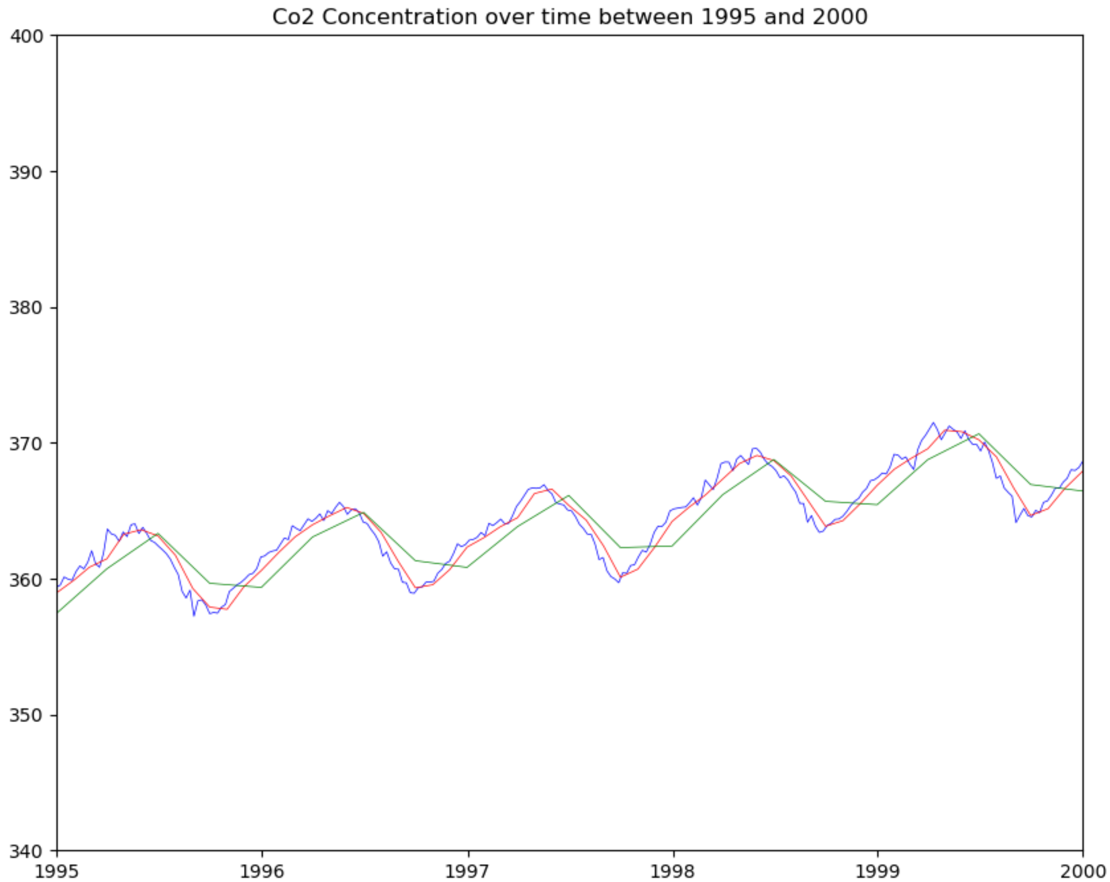
[14]:
```
fig, axs = plt.subplots(3,2,figsize=(10.0, 8.0),sharex=False,sharey=False)
axs[0,0].plot(sorted_data.
↪index,sorted_data["co2_concentration"],color='b',linewidth=0.3,label="Per␣
↪week")
axs[0,0].plot(sorted_data.resample("M").mean().index,sorted_data.resample("M").
↪mean()["co2_concentration"],color='r',linewidth=0.5,label="Per month")
axs[0,0].set_title("Co2 Concentration over time: Per Week vs Per Month")

axs[0,1].plot(sorted_data.
↪index,sorted_data["co2_concentration"],color='b',linewidth=0.3,label="Per␣
↪week")
```

```
axs[0,1].plot(sorted_data.resample("3M").mean().index,sorted_data.
 ↪resample("3M").mean()["co2_concentration"],color='r',linewidth=0.
 ↪5,label="Per quarter")
axs[0,1].set_title("Co2 Concentration over time: Per Week vs Per Quarter")

axs[1,0].plot(sorted_data.
 ↪index,sorted_data["co2_concentration"],color='b',linewidth=0.3,label="Per␣
 ↪week")
axs[1,0].plot(sorted_data.resample("6M").mean().index,sorted_data.
 ↪resample("6M").mean()["co2_concentration"],color='r',linewidth=0.
 ↪5,label="Per semester")
axs[1,0].set_title("Co2 Concentration over time: Per Week vs Per Semester")

axs[1,1].plot(sorted_data.
 ↪index,sorted_data["co2_concentration"],color='b',linewidth=0.3,label="Per␣
 ↪week")
axs[1,1].plot(sorted_data.resample("Y").mean().index,sorted_data.resample("Y").
 ↪mean()["co2_concentration"],color='r',linewidth=0.5,label="Per year")
axs[1,1].set_title("Co2 Concentration over time: Per Week vs Per Year")

axs[2,0].plot(sorted_data.
 ↪index,sorted_data["co2_concentration"],color='b',linewidth=0.3,label="Per␣
 ↪week")
axs[2,0].plot(sorted_data.resample("5Y").mean().index,sorted_data.
 ↪resample("5Y").mean()["co2_concentration"],color='r',linewidth=0.
 ↪5,label="Per 5 years")
axs[2,0].set_title("Co2 Concentration over time: Per Week vs Per 5 Years")

axs[2,1].plot(sorted_data.
 ↪index,sorted_data["co2_concentration"],color='b',linewidth=0.3,label="Per␣
 ↪week")
axs[2,1].plot(sorted_data.resample("10Y").mean().index,sorted_data.
 ↪resample("10Y").mean()["co2_concentration"],color='r',linewidth=0.
 ↪5,label="Per 10 years")
axs[2,1].set_title("Co2 Concentration over time: Per Week vs Per 10 Years")

axs[0,0].legend(loc='center left', bbox_to_anchor=(1, 0.5))
axs[0,1].legend(loc='center left', bbox_to_anchor=(1, 0.5))
axs[1,0].legend(loc='center left', bbox_to_anchor=(1, 0.5))
axs[1,1].legend(loc='center left', bbox_to_anchor=(1, 0.5))
axs[2,0].legend(loc='center left', bbox_to_anchor=(1, 0.5))
axs[2,1].legend(loc='center left', bbox_to_anchor=(1, 0.5))

fig.tight_layout()
fig.autofmt_xdate()
plt.show()
```



Viewing all those results and comparisons are telling us that if we want to build the best model that would fit best the CO2 Concentration evolution we have to look closer into how the frequency is build and avoid using grouping over per quarter.
We are therefore creating a graph for a shorter period of 5 years to understand better how the values are evolving over time.

[29]:
```
fig, ax = plt.subplots(figsize=(10.0, 8.0),sharex=False)
ax.plot(sorted_data.
 ↪index,sorted_data["co2_concentration"],color='b',linewidth=0.5)
ax.plot(sorted_data.resample("M").mean().index,sorted_data.resample("M").
 ↪mean()["co2_concentration"],color='r',linewidth=0.5)
ax.plot(sorted_data.resample("3M").mean().index,sorted_data.resample("3M").
 ↪mean()["co2_concentration"],color='g',linewidth=0.5)
ax.set_xlim([datetime.date(1995, 1, 1), datetime.date(2000, 1, 1)])
ax.set_ylim([340,400])

ax.set_title("Co2 Concentration over time between 1995 and 2000")

plt.show()
```



We can see first that there is monthly frequency that exist with a curve is at its top in the summer and bottom in September. We are looking deeper into one month starting in February to be neither in a top or bottom position.

[16]:
```
sorted_data.resample("M").mean().loc[datetime.date(1996, 2, 1): datetime.
↪date(1997, 2, 1)]
```

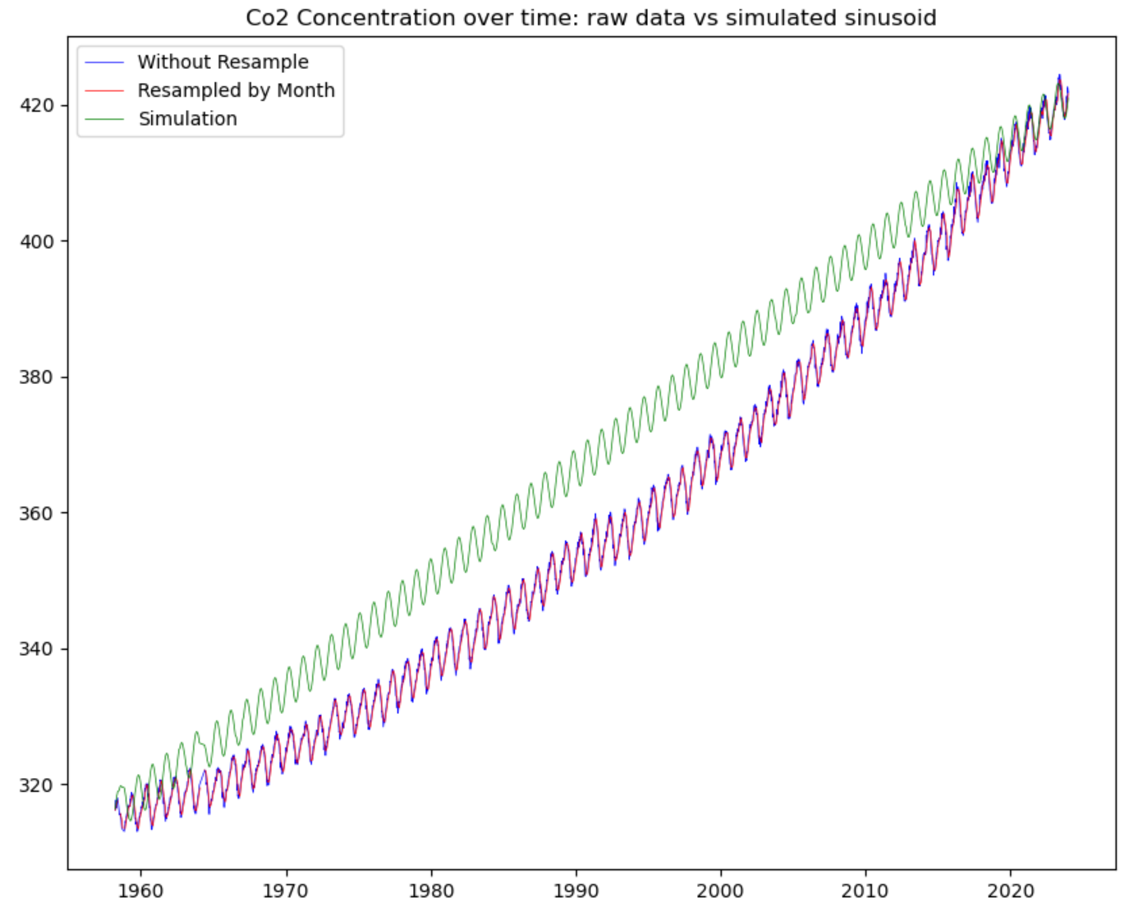
[16]:

date_index	co2_concentration
1996-02-29	363.0725
1996-03-31	363.9600
1996-04-30	364.6175
1996-05-31	365.2350
1996-06-30	364.7940
1996-07-31	363.4100
1996-08-31	361.2380
1996-09-30	359.3250
1996-10-31	359.5475
1996-11-30	360.6560

```
1996-12-31          362.3150
1997-01-31          363.0350
```

We are now exploring and trying to find manually a model that could be close to the real frequency. We can see from the previous graph that the curve is a sinusoid and inspired by https://mathbitsnotebook.com/Algebra2/TrigGraphs/TGsinusoidal.html and https://math.libretexts.org/Bookshelves/Precalculus/Book%3A_Precalculus_*An_Investigation_of_Functions%*
we have been exploring the data.

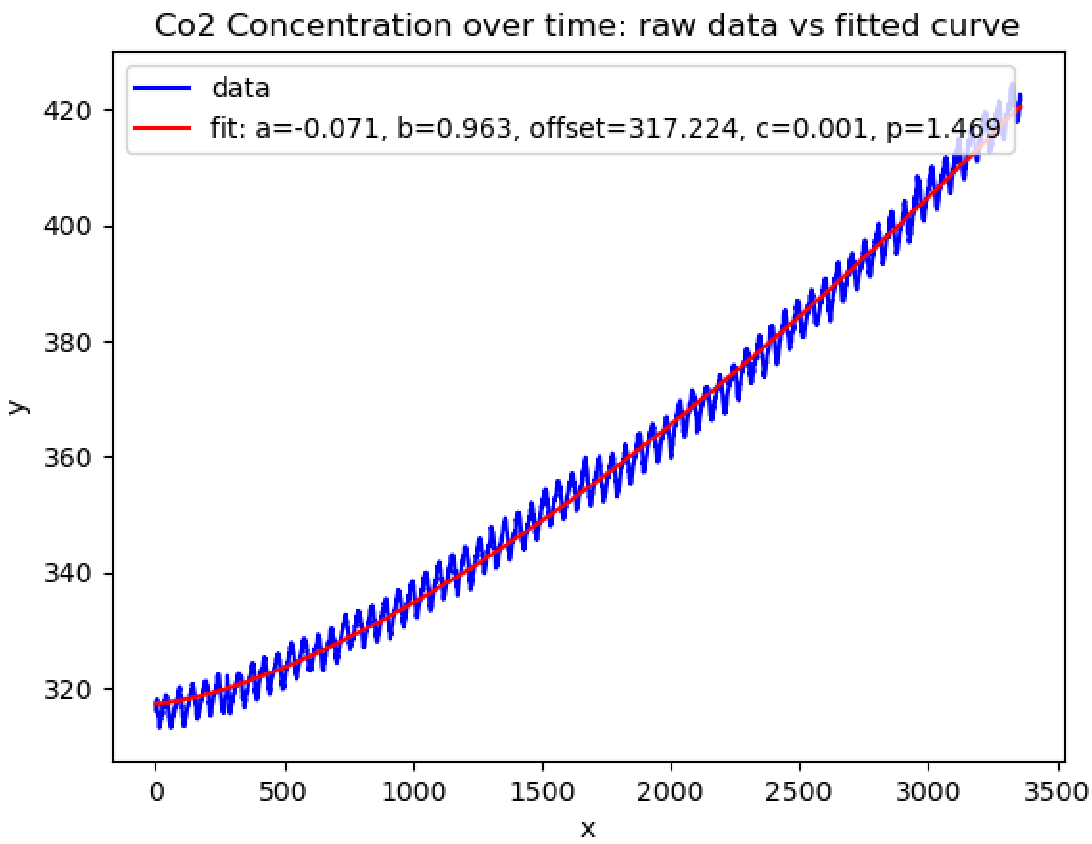
[32]:
```
fig, ax = plt.subplots(figsize=(10.0, 8.0),sharex=False)
ax.plot(sorted_data.
 ↪index,sorted_data["co2_concentration"],color='b',linewidth=0.
 ↪5,label="Without Resample")
ax.plot(sorted_data.resample("M").mean().index,sorted_data.resample("M").
 ↪mean()["co2_concentration"],color='r',linewidth=0.5,label="Resampled by␣
 ↪Month")

# First we are calculating an amplitude over a month period: Average between␣
 ↪the min and max / 2
amplitude = ((sorted_data.resample("M").mean().loc[datetime.date(1996, 2, 1):␣
 ↪datetime.date(1997, 2, 1)].max()-\
sorted_data.resample("M").mean().loc[datetime.date(1996, 9, 1): datetime.
 ↪date(1997, 9, 1)].min())/2).iloc[0]

# We define the initial offset that will be where the curve will begin
offset = sorted_data.resample("M").mean().min().iloc[0] + amplitude

# We are creating the frequency based on the period
f = len(sorted_data.resample("Y").mean().index)
sample = len(sorted_data.index)
x = np.arange(sample)

# Playing manually with the numbers we can find a line following the same␣
 ↪frequency having the same gradient.
y = amplitude*np.sin((2 * np.pi * f * x / sample)) + offset + x/32
ax.plot(sorted_data.index, y, linewidth=0.5,color='g',label="Simulation")

ax.set_title("Co2 Concentration over time: raw data vs simulated sinusoid")

ax.legend(loc='upper left')

plt.show()
```



The model that we have looked at is telling us that we are heading in the right direction exploring a sinusoidal curve. Using the curve_fit function from the scipy package we can work in finding the best parameters to best fit the evolution of the CO2 concentration.

[35]:
```
# We are defining the model using a com function considering that there is a␣
↪polynomial element as the values are increasing "exponentially"
# We define p as the "polynomaial" variable. Other variables are the other␣
↪variables to take into account in a sinusoidal function.
def func_sin(x, a, b, offset, c, p):
    return a * np.sin(2 * np.pi * b * x) + offset + c*x**p

sample = len(sorted_data.index)
x = np.arange(sample)
y = sorted_data["co2_concentration"]
plt.plot(x, y, 'b-', label='data')

popt, pcov = curve_fit(func_sin, x, y)
popt
```

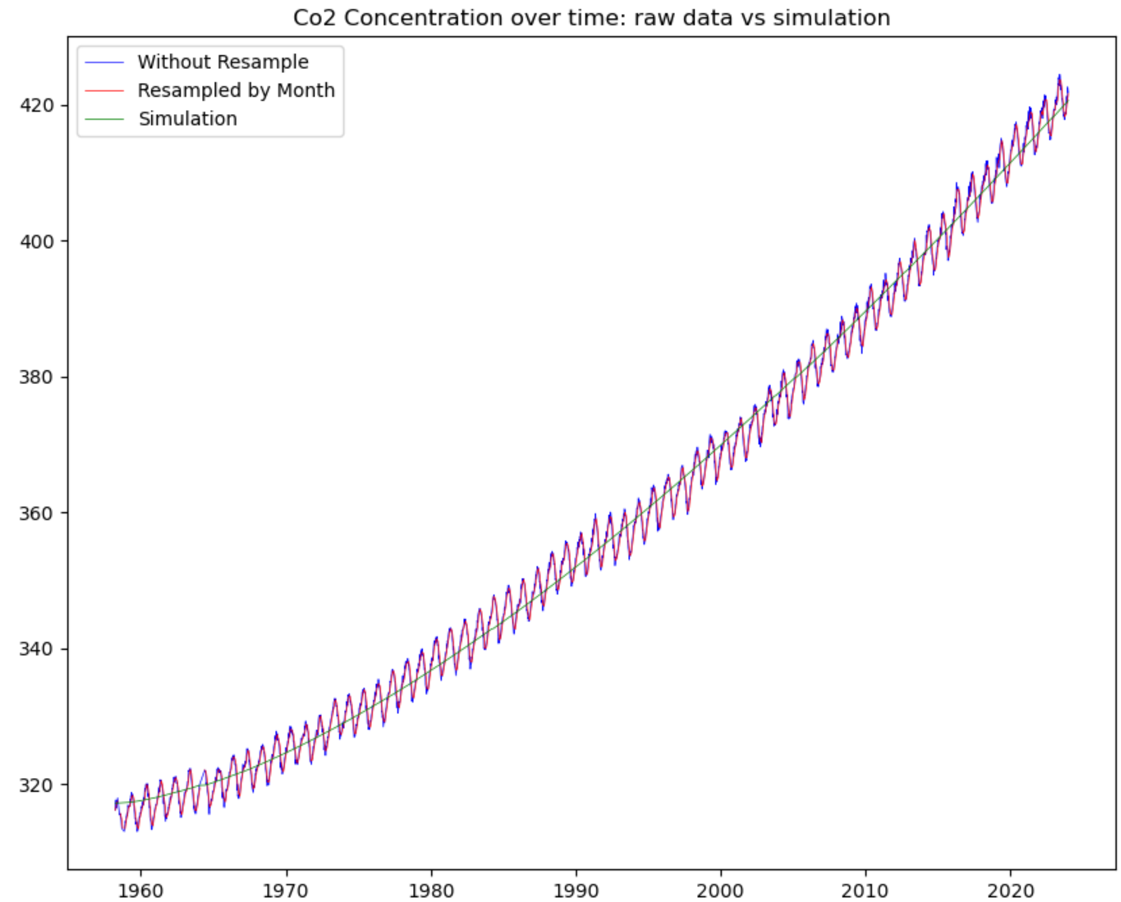
```
# We are ploting in red the fitted curve calculated
plt.plot(x, func_sin(x, *popt), 'r-',
         label='fit: a=%5.3f, b=%5.3f, offset=%5.3f, c=%5.3f, p=%5.3f' %␣
 ↪tuple(popt))

plt.title("Co2 Concentration over time: raw data vs fitted curve")

plt.xlabel('x')
plt.ylabel('y')
plt.legend(loc='upper left')
plt.show()
```



We are then taking the calculated variables and compare them with the initial data raw to identify if the prediction is close to the real values.

[36]:
```
fig, ax = plt.subplots(figsize=(10.0, 8.0),sharex=False)
ax.plot(sorted_data.
 ↪index,sorted_data["co2_concentration"],color='b',linewidth=0.
 ↪5,label="Without Resample")
```

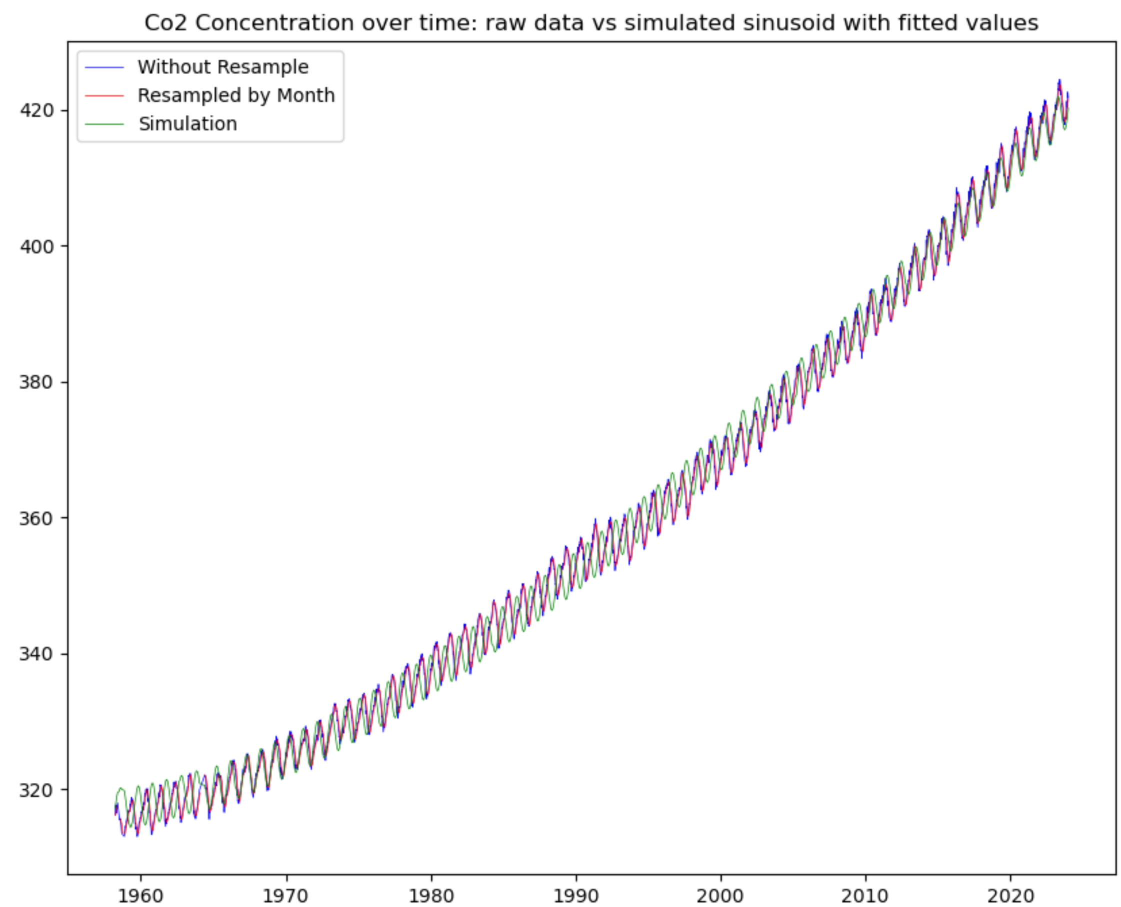
```python
ax.plot(sorted_data.resample("M").mean().index,sorted_data.resample("M").
 ↪mean()["co2_concentration"],color='r',linewidth=0.5,label="Resampled by␣
 ↪Month")

# We are calculating an amplitude over a month period: Average between the min␣
 ↪and max / 2
amplitude = ((sorted_data.resample("M").mean().loc[datetime.date(1996, 2, 1):␣
 ↪datetime.date(1997, 2, 1)].max()-\
sorted_data.resample("M").mean().loc[datetime.date(1996, 9, 1): datetime.
 ↪date(1997, 9, 1)].min())/2).iloc[0]

# We define the initial offset that will be where the curve will begin
offset = sorted_data.resample("M").mean().min().iloc[0] + amplitude/2

# We are creating the frequency based on the period
f = len(sorted_data.resample("Y").mean().index)
sample = len(sorted_data.index)
x = np.arange(sample)

# Playing with the numbers we can find a line following the same frequency␣
 ↪having the same gradient.
y = popt[0]*np.sin((2 * np.pi * popt[1]  * x/sample)) + popt[2]  + popt[3]␣
 ↪*x**popt[4]
ax.plot(sorted_data.index, y, 'g', linewidth=0.5,label="Simulation")

ax.set_title("Co2 Concentration over time: raw data vs simulation")

ax.legend(loc='upper left')

plt.show()
```



The result is displaying a line that is closed to the initial values. We are expecting to get a preidction with a sinusoid to get also into the fact that the values are fluctuating. To change from a line to a sinusoid only the last 3 variables of the func_sin are used and for the others we are using the original values.

[41]:
```
fig, ax = plt.subplots(figsize=(10.0, 8.0),sharex=False)
ax.plot(sorted_data.
 ↪index,sorted_data["co2_concentration"],color='b',linewidth=0.
 ↪5,label="Without Resample")
ax.plot(sorted_data.resample("M").mean().index,sorted_data.resample("M").
 ↪mean()["co2_concentration"],color='r',linewidth=0.5,label="Resampled by␣
 ↪Month")

# We are calculating an amplitude over a month period: Average between the min␣
 ↪and max / 2
amplitude = ((sorted_data.resample("M").mean().loc[datetime.date(1996, 2, 1):␣
 ↪datetime.date(1997, 2, 1)].max()-\
```

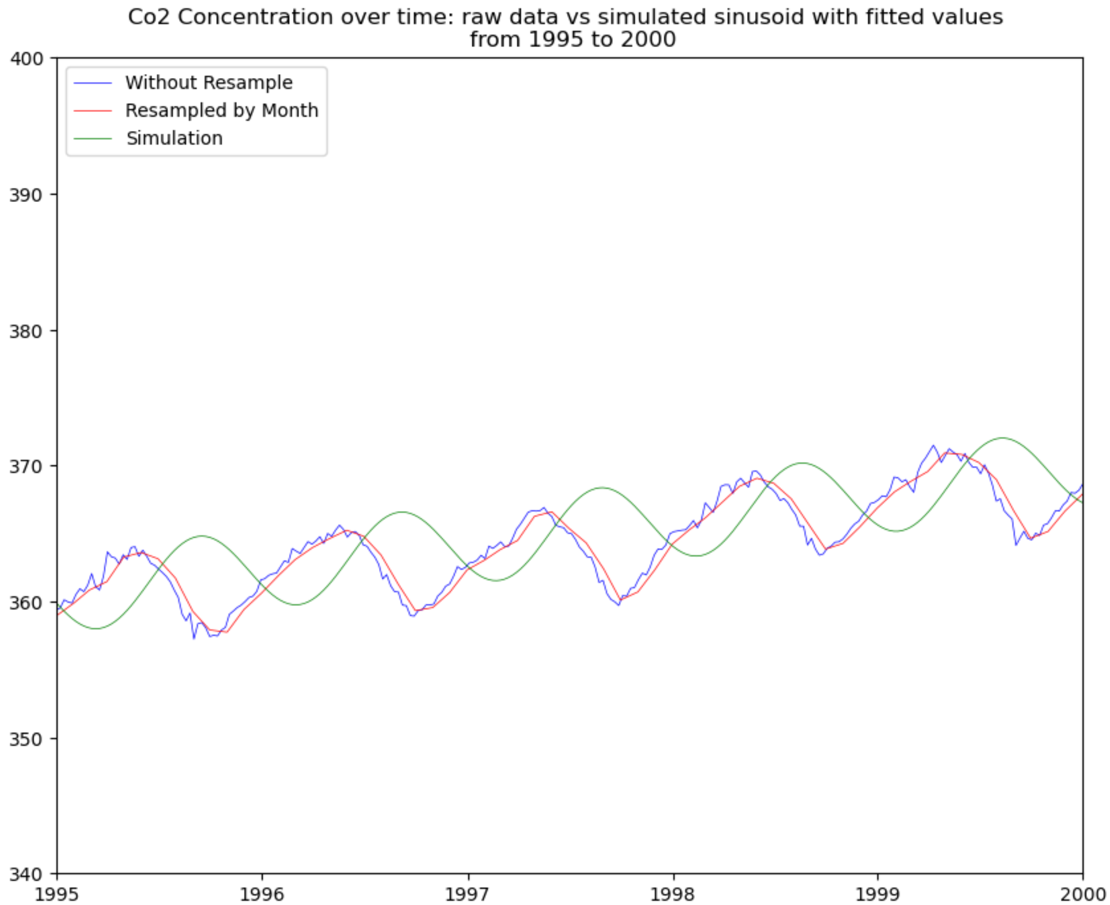
```
sorted_data.resample("M").mean().loc[datetime.date(1996, 9, 1): datetime.
↪date(1997, 9, 1)].min())/2).iloc[0]

# We define the initial offset that will be where the curve will begin
offset = sorted_data.resample("M").mean().min().iloc[0] + amplitude/2

# We are creating the frequency based on the period
f = len(sorted_data.resample("Y").mean().index)
sample = len(sorted_data.index)
x = np.arange(sample)

# Only the last 3 variables of the func_sin are used and for the others we are␣
↪using the original values.
y = amplitude*np.sin((2 * np.pi * f  * x/sample)) + popt[2]  + popt[3]␣
↪*x**popt[4]
ax.plot(sorted_data.index, y, 'g', linewidth=0.5,label="Simulation")

ax.set_title("Co2 Concentration over time: raw data vs simulated sinusoid with␣
↪fitted values")

ax.legend(loc='upper left')

plt.show()
```



It is really close but there is a need to investigate closer and we ar elooking in more details for data in between 1996 and 1997.

[38]:
```
fig, ax = plt.subplots(figsize=(10.0, 8.0),sharex=False)
ax.plot(sorted_data.
 ↪index,sorted_data["co2_concentration"],color='b',linewidth=0.
 ↪5,label="Without Resample")
ax.plot(sorted_data.resample("M").mean().index,sorted_data.resample("M").
 ↪mean()["co2_concentration"],color='r',linewidth=0.5,label="Resampled by␣
 ↪Month")

# First we are calculating an amplitude over a month period: Average between␣
 ↪the min and max / 2
amplitude = ((sorted_data.resample("M").mean().loc[datetime.date(1996, 2, 1):␣
 ↪datetime.date(1997, 2, 1)].max()-\
sorted_data.resample("M").mean().loc[datetime.date(1996, 9, 1): datetime.
 ↪date(1997, 9, 1)].min())/2).iloc[0]
```

```
# We define the initial offset that will be where the curve will begin
offset = sorted_data.resample("M").mean().min().iloc[0] + amplitude/2

# We are creating the frequency based on the period
f = len(sorted_data.resample("Y").mean().index)
sample = len(sorted_data.index)
x = np.arange(sample)

# Playing with the numbers we can find a line following the same frequency␣
↪having the same gradient.
y = amplitude*np.sin((2 * np.pi * f  * x/sample)) + popt[2]  + popt[3]␣
↪*x**popt[4]
ax.plot(sorted_data.index, y, 'g', linewidth=0.5,label="Simulation")
ax.set_xlim([datetime.date(1995, 1, 1), datetime.date(2000, 1, 1)])
ax.set_ylim([340,400])

ax.set_title("Co2 Concentration over time: raw data vs simulated sinusoid with␣
↪fitted values \n from 1995 to 2000")

ax.legend(loc='upper left')

plt.show()
```

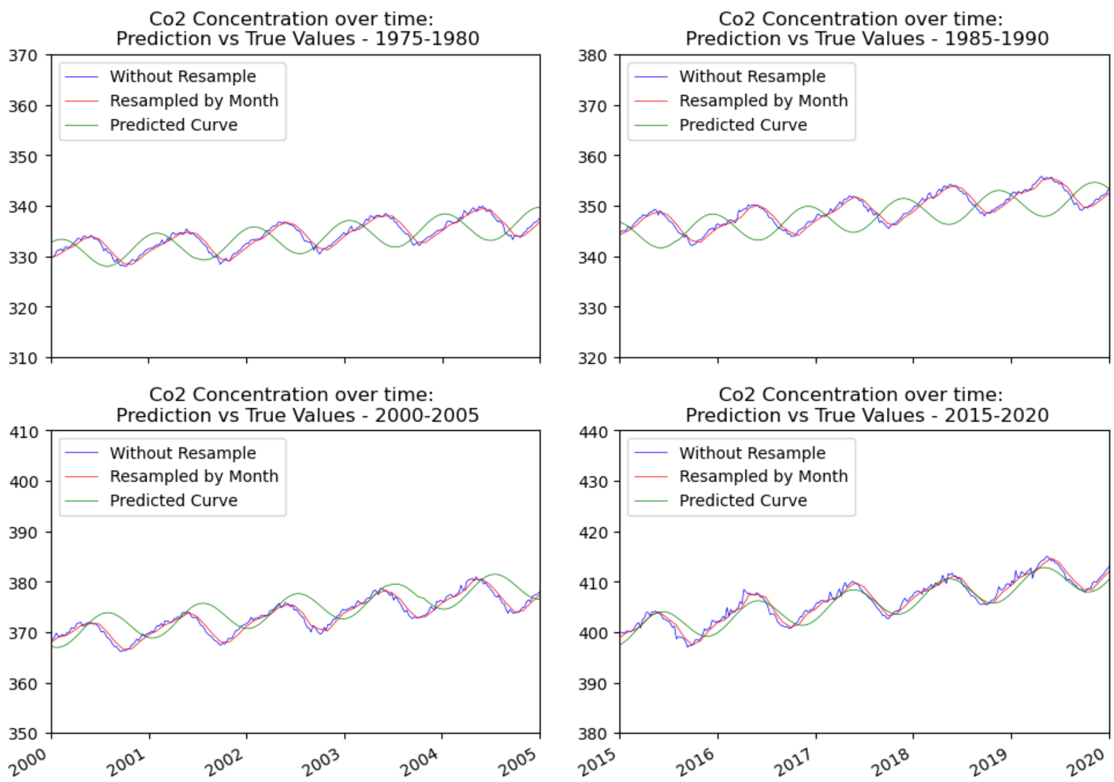


The pick and lowest values are not fitting well and we are now looking into a selection of dates (beginning, middle and end) to see how it is fitting together.

[43]:
```
fig, axs = plt.subplots(2,2,figsize=(10.0, 8.0))
axs[0,0].plot(sorted_data.
 ↪index,sorted_data["co2_concentration"],color='b',linewidth=0.
 ↪5,label="Without Resample")
axs[0,0].plot(sorted_data.resample("M").mean().index,sorted_data.resample("M").
 ↪mean()["co2_concentration"],color='r',linewidth=0.5,label="Resampled by␣
 ↪Month")
axs[0,0].set_xlim([datetime.date(1975, 1, 1), datetime.date(1980, 1, 1)])
axs[0,0].set_ylim([310,370])
axs[0,0].set_title("Co2 Concentration over time: \n Prediction vs True Values -␣
 ↪1975-1980")

axs[0,1].plot(sorted_data.
 ↪index,sorted_data["co2_concentration"],color='b',linewidth=0.
 ↪5,label="Without Resample")
```

```
axs[0,1].plot(sorted_data.resample("M").mean().index,sorted_data.resample("M").mean()["co2_concentration"],color='r',linewidth=0.5,label="Resampled by Month")
axs[0,1].set_xlim([datetime.date(1985, 1, 1), datetime.date(1990, 1, 1)])
axs[0,1].set_ylim([320,380])
axs[0,1].set_title("Co2 Concentration over time: \n Prediction vs True Values - 1985-1990")

axs[1,0].plot(sorted_data.index,sorted_data["co2_concentration"],color='b',linewidth=0.5,label="Without Resample")
axs[1,0].plot(sorted_data.resample("M").mean().index,sorted_data.resample("M").mean()["co2_concentration"],color='r',linewidth=0.5,label="Resampled by Month")
axs[1,0].set_xlim([datetime.date(2000, 1, 1), datetime.date(2005, 1, 1)])
axs[1,0].set_ylim([350,410])
axs[1,0].set_title("Co2 Concentration over time: \n Prediction vs True Values - 2000-2005")

axs[1,1].plot(sorted_data.index,sorted_data["co2_concentration"],color='b',linewidth=0.5,label="Without Resample")
axs[1,1].plot(sorted_data.resample("M").mean().index,sorted_data.resample("M").mean()["co2_concentration"],color='r',linewidth=0.5,label="Resampled by Month")
axs[1,1].set_xlim([datetime.date(2015, 1, 1), datetime.date(2020, 1, 1)])
axs[1,1].set_ylim([380,440])
axs[1,1].set_title("Co2 Concentration over time: \n Prediction vs True Values - 2015-2020")

# First we are calculating an amplitude over a month period: Average between the min and max / 2
amplitude = ((sorted_data.resample("M").mean().loc[datetime.date(1996, 2, 1): datetime.date(1997, 2, 1)].max()-\
sorted_data.resample("M").mean().loc[datetime.date(1996, 9, 1): datetime.date(1997, 9, 1)].min())/2).iloc[0]

# We define the initial offset that will be where the curve will begin
offset = sorted_data.resample("M").mean().min().iloc[0] + amplitude/2

# We are creating the frequency based on the period
f = len(sorted_data.resample("Y").mean().index)
sample = len(sorted_data.index)
x = np.arange(sample)
```

```
# Playing with the numbers we can find a line following the same frequency␣
↪having the same gradient.
y = amplitude*np.sin((2 * np.pi * f  * x/sample)) + popt[2]  + popt[3]␣
↪*x**popt[4]

axs[0,0].plot(sorted_data.index, y, 'g', linewidth=0.5, label="Predicted Curve")
axs[0,1].plot(sorted_data.index, y, 'g', linewidth=0.5, label="Predicted Curve")
axs[1,0].plot(sorted_data.index, y, 'g', linewidth=0.5, label="Predicted Curve")
axs[1,1].plot(sorted_data.index, y, 'g', linewidth=0.5, label="Predicted Curve")

axs[0,0].legend(loc='upper left')
axs[0,1].legend(loc='upper left')
axs[1,0].legend(loc='upper left')
axs[1,1].legend(loc='upper left')

fig.tight_layout()
fig.autofmt_xdate()
plt.show()
```

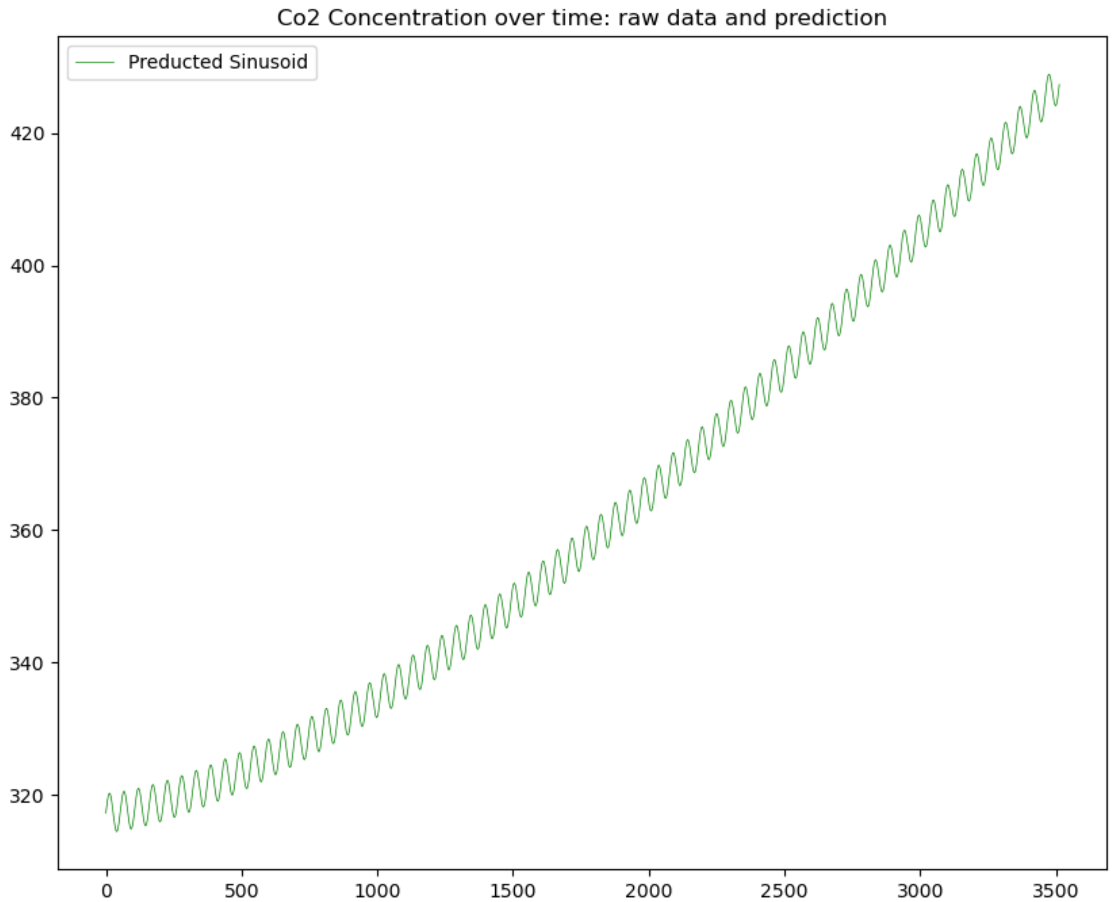


There are few fluctuations but the end values are fitting better. The explanation might come from the fact that the fitted curve is a "polynomial". More investigation are to be made to explain those differences.

We can now look for a prediction with more values to be added. Unfortunately changing the Index into datetime has been challenging and is left to be done.

[44]:

```
fig, ax = plt.subplots(figsize=(10.0, 8.0),sharex=False)

# First we are calculating an amplitude over a month period: Average between␣
↪the min and max / 2
amplitude = ((sorted_data.resample("M").mean().loc[datetime.date(1996, 2, 1):␣
↪datetime.date(1997, 2, 1)].max()-\
sorted_data.resample("M").mean().loc[datetime.date(1996, 9, 1): datetime.
↪date(1997, 9, 1)].min())/2).iloc[0]

# We define the initial offset that will be where the curve will begin
offset = sorted_data.resample("M").mean().min().iloc[0] + amplitude/2

# We are creating the frequency based on the period
f = len(sorted_data.resample("Y").mean().index)
sample = len(sorted_data.index)+(52*3)
x = np.arange(sample)

# Playing with the numbers we can find a line following the same frequency␣
↪having the same gradient.
y = amplitude*np.sin((2 * np.pi * f  * x/sample)) + popt[2]  + popt[3]␣
↪*x**popt[4]
ax.plot(x, y, 'g', linewidth=0.5, label="Preducted Sinusoid")

ax.set_title("Co2 Concentration over time: raw data and prediction")

ax.legend(loc='upper left')

plt.show()
```


Co2 Concentration over time: raw data and prediction
Predučted Sinusoid
420
400
380
360
340
320
0
500
1000
1500
2000
2500
3000
3500