World CO2 Emissions: Simple Analysis and its Relationship with Global Temperature Change

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Abstract. In the nature, booming CO2 emissions from the behaviors of human have adverse impact on the original Global Carbon Cycle. And this imbalance could cause the rise of global temperatures. This project collects the data of annual CO2 emissions as well as the global temperature change, trying to build their time-driving models independently with the help of regression functions and time prediction methods. By comparing between different models, we want to preliminary verify an assumption that there exists a limit of the ability of natural Global Carbon Cycle. If the amounts of CO2 in the atmosphere exceed this limit, the global temperature will increase. Also, whether the relationship between the increasing rate of global temperature and the CO2 emissions is linear or not is investigated. The conclusion shows that CO2 emissions and global temperature change have a strong and positive linear correlation, and if people produced less than around 20,000 Mt CO2 into the air, the global temperature could keep in dynamic equilibrium to some extent.

Keywords: Global temperature change, Greenhouse gas emissions, Environmental protection.

1. Introduction

The CO2, or the carbon dioxide, is a kind of Greenhouse gases, which means that its emissions contribute to the global warming. In the nature, there exists a circulation called the Global Carbon Cycle which can prevent the CO2 in the air from being excessive to influence the global temperature. However, as CO2 emissions from human activities such as fuel burning keep increasing, the cycle becomes less effective to adjust the Carbon balance and as a result, the global average temperature becomes higher along with the rising CO2 contents in the atmosphere. Hence, make it clear that how exactly does the amount of CO2 emissions affect the temperature is important in environmental protection work.

This project focus on dealing with the annual CO2 emissions data and global average temperature change data from 1960 to 2019 separately. We try to verify an assumption that there exists a limit of Global Carbon Cycle and the global temperature will keep increasing if CO2 in atmosphere exceeds such a limit. Moreover, the increasing rate of temperature is defined by the increasing rate of CO2 in atmosphere. In this project, we assume that the CO2 produced by the nature remains stable. Then the CO2 emissions decide the CO2 in atmosphere and can be used to represent the CO2 amount in atmosphere.

To complete the verification, firstly, we want to construct time varying models under different approaches and find the most accurate one to describe the annual changes in CO2 emissions and global temperature. Methods include SVR regression model, ARIMA model and Holt's Model linear trend method. Then, compare their changing trends referring to the models. If the two trends are similar, we can make a primary judgement that the two factors do have positive correlation, and the similarity decides whether the relationship is strong or not as well as whether this relationship is linear or not. Moreover, through finding the time node at which the global temperature started to have a distinguish increase with the help of models and K-means clustering method, we can roughly determine the carbon dealing ability of the nature Carbon Cycle.

The results shows that if people produce more than 20,000 Mt CO2 emissions, the global temperature will begin to have a distinguished increase. Also, by computing the correlation coefficient R between the two variables, we find that the CO2 emissions and the global temperature change have a strong correlation. Both data have shown fitness with the Holt's linear trend model and have increasing trends with nearly stable rate, which means that the relationship between the two datasets is almost linear. Or we can explain this result as: every year, the same increase of CO2 in the atmosphere will cause a certain amount of rise in global average temperature.

2. Related Works

Our World in Data [1] is a website which gathers data about CO2 emissions from different dimensions. For example, it has calculated the CO2 emissions amount of the world and of different countries:

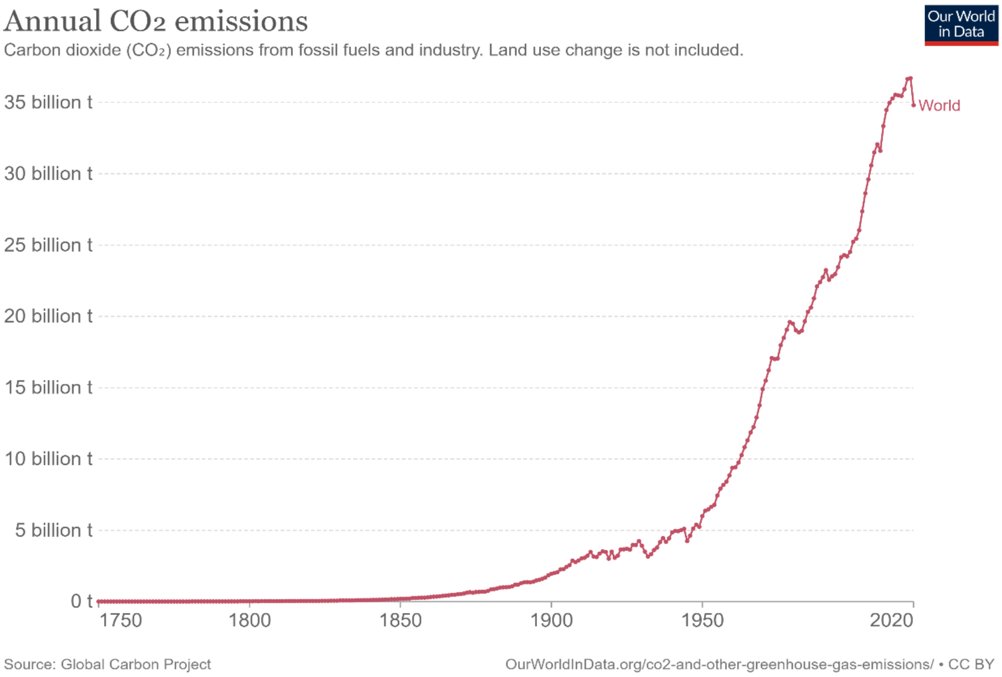


Fig. 1 World CO2 Emissions (From 1750 to 2020) [1]

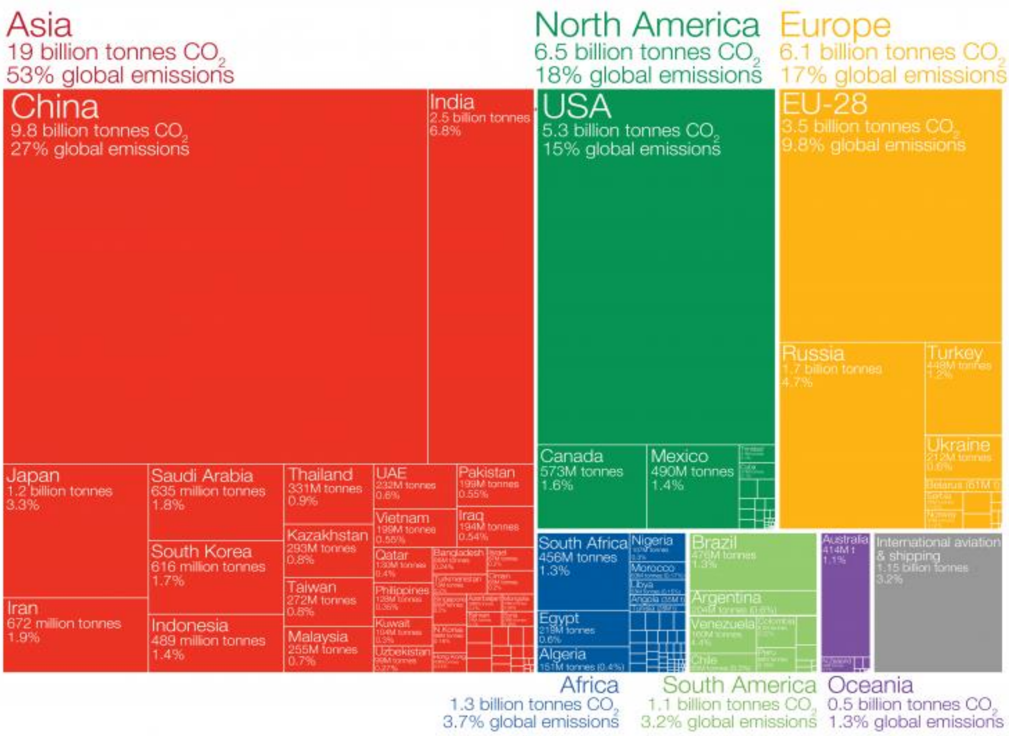


Fig. 2 Global CO2 Emissions by Regions in 2017 [1].

From which we can see that there exists an increasing tendency of global CO2 emissions. Also analyzing from the tree map which represents CO2 emissions in 2017 by different countries, we have the following results that CO2 emissions may be related with the area of a country. For example, countries like China, Russia and USA are all of great areas and also have great amounts of CO2 emissions. In total, the more developed countries usually have more CO2 emissions.

So where do all the CO2 emissions come from? Do our environmental actions like reducing the use of private cars and power saving really do benefits to decreasing the emissions of greenhouse gases? We use the data from Our World in Data [1] and plot the pie chart of CO2 emissions by sectors from 1990 to 2019 as follows:

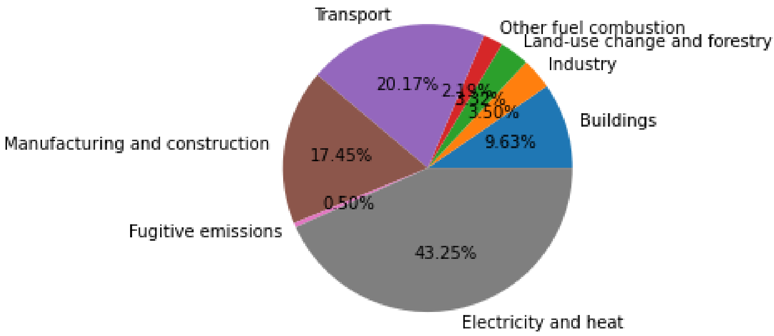


Fig. 3 CO2 Emissions Resources (From 1990 to 2019)

From this chart, we know that most of the CO2 emissions come from electricity and heat produced in our daily life since 1990. Transport and construction also have a great proportion. The CO2 emissions are closely related with our daily life, which means that even small behaviors can make a difference.

Another related research is worked by Steven, Ken and H. Damon to study how our climate will change if we stopped adding infrastructures that consuming fossil fuels, or in other word, if we kept the CO2 emissions resources as present and let them fail over time [2]. It assumpts a model that the CO2 emissions changing rate would gradually decrease from now on and it tries to predict the temperature change till 2060 under this model. Below are the predictions of CO2 amount changes and temperature changes:

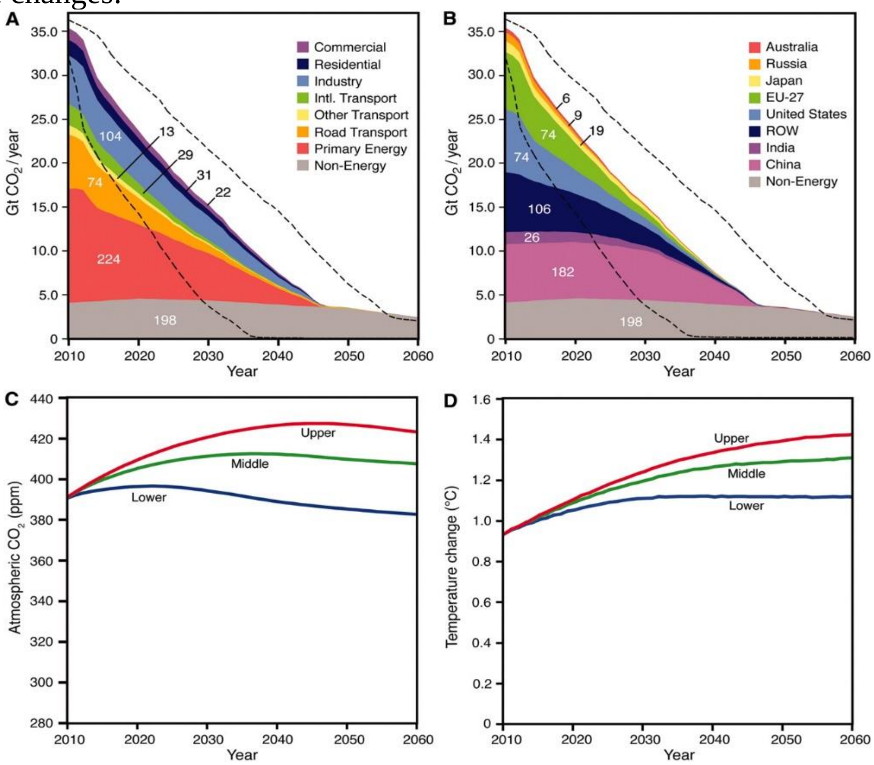


Fig. 4 Future CO2 Emissions and Climate Change [2]

This work shows that even we deduced CO2 emissions immediately, the CO2 contents in the atmosphere will keep increasing in the next thirty to forty years and so does the global average temperature. Even the CO2 amount in the atmosphere deduced, by comparing between picture C and picture D, we can see that the global temperature still increases but in a slower rate.

Actually, this model is suitable with our assumption above to a certain degree: before the CO2 contents reduced to a certain quantity which is assumpted as the limit of the ability of Global Carbon Cycle, the global temperature will keep increasing; and furthermore, the amount of CO2 influences the increasing rate of temperature.Next, we will analyze some datasets about CO2 emissions and global temperature and prove our assumption.

3. Materials

All over this project, we employ the data imported from the website Our World in Data [1], which is supported by Global Change Data Lab and is a powerful resource to gain statistical information. It collects data of annual CO2 emissions in various countries (regions) and from different resources. We choose the data among 1960 and 2019 as our target.

Table 1. CO2 Emissions in Different Regions

Year\Country	Afghanistan	Albania	Algeria	...	Yemen	Zambia	Zimbabwe
1960	0.41388	2.0225	6.1512	…	3.631	4.3553	5.9431
1961	0.4908	2.279	6.0559	…	2.6637	3.709	5.0613
…	…	…	…	…	…	…	…
2019	12.1467	4.8635	166.6419	…	10.0204	7.0472	10.9491

Do addition horizontally and get the annual amount of CO2 emissions around the world. Plot the data as below:

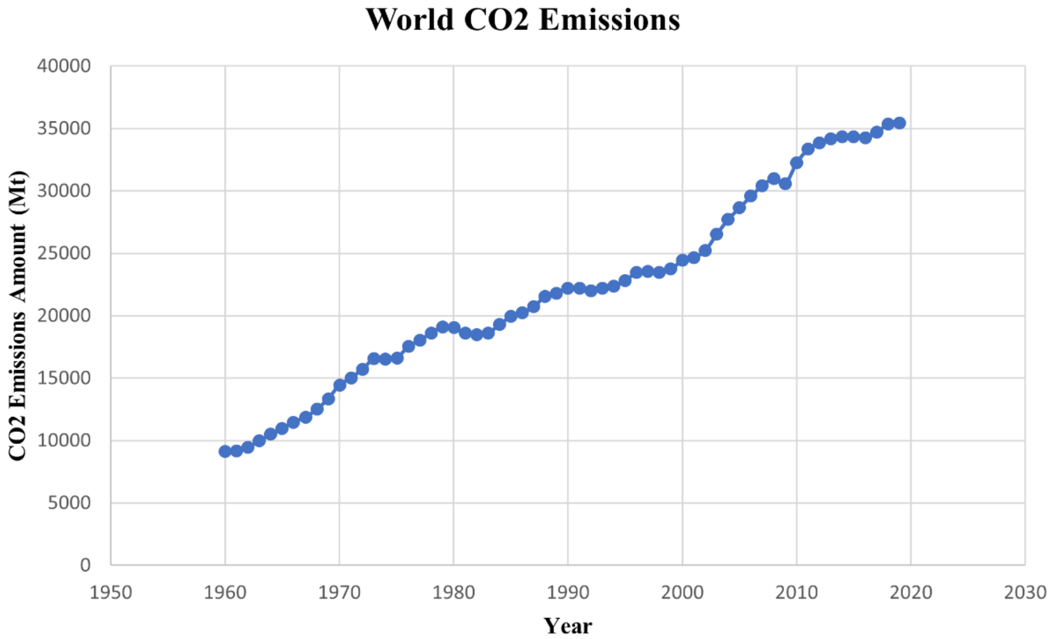


Fig. 5 World CO2 Emissions (From 1960 to 2019)

The blue points express CO2 emissions amount in different years, and they are connected by segments. A simple judgement can be made at first glance of this figure that the annual amount of CO2 emissions keeps increasing since 1960 under a steady rate. Then this makes our study about the relationship between CO2 emissions and global temperature easy. Similarly, we download the global temperature data from this website and plot it:

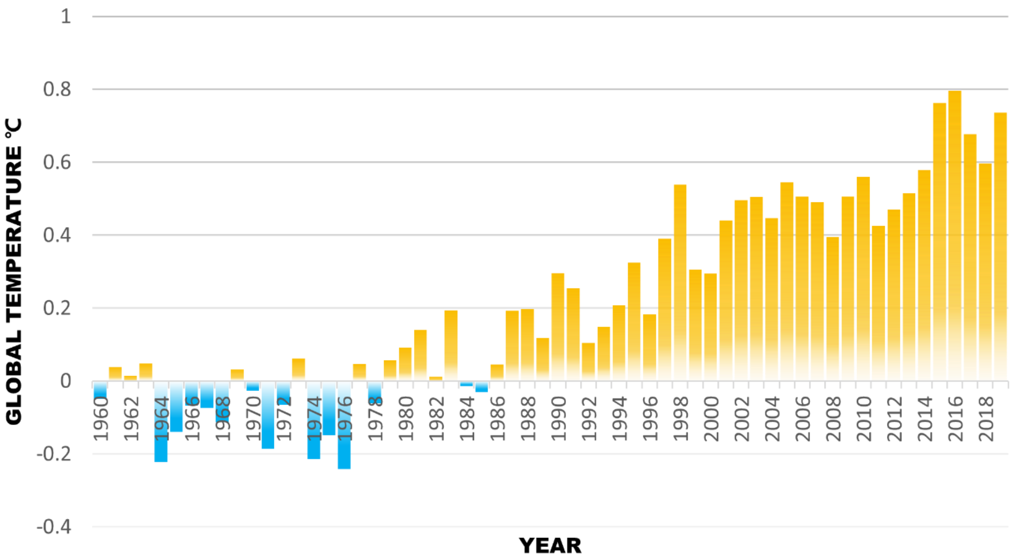


Fig. 6 Global Temperature Change

Blue color means the temperature is less than zero while orange means that the temperature exceeds zero. Since 1980s, we can see through this figure, the world average temperature keeps increasing and in 2019, it has increased by nearly 1℃.

Then if we combine the two figures together and plot the bubble chart, we will have a more intuitive feeling about the relationship between CO2 emissions and global temperature:

Fig. 7 Global Temperature Change and CO2 Emissions From 1960 to 2019 (Every 5 Years)

In this chart, the x-label is the years and the y-label is global temperature of every year. Annul global CO2 emissions are expressed by the widths of the bubbles. We can make a basic judgment that as the CO2 emissions increase year by year, the world average temperature also increases.

Actually, if we compute the correlation coefficient R between temperatures and CO2 emissions from 1960 to 2019, we will find that they have a strong correlation with each other.

```
data = pd.DataFrame({'CO2 Emissions': x,'Global Temperature':y})
data.corr()
```

	CO2 Emissions	Global Temperature
CO2 Emissions	1.000000	0.895276
Global Temperature	0.895276	1.000000

Fig. 8 Python Code to Calculate the Correlation Coefficient and the Result

Note that the correlation coefficient is around 0.9, which is a quite high value and proves that the two variables, CO2 emissions and temperature changes, are highly related with each other. Then we construct time varying models of two variables separately, and therefore find their changing trends according to time.

4. Method

4.1. Preprocess the Data and Define the Comparing Target.

Firstly, to simplify the data analyzing process, and make it convenient to compare between different models, we need to normalize the data. In this project we use the min-max normalization method. The function is given by:

$$x^* = \frac{x - min}{max - min}. \tag{1}$$

In this way, we keep the relationship within the data itself and at the same time deduce the influence generated from numerical values. Also, removing the effect of values makes us focus on the changing trend of the two datasets only, which makes the relationship between CO2 emissions and global temperature more intuitive.

Moreover, before constructing the models, we will divide the data into train set and test set according to time varying order, and define the division ratio as 0.7. The first 42 numbers (60 * 0.7 = 42) of year from 1960 to 2001 will serve as the train data while the remaining 18 values (from 2002 to 2019) serve as the test data.

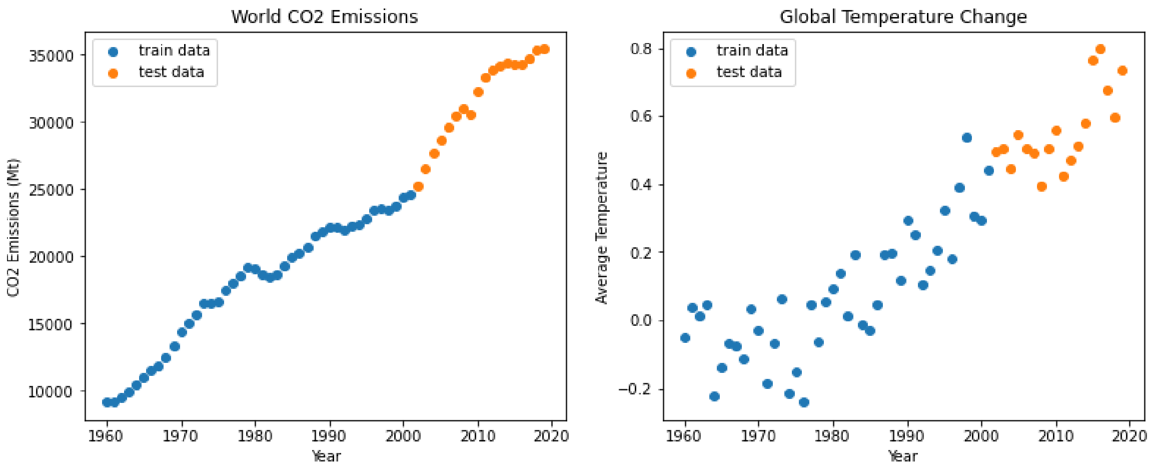


Fig. 9 Train and Test Data of Two Datasets

Next, on the basis of data normalization, we can choose the mean squared error (MSE) as the index to judge whether a model is good or not and to compare between different models. The calculating function of MSE is:

$$\text{MSE} = \frac{\sum(\hat{y} - y)^2}{n}. \tag{2}$$

Where $\hat{y}$ stands for the predict value of the test data by the model and y is the exact value of test data. A smaller MSE value means that the prediction values deviate the observations less and hence means a more accurate model. By doing so, we can determine the best model by finding the smallest MSE value.

4.2. Train and Test the Data to Construct Models

4.2.1 SVR regression method

The first model we use is the support vector regression (SVR) model. The main purpose is to find a line which minimizes the distances between the data points and the line itself. In this model, we regard the predict data lying within an error region of the initial data as a well fitted one [3].

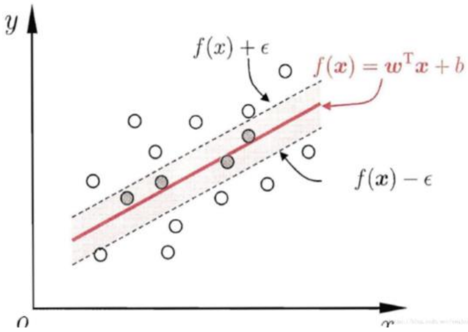


Fig. 10 Concept of SVR Model [3]

There are different types of kernel functions in SVR model: linear function, sigmoid function and radial basis function (rbf). These functions deal with different data distributions to do regression tasks. To justify which one fits out data best, we can simply use code below to accomplish going through all the models and finding the most suitable one.

```
model = GridSearchCV(SVR(), param_grid={"kernel": ("linear", 'rbf', 'sigmoid'),
                                        "C": np.logspace(-3, 3, 7),
                                        "gamma": np.logspace(-3, 3, 7)})
model.fit(train_data_x, train_data[y])
```

Fig. 11 SVR Fitting Code

Then by applying prediction function to the models, we do predictions on the test data to observe its performance on test sets. Sketch the SVR models we gain and calculate the MSE respectively, the results are shown in Fig. 12 and Fig. 13. And Table 2 shows the calculated MSE values.

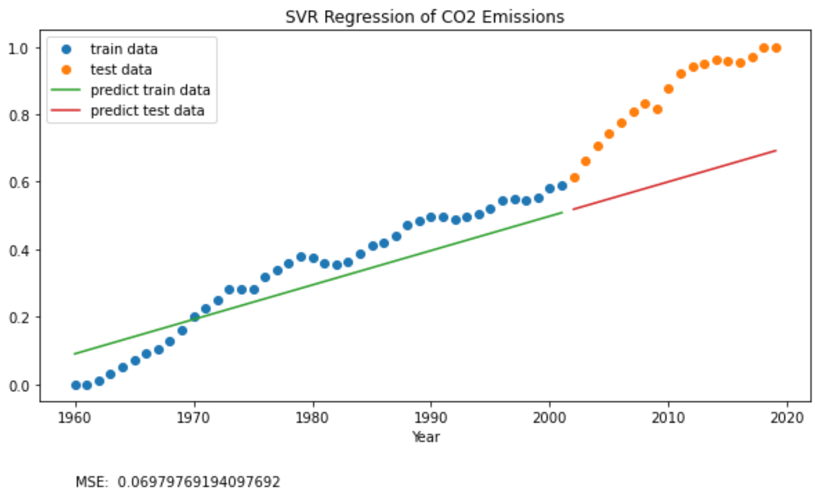


Fig. 12 SVR Regression Model of World CO2 Emissions

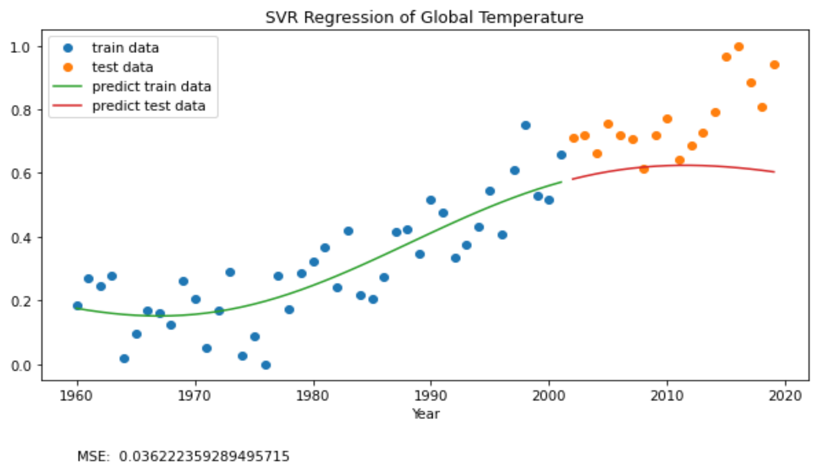


Fig. 13 SVR Regression Model of Global Temperature Change

Table 2. MSE Values of Different Models

Model\Dataset	CO2 Emissions	Temperature Change
SVR Regression	0.06979769194097692	0.036222359289495715

4.2.2 ARIMA method

ARIMA means autoregressive integrated moving average, and ARIMA model utilizes historical values in a time series to forecast future values [4]. During transforming the unstable time series into a stable one, ARIMA model casts notice on the fluctuation of the variable and do regression on it.

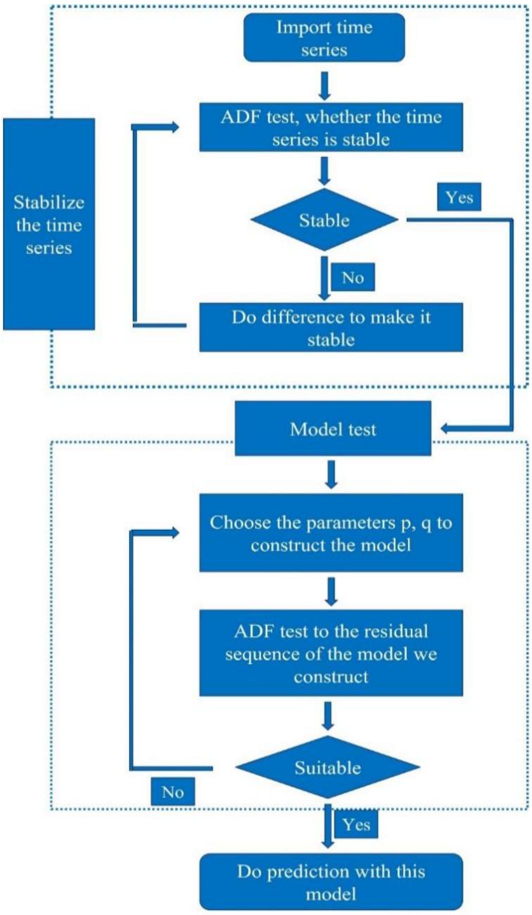


Fig. 14 Flowchart of ARIMA.

The flowchart above represents the process of ARIMA method. Our data are both time varying series, hence the ARIMA model will be a powerful tool to help construct prediction models.

Firstly, we apply ADF test to both datasets and list the results in tables below. If the T-value (test statistic value) is less that the critical values, then the data is stable (do not change along time) and it passes the ADF test. Otherwise, we need to difference the data.

This table and figure tell us that before we do difference on CO2 emissions data, it is an unstable time series.

Table 3. ADF Test on CO2 Emissions Data Before and After Difference

ADF Test on CO2 Data Without Difference		ADF Test on CO2 Data After Difference	
Statistical Metrics	Value	Statistical Metrics	value
Test Statistic Value	-0.474205	**Test Statistic Value**	-5.165412
p-value	0.896953	**p-value**	0.00001
Lags Used	1	Lags Used	0
Number of Observations Used	58	Number of Observations Used	58
Critical Value (1%)	-3.548494	Critical Value (1%)	-3.548494
Critical Value (5%)	-2.912837	Critical Value (5%)	-2.912837
Critical Value (10%)	-2.594129	Critical Value (10%)	-2.594129

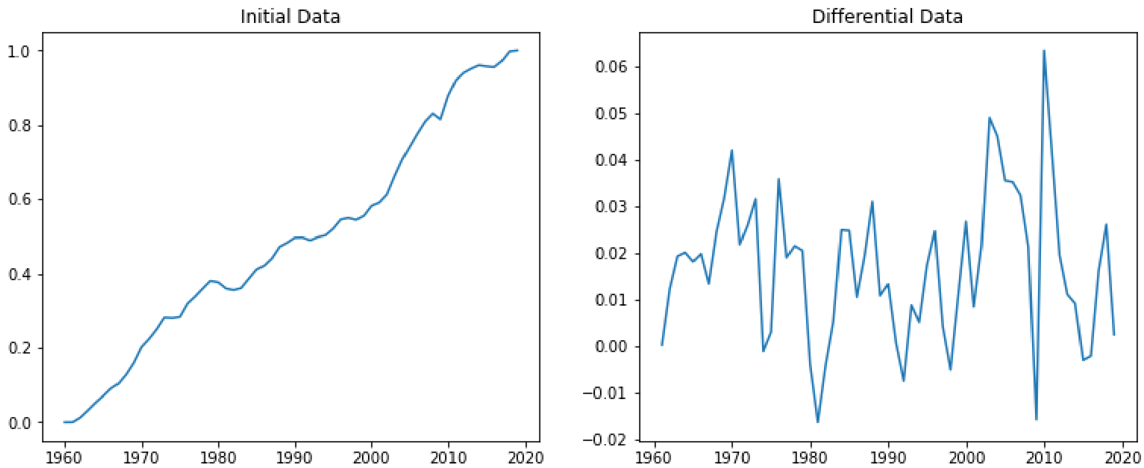


Fig. 15 CO2 Emissions Data

Also, we do the similar things to the dataset about global temperature change:

Table 4. ADF Test on Global Temperature Data Before and After Difference

ADF Test on Temperature Data Without Difference		ADF Test on Temperature Data After Difference	
	value		value
Test Statistic Value	-0.474205	Test Statistic Value	-5.165412
p-value	0.896953	p-value	0.00001
Lags Used	1	Lags Used	0
Number of Observations Used	58	Number of Observations Used	58
Critical Value (1%)	-3.548494	Critical Value (1%)	-3.548494
Critical Value (5%)	-2.912837	Critical Value (5%)	-2.912837
Critical Value (10%)	-2.594129	Critical Value (10%)	-2.594129

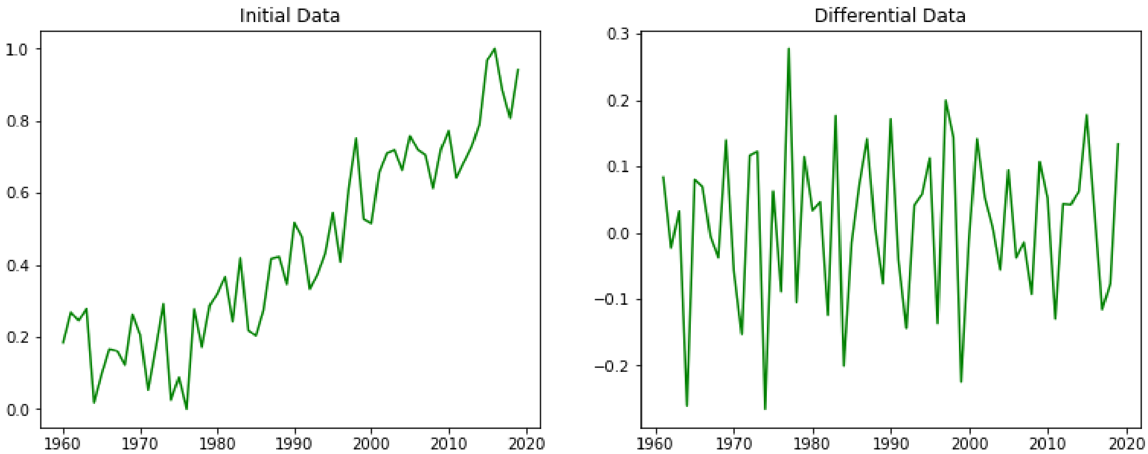


Fig. 16 Global Temperature Data

Both CO2 emissions data and global temperature data are not stable series, so we need to make a difference on each of them. Also, we note that, after first order difference, the p-values become closer to zero, which means that the new datasets can be suitable for ARIMA model.

Next, we need to find the most suitable coefficients (p, q) according to different datasets to construct the ARIMA models. Estimate different models and calculate AIC and BIC values, we finally find the parameters (p, d, q) required for ARIMA models.

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   42
Model:                 ARIMA(4, 1, 3)   Log Likelihood                 125.680
Date:                Sat, 24 Sep 2022   AIC                           -235.359
Time:                        08:56:21   BIC                           -221.651
Sample:                             0   HQIC                          -230.367
                                 - 42
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.4572      0.746      0.613      0.540      -1.005       1.919
ar.L2          0.3052      0.608      0.502      0.616      -0.887       1.497
ar.L3          0.4762      0.326      1.460      0.144      -0.163       1.115
ar.L4         -0.2598      0.376     -0.691      0.490      -0.997       0.477
ma.L1          0.2761      0.832      0.332      0.740      -1.354       1.906
ma.L2         -0.5906      0.216     -2.728      0.006      -1.015      -0.166
ma.L3         -0.4683      0.449     -1.042      0.297      -1.349       0.412
sigma2         0.0001   3.97e-05      3.137      0.002    4.68e-05       0.000
===================================================================================
Ljung-Box (L1) (Q):                   0.13   Jarque-Bera (JB):                 0.89
Prob(Q):                              0.72   Prob(JB):                         0.64
Heteroskedasticity (H):               0.73   Skew:                            -0.24
Prob(H) (two-sided):                  0.57   Kurtosis:                         2.47
===================================================================================
```

Fig. 17 Model Estimation Result of CO2 Emissions Data

```
                                         SARIMAX Results
===============================================================================================
Dep. Variable:     Median temperature anomaly from 1961-1990 average   No. Observations:     42
Model:                                                ARIMA(3, 1, 2)   Log Likelihood    38.970
Date:                                               Sat, 24 Sep 2022   AIC              -65.939
Time:                                                       08:55:04   BIC              -55.658
Sample:                                                            0   HQIC             -62.195
                                                                - 42
Covariance Type:                                                 opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.9699      0.116     -8.347      0.000      -1.198      -0.742
ar.L2         -1.2210      0.061    -20.120      0.000      -1.340      -1.102
ar.L3         -0.5744      0.113     -5.062      0.000      -0.797      -0.352
ma.L1          0.4935      0.261      1.894      0.058      -0.017       1.004
ma.L2          0.9705      0.928      1.046      0.296      -0.848       2.790
sigma2         0.0076      0.007      1.154      0.249      -0.005       0.021
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):                 3.06
Prob(Q):                              0.93   Prob(JB):                         0.22
Heteroskedasticity (H):               0.85   Skew:                            -0.67
Prob(H) (two-sided):                  0.77   Kurtosis:                         2.88
===================================================================================
```

Fig. 18 Model Estimation Result of Global Temperature Data

We choose (4, 1, 3) to construct the model of CO_2 emissions and (3, 1, 2) for temperature change. And the models are plotted as below:

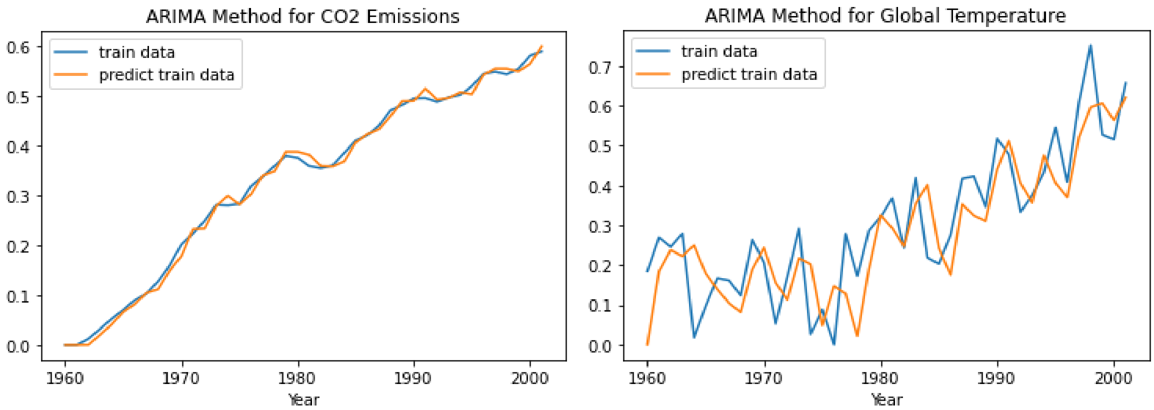


Fig. 19 ARIMA Models about difference datasets

Next, we do ADF tests on the residuals of the two models to justify that they are indeed well fitted models.

Table 5. ADF Test on Residuals of ARIMA Models

ADF Test on Residual of CO2 Emissions Model		ADF Test on Residual of Temperature Change Model	
	value		value
Test Statistic Value	-5.755015	Test Statistic Value	-6.209845
p-value	0.000001	p-value	0.0
Lags Used	0	Lags Used	0
Number of Observations Used	41	Number of Observations Used	41
Critical Value (1%)	-3.600983	Critical Value (1%)	-3.600983
Critical Value (5%)	-2.935135	Critical Value (5%)	-2.935135
Critical Value (10%)	-2.605963	Critical Value (10%)	-2.605963

The models pass the ADF test, so we can make predictions on test data using the ARIMA models and have following figures:

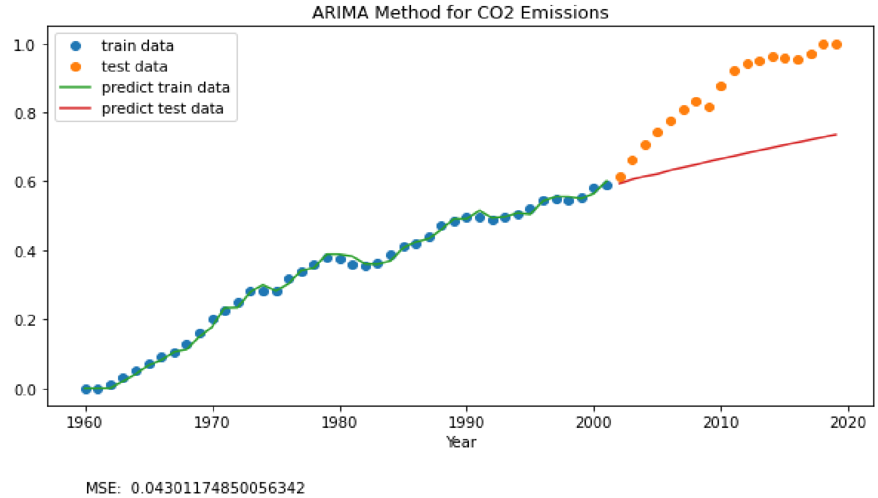


Fig. 20 ARIMA Model of World CO2 Emissions

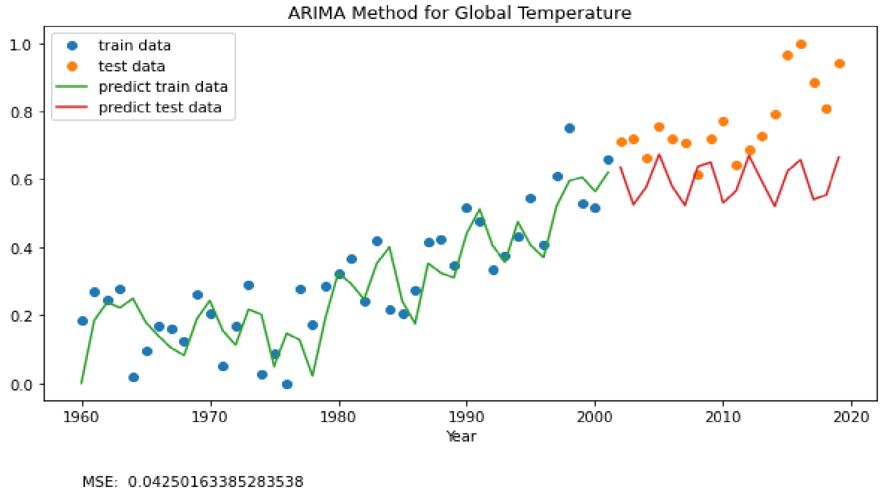


Fig. 21 ARIMA Model of Global Temperature Change

Calculate the MSE values, we achieve:

Table 6. MSE Values of Different Models

Model\Dataset	CO2 Emissions	Temperature Change
SVR Regression	0.06979769194097692	0.036222359289495715
ARIMA Model	0.04301174850056342	0.04250163385283538

4.2.3 Holt's linear trend method

Holt's linear trend is another time series analysis method and is quite suitable for long term prediction. Its models are described by functions like:

Forecast equation: $\hat{y}_{t+h|t} = l_t + hb_t$

Level equation: $l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1})$

Trend equation: $b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1}$

Fig. 22 Forcast Function of Holt's Linear Trend Model [5]

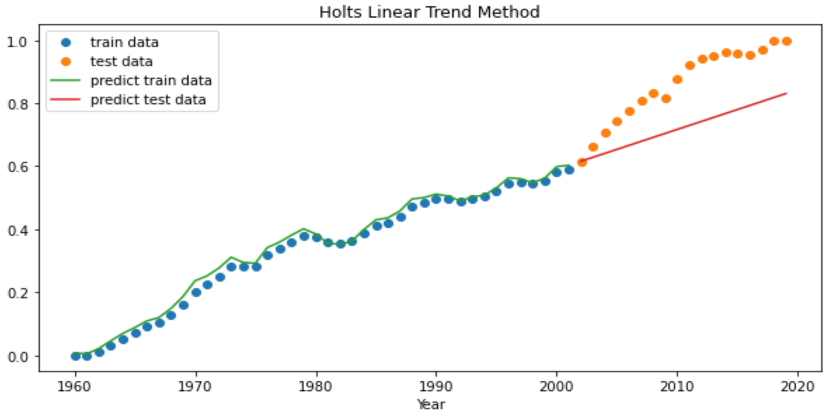
Where 0 < α, β < 1.

We can use the tool in python named statsmodels.tsa.holtwinters. Holt and plot the Holt's linear trend models directly by using the code:

```
from statsmodels.tsa.holtwinters import Holt
holt_linear_trend =  = Holt(train_set).fit()
prediction_test_data = holt_linear_trend.predict(start = 43, end = 60)
```

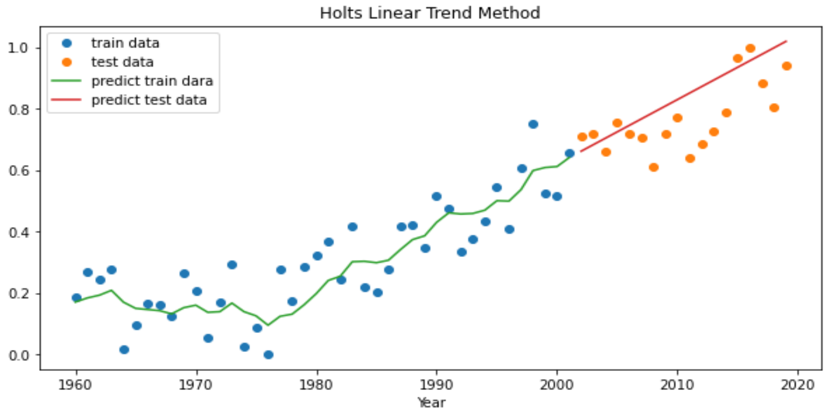
Fig. 23 Holt's Linear Trend Model Construction Code

And plot the models as below:



MSE: 0.0222011341980211

Fig. 24 Holt's Linear Trend of World CO2 Emissions



MSE: 0.012820288391258285

Fig. 25 Holt's Linear Trend of Global Temperature Change

Finally, list all the MSE values in a table to make comparisons:

Table 7. MSE Values of Different Models

Model\Dataset	CO2 Emissions	Temperature Change
SVR Regression	0.06979769194097692	0.036222359289495715
ARIMA Model	0.04301174850056342	0.04250163385283538
Holt's linear trend	0.0222011341980211	0.012820288391258285

4.3. Compare the Models

We have plotted three models by different methods of each dataset and constructed the MSE value table. Note that the smaller the MSE value is, the more suitable the corresponding model is. So we can easily find the best ones by comparing the MSE values of different models. The MSE value table shows that both datasets, the CO2 emissions and global temperature change, fit with Holt's linear trend models best, then we choose the Holt's models to express and predict the data.

5. Results

Observe and analyze the Holt's models we plot, the points represent CO2 emissions or temperature change data after normalization which we have done at the begining and the lines express predict values by the models we build.

We see that the changing trend of CO2 emissions can be approximated as a linear straight line, which means that global CO2 emissions keep increasing annually under a nearly stable rate. Hence, we can make predictions using this model that with no other influencing factors added like new environmental protection policies, the world CO2 emissions will keep increasing under the same or similar rate at least in the near future.

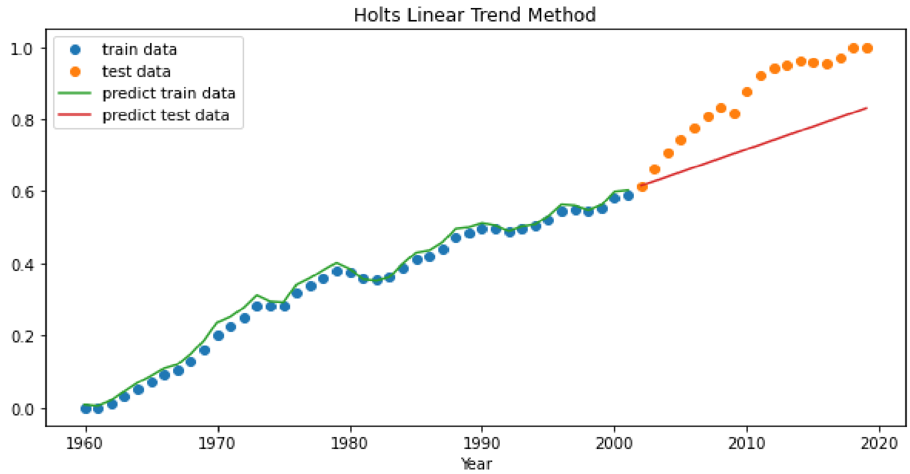


Fig. 26 Holt's Linear Trend of World CO2 Emissions

On the other hand, the Holt's model of temperature change shows a distinguished difference of trends before and after year 1980. The global temperatures before 1980 are nearly in a dynamic equilibrium; however, after 1980, the global average temperatures have a continued growth and the increasing rate almost keeps unchanged.

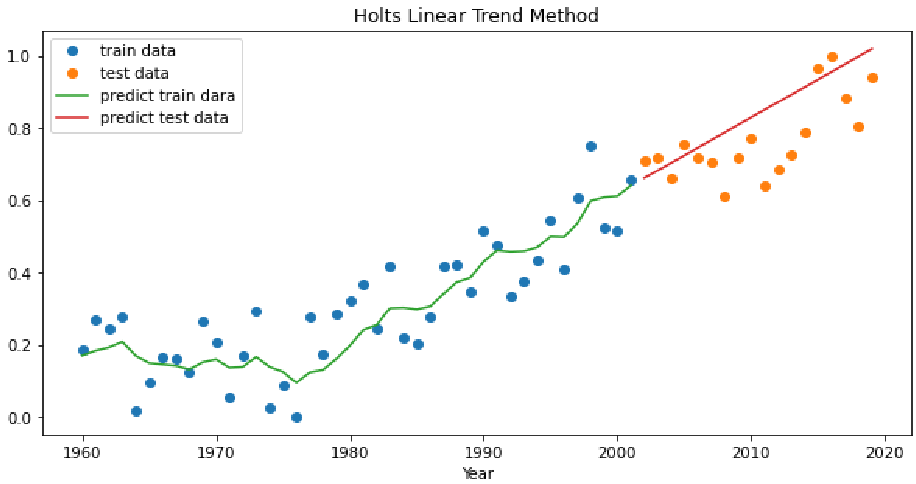


Fig. 27 Holt's Linear Trend of Global Temperature Change

Moreover, if we apply K means clustring on global temperatures from 1960 to 2019, we will find that such division from year 1980 makes sense:

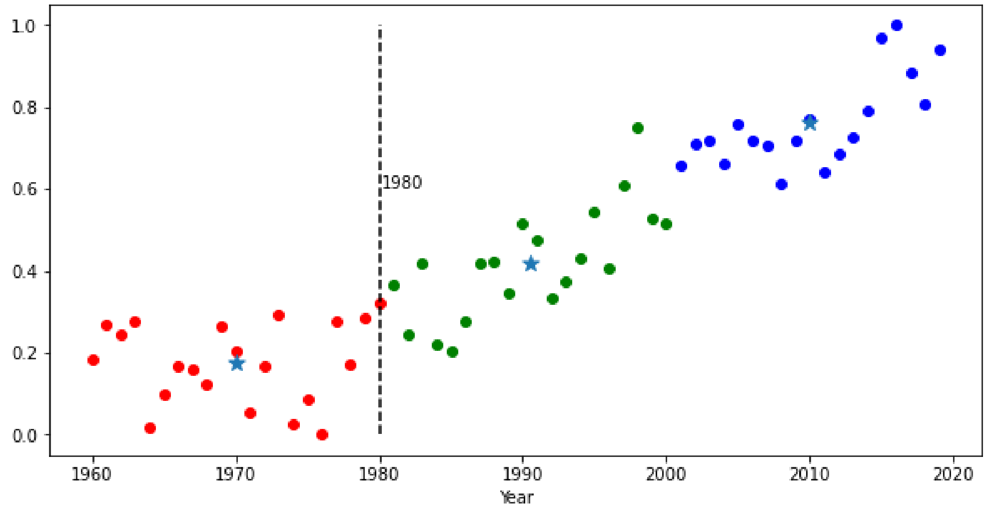


Fig. 28 K-means Clustering of Global Temperature From 1960 to 2019 (K = 3)

The clusters prove that there exists a difference between temperatures before 1980 and after it.

If we plot the two models of CO2 emissions and temperature change together to compare their rates and increasing trends, we will get a more intuitive image:

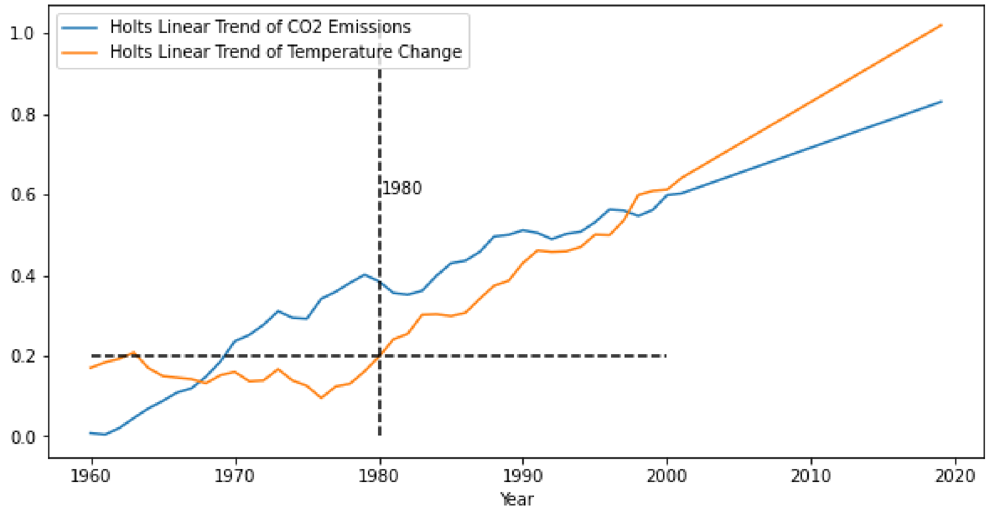


Fig. 29 Holt's Linear Trend Models of Two Datasets

This sketch focus on the trends and we mark the year 1980 to highlight the divisions of global temperature change trends. The differences before and after 1980 can be explained by our assumption that before 1980, although CO2 emissions kept increasing, the CO2 in atmosphere did not exceed the ability of Global Carbon Cycle and as a result, the global temperature did not increase; while after 1980, higher CO2 emissions made the CO2 contents in atmosphere exceed the limit that Global Carbon Cycle can deal with, and caused the CO2 in the air growing which eventually brought the increase in global temperature. This exactly helps us confirm the assumption. Furthermore, the world average temperature has a steady increase rate which is determined by the linear growth of annual CO2 emissions.

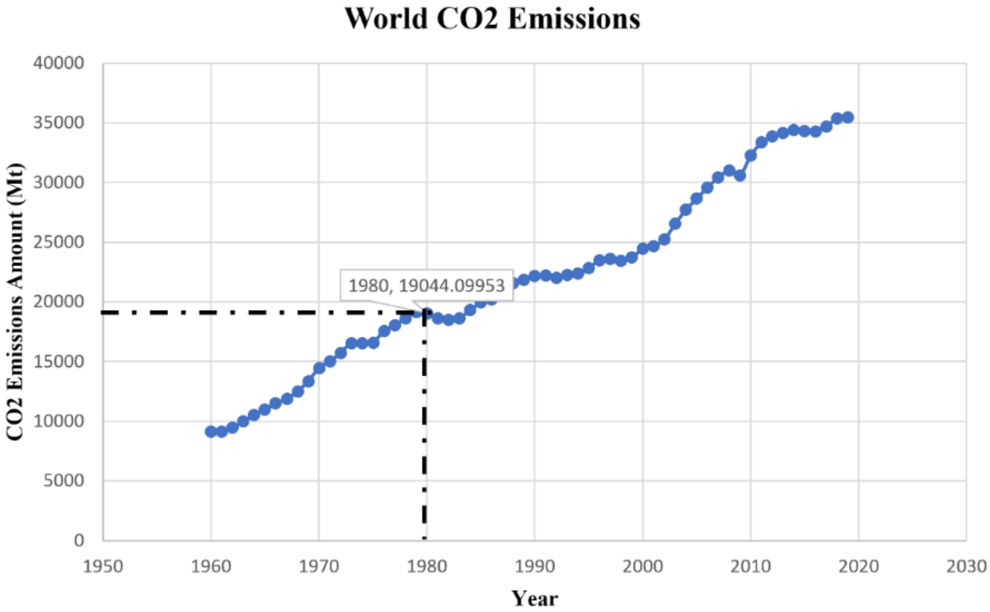


Fig. 30 World CO2 Emissions (From 1960 to 2019)

Going back to the world CO2 emissions we plotted before, we can find that when people produce around 20,000 (Mt) CO2 to the atmosphere, under the assumption that CO2 produced by the nature keeps unchanged, the Global Carbon Cycle fails to transport all the CO2 in atmosphere to cycle.

6. Discussion and Conclusionss

With all the work done above, we have an elementary proof of our assumption that the ability of Global Carbon Cycle is limited to some certain value, and when CO2 contents in the atmosphere exceed this limit, it will cause global warming. This project have roughly proved the assumption proposed at the beginning, meanwhile it still remains some limitations.

Firstly, this project simply draws a conclusion by merely comparing the changing trends of CO2 emissions and global temperatures. It lacks a strict and scientific test-and-prove process along with controlling variables. This makes the conclusion not quite rigorous.

Secondly, the size of the database we choose in this project is quite narrow since data in 19th century and before are not comprehensive and even not accessible. Then the project cannot eliminate the interference of special circumstances or special periods, and cannot draw a fine and extensive conclusion. Also, the limited size of the data may make the models we constructed in this project not accurate enough, which can also influence the conclusions we get from comparing models.

Last but not least, except CO2, there still exist other greenhouse gases produced from human activities that can influence the climate, but this project ignored the effects caused by these gases. Then the conclusion may magnify the effect of CO2 emissions to global temperature.

In future research, we may manufacture environments simulating the atmosphere in laboratory. Then we can control variables through changing the amount of CO2 merely in the simulation environments. Then compare the models of simulation environments and the natural atmosphere, we can clarify the influences of CO2 emissions to temperature changes.

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