Robert Bona, Pradeep Sharma, Maysarah Sukkar

EK 125

Lab C3

8 December 2021

EK 125 Final Project - How Global Climate Change Will Impact the World's Food Supply Continent by Continent - Analysis

Climate change is a global problem that has picked up traction especially in the last 30 years. While many countries are well off financially dealing with climate change, many are not. Therefore, for a problem that is caused by every person on this globe, some parts of the world are affected more than others. One significant part of human existence is the production and consumption of food. Because basic foods like wheat, rice, and maize are all dependent on the environment in which they grow, it makes sense how climate change could have an impact on them and ultimately the food supply and production in a nation or even throughout an entire continent. Some of the world's leading emitters of carbon dioxide (CO_2) are some of the richest countries in the world and are wreaking havoc on lower income countries such as the developing countries in Africa. The consensus among scientists today is that if global emissions remain constant, atmospheric CO_2 will only continue to rise, which causes more climate change and exacerbates its effects. Therefore, it is urgent to address which areas of the world are going to have their food supply and production most impacted by rising levels of atmospheric CO_2 and climate change in order for major global health and international organizations like the United Nations so the world can address this global issue and those that are most well off know who is most affected and therefore could help their food supply stay afloat so world hunger does not become a future problem in continents heavy in developing countries, such as in Africa.

Going into this analysis, we hypothesized that developing countries in continents like Africa will likely experience the hardest hit to their food supply as atmospheric CO_2 continues to rise over time. Additionally, we believe that North America will be the most well off. These are both based on their abilities to respond to the threat of atmospheric CO_2 and the resulting global warming and ecosystem shifts due to climate change. Our goals include finding the most well off continents and least well off continents to see which two are best paired to together mitigate climate change to stabilize global food production and making a clear distinction between the developing world and developed world in terms of their ability to mitigate environmental threats financially and resourcefully by ranking their ability to withstand higher levels of atmospheric CO2 in their staple crop production cycles based off models from our scatterplots.

To look into this, we analyzed a dataset from a study developed by Ana Iglesias of the Universidad Politécnica de Madrid and Cynthia Rosenzweig of the NASA Goddard Institute for Space Studies, managed by CIESIN at Columbia University in March 2010. Their goal was to assess potential climate change impacts on world staple crop production in terms of wheat, rice, and maize production, focusing on changes in gross production yields based on multiple climate scenario runs. These different runs included different levels of predicted atmospheric CO2 through three different decades: the 2020's, 2050's, and 2080's, with four different scenarios set up in 2000 by the Special Report on Emissions Scenarios (SRES) developed by researchers at Columbia University.

Before beginning to scrub the data, we first checked to see if there was any bias according to the dataset. After studying an article by Telus International, we determined that this dataset did not have any bias. The article described the seven types of data bias in machine learning, which include sample bias, which is when a dataset ignores the realities of the environment in which the model will run, exclusion bias, which is when valuable data is deleted when it was initially thought to be unimportant, measurement bias, which is when data collected for training is different from that in the real world, recall bias, which is when data is labeled inconsistently, observer bias, which is when researchers go into a study knowing what they want to see in the results, racial bias, and association bias, which is when the data for a machine learning model reinforces a cultural bias. This dataset did not fall under any of these categories. The article also touched on ways to avoid data bias in machine learning, with bias testing being a key part of the development cycle and ensuring the team of data scientists and data labeling is diverse being a few discussed.

First, we imported our excel file into MATLAB using the readtable function, reading it as a .csv file. Next, we scrubbed the data to isolate the data that was necessary.for our analysis. The dataset gave the change in percent gross food production for wheat, maize, and rice individually but also their total percent yield for each of the four predicted atmospheric CO2 scenarios for each of the three decades modeled. These percentages are based off of given values of production totals for each staple crop for between the years 2000 and 2006, which was used as the baseline timeframe. Separating the 167 countries that had data into continents would give us the best idea of how climate change would impact the world on a broader scale, so the first thing done was to split the countries into six continents: North America, South America, Europe, Asia, Africa, and Oceania (includes Australia, New Zealand, and Papua New Guinea). We knew we were eventually aiming to create two-column tables with the atmospheric CO2 as the predictor and the change in percent total gross production of the staple crops studied as the response, so we indexed into the large dataset and created arrays for each decade (2020's, 2050's, 2080's) by combining the percent yield for each scenario for atmospheric CO2 into a single array for each year for each country. These arrays were then combined to create the total array. Next, we cleared all the NaN values in the array using nested for loops by replacing them with zeroes. Further, we created another column with the associated atmospheric CO2 levels according to the SRES scenarios given in ppmv. We did this for each of the six continents. We initially tried to use year instead of atmospheric CO2 levels, but we figured it would only give three predictors and not represent climate change and its effects more than just time, even though the dataset and SRES scenarios make it clear that atmospheric CO2 will continue to rise in the coming decades. Using these newly created tables for each continent, we were able to use the ML Toolbox to plot each scatterplot and visually analyze our data, which we analyzed by continent. These are presented in the order in which we analyzed them in:

Here is example code used to create such a table and an example of the table format used for each scatterplot. Here, the continent of Oceania is an example.

```
CO2_Levels_ppmv = [];
%Below is the creation of the cumulative
%Oceania_Change_in_Percent_Gross_Product column with all values from all
%decades and SRES modeled future scenarios in one column%
Oceania_2020 = [climateDataTable.A2020_TGP([8 109 117]) ; climateDataTable.B2020_TGP([8 109 117]) ; climateDataTable.C2020_TGP([8 109 117])
Oceania_2050 = [climateDataTable.A2050_TGP([8 109 117]) ;climateDataTable.B2050_TGP([8 109 117]) ;climateDataTable.C2050_TGP([8 109 117]) ;c
Oceania_2080 = [climateDataTable.A2080_TGP([8 109 117]) ;climateDataTable.B2080_TGP([8 109 117]) ;climateDataTable.C2080_TGP([8 109 117]) ;c
Oceania_Change_in_Percent_Gross_Product = [Oceania_2020 ; Oceania_2050 ; Oceania_2080];
%Below is the initialization of the CO2_Levels_ppmv vector to the values
%for the corresponding SRES scenarios for each decade%
for i = 1:12
    CO2_Levels_ppmv(i, :) = 432;
end
for j = 13:15
    CO2_Levels_ppmv(j, :) = 421;
end
for k = 16:21
    CO2_Levels_ppmv(k, :) = 422;
end
for l = 22:24
    CO2_Levels_ppmv(l, :) = 590;
end
for o = 25:33
    CO2_Levels_ppmv(o, :) = 549;
end
for t = 34:36
    CO2_Levels_ppmv(t, :) = 492;
end
for s = 37:42
    CO2_Levels_ppmv(s, :) = 488;
end
for m = 43:45
    CO2_Levels_ppmv(m, :) = 810;
end
for v = 46:54
    CO2_Levels_ppmv(v, :) = 709;
end
for z = 55:57
    CO2_Levels_ppmv(z, :) = 527;
end
for d = 58:63
    CO2_Levels_ppmv(d, :) = 561;
end
OceaniaData = table(CO2_Levels_ppmv, Oceania_Change_in_Percent_Gross_Product)
[slope] = polyfit(CO2_Levels_ppmv, Oceania_Change_in_Percent_Gross_Product, 1)
```

OceaniaData = 63×2 table

	CO2_Levels_ppmv	Oceania_Change_in_Percent_Gross_Product
1	432	0.8500
2	432	0.2500
3	432	-1.0300
4	432	0.4700
5	432	0.2700
6	432	-0.8000
7	432	0.9800
8	432	0.8500
9	432	-0.8100

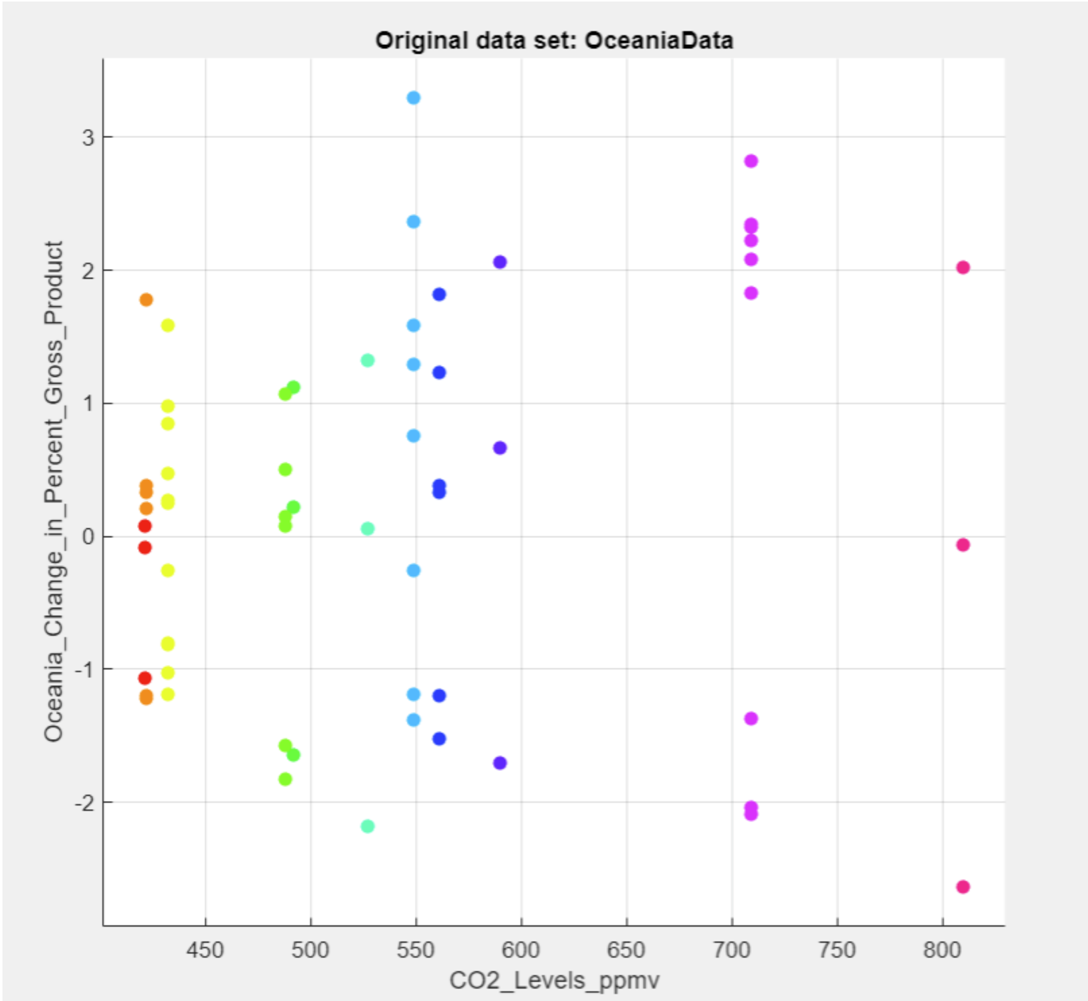

Figure 1 - This shows atmospheric CO2 levels in ppmv versus the total change in percent gross product of the three staple crops studied (wheat, maize, rice) for countries in the Oceania continental region.

Our first thoughts when looking at this scatter plot was that there was no clear upward or downward trend that we could just visually analyze. Therefore, we used a linear regression using the polyfit function to determine whether there was a positive or negative trend in change in percent gross product as atmospheric CO2 levels are predicted to increase over time. Further, we decided to do this for each continent that we plotted. Our trend line for the scatter plot in Figure 1 yielded a slope of approximately 0.0018. This means that for each ppmv of atmospheric CO2, the percent gross product will increase by approximately 0.0018. This means that the Oceania region is fairly well off when it comes to atmospheric CO2 impacting staple crop production, likely due to them being a developed region that has the resources to combat such threats.

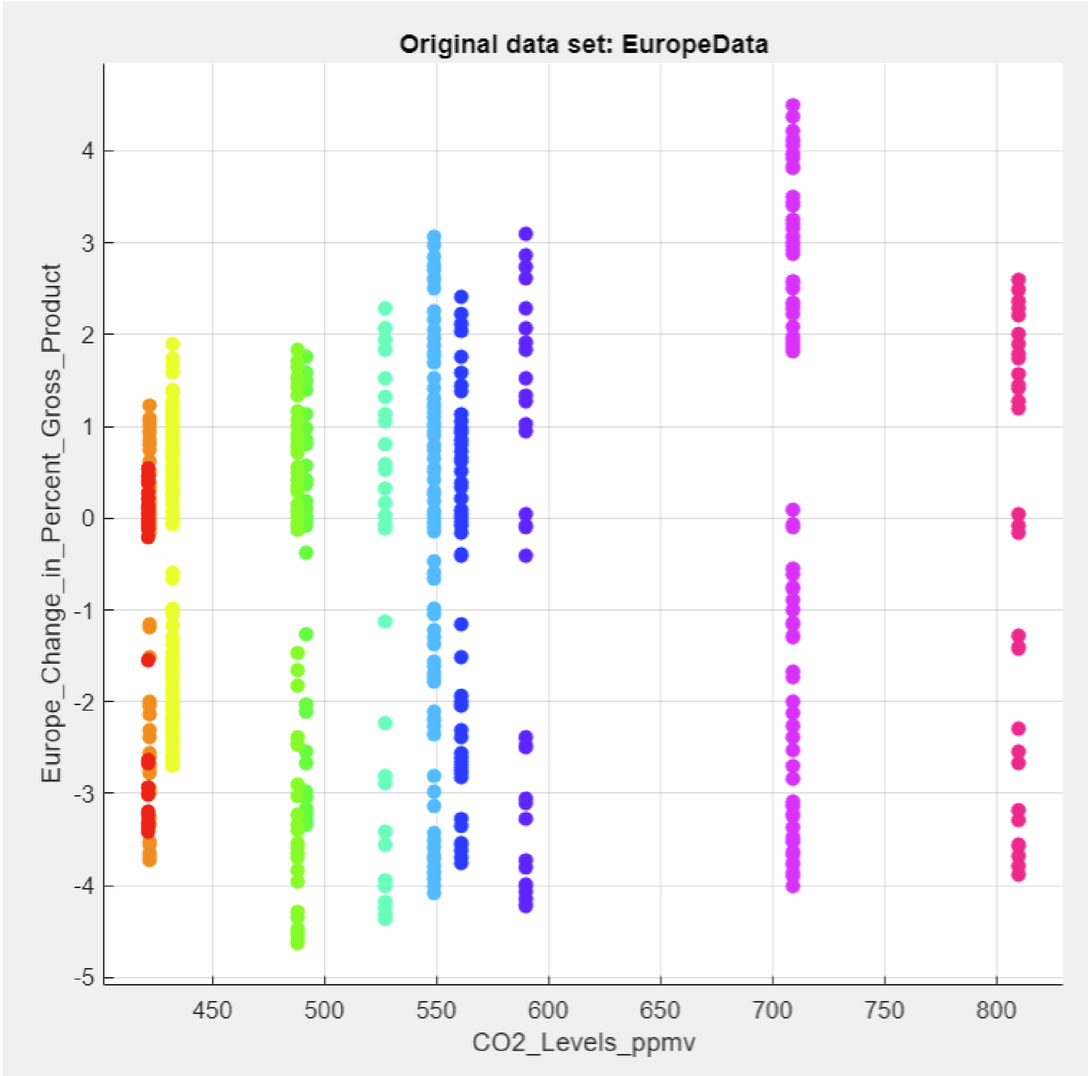

Figure 2 - This shows atmospheric CO2 levels in ppmv versus the total change in percent gross product of the three staple crops studied (wheat, maize, rice) for countries in Europe.

Visually, there is again little evidence of an increase or decrease in total gross product as a result of an increase in atmospheric CO2 in Europe. Our linear regression of this scatterplot yielded a slope of approximately 0.0030, meaning it is even more well off than the Oceania region.

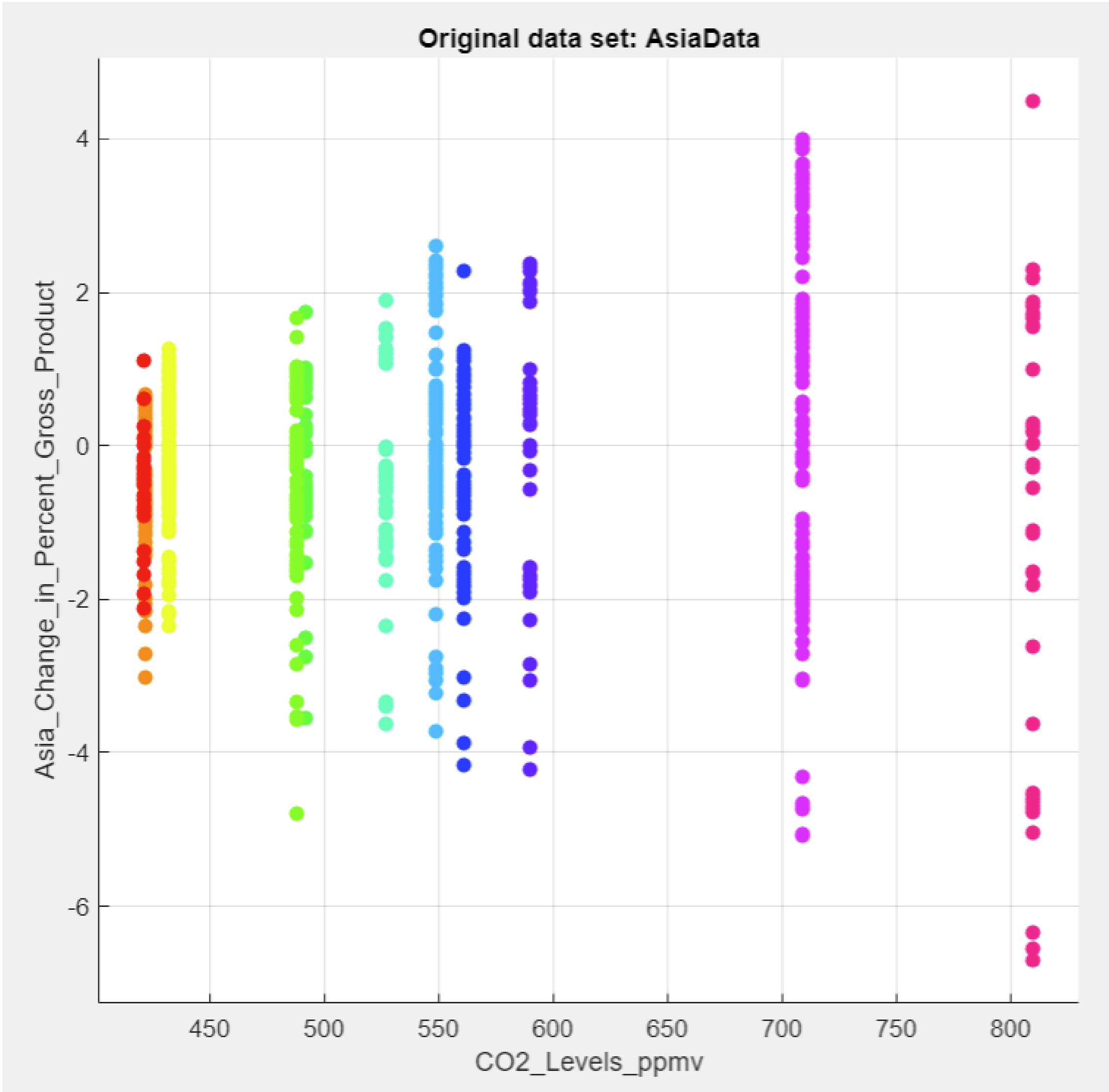

Figure 3 - This shows atmospheric CO2 levels in ppmv versus the total change in percent gross product of the three staple crops studied (wheat, maize, rice) for countries in Asia.

Figure 3 shows little evidence of an increase or decrease in total gross product as a result of an increase in atmospheric CO2 in Asia. Our linear regression of this scatterplot yielded a slope of approximately 0.0003, meaning it is overall less well off than Oceania and Europe in the long run.

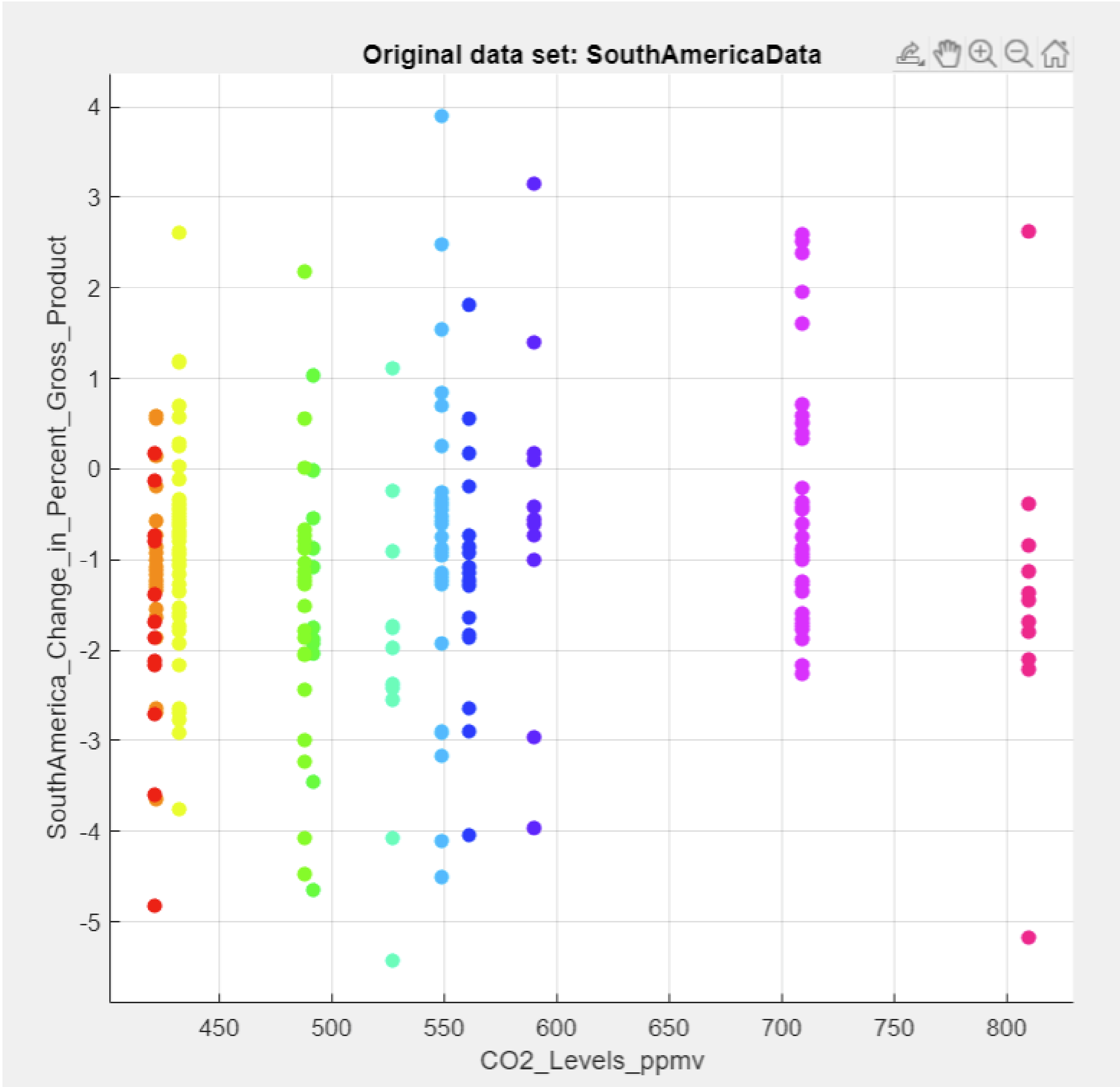

Figure 4 - This shows atmospheric CO2 levels in ppmv versus the total change in percent gross product of the three staple crops studied (wheat, maize, rice) for countries in South America.

Figure 4 shows little evidence of an increase or decrease in total gross product as a result of an increase in atmospheric CO2 in South America. Our linear regression of this scatterplot yielded a slope of approximately 0.0013, meaning less well off than Oceania and Europe, but better off than Asia.

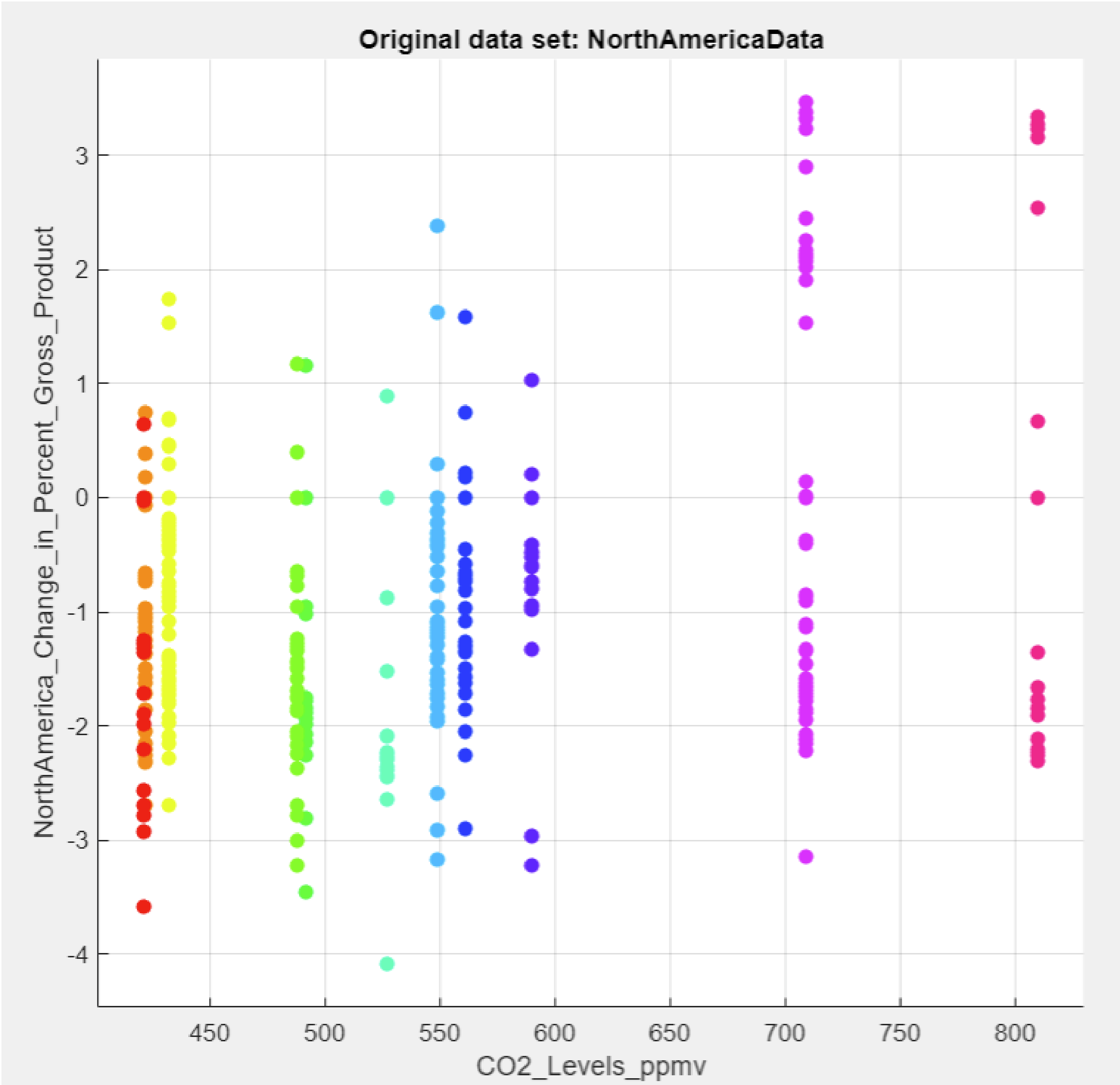

Figure 5 - This shows atmospheric CO2 levels in ppmv versus the total change in percent gross product of the three staple crops studied (wheat, maize, rice) for countries in North America.

Figure 5 shows a bit more of an upward trend visually in North America. Our linear regression gave a slope of around 0.0031, meaning North America is the most well off country in terms of food production as a function of atmospheric CO2 levels.

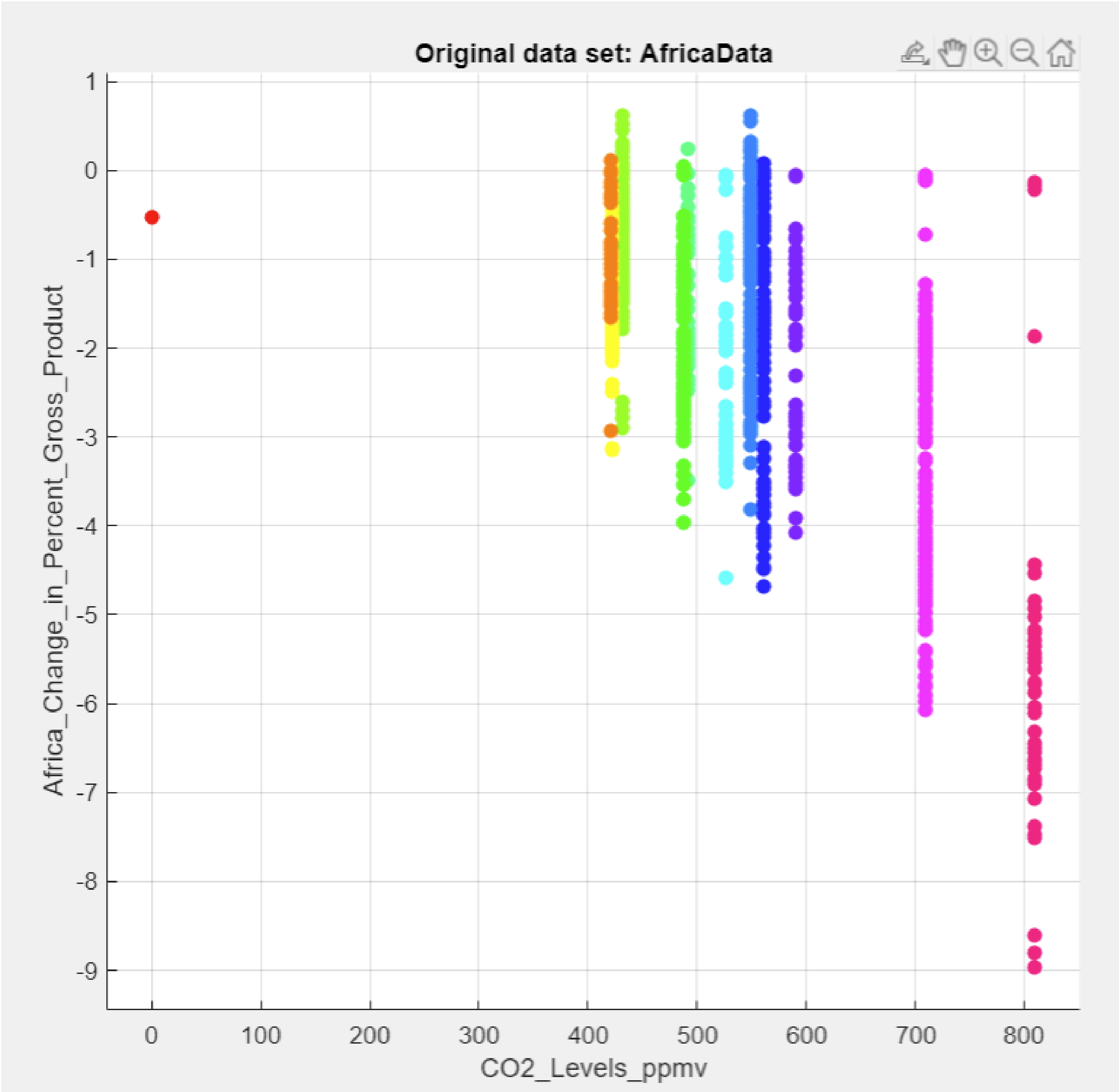

Figure 6 - This shows atmospheric CO2 levels in ppmv versus the total change in percent gross product of the three staple crops studied (wheat, maize, rice) for countries in Africa.

Figure 6 shows a clear downward trend in terms of percent gross product as a function of atmospheric CO2 in Africa. Our linear regression yielded a slope of approximately -0.0094, making it the least well off continent out of the six we analyzed. This makes sense as the country is mostly filled with developing countries that lack effective strategies and resources to mitigate climate change and the increase of atmospheric CO2 in the long run.

Therefore, based on our scatterplots and consequential linear regressions, the ranking of the continents from most well off to least well off for food production of staple crops while atmospheric CO2 increases over time are North America, Europe, Oceania, South America, Asia, then Africa. This infers that North America is the most prepared to combat the impact of atmospheric CO2 increases on their staple crop production out of the six continents we analyzed, and Africa is the least prepared. This proves our hypothesis correct. Based on these rankings it is clear that the more prepared countries should begin to help Africa, who, according to models, is the only continent that will experience a net decrease in total gross product for staple crop production over the next few decades as atmospheric CO2 increases around the world. If countries like North America and Europe, who are well off to combat atmospheric CO2's impact on food production, helped Africa, the world's food supply and production would be more stable, and the people in those developing countries within the continent would be more well off and would be better prepared. Climate change is only going to become more of a threat to the entire globe, so it is important for those countries that are more fortunate and prepared to help those greatly in need. This analysis showed exactly how and who that can be targeted in response to rising global atmospheric CO2 levels due to climate change over the next few decades impacting the global food supply and production.

Works Cited

- "7 Types of Data Bias in Machine Learning." Www.telusinternational.com, www.telusinternational.com/articles/7-types-of-data-bias-in-machine-learning.
- Dataset: https://docs.google.com/spreadsheets/d/13oF9zbpURR7SQ-UrKw-2lzXOdYQZBmOu/edit#gid=613312681
    - Source: Effects of Climate Change on Global Food Production from SRES Emissions and Socioeconomic Scenarios (nasa.gov)