Global Climate Change
Visual Analysis Tool

by

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Supervised by

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The project proposal “Global Climate Change Visual Analysis Tool” by Dylan Beaufort Dias has been examined and approved by the following Examination Committee:

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Abstract

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Visual Analysis Tool

Dylan Beaufort Dias

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Climate change can be defined as the change in the usual weather conditions of a certain region. We can also define climate change as the change in Earths climate like rise in temperature, melting of glaciers, and more frequent hurricanes, floods, storms, etc. The main reason for the current climate change is due to human activities like burning of fossil fuels like natural gas, oil, and coal which in turn trap heat inside the atmosphere causing the Earths average temperature to rise. The main goal of this climate change interface is to analyze the Earths climate over the years and predict future climate change based on human activities. Through this analysis, we can understand what changes are taking place in the Earths atmosphere and over the world. The ARIMA-based statistical forecasting model is used to predict future temperature values, and $k$-means clustering is used to group countries based on their carbon dioxide emission levels. Climate change is a serious global environmental problem, and this paper provides an overview on how the rate of climate change has escalated over these years leading to global warming.
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</tbody>
</table>
1 Introduction

Climate can be described as the change in the average weather conditions (like rainfall, snow, temperature) of a region over a long period of time. Global climate change refers to the average weather changes taking place over the entire Earth. Such effects can be seen by rising sea levels, shrinking glaciers, melting of ice, changes in plants blooming times, etc. According to a study conducted by NASA (National Aeronautics and Space Administration) over the past 150 years Earth’s average temperature has been increasing at a much quicker rate. Some parts of Earth are getting much warmer than other. The past five years have been recorded as the warmest years. In facts, the Earths surface temperature has increased by 2° C in the past 100 years which is growing concern among many scientists. Earths climate is constantly changing but due to human interaction, this effect has been accelerated. Certain gases are preventing the heat from escaping the atmosphere which is making the Earth hotter. This is called the greenhouse effect. Human activities such as burning fuel to power factories, cars, and buses are changing the natural greenhouse, leading to a warmer Earth.

Climate change is a global environmental problem that affects not only us but even plants, animals, air, land mostly everything. If efforts are not taken now to reduce CO2 emission it can lead to disastrous effects in the near future. We need to analyze which parts of the Earth are getting hotter so that initiatives can be taken to reduce the carbon footprint in those parts of Earth.

In this project, we will develop a global climate change interface that will help us to give a brief overview on how Earths climate has been changing over all these years. We will develop this interface using Dash which is a web microframework of python. We will generate all the necessary visualizations based on the data which will help to analyze the situation at hand. Also, we will be implementing a time series model to predict future temperature change values and cluster countries into groups based on their emission rate. All of this will help us understand the overall changes taking place all over the Earth so that the necessary precautions will be taken to reduce it as much as possible.

2 Problem Statement

Ideal:
Climate change is a global problem and efforts need to be made to reduce it as much as possible. Carbon emissions from fossils fuels have been linked to global warming and climate change. Developing this interface can help analyze how the burning of fossil fuel over all these years has caused the Earths temperature to rise. Implementing a time series model to predict future climate change can also help. In turn, necessary steps can be taken to reduce carbon emission levels.

Reality:
According to research done by National Aeronautics and Space Administration “Climate change: Vital signs of the planet,” n.d. carbon dioxide levels in the air are at their highest
in 65000 years and the main source of this rise is due to human activities such as deforestation and burning fossil fuels, as well as natural processes such as respiration and volcanic eruptions. The temperature of the earth is also changing in fact nineteen of the hottest years have occurred since 2000. If measures are not taken to reduce the level of carbon dioxide in the air it will keep increasing at an immeasurable rate and which in turn will affect the global temperature of the earth.

**Consequences:**
To solve this problem we need to identify countries who are the main sources of carbon dioxide emission by clustering them into various groups based on their emission levels. By knowing which countries have been emitting more carbon dioxide than the other restrictions can be put on such countries to prevent future emissions. In order to check how the climate will change in the future, forecasting models can be implemented to give us an overview on future climate change. But for these models to give accurate predictions, we need to supply them with as much historical data as possible.

### 3 Goals and Objectives

Develop a visualization tool to analyze fossil fuel and temperature data, predict future temperature change values and group countries based on their carbon dioxide emission level.

**Goal 1:** Implement the visualization tool by storing the data on the cloud server using MongoDB Atlas and deploying the application on AWS Elastic Beanstalk.

**Objective 1:** Collect the data for fossil fuel types such as fuel, coal and gas and also for temperature change for various countries.

**Objective 2:** Perform exploratory analysis on the data collected.

**Objective 3:** Implement a user-friendly dashboard.

**Objective 4:** Create a web-interface which consists 4 sections that are introduction, exploratory analysis, dashboard and statistical models.

**Goal 2:** Implementing ARIMA forecasting model and K-means clustering algorithms.

**Objective 1:** Determine the number of clusters for K-means using Elbow method.

**Objective 2:** Implement the K-means algorithm to cluster countries into similar groups based on the carbon dioxide emission level.

**Objective 3:** Divide the dataset as training dataset and test dataset and test dataset in the ratio of 70:30.

**Objective 4:** Find the optimum values of p, d and q using grid search method.

**Objective 5:** Validate the model accuracy using the RMSE score with the test dataset.

**Objective 6:** Implement the new ARIMA with the new order score to predict future temperature change values.
4 Related Work

Webster et al. (2003) wanted to improve the climate change policies, and came to a conclusion that accurate quantitative descriptions of the uncertainty in climate outcomes under various possible policies are needed. Here they applied two different policies on earths ecosystem. The first policy talks about the absence of greenhouse gases on earths ecosystem and the second policy talks about the presence of greenhouse gases on earths ecosystem. Based on the first policy there is a one in forty chance that global mean surface temperature change will exceed 4.9 °C by the year 2100 and based on the second policy there is a lower chance that temperature will exceed 3.2 °C, thus reducing but not eliminating the chance of substantial warming. In reality it will take time to implement such policies, but it is a great effort overall.

Scholze et al. (2006) analyzed climate change risk on world ecosystem. Here they considered distribution of outcomes based on three set of models. First model talks about global temperature less than 2°C, second model talks about global temperature between 2-3°C, and third model talks about temperature more than 3°C. This method helps to give an overview of climate change for three different scenarios.

El-Mallah and Elsharkawy (2016) developed an ARIMA time series model to predict the annual warming trend. They found out that the non-seasonal linear trend model ARIMA (3-1-2) and quadratic trend model ARIMA (3-2-3) are most optimum models obtained for the data.

Girvetz et al. (2009) developed a web-based tool called Climate Wizard. The main purpose for developing this tool is to provide non-climate specialist with simple analyses and innovative graphical depictions for conveying how climate has and is projected to change within specific geographic areas throughout the world.

Lai and Dzombak (2020) implemented an ARIMA-based forecasting model to provide estimates of confidence intervals for temperature and precipitation extremes in different return periods, and to provide future daily temperature and precipitation simulations. It said that ARIMA model is an efficient, interpretable, and reliable method for obtaining near-term (220 years) regional temperature and precipitation forecasts for use in various engineering applications.

Kodinariya and Makwana (2013) compared various methods available to determine the value of K which is the most controversial issues in clustering algorithms.

A thorough review of the literature revealed that the ARIMA model is best suited to tackle the on-going climate change issue. The correct model can accurately predict the next 5-10 years of climate change values. Also by using k-means clustering, countries can be grouped based on their emission level in order to identify highly emitting countries.
5  Methodology

5.1  Dataset Selection and Quality

The source of this dataset is (Andrew & Peters, 2021). The fossil fuels dataset consists of 3 csv files for coal, oil, and gas fossil fuel type. Each csv file contains 223 countries and carbon dioxide emission per million tonnes between the years 2000 to 2019 for all those countries.

The source of this dataset is (SY, 2020). The temperature change dataset consists of a single csv file containing temperature change data for 274 countries, major cities, and continents. It contains temperature change data between the years 2000 to 2019 for all those countries, cities, and continents.

While checking for the completeness of the fossil fuels dataset it consisted of missing values which were indicated by "None" which meant that the fossil fuel emission for that particular country and year was 0. By making use of Excel’s "Replace By" function those "None" values were replaced with the value 0.

5.2  User Interface Design

5.2.1  Interface Flowchart

Figure 1 show the flowchart that demonstrates how the web interface will be deployed.

![Web interface flowchart](image)
Firstly, the datasets were stored on a cloud server which can be seen in figure 2. The cloud server used for this project is MongoDB Atlas. MongoDB Atlas is a fully managed cloud database that can be used to store and manage databases on the cloud server of your choice which in this case is AWS. The datasets were then stored in the cloud server under the database name "climate_change" and the IP address was set to 0.0.0.0/0 indicating the datasets can be accessed from any network. Using the driver code the datasets were then accessed by the python code created.

![Figure 2. MongoDB Atlas](image)

Figure 2. MongoDB Atlas

Figure 3 shows the web interface that was created using Dash which is a python framework created by Plotly for creating interactive web applications. Dash makes use of a callback function which is used to update the visualizations in real-time. The main plus point of plotly is its interactive nature and of course visual quality.
Finally, the web interface was deployed using AWS Elastic Beanstalk which is seen in figure 4 which is a compute service used for quickly deploying high-scaled applications. This is done by creating a requirements.txt file which contains a list of python libraries used along with their version numbers. The python file, text file, assets folder containing .css file, and image are then all zipped together and uploaded on Elastic Beanstalk. AWS Elastic Beanstalk automatically handles the details of capacity provisioning, load balancing, scaling, and application health monitoring.

![AWS Elastic Beanstalk](image)

**Figure 4. AWS Elastic Beanstalk**

### 5.3 Exploratory Data Analysis

**Fossil Fuels Dataset:** Exploratory data analysis is an approach to analyze the data which in turn can help to summarize the main characteristics of the dataset which can be used to detect various patterns and get a better understanding of the data.

In order to get a summary of the dataset various statistical parameters have been calculated which can be seen in figure 5.

- **Count:** Count of the number of data points.
- **Mean:** Average fossil fuel value for the country.
- **std:** Standard deviation is a measure of how spread the data is.
- **Min:** Minimum fossil fuel value for the country.
- **25%:** 25th percentile is the value at which 25% of the data lie below that value, and 75% of the data lie above that value.
- **50%:** 50th percentile is the median of data.
- **75%:** 75th percentile is the value at which 75% of data will be less than 75th percentile; 25% of data will be more than 75th percentile.
- **Max:** Maximum fossil fuel value for the country.
Figure 5. Carbon dioxide data description

There is also a violin plot generated which can be seen in figure 6 to visualize the distribution of the data and its probability density. This chart is a combination of a Box Plot and a Density Plot that is rotated and placed on each side, to show the distribution shape of the data. The user can add the country and the fossil fuel type they wish to visualize which is used to compare the violin plots for various countries using this visualization.

5.4 Temperature Dataset:

In order to get a summary of the dataset, various statistical parameters have been calculated which can be seen in figure 7.

Count: Count of the number of data points.
Mean: Average temperature value for the country.
std: Standard deviation is a measure of how spread out data is.
Min: Minimum temperature value for the country.
25%: 25th percentile is the value at which 25% of the data lie below that value, and 75% of the data lie above that value.

50%: 50th percentile is the median of data.

75%: 75th percentile is the value at which 75% of data will be less than 75th percentile; 25% of data will be more than 75th percentile.

Max: Maximum temperature value for the country.

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Figure 7. Temperature data description

In figure 8 we have created a violin plot which is used to see the distribution of temperature change data for all 7 seven continents. Figure 9 shows a time series line plot showing the temperature change taking place in these continents from 2000 to 2019. It can be seen from the line plot that the temperature is mostly stationary in those regions. Figure 10 is a bar plot for the 10 ten hottest countries based on the year selected. The user can select the year they desire to view and based on the selected year a bar plot will be generated ranking the top 10 countries.

Figure 8. Continents violine plot
Figure 9. Continents time series line plot

The line plot below shows the temperature change happening from 2000 - 2019 for all the continents.

Figure 10. Top 10 hottest countries

The bar plot below shows the top 10 hottest countries for the selected year: 2001.
5.5 Dashboard

The dashboard created helps in giving useful insights of the data at hand and also helps to identify trends. Using this dashboard the user will be able to interact with the data and manipulate the visualizations that are created.

5.5.1 Fossil fuels data:

The fossil fuels dashboard consists of 5 major visualizations. Visualization 1 can be seen in figure 11 where the user will be able to view the million tonnes of coal, oil, and gas emitted based on the year and country selected. In figure 12 we can see the second visualization which consists of a geo chart which the user can hover over to view the emission level of that country. The user can change the fossil fuel type of the geo chart by using the radio buttons and also change the year using the slider. Figure 13, shows visualization 3 and 4 which consists of a radar plot and time-series area plot. The radar plot consists of three variables total coal, total oil, and total gas emission. Using the dropdown box the user can add n number of countries to compare the total emission levels for each fossil fuel type. The time-series area plot shows the total emission level for each fossil fuel type between the years 2000 to 2019. It also consists of a range slider to select a particular range of years. Finally, visualization 5, consists of a time series line plot. The user can select the fossil fuel type using the radio buttons, select n number of countries using the dropdown box and also select a range of years using the range slider.

![Figure 11. Fossil fuel values](image)

5.5.2 Temperature data:

The temperature change dashboard consists of 4 major visualizations. Visualization 1 can be in figure 15 which is a time series line plot for the temperature change of the entire world. In figure 16 we can see the 2nd visualization which consists of time series line chart for countries. The user can add n number of countries from the dropdown list. In figure 17 we can see the 3rd visualization which consists of a geo chart which the user can hover over to view the temperature of that country. The user can also change the year by selecting a year from the slider. And finally, from figure 18 we can see the 4th visualization which consists of a violin plot to show the distribution of temperature change data. The user can add n number of countries from the dropdown list to this visualization.
Figure 12. Fossil fuels geochart

Figure 13. Fossil fuels radar and area plot
Figure 14. Fossil fuels line plot

Figure 15. World temperature change line plot
Figure 16. Temperature change geochart

Figure 17. Temperature change line plot
5.6 Core Algorithms

5.6.1 K-means Clustering

K-means Algorithm:  K-means clustering algorithm is an unsupervised learning algorithm that is used to cluster items into K groups. In k-means clustering, we need to first define k. Based on the k value it will randomly select k distinct centroids. After the k centroids have been selected it will calculate the Euclidean distance between each point and the centroid. Each point will be assigned to the nearest cluster based on the smallest euclidean distance. We then calculate the mean of this cluster and based on the mean the new euclidian distance are calculated. K-means algorithm aims to select the centroids that minimize sums of the squared error function. K-means keeps track of the total variance of each cluster and chooses the cluster with the lowest sum of variance.

K-means clustering metrics: In order to get the best out of the k-means clustering algorithm, we need to determine the value of k. In this case, we will make use of the Elbow method to give us an idea on what a good k number would be based on the sum of squared distance (SSE) between data points and their assigned clusters centroids. In the Elbow method, you start with k=1 and keep increasing the value of k by 1, calculating your clusters and the cost. At some value for K, the cost drops dramatically, and after that, it decreases at a very slow rate. That is the K value needs to be selected.

5.6.2 ARIMA

ARIMA Model  The autoregression integrated moving average(ARIMA) model is a combination of the autoregressive model(AR) and moving average model(MA). ARIMA model
Figure 19. K-means clustering steps
makes use of past data to predict future values as it believes that the future reflects the past. The ‘AR’ part of ARIMA shows that the time series is regressed on its own past data. The ‘MA’ part of ARIMA indicates that the forecast error is a linear combination of past errors. The ‘I’ part of ARIMA shows that the data values have been replaced with differenced values of d order to obtain stationary data, which is the requirement of the ARIMA model approach. Each part is included in the ARIMA model as parameters p, q, and d. p indicates the number of lags, q is the number of forecast errors in the model, and d is known as the degree of differencing indicating the number of times the lagged indicators have been subtracted to make the data stationary.

\[ Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} \varepsilon_t + \beta_1 Y_{t-1} \varepsilon_t + \phi_2 \varepsilon_{t-2} + \ldots + \phi_q \varepsilon_{t-q} \]  

**ARIMA model metrics:** In order to obtain the best value of p, q, and d the grid search method was used. Grid search is a tuning technique that attempts to compute the optimum values of hyperparameters. It is an exhaustive search that is performed on the specific parameter of the model. The value of p was set to a range of 0 to 10 while the value of d and q was set to a range of 0 to 5. The models were evaluated using their root mean squared error (RMSE) score and the model with the lowest RMSE score is selected.

### 6 Experiments and Results

#### 6.1 Exploratory data analysis queries:

Three queries were created in order to get a better understanding of the fossil fuels data. While browsing through the dataset for each fossil fuel type it was noticed that some countries did not emit any carbon dioxide for the past 20 years. So a count query was generated to return the number of countries that have 0 carbon dioxide emissions for the past 20 years. Table 1 shows the results of the count of countries with 0 carbon dioxide emission and with some carbon dioxide emission in the past 20 years.

<table>
<thead>
<tr>
<th>Fossil Fuel Type</th>
<th>Countries with 0 CO2 emission</th>
<th>Countries with some CO2 emission</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>91</td>
<td>130</td>
</tr>
<tr>
<td>Gas</td>
<td>94</td>
<td>127</td>
</tr>
<tr>
<td>Oil</td>
<td>8</td>
<td>213</td>
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</tbody>
</table>

Table 1. Count of countries with 0 carbon dioxide emission and with some carbon dioxide emission.
emission, count of countries that have between 500 to 5000 million tonnes of carbon dioxide emission, and a count of countries with more than 5000 million tonnes of carbon dioxide emission. Table 2 shows the results of the count of countries for various ranges of carbon dioxide emission.

<table>
<thead>
<tr>
<th>Fossil Fuel Type</th>
<th>Less than 500 MtCo2</th>
<th>Between 500 to 5000 MtCo2</th>
<th>More than 5000 MtCo2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>187</td>
<td>27</td>
<td>7</td>
</tr>
<tr>
<td>Gas</td>
<td>179</td>
<td>39</td>
<td>3</td>
</tr>
<tr>
<td>Oil</td>
<td>168</td>
<td>43</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 2. Count of countries for various ranges of carbon dioxide emmission.

Table 3 ranks the top 10 countries based on their emission level for each fossil fuel type.

6.2 K-means clustering:

6.2.1 Elbow plot:

In order to determine the value of k, an elbow plot was created which can be in figure 21. From the plot, we can see that at 5 the value of SSE begins to decrease indicating that 5 is the ideal number of clusters for this dataset.

![Elbow plot](image)

Figure 20. Elbow plot

6.2.2 Clusters Formed:

By setting the value of k to 5 the k-means clustering algorithm was implemented. The scatter plot below shows the cluster each country was assigned to.
### Table 3. Top 10 countries ranked based on their total million tonnes of carbon dioxide emission for each fossil fuel type.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Country</th>
<th>Coal Emission</th>
<th>Gas Emission</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>China</td>
<td>113.2969k</td>
<td>27.05318k</td>
</tr>
<tr>
<td>2</td>
<td>USA</td>
<td>37.09321k</td>
<td>15.22427k</td>
</tr>
<tr>
<td>3</td>
<td>India</td>
<td>21.32379k</td>
<td>5380.543</td>
</tr>
<tr>
<td>4</td>
<td>Japan</td>
<td>8658.594</td>
<td>4716.607</td>
</tr>
<tr>
<td>5</td>
<td>Russia</td>
<td>8326.758</td>
<td>4283.579</td>
</tr>
<tr>
<td>6</td>
<td>South Africa</td>
<td>7736.58</td>
<td>3841.138</td>
</tr>
<tr>
<td>7</td>
<td>Germany</td>
<td>6921.295</td>
<td>3648.633</td>
</tr>
<tr>
<td>8</td>
<td>South Korea</td>
<td>4994.114</td>
<td>3418.595</td>
</tr>
<tr>
<td>9</td>
<td>Poland</td>
<td>4300.983</td>
<td>2933.77</td>
</tr>
<tr>
<td>10</td>
<td>Australia</td>
<td>3774.14</td>
<td>2932.787</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rank</td>
<td>Country</td>
<td>Oil Emission</td>
<td></td>
</tr>
<tr>
<td>------</td>
<td>-------------</td>
<td>----------------</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>USA</td>
<td>47.59442k</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>China</td>
<td>21.06458k</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Japan</td>
<td>11.12963k</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>India</td>
<td>9091.686</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Russia</td>
<td>6995.889</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Saudi Arabia</td>
<td>6097.1</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Germany</td>
<td>5828.727</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Brazil</td>
<td>5476.419</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Mexico</td>
<td>5367.562</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Canada</td>
<td>5191.643</td>
<td></td>
</tr>
</tbody>
</table>
In order to get a better understanding of the clusters, a word cloud of country names was created for each cluster. It can be seen in figure 23 that cluster 0 consists of 205 countries, clusters 1, 2, and 4 consist of 1 country each, and cluster 3 consists of 13 countries.

![Countries word cloud](image)

**Figure 22. Countries word cloud**

### 6.3 ARIMA Model:

#### 6.3.1 Augmented Dickey-Fuller Test:

In order to implement the ARIMA model we need to check if the data is stationary or not for that, we will be using the ADF (Augmented Dickey-Fuller) test. From the ADF test, we get a p-value of 1.92e-06 which means that we can reject the null hypothesis. Therefore, inferring that the data is stationary.

```
ADF: -5.615953491463222
p-value: 1.924911767639346e-06
Number of lags: 0
Number of observations used for ADF Regression and Critical value calculation: 19
Critical Value:
1% -3.832603141857436
5% -3.031227170141629
10% -2.65551958487535
```

**Figure 23. Augmented Dickey-Fuller Test**
6.3.2 Forecasting Results:

We will be dividing the dataset into training and testing sets where the last 9 instances will be to test the model. We will be using the RMSE score to validate the model which basically tells us the difference between the predicted and observed values. We got an RMSE score of 0.187 for the model with values (9, 1, 0). From figure 24 we can see the ARIMA model predictions on the test dataset.

![Test set predictions](image)

Using this model we were able to predict the next 10 years of temperature change values which can be seen in figure 25 and table 4.

![10 years of temperature change values prediction](image)

<table>
<thead>
<tr>
<th>Year</th>
<th>2020</th>
<th>2021</th>
<th>2022</th>
<th>2023</th>
<th>2024</th>
<th>2025</th>
<th>2026</th>
<th>2027</th>
<th>2028</th>
<th>2029</th>
<th>2030</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature °C</td>
<td>1.30</td>
<td>1.52</td>
<td>1.46</td>
<td>1.20</td>
<td>1.52</td>
<td>1.54</td>
<td>1.51</td>
<td>1.51</td>
<td>1.41</td>
<td>1.406</td>
<td>1.55</td>
</tr>
</tbody>
</table>

Table 4. ARIMA model predictions.
6.4 Visualization Tool:

The final visualization tool consists of 4 main sections introduction section, dashboard section, exploratory analysis section, and statistical models sections. The introduction section as seen in figure 26 consists of a small introduction about the project, what is climate change and its effects, various types of fossil fuels, and the effects of fossil fuels. Figure 27 shows the dashboard that has been implemented. Using this dashboard the user will be able to choose between 2 sets of dashboards i.e. fossil fuels and temperature by using the radio buttons. Each dashboard consists of a set of visualizations that the user can manipulate to compare countries. In figure 28 we can see the exploratory analysis section. In the exploratory analysis section, the user will be able to choose between 2 exploratory analyses i.e. fossil fuels and temperature by using the radio buttons. This section consists of a description of the data along with various queries that have been created to give a better overview of the data. Finally, figure 28 and 29 is the statistical model’s section which consists of 2 models that have been created for each dataset. For the fossil fuels, the k-means clustering model has been implemented to group countries based on their emission levels and for the temperature dataset, an ARIMA model was implemented to predict temperature values till 2030.

Figure 26. Introductory section
Figure 27. Dashboard section

Figure 28. Exploratory analysis section
Figure 29. K-means clustering section

Figure 30. ARIMA section
7 Future Work

ARIMA model makes its predictions using past values. In order to obtain more accurate predictions from the models we can supply it with more historical data. The interface can be made more responsive as in order to make it render on various other devices and windows.

8 Conclusion

The final web interface consists of 4 major sections an introductory section, dashboard, exploratory analysis section, and statistical models section. The introductory section gives a brief overview on what is climate change, causes of climate change, the effects of climate change, fossil fuel type, and its impacts on the environment. The dashboard can be changed between fossil fuel and temperature change data. Each dashboard consists of a number of visualizations with which the user can interact by adding countries of their choice and even changing the year they want to view. The exploratory analysis section gives a brief overview of the fossil fuels and temperature change datasets. This is done with the help of queries generated, visualizations, and descriptions of the data. Finally, the statistical model’s section consists of the two major models implemented which are the clustering model and the ARIMA forecasting model. For the clustering model, the \( k \)-means model was implemented where we used to elbow plot to determine the value of \( k \) as 5, divided the countries into 5 clusters, and created a word cloud of countries for each cluster. Finally for the ARIMA model we used the augmented dickey-fuller test to check if the dataset is stationary or not. A p-value of 1.92e-06 indicated that the dataset is stationary we then used the grid search tuning method to find the most optimum order for the model where the last 9 instances were used to test the model. The model with the order (9, 1, 0) was selected which had the lowest RMSE score of 0.187 and this model was used to predict the next ten years of future climate change values.

References


Climate change: Vital signs of the planet. (n.d.). https://climate.nasa.gov/
