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Data Visualization

Project Report

Global Warming Analysis and Predictions

Under the guidance of Prof. Annapurna

School: SCOPE

Course Code: CSE3020

Slot: E2

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Problem Statement:

Given the immense amount and variety of data collected such as CO_2 emissions over the past 100 years, sea-level changes calculated around the world, locating holes in the ozone layer, glacier water content etc, predict the effects of global warming in the future using Machine learning models and Neural Networks and visualise the data in a user-friendly manner to aid in the understanding of the results.

Introduction:

i. Motivation:

With the increasing dependence of humans on machines, the need for energy has grown exponentially with it. Most energy generated in the world is from Fossil fuels which release a large number of pollutant gasses such as CO_2, SO_2, NO_x etc. These gases, also known as greenhouse gases, have the effect of trapping heat radiated from the sun. When done in excess, it leads to catastrophic effects such as global temperature rise, melting the polar ice caps, causing holes in the ozone layer etc. While there is enough research and scientific proof regarding this, it is hard to comprehend numbers on a paper. This has resulted in many people shunning it as a conspiracy or not realising the gravity of the situation. By using appropriate visualisation to demonstrate the effects of global warming and its effects, it becomes easier to understand the issue at hand and adopt more eco-friendly approaches.

ii. Significance:

Global warming has resulted in shifting of monsoon schedules and season durations and starts. It has made summers warmer and winters cooler, bringing about new weather patterns like snow in Egypt, Heat Waves in Nevada. This impacts the livelihood of people directly as it affects agriculture drastically resulting in less yield and destroyed crops. It also results in intense rains which flood cities and major storms such as the series of 3 continuous storms which hit the US. This result is damage estimated at more than a trillion dollars worldwide. Hence it is important to address this issue as soon as possible and as efficiently as possible before we reach a point of no return.

iii. Applications:

It has become evident that climate change impacts are not an isolated threat that selectively affects a few countries but rather something that takes its toll on the entire world, instead of needing more holistic responses alongside addressing other societal issues. Environmental change is a complex logical and multifaceted issue, agreeable to ML and AI examination, yet in general, this has not yet happened. Numerous ML calculations have been accessible for quite a long time, and conceivably most remarkably neural organizations. Be that as it may, until as of late, requirements of computational design also, power have limited their application, and particularly for issues as serious as climate change. The first application is a recent extreme event, likely caused by multiple forcings to be determined. Second is a major uncertainty in overall climate response, again likely due to many Earth System interactions. The final application is building unknown ecological-climate interaction equations.

Literature Survey:

Title	Summary	Gaps Identified
“Machine learning and artificial intelligence to aid climate change research and preparedness. Published by IOP Publishing Ltd (2019)”	This paper says that many scientific measures show routine methods of ML techniques which have shown a great level of success. ML application to the Earth System will fall in the effective classification, conveying new experiences into the extraordinarily rich variety of interconnected Earth System practices and their different communications with biochemical cycles. At present, AI is a usually used thing in society, yet for climate investigation, it is believed to be perfect for use. While ML will uncover atmosphere framework credits and improve forecasting across time scales, it is AI that would then be able to embrace this data to help choices. It is the guidance of activities needed to guarantee security through natural limits where ML becomes AI. The paper describes 4 common ML methods and what they are used for best.	1. Gradient descent method works best for supervised learning algorithms but its problem is that it can converge at local minima and saddle points and Slower learning since an update is performed only after we go through all observations. 2. Gaussian processes are also supervised ML methods and are not scattered meaning that they use all of the features or samples of information to perform or analyze the prediction; they also lose efficiency in the high dimensional spaces which happens mainly when the number of samples crosses or exceeds a few dozens.

Analysis of global warming in India over maximum temperature using Pearson and machine learning," *2017 International Conference on Trends in Electronics and Informatics (ICEI)*, Tirunelveli, 2017	In this paper it's found in test information that the temperature step by step increments because of deforestation, changing fields over to businesses. A dangerous atmospheric deviation will influence the human climate like an expansion in the ocean level, ceaseless expansion in temperature. Subsequently, the 5 characteristics can be dropped down. Furthermore, the machine has figured out how traits are related to one another. For example, while considering PEAK esteem just MHR worth can be thought of and everything others can be disregarded. In this situation, a dangerous atmospheric deviation in India over the greatest temperature can be resolved with only 5 features. It predicts the real-time data of the separated maximum temperature (1.2 m above sea level) data from more than 350 stations spread over the country resulting in global warming. The time-series taken from the year 1970 to 2011 shows global warming over India during recent years, with 5 traits.	1. Pearson Correlation is used for relating attributes and is comparatively difficult to calculate as its computation involves intricate algebraic methods of calculations but it is not much of a problem for an ML machine as this is that it is very much affected by the values of the extreme items and also takes much time to arrive at the results. 2. It is based on a large number of assumptions viz. linear relationship, cause and effect relationship etc. which may not always hold good and it is very much likely to be misinterpreted particularly in case of homogeneous data and is subject to probable error which its propounder himself admits.
Predicting Ozone Layer Concentration Using Machine Learning Techniques. In: Social Network Forensics, Cyber Security, and Machine Learning. SpringerBriefs in Applied Sciences and Technology. Springer,	This paper shows the proposed work of forecast of centralization of ozone in the earth's environment by executing two AI models. The test and train dataset are in the proportion of 8:4 and the outcome from each of the two models appeared. By executing two expectation models, it's found that the Multivariate Adaptive Regression Splines (MARS) model shows the dataset	Two models compared in this paper are MARS and Random Forest. We can see what are the problems that occurred here. 1. Random Forest creates a lot of trees (unlike only one tree in case of decision trees) and combines their outputs. As a matter of course, it makes 100 trees in the Python sklearn library. To do as such, this

Singapore. (2019)	interestingly and better and has improved forecast precision when contrasted with the Random Forest expectation model. MARS gives the arrangement by conveying fewer regression factors when contrasted with the Random Forest forecast model. MARS is better as it utilizes 8 factors while Random Forests all factors. At the point when Random Forest and MARS are analyzed, MARS gives the closest/precise diagram for test and train set than Random Forest. After thinking about all the diagrams and yields, presumed that Multivariate Model mistake measures for a random forest. .Variable significance for arbitrary backwoods Predicting Ozone Layer Concentration Using Machine Learning Techniques Adaptive Regression Splines (MARS) regression model is a productive method and can be utilized to anticipate convergence of ozone gas in earth's air.	calculation requires substantially more computational force and assets. Then again, the decision tree is straightforward and doesn't need so many computational assets. What's more, it requires substantially more of an ideal opportunity to train when contrasted with decision trees as it produces a ton of trees and settles on choices on most votes. 2. MARS(Multivariate Adaptive Regression Splines). Other than speed, there is likewise the issue of worldwide advancement versus local advancement. Likewise, with Decision Trees, the fitting cycle for MARS regression is done in a stepwise greedy way. That way, simply the best work given the current model is added/taken out. One expected approach to comprehend this is to consider all possible fundamental pivot works on the double and afterwards run a Lasso or comparative punished Regression to locate the best ones.
Machine learning-based analysis for the relation between global temperature and concentrations of greenhouse gases	As shown by the results it is extremely evident that an upward example can be found in temperature, which is in direct relationship with the upward pattern found in CO2, CH4, and N2O fixations. Additionally, with the use of different AI computations makers have gathered assessors for global temperatures using global ozone harming substance fixations.	This paper used 4 kinds of ML models which are decision trees, Artificial neural network, linear regression and random forests. After evaluating means square error i.e, MSE they find that ANN proved to be the most useful and performs better than the others. So some of the gaps we identified were that 1. Decision trees are flimsy, implying that a little change in the information can prompt a

	These models can be used to anticipate future global temperatures using the evaluated future gas focuses. By then makers have dissected their estimates of temperature using the centralizations of ozone-depleting substances dependent on MSE. From the results, the best estimation of the four evaluated is ANN. Change Importance or burdens allowed by ANN to each independent variable Feature Permutation Importance/Weight Carbon Dioxide (ppm) 0.3842 Methane (ppb) 0.2661 Nitrous Oxide (ppb) 0.3094 Furthermore, by using ANN, makers have decided component significance/stage criticalness/weight consigned to each ozone harming substance focus from which it is assumed that the effect of CO_2 is most extreme in the development of global temperatures, followed by N_2O, and CH_4. Just CO_2, CH_4, and N_2O are considered as a factor adding to temperature change in the current work. Other ozone-depleting substances like tropospheric ozone can moreover be considered alongside components, for instance, ocean streams, wind and air masses, and biodiversity.	huge change in the structure of the ideal decision tree. They are frequently generally not accurate. Numerous different indicators perform better with comparative information. This can be helped by changing one decision tree with a random forest of decision trees, however, a random forest isn't as simple to decipher as one decision tree, for clear cut factors with the various number of levels, data gain in decision trees is one-sided for those characteristics with more levels and their computations can get exceptionally unpredictable, especially if numerous qualities are not certain or if numerous results are connected. 2. Random forest models can not be interpreted easily at all; they are like black boxes. 3. At the point when ANN produces an examining solution, it doesn't provide some insight regarding why and how. This decreases trust in the network. There is no particular guideline for deciding the structure of artificial neural networks. Issues must be converted into mathematical values before being shown to ANN. The presentation system to be resolved here will straightforwardly impact the performance of the network.
Scenario Planning for Sea Level Rise via Reinforcement	A proactive government model for the ocean level rise issue in a city climate thinking about the	This paper utilizes reinforcement learning to limit the normal financial expense over the long run. Reinforcement learning as a

Learning Salman S. Shuvo, Yasin Yilmaz, Alan Bush, Mark Hafen	effects of nature and inhabitants. The proactive government, which learns the ideal framework investment policy (yes or no at each time venture) through support learning how to limit the normally expected expense over time, monitors the ocean level state along with the infrastructure state and makes infrastructure speculation to reduce the impacts of ocean level rise issue at whatever point the normal future expense of no investment surpasses the quick expense of investment. This proactive technique was shown to significantly beat the straightforward investment policy which improves the framework in the consequence of a genuine monetary expense from nature. They also demonstrated that the average total expense can be altogether reduced as the government and inhabitants become more helpful intending to the ocean level rise issue.	structure isn't right from numerous points of view. An excess of reinforcement learning can prompt an over-burden of states, which can lessen the results. It isn't desirable overuse for settling straightforward problems. It needs a ton of information, a ton of calculation and is information hungry. Reinforcement learning expects the world to be Markovian, which it isn't. The Markovian model depicts a succession of potential functions where the likelihood of every function relies just upon the state achieved in the past function. The curse of dimensionality limits reinforcement learning intensely for genuine physical frameworks. As indicated by Wikipedia, the curse of dimensionality alludes to different events that emerge while dissecting and arranging information in high-dimensional spaces that don't happen in low-dimensional settings To take care of numerous issues of reinforcement learning, we can utilize a mix of reinforcement learning with different methods instead of leaving it alone. One famous blend is Reinforcement learning with Deep Learning.
Using Machine Learning to Parameterize Moist Convection: Potential for Modeling of Climate, Climate Change, and Extreme Events	This paper has explored how an RF-based algorithm of moist convection acts when implemented in a GCM in an ideal setting. Reassuringly, the RF definition was found to prompt robust and precise simulations of the control climate. The utilization of a decision-tree-based algorithm made it clear to guarantee actual requirements, for example,	The gaps found in this paper are that the RF trained in the control climate did not generalize to the warm climate, and the cutoff latitude at which it failed to generalize is approximately equal to the latitude at which the mean temperature in the warm climate is equal to the maximum mean temperature (near the equator) in the control climate. Some of the interesting issues that remain to be explored here include whether an ML parameterization

	energy preservation is protected by the parameterization. Different algorithms could be utilized to guarantee actual limitations have complied, but a decision-tree approach is appealing in ensuring they are satisfied to the extent that they hold in the training data. The RF algorithm was likewise found to perform well in the GCM regarding simulation of precipitation events, without the requirement for specific preparation on those events.	should be nonlocal in space and time, whether it should be applied in addition to the boundary layer, radiation, and large-scale cloud schemes or replace all of these, and the extent to which convective-momentum tendencies can be predicted. GCM with land brings up additional technical problems such as the strong diurnal cycle over land and the need to predict convection at different elevations in the presence of topography. GCM with land raises extra specialized issues, for example, the solid diurnal cycle over land and the need to foresee convection at various rises within the sight of geology. Even though GCM have improved their capacity to foresee future climatic changes throughout the most recent decade, their assessments are as yet restricted by their deficient portrayals of atmosphere influencing measures and by inadequate PC power, researchers don't completely see how the atmosphere framework reacts to conceivably significant physical, compound, and organic cycles, the absence of PC power expects researchers to utilize rearranged suspicions and structures that expand the vulnerability of the models' expectations and researchers are leading exploration to beat the constraints of the PC models.
Anthropogenic influence on global warming for effective cost-benefit analysis: a machine learning	In this examination, they propose a data-driven methodology dependent on machine learning to investigate which natural and anthropogenic compelling	This paper uses a **dynamics model** which is only capable of running one version of a situation at a time, although it may capture a great deal of variety in the changing values of its variables. However, besides their

perspective	components contributed most to the conduct of global temperature in the most recent years of the 20th century. Specifically, they played out regression analysis by methods for the random forest algorithm, whose predictive performance was surveyed inside various out-of test evaluation frameworks. Their experimental discoveries demonstrated an apparent connection between greenhouse gases and temperature increment, further supporting the after-effects of past attribution examinations which highlighted the predominant influence of anthropogenic forcings on environmental change since 1950. Among the normal input variables, the Atlantic Multidecadal Oscillation ended up being the most relevant one. The paper adds to the current discussion on the anthropogenic reasons for atmosphere changes by giving objective data-driven experiences on the impact that GHG emissions have on the global temperature rise.	intrinsic complexity, these methods are not data-driven, have limitations in testing their validity on novel data, are based on discretization into grid boxes and also fail to highlight the relative importance of the different forcing factors. The former econometric techniques suffer in turn from limitations, as most hidden relationships in climate analysis are nonlinear. Therefore, methods that are based on implicit or explicit independence assumptions concerning input data have limited appropriateness in the climate domain. Random Forest is being used in this paper too but we have already discussed its disadvantages earlier.

Implementation:

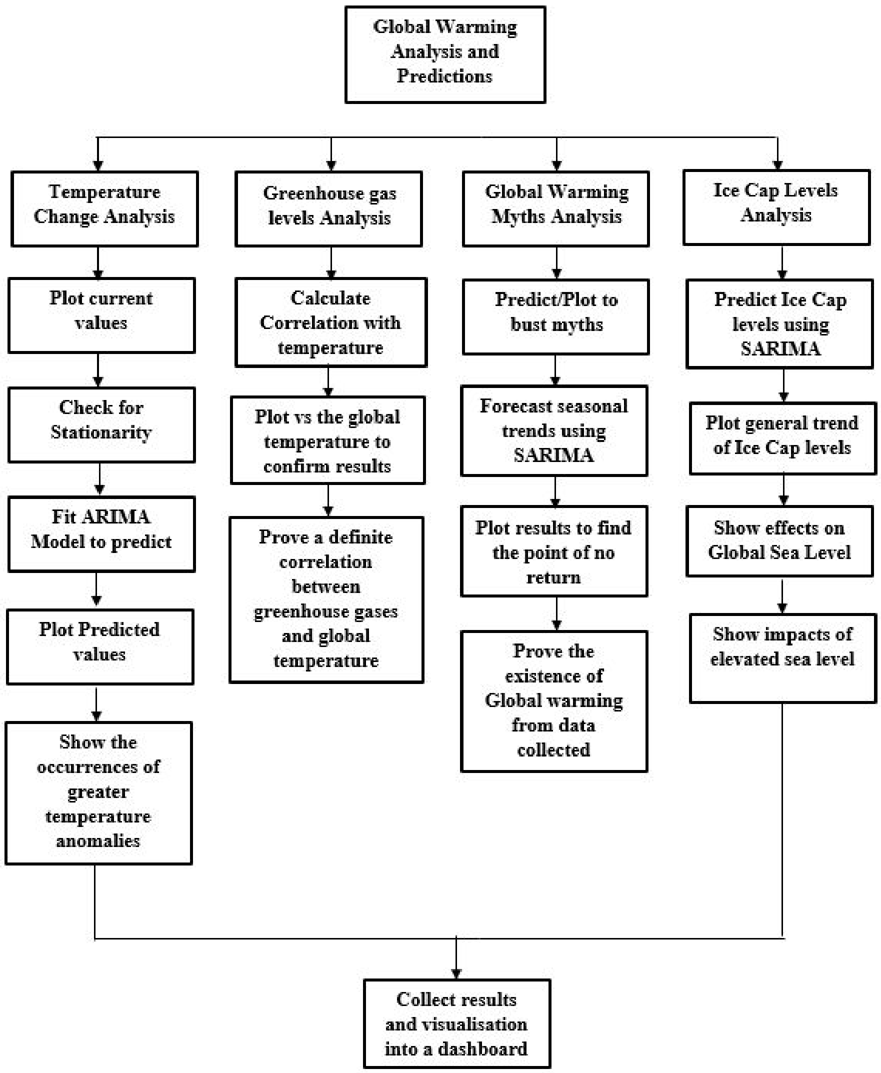

Fig 1: Flow Diagram of the project

Project Code Link:
https://drive.google.com/drive/folders/1YUBzGX-U5OmSbuZ_ESlNgONoa55525hD?usp=sharing

Our project is divided into 4 components:

1. Global Temperature Changes
2. Greenhouse gas levels analysis and their impacts
3. Debunking Common Myths
4. Icecap/ Sea level Analysis

Global warming and climate change are growing threats to the very existence of our species on earth. Although the two terms are used interchangeably, global warming refers only to a change in global temperatures, whereas climate change includes global warming and the effects of this change. Although most scientific societies agree on the existence of global warming, its causes, and its threat to humanity, many people deny this fact. The purpose of this project is to examine the details of global warming and its effects to raise awareness of the impending global crisis and to assist in discussions on mitigation efforts and solutions.

Rising atmospheric temperature levels due to the advent of the Industrial Revolution (1760 - 1820) and the modern industrialization have created a dangerous environment in which it is difficult for the planet to cool down. Under normal conditions, the Earth can release excess heat into space in the form of infrared radiation. However, the increasing concentration of greenhouse gases absorbs this radiant energy and prevents it from escaping, increasing the temperature of the lower atmosphere and upper atmosphere.

Climate scientists are calling for the immediate action of this greenhouse gas effect, with many estimates indicating that if global temperatures were to rise by 2.0 degrees Celsius, the Earth would be in dire straits. In this case, the planet will not only be able to cool itself naturally, it will also create a self-sustaining response that can contribute to global warming on an ongoing basis. As the planet warms, ice sheets and ice packs can melt. As glaciers and ice packs melt, Earth's ability to reflect the radiant energy of the sun is diminishing, resulting in a progressive increase in temperature. In addition, melting glaciers and ice packs will eventually increase sea levels around the globe, greatly reducing the continental habitat. Milankovitch's orbits are related to changes in the Earth's orbit and the rotation of the sun's orbit. These variations contribute to global warming, but they occur over thousands of years. Global warming concerns Scientists began in the early 1900s, and global temperatures have been rising by 0.93 degrees Celsius. It is important to note that most climate studies use a temperature variant that is different from the green temperature. This temperature change refers to the variation in temperature from baseline, the global temperature record from 1951 to 1980.

Results Analysis:

i. Global Temperature Change:

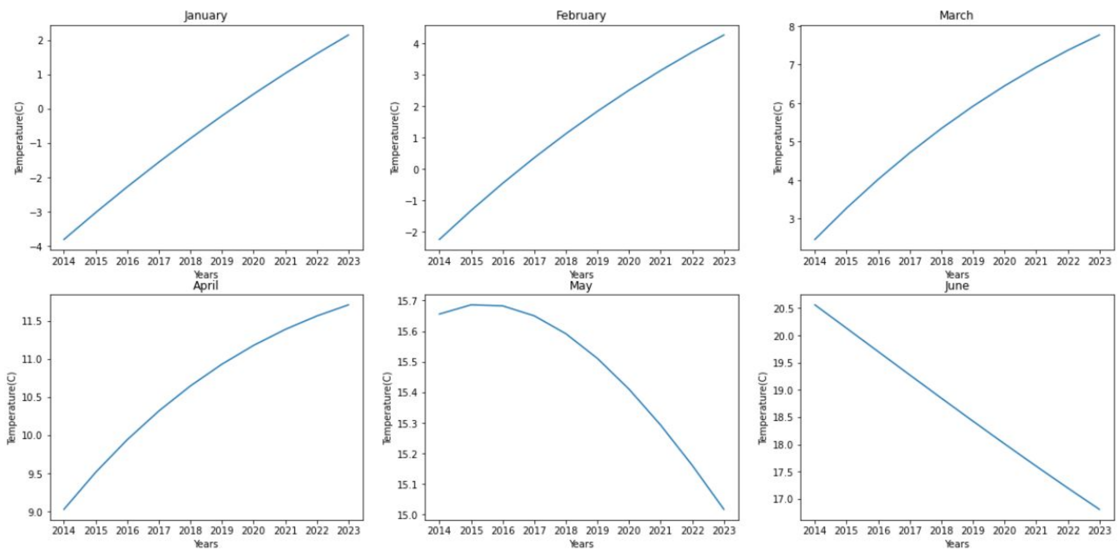

Fig 2: Average monthly temperature change of January - June

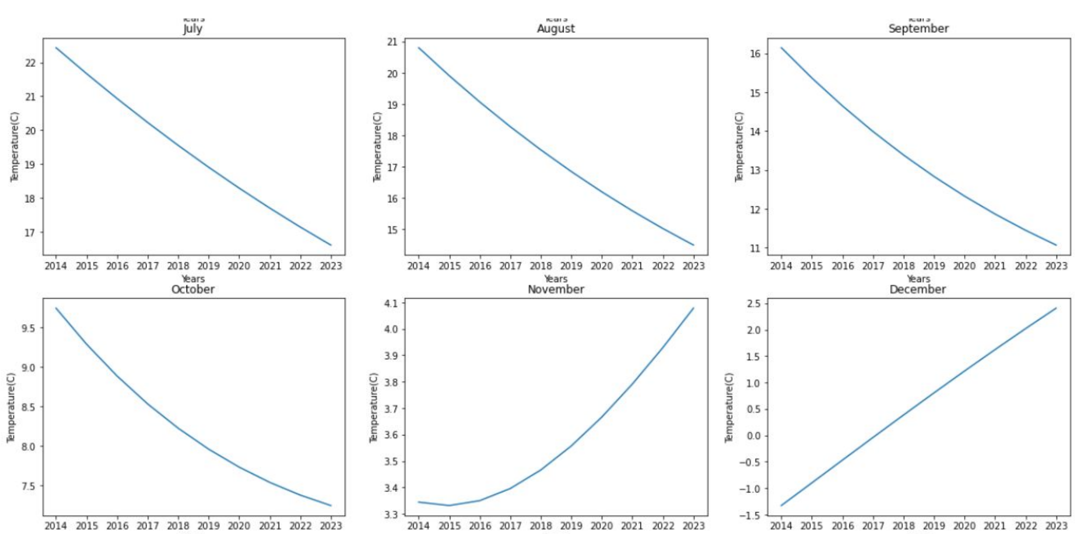

Fig 3: Average monthly temperature change of July - December

We see a shift in the arrival of Summer and Winter. The classic summer month sees an increase in the average temperature while months like September, October see a decrease in average temperature. This is consistent with the effects of global warming where the summers get hotter and winters get colder

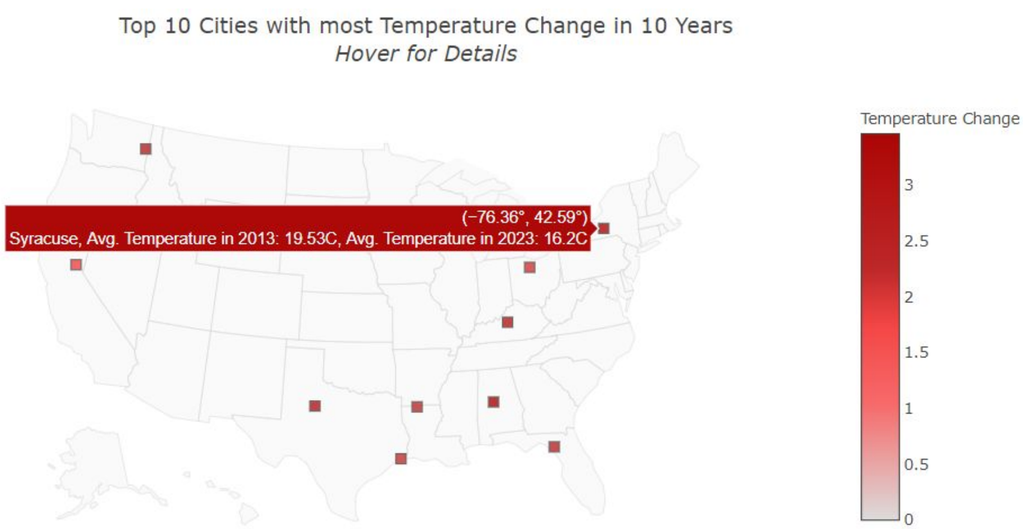

Fig 4: Top 10 American cities which showed the greatest temperature change

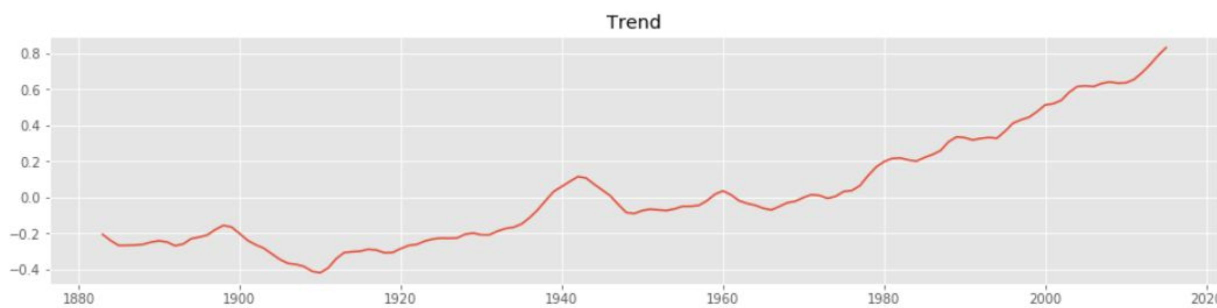

Fig 5: General trend of Temperature Anomalies

After predicting the rate of global anomalies using the SARIMA model, we can see that the rate of anomalous behaviour is increasingly suggesting that the global average temperature is deviating further from its seasonal patterns(i.e. Hotter summers, colder winters)

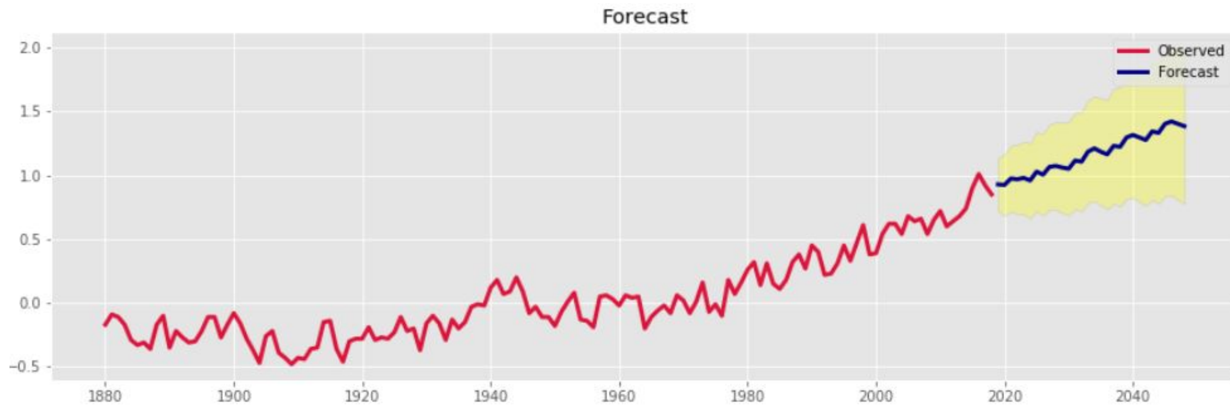

Fig 6: Forecast of future Global average temperatures using the SARIMA model

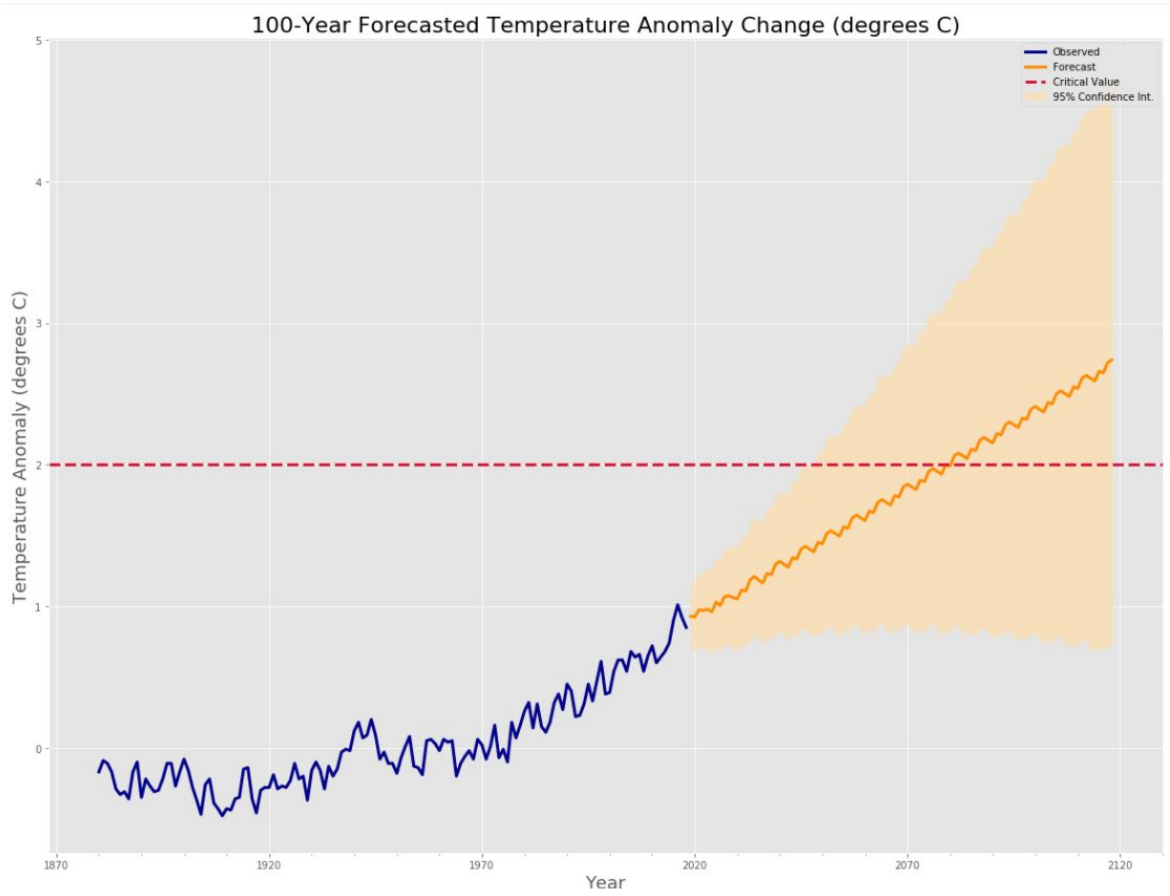

Fig 7: Predicting the point of no return where the global temperature increases by over 2 degrees celsius

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Model Performance Measures:
Root Mean Squared Error: 0.10073793374249695
R-Squared: 0.7469181741158673
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Fig:

From the plot of predictions for the global average temperatures, we can see that it is rising at an increased rate with even the most optimistic predictions with a 95% confidence interval showing that irreversible damage would be done to the environment by 2030 unless drastic measures are taken.

ii. <u>Greenhouse Gas Levels Analysis</u>:

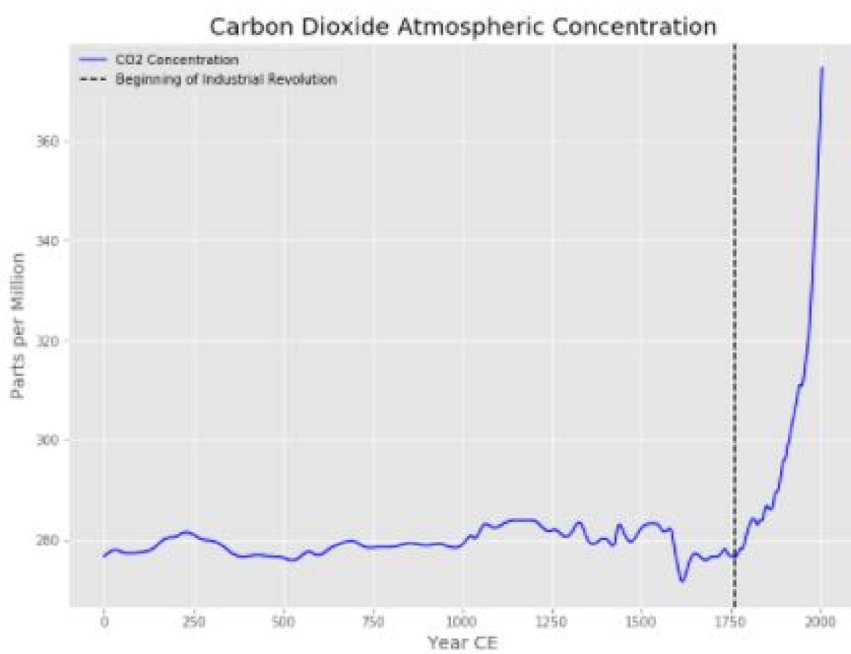

Fig 8: CO2 levels in ppm since 0 AD

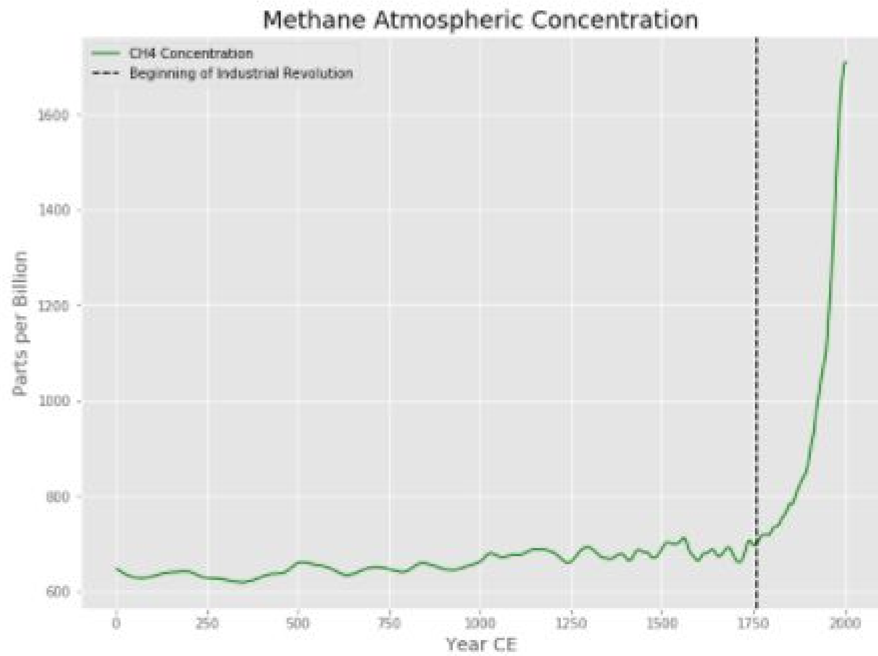

Fig 9: CH4 levels in ppm since 0 AD

Fig 10.1: Temperature change compared with the levels of SO2, CO and N2O

Here we see the exponential increase in the levels of greenhouse gases like carbon dioxide, methane and sulphur di-oxide since the start of the industrial revolution(1700's). We see a small dip in the mid-2000's when the Montreal Climate agreement was ratified and renewed.

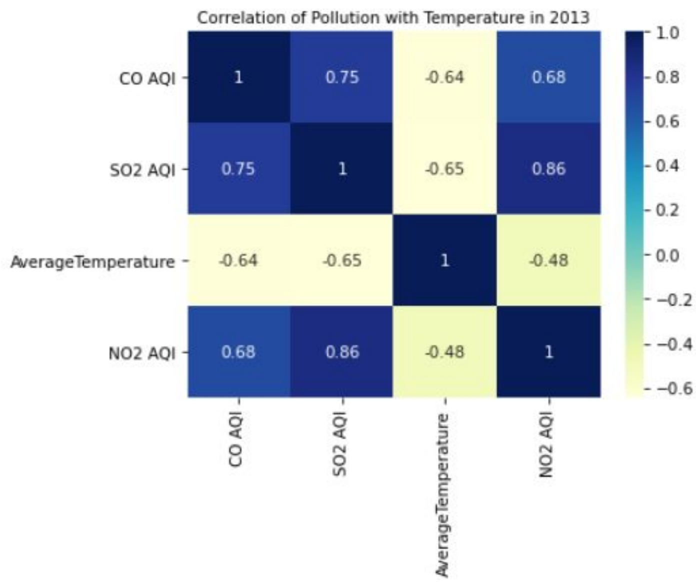

Fig 10.2: Correlation between temperature and average temperature

We can see from the correlation coefficients that SO2 has the greatest effect on average temperature followed by CO and then N02. (SO2 > CO > NO2).

SO2 :- -0.65

CO :- -0.64

NO2:- -0.48

<u>Note</u>: The correlation values are negative as they are calculated between temperature and each gas's Air Quality Index (AQI) where a lower AQI indicates higher levels of the gas.

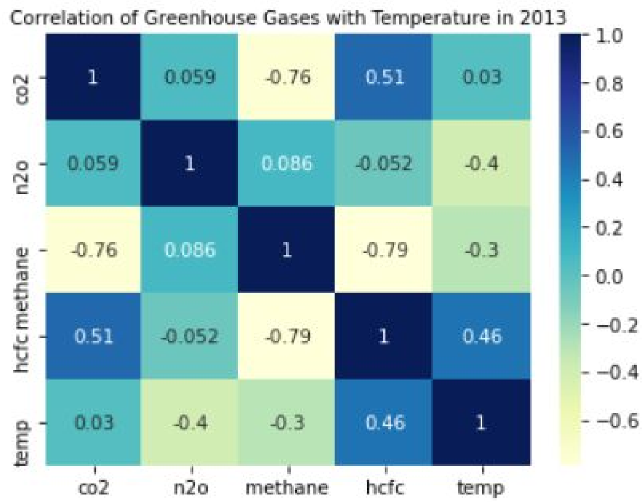

Fig 10.3: Correlation coefficient between greenhouse gases

Analysis: Here we plot the correlation matrix between global average temperatures and more potent greenhouse gasses. This includes HCFC, methane and N2). Here we see that the most potent greenhouse gas is HCFC followed by N20 and Methane. (HCFC > N20 > CH4).

HCFC:- 0.46

N20:- -0.4

Methane (CH4):- -0.3

CO2:- 0.03

Note: We calculate the correlation between global average temperatures and Air Quality Index (AQI) for N20 and CH4 where a lower AQI indicates higher levels of the gas. This is done as they are measured due to their harmful effects and lower quantities compared to gasses like O2, CO2. We use the concentration of CO2 as it is too abundant compared to other greenhouse gasses to measure through AQI. HCFC is no longer measured in most stations as it was banned from use in the mid-2010s.

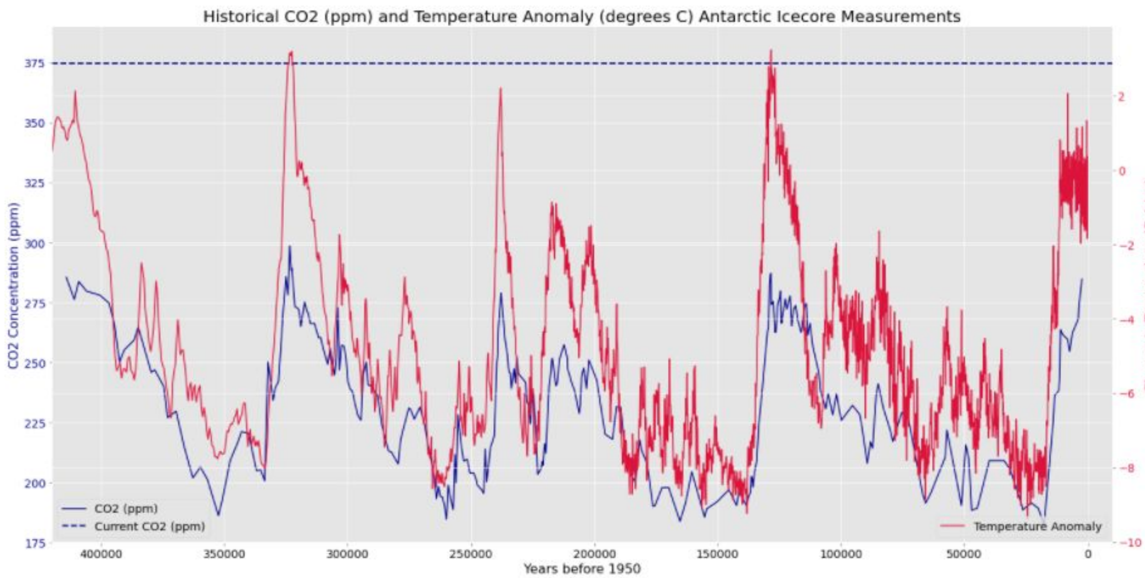

Fig 11.1: Temperature anomalies compared with the levels of CO2

We can see that every spike in the CO2 concentration level (ppm) also corresponds to a larger spike in the occurrence of global temperature anomalies. This matches the results obtained by calculating the correlation between global average temperature and CO2 concentration as it showed a high positive correlation. This proves its effect on the environment as a greenhouse gas.

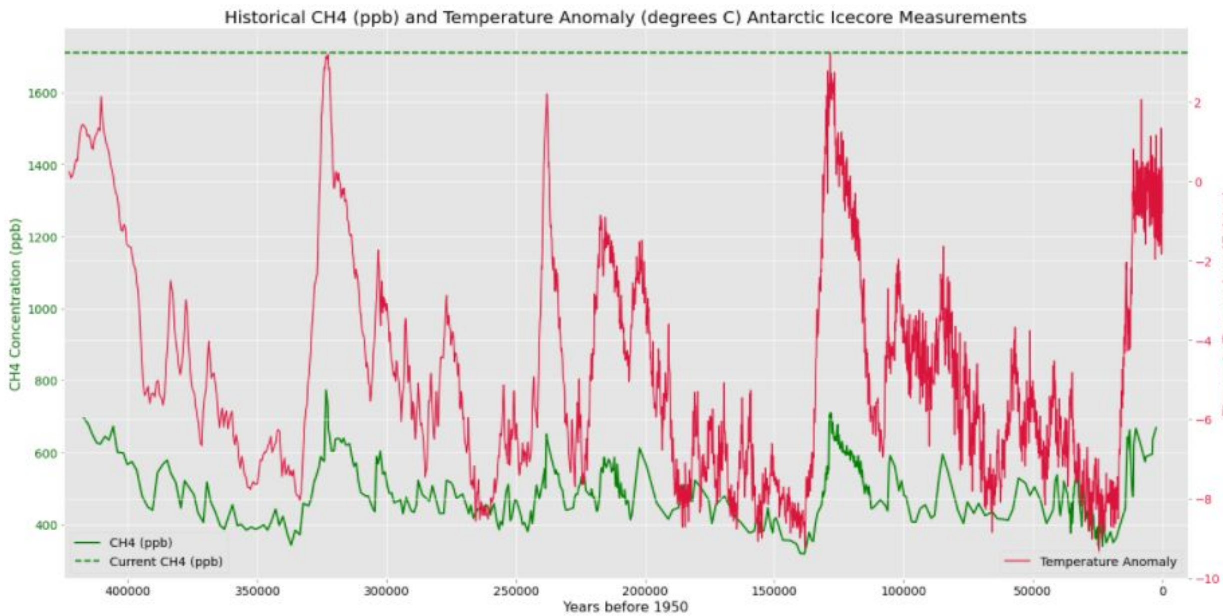

Fig 11.2: Temperature anomalies compared with the levels of CH4

We can see that every spike in the CO2 concentration level (ppm) also corresponds to a larger spike in the occurrence of global temperature anomalies. This matches the results obtained by calculating the correlation between global average temperature and CO2 concentration as it showed a high positive correlation. This proves its effect on the environment as a greenhouse gas.

Figure 12: Relation between average temperature and methane, HCFC

This can be seen in the direct effect a reduction in HCFC levels has on the global average temperature. HCFCs used to be produced as a coolant for air-conditioners and refrigerators before they were banned due to their effect.

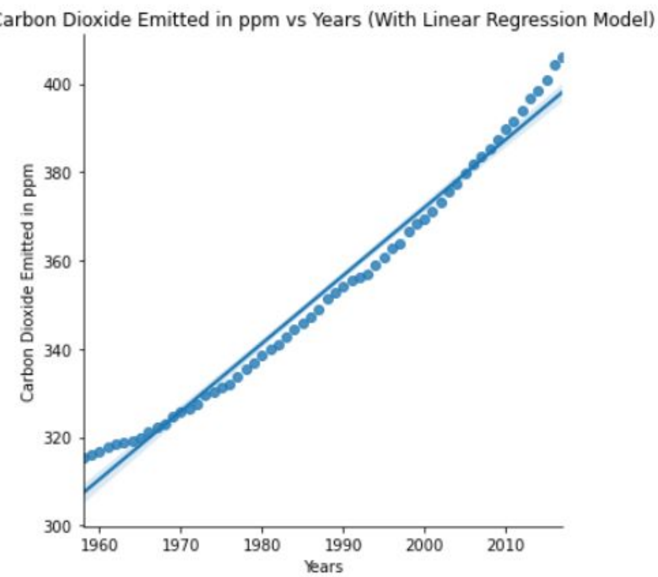

Fig 13.1: Linear Prediction of CO2 emissions

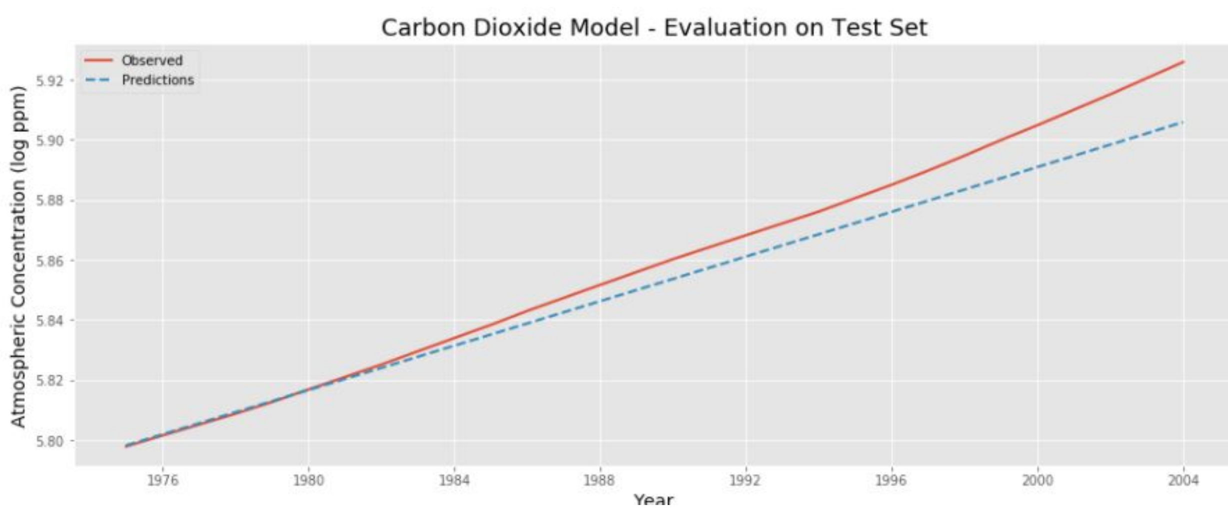

Fig 13.2: Linear Prediction of CO2 emissions

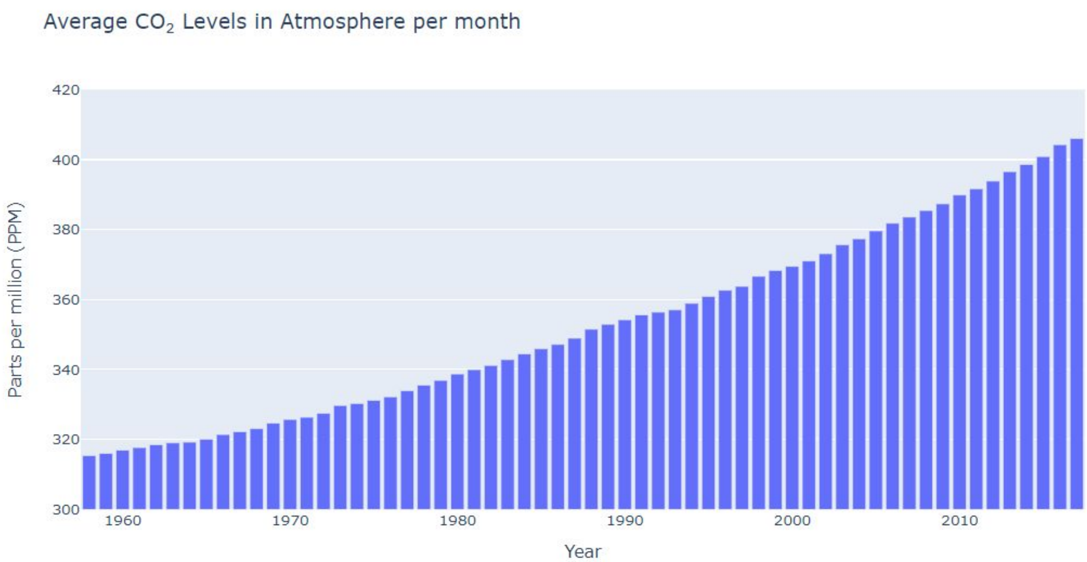

Fig 13.3: Plotting of CO2 levels on parts per million

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Root Mean Squared Error: 0.008881423646072688
Standard deviation of test set: 0.038538212714851035
R-Squared: 0.9450578954773309
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Fig 13.4: Holt Prediction Model Results for CO2 levels

We can see that the concentration of CO2 (ppm) in the atmosphere can be modelled using a polynomial regression curve of order 2. Given the effect that it has on the global average temperature, a polynomial increase in CO2 levels causes an even greater increase in temperature.

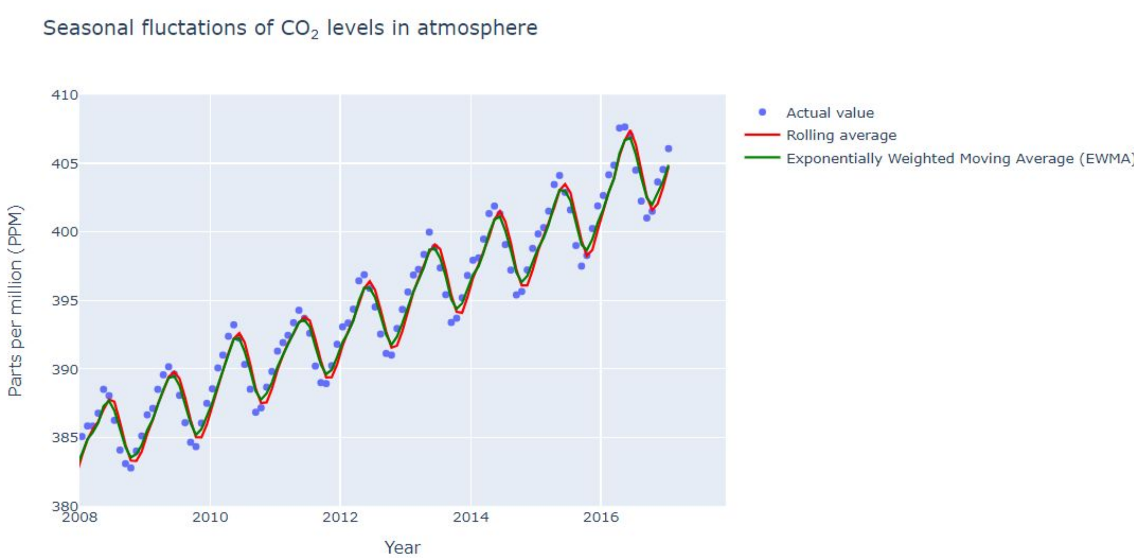

Fig 13.5: Plotting of CO2 levels on parts per million

Here we see the seasonal fluctuations in the CO2 levels as at different temperatures, CO2 reacts with other existing compounds to transform into CO, CO3- etc. We take a rolling average to smoothen the fluctuation in the CO2 levels between months.

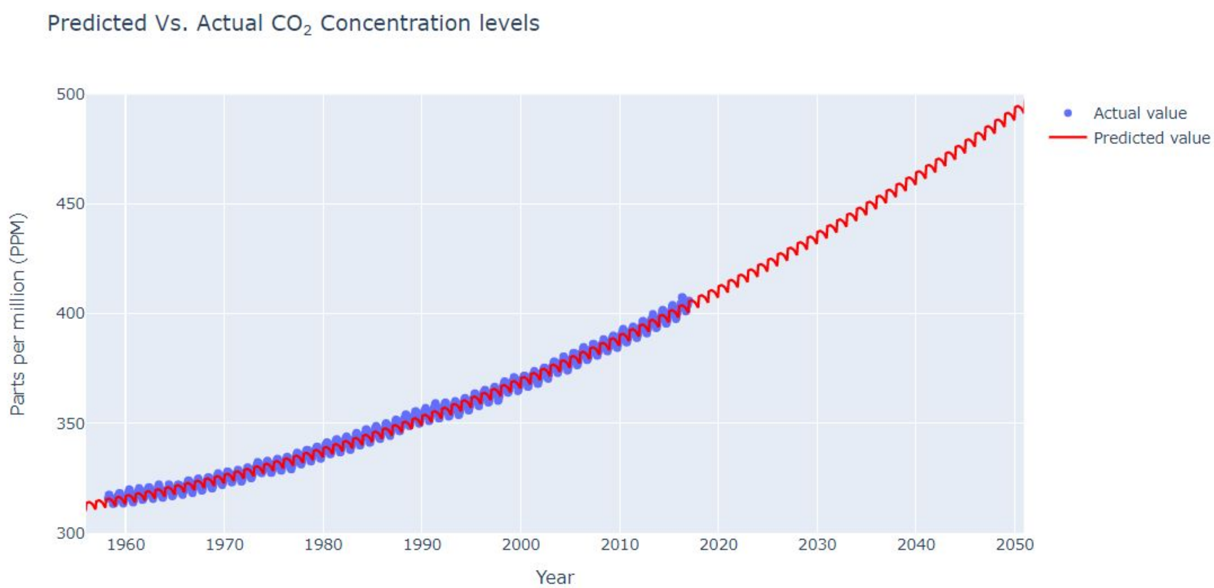

Fig 13.6: Predicting the CO2 levels using the ARIMA model

We see a gradual exponential increase in the CO2 levels of order 2. This is an extension of the plotting we did earlier for the CO2 levels used to predict future concentration levels.

iii. Debunking Common Myths

While the existence of global warming is something that has been proven scientifically through numerous ways there are still people who are confused about its effects and people who don't believe in it. We have compiled a few famous myths about global warming and debunked them to prove its existence beyond doubt.

a. **Claim 1**: The Earth isn't getting warmer. The summers are hot and winters cold. This is just seasonal and nothing more.

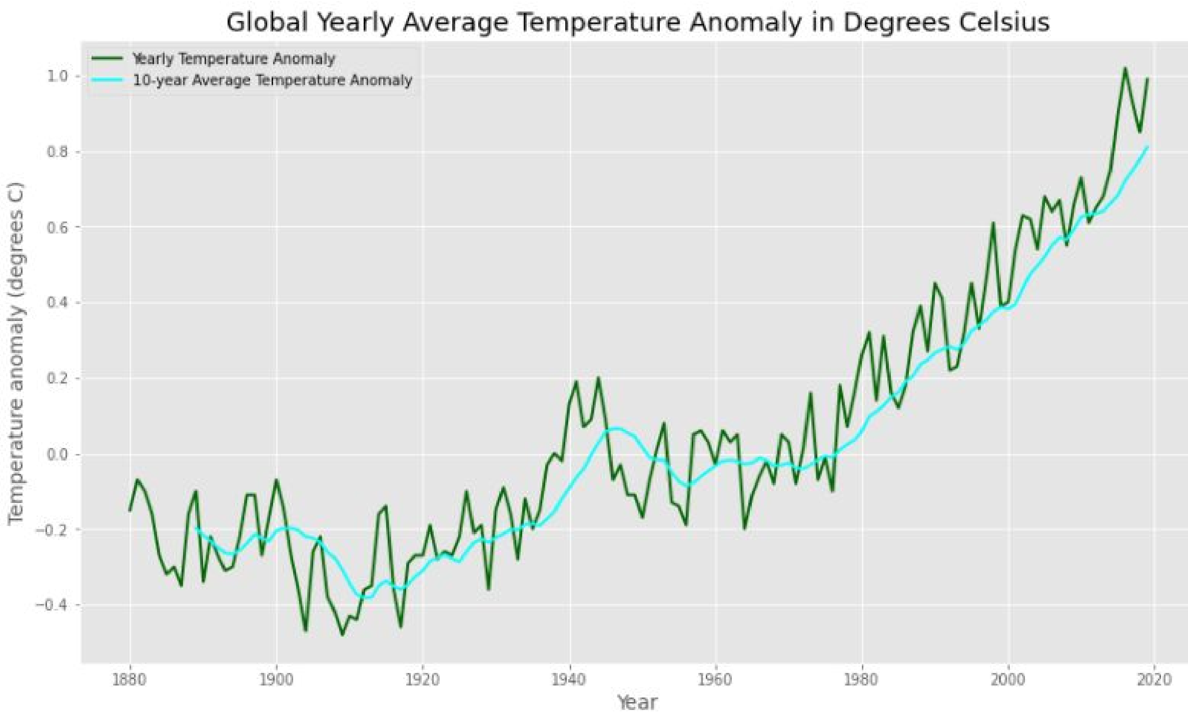

Fig 14: Global Average Temperature Anomalies over the years

The global average temperature anomaly displays a steady increasing trend beginning around 1980. The global average temperature anomaly in January of 1980 and 2018 (end of the dataset) is 0.26 C and 0.85 C, respectively. Therefore, the global average temperature anomaly increased by 0.0155 C per year over that span of 38 years. However, the temperature anomaly over the past 18 years (2000 to 2018) has been increasing at a rate of 0.0256 C per year, indicating that the global average temperature anomaly is increasing at a non-linear rate. In simpler terms, this shows that summers are getting hotter and winters are getting colder, deviating from their average temperatures and hence showing anomalous behaviour.

b. <u>Claim 2</u>: What is "temperature anomaly"? It seems like it is a convenient transformation of the data to support global warming research.

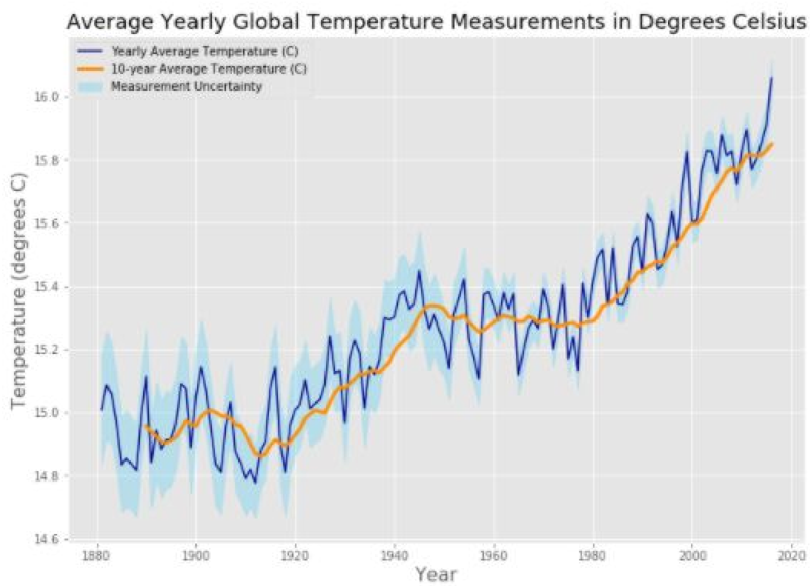

Fig 15: Global Average Temperatures every year

In the fig, we have plotted the actual global yearly average temperature measurements in degrees celsius. The upward trend in the temperature anomaly graph (left) beginning around 1980 is seen in the yearly average measurements at the same time. Thus, temperature anomaly is not an arbitrary transformation of temperature data. The results we see in the anomalous temperatures chart is backed by the general increase in global average temperature.

c. **<u>Claim 3</u>:** You've only reported yearly average temperatures. What if there was just one really hot month each year that is giving a false sense of global warming?

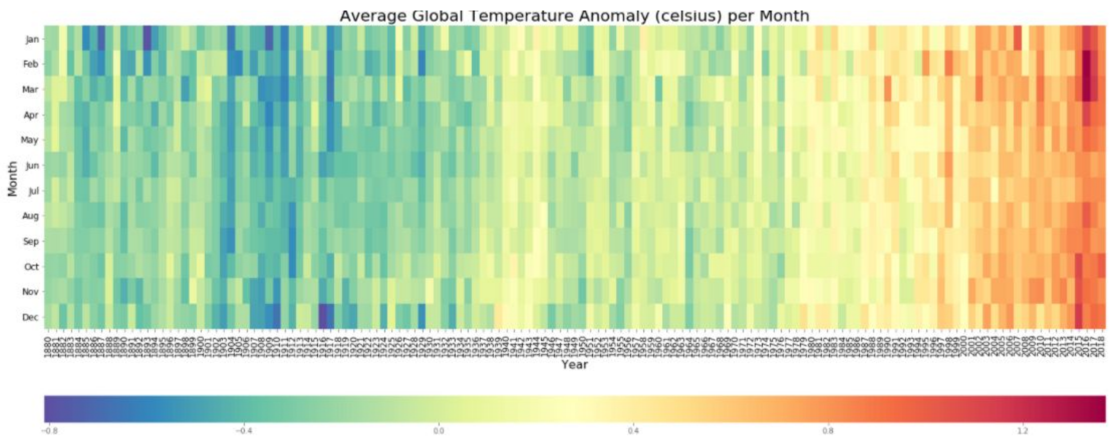

Fig 16: Monthly Average Temperatures 1880 - 2015

Over the 138 years in which this dataset spans, the global average monthly temperature anomalies appear to be increasing. Additionally, the increase in monthly temperature anomalies seems to be relatively consistent within each year. If the claim that *"one sweltering month each year is skewing the yearly average temperature measurements"* were true, then the figure above would be a fairly uniform yellowish-green colour (corresponding to a temperature anomaly of 0) with one dark red square (indicating a large positive temperature anomaly) per year. That pattern is not seen in this figure and the general trend of the colour gradation indicates the average global temperature is increasing.

d. **<u>Claim 4</u>:** What if the rise in global average temperatures is caused by the sun radiating more heat?

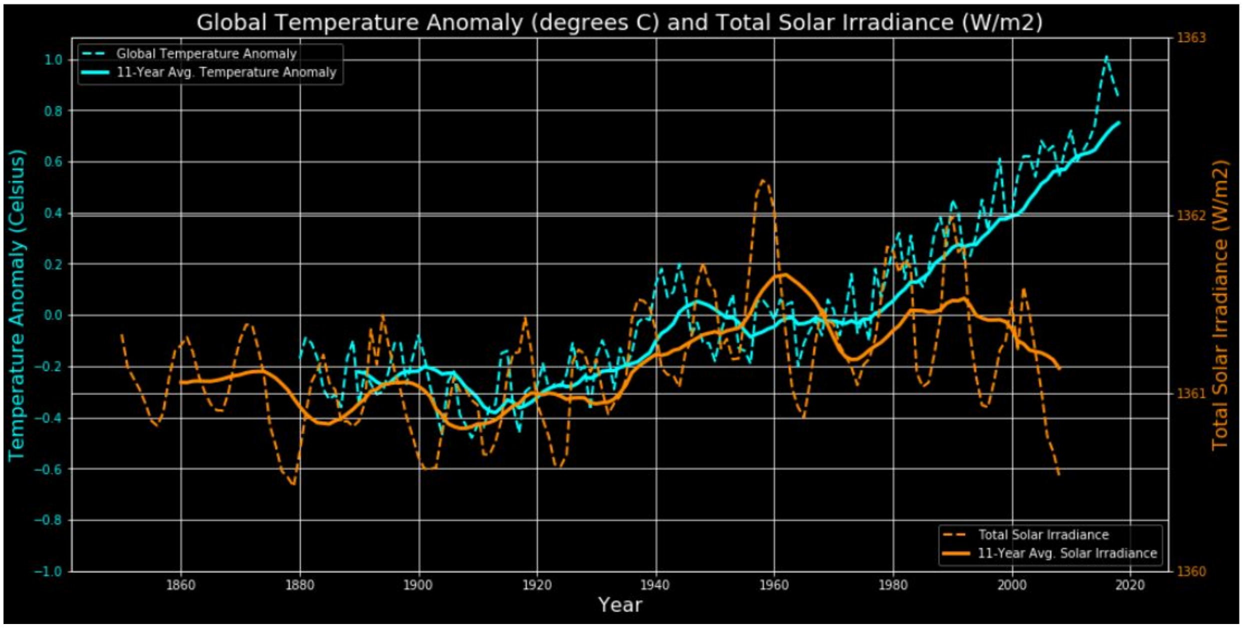

Fig 17: Sun Radiance levels vs Global Average Temperatures

The graph displays the global yearly temperature anomalies (green) and the total solar irradiance (orange) between 1850 and 2018. While the fluctuations make it a little difficult to analyze, there does not appear to be strong evidence suggesting the sun is radiating more heat as the total solar irradiance values fluctuate within a small range (2 W/m2) and do not display an obvious trend. Additionally, there is a spike in global yearly temperature anomaly around 1945 that **precedes** a spike in total solar irradiance. If the claim were true, then it would be expected for the graph to show the opposite, i.e a spike in total solar irradiance preceding a spike in global temperature anomalies.

iii. Ice Cap / Sea level Analysis

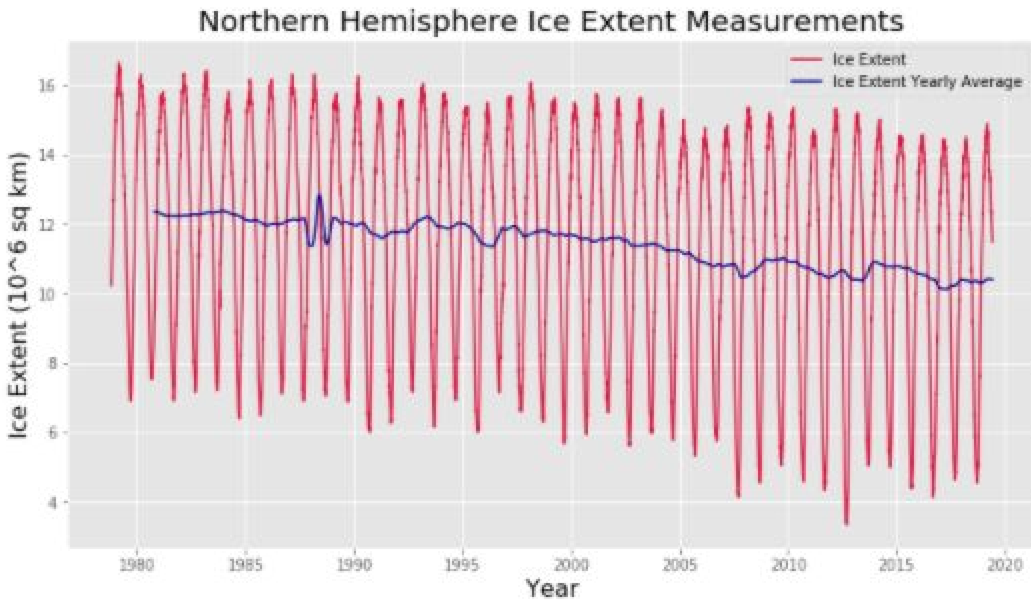

Fig 18: Northern Hemisphere Ice Cap levels

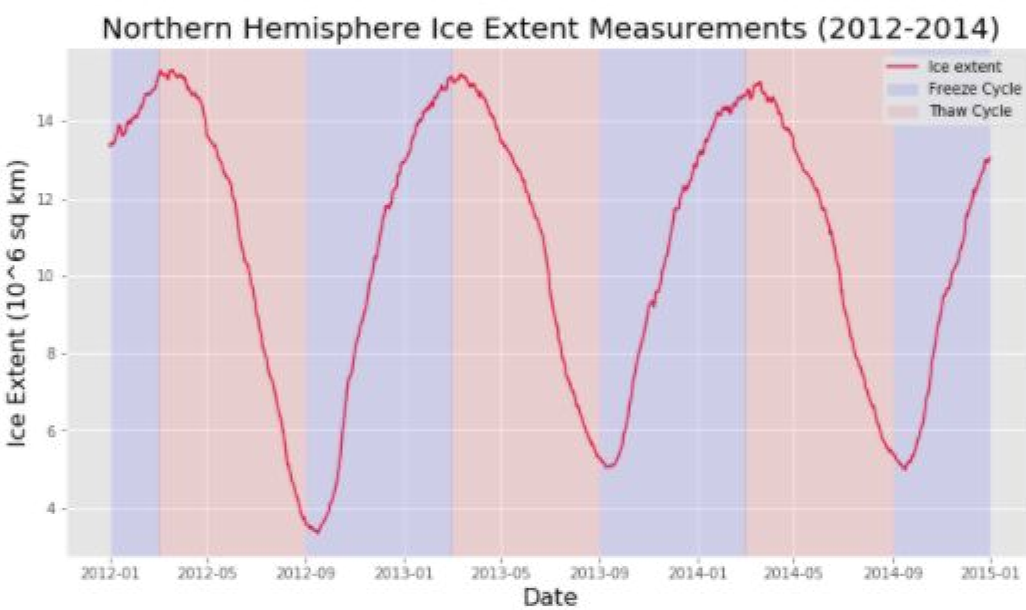

Fig 19: Northern Hemisphere Freeze and Thaw cycles

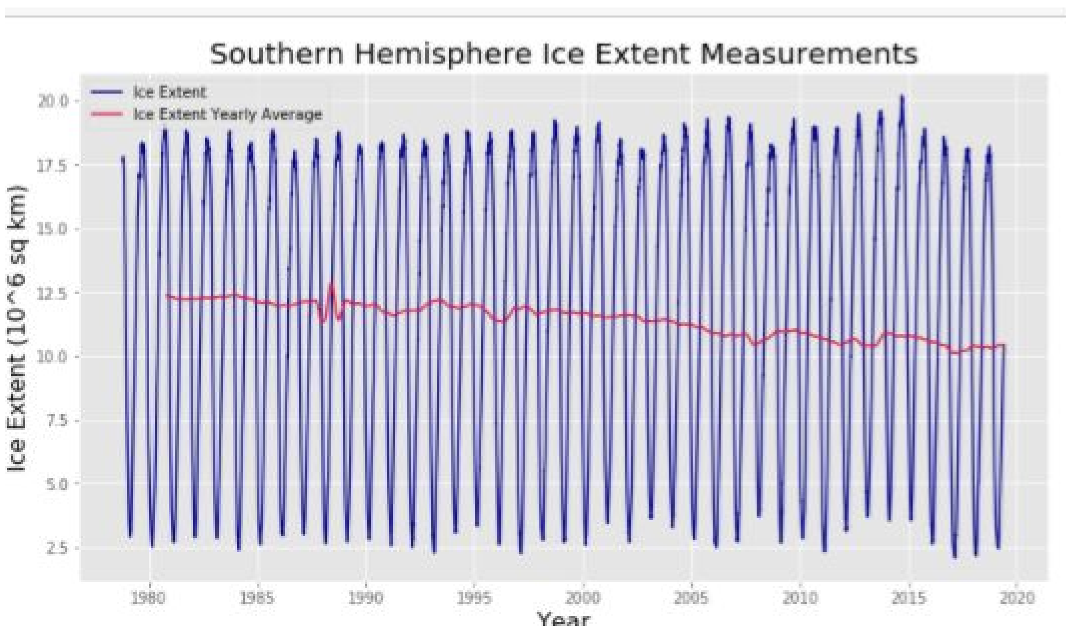

Fig 20: Southern Hemisphere Ice Cap levels

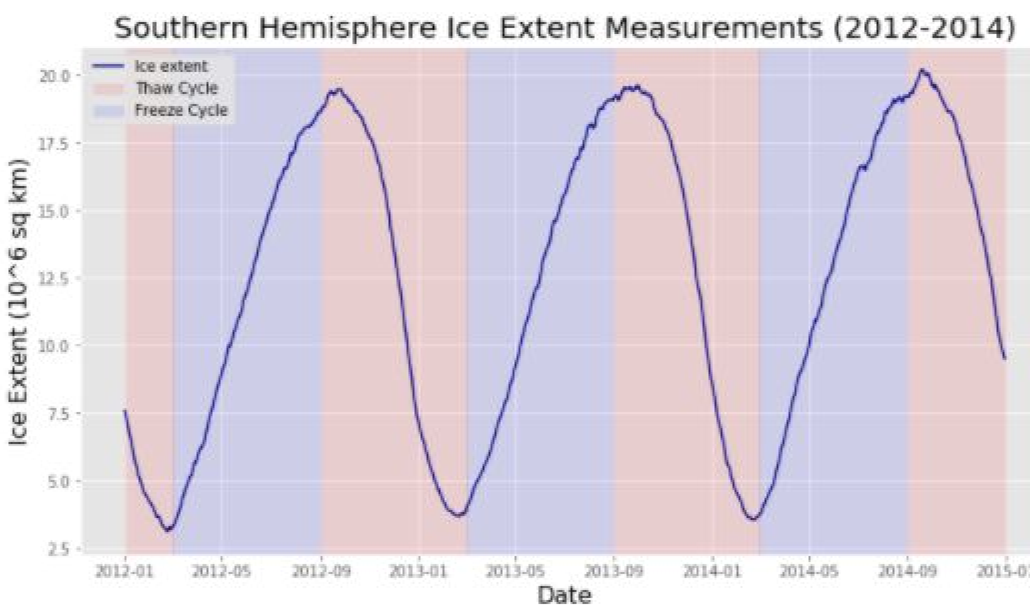

Fig 21: Southern Hemisphere Freeze and Thaw cycles

The fluctuations in ice extent measurements correspond to seasonal freeze-thaw cycles. Additionally, these cycles are shifted by six months between the two hemispheres due to each hemisphere's opposite seasonal pattern. While the range of freeze-thaw extent fluctuation doesn't appear to be changing dramatically, the yearly average of the ice extent measurements demonstrates a general downward trend. Furthermore, the rate of ice loss is occurring faster in the northern hemisphere (-0.048 million sq km per year) than it is in the southern hemisphere (-0.015 million sq km per year).

Because the freeze-thaw cycles are shifted by six months between the hemispheres, when the northern ice is melting the southern ice should be freezing, resulting in a net-zero change in global ice extent. However, since both hemispheres are experiencing a loss in total ice extent each year, the thaw in one hemisphere is not being compensated by an equal freeze in the other hemisphere, suggesting that either the freeze cycle in each hemisphere is becoming shorter (due to climate change) or because average global temperatures are rising and inhibiting freezing.

a. <u>Northern Hemisphere</u>

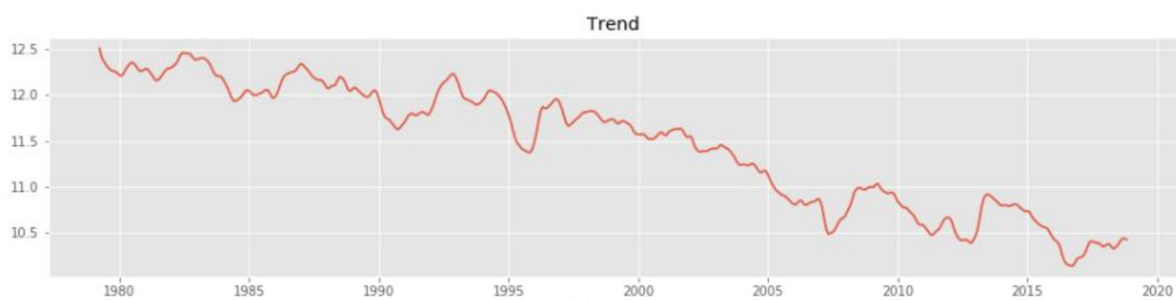

Fig 22: Northern Hemisphere Ice Depth Trend

We see this in the results when we apply this data to our SARIMA model to plot out the general trend of average ice cap depth levels. We see dip in the average depth from 12.5 m in 1980 to nearly 10.5m in 2020. We also notice that while this descent starts gradually, it starts getting steeper as time passes. This makes sense when we analyse the greater frequency of anomalous temperatures resulting in shorter, less effective freeze cycles.

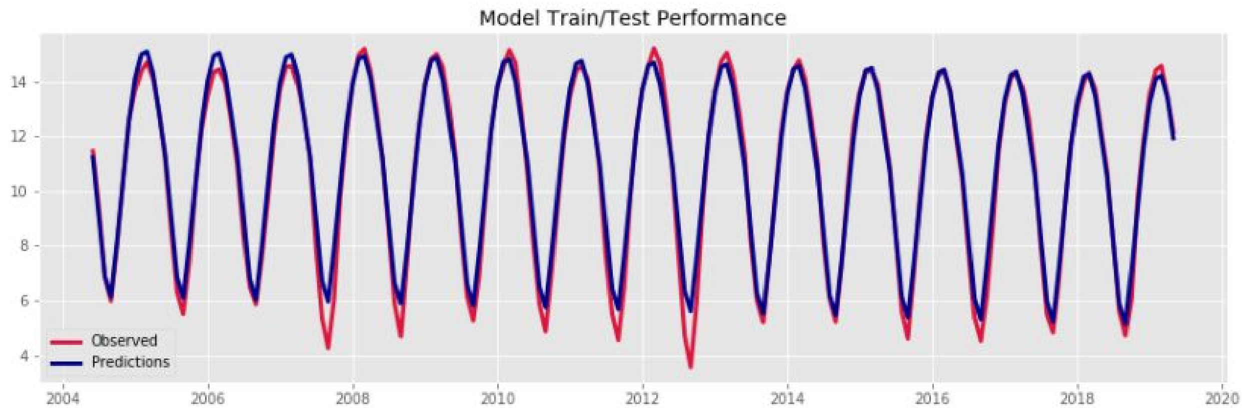

Fig 23: Northern Hemisphere Ice Depth Forecast Performance

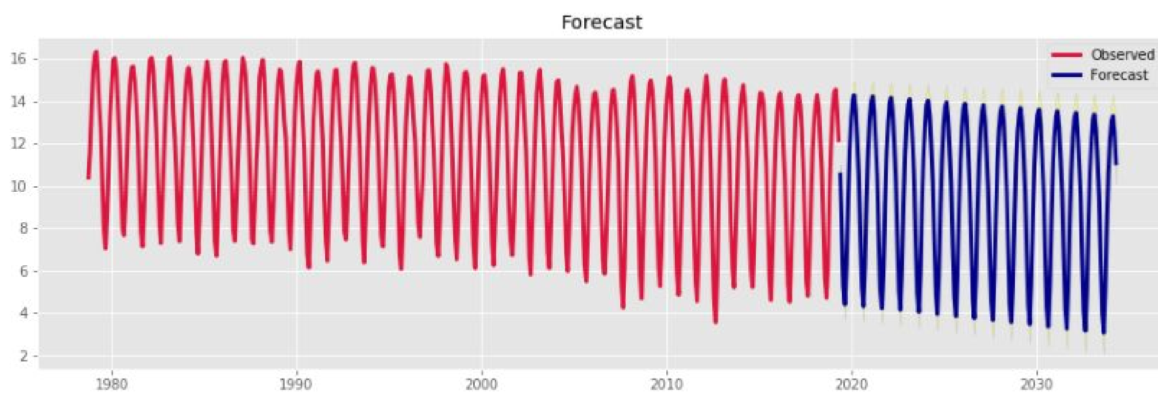

Fig 24: Northern Hemisphere Ice Depth Forecast

```
Model Performance Measures:
Root Mean Squared Error: 0.5313177116126091
R-Squared: 0.9751300265281895
```

Fig 25: Northern Hemisphere Ice Depth Forecast Performance Metrics

Using our SARIMA model we can predict the average ice cap depth and its seasonal fluctuations in the northern hemisphere. We have done so till 2035 and noticed critically low levels indicating drastic action that needs to be taken. We have also included the performance metrics for our model. It shows a model accuracy of 97.5% and a minimum mean square error of 0.531.

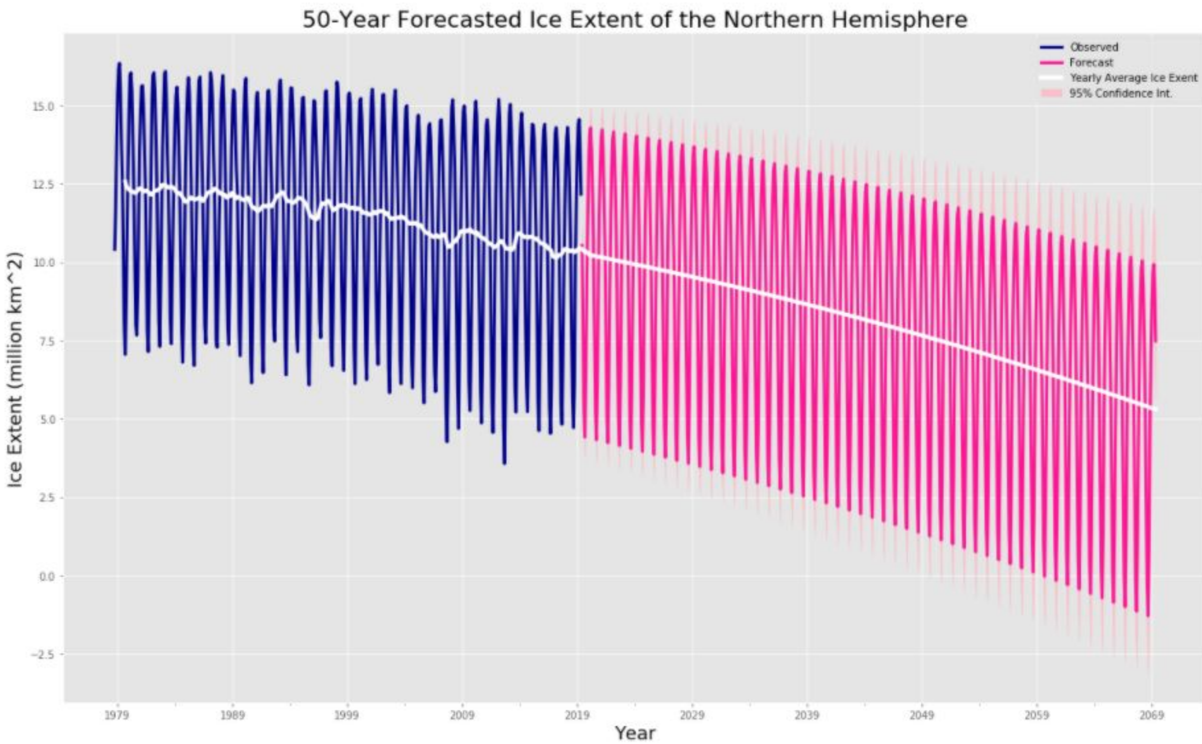

Fig 26: Northern Hemisphere 50 year forecast

With the given model and its high degree of accuracy, we can make a forecast 50 years into the future on the ice cap levels in the northern hemisphere. We can see that the entire north pole melts by 2060 assuming the best case and by 2032 in the worst case (lower bound of 95% confidence limit.

b. Southern Hemisphere

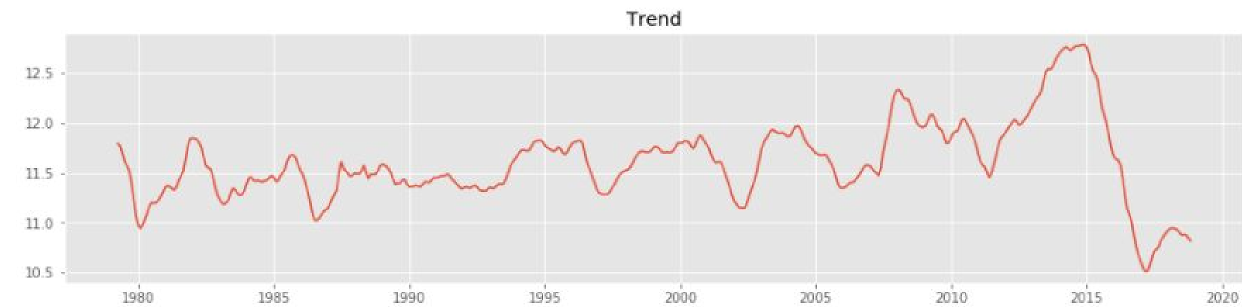

Fig 27: Southern Hemisphere Ice Depth Trend

Fig 28: Southern Hemisphere Ice Depth Forecast Performance

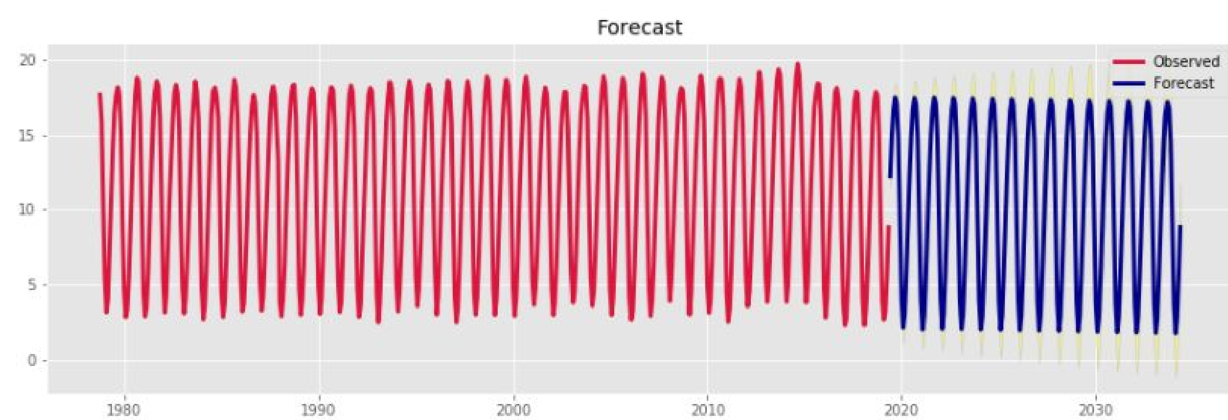

Fig 29: Southern Hemisphere Ice Depth Forecast

```
Model Performance Measures:
Root Mean Squared Error: 0.7529260612146246
R-Squared: 0.9823064030986002
```

Fig 30: Southern Hemisphere Ice Depth Forecast Performance Metrics

Using the data collected we can predict the future ice cap depth levels in the southern hemisphere. Here we can see that our model accurately predicts the ice cap levels with an accuracy of 98.2% and a mean square error of 0.753. We tested this data till 2035 and noticed a far more gradual decrease to a point where it even levels out on average. This matches with scientific research showing how the northern hemisphere is far more susceptible to heating than the southern hemisphere.

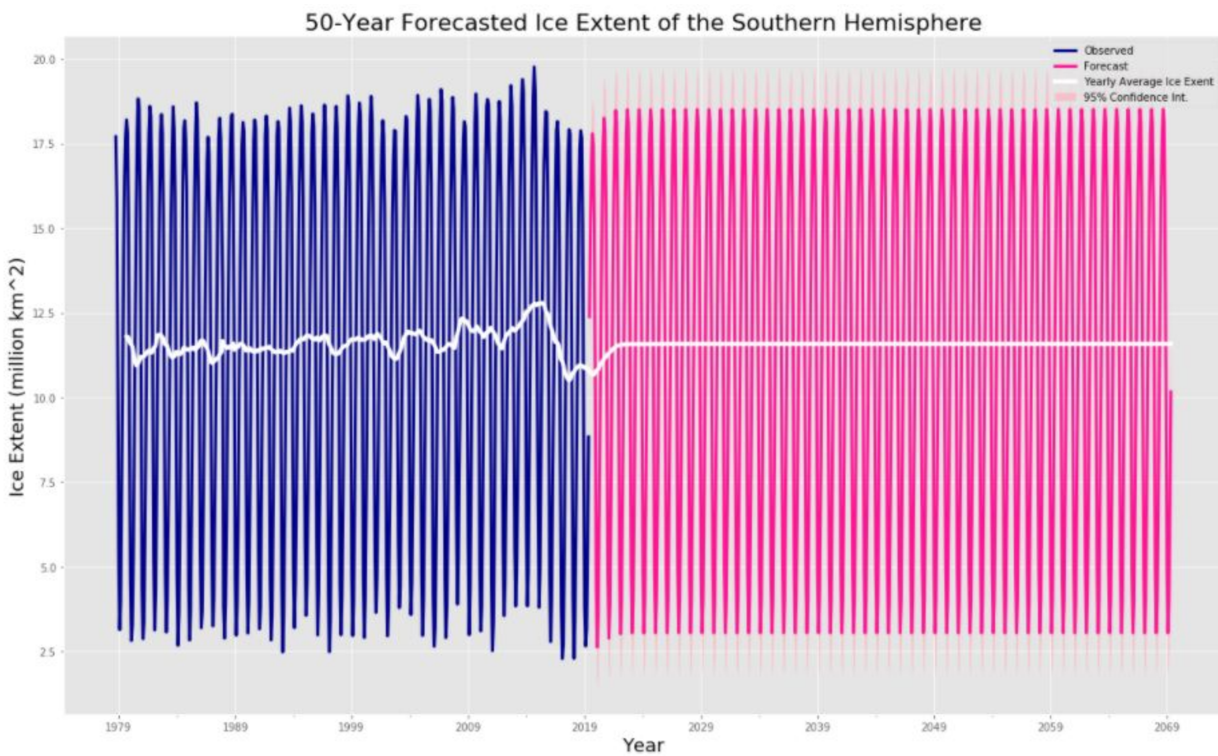

Fig 31: Southern Hemisphere 50 year forecast.

Based on the predictions from the model, the ice extent of the southern hemisphere is not expected to change. While this differs from what would be expected as the planet warms, it is not necessarily surprising as research has indicated that the northern hemisphere is warming to a greater degree than the southern hemisphere. Thus, the ice extent in the northern hemisphere would be expected to decrease faster than the ice in the southern hemisphere.

c. Sea Levels

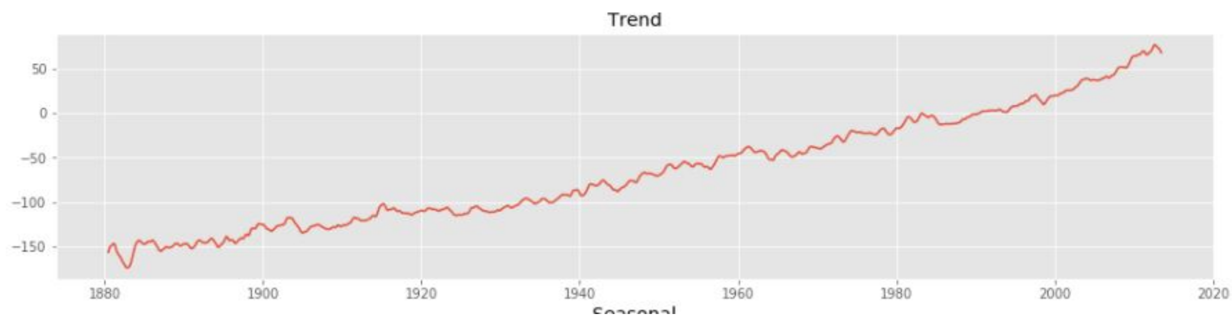

Fig 32: Global sea levels trend

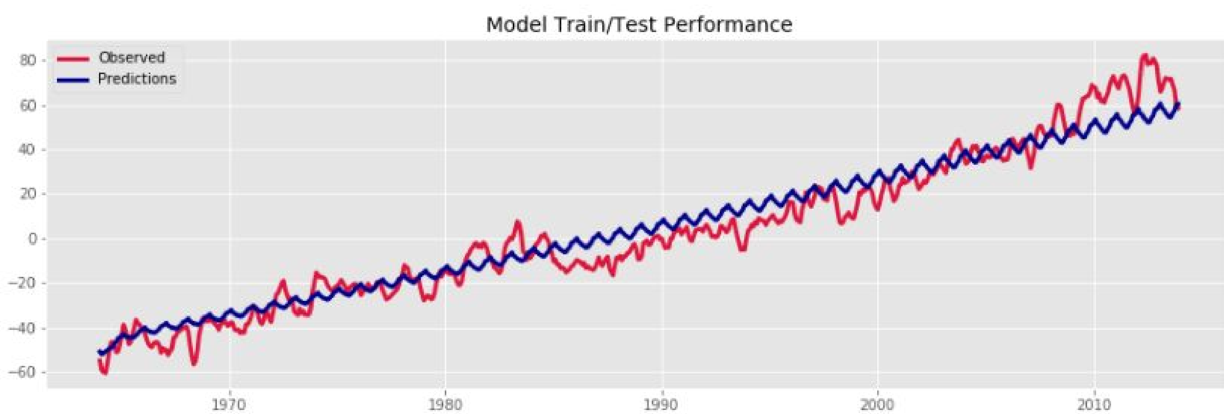

Fig 33:Global sea levels model performance

```
Model Performance Measures:
Root Mean Squared Error: 8.55579270194111
R-Squared: 0.9357431100773761
```

Fig 34: Global sea levels model performance metrics

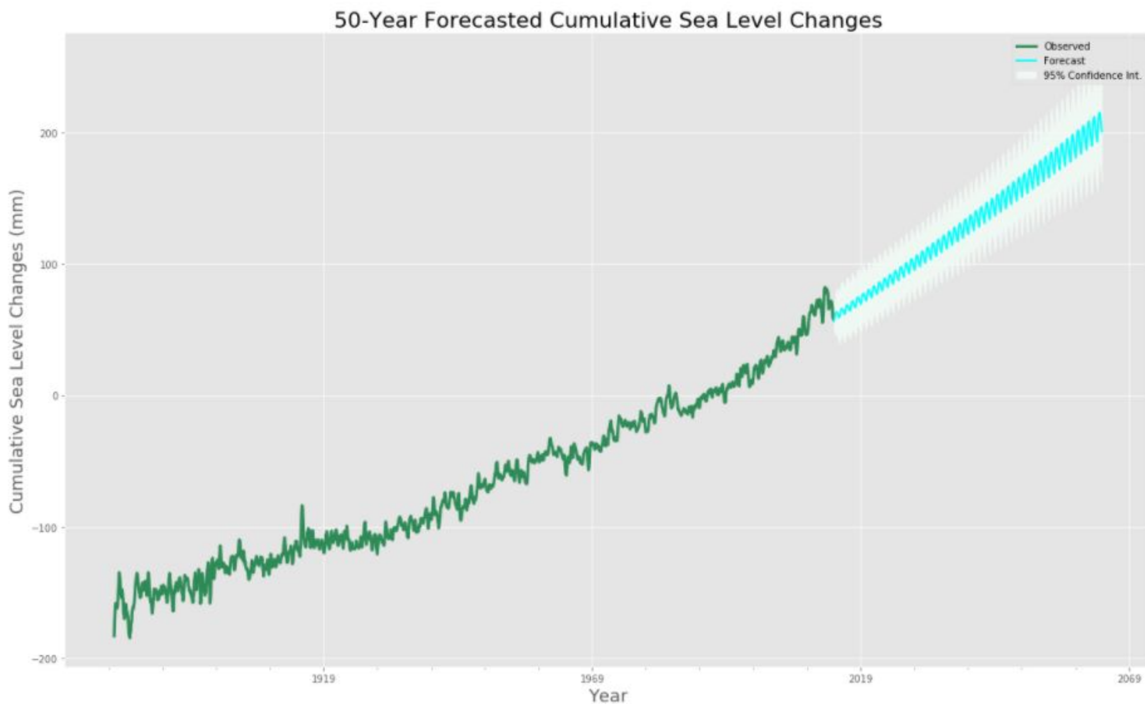

Fig 35: Global Sea Levels 50-year forecast

The global mean sea level is predicted to continue rising at a rate of 2.8 mm per year. In fifty years, the global mean sea level is predicted to be 15 centimetres above current levels.

Climate Change Aspect	**Model Type**	**Accuracy**
CO2 Concentration Forecast	ARIMA	99.6%
Global Temperature Anomaly	SARIMA	74.6%
Sea Ice Extent (N. Hemisphere)	SARIMA	97.5%
Sea Ice Extent (S. Hemisphere)	SARIMA	98.2%
Sea Level	SARIMA	93.6%

Atmospheric CO_2 Conc.	Holt	94.5%
Atmospheric CH_4 Conc.	Holt	95.8%

Fig 36: Models Performance Metrics

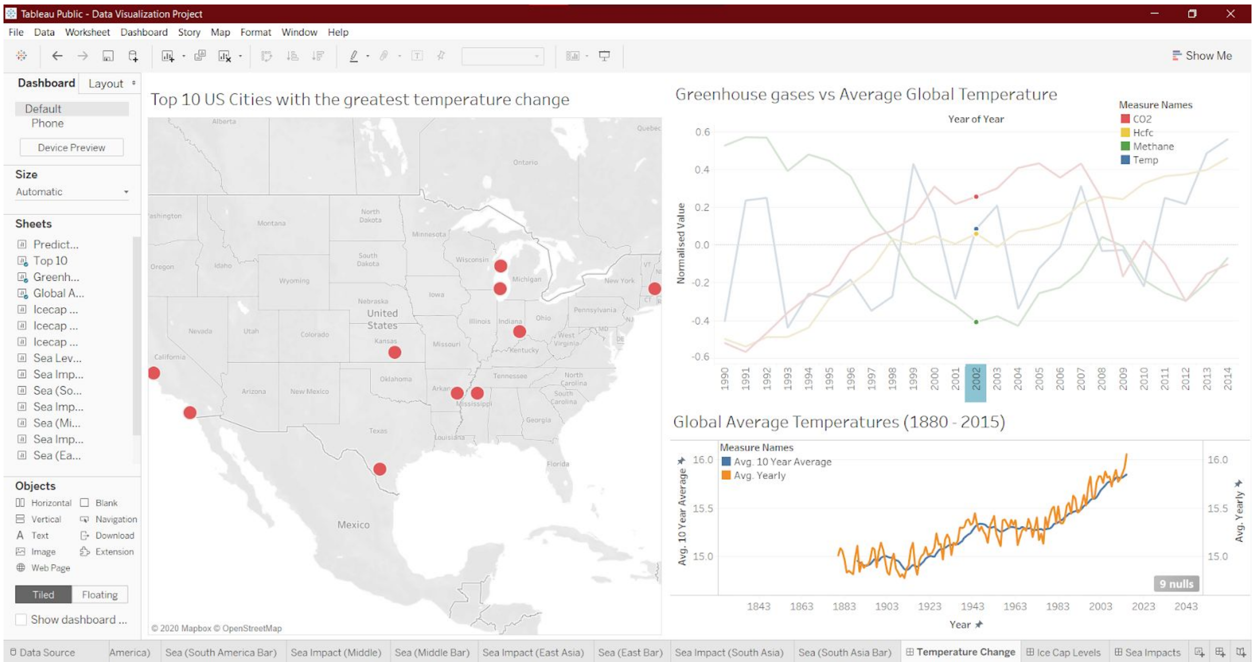

Fig 37.1: Project Dashboard (Temperature Change)

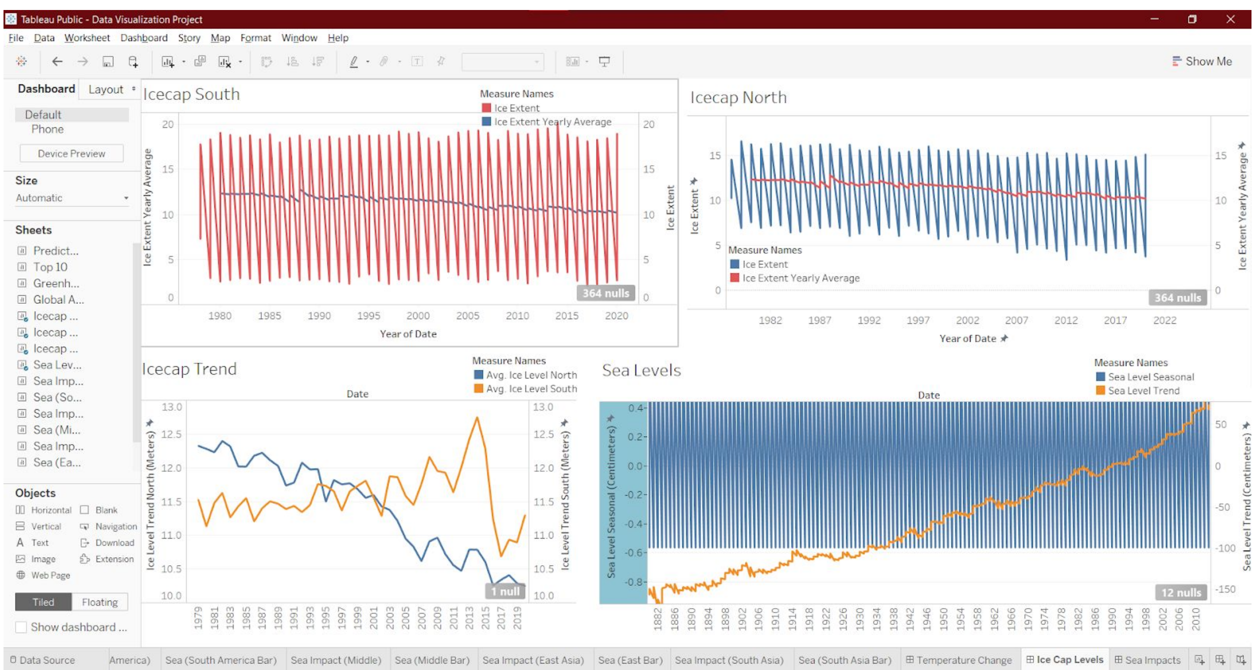

Fig 37.2: Project Dashboard (Ice Cap Levels)

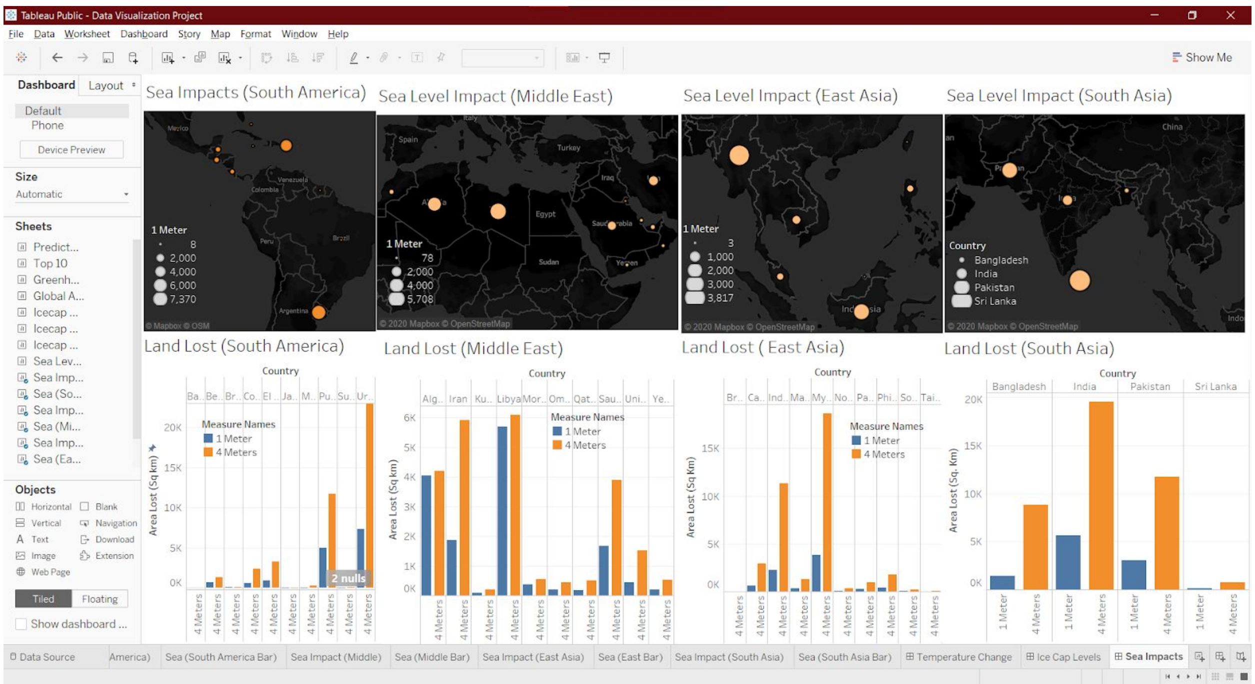

Fig 37.3: Project Dashboard (Sea Level Impacts)

<u>Future Work</u>:

- Create a model that combines the global temperature data with the GHGs to increase forecasting accuracy
- Create a model to analyze/predict the effectiveness of proposed GHG emissions reduction strategies

- Create an app to visually display the effects of global warming and increase awareness of the crisis

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