Using Analytics to Address UN Sustainable Development Goals 13: Climate Action

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Executive Summary

This essay highlights the importance of utilising analytics to address UN Sustainable Development Goal 13 (SDG 13): Climate Action. By leveraging data-driven insights, decision-makers can understand climate change patterns, measure greenhouse gas emissions, model future scenarios, and develop effective strategies for mitigation and adaptation. Analytics plays a critical role in informing evidence-based policies and interventions, driving sustainable development, and mitigating the adverse impacts of climate change. Embracing analytics is essential in our collective efforts to achieve a resilient, low-carbon future.

1. Introduction

"The Sustainable Development Goals (SDGs), also known as the Global Goals, were adopted by the United Nations in 2015 as a universal call to action to end poverty, protect the planet, and ensure that by 2030 all people enjoy peace and prosperity" (UNDP, 2022)

SDG 13 calls for urgent action to combat climate change and its impacts. This includes reducing greenhouse gas emissions, adapting to the impacts of climate change, and building resilience to climate shocks.

In this paper we would look at various datasets to explore the level of CO2 emissions globally, changes of temperature around the world, changes in sea level, and trends of natural disasters. We will focus on time series analysis with Facebook's Prophet Forecasting model to forecast the trends in the next few years. Prophet is a package created by Facebook for forecasting time series data based on an additive model and follows sklearn model (Prophet, 2019). The key benefit on using Prophet is its ability to handle seasonality, outliers, and missing values well and as we gather data from different organisations, this will help speed up process of forecasting by eliminating steps such as differencing when compared to traditional ARIMA modelling.

2. Exploratory Data Analysis

We first gathered all the relevant datasets from Kaggle for:

1. CO2 emissions
2. Temperature
3. Sea level
4. Natural disasters

2.1 Data Description

- "The CO2 emissions dataset provides a comprehensive overview of the amount of CO2 emitted by each country. The dataset includes information on CO2 emissions by country from 1960 to the present day" (www.kaggle.com, n.d.)
- FAOSTAT Temperature Change on land domain shows statistics of mean surface temperature change by country, with annual updates covering period from 1961 to 2019 (kaggle.com, n.d.).
- "Global Average Absolute Sea Level Change, 1880-2014 from the US Environmental Protection Agency" (kaggle.com, n.d.).

- Emergency Events Database (EM-DAT) “contains essential core data on the occurrence and effects of over 22,000 mass disasters in the world from 1900 to the present day” (EM-DAT, 2015).

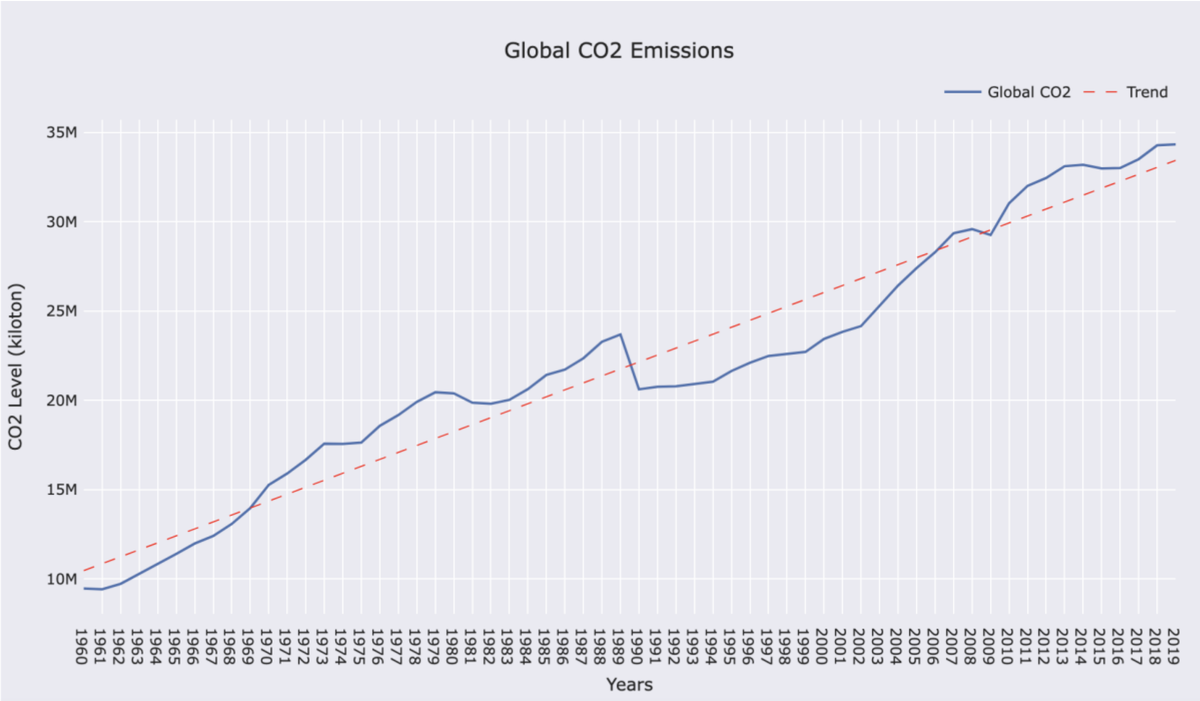
Using the above 4 files, we focus on the period between 1960 and 2019 to ensure consistency for time-series analysis. Furthermore, while some files have data regarding specific region, in this paper we look at the values at a global level. Below shows the detail of columns for each file.

Category - File	Columns Provided in the File
Temperature - Environment_Temperature_change_E_All_Data_NOFLAG	Area Code, Area, Months Code, Months, Elements Code, Element, Unit, Y1961…Y2019
Natural Disaster - EMDAT_1900-2021_NatDis	Dis No, Year, Seq, Disaster Group, Disaster Subgroup, Disaster Type, Disaster Subtype, Disaster Subsubtype, Event Name, Entry Criteria, Country, ISO, Region, Continent, Location, Origin, Associated Dis, Associated Dis2, OFDA Response, Appeal, Declaration, Aid Contribution, Dis Mag Value, Dis Mag Scale, Latitude, Longitude, Local Time, River Basin, Start Year, Start Month, Start Day, End Year, End Month, End Day, Total Deaths, No Injured, No Affected, No Homeless, Total Affected, Reconstruction Costs, Insured Damages, Total Damages, CPI
Sea Level changes - sea_levels_2015	Time, GMSL, GMSL uncertainty
CO2 Emission - co2_emissions_kt_by_country	Country_code, country_name, year, value

For each of the 4 factors, we would see in the follow up sub-section the trend globally as a starting point.

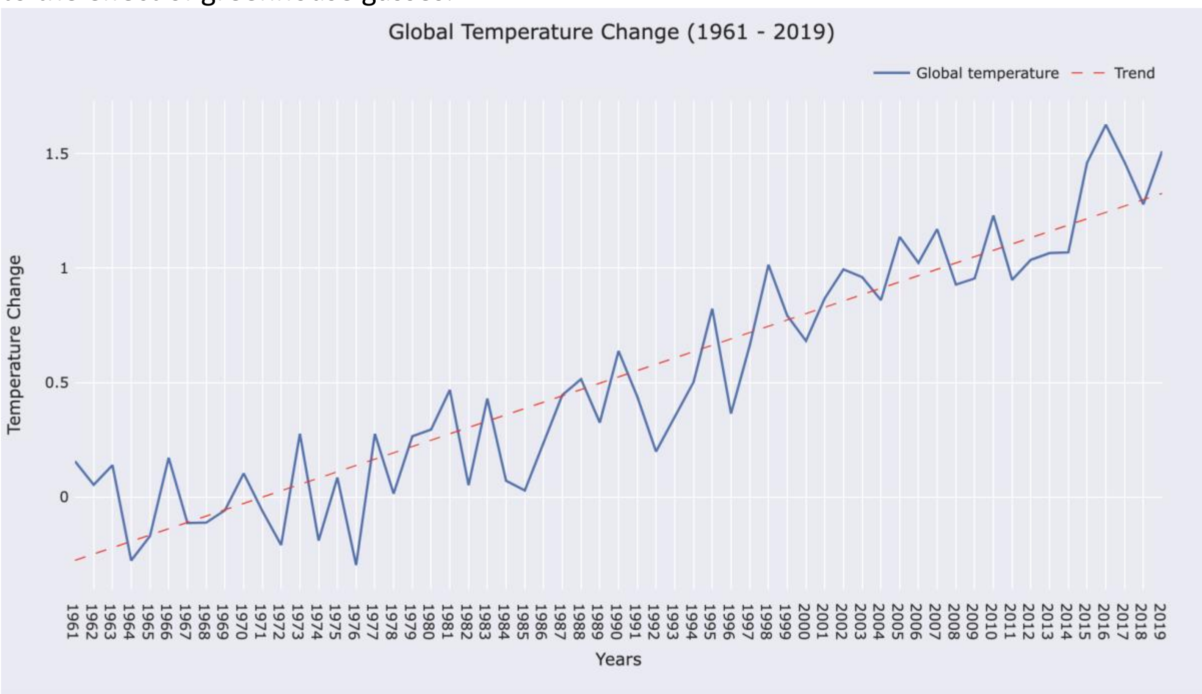
2.2 CO2 Level

“The effect of carbon dioxide is to increase the earth's temperature” (Madden, R.A. and Ramanathan, V., 1980). We could see in the below figure how there is an rising trend in CO2 emissions.



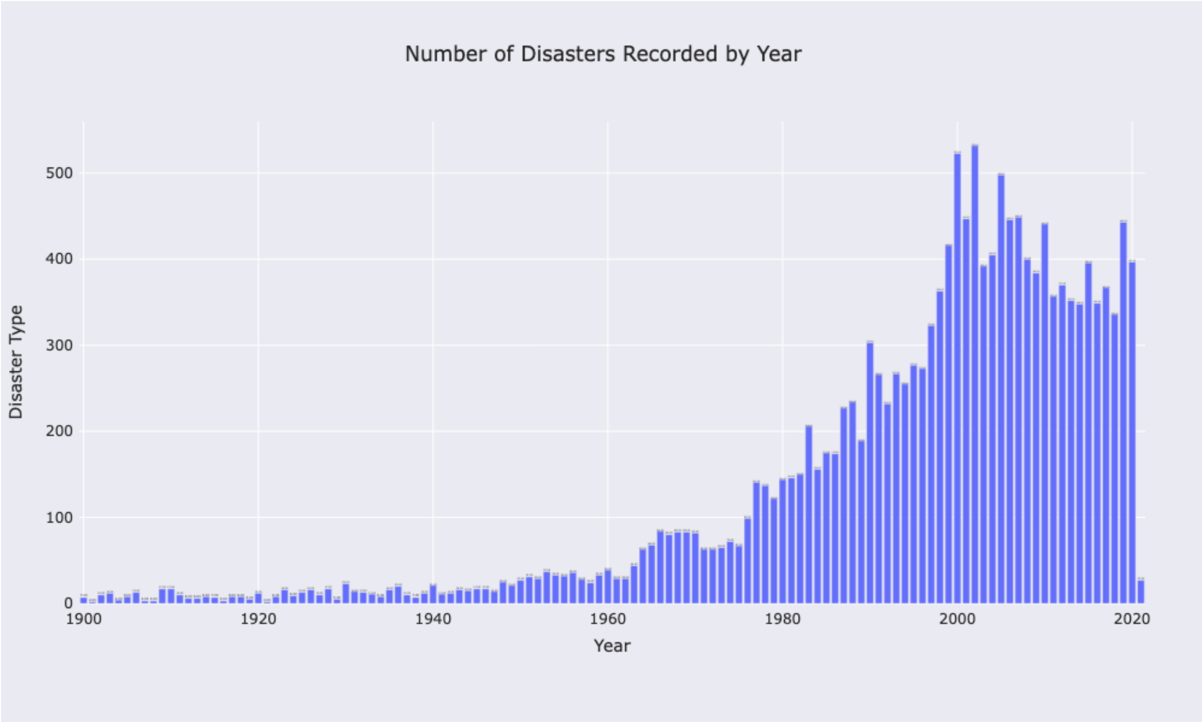
2.3 Temperature

Similar to CO2 emissions, we find the trend of change of global temperature to be rising due to the effect of greenhouse gasses.

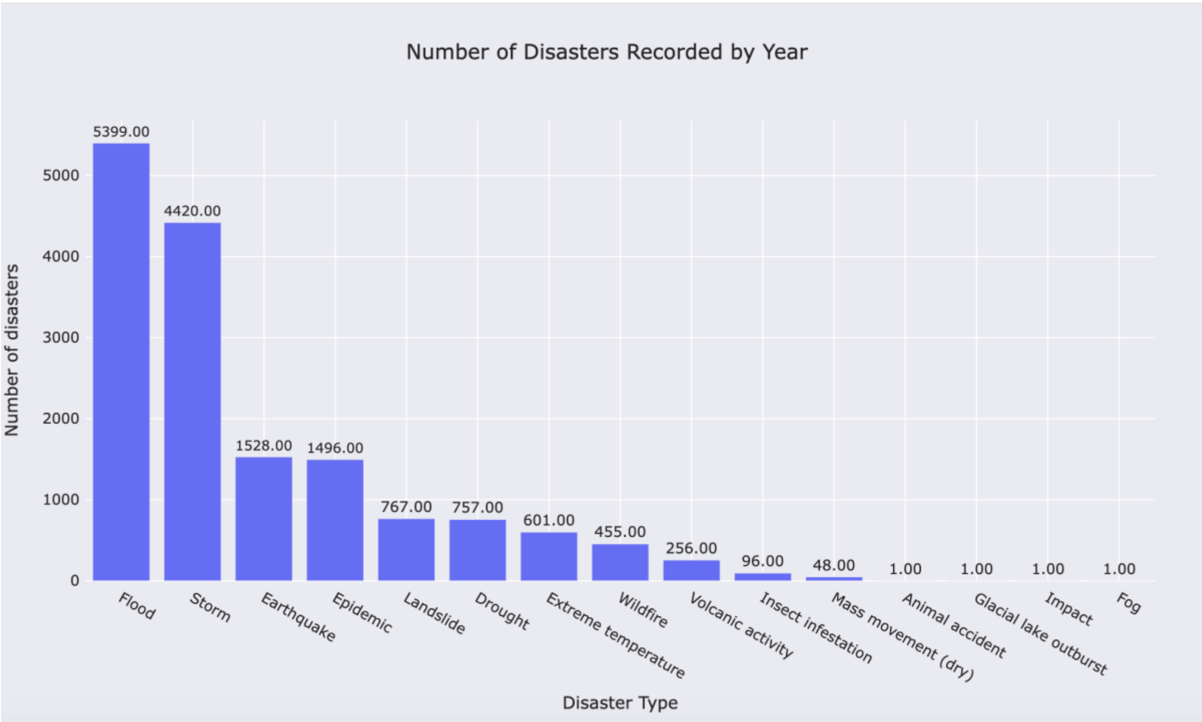


2.4 Natural Disasters

Since 1960s, there has been very significant increase in the number of natural disasters as shown in the data below. While we attribute the cause of these numbers to climate change, it is also important to note that advances in technology and communication have made it possible to report and document natural disasters more easily and quickly than ever before. This can lead to the perception that natural disasters are becoming more frequent, even if the actual frequency of these events has not changed.

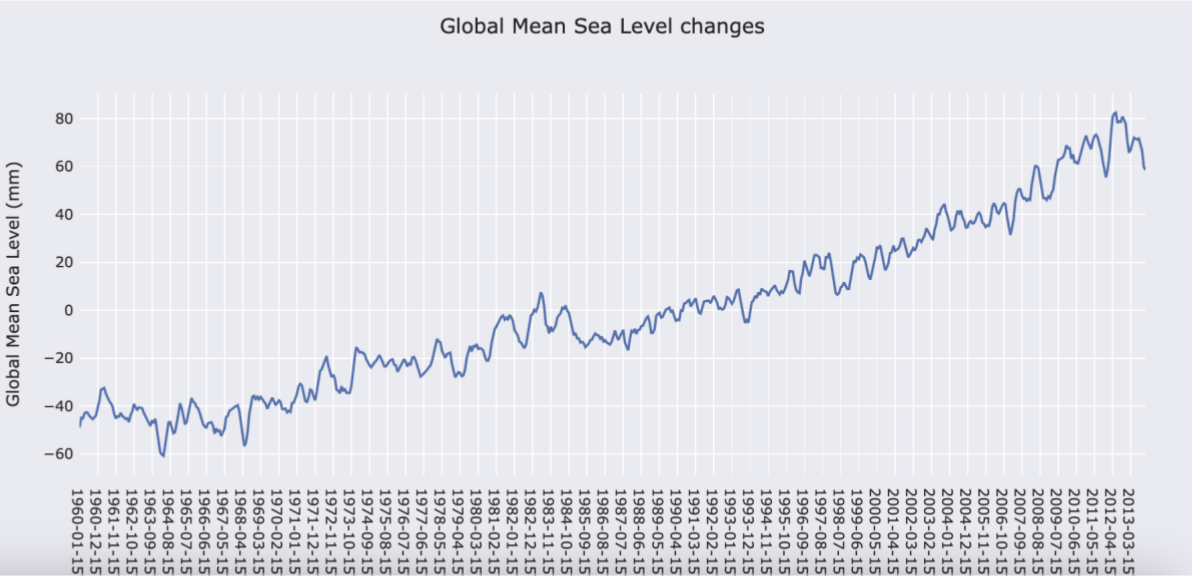


Flood and storm show to be the most frequent natural disaster globally. Our hypothesis is that these are attributed to warming of earth which causes the earth to hold more water vapour. This means that storms can produce more rain or snow, which can lead to flooding. Additionally, climate change is also causing sea levels to rise, which can increase the risk of coastal.



2.4 Global Sea Level Rise

Nicholls, R.J, 2022 described on his paper titled “Analysis of global impacts of sea-level rise” that a rise in sea level would exacerbate storm flooding and damage. As shown below, the level of sea level has been rising. This “recent GMSL rise has been dominated by thermal expansion and glacier loss, which collectively explain ~75% of the observed rise since 1971” (Dutton, A et al 2015).



3. Forecasting

We use Facebook's Prophet package to fit our data and forecast up to 2050. For each factor, the model output the trend (indicated by the line) as well as the upper and lower bound of forecast (indicated by the shaded blue color).

There are several reasons why we use Prophet:

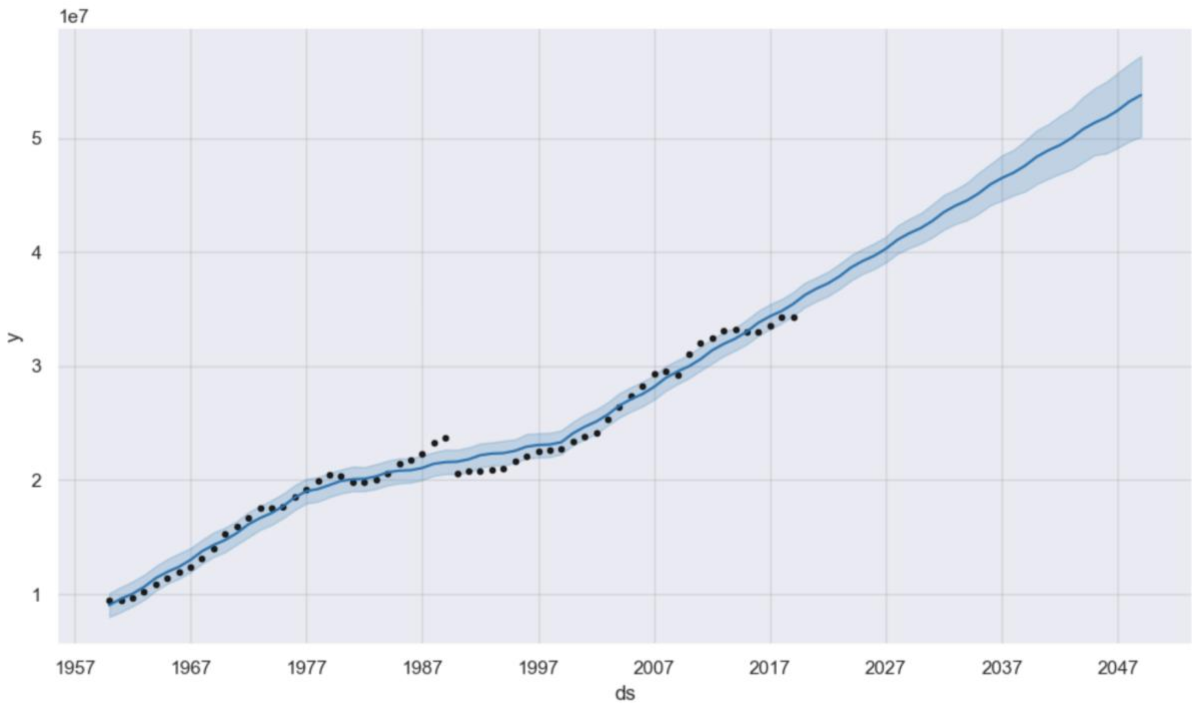
- It is relatively easy to use model.
- In a study by Meta, Prophet was found to outperform other forecasting methods on a variety of datasets by having substantially lower prediction error (Taylor, S.J. and Letham, B., 2018).
- Additionally, it is robust to missing data and outliers

3.1 CO2 Emissions

In order to meet the Paris Agreement signed in 2015, carbon emissions must fall by 7.6% yearly between 2020 and 2030; to meet the 2 °C target (Wang, Y. et al 2023).

However, our model shows that global CO2 emissions have been increasing since 1960s and in 2050 the forecasted values are as follows:

- Forecasted: 53.3 million kilotons
- Lower: 50.3 million kilotons
- Upper: 58.0 million kilotons

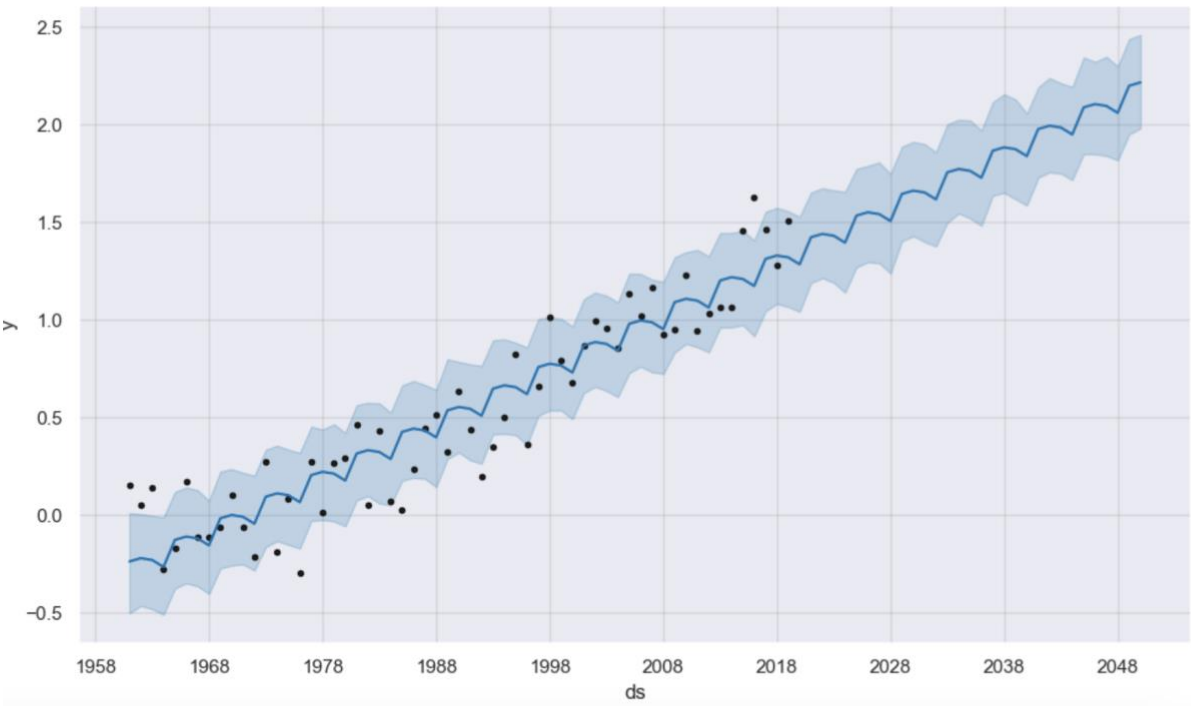


3.2 Temperature

Global temperature have been increasing since 1960s and in 2050 the forecasted values are as follows:

- Forecasted: 2.20
- Lower: 1.98
- Upper: 2.46

A key part of achieving the net-zero goal by 2050 was agreed during COP21 in Paris on December 2015. In the agreement, all countries agreed to limit work together to limit the temperature rise to 1.5 degree Celsius (United Nations, 2018). However, based on our forecast below we are currently on the trajectory of going above the limit.

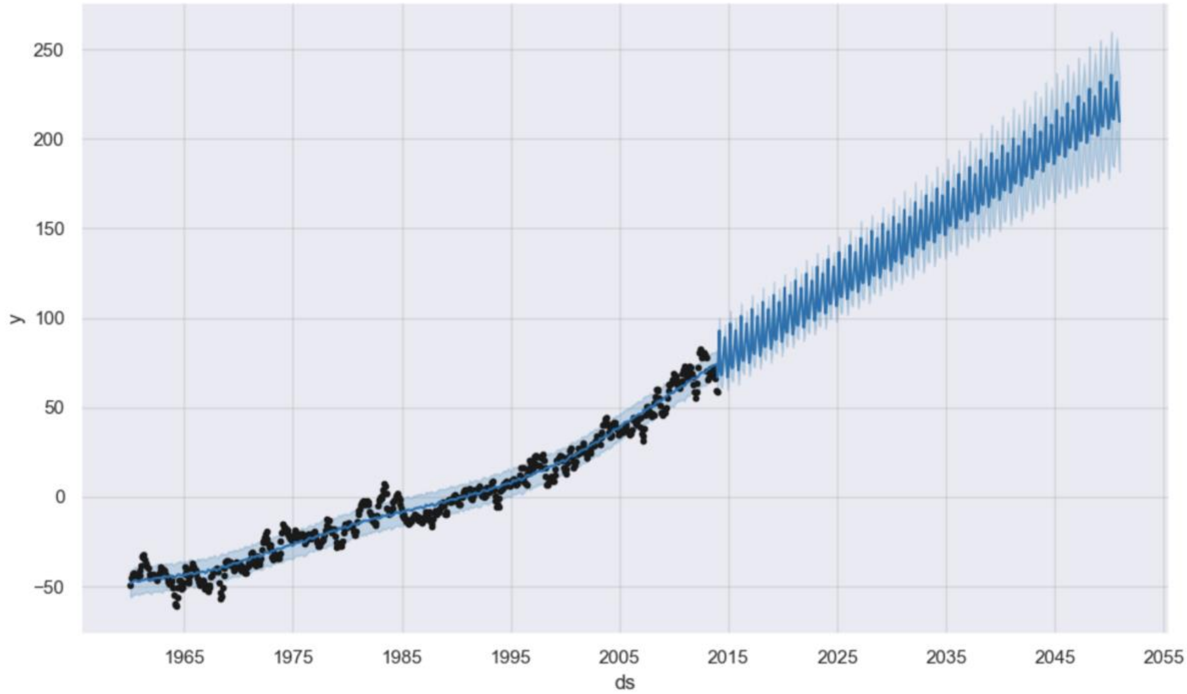


3.3 Sea level changes

Global sea level has been increasing since 1960s and in 2050 the forecasted values are as follows:

- Forecasted: 209 cm
- Lower: 181.7 cm
- Upper: 234.8 cm

Cazenave, A. and Cozannet, G.L., 2014 described on their paper that most models indicate by 2100, global mean sea level should be on average higher than today in the range of 40–75 cm. Our model shows this year GMSL to be 102 mm; which means that between now and 2050, we could see a rise in the range of 79-133 cm.

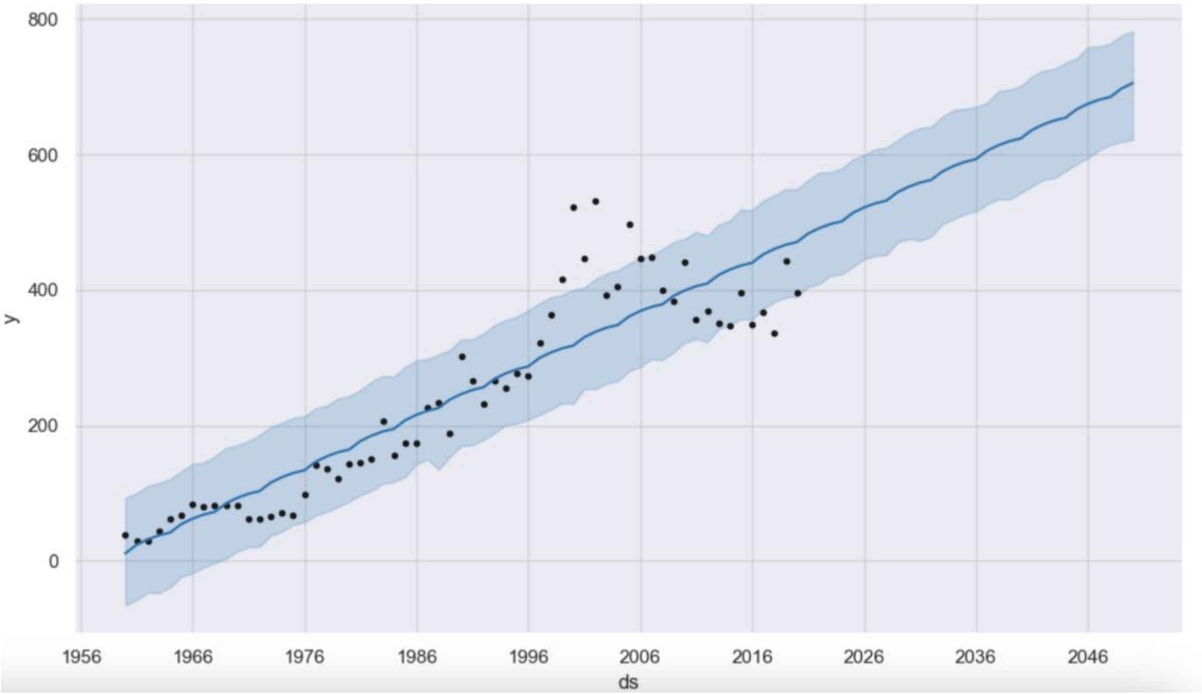


3.4 Natural disasters

Number of natural disaster globally has been increasing since 1960s and in 2050 the forecasted values are as follows:

- Forecasted: 705
- Lower: 622
- Upper: 781

Previously we have shown how sea level is projected to rise up to 2050 in the current rate. The model visualisation below supports our hypothesis that increasing sea level will likely lead to higher number of natural disasters, primarily floods and storms.

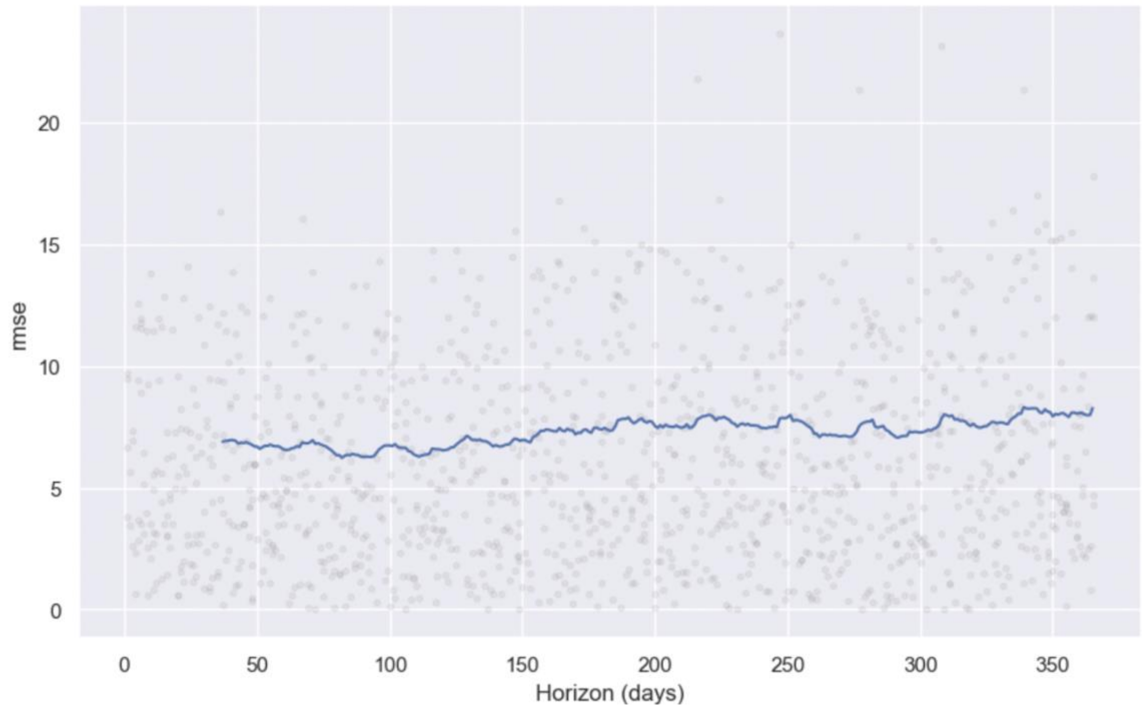


3 Diagnostic of model

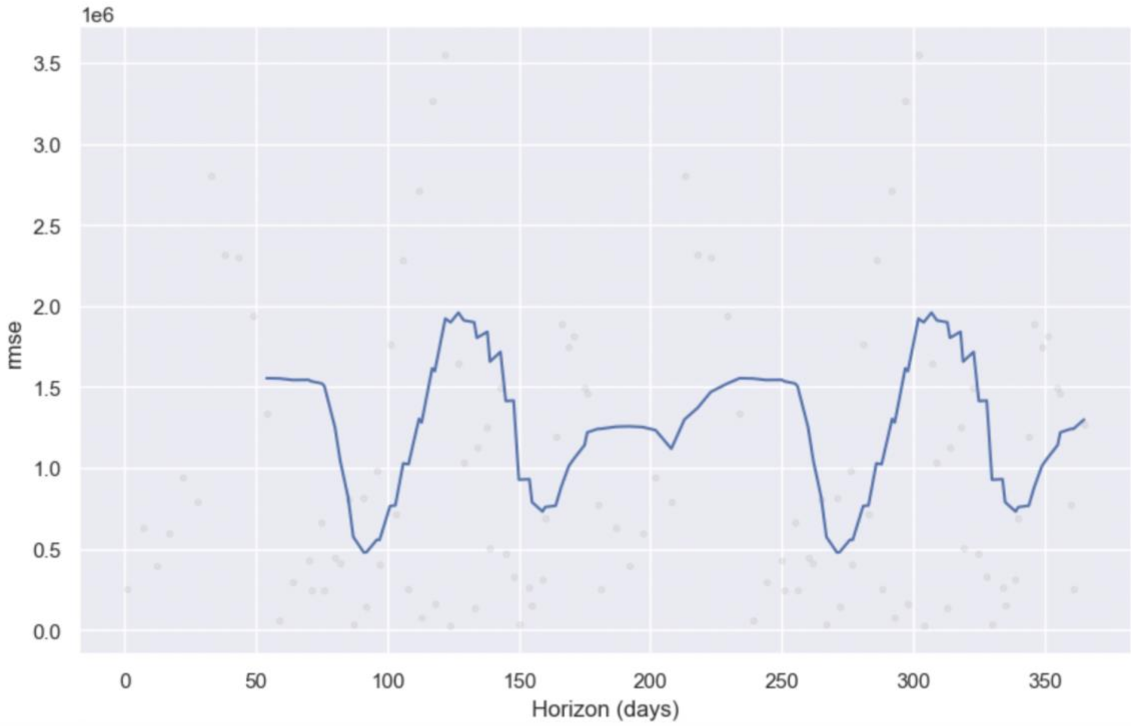
Prophet has built-in validation method called cross validation which simply uses a selected portion of the time to fit the model and proceed with comparing the forecasted values to the actual values. In the section below, we will see for each factor the RMSE error measurement in 1 year horizon. For further error measurements such as MAE and MAPE, see appendix.

Overall, we observe that Prophet's diagnostic cross validation method is best suited for dataset which has daily data. Thus, we find our results to perform better for sea level where we have a more complete daily dataset that shows a more stable error.

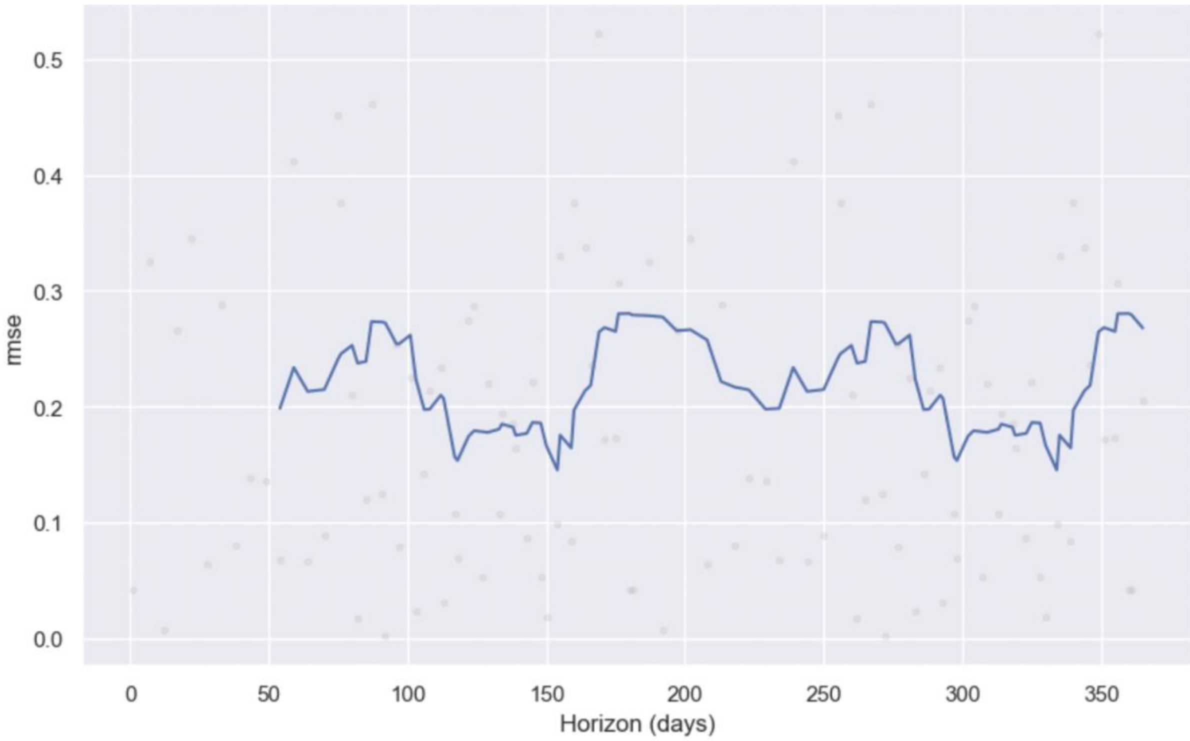
4.1 Sea Level forecasting error



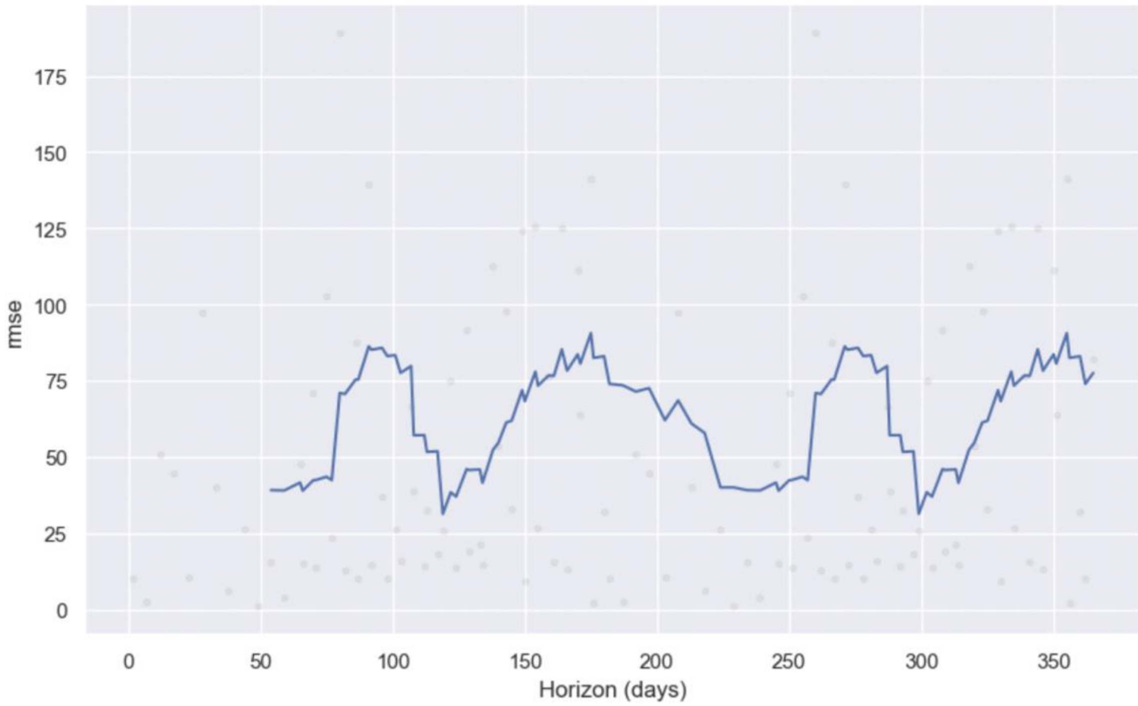
4.2 CO2 Emission forecasting error



4.3 Temperature forecasting error



4.4 Natural disaster forecasting error



4 Limitations and Future Analysis

There are several other factors affecting climate change which are outside the scope of this paper. Some few examples include deforestation, agriculture, industry, and manufacturing, etc. The effects of these activities are also outside of this paper.

Furthermore, there is a huge amount of machine learning opportunities to be used in the field. Particularly looking at the relationship between several factors/variables affecting climate change through various machine learning models, natural language processing and spatial analysis. By combining these different tools, it is possible to gain a deeper understanding of the challenges and opportunities facing the world and develop more effective solutions. The univariate time series modelling focused on this paper cannot capture the interactions and dependencies between different variables.

Lastly, while time series analysis is a powerful tool for modelling historical climate data, but it is less accurate when projecting future climate change. This is because future projections rely on assumptions about future emissions, technological advancements, and climate sensitivity, which are all uncertain. As a result, future climate projections are often accompanied by a high degree of uncertainty.

5 Conclusion

In this paper we have reviewed the trends of climate change in order to show how analytics can contribute to the UN SDG Goals 13: Climate Change. We focused on time series analysis on CO2 emissions, changes in temperatures, sea level and number of natural disasters since 1960s.

Overall, we observed increasing trends on all factors above and analytics such as time series forecasting can be a valuable tool for helping to achieve the UN SDGs. By providing insights into past trends, current status, and future projections, analytics can help decision-makers make informed choices about how to allocate resources and implement policies that will have the greatest impact on achieving the goals.

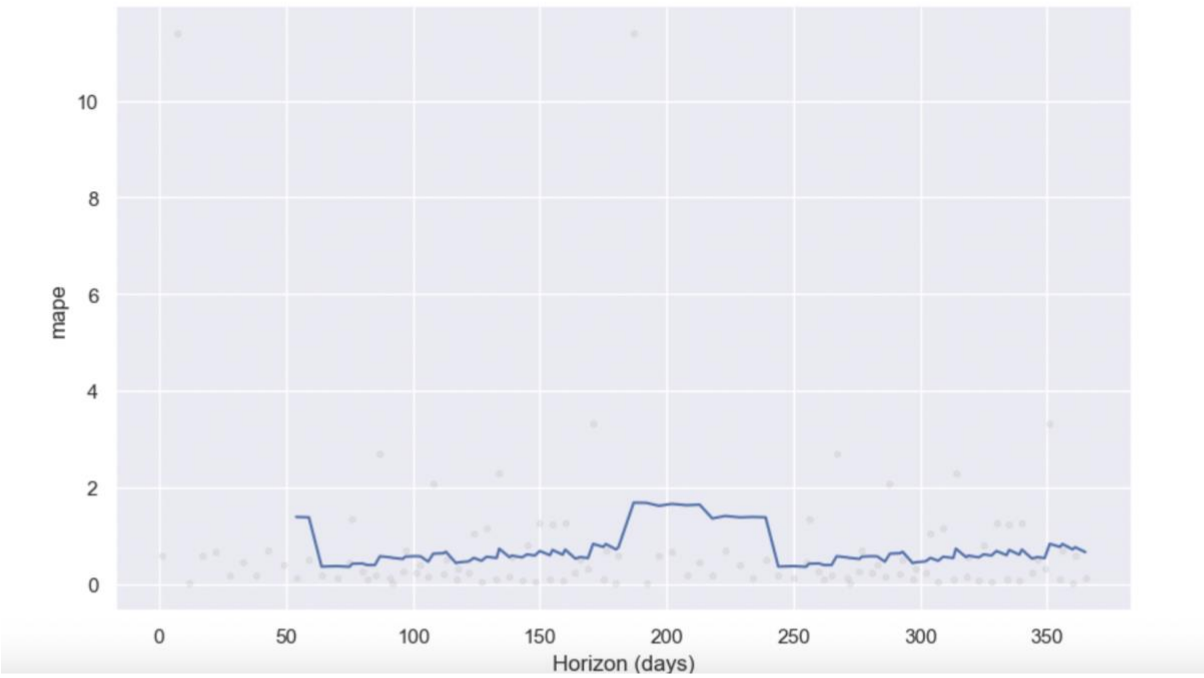
6 References

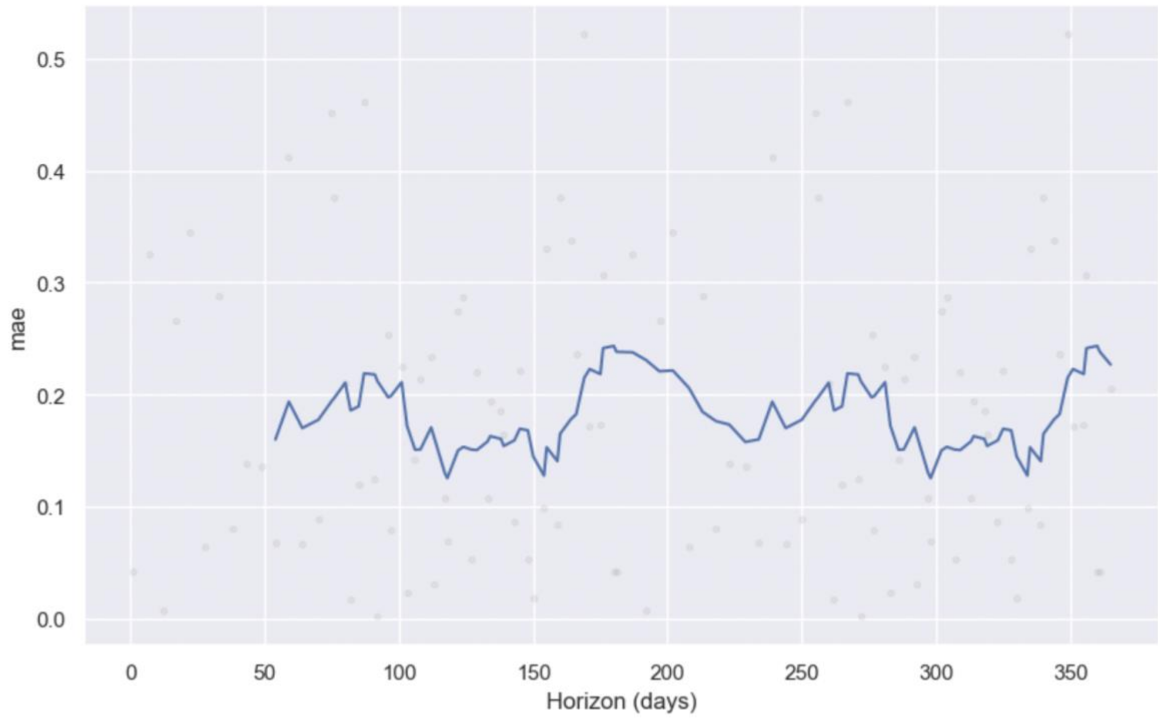
1. Rolnick, D., Donti, P.L., Kaack, L.H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A.S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A. and Luccioni, A.S., 2022. Tackling climate change with machine learning. ACM Computing Surveys (CSUR), 55(2), pp.1-96.
2. EM-DAT (2015). *EM-DAT | The international disasters database*. [online] Emdat.be. Available at: https://www.emdat.be/.
3. www.kaggle.com. (n.d.). *CO2 Emissions*. [online] Available at: https://www.kaggle.com/datasets/ulrikthygepedersen/co2-emissions-by-country.
4. kaggle.com. (n.d.). *Climate Change*. [online] Available at: https://www.kaggle.com/code/sevgisarac/climate-change [Accessed 11 Jul. 2023].
5. Madden, R.A. and Ramanathan, V., 1980. Detecting climate change due to increasing carbon dioxide. Science, 209(4458), pp.763-768.
6. UNDP (2022). Sustainable Development Goals. [online] Sustainable Development Goals. Available at: https://www.undp.org/sustainable-development-goals.
7. Nicholls, R.J., 2002. Analysis of global impacts of sea-level rise: a case study of flooding. *Physics and Chemistry of the Earth, Parts A/B/C*, *27*(32-34), pp.1455-1466.

8. Prophet. (2019). *Prophet*. [online] Available at: https://facebook.github.io/prophet/.
9. Dutton, A., Carlson, A.E., Long, A.J., Milne, G.A., Clark, P.U., DeConto, R., Horton, B.P., Rahmstorf, S. and Raymo, M.E., 2015. Sea-level rise due to polar ice-sheet mass loss during past warm periods. science, 349(6244), p.aaa4019.
10. United Nations (2018). *Climate Action - United Nations Sustainable Development*. [online] United Nations Sustainable Development. Available at: https://www.un.org/sustainabledevelopment/climate-action/.
11. www.kaggle.com. (n.d.). *Sea Level Change*. [online] Available at: https://www.kaggle.com/datasets/somesh24/sea-level-change.
12. Cazenave, A. and Cozannet, G.L., 2014. Sea level rise and its coastal impacts. *Earth's Future*, *2*(2), pp.15-34.
13. Wang, Y., Yang, P., Song, Z., Chevallier, J. and Xiao, Q., 2023. Intelligent prediction of annual CO2 emissions under data decomposition mode. Computational Economics, pp.1-30.
14. Taylor, S.J. and Letham, B., 2018. Forecasting at scale. The American Statistician, 72(1), pp.37-45.

Appendix

Temperature error





0.5
0.4
0.3
0.2
0.1
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mae
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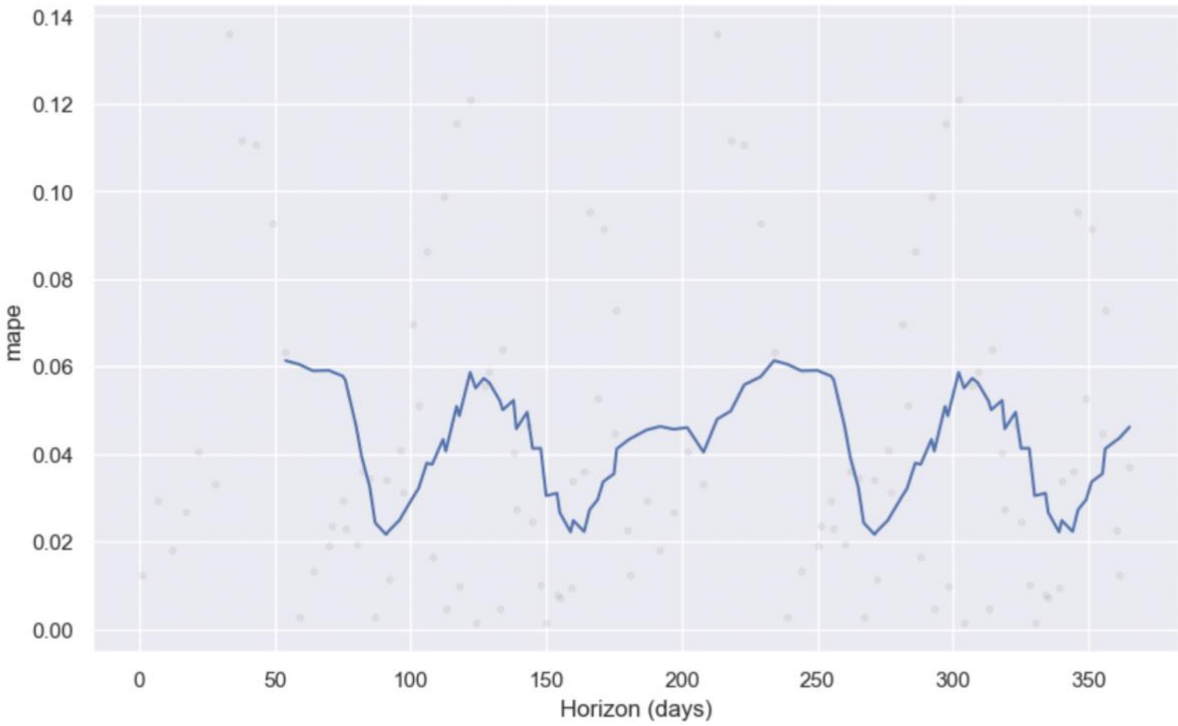
100
150
200
250
300
350
Horizon (days)

CO2 error



0.14
0.12
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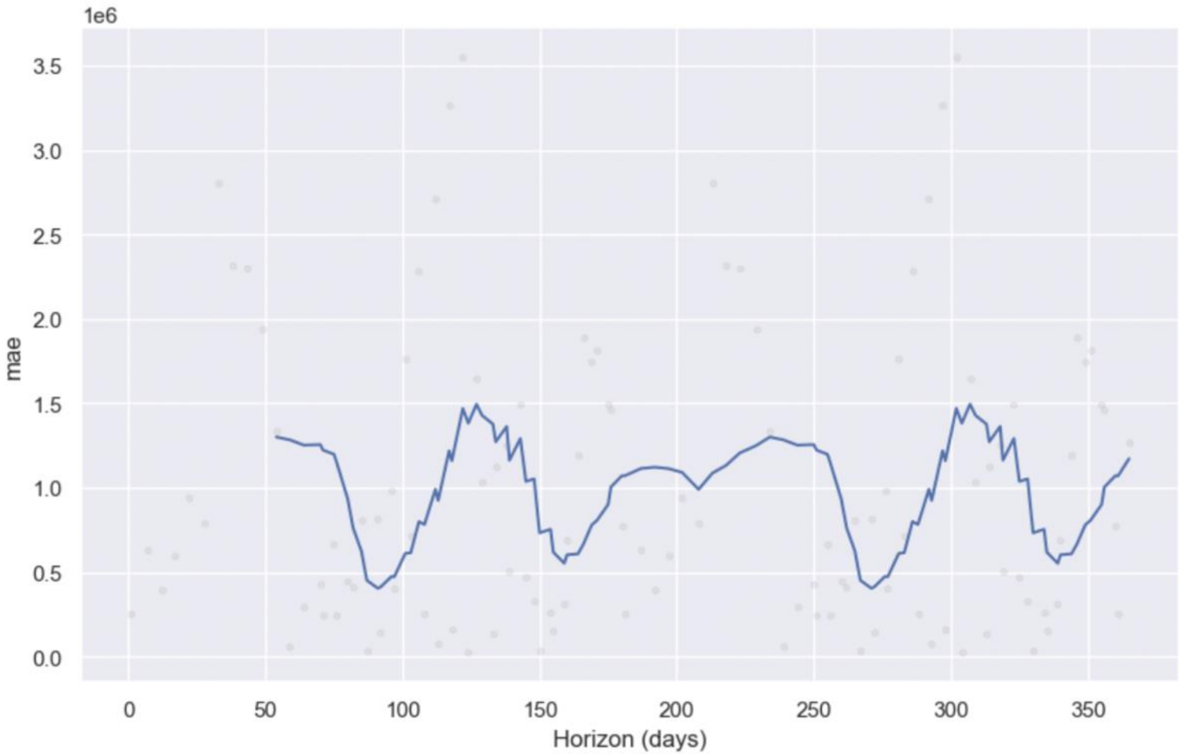
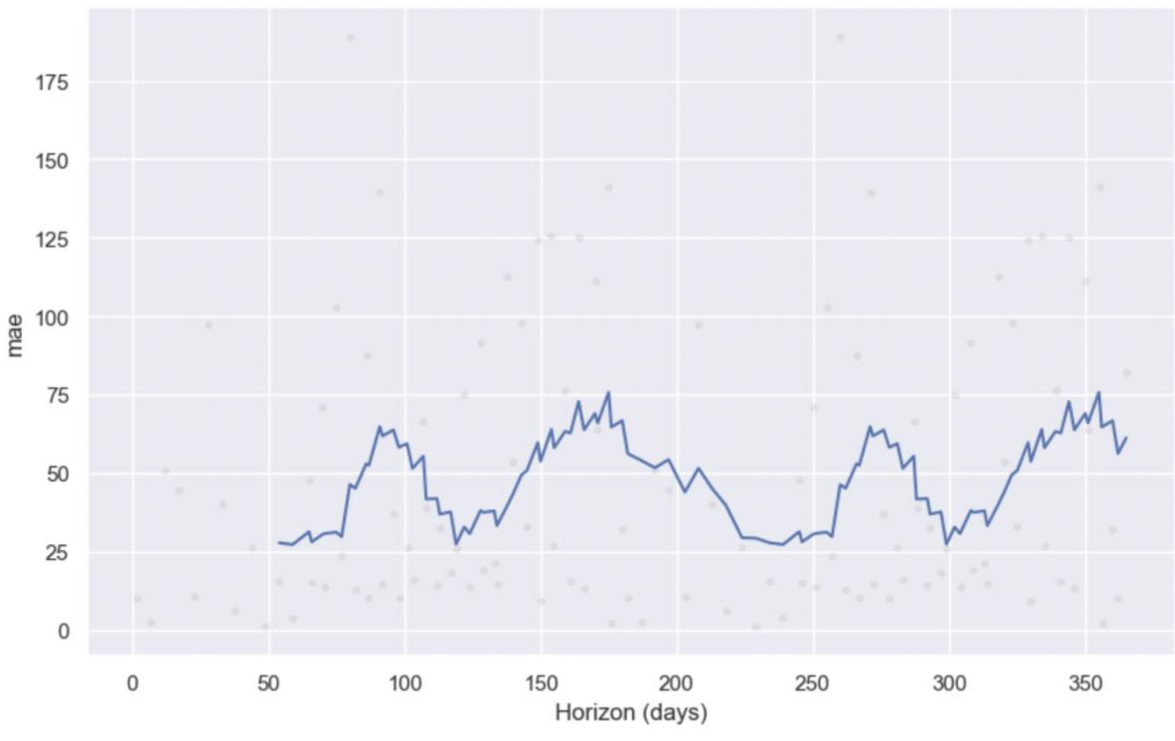
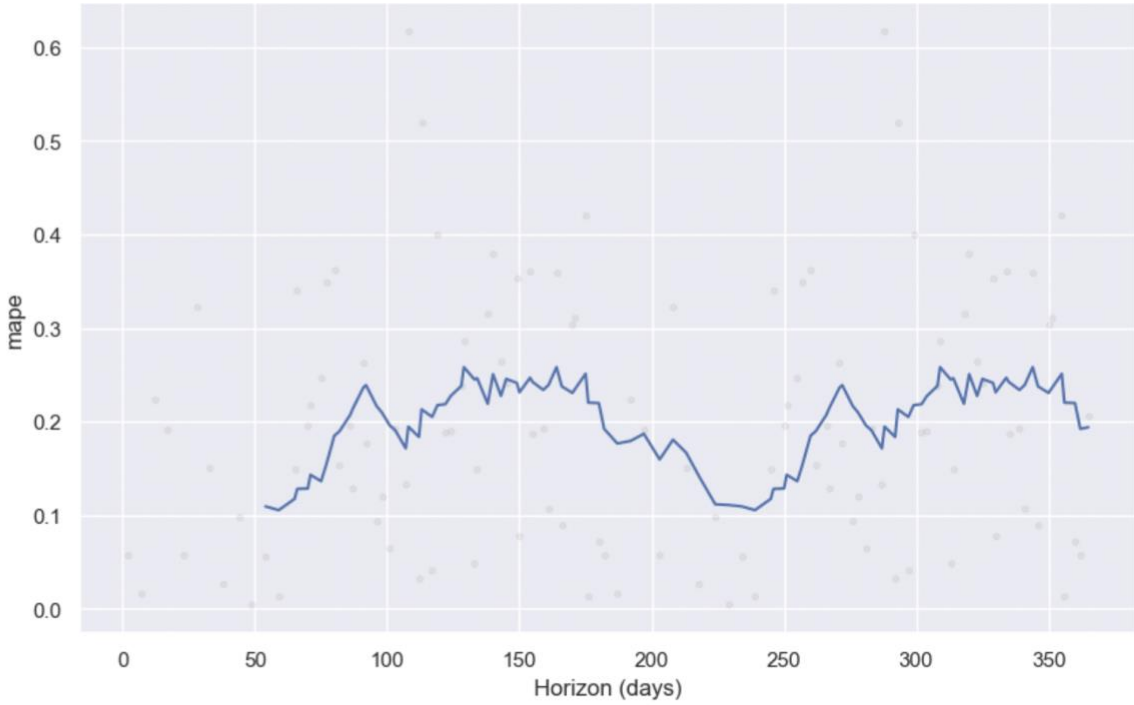
Horizon (days)

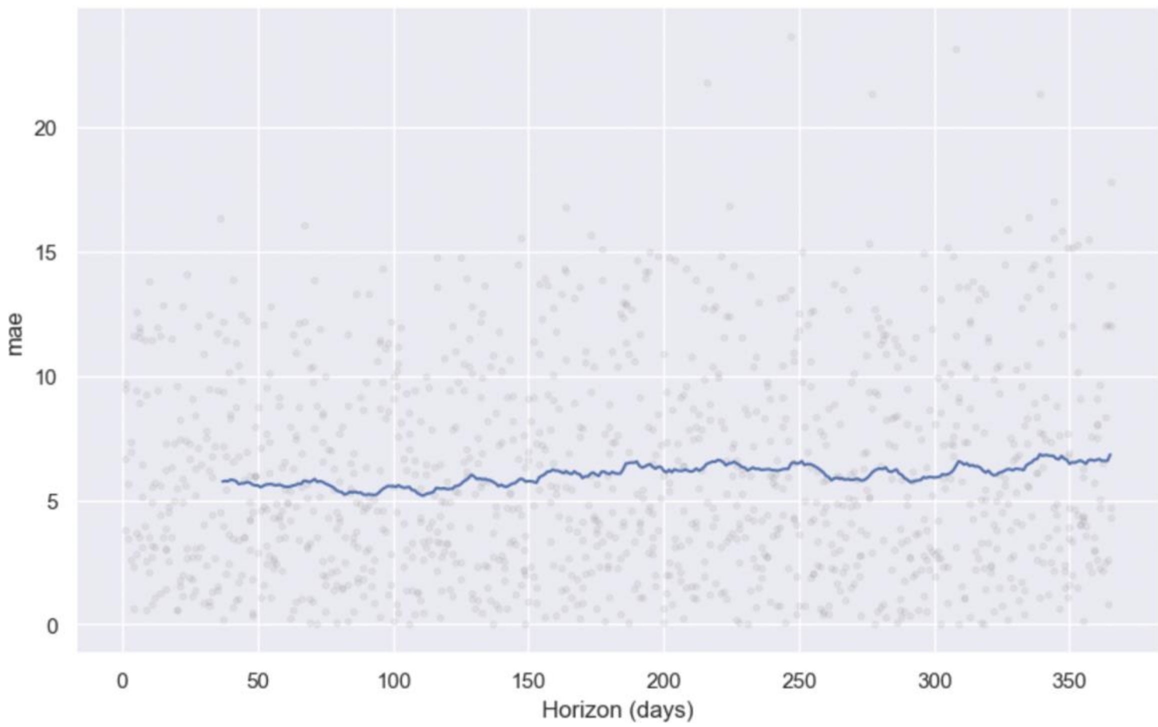


Natural disaster error





Sea level error



7 Self reflection

This project has allowed me to explore the industry domain that I am passionate about – climate change and furthermore, allowed me to use a new ML package which I never used before. Some of the challenges are finding a complete dataset from Kaggle for different factors of climate change and finding support online to diagnose coding problems related to the Prophet package. I am very grateful to Imperial and the programme structure which allowed me to freely explore the field I want using the foundational analytics skills I gained the past 2 years from the various modules.