Bayesian Question Clustering of Climate Change

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Abstract

Flooding and tropical storms are becoming more common and deadly, and energy production is changing as sustainable power comes to the fore. Climate change is one of the most important and pressing issues of our day. In this paper, we are aiming to use Bayesian Question Clustering to create three near-term forecasts regarding climate change, focusing on the UK. We analysed data from *Metaculus* and *GJOpen*, as well as various datasets released by the UK government. This data was then used to forecast the number of flood warnings in the UK in May, the number of tropical storms that would kill over 1000 people in April and May, and the amount of solar and wind energy produced by the UK in May. This project has given us a useful insight into different methods of forecasting and the important uses of the field.

Acknowledgements

We would like to thank Mr Jonathon Kitson, our mentor in the project. His advice on how to optimally gather data and his provision of feedback on our forecasting methodology have both proved invaluable for allowing the optimal progression of the project.

We would also like to thank Mr Tamay Besiroglu for being of great assistance in our research of which topics were covered by existing forecasts on Metaculus, providing the data required to undertake the regression for determining which factors predicted the quantity of forecasting performed by a country.

Additional thanks is merited to Mrs Emma Lawsen and Mr Toby Jones, who both facilitated advice regarding how to conduct the project, and how to maximise the quality of the write-up and output, and helped facilitate communication with our mentor.

Contents

1 Introduction

This report consists of a series of medium term forecasts regarding climate change and action undertaken to mitigate it. Climate change has already caused considerable damage, estimated to have displaced around 23 million people in 2017 [1]. This means that accurate forecasts are vital for policymakers to inform decisions on how to allocate resources between the myriad of different risks climate change poses.

Climate change consists of the heating of the atmosphere due to emissions of greenhouse gases, with 74.4% due to carbon dioxide (CO_2), 17.3% due to methane, 6.2% due to nitrous oxide and 2.1% due to other gases such as hydrofluorocarbons [2]. These result in radiation from the Sun becoming trapped in the atmosphere for longer, increasing the temperature of the Earth, by 1.1 degrees Celsius to date [3]. Human emissions of these have increased from 34.97 to 49.36 Gigatons of carbon dioxide equivalents between 1990 and 2019, representing average annual growth of 1.7%, although are displaying some signs of having reached a peak with annual growth averaging only 0.4% between 2012 and 2016 [4]. However, this represents the situation becoming worse at a constant rate, as until the net impact of humanity is zero each additional ton of CO2 will result in increased damage. Additionally, there is a considerable time lag between emissions and warming, as when atmospheric CO2 concentrations last equaled their modern levels temperatures were 3 degrees higher, sea levels 20m higher and trees grew in Antarctica [5]. All of these effects mean that climate change will cause a reduction in human prosperity, and that the long-term outlook is dire due to the fact that growth in carbon emissions remains positive, net emissions remain positive and the climate has not fully adjusted to the quantity of carbon in the atmosphere.

Although the long-term impacts of climate change are subject to much discussion and forecasting, the more immediate impacts receive less attention. This does not mean that they will not require substantial resources devoted to them to mitigate their consequences, however. A temperature increase of 1.1 degrees Celsius is already sufficient to disrupt the climate in numerous ways, with 54% of the damages of Hurricane Harvey being attributed to climate change, and climate change affecting the likelihood or severity of extreme weather events in 79% of cases studied, 70% of which climate change had made them worse [6] [7]. Existing warming has also driven the desertification of the Sahel region of Africa, which has contributed to a major jihadist insurgency which has resulted in 2 million people becoming displaced, 1.5 million of which in the last 2 years alone, and 31 million needing food aid, with 5100 French troops still deployed to try to prevent the country from collapsing [8] [9]. Additionally, wet-bulb temperatures – temperatures accounting for humidity and thus the ability of the body to cool itself down via sweating - exceeding 35 degrees Celsius have already been reported in Jacobabad in Pakistan and Ras Al Kaimah in the United Arab Emirates, which means that the body is incapable of cooling itself and will die within 6 hours if temperatures do not fall, regardless of the quantities of water or shade available [10]. Near term impacts thus represent an issue that is of a large scale, is neglected, and is tractable with intervention - but focusing funding on optimal areas is vital. How to do so is explored below.

The effects these can have are severe, so the precise, quantitative predictions forecasting can give can help mitigate these impacts by optimally allocating response funds. Quantitative forecasters can achieve extremely high accuracy – relative Brier scores measure forecasting ability, with a score of 0 is perfect accuracy with 100% confidence, 0.5 is achieved by guessing randomly and 2 is answering exactly incorrectly with 100% confidence. The best forecasters can have Brier scores approaching 0.2 across hundreds of forecasts, a phenomenal level of accuracy that will help inform policymakers' decisions in how to prioritize resource allocation between different risks [11]. The two key qualities of forecasters are calibration, meaning that events that a forecaster is a certain percentage sure will occur occurring, on average, that percentage of the time, and discrimination, which is the ability to distinguish between high and low probability scenarios [12] [13].

This paper aims to assist in ameliorating the present shortages of immediate-term forecasts regarding climate change. We will achieve this by discovering which topics related to climate change have particularly large disparities between the relative volume of pre-existing forecasting, accounting for both numbers of questions and forecasters, on the topic and the importance of the topic, and then producing quantitative forecasts regarding these areas.

2 Literature Review

To complete our climate change forecasting project, we needed to perform an extensive quantity of individual research prior to any attempts at creating, and conducting, forecasts. Consequently, all group members were assigned a range of sources which we deemed useful to developing our understanding of the project as a whole, looking at a variety of books and articles on both the fields of forecasting and climate change and the effects it will have on society. We needed to research information at this stage to enable us to gain an understanding of the issues we are facing, and an idea of how we can begin making our own forecasts that will be useful to the rest of society.

To begin, we tried to gain an understanding the field of forecasting and how effective forecasts are made. In *Superforecasting*, Philip Tetlock and Dan Gardiner evaluate the performance of the most successful forecasters and the techniques they use to achieve their results.[14] They discuss the results of numerous tournaments they have conducted, under various conditions, to reject various hypothesises for the success of their subjects and discover which techniques and abilities to attribute their skill to. Their research focuses on what differs between the median participant in their studies and those who were most effective. Philip Tetlock is a professor at the University of Pennsylvania and has published numerous books and papers on the topic, as well as running the Good Judgement Project, one of the two main forecasting websites, so he is a credible and reliable source for this subject. The book is useful for our research as it gives many mechanisms to ensure that forecasts have the highest possible accuracy, and common areas of failure. For example, the importance of using a wide range of sources, and finding good heuristics to obtain information with which to update our forecasts. We also learned how important it is to frequently update our predictions. Common areas of failure included bias, which usually arises from a lack of an open mind and the failure to define a question clearly. This source is intended for consumption by the public, so does not make any assumption about prior knowledge in the topic area. This resource will form the basis of our research due to the detailed analysis of how to forecast that it gives.

Whilst *Superforecasting* proved to be of great use, to further develop our knowledge on the field of forecasting we looked at an article on forecasting, titled 'How spooks are turning to super forecasting in the cosmic bazaar', published by well-respected and reliable newspaper, *The Economist* [15]. The article discusses the field of forecasting as a whole, looking at forecasting platforms such as tournaments and websites, whilst also mentioning methods of forecasting, i.e. Bayesian question clustering, all while exploring how forecasting will be relevant in the future, and the politics involved. It also touches on concepts and theories supported by research which is useful in evaluating overall chance of success when making a forecast. The article is intended to highlight the rise in forecasting globally, and how 'super forecasters' can be of great use and importance to us in the future, in the modern world. The article provides us with information on particular forecasting tournaments and their magnitude, whilst informing us how many people actually made forecasts in these tournaments/websites. Yet, it also discusses how forecasting demand is increasing, and provides examples of when changes have been imposed by government in direct relation to this. This information is useful as it could potentially be employed to help predict the chances of a particular question being asked, and predict numbers of forecasters asking it. Therefore we will be able to identify the niche areas within the wider umbrella of climate change where our forecasts will have the largest impact. However, there is a focus on high income countries such as the United States and United Kingdom, and correspondingly little information about the development of forecasting in lower income countries. Consequently, this article is of limited use for looking at global forecasting, for which other sources will be used. Hence, this article will not form the basis of our research, but will be useful supplementary information to help understand forecasting as a whole, and identify the topics which see a relative deficit of forecasts, given their importance.

We also began investigations to gain an understanding of climate change, and the statistics relating to the effects of climate change, as well as the impacts it has already had. American journalist, and University of Chicago graduate, David Wallace-Wells' 2019 book, *The Uninhabitable Earth*, provides a detailed breakdown of the effects global warming will have on all environmental, social and economic spectrums globally [16]. The book is intended to portray the catastrophic chain of events that we will face in the next century or so, using statistics and past events to help provide an idea of the severity of the issues we face. Wallace-Wells pinpoints specific regions internationally, such as California, Chicago and Cape Town and multiple cities in Europe, however he still maintains a considerable amount of globally relevant data. The piece of literature therefore, is very useful to us in the sense that it provides a huge number of past events, whether this is a natural disaster, wildfire, drought, or climate-induced conflict; the events are clearly defined and well explained and are backed with comprehensive analysis from well-educated and trustworthy sources. He makes predictions such as 30% of global electricity will be used on fans and air conditioning by 2050, and that the global temperature will rise by minimum four degrees celcius by 2100. The book is, however, generally focused on much longer timescales than are applicable for our project, although the wealth of data contained within the book is such that it still has considerable data to aid us in our project. The data about the economic impacts of climate change is rather sparse in this source, which is unfortunate as this is an area of particular interest to us. This means that it will not form the basis of our project as it does not reflect the time scales relevant for this paper, but still provides much useful understanding on the topic.

With newly found knowledge on the impacts climate change will have, we decided to use a paper looking into already existing forecasts created surrounding the topic of climate change.[17] This paper, by the UNFCCC (United Nations

Framework Convention on Climate Change), describes climate change forecasts made by experts for the next five years. The UNFCCC is a multilateral climate change agreement signed by 154 countries at the United Nations Conference on Environment and Development (UNCED) in 1992, in order to try to combat climate change. The article assesses likelihoods of certain things happening around the globe as a result of climate change, and makes predictions for the next five years, highlighting events which are likely to occur. Their research comes from different reports published by the World Meteorological Organization (WMO), throughout 2020 and 2021, selecting forecasts on specific climate change-related effects relevant to the five-year period 2021-25 – reliable, unbiased data relevant to our project. This article is useful to us because it does a very similar thing to our project brief - it makes short-term forecasts regarding climate change. This makes it very useful, since we can see what has been forecast already, showing us areas to avoid or build upon, and ensuring that we can devote our research to where it is most useful. However, almost all predictions examine all five years until 2026, and our forecasts will be even shorter-term - two to three years at most, meaning that its timescales are too long for our purposes. Overall, this article is useful in many relevant areas, most notably finding out which areas to devote less attention to in our project, given that similar predictions have already been made regarding them. It does not provide us with information regarding how to make our forecasts, only which questions would be more useful to make forecasts on.

However, we wished to further develop our understanding of relatively near-term climate change effects and so researched into more present predictions and forecasts. We used an article written for Business Insider in late 2019 [18]. This article outlines many of the most severe global effects of climate change over the next 10 years, according to a variety of different expert sources. The author, Morgan McFall-Johnsen, graduated from Northwestern University in Illinois, US, in 2019 with a Bachelor's Degree in Science and Journalism, whereupon she became a science reporter at Insider, covering space, the climate and infectious diseases. In her article, she uses IPCC (Intergovernmental Panel on Climate Change), USGCRP (United States Global Change Research Program), WMO, University of Wisconsin and University of Idaho data, scattered with various expert opinions. Her research appears reliable due to the variety of reputable sources to support her case. One limitation is that some of the sources she uses are already outdated, for example a 2015 World Bank report, and a 2017 study from the NOC (National Oceanography Centre), making them less relevant. It describes the likelihoods of different predictions for climate change coming true before the year 2030, addressing areas such as ocean acidification, human displacement due to climate change and extreme weather. This is useful in some respects, as it shows us which areas are already being forecast as well as giving us some insight into the current forecasts already made, which will help us immensely if we research similar areas. However, beyond three or so years, accurate forecasts are extremely difficult to make and to test, so we will make our forecasts not for 2030, but the much shorter term. Building upon the previous articles by cross-referencing them and adding more items to our list of commonly-covered topics within climate change, we can again use this article to identify areas where more research has already been done, although the discrepancies in timescales will limit its use for our overall project.

In conclusion, these five sources will form the basis of our research. *Superforecasting* and the Economist 'Spooks' article have given us numerous useful insights into the field of forecasting, and the articles by the UNFCCC and Business Insider alongside *The Uninhabitable Earth* give us useful information going forward regarding current predictions and forecasts on climate change. For example, *Superforecasting* will be the basis of our technique when forecasting, and the information gleaned from the articles will form the basis of the questions which we forecast for. However, some sources will be more useful to us than others. For example, while *Superforecasting* will contribute significantly to our project, the Insider article may be of less utility due to the timescales discussed. We will develop the project by investigating the areas with the largest discrepancy between importance and current effort devoted to predicting them, which we will then forecast on. To help us further, we will contact the major forecasting website Metaculus in order to collect more information to help us when deciding the questions that we will be investigating in our project.

3 Methodology

3.1 Roles

Duncan:

Duncan was leader of the group and responsible for allocating tasks for each project. He specialized in the programming and mathematical modelling aspects of the project, writing the code necessary for the linear regressions and time series analyses, and forecasting the deaths from tropical storms. In addition, he contacted Metaculus in order to ascertain what data they had about existing distributions of forecasters and forecasts.

Max:

Max was responsible for collecting background information on the current and future effects of climate change, and was responsible for the analysis of the effects of climate change. Furthermore, he was responsible for forecasting the UK energy mix, in particular wind and solar energy. He also attained data on the distribution of climate change related forecasts on Metaculus, and led the analysis of the data regarding the distribution of all questions relating to climate change on Metaculus and GJ Open.

Noah:

Noah initially did the research regarding existing forecasts for short-term climate change and led the collection and interpretation of data in order to forecast flooding in the UK, as well as making sure that every citation were in the correct format and order. He also secured data from GJ Open on the questions relating to climate change they had held, and he gathered data necessary for predicting the quantity of a country's forecasting on Metaculus.

3.2 Organisation

After our project brief was allocated to us, we first discussed what we aimed to achieve from the project. We wanted to plan effectively to ensure our project was carried out efficiently and that the work we were doing was the most beneficial to society. We decided to formalise our planning through use of a Gantt chart as seen in Figures 1-3, which we used to discover the focal points of our project, providing us with a clear sense of direction that meant our project would run smoothly and efficiently.

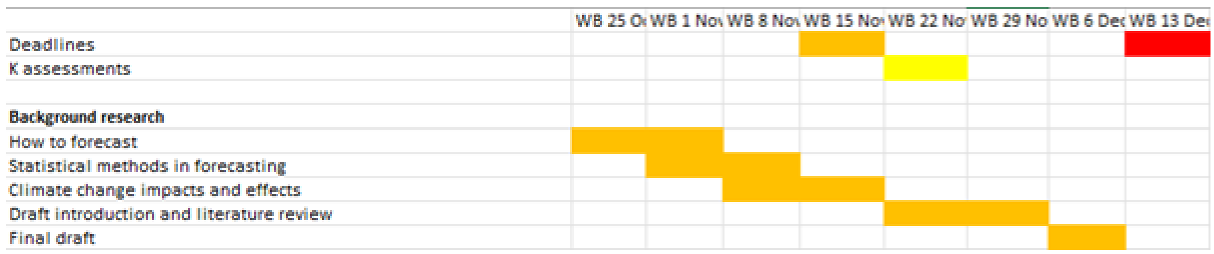

Figure 1: *The Gantt chart part 1*

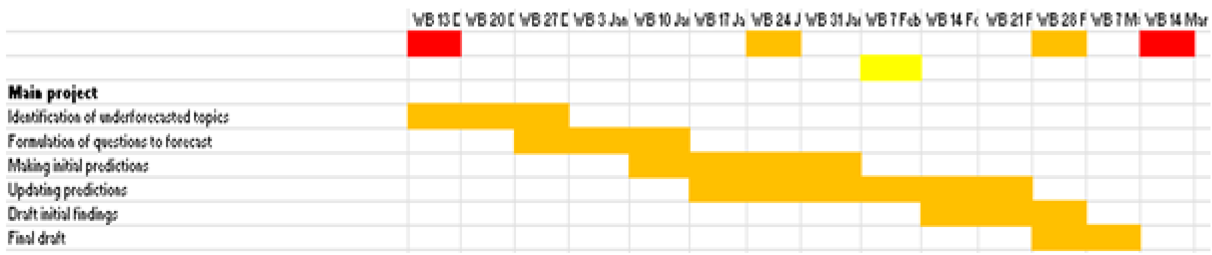

Figure 2: *The Gantt chart part 2*

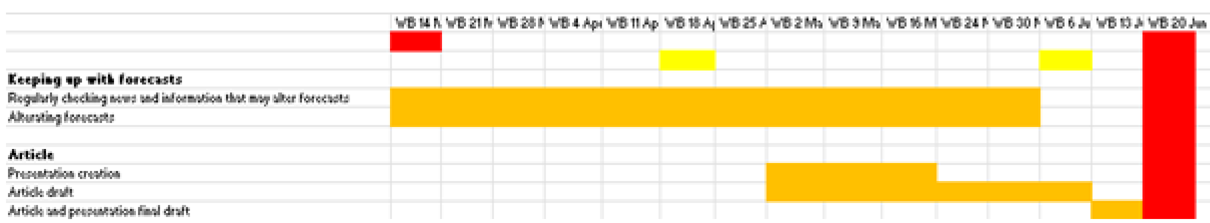

Figure 3: *The Gantt chart part 3*

The Gantt chart in Figure 1, Figure 2 and Figure 3 was employed to optimize planning for the project. Not only did it enable us to devote a portion of time to actually gaining the background knowledge required to carry out this project, it also allowed the group to devote large quantities of time to refining forecasts in response to incoming data, allowing us to respond to new information constantly and adjust our forecasts accordingly. It also provided a mechanism for constantly tracking progress compared to requisite levels for project completion, allowing team members to increase workload when project progress was contingent upon it.

3.3 Analysis Concepts

3.3.1 Forecasting

Forecasting relies on making quantitative, testable predictions about the future. Predictions are made with specific probabilities, and resolution conditions are specified precisely in order to accurately determine the level of accuracy of the forecasters. This is calculated using Relative Brier scores. A Relative Brier score is calculated retrospectively, treating the probability of an event that occurred as 1, and of an event that did not occur as 0, and then taking the sum of the square of the differences between the predicted probabilities and what in fact occurred. For example, if a probability of 0.7 was given for an event that occurred, the relative Brier score would be $0.3^2 + (-0.3)^2 = 0.18$. The best possible Relative Brier score is zero, representing always giving a chance of 1 to events that occurred and 0 to those did not, while a Relative Brier score of two signals the reverse [19].

In order to conduct forecasts, first, the base rate is calculated using historical data. This is then adjusted to take into account any other relevant factors, in order to provide the initial probability. As new information becomes available, the forecast can be constantly updated to account for this. This allows for Relative Brier scores to account for the length of time before the forecasting deadline a particular probability was issued, and means that changes in circumstances after one forecast is created will be reflected in the next.

3.3.2 Linear Regressions

Linear regressions try to predict set of outputs $y_1, y_2, ..., y_n$ from a set of inputs $x_{1:1}, x_{1:2}, .., x_{1:n}, x_{2:1}, ..., x_{m:n}$. The x_i will predict each y_i according to the formula:

$$y_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_m x_m + \epsilon$$

where $\beta_0, \beta_1, ..., \beta_m$ are constants and ϵ is the error term. The constants $\beta_0, \beta_1, ..., \beta_m$ are selected so as to minimse the sum of the squares of the error terms in the $y_1, y_2, ..., y_n$ given as inputs.This then allows future y_i to be predicted given a net set of corresponding $x_1, x_2, ...x_m$ [19].

3.3.3 Time Series Analysis: Holt Winters Additive Method

The Holt Winters additive method takes a time series x_t, and smooths it, producing new time series $s_t = \gamma x_t + (1 - \gamma)s_t - 1$. This is called simple exponential smoothing. The data is then smoothed again, called the Holt method, producing another time series $s_t = \gamma x_t + (1 - \gamma)(s_t - 1 + b_t - 1)$

where $b_t = \beta(s_t - x_t - 1) + (1 - \beta)b_t - 1$ [20]. The Winters component adds seasonality, producing an additional term l. This gives the final set of equations as follows [20]:

$$y_{t+h|t} = hb_t + s_{t+h-m(k+1)}$$

$$l_t = \alpha(y_t - s_{t-m}) + (1 - \alpha)(l_{t-1} + b_{t-1})$$

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

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m}$$

Fitting the model then consists of selecting the constants α, β and γ to maximise the fit with the inputted data.

4 Initial Results

In this section we describe our initial forecasts and the models and reasoning that implied them. First, the data about forecasting which we analysed in order to create questions to forecast for. Then, our three questions: how many individual flood warnings will be issued from the UK government in May 2022; the quantity of wind and solar energy produced in May 2022: and whether deaths from tropical storms would exceed 1000 globally in the period 1st April 2022 - 1st June 2022.

4.1 Metaculus and Good Judgement Open Data Analysis

In order to decide which areas would generate the greatest returns to additional research, we investigated which areas have experienced the fewest forecasts. Table 1, which shows the total number of forecasts by topic area since records began on Metaculus and GJ Open, using the data from Table 14 and Table 15 - see section 8.

Table 1: Forecasting quantity by topic on Metaculus and Good Judgement Open [21] [22]

Topic	Total number of forecasts
Temperatures	5401
Natural disasters	2152
Politics	1883
Greenhouse gas emissions	956
Renewables	864
Global catastrophe	533
Ice cap melting	463
CCS	446
Power/electricity/technology	393
Human intervention with climate (geoengineering etc)	344
Social impacts	319
Economic impacts	307
Fossil fuels	269
Environment	193
Population	189
Water shortages	97
Climate	62
Sea level rise	61
Nuclear power	54
Carbon tax	54
Floods	0
Food shortages	0
Heatwaves	0
Wet bulb temperatures	0
Conflict	0

Table 2 shows the percentage of each continent of the world's population and GDP, and then how much these areas are over or under-weighted in relation. A value greater than 1 means that the region receives more attention than these figures would suggest: a value less than 1, less attention. These results suggest that the continent, excluding Antarctica, that receives the most disproportionate attention is North America, and the most underrepresented continent is Africa, which has no recorded forecasts.

Table 2: Forecasting GDP and population ratios by continent [23] [24] [25]

Continent	% population	% GDP	% forecasts	Population ratio	GDP ratio
N.America	0.0473	0.282	0.5714	12.0809	2.0263
S.America	0.0837	0.034	0.0238	0.2845	0.7003
Europe	0.0977	0.248	0.0952	0.9748	0.3841
Asia	0.5933	0.387	0.1429	0.2408	0.3691
Africa	0.1751	0.028	0	0	0
Oceania	0.0056	0.02	0.0238	4.2517	1.1905
Antarctica	3.85E-07	0.0000125	0.1429	371428.5714	11428.5714

Table 3, the regression on Table 16, Table 17, Table 18 and Table 19 - see section 9 - found that GDP per capita, Freedom House's political rights index, the Heritage Institute's Economic Freedom Index, the Gini coefficient, the Gender Inequality index, expected years of education and life expectancy were all not statistically significant, while Freedom House's civil liberties index, the English speaking population of a country and its happiness index were all statistically significant.

Table 3: Linear regression results for forecasting quantity

Results	Coeff	SE	t-stat	Stand Coeff	p-value	VIF
b	-6.6833	0.8814	-7.5822	0.00000	1.9207e-10	N/A
Ln(Civil liberties)	0.4806	0.1969	2.4413	0.2403	0.0175	1.5774
Ln(English speaking)	0.5688	0.0628	9.0557	0.7259	5.1847e-13	1.0459
Ln(Happiness)	1.5809	0.5841	2.7066	0.2622	0.0087	1.5268

In conclusion, it appears that some areas of forecasting receive orders of magnitude more attention than others, and so marginal returns to research will be far higher in some areas that others.

4.2 Flooding Forecasting

Our main goal regarding flooding was to forecast how many individual flood warnings would be issued by the UK government's FWD (Flood Warning Detection) system throughout the whole of the UK in the month of May 2022.

4.2.1 Flood Warning Data Analysis

Our main dataset for this forecast was the *Historic flood warnings* dataset released by the UK government [26]. This is an Excel spreadsheet, with each flood warning in the UK since the FWD system was put in place on 31st January 2006 listed, along with the date, exact place in which it occurred, and also how severe the flood warning was, from "flood watch" to "flood warning" to "severe flood warning". For the purposes of this forecast, only the dates were utilized. We made a data table with the total number of flood warnings for each month from

February 2006, the first full month of data collection, until December 2021, the last full month of data thus far released. We then plotted Figures 4 and 5 to chart flood warnings over the relevant time period.

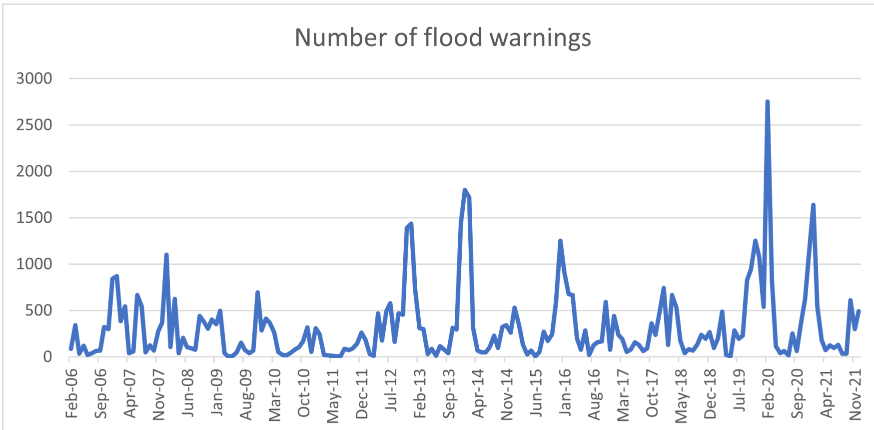

Figure 4: *The number of flood warnings by time.*

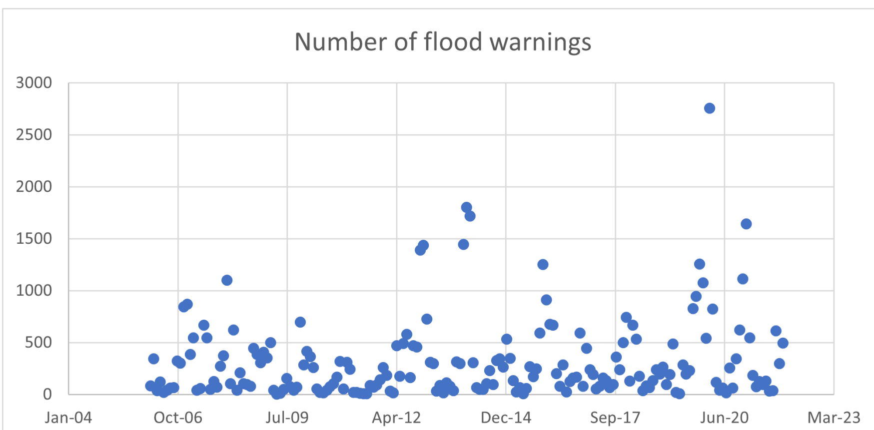

Figure 5: *The number of flood warnings by time.*

Some of these results are very insightful. Figure 4 shows clear seasonal variations, with flood warning numbers higher in the winter than in the summer. Figure 5 implies that there is an anomalously high year every three to four years, however based on this trend, 2022 is not going to be an anomalously high year and May 2022 not an anomalously high month. Due to this graph showing every datapoint, a graph such as Figure 6 would be more useful to compare each year's results, in order to see if we could see any general trends.

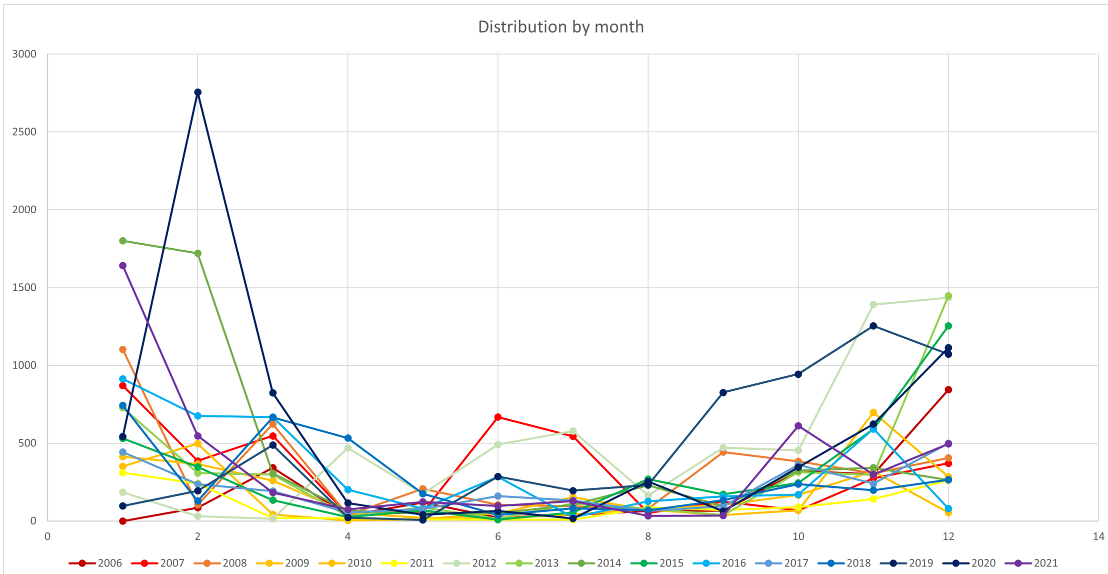

Figure 6: *Number of flood warnings by year by month.*

Figure 6 would show a neat colour spectrum should there be any long-term trends throughout time, implying that there are not. It does, however, further imply the existence of seasonal variations, with flood warnings being highest in winter and lowest in summer.
We then assembled the data into a table, one axis being year, and the other being month. This way, figures can be analysed by month. We also made box-and-whisker diagrams for each month to eliminate outliers - see section 10. This gave us a range in which values are likely to fall, based on interquartile range, and a range in which it is possible for values to fall, based on the range.

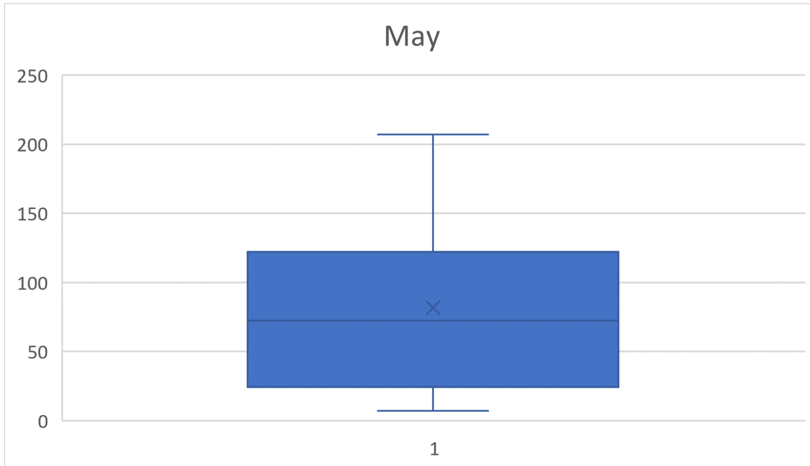

Figure 7: *Distribution of May flood warnings.*

From Figure 7, which pertains to the month which we are forecasting for, we can tell that the probable range (interquartile range) of values for flood warnings is roughly 25-125, with ranges from 5-205 being possible but improbable. In order to try to make our range of probable values more accurate, we ran a time-series analysis on R. We took the base 10 logarithm of each datapoint, so as not to allow any negative values, which are impossible, making our estimates more accurate.

Figure 8 gives us a lower bound of 1.494, at an 80% confidence interval, which we deem to be acceptable. When we raised 10 to the power of 1.494, we obtained a value of 31 (to the nearest integer). Therefore, we can update our probable range of values for the number of flood warnings in May to 31-125.

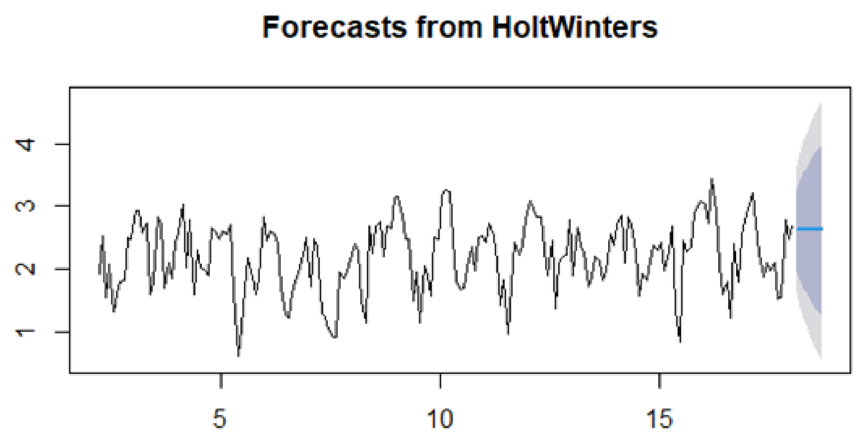

Figure 8: *Time series analysis results for flood warnings.*

4.2.2 Unsuccessful Attempts to Find Indicators

Given this information, we began to test variables for any correlation to our data. First, we ran a linear regression, Figure 9, comparing UK government statistics on annual CO2 emissions [27] with annual flood warnings.

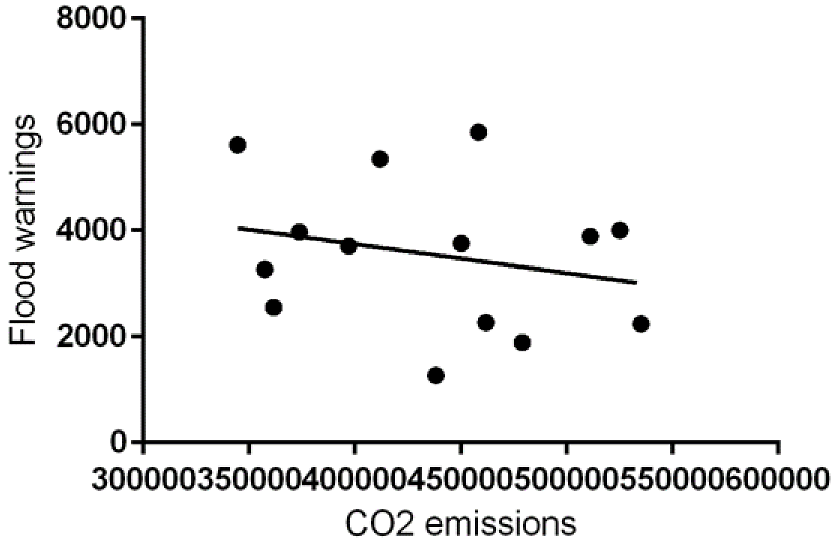

Figure 9: *CO_2 emissions vs flood warnings linear regression*

The R squared value of this linear regression is 0.06031, indicating a very poor fit. Furthermore, the P-value is 0.3974, indicating an insignificant deviation from the horizontal. Therefore, based on figure 9, we concluded that there was no significant correlation between CO2 emissions and flood warnings within the UK.

4.2.3 Rainfall Data Analysis

We then ran another linear regression, Figure 10, this time comparing Met Office monthly rainfall data (average rainfall across the UK in mm) [28] over the last four years to monthly flood warning data during the same period.

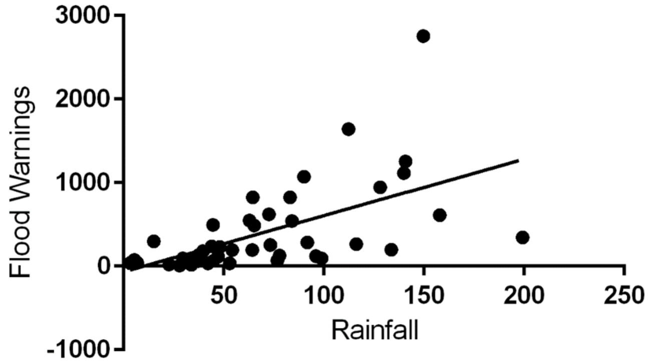

Figure 10: *Rainfall (mm) vs flood warnings linear regression.*

Figure 10 showed a far better correlation than the previous regression (Fig. 9). Its R squared value was 0.33, showing that the points fit the line of best fit fairly well. The P-value was less than 0.0001, indicating a negligible probability that this data has no correlation, and rainfall thus being a statistically significant predictor of flood warnings.

Based on this conclusion, a graph was made comparing monthly flood warnings in the UK and average rainfall in the same month in the UK on one axis. Figure 11 clearly shows a significant positive correlation between rainfall and flood warnings in the UK over the last four years. The number we multiplied each rainfall data point by was (mean number of flood warnings)/(mean amount of rainfall in mm). We chose this because it means that the mean value of the rainfall in mm per month is equal to the mean value of flood warnings per month.

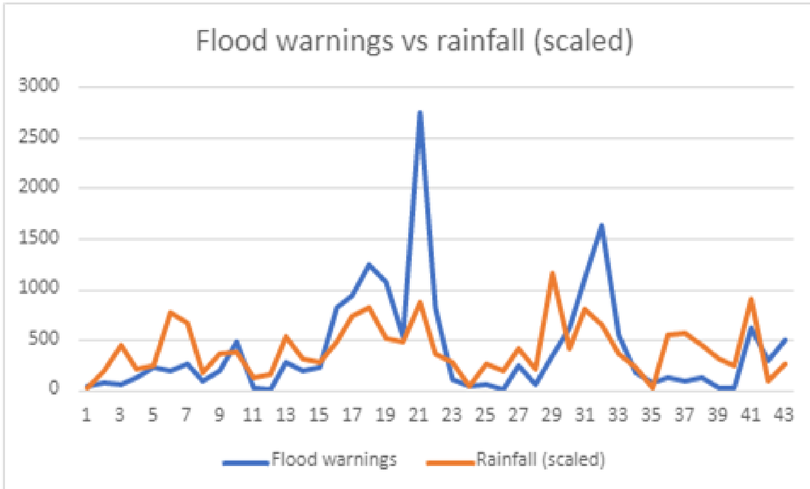

Figure 11: *Rainfall (scaled) vs flood warnings.*

We next decided to run a linear regression across every datapoint (February 2006 – December 2021), in order to see if rainfall and flood warnings correlate well over longer periods of time. Figure 12 produces an R squared value of 0.41 and has a P-value of less than 0.0001, showing that this graph has a clear fit and is extremely unlikely to be random. Therefore, as predicted, there is a correlation between rainfall and flood warnings on a month-to-month basis, over a longer period of time. Therefore, we can definitely use rainfall as an indicator for flood warnings when forecasting. We also obtained a formula which will roughly convert rainfall to flood warnings: $Y = 5.032X - 218.9$, where Y is the number of flood warnings and X is the rainfall in mm.

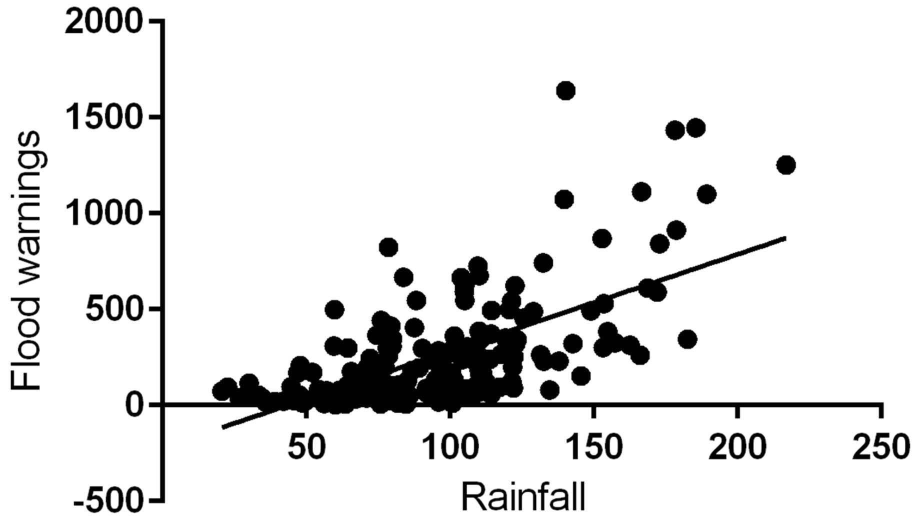

Figure 12: *Rainfall (mm) vs flood warnings linear regression.*

Weather forecasting (including rainfall) is notoriously difficult to do accurately beyond fourteen days [29]. Therefore, it would be difficult to forecast the amount of May rainfall in March of the same year, so we investigated whether there was a correlation between rainfall in the first three months of the year and rainfall in the following May by running a linear regression between the total rainfall in May and the corresponding average total rainfall in the first three months, Figure 13.

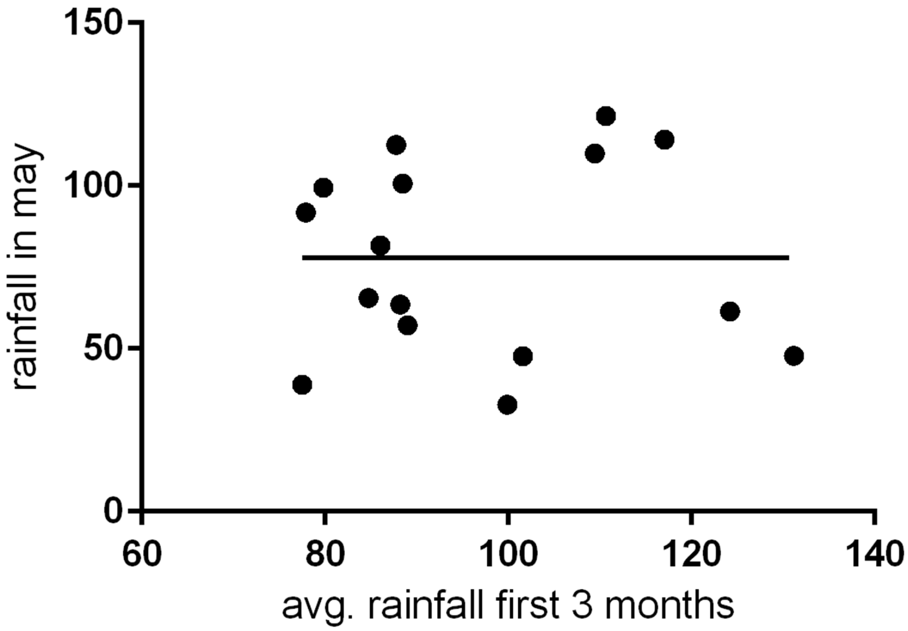

Figure 13: *Rainfall during first 3 months (mm) vs rainfall in May (mm).*

The R squared value of was 0.000005, meaning that the data does not fit the line of best fit. Furthermore, the P-Value is 0.9933, meaning that these results are extremely unlikely to have any correlation whatsoever. Therefore, we can be sure that there is no significant link between the amount of rainfall in the first three months of a year and the amount of rainfall in May of the same year.

Even though it is nearly impossible to forecast accurately beyond fourteen days [29], long-term forecasts exist based on existing climate models, such as the Climate Forecast System v2 used by the NOAA, which can indicate whether there will be higher or lower than average rainfall in a given month in the same season, such as May [30].

We calculated the mean value of rainfall in May to be 77.91875mm. It is predicted that May 2022 will receive "slightly below average" rainfall. We reviewed all previous available seasonal forecasts [31] that had predicted a month's rainfall to be "slightly below average", collecting data on how accurate they were. We then created a box-and-whisker diagram, Figure 14, with our results, where each number is the percentage of the mean average for that specific month divided by 100.

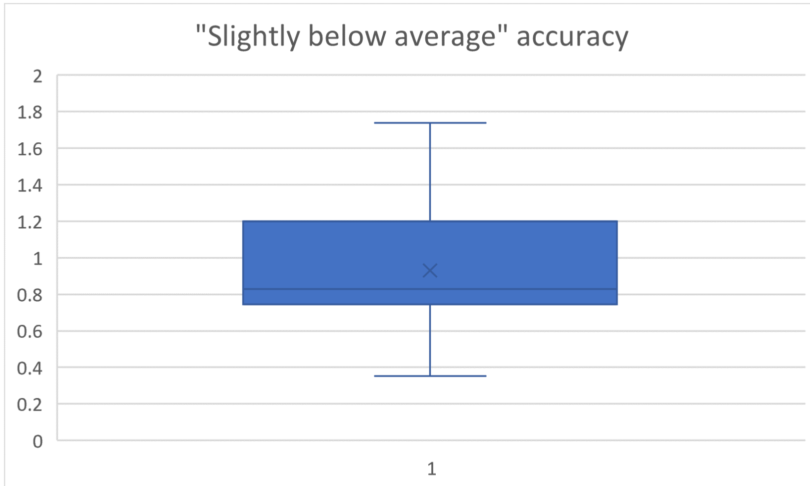

Figure 14: *Distribution of rainfall forecasts labelled "slightly below average" relative to the overall mean average*

The median value in Figure 14 is 0.81. That is, the median percentage of the average rainfall denoted by “slightly below average” is 81%. Therefore, we can calculate 81% of 77.91875, which equals 63 (rounded to the nearest integer).

4.2.4 Initial Forecast

Therefore, our provisional forecast, as of March 16th, for the total amount of rainfall in the UK in May 2022 is 63mm. When we put this number into the formula given to us by figure 23, we calculated the number of flood warnings in May to be 98, to the nearest integer. This is a plausible figure, since it falls inside our probable range of 31-125. We cannot predict any number at this stage with a high degree of certainty, however the number will naturally become more accurate as we continue to adjust it, since weather forecasting for a particular date will always become more accurate as one approaches that date [29].

4.3 Energy market forecasting

For our forecasts regarding the UK energy mix, our data source was the National Statistics Publication, Energy Trends, produced by the Department for Business, Energy and Industrial Strategy. This includes the energy production from many different energy sources, including coal, oil, gas, solar, wind, biofuels and more, and looks at the statistics of each year from 1998 Q1-2021 Q3, looking at production rates in each different quarter [32]. The question forecasted pertains to the quantity of wind and solar energy produced in May 2022.

4.3.1 Quantity of wind energy produced

Initially, we predicted based off averages of previous years using a linear regression. We also carried out a time series analysis of the data. We took the measurements from the past 24 years (1998-2021), taking the amount of energy produced in Q2 of each year, which we determined to be suitable information as a representation of the total energy produced by wind powered generators in May when dividing each value by 3, and compiled it into Table 4. Figure 15 represents these measurements graphically, by time.

Table 4: Wind energy production by year [32]

Year	Wind energy production Q2 (Mtoe)	Change
1998	0.02	N/a
1999	0.02	0
2000	0.02	0
2001	0.02	0
2002	0.02	0
2003	0.02	0
2004	0.03	0.01
2005	0.05	0.02
2006	0.07	0.02
2007	0.08	0.01
2008	0.11	0.03
2009	0.17	0.06
2010	0.14	-0.03
2011	0.32	0.18
2012	0.33	0.01
2013	0.56	0.23
2014	0.44	-0.12
2015	0.77	0.33
2016	0.68	-0.09
2017	0.98	0.30
2018	0.86	-0.12
2019	1.05	0.19
2020	1.15	0.10
2021	0.99	-0.16

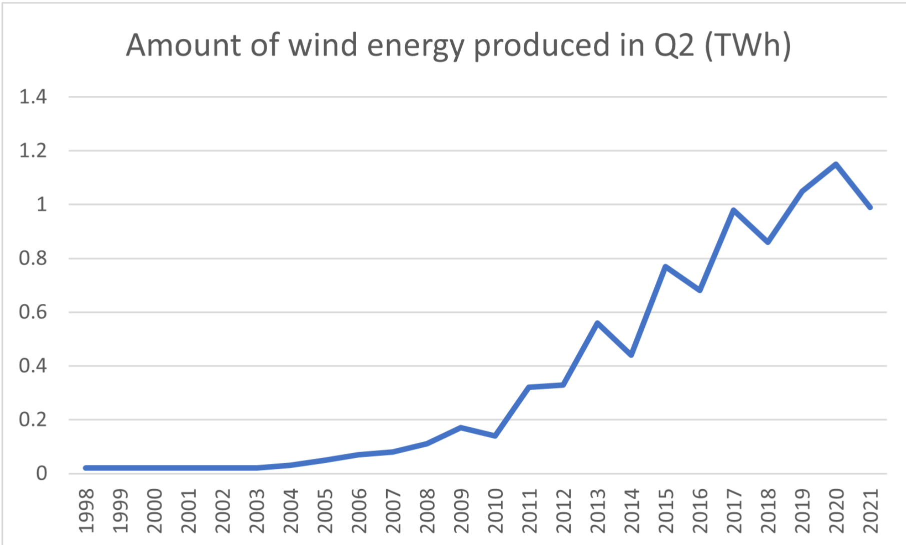

Figure 15: *Quantity of wind energy produced in Q2, Mtoe*

The trend was broadly positive, but had a relatively high volatility, implying a probable further increase in 2022. We began modelling using a linear regression and using the trend equation provided to make a prediction. (Figures 16-17).

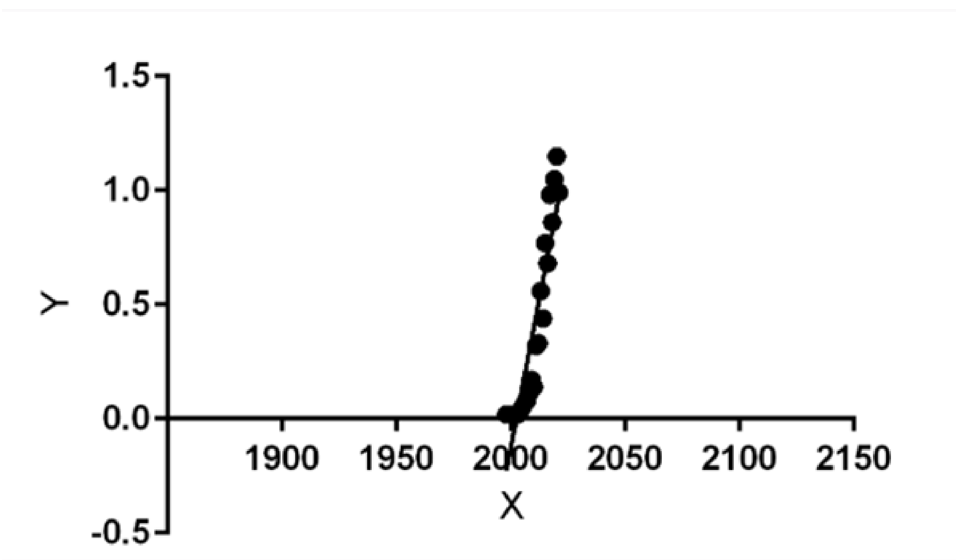

Figure 16: *Wind energy production by year, Mtoe*

Best-fit values	
Slope	0.05209 ± 0.004604
Y-intercept	-104.3 ± 9.251
X-intercept	2002
1/Slope	19.20
95% Confidence Intervals	
Slope	0.04254 to 0.06163
Y-intercept	-123.5 to -85.11
X-intercept	2000 to 2004
Goodness of Fit	
R square	0.8534
Sy.x	0.1561
Is slope significantly non-zero?	
F	128.0
DFn,DFd	1,22
P Value	< 0.0001
Deviation from horizontal?	Significant
Data	
Number of XY pairs	24
Equation	Y = 0.05209*X - 104.3

Figure 17: *Simple wind regression results*

R Squared is 0.85 implying a strong correlation. We can therefore deduce that the graph trend fits the data very well. It was very clear to see that as time progressed the amount of wind energy produced in Q2 of each year increased significantly despite fluctuation.

The equation the linear regression implied was thus:

Amount of wind energy produced in Mtoe = (0.05209∗year) − 104.3

Thus, inputting a value of 2022 enabled us to attain a prediction of 1.02598 Mtoe of wind energy produced in Q2 in 2022.

We then ran a time series analysis on the data (Figures 18-19).

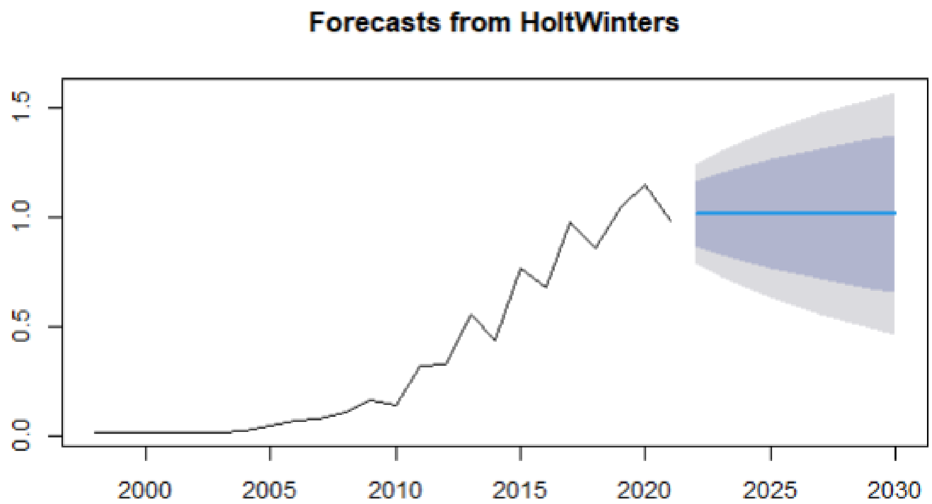

Figure 18: *Time series analysis results for Q2 wind energy production*

```
            80%       95%
2022 0.8701048 0.7919949
2023 0.8297272 0.7302427
2024 0.7966059 0.6795881
2025 0.7678380 0.6355913
2026 0.7420567 0.5961622
2027 0.7184890 0.5601185
2028 0.6966469 0.5267139
2029 0.6761991 0.4954417
2030 0.6569085 0.4659393
> storm_deaths_forecast_2[["mean"]]
Time Series:
Start = 2022
End = 2030
Frequency = 1
[1] 1.017658 1.017658 1.017658 1.017658 1.017658 1.017658 1.017658 1.017658 1.017658
```

Figure 19: *Time series analysis confidence intervals for Q2 wind energy production*

From this time series analysis, we attained a prediction of 1.017658 Mtoe for the amount of wind energy produced in Q2 of 2022.

This was a figure very similar to the prediction our linear regression formulated. The clear similarity between results made us very confident of our predictions.

In conclusion, taking a mean and accounting for uncertainty of our two results from the time series analysis and the linear regression and utilising for May specifically gives a central prediction for May 2022 of 0.341 ± 0.129 Mtoe, or 3.97 ± 1.51 TWh.

4.3.2 Quantity of solar energy produced

For this forecast, we once again utilised a linear regression and time series analysis, inputting the Q2 data of solar energy production levels by all solar powered generators, of the past 10 years, from 2012 to 2021. This data we collected and used is represented in Table 5 and Figure 20.

Table 5: Solar energy production by year [32]

Year	Solar energy production Q2 (Mtoe)	Change
2012	0.04	N/a
2013	0.06	0.02
2014	0.13	0.07
2015	0.27	0.14
2016	0.33	0.06
2017	0.39	0.06
2018	0.42	0.03
2019	0.40	-0.02
2020	0.47	0.07
2021	0.42	-0.05

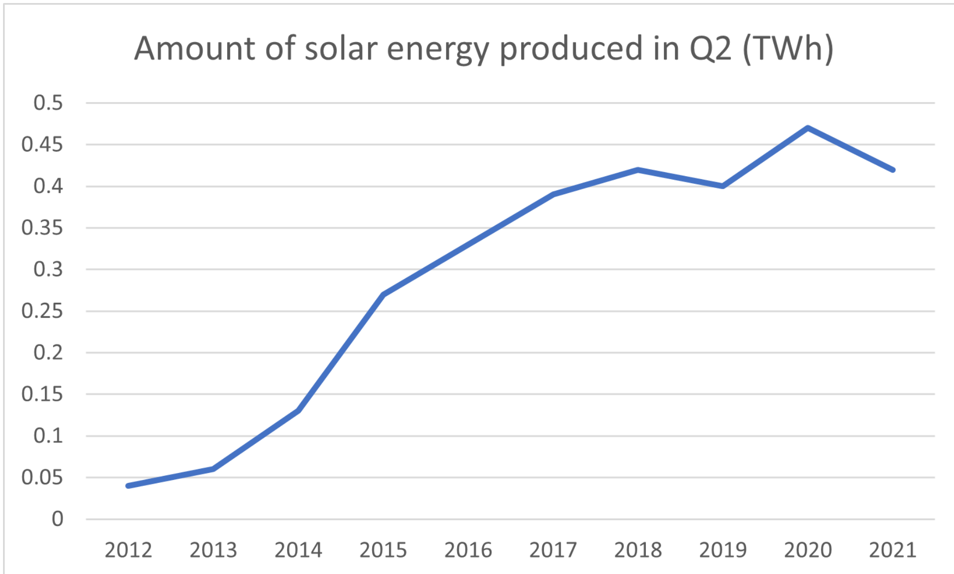

Figure 20: *Quantity of solar energy produced in Q2, Mtoe*

Once again, we attained our data and decided to plot this as a graph to try and spot a general overall trend. Positive correlation was obviously apparent once again, however, what is interesting to take note of is that once we reach 2018, amount of solar energy produced fluctuates year by year, resulting in an overall plateau from 2018 to 2021. (2018 – 0.42, 2021 – 0.42).

There were major increases in amount of solar energy produced from the years 2014-2017, and it was here the gradient of the graph was steepest, before it began to plateau as it reached 2018. Our linear regression results are represented in Figure 21-22.

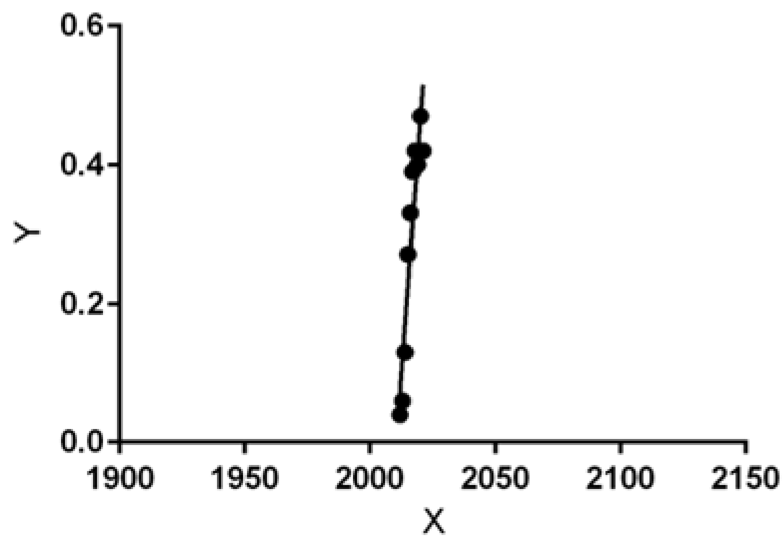

Figure 21: *Linear regression solar energy quantity in Q2 by year, Mtoe*

Best-fit values	
Slope	0.04939 ± 0.006734
Y-intercept	-99.31 ± 13.58
X-intercept	2011
1/Slope	20.25
95% Confidence Intervals	
Slope	0.03387 to 0.06492
Y-intercept	-130.6 to -68.00
X-intercept	2008 to 2012
Goodness of Fit	
R square	0.8706
Sy.x	0.06117
Is slope significantly non-zero?	
F	53.80
DFn,DFd	1,8
P Value	< 0.0001
Deviation from horizontal?	Significant
Data	
Number of XY pairs	10
Equation	Y = 0.04939*X - 99.31

Figure 22: *Solar linear regression results*

R squared was 0.8706, implying a strong correlation once again, like in the case of wind energy. Hence this implied that we could clearly see that as time progressed, solar energy production increased alongside it. This made it obvious to us that over time there has been a sustained and noticeable increase in renewable energy production as a whole in the UK.

The equation attained from our linear regression was:

Amount of solar energy produced in Mtoe = (0.04939*year) - 99.31

This implies a prediction of 0.55658 Mtoe for 2022 solar energy production levels, when we inputted 2022 as our 'year' value.

Following the linear regression we ran a time series analysis on the data, using the Holt-Winters additive method, shown in figures 23-24.

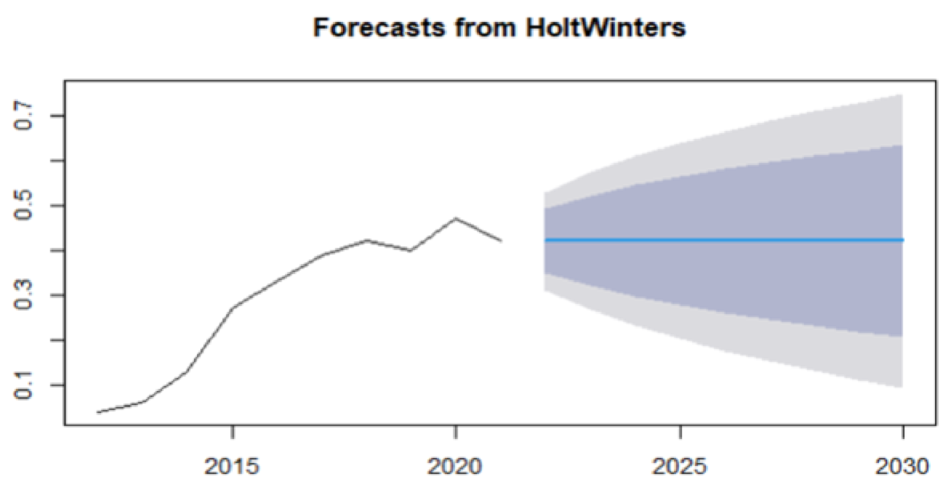

Figure 23: *Q2 solar energy production time series analysis, Mtoe*

```
          80%       95%
2022 0.3487135 0.3109748
2023 0.3191878 0.2658192
2024 0.2965315 0.2311693
2025 0.2774311 0.2019578
2026 0.2606033 0.1762219
2027 0.2453897 0.1529548
2028 0.2313994 0.1315584
2029 0.2183775 0.1116431
2030 0.2061470 0.0929382
> storm_deaths_forecast_2[["mean"]]
Time Series:
Start = 2022
End = 2030
Frequency = 1
[1] 0.4200036 0.4200036 0.4200036 0.4200036 0.4200036 0.4200036 0.4200036 0.4200036 0.4200036
```

Figure 24: *Confidence intervals for solar time series analysis*

From running this time series analysis we attained a prediction of 0.4200036 Mtoe for the amount of solar energy produced in Q2 of 2022. This outcome indicated essentially no difference from the previous year (2021), which was a surprising statistic, given that the linear regression we ran on the same inputs suggested a much higher output was to be expected.

In conclusion, the two methods resulted in the attainment of predictions of 0.55658 Mtoe and 0.4200036 Mtoe respectively for Q2 2022. By taking the mean of these two values, accounting for uncertainty and dividing by three to attain a value for May alone, we are given a mean estimate for May 2022 of 0.1628 ± 0.0542 Mtoe, or 1.89 ± 0.63 TWh.

4.4 Storm deaths forecasting

For this forecast, the question was whether tropical storm deaths would exceed 1000 between 1st April 2022 and 1st June 2022. Historic data on the topic is shown in Table 6.

Table 6: Storm deaths by year [33] [34] [35] [36] [37] [38] [39] [40] [41] [42] [43] [44] [45] [46] [47] [48] [49]

Year	Number of storms with deaths greater than 1000	Deaths of biggest storm
1992	0	46
1993	0	2
1994	1	1152
1995	0	936
1996	1	1077
1997	1	3123
1998	2	18374
1999	2	16287
2000	0	722
2001	0	379
2002	0	238
2003	0	260
2004	2	3042
2005	2	1836
2006	1	1500
2007	1	15000
2008	2	138373
2009	0	789
2010	0	204
2011	1	2546
2012	1	1901
2013	1	6352
2014	0	222
2015	0	81
2016	0	550
2017	1	3057
2018	0	170
2019	1	1303
2020	0	175
2021	0	410

4.4.1 Simple linear regression

The simplest model, a linear regression setting the years in which a storm occurred that killed over 1000 to 1 and all others to 0, gave a probability of 45.28% that a storm would occur that killed over 1000, and thus a 7.5% probability that one will occur within the timeframe of the question. This is shown in Figure 25 and Figure 26.

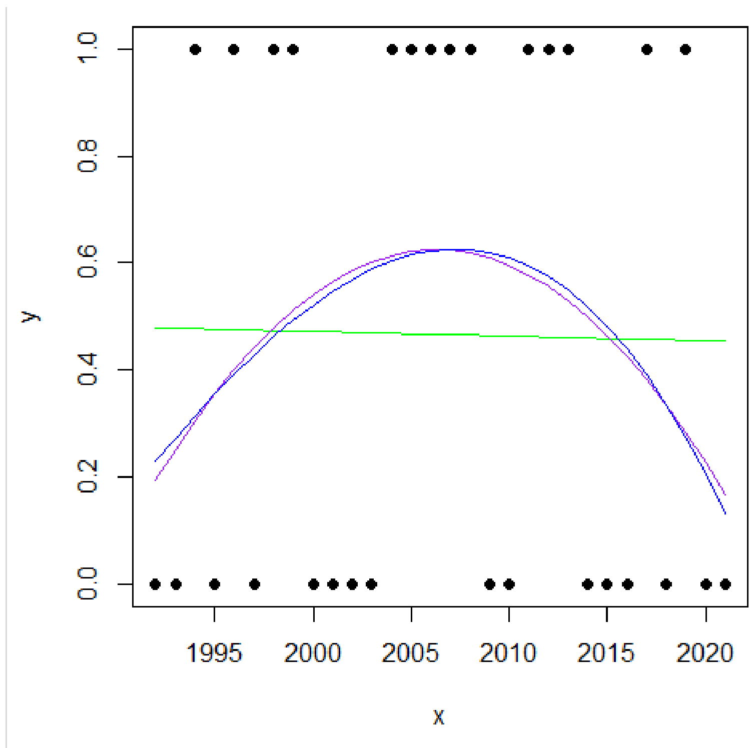

Figure 25: *Comparison of storm frequency by year*

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.2522062 21.8537492   0.103    0.919
x           -0.0008899  0.0108914  -0.082    0.935

Residual standard error: 0.5163 on 28 degrees of freedom
Multiple R-squared:  0.0002384, Adjusted R-squared:  -0.03547
F-statistic: 0.006676 on 1 and 28 DF,  p-value: 0.9355

>
```

Figure 26: *Simple linear regression results for storm deaths*

4.4.2 Linear regression accounting for previous years

The successor to this model, shown in Figure 27, which took into account whether the previous year saw such a storm, found that there was a 39.79% chance of such a storm occurring in 2022, and thus a 6.6% chance that such a storm will occur within the timeframe of the question.

```
Residuals:
    Min      1Q  Median      3Q     Max
-0.5559 -0.4833 -0.4018  0.4984  0.5891

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)   9.543406  23.444358   0.407    0.687
year         -0.004523   0.011683  -0.387    0.702
prev_outcome  0.036457   0.195611   0.186    0.854

Residual standard error: 0.5259 on 26 degrees of freedom
Multiple R-squared:  0.006837,  Adjusted R-squared:  -0.06956
F-statistic: 0.08949 on 2 and 26 DF,  p-value: 0.9147
```

Figure 27: *Linear regression results for storm deaths*

4.4.3 Time series analysis

A time series analysis was run on the base ten logarithms of the data. The interpolated results are shown in Figure 28, and the forecast in Figure 29. This gave a 41.4% probability that a storm would kill 1000 people in 2022, and thus a 6.9% probability that one will occur within the timeframe modelled.

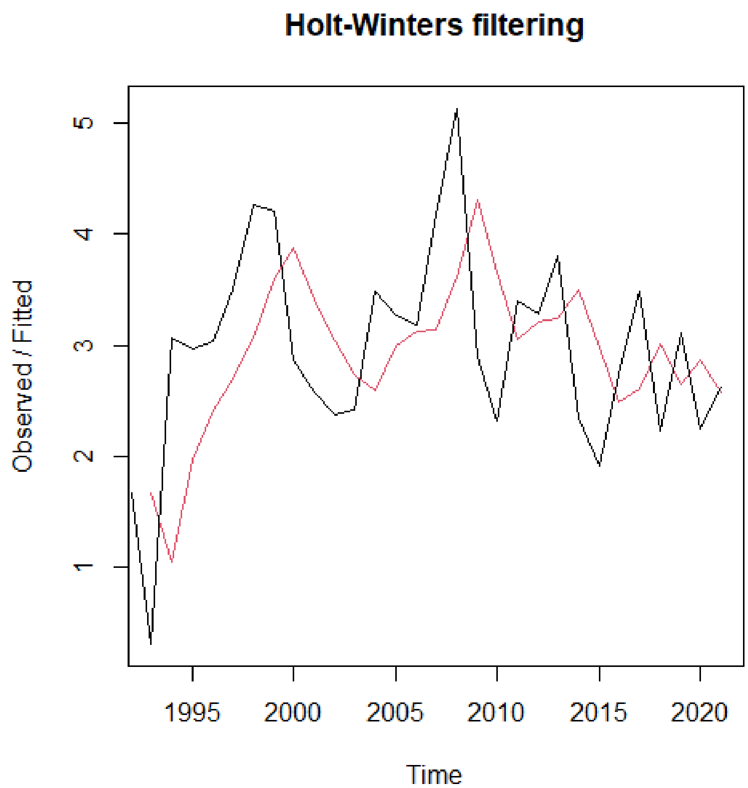

Figure 28: *Holt Winters inter-year predictions for storm deaths*

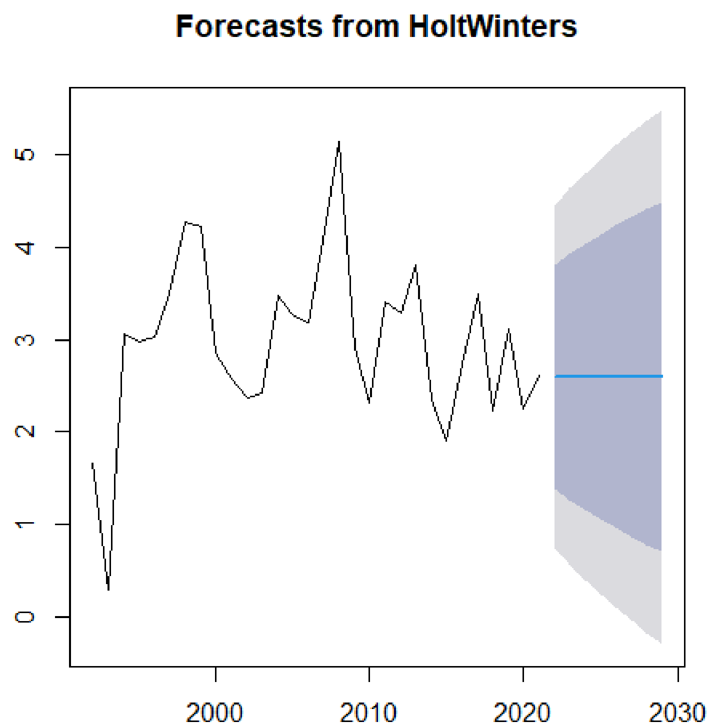

Figure 29: *Time series analysis for storm deaths*

4.4.4 Conclusion

The chance of a tropical storm occurring which kills 1000 or more people between April 1st and June 1st 2022 is predicted to be 6.9%.

4.5 Conclusion

These initial findings thus provide predictions of 98 flood warnings, 3.97 TWh of wind energy produced in May 2022 in the UK, 1.89 TWh of solar energy in May 2022 in the UK and 6.9% for the probability that a storm will kill 1000 or more people between 1st April 2022 and 1st June 2022.

5 Additional Results

5.1 Flooding Forecasting

5.1.1 March 30th

With the end of May 2 months away, it was still impossible to predict with certainty the amount of rainfall. However, a rough estimate for the number of 'rainy days' and 'sunny days' in May is possible to predict. The CFSv2 model, which we used before, approximates that there will be 10 rainy days in the month of May [50]. We can then multiply this by the average rainfall in a rainy day, which is approximately 6.654mm [51], giving us an estimate for the total amount of rainfall in May, which is 66.5mm. Converting this into a number of flood warnings using our formula, we get 97 flood warnings.

This is very similar to our initial prediction, and also falls in our range of probable values, showing that it is a reasonable estimate and that our initial prediction is more likely to be accurate.

5.1.2 April 14th

With mid-May only 1 month away, we can use the first half of the more accurate 30-day forecast. This does not tell us exactly how much precipitation there will be, but tells us, with some certainty, the level of precipitation relative to the average for that month. BBC and MeteoGroup predict that in the first half of May, rainfall levels will be close to average [52]. For now, we can assume that the second half of May will be similar to the first, since no accurate predictions can yet be made. Therefore, we can roughly predict a value of rainfall in May to be 78mm, the average since 2006. Converting this figure into a number of flood warnings, we obtain the figure 173 flood warnings.

This result seems unlikely, given that it is outside of our probable range, and is dissimilar to our previous guesses. Perhaps using a different method or a different source yielded different results.

5.1.3 April 29th

At the end of April, we had all of the data for the flood warnings this month. We ran a linear regression between the number of flood warnings in April, and the number of flood warnings in May.

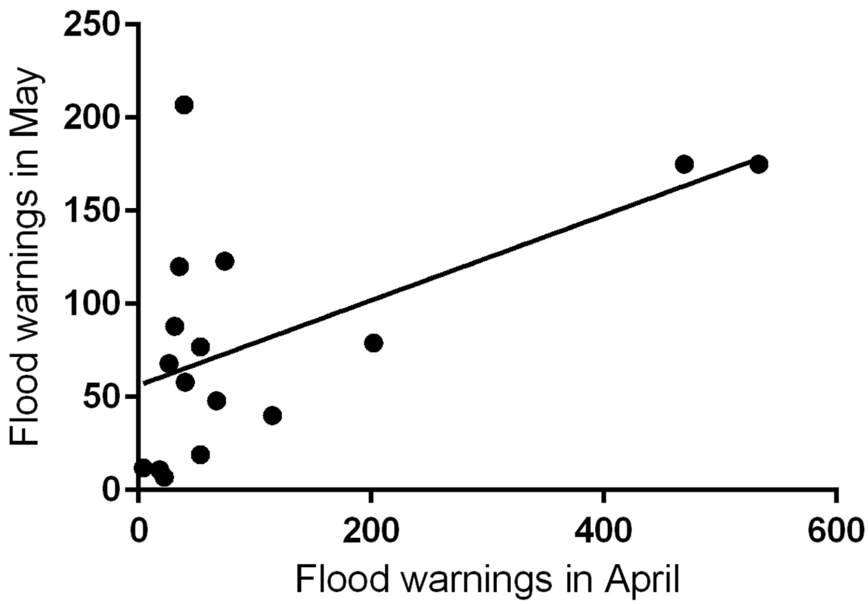

Figure 30: *Linear regression between the number of flood warnings in April and in May.*

The R-squared value for this regression is 0.34, which indicates a fairly good fit, but importantly the P Value is 0.0186, showing that there is a significant correlation between flood warnings in April and flood warnings in May. This regression gives us the formula $y = 0.2284x + 56.25$, where y is the number of flood warnings in May and x is the number of flood warnings in April. We can use this to estimate the number of flood warnings in May based off the number of flood warnings in April. The number of flood warnings issued by the UK Flood Warning System in April 2022 was 9 [53]. Putting this number into our formula, we can update our prediction to 58 flood warnings.

This is much lower than our previous estimates, but falls into our probable range. It is more likely to be accurate since it is using the original source, and as it begins to warm up, the likelihood of many flood warnings in May continues to decrease.

5.1.4 May 18th

Due to an unexpected heatwave, the number of flood warnings in May is likely to be abnormally low. In the first 18 days of May 2022, only 3 flood warnings were issued in England. The amount of rainfall predicted for the next 14 days until the end of May is 37.2mm [54], which is too low to use in the formula obtained from our linear regression.

Let us assume that all other factors are the same throughout the month. In the first 16 days of May, there was 29.06mm of precipitation [55], during which there were 3 flood warnings. We can model this as 1 flood warning per 9.69mm of rain. Given that it is predicted that there will be a further 37.2mm, we can predict a further $\frac{37.2}{(\frac{29.06}{3})}$, which is equal to 4 flood warnings, to the nearest integer. Therefore, we can reasonably predict 7 flood warnings for May.

This number is abnormally low, but not unheard of. Furthermore, low numbers of flood warnings in April tend to predict low flood warnings in May. Given the very high temperatures in May, and very low precipitation, it is a reasonable prediction.

5.2 Energy market forecasting

5.2.1 Wind energy

In order to further develop our forecasts for the wind energy sector in May, we decided to utilise prior data relating wind speeds and wind energy production.

We attained the following information regarding average wind speeds in knots by year, going all the way back to 2001. The following data can be seen alongside our previous data of wind energy production levels in table 7.

Table 7: Wind energy production and wind speeds by year [30] [56]

Year	Wind energy production	Wind speed, knots
2001	0.02	8.6
2002	0.02	9.1
2003	0.02	8.9
2004	0.03	9
2005	0.05	8.9
2006	0.07	9
2007	0.08	9
2008	0.11	9.3
2009	0.17	9
2010	0.14	7.8
2011	0.32	9
2012	0.43	8.2
2013	0.56	8.6
2014	0.44	8.7
2015	0.77	9.4
2016	0.68	8.4
2017	0.98	8.7
2018	0.86	8.5
2019	1.05	8.2
2020	1.15	9
2021	0.99	7.9

We then decided we would go about using this information through running a multiple linear regression. This regression would allow us to use our data of both wind energy production and wind speed, and it identifies any correlation between the two inputs, as well as its trend in relation to time. Running this linear regression allowed us to form a new and updated forecast on wind energy production levels in May of 2022. The results from this multiple linear regression can be seen in Table 8.

Table 8: Wind energy market regression results

Predictor	Coefficient	Estimate	Standard Error	t-statistic	p-value
Constant	β_0	-127.7210018	10.4727602	-12.19554343	0
Year	β_1	0.06343012	0.00507072	12.50910711	0
Wind speed, knots	β_2	0.06748605	0.07297168	0.92482523	0.36729

This gave an r^2 value of 0.907855, which is very significant, resulting the function predicting the data well. The initial value used for wind speed was 7.2, and this prediction was calibrated further with time to produce the optimal output [57]. This gives a value of 0.96 Mtoe for the wind energy in 2022, resulting in our prediction being updated to 0.21 ± 0.09 Mtoe for May.

5.2.2 Solar energy

In order to further develop our forecasts for the solar energy sector in May, we decided to utilise historic data for the relationship between sunlight hours and solar energy production.

We attained the following data on sunlight hours of May for the past 7 years, and combined this with the data we already attained from the past 7 years of solar energy production levels. The following data can be seen in table 9.

Table 9: Solar energy production and sunlight by year [30] [58]

Year	May production (TWh)	Sunlight hours, May
2015	0.27	173.8
2016	0.33	208.3
2017	0.39	207.8
2018	0.42	240.5
2019	0.4	186.9
2020	0.47	265.5
2021	0.42	160.4

Using this data attained, we carried out a multiple linear regression, which took into account the sunlight hours from each year, as well as the energy production of that year, and created a new trend line, resulting in a new prediction. The results from this multiple linear regression can be seen in table 10.

Table 10: Solar energy market energy regression results

Predictor	Coefficient	Estimate	Standard Error	t-statistic	p-value
Constant	β_0	-50.01038561	6.95581207	-7.18972639	0.00198275
Year	β_1	0.02489075	0.00344911	7.21657988	0.00195515
Sunlight hours	β_2	0.00080786	0.0002013	4.01311264	0.01595532

This gave an r^2 value of 0.94971831, which is extremely high, meaning that our model predicts the data well. The average UK value for sunshine is 191 hours per year [59], giving a prediction of 0.473 ± 0.35Mtoe, or 5.501 ± 4.071TWh, which when accounting for the r^2 value gives an updated prediction of 1.22 ± 0.34 TWh for solar energy production in May.

5.3 Storm deaths forecasting

Table 11: Tropical storm deaths by month
[60] [61] [62] [63] [64] [65] [66] [67] [68] [69] [70] [71] [72] [73] [74] [75] [76] [77] [78] [79] [80] [81] [82] [83] [84] [85] [86] [87] [88] [89] [90] [91] [92] [93] [94] [95] [96] [97] [98] [90] [91] [92] [93] [94] [95] [96] [97] [98] [99] [100] [101] [102] [103] [104] [105] [106] [107] [108] [109] [110] [111] [112] [113] [114] [115] [116] [117] [118] [119] [120] [121] [122] [123] [124] [125] [126] [127] [128] [129] [130] [131] [132] [133] [134] [135] [136] [137] [138] [139] [140] [141] [142] [143] [144] [145] [146] [147] [148] [149] [150] [151] [152] [153] [154] [155] [156] [157] [158] [159] [160] [161] [162] [163] [164] [165] [166] [167] [168] [169] [170] [171]

Year	January	February	March	April	Coding	Deaths
2022	266	29	73	648	0	-
2021	33	1	0	261	0	205
2020	103	2	5	30	0	192
2019	46	1	1313	139	0	0
2018	12	17	30	2	0	133
2017	11	282	113	15	0	144
2016	5	44	0	15	0	137
2015	83	5	57	0	0	8
2014	80	1	18	40	0	3
2013	40	50	0	0	0	112
2012	76	114	19	0	0	3
2011	6	52	0	0	0	65
2010	6	0	89	0	1	314
2009	26	3	2	18	0	418
2008	21	93	16	138399	0	85
2007	0	14	156	4	0	24
2006	6	0	11	37	0	309
2005	78	0	12	0	0	5
2004	33	4	370	11	0	257
2003	15	27	2	63	1	390
2002	15	14	35	0	0	42
2001	0	19	2	9	0	120
2000	3	484	114	0	0	0

In order to utilise data that became available following the creation of our initial forecasts, we investigated the correlation between the number of storm deaths in January, February, March and April, and storm deaths in May. We approached this from two directions: retrospectively setting the probability of a storm that killed 1000 people to 1, and fitting a model utilising this, or producing a model to predict the number of deaths.

Table 12: Probabilistic regression results

Predictor	Coefficient	Estimate	Standard Error	t-statistic	p-value
Constant	β_0	16.09826975	23.58926092	0.68244062	0.504154
Year	β_1	-0.00793423	0.01174371	-0.67561534	0.508372
January	β_2	-0.00058021	0.0013453	-0.43128463	0.67168
February	β_3	-0.00042183	0.00061863	-0.68188093	0.5045
March	β_4	-0.00004842	0.00024815	-0.19513093	0.847604
April	β_5	-8.20E-07	0.00000234	-0.3506388	0.730166

The probabilistic regression did not prove very effective, with an r^2 value of 0.08461942, which indicates an extremely poor fit. Additionally, the absolute value of the t-statistic coefficients were also extremely low, indicating insignificant differences from the mean.

Table 13: Deaths regression results

Predictor	Coefficient	Estimate	Standard Error	t-statistic	p-value
Constant	β_0	-962.2389697	9827.831258	-0.09790959	0.92322
Year	β_1	0.58929905	4.89391609	0.12041462	0.905654
January	β_2	-1.60960387	0.98449301	-1.63495714	0.121576
February	β_3	-0.41015847	0.25772719	-1.59144428	0.1310714
March	β_4	-0.10180326	0.10278808	-0.99041886	0.336712
April	β_5	-0.00045021	0.00096745	-0.46535302	0.64795

In contrast, the deaths regression proved much more effective, achieving an r^2 value of 0.25916484, and has absolute values of t-statistic coefficients considerably greater than the previous regression. Utilising this regression, and accounting for the r^2 value, increases the forecast probability to 9.4%.

6 Final Results and Discussion

6.1 Relative Brier Scores

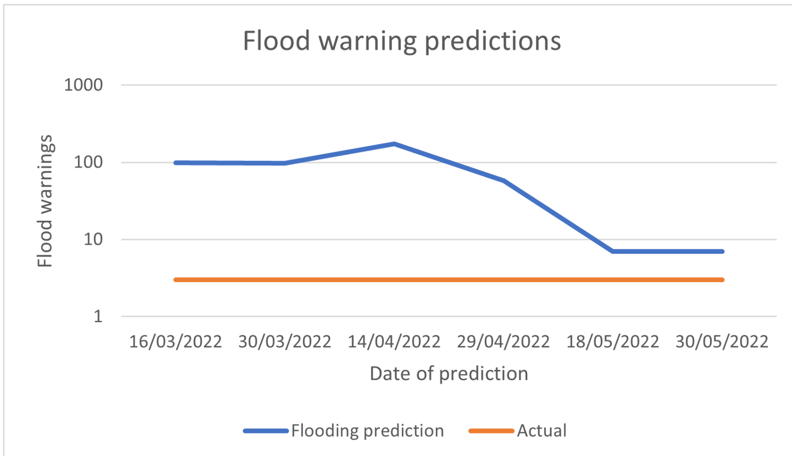

Figure 31: *Flood warning predictions by day*

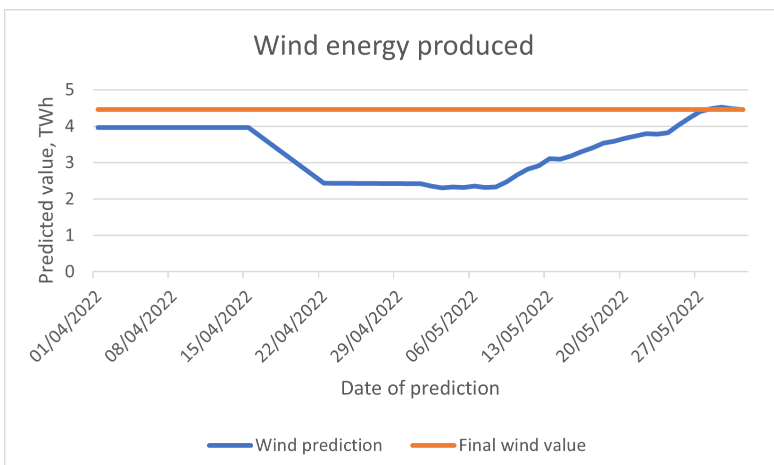

Figure 32: *Wind energy forecasting prediction by day*

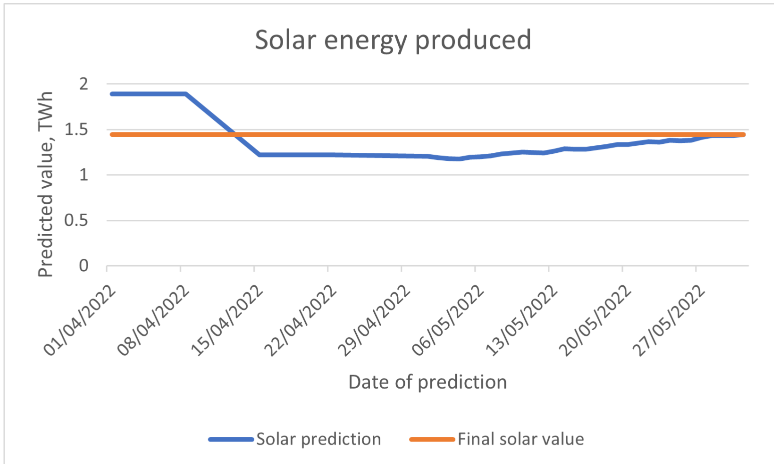

Figure 33: *Solar energy forecasting prediction by day*

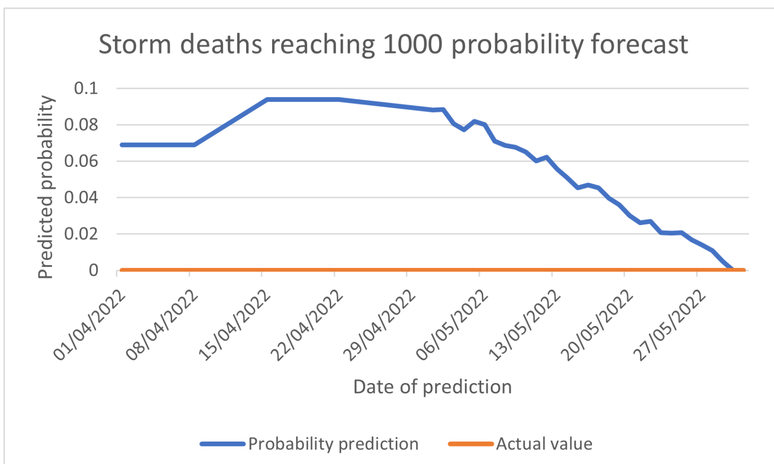

Figure 34: *Storm forecasting prediction by day*

Our predictions over time can be seen in Figure 32, Figure 33, Figure 34 and Figure 31, which show that we achieved relative Brier scores of 1.60, 0.383, 0.135 and 0.018.

6.2 Flooding forecasting evaluation

The data which we used to look for trends and correlations was very useful - it gave us every detail that we need, such as the exact date of occurence. This allowed us to make very specific and useful graphs based on this data, such as figures 35-46.

One thing we could have done better is found better correlations. The lowest R-squared value that we used to indicate a correlation was 0.33, which does indicate a significant correlation, however the accuracy of its derived formula leaves much to be desired.

When forecasting the number of flood warnings, we used a plethora of different techniques, each to different effect. This is because we wanted to test which techniques work better than others for the future, and so that if we picked a flawed technique, it would impact our results less.

The first technique we used was using the correlations we found to predict a provisional estimate based on the projected amount of rainfall that month based on yearly trends. This ended up being far too high, at 98, but made good use of the correlations which we had proven previously, and was the best way of determining an initial prediction.

The second technique was using 'rainy days' forecasts to predict the amount of rainfall, therefore the amount of flood warnings. This gave us a remarkably similar number to our initial forecast, implying that, with the data available, this technique worked, since it is corroborated with the prediction 2 weeks previous.

Our third technique was flawed. This involved making a very rough estimate for the first half of May, and then assuming that the second half would be the same. In fact, this was not the case, as the first half of May had heatwaves whereas the weather in the second half was cooler and more unpredictable. This might be why our figure obtained was extremely high, and therefore very inaccurate. This shows us that we cannot use this technique when forecasting, nor can we make the same assumptions, in the future.

Our fourth prediction used the same technique as our initial result - running linear regressions on correlations in order to not only show their correlation, but to obtain their formulae. This seemed to work to an extent, as our prediction went lower than our original estimate, projecting a low number. However, it was far from low enough, and this method continued to suffer from the same problems as our initial results - the regression formulae do not yield an accurate figure.

Our final technique seemed to work the best. This is to be expected, since we already had half of the data we were trying to predict. However, it clearly worked better than some of the previous techniques considering how much closer it got to the true value. Since the abnormally low rainfall did not fit our previous models, we modelled 1 flood warnings for every $x$mm of rain, in this case 9.69. We then used the projected rainfall for the second half of the month to calculate a result. This was far from perfect, since we predicted four more flood warnings and there were none. However, it worked better than any of our other techniques for small numbers, which is what was required in that circumstance.

In the end, there were 3 flood warnings in May. None of our predictions were completely accurate, however the decreasing trend towards the true value shows that our predictions did tend to get more accurate over time, showing that, to an extent, most of our techniques worked, and we have gained valuable experience from knowing which were and weren't successful.

6.3 UK energy mix forecasting evaluation

The UK government data set we attained, proved to be extremely useful. It gave us essentially all information that we needed on the levels of energy production for both wind and solar energy, and was what we used to make predictions throughout the whole of the project.

Analysing our data, and spotting trends in the dataset, proved to be very useful. It provided us with a great idea on what we actually should expect to see from our forecasts, and where our research was headed towards.

Following the analysis of our results, we began forecasting. The two methods we decided to use for our UK energy mix forecasting was the use of a linear regression, and a time series analysis using the holt winters additive method.

Starting off with using only previous years results proved to be a good starting point. It did provide us with initial estimations in which gave us relatively good results, in which fit the trend we observed in our initial analysis of the data. However we realised this was not extremely accurate, given that it took into account no other factors that may affect the energy production levels. This was immediately something we knew we had to implement into our work to improve accuracy and make our forecasts as realistic as possible.

To deal with this, we decided to look at sunlight hours in the month of may and average wind speeds. Taking these factors into account proved to be beneficial and through combining this data with the data on energy production, in which we had previously attained, by implementing it all into a multiple linear regression, enabled us to attain newer, and more updated forecasts. We used a multiple linear regression here as it enabled us to look at multiple variables at once, and this regression method appeared to be better for making estimations than the time series analysis method. We took these to be our final predictions of both solar and wind energy production.

The results of these predictions were very good attaining relative brier scores of 0.383 and 0.135 for the two forecasts. The lower of the two being for our solar energy forecast. This was extremely promising to see, and we were very happy with the final outcome of these forecasts as it suggested great accuracy in our estimations.

Of course this method also had its flaws. There are many factors in which can impact the final production levels, that we were unable to account for. This is something that we would be keen to improve on in the future provided we were to try and forecast for other months. On top of this we also could have tried to find more precise and larger data sets, as we only were able to locate one and this data set only went to two decimal places. Furthermore, we only went back to 2012 for solar energy, and hence we had less confidence in the trend line formulated than we did for wind energy production rates. Lastly, given that our relative brier score for wind energy production was not as low as for solar, we would in the future try to improve on our wind energy forecast. This could be done by looking for more specific data for the month of may especially as we took the yearly average wind speed and assumed that for May.

6.4 Storm deaths forecasting evaluation

We initially utilised a multiple linear regression, finding the time variable to be negative, implying that storm deaths were actually decreasing over time, while the probability of a storm that killed over 1000 individuals occurring was 3.6% higher if such a storm had occurred in the previous year. This method provided a probability of 6.6%. However, these estimates all had t-statistics below 0.5, had an r^2 value of 0.0068 and had a p-value of 0.915, all indicating exceptionally poor fits.

The Holt Winters time series analysis method proved more informative. The predictions the function interpolates are shown, and these closely correspond to the predicted values. The forecast this implied resulted gave a 6.9% probability of a storm occurring that killed over 1000 people in April or May 2022, slightly higher than the previous estimate of 6.6% but achieved at a much higher accuracy.

This was further developed with the insight that, although a probabilistic regression on whether a storm killed 1000 individuals may fail alone, instead estimating the number of deaths and using the errors on the coefficients to determine the probability of deaths exceeding 1000 may be more useful. This method provided a much improved r^2 of 0.26, which although low is tolerable, with the t-statistics and p-values of the various variables visible. This provided a prediction of 9.4% for the probability of a storm occurring.

No such storm occurred within the timeframe of the question, giving us a relative Brier score of 0.018, weighting for the time each forecast was active for.

Several potential methods could have improved accuracy. Storm deaths were only counted if they occurred post-1997, while reliable historic data are available for longer periods, so potentially accuracy could have been raised by including these. Additionally, some effects that vary on multi-year cycles, such as the El Niño and La Niña effects, would not have been captured by the linear regression models, resulting in their accuracy being lower than possible.

7 Conclusion

Our aim during this project was to produce forecasts relating to the impact of climate change. We analysed data from the main forecasting platforms, Metaculus and Good Judgement Open, relating to climate change forecasting, and found that they displayed considerable bias towards forecasting disproportionately related to Western countries measured on both a population and GDP basis. To increase understanding relating to global warming, we predicted the number of flood warnings that would occur in the UK, the amount of wind and solar energy produced and the chance of a storm killing 1000 or more people, as these were all topics that had received relatively low attention.

We achieved relative Brier scores of 1.60, 0.383, 0.135 and 0.018, resulting in a geometric mean score of 0.1105. This is equivalent to predicting events that do not occur as having 23.5% probability, or events that do occur with 0.765% probability. This places us in the top 12.9% of forecasters on GJ Open.

However, limitations are present in our research. Our research focused on UK-related questions, due to ease of data gathering and increased familiarity with local context increasing our accuracy, but this has likely resulted in the marginal benefit from research being lower than potential. Questions that had more exposure to the politics of developing countries could have increased total benefit, at the expense of increasing total cost due to increased time expenditure. It remains unclear where marginal benefit equals marginal cost and thus where the optimal point is to make forecasts.

Additionally, the small number of forecasts that were possible to make in the paper due to time constraints means that it was not possible to calculate calibration. Calibration is how closely your predictions correspond to real-world events: if events predicted with probability p occur p of the time, a forecaster is well calibrated. Calibration is important for judging whether a forecaster is over-confident, under-confident or neither, but this project only allows our measurement of accuracy.

Any individuals interested in developing their analysis further should achieve utility from reading the summary of the field and description and application of forecasting methods described here. The future possibilities of this field are immense; forecasting the increase in the number of forecasters attributable to this paper is an exercise left to the reader.

8 Appendix A - Metaculus and GJ Open data

Table 14: Metaculus and Good Judgement Open Climate Change Forecasts [21] [22] [23]

Topic	Forecasts	Forecasters	Duration
Social cost of carbon	Metaculus	20	12
Carbon capture costs	Metaculus	58	34
Nuclear power	Metaculus	54	37
Solar power	Metaculus	26	10
Temperatures	Metaculus	109	82
Fossil fuel plants	Metaculus	143	43
Human interference with climate	Metaculus	344	177
Cost of solar power	Metaculus	38	17
Fossil fuel consumption	Metaculus	35	19
Antarctic sea ice	Metaculus	42	7
Arctic sea ice	Metaculus	3	2
CO2 emissions	Metaculus	51	19
Global warming/temperature	Metaculus	601	294
Texas electricity outage	Metaculus	53	14
Energy sources	Metaculus	18	8
Natural disasters - Hurricane	Metaculus	22	12
Carbon capture cost	Metaculus	23	13
Carbon capture	Metaculus	104	26
Carbon capture	Metaculus	68	23
Carbon capture	Metaculus	65	15
Politics - paris agreement	Metaculus	352	216
Global catastrophe and population	Metaculus	189	117
Fossil fuel stations	Metaculus	46	18
Methane emissions	Metaculus	24	15
Global warming/temperature	Metaculus	166	92
Arctic sea ice	Metaculus	28	10
Global warming/temperature	Metaculus	413	254
Carbon capture costs	Metaculus	74	16
Solar power	Metaculus	71	27
Carbon capture	Metaculus	54	22
Arctic sea ice	Metaculus	37	16
Antarctic sea ice	Metaculus	36	16
Politics and CO2 emissions	Metaculus	169	54
Atmospheric CO2 emissions	Metaculus	188	61
Wildfires	Metaculus	85	48
Solar radiation management	Metaculus	47	25

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Table 14 – continued from previous page

Topic	Forecasts	Forecasters	Duration
Antarctic sea ice	Metaculus	36	14
Arctic sea ice	Metaculus	24	11
Antarctic sea ice	Metaculus	33	9
Arctic sea ice	Metaculus	24	10
Antarctic sea ice	Metaculus	29	9
Atmospheric CO2 emissions	Metaculus	24	13
Global warming/temperatures	Metaculus	174	83
Solar power	Metaculus	138	28
Renewable energy	Metaculus	177	53
Economic impacts	Metaculus	37	15
EU Paris agreement targets	Metaculus	329	192
Antarctic sea ice	Metaculus	11	6
Arctic sea ice	Metaculus	12	6
Climate change targets	Metaculus	293	97
Greenhouse gas emissions	Metaculus	86	44
Global warming/temperatures	Metaculus	557	200
Global carbon emissions	Metaculus	133	77
CO2 emissions from transport	Metaculus	32	20
Extinction	Metaculus	115	49
Sea level rise	Metaculus	33	12
Economic impacts of wildfires	Metaculus	40	16
Economic impacts of hurricanes	Metaculus	230	44
Oil consumption	Metaculus	45	23
Wind energy	Metaculus	73	34
Land area of Singapore	Metaculus	28	10
Hurricanes	Metaculus	351	150
Water shortage in USA	Metaculus	97	41
Global warming/temperatures	Metaculus	429	126
Wildfires	Metaculus	75	36
USA & Paris agreement	Metaculus	293	105
Global warming/temperatures	Metaculus	218	71
Global warming/temperatures	Metaculus	384	298
USA & Paris agreement	Metaculus	116	47
Ozone layer	Metaculus	122	84
Storms	Metaculus	316	51
Concern about climate change	Metaculus	100	34
Wildfires	Metaculus	251	100
Global warming/temperatures	Metaculus	566	232
Arctic sea ice	Metaculus	148	87
Global warming/temperatures	Metaculus	460	261
Global warming/temperatures	Metaculus	765	402

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Table 14 – continued from previous page

Topic	Forecasts	Forecasters	Duration
Seasons and climate	Metaculus	62	38
Solar and wind energy	Metaculus	174	133
Global warming/temperatures	Metaculus	330	234
Electric vehicles	GJ Open	43	28
Electric vehicles	GJ Open	51	39
Politics and laws	GJ Open	331	177
Electric vehicles	GJ Open	115	53
Electric vehicles	GJ Open	113	45
Air quality	GJ Open	71	24
Solar panels	GJ Open	120	36
Atmospheric temperatures	GJ Open	113	51
Litter and pollution	GJ Open	104	52
Carbon pricing mechanism	GJ Open	249	89
Wildfires	GJ Open	782	175

Table 15: Metaculus and Good Judgement Open Climate Change Forecasts [21] [22] [23]

Topic	Opened	Closes	Resolves
Carbon tax	Sep 10 2021	Jan 3 2031	Jan 3 2050
Social cost of carbon	Dec 24 2021	Dec 31 2022	Jan 1 2023
Carbon capture costs	Jun 17 2020	Jan 2 2067	Jan 2 2100
Nuclear power	Dec 6 2021	Apr 11 2026	Jan 1 2032
Solar power	Dec 1 2021	Jul 10 2027	Jan 1 2032
Temperatures	Dec 11 2021	Dec 31 2022	Jan 30 2023
Fossil fuel plants	Jul 1 2020	Apr 10 2040	Dec 30 2100
Human interference with climate	Oct 13 2018	Jan 1 2100	Jun 1 2100
Cost of solar power	Nov 19 2021	Jul 10 2027	Jan 1 2032
Fossil fuel consumption	Nov 19 2021	Oct 8 2038	Jan 1 2100
Antarctic sea ice	Sep 24 2021	Nov 15 2029	Mar 15 2030
Arctic sea ice	Sep 29 2021	Nov 15 2029	Apr 15 2030
CO2 emissions	Aug 22 2020	Jan 1 2030	Jan 1 2037
Global warming/temperature	Dec 21 2017	Jan1 2030	Jan 1 2100
Texas electricity outage	Jun 20 2021	Oct 13 2028	Jun 17 2031
Energy sources	Dec 6 2021	Jul 10 2027	Jan 1 2032
Natural disasters - Hurricane	Dec 7 2021	Jan 1 2025	Jan 1 2030
Carbon capture cost	Jul 27 2020	Jul 1 2029	Jul 1 2030
Carbon capture	Jul 27 2020	Jul 1 2029	Jul 1 2030
Carbon capture	Jul 27 2020	Jul 1 2029	Jul 1 2030

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Table 15 – continued from previous page

Topic	Opened	Closes	Resolves
Carbon capture	Jul 27 2020	Jul 1 2029	Jul 1 2030
Politics - paris agreement	Jul 17 2017	Jun 15 2025	Jan 1 2030
Global catastrophe and population	Dec 4 2018	Nov 17 2045	Jun 24 2100
Fossil fuel stations	Sep 2 2021	Dec 30 2030	Dec 30 2038
Methane emissions	Jun 12 2021	Dec 32 2021	Dec 31 2026
Global warming/temperature	Nov 5 2018	Jan 1 2094	Jul 16 2100
Arctic sea ice	Sep 24 2021	Nov 15 2022	Apr 15 2023
Global warming/temperature	Nov 21 2017	Jan 1 2030	Jun 15 2100
Carbon capture costs	Jul 27 2020	Jul 1 2029	Jul 1 2030
Solar power	Oct 15 2021	Jun 28 2025	Jan 1 2032
Carbon capture	Jul 27 2020	Jul 1 2029	Jul 1 2030
Arctic sea ice	Sep 24 2021	Apr 15 2023	Oct 15 2023
Antarctic sea ice	Sep 24 2021	Nov 15 2022	Mar 15 2023
Politics and CO2 emissions	Mar 10 2020	Dec 31 2024	Sep 1 2025
Atmospheric CO2 emissions	Jan 17 2019	Dec 31 2024	Dec 31 2030
Wildfires	Aug 24 2019	Dec 31 2023	Dec 31 2029
Solar radiation management	Jun 5 2020	Jan 1 2066	Jan 1 2101
Antarctic sea ice	Sep 24 2021	Apr 15 2023	Oct 15 2023
Arctic sea ice	Sep 24 2021	Mar 15 2025	Oct 15 2025
Antarctic sea ice	Sep 24 2021	Nov 15 2024	Mar 15 2025
Arctic sea ice	Sep 24 2021	Nov 15 2024	Apr 15 2025
Antarctic sea ice	Sep 24 2021	Mar 15 2025	Nov 15 2025
Atmospheric CO2 emissions	Oct 16 2021	Feb 21 2061	Jan 1 2100
Global warming/temperatures	Nov 26 2018	Dec 31 2025	Dec 31 2100
Solar power	Jan 26 2020	Oct 1 2022	Jan 1 2024
Renewable energy	Feb 2 2020	Feb 1 2022	Jan 1 2023
Economic impacts	Oct 9 2020	Jan 1 2066	Jan 1 2101
EU Paris agreement targets	Jul 12 2017	Mar 15 2025	Jan 1 2030
Antarctic sea ice	Sep 29 2021	Mar 15 2030	Nov 15 2030
Arctic sea ice	Sep 29 2021	Apr 1 2030	Oct 15 2030
Climate change targets	Dec 12 2020	N/A	Nov 1 2021
Greenhouse gas emissions	May 8 2021	Jan 1 2026	Jun 1 2032
Global warming/temperatures	Dec 12 2020	Oct 31 2021	Jan 1 2022
Global carbon emissions	Mar 4 2021	Sep 10 2021	May 13 2022
CO2 emissions from transport	Nov 9 2020	Dec 31 2023	Mar 1 2026
Extinction	Jan 25 2020	Dec 31 2099	Dec 31 2099
Sea level rise	Oct 14 2021	Jan 1 2100	Jan 1 2100
Economic impacts of wildfires	Sep 15 2021	Nov 1 2021	Jan 10 2022
Economic impacts of hurricanes	Mar 31 2021	Sep 1 2021	Jan 10 2022
Oil consumption	Nov 16 2020	Jan 1 2032	Jan 1 2036
Wind energy	Feb 5 2020	N/A	N/A

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Table 15 – continued from previous page

Topic	Opened	Closes	Resolves
Land area of Singapore	Aug 19 2021	Jan 1 2070	Dec 31 2044
Hurricanes	Sep 25 2017	Nov 30 2019	Dec 31 2022
Water shortage in USA	Jun 14 2021	N/A	N/A
Global warming/temperatures	Jun 9 2020	N/A	N/A
Wildfires	May 24 2020	N/A	N/A
USA & Paris agreement	Dec 12 2020	N/A	N/A
Global warming/temperatures	May 13 2020	N/A	N/A
Global warming/temperatures	Apr 23 2016	N/A	N/A
USA & Paris agreement	Nov 5 2018	N/A	N/A
Ozone layer	Oct 13 2016	N/A	N/A
Storms	Sep 1 2020	N/A	N/A
Concern about climate change	Aug 1 2020	Jan 1 2021	Jan 31 2026
Wildfires	Jan 14 2020	N/A	N/A
Global warming/temperatures	Sep 21 2018	N/A	N/A
Arctic sea ice	Nov 17 2018	N/A	N/A
Global warming/temperatures	Aug 16 2017	N/A	N/A
Global warming/temperatures	Feb 8 2016	N/A	N/A
Seasons and climate	Jul 10 2017	N/A	N/A
Solar and wind energy	Mar 30 2016	N/A	N/A
Global warming/temperatures	Aug 13 2016	N/A	N/A
Electric vehicles	Dec 13 2021	Jan 1 2023	Jan 1 2023
Electric vehicles	Dec 13 2021	Jan 1 2023	Jan 1 2023
Politics and laws	Nov 26 2021	Jan 13 2022	Jan 13 2022
Electric vehicles	Nov 5 2021	Jan 1 2023	Jan 1 2023
Electric vehicles	Oct 29 2021	Apr 29 2022	Apr 29 2022
Air quality	Oct 1 2021	Mar 31 2022	Mar 31 2022
Solar panels	Sep 30 2021	Jan 1 2022	Jan 1 2022
Atmospheric temperatures	Sep 24 2021	Oct 1 2022	Sep 30 2022
Litter and pollution	Sep 24 2021	Jan 8 2023	Jan 8 2023
Carbon pricing mechanism	Apr 30 2021	Jan 1 2022	Jan 1 2022
Wildfires	Nov 13 2020	Dec 31 2021	Jan 1 2022

9 Appendix B - forecasting statistics and predictors by country

Table 16: Forecasting statistics and predictors by country, part 1 [23] [172] [173]

Country	Percentage	GDP per capita	Political Rights
United States	53.49%	65279	32
United Kingdom	8.49%	42354	39
Canada	4.75%	46327	40
Australia	2.60%	55057	40
Germany	1.98%	45724	39
India	1.61%	2101	34
Netherlands	1.14%	52295	40
France	0.99%	44033	38
Turkey	0.98%	9127	16
Philippines	0.95%	8361	25
China	0.87%	10500	1
Nigeria	0.84%	5887	21
Sweden	0.80%	51405	40
Brazil	0.76%	15553	31
Spain	0.68%	39037	37
Italy	0.64%	40924	36
Russia	0.62%	25763	5
Poland	0.55%	29924	34
Pakistan	0.48%	5539	15
Switzerland	0.47%	66307	39
New Zealand	0.47%	40780	40
Singapore	0.46%	94105	19
Mexico	0.44%	18656	27
South Africa	0.44%	13526	33
Ireland	0.42%	76745	39
Israel	0.40%	38868	33
Belgium	0.40%	49367	39
Czechia	0.40%	38020	36
Vietnam	0.39%	6790	3
Denmark	0.39%	54536	40
Japan	0.38%	42067	40
Thailand	0.38%	17910	5
Finland	0.38%	46344	40
Norway	0.37%	62183	40
Bangladesh	0.35%	3877	15
Romania	0.34%	26660	35
Greece	0.32%	28583	37
South Korea	0.32%	38824	33
Hong Kong	0.31%	61671	15

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Table 16 – continued from previous page

Country	Percentage	GDP per capita	Political Rights
Malaysia	0.31%	29511	21
Portugal	0.30%	32554	39
Austria	0.30%	53879	37
Ukraine	0.29%	8699	26
Argentina	0.26%	20829	35
Mongolia	0.25%	12946	36
Egypt	0.24%	11608	6
Hungary	0.23%	28799	26
Kenya	0.23%	3292	19
UAE	0.17%	74035	5
Bulgaria	0.16%	20948	33
Serbia	0.16%	15432	22
Colombia	0.15%	14503	29
Iran	0.15%	20885	6
Croatia	0.15%	26296	36
Algeria	0.15%	15293	10
Ethiopia	0.14%	1903	9
Sri Lanka	0.13%	12863	23
Cambodia	0.13%	4018	5
Nepal	0.13%	2702	25
Slovakia	0.13%	32371	37
Chile	0.13%	24747	38
Lithuania	0.12%	33523	38
Zimbabwe	0.11%	2434	11
Slovenia	0.11%	36387	39
Peru	0.11%	13463	29
Estonia	0.10%	33448	38
Saudi Arabia	0.10%	53893	1

Table 17: Forecasting statistics and predictors by country, part 2 [23] [173] [174] [175]

Country	Civil liberties	Million Anglophone	Economic freedom
United States	51	316.1	74.8
United Kingdom	54	62.9	78.4
Canada	58	30.5	77.9
Australia	57	21.7	82.4
Germany	55	45.4	72.5
India	33	194.1	56.5

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Table 17 – continued from previous page

Country	Civil liberties	Million Anglophone	Economic freedom
Netherlands	58	15.3	76.8
France	52	23	65.7
Turkey	16	12	64
Philippines	31	64.02598	64.1
China	11	10	58.4
Nigeria	24	178.19804	58.7
Sweden	60	9.236	74.7
Brazil	43	10.542	53.4
Spain	53	10.4	69.9
Italy	54	17	64.9
Russia	15	17.574303	61.5
Poland	48	14.3	69.7
Pakistan	22	102.321703	51.7
Switzerland	57	4.68	81.9
New Zealand	59	4.181902	83.9
Singapore	29	4.218737	89.7
Mexico	34	15.686262	65.5
South Africa	46	16.424417	59.7
Ireland	58	4.35	81.4
Israel	43	6.205	73.8
Belgium	57	6.25	70.1
Czechia	55	2.85	73.8
Vietnam	16	52.378645	61.7
Denmark	57	4.77	77.8
Japan	56	18.826121	74.1
Thailand	25	17.121187	69.7
Finland	60	3.8	76.1
Norway	60	4.5	73.4
Bangladesh	24	19.838772	56.5
Romania	48	5.9	69.5
Greece	50	5.5	60.9
South Korea	50	22.2654	74
Hong Kong	37	3.136784	58.4
Malaysia	30	15.58	74.4
Portugal	57	2.9	67.5
Austria	56	6.15	73.9
Ukraine	34	7.207962	56.2
Argentina	49	2.752681	52.7
Mongolia	48	0.725	62.4
Egypt	12	28.101325	55.7
Hungary	43	2	67.2

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Table 17 – continued from previous page

Country	Civil liberties	Million Anglophone	Economic freedom
Kenya	29	8.1	54.9
UAE	12	7.4175	76.9
Bulgaria	45	1.9	70.4
Serbia	42	4.8356	67.2
Colombia	36	2.01295	68.1
Iran	10	49.8147	47.2
Croatia	49	2.6	63.6
Algeria	22	2.51678	49.7
Ethiopia	13	0.171712	51.7
Sri Lanka	33	13.51786	55.7
Cambodia	19	3.5	57.3
Nepal	31	10.700866	50.7
Slovakia	53	1.4	66.3
Chile	55	1.585027	75.2
Lithuania	52	1.16	76.9
Zimbabwe	17	11.85071	39.5
Slovenia	56	1.21	68.3
Peru	42	2.6376	67.7
Estonia	56	0.65	78.2
Saudi Arabia	6	22.755	66

Table 18: Forecasting statistics and predictors by country, part 3 [23] [176] [177] [178]

Country	Gini coefficient	Happiness	Gender Inequality
United States	0.411	6.951	0.204
United Kingdom	0.351	7.064	0.109
Canada	0.333	7.103	0.08
Australia	0.344	7.183	0.097
Germany	0.319	7.155	0.084
India	0.357	3.819	0.488
Netherlands	0.281	7.464	0.043
France	0.324	6.69	0.049
Turkey	0.419	4.948	0.306
Philippines	0.423	5.88	0.43
China	0.385	5.339	0.168
Nigeria	0.351	4.759	0.518
Sweden	0.3	7.363	0.045
Brazil	0.534	6.33	0.408

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Table 18 – continued from previous page

Country	Gini coefficient	Happiness	Gender Inequality
Spain	0.347	6.491	0.07
Italy	0.359	6.483	0.069
Russia	0.375	5.477	0.225
Poland	0.302	6.166	0.115
Pakistan	0.316	4.934	0.538
Switzerland	0.331	7.571	0.025
New Zealand	0.362	7.277	0.094
Singapore	0.459	6.377	0.065
Mexico	0.454	6.317	0.322
South Africa	0.63	4.956	0.406
Ireland	0.314	7.085	0.093
Israel	0.39	7.157	0.123
Belgium	0.272	6.834	0.045
Czechia	0.25	6.965	0.136
Vietnam	0.257	5.411	0.296
Denmark	0.282	7.62	0.043
Japan	0.329	5.94	0.075
Thailand	0.349	5.985	0.359
Finland	0.273	7.842	0.039
Norway	0.276	7.392	0.038
Bangladesh	0.324	5.025	0.537
Romania	0.358	6.14	0.276
Greece	0.329	5.723	0.116
South Korea	0.314	5.845	0.047
Hong Kong	0.539	5.477	0.168
Malaysia	0.411	5.384	0.253
Portugal	0.335	5.929	0.079
Austria	0.308	7.268	0.069
Ukraine	0.266	4.875	0.234
Argentina	0.429	5.295	0.328
Mongolia	0.327	5.677	0.322
Egypt	0.315	4.283	0.449
Hungary	0.296	5.992	0.233
Kenya	0.408	4.607	0.518
UAE	0.26	6.561	0.079
Bulgaria	0.413	5.266	0.206
Serbia	0.362	6.078	0.132
Colombia	0.513	6.012	0.428
Iran	0.42	4.721	0.459
Croatia	0.297	5.882	0.116
Algeria	0.276	4.887	0.429

Continued on next page

Table 18 – continued from previous page

Country	Gini coefficient	Happiness	Gender Inequality
Ethiopia	0.35	4.275	0.517
Sri Lanka	0.393	4.325	0.401
Cambodia	0.379	4.83	0.474
Nepal	0.328	5.269	0.452
Slovakia	0.25	6.331	0.191
Chile	0.444	6.172	0.247
Lithuania	0.357	6.255	0.124
Zimbabwe	0.503	3.145	0.527
Slovenia	0.246	6.461	0.063
Peru	0.415	5.84	0.395
Estonia	30.3	6.189	0.086
Saudi Arabia	0.459	6.494	0.252

Table 19: Forecasting statistics and predictors by country, part 4 [23] [179]

Country	HDI	Expected education years	Life expectancy
United States	0.926	16.5	78.4
United Kingdom	0.932	17.4	81.3
Canada	0.929	16.4	82.2
Australia	0.944	22.9	83
Germany	0.947	17	81.7
India	0.645	12.3	70.8
Netherlands	0.944	18	81.8
France	0.901	16.4	82.5
Turkey	0.82	15.2	78.6
Philippines	0.718	12.6	70.4
China	0.761	13.8	77.4
Nigeria	0.539	10	62.6
Sweden	0.945	17.6	82.4
Brazil	0.765	15.4	75.9
Spain	0.904	17.9	83.2
Italy	0.892	16.3	83
Russia	0.824	15.5	73.2
Poland	0.88	16.4	78.3
Pakistan	0.557	8.6	69.3
Switzerland	0.955	16.2	83.4
New Zealand	0.931	18.9	82
Singapore	0.938	16.2	83.2

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Table 19 – continued from previous page

Country	HDI	Expected education years	Life expectancy
Mexico	0.779	14.1	76
South Africa	0.709	13.3	65.3
Ireland	0.955	19.6	81.8
Israel	0.919	15.9	82.6
Belgium	0.931	19.8	81.4
Czechia	0.9	16.9	79.1
Vietnam	0.704	12.7	73.7
Denmark	0.94	19.1	81.3
Japan	0.919	15.2	84.3
Thailand	0.777	14.7	77.7
Finland	0.938	17.6	81.6
Norway	0.957	17.9	82.6
Bangladesh	0.632	11.4	74.3
Romania	0.828	14.3	75.6
Greece	0.888	17.3	81.1
South Korea	0.916	16.5	83.3
Hong Kong	0.949	16.3	84.9
Malaysia	0.81	13.7	74.7
Portugal	0.864	16.3	81.6
Austria	0.922	16.1	83
Ukraine	0.779	15	73
Argentina	0.845	17.4	76.6
Mongolia	0.737	15.5	68.1
Egypt	0.707	13.1	71.8
Hungary	0.854	15.1	76.4
Kenya	0.601	12.1	66.1
United Arab Emirates	0.89	13.6	76.1
Bulgaria	0.816	14.8	75.1
Serbia	0.806	14.6	75.9
Colombia	0.767	14.4	79.3
Iran	0.783	14.9	77.3
Croatia	0.851	15	78.6
Algeria	0.748	14.4	77.1
Ethiopia	0.485	8.5	68.7
Sri Lanka	0.782	13.9	76.9
Cambodia	0.594	11.7	70.1
Nepal	0.602	12.2	70.9
Slovakia	0.86	15	78.2
Chile	0.851	16.4	80.7
Lithuania	0.882	16.1	76
Zimbabwe	0.571	10.3	60.7

Continued on next page

Table 19 – continued from previous page

Country	HDI	Expected education years	Life expectancy
Slovenia	0.917	17.2	81.3
Peru	0.777	13.8	79.9
Estonia	0.892	16.1	78.9
Saudi Arabia	0.854	16.9	74.3

10 Appendix C - flood warnings distributions by month

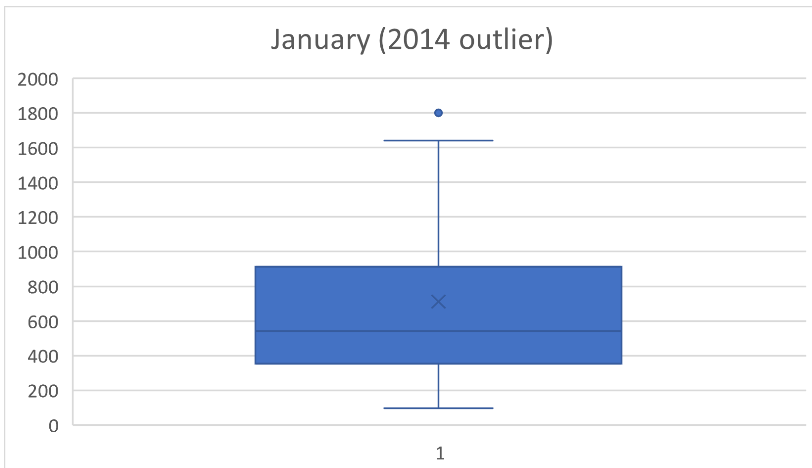

Figure 35: *Distribution of January flood warnings.*

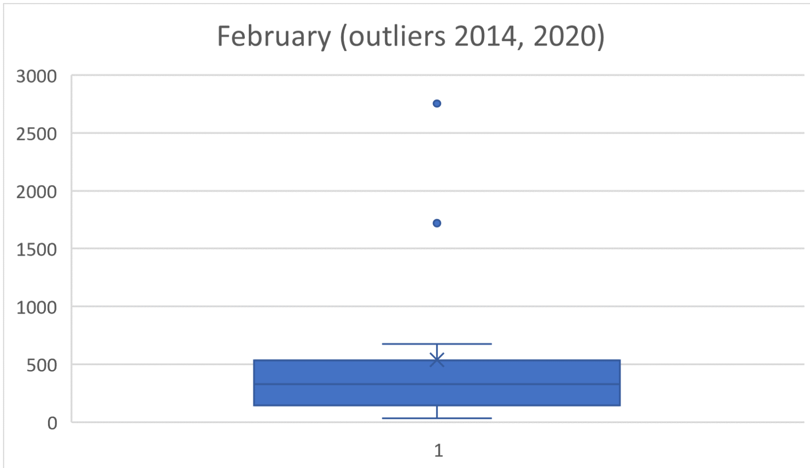

Figure 36: *Distribution of February flood warnings.*

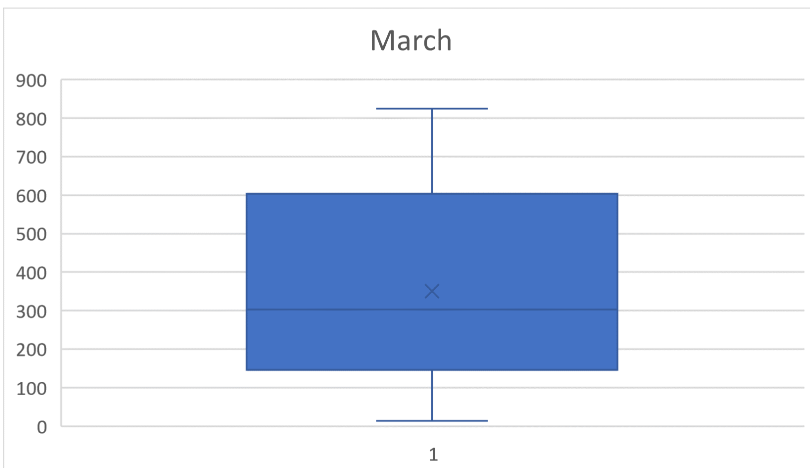

Figure 37: *Distribution of March flood warnings.*

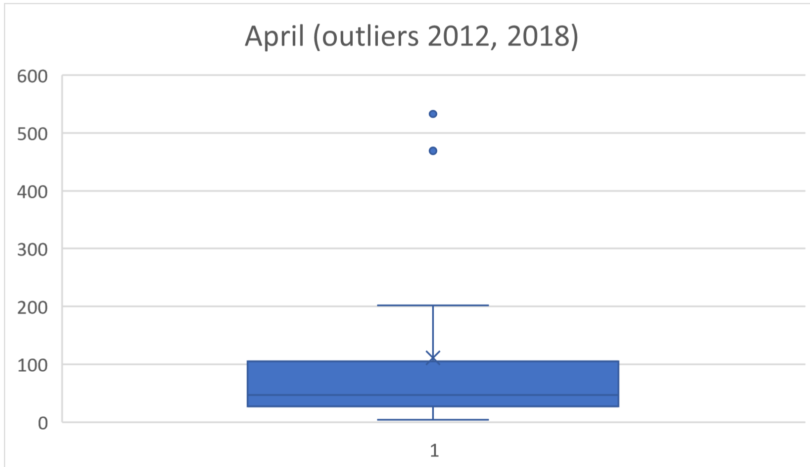

Figure 38: *Distribution of April flood warnings.*

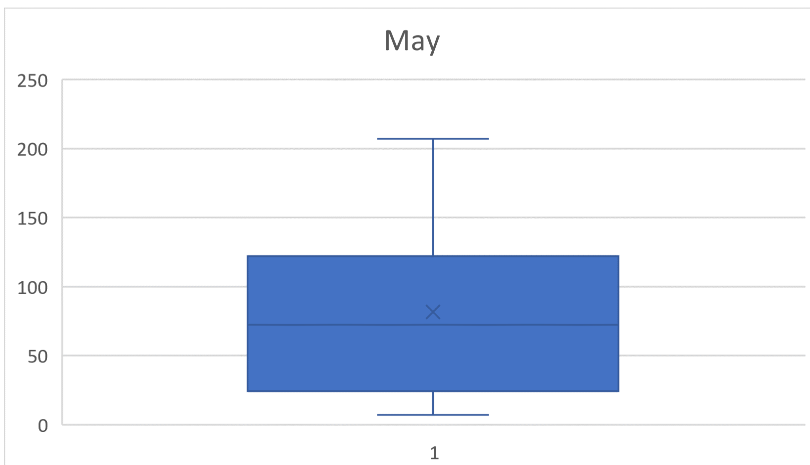

Figure 39: *Distribution of May flood warnings.*

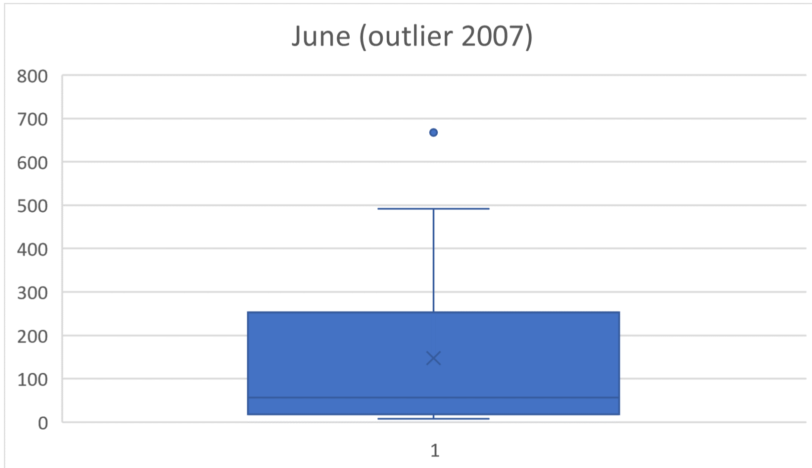

Figure 40: *Distribution of June flood warnings.*

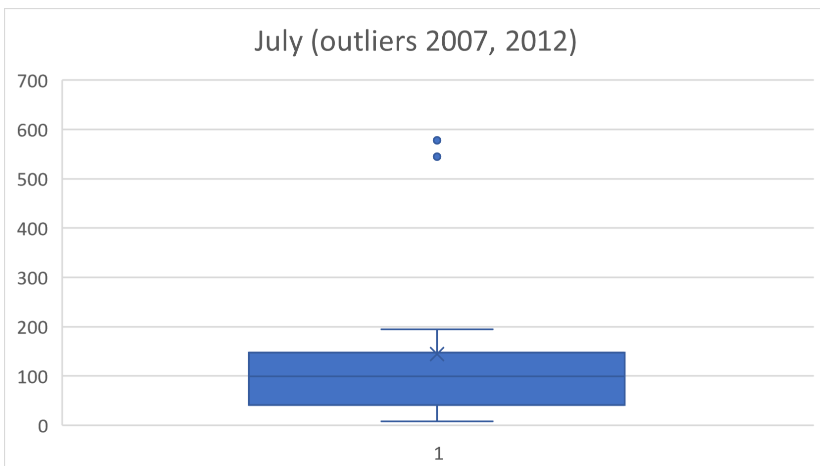

Figure 41: *Distribution of July flood warnings.*

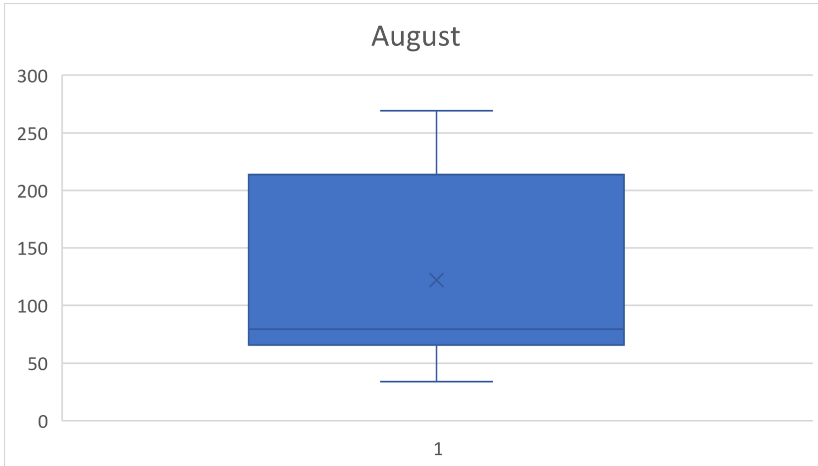

Figure 42: *Distribution of August flood warnings.*

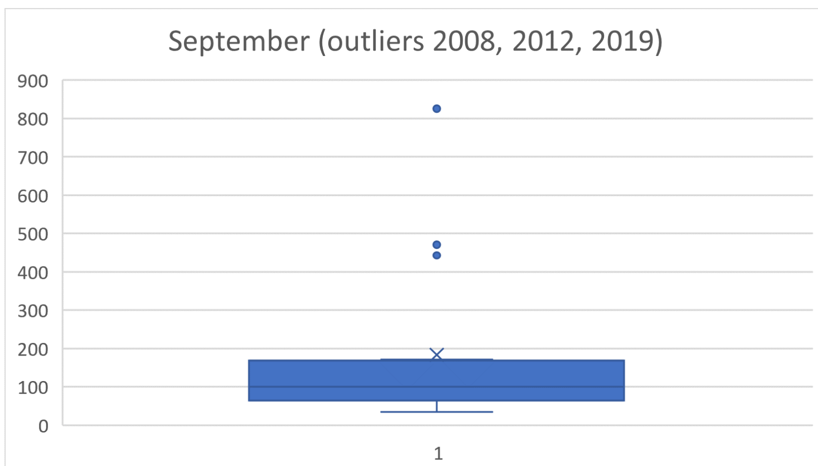

Figure 43: *Distribution of September flood warnings.*

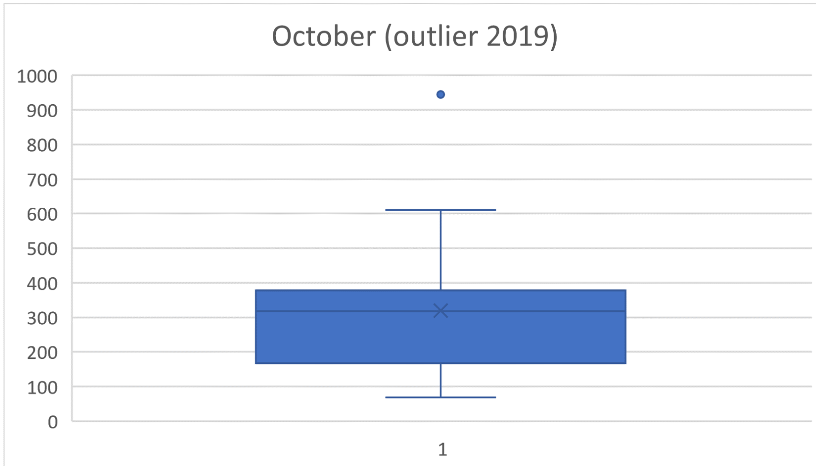

Figure 44: *Distribution of October flood warnings.*

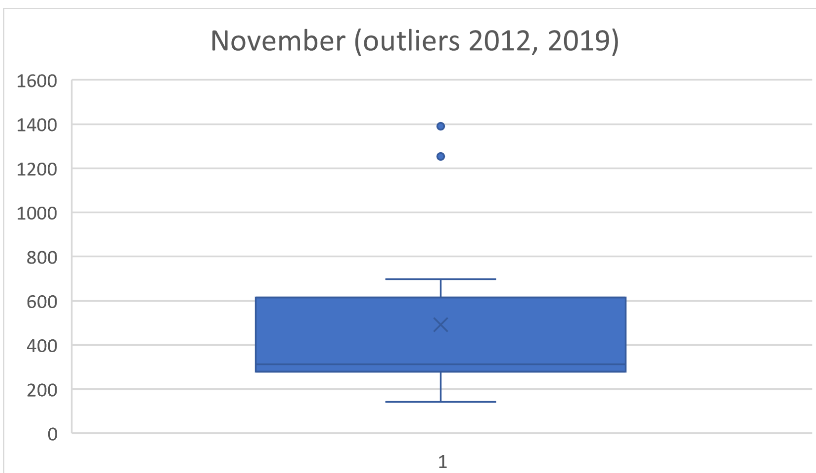

Figure 45: *Distribution of November flood warnings.*

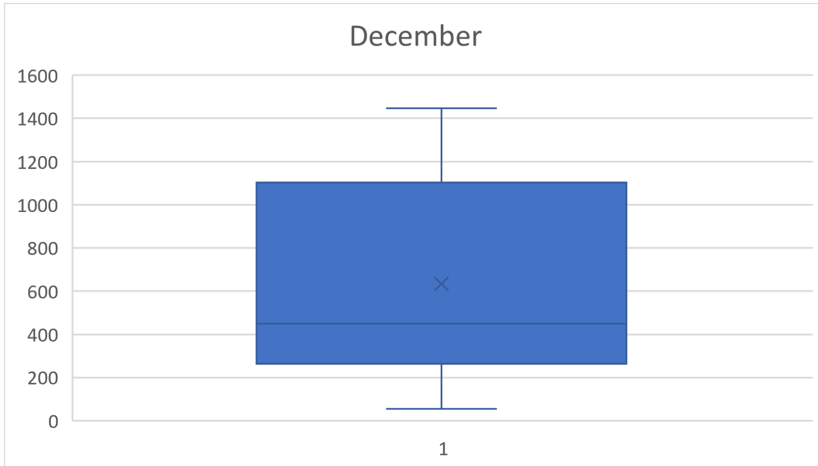

Figure 46: *Distribution of December flood warnings.*

11 Bibliography

1. Podesta J. The climate crisis, migration, and refugees [Internet]. Brookings. 2022 [cited 17 June 2022]. Available from: https://www.brookings.edu/research/the-climate-crisis-migration-and-refugees/ 2. Ritchie H, Roser M, Rosado P. CO_2 and Greenhouse Gas Emissions [Internet]. Our World in Data. 2022 [cited 17 June 2022]. Available from: https://ourworldindata.org/greenhouse-gas-emissions 3. Three degrees of global warming is quite plausible and truly disastrous [Internet]. The Economist. 2021 [cited 12 December 2021]. Available from: https://www.economist.com/briefing/2021/07/24/three-degrees-of-global-warming-is-quite-plausible-and-truly-disastrous

4. Ritchie H, Roser M. CO_2 and Greenhouse Gas Emissions [Internet]. Our World in Data. 2021 [cited 12 December 2021]. Available from: https://ourworldinda ta.org/greenhouse-gas-emissions

5. Carrington D. Last time CO2 levels were this high, there were trees at the South Pole [Internet]. the Guardian. 2021 [cited 12 December 2021]. Available from: https://www.theguardian.com/science/2019/apr/03/south-pole-tree-fossils-indicate-impact-of-climate-change

6. Texas University Corpus Christi. The Economic Aftermath of Harvey [Internet]. Stedc.tamucc.edu. 2021 [cited 12 December 2021]. Available from: http://stedc.tamucc.edu/files/HARVEY_Update_STEDC_2018Q3.pdf

7. Pidcock R, McSweeney R. Mapped: How climate change affects extreme weather around the world [Internet]. Carbon Brief. 2021 [cited 12 December 2021]. Available from: https://www.carbonbrief.org/mapped-how-climate-change-affects-extreme-weather-around-the-world

8. UNHCR. Grim milestone as Sahel violence displaces 2 million inside their countries [Internet]. UNHCR. 2021 [cited 12 December 2021]. Available from:

https://www.unhcr.org/uk/news/briefing/2021/1/600a92e4125/grim-milestone-sahel-violence-displaces-2-million-inside-countries.html
9. France's forever war in the Sahel [Internet]. The Economist. 2021 [cited 12 December 2021]. Available from: https://www.economist.com/middle-east-and-africa/2021/02/17/frances-forever-war-in-the-sahel
10.The Economist. See what three degrees of global warming looks like | The Economist. 2021. See what three degrees of global warming looks like | The Economist
11. Good Judgment® Open [Internet]. Gjopen.com. 2021 [cited 13 December 2021]. Available from: https://www.gjopen.com/faq 12. Cultivate Labs. What is forecast calibration?
https://www.cultivatelabs.com/prediction-markets-guide/what-is-forecast-calibration [Accessed 14th December 2021] 13. Pencina M, D'Agostino R. Evaluating Discrimination of Risk Prediction Models. JAMA. 2015;314(10):1063-1064. https://jamanetwork.com/journals/j-
ama/fullarticle/2434669. 14. Tetlock P, Gardiner D. Superforecasting. London: Random House Business; 2021. 15. The Economist. How spooks are turning to super forecasting in the cosmic bazaar. The Economist. April 17 2021. How spooks are turning to superforecasting in the Cosmic Bazaar | The Economist [Accessed 7th December 2021] 16. D. Wallace-Wells. The Uninhabitable Earth: Life after warming, first edition. New York: Tim Duggan books; 2019, The Uninhabitable Earth (crisrieder.org)
17. United Nations Framework Convention on Climate Change. New Climate Predictions Increase Likelihood of Temporarily Reaching 1.5 °C in Next 5 Years. https://unfccc.int/news/new-climate-predictions-increase-likelihood-of-temporarily-reaching-15-degc-in-next-5-years [Accessed 30th November 2021].
18. Morgan McFall-Johnsen. Painfully slow hurricanes, deadly heat, and cities without water: What the climate crisis will look like in the next 10 years, according to experts. https://www.businessinsider.com/climate-change-in-the-next-decade-2019-11?r=US&IR=T [Accessed 15th November 2021]
19. Al-Masri A. How Does Linear Regression Actually Work? [Internet]. Medium. 2022 [cited 15 March 2022]. Available from: https://towardsdatascie nce.com/how-does-linear-regression-actually-work-3297021970dd
20. SolarWinds. Holt-Winters Forecasting and Exponential Smoothing Simplified [Internet]. Orange Matter. 2022 [cited 15 March 2022]. Available from: https://orangematter.solarwinds.com/2019/12/15/holt-winters-forecasting-si - mplified/#: :text=The%20Holt%2DWinters%20method%20uses,%E2%80%9C-smooth%E2%80%9D%20a%20time%20series.
21. GJ Open. Good Judgment® Open [Internet]. Gjopen.com. 2022 [cited 15 March 2022]. Available from: https://www.gjopen.com/questions?status=act ive&tags=Environment
22. Metaculus. Metaculus [Internet]. Metaculus.com. 2022 [cited 15 March 2022]. Available from: https://www.metaculus.com/questions/?search=cat:en vironment–climate
23.Tamay Besiroglu, Email sent to Duncan McClements. 2nd December 2021
24. Statistics times, Continents by GDP, https://statisticstimes.com/economy/

continents-by-gdp.php, [accessed 15/03/2022]
25.Worldpopulationreview, population by continent 2022, https://worldpopulationreview.com/continents, [accessed 15/03/2022]
26. Environment Agency (2021). Historic Flood Warnings. UK Government Open Data. Dataset. 88bed270-d465-11e4-8669-f0def148f590
27. Department for Business, Energy and Industrial Strategy (2021) UK local authority and regional carbon dioxide emissions national statistics: 2005 to 2019. 2005 to 2019 local authority carbon dioxide (CO2) emissions dataset (revised). UK Government Open Data. Dataset.
28. Met Office; Hollis, D.; McCarthy, M.; Kendon, M.; Legg, T.; Simpson, I. (2021): HadUK-Grid Gridded Climate Observations on a 1km grid over the UK, v1.0.3.0 (1862-2020). NERC EDS Centre for Environmental Data Analysis, 08 September 2021. doi:10.5285/786b3ce6be54468496a3e11ce2f2669c
29. NOAA. *How Reliable Are Weather Forecasts?* https://scijinks.gov/forecast-reliability/#: :text=T
he%20Short%20Answer%3A,right%20about%20half%20the%20time [Accessed 16th March 2022]
30. Brian Gaze. *UK Seasonal Outlook* https://www.theweatheroutlook.com/forecast/uk-seasonal-weather-forecast [Accessed 16th March 2022]
31. Internet Archive. https://web.archive.org/web/2021*/https://www.theweatheroutlook.com/forecast/uk-seasonal-weather-forecast [Accessed 16th March 2022]
32. Uk energy mix data set UK Government, Fuel used in electricity generation and electricity supplied, https://www.gov.uk/government/statistics/electricity-section-5-energy-trends, 12/03/2022
33. Emelia Sithole, Mozambique's Chissano urges post-cyclone aid, Mozambique's Chissano urges post-cyclone aid - Mozambique | ReliefWeb, [accessed 14/03/2022]
34. Metoc.Navy, 2001 Annual tropical cyclone report, https://www.metoc.navy.mil/jtwc/products/atcr/2001atcr.pdf, [accessed 14/03/2022]
35. HurricaneScience, 2004 – Hurricane Jeanne, Hurricanes: Science and Society: 2004- Hurricane Jeanne (hurricanescience.org), [accessed 14/03/2022]
36. National Hurricane center, Tropical Cyclone report Hurricane Jeanne 13-28 September 2004, Tropical Cyclone Report (noaa.gov), [accessed 14/03/2022]
37. National hurricane center, Tropical cyclone report Hurricane Katrina 23-30 August 2005, Tropical Cyclone Report (noaa.gov), [accessed 14/03/2022]
38. The Guardian, More than 500 dead in typhoon Morakot, More than 500 dead in typhoon Morakot | Natural disasters and extreme weather | The Guardian, [accessed 14/03/2022]
39. Hui Hsuan Yang, Forensic investigation of Typhoon Morakot disaster: Nansalu and Daniao village case study, http://www.irdrinternational.org/wp-content/uploads/2013/04/Morakot-Report.pdf, [accessed 14/03/2022]
40. International federation of Red cross and Red crescent societies, Tropical storm Agatha, Final report, http://reliefweb.int/sites/reliefweb.int/files/resources/Full_Report_3835.pdf, [accessed 14/03/2022]
41. International federation of Red cross and Red crescent societies, Tropical

Stor
m washi, http://www.ifrc.org/docs/Appeals/11/MDRPH008fr.pdf, [access
ed 14/03/2022]
42. Phongchongthientai, ANG TONG HOP THIET HAI DO THIEN TAI, BAO
, LU NAM 2014, BlUQvfGh60KTfd2i2014-Tong hop 2014-CT.pdf (mard.gov.v
n), [accessed 14/03/2022]
43. Hindustantimes, Monsoon rain 24% excess so far, 60 die in Gujarat floods, Monsoon rain 24% excess so far, 60 die in Gujarat floods (archive.org), [accessed 14/03/2022]
44. Typhoon Committee, Reports on TC's key activities and main evnts in the region,2
016, Microsoft Word - 6.1 REPORT TC Chair_9 Dec..docx (typhooncommittee.org),
[accessed 14/03/2022]
45. CBS News, Hurricane Maria caused an estimated 2975 deaths in Puerto Rico new
study finds, Hurricane Maria: Death toll in Puerto Rico much higher, estimated at 2,
975, new study finds - CBS News, [accessed 14/03/2022]
46. National hurricane center,Tropical cyclone report: Hurricane Maria, https://www.nhc.noaa.gov/data/tcr/AL152017_Maria.pdf, [accessed 14/03/2022]
47. AON Benfield, Global catastrophe recap November 2020, Microsoft Word - Nov
ember Global Recap IF 2020.docx (aon.com), [accessed 14/03/2022]
48. Agence France-Presse, 27 killed by heavy storm in Western Burma, [accessed 14/03/2022]
49. Xinhua General News, storm kills 27 persons in Western Myanmar state [accessed 14/03/2022]
50. Brian Gaze. *United Kingdom regional outlook for days 30 to 150*
https://www.theweatheroutlook.com/twoforecasts/daily-ultra-long-range.aspx?region=6 [Accessed 15th March 2022]
51. Current Results. *Average Annual Precipitation for the United Kingdom.* https://en.climate- https://www.currentresults.com/Weather/United-Kingdom
/average-yearly-precipitation.php [Accessed 30th March 2022]
52. BBC. *Monthly Outlook.* https://www.bbc.co.uk/weather/outlook [Accessed 15th April 2022]
53. Environment Agency. *Flood alerts and warnings.* https://web.archive.org/w
eb/*/https://check-for-flooding.service.gov.uk/alerts-and-warnings [Accessed 2
9th April 2022]
54. theweatheroutlook. *London 16 day weather forecast.*
https://www.theweatheroutlook.com/forecast/uk/London [Accessed 18th April 2022]
55. Met Office. *Daily England & Wales precipitation (mm).*
https://www.metoffice.gov.uk/hadobs/hadukp/data/daily/HadEWP_daily_totals.txt
[Accessed 18th April 2022] 56. Jaganmohan M. Average wind speed UK 2001-2020 | Statista [Internet]. Statista. 2022 [cited 10 May 2022]. Available from:

https://www.statista.com/statistics/
322785/average-wind-speed-in-the-united-kingdom-uk/
57. Luza R. Wind Speed March 2019 - Willand Weather [Internet]. Web.archive.org. 2022 [cited 10 May 2022]. Available from: http://web.archive.org/web/20190318013519/https://www.willandweather.org.uk/wxwugraphs/graphm5a.php
58. Jaganmohan M. UK: hours of sunlight 2022 | Statista [Internet]. Statista. 2022 [cited 4 May 2022]. Available from: https://www.statista.com/statistics/584898/monthly-hours-of-sunlight-in-uk/
59. UK Met Office. UK climate averages [Internet]. Met Office. 2022 [cited 4 May 2022]. Available from: https://www.metoffice.gov.uk/research/climate/maps-and-data/uk-climate-averages
60. The Manila times, 8 dead, 15 missing as 'Dante' batters PH, https://www.manilatimes.net/2021/06/03/latest-stories/8-dead-15-missing-as-dante-batters-ph/1801799, [accessed 19/06/2022]
61. Joint typhoon warning center, Joint typhoon warning center, https://en.wikipedia.org/wiki/Joint_Typhoon_Warning_Center, [accessed 19/06/2022]
62. Vanuatu meteorological service, environmental degradation and migration – the experiences of Vanuatu, http://ips.ac.nz/events/downloads/2009/Climate%20Change%20and%20Migration%209-10%20July/BrianPhillips.pdf, [accessed 19/06/2022]
63. AP News Archive, Island Cyclone kills two, Island Cyclone Kills Two | AP News, [accessed 04/05/2022]
64. Liberation Societe, La Reunion Echappe au cyclone Connie, http://www.liberation.fr/societe/2000/01/31/la-reunion-echappe-au-cyclone-connie_312939 , [accessed 04/05/2022]
65. La Saison Cyclonique A Madagascar, Centre des cyclones Tropicaux de La reunion, http://www.meteo.fr/temps/domtom/La_Reunion/webcmrs9.0/anglais/archives/publications/saisons_cycloniques/index19992000.html, [accessed 04/05/2022]
66. Reliefweb, cyclone Hudah bringing heavy rain flood hit Mozambique, http://reliefweb.int/report/madagascar/cyclone-hudah-bringing-heavy-rain-flood-hit-mozambique, [accessed 04/05/2022]
67. Northern Territory news, Storm chaos: 2 feared dead; High winds lash Top End, [accessed 04/05/2022]
68. Reliefweb, Vanuatu and Fiji Islands - Tropical Cyclone Paula OCHA Situation Report No. 1, http://reliefweb.int/report/fiji/vanuatu-and-fiji-islands-tropical-cyclone-paula-ocha-situation-report-no-1, [accessed 04/05/2022]
69. Reliefweb, Vanuatu and Fiji Islands - Tropical Cyclone Paula OCHA Situation Report No. 2, http://reliefweb.int/report/fiji/vanuatu-and-fiji-islands-tropical-cyclone-paula-ocha-situation-report-no-2, [accessed 04/05/2022]
70. RSMC La Réunion, cyclone season 2001-2002, http://www.meteo.fr/temps/domtom/La_Reunion/webcmrs9.0/anglais/archives/publications/saisons_cycloniques/index20012002.html, [accessed 04/05/2022]
71. Gary Padgett, Monthly global tropical cyclone summary January 2002, http://www.australiansevereweather.com/cyclones/2002/summ0201.htm, [accessed 04/05/2022]

72. Pan African news agency, Cyclone takes heavy toll in Mauritius, http://reliefweb.int/report/mauritius/cyclone-takes-heavy-toll-mauritius, [accessed 04/05/2022]
73. Risques Naturales, Synthese des evenements: Dina, cyclone tropical intense, http://www.risquesnaturels.re/pdf/EVENEMENTS_HISTORIQUES/evenement_historique_Dina.pdf, [accessed 04/05/2022]
74. Bureau of meteorology, Australian tropical cyclone database, http://www.bom.gov.au/clim_data/IDCKMSTM0S.csv, [accessed 04/05/2022]
75. Associated press worldstream, Cyclone Chris batters remote coast of North-West Australia, https://web.archive.org/web/20121104095110/http://www.highbeam.com/doc/1P1-50006809.html, [accessed 04/05/2022]
76. Gary Padgett, Monthly global tropical cyclone summary March 2002, http://www.australiasevereweather.com/cyclones/2002/summ0203.htm, [accessed 04/05/2022]
77. National Oceanic and Atmospheric Administration, Storm data and unusual weather phenomena with late reports and corrections, https://www.webcitation.org/6RSd80qEJ?url=http://www1.ncdc.noaa.gov/pub/orders/IPS/IPS-5BA15DB9-B6A1-4BB8-A7F7-03D6F13F4E3B.pdf, [accessed 04/05/2022]
78. India Meteorological Department, Best tracks data: 2002, https://web.archive.org/web/20091116093857/http://www.imd.gov.in/section/nhac/dynamic/bestpara.xls, [accessed 04/05/2022]
79. World meteorological organisation, Panel on tropical cyclones annual review 2002, http://www.preventionweb.net/files/1527_7895.pdf, [accessed 04/05/2022]
80. Mannava V.K, Natural disasters and extreme events in agriculture: impacts and mitigation, https://books.google.com/books?id=SquWkdG19o8C&q=cyclone+kesiny&pg=PA13, [accessed 04/05/2022]
81. Reliefweb, two dead in Madagascar flooding, http://reliefweb.int/report/madagascar/two-dead-madagascar-flooding, [accessed 04/05/2022]
82. Wikileaks, Madagacsar after the political crisis: Averting a Humanitarian crisis, https://web.archive.org/web/20130615210205/http://www.cablegatesearch.net/cable.php?id=02ROME5132, [accessed 04/05/2022]
83. Tongan Ministry of Civil Aviation, A list of tropical cyclones that has affected at least a part of Tonga from 1960 to present, http://www.met.gov.to/index_files/tc_history.pdf, [accessed 04/05/2022]
84. Island vulnerability, an evaluation of participatory damage assessment policy and practice in Fiji, http://www.islandvulnerability.org/phd/meheuxphd.pdf, [accessed 04/05/2022]
85. The International Best Track Archive for Climate Stewardship, 2003 Gerry, http://www.atms.unca.edu/ibtracs/ibtracs_current/index.php?name=v04r00-2003037S12061, [accessed 04/05/2022]
86. Panapress, Cyclone Gerry leaves one dead in Mauritius, http://www.panapress.com/Cyclone–Gerry–leaves-one-dead-in-Mauritius–13-472638-17-lang2-index.html, [accessed 04/05/2022]
87. The Vancouver Sun, Earthweek: A Diary of the Planet, [accessed 04/05/2022]
88. ReliefWeb, WFP emergency report no 10, http://reliefweb.int/report/afghanistan/wfp-emergency-report-no-10-2003, [accessed 04/05/2022]
89. Africa News, Government reports on disaster, [accessed 04/05/2022]

90. Africa News, Zimbabwe; Elaborate Disaster Preparedness Plan Needed, [accessed 04/05/2022]
91. The Age, Cyclone Graham winds down, http://www.theage.com.au/articles/2003/03/01/1046407799918.html, [accessed 04/05/2022]
92. ABC news, WA cyclone warning downgraded, https://web.archive.org/web/20140103210040/http://www.abc.net.au/cgi-bin/common/printfriendly.pl?http%3A%2F%2Fwww.abc.net.au%2Fnews%2Fnewsitems%2F200303%2Fs795810.htm, [accessed 04/05/2022]
93. Radio New Zealand international, Repairs underway in new Caledonia after devastation of cyclone Erica, http://www.rnzi.com/pages/news.php?op=read&id=4009, [accessed 04/05/2022]
94. NDRRMC, NDDC media update typhoon 'Queenie', http://reliefweb.int/report/philippines/philippines-ndcc-media-update-typhoon-queenie-chebi-13-nov-2006, [accessed 17/06/2022]
95. Reliefweb, Mozambique: floods and cyclones fact sheet, http://reliefweb.int/report/mozambique/mozambique-floods-and-cyclone-fact-sheet-1-fy-2007, [accessed 17/06/2022]
96. International strategy for disaster reaction, Africa weekly spotlight, https://web.archive.org/web/20110526011719/http://www.unisdr.org/africa/af-whatnew/spotlight/march-2007-eng.pdf, [accessed 17/06/2022]
97. Agence France Presse, Cyclone Gamede sweeps over Indian Ocean islands, https://web.archive.org/web/20120523180408/http://mg.co.za/articlepage.aspx?area=%2Fbreaking_news%2Fbreaking_news__africa%2F&articleid=300217, [accessed 17/06/2022]
98. Réunion Regional Directorate for the Environment, http://www.reunion.developpement-durable.gouv.fr/IMG/pdf/epri_complet_web.pdf, [accessed 17/06/2022]
99. Reliefweb, Typhoid strikes Fiji in aftermath of cyclone Gene, http://www.reliefweb.int/rw/rwb.nsf/db900sid/EMAE-7BJR6R?OpenDocument&query=Cyclone%20Gene, [accessed 17/06/2022]
100. Reliefweb, Cyclone hits Madagascar threatens Mozambique, http://reliefweb.int/rw/rwb.nsf/db900sid/EVOD-7BXMK8?OpenDocument&query=Cyclone%20Ivan, [accessed 17/06/2022]
101. Meteo France, Moderate tropical storm Jokwe warning NR 004, ftp://ftp.met.fsu.edu/pub/weather/tropical/Seychelles/2008030512-FMEE, [accessed 17/06/2022]
102. An Lu, China evacuates 120,000 people as Typhoon Neoguri nears, http://news.xinhuanet.com/english/2008-04/18/content_8004532.htm, [accessed 17/06/2022]
103. National Oceanic and atmospheric administration, the worst natural disasters by death toll, http://docs.lib.noaa.gov/noaa_documents/NOAA_related_docs/death_toll_natural_disasters.pdf, [accessed 17/06/2022]
104. Eric S. Blake, Tropical cyclone report: Tropical storm Arthur, https://www.nhc.noaa.gov/data/tcr/AL012008_Arthur.pdf, [accessed 17/06/2022]
105. Joint typhoon warning center, JTWC tropical cyclone warning, https://www.webcitation.org/5sLaAab7C?url=https://listserv.illinois.edu/wa.cgi?A2=ind

1001c&L=wx-tropl&T=0&X=558D791777B97BA4EA&P=28897, [accessed 17/06/2022]
106. Bureau of meteorology, Issued at 11:03pm CST Monday 25 January 2010. Refer to tropical cyclone advice number 16, https://www.webcitation.org/5mZ31kczl?url=http://www.dynamicwebspace.com/10MB/duke_andy/IDD20040.TXT, [accessed 17/06/2022]
107. Webcitation.org, Webcite query result, https://web.archive.org/web/20171027032624/http://www.rnzi.com/pages/news.php?op=read&id=58438, [accessed 17/06/2022]
108. The Sydney morning Herald, Bianca's forerunner brought death and destruction, https://www.smh.com.au/environment/weather/biancas-forerunner-brought-death-and-destruction-20110130-1a9iv.html, [accessed 17/06/2022]
109. UN office for the coordination of Humanitarian affairs, Sri Lanka: Monsoon flood update situation report 13, http://reliefweb.int/sites/reliefweb.int/files/resources/74102ABFE9DAC5BAC12578360031639B-Full_Report.pdf, [accessed 17/06/2022]
110. Global post, Mozambique: Mozambique flood storms kill 22 and cut off Maputo, https://web.archive.org/web/20120126094148/http://www.globalpost.com/dispatch/news/regions/africa/120123/mozambique-floods-cyclone-funso-tropical-storms, [accessed 17/06/2022]
111. Linfo Re, L'ile Rodrigues epargnee par Ethel, http://www.linfo.re/-Societe,402-/L-ile-Rodrigues-epargnee-par-Ethel, [accessed 17/06/2022]
112. iol, Madagascar cyclone death toll at 31, http://www.iol.co.za/news/world/madagascar-cyclone-death-toll-at-31-1.1242464, [accessed 17/06/2022]
113. danida, Dac diem Khi truong Thuy van nam, http://danida.vnu.edu.vn/cpis/files/Dac_Diem_KTTV/dacdiemkttv_2012.pdf, [accessed 17/06/2022]
114. Agence France Presse, Tonga reports widespread damage and one death from cyclone Ian, https://www.news.com.au/tonga-takes-cover-as-category-four-cyclone-ian-crosses-over/news-story/4eeb630a07e62b6deb97aa275cff0e91, [accessed 17/06/2022]
115. National Disaster Risk Reduction and Management Council, Effects of tropical depression Agatone, https://www.webcitation.org/6UToo3By1?url=https://web.archive.org/web/20140329093236/http%3A//www.ndrrmc.gov.ph/attachments/article/1139/NDRRMC%20Update%20Sitrep%20No.%2033%20%201Feb%202014%206AM.pdf, [accessed 17/06/2022]
116. NC 1ere, June a fait une premiere victime, http://nouvellecaledonie.la1ere.fr/2014/01/21/june-fait-une-premiere-victime-102279.html, [accessed 17/06/2022]
117. L'Express de Madagascar, Le cyclone Deliwe devaste, https://web.archive.org/web/20140125180859/http://www.lexpressmada.com/blog/actualites/le-cyclone-deliwe-devaste-louest-de-madagascar-2137, [accessed 17/06/2022]
118. National Disaster Risk Reduction and Management Council, Final report: effects of tropical storm Basyang, https://www.webcitation.org/6jRnPYCI1?url=http://www.ndrrmc.gov.ph/attachments/article/2792/FINAL_REPORT_re_Effects_of_Tropical_Storm_BASYANG_(Kajiki)_30JAN_-_01FEB_2014.pdf, [accessed 17/06/2022]
119. National Oceanic and atmospheric administration, Event details: Rip cur-

rent Guam, http://www.ncdc.noaa.gov/stormevents/eventdetails.jsp?id=508938, [accessed 17/06/2022]
120. Reliefweb, Asia Pacific region; Weekly regional humanitarian snapshot, https://reliefweb.int/report/vanuatu/asia-pacific-region-weekly-regional-humanitarian-snapshot-11-17-march-2014, [accessed 17/06/2022]
121. Reliefweb, Tropical depression Hellen overview, http://reliefweb.int/map/madagascar/tropical-depression-hellen-overview-1-april-2014, [accessed 17/06/2022]
122. Reliefweb, Solomon's diarrhoea outbreak kills at least 18 children, http://reliefweb.int/report/solomon-islands/solomons-diarrhoea-outbreak-kills-least-18-children, [accessed 17/06/2022]
123. El Universal, Amanda rains leaves two dead in Michigan, http://reliefweb.int/report/solomon-islands/solomons-diarrhoea-outbreak-kills-least-18-children, [accessed 17/06/2022]
124. Philippine news agency Interaksyon, Storm 'Amang' leaves 3 people dead, https://web.archive.org/web/20150402112905/http://www.interaksyon.com/article/103439/storm-amang-leaves-3-people-dead-p318-7m-in-damages-in-bicol, [accessed 17/06/2022]
125. Chicago tribune, Flood death toll across Southern Africa reaches 260, http://www.chicagotribune.com/news/sns-wp-blm-news-bc-africa19-20150119-story.html, [accessed 17/06/2022]
126. The weather company, Tropical depression nine-C dissipates; caps off a record central pacific hurricane season, http://www.weather.com/storms/hurricane/news/central-pacific-tropical-depression-nine-c-storm-pali, [accessed 19/06/2022]
127. National Hurricane centre, Tropical cyclone report; Hurricane Alex, http://www.nhc.noaa.gov/data/tcr/AL012016_Alex.pdf, [accessed 19/06/2022]
128. Jeff Masters, Winstons damage highest in South Pacific history; Extreme February warmth in Eurasia, https://www.wunderground.com/blog/JeffMasters/winstons-damage-highest-in-south-pacific-history-extreme-february-wa.html, [accessed 19/06/2022]
129. One news NZ, Fijian residents prepare for long night as Cyclone Zena set to make landfall, https://www.tvnz.co.nz/one-news/world/fijian-residents-prepare-long-night-cyclone-zena-set-make-landfall, [accessed 19/06/2022]
130. Seychelles News Agency, $4.5 million in damage from cyclone that hit remote Seychellois island, world bank says, http://www.seychellesnewsagency.com/articles/5175/.+million+in+damages+from+cyclone+that+hit+remote+Seychellois+island%2C+World+Bank+says, [accessed 19/06/2022]
131. The Japan times, Sri Lanka finds more landslide fatalities, warns of flood-triggered health crisis, http://www.japantimes.co.jp/news/2016/05/23/world/sri-lanka-finds-landslide-fatalities-warns-flood-triggered-health-crisis/#.V0JrhpF97IV, [accessed 19/06/2022]
132. WECT news, Body of missing swimmer found on Kure beach, http://www.wect.com/story/32107325/crews-respond-to-body-found-on-kure-beach?sf27597408=1, [accessed 19/06/2022]
133. AON Benfield, global catastrophe recap January 2017, http://thoughtleadership.aonbenfield.com/Documents/20170208-ab-analytics-if-january-global-reca

p.pdf, [accessed 19/06/2022]
134. AON Benfield, global catastrophe recap March 2017, http://thoughtleadership.aonbenfield.com/Documents/20170407-ab-analytics-if-march-global-recap.pdf, [accessed 19/06/2022]
135. AON Benfield analytics, global catastrophe recap April 2017, http://thoughtleadership.aonbenfield.com/Documents/20170509-ab-analytics-if-april-global-recap.pdf, [accessed 19/06/2022]
136. The watchers, Cyclone "Cook" hits New Caledonia, leaving 1 dead, 20000 without power, https://watchers.news/2017/04/10/cyclone-cook-hits-new-caledonia-leaving-20-000-without-power/, [accessed 19/06/2022]
137. Philstar, Crising death toll in Cebu rises to 10, http://news.mb.com.ph/2017/04/17/crising-death-toll-in-cebu-rises/, [accessed 19/06/2022]
138. DVB, 4 killed as Cyclone Maarutha hits Irrawaddy Delta, https://web.archive.org/web/20170602105548/http://www.dvb.no/news/4-killed-cyclone-maarutha-hits-irrawaddy-delta/75157, [accessed 19/06/2022]
139. Solomon star, Damages reported in Temotu, https://www.webcitation.org/6qVuWt2lq?url=http://www.solomonstarnews.com/news/national/12838-damages-reported-in-temotu, [accessed 19/06/2022]
140. UN News, Sri Lanka: UN agency deploys rapid assessment teams to assist in wake of monsoon floods, landslides, https://www.un.org/apps/news/story.asp?NewsID=56866#.WUYh3BE6zIU, [accessed 19/06/2022]
141. AON Benfield, global catastrophe recap April 2018, http://thoughtleadership.aonbenfield.com/Documents/20180509-ab-analytics-if-april-global-recap.pdf, [accessed 19/06/2022]
142. NDRRMC, SitRep No. 11 re re Preparedness Measures and Effects for Tropical Storm "BASYANG" (I.N. SANBA), https://web.archive.org/web/20181012193123/http://www.ndrrmc.gov.ph/attachments/article/3317/SitRep_No_11_re_Preparedness_Measures_and_Effect_for_TS_Basyang_SANBA_as_of_23FEB2018_0800H.pdf, [accessed 19/06/2022]
143. Dailypost, two more TC Hola deaths confirmed, http://dailypost.vu/news/two-more-tc-hola-deaths-confirmed/article_eafa4194-e320-5fe9-b569-5d03bb4b4ffa.html, [accessed 19/06/2022]
144. Prensa Latina, Dozens deaths confirm Malagasy's fear of cyclone, http://www.plenglish.com/index.php?o=rn&id=25871&SEO=dozens-deaths-confirm-malagasys-fear-of-cyclone, [accessed 19/06/2022]
145. Reliefweb, World vision East Africa hunger crisis situation report: Ethiopia, https://reliefweb.int/sites/reliefweb.int/files/resources/Ethiopia-May2018-final.pdf, [accessed 19/06/2022]
146. WHEC news, cyclone death toll in Oman, Yemen rises to at least 13, https://web.archive.org/web/20180528220032/http://www.whec.com/national/oman-raises-death-toll-in-aftermath-of-cyclone-mekunu-to-6/4926039/?cat=10049, [accessed 19/06/2022]
147. AON Benfield, global catastrophe recap June 2018, http://thoughtleadership.aonbenfield.com/Documents/20180710-ab-analytics-if-june-global-recap.pdf, [accessed 19/06/2022]
148. Xinhua, 5 killed 1400 houses destroyed by cyclone in Myanmar, http://www.xinhu

anet.com/english/2018-05/31/c_137220716.htm, [accessed 19/06/2022]
149. CNN, storm kills 3 in Thailand, moves into Andaman sea, https://www.cnn.com/2019/01/04/asia/thailand-tropical-storm-pabuk-intl/index.html, [accessed 19/06/2022]
150. Alfred Dalizon, Landslide buried 7 treasure hunters in Agusan del norte, https://journal.com.ph/news/provincial/landslide-buries-7-treasure-hunters-agusan-del-norte, [accessed 19/06/2022]
151. BBC news, hundreds feared dead after cyclone Idai, https://www.bbc.com/news/world-africa-47609676, [accessed 19/06/2022]
152. The associated press, Mozambique church a refuge for Muslim cyclone survivors, https://www.sfgate.com/news/world/amp/Mozambique-church-a-refuge-for-Muslim-cyclone-13809328.php, [accessed 19/06/2022]
153. NDTV, number of dead from cyclone Fani rises to 29 in Odisha, https://www.ndtv.com/india-news/number-of-dead-from-cyclone-fani-rises-to-29-in-odisha-2033234, [accessed 19/06/2022]
154. Stuff, Cyclone Tino: 2 missing as cyclone gains strength over Fiji, https://www.stuff.co.nz/world/south-pacific/118881266/cyclone-tino-to-make-landfall-on-fijis-vanua-levu-by-midnight, [accessed 19/06/2022]
155. Reliefweb, Madagascar heavy rains and floods flash update no. 1, https://reliefweb.int/report/madagascar/madagascar-heavy-rains-and-floods-flash-update-no-1-26-january-2020, [accessed 19/06/2022]
156. BBC News, dozens dead in Brazil flooding and landslides, https://www.bbc.com/news/world-latin-america-51254669, [accessed 19/06/2022]
157. news.com, swimmer drowns at Bondi beach, https://www.news.com.au/national/nsw-act/news/swimmer-drowns-at-bondi-beach/news-story/06f7a43432f39c9f2c31a0a2afb80ca1, [accessed 19/06/2022]
158. Imaz press reunion, Francisco: un mort et plus d'un millier de sinistres a Madagascar, http://www.ipreunion.com/actualites-reunion/reportage/2020/02/17/il-s-agirait-d-une-fillette-de-deux-ans-francisco-un-mort-et-des-milliers-de-sinistres-a-madagascar,114837.html, [accessed 19/06/2022]
159. L'express de Madagascar, Herold drenches Madagascar, https://lexpress.mg/17/03/2020/sava-et-analanjirofo-plus-de-trois-mille-sinistres-de-herold/, [accessed 19/06/2022]
160. The weather channel, Tropical cyclone Harold scraping parts of Tonga after hammering Fiji and Vanuatu, https://weather.com/storms/hurricane/news/2020-04-04-tropical-cyclone-harold-forecast-south-pacific-vanuatu-fiji, [accessed 19/06/2022]
161. Manila standard, 5 dead P80 million lost in Typhoon 'Ambo' wake, https://manilastandard.net/news/national/323946/5-dead-p80-million-lost-in-typhoon-ambo-wake.html, [accessed 19/06/2022]
162. rsmcnewdelhi.imd.gov.in, super cyclonic storm Amphan over the Southeast bay of Bengal, http://www.rsmcnewdelhi.imd.gov.in/images/pdf/publications/preliminary-report/amphan.pdf, [accessed 19/06/2022]
163. Summer Dashe, drowning reported in Myrtle beach Wednesday after tropical storm Bertha hit coast, https://wpde.com/news/local/drowning-reported-in-myrtle-beach-wednesday-after-tropical-storm-bertha-hit-coast, [accessed 19/

06/2022]
164. Gulf news, three people die due to heavy rains in Oman, https://gulfnews.com/world/gulf/oman/three-people-die-due-to-heavy-rains-in-oman-1.71772435, [accessed 19/06/2022]
165. National Hurricane centre, Tropical cyclone report: tropical storm Amanda, https://www.nhc.noaa.gov/data/tcr/EP022020_Amanda.pdf, [accessed 19/06/2022]
166. AON Benfield, global catastrophe recap 2021, http://thoughtleadership.aonbenfield.com//Documents/20210209_analytics-if-january-global-recap.pdf, [accessed 19/06/2022]
167. NDRRMC, SitRep no 12 re preparedness measures and effects for TEFS, LPA's and ITCZ, https://ndrrmc.gov.ph/attachments/article/4142/Sitrep_No_12_TEFS_LPA_ITCZ_Update.pdf, [accessed 19/06/2022]
168. NDRRMC, SitRep no 09 preparedness measures and effects for STS Auring, https://ndrrmc.gov.ph/attachments/article/4144/SitRep_No_9_TC_Auring_2021_Update.pdf, [accessed 19/06/2022]
169. Xinhua, death toll from tropical cyclone Seroja in Indonesia rises increases to 181, 47 still missing, http://www.xinhuanet.com/english/asiapacific/2021-04/14/c_139880477.htm, [accessed 19/06/2022]
170. NDRRMC, SitRep no 06 re preparedness measures and effects for Typhoon Bis
ing, https://ndrrmc.gov.ph/attachments/article/4150/SitRep_No_6_TC_Bising_2021_Update.pdf, [accessed 19/06/2022]
171. Reliefweb, India – Tropical cyclone TAUKTAE updates (GDACS, IMD, NDM India) (ECHO daily flash of 19 May 2021), https://reliefweb.int/report/india/india-tropical-cyclone-tauktae-update-gdacs-imd-ndm-india-echo-daily-flash-19-may-2021, [accessed 19/06/2022]
172. worldometers, GDP per capita, https://www.worldometers.info/gdp/gdp-per-capita/, [accessed 15/03/2022]
173. Freedom house, Countries and territories, https://freedomhouse.org/countries/freedom-world/scores, [accessed 15/03/2022]
174. worldpopulationreview, English speaking countries 2022, https://worldpopulationreview.com/country-rankings/english-speaking-countries,[accessed 15/03/2022]
175. Heritage (2022). Index of Economic Freedom. 2022. Heritage. Dataset. https://www.heritage.org/index/ 176. worldpopulationreview, Gini coeffecient by country 2022, https://worldpopulatio
nreview.com/country-rankings/gini-coefficient-by-country, [accessed 15/03/2022]
177. Human development reports, Gender inequality index (GII), https://www.hdr.undp.org/en/content/gender-inequality-index-gii, [accessed 15/03/2022]
178. worldpopulationreview, Happiest countries in the world 2022, https://worldpopulationreview.com/country-rankings/happiest-countries-in-the-world, [accessed 15/03/2022]
179. Ourworldindata, Human development index (HDI), https://ourworldindata.org/human-development-index, [accessed 15/03/2022]