Who Will Become Climate Refugees?

An Analysis of Climate Change's Future Impact on Least Developed Countries

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1 Executive Summary

In this report I identify the Least Developed Countries which are most likely to be adversely impacted by climate change. Specifically, I determine which countries are expected to see rising instances of extreme heat and increased heavy precipitation events over the next decade. This analysis will better inform governments as they create climate refugee programs in the years ahead.

1.1 Background

The United Nation's 2018 Intergovernmental Panel on Climate Change highlights the numerous adverse consequences climate change will have on human populations. However, these adverse impacts are not evenly distributed. One group which is identified as being disproportionately at risk are individuals living in one of the world's 46 Least Developed Countries (countries with the lowest indicators of socio-economic development) [1] [2] .

Climate change can affect populations through a variety of channels such as health effects, natural disasters food security, water supply, among others. What makes the populations of Least Developed Countries particularly vulnerable is because of their low development they will struggle to marshal the necessary resources to adequately mitigate the future effects of climate change. For example, it is difficult to mitigate the health effects of climate change induced extreme heat in countries where the electricity grids are unreliable, and air conditioning is prohibitively expensive. There is also a basic fairness issue at play in that the richest most developed countries, which are also the largest carbon emitters, have largely caused climate change, but the Least Developed Countries are the ones most likely to be adversely impacted by it.

The potential for climate change to accelerate in the decades ahead has to led calls for the refugee system to adapt to accommodate individuals who have been displaced by climate change [7]. The current system's shortcomings are made clear when considering the refugee policies of Canada, a country with one of the most robust immigration policies in the world. In Canada, in order to resettle as a refugee one must either apply as a convention refugee (individuals who cannot return to their home country based on fear of persecution based on such things as race, religion, and gender) or an asylum seeker (individuals seriously affected by armed conflict or having being denied human rights on an ongoing basis); clearly there is no category which would accommodate individuals displaced by climate change [4].

Two impacts of climate change which are likely to adversely impact populations in Least Developed countries are extreme heat and extreme precipitation. Extreme heat is associated with a number of negative health outcomes such as heat exhaustion, a worsening of cardiovascular/respiratory/diabetes conditions, and increased transmission of food and water-borne diseases. On the other hand, extremely high precipitation will lead to an increased prevalence of flooding, and the health and economic effects that go with it.

Identifying Least Developed Countries which are most likely to experience more instances of extreme heat and extreme precipitation will help policy-makers craft effective, and compassionate, climate refugee policies, to the benefit of those likely to be displaced by climate change. These policies will become more important in the years ahead as the effects of climate change become more intensely felt.

Figure 1: Individuals in Mozambique displaced by Cyclone Idai, which featured strong winds and extremely heavy precipitation. Scientists believe that rising temperatures can lead to increased cyclone intensity. *Photo taken March 2019 - UNICEF*

1.2 Summary of Findings

From a statistical analysis of historical temperature and precipitation data I was able to identify a number of Least Developed Countries that are most at risk from increased extreme heat and extreme precipitation in the years ahead[1]. Generally, these are countries that currently experience high maximum temperatures where there is strong evidence they will increase over the next decade, as well as countries which presently experience heavy rains with strong evidence of these rains intensifying over time.

Country Name	Increased Extreme Heat	Increased Extreme Precipitation
Bangladesh	✓	✓
Benin		✓
Burkina Faso	✓	✓
Cambodia		✓
Central African Republic	✓	✓
Chad		✓
Gambia	✓	
Guinea	✓	✓
Guinea-Bissau		✓
Mali	✓	✓
Niger	✓	
Uganda	✓	

Table 1: Least Developed Countries identified as being at risk from climate change induced increased extreme heat and extreme precipitation events.

From the above table it appears the countries which most urgently need to be prioritized in climate refugee policies include: Bangladesh, Burkina Faso, The Central African Republic, Guinea, and Mali, as they are at risk of increases in both extreme heat and extreme precipitation.

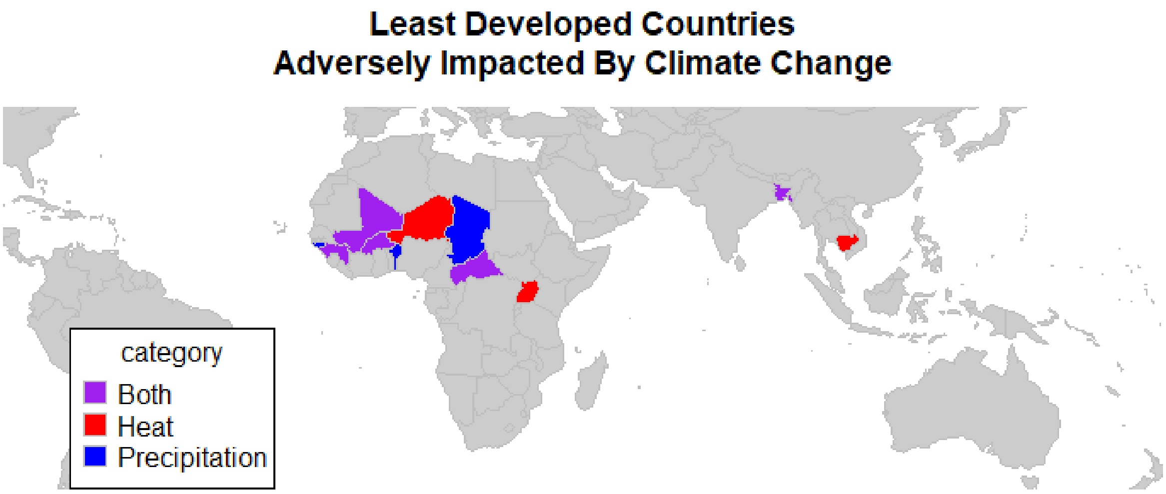

Figure 2: Least Developed Countries identified as being at risk from climate change induced increased extreme heat and extreme precipitation events.

[1]Note throughout this report extreme precipitation refers to extremely high levels of precipitation.

2 Technical Exposition

In this section, I describe the statistical tools I utilized in order to arrive at my conclusions. I will begin with a brief discussion of the dataset in Section 2.2, in Section 2.3 I will discuss my analysis of trends in extreme heat, and in Section 2.4 I will discuss my analysis of trends in extreme precipitation. Areas of further analysis are discussed in the Appendix in Section 3.3.

2.1 General Approach

The approach I took to answering these two questions was very much a hypothesis testing approach where I sought to answer the question “is there strong evidence that maximum temperatures and/or extreme precipitation are increasing over time in a specific country”. Given this, I utilized two statistical procedures to test for the existence of trends in the temperature and precipitation time series I used.

2.2 Data Collection & Cleaning

2.2.1 Description of Dataset

Both datasets which I utilized came from the United State’s National Oceanic and Atmospheric Administration (NOAA). Both datasets are daily estimates of maximum temperatures, and precipitation levels, for each cell in a grid covering the world with a resolution 0.5 latitude x 0.5 longitude (259,200 grid cells total). The datasets can be accessed at `ftp2.psl.noaa.gov` [6]. The time period covered is from 1980-2020.

From this dataset I extracted the time series of daily maximum temperature and precipitation observations of the capital city of each Least Developed Country. There were a small number of countries where data was missing for several years leading up to and including 2020. These countries were predominantly small island nations and are listed in Section 3.2. Given the importance of this missing data these countries were not analysed, leaving 36 countries for analysis. To deal with the remaining anomalous missing values I replaced each missing value with the last observation in each time series. The NOAA lists 25 days (out of 14695) where all grid squares have missing data.

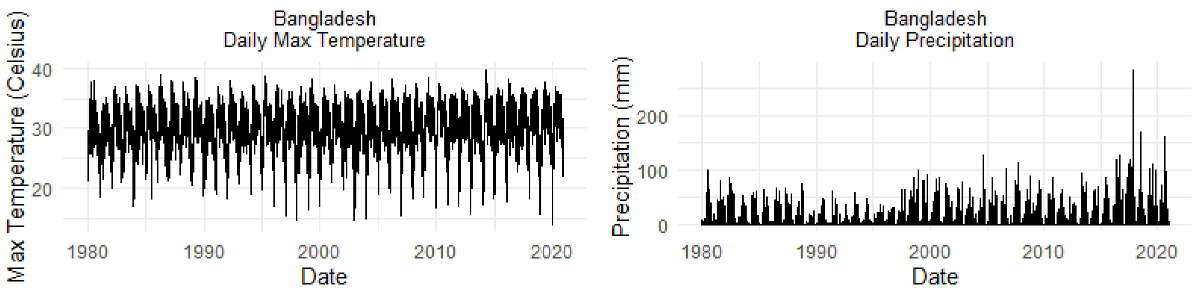

Figure 3: Example time series extracted from NOAA dataset of daily maximum temperature and daily precipitation for the country of Bangladesh 1980-2020.

2.2.2 Seasonality in the Data

I dealt with seasonality for each problem slightly differently. For investigating extreme heat I took weekly maximum temperatures and subtracted from each week the average value of its maximum temperatures over 1980-2020 in order to arrive at a time series of temperature anomalies, which I then conducted statistical tests on, to see if these anomalies were increasing.

For the investigation of precipitation I divided the year into 13 four-week periods, and in my statistical analysis utilized a dummy variable to represent which period each observation was for. From the output of my regression analysis I could then infer what the seasonal effects were. Note that I used 13 four-week periods instead of 52 weeks to arrive at clearer statistical conclusions (i.e. I only had to make inferences about what will happen to precipitation in 13 periods throughout the year instead of a more unwieldy 52 periods).

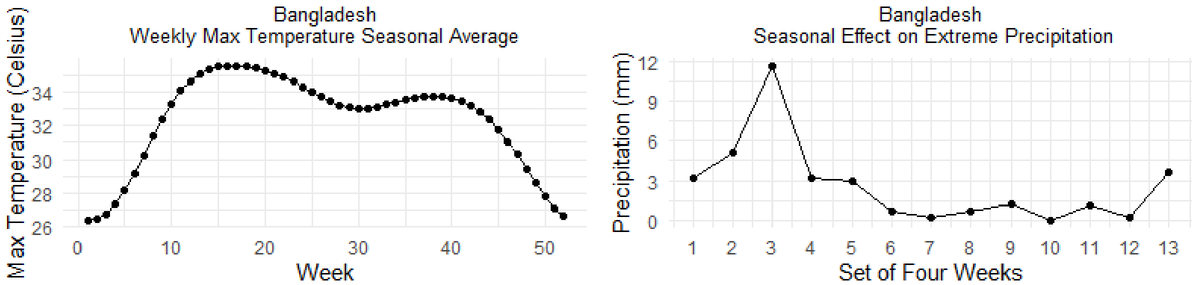

Figure 4: Example of seasonal effects on maximum temperature and precipitation for the country of Bangladesh 1980-2020.

2.3 Extreme Heat Analysis

2.3.1 Setup

In analysing which countries' populations may become increasingly affected by the impacts of climate change, the most important questions that arise have to do with what will climate will look like in the distant future. Knowing whether there will be a heatwave in a country next year is far less important than knowing if in 10 or 20 years time there will be recurring heatwaves of high intensity every year, necessitating the resettlement of individuals affected. However, forecasting far into the future is fraught with difficulty, and requires a far different toolkit than short-term forecasts.

Long-term forecasting of time series can be made much easier if we can be confident in what the underlying trend is. Given that any time series at time t can be described as

$$\text{Observed Value}_t = \text{Trend}_t + \text{Noise}_t \tag{1}$$

if we are able to confidently say that as t changes Trend_t follows a parametric form (e.g. it evolves linearly with t, or is a quadratic function), then we should be able to say, with some confidence, what Trend_t will be in the future. On the other hand, if we are unable to confidently say how Trend_t evolves, guessing what its values far into the future with any confidence will be extremely difficult to do.

In the analysis of extreme heat, I have sought to categorize the trend in the maximum temperatures of Least Developed Countries. Then, for countries where I can say with high confidence that the trend is linear or quadratic, I calculate how much maximum temperatures will have changed by 2030 to determine which countries are most at risk from increased extreme heat events.

2.3.2 Testing Parametric Assumptions in Trends of Maximum Temperatures

In order to classify the trend in the maximum temperatures of different countries I have implemented the paper *Testing Parametric Assumptions of Trends of a Nonstationary Time Series* - Biometrika (Zhang, Wu 2011) [8] in R; a modern method for which no R package currently exists. The key reason behind using this paper is the statistical test it proposes is robust to nonstationarity (i.e. does the noise around the trend change over time). Time series from climatology almost always exhibit some sort of nonstationarity, and if possible, it is vitally important to take this into account when testing for trends. To see why consider Figure 5:

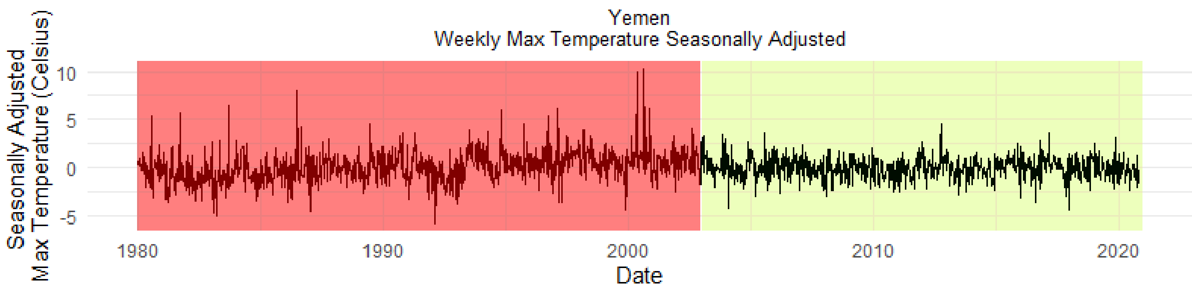

Figure 5: Seasonally adjusted weekly max temperatures in Yemen. It appears that there was more variability in the measurements of Yemen's temperature before 2002, and less afterwards.

As one can see the readings of Yemen's temperatures are significantly less volatile after 2002. Running a simple linear regression results in a statistically significant positive linear trend which is likely a spurious result due to the high variability around the year 2000 and lower variability afterwards.

At a high level what the method proposed by Zhang and Wu does is use a locally linear smoother to obtain a non-parametric estimate of the trend function. Then, they compare this estimate to a parametric trend. If the non-parametric estimate is similar to the parametric one then one can conclude the trend is likely of a parametric form. We can see an example of this in Figure 6 where the parametric trend defined by a quadratic function fits reasonably closely to the non-parametric trend estimate.

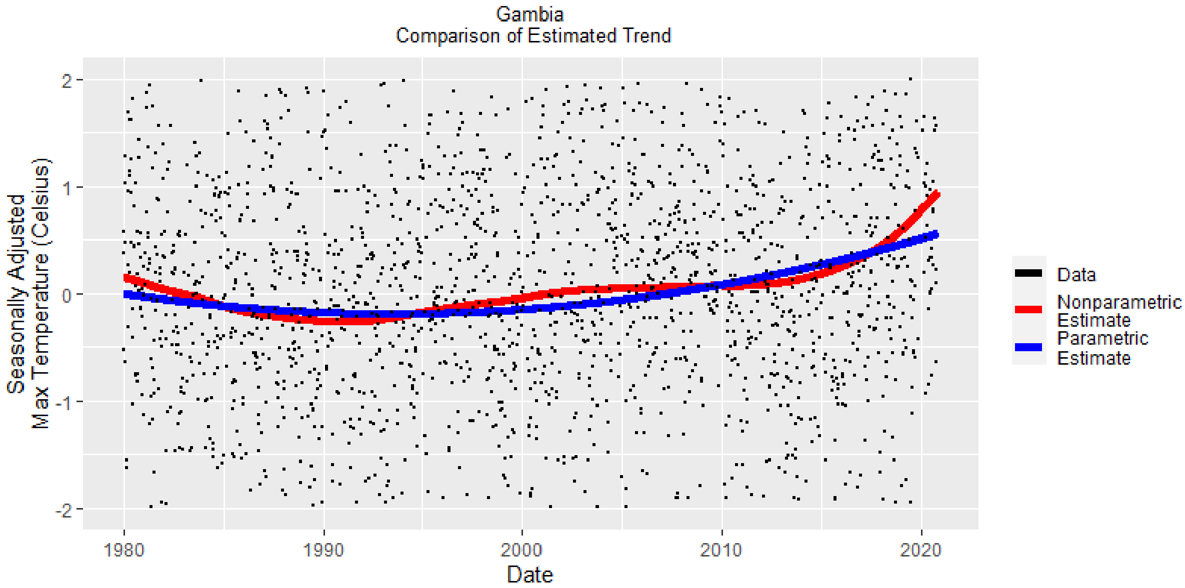

Figure 6: Seasonally adjusted weekly max temperatures in Gambia. One can see the quadratic parametric trend estimate closely matches the non-parametric estimate, suggesting the true trend follows a quadratic parametric form. Note the y-axis has been truncated to allow for better examination of the trends.

I would note that in order to use this method, a bandwidth parameter must be selected. Details on the cross validation procedure used to select this bandwidth is given in Section 3.6. A more thorough technical explanation of this statiscial method is given in Section 3.5.

2.3.3 Results

For each country a constant, linear, and quadratic parametric trend were tested. The parametric trend with the least complexity (i.e. constant<linear<quadratic) which was not rejected by the testing procedure at a significance level of .01 was then used for estimating the change in level of maximum temperatures a decade out. Some countries' trends were unable to be detected by this testing method, and hence it is vastly more difficult to anticipate what the trend going forward for them will be. Countries of this nature fall under 'Uncertain Trend in Table 2, and a closer analysis of them involving significant subject matter expertise would be warranted, this is discussed in Section 3.3. An example of a country with an uncertain trend can be found in Section 3.9.

Constant Trend	Linear Trend	Quadratic Trend	Uncertain Trend
Democratic Republic of the Congo	Bangladesh	Burkina Faso	Afghanistan
Ethiopia	Benin	Chad	Angola
Lesotho	Cambodia	Gambia	Bhutan
Liberia	Central African Republic	Nepal	Burundi
	Eritrea	Togo	Djibouti
	Guinea	Uganda	Guinea Bissau
	Haiti		Laos
	Madagascar		Malawi
	Mali		Mozambique
	Niger		Rwanda
			Somalia
			South Sudan
			Sudan
			United Republic of Tanzania
			Zambia
			Yemen

Table 2: Parametric trends of extreme heat in Least Developed Countries. Countries where the statistical test was inconclusive with respect to the trend's parametric form are labelled 'Uncertain Trend'.

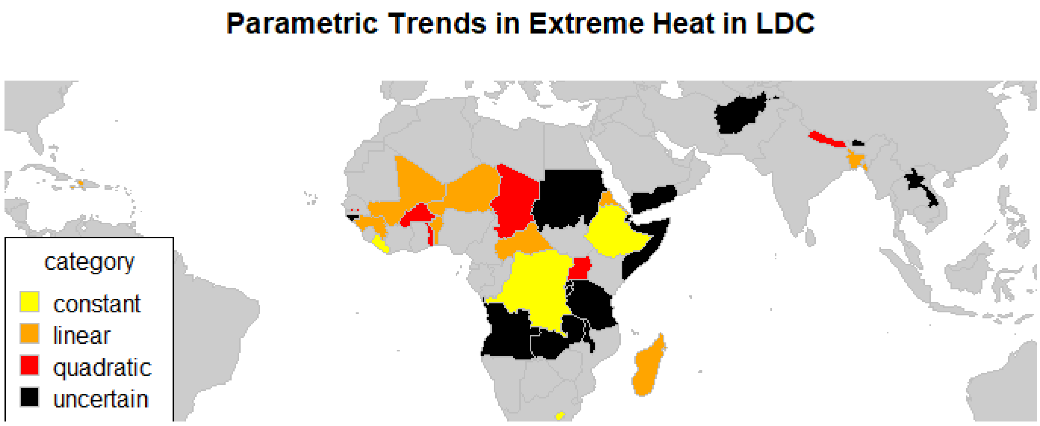

Figure 7: Map of estimated type of parametric trend occurring in countries' maximum weekly temperatures.

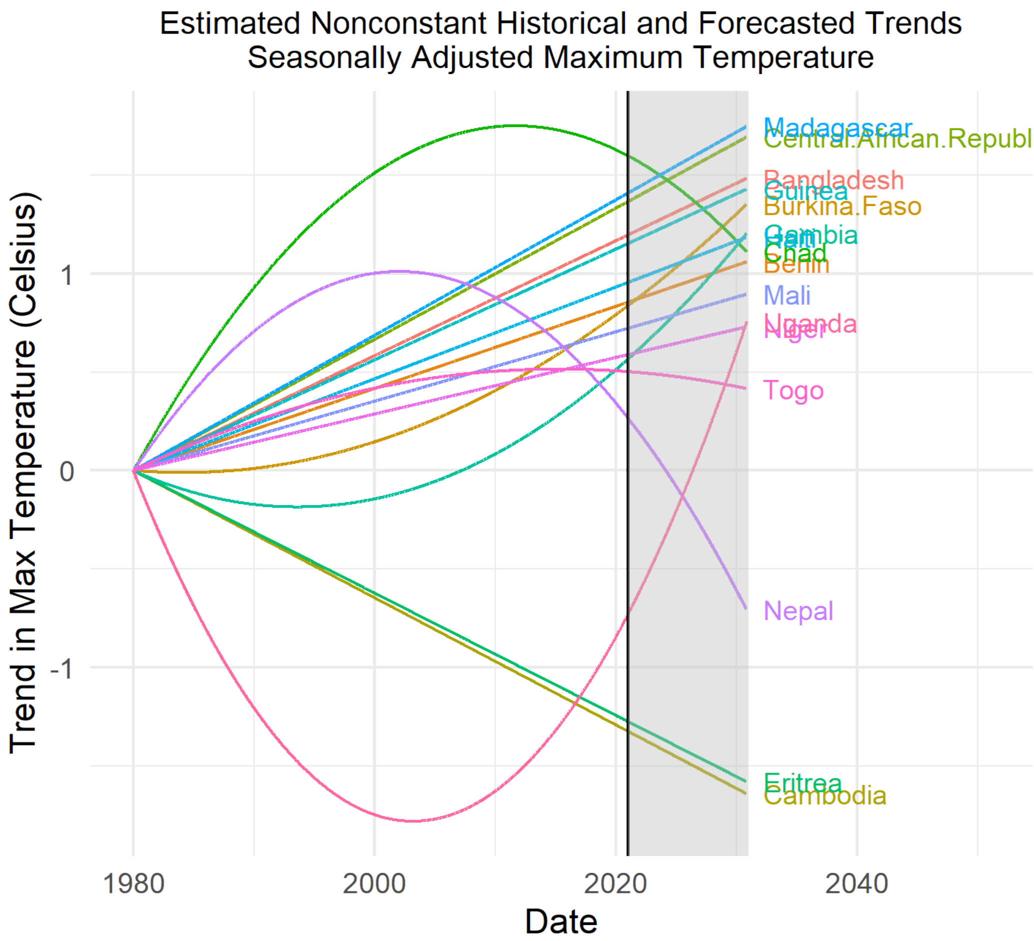

Figure 8: Estimated values of the nonconstant trends for past and dates 10 years in the future. While caution must be taken extrapolating the quadratic trends too far in the future, these trends give a good sense of where maximum temperatures are heading in the decade ahead.

2.3.4 Countries Most at Risk

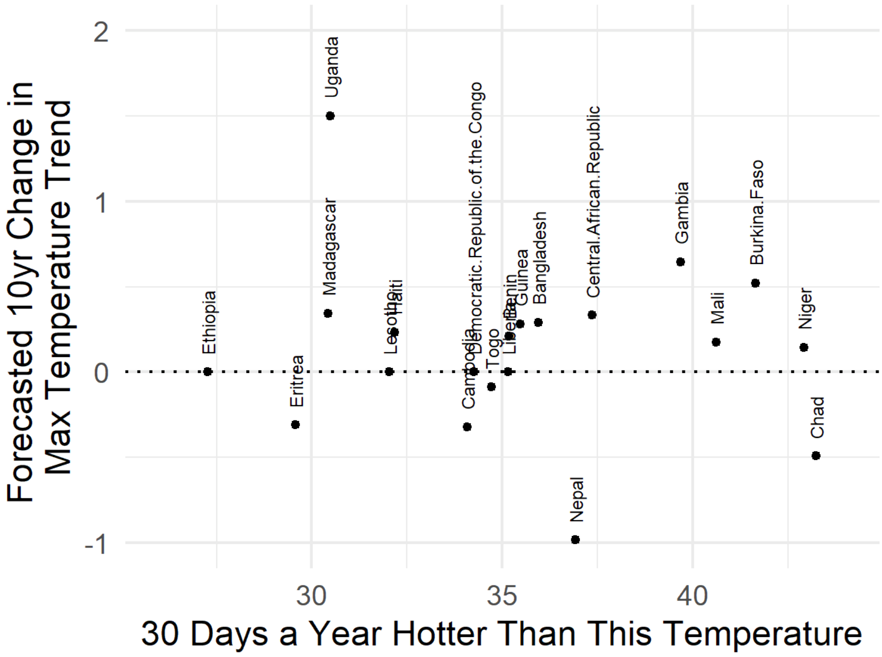

Figure 9: Comparison of the forecasted increase in the trend of maximum temperature over the next 10 years, and the temperature at which historically we expect only 30 days a year to be hotter than in a given country.

Based on Figure 9 we can see that there are a number of countries expected to warm up over the next decade which also currently experience high maximum temperatures. These countries represent ones which are more likely to be adversely impacted by climate change. While there is no hard and fast rule as to what the correct trade-off between how temperatures are expected to change, versus how they are presently (this is discussed in Section 3.3), it would be reasonable to say the countries in the upper-right of Figure 9 should be considered for climate refugee policies. Therefore I would suggest Bangladesh, Burkina Faso, Central African Republic, Gambia, Guinea, Mali, Niger are good candidates for inclusion. As well, Uganda would also be a good candidate for inclusion; while I suspect the trend probably overestimates how much its maximum temperature is likely to increase, its temperature has been increasing in a non-linear way in recent years (see Section 3.4), so there would appear to be a risk it continues increasing fairly rapidly.

2.4 Extreme Precipitation Analysis

Next I turn my attention to identifying countries at risk of suffering increased extreme precipitation events due to climate change. In this analysis, I am interested in changes in the right tail of precipitation since this is what will lead to increased flood risk. This is slightly different from the analysis of extreme heat because in that analysis we were concerned about the general trend of the weekly maximum temperature, and not what the most extreme values weekly maximum temperatures could take were.

2.4.1 Setup

In order to model the right tail of precipitation I utilize regularized quantile regression. Whereas standard regression models describe the behaviour of the expected value (i.e. the 50th percentile) of the response variable given the covariates, quantile regression allows one to model any quantile. An illustrative example is given in Figure 10.

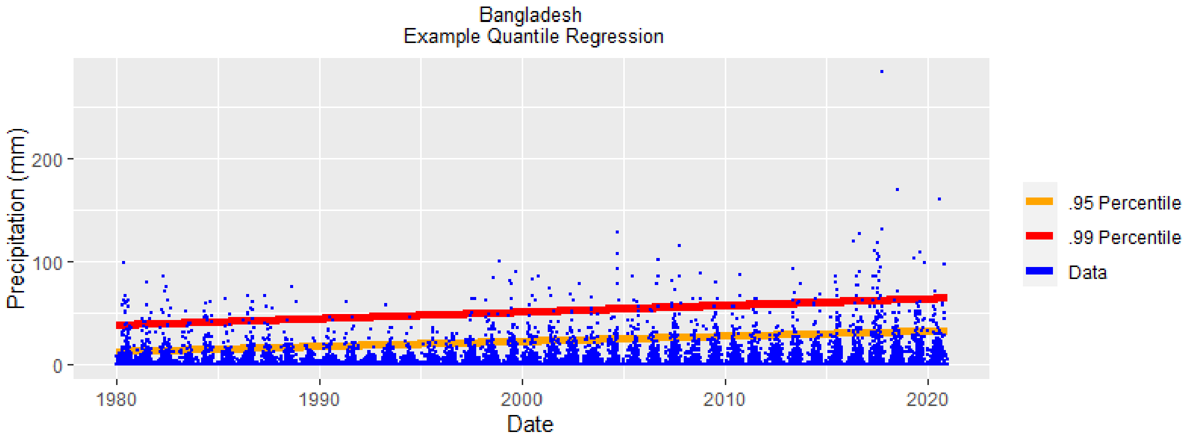

Figure 10: An example of a quantile regression model with time as a covariate. As you can see the red line representing the 99th percentile is exceeded only infrequently.

In the analysis that follows I use quantile regression to model the 96.5% quantile of precipitation (we would expect to see daily precipitation exceed this value only once over a four week period).

2.4.2 Model Fitting

The hypothesis I wish to test is whether the 96.5% quantile of precipitation is increasing over time. In order to isolate this effect I model the quantile as follows

$$96.5\%\ \text{Quantile}_t = \text{Seasonal Effect}_t + \text{Time}_t \times \text{Time Trend of Seasonal Effect}. \tag{2}$$

I chose this model specification because precipitation is so seasonal, and in some countries, such as Bangladesh, there are monsoon seasons. As such, this type of model can isolate the time trend during these heavy rainy periods.

In order to avoid detecting spurious relationships I have fit a regularized model. The loss function takes the form of

$$L(\text{Observed Precipitation}, \text{Time}) = \left(\sum_{i=1}^{n} \text{Individual Loss}_i \right) + \lambda \sum_{k=1}^{13} |\beta_k| \tag{3}$$

where the β_k's are coefficients associated with the seasonal time trends and individual loss is based off of the standard check-loss function based on the 96.5% quantile [3]. Note that no regularization was applied to the constant seasonal effects.

In order to choose an appropriate regularization amount λ I ran a cross validation procedure using the first 36 years as a training set and the final 5 years as a validation set. For each country I selected the lowest value of λ which resulted in the number of observations in the validation set exceeding the 96.5% quantile to be $\approx 3.5\%$. An example of this can be found in Section 3.7.

2.4.3 Results

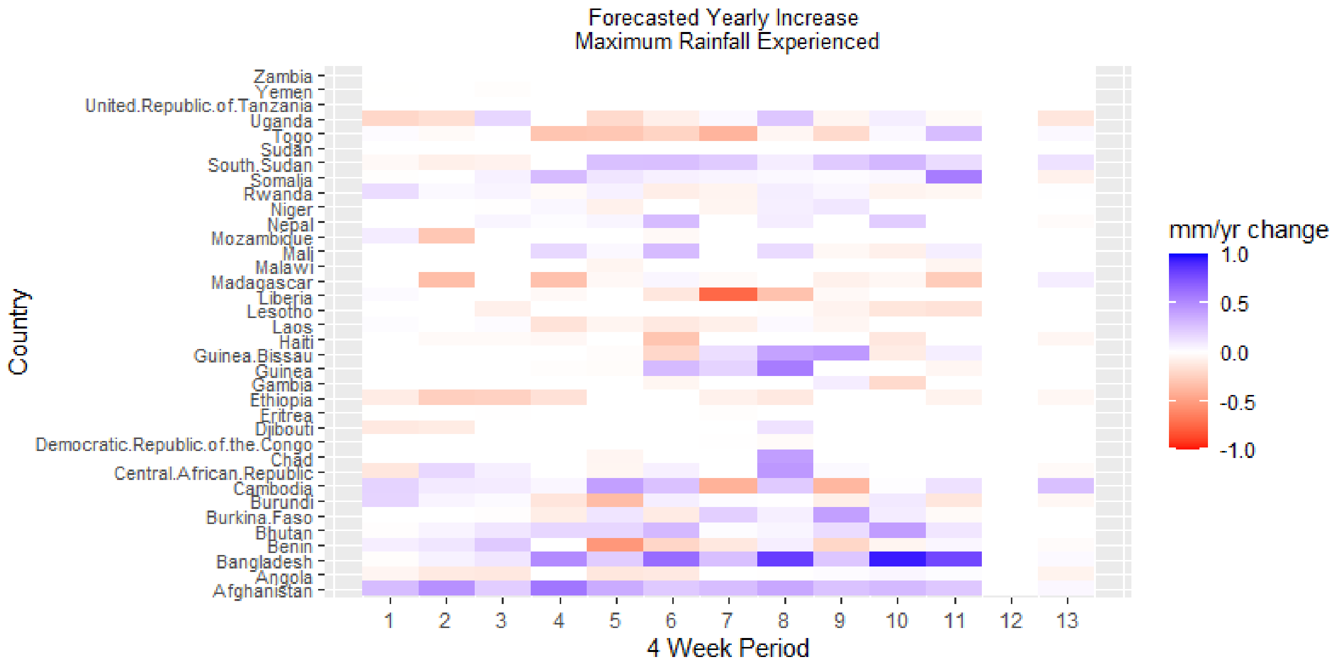

Figure 11: Each cell represents the trend from 1980-2020 in the amount of rain received in the rainiest day in a four week period. The dates of each period can be found in Section 3.8.

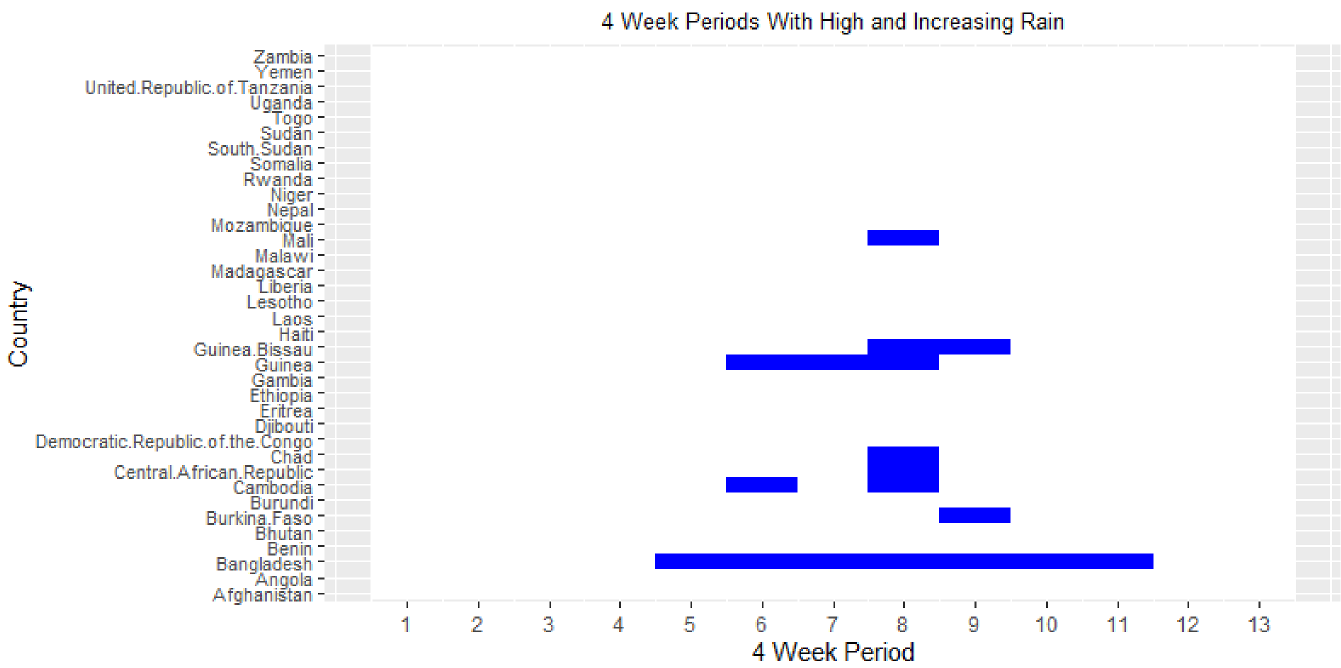

Figure 12: Cells in blue represent four week periods in countries that are the top 10% with respect to extreme precipitation, and also have had the trend from 1980-2020 in the amount of rain received in the rainiest day increase by at least 0.1mm/year. The dates of each period can be found in Section 3.8.

The results in Figure 11 and Figure 12 are based off of the coefficients found by the regularized quantile regression models for the optimal amount of regularization. From these models one can extract the seasonal effect (the ‘typical’ rainiest day in a four week period) and the time trend of the seasonal effect (the yearly trend in the amount of precipitation experienced for a period’s rainiest day).

As can be seen in Figure 11 the effect on extreme precipitation across countries and four week periods (a listing of the dates of each period can be found in Section 3.8) is not uniform across countries or time periods. What does appear is that extreme precipitation seems to be increasing in many countries during periods 8-11 (mid-July to early-November).

With that being said, the increase will be most impactful to the populations living in these countries if they occur during already high precipitation periods. To assess this, Figure 12 shows the countries and time periods where the level of extreme precipitation is already high, and the amount has increased by 0.1mm/year since 1980. Specifically, a four week period has high levels of extreme precipitation if the expected rainiest day in that period is in the top 10% of expected rainiest days across all periods and countries.

2.4.4 Countries Most at Risk

Country Name	**Number of Four Week Periods With High and Increasing Extreme Precipitation**
Bangladesh	7
Guinea	3
Guinea-Bissau	2
Cambodia	2
Mali	1
Chad	1
Central African Republic	1
Burkina Faso	1

Table 3: Countries most at risk of climate change induced increased extreme precipitation events. Bangladesh has experienced increased extreme precipitation over half of the year in already rainy periods.

Table 3 summarizes Figure 12. Namely it shows Bangladesh, Guinea, Guinea-Bissau, and Cambodia are most at risk, as well as Mali, Chad, the Central African Republic and Burkina Faso.

2.5 Conclusion

Referring back to Table 1 in the Executive Summary, the countries of Bangladesh, Burkina Faso, The Central African Republic, Guinea, and Mali should be considered priorities when designing a climate refugee policy as they are likely to see increased extreme heat and extreme precipitation in the years ahead. This analysis is not exhaustive, and many of the 8 countries with substantial missing data (refer to Section 3.2) would be worthy of inclusion as well; particularly the small island nations which may be threatened by higher sea levels. An analysis of these countries, and other topics, are admirable directions for future research. A list of potential future research directions can be found in Section 3.3.

While a list of five countries for priority seems manageable, when one considers that the combined population of these countries is 221 million people, the scale of the problem becomes apparent. As well, this number surely understates the scale of the problem as this analysis only considered two (heat and rain) of the numerous adverse consequences of climate change.

Governments must act swiftly, compassionately, and proactively to setup climate refugee programs before these populations are even more so adversely affected by climate change induced extreme heat and rain.

3 Appendix

3.1 List of UN's Least Developed Countries

Afghanistan, Angola, Bangladesh, Benin, Bhutan, Burkina Faso, Burundi, Cambodia, Central African Republic, Chad, Comoros, Democratic Republic of the Congo, Djibouti, Eritrea, Ethiopia, Gambia, Guinea Guinea-Bissau, Haiti, Kiribati, Lao People's Democratic Republic, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania Mozambique, Myanmar, Nepal, Niger,Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Solomon Islands, Somalia, South Sudan, Sudan, Timor-Leste, Togo, Tuvalu, Uganda, United Republic of Tanzania, Yemen, Zambia [1].

3.2 Countries with Substantial Missing Data

The following countries had missing data for a number of years leading up to and including 2020. Hence, they were not analysed.

East Timor, Comoros, Mauritania, Myanmar, Sao Tome and Principe, Senegal, Sierra Leone, Solomon Islands.

3.3 Areas for Further Analysis

1. **Analysis Beyond Capital Cities**: in my analysis I analysed how the climate is expected to change in each country's capital city. Further analysis could look at other cities, particularly rural areas responsible for food production as extreme heat and precipitation will likely disrupt this. The dataset I have used is well suited for this type of analysis given it contains temperature/precipitation estimates for all 0.5x0.5 latitude/longitude grid squares in the world. However, much more care would need to be taken with sparsely populated areas since the temperature and precipitation recordings would be less reliable than ones in capital cities closer to weather monitoring stations.

2. **Multiple Testing**: in conducting my hypothesis tests for temperature trends I controlled for Type I (detecting false positives) error at the individual level. However, since I am conducting multiple tests ideally I could control for it at the group level. To the best of my knowledge, conducting this type of test for nonstationary time series and controlling the Type I error at a group level is an open research problem.

3. **Spatial Analysis**: in my analysis I treated countries as separate entities. However, looking at which countries were identified as being at risk of extreme heat and extreme precipitation there is clearly a spatial component (i.e. the countries expected to experience these extremes are generally clustered close together). Future analysis could explicitly include a spatial effect in the testing procedure.

4. **Defining Extremes:** I used a somewhat ad-hoc method in determining what constitutes extreme heat and extreme precipitation. Countries at risk of extreme heat were defined as countries with rising temperatures and where 30 days a year are expected to be over 35 Celsius (the midpoint of what the City of Toronto determines as the temperature on a given day where residents are at risk of suffering health related effects of extreme heat). Countries/periods at risk of extreme precipitation who already experienced heavy precipitation (the period was in the top 10% of periods for extreme precipitation events) and are expected to have this precipitation increase by at least 0.1mm/year going forward. Very likely there are more informed cutoffs to use to define extreme heat and precipitation; the input of someone with extensive background knowledge in climates (particularly African climates) would be greatly beneficial to improving these measures.

5. **Other Parametric Trends**: the parametric trend framework I used is extremely powerful, and I believe the 'correct' framework for constructing long-term forecasts. In a future analysis it would be interesting to run it again using more complex parametric forms. For example, these could include 'kinked' linear trends where the linear trend begins in the middle of the time series, or could include non-linear that are constrained as to not increase 'too rapidly'. This framework could also accommodate parametric trends defined by more flexible machine learning methods. Since climate change is very much not a 'perfectly linear' phenomenon this would be a fruitful line of analysis.

6. **Drivers of Trends**: my analysis was primarily focused on statistical tests for the existence of trends in extreme heat and extreme precipitation. This is useful in itself, but it would be worthwhile examining how these trends are correlated with the amount of different pollutants in the atmosphere. Knowing these relationships, and then forecasting future paths of these pollutants would help strengthen the forecasts of extreme temperature and precipitation.

7. **Extreme Precipitation Events**: in my analysis I focused on how the rainiest day in a 28 day period may change as it is a problem amenable to regression. It would be interesting to examine even more extreme events, such as how the rainiest day in a five year period has changed over time. The type of tools to address this problem could be found in Extreme Value Theory, an active area of statistical research.

3.4 Graph of Uganda's Maximum Temperature

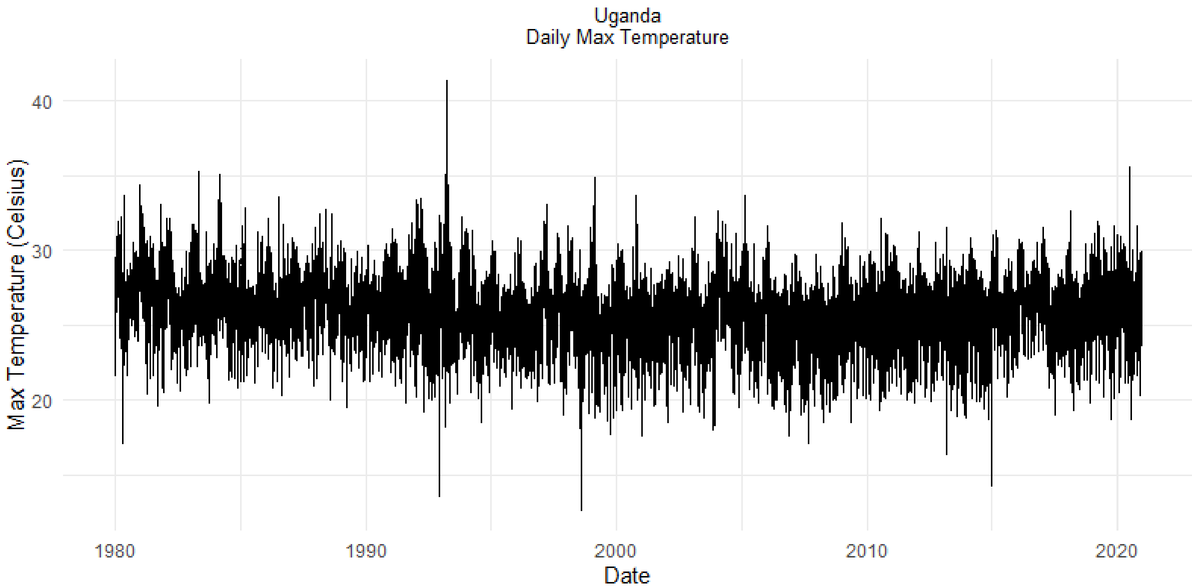

Figure 13: Uganda's maximum temperature seems to be following a mildly quadratic trend; specifically since the mid 2000s.

3.5 Description of Parametric Trend Testing Method

The statistical testing procedure for testing the existence of parametric trends is as follows

1. Perform a local linear fit for all t of the mean of the time series

$$\tilde{\mu}(t) = \sum_{i=1}^{n} Y_i w_i(t) \tag{4}$$

$$w_i(t) = K[(i/n - t)/b_n][S_2(t) - (t - i/n)S_1(t)]/[S_2(t)S_0(t) - S_1^2(t)] \tag{5}$$

$$S_j(t) = \sum_{i=1}^{n} (t - i/n)^j K[(i/n - t)/b_n] \tag{6}$$

$$b_n \in (0,1) \text{ a bandwidth parameter} \tag{7}$$

where $K(\cdot)$ is the Bartlett Kernel

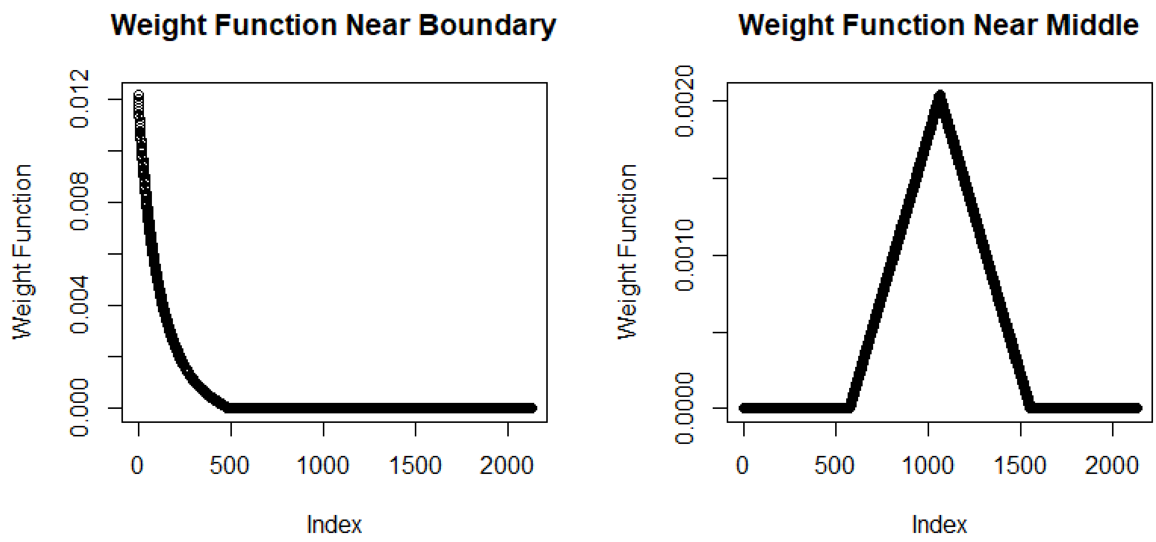

Figure 14: Weights $w_i(t)$ at leftmost boundary and $t = .5$.

2. Calculate the estimated noise of the time series as

$$\tilde{e}_i = Y_i - \tilde{\mu}_n(i/n) \tag{8}$$

3. Compute an estimate of the time varying long-run variance $\hat{g}(t)$ via

$$\hat{g}(t) = \frac{\sum_{i=1}^{n} Q_i I(|i/n - t| \leq b_n)}{\sum_{i=1}^{n} I(|i/n - t| \leq b_n)} \tag{9}$$

$$Q_i = e_i \sum_{|j-i| \leq m_n} e_j \tag{10}$$

$$m_n = (nb_n)^{1/3} \tag{11}$$

$$I = \text{ the indicator function} \tag{12}$$

4. For each parametric trend you are testing, f_θ, calculate the optimal value $\hat{\theta}$ using least squares

5. Calculate the residuals of the parametric trend as

$$\hat{e}_i = Y_i - f_{\hat{\theta}}(i/n) \tag{13}$$

6. Calculate the smoothed parametric trend as

$$\mu_{\hat{M}}(t) = \sum_{i=1}^{n} f_{\hat{\theta}}(i/n) w_i(t) \tag{14}$$

7. Compare the smoothed parametric trend with the local linear fit of the trend of the time series $\tilde{\mu}(t)$ to calculate the test statistic

$$\text{TestStat}_{\hat{M}} = \sum_{i=1}^{n} (\tilde{\mu}(i/n) - \mu_{\hat{M}}(i/n))^2 \tag{15}$$

note that this test statistic will be large is the local linear estimate of the time series trend differs substantially from a smoothed version of the parametric trend.

8. Generate critical values for $\text{TestStat}_{\hat{M}}$ via bootstrap. To do so for each bootstrap iteration generate iid $Z_1, \ldots, Z_n \sim \mathcal{N}(0,1)$, let $Y_i^\diamond = \hat{g}(i/n)^{1/2} Z_i$ and then calculate $\tilde{\mu}^\diamond$ and $\mu_{\hat{M}}^\diamond$ in a similar way as before. For each bootstrap iteration $b \in 1, \ldots, B$ calculate ${\text{TestStat}_{\hat{M}}^\diamond}^{(b)}$.

9. Get the critical value of the test by taking the $1 - \alpha$ quantile of $\{{\text{TestStat}_{\hat{M}}^\diamond}^{(b)}\}_{b=1}^{B}$.

10. Reject the null hypothesis that the trend follows the specified parametric form if $\text{TestStat}_{\hat{M}}$ is greater than this quantile.

This procedure is repeated for parametric trends of increasing complexity. The first parametric form which does not reject the null hypothesis (i.e. there is evidence the underlying trend is of a parametric form) is accepted as the time series' parametric trend.

3.6 Cross Validation - Extreme Heat

In order to use the statistical test for the trends underlying the time series one must select a bandwidth parameter governing the smoothness of the non-parametric trend one compares the parametric trend to. A low bandwidth gives a 'bumpier' trend relative to a high bandwidth as seen in Figure 17. Selecting a low bandwidth makes it less likely to select a parametric trend as fitting the data, and leads more countries to be classified as Uncertain Trend.

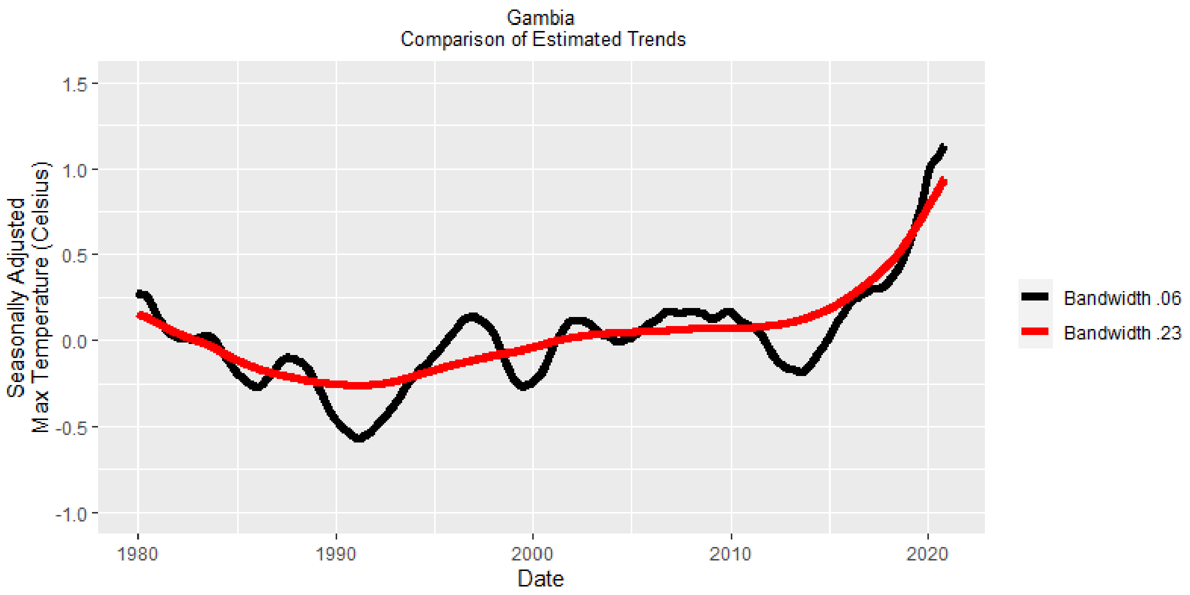

Figure 15: The bandwidth parameter governs how smooth the non-parametric trend which we compare the parametric trend alternative to.

In order to select the appropriate bandwidth level a cross validation procedure was used. The procedure was as follows

1. Select a bandwidth b_n from the range (0.10,0.11,...,.30). This range was chosen given that in the paper the ideal bandwidth the authors suggested was $n^{-1/5} = .21$ in our case.

2. Run the trend testing algorithm on the first 39 years of data and find which countries have a parametric trend.

3. Of these countries, use this trend to estimate the next two years of data. Take the average mean squared error across all countries as the validation error.

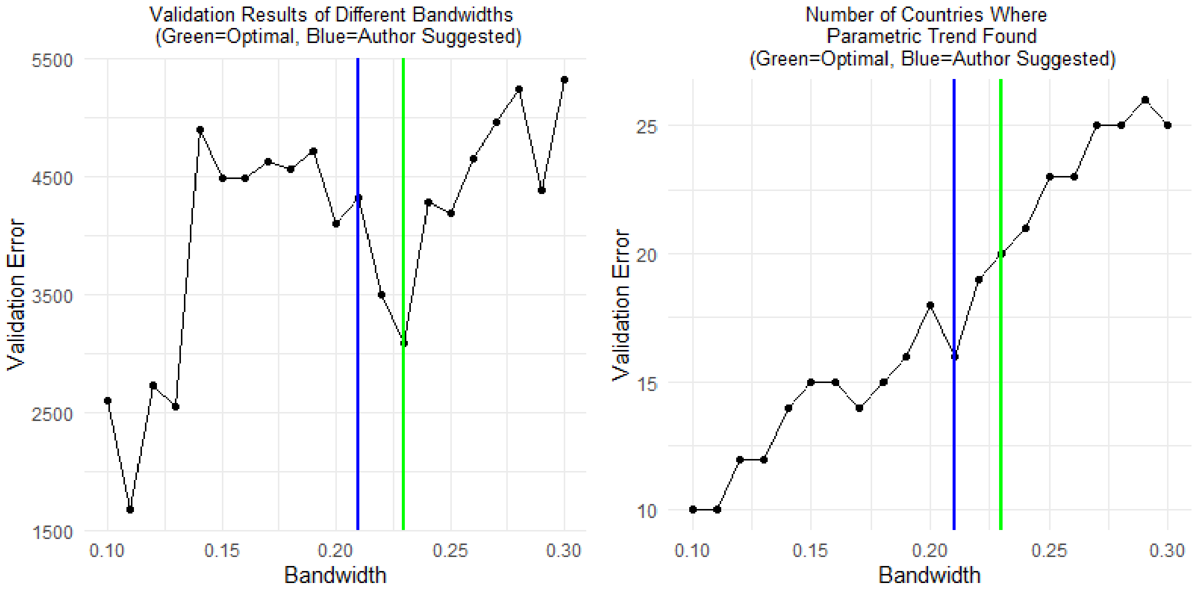

Figure 16: Cross validation results selecting the bandwidth for the statistical test of a parametric trend.

In Figure 16 we see that lower bandwidths are associated with lower power for the test in that we identify fewer parametric trends across all countries. At a bandwidth level of 0.23, which is very close to the authors suggested level of 0.21, we see a noticeable trough in the validation error. A bandwidth of 0.23 was selected, and appeared to be a reasonable trade-off between the validation error and power of the test.

3.7 Cross Validation - Extreme Precipitation

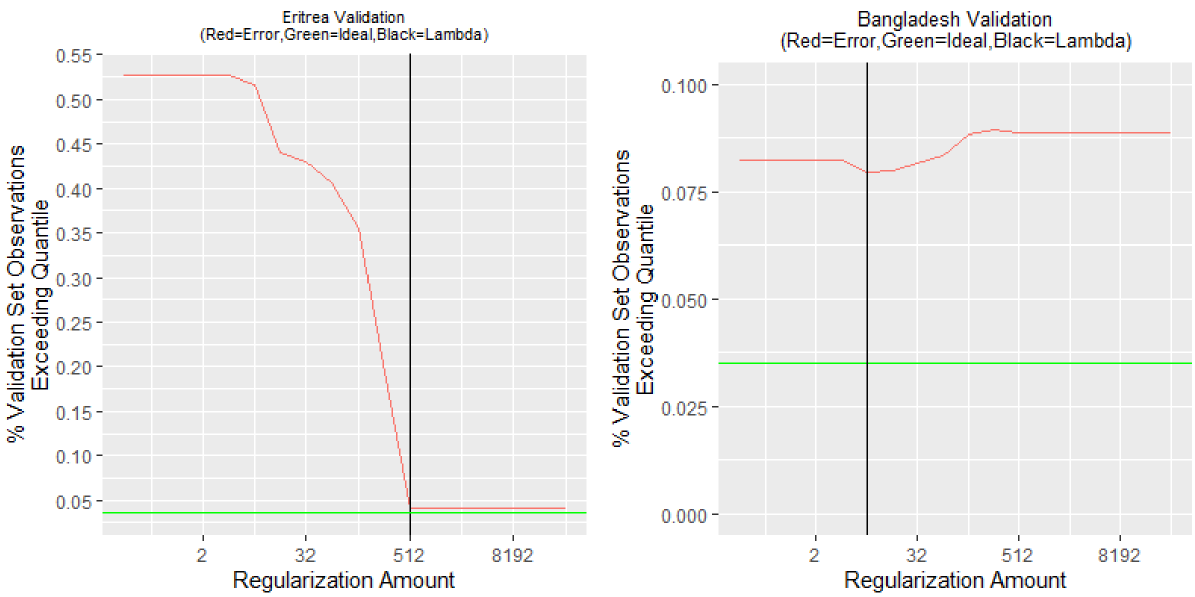

Figure 17: Example for cross validation results to choose the regularization parameter λ. Eritrea's large regularization amount suggests there is minimal time trend in extreme precipitation levels, whereas Bangladesh's low amount suggest there is.

3.8 Dates of Four Week Periods

1. January 1-January 28
2. January 29-February 25
3. February 26-March 24
4. March 25-April 21

5. April 22-May 19
6. May 20-June 16
7. June 17-July 14
8. July 15-August 11
9. August 12-September 8
10. September 9-October 6
11. October 7-November 3
12. November 4- December 1
13. December 2-December 31*

3.9 Example of a Country with an Uncertain Trend - Zambia

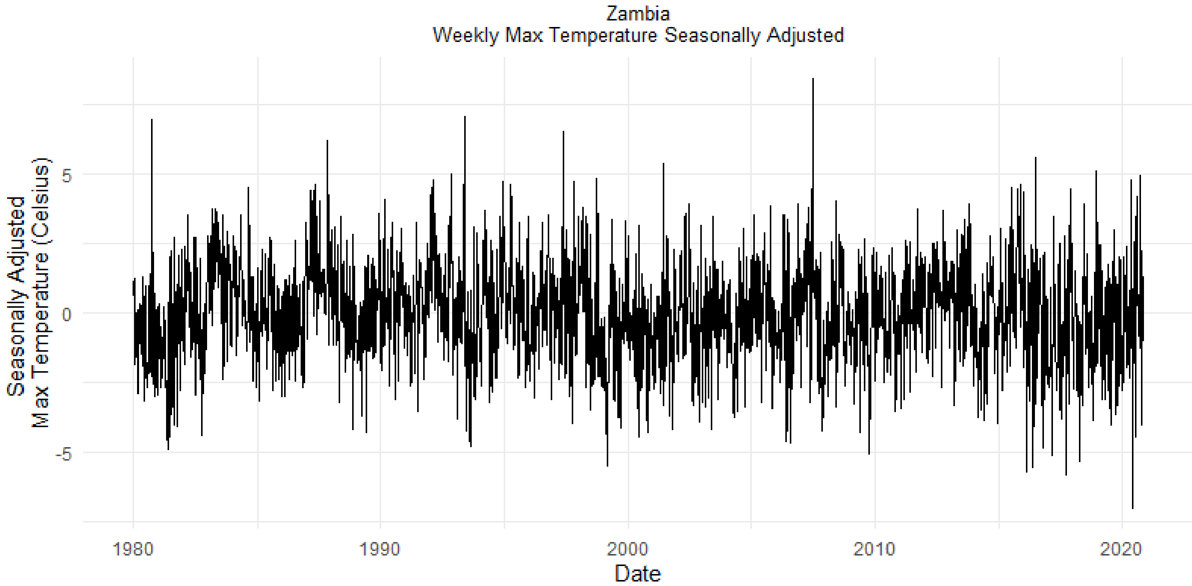

Figure 18: An example of a country that does not appear to have a parametric trend. It appears the trend is increasing from 1980-1990, decreasing from 1990-2000, increasing again from 2000-2015, and then decreasing from 2015-2020. Given the complex nature of this trend, it would be difficult to make forecasts of it far into the future.

3.10 Analysis Pathway Not Taken - Short-haul Flights

One really interesting line of analysis I did not take, but was considering, was based off the article *Quantifying the Potential for Climate Change Mitigation of Consumption Options* [5]. In this article, one of the options which offered the most mitigation potential was encouraging travellers to take more direct flights and fewer connecting flights, since takeoff/landing are times during a flight which involve significant pollution. This seems like a mitigation measure which is very manageable, especially in Europe where many short-haul flights can be replaced by rail. There is even a website `www.ecopassenger.org` which takes a flight route in Europe, suggests an alternative train route, and compares the carbon emissions from both. For shorter flights in many cases the times are comparable, but the emissions are far less. I did not choose this pathway because I was unsure how to apply much statistical rigour to it other than just suggesting busy flight routes that have comparable train times.

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