ECONOMETRIC ESTIMATION OF THE LINK BETWEEN FLOODS AND CLIMATE CHANGE IN THE PROVINCE OF NEW BRUNSWICK

by

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ABSTRACT

Over the past decades, New Brunswick has recorded many extreme weather and climate events such as winter storms, hurricanes, floods, storm surges, and severe thunderstorms resulting in huge damages to individuals, firms, and Governments. Among these events, it has been proven that flood is the most occurring one.

In this study, we estimated the relationship between floods and climatic variables such as temperature, rainfall, sea-level and Green House Gases (GHG) emissions using the logit model. River discharge was used as a hydrological control variable. The model showed that, there exists statistically significant positive relationship between flood and rainfall and GHG emissions. Moreover, temperature and sea-level are close to being significant showing negative and positive relationships with flood respectively. However there exists an insignificant positive relationship between discharge and flood.

Results from the logit model were used to predict the probability of future floods in New Brunswick by taking into consideration the long run dynamics of the hydrological variable and climatic variables. It was established in this study that, the probability of flood in New Brunswick will be 100% in 2057 if the effects of temperature, rainfall, sea-level, discharge and GHG emissions are considered.

The significance of this study is to provide economic justification for the investments into preventive and mitigation measures in the region.

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Chapter 1. Introduction

The Intergovernmental Panel on Climate Change (IPCC,2007) defines climate change as "a change in the state of the climate that can be identified by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer". In the past decades, the issue of global climate change has become very important. Scientists have shown that, climate change is mostly caused by human activities such as cutting down and burning of forests, combustion of fossil fuels and cement production (IPCC,2001).

According to the United Nations, average global temperature increased by 0.85^{0}C between 1880 and 2012, global average sea-level rose by 19cm from 1901 to 2010, and greenhouse gas emissions continue to rise and are 50% higher than their 1990 level. However, it is important to note that climate change occurs in various forms in different locations. In New Brunswick, climate change refers to four major features: increase in temperature, changes in precipitation patterns, sea level rise and increase in the frequency of large weather events. Other locations aside from New Brunswick also experience frequent occurrence of large weather events and it is associated with harmful impacts.

For instance, Smith et al.(2018) showed that, between the years 1980 and 2018, the United States (U.S) experienced 241 weather and climate disasters in which the overall damages exceeded US$ 1 billion and the total bill for these events exceed US$1.6 trillion. According to Picazo (2019), the U.S experienced 14 separate billion-dollar disasters comprising of one drought event, eight severe storm events, two tropical cyclone events, one wildfire event, and two winter storm events, resulting in the death of two hundred and forty-seven individuals in 2018. It was further revealed by the author that as at the end of 2018, the U.S had an average record of 15 disasters per year.

Kron (2012) proved that among six continents, North America is highly exposed to every form of extreme weather events such as tropical cyclones, thunderstorms, winter storms, tornadoes, wildfires, droughts, floods among others. It was further revealed that, in the last 30 years the intensity and frequency of these events have been on an upward trend resulting in an increase in economic and insured losses in North America.

The Canadian Disaster Database (CDD) has a record of numerous extreme weather events across Canada. Table 1.1 below reveals that flood is the most occurring extreme weather event in the Maritime provinces. Burina (2017) estimated the expected average loss from floods in the Maritime provinces as $9.5 million per annum.

Table 1.1: *Extreme weather events in Canada's maritime provinces from 1900 to 2014*

Type of event	Quantity of events in different years							
	1990–2014		1965–1989		1940–1964		1900–1939	
	Total quantity	Quantity per year	Total quantity	Quantity per year	Total quantity	Quantity per year	Total quantity	Quantity per year
Flood	22	0.88	17	0.68	9	0.36	10	0.25
Winter storm	15	0.6	2	0.08	2	0.08	1	0.025
Hurricane, tropical storm	11	0.44	5	0.2	6	0.24	3	0.075
Severe thunderstorm	8	0.32	7	0.28	1	0.04	2	0.05
Storm surge	4	0.16	3	0.12	0	0	0	0
TOTAL	60	2.4	3.4	1.36	18	0.72	16	0.4
Source: Burina (2017)								

Considering the adverse impacts of extreme weather events on individuals, homes, businesses and governments, Kron (2012) admonishes researchers and scientists to "continue improving forecast and early-warning systems". In that regard, this study which will be based on the most significant extreme weather event in New Brunswick-flood, has two main objectives. First and foremost, the frequency of flood in New Brunswick over time will be tested. Secondly, the study will test whether the frequency of flood in New Brunswick is caused by climate change. In both cases statistical methods, discussed later in the study, will be employed. The structure of the study is as follows: Chapter 2 covers Literature review on estimation of the probability of flood. Chapter 3: Methodology. Chapter 4: Data description, empirical framework, and findings. Chapter 5: Conclusions, limitations and recommendations.

Chapter 2. Literature Review

This study follows the classification of literature on estimation of probability of flood as presented in Hetalo (2018). There are two main streams of literature namely: (1) hydrological stream, and (2) statistical stream. Unlike the statistical stream, the hydrological stream requires expertise and training in terms of hydrology background to better understand the models used.

The widely-used model under the hydrological stream of literature is the *rainfall-runoff model*. The runoff model is a mathematical representation of the relationship between rainfall catchment area, watershed and drainage basin. The model produces a hydrograph which estimates the conversion of rainfall into runoff.

Zhijia et al. (2008) applied the rainfall-runoff model to forecast flood at the Huaihe Basin which is situated at the upper region of the Hongze Lake in China. The study adopted the least square error regression method for real time correction. The hydrological model provided different parameters each of the 23 sub-basins under the Huaihe basin. The model proved to be consistent with observed data from flood especially in 2005. Despite the accurate results provided, the model was limited by the exclusion of factors such as flood diversion, retarding areas, flood and irrigation gates which could have provided more information on the integrated effect of these factors.

Naden et al. (1996) used the rainfall-runoff model to estimate the impact of climate change on flood event at River Severn in the United Kingdom (U.K). According to the study, the magnitude of flood will increase daily by 13.7% at the River Severn between the years 2050 and 2059.

Cameron et al. (2000) were of the view that the study by Naden et al. (1996) made use of just a single optimal parameter set and failed to account for uncertainties in their models. Hence Cameron et al. (2000) modified the rainfall-runoff models of the two former studies and examined the effects of climate change on the frequency of flood for the Wye catchment at Plynlimon in the United Kingdom. The study employed the continuous simulation methodology developed by Cameron et al (1999). The "medium-high" UKCIP98 climate change scenario was used as a starting point for a variety of different scenario conditions at the catchment scale. Some of the different scenarios included uniform changes to hourly rainfall for three 30-year time slices starting from 2020, changes to the hourly rainfalls of the most extreme storms and increases to the number of winter storms. The study compared the effects of the current scenario condition to the different scenarios. The results of the study showed that, the different scenarios only had a little impact on the weighted flood frequency relative to the current conditions scenario. Due to the contradictory results in terms of the size of the impact of climate change on flooding relative to Naden et al. (1996), Cameron et al. (2000) suggest that, there is a need to explicitly account for uncertainty when using a hydrological model to estimate the impact of climate change.

Vaze et al. (2011) confirm that it is possible to improve the rainfall-runoff model by incorporating alternative methods and data sets for instance by "using multi-model and multi-donor ensembles, applying regional calibration that directly accounts for different catchment attributes, calibrating models against new data types like remotely sensed evaporation, integrating other data types like leaf area index, etc".

Some other studies that made use of the rainfall-runoff model are Hlavcova et al. (2005), Zhijia et al. (2008), Vaze et al. (2012) and many more.

Urbonas (2007) revealed that rainfall-runoff models “rely on calibration to achieve an accurate representation of the hydrology they model”. However, these data are not readily available. He continued by stating that, “even when such data are available, it may not have sufficient time of record and may not be of sufficient temporal or spatial density.” Another challenge associated with the rainfall-runoff models is deciding on the appropriate model for a specific location since some models are best for urban areas dealing with small sub-catchments whereas others are best for large non-urban catchments. These factors create challenges for researchers who do not have substantial hydrological knowledge. To run these models, I need to be an expert in hydrology. Since I do not have any professional training in hydrology, I will use statistical methods to estimate the probability of floods in New Brunswick. The significance of the theoretical stream of literature is to help us identify control variables that can be included in a statistical model.

The statistical stream of literature can be divided into two sub-groups namely: (1) non-parametric models, and (2) parametric models. Parametric models refer to models that have a specified functional form which require estimation of those parameter(s). On the other hand, non- parametric models do not need any specification of the functional form. Instead, in non-parametric models, the functional forms are determined by the data used. Under the statistical stream of literature, a lot of researchers have experimented on various model specifications and data types such as time series, cross sectional and panel data. Some studies employed straight-forward frameworks such as linear models, whereas others used more complex frameworks like non-linear models. The significance of the statistical stream of literature is to guide us to choose the right type of data and the best possible specification for our study. The studies below show how statistical methods have been used in predicting the probability of flood.

Paeth et al. (2010) verified the claim by media organizations that the severe flood that hit major parts of sub-Saharan Africa in 2007 was mainly due to extreme rain events. The study used daily rainfall data from 1998 to 2007 to estimate the return times of flood-producing precipitation. First and foremost, the results showed that most of the regions had return periods longer than 10 years (length of the data) which attested to the fact that the flood was extreme. Secondly, daily rainfall events during the June to September period in 2007 were extreme at a level of 5-day to 20-day accumulated rainfall totals signifying that, the large-scale flood was indeed caused by rainfall. Even though the Monte Carlo approach was used to account for uncertainty, the authors revealed that, "extrapolation of return times beyond two times the length of the data record (=10 years) are subject to large uncertainty''.

Kilsby et al. (1998) estimated regression models that could be used to predict point rainfall statistics in England and Wales. The authors used daily (1961-1990) data on rainfall and gridded data of four atmospheric circulation variables (mean sea-level pressure, total shear vorticity, zonal and meridional components of geostrophic air-flow) at 67 sites throughout England and Wales. The data was initially developed by Jenkinson and Collison (1977) and later used by Jones et al. (1993). Kilsby et al. (1998) transformed the mean daily rainfall and the proportion of days with less than 0.2mm of rain (proportion of dry days at a particular site) into their natural logarithm forms and for each of them the linear least squares regression was used to estimate the coefficients of all independent variables. The model assumed that there existed a linear relationship between the natural logarithm of rainfall and all the independent variables. The results of this study showed that for the two estimated models, there were no systematic departures in the assumptions of the model. However, their study points out that, “the use of rather coarse resolution circulation data means that some important regional climatic effects may be ignored.”

Lins and Slack (1999) used a non-parametric approach to investigate changes in hydrologic regime in the conterminous U.S during the twentieth century by determining whether trends occurred in streamflow over a range of selected discharge quantiles. This test was carried out by first using the Mann-Kendall test to evaluate trends (monotonic changes with time) in the various quantiles and then evaluating the differences between low-flow, medium-flow and high-flow regimes. It was observed that trends were most prevalent in the annual minimum to median flow categories but least prevalent in the annual maximum category indicating that the conterminous U.S was getting wetter, but less extreme over the said period. Some of the benefits of the Mann-Kendall test include its resistance to extreme values since it is a rank-based procedure. Also, the test is good for skewed variables and does not require the assumption of normality. One major limitation of this study is its failure to determine if changes in streamflow are characterized as a gradual monotonic change or an abrupt “step” change. The implications of a step change are different from those of a gradual trend.

McCabe and Wolock (2002) addressed the above mentioned limitation of Lins and Slack (1999) by using standardized departures analysis and trend test approaches to evaluate temporal changes in annual streamflow statistics in the conterminous US during the 1941-1999 period. They found that, all the increases in annual streamflow statistics during the period resulted from a step increase around 1970 rather than as a gradual trend. This meant that in 1970 the climate system shifted to new regime that was likely to remain constant until a new shift occurred.

Cunderlik and Ouarda (2009) also used non-parametric models in their investigation of the trends in the timing and magnitude of seasonal maximum flood events across Canada during the 1974-2003 period. Since actual dates (directional variables) were used in this study, authors revealed that, “dates of flood occurrence that are close together may be very scattered when plotted in Cartesian coordinates.” Hence, the authors first transformed the original directional series into a new series by defining a new location of the origin. Then, the Mann-Kendall test along with the pre-whitening method were used in the trend analysis. The issue of multi-modality associated with the use of the directional variables were solved by analyzing trends separately in each flood season. The results of this study showed that there were no significant trends in the magnitude and timing of fall rainfall floods. However, significant trends in the magnitude and timing of spring snowmelt floods were observed with the trend in the magnitude of snowmelt floods being more pronounced. Most of the negative significant trends in timing of spring snowmelt floods were found in southern Ontario, Northern Saskatchewan, Alberta and British Columbia whereas positive significant trends were identified in western Canada. The strength of their study lies in their ability to account for the directional character (actual dates) and multi-modality of flood occurrences in Canada. However, no reason was given to the significant positive trends found in Western Canada.

Hetalo (2018) used annual data on rainfall from 1930 -2015 to perform a Zivot-Andrews test and identified 1972 as the year when significant increase in rainfall had begun in New

Brunswick. With the help of complementary log-log model, Hetalo (2018) proceeded to predict that the annual change of probability of flood in New Brunswick is equal to 0.0233%. This study was limited by the fact that prediction of the annual probability of flood was based on only one factor-the impact of rainfall on flood. However, studies like Jaafar et al. (2015) have shown that flood is caused by many other climate variables. This limitation will be addressed later in this study.

Mouri et all. (2013), Mohr, Kunz and Keuler (2015), Aich, Kone, Hattermann, and Paton (2016) are a few other examples of literature that fall under the statistical stream.

Since I do not have any training in hydrology and my goal is to produce results that can be easily understood by any individual, I will follow the statistical stream of literature. Based on my literature review, to produce more precise estimates for probability of flood, it is necessary to use daily data like in Kilsby et al. (1998). However, due to lack of data at the daily level and even on monthly and quarterly basis, the study will make use of available annual time series data. To address the issue of potential non-linearity in this study, generalized linear models for binary response variables such as probit, logit and complementary log-log models will be considered as was previously done in Hetalo (2018).

Chapter 3. Methodology

As mentioned in the first chapter, this study seeks to find out whether the increased occurrence of floods in New Brunswick is caused by climate change. This objective is achieved by following a two-step procedure: In the first stage, we identify the best statistical model as a function of climatic variables and other control variables, that can be used in predicting the probability of floods. In the second stage, we analyze the dynamics of the chosen climatic and control variables. These two steps will lead us in estimating the probability of future floods caused by climate change in New Brunswick. Results of this study will guide policy makers in their investment decisions concerning flood mitigation in New Brunswick. The methodology used in this study follows that of Hetalo (2018) with some modifications.

According to that methodology, an Ordinary Least Squares (OLS) regression is not beneficial in estimating the probabilities of future floods, because our dependent variable takes on only two values: 1 = flood in a given year and 0 = no flood in a given year. Hence the binary response model is appropriate in this case.

According to Gujarati (2004), there are three main approaches that can be used to develop a probability model for a binary response variable. They are: (1) linear probability model (2) logit model, and (3) probit model.

Linear probability model can be presented as follows:

$$Y_i = \beta 1 + \beta 2X_i + U_i \qquad \text{Equation (1)}$$

where,

Y_i is the response variable that takes on values explained above, β1 is the constant term, β2 is the coefficient of the independent variable and U_i is the error term. This model looks like a typical linear regression model. However, because the response variable is binary, it is known as a linear probability model.

Assuming $E(U_i) = 0$ then we obtain

$$E(Y_i \mid X_i) = \beta 1 + \beta 2 X_i \qquad \text{Equation (2)}$$

If P_i is the probability that $Y_i=1$ and $(1-P_i)$ is the probability that $Y_i=0$, then

$$E(Y_i) = 0\,(1-P_i) + 1(P_i) = P_i \qquad \text{Equation (3)}$$

Comparing equations 2 and 3, we can state that,

$$E(Y_i \mid X_i) = \beta 1 + \beta 2 X_i = P_i \qquad \text{Equation (4)}$$

We can observe from equation (4) that the linear probability model is not an adequate statistical model since it does not satisfy the restriction of probability which states that $0 \leq E(Y_i \mid X_i) \leq 1$. Moreover, the linear probability model is characterized by other weaknesses such as the non-normality of the disturbances (U_i) and the heteroscedasticity of U_i.

According to Davidson and MacKinnon (2004), binary response models which satisfy the restriction $0 \leq Pt \leq 1$ have the specification, $P_t \equiv E(Y_t \mid \Omega_t) = F(X_t \beta)$, where, $X_t\beta$ is the index function, which maps vector of independent variables and vector of parameters into some scalar index and F(x) is a transformation function which satisfies the following properties:

1. $F(-\infty) = 0$

2. $F(+\infty) = 1$

3.f (x) = $\frac{dF(X)}{dx} > 0$

Given a cumulative standard normal distribution function shown below;

$$\phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-1/2(x^2)} \, dx$$

and using it as the transformation function $F(X_t\beta) = \phi\,(X_t\beta)$, the model becomes a probit model.

However, if the transformation function is a logistic function in the form shown below,

$$\Lambda\,(x) \equiv \frac{1}{1+e^{-x}} = \frac{e^{x}}{1+e^{x}}$$

then the model is called a logit model.

Another binary response model that can be used in predicting extreme events such as flood is the Gumbel distribution also known as the Fisher-Tippett Type I distribution of extreme values. Oosterban (1994) described the standard Gumbel distribution as

$$F(X_N < X_r) = e^{-e^{-y}} \quad \text{where,}$$

X_N = the maximum x from a sample of size N

X_r = a reference value of X_N

$y = \alpha(Xr - u)$, the reduced Gumbel distribution

$u = \mu - c/\,\alpha$, the mode of the Gumbel distribution

μ = mean of the Gumbel distribution

c = Euler’s constant =0.577

$\alpha = \frac{\pi}{\sigma\sqrt{6}}$

Zelenhasic (1970), Haan (1977), Shaw (1983) and Mujere (2011) have used the Gumbel distribution in this regard.

In general, the concept of a link function was introduced to ensure that binary response models are consistent with the broader class of Generalized Linear Models (GLM). With the help of the lecture notes on GLM prepared by Rodriguez (n.d), we will explain the theory behind these models.

Rodriguez (n.d) states that "any transformation that maps probabilities into the real line could be used to produce a generalized linear model, as long as the transformation is one-to-one, continuous and differentiable."

For instance, if F(.) is a cumulative distribution function (CDF) of a random variable defined on the real line as shown below;

$$\pi_i = F(\eta_i) \quad \text{where} \quad -\infty < \eta_i < \infty$$

then, the inverse transformation can be used as the link function such that:

$$\eta_i = F^{-1}(\pi_i) \quad \text{where} \quad 0 < \pi_i < 1$$

This concept can be applied to models for binary data in terms of latent variables. Let Y_i denote a random variable representing a binary response which is coded 0 and 1 as usual. If we assume that there exists an unobservable continuous random variable G^* which can be represented on the real line such that $Y_i=1$ if G^* exceeds a certain threshold θ. Then G^* is referred to as a latent variable hence we can write:

$$\pi_i = \Pr(Yi = 1) = \Pr(G_i^* > \theta)$$

However, latent variables are not directly observed but are rather inferred from other observed variables through a mathematical model. Hence, to identify the model for a latent variable, the common practice is to take the threshold to be zero and standardize G_i^* to have a fixed value for the standard deviation. For example, the standard deviation can be 1.

Suppose the outcome depends on a vector of covariates x. Then, the linear model for the latent variable can be written as:

$$G_i^* = x_i' \beta + U_i$$

where

β is a vector of coefficients of the covariates x_i

U_i is the error term which has a distribution with CDF as F(u).

The probability π_i of observing a positive outcome is

$$\pi_i = \Pr(Y_i > 0) = \Pr(U_i > -\eta_i) = 1 - F(-\eta_i)$$

Where $\eta_i = x_i' \beta$ is the linear predictor

If U_i is symmetric around zero, then $F(U) = 1 - F(-U)$. Hence, $\pi_i = F(\eta_i)$.

Therefore, a generalized linear model with binary response has a link function which can be defined as:

$$\eta_i = F^{-1}(\pi_i)$$

However, if the distribution of the error term is not symmetric, then the link function can be written as:

$$\eta_i = -F^{-1}(1 - \pi_i)$$

Two common link functions, probit and logit, which are often used in literature, rely on a symmetric CDF. However, another popular link function, known as the complementary log-log transformation, does not depend on the assumption of a symmetric CDF. This means that the complementary log-log transformation is appropriate if for a given data, the probability increases slowly at small to moderate values but increases sharply near 1. The above-mentioned three functions are characterized by the following features:

1.Probit

$\pi_i = \phi\,(\eta_i)$

$\eta_i = \phi^{-1}\,(\pi_i)$

2.Logit

$\pi_i = F(\eta_i) = e^{\eta i} / (1 + e^{\eta i})$

$\eta_i = F^{-1}(\pi_i) = \log [\ \pi_i\ / (1- \pi_i)\ ]$

3.Complementary log-log

$\pi_i = e^{-e\wedge-\eta i}$

$\eta_i = \log [\ -\log(1- \pi_i)\ ]$

Results for the probit and logit models tend to be very similar. The only distinguishing factor in these two models lies in the assumption about the distribution of the errors. The probit model assumes that errors are normally distributed whereas the logit model assumes that the errors have a standard logistic distribution. According to Rodriguez (n.d), "the complementary log-log transformation has a direct interpretation in terms of hazard ratios, and thus has practical applications in terms of hazard models”.

In this study, we shall test all the three binary response models and choose the one that serves as the best fit.

With regards to the second stage of our procedure, we will begin by determining the breakpoint in each of the climatic variables using the Zivot-Andrews test. This test which was introduced in Zivot and Andrews (1992), employs the full sample and uses a different dummy variable for each possible break date. The test chooses the break date where the evidence is least favorable for the unit root and hence has the minimum (most negative) t-statistic.

Enders (2014) suggests that the best way to capture the long run dynamics of a series is to account for the autoregressive process of order one or AR (1) with linear time trend and seasonal component. However, since the data used in this study are annual, we have no information of the seasonal components. Hence, we will only focus on the AR (1) process with linear time trend for all climatic variables that are used in our models. Therefore, the model which will be used in the second stage is presented below:

$$Y_t = \alpha_0 + \alpha_1 \text{trend} + \alpha_2 \text{dummy} + \alpha_3 \text{ dummytrend} + \alpha_4 Y_{t-1}$$

where,

Y_t is the climatic variable at year t

α_0 is the constant term

α_1 is the coefficient of the trend term “dummy” is a dummy variable which takes on the value “0” before the breakpoint and “1” after the breakpoint

α_2 is the coefficient of the dummy variable

α_3 is the coefficient of the interaction between the dummy variable and the trend variable

α_4 is the coefficient of the first lag of the climatic variable.

In a nutshell, the two-stage procedure proposed in this chapter will provide the most parsimonious model but not the most convincing or reliable forecast, for predicting the probability of future floods caused by climate change in New Brunswick. The model will assume that temperature, rainfall, sea-level, river discharge and GHG emissions are the main determinants of flood in New Brunswick.

Chapter 4. Data description, empirical framework, and findings

4.1. Background

From the literature review presented in chapter two, we noticed that time series analysis was the main statistical tool used to predict probability of floods. In this study, we follow the same approach.

In our literature review, we obtained a wide range of variables used in flood prediction. These variables include intensity of rainfall, rainfall distribution, direction of the prevailing wind, deviation of average precipitations from historical trends, snowfall, total precipitation and some other relevant variables. However, due to lack of data in the case of New Brunswick, we will focus on five major variables.

Based on the hydrological stream of literature, river discharge served as our hydrological control variable in this study. GHG emissions was also used to control for the contribution of human activities to flood. The climatic variables used in this study are: temperature, rainfall and sea-level. Our dependent variable in this study is flood occurrence in a given year. Definitions of these variables are presented below:

Year – year of observation

Flood – a dummy variable which takes on the value of “1” if there was flood in a given year and “0” if there was no flood in a given year. According to Burina (2017), flood refers to “the overflowing of the normal confines of a stream or other body of water, or the accumulation of water over areas that are not normally submerged.” Since we are interested in extreme weather events, we only considered major floods in New Brunswick. The New Brunswick flood history database does not have a record on the cost of damage for all the flood events, so we are unable to set a threshold based on damages. However, the database provided a qualitative description for each of the events. In this study, extreme floods were identified using words such as *major*, *excessive* and *heavy* in the database.

Discharge – The volume of water that flows through a river in a given year.

Temperature – Annual average mean temperature.

Rainfall – Annual amount of rain.

Sea-level – Annual mean sea level.

L.GHG – First lag of annual GHG emissions.

We expect a negative relationship between flood and temperature and a positive relationship between flood and rainfall, sea-level, discharge and the previous year's GHG emissions. The reasoning behind our expectations is as follows:

Higher temperature often results in warmer and drier climate leading to droughts and heat waves, hence it is unlikely for floods to occur.

Moreover, if there is heavy rainfall, infiltration becomes difficult. This means that there is less chance of the rain being soaked up by the soil, thereby causing the rain to run into any nearby river. The faster the water reaches the river, the more likely flood to occur.

Sea-level rises cause waterbodies to wash over their barricades through storm drains thereby causing houses and roads to be flooded.

Also, floods are likely to occur when a river's discharge exceeds its channel's volume causing the river to overflow onto the surrounding area.

Increased GHG emissions cause oceans to warm and hence expand in volume. When the volume of waterbodies increases beyond certain point it results in flood. We assumed that it takes a year for GHG emissions to cause flood.

Table 4.1 below provides information on the source and unit of measurement of all the variables used in the study. The descriptive statistics of the variables are shown in table 4.2.

Table 4.1: *Source and unit of measurement of data*

VARIABLE	UNIT OF MEASUREMENT	STATION	SOURCE
Flood	-	New Brunswick	New Brunswick Flood History Database
Temperature	^{0}C	Fredericton A	Environment and Climate Change Canada
Rainfall	mm	Fredericton A	Environment and Climate Change Canada
Sea-level	mm	Saint John	Permanent Service for Mean Sea level (PSMSL)
Discharge	(m^3/s)	Saint John River, Grand Falls	Environment Canada
L.GHG	$ktCO_2$ eq	New Brunswick	Environment and Climate Change Canada

Table 4.2: *Descriptive statistics*

VARIABLE	NUMBER OF OBSERVATIONS	MEAN	MINIMUM	MAXIMUM
Flood	66	0.8787879	0	1
Temperature	66	5.465591	4.2	7.4
Rainfall	66	859.6813	540.3	1266.1
Sea-level	66	7036.288	6946	7175
Discharge	66	3350.424	915	7500
L.GHG	66	23893.54	10505	31990.67

4.2 Probability of flood in New Brunswick

We begin our analysis with the first stage of our methodology. With the help of Stata software, we estimated the probit, logit and complementary log-log statistical models. Table 4.3 below shows the results of our estimation of these models with their robust standard errors quoted in parenthesis.

Table 4.3: *Estimation Results in levels for all variables (standard errors in parenthesis)*

VARIABLE	PROBIT		LOGIT		COMPLEMENTARY LOG-LOG	
	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value
Temperature	-0.4244172 (0.3077312)	-1.38	-0.7653624 (0.5448215)	-1.4	-0.363286 (0.2777374)	-1.31
Rain	0.0035003 (0.0016481)	2.12	0.0063139 (0.0029874)	2.11	0.0028573 (0.0013811)	2.07
Sea-level	0.005464 (0.0043667)	1.25	0.0097784 (0.0078399)	1.25	0.0047118 (0.0038765)	1.22
Discharge	0.0000493 (0.0001856)	0.27	0.0001252 (0.0003547)	0.35	0.0000286 (0.0001445)	0.2
L.GHG	0.0000497 (0.0000243)	2.05	0.0000795 (0.000041)	1.94	0.0000475 (0.0000229)	2.07
Constant	-39.16668 (30.08111)	-1.3	-70.06047 (53.78332)	-1.3	-34.00525 (26.83953)	-1.27
	AIC: 53.35273		AIC: 53.33674		AIC: 53.42634	
	BIC: 66.39906		BIC: 66.38306		BIC: 66.47266	
	Pseudo R2: 0.1472		Pseudo R2: 0.1475			

It is important to note that all three models produced the expected signs. At 5% significance level we reject the null hypothesis, which states that a variable is not significant, if the absolute value of the Z-statistics is greater than the critical value of 1.96. All the models suggest that rainfall is statistically significant at 5% level in estimating the probability of flood. The first lag of GHG is significant in both probit and complementary log-log models and very close to being significant in the logit model. Whereas temperature and sea-level are almost significant in all the models, discharge is far from being significant in the three models. However, we kept all five independent variables since in climate literature, they all play vital roles in causing flood. In deciding which model is the best, we compared the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) of the three models and chose the one with the smallest value. In our case, the logit model became the best among them. This concludes the first stage of our methodology. Now we need to analyze dynamics of all variables used in our probability model. editing

4.3. Long-run dynamics of the variables

We started our second stage with a unit root test on all variables. Table A1 in the appendix shows that all these variables are not stationary at a 10% significance level. However, the first differences of all time-series are all stationary at a 10% significant level, which means that these series are I(1) or integrated of order one. However, in logit models the issue of stationarity does not matter. According to an online source, https://www.statisticssolutions.com/assumptions-of-logistic-regression/ , the logistic regression does not require a linear relationship between the dependent and independent variables. Hence, the issue of spurious results does not arise in binary response models. Since all the explanatory variables are non-stationary at levels, we assumed that the source of non-stationarity is long run memory which can be captured by linear time trend as suggested in Enders (2014).

Again, we assumed that the long run memory is not continuous but is subject to change. Hence, there is a need to conduct a Zivot-Andrews test to identify the potential breakpoint in each of the series. Results of this test shown in table A2.1- A2.5 in the appendix suggest that the breakpoints in temperature, rainfall, sea-level, discharge and GHG occurred in:

2007, 1982, 2000, 1975 and 1991 respectively. Given these results, we proceeded with estimation of the long run dynamics of the five variables using the model described in chapter three. Results of these estimations are presented in Table 4.4 below:

Table 4.4: *Dynamics of temperature, rain, sea-level, discharge and GHG in New Brunswick*

	Variable (Yt)				
	Temperature	**Rainfall**	**Sea-level**	**Discharge**	**L.GHG**
constant	-0.2487687 (0.2266187)	-70.35911 (107.3627)	-2.887746 (11.77258)	-453.9516 (755.0065)	6805.363 (1203.878)
trend	0.0089372 (0.0073959)	4.950184 (5.81731)	0.3159914 (0.4389274)	43.2021 (46.62214)	1.037565 (27.97477)
dummy	-5.421665 (2.648353)	-41.99125 (131.8417)	-168.7803 (165.2226)	130.5744 (1169.019)	-3330.794 (34.4682)
dummytrend	0.081023 (0.0425866)	-2.826643 (5.939156)	2.589384 (2.823348)	-37.43772 (50.17034)	4.98208 (34.4682)
AR(1)	-0.5175894 (0.1115013)	-0.4947912 (0.1115487)	-0.3693348 (0.1102279)	-0.4033668 (0.1189103)	0.7721135 (0.0503108)

We notice that the coefficients of the trend terms for each of the variables are statistically insignificant. This may be because we used a more aggregated data. However, since we are limited by the availability of data and our goal is to find qualitative but not quantitative trends we will keep these trends.

The positive signs for the “dummytrend” variables of *temperature, sea-level* and *L.GHG* imply that the annual averages of mean temperature, sea-level and in New Brunswick have increased at a faster rate since 2007, 2000 and 1991 respectively. However, annual amount of rainfall and annual river discharge have increased at a slower rate since 1982 and 1975 respectively.

The AR(1) terms of the variables are for technical purposes hence they do not have any meaning at this point.

4.4. Estimating the probability of future flood in New Brunswick

As discussed in chapter three, now we can combine our results from the first stage with results from the second stage to forecast the probability of flood in New Brunswick. To do this, we first estimated the probability of flood in 2018 - the first year after our last year of observation in the data set. Afterwards, we calculated the annual rate of change of probability by summing the products of the trend coefficients of each of the five independent variables (stage two) by their marginal effects (stage one).

Table 4.5 below shows that, according to the previously chosen logit model, the mean estimated probability of flood in 2018 is 0.8769231.

Table 4.5: *Mean Estimated Probability of Flood in 2018*

	Margin	**Standard Deviation**	**z**	**P>|z|**
_cons	0.8769231	0.0379938	23.08	0.000

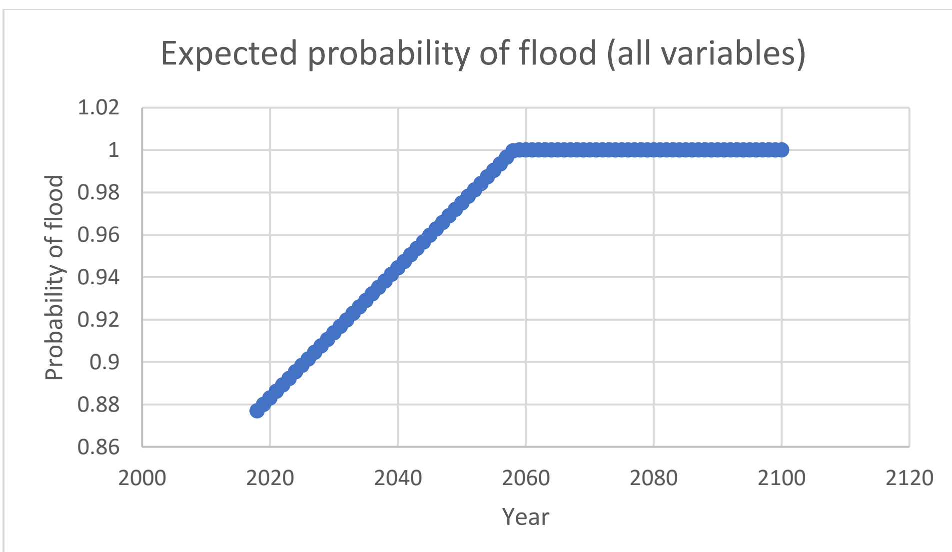
Table 4.6 below shows contribution each variable makes to the annual rate of change of probability of flood in New Brunswick**.**

Table 4.6: *Contribution of Variables to The Annual Rate of Change of Probability of Flood*

VARIABLE	Trend Coefficient	Marginal Effect	Product
Temperature	0.0089372	-0.0711787	-0.00063614
Rainfall	4.950184	0.0005872	0.002906748
Sea-level	0.3159914	0.0009094	0.000287363
Discharge	43.2021	0.0000116	0.000501144
L. GHG	1.037565	0.0000074	7.67798E-06
Annual rate of change of probability			0.003066795

We can now estimate future probability of flood in New Brunswick given the initial probability of flood in 2018 derived from the logit model and the annual rate of change of probability which was estimated based on the dynamics of the five chosen variables. Figure 4.1 below shows the time path of the probability of flood in New Brunswick from 2018 to 2100. It can be observed that from the year 2057 onwards the probability of flood becomes 100%.

Figure 4.1



Probability of Flood Given Temperature, Rain, Sea-level, Discharge, and GHG emissions

4.5. Significance of Green House Gas Emission in Estimating the Probability of Future Flood

Over the years, the issue of GHG emissions has become very important. Therefore, we would like to go further by analyzing the effect of GHG emissions on the probability of flood in New Brunswick. We will do this by replicating our initial model with GHG by the model without GHG emissions. This latter is presented in table 4.7 below.

Table 4.7: *Estimation Results in levels without GHG emissions (standard errors in parenthesis)*

VARIABLE	PROBIT		LOGIT		COMPLEMENTARY LOG-LOG	
	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value
Temperature	-0.4398626 (0.2758222)	-1.59	-0.7905437 (0.4915869)	-1.61	-0.3712471 (0.2432846)	-1.53
Rainfall	0.0028553 (0.0016051)	1.78	0.005336 (0.0030506)	1.75	0.0022449 (0.0012294)	1.83
Sea-level	0.0032921 (0.0043326)	0.76	0.006574 (0.0082045)	0.8	0.002377 (0.0034339)	0.69
Discharge	0.0000682 (0.0001816)	0.38	0.0001486 (0.0003421)	0.43	0.0000461 (0.0001409)	0.33
Constant	-22.1677 (29.69272)	-0.75	-44.77559 (56.02682)	-0.8	-15.97354 (23.62725)	-0.68
	AIC: 53.6794		AIC: 53.44395		AIC: 53.97663	
	BIC: 64.62768		BIC: 64.39223		BIC: 64.9249	
	Pseudo R2: 0.1040		Pseudo R2: 0.1089			

We follow the same steps we used for the model with GHG emissions. First, we defined probability of flood in 2018:

Table 4.8: *Mean Estimated Probability of Flood in 2018 without GHG emissions*

	Margin	**Standard Error**	**z**	**P|z|**
_cons	0.8787879	0.0379193	23.18	0.000

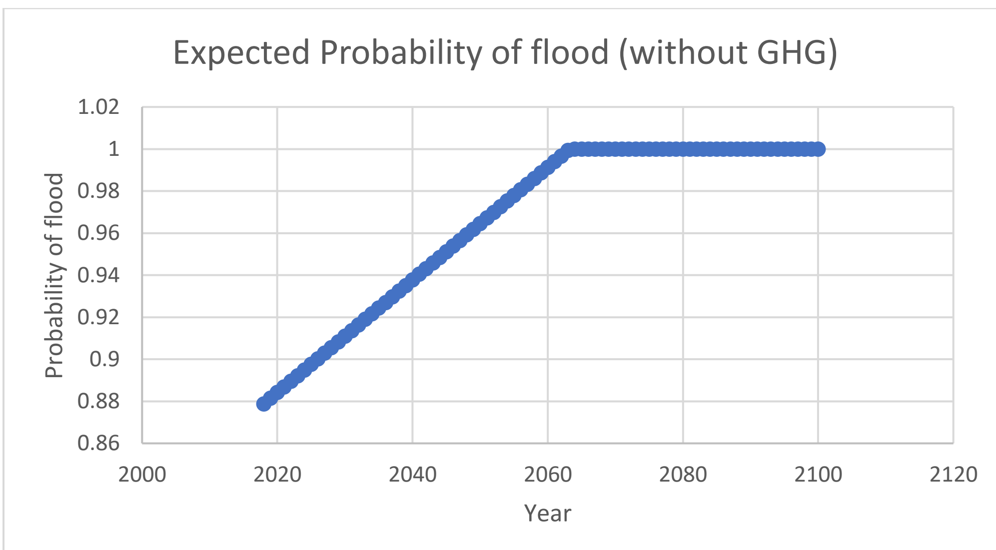
Then we calculated the annual rate of change of probability based on the dynamics of each variable considered. The results are shown in table 4.9 below.

Table 4.9: *Contribution of variables (without GHG emissions) to the annual rate of change of probability of flood*

VARIABLE	Trend Coefficient	Marginal Effect	Product
Temperature	0.0089372	-0.0760493	-0.000679668
Rainfall	4.950184	0.0005133	0.002540929
Sea-level	0.3159914	0.0006324	0.000199833
Discharge	43.2021	0.0000143	0.00061779
Annual rate of change of probability			0.002678885

Finally, we generated the new time path of the probability of flood in New Brunswick based on our restricted model. This is presented in figure 4.2 below.

Figure 4.2



Probability of Flood Given Temperature, Rain, Sea-level and Discharge

Comparing models with GHG emissions (see Figure 1) and without GHG (see Figure 2) we can see that beginning from 2018, it takes 39 years for the probability of flood to reach 100% if we include GHG emissions and it takes 46 years if we disregard this impact. It means that if we do not take GHG emissions into account, our future probability of flood in New Brunswick will be misleading.

In conclusion, based on the results of our statistical work, we found that the probability of flood in New Brunswick increases over time, and climate change is one of the decisive factors of this increase. If nothing is done, then this probability will reach 100% by 2057 according to our model. Using our trend point estimates we can state that the probability of flood increases overtime reaching a 100% probability by 2057. If probability of flood is combined with economic damage from flood, it can give us the expected value of the investments into flood prevention measures which is very important from a standpoint of public policy recommendations.

Chapter 5. Conclusion, limitations and recommendations

Evidence from past studies have shown that flood is the most frequent large weather event in New Brunswick. In this study we consider major floods in New Brunswick based on the qualitative description of floods in the New Brunswick flood history database. Extreme floods were identified in the database by using words such as *major*, *heavy* and *excessive*. Due to extreme floods, many lives have been lost, properties have been destroyed and homes have been displaced. Moreover, the provincial Government in New Brunswick incurs huge costs in providing support to individuals and families affected by these floods. Also, insurance companies cover some damages. However, there is no universal and clear methodology to define those economic damages. Therefore, there is a need to predict the probability of flood to guide policy makers in their decision making with regards to flood mitigation.

In this regard, two objectives were set for this study: (1) to determine whether floods in New Brunswick are caused by climate change and (2) to know whether the frequency of flood increases over time. These objectives were achieved by following a two-stage approach. In the first step, the logit model was employed in estimating the probability of flood using discharge as a hydrological control variable and three climatic variables namely: temperature, rainfall and sea-level. GHG emissions was also used as a control variable for the contribution of human activities to flood. Results at this stage showed that whereas higher temperature decreases the predicted probability of flood, the reverse was true for rain, sea-level, discharge and GHG emissions. In the next stage we analyzed the long run dynamics of each of these variables. It was observed that temperature, sea-level and GHG emissions increased at faster rates since 2007,2000 and 1991 respectively, whereas rainfall and discharge and GHG emissions increased at slower rates since 1982 and 1975 respectively. According to the definition of climate change by IPCC (2007), these results support our hypothesis of the ongoing climate change in New Brunswick. Results from stages one and two were combined to derive the future time path of the probability of flood. According to our model, the probability of flood in New Brunswick increases over time, reaching 100% in the year 2057.

This study enhanced the model previously developed in Hetalo (2017) by accounting for the effects of four additional variables on the probability of flood in New Brunswick: temperature, sea-level, discharge, and GHG emissions. Moreover, the break date for rainfall found in this study is similar to the one obtained previously by Kosenchuk (2015).

However, this study is limited by the fact that most of the linear time trends of the variables considered were not statistically significant. This may be due to failure to capture the seasonal components in these variables as suggested by Enders (2014) or not long enough time series. Moreover, the study focused on only hydrological and climatic variables to the neglect of some micro and macroeconomic variables. Social factors such as public education and people's response to floodplain regulations could also have served as determinants of future occurrence of flood.

Future research should address the above-mentioned limitations and employ either daily, monthly or quarterly data to obtain more precise trend coefficients. We hope this study elicits more interest in this area.

APPENDIX

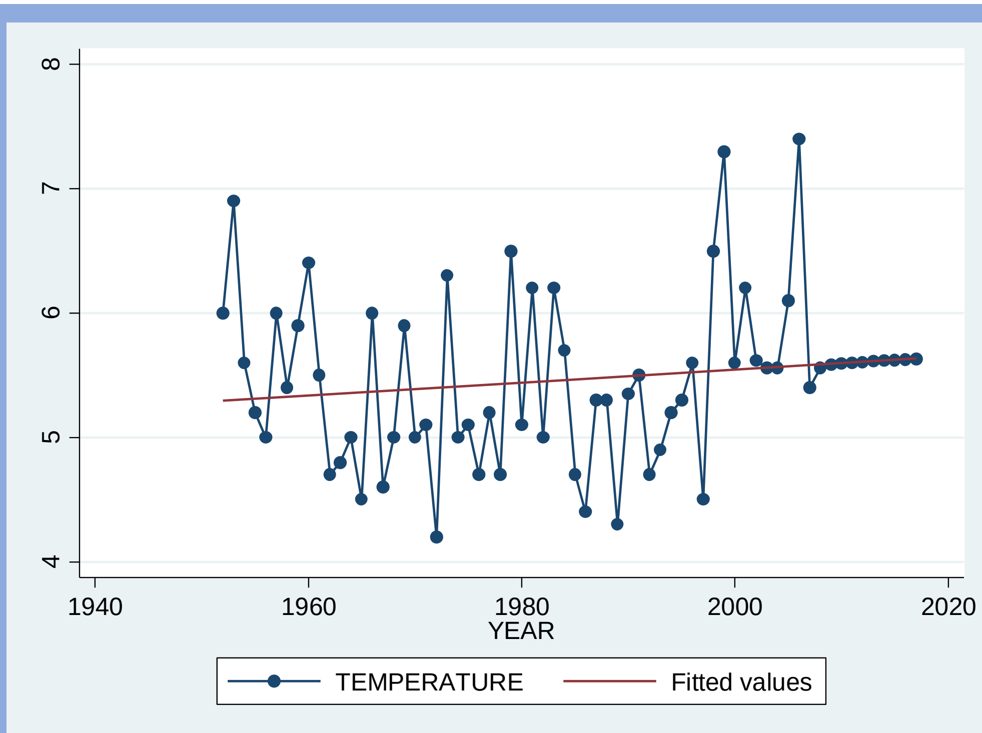


Fig. A 1.1a: Temperature (at levels)

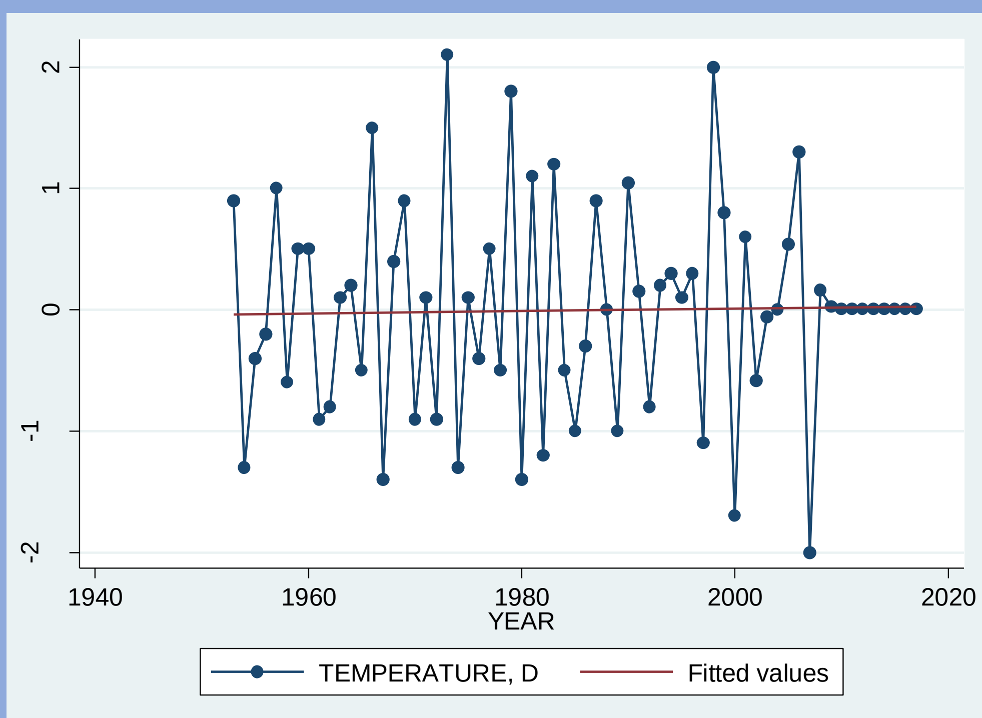


Fig. A 1.1b: Temperature (at first difference)

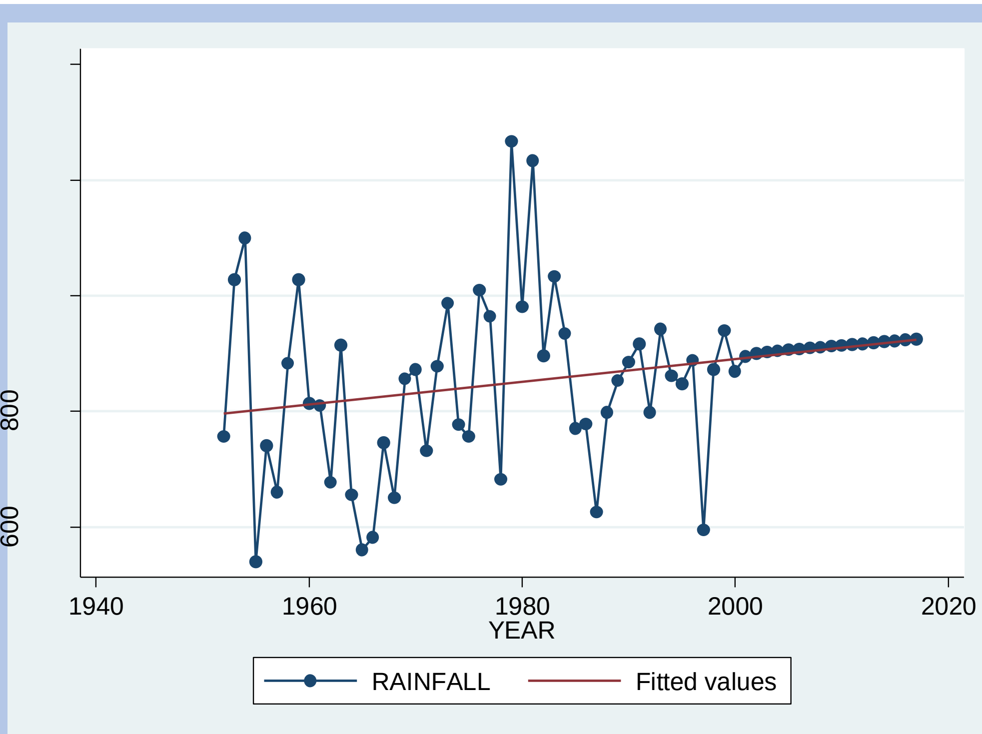


Fig. A 1.2a: Rainfall (at levels)

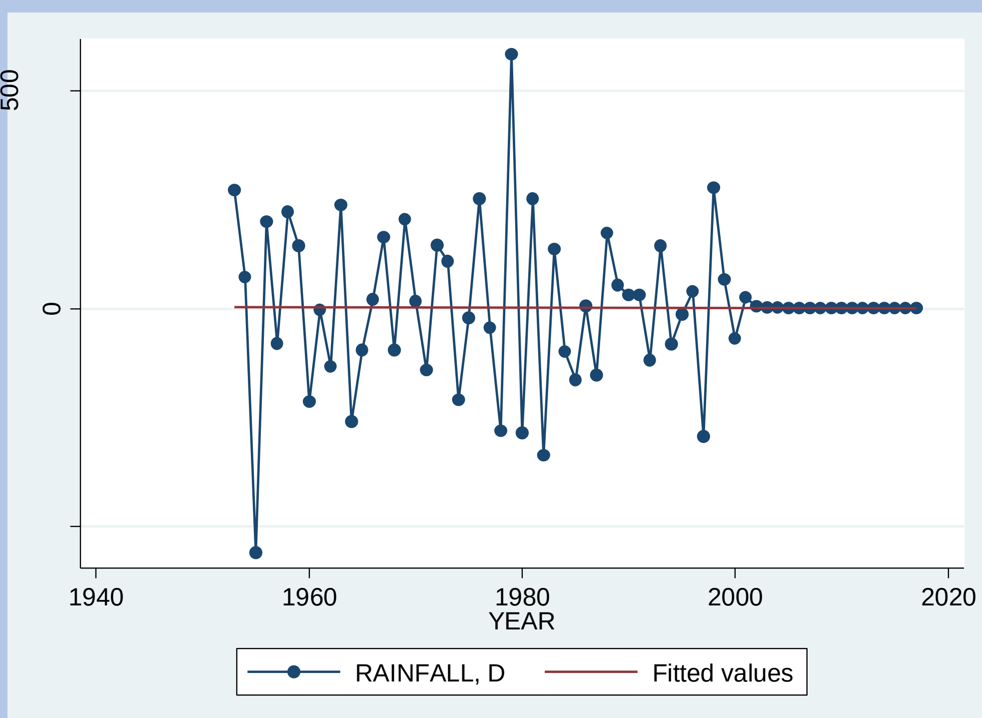


Fig. A 1.2b: Rainfall (at first difference)

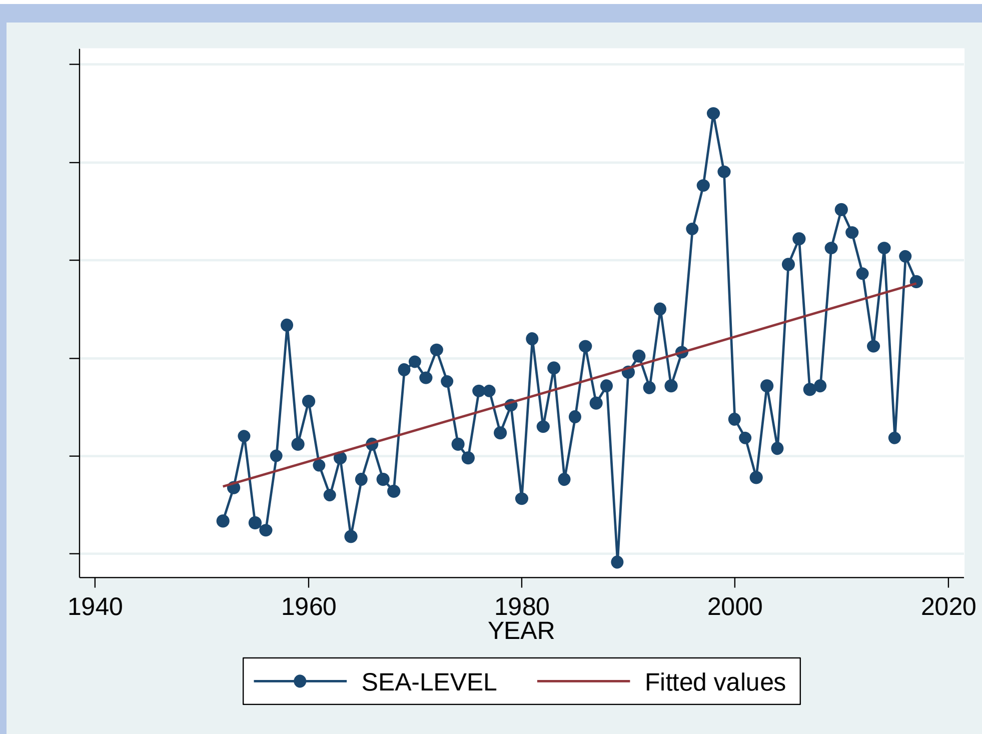


Fig. A 1.3a: Sea-level (at levels)

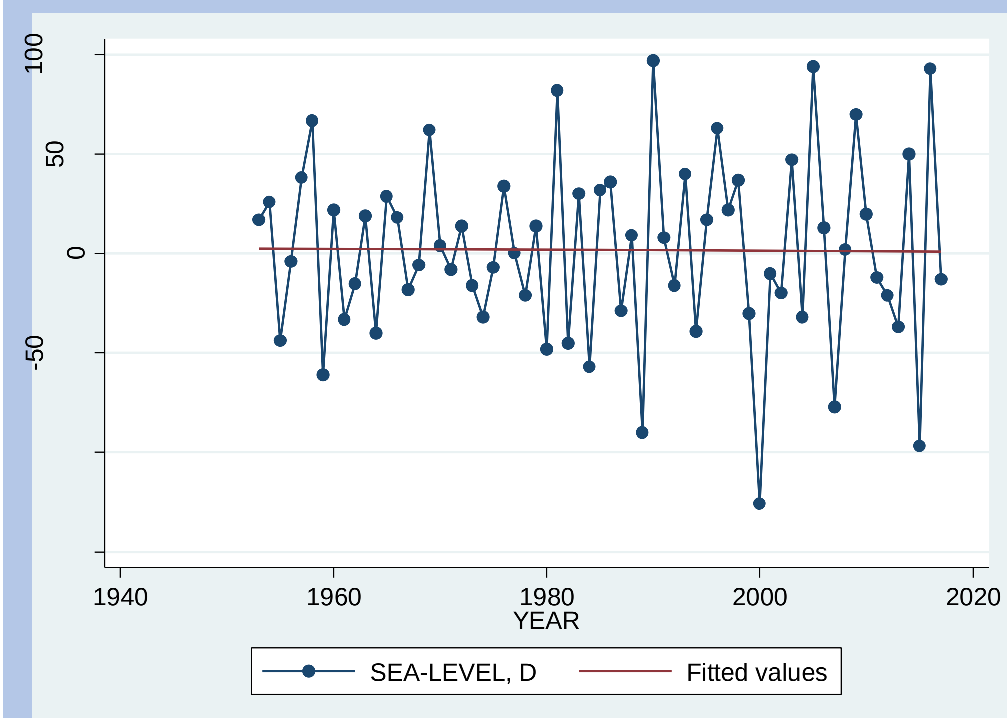


Fig. A 1.3b: Sea-level (at first difference)

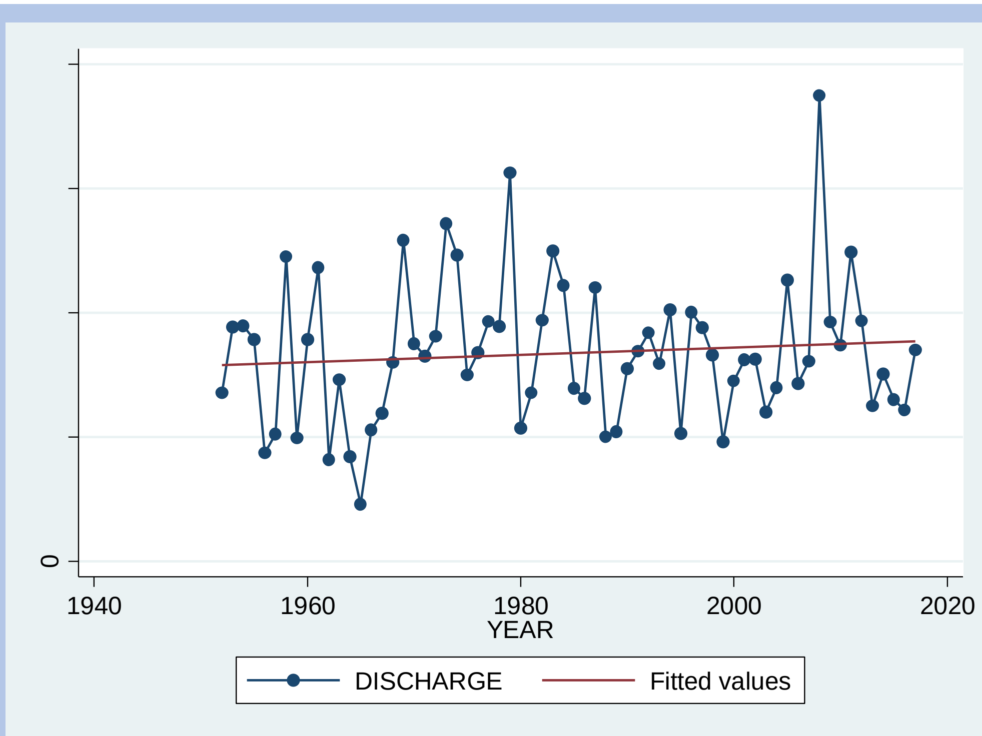


Fig. A 1.4a: Discharge(at levels)

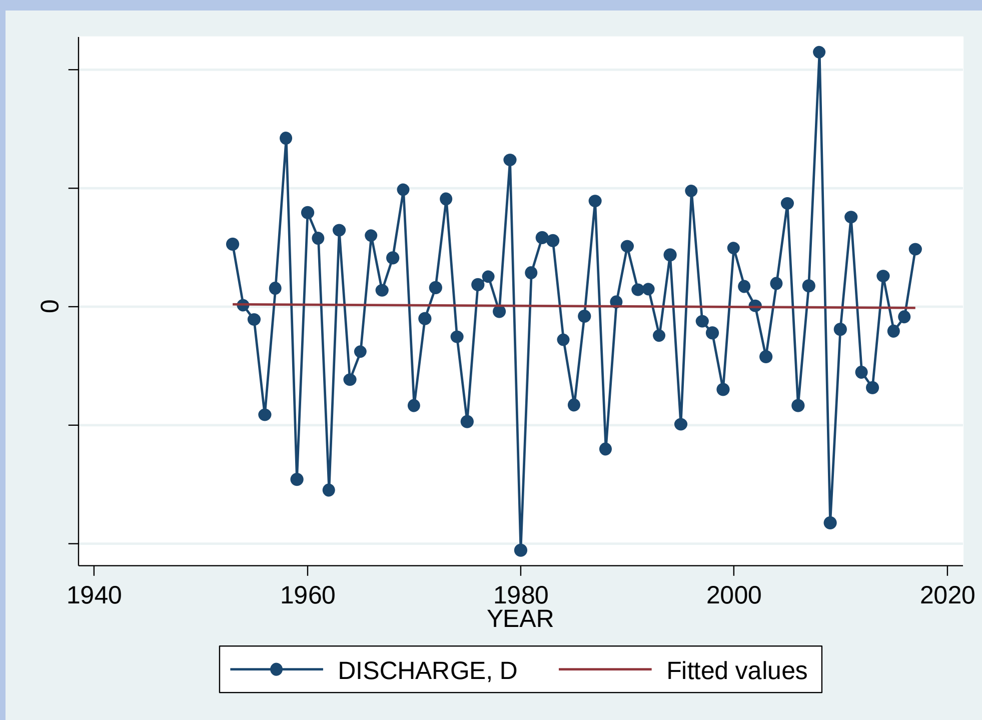


Fig. A 1.4b: Discharge (at first difference)

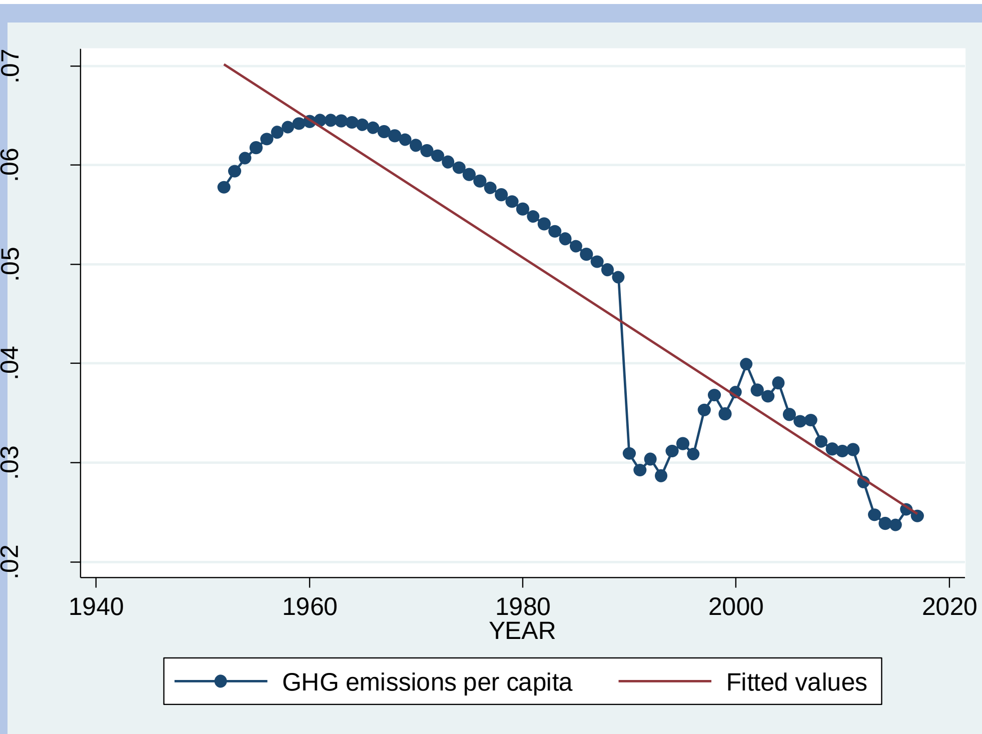


Fig. A 1.5a: GHG (at levels)

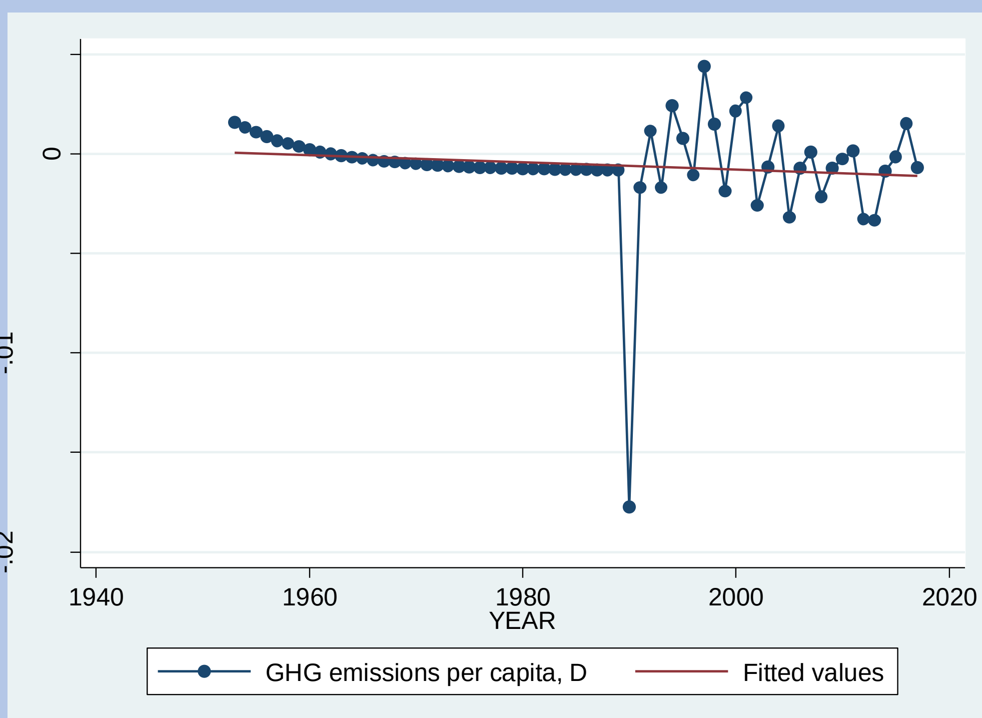


Fig. A 1.5b: GHG (at first difference)

For temperature and rainfall, there were missing data at the end of the series, so I estimated those missing values. Because these missing values do not fall between two observed values, I could not use the mean of the observed values to estimate those missing values. So, for each variable I developed a model which accounts for the trend and first lag of the variable and used this model to estimate the missing values at the end of the series. Similarly, for GHG emissions, there were missing values at the beginning of the data set, so I used the backward iteration method to estimate those values.

Table A1: AUGMENTED DICKEY FULLER TEST

	VARIABLE	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Level	Temperature	-0.626	-2.614	-1.95	-1.61
	Rainfall	-0.475	-2.614	-1.95	-1.61
	Sea-level	0.407	-2.614	-1.95	-1.61
	Discharge	-1.202	-2.614	-1.95	-1.61
	GHG	-1.501	-2.614	-1.95	-1.61
First Difference	Temperature	-9.196	-2.615	-1.95	-1.61
	Rainfall	-9.286	-2.615	-1.95	-1.61
	Sea-level	-7.053	-2.615	-1.95	-1.61
	Discharge	-11.21	-2.615	-1.95	-1.61
	GHG	-5.312	-2.615	-1.95	-1.61

ZIVOT ANDREWS TEST

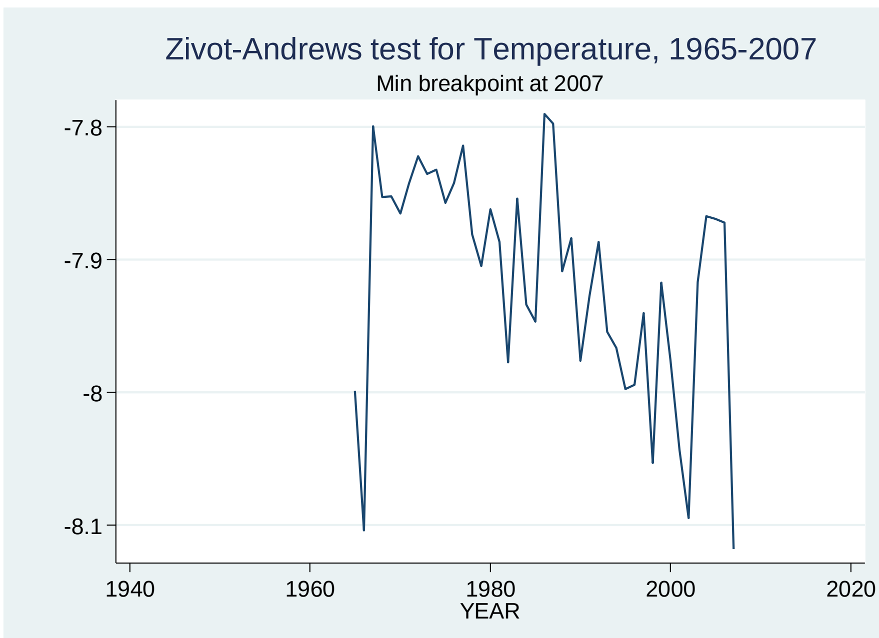


Figure A 2.1

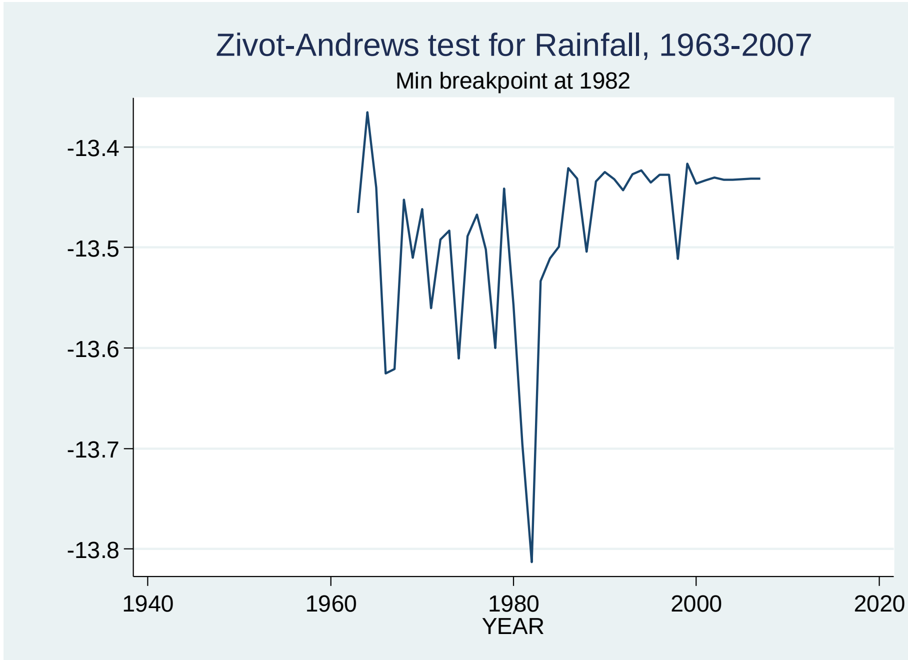


Figure A 2.2

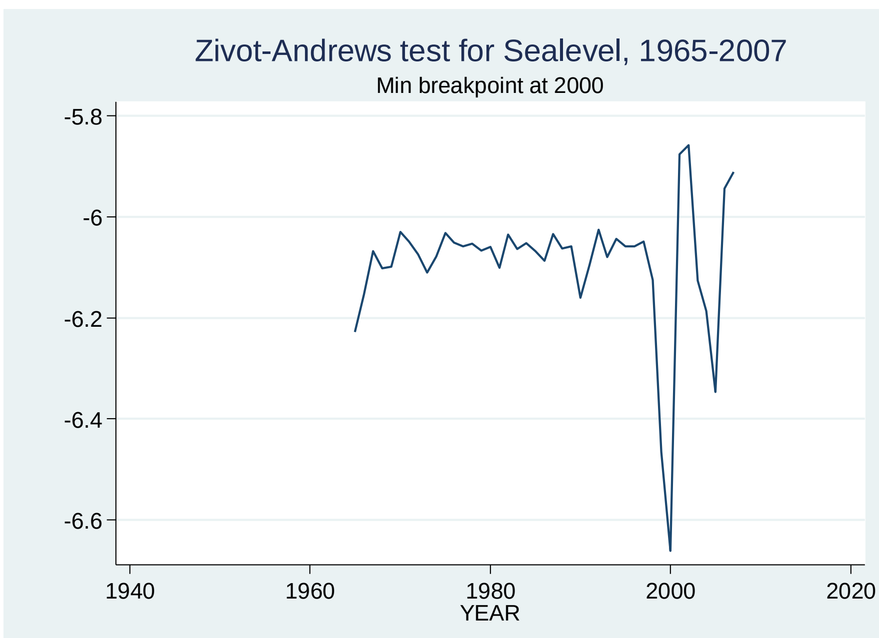


Figure A 2.3

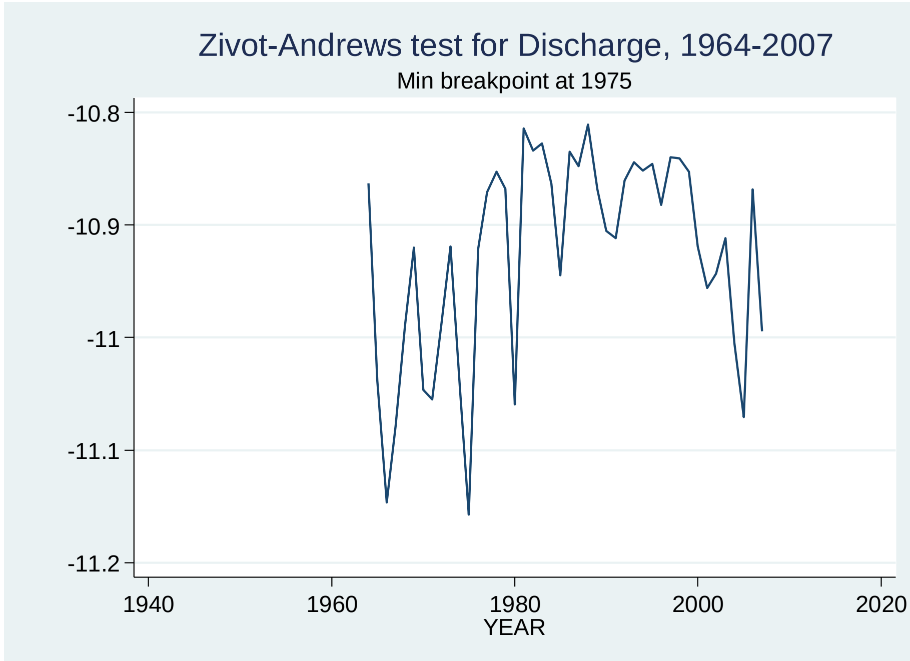


Figure A 2.4

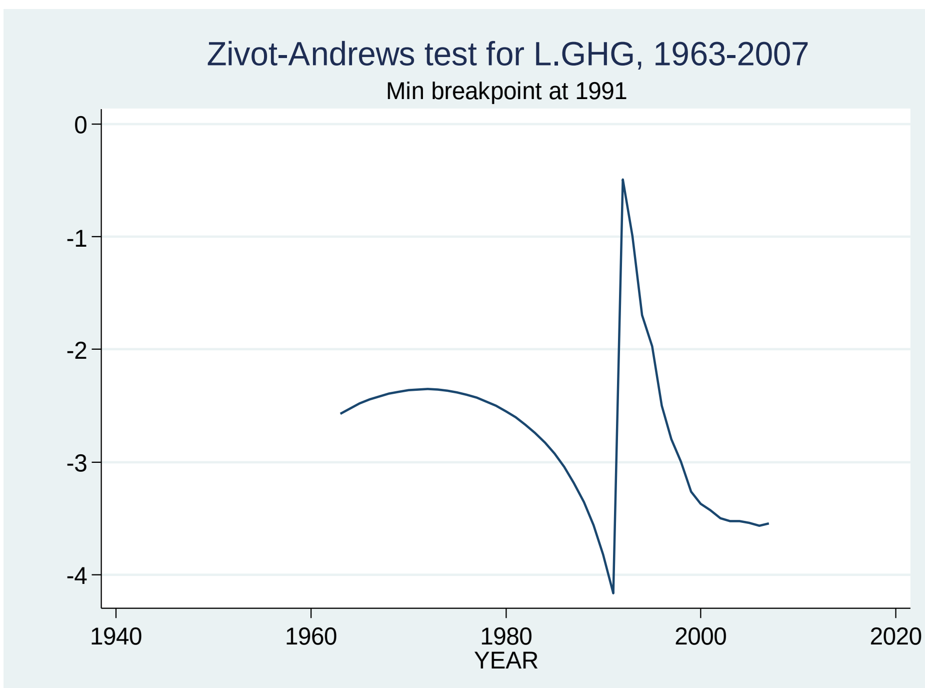


Figure A 2.5

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Curriculum Vitae

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Publications: None

Conference Presentations: *Econometric evaluation of extreme weather and climate events in Atlantic Canada* at the Eleventh International Conference on Climate Change: Impacts and Responses held at the Catholic University of America, Washington DC, USA from 16^{th} -17^{th} April 2019.