EVOLUTIONARY DYNAMICS OF PRECIPITATION IN ATLANTIC CANADA

by

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ABSTRACT

We model long run dynamics of precipitation at five transportation hubs in Atlantic Canada. In doing so, we designed methodology and applied it to twelve precipitation time series – six rainfall series and six snowfall series. Eleven out of twelve time series were estimated with OLS, and only Saint John rainfall series was estimated with GLM to deal with non-normal distribution of error terms. Based on our methodology and estimation, we detected that four precipitation series do not contain significant time trends over the latest period: Three of them are rainfall series with one snowfall series. Six out of remaining eight precipitation series do contain significant time trends that started in 1950s-1960s or 1980s. Moreover, we have similar trends of -3 mm per year in three snowfall series. All of them have started in 1950s-1960s. This result directly points towards potential climate change in the region and supports the conclusion of many climatologists of less snow in Atlantic Canada due to climate change. In general, our estimation showed that snowfall series are more deterministic, and they exhibit negative trends. Rainfall series are less predictable exhibiting either negative or positive trend.

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Chapter 1. Introduction

Intergovernmental Panel on Climate Change (IPCC) defines climate change as any change in climate by any reason, if the change can be identified by statistical tests and last decades or longer (Berstein, 2007). Despite the reason-neutral definition of climate change, the most common hypothesis of climate change is connected to human activity. Greenhouse gases emission is extremely high in the 20th century growing with high speed over decades. Since the middle of the 20th century global ecological balance has changed. The clearest expression of climate change is the global warming, growing trend in the temperature over the world.

According to IPCC AR5 report (Pachauri and Meyer, 2014) the climate change in precipitation in 20th century is not as doubtless as in temperature. In general, they support anthropogenic hypothesis of climate change but mention important regional differences in precipitation dynamics. Global effect on the local precipitation processes is very heterogeneous. This predetermines the necessity of local studies in this area.

Climate change has significant impact on economy, mostly negative impact. There are many estimates of future global damage due to climate change. They differ in range from 1% to 5% constant decline in global GDP. Climate change has influence on many sides of socio-economic activities including healthcare, agriculture, transportation etc.

Main comprehensive models of climate change impact on the economy are Integrated Assessment Models (IAMs). Typical elements of IAMs include modeling of the greenhouse gas emission, its impact on the climate change, damage function of climate change, and social welfare function which reflects damage distribution among countries and generations. Damage function reflects dependence of economic variable as GDP on the climate variables, controlling the effects of other economic variables. In other words, it adds climate factors into production function.

Pindyck (2013) notice that “the damage functions used in most IAMs are completely made up, with no theoretical or empirical foundation”. This fact defines the area of studies which are important today.

Most of the existing studies of climate change impact on the economy concentrate on the temperature as a climate variable. There are not a lot of IAMs which deal with precipitation. This happens not occasionally. Precipitation dynamics is much more heterogeneous over the world than temperature dynamics. Climate change impact on precipitation has strong local specific. Nevertheless, the local specific in climate change is a prospective area of future studies. Dell, Jones, and Olken (2014) conclude: “The more we grow to understand mechanisms, the more accurately responses can be devised. Narrowly identifying mechanisms is thus an important area for future research”.

The purpose of this study is to analyze evolutionary dynamics of rainfall and snowfall series in Atlantic Canada. In total we model twelve time series which correspond to six meteorological stations. This study is a part of the project “Modelling of climate change impact on ground transportation of Atlantic Canada”, and is necessary for understand and quantify the impact of climate change on ground transportation. The choice of the meteorological stations is defined by ground transportation hubs in the regions.

Therefore, we narrow down study to precipitation dynamics in Atlantic Canada in order to define local climate change impact. It is completely agreed with modern area of research.

Our main purpose is to define long run trends in series and structural breaks in them. If global climate change process due to human activity has impact on precipitation in Atlantic Canada, we can expect on structural breaks in the middle and second part of 20th century when greenhouse gas emission increased substantially. There are also possible climate changes due to natural reasons. In case of a structural break, today's trend in precipitation can differ substantially from the trend estimated over the all available data series since 19th century. For the purpose of the economic analysis we have to define actual trend. Besides the linear trend component in long run dynamics, we try to model cyclical component with techniques of time series analysis.

The report has the following structure. Chapter 2 is a literature review where we consider macro- and microeconomic models of climate change influence on economy, econometric studies of structural breaks, and pure meteorological studies about trend analysis and breaks diagnostics in precipitation. We pay special attention to studies related to Atlantic Canada. In chapter 3 we describe the methodology developed to estimate evolutionary dynamics in climatological data. In particular, we use Bai-Perron test for structural break analysis, Ordinary Least Squares (OLS) and Generalized Linear Model (GLM) for modeling trend with breaks, and Autoregressive Moving Average (ARMA) for modeling cyclical component in the process. The 4th chapter contains description of the data and detailed estimation results and diagnostics of the models. Finally, in 5th chapter we discuss main results and conclusions of the study.

Chapter 2. Literature review

Climate change is one of the most discussed topics in modern world and one of the problems people are most concerned about. In 2011, European Commission published a survey in which 20% of EU population mentioned climate change as the most serious problem in the world today ("Climate Change". Survey. 2011). Survey conducted in Canada in 2014 showed that 17% of Canadians were extremely concerned about climate change and 33% were definitely concerned ("Focus Canada 2014. Canadian Public Opinion about Climate Change". Survey. 2014).

This study is associated with evolutionary dynamics of precipitation in Atlantic Canada. The literature review was done in order to address the following three points: (i) how climate change impacts have been incorporated into economic models, (ii) how dynamics of climate variables associated with the change has been modeled, and (iii) how dynamics of precipitation has been estimated.

We begin our review with Annual Reports produced by Intergovernmental Panel on Climate Change (IPCC) because they are the most reliable sources in the field of climate change. Among other things these reports present regional dynamics of climate variables as well as their forecast. Since this study takes on regional perspective, we are interested mostly in regional dynamics of climate variables. In this regard, IPCC's 4th Annual Report (AR4, Berstein, 2007) concludes that climate simulation models give reliable forecasts at the global and/or continental level but not at the regional level. Pitman et al. (2011) emphasize on the necessity of "regionalization of global climate models".

There exist attempts of downscaling of the Global Climate Models, for example, Dibike and Coulibaly (2006), Chen (2002), and development of regional models as Gutowski et al. (1998). There are many publications dedicated to global warming impact on some specific geographic areas, for example, Abbaspour et al. (2009), Sanghi and Mendelsohn (2008), Goswami et al. (2006), Alongi (2015), Vuille et al. (2015), Perez et al. (2015) and others.

Since this study focuses on regional precipitation, we are interested in previous work done in this specific area. IPCC AR5 (Pachauri and Meyer, 2014) contains analysis of precipitation trends all over the world. In their research, authors mostly used datasets for 1900-2008 period. They found various changes in trend slopes and even trend signs across regions, structural breaks in trends, combinations of significant and insignificant trends segments. They conclude that precipitation has been increasing across the world but with medium confidence in 1900-1950 period and high confidence since 1951 (Pachauri and Meyer, 2014). Nevertheless, precipitation dynamics has very significant regional specifics more pronounced than the temperature dynamics. That is why we cannot talk about an increase in global precipitation with the same confidence as an increase in global warming. Therefore, investigation of precipitation dynamics at regional level within specific climate zones is necessary.

Economic impact of changes in precipitation patterns has even deeper regional specifics. In general, economic regions do not coincide with climate zones/regions. Different countries have different types of economy. There are many studies about social and institutional differences across countries to adapt for climate change, for example, Acosta-Michlik and Espaldon (2008), Saldana-Zorilla (2008), Vedwan (2006), Mertz et al. (2009). As a matter of fact, adaptation and its regional differences is one of core topics in AR4 (Berstein, 2007) and AR5 (Pachauri and Meyer, 2014) IPCC. Therefore, economic analysis of climate change impacts should be global since the problem has global roots as well as detailed enough to capture all regional geographical and socio-economic characteristics. Therefore, we now turn our attention to the first point mentioned at the beginning of this section.

At the global level, Integrated Assessment Models (IAMs) are used to incorporate climate change impacts into models of economic growth. A very broad definition of IAM is "any model which combines scientific and socio-economic aspects of climate change primary for purpose of assessing policy options for climate change control" (Kelly and Kolstad, 1998). In general, IAMs estimate damage from climate change impacts and the required abatement costs with the goal of finding optimal combination of pollution and potential investment. Changes in trends underlying dynamics of climate variables are a global problem with characters of externality. The problem becomes even more difficult because of its inter-temporal nature. Climate change is a long run process which involves many generations. Fair distribution of the climate change impact among generations is a philosophical question. Authors impose the rules of distribution as assumptions behind their models following some ideologies.

Theoretical basis for many IAMs is the Ramsey model (Ramsey, 1928) which is quite popular approach in economic modeling of climate change (Baum, 2007). Examples of IAMs are MERGE (Manne, 1993), RICE (Nordhaus and Yang, 1996), DICE (Nordhaus, 1993), SLICE (Kolstad, 1996), PAGE (PAGE User Manual. CEC. 2002) etc. IAMs estimates can vary with assumptions behind the models very substantially. For example, PAGE2002 modeled by Hope (2006) estimates the future damage as 0.6% GDP decline.

The Stern Review (Stern, 2007) technically uses the same model but the predicted damage is almost 5% decline in global GDP.

Ackerman et al. (2009) show limitations of IAMs which lead to such ambiguity in results. They are: choice of a discount rate, assignment of monetary values on the basis of incomplete information or even personal judgments, ignoring the possible effects of policies to reduce greenhouse gas emission and some others. The Stern Review uses near-zero (0.1%) discount rate assuming that consumption of different generations should be valued equally. Nordhaus (2007) and Weitzman (2007) criticize Stern for that.

Nordhaus (2007) views climate change abatement as a possible alternative for capital investment, the same as investment into human capital, industrial capital and other areas. In his DICE model (Nordhaus, 1994), he uses a 3% discount rate. Dasgupta (2008) criticizes both DICE model and the Stern Review. He argues that “ethical” choice of discount rate and real values of elasticity of marginal utility should and can be revealed from real priorities of a society. In addition, high level of uncertainty is always present in IAMs. The models assume known (usually fixed) preferences of future generations which is, of course, not a realistic assumption.

As intermediate conclusion, main usefulness of IAMs is not in predicted values of economic and climate variables but in discussion associated with society’s priorities which they trigger. Eventually, their goal by definition is to help with climate control policy which requires global framework.

Besides IAMs, there are models of climate change at the level of a country, a region as well as specific market or microeconomic level. For example, U.S. Environmental Protection Agency (EPA) in addition to IAMs uses Economy-Wide Models, Mitigation Models, and

Detailed Electricity Sector Model (EPA. Climate economic modeling. Web-page). Economy-Wide Models belong to class of general equilibrium models. General equilibrium analysis is a standard computational approach for large-scale economic models including climate change models (DeCanio, 2003). Basic theory was created by Walras (1874) and further developed by Pareto (1909), Arrow (1951), Debreu (1951) and others. Examples of economy-wide models are the Applied Dynamic Analysis of the Global Economy (ADAGE), Intertemporal General Equilibrium Model (IGEM). Mitigation models usually simulate some particular policy solutions to reduce greenhouse gases emission, mostly with the goal of assessing the required cost per unit of emission reduction. Examples of these models are non-CO2 emission models and Forestry and Agricultural Sector Optimization Model. Integrated Planning Model (IPM) simulates effects of environmental policies on U.S. electric power sector. It allows to estimate impacts of a policy to reduce emission of sulfur dioxide, CO2, mercury, and nitrogen oxides on electric power sector (EPA. Climate economic modeling web-page).

Besides abatement cost approach, there are also attempts to measure climate change impacts in terms of loss in GDP growth. For that goal, researchers incorporate climate change effects into models of economic growth. Aggregate production function within Solow-Swan framework (Barro, Sala-i-Martin, 1995) is still the most popular tool in these models. Good examples of such studies are Brechet et al. (2013) who use Solow-Swan model to find optimal combination between adaptation to and mitigation of climate change impacts, and Azomahou et al. (2015) who investigate how long run memory in environmental and population growth processes affect economic growth using modified version of Solow-Swan model. The authors modified Solow-Swan model by including “non-mean converting stochastic shock in the population growth”. With the help of ARFIMA (Autoregressive Fractionally Integrated Moving Average) model they show that mean-reversion property of shocks in economic growth depends on the evolutionary paths of environmental and population growth.

As part of a large project on Modelling Economic Consequences of the Climate Change Impacts on Ground Transportation in Atlantic Canada, this study follows the theoretical approach that is based on a modified general equilibrium model similar to other papers mentioned above while empirical work uses the concept of Solow residuals. The large project defines a dynamic hierarchical general equilibrium model of a road transportation network in Atlantic Canada in which there are three levels of models: The highest Level 1 is associated with a system of dynamic equations for price and volume of transportation services in the region. The system produces equilibrium price of transportation and traffic. Level 2 consists of five regional hubs: Fredericton, Moncton, St. John, Northern New Brunswick (North), and Halifax. At Level 2, the equilibrium price of transportation is taken as an input along with local geographical and industrial characteristics as well as local traffic volume to define value added generated by each hub, and Level 3 represents disaggregation of each transportation hub into major local consumers of transportation. Climate change impacts are incorporated into the model via Level 2 through the “Solow residuals”, which are regarded as productivity shocks that take the regional road transportation network away from its previous time path. Precipitation in terms of rainfall and snowfall is an important part of the climate change shocks in this framework.

In order to capture the long-run dynamics of precipitation, in this study we investigate trends in rainfall and snowfall time series at all five regional transportation hubs mentioned above. According to that goal, we reviewed trend analysis in climatology and found that climatologists mostly use non-parametric analysis. The main argument behind this approach is that frequently climate data is not normally distributed. The non-parametric approach is recommended by World Meteorological Organization (Machiwal and Jha, 2012).

Non-parametric approach includes Mann-Kendall test to detect trend and Theil-Sen estimator to find the trend's magnitude. Mann-Kendall test was developed by Mann (1945) and generalized by Kendall (1955). It detects whether climate variable Y increases or decreases with monotonic increase in time. It is a rank-based test which means that it deals not with the original series but with its order (rank). For example, if next value is higher than the previous one, it states there is a positive trend. Technically it treats equally an increase by 1% and an increase by 1,000%.

Theil-Sen estimator was developed by Theil (1950) and generalized by Sen (1968). In fact, it is a median among slopes of lines that connect all points in time series. This approach is used in climate change studies of different scope - global, country level, and regional. Alexander et al. (2006) analyze global trends and changes in data distributions. Wang and Swail (2001) investigate dynamics of extreme wave heights in Northern Hemisphere Oceans. Afzal et al. (2015) use it for trend analysis of total precipitation and its variability in Scotland.

Vincent and Mekis (2006, 2011) use non-parametric approach to test trends in precipitation series in Canada including Atlantic Canada, the region we are interested in. Vincent and Mekis (2006) paper contains more details about methodological basis. Vincent and Mekis (2011) paper mostly concentrates on the adjustments in new database (APC2), and on the effects these adjustments have on the trend estimation. The article presents main results for South Canada and the rest of Canada. Data is aggregated in two steps.

As the first step, the country is divided into 5^0x5^0segments.Then the authors take average value among meteorological stations in each segment. In second step, they aggregate segments' data into country level data. This approach is very similar to Alexander et al. (2006). The main idea of the approach is to obtain equal weights from the regions with different number of meteorological stations. While providing trend equations for aggregate data, the authors present calculated trends for all meteorological stations in Canada.

We use the same database APC2 which is currently the best precipitation database in Canada. As a matter of fact, Vincent and Mekis (2011) do not provide any formal testing for structural breaks in the long-run trends. The authors show trends estimation for South Canada for two periods 1900-2009 and 1950-2009, and for Canada as a whole for 1950-2009. There are trends for all stations in Canada in 1950-2009 period, shown on the map with some symbols. Most detailed analysis is presented for aggregate trends in South Canada. Breaks in trends are found approximately using graphs of data and 11-year moving average. The authors report negative trend in rainfall before 1920s and positive one since 1920s and up to 2009. Snowfall was growing from 1920s to 1970. Then, it was decreasing until 1980s, and stayed steady until the end of the observed period.

We also found studies that used parametric approach to test the same time series in Atlantic Canada. Thistle and Caissie (2013) use the same database APC2 as Vincent and Mekis (2011), although they analyze dynamics of total precipitation instead of rainfall and snowfall separately. They estimate separately trends for the last 60 years (1951-2010), and the last 30 years (1981-2010). Like other authors mentions above Thistle and Caissie

(2013) do not analyze possible structural breaks formally. Changes in trends are found by comparing results of two periods - 60 years of data with 30 years of data. The authors use linear model to test for trend and analyze residuals. They test them for homoscedasticity, normality, independence, and autocorrelation. If residuals do not satisfy conditions of homoscedasticity, normality, independence of variance or the trend estimator's p-value is between 0.01 and 0.09, they re-evaluate trend using generalized linear model (GLM), assuming gamma error distribution and identity link function.

Both parametric and non-parametric approaches have their pros and cons. Major theoretical advantage of non-parametric methods is that they do not depend on distribution of error terms. On the other hand, GLM as a representative of parametric approach works with the family of exponential distributions (normal, binomial, gamma, Poisson, inverse Gaussian, and some others) which allows to overcome dependence of Ordinary Least Squares (OLS) on normal distribution, and, probably, is good enough to cover main cases of non-normality in climate data.

Mann-Kendall test has undeniable advantage in trend detection in small samples. For example, Kendall shows normal distribution of his Zs statistic for 8 and more observations (Kendall, 1955). Parametric t-statistic relies on the Central Limit Theorem (CLT). It follows asymptotic normal distribution in large samples, which can be approximated with t-distribution in moderate samples (Greene, 2012). So, theoretically t-test is weaker with respect to trend detection but as the sample size becomes bigger this weakness disappears. In addition, Mann-Kendall test is a rank-based test. It exhibits robustness to outliers which is also its advantage. However, it is appropriate only for the monotonic trends. Theil-Sen estimator is unbiased and consistent (Sen, 1968) similar to the OLS/GLM estimators.

Wilcox (2010) proves that Theil-Sen estimator is at least as efficient as OLS, but it does not mean that it is more efficient than GLM estimator.

There are many studies that compare parametric and non-parametric trend estimations empirically, either with real data or on the basis of simulation. Most of them use parametric t-statistic under OLS. Onoz and Bayazit (2003) perform Monte-Carlo simulation for different probability distributions. They show that t-test is less powerful in trend detection than Mann-Kendall test in cases of skewed probability distribution. On the other hand, if skeweness is not very high both tests can be equally used in practical applications. Widmann and Schar (1997) while analyzing precipitation trends in Switzerland, prefer Mann-Kendall test. They argue that t-test is unreliable in the case of non-normal distribution of error terms. Yue and Pilon (2004) conclude on the basis of Monte-Carlo simulation that power of the parametric t-test is even higher for the cases of normal distribution of error terms, but Mann-Kendall test has more power for the cases of non-normal distributions. Muita et al. (2012) use GLM and Mann-Kendall method to test for trends of dry spells in Kenya. They find that in general trend detection power is similar but Mann-Kendall test gives higher values for positive trends and lower values for negative trends than GLM. So, as intermediate conclusion, we treat both approaches to trend estimation equally in all cases when we can refer to CLT.

In this study, we use parametric approach due to the following two fundamental reasons. First, our main goal is to capture dynamic process behind precipitation time series that can be easily incorporated into above described economic model of regional road transportation network. Since the overall model is parametric our choice of parametric approach to capture evolutionary dynamic of precipitation is obvious.

Second, we conduct analysis of s*tructural* breaks in the trends associated with precipitation time series. We think that the ranked-based non-parametric test is less appropriate for such analysis. It does not distinguish between small, marginal changes in trend value and large, structural changes. In our opinion, the latter are real structural breaks in the underlying dynamic process associated with climate change.

As a matter of fact, we found two methods of structural break detection developed for Mann-Kendall test. By design, Pettitt test (Pettitt, 1979) assumes only one potential break in a time series. Sequential Mann-Kendall test developed by Sneyres (1990) does not make this assumption but it is also a ranked-based test.

On the other hand, there are a lot of methods to detect structural breaks developed for parametric regression (see Enders 2010 as an example). In this study, we look for potential multiple endogenous breaks – break points at unknown dates. Bai and Perron (1998, 2003) suggest a methodology to test hypothesis of no breaks versus some number of unknown breaks, and that is why we use Bai-Perron method in this study.

Chapter 3. Methodology

In this study, by evolutionary dynamics of precipitation we mean long-run tendencies in precipitation patterns which we try to capture with the help of statistical methods. In our opinion, what we observe as specific level of precipitation is a result of some dynamic process that drives it. This dynamic process has long-memory which translates into some degree of determinism that can be explained mathematically and used for forecast. We call this evolutionary or long-run dynamics of precipitation. And in order to capture this long-run dynamics of precipitation, we investigated long-run trends in rainfall and snowfall time series at all five regional transportation hubs mentioned above. Climate change with respect to precipitation means a *structural* break in precipitation trend or a change in the long-run, evolutionary dynamics. As a result, we developed a methodology that consists of the following six steps which were applied to the precipitation time series:

(i) Run OLS regression on constant and time trend

(ii) Use Bai-Perron test to detect endogenous structural breaks in the obtained trend regression

(iii) Add dummy variables associated with detected structural breaks

(iv) Test error term for normality (Jarque-Berra test), serial correlation (correlograms) and homoscedasticity;

(v) If necessary, model serial correlation in residuals with ARMA (Autoregressive moving average) process;

(vi) If the last version of the model produces non-normally distributed, serially correlated or heteroscedastic residuals, use Generalized Linear Model (GLM) with gamma distribution and identity link function.

Since we look for unknown number of endogenous breaks, we use the Bai-Perron test. The test is described in detail in Bai and Perron (2003). Major advantage of the test is that it can be used even with non-*iid* (independently and identically distributed) error terms which is crucial advantage for meteorological data.

The test starts with a multiple linear regression model with T periods and L potential breaks which create $L+1$ regimes. Within each regime $j = 1, \ldots L+1$ we have the following model:

$$y_i = X_t{'}\beta + Z_t{'}\delta_j + \varepsilon_t \qquad \text{(Bai and Perron, 2003) (3.1)}$$

where Xt is a vector of variables constant over entire series; Z_t is a vector of variables that contain breaks; δj is a set of regime specific coefficients, and β is a set of coefficients that are constant within regimes. Bai-Perron test minimizes total sum of squared residuals (S) with some pre-specified number of regimes, L:

$$\min S(\beta, \delta|\{T\}) = \sum_{j=1}^{L+1}\{\sum_{t=T_{j-1}+1}^{T_j}\left(y_t - X_t{'}\beta - Z_t{'}\delta_j\right)^2\} \quad (3.2)$$

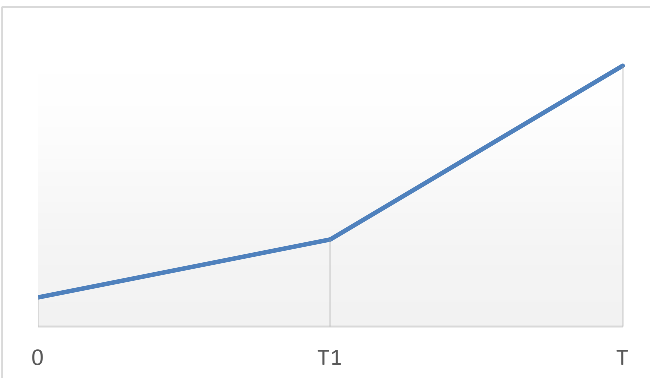
T_j is a breakpoint observation, j is the number of regimes, t is a time, T_0=0, T_{L+1}=T by convention. At this point they treat number of breaks $L+1$ as known value.

In our case of linear regression on constant term (C) and time trend variable (*TIME*), we do not have regime constant variables X. Therefore, both C and *TIME* belong to the vector Z. This case is called a pure structural change model, and it means we do not have to estimate vector β.

Bai and Perron (2003) describe dynamic programming algorithm which allows to minimize S and define appropriate estimates of the vectors $\delta_j = [\delta_1, \ldots, \delta_{L+1}]$ and $T_j = [T_1, \ldots, T_{L+1}]$. We do not present it here but we want to explain the global minimization procedure.

Let us analyze the case of a structural break at time T_1 (Figure 3.1) where T_1 is a variable. We allow this variable to take on values from *1* to *T-1* for simplicity. In their algorithm, Bai and Perron assume some minimal number of observations before the first break and after the last break. This number is necessary to estimate trend on these segments. It is a parameter which can be specified in the test. Technically the minimal number of observations in each segment must be higher than the number of variables in *Z*. This condition is similar to OLS and, for example, Eviews reserves 15% of the sample for these border segments by default. We keep this default option.

Figure 3. 1. Case with one structural break in trend at T1



In order to estimate δ_1 associated with regime 1 $t \in [0, T_1]$, we can start with assumption of no break and estimate time trend regression over the whole period [0,T] with usual OLS. Equation (3.2) simplifies to $\sum_{t=1}^{T}(y_t - z_t\delta_1)^2$ (3.3). Solving it we obtain estimate $\widehat{\delta_1}$ which contains the intercept and the slope of the time trend associated with regime 1 or before the break.

Now we can analyze the two-regime case. Minimization (3.2) takes the form of $\min S = \sum_{t=1}^{T1}(y_t - z_t\delta_1)^2 + \sum_{t=T1+1}^{T}(y_t - z_t\delta_2)^2$ (3.4).

We can estimate it with OLS as well to obtain $\widehat{\delta_2}|\widehat{\delta_1}, T_1$. This is a valid estimate associated with a segment after the break given the trend segment before the break and the break point T_1. We can apply this procedure for all possible breakpoints T_1 and choose the one which minimizes *S*. As a result, we obtain estimate of a breakpoint $\widehat{T_1}$ and appropriate estimate $\widehat{\delta_2}|\widehat{\delta_1},\hat{T}_1$. Equation 3.2 generalizes this procedure for some specific number of regimes. In their study, Bai and Perron (1998) show consistency of breakpoint estimates $\widehat{T_J}$.

One disadvantage of the described global optimization is a non-nested set of breaks. If we specify maximum number of breaks as *L* or *L+1*, test estimates from *L+1* set will not necessarily contain the same breakpoints as the estimates from *L* set. In this regard, Bai and Peron suggest alternative sequential version of the test. It assumes minimum *S* in each segment separately. When the first break is detected, it is taken as given from that time on. Second break is chosen from *S*- minimization in the sample after the first break and so on. In such case, the set of break points becomes nested. Moreover, Altissimo and Corradi (2003) show that under global minimization only the biggest break points get detected which is an important advantage for our goal.

Bai and Perron use F-statistic to test each number of break points for significance. The null hypothesis is that all δs are equal. They refer to test as sup F(k,q). We cite formulas from Bai and Perron (2003), and follow their notations:

$\sup F(k;q) = F_T(\widehat{\lambda_1}, \dots, \widehat{\lambda_k}; q)$,

$\lambda_1, \dots, \lambda_k$ is a set of break fractions. Break fraction is a ratio of time segment before break point to the whole available data period (0,T);

q is a number of variables with breaks;

k is a number of breaks;

$\widehat{\lambda_1}, \dots, \widehat{\lambda_k}$ is a set of estimates of break fractions which "minimize the global sum of squared residuals which is equivalent to maximizing the F-test assuming spherical errors". In other words, this set of estimates maximize F(k;q).

$F_T(\lambda_1, .., \lambda_k; q) = (\frac{1}{T}\left(\frac{T-(k+1)q-p}{kq}\right)\hat{\delta}'R'\left(R\hat{V}\left(\hat{\delta}\right)R'\right)^{-1}R\left(\hat{\delta}\right)$, where

p is a number of variables constant over entire series (variables X in notations above)

δ is a vector of coefficients of variables with breaks (the same notations as above)

R is a conventional matrix, such that $(R\delta)' = (\delta_1' - \delta_2', \dots, \delta_k' - \delta_{k+1}')$

For case of all variables have breaks, and serial correlation, different data distributions over different trend segments are allowed:

$\hat{V}\left(\hat{\delta}\right) = diag((V(\widehat{\delta_1}), \dots, V(\widehat{\delta_{m+1}})),$

$V\left(\widehat{\delta_\iota}\right) = plim\ (\Delta T_i)(Z_i'Z_i)^{-1}Z_i'\Omega_i Z_i(Z_i'Z_i)^{-1},$

where Ω_i is a variance-covariance error term matrix which can be estimated with HAC estimator, Z is a vector of variables with breaks.

To choose among different number of breaks, they use two tests called double maximum tests – unweighted and weighted. Both tests choose the maximum of F-statistics. The difference is that unweighted double maximum test (UDmax) treats sup F(k,q) test for any number of breaks equally. The problem is that the critical values for supF(k,q) test depend on the number of breaks. As the number of breaks increase, the critical values decrease which can decrease the power of the test. In turn, weighted double maximum test (WDmax) assigns some weight to each sup F(k,q). The weight is equal to the ratio of critical value for single break-test to the critical value for appropriate number of breaks. As a result, WDmax assigns higher weights to supF(k,q) test with larger number of breaks.

In this study, we use the UDmax test version. Weighted correction helps reveal trend breaks in cases when F-statistic is close to critical values. This means a marginal not a structural break which is not subject of our analysis.

Bai-Perron test can produce robust estimates with non-*iid* error terms and even different distributions associated with different regimes. It requires construction of heteroscedasticity and autocorrelation (HAC) stable confidence intervals. Bai and Perron use “quadratic kernel with automatic bandwith selection based on AR(1) approximation” developed by Andrews (1991), and pre-whitening of residuals with VAR(1) suggested by Andrews and Monahan (1992).

This procedure allows us to obtain HAC robust estimates in trend equation as well as robust breakpoint estimates with Bai-Perron test.

Steps (iii) and (iv) of our methodology include quite standard procedures of OLS regression and diagnostics of residuals. Based on the results of the Bai-Perron test, we introduce dummies associated with different regimes as follows:

$$Y_t = a_0 + a_1 TIME + (b_0 + b_1 TIME) * DUMMY_1 + \cdots + (b_{k-1} + b_k) * DUMMY_k + e_t$$

(3.5),

where Y_t is rainfall (snowfall) in millimeters in year t; *TIME* is trend variable expressed in terms of years; parameters a_0 and a_1 describe original time trend in the first segment (its intercept and slope); set of parameters (b_0,..b_k) is associated with the set of dummies $DUMMY_1, \ldots, DUMMY_k$ along with cross products with *TIME* such as $DUMMY_k$*TIME*, and describe time trends associated with other regimes (segments); e_t is iid error terms (white noise).

In fact, the above specification describes the so-called piecewise function. Time trend within each regime can be expressed by the following separate equations:

$Y_t = a_0 + a_1 TIME + e_t$, for the first regime

$Y_t = a_0 + b_0 + (a_1 + b_1)TIME + e_t$, for the second regime

$Y_t = a_0 + b_2 + (a_1 + b_3)TIME + e_t$, for the third regime and so on.

Basis trend $Y_t = a_0 + a_1 TIME$ is the same throughout series no matter how many breaks we detect.

Jarque-Berra test (JB) statistic $JB = T[\frac{S^2}{6} + \frac{(EK)^2}{24}]$ (3.6) follows χ^2 distribution with 2 degrees of freedom.

$S = \left(\frac{1}{T}\right)[(\sum_{i=1}^{T}(x_i - \bar{x})^3/(\sigma^2)^{\frac{3}{2}}]$ (3.7) is a sample skewness,

$K = \left(\frac{1}{T}\right)[(\sum_{i=1}^{T}(x_i - \bar{x})^4/(\sigma^2)^2]$ (3.8) is a sample kurtosis,

$EK = K - 3$ is an excess kurtosis.

Null hypothesis of the test is that the data is distributed normally with zero skewness and zero kurtosis. Alternative hypothesis is that the distribution is not normal. This test is appropriate in our case since from the literature review we learned that major argument against parametric models is the presence of skewness in climate and meteorological data.

In order to detect serial correlation in residuals, we use autocorrelation and partial autocorrelation functions with appropriate Q-statistic.

Presence of heteroscedasticity is analyzed with the Breusch-Pagan-Godfrey (BPG) test (see Gudjaratti 1995). BPG test includes the following steps:

- estimate OLS residuals u_i;

- calculate variance estimation $\widehat{\sigma^2} = \frac{(\sum_{i=1}^{T} u_i^2)}{T}$;
- generate variable $p_i = \frac{\widehat{u_i^2}}{\widehat{\sigma^2}}$;
- regress variable p_i on matrix *Z; Z* includes some non-stochastic variables, for instance, regressors;
- define variable $\Theta = \frac{1}{2} ESS$, where *ESS* is an explained sum of squares.

$\Theta \sim \chi^2_{m-1}$, where m is the number of parameters. This is an asymptotic property under imposed assumption that u_is are normally distributed. So, we perform this test after *JB* test for normality.

In the presence of serial correlation in residuals, we try to model it with ARMA approach (**step v**). Using Box-Jenkins methodology, we define appropriate number of AR and MA terms and add them to the trend regression. Technically, in such case Eviews uses Maximum Likelihood (ML) estimation rather than OLS. We assume that precipitation series can be described by both long-run linear time trend and cyclical component. Since we are interested in cyclical component for the next stage of the study, statistically significant ARMA terms could help us capture cyclical character of the process.

If we still have a model that violates the *iid* assumption or the normality assumption, we move to **step vi** and use GLM. GLM allows us to work with distributions from exponential family such as normal, binomial, gamma, Poisson, inverse Gaussian, and some others.

Let us assume that we have a set of observations *yi, …, yn*. We treat each *yi* as a realization of random variable *Yi* which is subject to some distribution. Family of exponential distributions can be shown with the help of the following density function:

$$f(y_i) = \exp\left\{\frac{y_i\theta_i - b(\theta_i)}{a_i(\varphi)} + c(y_i, \varphi)\right\}\ (Wood)\ (3.9)$$

Density function depends on parameters Θi (location parameter) and φ (scale parameter). Θi can be different for each i. $a_i(\varphi)$ is usually assumed to be equal φ/p_i. p_i is called prior weight often taken as 1. Such assumption simplifies derivation, although there is a proof for general case function which leads to the exactly same estimator (see McCullagh and Nelder, 1989).

It can be shown that:

$E(Yi) = \mu i = b'(\Theta i)$ (3.10) and

$Var(Yi) = \sigma i2 = b''(\Theta i) a_i(\varphi)$ (3.11),

where b' and b'' are the first and the second derivatives.

GLM states that there is a linear predictor $\eta i = x_i'\beta = g(\mu_i)$. In other words, there is a linear model of some function $g(\mu_i)$ on $x_i'\beta$ matrix. OLS assumes such relationship directly with μi.

$g(\bullet)$ is assumed to be continuous and differentiable function, called the link function. Choice of the link function depends on distribution of original data. Link function has to make linear predictor ηi the same as parameter Θi. In this case, it is called canonical link. Canonical link assures that there is a minimal sufficient statistic for β.

According to Fisher (1922) sufficient statistic means “no other statistic that can be calculated from the same sample provides any additional information to the value of parameter”.

Minimal sufficient statistic means it is sufficient and can be expressed as a function of any other sufficient statistic.

Therefore, appropriate link function assures that the estimator we obtain from GLM gives us all possible information from the data. The most popular algorithm to find GLM estimator is iteratively re-weighted least squares. It includes the following steps:

- Start with a trial estimate $\hat{\beta}$ and calculate linear predictor ηi;
- Calculate working dependent variable $z_i = \eta_i + (y_i - \mu_i) * d\eta_i/d\mu_i$;
- Calculate iterative weights $w_i = \frac{p_I}{b''(\theta_i)\left(\frac{d\eta_i}{d\mu_i}\right)^2}$;
- Regress z on x with weight w using weighted least square approach; as a result, we obtain estimator $\hat{\beta} = (X'WX)^{-1}XWz$, where W is a diagonal matrix with entries w_i, z is a response vector with entries z_i;
- Steps repeat iteratively until change in estimates reaches some specified small amount.

McCullagh and Nelder (1989) show that this procedure produces the same estimator for GLM as for ML.

For hypothesis testing, Wald test is usually used with GLM. Inference relies on the same Central Limit Theorem (see Dobson, 2002) as usual ML estimation. Maximum likelihood estimator (MLE) is asymptotically normally distributed which can be shown using Lindberg-Levi Central Limit Theorem (see Greene 2012). Therefore, GLM estimator is also asymptotically normally distributed. GLM's dependent variable is a linear predictor η_i, but since we use the identity link function, it is the same as the original precipitation variable.

In general, we can use HAC estimator discussed previously in step (vi) instead of GLM approach. However, now we follow Thistle and Caissie (2013) and their GLM specification with gamma distribution. They obtained a small number of time series with non-normal data distribution. Thus, the problem can be minor in our case. It is important to mention that Thistle and Caissie (2013) use GLM as the universal remedy for non-normality, heteroscedasticity and autocorrelation in OLS model. They do not actually test GLM.

However, GLM approach also contain residual diagnostics. If model is misspecified, it will not solve OLS problems. Following McCullagh and Nelder (1989) we test standardized (Pearson) residuals of GLM.

Pearson residual is defined as $r_i = \frac{y_i - E(y_i)}{\sqrt{Var(y_i)}}$, where

E(•) is expected value, Var(•) is a variance.

Normal distribution of Pearson residuals is an important argument for the right choice of distribution of original data. We check it with Jacque-Bera test (JB). We also test for serial correlation in Pearson residuals with Q-statistic and correlogram.

Last diagnostic procedure is a plot of Pearson residuals versus fitted values. McCullagh and Nelder (1989) refer to this graphical diagnostic as the very important and mandatory part of GLM testing. If model is correctly specified, graph will not reveal any tendency in mean or variance. There are possible tendencies in mean, if all points are subject to a non-linear function, or variance, if spread of the points is growing. Graph is used for diagnostics of heteroscedasticity, and for the test of mean-variance relationship which is crucial for GLM. For the gamma distribution, its mean is equal to variance.

In the case of no patterns in Pearson residuals versus fitted values, mean-variance relationship is stable. This means correct model specification.

Our methodology described in this section allows us to obtain consistent estimates of the long run linear trends as well as cyclical components in dynamics of precipitation. As a result, we can detect structural breaks in trends which is crucial for understanding of the evolutionary dynamics of precipitation. In the next chapter, we present empirical application of our methodology in order to describe evolutionary dynamics of rainfall and snowfall series at five regional hubs in Atlantic Canada road transportation system.

Chapter 4. Data description and estimation

Based on our methodology, we analyze evolutionary dynamics of precipitation in Atlantic Canada. We estimate rainfall and snowfall precipitation series separately. We have twelve precipitation time series from six meteorological stations: six snowfall series and six rainfall series. They are associated with five transportation hubs in Atlantic Canada mentioned before. Two stations (Miramichi and Edmundston) belong to one hub (New Brunswick North). Understanding of the evolutionary processes in these series is a necessary step to modeling economic consequences of climate change impacts on road transportation in Atlantic Canada.

This chapter contains seven sections presented below. In the first section, we present description of our data. Estimation results are presented in sections two through six. In the second section, we present results of Bai-Perron (2003) test for structural breaks. This procedure is the same for all series. Sections three through sixth contain estimations grouped by type of the model we accepted as final. Choice of the final model depends on the diagnostic procedures. Eleven out of twelve series are estimated with OLS. Five of them show significant trends and exhibit independent and identically distributed (*iid*) error terms. We present this group in section three. Three of precipitation series do not exhibit significant trends but also have *iid* error terms. We present this group in section four. The last three series estimated with OLS do show significant time trends but residuals exhibit serial correlation. That is why we model residuals with ARMA model. In this way, we capture not just linear time trends but also cyclical component in precipitation dynamic process. We present this group in section five. In section six, we present the only series we estimated with GLM due to its non-normal residuals. All these sections contain parameter estimates and residual diagnostics. Finally in section seven, all major results are combined to give us general overview of our estimation.

Notations of coefficients in trend estimations correspond to equation 3.5. Number in parenthesis near the coefficient means a year of structural break. It is also first year of regime described with dummy variable related to that coefficient.

4.1. Data description

Our precipitation data is taken from the second generation Adjusted Precipitation for Canada (APC2) dataset. Data is annual, obtained from monthly values for rainfall and snowfall in millimeters. We took the data from meteorological stations that are close to regional transportation hubs we are interested in. Information about the stations is presented in table 4.1.

Table 4. 1. List of synoptic stations: APC2 metadata

Station Id	Station Name	Province	From/To	Obs
810AL00	Edmundston	NB	1916/2005	90
8101000	Miramichi	NB	1873/2004	132
8103200	Moncton	NB	1898/2011	114
8202250	Halifax	NS	1872/2011	140
8104900	Saint John	NB	1871/2011	141
8101500	Fredericton	NB	1874/2009	136

Tables 4.2 and 4.3 contain descriptive statistics of rainfall and snowfall series. We can see from coefficient of variation (CV, ratio of std. deviation to mean) that dispersion of snowfall values is higher than for rainfall values. Average share of rainfalls in total precipitation among all 6 stations is 72%. The highest share of rainfalls in total precipitation

is near the ocean, 82% at Halifax, and 76% at Saint John. Appendices A, B contain graphs of all series.

Table 4. 2 Descriptive statistics of rainfall series, mm

Station Name	Mean	Std.Dev.	CV, %	Min	Max	Range
Edmundston	751	141	19%	415	1139	724
Miramichi	816	143	18%	520	1156	636
Moncton	844	172	20%	485	1362	877
Halifax	1297	198	15%	815	1748	933
Saint John	1110	193	17%	619	1863	1244
Fredericton	853	155	18%	504	1326	822

Table 4. 3. Descriptive statistics of snowfall series, mm

Station Name	Mean	Std.Dev	CV,%	Min	Max	Range
Edmundston	293	72	25%	115	472	357
Miramichi	421	106	25%	202	766	564
Moncton	393	132	34%	97	737	640
Halifax	289	93	32%	114	520	406
Saint John	346	100	29%	120	665	545
Fredericton	357	82	23%	108	616	508

4.2. Bai-Perron test

As already explained in methodological part, the test detects potential structural breaks in all series, and its results are presented in table 4.4.

Table 4. 4 Bai-Perron test of 1 to M globally determined breaks

Series name	Number of detected breaks	UDMax statistic	Critical Value*	Breakpoints, years
Edmundston rainfall	2	23.21	9.75	1942,1955
Edmundston snowfall	2	24.44	9.75	1933,1946
Miramichi rainfall	2	17.14	9.75	1902, 1921
Miramichi snowfall	1	44.74	11.47	1954
Moncton rainfall	2	13.03	9.75	1964,1982
Moncton snowfall	1	40.33	11.47	1961
Halifax rainfall	3	21.70	8.36	1893,1916, 1955
Halifax snowfall	1	23.20	11.47	1894
Saint John rainfall	2	15.16	9.75	1925,1985
Saint John snowfall	1	36.24	11.47	1916
Fredericton rainfall	2	18.23	9.75	1964,1984
Fredericton snowfall	1	17.67	11.47	1961
***5 % significance critical value. Bai and Perron [2003] also provide critical value for UDMax statistic = 11.7 the same for any number of breaks**				

As can be seen from the table, the test revealed one or two breakpoints in each series except for Halifax rainfall series which produced three breakpoints. The breakpoints are spread over time. In total, the test identified 20 breakpoints. Seven of them occurred in 19^{th}-beginning of 20^{th} century; three breaks occurred in 1930s-1940s; seven occurred in 1950s-1960s and the latest three breaks took place in 1980s.

Based on these results, we cannot support the anthropogenic hypothesis of the climate change in Atlantic Canada in terms of rainfall and snowfall precipitation. It is so because half of all regime breaks have occurred in the distant past. It is unlikely that these regime breaks were caused by the anthropogenic climate change. Actually, at this point we can only confirm general conclusion of the IPCC annual reports that precipitation trends exhibit strong regional specifics.

4.3. OLS estimation of the precipitation time series with significant trends and *iid* errors

Edmundston rainfall series

According to Bai-Perron test, this series has structural breaks in 1942 and 1955 which defines three regimes in time trend. Estimation results (see Table 4.5) show significant trends in all three regimes. Coefficient a_1 shows positive trend of 8mm per year over the first regime (1916-1941). Since 1942 we have second regime with positive trend of 33mm per year. To find it we have to sum up 8mm, which is an estimate of the coefficient a_1 and 25mm which is an estimate of the coefficient b_1. Finally, we have negative trend of -1mm per year at the third regime, starting in 1955. To find it we sum up again 8mm (estimate of the base trend) and -9mm which is an estimate of the coefficient b_3 . Further we will just specify numbers of trend estimates without description of summation steps.

Table 4. 5. Edmundston rainfall series. OLS estimation results

Sample: 1916 – 2005. Included observations : 90			
Variable	**Coefficient**	**t-statistic**	**p-value**
a_0	-14772	-2.4	0.02
a_1	8	2.5	0.01
b_0 (1942)	-47694	-2.5	0.01
b_1 (1942)	25	2.5	0.01
b_2 (1955)	17209	2.6	0.01
b_3 (1955)	-9	-2.6	0.01
R-squared	0.28	**F-statistic**	6.63
Adjusted R-squared	0.24	**Prob(F-statistic)**	0.00

Table 4.6 shows that residuals of the model have normal distribution, homoskedastic, and there is no serial correlation. We accept this model.

Table 4. 6. Edmundston rainfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		**Serial Correlation**		
Skewness	-0.16	Lag #	Q statistic	p-value
Kurtosis	3.22	1	0.2708	0.603
Jarque-Berra statistic	0.59	2	2.5582	0.278
p-value	0.74	3	2.7792	0.427
Heteroskedasticity		4	3.1734	0.529
F statistic	1.05	5	6.9434	0.225
p-value	0.40	6	8.3144	0.216

Miramichi rainfall series

According to Bai-Perron test, this series has structural breaks in 1902 and 1921 years which defines three regimes. Estimation results (Table 4.7) show significant (with 90% confidence) negative trend of 6mm per year over 1873-1901, then change to a significant (with 90% confidence) positive trend of 6mm per year over 1902-1920, and finally flatter positive significant trend of 1mm per year over 1921-2004.

Table 4. 7. Miramichi rainfall series. OLS estimation results

Sample: 1873 – 2004. Included observations : 132			
Variable	**Coefficient**	**t-statistic**	**p-value**
a_0	11778	2.04	0.04
a_1	-6	-1.90	0.06
b_0 (1902)	-22666	-1.82	0.07
b_1 (1902)	12	1.83	0.07
b_2 (1921)	-13084	-2.21	0.03
b_3 (1921)	7	2.21	0.03
R-squared	0.10	**F-statistic**	2.92

Adjusted R-squared	0.07	**Prob(F-statistic)**	0.02

Table 4.8 shows that residuals of the model have normal distribution, homoskedastic, and there is no serial correlation. We accept this model.

Table 4. 8. Miramichi rainfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		**Serial Correlation**		
Skewness	0.10	Lag #	Q statistic	p-value
Kurtosis	2.29	1	0.6069	0.436
Jarque-Berra statistic	2.98	2	0.7082	0.702
p-value	0.23	3	0.7124	0.870
Heteroskedasticity		4	2.3876	0.665
F statistic	1.64	5	2.5368	0.771
p-value	0.15	6	3.0243	0.806

Moncton snowfall series

Series has one structural breaks in 1961 years which form two regimes in trend. Estimation results (Table 4.9) show significant positive trend 2mm per year over 1898-1960, and change to negative significant trend -3mm per year in 1961-2011.

Table 4. 9. Moncton snowfall series. OLS estimation results

Sample: 1898 – 2011. Included observations: 114			
Variable	**Coefficient**	**t-statistic**	**p-value**
a_0	-4259	-3.17	0.00
a_1	2	3.42	0.00
b_0 (1961)	10753	4.63	0.00
b_1 (1961)	-5	-4.58	0.00
R-squared	0.44	**F-statistic**	28.5
Adjusted R-squared	0.42	**Prob(F-statistic)**	0.00

Table 4.10 shows that residuals of the model have normal distribution, homoskedastic, and there is no serial correlation. We accept this model.

Table 4. 10. Moncton snowfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		**Serial Correlation**		
Skewness	0.18	Lag #	Q statistic	p-value
Kurtosis	3.00	1	0.0009	0.977
Jarque-Berra statistic	0.61	2	0.2364	0.889
p-value	0.74	3	1.0756	0.783
Heteroskedasticity		4	2.2777	0.685
F statistic	0.70	5	2.6177	0.759
p-value	0.55	6	2.6385	0.853

Saint John snowfall series

Series has one structural break in 1916 year which form two regimes in trend. Estimation results (Table 4.11) show significant negative trend -5mm per year over 1873-1915, and flat negative trend -1mm per years over 1916-2011.

Table 4. 11. Saint John snowfall series. OLS estimation results

Sample: 1871 – 2011. Included observations : 141			
Variable	**Coefficient**	**t-statistic**	**p-value**
a_0	9526	4.73	0.00
a_1	-5	-4.56	0.00
b_0 (1916)	-7540	-3.55	0.00
b_1 (1916)	4	3.60	0.00
R-squared	0.16	**F-statistic**	8.9
Adjusted R-squared	0.15	**Prob(F-statistic)**	0.00

Table 4.12 shows that residuals of the model have normal distribution, homoskedastic, and there is no serial correlation. We accept this model.

Table 4. 12. Saint John snowfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		Serial Correlation		
Skewness	0.34	Lag #	Q statistic	p-value
Kurtosis	2.96	1	0.0409	0.840
Jarque-Berra statistic	2.71	2	0.7180	0.698
p-value	0.26	3	1.0333	0.793
Heteroskedasticity		4	3.7508	0.441
F statistic	1.38	5	5.5606	0.351
p-value	0.25	6	7.1363	0.308

Fredericton snowfall series

Series has one structural break in 1961 year which form two regimes in trend. Estimation results (table 4.13) show significant negative trend -1mm per year over 1874-1960, and steeper negative trend -3mm per year since 1961.

Table 4. 13. Fredericton snowfall series. OLS estimation results

Sample: 1874 – 2009. Included observations : 136			
Variable	**Coefficient**	**t-statistic**	**p-value**
a_0	2105	3.33	0.00
a_1	-1	-2.77	0.01
b_0 (1961)	3673	2.20	0.03
b_1 (1961)	-2	-2.14	0.03
R-squared	0.13	**F-statistic**	6.74
Adjusted R-squared	0.11	**Prob(F-statistic)**	0.00

Table 4.14 shows that residuals of the model have normal distribution, homoskedastic, and there is no serial correlation. We accept this model.

Table 4. 14. Fredericton snowfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		Serial Correlation		
Skewness	0.06	Lag #	Q statistic	p-value
Kurtosis	2.92	1	0.4911	0.483
Jarque-Berra statistic	0.11	2	2.2580	0.323
p-value	0.95	3	2.2817	0.516
Heteroskedasticity		4	2.3155	0.678
F statistic	2.02	5	3.1694	0.674
p-value	0.11	6	3.1975	0.784

4.4. OLS estimation of the precipitation time series with *insignificant* trends and *iid* errors

Edmundston snowfall series

This series has structural breaks in 1933 and 1946 years which defines three regimes. We model them with dummy variables using OLS. Estimation results (Table 4.15) are all statistically insignificant.

Table 4. 15. Edmundston snowfall series. OLS estimation results

Sample: 1916 – 2005. Included observations : 90			
Variable	**Coefficient**	**t-statistic**	**p-value**
a_0	8546	1.5	0.14
a_1	-4	-1.4	0.15
b_0 (1933)	9339	0.9	0.37
b_1 (1933)	-5	-0.9	0.38
b_2 (1946)	-8000	-1.4	0.17
b_3 (1946)	4	1.4	0.17
R-squared	0.34	**F-statistic**	8.68
Adjusted R-squared	0.30	**Prob(F-statistic)**	0.00

Table 4.16 shows that residuals of the model have normal distribution, homoskedastic, and there is no serial correlation. We accept this model.

Table 4. 16. Edmundston snowfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		Serial Correlation		
Skewness	0.18	Lag #	Q statistic	p-value
Kurtosis	2.71	1	1.1994	0.273
Jarque-Berra statistic	0.79	2	2.2463	0.325
p-value	0.67	3	2.4686	0.481
Heteroskedasticity		4	5.0554	0.282
F statistic	1.59	5	5.1263	0.401
p-value	0.17	6	5.5408	0.477

Halifax snowfall series

Series has one structural break in 1894 year which form two regimes in trend. Estimation results (Table 4.17) show significant negative trend -10mm per year over 1872-1893. In 1894 we can see statistically significant positive change in trend by 10 mm per year. Trend becomes approximately equal to zero (-10mm per year + 10 mm per year).

Table 4. 17. Halifax snowfall series. OLS estimation results

Sample: 1872 – 2011. Included observations : 132			
Variable	**Coefficient**	**t-statistic**	**p-value**
a_0	18709	3.28	0.00
a_1	-10	-3.23	0.00
b_0 (1894)	-18901	-3.30	0.00
b_1 (1894)	10	3.30	0.00
R-squared	0.08	**F-statistic**	3.87
Adjusted R-squared	0.06	**Prob(F-statistic)**	0.01

So, we make conclusion that there is no significant trend since 1894.

Table 4.18 shows that residuals of the model have normal distribution, homoskedastic, and there is no serial correlation. We accept this model.

Table 4. 18. Halifax snowfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		**Serial Correlation**		
Skewness	0.43	Lag #	Q statistic	p-value
Kurtosis	2.89	1	0.0002	0.988
Jarque-Berra statistic	4.32	2	0.1744	0.917
p-value	0.12	3	1.5642	0.668
Heteroskedasticity		4	6.3684	0.173
F statistic	0.13	5	6.6642	0.247
p-value	0.94	6	6.7965	0.340

Fredericton rainfall series

Series has two structural breaks in 1964, and 1984 years which form three regimes in trend. Estimation results (Table 4.19) show insignificant trend over 1874-1963. Then, there is a significant positive trend 22mm per year over 1964-1983 years. Since 1984 it becomes insignificant again.

Table 4. 19. Fredericton rainfall series. OLS estimation results

Sample: 1874 – 2009. Included observations : 136			
Variable	**Coefficient**	**t-statistic**	**p-value**
a_0	-737	-0.66	0.51
a_1	1	1.40	0.16
b_0 (1964)	-44116	-4.00	0.00
b_1 (1964)	22	4.00	0.00
b_2 (1984)	-2703	-0.36	0.72
b_3 (1984)	1	0.36	0.72
R-squared	0.17	**F-statistic**	5.43
Adjusted R-squared	0.14	**Prob(F-statistic)**	0.00

Table 4.20 shows that residuals of the model have normal distribution, homoskedastic, and there is no serial correlation. We accept this model.

Table 4. 20. Fredericton rainfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		**Serial Correlation**		
Skewness	-0.15	Lag #	Q statistic	p-value
Kurtosis	2.77	1	0.9294	0.335
Jarque-Berra statistic	0.80	2	3.2383	0.198
p-value	0.67	3	3.9710	0.265
Heteroskedasticity		4	6.2750	0.180
F statistic	1.03	5	7.0721	0.215
p-value	0.41	6	7.0721	0.314

4.5. OLS estimation of the precipitation time series with significant trends and ARMA modeling of residuals

Miramichi snowfall series

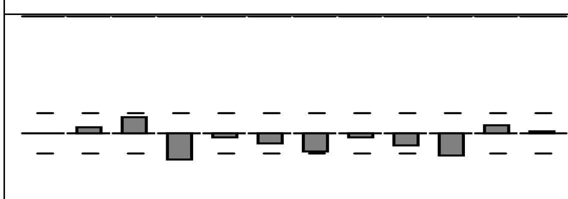
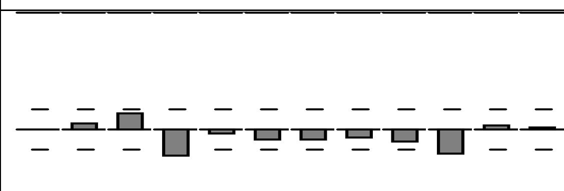
This series has one structural break in 1954 year which divides it in two regimes. Jarque-Bera test shows border value for normality, and there is serial correlation since lag 4 (Table 4.21).

Table 4. 21. Miramichi snowfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		**Serial Correlation**		
Skewness	0.45	Lag #	Q statistic	p-value
Kurtosis	2.79	1	0.0055	0.941
Jarque-Bera statistic	4.67	2	0.2547	0.880
p-value	**0.10**	3	3.2136	0.360
Heteroskedasticity		4	10.654	**0.031**
F statistic	1.98	5	10.821	**0.055**
p-value	0.12	6	11.768	**0.067**

Therefore, we model serial correlation in residuals. According to Augmented Dickey-Fuller test, residuals are stationary. Autocorrelation function (AC) shows significant lags 4, 7, 10 while Partial autocorrelation function (PAF) shows significant lags 4 and 10 (Table 4.22).

Table 4. 22. Miramichi showfall series. Correlogram of residuals of the OLS model

Autocorrelation function	Partial autocorrelation function
 1 2 3 4 5 6 7 8 9 10 11 12	 1 2 3 4 5 6 7 8 9 10 11 12

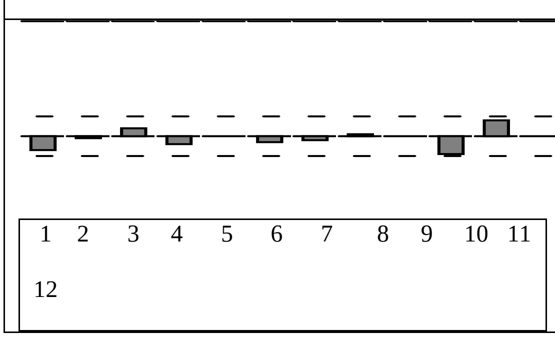
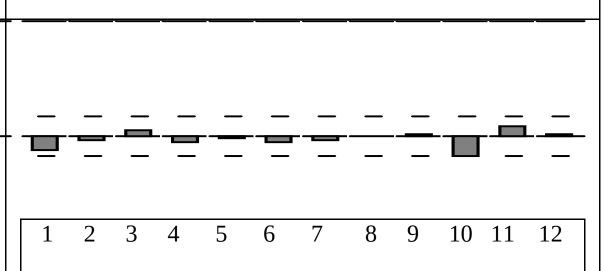
Following Box-Jenkins methodology, we specify ARMA model as AR(4,10) and MA(4,7,10). Our estimation shows significant AR(4,10) and MA(10) terms. Residuals of our ARMA model are normally distributed. Q-statistic for serial correlation has insignificant value (p-value =0.05) for lag 6. Q-statistic for all other lags does not exhibit serial correlation. We exclude insignificant MA(4) and MA(7) terms to simplify the model. New model of AR(4,10) and MA(10) is better in terms of Akaike information criteria (AIC). All coefficients are significant and residuals have normal distribution. Q-statistic shows insignificant value of lag 7 but p-value = 0.08 is higher and close to significance border. Q-statistic for other lags supports hypothesis of independently distributed data at the 5% level of significance (see Table 4.23).

Table 4. 23. Miramichi showfall series. Residuals diagnostic of AR(4,10) MA(10) model

Normality		Serial Correlation		
Skewness	0.29	Lag #	Q statistic	p-value
Kurtosis	2.62	1	1.8426	-
Jarque-Bera statistic	2.45	2	1.8819	-
p-value	0.29	3	2.5160	-
		4	3.1757	0.075
Breusch-Godfrey Serial Correlation LM Test (12 lags included)		5	3.1778	0.204
		6	3.5075	0.320
F-statistic	**0.79**	7	3.7374	0.443
p-value	**0.66**	8	3.7642	0.584
		9	3.7669	0.708
		10	7.7586	0.354
		11	10.289	0.245
		12	10.292	0.327

Correlogram of the residuals of this model (table 4.24) does not show serial correlation at lag 7. AC and PAC show values close to significance border at lag 10 but Q-statistic at lags 10 and higher shows absence of serial correlation.

Table 4. 24. Miramichi snowfall series. Correlogram of residuals of AR(4,10) MA(10) model

Autocorrelation function	Partial autocorrelation function
	

As additional argument in our choice of the model, we use Breusch-Godfrey Serial Correlation LM Test (Table 4.23). It also supports the hypothesis of no serial correlation. We accept the ARMA model with AR(4,10) MA(10). The model's estimates are presented in table 4.25.

Table 4. 25. Miramichi snowfall series. Estimation results of AR(4,10) MA(10) model of residuals from OLS trend model with structural breaks dummy variables

Sample: 1883 – 2004. Included observations : 122			
Variable	**Coefficient**	**t-statistic**	**p-value**
AR(4)	-0.16	-3.20	0.00
AR(10)	-0.77	-14.38	0.00
MA(10)	0.88	24.26	0.00
R-squared	0.20	**Adjusted R-squared**	0.19

Finally we can accept our base OLS regression with time trend and structural breaks with its estimates presented in Table 4.26.

Table 4. 26. Miramichi snowfall series. Estimation results of OLS model

Sample: 1873 – 2004. Included observations : 132			
Variable	**Coefficient**	**t-statistic**	**p-value**
a_0	6903	9.00	0.00
a_1	-3	-8.45	0.00
b_0 (1954)	-2382	-1.35	0.18
b_1 (1954)	1	1.46	0.15
R-squared	0.38	**F-statistic**	26.56
Adjusted R-squared	0.37	**Prob(F-statistic)**	0.00

Moncton rainfall series

Series has two structural breaks in 1964, and 1982 years which form three regimes in trend. We model them with dummy variables using OLS. Residuals of the model have normal distribution, homoskedastic, but serial correlation is present at first and second lags (Table 4.27). Residuals are stationary based on Augmented Dickey-Fuller test. Autocorrelation function (AC) and Partial autocorrelation function (PAC) show significant AR(1) and MA(1) terms, MA(2) term is close to significance border (Table 4.27). Q-statistic shows significant serial correlation at first and second lags. Second lag correlation is also close to significance border.

Table 4. 27. Moncton rainfall series. Correlogram of residuals of AR(1,2) MA(1,2) model

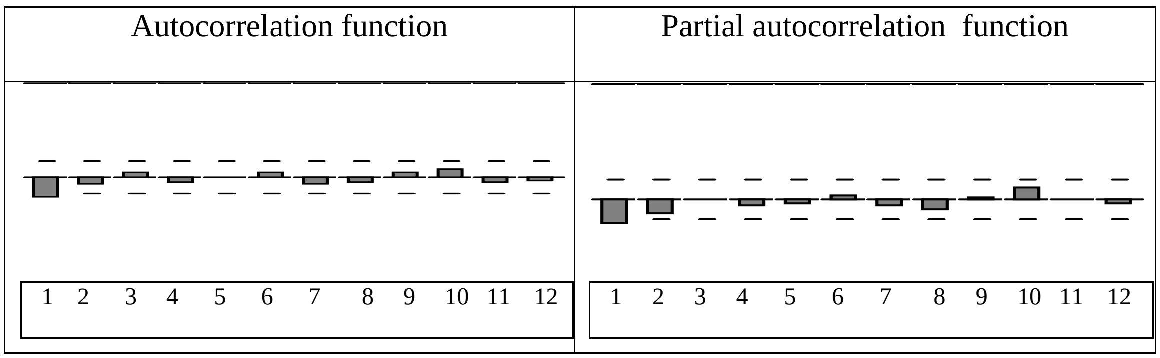


Table 4. 28. Moncton rainfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		**Serial Correlation**		
Skewness	-0.29	Lag #	Q statistic	p-value
Kurtosis	2.90	1	5.3302	0.021
Jarque-Berra statistic	1.67	2	5.8780	0.053
p-value	0.43	3	6.1097	0.106
Heteroskedasticity		4	6.4838	0.166
F statistic	1.26	5	6.4861	0.262
p-value	0.29	6	6.7037	0.349

We start with ARMA(2,2) as a first attempt. It shows significant AR(1) and MA(2) terms at the 5% level of significance, and MA(1) at the 10% level of significance. AR(2) term is insignificant. Residuals of ARMA(2,2) model are normally distributed. There is no serial correlation. Then, we run ARMA(1,1). Residuals of ARMA(1,1) model are normally distributed. There is no serial correlation. AR(1) term is insignificant.

We exclude insignificant AR(1) term and re-estimate MA(1) model. Tables 4.29 and table 5.26 show MA(1) estimation and residuals diagnostic.

Table 4. 29. Moncton rainfall series. Estimation of residuals model with MA(1)

Sample: 1898 – 2011. Included observations : 113			
Variable	**Coefficient**	**t-statistic**	**p-value**
MA(1)	-0.26	-2.89	0.00
R-squared	0.06	**Adjusted R-squared**	0.06

Residuals of MA(1) model have normal distribution. There is no serial correlation (Table 4.30). We can accept this model.

Table 4.31 shows that in terms of Akike information criteria MA(1) is better than ARMA(1,1) and ARMA(2,2). Following this result and the principal of parsimony we choose MA(1) model.

Table 4. 30. Moncton rainfall series. Residuals diagnostic of MA(1)

Normality		**Serial Correlation**		
Skewness	-0.34	Lag #	Q statistic	p-value
Kurtosis	2.77	1	0.0404	-
Jarque-Bera statistic	2.47	2	0.4998	0.480
p-value	0.29	3	0.5223	0.770
		4	0.8734	0.832
		5	0.8854	0.927
		6	0.9233	0.969

Table 4. 31. Moncton rainfall series. Akaike Information Criterion of ARMA models of residuals

ARMA(2,2)	ARMA(1,1)	MA(1)
12.78	12.76	12.75

Thus, we reveal linear trend component and cyclical component in the series. Table 4.32 shows the estimate of linear trend component.

Table 4. 32. Moncton rainfall series. Estimation results of OLS model with trend regimes dummy variables

Sample: 1898 – 2011. Included observations : 114			
Variable	**Coefficient**	**t-statistic**	**p-value**
a_0	-3073	-1.66	0.10
a_1	2	2.08	0.04
b_0 (1964)	-45299	-3.37	0.00
b_1 (1964)	23	3.37	0.00
b_2 (1982)	31679	2.15	0.03
b_3 (1982)	7	2.08	0.04
R-squared	0.29	**F-statistic**	8.77
Adjusted R-squared	0.26	**Prob(F-statistic)**	0.00

We see significant positive trends over all period. Until 1964 rainfall increases by 2mm per year. Since 1964 till 1981 growth becomes very steep and achieves 25 mm per year. Since 1982 it is more flat, 9 mm per year.

Halifax raifall series

Series has structural breaks in 1893, 1916 and 1955 years which form four regimes in trend. We model them with dummy variables using OLS. Residuals of the model have normal distribution, and homoskedastic, but strong serial correlation starts since first lag and does not disappear at the higher order lags. (Table 4.33).

Table 4. 33. Halifax rainfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		Serial Correlation		
Skewness	0.17	Lag #	Q statistic	p-value
Kurtosis	2.89	1	6.6472	0.010
Jarque-Berra statistic	0.73	2	7.4410	0.024
p-value	0.69	3	8.5133	0.037
Heteroskedasticity		4	9.2542	0.055
F statistic	1.29	5	11.261	0.046
p-value	0.26	6	12.207	0.058

Residuals of OLS model are stationary based on Augmented Dickey Fuller test. Autocorrelation function (AC) and Partial autocorrelation function (PAC) show significant AR(1) and MA(1) terms. So, we estimate residuals with ARMA(1,1) model.

Tables 4.34 and 4.35 show ARMA(1,1) estimation and diagnostic of residuals after ARMA(1,1).

Table 4. 34. Halifax rainfall series. Estimation of residuals with ARMA(1,1)

Sample: 1872 – 2011. Included observations : 139			
Variable	**Coefficient**	**t-statistic**	**p-value**
AR(1)	0.65	9.99	0.00
MA(1)	-0.99	-108.5	0.00
R-squared	0.16	**Adjusted R-squared**	0.15

We can see significant AR(1) and MA(1) terms. Residuals of ARMA(1,1) model are normally distributed. There is no serial correlation. We can accept this model.

Table 4. 35. Halifax rainfall series. Residuals diagnostic of ARMA(1,1)

Normality		Serial Correlation		
Skewness	0.21	Lag #	Q statistic	p-value
Kurtosis	3.15	1	0.1249	
Jarque-Bera statistic	1.15	2	0.3488	
p-value	0.56	3	0.3491	0.555
		4	0.3578	0.836
		5	2.9379	0.401
		6	3.2427	0.518

Thus, we reveal linear trend component and cyclical component in the series. Table 4.36 show the estimate of linear trend component.

Table 4. 36. Halifax rainfall series. Estimation results of OLS model with trend regimes dummy variables

Sample: 1872 – 2011. Included observations : 140			
Variable	**Coefficient**	**t-statistic**	**p-value**
a_0	-26433	-2.09	0.04
a_1	15	2.19	0.03
b_0 (1893)	18094	1.07	0.29
b_1 (1893)	-10	-1.08	0.29
b_2 (1916)	11282	0.83	0.41
b_3 (1916)	-6	-0.86	0.39
b_4 (1955)	21231	1.63	0.11
b_5 (1955)	-12	-1.66	0.10
R-squared	0.15	**F-statistic**	3.39
Adjusted R-squared	0.11	**Prob(F-statistic)**	0.00

We see significant basis positive trends 15mm per year. There are declines in trend by 10mm per year over 1893-1916, 6mm per year over 1916-1954, and 12 mm per year over

1955-2011. Nevertheless, all declines are statistically insignificant at the 5% significance level.

4.6. Estimation of the precipitation time series with GLM.

Saint John rainfall series

This series has two structural breaks in 1925, and 1985 years which form three regimes in trend. We model them with dummy variables using OLS. Jacque - Berra statistic shows that the null hypothesis of Normal distribution can be rejected at the 5% significance level. There is no serial correlation. Heteroskedasticity Breusch-Pagan-Godfrey (BPG) test rely on normality assumption and cannot be used (table 4.37). We cannot accept this model and therefore use GLM approach.

Table 4. 37. Saint John rainfall series. Residuals diagnostic of OLS model with trend regimes dummy variables

Normality		**Serial Correlation**		
Skewness	0.33	Lag #	Q statistic	p-value
Kurtosis	3.71	1	2.5186	0.113
Jarque-Berra statistic	5.59	2	2.5469	0.280
p-value	0.06	3	3.7099	0.295
Heteroskedasticity		4	3.7119	0.446
F statistic	-	5	3.9058	0.563
p-value	-	6	4.3236	0.633

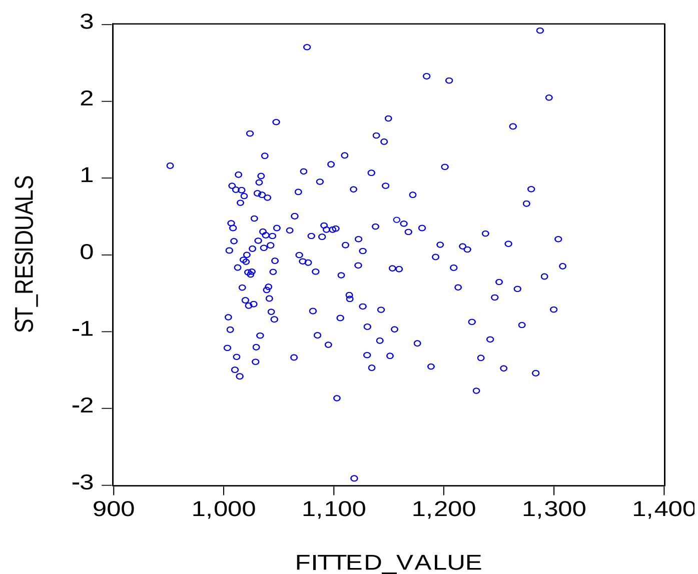
GLM standardized residuals diagnostic show normal distribution which is an argument that gamma distribution can be right choice. There is also an absence of serial correlation.

Table 4. 38. Saint John rainfall series. Standardized residuals diagnostic of GLM with trend regimes dummy variables

Normality		**Serial Correlation**		
Skewness	0.24	Lag #	Q statistic	p-value
Kurtosis	3.33	1	2.4033	0.121
Jarque-Bera statistic	1.95	2	2.4034	0.301
p-value	0.38	3	3.7831	0.286
		4	3.8218	0.431
		5	4.0745	0.539
		6	4.4498	0.616

To test for heteroscedasticity we have to plot standardized residuals against fitted values (see figure 4.1). Plot does not express any pattern. We can state homoscedasticity and stable mean. The plot and JB test for normality here support the same point that the model has correct specification. We accept the model.

Figure 4. 1. GLM diagnostic. Standardized residuals vs. fitted values



Estimation results (Table 4.39) reveal significant positive trend over 1925-1984 years. Since 1985 year trend is statistically insignificant.

Table 4. 39. Saint John rainfall series. Estimation results with GLM model

Sample: 1871 – 2011. Included observations : 141			
Variable	**Coefficient**	**z-statistic**	**p-value**
a_0	2641	1.39	0.17
a_1	-1	-0.85	0.40
b_0 (1925)	-9524	-2.95	0.00
b_1 (1925)	5	2.99	0.00
b_2 (1985)	-9301	-1.07	0.28
b_3 (1985)	5	1.09	0.28
LR statistic	37.31		
p-value	0.00		

4.7. Summary of the estimation results

Table 4. 40. Trends estimation summary

Series name	Last breakpoint, year	Significant trend after the last break, mm per year	OLS/ GLM trend estimation method	ARMA description of cyclical dynamic component in precipitation process
Edmundston rainfall	1955	-1	OLS	-
Edmundston snowfall	1946	No trend	OLS	-
Miramichi rainfall	1921	1	OLS	-
Miramichi snowfall	1954	-3	OLS	ARMA((4,10),(10)): $y_t = -0.16y_{t-4} - 0.77y_{t-10} + \varepsilon_t + 0.88\varepsilon_{t-10}$
Moncton rainfall	1982	9	OLS	MA(1): $y_t = \epsilon_t - 0.26 * \varepsilon_{t-1}$
Moncton snowfall	1961	-3	OLS	-
Halifax rainfall	1955	15	OLS	ARMA(1,1): $y_t = 0.65y_{t-1} + \varepsilon_t - 0.99\varepsilon_{t-1}$
Halifax snowfall	1894	No trend	OLS	-
Saint John rainfall	1985	No trend	GLM	-
Saint John snowfall	1916	-1	OLS	-
Fredericton rainfall	1984	No trend	OLS	-
Fredericton snowfall	1961	-3	OLS	-

Eleven of out twelve time series were estimated with OLS, and only Saint John rainfall series was estimated with GLM to deal with non-normal distribution. Four series do not contain significant time trend over the latest period: Three of them are rainfall series with one snowfall series. In general, snowfall series are more deterministic and exhibit negative trends. Rainfall series are less predictable exhibiting either negative or positive trend.

Besides linear trends we detected cyclical components in three time series. Estimation of Halifax rainfall series appears to be the most controversial. It contains three breaks - the highest number of breakpoints amongst all precipitation series. Its base trend of 15mm per year is also the highest. On the other hand, the last regime exhibits negative coefficient of another dummy variable of -12 mm per year with p-value of 0.10, which is exactly on the border of critical value. We did not include it in our final version but if included it could reduce the existing trend from 15mm to 3mm per year.

From our results we see that 6 out of 8 series with significant trends over the last period have breaks in 1950s-1960s or 1980s. Based on these results, we can think of climate change due to human activity as a potential reason for the changes in trends. According to Solomon et al. (2007) global temperature trend has breaks at these periods. Of course, global precipitation trends are not correlated with greenhouse emission as good as temperature trends. So, in our case it is just a hypothesis.

Nevertheless, we have similar trends of -3 mm per year in 3 snowfall series out of 6. All of them have started in 1950s-1960s. This result directly points towards potential climate change in the region and supports conclusion of many climatologists of less snow in Canada as an expected result of global warming.

Finally, as a result of our estimation, we have received specific econometric models which describe long run dynamics of precipitation series at all five transportation hubs in Atlantic Canada. These models can be used to simulate external climate change shocks in the hybrid general equilibrium model of the regional road transportation network.

Chapter 5. Conclusion

In this study, we have investigated evolutionary dynamics of precipitation in Atlantic Canada using statistical parametric methods, namely standard time series analysis. We worked with six rainfall and six snowfall series associated with five transportation hubs in the Atlantic Canada road transportation network: Edmundston and Miramichi (New Brunswick North), Moncton, Halifax, Saint John, and Fredericton. The data for our analysis in terms of annual amount of rain and snow was taken from the second generation Adjusted Precipitation for Canada (APC2) dataset. Most of the series contain around 140 observations.

We estimated the so-called long run, evolutionary dynamics, which was expressed via linear time trends in precipitation time series to detect structural breaks and analyze them as potential regime changes because of climate change. In doing so, we have run time trend regressions for rainfall and snowfall series with OLS and tested them for structural breaks with Bai-Perron test. Based on the test results, we specified statistical models with dummy variables to capture different regimes in the long memory processes behind precipitation dynamics and estimated them with OLS.

We did residuals diagnostics with respect to all estimated models. When we detected serial correlation in residuals, we modeled it with ARMA process to capture cyclical component of the precipitation dynamics. In the case of non-normally distributed residuals, we used GLM estimation assuming Gamma distribution and identity link function. We also did diagnostics of GLM standardized residuals in that case. Eventually we formulated our methodology for the analysis of evolutionary dynamics of precipitation.

Application of our methodology to the Atlantic Canada regional transportation network has brought the following results. Edmundston rainfall series has structural breaks in 1942 and 1955 and significant negative trend of -1mm per year since 1955. Edmundston snowfall series has structural breaks in 1933 and 1946, but insignificant current trend.

Miramichi rainfall series has structural breaks in 1902 and 1921 and significant positive trend of 1mm per year since 1921. Miramichi snowfall series has structural break in 1954 and significant negative trend of -3mm per year since 1954. It also contains a cyclical component. Cyclical component was captured as ARMA((4,10),(10)).

Moncton rainfall series has structural breaks in 1964 and 1982 and significant positive trend of 9 mm per year since 1982. It also contains a cyclical component which was captured as MA(1). Moncton snowfall series has structural break in 1961 and significant negative trend of -3mm per year since 1961.

Halifax rainfall series has structural breaks in 1893, 1916, 1955 and significant positive trend of 15 mm since 1955. It also contains a cyclical component captured as ARMA(1,1). Halifax snowfall series has structural break in 1894, but insignificant current trend.

Saint John rainfall series has structural breaks in 1925 and 1985 and does not contain current significant trend. This series was estimated with GLM. Saint John snowfall series has structural break in 1916 and significant negative trend of -1mm per year since 1916.

Fredericton rainfall series has structural breaks in 1964 and 1984, but with insignificant current trend. Fredericton snowfall series has structural break in 1961 and significant negative trend of -3mm per year since 1961.

IPCC AR5 report states that the effect of climate change on precipitation is not the same over the world. Moreover, precipitation dynamics has strong regional specifics. In our analysis, we assumed that if climate change has effect on precipitation in Atlantic Canada, we could see it through structural breaks in the second part of the 20^{th} century. Our analysis showed that six out of eight precipitation series exhibiting significant trends over the latest period produced breakpoints in 1950s-1960s or 1980s.

Our major contribution to the literature on economic consequences of climate change impacts is structural break analysis of precipitation series with parametric econometric models. Most of climatological studies perform regime break analysis with the help of nonparametric methods. As a matter of fact, we have not found studies with formal structural break analysis of time trends in the series we are interested in. We found only one non-parametric study of trends with the same precipitation data and one parametric study of trends in the total precipitation, rainfall and snowfall as one series. Both studies present trend analysis in different periods of 30 years or 60 years given exogenously and compare trends between those exogenously given periods. In our opinion, formal analysis of trends presented in this study produces more precise actual trends estimates. Besides, it allows us to use the entire series. It is especially important for parametric modeling as estimation is asymptotically unbiased in this group of methods. We are confident that 25-30 observations are not enough for consistent and unbiased estimates, especially with skewed data.

Finally, evolutionary dynamics that we have captured in this study is a part of climate change impacts module in a broader hybrid dynamic general equilibrium model developed to evaluate economic consequences of climate change impacts on road transportation network in Atlantic Canada.

Bibliography

1. Abbaspour, K.C. et al. 2009. Assessing the impact of climate change on water resources in Iran. *Water Resources Research, Vol.45, W10434: 1-16*
2. Ackerman, F. et al. 2009. Limitations of Integrated Assessment Models of Climate Change. *Climate Change 95: 297-315.*
3. Acosta-Michlik, L., Espaldon, V. 2008. Assessing vulnerability of selected farming communities in Philippines based on a behavioral model of agent's adaptation to Global Environmental Change. *Global Environmental Change, 18(4), 554-563.*
4. Afzal, M. 2015. Changes in the variability and periodicity of precipitation in Scotland. *Theoretical and Applied Climatology, 119: 135-159.*
5. Alexander, L.V. et al. 2006. Global observed changes in daily climate extremes of temperature and precipitation. *Journal of Geophysical Research, Vol. 111, D05109: 1-22.*
6. Alongi, D.M. 2015. The Impact of Climate Change on Mangrove Forests. *Current Climate Change Reports, 1: 30-39.*
7. Altissimo, F., Corradi, V. 2003. Strong rules for detecting the number of breaks in a time series. *Journal of Econometrics 117:207-244*
8. Andrews, D.W.K. 1991. Heteroskedasticity and autocorrelation consistent covariance matrix estimation. *Econometrica 59: 817-858.*
9. Andrews, D.W.K., Monahan, J.C. 1992. An improved heteroscedasticity and autocorrelation consistent covariance matrix estimator. *Econometrica 60: 953-966*.

10. Arrow, K. J. 1951. An Extension of the Basic Theorems of Classical Welfare Economics. *Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability, ed. J.Neyman.*

11. Azomahou, T. et al. 2015. Economic Growth under Stochastic Population and Pollution Shocks. *The Manchester School, Vol. 83, Issue 3: 314-345.*

12. Bai, J., and Perron, P. 1998. Estimating and Testing Linear Models with Multiple Structural Changes. *Econometrica 66: 1-22*

13. Bai, J., and Perron, P. 2003. Computation and Analysis of Multiple Structural Change Models. *Journal of Applied Econometrics 18: 1-22*

14. Barro, R.J., Sala-i-Martin, X. 1995. Economic Growth. *McGraw Hill, New York.*

15. Baum, S. 2007. Beyond the Ramsey model for climate change assessments. *Ethics in Science and Environmental Politics, vol.2007: 15-21.*

16. Berstein, L., et al. 2007. IPCC Fourth Assessment Report. Climate Change 2007: Synthesis Report. *Available online at:* https://www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr.pdf

17. Brechet, T. et al. 2013. Adaptation and Mitigation in Long-term Climate Policy. *Environmental Resource Economics 55: 217-243.*

18. Chen, S.-C. 2002. Model mismatch between global and regional simulations. *Geophysical Research Letters, Vol.29, No. 5, 1060: 4-1 – 4-4*

19. "Climate Change". Survey conducted by TNT at the request of Directorate-General Climate action of the European Commission. 2011. *Special Eurobarometer* 372. Available online at: http://ec.europa.eu/public_opinion/archives/ebs/ebs_372_en.pdf

20. Commission of the European Communities (CEC), PAGE User Manual (Brussels, 1992).

21. Dasgupta, P. 2008. Discounting climate change. *Journal of Risk and Uncertainty, Vol.37, Issue 2-3: 141-169.*

22. Debreu, G. 1951. The Coefficient of Resource Utilization. *Econometrica, Vol.19 No.3, pp. 273-292.*

23. DeCanio, S.J. 2003. Economic models of climate change: a critique. *New York: Palgrave Macmillan*

24. Dell, M., Jones, B.F., Olken, B.A. 2015. What do we learn from the weather? The New Climate-Economy Literature. *Journal of Economic Literature 52(3): 740-798.*

25. Dibike, Y.B., Coulibaly, P., 2006. Temporal neural networks for downscaling climate variability and extremes. *Neural Networks 19: 135-144*

26. Dobson, A.J. 2002. An Introduction to Generalized Linear Models. Second Edition. *Chapman &Hall/CRC*

27. Enders, W. 2010. Applied econometric time series, 3rd edition, *John Wiley & Sons, Inc.*

28. Fisher, R.A.1922. On the mathematical foundations of theoretical statistics. *Philosophical Transactions of the Royal Society. A 222: 309-368*

29. "Focus Canada 2014. Canadian Public Opinion about Climate Change". *Survey conducted by The Environics Institute and David Suzuki Foundation. 2014. Available online at:*

http://www.davidsuzuki.org/publications/downloads/2014/Focus%20Canada%20 2014%20-%20Public%20opinion%20on%20climate%20change.pdf

30. Goswami, B.N. et al. 2006. Increasing Trend of Extreme Rain Events Over India in a Warming Environment. *Science, Vol.314: 1442-1444.*

31. Greene, W. 2012. Econometric Analysis, 7th edition. Prentice Hall. Pearson Education Inc.

32. Gujarati, D.N. 1995. Basic Econometrics, 3rd edition. *McGraw-Hill, Inc*

33. Gutowski, W.J., Takle, E.S., Arritt, R.W. 1998. Meeting Summary. Project to Intercompare Regional Climate Simulation, Workshop II, 5-6 June 1997. *Bulletin of the American Meteorological Society, Vol. 79, No. 4: 657-659*

34. Hope, Ch. 2006. The Marginal Impact of CO2 from PAGE2002: An Integral Assessment Model Incorporating the IPCC's Five Reasons for Concern. *The Integrated Assessment Journal, Vol.6, Issue 1: 19-56.*

35. Kelly, D., Kolstad, Ch. 1998. Integrated Assessment Models For Climate Change Control. *Research supported by US Department of Energy grant number DE-FG03-96ER62277. Available online at:*
http://www.econ.ucsb.edu/papers/wp31-98.pdf

36. Kendall, M.G. 1955.Rank Correlation Methods. *Charles Griffin and Company. London, second edition*

37. Kolstad, C.D. 1996. Learning and Stock Effects in Environmental Regulation: the Case of Greenhouse Gas Emissions. *Journal of Environmental Economics and Management 31: 1-18.*

38. McCullagh, P., Nelder, J.A. 1989.Generalized Linear Models. Second Edition. *Chapman &Hall/CRC.*

39. Machiwal, D., Jha, M.K. 2012. Hydrological Time Series Analysis: Theory and Practice. *Springer Science and Business Media*

40. Mann, H.B. 1945. Nonparametric tests against trend. *Econometrica, 13: 245-259*

41. Manne, A.S. et al. 1993. MERGE: A Model for Evaluating Regional and Global Effects of GHG Reduction Policies. *Energy Policy, 23(1): 17-34.*

42. Mertz, O. et al. 2009. Adaptation to Climate Change in Developing Countries. *Environmental Management 43: 743-752.*

43. Muita, R.R. et al. 2012. Dry spell trend analysis in Kenya and the Murray Darling Basin using daily rainfall. *Geophysical Research Abstracts, Vol.14, EGU2012-6667*

44. Nordhaus, W.D. 1993. Rolling the 'DICE': an optimal transition path for controlling greenhouse gases. *Resource and Energy Economics. Vol. 15, Issue 1: 27-50.*

45. Nordhaus, W.D. 1994. Managing the Global Commons: The economics of climate change. *Cambridge MA: MIT.*

46. Nordhaus, W.D. 2007. A Review of the Stern Review on the Economics of Climate Change. *Journal of Economic Literature, Vol. XLV: 686-702.*

47. Nordhaus, W.D., Yang, Z. 1996. A Regional Dynamic General-Equilibrium Model of Alternative Climate-Change Strategies. *American Economic Review, 86: 741-765.*

48. Onoz, B., Bayazit, M. 2003. The power of statistical tests for trend detection. *Turkish Journal of Engineering and Environmental Sciences, 27: 247-251.*

49. Pachauri, R.K., Meyer, L.A. (eds.). IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. *Available online at:* https://www.ipcc.ch/report/ar5/syr/

50. Pareto, V. 1909. Manuel d'economie politique [Manual of Political Economy]. *Paris: V. Giard et E. Briere.*

51. Perez, L. et al. 2015. Modelling the Potential Impact of Climate Change on Agricultural Production in the Province of British Columbia. *Energy and Environmental Research, Vol.5, No.1:49-62.*

52. Pettitt, A.N. 1979. A Non-parametric Approach to the Change-point Problem. *Applied Statistics 28, No2: 126-135*

53. Pindyck, R. 2013. Climate change policy: what do the models tell us? *Journal of Economic Literature 51(3): 860-872.*

54. Pitman, A.J., A., Arneth, L., Ganzeveld. 2011. Regionalizing global climate models. *International Journal of Climatology. Vol. 32, Issue 3:* 321-337

55. Ramsey, F. 1928. A mathematical theory of saving. *Economic Journal 38: 543-559.*

56. Saldana-Zorilla, S.O. 2008. Stakeholders' view of reducing rural vulnerability to natural disasters in Southern Mexico: Hazard exposure and coping and adaptive capacity. *Global Environmental Change, 18(4), 583-597.*

57. Sanghi, A., Mendelsohn, R. 2008. The impact of global warming on farmers in Brazil and India. *Global Environmental Change 18: 655-665.*

58. Sen, P.K. 1968. Estimates of the Regression Coefficient Based on Kendall's Tau. *Journal of the American Statistician Association, Vol.63. No 324, pp. 1379-1389.*

59. Sneyres, R.M.1990. Technical note no.143 on the Statistical Analysis of Time Series of Observation. *World Meteorological Organization, Geneva, Switzerland*

60. Solomon, S.D. et al. 2007. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. *Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.*

61. Stern, N. 2007. The Economics of Climate Change: The Stern Review. *Cambridge and New York: Cambridge University Press. Available online at:* *http://mudancasclimaticas.cptec.inpe.br/~rmclima/pdfs/destaques/sternreview_report_complete.pdf*

62. Theil, H. 1950. A rank-invariant method of linear and polynomial regression analysis. *I, II, III, Nederl. Akad. Wetensch., Proc. 53: 386–392, 521–525, 1397–1412*

63. Thistle, M.E., Caissie, D. 2013. Trends in air temperature, total precipitation, and streamflow characteristics in eastern Canada. *Canadian Technical Report of Fisheries and Aquatic Sciences 3018*

64. U.S. Environmental Protection Agency (EPA). Climate Economic Modeling. *Web-page. Available online at:* http://www.epa.gov/climatechange/EPAactivities/economics/modeling.html

65. Vedwan, N. 2006. Culture, climate and the environment: Local knowledge and perception of climate change among apple growers in northwestern India. *Journal of Ecological Anthropology, 10(1), 4-18.*

66. Vincent, L.A., Mekis, E. 2006. Changes in Daily and Extreme Temperature and Precipitation Indices for Canada over the Twentieth Century. *Atmosphere-Ocean, 44(2) : 177-193.*

67. Vincent, L.A., Mekis, E. 2011. An Overview of the Second Generation Adjusted Daily Precipitation Dataset for Trend Analysis in Canada. *Atmosphere-Ocean, 49(2): 163-177.*

68. Vuille, M. et al. 2015. Impact of global warming hiatus on Andean temperature. *Journal of Geophysical Research: Atmospheres, 120: 3745-3757.*

69. Walras, L. 1874. Elements of Pure Economics or the Theory of Social Wealth. *Routledge. London and New York. Translated by W. Jaffe.*

70. Wang, X.L., Swail, V.R. 2001. Changes of extreme wave heights in northern hemisphere oceans and related atmospheric circulation regimes. *Journal of Climate, 14: 2204-2221*

71. Weitzman, M.L. 2007. A Review of the Stern Review on the Economics of Climate Change. *Journal of Economic Literature, Vol. XLV: 703-724.*

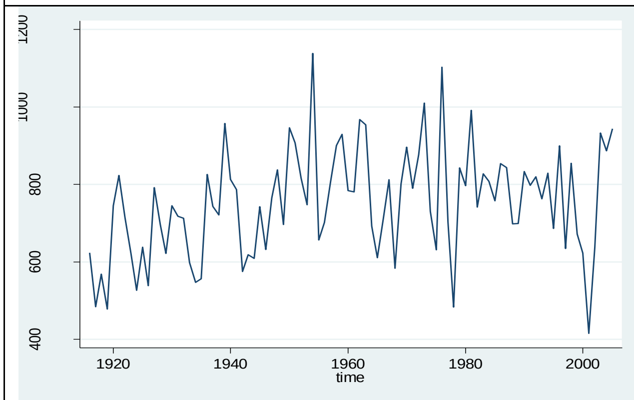
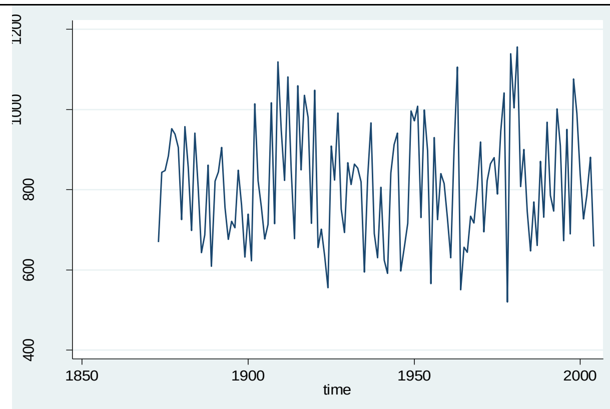
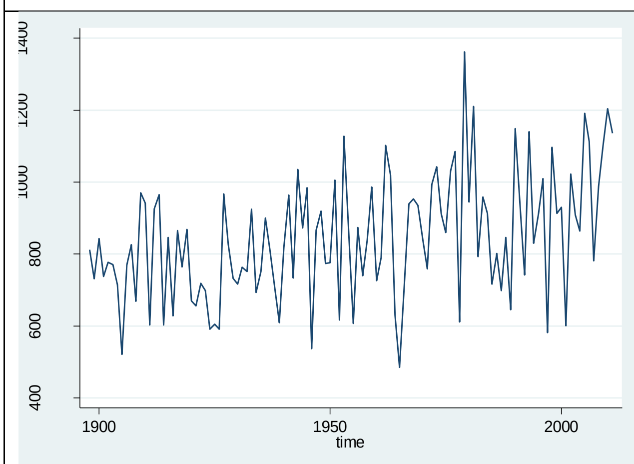
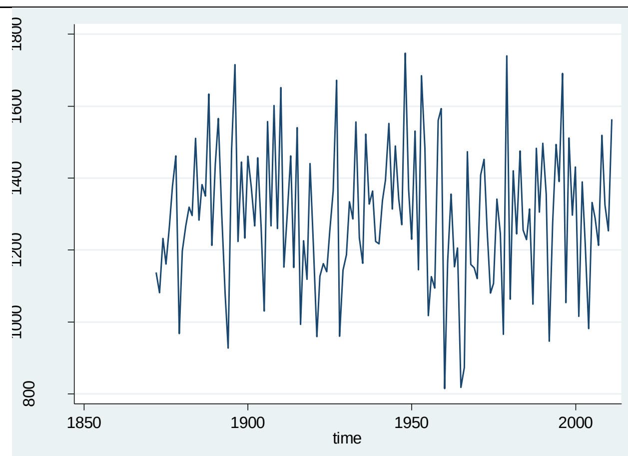
72. Widmann, M., Schar, C. 1997. A principal component and long-term trend analysis of daily precipitation in Switzerland. *International Journal of Climatology, Vol.17: 1333-1356.*

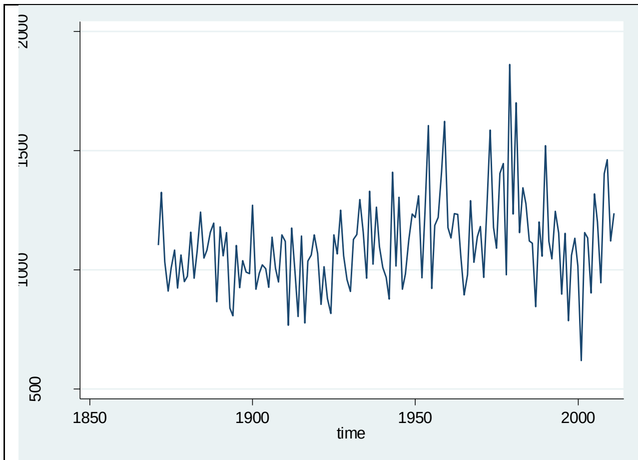
73. Wilcox, R.R. 2010. Fundamentals of modern statistical methods: Substantially improving power and accuracy. 2nd edition. *New York: Springer*

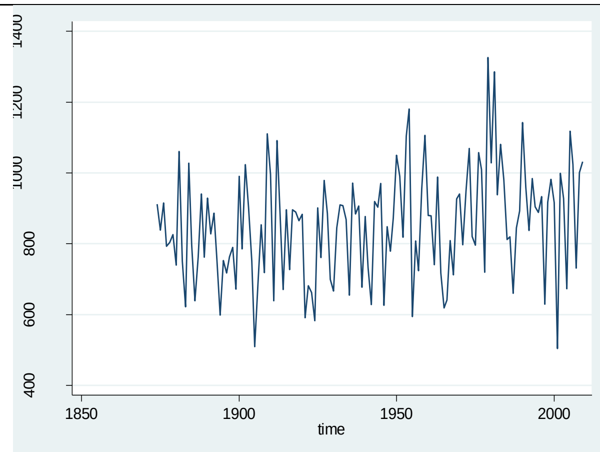
74. Wood, S. Lecture note about GLM in course “Statistics 2B (Linear Models)”. *University of Bath. UK. Available online at*: http://people.bath.ac.uk/sw283/MA20227/glm.pdf

75. Yue, Sh., Pilon, P. 2004. A comparison of the power of the t test, Mann Kendall and bootstrap tests for trend detection. *Hydrological Science Journal, 49:1, 21-37*

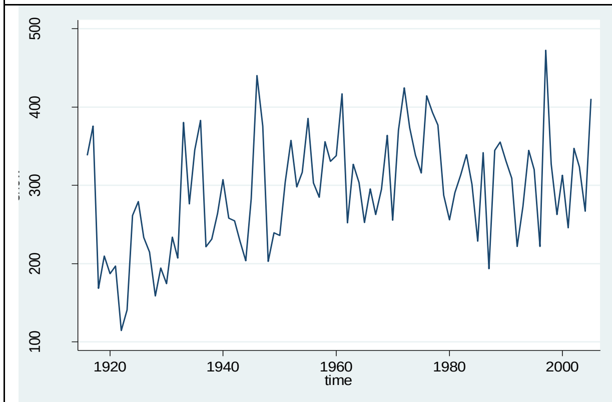
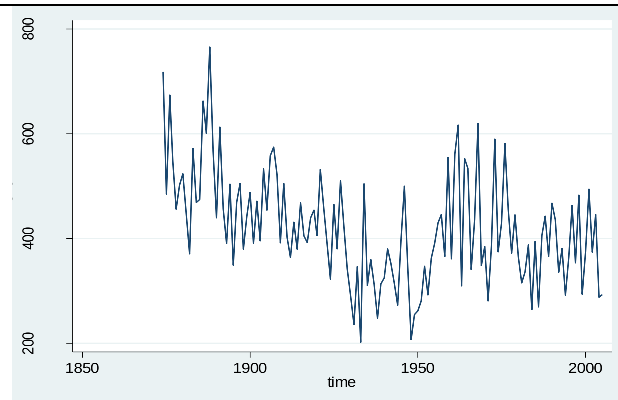
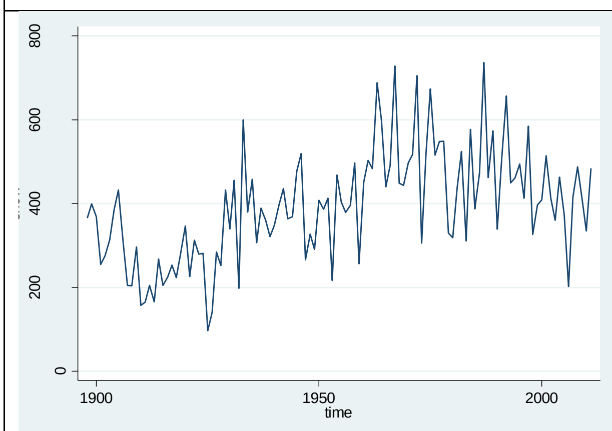
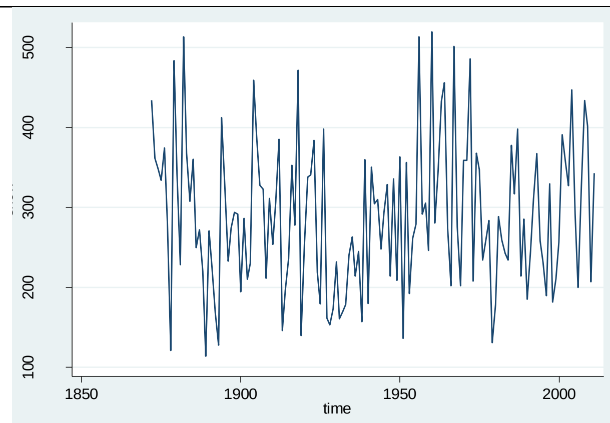
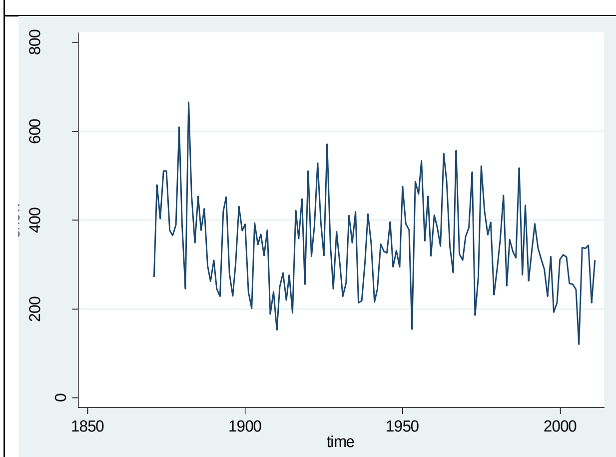
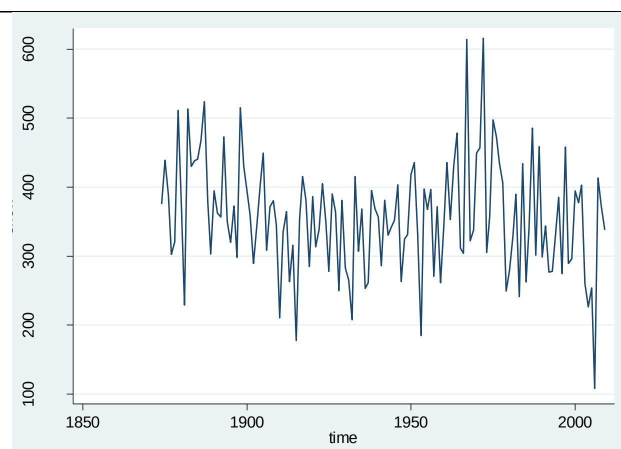
Appendix A: Dynamics of annual rainfalls, mm

Edmundston	Miramichi
	
Moncton	Halifax
	
Saint John	Fredericton


2000
1500
1000
500
1850
1900
1950
2000
time


1400
1200
1000
800
600
400
1850
1900
1950
2000
time

Appendix B: Dynamics of annual snowfalls, mm

Edmundston	Miramichi
	
Moncton	**Halifax**
	
Saint John	**Fredericton**
	

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