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Testing for Climate Change: Evolutionary Dynamics of Precipitation in Atlantic, Canada

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Abstract: Recent economic literature provides rigorous econometric evidence that climate change impacts such as increase in temperature, change in precipitation patterns, extreme weather events and others have significant effects on economic activity such as productivity, value added, total output and others. While some of them like increasing temperature definitely lead to negative economic consequences which is documented in recent literature, the impact of others and first of all precipitation is not that clear. In our study, we analyze literature dedicated to empirical evidence of the changing dynamics of precipitation and develop our own methodology on the basis of parametric time series analysis. We apply our methodology to study structural regime changes in dynamics of snowfall and rainfall time series associated with five regional road transportation hubs in Atlantic Canada since 1870s. As a result, we detected structural breaks in these series that can be explained by the climate change.

Key words: climate change, precipitation, econometrics, time series analysis, regional dynamics

1. Introduction

Climate change is one of the most discussed topics in modern world. In 2011, European Commission published results of a survey in which 20% of population in European Union (EU) mentioned climate change as the most serious problem in the world today [1]. Survey conducted in Canada in 2014 showed that 17% of Canadians were extremely concerned about climate change and 33% were definitely concerned [2].

According to the Intergovernmental Panel on Climate Change (IPCC), an increase in global temperatures will result in a number of impacts to the hydrological cycle, including changes in precipitation patterns [3]. Precipitation will be directly affected by changes in atmospheric circulation and increases in water vapour and evaporation associated with warmer temperatures. However, precipitation changes are expected to differ from region to region, with some areas becoming wetter and others becoming dryer. On the other hand, most models discussed in literature review section agree that precipitation will increase the most over high-latitude regions, while precipitation will decrease in most subtropical areas.

Our literature review presented below has shown that majority of authors agree that in Atlantic Canada climate is becoming wetter in general implying more rain and less snow in particular. In our study, we test this stylized fact statistically. In doing so, we needed rigorous methodology to study dynamic processes behind rainfall and snowfall precipitation time series. Therefore, this paper is organized as follows. First, we present our literature review regarding existing models to capture dynamics of precipitations. Second, we explain our methodology to estimate evolutionary dynamics of precipitation in Atlantic Canada. Third, we present results of our estimation of this dynamics for Atlantic Canada, and finally we make some conclusions and recommendations.

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2. Impact from Precipitation in Modern Literature

It is necessary to mention that all results presented further are a part of the New Brunswick Environmental Trust Fund Project "Modelling Economic Consequences of the Climate Change Impacts on Road Transportation Network in Atlantic Canada" [4]. Theoretical approach used in that project is based on a modified dynamic general equilibrium model with climate change impacts as productivity shocks. The Project defines a dynamic hierarchical general equilibrium model of a road transportation network in Atlantic Canada. The Project's model contains three levels. The highest level (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 (Edmundston and Miramichi), and Halifax. These hubs are located in two Maritime Provinces — New Brunswick (NB) and Nova Scotia (NS). 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. 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 residuals. In such a case climate change impacts are regarded as productivity shocks that affect regional road transportation network.

In this study, by evolutionary dynamics of precipitation we mean long term tendencies in precipitation patterns which are captured statistically. 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 implies a deterministic process behind it and which can be explained mathematically and further 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 analyzed 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.

According to that goal, we reviewed trend analysis in climatology and found that climatologists mostly use non-parametric approach. The main argument behind that approach is that frequently climate data is not normally distributed. The non-parametric approach is even recommended by the World Meteorological Organization (WMO) [5]. In our study we show that a simpler parametric approach can be used instead and it has the same explanatory power.

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 [6] and generalized by Kendall [7]. 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 or rank. For example, if the next value of Y is higher than the previous one, it states that there is a positive trend. Technically it treats equally a small increase in Y by 1% and a large increase by 100%.Theil-Sen estimator was developed by Theil [8] and generalized by Sen [9]. In fact, it is a median among slopes of lines that connect all points in a precipitation time series. For example, Afzal et al. [10] use it for trend analysis of total precipitation and its variability in Scotland. Vincent and Mekis [11, 12] use non-parametric approach to test trends in precipitation series in Canada including Atlantic Canada over the same period as this study. Vincent and Mekis [11] study contains more details about methodological basis while Vincent and Mekis [12] study mostly concentrates on the adjustments to the new precipitation database, and on effects these adjustments have on the trend estimation.

In the above studies, precipitation data is aggregated in two steps. As the first step, the country is divided into five by five degrees Celsius segments. Next 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 similar to Alexander et al. [13]. 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. It appears to be that Vincent and Mekis [12] do not provide any formal testing for structural breaks in the long-run trends. Instead the authors show estimation of trends for South Canada for two periods 1900-2009 and 1950-2009, and for Canada as a whole for 1950-2009. Vincent and Mekis found trends for all stations in Canada in 1950-2009 period. More detailed analysis is presented for aggregate trends in South Canada. Breaks in trends are found approximately using graphs of precipitation 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 increasing from 1920s to 1970, decreased 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 [14] used the same database as Vincent and Mekis [12], 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 mentioned above, Thistle and Caissie do not analyze possible structural breaks formally. Changes in trends are found by comparing results for two periods — 60 years of data with 30 years of data. The authors use linear model to test for trend and to 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 advantages and disadvantages. 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),It allows to overcome dependence of Ordinary Least Squares (OLS) on normal distribution, and, probably, is suitable to cover main cases of non-normality in climate data.

Mann-Kendall test, as a representative of a non-parametric approach, has undeniable advantage in trend detection in small samples. For example, Kendall shows normal distribution of his *Zs* statistic for small number of observations [7]. Parametric t-statistic relies on the Central Limit Theorem (CLT). Asymptotically it follows normal distribution in large samples, which can be approximated with t-distribution in moderate samples. So, theoretically t-test is weaker compared to non-parametric approach with respect to trend detection but as the sample size becomes bigger this weakness disappears. As a matter of fact, we work with large enough sample size of about 140 observations.

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 similar to the OLS/GLM estimators. Wilcox [15] 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 [16] performed 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 [17] analyzed precipitation trends in Switzerland. In doing so they used Mann-Kendall test. They argue that t-test is unreliable in the case of non-normal distribution of error terms. Yue and Pilon [18] 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. [19] 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, both approaches to time trend estimation have similar explanatory power if data set is large enough — 100 and more observations. In this study, we prefer 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 our modified general equilibrium model of regional road transportation network is parametric, our choice of parametric approach to capture evolutionary dynamics of precipitation is obvious.

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

3. Methodology

Based on our literature review, we found only two methods of structural break detection developed within non-parametric approach: (i) Pettitt test [20] that assumes only one potential break in a time series and (ii) sequential Mann-Kendall test developed by Sneyres [21] that does not make this assumption but it is also a rank-based test. On the other hand, there are many methods of structural break detection developed within parametric approach (see Enders [22] as an example).

In our study, we looked for potential multiple endogenous breaks — breakpoints in time trends at unknown dates. Bai and Perron [23]suggested a method to test hypothesis of no breaks versus some number of endogenous breaks, and that is why we used Bai-Perron method in this study. We developed a methodology that consists of the following six steps which were applied to the precipitation time series:

1) Run OLS regression on constant and time trend
2) Use Bai-Perron test to detect endogenous structural breaks in the obtained trend regression
3) Add dummy variables associated with detected structural breaks
4) Test error terms for normality (Jarque-Berra [24] test), serial correlation (correlograms) and homoscedasticity
5) If necessary, correct for serial correlation
6) 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.

The above methodology leads to the following statistical model specification:

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

where Y_t is rainfall (snowfall) in millimetres 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 $b_0,\ldots,$ b_k associated with dummies $DUMMY_1,\ldots,DUMMY_k$ along with cross products with $TIME$ such as $DUMMY_k{*}TIME$ describe time trends associated with other regimes (segments); e_t is independent and identically distributed (*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 a series no matter how many breaks we detect in that series.

4. Data and Estimation

In our study, we estimated rainfall and snowfall precipitation series separately. Our precipitation data is taken from the second generation Adjusted Precipitation for Canada (APC2) dataset. Our data set is composed of annual data obtained from monthly values for rainfall and snowfall in millimetres. We took the data from meteorological stations that are close to regional transportation hubs we are interested in. Information about these stations is presented in Table 1.

We have applied our methodology to test twelve precipitation time series associated with five regional transportation hubs in Atlantic Canada — six rainfall series and six snowfall series. Tables 2 and Table 3 present descriptive statistics of those series.

As can be seen from coefficient of variation (CV, ratio of standard deviation to mean) dispersion of snowfall values is higher than for rainfall values. This means that snowfall estimates will produce less precise and broader confidence intervals. Average share of rainfall in total precipitation among all 6 stations is 72%. The highest share of rainfall in total precipitation is near the ocean, 82% at Halifax transportation hub and 76% at Saint John transportation hub. This is not surprising given geographical location of these hubs.

Table 1 List of synoptic stations: APC2 metadata.

Station ID	Station Name	Province	From Year to Year	Number of Observations
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

Table 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 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

As a result of our estimation, we identified time trends in all of them. Five time series, estimated with OLS, produced statistically significant time trends with *iid* residuals. Three time series, estimated with OLS, produced statistically insignificant time trends with *iid* residuals. In terms of our methodology, estimation of these eight time series produced statistically acceptable models after first four steps.

Three time series, estimated with OLS, produced statistically significant time trends but serially correlated residuals. For those series, residuals were estimated with Autoregressive Moving Average (ARMA) models to capture serial correlation. In terms of dynamics it means that along with different time trends in a precipitation time series there exists a cyclical component which is statistically significant. In terms of our methodology, estimation of these three time series produced statistically acceptable models after five steps.

Finally one time series required application of all six steps of the designed methodology because OLS estimation of the time trends resulted in non-normally distributed residuals. That is why this model was estimated with GLM. Below we present results of our econometric estimation according to the above discussed structure.

4.1 Precipitation Time Series with Statistically Significant Time Trends and IID Error Terms

Five time series fall into group: (i) Edmundston rainfall, (ii) Miramichi rainfall, (iii) Moncton snowfall, (iv) Saint John snowfall, and (v) Fredericton snowfall. All five series produced significant structured breaks but in different years. Table 4 summarizes estimation of these series.

As an illustration of the obtained results, the model for Edmundston rainfall series can be presented by the following piecewise function:

Y_t= -14772+8×$TIME$ for the period before 1942

Y_t= -62466+33×$TIME$ for the period 1942-1955

Y_t= 2437-1×$TIME$for the period since 1955

4.2 Precipitation Time Series with Statistically Insignificant Time Trends and Iid Error Terms

The following three precipitation series fall into this group: (i) Edmundston snowfall, (ii) Halifax snowfall, and (iii) Fredericton rainfall. The following Table 5 summarizes our estimation of these series.

4.3 Precipitation Time Series with Statistically Significant Time Trends and Cyclical Component

The following three precipitation series fall into this group: (i) Miramichi snowfall, (ii) Moncton rainfall, and (iii) Halifax rainfall. As a result of serial correlation in these series, a cyclical component was estimated with ARMA model in addition to time trend estimation. In each case, cyclical component follows different process, and therefore we present our estimation results for each series separately.

Table 4 Results of OLS estimation of time trends (p-value).

Series name	a_0	a_1	Break years	b_0	b_1	b_2	b_3
Edmundston rainfall	-14,772 (0.02)	8 (0.01)	1942 1955	-47,694 (0.01)	25 (0.01)	17,209 (0.01)	-9 (0.01)
Miramichi rainfall	11,776 (0.04)	-6 (0.06)	1902 1921	-22,666 (0.07)	12 (0.07)	-13,084 (0.03)	7 (0.03)
Moncton snowfall	-4,259 (0.00)	2 (0.00)	1961	10,753 (0.00)	-5 (0.00)		
Saint John snowfall	9,526 (0.00)	-5 (0.00)	1916	-7,540 (0.00)	4 (0.00)		
Fredericton snowfall	2,105 (0.00)	-1 (0.01)	1961	3,673 (0.03)	-2 (0.03)		

Table 5 Results of OLS estimation of time trends (p-value).

Series name	a_0	a_1	Break years	b_0	b_1	b_2	b_3
Edmundston snowfall	8,546 (0.14)	-4 (0.15)	1933 1946	9,339 (0.37)	-5 (0.38)	-8,000 (0.17)	4 (0.17)
Halifax snowfall	18,709 (0.00)	-10 (0.00)	1894	-18,901 (0.00)	10 (0.00)		
Fredericton rainfall	-737 (0.51)	1 (0.16)	1964 1984	-44,116 (0.00)	22 (0.00)	2,703 (0.72)	1 (0.72)

Miramichi snowfall. Bai-Perron test produced one structural break in 1954 which divides this series into two regimes. In turn, Jarque-Bera test showed border value for normality but serial correlation since lag 4. Therefore, we modelled serial correlation in residuals with ARMA process. According to Augmented Dickey-Fuller test, residuals are stationary which means we can apply Box-Jenkins methodology. This methodology produced ARMA with two autoregressive (AR) terms for lags 4 and 10 and one moving average (MA) term for lag 10. The following Tables 6 and 7 show estimation results of the base model of the time trends as well as ARMA process.

Table 6 Results of OLS estimation (p-value).

Series name	a_0	a_1	Break years	b_0	b_1	b_2	b_3
Miramichi snowfall	6,903 (0.00)	-3 (0.00)	1954	-2,382 (0.18)	1 (0.15)		

Table 7 Estimation results of AR(4,10) MA(10) model of residuals from OLS trend estimation.

Variable	Coefficient	p-value
AR(4)	-0.16	0.00
AR(10)	-0.77	0.00
MA(10)	0.88	0.00

Moncton rainfall. Series has two structural breaks in 1964 and 1982 which defines three regimes in time trend. Residuals of the model are normally distributed and homoskedastic but serial correlation is present since lag 1. Residuals are stationary based on Augmented Dickey-Fuller test. Application of Box-Jenkins methodology produced pure MA(1) process. Tables 8 and 9 summarize results of our estimation.

Halifax rainfall. This is the only precipitation series with three structural breaks in 1893, 1916 and 1955 which defines four regimes in time trend. Residuals of the model are normally distributed and homoskedastic but serial correlation is present since lag 1.Residuals of OLS estimation are stationary based on Augmented Dickey Fuller test. Application of Box-Jenkins methodology produced ARMA process with AR(1) and MA(1). Tables 10 and Table 11 summarize results of our estimation.

4.4 Precipitation Time Series with Statistically Significant Time Trends and Non-Normally Distributed Error Terms

The only series that falls into this category is Saint John rainfall. Series has two structural breaks in 1925and 1985which defines three regimes in time trend. Residuals of the base OLS model have non-normal distribution but there is no serial correlation. According to our methodology, in this case we should use GLM. Results of GLM estimation are presented below in Table 12.

Table 8 Results of OLS estimation of time trends (p-value).

Series name	a_0	a_1	Break years	b_0	b_1	b_2	b_3
Moncton rainfall	-3,073 (0.10)	2 (0.04)	1964 1982	-45,299 (0.00)	23 (0.00)	31,679 (0.03)	7 (0.04)

Table 9 Estimation results of MA(1) model of residuals from OLS trend estimation.

Variable	Coefficient	p-value
MA(1)	-0.26	0.00

Table 10 Results of OLS estimation of time trends.

Coefficient	**Value**	**p-value**
a_0	-26,433	0.04
a_1	15	0.03
b_0	18,094	0.29
b_1	-10	0.29
b_2	11,282	0.41
b_3	-6	0.39
b_4	21,231	0.11
b_5	-12	0.10

Table 11 Estimation results of AR(1) and MA(1) model of residuals from OLS trend estimation.

Variable	Coefficient	p-value
AR(1)	0.65	0.00
MA(1)	-0.99	0.00

Table 12 Results of GLM estimation of time trends (p-value).

Series name	a_0	a_1	Break years	b_0	b_1	b_2	b_3
Saint John rainfall	2,641 (0.17)	-1 (0.40)	1925 1985	-9,524 (0.00)	5 (0.00)	-9,301 (0.28)	5 (0.28)

From Table 12, structural break in 1925 is significant the one in 1985 is not on the basis of p-values.

5. Conclusion

Table 13 presents summary of our estimation.

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. 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

Table 13 Summary of estimation results.

Series name	Last breakpoint, year	Significant trend after the last break, mm per year	OLS/ GLM trend estimation method	ARMA description of cyclical component in precipitation series
Edmundston rainfall	1955	-1	OLS	-
Edmundston snowfall	1946	No trend	OLS	-
Miramichi rainfall	1921	1	OLS	-
Miramichi snowfall	1954	-3	OLS	AR(4,10) MA(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): $y_t = \varepsilon_t - 0.26 * \varepsilon_{t-1}$
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	-

more deterministic or more predictable, and they exhibit negative trends. Rainfall series are less predictable or more random 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 15 mm 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, and that is why we did not include it in our conclusions. In addition, cyclical component in this series expressed via ARMA(1,1) has MA coefficient with absolute value close to one which also makes the estimates suspicious.

From our results, 6 out of 8 series with significant time trends over the last period have breaks in 1950s-1960s or 1980s. Based on these results, we can think of climate change as a potential reason for the changes in the trends. Moreover, 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 the conclusion of many climatologists of less snow in Atlantic Canada due to climate change.

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

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