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Climate Change Influence On Ontario Corn Farms' Income

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Abstract
Our study quantifies the impact of climate change on the income of corn farms in Ontario, at the 2068 horizon, under several warming scenarios. It is articulated around a discrete-time dynamic model of corn farm income with an annual time-step, corresponding to one agricultural cycle from planting to harvest. At each period, we compute the income of a farm given the corn yield, which is highly dependent on weather variables: temperature and rainfall. We also provide a reproducible forecast of the yearly distribution of corn yield for the regions around ten cities in Ontario, located where most of the corn growing activity takes place in the province. The price of corn futures at harvest time is taken into account and we fit our model by using 49 years of county-level historical climate and corn yield data. We then conduct out-of-sample Monte-Carlo simulations in order to obtain the farm income forecasts under a given climate change scenario, from 0°C to + 4°C.

Keywords Climate change · Corn futures · Generalized extreme value distributions · Linear regressions · Multi-linear regressions · Monte-Carlo simulations

1 Introduction

Climate change is now an accepted scientific fact and its denial is increasingly becoming an intellectually untenable position, as described in Björnberg et al. [1]. In his famous speech given at Lloyd's of London in 2015,[1] Bank of Canada and later Bank of England governor Mark Carney has encouraged worldwide banking and financial regulators to disclose their climate-relate risks. All sectors of the economy are affected, but agriculture is naturally among the most exposed. The literature focusing on the economic and financial aspect of climate change is extensive, with numerous papers like Tol [2] focusing on how the global economy should adapt and how climate change will impact the stability of the global financial system. For instance, Kolk and Pinkse [3] explore how companies in many different sectors of activity adapt their financial and corporate strategy with respect to climate change, both from a purely operational point of view, since climate change is expected to directly or indirectly influence their business, and from the perspective of government policies and the regulatory response. Dafermos et al. [4] studied from a macro-economic point of view how climate change will impact global financial stability and monetary policy. How to hedge climate risk in a long-term investment strategy is also a much discussed topic, as detailed in Andersson, Bolton and Samama [5]. The influence of climate change on farming from the point of view of agronomy and agricultural yields is well studied, for instance in Bootsma et al. [6], in Deryng et al. [7] or in Lobell and Field [8]. The impact of climate change on food production, though its influence on crop yields, has also been discussed in many research papers, as in Katz [9] or Almaraz et al. [10]. On the other hand, the question of how climate change will impact the financial situation of farmers is still a relatively unexplored topic. Kaiser et al. [11] developed a farm-level analysis of a gradual climate warming on the economic situation of grain farmers in southern Minnesota under various climate scenarios and we took inspiration from their discrete-time dynamic model. Wang et al. [12] created a multinomial logit model to study how farmers in China choose the optimal crop under several warming scenarios and use that model to make previsions at the 2100 horizon.

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[1] https://www.bankofengland.co.uk/speech/2015/breaking-the-tragedy-of-the-horizon-climate-change-and-financial-stability

Fig. 1 Cities representative of corn farming in Ontario

Our own novel approach is focused on the financial health of corn farms in Ontario from a credit risk point of view. We study the income of farms, which directly impacts the owners' ability to repay their loans. In our whole study, we limit ourselves to grain corn, excluding fodder varieties. We study how several climate change scenarios, from no warming at all (+0°C) to +4°C over the next 49 years at the horizon 2068, might impact the probability of default on loans granted to a corn farmers in Ontario. Our model is fitted using available historical data between 1970 and 2019. We consider the temperature, in order to compute the corn heat units, and rainfall, that enables us to determine the start and the end of the corn growing season for each year. We took our inspiration from the work of McDermid et al. [13] for the climate change scenarios. The price of corn futures is assumed to be constant and equal to the average price between 2009 and 2019 of a generic corn price future. This approximation is made in order to focus exclusively on the influence of climate change in our model. We then conduct Monte-Carlo simulations at the 2068 horizon in order to estimate the average income forecasts of the corn farms in the regions surrounding ten Ontario cities. This new approach mixes both climate variables and financial aspects. Our results are expected to be of great interest to both the financial institutions providing the loans and to the farmers receiving them, as well as to government planners at the local, national and international levels who are tasked with mitigating the harmful effects of climate change on the agricultural sector. While our numerical study is focused on corn farming in Ontario, our farm income model and Monte-Carlo techniques could be applied to any region and any crop, provided that the needed data is available.

2 Simulated Climate Change Paths

We articulate our corn farm income simulations study around Brockville, Cornwall, Fergus, Kapuskasing, Kingsville, North Bay, Ottawa, Toronto, Trenton and Woodstock. Those ten cities, shown on the map in Fig. 1, are representative of the corn farming regions in Ontario according to the Ontario Ministry of Agriculture, Food and Rural Affairs (OMAFRA) census of land use conducted in 2011.[2] The first step is to create, for each city, simulated daily temperature and rainfall paths under a given climate change scenario between 2019 and 2068. We need to simulate the daily maximum temperature, the daily minimum temperature and the daily rainfall. The temperature values enable us to compute the corn heat units, which in turn give us the simulated corn yield. The rainfall value enable us to decide, through a set of rules explained later in Section 3, the dates for the start and the end of the corn growing season on a given year. All our historical weather data is obtained from the Global Historical Climatology Network Daily (GHCND) database of the National Oceanic and Atmospheric Administration (NOAA). The global identification number and precise location of the weather stations which have created the data used in our study is provided as supplementary online material. For a given climate change scenario, we create 1500 paths. We will see later that this number is sufficient to obtain a stable and reproducible distribution of the corn yield for a given city and a given year of the simulation. To create an individual climate path, we adopt the block bootstrap method

[2] http://www.omafra.gov.on.ca/english/landuse/gis/maps/Census2011/corn_cd.png

Table 1 Historical climate trends per year in Ontario (1970-2019), expressed in tenth of degree Celsius for the temperatures and in tenth of millimeter for the rainfall

	$\mathscr{T}^j_{tmax}$	$\mathscr{T}^j_{tmin}$	$\mathscr{T}^j_{rain}$
Brockville	0.456	0.457	-0.116
Cornwall	0.547	0.433	0.052
Fergus	0.246	0.784	0.072
Kapuskasing	0.291	0.348	0.078
Kingsville	0.219	0.364	0.020
North Bay	0.472	0.255	-0.139
Ottawa	0.402	0.415	0.114
Toronto	0.450	0.617	0.033
Trenton	0.264	0.326	0.132
Woodstock	0.323	0.245	0.143

Table 2 Historical climate variance in Ontario (1970-2019)

	$\mathscr{V}^j_{tmax}$	$\mathscr{V}^j_{tmin}$	$\mathscr{V}^j_{rain}$
Brockville	91.6	106.4	13.2
Cornwall	97.0	91.3	12.3
Fergus	100.2	103.8	13.1
Kapuskasing	111.5	137.5	7.4
Kingsville	75.5	169.5	18.3
North Bay	106.9	124.5	19.9
Ottawa	92.0	83.7	10.2
Toronto	114.3	158.7	9.9
Trenton	81.0	81.7	11.4
Woodstock	98.6	86.3	21.1

detailed below. This technique is inspired from Lahiri [14] and more advanced results on boostrapping can be found in Härdle et al. [15].

1. The 49 years of historical temperature and rainfall data are sliced by blocks of one year, from January 1st to December 31st. We consider that every year is constituted of 365 days, disregarding leap years. For each of the ten cities (Brockville: j=1; Cornwall: j=2; Fergus: j=3; Kapuskasing: j=4; Kingsville: j=5; North Bay: j=6; Ottawa: j=7; Toronto: j=8; Trenton: j=9 and Woodstock: j=10), the blocks are called $TMAX^j(i)$, $TMIN^j(i)$, $RAIN^j(i)$, for $i \in [\![1, 49]\!]$. The year 1970 corresponds to $i = 1$ and the year 2019 corresponds to $i = 49$.
2. For each city j and for each year i of the historical data, the average maximum daily temperature, minimum daily temperature and daily rainfall is computed. We call them $\overline{TMAX^j}(i)$, $\overline{TMIN^j}(i)$, $\overline{RAIN^j}(i)$. We then perform, for each city, a linear regression by the least squares method on the 49 values of $\overline{TMAX^j}(i)$, $\overline{TMIN^j}(i)$, $\overline{RAIN^j}(i)$. The independent variable for the linear regression is the year. We assume all historical climate trends to be linear progressions. We therefore obtain yearly trends $\mathscr{T}^j_{tmax}$, $\mathscr{T}^j_{tmin}$ and $\mathscr{T}^j_{rain}$ for the minimum daily temperature, maximum daily temperature and daily rainfall, respectively. Those trends from 1970 to 2019 represent the historical climate change. We assume that they continue unchanged for rainfall and they are replaced by our climate change scenarios, from 0°C to +4°C, for the maximum and the minimum temperature in the future between 2019 and 2068. The values we obtained for the historical climate trends and the variance $\mathscr{V}^j_{tmax}$, $\mathscr{V}^j_{tmin}$ and $\mathscr{V}^j_{rain}$ of the series of $\overline{TMAX^j}(i)$, $\overline{TMIN^j}(i)$, $\overline{RAIN^j}(i)$ are displayed in Table 1 and Table 2. Those values for our ten cities in Ontario are consistent with the findings of an April 2019 report by the Canadian Government[3]. They underline the scale of climate change in Canada, with warming trends as high as three times the global average.
3. For each city j, the 49 years of a simulated climate path, under a given climate change scenario that assumes a warming of $+W$ °C ($W \in [\![0, 4]\!]$) and no extra rainfall besides the historical trend over the next 49 years, are sliced by blocks of one year from January 1st to December 31st. The new blocks are called $TMAX\_S^j(i)$, $TMIN\_S^j(i)$, $RAIN\_S^j(i)$, $i \in [\![1, 49]\!]$. The year 2020 corresponds to $i = 1$ and the year 2068 corresponds to $i = 49$. We perform a random permutation $\mathscr{P}$ of the integers between 1 and 49 and choose $TMAX\_S^j(i) = TMAX^j(\mathscr{P}(i))$; $TMIN\_S^j(i) = TMIN^j(\mathscr{P}(i))$ and $RAIN\_S^j(i) = RAIN^j(\mathscr{P}(i))$.
4. We remove the historical trend, to be replaced by our scenarios in the next step, for the temperatures from each block, according to its former place in the historical data: $TMAX\_S^j(i) = TMAX^j(\mathscr{P}(i)) - \mathscr{T}^j_{tmax} \times \mathscr{P}(i)$; $TMIN\_S^j(i) = TMIN^j(\mathscr{P}(i)) - \mathscr{T}^j_{tmin} \times \mathscr{P}(i)$. For the rain, we add to each block the historical trend according to its place in the simulation, as shown in the following formula:
$$RAIN\_S^j(i) = RAIN^j(\mathscr{P}(i)) + \mathscr{T}^j_{rain} \times (49 - \mathscr{P}(i) + i). \tag{1}$$
5. For the maximum and minimum temperature, we add to each block a random Gaussian perturbation term $\mathscr{N}(m, v)$, with mean m and variance v, according to our chosen climate scenario and the block's position in the simulation. We added this noise to account for the variability of annual climate around the trend. Failing to do so would have left the climate paths with an unrealistic lack of variability. We lastly add a corrective term to account for the realized warming trends in the historical

[3] Canada's Changing Climate Report. https://changingclimate.ca/CCCR2019/

data. This is done in order to avoid a discontinuity in our climate paths at the interface between the historical and simulated parts. We obtain the following equations:

$$\begin{aligned} TMAX\_S^j(i) =& TMAX^j(\mathscr{P}(i)) - \mathscr{T}^j_{tmax} \times \mathscr{P}(i) \\ &+ \mathcal{N}(\frac{W \times i}{49}, \sqrt{\mathscr{V}^j_{tmax}}) + \mathscr{T}^j_{tmax} \times 49, \end{aligned} \tag{2}$$

$$\begin{aligned} TMIN\_S^j(i) =& TMIN^j(\mathscr{P}(i)) - \mathscr{T}^j_{tmin} \times \mathscr{P}(i) \\ &+ \mathcal{N}(\frac{W \times i}{49}, \sqrt{\mathscr{V}^j_{tmin}}) + \mathscr{T}^j_{tmin} \times 49. \end{aligned} \tag{3}$$

It is important to note that the blocks, corresponding to one year of climate data, that we use in our bootstrapping method are de-trended, which means that the historical climate change is removed from them, before any innovation is added. Indeed, stationarity of the data is essential when considering bootstrapping methods, as explained in Härdle et al. [15]. For the temperatures, the historical trend is removed at the fourth step of the method detailed above, before the normal perturbation term is added at the fifth step in Eqs. (2) and (3). For the rainfall, since we assumed that the historical trend is continuing in the future, we remove at the fourth step the historical trend corresponding to a block's former position in the historical data and then add the correct trend corresponding to the block's current position in the simulation, as detailed in Eq. (1). While the data is rendered stationary on a yearly scale through the removal of the climate change trends before any innovation is added to them, we do intend to preserve the seasonal trends inside the blocks themselves. Those are indeed essential to our simulated climate paths, but their presence does not jeopardize the validity of our approach since the data is stationary on a yearly scale before the innovations are added. Our climate scenarios assume the value of the variable W to be an integer between 0 and 4 degrees Celsius. According to the values in Table 1, the historical realized maximum temperature warming for the 49 years between 1970 and 2019 is between 1.2 °C for Fergus and almost 2.7 °C for Cornwall with an average of 1.8 °C for the whole province. The historical realized minimum temperature warming for the 49 years is generally higher, from 1.2 °C for Woodstock to more than 3.8 °C for Fergus with an average of 2 °C for the province. Roughly speaking, we can say that our historical climate data shows that, on average, the corn growing regions of Ontario have experience a 2 °C warming over the past five decades. Since we have removed the historical trend between 1970 and 2019 at the fourth step of the climate path creation method, a climate scenario at the 2068 horizon defined by $W = 0$ °C in our framework corresponds to a break of the historical trend and no warming at all over the length of the simulations. It is obviously not meant to be a realistic depiction of a possible future for the climate in Ontario but it will provide us with a useful limit case. Similarly, the climate scenario defined by $W = 1$ °C corresponds to a slowing down of the climate warming trend, possibly through climate change mitigation programs. The climate scenario defined by $W = 2$ °C represents a continuation of the warming trend that has been going on since 1970 and the climate scenarios corresponding to $W = 3$ °C and $W = 4$ °C describe an accelerating warming of the climate. The rainfall aspect of a climate scenario is modeled differently since we always assume a continuation of the historical trend, which is very small for all cities considered. All our climate simulation results, for each of the ten cities and each of the five values of W, are available as supplementary online material as well as the computer code in MATLAB language.

3 Simulated Corn Yield Paths

Now that we have simulated paths for the climate variables, we switch our attention to creating corn yield paths. The first step is to compute, for each year in the future and for each city, the sum over the growing season of the daily corn heat units (CHU). Let us consider one climate path, constituted of the daily maximum temperature, the daily minimum temperature and the daily rainfall. For each year $i \in [\![1, 49]\!]$ of the simulation and for each city $j \in [\![1, 10]\!]$, we can compute the daily CHU. The corn heat units depend only on the temperature maximum and minimum. We call H_i^j the sum of the daily corn heat units over the corn growing season. The computation of H_i^j is achieved by using a well-established method, given in the following formula:

$$\begin{aligned} H_i^j = \sum_{k=1}^{N_i^j} \frac{1}{2}[&1.8(Tmin_k^j - 4.4) + 3.3(Tmax_k^j - 10)) \\ &- 0.084(Tmax_k^j - 10)^2]. \end{aligned} \tag{4}$$

It is used both in academic papers like Kwabiah et al. [16] as well as in industry reports and handbooks like Brinkman et al. [17]. The numerical coefficients in the formula are computed for corn farming in Ontario, but as explained in Kwabiah et al. [16], we believe that the formula would still be valid for corn farming in similar cool climate ecosystems. In Eq. (4), the sum is over each day k of the growing season of length N_i^j. The length of the growing season has been studied as an important indicator of climate change for agriculture, as explained in Brinkmann [18]. According to Cabas et al. [19], the length of the growing season, which depends only on rainfall in our framework, has a very strong impact on several crop yields, especially corn, in southwestern Ontario. The effects of climate change on crop yields in Ontario are

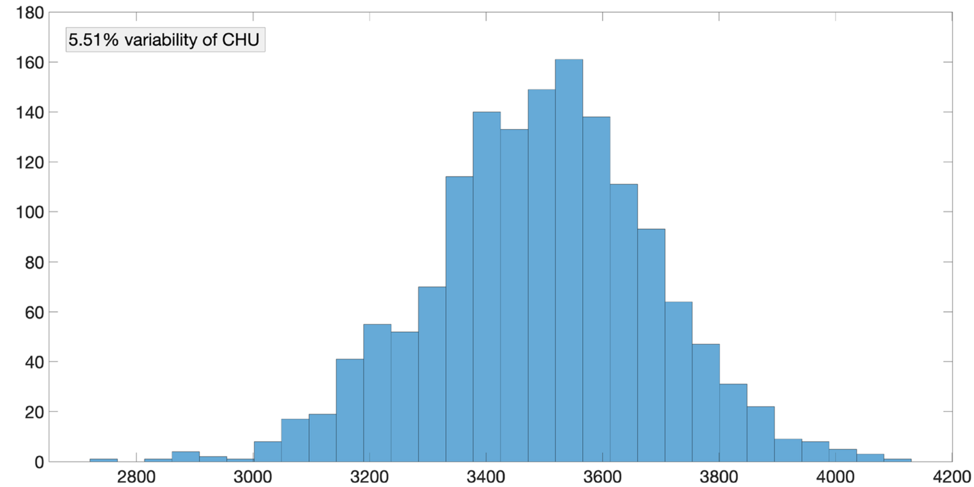

Fig. 2 Distribution of CHU for Cornwall in 2068 under the +4°C scenario

also studied in details in Smit et al. [20]. Again, the length of the growing season is one of the determining factors.

Since precise county level historical data was not available to us for the growing seasons in Ontario, we adopted an approach that is based on published agronomic studies that we modified to include the influence of our climate change scenarios through a set of rules based on rainfall. We do not claim that this model is very realistic, but it serves our purposes for this study and it relies on the common sense consideration that corn farmers need a relatively wet soil to plant their seeds at the end of Spring and a firm ground to harvest their relatively dry crop at the beginning of Autumn. We grounded our approach in average historical planting and harvesting dates for corn discussed in Sacks et al. [21]. In this wide ranging paper about planting and harvesting patterns for a variety of crops, the authors state that corn planting in the northern hemisphere generally occurs in April and May, while harvesting takes place in mid to late October. They also found that soil moisture often determines the length of the growing season, much more than temperature related considerations. The work of Kucharik [22] about corn planting trends in the USA was also inspirational to us. To determine the length of the growing on a given year of the simulated path for one of our ten cities in Ontario, we started from the time-averaged historical corn planting and harvesting dates provided by Sacks et al. [21]. We used the online database associated with the paper as well.[4]. That is June 1st (D_1) for planting and October 25th (D_2) for harvest. This is a simplification of the author's work for the purpose of our study. Sacks et al. [21] differentiate between the date when planting (resp, harvesting) start and the date when planting (resp, harvesting) stops, making the boundaries of the growing season more complicated, as it is of course in real life. We chose D_1 and D_2 as the average of the start and end dates provided in Sacks et al. [21]. Starting from those dates that we use to anchor our simulated growing seasons, we add the following rules based on our simulated rainfall data:

- The growing season starts (planting) ± 15 days around D_1, after the first occurrence of three consecutive days with a strictly positive rainfall, or at $D_1 + 15$.
- The growing season ends (harvest) ± 15 days around D_2, after the first occurrence of three consecutive days with zero rainfall, or at $D_2 + 15$.

The length of the growing season, which drives the size of the H_i^j and therefore the corn yield, upon which the farm income depends, has a large influence. Rainfall is essential in order to properly model the impact of climate change on the income of corn farms in Ontario. That is a very interesting result. Indeed, even though one could be tempted to draw the simplistic conclusion that a warming climate is purely beneficial for corn crops, the equation in Eq. (4) is a quadratic relation. While it is true that CHU generally increases with heat, and the corn yield in turn increases with CHU, extreme heat events will have the opposing effect. Also, another influence of climate change is expressed through shorter growing seasons due to extreme rainfall events, which could be much more unpredictable and detrimental to corn crops. In Fig. 2, we represented the histogram of CHU for Cornwall in the last year of the simulation under the +4°C scenario. The coefficient of variation is 5.51% and reflects the variability of our climate paths. Now that we know how to compute the CHU, we move to the computation of the corn yield Y itself.

- For any year $i \in [\![1, 49]\!]$ of the historical data, the yield for the city j is given by the following formula :

[4] https://nelson.wisc.edu/sage/data-and-models/crop-calendar-dataset/index.php

Table 3 Regressed coefficients for the historical yields (tonnes per hectare) and goodness of fit

	C_0^j	C_1^j	C_2^j	gof
Brockville	1.19	1.21E-01	8.68E-04	82.86%
Cornwall	0.64	1.44E-01	1.18E-03	88.22%
Fergus	0.57	1.19E-01	1.44E-03	82.07%
Kapuskasing	3.00	8.60E-02	4.68E-06	42.03%
Kingsville	4.36	1.48E-01	-4.00E-05	62.32%
North Bay	1.59	7.67E-02	8.13E-04	43.44%
Ottawa	4.26	1.45E-01	-1.50E-04	82.26%
Toronto	3.90	1.14E-01	7.33E-05	76.75%
Trenton	2.81	1.08E-01	3.30E-04	67.85%
Woodstock	3.49	1.36E-01	5.91E-04	86.45%

$$Y_i^j = C_0^j + C_1^j \times i + C_2^j \times H_i^j. \tag{5}$$

The coefficients C_0^j, C_1^j and C_2^j are obtained by multilinear regression of the historical county-level yield data against the year and the CHU. The constant C_1^j represents the technology improvement trend, responsible for most of the increase in corn yield over the last five decades. The influence of the warming climate on the corn yield since 1970, as we have seen with the temperature trends contained in Table 1, is realized through the CHU. The database of historical corn yields at county level in Ontario, expressed in bushel per acre and converted to tonnes per hectare in our study, is available as supplementary online material. The coefficients that we obtained for each city and the goodness of fit are contained in Table 3. In order to visualize the pertinence of the chosen regression model and the goodness of its fit, we provide Figs. 3 and 4. They show the regressed hyperplane and the historical corn yield data for Brockville and allow us to intuitively verify the validity of our approach.

The goodness of fit is excellent for all cities, which validates our approach, except for the two northern ones. It was to be expected given the gaps in the historical data, which produced plateaus once we carried over the last

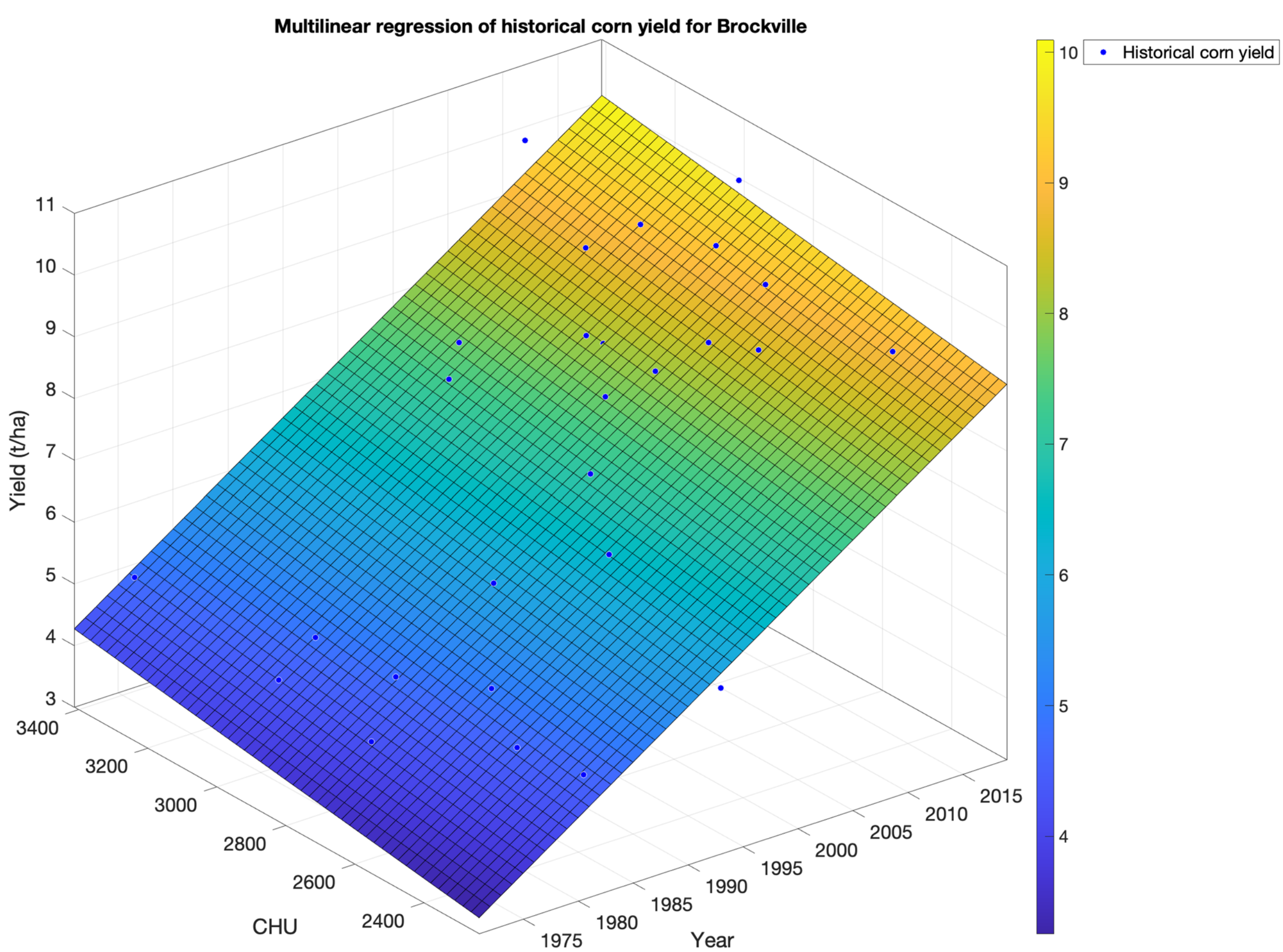

Fig. 3 Historical corn yield regression for Brockville against time and CHU (side view)

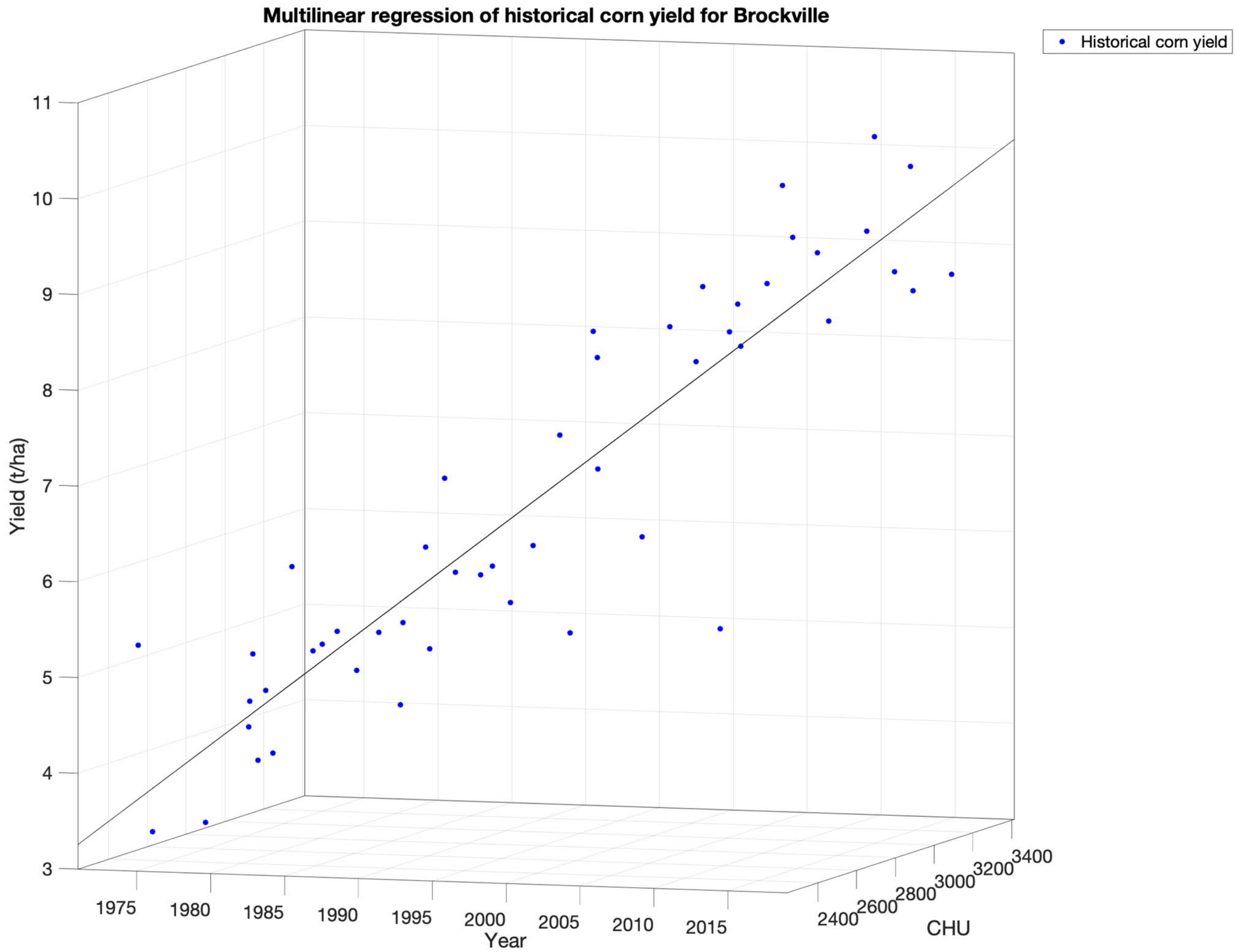

Fig. 4 Historical corn yield regression for Brockville against time and CHU (orthogonal view)

valid entry. As expected, the technological trend C_1^j dominates the influence of climate change: The coefficient C_2^j is always small relative to C_1^j. More surprisingly, C_2 is negative for Kingsville and Ottawa. This shows that in our study, the yield does not necessarily always increase with the CHU, which may sound strange at first but does reflects the fact that we have included both temperature and rainfall in our framework. More heat, within reason since Eq. (4) is quadratic, tends to help corn crops, but increased variability of rainfall, accompanied by the possibility of more frequent extreme events, may shorten the growing season. These competing effects of temperature and rainfall on corn farming in Ontario renders the real influence of climate change difficult to predict for the province as a whole. The choice of Eq. (5) as a bilinear function of the CHU and time was not the only one available to us. Liang et al. [23] propose a more elaborate model of corn yield that explicitly includes rainfall, while our approach keeps the influence of rainfall limited to the computation of the CHU, through the length of the growing season. Their model for the corn yield does not feature a technology trend however. Fitting it to our historical data over the last five decades would therefore have implied that the large increase of corn yield in Ontario was due only to climate variables, which was clearly unreasonable.

- For any year $i \in [\![1, 49]\!]$ in the future, given a climate path under a chosen climate scenario of $+W$ °C ($W \in [\![0, 4]\!]$), the yield, expressed in tonnes per hectare, for the city j is given by the formula

$$Y_i^j = C_0^j + C_1^j \times 49 + C_2^j \times H_i^j. \tag{6}$$

While Eq. (6) may seem simplistic, modeling the corn yield as a linear function of CHU is often used in agronomic studies, particularly in the context of climate change. This is for example the case in the reports from

Agriculture and Agri-Food Canada (AAFC) about climate change scenarios for agriculture[5]. Our purpose in this study is to measure the influence of climate change only. We therefore assume that the technology will not improve after 2019 and thus we made constant the term containing the technology trend C_1^j in Eq. (6). In order to avoid any discontinuity at the interface between historical and simulated yield data, a simulated corn yield path is given at its start all the accumulated technology trend since 1970. This is of course a simplification. Indeed, while the corn yield will necessarily tend to plateau in the future because the big technological changes in agriculture, like the advent of pesticides, fertilizers and machines, are in the past, it is very conceivable that technological advances will still drive a large increase of farms efficiency for many years. The coefficients C_0^j and C_2^j are those that were computed for a given city j by fitting Eq. (5) to the historical county level corn yield data.

4 Corn Yield Distributions and Farm Income

We now have successfully created corn yield paths from our temperature and rainfall paths under a given climate change scenario. Given one of our ten cities in Ontario and a warming factor W, we now wonder how many climate paths are needed in order to obtain stable and reproducible results. More precisely, we need a stable and reproducible distribution of the simulated corn yield for each year between 2020 and 2068. In our framework, we have chosen to use 1500 climate paths for one realization of the model and we will show that this number of paths is enough for our purposes and demonstrate that fact by studying 200 independent realizations of the model for a given city $j \in [\![1, 10]\!]$ and a given scenario $W \in [\![0, 4]\!]$. We decided to work with generalized extreme value distributions (GEV). We initially considered fitting our simulated data to a Gaussian distribution for simplicity, however even though the log-likelihood of a Gaussian fit was of the same order of magnitude as the one obtained for a GEV fit, the versatility of this latter type of densities and its ability to fit data with heavy shifting skew and fat tails made us decide to abandon a normal approach. The probability density function Ψ of a GEV is provided in the following formula,

$$\Psi(x) = (1 + k\frac{x-\mu}{\sigma})^{(-1-\frac{1}{k})}\frac{1}{\sigma}e^{-(1+k\frac{x-\mu}{\sigma})^{-\frac{1}{k}}}, \tag{7}$$

where the parameter μ is the mean, σ is the scale and k is the shape. We assume $k \neq 0$ and $(1 + k\frac{x-\mu}{\sigma}) > 0$. For each of our ten cities in Ontario under a given climate scenario and for each of the 49 years of the simulation at the 2068 horizon, we look at the evolution of those three coefficients and the reproducibility of the results over the 200 distinct independent realizations of our model, consisting of 1500 climate paths.

Under a given climate scenario, for each year of the simulation, for each city and for each of the 200 realizations, we fit a GEV distribution to our simulated data constituted of 1500 points. We obtain 200 sets of three coefficients (k, σ, μ) each year in the future, for each city under each climate scenario. We compute the coefficient of variation, defined as the quotient of the standard deviation by the mean and expressed in percentage, of the 200 values at hand for each of the three coefficients. We finally take the average of the 49 coefficients of variation over the whole simulation in the future and obtain a measure of the stability and reproducibility of the GEV fit for the corn yield in our framework. The results are presented in Table 4 and they are excellent for each of the ten cities under every climate scenario. During our computations, we also noticed that the values of the coefficients of variation became stable after only around 100 independent realizations, so our choice to conduct 200 independent realizations appears to be more than sufficient to demonstrate the stability and reproducibility of our GEV fits. The average variability of the mean is very small, in the order of magnitude of a few hundredth of a percent. The mean of the yield is the most important parameter from the point of view of the study of farm income. The average variability of the shape and scale of the fitted GEV is always below 10%, which is remarkable given the natural unpredictability of agricultural yields and weather patterns. This underlines the quality of the simulated weather paths within our framework. Given that the 200 realizations lead to stable fits of a GEV density to the simulated yield paths, we are confident that limiting ourselves to 1500 paths per realization is indeed a valid approach. In the following of this study, we will therefore consider only one realization constituted of 1500 yield paths.

We are now in a position to compute the income $\mathscr{I}_i^j$ of a typical corn farm in the region around the city $j \in [\![1, 10]\!]$ at each step $i \in [\![1, 49]\!]$ in the future. The computation of the farm income is given in the following formula:

$$\mathscr{I}_i^j = A \times Y_i^j \times P. \tag{8}$$

- A is a constant scale factor representing the size of the farm in hectares. We assume that it does not change over time. A is chosen as the average farm size in Ontario.

[5] Climate Change Scenarios for Agriculture www.mcgill.ca/brace/files/brace/Gameda.pdf

Table 4 Average coefficients of variation (in %), for the three GEV parameters, for each city and each climate scenario, over 49 years in the future, considering 200 independent realizations of our model, each consisting of 1500 corn yield paths

$W = 0\,°C$	k	σ	μ	$W = 1\,°C$	k	σ	μ
Brockville	7.4975	2.0869	0.0715	Brockville	7.7290	2.0796	0.0724
Cornwall	8.2333	2.0830	0.0669	Cornwall	8.3916	2.1192	0.0654
Fergus	7.9664	2.1905	0.1112	Fergus	7.8532	2.1804	0.1044
Kapuskasing	7.4003	2.1769	0.0006	Kapuskasing	7.4052	2.1741	0.0006
Kingsville	8.6566	2.0859	0.0026	Kingsville	8.4763	2.0332	0.0026
North Bay	8.0984	2.0468	0.1069	North Bay	8.0699	2.0544	0.1034
Ottawa	8.4624	2.0447	0.0084	Ottawa	8.7273	2.0494	0.0082
Toronto	8.3390	2.1186	0.0057	Toronto	8.1789	2.1272	0.0055
Trenton	7.8473	2.1197	0.0237	Trenton	7.8075	2.1305	0.0232
Woodstock	7.4121	2.0736	0.0345	Woodstock	7.4579	2.0520	0.0333
$W = 2\,°C$	k	σ	μ	$W = 2\,°C$	k	σ	μ
Brockville	7.8044	2.0696	0.0699	Brockville	7.8840	2.0790	0.0703
Cornwall	8.2863	2.1094	0.0624	Cornwall	8.3009	2.0884	0.0610
Fergus	7.9139	2.1691	0.1008	Fergus	7.8716	2.1946	0.0959
Kapuskasing	7.5246	2.2139	0.0006	Kapuskasing	7.6792	2.1791	0.0006
Kingsville	8.5421	2.0730	0.0025	Kingsville	8.4920	2.0953	0.0025
North Bay	8.1685	2.0946	0.1006	North Bay	7.9811	2.0994	0.0995
Ottawa	8.6767	2.0407	0.0078	Ottawa	8.4875	2.0251	0.0079
Toronto	8.2536	2.0966	0.0053	Toronto	8.2343	2.1202	0.0053
Trenton	7.8170	2.0997	0.0224	Trenton	7.8464	2.1427	0.0214
Woodstock	7.5972	2.0602	0.0325	Woodstock	7.5331	2.0454	0.0315
$W = 4\,°C$	k	σ	μ				
Brockville	8.2291	2.0936	0.0687				
Cornwall	8.2129	2.1418	0.0585				
Fergus	7.8428	2.1683	0.0945				
Kapuskasing	7.6367	2.2221	0.0006				
Kingsville	8.5895	2.0276	0.0024				
North Bay	8.0870	2.0668	0.0965				
Ottawa	8.6664	2.0452	0.0077				
Toronto	8.2753	2.0659	0.0051				
Trenton	8.0455	2.1669	0.0208				
Woodstock	7.6665	2.0586	0.0304				

According to Statistics Canada in a report entitled *Farm and Farm Operator Data, 2016 Census of Agriculture*[6], the average farm size in Ontario is presently 249 acres, which is approximately 100 hectares. Assuming that the typical size of a corn farm in Ontario matches the provincial average, which is a reasonable assumption given that corn is the dominant crop in the province, we choose $A = 100$ for the duration of our study. While this is an approximation, the statistical study of Eastwood, Lipton and Newell [24] shows that, in North America, the mean farm size, despite a slight trend toward larger values over the years, has not dramatically changed since 1970.

- Y_i^j is the simulated corn yield (in tonnes per hectare) for the city j at the year i of a given path among the 1500 constituting a realization of the model.
- The value of P, expressed in Canadian Dollars, is derived from the historical price of the Generic First Corn Future (C1 Comdty) corresponding to one metric tonne of grain corn. First we obtained from Bloomberg a time series of C1 Comdty in U.S Dollars between 2009 and 2019. We compensated for the effects of inflation by using a time series of Inflation GDP Deflator (IFGDPUSA) provided by the World Bank as an annual percentage. We then used a time series of the exchange rate of the U.S Dollar versus the Canadian Dollar (USDCAD), also obtained from Bloomberg, to convert the original C1 Comdty time series into inflation adjusted Canadian Dollars between 2009 and 2019. We computed for each city $j \in [\![1, 10]\!]$ the starting (planting) and ending (har-

6 www.statcan.gc.ca/eng/ca2016

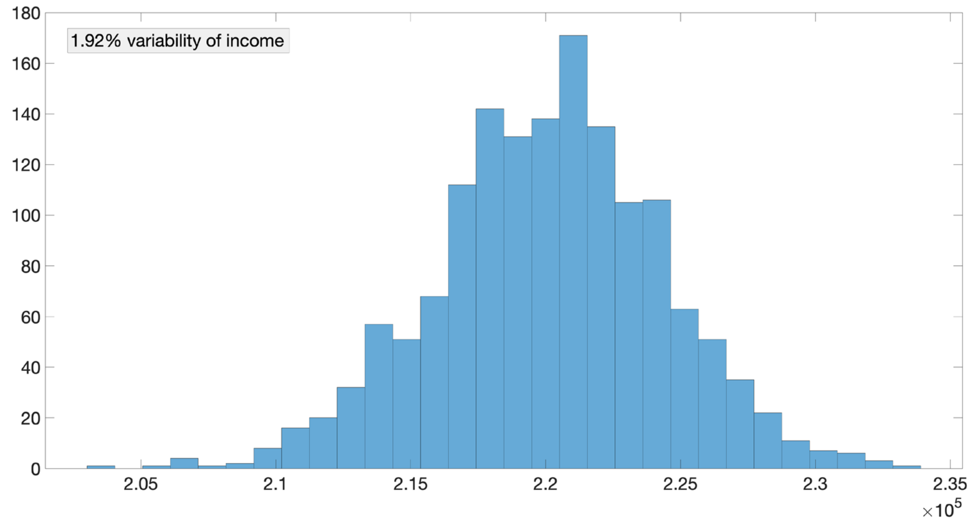

Fig. 5 Distribution of farm income (Canadian Dollars) for Cornwall in 2068 under the +4°C scenario

vest) dates of the historical growing seasons between 2009 and 2019. Those dates are obtained by using the same method as described before for the future years in the simulations, except of course that there is only one climate path, which is the realized historical data from NOAA. For each city j and for each year i, we compute a local price p_i^j as the average of the inflation adjusted C1 Comdty expressed in Canadian Dollars over the two weeks located around the middle of the growing season. This is the time when corn farmers will sell their crop on the futures market and plan for storage. Since we thought that it was unrealistic to keep local prices for each city, we then defined the price of corn future p_i in Ontario at year i as the mean of the values of p_i^j for $j \in [\![1, 10]\!]$. Finally, P as it appears in Eq. (8), is computed as the mean of the values of p_i for $i \in [\![1, 10]\!]$, between 2009 and 2019. We found $P = \$186.12$ CAN. We chose to work with a constant corn price in our study in order to focus exclusively on the impact of several climate change scenarios.

The histogram of farm income for Cornwall in 2068 under the +4°C scenario is represented in Fig. 5. The coefficient of variation is 1.92%. As we expected, there is much less variability in income than in CHU. Indeed, in Eq. (6) the value of C_0^2 is much larger than the value of C_2^2, according to Table 3. By computing $\mathscr{I}_i^j$ for $W = 4\,°\mathrm{C}$ and taking the average over the 1500 paths that constitute a realization of the model, we obtain Fig. 6. The x-axis represents the years of the simulation in the future, from 2020 to 2068 and the y-axis the farm income in Canadian Dollars. Figure 7 shows how the income of farms in the regions around Cornwall, Ottawa and Woodstock is modified when considering $W \in [\![0, 4]\!]$. The influence of climate change on corn farm income is subtle but very measurable. The farm income of most cities suffers under the scenarios $W = 0\,°\mathrm{C}$ and $W = 1\,°\mathrm{C}$, because they, respectively, represent a disappearance and a slowing down of the historical warning trend since 1970. Corn needs heat to grow and the CHU is an increasing function of heat so this result is not surprising. This is however not true for Ottawa and Kingsville where, unexpectedly, farm income benefits in those cases. The scenario $W = 2\,°\mathrm{C}$ represents a continuation of the historical climate trend, so farm income in most cities is stable. Since we have eliminated the technology trend in our computation of the yield paths for the future years, this result is not surprising. In the absence of a technology trend, the only way for the CHU, and thus the yield, to increase is to get more heat and no extreme rainfall events that would interfere with the length of the growing season. For the scenarios $W = 3\,°\mathrm{C}$ and $W = 4\,°\mathrm{C}$, representing an acceleration of climate change, the farm income in most cities benefits from the extra heat that boosts the CHU and thus the yield. Ottawa and Kingsville however do see a degradation of their income. This underlines the reality that the impact of climate change on corn farming is more complex than merely increased average minimum and maximum temperatures. It also includes the possibility of extreme temperature and rainfall events (see Figs. 6 and 7).

In order to better understand the impact of climate change under our five scenarios on each city, we compute in Table 5 the difference between averaged income over 1500 paths at the first year of the simulation (2020) and at the last year of the simulation (2068). The influence of rainfall and extreme temperature events on the growing season makes it so some cities see their farms suffer a loss of expected income under the more extreme climate change scenarios. There are obvious gains under a scenario that includes more warming for North Bay. Kapuskasing, on the other hand, does not seem to benefit much, but its corn industry is very small and there were gaps in its

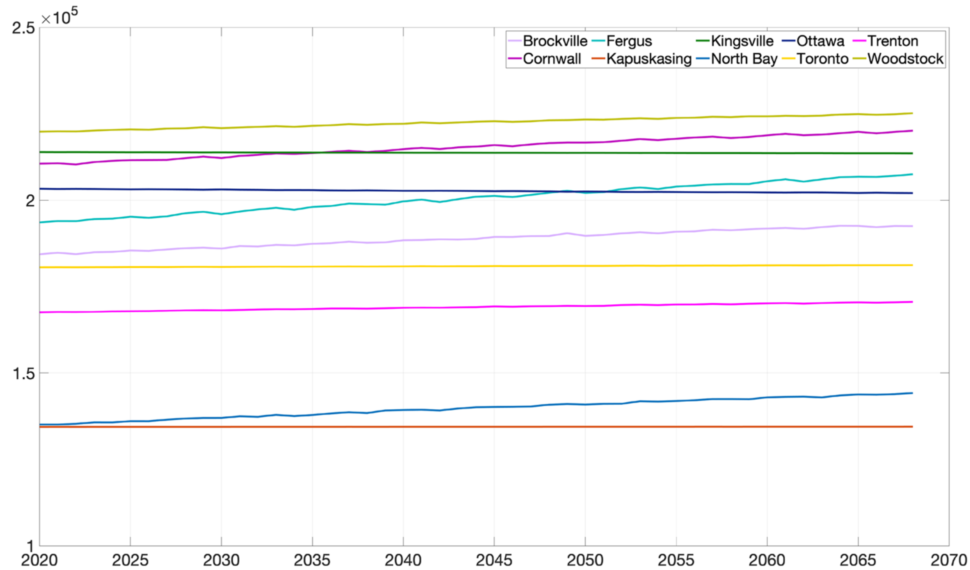

Fig. 6 Farm income (Canadian Dollars) for $W = 4\ °C$

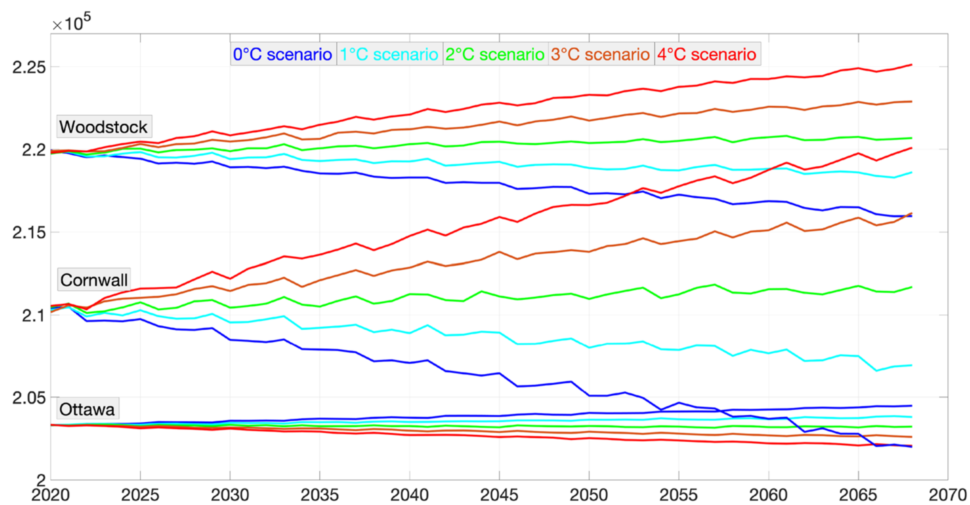

Fig. 7 Evolution of farm income for Ottawa, Cornwall and Woodstock

Table 5 Yearly income variation forecasts at the 2068 horizon (Canadian Dollar)

	$W = 0\ °C$	$W = 1\ °C$	$W = 2\ °C$	$W = 3\ °C$	$W = 4\ °C$
Brockville	-6277.18	-1952.15	1553.14	5017.80	8130.28
Cornwall	-8398.41	-3359.17	1220.74	5979.81	9556.66
Fergus	-9687.55	-3678.77	2657.68	8264.18	13898.55
Kapuskasing	-47.18	-22.94	0.95	22.40	43.34
Kingsville	248.43	84.37	-75.36	-205.79	-369.43
North Bay	-5893.04	-2041.14	2160.78	5535.98	9095.75
Ottawa	1177.21	486.73	-95.18	-718.34	-1270.15
Toronto	-447.98	-159.29	120.37	378.84	635.45
Trenton	-2266.69	-788.77	507.70	1847.96	3072.64
Woodstock	-3963.35	-1262.66	938.82	2992.10	5345.16

historical time series for the yield. Brockville and Cornwall to the East benefit as well in a spectacular fashion under the scenarios corresponding to the larger values of W, and so do Woodstock and Fergus to the West. Toronto and Trenton in the center of the province see increased income for their corn farms under more extreme climate change scenarios but Toronto seems to benefit less. Corn farming in Ontario seems to generally benefit from a warmer climate, but there are notable exceptions. Kingsville to the West sees a clear fall in the revenue as we consider more extreme climate scenarios and so does Ottawa to the East. The loss for Kingsville is modest as the climate gets warmer but Ottawa seems to follow the opposite trend as the rest of the province. Those geographical disparities in the way that local ecosystems in Ontario react to climate change have also been demonstrated in Alberta in the work of Dan and Williams [25]. They underline the financial risks associated with climate change.

5 Conclusions

As a conclusion, we see that even a simple model of corn farm income can produce very interesting results underlining the financial risks associated with climate change. Our model is not meant to be a comprehensive depiction of the financial challenges encountered by corn farms in Ontario, but it shows that climate change means uncertainty of income. It shows that the naive expectations (more heat equals more CHU and thus a better yield) are not always true. Indeed, other factors like rainfall, which determines the length of the growing season, and extreme temperature events, since Eq. (4) is a quadratic relation, are at play. In Ontario, while more heat under a climate scenario that assumes an acceleration of the historical warming trends, tends to benefit corn farming and results in increased income for the corn farms in most areas, there are notable exceptions. Those exceptions, like the region around Ottawa and Kingsville, have no obvious geographical explanation and seem to find their roots in the characteristics of the local climate. This demonstrates that climate change brings uncertainty in corn farm income and uncertainty means risk, which is expensive to handle from a financial point of view. Our simple model could be used as a first step toward developing a more extensive credit risk framework. Such an extended framework could include modeling of corn future prices and interest rates. This would open the possibility of computing the default probability of a farm recipient of a loan. Our future research will build upon the simple model presented in this study and attempt to refine our understanding of the financial implications of climate change on the agricultural sector.

Author Contributions Both authors contributed equally to conceptualization of the paper. Antoine Kornprobst wrote the code and prepared the first draft of the manuscript, and both authors discussed results and polished the paper.

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Availability of Data and Material All the climate data was obtained from NOAA's public FTP server

Code Availability All the code is written in Matlab. It is available to readers as supplementary online material. (ftp://ftp.ncdc.noaa.gov/pub/data/noaa). The historical county-level corn yield data is original and was compiled by us from publicly available online sources and from data provided directly to us by the Ontario Ministry of Agriculture, Food and Rural Affairs (OMAFRA). It is available to readers as supplementary online material.

Declarations

Conflicts of Interest None to declare

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