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An Assessment of the Canadian Federal-Provincial Crop Production Insurance Program under Future Climate Change Scenarios in Ontario

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Abstract

Research and observations indicate climate change has and will have an impact on Ontario field crop production. Little research has done to forecast how climate change might influence the Canadian Federal-Provincial Crop Insurance program, including its premium rates and reserve fund balances, in the future decades. This paper proposes using a mixture of two normal yield probability distribution model to model crop yield conditions under hypothetical climate change scenarios. Then superimposes Crop Insurance premium rate and reserve fund balance calculations onto the yield model to forecast their trends and fluctuation situations in the future decades. We find under the scenarios where climate change alters the probability of a lower yield year occurring and where climate change alters yield averages, both have more significant impacts on premium rates and reserve fund balances, compared to the scenarios where climate change alters yield variations. The results of this research will help Agricorp Ltd. identify the likely frequency and magnitude of both insurance premium rate fluctuations and reserve fund balance fluctuations under different climate change scenarios. Therefore the results can be used to help Agricorp Ltd. identify and forecast both premium rate fluctuation risk and reserve fund liquidity risk.

Keywords: Climate Change, Crop Yield Modeling, Crop Insurance Forecasting, Policy Analysis, Risk Management.

Introduction

The objective of this paper is to assess climate change's potential impacts on the Canadian Federal-Provincial Crop Insurance program. It includes several climate change scenarios that have different levels of impact on crop yield, both positive and negative, and their impacts on the Crop Insurance premium rates and reserve fund balance in the next 40 years.

Crop Insurance has a long history in Canada. In 1939, the Prairie Farm Assistance Act was introduced by the Canadian Government. It provided assistance to grain producers in the Prairies and the Peace River area against crop loss. In 1959, the Crop Insurance Act was passed to replace the Prairie Farm Assistance Act, with a wider coverage that includes all provinces. Crop Insurance has been helping farmers stabilizing farm incomes against crop production related risks ever since. Crop Insurance in Canada was designed in the tripartite responsibility format, where the insurance premium costs and administrative costs are shared among the federal government, provincial government and the producers. A CI program Reserve Fund is established at each province for meeting indemnity payments. The CI program is expected to be self-sustaining, that is, over time, farmers premiums and government contributions have to equal to the insurance indemnities paid to farmers. The Crown Corporation in Ontario, Agricorp Ltd., is responsible for delivering CI to producers, and maintaining the actuarially soundness of the program.

In light of evidence suggesting climate change has and will have impacts on field crop production, it is not clear how climate change will in turn affect the Crop Insurance Program. In Ontario, the Crown Corporation responsible for Crop Insurance (Agricorp Ltd.) would face two kinds of risks. First is the insurance premium rate fluctuation risk. Agricorp has the responsibility to minimize the year-to-year fluctuations in premium rates to provide stability for farmer customers and predictability for the budgeting process of the federal-provincial governments who fund the program (Nayak and Turvey, 1999). Second is the reserve fund liquidity risk. Agricorp is also responsible for maintaining the actuarially soundness of the CI program. In other words, farmers premiums and government contributions collected have to equal to the insurance indemnities paid to farmers. A reserve fund is established to meet indemnity payments and it is targeted at 14% of the insured liability of the same year.

From the risk management perspective for the CI program provider, Agricorp Ltd., the first step is to identify the risks it is facing and determine the size of the risks. The results of this research will help Agricorp Ltd. identify the frequency and magnitude of both insurance premium rate fluctuation and reserve fund balance fluctuation under climate change conditions. Therefore the results can be used to help Agricorp Ltd. identify and measure both premium rate fluctuation risk and reserve fund liquidity risk.

This research utilizes the mixture of two normal probability distributions model to model field crop production under current and future hypothetical climate change scenarios. And superimpose Crop Insurance premium rate and reserve fund balance calculation onto the yield model, to estimate the CI program premium rate and reserve fund balance under current and future hypothetical climate change scenarios. Three major field staple crops in Ontario are studied: grain corn, soybean and winter wheat.

Literature Review

In order to analyse climate change scenarios impacts on Crop Insurance program, crop productions under both current and future climate change scenarios have to be modeled first.

1. Climate change and its potential impacts on crop production

Ackerman and Stanton (2013) reviewed the recent climatology and crop science research findings on climate changes impacts on field crop production. Implications from those researches are: first, climate change will increase some extreme weather events occurrences which will likely increase chances of extreme yield conditions. Second, climate change not only has possibility to affect crop production in positive ways, but also can affect crop production negatively. Third, C4 crops (e.g. corn) would show less yield increase under some favorable climate conditions compared to C3 crops (e.g. soybean and winter wheat).

In the climatology sphere, there have been research that uses stochastic weather generators to obtain climate scenarios, then, use crop bio-physical models to simulate climatedriven weather changes effects on crop yields (examples include Mearns et al., 1992, 1996, 1997; Peiris et al., 1996; Olesen and Bindi, 2002; and Wang, Wang and Liu, 2011). One of the main findings of this line of research, is that changes in the weather variable affect both the mean and variability of crop yields, with the magnitude of the effect depending on the crop and location used in the study.

2. Crop yield modeling

In the agricultural economics sphere, there are also studies trying to model yield variability in response to climate change (climate-driven weather changes). Those studies can be split into two categories based on their general approaches.

One major approach uses a regression based crop production function that utilizes historical data to identify the effects of weather variables on both the mean and variability of yield (examples include Adams et al., 2001; Isik and Devadoss, 2006; McCarl, Villavicencio and Wu, 2008; Barnwal and Kotani, 2010). Tack, Harri and Coble (2012) relaxes the restriction of linking mean and variation of weather inputs to the same moments of output (yield) by conditioning higher-order moments of the yield distribution on weather and irrigation variables. However, one difficulty of such approach is that it is hard to select a crop production function without creating omitted-variable bias.

The second approach involves parametric, semi-parametric and nonparametric yield probability distribution modeling. The advantage of using such approach is that it produces yield distribution without relying on a fixed yield function (yield as a function of crops climatic requirements for growth relative to the thermal and moisture conditions under each climatic scenario). Because yield functions are usually tested by field experiments at fixed locations, which may not be able to represent yield patterns at other locations or represent crop production conditions at aggregated levels. Therefore, such approach could be used to study general pattern of crop production under climate change. Tack, Harri and Coble (2012) argue for these types of probability distribution modeling taken as a whole, the main impetus is to minimize the possibility of ex ante specification errors while maintaining empirical tractability and the ability to capture stylized features of the data. In fact, each of those modeling techniques correlate with some unique contexts that it is most suitable for.

The nonparametric approach uses observed yield data to derive yield distribution. Norwood, Roberts, and Lusk [NRL] (2004) commented the Goodwin and Ker (1998) approach of using kernel techniques to estimate county level crop yield in the US, provides the best out-of-sample forecasting performance (in other words best approach of approximating current/historical actual yield probability distribution) compared with traditional parametric methods.

Ker and Coble (2003) proposed a semi-parametric method to estimate corn yield densities. Their simulation results indicated that the semi-parametric estimator with a normal distribution is more efficient than the competing parametric models (Normal and Beta) and the standard nonparametric kernel estimator.

Under the parametric approach, a specific parametric distribution is selected based on the perceived yield probability distribution shape, usually from one of the well-known statistical distributions, and parameters of the distribution are estimated using collected yield data. Gallagher (1987) used gamma distribution frontier model to incorporate negative skewness found in national level soybean yield probability distributions in the US. Nelson and Preckel (1989) used the beta model where the two shape parameters of the beta distribution were used to represent fertilizers application levels. Ramirez, Moss and Boggess (1994) used inverse hyperbolic sine (HIS) model to incorporate the possible non-normality yield probability distribution. Just and Weninger (1999) used normal distribution to study farm-level crop yield at Kansas for corn, wheat, soybean, alfalfa, and sorghum.

2.1 Skewness discussions

In pair with the efforts of minimizing the possibility of ex ante specification errors in yield probability distribution modeling, there have been lots of discussions among agricultural economists on the skewness of crop yield distribution. Day (1965) argued that crop yield distributions are non-normal and positively skewed because excellent weather condition must prevail throughout the entire growing season if high yields are to be obtained while bad weather during any critical period can significantly reduce yields. However, positive skewness was found only for cotton and no significant skewness or negative skewness was found for corn and oats. Ramirez, Misra, and Field (2003) also found that Texas dryland cotton data exhibit positive skewness. On the contrary, there are studies that discovered negative skewness of crop distributions. Gallagher (1987) found negative skewness for U.S. average soybean yields and he reasoned, Yield cannot exceed the biological potential of the plant, yet it can approach zero under blight, early frost or extreme heat. He also found that soybean yield variability has changed systematically over the past five decades and the variance of U.S. soybean yields has been increasing. Other agricultural economics studies in support of negative skewness include: Ramirez, Misra, and Field (2003) also concluded that Corn Belt corn and soybean yields are negatively skewed. Nelson and Preckel (1989) and Moss and Shonkwiler (1993) found evidence of negative skewness for corn. Just and Weninger (1999) challenged the predominant view that crop yield distributions are non-normal by arguing that rejection of normality may be the result of inappropriate detrending and failure to properly model heteroskedasticity. And they found previous studies using time-series data at aggregated levels cannot reflect farm-level randomness. They failed to reject normality when using flexible polynomial trends for mean yield and yield variance. Ramirez Misra and Field (2003) addressed the procedural issues raised by Just and Weninger by using improved model specifications, estimation and testing procedures. However they found Corn Belt corn and soybean yields are negatively skewed, and Texas dry-land cotton yield is positive skewed (as mentioned before). They argued because the type-two errors in the normality tests are unknown, non-rejection does not prove yield normality.

2.2 Beyond traditional parametric yield distribution modeling: a mixture of normal probability distributions

Ker and Goodwin (2000) argued though the traditional parametric yield probability distribution models (such as gamma, beta and HIS distributions) can accommodate yield distribution skewness observed in historical data, it doesn't mean they are the best approximations for yield distribution. Therefore, Ker and Goodwin (2000) suggested it is possible for the unknown yield distribution to be bimodal and negatively skewed due to the effects of catastrophic events such as drought, flood and freeze. Observed yields can be seen as drawn from one of two distinct subpopulations: a catastrophic sub-population and a non-catastrophic sub-population. That is, if a catastrophic event occurs in a particular year, yields are drawn from the catastrophic sub-population; if no such an event occurs in a year, yields are drawn from the non-catastrophic population. The distribution from catastrophic years (secondary distribution) lies on the lower tail of the distribution from non-catastrophic years (primary distribution) and has considerably less mass, which leads to negative skewness of yields. The secondary distribution lies to the left of the primary distribution because yields tend to be much lower in catastrophic years. It would also be expected that the secondary distribution has less mass since catastrophic events occur with much less frequency than their complement. Therefore, yield distribution could be negatively skewed and bi-modal if the mass of catastrophic distribution is non-negligible and the catastrophic distribution is relatively peaked.

Few empirical applications used a mixture of normal distributions to model yields. However the mixture of normal probability distributions model have been around for a long time, especially in statistical analysis, examples include: Everitt and Hand (1981), Titterington, Smith and Makov (1985), and Mclachlan and Peel (2000). Wirjanto and Xu (2009) applied the mixture of normals model in modeling returns on financial assets. As Wirjanto and Xu (2009) addressed: the advantage of the mixture of normals model is that it is flexible enough to accommodate various shapes of continuous distributions, and it is able to capture leptokurtic, skewed and multimodal characteristics.

In fact, the mixture of two normal yield probability distribution model suggested by

Ker and Goodwin (2000) can not only accommodate negative yield skewness, it is flexible enough to also capture positive yield skewness and normal yield distribution that observed by a few researchers mentioned above, and the possibility of positive yield skewness or normal yield distribution happening in the future under climate change.

Data and Methods

County level annual crop yield data are obtained from the Ontario Ministry of Food, Agriculture and Rural Affairs (OMAFRA) from 1949 to 2010. 49 counties data are available. However some counties have many missing values due to the fact corn, soybeans and winter wheat are not cultivated a lot in the northern regions. And according to Statistics Canada (2009), soybeans were restricted by climate primarily to southern Ontario before mid-1970s.

According to Intergovernmental Panel of Climate Change (IPCC, 2008), World Meteorological Organization (WMO) and Environment Canada (2013), climate change refers to a long term weather pattern and usually takes 30 years or longer for a particular region. Therefore, we set our forecasting period to be 40 years. That is: from the year (2011) we start to apply climate change scenarios, to the end of yield forecasting and CI program evaluation in year 2050, we will have 40 years of data on crop yield, CI premium rates and reserve fund balances.

The following subsections introduce the techniques used to model yield and construct sample farms for CI premium rates and reserve fund balance estimation.

1. Yield model

Recall the purpose of this study, not only do we want to model yield under current conditions, most importantly we want to show the potential impacts of climate change on crop production. We propose to use parametric probability distribution model to model yield. Because, first, probability distribution model looks pass the complicated mechanisms of climate-driven weather variables effects on crop yield, but focusing on climate changes net effect on yield. Second, by altering the parameters of the parametric model, we can mimic climate changes effect on yield.

More specifically, we propose to use the mixture of two normal probability distributions model as suggested by Ker and Goodwin (2000). Because it is flexible enough to accommodate all types of yield distribution skewness found in previous literature. The general functional form of the model is as the following:

$$P(y) = \lambda \times N(\mu_1, \sigma_1^2) + (1 - \lambda) \times N(\mu_2, \sigma_2^2)$$
(1)

Where, P(y) is the probability of yield. The first normal distribution with a lower mean μ_1 represents the yield probability distribution in a lower yield year; and the second distribution with a higher mean μ_2 represents a higher yield year. λ is the probability of a lower yield year occurring. With this yield distribution model, we can alter the five parameters to study multiple hypothetical climate change scenarios' impacts on crop yield distribution. For example, we can change λ value to represent climate changes impact on the frequency of a lower yield year occurring; we can change μ_1 and μ_2 to represent climate changes impact on average crop yield.

We also plotted the non-parametric density plots for each county using the historical yield data. We de-trended the data and corrected for heteroskedasticity using the simple technique suggested by Glejser (1969). Most of the plots show signs of negative skewness and bi-modal (see figure 1 in Appendix for examples).

2. Model yield trend

We are not satisfied by the simple de-trending approach suggested by Glejser (1969), and found there are several other detrending methods suggested in literature, including firstand higher-ordered polynomials(Atwood, Shaik and Watts, 2003; Sherrick, et al., 2004; Goodwin and Mahul, 2004; Oazki, et al., 2005) and autoregressive integrated moving average models (Goodwin and Ker, 1998; Ker and Goodwin, 2000). However Chen and Miranda (2006) summarized none of the above detrending approaches are perfect due to over-fitting problems.

In light of the common yield increasing trends in the crops we are studying which are mainly because of technology and farming practice advancements. Unfavorable weather conditions could undermine the performance of crop hybrids and farming efforts. So we propose to use two linear trend lines to model yield trends under normal weather and extreme weather conditions. Therefore the modified yield probability distribution becomes:

$$P(y) = \lambda \times N(A_1 + B_1 \times t, \sigma_1^2) + (1 - \lambda) \times N(A_2 + B_2 \times t, \sigma_2^2)$$
(2)

All the symbols remain the same meaning as in equation 1, except the $A_1+B_1^* t$ and $A_2+B_2^*t$ replace the two mean (μ_1 and μ_2) values for the two normal components. The underline assumption is that there is generally a linear yield growth trend over time. A_1 , A_2 are the intercepts and B_1 , B_2 are slopes. One better interpretation would be that A_1 , A_2 are the starting average yield values at the beginning of the sampling period (1949), and B_1 , B_2 are the net yield growth rates as the results of technology advancement, weather, and farming practice changes. t takes value of 1 at year 1949, by end of the sample period (2010) t is 52, at the beginning of the forecasting period (2011) t is 53, and at the end of the forecasting period (2050) t will be 102. A_1 and A_2 , B_1 and B_2 are not necessarily equal. In fact, B_1 could be lower than B_2 as crop performance under stress is not as good as under normal growth condition given the same hybrid variety and same farming practices applied.

3. Estimate parameters in the yield model

To obtain the seven parameters in equation 2, annual crop yield data at each county over the last 52 years are used as input data. Then the Expectation Maximization (EM) algorithm technique is used to estimate those parameters. Because EM algorithm with lower amount of input data could be very starting-value-sensitive, that could result in generating local optimum rather than global optimum. Counties with many missing values could add on to the difficulty of obtaining the global optimum solutions. To solve this problem, all the EM generated parameter results are compared against each other for each crop species, and the counties with extreme parameter values are taken out. The final usable number of counties for corn is 27, for soybean is 13, and for wheat is 22. The estimation results are summarized in Table 1-3 in the Appendix. Figure 2 in the Appendix shows some sample plots of the two estimated yield trend-lines against the original yield value scatter plots.

Once the parameters at county level are estimated, they are used to help determine the possible range of each parameter at provincial level. We first tried to study the general distribution pattern of each parameter $(A_1, A_2, B_1, B_2, \sigma_1, \sigma_2, \lambda)$ by plotting those usable parameters into histograms. Many of them showed the tendency of being uniformly distributed (see Figure 3 in the Appendix for details). For the sake of simplicity, we made the assumption that all of the seven parameters (estimated at county level) are uniformly distributed within Ontario. The maximum and minimum values of each parameter can be drawn from the final pool of usable parameters, and they are set ready for the next step of sampling.

4. Sampling correlated farm samples

To study climate changes impacts on crop yield and the CI program at the provincial level, ideally one would gather all the farms that enrolled in the CI program, study their yields and CI premiums and reserve funds. Without farm level data, our approach is to draw random samples from the pool of uniformly distrusted yield distribution parameters (identified in the previous step) to represent the farms enrolled in CI program across Ontario. Through consulting with OMAFRA employees, the current number of farms enrolled in CI program for each crop species are identified as approximately: 9000 corn farms, 11000 soybean farms, and 6000 winter wheat farms. These numbers are used as our sample sizes, and again for the sake of simplicity we assume the farms are of the same size for each crop species we study.

Given the fact these seven parameters in the yield distribution model should be some-

what correlated depends on the location they might represent. Separated random samples of these parameters will loss the correlation characteristics between parameters within each sample farm. To fix this problem, we use Iman and Conover (1982) method to obtain samples that have similar correlations between parameters as the correlations from the pool of usable country level estimates (target correlations). For example for corn, we first randomly select same number of samples from each uniformly distributed parameter frame, in this case, would be 9000 samples representing 9000 farms. Then use Iman and Conover (1982) method to impose correlations and create a 9000 \times 7 matrix with its correlation matrix equals the target correlations. Therefore, 9000 different yield probability distributions representing 9000 randomly selected farms in Ontario are created. As t increases over the years, the yield probability distribution will change accordingly, reflecting multiple factors (including weather, technology, farming practices, etc.) shift crop production in the same way they've done in the past 52 years.

Even though the sample farms are uncorrelated with respect to the farming practices they carry out, the crop productions are likely to be influenced in the similar ways by the weather conditions within their region. In other words, if one farm experienced a lower yield year due to unfavorable weather conditions, farms in the same region would likely to experience a lower yield year as well. This intuition can be captured in the following way. Imagine if there is only one farm, to determine whether it is going to have a lower yield year or higher yield year: we first randomly select a value from a uniform distribution with boundaries of 0 and 1, and then compare it against our lambda value. If the random value is greater than lambda, the yield distribution would fall into the second normal component (i.e. the farm will have a higher yield year), and vice versa. When there is more than 1 farm, we assume the correlation between farms experiencing similar weather impacts is 0.8. And still using Iman and Conover (1982) method, we obtain a set of 9000 random values (for corn) between 0 and 1 (obtained again from the uniform distribution) with correlation of 0.8, which will in turn determine for each sample farm which normal component it falls into.

CI Premium Rate and Reserve Fund Balance Estimations

In order to understand how the Crop Insurance program performs, three important measurement factors are estimated for the next 40 years: actuarially fair rate, the Agricorp rate, and the reserve fund balance.

1. The actuarially fair rate

Under the ideal case, the CI program provider wants to keep the total premium collected equals the indemnity paid over time, and the insurance premium rate under this case is called actuarially fair rate. The actuarially fair rate is simply the ratio of the expected loss (E(L)) to insured liability (Yg) of the same year.

$$R = \frac{E(L)}{Yg} \tag{3}$$

The expected loss can be estimated if known the yield probability distribution in the following way:

$$E(L) = Pro(y < Yg) \times [Yg - E(y/y < Yg)] + Pro(y = 0) \times Yg$$
(4)

Under the mixture of two normal yield distribution model, the expected losses under each distribution are calculated first, then times the weight of λ or $(1 - \lambda)$, and add them together.

$$E(L) = E_1(L) \times \lambda + E_2(L) \times (1 - \lambda)$$
(5)

The yield guarantee, or liability for Agricorp, is first measured bushels. It is the product of average farm yield (AFY) of the past 10 years times percentage coverage level.

$$Yg = AFY \times CoverageLevel \tag{6}$$

To calculate average farm yield (AFY), two treatments have to be made onto historical

yields before taking the 10 year average according to Agricorp (2010).

The first treatment is called the yield adjustment factor (yaf), which adjusts historical yield to reflect technology and/or practice changes. It is a value to be multiplied to the actual yield. The current value provided by Agricorp for corn it is 1.0215, meaning a 2% increase of yield per year among recent historical yields. Because this study looks at a longer period of 40 years, we created a closer approach to adjust yield through the following 2 steps:

$$yaf_{t} = 1 + \frac{mean(\lambda \times B_{1} + (1 - \lambda) \times B_{2})}{mean(y_{(t-62):(t-53)})}$$
(7)

$$ay_i = (yaf^{11-i}) \times y_{t-63+i}$$
 (8)

where, yaf_t is the yield adjustment factor in year t. t takes values from 63 to 102 representing the historical 10 years (under base climate conditions from 2001 to 2010) and the future 40 years (from 2011 to 2050) for our forecasting period. ay is the adjusted yields after the yield adjustment factor. i takes value from 1 to 10 representing the 10 historical years used to determine average farm yield.

The second treatment is called yield buffering which is applied after the yield adjustment factor. Unusual high or low yields are buffered to reduce the extreme effects on the AFY. If yield is above the upper threshold, which is 130% of AFY, it will be buffered 2/3 of the way down to the upper threshold. If yield is below the lower threshold, which is 70% of AFY, it will be buffered up 2/3 of the way up to the lower threshold.

$$AFY = y \times f - (y \times f - ut) \times \frac{2}{3} \text{ if } y \times f > ut$$
$$= y \times f - (lt - y \times f) \times \frac{2}{3} \text{ if } y \times f < lt.$$
(9)

ut is the upper threshold, it equals $y \times f \times 1.3$. It is the lower threshold, it equals $y \times f \times 0.7$. y is the actual historical yield, which is sampled directly from the yield probability distribution. f is the yield adjustment factor.

The coverage level takes values of 75%, 80%, 85% and 90% according to Agricorp (2010) for corn, soybean and winter wheat. For the sake of simplicity in our study, we only conduct estimations under 75% and 90% coverage levels.

2. The Agricorp rate and reserve fund balance

Agricorp Ltd., as the Crown Corporation in Ontario, is responsible for providing CI to producers, and maintaining the actuarially soundness of the program.

It is only an idealistic assumption that CI provider, Agricorp, knows the exact yield probability distribution from year to year. Therefore the exact actuarially fair rate cannot be accomplished. CI provider uses a series of calculations to approximate the actuarially fair rate, which here we refer to as Agricorp rate.

According to Agricorp publications, the insurance premium is calculated as the following:

$$PR_t = (PR_{t-1} - FR_{t-1}) \times (1+D)$$
(10)

Where PR_t is the Agricorp premium rate at year t, FR_t is the reserve fund adjustment factor identified at year t - 1, and D is the individual farm discount or surcharge. From the formula can tell that the Agricorp rate charged to one farm at a certain year is based on previous year's premium rate and adjusted by reserve fund balance condition and individual farm performance condition. The objective of this study is to identify the general CI premium rate and reserve fund balance conditions at provincial level. Averages will be taken from the individual rates calculated in the above. Therefore, the individual discounts or surcharges will eventually be averaged out. So we take an easier approximation by defining the Agricorp insurance premium rate as:

$$PR_t = (PR_{t-1} - FR_{t-1}) \tag{11}$$

Assume at the beginning of the 40 year forecast period, CI provider has good knowledge of the yield probability distribution and charges farmers at the actuarially fair rate. Therefore, PR_1 equals R_1 .

In order to have enough fund to pay for indemnity, the CI reserve fund balance is targeted at 14% of insured liability of the same year, which is also 14% of the total yield guarantee. If the fund reserve of the year is greater than 14% of liability, then the additional is divided by 25 and subtracted from the base premium rate for the coming year. If the fund reserve is greater than 14% of liability of the year, the difference is divided by 15 and added to the base premium for the coming year.

$$FR_t = (B_t/L_t - 0.14)/15, \text{ if } B_t/L_t < 0.14$$
$$= (B_t/L_t - 0.14)/25, \text{ if } B_t/L_t > 0.14$$
(12)

Where B is reserve fund balance at the end of the year. The fund balance of this year equals the fund balance of previous year plus this year's program revenue. L is the total liability of the year, which equals the sum of guaranteed yield (Yg) among all farms enrolled in the program.

$$B_t = B_{t-1} + (E_t - C_t) \tag{13}$$

$$E_t = \sum_{i=1}^{I} (Yg_{it} \times PR_{it}) \tag{14}$$

$$C_t = \sum_{i=1}^{I} (Yg_{it} - y_{it}), \text{ for } y_{it} < Yg_{it}$$
 (15)

Where E_t is the insurance premiums gathered at the beginning of the year t from all the farmers, and C_t is the total insurance claims farms made at the end of the year t. The "i" represents the ith farm, and I is the total number of farms enrolled in the program. The "t" represents the number of years farmers have enrolled in the insurance program. The difference between E_t and C_t is the program revenue (in bushels) of the year. PR is the premium rate Agricorp charges the farmer when enrolling in the program at the beginning of the year.

The whole calculation process for estimating those three factors is repeated 10 times and averages are taken among the 10 simulations in order to represent the general changes over years in smoother ways.

Climate Change Scenarios Simulation Results

The hypothetical climate change scenarios we studied can be organized into three categories according to how climate change may affect the yield distribution (i.e. affect the value of the parameters): 1) climate change alters the probability of a lower yield year occurring (λ changes). 2) Climate change alters the mean yields (B1 & B2 changes). 3) Climate change alters yield variations ($\sigma_1 \& \sigma_2$ changes). And within each category, different levels of impacts are studied, including both positive impacts and negative impacts:

Climate	λ	B1 & B2	$\sigma_1 \& \sigma_2$					
alters pa-								
rameters								
general	$\lambda_t = \lambda_{t=0} \times (1 + 1)$	$B_{i,t} = B_{i,0} \times (1 +$	$SD_{i,t} = SD_{i,0} \times$					
formula	$k \times t$)	$k \times t$)	$(1+k \times t)$					
variable	t represents the year, takes value from 1 to 40; k							
meanings	is the annual rate of change; i takes value of either							
	1 or 2							
levels of	k= 0.01, 0.05, -	k = 0.01, -0.01,	k = 0.01, 0.05, or					
change	0.01 or -0.05	or -0.025	-0.01					

For each climate scenario, the maximum and minimum insurance coverage levels (90% and 75%) are applied separately to study premium rates and reserve balances under each coverage level. There are 30 scenarios in total that we studied.

The premium rates Agricorp published are in dollar per acre format, which is the rates in bushels per acre times the locked in crop price (for fixed rates) in dollars per bushel and times farmer's share of the premium responsibility. The bushels per acre rates can be calculated by simply multiplying the rates in percentage forms (equation 3 and equation 10) by the average yield guarantee (in bushels per acre). According to Agriculture and Agri-Food Canada (2010), farmers are responsible for 40% of the premium, while the federal and provincial governments absorb 60%, splitting it 60/40. To make it consistent with current Agricorp publications, the premium rates, both Agricorp rates and actuarially fair rates, are converted into dollars per acre format using the current fixed rate claim prices for each crop published by Agricorp (2013): corn (\$5.36/bu),

soybeans (\$11.14/bu) and winter wheat (\$7.05/bu).

We also include, in the results display, the average yield guarantee per acre, the average expected yield loss per acre (when yield fall below the yield guarantee) (as in equation 5) and the total insured liability in dollar values which can be calculated by the following:

$$L_{i,t} = Yg_{i,t} \times p_i \times A_i \tag{16}$$

Where $L_{i,t}$ is the total insured liabilities in CND value among all farms for crop i in year t, $Yg_{i,t}$ is the total insured liabilities among all farms in bushels for crop i in year t, p_i is the estimated average price of crop i (in CND per bushel), and A_i is the total insured acreage of crop i in Ontario. Price values are the current (2013) fixed Crop Insurance claim prices. A_i values are estimated using the average insured acreages between 2011 and 2012 crop years: corn (1.5 million acre), soybean (1.9 million acre), winter wheat (0.65 million acre) (information obtained from OMAFRA staff)

For simple demonstration purpose, the below plots are examples of grain corn in Ontario, assuming all participating farms choose 90% insurance coverage level, and under all three climate change scenario categories, the six variables of interest mentioned above in the next 40 years will be:

Scenario category 1: climate change alters the probability of a lower yield year occurring

For corn at 90% coverage level when λ changes:









Corn reserve fund balance and total insured liability under 90% coverage level

Scenario category 2: climate change alters average yields

For corn at 90% coverage level when B1 & B2 change:



yield guarantee and expected loss of corn under 90% coverage level (bu/ac)



Corn agricorp rates and actuarially fair rates under 90% coverage

Corn reserve fund balance and total insured liability under 90% coverage level



Scenario category 3: climate change alters yield variations

For corn at 90% coverage level when $\sigma_1 \& \sigma_2$ change:



yield guarantee and expected loss of corn under 90% coverage level (bu/ac)



Corn reserve fund balance and total insured liability under 90% coverage level



Result summary:

The result plots of all the crops under all the scenarios and insurance coverage levels can be summarized as below:

Changing pa-	λ	B1 and B2	σ_1 and σ_2
rameter			
Yg general	always increase	follows the direc-	always increase
trends	(except for some	tion of B1&B2	
	crops under 5%	changes	
	λ increase sce-		
	narios)		
Yg under dif-	positive λ	positive B1 & B2	no significant de-
ferent levels	changes result in	changes result in	viations between
of parameter	negative rates of	positive rates of	different levels of
change	Yg change	Yg	sd changes
E(L) general	increase (except	increase (except	always increase
trends	for some crops	for some crops	
	under 5% λ de-	under 2.5% B1 &	
	crease scenarios)	B2 decrease sce-	
		narios)	
${ m E(L)}$ under	not follow the	experience an	follow the same
different levels	change of λ	adjustment pe-	patterns as the
of parameter	(because is also	riod (usually	SD1 & SD2
change	determined by	10-20 years),	changes (posi-
	yield distribu-	but eventually	tive SD changes
	tion situation	follow the same	result in positive
	and the starting	patterns as	levels of $E(L)$)
	λ value	the B1 & B2	
		changes (posi-	
		tive B changes	
		result in positive	
		levels of $E(L)$)	

1) Yield guarantee (Yg) & expected loss (E(L))

Both yield guarantee and expected loss experience greater deviations between different levels of parameter changes under 90% insurance coverage level compared to the 75% coverage level, for both λ changes and B changes.

2) Actuarially fair rate in dollars per acre, as expected loss (E(L)) times fixed claim price then times producers share of responsibility (40%). The actuarially fair rates under all three scenario categories follow exactly the same trends of expected loss. 3) Agricorp rate in dollars per acre, follows the general trends of the corresponding actuarially fair rates for all the crops and all parameter change scenarios. But they always have greater fluctuations than the corresponding actuarially fair rates over time, as Agricorp rates are approximations to actuarially fair rates when the crop yield distributions are unknown.

Comparing with the Agricorp 2013 fixed claim premium rates, our estimated Agricorp rates tends to be smaller than that of the rates posted on Agricorp website. For example, under the 90% insurance coverage level our estimated Agricorp rate (under base condition) is around \$10/bu in 2013 while the actual rate Agricorp charged is around \$14/bu. There are mainly two reasons contributed to the difference. First, our forecasting period starts in 2011 with the base rate estimated from 2010 crop yield probability distribution condition (equation 2), the actual Agricorp rates would have used different starting rates at a different year. Second, the actual starting Agricorp rate is determined by the actual indemnity payments and actual liabilities collected in the past, while the estimated Agricorp rates are derived from yield distribution probability models. Given these said, the value of the mixture of two normal yield probability distribution model lies in the trend forecasting and its flexibility of multiple scenario displaying, rather than point estimation.

Both actuarially fair rates and Agricorp rates experience greater changes over time under 90% coverage level compared to those under 75% coverage level.

4) Reserve fund balance rates (reserve fund balance over total liability) have general increasing trends. Because the way fund reserve adjustment is calculated (equation 11): when reserve is greater than 14% of liability, premium rate is reduced by 1/25 of the difference; but when reserve is less than 14% of liability, premium rate is increased more at 1/15 of the difference. In other words, when reserve fund is low, Agricorp charges producers more through premiums they pay, but when there is surplus in reserve fund, producers only get a fraction of it as rebates. We also observe the balance rates under 90% coverage level experience greater fluctuations compared to those under 75% coverage level over the years.

Both Agricorp rates and reserve fund balance over the years show signs of cyclical

changing patterns. This pattern could be explained by working through the equations that were used to calculate Agricorp rates (equation 10-13). They were designed to adjust the Agricorp rates and reserve fund balances to stay with the reserve fund balance target (at 14% of total liability). However laggings in information flow (using (t-1)th years information to adjust t th years rate) cannot send those rates to their target values (balance rates to be equal to 14% and Agricorp rates to be equal to actuarially fair rates), but letting them fluctuates around the target values. (Appendix provides more detail on this issue.)

5) Total insured liabilities in dollar value follows the exact same trends as yield guarantee. The gaps between different magnitudes of λ and B1 & B2 changes get wider as time goes by, and the liability plots under 90% coverage level show wider gaps than under 75% coverage level.

Conclusions and Future Research

Using the mixture of two normal yield probability distribution model, we could not only model historical crop yield patterns, but also apply climate change scenarios by altering the parameters to forecast crop yield and Crop Insurance program performances in the future. The three climate change scenario categories provide approximations of the yield situations that facing Ontario crop producers, and CI program premium rate and reserve fund balance fluctuation situations CI provider would likely to experience in the future decades. The two climate change scenario categories, where climate change alters the probability of lower year occurring and where climate change alters the average yield, both have significant impacts on crop yield, CI premium rates and reserve fund balances. However, the third scenario category, where climate change alters yield variation, it alone wont have very significant impacts on CI rates and reserve fund balances compared to the previous two scenario categories.

The advantages of the approaches introduced in this study are two-fold: first, the mixture of two normal yield probability distribution model provides a flexible and trans-

parent way to impose climate change scenarios onto the base yield model. Second, the yield trends and CI program premium rates and reserve fund fluctuations over the future decades can be forecasted.

However, we observe our estimated Agricorp rates (under our base condition) are generally little smaller than what Agricorp actually charges in 2013. This is due to the difference in the starting years used to determine Agricorp rate between our study and Agricorps choice, plus some limitation in the goodness of fit of our estimated yield model which can be traced back to the limit number of usable counties to draw input data from.

Although our approach may not be the best for point estimation for premium rates, the yield trends and CI program and reserve fund balance fluctuation situation forecasts would still provide CI program provider valuable information on the frequency and magnitude of both insurance premium rate fluctuation and reserve fund balance fluctuation under climate change conditions. Therefore the results can still be used to help Agricorp Ltd. identify and forecast both premium rate fluctuation risk and reserve fund liquidity risk.

There are several areas future research could be carried out. First is to include the scenarios where both yield averages and standard deviations are altered simultaneously. Current research indicates climate change is likely to alter both mean yield and yield variation, but the degree of change depends on location and crop species. If information/predictions on the mean yield and yield variation relationship at aggregated (provincial) level become available in the future, better approximations for yield probability distribution and CI program performances under climate change could be obtained. Second is to be species-specific when applying climate change (yield distribution parameter changes) scenarios. Again this would depend on future climatology and crop science research advancement to better predict different crop species performances at provincial level. Then using the approaches introduced in this study, we can be more precise with the yield and CI program trend forecasting. Third, the same approaches used in this study could be adopted for trend forecasting purposes for other crop species and other provinces, or even other countries.

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Appendices

Appendix 1. EM Algorithm Estimation Results

Table 1, EM algorithm estimation results for corn (27 usable counties)							nties)	
county names	alfa1	alfa2	beta1	beta2	sd1	sd2	lambda	data length [*]
Brant	54.589	45.498	1.073	1.756	8.401	5.672	0.698	62
Bruce	47.484	47.841	1.163	1.635	8.002	4.952	0.763	62
Dufferin	53.904	44.467	0.395	1.290	6.405	11.490	0.290	62
Elgin	62.711	47.148	0.719	1.665	7.164	8.464	0.105	62
Essex	53.088	46.335	0.573	1.699	10.544	8.986	0.139	62
Grey	55.554	45.890	0.484	1.235	6.681	9.051	0.296	62
Haldimand-Norfolk	60.385	44.866	0.344	1.425	0.101	11.484	0.046	62
Halton	63.744	47.158	0.363	1.272	7.934	8.025	0.355	62
Hamilton	47.362	52.013	1.101	1.568	5.117	8.506	0.570	62
Huron	51.781	45.643	1.035	1.660	9.442	9.153	0.127	62
Kawartha.Lakes	48.502	41.544	0.813	1.505	8.670	8.838	0.641	62
Lambton	57.512	43.468	0.551	1.719	1.101	9.620	0.074	62
Lanark	43.765	36.559	0.813	1.625	14.292	9.900	0.361	62
Leeds_Grenville	38.021	44.928	1.008	1.451	9.063	5.956	0.521	62
Lennox_Addington	46.460	39.767	0.646	1.404	11.509	10.111	0.444	62
Middlesex	47.136	46.453	1.130	1.745	6.758	8.241	0.129	62
Niagara	48.013	42.279	0.911	1.640	8.926	5.785	0.716	62
Northumberland	50.146	41.484	0.917	1.521	8.973	6.047	0.510	62
Oxford	54.545	46.778	1.079	1.757	3.536	9.517	0.143	62
Peel	54.411	45.946	0.660	1.403	8.444	7.590	0.281	62
Perth	48.372	44.863	0.957	1.731	7.955	8.756	0.087	62
Peterborough	51.510	43.549	0.562	1.228	9.582	7.735	0.200	61
Prescott_Russell	37.006	34.877	1.096	1.842	13.835	7.844	0.406	62
Simcoe	49.028	43.661	0.898	1.442	4.389	10.368	0.472	62
Waterloo	37.021	51.385	1.128	1.286	3.990	9.208	0.039	62
wellington	58.296	50.252	0.666	1.357	6.778	9.574	0.474	62
York	55.233	46.693	0.760	1.339	6.444	7.492	0.553	62
average	50.947	44.865	0.809	1.526	7.557	8.458	0.350	62

Table 2, EM	argorium	in estima	thom re	suits ioi	soybe	an (15	usable cc	junities)
county names	alfa1	alfa2	beta1	beta2	sd1	sd2	lambda	data length*
Bruce	17.304	14.015	0.297	0.882	1.532	4.292	0.326	34
Elgin	22.820	18.805	0.109	0.426	4.653	2.099	0.165	62
Essex	18.285	25.342	0.232	0.308	2.763	3.624	0.294	62
Haldimand-Norfolk	21.869	18.922	0.087	0.338	4.218	2.982	0.257	62
Hamilton	17.888	16.040	0.185	0.529	4.447	2.844	0.189	51
Huron	16.574	13.662	0.330	0.627	3.422	2.636	0.312	57
Lambton	20.209	20.597	0.163	0.401	3.982	2.285	0.196	62
Middlesex	21.661	18.627	0.123	0.446	3.767	2.740	0.199	62
Oxford	17.293	16.833	0.286	0.605	5.794	3.071	0.156	54
Peel	18.805	12.698	0.052	0.759	1.172	3.383	0.319	39
Perth	17.213	14.076	0.281	0.701	2.746	3.378	0.154	51
Waterloo	18.158	12.502	0.171	0.823	2.567	3.381	0.289	40
Wellington	19.995	15.529	0.102	0.600	1.179	3.374	0.222	48
average	19.083	16.742	0.186	0.573	3.249	3.084	0.237	53

Table 2, EM algorithm estimation results for soybean (13 usable counties)

Table 3, EM algorithm estimation results for winter wheat (22 usable counties)

county names	alfa1	alfa2	beta1	beta2	sd1	sd2	lambda	data length*
Brant	32.895	25.586	0.073	0.683	1.988	5.678	0.135	62
Bruce	36.945	24.108	0.137	0.877	0.303	4.626	0.097	62
Chatnam-Kent	33.206	30.404	0.299	0.884	1.286	5.599	0.057	62
Dufferin	30.982	26.592	0.191	0.717	5.689	4.424	0.208	62
Durham	35.448	27.283	0.241	0.686	2.881	4.430	0.206	62
Elgin	29.162	24.079	0.511	0.931	6.166	4.079	0.408	62
Essex	27.682	29.435	0.658	0.927	5.564	4.515	0.484	62
Haldimand-Norfolk	33.387	23.772	0.060	0.647	4.104	5.743	0.202	62
Halton	32.934	27.088	0.132	0.587	3.403	4.977	0.233	62
Hamilton	32.831	24.742	0.014	0.682	3.416	6.663	0.133	62
Lambton	34.971	24.480	0.030	0.909	0.024	5.857	0.028	62
Middlesex	33.309	24.437	0.191	0.937	2.140	5.521	0.107	62
Niagara	27.973	22.771	0.186	0.672	4.727	5.387	0.455	62
Northumberland	28.957	27.672	0.445	0.628	2.465	5.041	0.499	62
Peel	34.265	28.183	0.099	0.661	3.692	5.143	0.246	62
Perth	33.667	26.082	0.372	1.009	3.713	5.152	0.160	62
Peterborough	29.787	25.049	0.332	0.611	3.471	3.325	0.561	62
Prince.Edward	28.573	23.964	0.261	0.603	1.023	6.238	0.257	62
Simcoe	29.315	25.117	0.453	0.787	3.948	4.063	0.349	62
Waterloo	41.083	26.717	0.082	0.760	3.742	4.138	0.170	62
wellington	33.798	26.713	0.221	0.789	4.453	5.010	0.193	62
York	35.896	31.080	0.199	0.526	3.251	3.944	0.168	62
average	32.594	26.152	0.236	0.751	3.248	4.980	0.243	62

Appendix 2.



Figure 1, Yield Probability Density Non-parametric Plots

Appendix 3.



Figure 2, Yield Plots and Trendlines



Figure 3, Yield Probability Distribution Parameter Estimates

corn yield probability distribution parameter estimate histograms

soybean yield probability distribution parameter estimate histograms







beta1



B2





6











wheat yield probability distribution parameter estimate histograms

Appendix 5.

To explain the formation of the "cyclical patterns" in Agricorp rates and reserve fund balances over the years, we need to recall the series equations in premium calculation introduced before (equation 10-13). To make the case less complicated, assume there is only one farm, under no climate change condition:

$$PR_{t} = PR_{t-1} - FR_{t-1}$$
$$B_{t} = B_{t-1} + (E_{t} - C_{t})$$
$$E_{t} = (Yg_{t} \times PR_{t})$$

Recall that:

 $FR_t = (B_t/L_t - 0.14)/15, \text{ if } B_t/L_t < 0.14$ = $(B_t/L_t - 0.14)/25, \text{ if } B_t/L_t > 0.14$

 FR_t is the key to connect the above three equations together. However, the value of FR_t is case specific, but can work out two extreme conditions where: $FR_t = (B_t/L_t - 0.14)/15$, or $= (B_t/L_t - 0.14)/25$ Therefore, The reserve fund balance equation can be re-written as:

$$B_t = B_{t-1} - (1/15) \times [B_1 + B_2 + \dots + B_{t-1}] + (0.14/15) \times L \times (t-1) + R \times L - C_t$$

or

$$B_t = B_{t-1} - (1/25) \times [B_1 + B_2 + \dots + B_{t-1}] + (0.14/25) \times L \times (t-1) + R \times L - C_t$$

The reserve fund equations plots are:



Where the green plots (fbalance1) are generated by the first equation and the yellow plots (fbalance2) are generated by the second equation.