WEATHER INSURANCE, CROP PRODUCTION AND SPECIFIC EVENT RISK

by

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The role of weather in agriculture and other industries is creating an emerging market for weather based insurance and derivative products. In the U.S.A. companies such as WorldWide Weather Insurance Inc., American Agrisurance Inc. and Natsource (a New York City brokerage) all offer weather risk products, and in Canada, Royal Bank Dominion Securities Inc are now brokering weather specific derivative products. Applications are wide spread among natural gas, oil, and electricity sectors, but more and more such products are being used for agriculture insurance purposes.

Weather derivatives provide a hedge against production risk rather than price risk. Conditions that are too cool or too hot, too dry or too wet affect production of crops in variety of ways. Most perils commonly insured in crop production can be linked to specific weather events. Rainfall and heat extremes affect evapotranspiration and phenologic growth directly, but certain conditions will also give rise to pestilent and viral infestations. Area yield insurance such as U.S.A. Group Revenue Protection (GRP) or the Quebec area plans are designed to insure these risks when they are systemic (Miranda, Miranda and Glauber, Turvey and Islam).

The weather derivative can be brokered as an insurance contract or as an over-the-counter (OTC) traded option. It is described by specific language which identifies 3 main criteria: 1) the insured event, 2) the duration of the contract and 3) the location at which the event is measured.

The types of contracts used to insure weather events are varied, but in general there are two different types. First, there are multiple event contracts. An agribusiness firm may want to insure against multiple events of daily high temperature exceeding 90^oF for 7 days straight in order to compensate for yield and/or quality loss or a crop insurer may want to insure against drought events such as no rain for 14 days straight during critical stages in crop development. Such contracts may allow for multiple events and will usually provide a fixed payoff per event.

Second, are straight forward derivative products based upon such notions as cooling degree days above 65^oF (an indication of electricity demand for air conditioning), heating degree days below 65^oF (an indication of electricity, oil, and gas demand required for heating), and growing degree days or crop heat units measured by average daily temperatures above 50^oF. For example a contract based on crop heat units (or growing degree-days GDD) might be written as "The Company will insure from May 1, 1999 to August 31, 1999 that there will be 1000 or more Crop Heat Units at the Environment Canada weather station located at Woodstock Ontario.

Everyday where the average temperature exceeds 50 degrees Fahrenheit, there will be {average temperature – 50} heat units for that day".

The purpose of this paper is to explore the economics and pricing of weather related insurance products for agriculture. The advantage of considering these products over conventional individual yield crop insurance, area yield crop insurance or crop insurer reinsurance is that the payoff is contingent on a specific event occurring. The specific event, heat based or rainfall based, is correlated with yield shortfalls, but unlike conventional insurance the payoff structure is independent of actual crop yields or crop yield indemnities. This removes the role of the adjuster in calculating yield claims while eliminating any possibility of moral hazard. Adverse selection is minimized or eliminated because premiums based on specific events such as rainfall are uncorrelated with the participation rates of producers in the program.

In this paper a variety of weather derivative products are examined using crop heat units based on excess degrees of daily mean temperatures above 50^{o}F and rainfall measured in cumulative mm from June 1 to August 31 at the Environment Canada weather station in Woodstock Ontario. It is shown, using a Cobb-Douglas production function that there is a historical relationship between heat units, rainfall, and crop yields. Estimates of specific event heat and rainfall derivative/insurance product premiums are then calculated.

There are empirical issues related to weather derivatives. First, there is no forward market such as a marked-to-market weather index that can span underlying risk. Individuals might speculate on what a heat index might be 90 days hence, but unlike stock market indexes there is no fundamental information to base such a prediction, and nature is under no obligation to comply. Second, rain or heat or any other insurable condition does not have a tangible form that is easily described (in contrast with common stock or a futures contract). Third, because there is no forward market weather index, there is no mechanism that would allow brokers, traders, and insurers to price such derivatives on an ongoing and transparent basis, and this can impact liquidity in the market. (Currently the holder of an option would have to wait until the date of expiration to find out if the option expired in or out of the money). Fourth, the mechanics of brokering weather contracts depends specifically on the nature of the contract. Currently, the common approach is to use historical data and from this use traditional insurance 'burn-rate' methods to determine actuarial probabilities of the outcome. This convention limits trade. For the most part counterparties must agree on a price prior to the opening contract date and are in general restricted by lack of data to efficiently price and trade the contract during the period in which it is active.

For multiple event contracts an efficient design would price the contract according to a Markov process. This in fact would be necessary for a liquid over-the-counter market to emerge. Using a Markovian process the likelihood of two or three more events occurring, given that one event has already occurred can be calculated. Furthermore, the process will fully account for the time in which the first event takes place. For example, when the likelihood of one event exceeds the likelihood of two events and so on, it would most surely be true that the likelihood a second, third or fourth event would be higher if the first event occurred nearer the origination of the contract than at its end.

Defining Specific Event Risk

In order to fully understand the significance of weather insurance it is important to understand that the implied insured events make up less than 100% (in most cases) of crop yield variance. This contrasts with conventional multiple peril crop insurance which is measured by total variance and generally includes all semivariance events below a specified coverage level. This section discusses the nature of these specific event risks.

The determination of crop yield distributions depends conditionally on specific events throughout the growing season defined by state variables such as weather or disease. These state variables take on any value at any moment in time and crop growth, yield quantity, and yield quality are conditioned upon these events. For purposes of insurability the conventional economic concern facing farmers, input suppliers, processors, marketers and creditors is in regards to final yield outcomes, which is in essence the sum effect of all specific events.

Specific event risk does not require an economic representation of yield growth and risk although there would be obvious advantages to correlating weather events to specific phenological events. A recent paper on biophysical modeling of corn by Kaufmann and Snell identifies such Phenological stages such as sowing to germination, seedling emergence, tassel initiation to silking, or grain filling. In this context, specific event risk refers to specific outcomes in state variables that occur at specific or unknown points along the growth curve. Examples of specific event risk include 2-week drought prior to the tassling stage in corn growth; excessive pre-harvest heat which causes diminished oil production from soybeans; frost prior to a specific date; hail at any point prior to harvest, or excessive rains after crop maturation that inhibits or prohibits harvest.

In the above examples the state variable is defined as weather, and the conditioning parameters are defined in reference to specific times along the growth curve. In this study the effects of heat and rainfall on crop yields is measured from June 1 to August 31 which captures a broad spectrum of risks. However we could have selected a specific month, week, or even day to assess the risks. This is because each specific risk is explicitly defined as a single insurable peril, which contributes marginally to total variance. Here the cause is insured, not the effect.

Weather Events and the Economics of Production

Classical economic tools can capture the economics of certainty within a framework of specific event risks. By the economics of certainty I mean the deterministic outcomes that would most surely result from stochastic events. Understanding this requires a slight departure from classical production economics that measures output as a function of endogenously determined inputs such as fertilizer, chemicals and labour with all exogenous factors such as weather relegated to white noise and the source of variance. In what follows the relationship between exogenous weather factors and output, holding the endogenous inputs constant, is assessed. In a deterministic sense the marginal effects of heat and rainfall on yields and the marginal productivity of weather can be measured. This approach differs from previous biophysical modeling such as Kaufmann and Snell and those reviewed in Mjelde et al and Podbury et al. These studies tend to focus on the prediction accuracy of final yields. In contrast, a study of weather-based crop productivity for the purpose of insurability views variability as being informational and important and seeks to correlate specific yield outcomes with specific weather events.

To examine the economic impact of weather on production and profits assume that farm profits are represented by $\Pi(\Omega|\omega)$ where ω spans weather events and Ω is the set of resources used in production. Under this specification, $\Pi(\Omega|\omega)$ is determined by the input set but the ultimate measure of profits is conditioned on the specific weather events. Profits are determined from revenues $P^*Y(\Omega|\omega)$ and the cost function $C(\Omega|\omega)$. The economic effect of weather risk is probably measured by both. It is assumed that Ω is predetermined and deterministic so that marginal profits can be measured relative to ω alone.

It is assumed that Y() is concave in ω while C() is convex in ω which implies that as heat and/or rainfall increases $dY/d\omega > 0$ up to some point at which ω^* is optimal and $dY/d\omega = 0$. Depending upon the crops being evaluated and the functional form used $dY/d\omega < 0$ might exist over some range for excessive heat and/or rainfall. The convexity argument in the cost structure is justified by a symmetric argument. There will be some ω^* such that $dC/d\omega = 0$. For $\omega < \omega^*$ costs will be increasing as the costs associated with drought and/or excessive heat (e.g., labour, capital, and energy costs associated with irrigation) increases and for $\omega > \omega^*$ costs associated with excess rain (e.g. capital costs of tiling or drainage, down time etc.) are incurred[1].

Marginal profits are then equal to

(1) $$\partial \Pi(\Omega|\omega)/\partial\omega = P\,\partial Y(\Omega|\omega)/\partial\omega - \partial C(\Omega|\omega)/\partial\omega$$

and will be convex with $\partial\Pi()/\partial\omega > 0$ for $\omega < \omega^*$, $\partial\Pi()/\partial\omega = 0$ for $\omega = \omega^*$ or $\partial\Pi()/\partial\omega < 0$ for $\omega > \omega^*$.

In this paper a production function of the Cobb-Douglas type is assumed[2]

(2) $$Y = AR^{\beta_1} H^{\beta_2}.$$

Where Y represents annual crop yields detrended to match current technologies, A is an intercept multiplier, R is cumulative daily rainfall in mm, H is cumulative crop heat units above 50 degrees Fahrenheit, and β are the production coefficients. Using equation (2) the marginal productivities of rainfall and heat are given by

(3) $$\partial Y/\partial R = \beta_1 Y/R,$$

(4) $$\partial Y/\partial H = \beta_2 Y/H,$$

and

(5) $$\partial^2 Y/\partial R \partial H = \beta_1 \beta_2 Y/R$$

[1]As in note 2, setting $dC/d\omega \geq 0$ or $dC/d\omega \leq 0$ instead of $dC/d\omega > 0$ or $dC/d\omega < 0$ for $\omega < \omega^*$ or $\omega > \omega^*$ is entirely acceptable and depends on specific circumstances.

[2] We could also have used a quadratic function for this part of the analysis. However, upon estimation of the actual parameters we found that the quadratic function was not a good a fit while the log-linear Cobb-Douglas form was. See Kaufmann and Snell for a quadratic estimating equation that reasonably explains the effects of weather on yield. Since they used a quadratic form they were also able to identify optimal conditions along the estimated growth-yield curve. Their model does not appear to include rainfall-heat interaction, however as will be discussed later this may not be that important.

The necessary conditions for weather insurance to be meaningful and effective are that $\partial Y/\partial R>0$, $\partial Y/\partial H>0$, and $\partial^2 Y/\partial R\partial H \geq 0$. If $\partial^2 Y/\partial R\partial H > 0$ then both rain and heat jointly impact yields and if $\partial^2 Y/\partial R\partial H = 0$ then either rain or heat or both have no effect on yields. The hypothesis to be tested is that $\beta_1 = \beta_2 = 0$. Failure to reject the null hypotheses would indicate that weather does not impact crop yields and thus weather insurance products would be ineffective. If either one or both of the hypotheses is rejected then specific event weather insurance could be effective. Effectiveness can be measured by the weather elasticity or the value of β which measures the percentage change in the crop's yield given a percentage change in weather.

Estimating Weather Effects on Crop Yields

In this section the effects of cumulative rainfall and cumulative degree-days above 50F on corn, soybean, and hay yields in Oxford County Ontario are estimated. Data on county yields was collected from 1935 to 1996 using statistical reports from the Ontario Ministry of Agriculture Food and Rural Affairs (OMAFRA). Daily rainfall and average daily temperatures were obtained from the Environment Canada weather station at Woodstock Ontario that is somewhat central to the county. Three years (1942, 1948, and 1972) are excluded from the analysis due to missing weather data (at least one observation missing). The specific event examined is the cumulative rainfall and cumulative degree-day heat units from approximately June 1 to August 31 as measured on a calendar day (rather than date) to avoid leap-year problems.

Several issues need to be discussed before proceeding to the results. First, and perhaps most important, is that the insurable event is very specific. The procedure isolates only that portion of total yield variance attributable to the June-August weather conditions specified. Other risk-contributing events such as hail, dry springs, August frost, or rainy autumn and fall are not measured. Second, the yields represent county averages while the weather measure is location specific. While the assumption that the heat measure is systematically correlated across all county farms is reasonable the same assumption for rainfall may not be. Indeed, it is not uncommon for one township within a county to receive rain on any given day while another does not. However, over the time frame examined, the cumulative rainfall measure is probably a good proxy measure, but the potential for bias should be noted.

Yields were detrended using a linear trend equation. Table 1 presents the sample data used in the analysis. Mean yields for corn, soybeans and hay are 125 bu./acre, 39 bu./acre and 4.13 tonnes/acre (over 2 to 3 cuts) respectively. Yields tend to be somewhat negatively skewed with soybeans showing the largest negative skewness. The range in yields was 43 bu./acre, 22 bu./acre, and 2 tonnes/acre for corn soybeans and hay. Average rainfall was 250 mm and the average cumulative crop heat units was 1,532. The standard deviation in rainfall is approximately 76 mm and the range between the highest and lowest rainfall was 331mm. The standard deviation and rainfall for heat units was 164 and 957 respectively.

Also in Table 1 are the correlations between the variables. Of importance are the correlations between rainfall, heat and crop yields. With a correlation coefficient of approximately .30, the data indicate that the most significant factor for corn and soybeans is heat. Rainfall does not appear to contribute to corn or soybean yield variability. In contrast, hay yield is not affected to any great extent by heat, but with a correlation coefficient of .32 it is very sensitive to rainfall. The effect of heat on hay is minimal and negative, but still indicates that hay is perhaps more prone to heat stresses than corn or soybeans.

The correlation between heat and rainfall is low and negative. This indicates that an increase in heat units will most likely correspond with lower rainfall, but overall the relationship is not that strong.

The Cobb-Douglas equations were estimated by converting the data into logarithms. Table 2 presents the results of the least squares regressions for the detrended yields. As might be expected from examining the correlation, statistical significance of rainfall is low for corn and soybeans and high for hay. The multiple R-Square measures are also low around .30 for all equations. This result is expected since direct physical inputs into the equation were assumed constant, and by construction the nature of specific event risks was restricted to the rain and heat between June 1 and August 31. Rather than interpreting the R-Square in terms of low predictive ability it should be interpreted as the percent of total yield variability explained by the specific weather event.

The regression equations provide a means to assess in a deterministic sense the effects of random variables on yields. Holding all other factors constant it is important to illustrate how effectively the equations explain the portion of annual yield volatility caused by the specific event. To do this the prediction success of each equation was calculated and is reported in Table

3. In Table 3 variability was measured as a simple Boolean; 1 if the detrended yields increased over the previous year and 0 otherwise. The table reports the number of times that actual yields increased or decreased relative to the number of times that the equation estimate increased or decreased. For example corn yields increased over the previous year in 25 of the 58 years. The regression equation estimate was consistent in measuring the rise and fall of yields in 20 of the 25 years for a predictive success of 80%. Likewise, of the 33 years in which yields fell the model accurately predicted 24 of them for a total of 73%. The overall accuracy was 76% for corn, and by similar calculations the overall accuracy for soybeans and hay was 74% and 62% respectively.

The results indicate that weather does have a predictable effect on crop yield variability. The intention was not to explain all crop-yield variability, as the specific event measured by heat and rainfall from June1 to August 31^{st} is not the source of all variability. However the results do indicate that it is a significant source of variability and with between 60% and 80% accuracy can explain the year by year rises and falls in crop yields.

Table 4 illustrates the sensitivity of crop yields to weather variability. The cells in Table 4 correspond to the estimated yields from the detrended data using the highest (438, 1886), mean (250, 1532), and lowest (107, 929) amounts of rainfall and heat. The highest yields for corn (132 bu./acre) and soybeans (41.91 bu./acre) result from hot temperatures with lots of rain. Hay seems to thrive on lots of rain but cooler temperatures (4.44 tonnes/acre). The lowest yields resulted from low heat and rain for corn (111 bu./acre) and soybeans (33 bu./acre) and high heat and low rain for hay (3.77 tonnes/acre).

Economics and Weather Insurance

In the previous section it was shown first that weather explains a large amount of crop yield variability, and second that specific event outcomes are predictable. Since cause and effect has been established this section explores the design and pricing of weather derivatives. The insured can select a put option which would provide an indemnity if rainfall or heat falls below $\omega_{a,}$ a call option if rainfall exceeds ω_b, or both (a collar). In general the price of these contracts (in the absence of time value) would be

(6) $$V_{put} = \int^{w_a} P\ (w)\,(w_a - w)f(w)dw \quad \text{for} \quad w < w_a$$

and

(7) $$V_{call} = \int_{\omega_b} \Pi(\omega)\,(\omega - \omega_b) f(\omega)\,d\omega \quad \text{for} \quad \omega > \omega_b.$$

Equations (6) and (7) rely on several factors to be priced. First, $f(\omega)$ represents the probability distribution function which describes rainfall throughout the growing season; second the insured must have some idea of the specific event to be insured. For the put option in equation (6) the specific event is $\omega < \omega_a$, and for the call option in equation (7) the specific event is given by $\omega > \omega_b$ where ω_a and ω_b are strike levels. Finally, the third element is the absolute value of $\Pi(\omega)$ which will increase as weather events move away from the optimum. As written in (6) and (7) a pure-form derivative product would increase compensation at an increasing rate as the option moved (spread) further into-the-money.

In practice $\Pi(\omega)$ would not be computed directly but would be stipulated as a constant payoff for each unit that the option expires in-the-money. Options of this type are similar to European call and put options and will be referred to as European-type options. Alternatively $\Pi(\omega)$ may be a fixed payoff on a specific event. By setting $(\omega_a - \omega) = 1$ and $(\omega - \omega_b) = 1$ in equations (6) and (7) the options are converted to a form in which the premium equals the cumulative probability of the event happening times the payoff assigned to the event. Options of these types are similar to specific event insurance contracts.

In this section options of both types will be calculated. The European-type options will be priced using the 'burn-rate' approach and will use historical observations to predict current risks. This implicitly assumes that history will repeat itself in one form or another. It is assumed that the hedger is a crop insurance corporation, which faces the average yield risk in Oxford County for each of the three crops. It is also assumed for practical purposes that the weather station in Woodstock is the only weather station in the county that has complete information[3]. Based on the previous regressions the crop insurer would face significant liabilities for corn and soybeans if heat units were below average. Likewise low rainfall would increase the liability for forage crops such as hay.

[3] This is quite critical especially for rainfall insurance. Currently, Agricorp ltd., the provincial crop insurer offers a rainfall based forage plan which requires insureds to record weather on their own farm. This is then entered into a computer program and the yield is simulated. Indemnities are paid on the variance in the simulated yields. However the program faces some problems of which moral hazard and errors in measurement are significant. The move to rainfall derivatives with a strike based on rainfall rather than yields has some attractiveness since damage does not have to be proven. However, the problem of disparate rainfall is still a significant issue. One solution would be to triangulate rainfall from a number of rainfall stations throughout the county thus creating a matrix with each intersecting point representing a weighted average (by distance) of the various weather stations.

The strike levels for either derivative is contingent on the relationship between yields and weather. Because the insurer's portfolio risk is comprised of the systematic risk within the county even an average outcome of mean yields would result in some farmers suffering losses below insurance coverage levels. The number of farms suffering losses would likely increase at an increasing rate as average county yields decrease. Consequently if the insurer offers products to customers with 80% coverage, an average county yield above the average does not at all imply that no indemnities are paid. On the contrary, if average county yields equaled 80% of the long run average this would imply that some farms had devastating losses while most farms had some losses.

To be consistent with the equations, several strike prices for rainfall and heat units are calculated by inverting equation (2) and using the estimated parameters in Table 2 and the mean values in Table 1. To determine strike prices for rainfall insurance on hay, heat units are held constant at the mean E[H] and critical yields, Y^* ,are fixed at the mean in the first case and at 95% of the mean in the second case. The rainfall strike level is determined by $R^* = R(Y^*, E[H], A, \beta_1, \beta_2)$. Likewise the strike level for a cumulative degree-day derivative is given by $H^* = H(Y^*, E[R], A, \beta_1, \beta_2)$.

The prices of European-type put option using the burn-rate methodology and assuming a payoff of $10,000/mm rain or $10,000/degree F. are found for the following cases;

- A degree-day strike of 1,528F to hedge against average corn yields falling below the mean (125.19 bu./acre),
- A degree-day strike of 1,152F to hedge against county average corn yields falling below 95% of the mean (118.92 bu./acre),
- A degree-day strike of 1,545F to hedge against county average soybean yields falling below the mean (39.14 bu./acre),
- A degree-day strike of 1,265F to hedge against county average soybean yields falling below 95% of the mean (37.18 bu./acre),
- A degree-day strike of 1,024F to hedge against county average soybean yields falling below 90% of the mean (35.23 bu./acre),
- A cumulative rainfall strike of 249 mm to hedge against county average hay yields falling below the mean (4.13 tonnes./acre),

- A cumulative rainfall strike of 147 mm to hedge against county average hay yields falling below 95% of the mean (3.9 tonnes/acre).

Specific Event Options

To this point the pricing of options has focused on the European-type model which pays out for each unit that the option expires in the money on August 31. In other words the specific event was defined by cumulative rainfall or heat units between June 1 and August 31. Alternative options can be much more specific. For example the crop insurer may want to insure that cumulative degree-days exceed 1,200. If on August 31 degree-days are below 1200 then this type of option will make a single lump sum payment. Contracts may also be written on multiple events. For example the insurer may want to insure that it rains at least once in any 14-day period. If it does not rain then an event has occurred and the option would pay a lump sum of $100,000. The contract may allow for two or more events over the insured time horizon. To illustrate the pricing of specific event risks the following specific event options are evaluated for the June 1 to August 31 period;

- To reinsure against heat related stresses payment of $500,000 is made if average daily temperatures exceed 75 degrees Fahrenheit for 5 days straight. Up to four non-overlapping events are allowed.
- To reinsure against heat related stresses a payment of $1,000,000 is made if cumulative heat units between June 1 and August 31 is greater than 1,700.
- To reinsure against heat related stresses a payment of $1,000,000 is made if cumulative heat units between June 1 and August 31 does not exceed 1,200.
- To reinsure against drought related stresses a payment of $100,000 is made if zero rainfall is recorded during any 14-day period. Up to four non-overlapping events are allowed.
- To reinsure against drought related stresses a payment of $1,000,000 is made if cumulative rainfall between June 1 and August 31 is less than 150mm.

Results of Insurance Calculations

The results of the premium calculations are found in Tables 5 and 6. In Table 5 results for European-type options, computed using the burn rate, are presented. For the two rainfall derivatives with strikes at 249 mm and 147 mm respectively, and payoffs of $10,000 per mm in-the-money, the estimated premiums were $299,613 and $18,290 respectively. The premiums reflect the rarity of the second event over the first (the Markov effect). For Woodstock the likelihood of rainfall being less than 249 mm was significantly higher than the likelihood of rainfall being less than 147. In fact, the mean indemnity was paid on an average of 29.96 mm with a maximum payoff on 142.5 mm in the former case, while the mean payoff was on only 1.83 mm with a maximum of 40.5 mm in the latter case. The maximum premium that could have been paid out with the data used was $1,425,00 and $405,000. Even with the lower strike and its low probability of expiring in-the-money the payoff could be quite sizeable. Rare events do happen.

The degree-day put spread options based on a crop heat unit of mean daily temperatures in excess of 50 F. also exhibit properties consistent with modern options pricing. For a strike of 1,545 F the estimated premium is $696,854 with a maximum potential payoff of $6,160,200. As the specific event becomes rarer the likelihood of the option expiring in-the-money decreases as does the premium. For a strike of 1,265 F. the premium falls to $437,908 with a maximum potential payoff of $3,360,200, and a strike of 1,024 F. results in a premium of only $16,105 with a maximum potential payoff of $950,200.

Table 6 presents results for specific event options. The first case is an option that pays $1,000,000 if rainfall from June 1 through August 31 is less than or equal to 150mm. The expected payoff and premium for this product is $80,645 and the event occurred with a likelihood of about 8%. The second option is a multiple event option that pays $100,000 if there is zero mm of rainfall in any non-contiguous 14-day period. In only 13% of the years did this event happen once and in only 8% did it happen twice. Although the option would allow for up to four events the likelihood of more than two events was zero. The premium on this product was $29,032.

The third specific event is a heat trigger that pays $500,000 if the mean daily temperature exceeds 75F for 5 days straight. This is expected to occur once in approximately 19% of the years, twice in only 6.8% of the years and not at all in about 75% of the years. The premium calculated for this product was $161,017 and the maximum potential payoff would have been $1,000,000. The fourth event is based on cumulative heat units above 1,700 as at August 31 and is therefore like a call option. If the actual cumulative heat units are greater than 1,700 then a payoff of $1,000,000 is received. In only 13.6% of the years did this event happen. The premium was $135,593. The last specific event example hedges excessive cooling. If, on August 31, cumulative heat units are less than 1,200 a payment of $1,000,000 is made. This event happened only about 1.6% of the time and the premium is only $16,949.

Discussion and Conclusions

An emerging market for weather-based derivative products could offer new hedging possibilities for agricultural production. Unlike commodity hedges using futures contracts and options on prices, the use of weather derivatives provides a market mechanism for insuring against output. The efficacy of weather derivatives on rainfall or heat depend on a number of factors of which the most important is the identification of specific risks. In this paper daily rainfall and temperature data from 1935 to 1996 at Woodstock Ontario was examined. In the first part of the paper cumulative rainfall and cumulative degree-days above 50 degrees Fahrenheit were correlated with average county yields. Using a Cobb-Douglas production function it was shown that corn and soybeans are more sensitive to low temperatures, while hay was more sensitive to low rainfall. The variability in year over year changes in crop yield increases or decreases was mapped with about 80% accuracy for the corn model and 60% for the hay model. The results indicate that specific-event weather conditions can contribute significantly to crop yield risk. Although average county yields were used it was argued that the evidence of correlation on the average would be magnified at the individual farm level. Even so, the idea of weather contingent insurance at the farm level can still be accomplished through a variety of techniques. One promising approach that requires further study is to triangulate a particular farm's location to three or more weather stations and weight each weather station record by the triangulated distances. Using such an approach a crop insurer could provide farm level weather insurance while taking an opposite position in the reinsurance market. In addition, such an approach would virtually eliminate all forms of moral hazard and adverse selection.

That weather events can be tied to production risk is important because it implies that new weather based derivative instruments can be designed. With these products the underlying risk is not in crop yield variability but in the source of that variability. In terms of specific event risks yield variability is the effect, so it is not unreasonable to insure the cause directly. The advantage to a crop insurer or reinsurer is that a payoff based on such an objective measure does not require any proof of damage.

Based on the notion of specific event risks a number of different insurance/derivative contracts were introduced and their premiums (before transaction costs) computed. The results showed, as expected, that insuring weather has properties similar to conventional options. The higher the strike prices the higher the potential payoff and therefore the higher the premium. For example a cumulative degree-day put spread calculated from historical data and a payoff of $10,000 for every degree the option expired in-the-money was priced at $696,854 for a strike of 1,545 degrees, whereas a put option with a lower strike of only 1,024 degrees cost only $16,105.

It was shown that weather derivatives need not be confined to European-type options. Single payoff and multiple event contracts could also be written. An example of drought insurance, which provided a payoff of $1,000,000 if the expiry date cumulative rainfall was less than 150 mm had a premium of $80,645. A multiple (4) event call option that had a payoff of $500,00 if mean daily temperature exceeded 75F for 5 days straight had a premium of $161,017.

The advantages of weather insurance are that the insured event relies on authoritative data and because it does there are many crop reinsurers and other financial institutions that are willing to sell or broker weather derivative products. There is likely an excess supply of sellers, because potential buyers may not be aware of the new products. As empirical research such as that presented in this paper shows that buyers can benefit from insuring specific event risks with weather derivatives, the market will likely increase in volume and liquidity.

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Table 1: Sample Statistics On Weather And Yields

	corn	soy	hay	rainfall	d-days
	bu./acre	bu./acre	tonnes/acre	mm	degrees f
Mean	125.19	39.14	4.13	250.08	1532.41
Median	125.71	39.61	4.16	252.10	1534.50
Standard Deviation	8.18	3.88	0.43	76.56	164.31
Kurtosis	0.68	2.84	-0.12	-0.41	2.11
Skewness	-0.13	-1.17	-0.06	0.19	-0.62
Range	43.05	22.16	2.06	331.30	957.60
Minimum	103.83	25.03	3.14	106.50	928.98
Maximum	146.88	47.19	5.20	437.80	1886.58
Correlation Matrix					
	corn	soy	hay	rainfall	d-days
corn	1				
soy	0.493484	1			
hay	0.340846	-0.04568	1		
rainfall	0.09173	0.005613	0.3215823	1	
d-days	0.297817	0.302775	-0.097517	-0.20011	1

Table 2: Estimated Regression Equations (Std Error In Parenthesis)

Dependent	Intercept	Rain	Degree-Days	R-Square
corn	3.33	0.03	0.18	0.33
	(0.58)	(0.03)	(0.07)	
Soy	1.62	0.03	0.26	0.27
	(0.97)	(0.04)	(0.12)	
Hay	1.12	0.10	-0.03	0.31
	(0.94)	(0.04)	(0.12)	

Table 3: Prediction Accuracy of Regression

	Actual Count		
	Corn		
Predicted Count	up	down	total
up	20	9	29
down	5	24	29
total	25	33	58
%correct	0.80	0.73	0.76
	Soybeans		
up	22	12	34
down	3	21	24
total	25	33	58
%correct	0.88	0.64	0.74
	Hay		
up	19	10	29
down	12	17	29
total	31	27	58
%correct	0.61	0.63	0.62

Table 4: Sensitivity Of Crop Yields To Weather Variability

	Corn			
		High	Mean	Low
	Rain →	437.80	250.08	106.50
	Heat ↓			
High	1886.58	132.33	130.08	126.72
Mean	1532.41	127.42	125.25	122.02
Low	928.98	116.33	114.35	111.40
	Soybeans			
High	1886.58	41.91	41.19	40.12
Mean	1532.41	39.74	39.05	38.04
Low	928.98	34.96	34.36	33.46
	Hay			
High	1886.58	4.33	4.10	3.77
Mean	1532.41	4.36	4.13	3.80
Low	928.98	4.44	4.20	3.86

Table 5: European-Type Option Calculations For Rainfall And Crop Heat Units							
Item	**Rainfall (mm)**		**Crop Heat Units (Degrees Fahrenheit > 50 degrees)**				
Strike Level	249	147	1,545	1,528	1,265	1,152	1,024
Mean units in- the-money	29.96	1.83	69.69	61.06	6.15	3.78	1.61
Standard Deviation of Units in-the-money	41.00	7.58	108.41	103.15	43.79	29.03	12.37
Minimum Units	0	0	0	0	0	0	0
Maximum Units	142.5	40.5	616.02	599.02	336.02	223.02	95.02
Premium ($)	299,613	18,290	696,854	610,624	61,454	37,800	16,105
Standard Deviation, Premium ($)	419,649	75,750	1,084,072	1,031,539	437,908	290,347	123,706
Minimum Payoff ($)	0	0	0	0	0	0	0
Maximum Payoff ($)	1,425,000	405,000	6,160,200	5,990,200	3,360,200	2,230,200	950,000

Table 6: Specific And Multiple Event Rainfall And Heat Unit Premium Calculations					
	Rainfall (mm)		**Heat**		
Item	**< 150 mm cumulative**	**0 mm/day**	**> 75F**	**> 1,700 Heat Units**	**< 1,200 Heat Units**
# Events	1	4	4	1	1
Length of Event (days)	term	14	5	term	term
Payoff /Event ($)	1,000,000	100,000	500,00	1,000,000	1,000,000
Premium ($)	$80,645	29,032	161,017	135,593	$16,949
% 0 Events Occurred/Year	92%	79%	74.6%	87.1%	98.4%
% 1 Event Occurred/Year	8%	13%	18.6%	12.9%	1.6%
% 2 Events Occurred/Year	0	8%	6.8%	0	0
% 3 or 4 Events Occurred/Year	0	0	0	0	0