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Palmer's Z-Index as an underlying index for a weather-based crop insurance policy:
Saskatchewan study case

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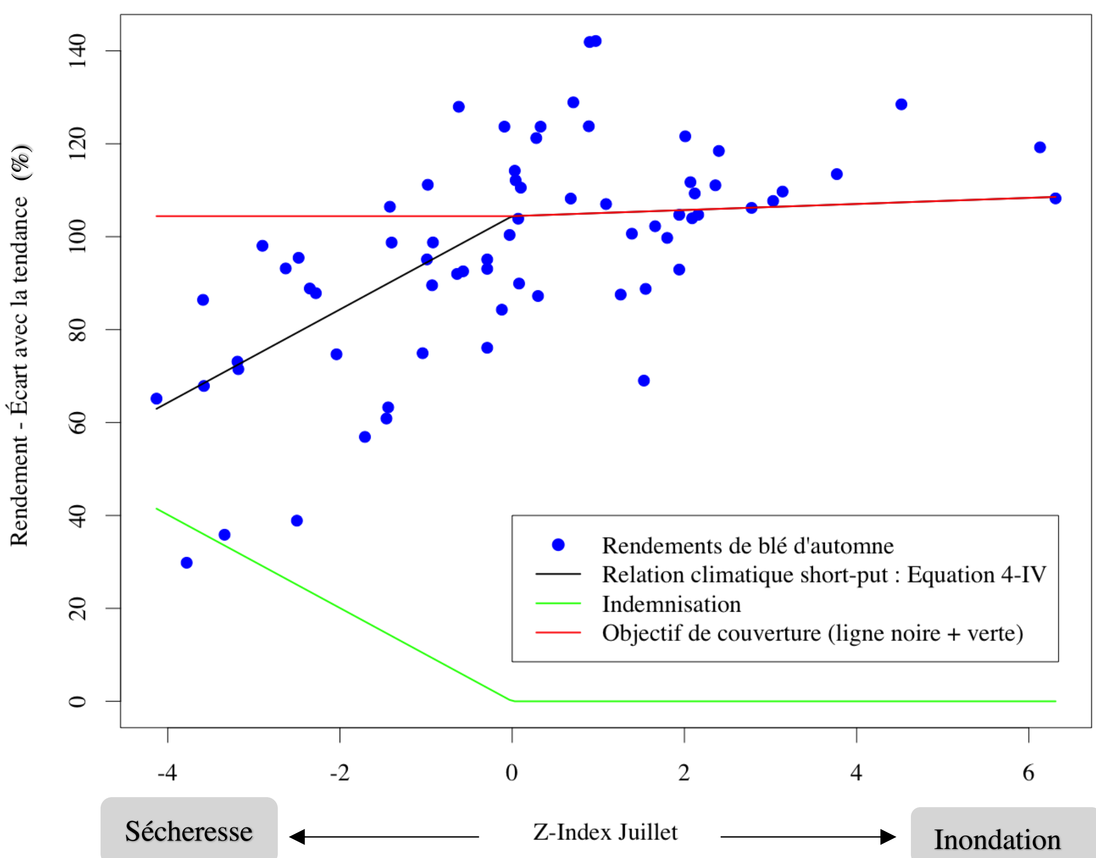
Résumé

Ce mémoire porte sur un outil de gestion de risque climatique des productions de grain dans la province de la Saskatchewan au Canada. Alors que les sécheresses agricoles sont reconnues pour affecter les rendements des grains, et que ce phénomène est susceptible de s'intensifier dû aux changements climatiques, la question de recherche est la suivante : est-ce possible d'élaborer un produit d'assurance basé sur un indice climatique pour couvrir les productions de grain en Saskatchewan ? Ce papier a pour but de présenter un contrat d'assurance pour couvrir une relation ''short-put'' entre le Palmer Z-Index et le rendement des productions de blé d'automne, d'orge, d'avoine et de canola. Cette stratégie de couverture vise à couvrir les rendements lors de sécheresses de faible intensité et de haute fréquence.

INDEMNISATION BASÉE SUR UN INDICE CLIMATIQUE, PALMER Z-INDEX, POUR UNE PRODUCTION DE BLÉ D'AUTOMNE EN SWIFT CURRENT, SASKATCHEWAN



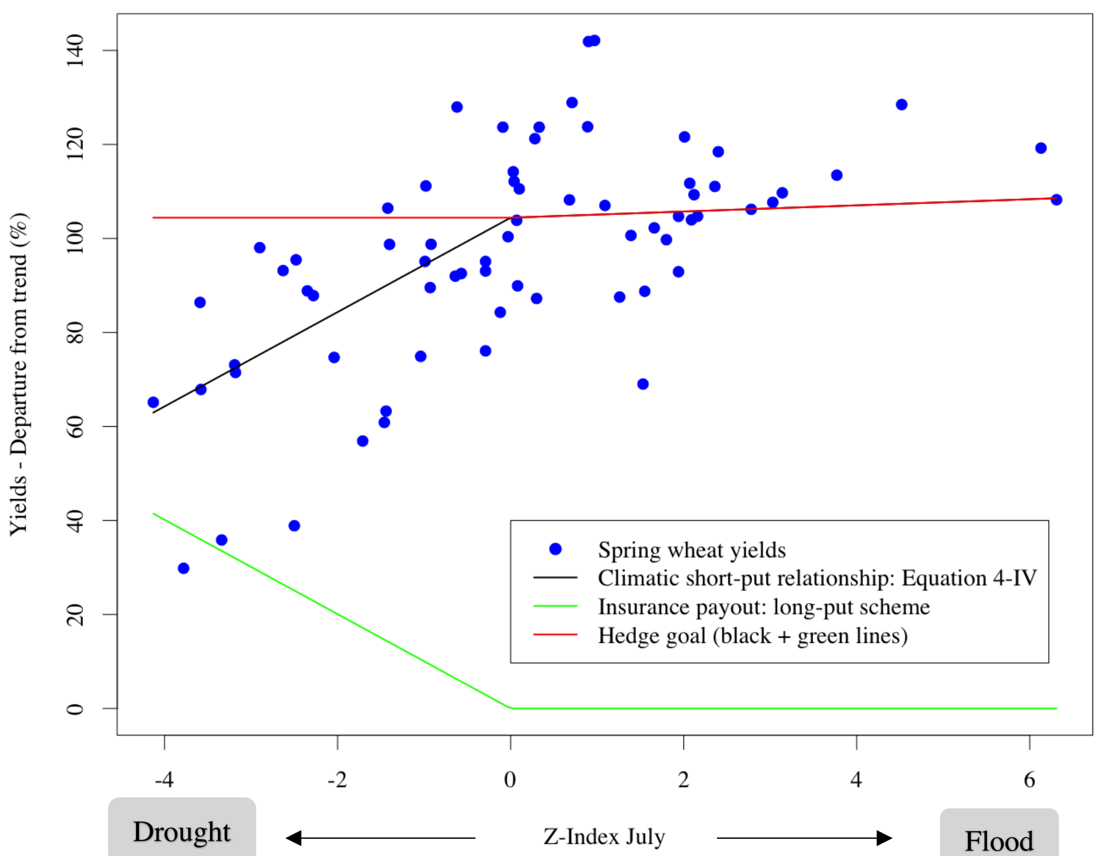
Dans l'optique de reproduire un schéma d'assurance pour un producteur agricole, ce papier présente un contrat d'assurance pour couvrir les rendements des grains de sécheresse enregistrée par une station climatique dans un rayon de 40 kilomètres. Cette relation fut estimée grâce à des données couplant 144 municipalités rurales, 36 stations climatiques et 4 productions rassemblées dans un panel de 1951 à 2019. L'indice climatique Z-Index, développé par Palmer (1965), est présenté par Quiring et Papakryiakou (2003) comme le meilleur indice pouvant prédire la diminution de rendement de grain lors de période de sécheresse pour les Praires Canadiennes. Afin de poursuivre cette réflexion dans un contexte d'assurance, ce papier présente un contrat d'assurance paramétrique basé sur les observations du Z-Index en juin et juillet pour couvrir les rendements des grains.

Une analyse géo-spatiale et une analyse temporelle complète ce mémoire. D'abord, une analyse géo-spatiale présente les profils de risque hétérogènes des municipalités rurales agricoles dispersées sur l'étendue de la Saskatchewan. Cette analyse illustre l'importance d'ajouter des caractéristiques géographiques dans le produit d'assurance. L'analyse temporelle poursuit sur la pertinence d'estimer les paramètres du modèle économétrique sur une série temporelle tenant compte des progrès technologiques récents, notamment la résistance des grains au stress hydraulique ainsi que de meilleures pratiques agricoles pour mieux évaluer l'élasticité des rendements aux sécheresses climatiques.

Abstract

This thesis focuses on a climate risk management insurance policy for grain production in the province of Saskatchewan, Canada. As agricultural droughts are known to affect grain yields, and that this issue is likely to intensify due to global warming, we aimed to develop a financial product based on a climate index that covers grain production in Saskatchewan. This paper proposes a single insurance contract to cover a "short-put" relationship between the Palmer Z-Index and yields of spring wheat, barley, oats and canola. The purpose of this hedging strategy is to cover yields during low intensity, high frequency drought conditions.

WEATHER-BASED INSURANCE PAYOFF FOR WHEAT PRODUCTION, SWIFT CURRENT, SASKATCHEWAN



This paper proposes an insurance policy that would cover grain yields for agricultural producers in a rural municipality based on periods of drought recorded by a selected climate station within a radius of up to 40 kilometers. This ''short-put'' relationship is estimated using 144 rural municipalities, 36 climate stations and 4 different species of grain gathered in a panel dataset from

1951 to 2019. The Z-Index climatic index, developed by Palmer (1965), is presented by Quiring and Papakryiakou (2003) as the best index for predicting a decrease in grain yield during drought periods in the Canadian Prairies. In order to pursue this reflection in an insurance context, this paper presents a parametric insurance contract to cover grain yields based on observations of the Z-Index for the month of June and July.

A geo-spatial and temporal analysis complete this paper. The geo-spatial analysis illustrates the heterogeneity of rural agricultural municipalities scattered across Saskatchewan. The temporal analysis highlights the importance of selecting a time series of crop yields with a time horizon that accounts for technological developments, including improved grain resistance to water stress, and best agricultural practices to assess yield elasticity with respect to agricultural droughts.

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Finalement, je dédie ce mémoire à mes grands-parents !

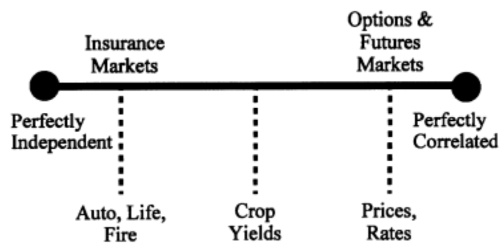
Introduction

Weather risk is recognized as the major production risk for crop producers in the Canadian agriculture industry. In its 2019 Vision Survey, Farm Credit Canada reported that 94% of crop producers declared weather to be the principal cause of production risk, followed by unfavorable yield outcome and pests/diseases. To manage production risk, 81% of Canadian crop producers use insurance contracts to stabilize their income.

Weather risk consequences in agriculture are defined as shortfalls in production volume due to climatic events outside of the producer's control. In the literature, weather risk is separated into two categories: catastrophic risk and non-catastrophic risk (Singh et Agrawal, 2019). The former refers to climatic catastrophes with high intensity but low frequency that impact crop producers over a large geographical area. This kind of risk, with its systematic impact, needs to be transferred to the international market with financials tools such as catastrophe bonds, or insured by a reinsurer for the domestic market. Non-catastrophic risk refers to the low intensity but high frequency risk of soil moisture stress. A farmer can manage this risk through an informal risk management strategy: soil manipulation to preserve natural soil moisture; diversification with drought-resistant crops; social capital; or off-farm incomes. However, the weather remains a strong adversary for many farmers and pre-drought adaptation practices can be overwhelmed by multiple years of dry soil episodes, especially in the context of increased weather variability due to global warming.

Since such mitigation strategies are insufficient to hedge farmers against weather risk, the use of post-drought income stabilizing strategies is required, the most popular of these being the insurance market. Insurance contracting is a practice in which a public or private entity provides a guarantee of specified events in return for payment of a premium. Major crop insurance agencies are managed by governments, as the literature provides strong historical evidence of market failure in private crop insurance. This private market failure is due to the high level of systematic risk: as climatic events tend to impact farmers across a large geographic area, natural diversification by pooling risk across farms is not possible for the insurer. Thus, the capital required to cover catastrophic losses in cases of widespread natural disaster is prohibitive for a private company.

FIGURE I: CORRELATION SCALE OF SYSTEMATIC RISK



Source : Miranda & Gaubler, 1997

Miranda and Gaubler (1997) present a correlation scale for known insurance markets (see Fig. 1). To the left of the scale are uncorrelated risks such as fire, automobile and life insurance that can be pooled together so that independent risks are diversified in a classic insurance market. To the right of the scale are perfectly correlated risks, which impact every agent in a market to the same extent and can be hedged using standardized options and/or futures markets. Between these two categories lie weather-related risks affecting crop yields. Using an empirical model of the U.S. crop insurance market, the authors find that U.S. crop insurer portfolios are twenty to fifty times riskier than they would be otherwise if yields were stochastically independent across farms. This risk presents the specific criteria of not being perfectly correlated: systemic weather risk impacts all farmers in a large geographical area, but also has varying individual impacts based on a given farm's soil management, species selection and micro-climates. As a result, insuring farmers in a framework based on individual portfolios will not naturally diversify the idiosyncratic component of risk. At the same time, offering an average indemnity will underinsure highly impacted farms while over insuring those barely affected, leading to adverse selection that undermines insurance sustainability.

Miranda and Gaubler (1997) concluded that an area-yield options contract would offer numerous advantages to the existing government reinsurance program. Based on an area-scale insurance framework, the premiums would incorporate all private information specific to the hedged area. Since all private information is included in premium pricing techniques, actuarially fair compensation for the hedged area will reduce adverse selection. While current government insurance programs are only available to farmers, area-yield options could be purchased by any agent in the supply chain (e.g., rural banks, food processors, grain elevators, wholesalers, etc.) that are indirectly impacted by yield shortfalls due to weather risk.

As insurance contracts are not offered by the private crop insurance market due to adverse selection, moral hazard and the presence of systemic weather risk, the demand must be answered by someone who can bear such risk: governments. From a broader perspective, the public sector has several reasons to supply crop insurance. First, the need to protect food autonomy at a national level implies protecting farmers from bankruptcy when catastrophic disaster drastically reduces their incomes. In addition, agricultural insurance that stabilizes income can help producers finance new technologies to improve productivity and maintain a high level of competitiveness. Lastly, farm investments are often initially government-subsidized, and supplying insurance helps farmers protect those investments from uncontrollable events. These arguments justify why crop insurance premiums are heavily subsidized (up to 60% of the primes) by the federal governments in Canada and the United States. Government financial support allows the insurance market to offer a supply that meets the crop insurance demand.

Singh and Agrawal (2019) offer an extensive integrative literature review of scientific articles on weather index insurance (WII) for mitigating weather risk in agriculture. They identify four main phases of WII literature development. The first is the origin phase (1998-2002), when the first weather-based derivatives were exchanged, these being supported by the literature as effective risk management tools. This was followed by the evolution phase of weather insurance (2003-2007), when actuarial industry and academic community studies focused on heating degree-day (HDD) insurance plans and the efficiency of weather-based insurance in changing weather conditions as a potential low-cost substitute for individual informal farmer risk management strategies. Pricing techniques were also largely covered in this phase. Next was the development phase (2008-2012), when the literature on WII expanded in both developed and developing countries with a focus on studying the willingness to pay for WII contracts, further potential implications of climate change, and challenges in the use of WII insurance. Lastly, in the advancement phase (2013-2018), the literature expanded into several areas of interest including precise meteorological dataset standardization using machine learning technologies, the role of governments in premium subsidies, and climate risk management oriented to improving quality of life for human populations. In this phase, much work was done to come to a more precise understanding of the complex relationship between crop yields and the climatic environment. From the insurer's perspective, this work is very useful because it helps to mitigate basis risk, a current limitation in weather-based insurance policy that arises from an imperfect correlation between the damage and the indicator measuring the climatic hazard. To further advance these objectives, this paper attempts to identify a relationship between the Palmer Z-Index (Palmer, 1965) and crop yields and to develop a single insurance framework to hedge four distinctive crops yield shortfall for Saskatchewan producers against non-catastrophic drought spells.

An agricultural drought is considered to have set in when the soil moisture available to plants has dropped to such a level that it adversely affects crop yield and hence agricultural profitability (Mannocchi, Francesca et Vergni, 2004). The Palmer Z-Index (Palmer, 1965) monitors droughts based on a hydraulic soil supply-and-demand model in order to assess the level of soil moisture available for each month of the crop-growing season. This index is a standardized metric that integrates data on soil water storage, volume of water runoff, potential evapotranspiration from plants, temperature, and precipitation levels. The index is monitored on a monthly basis and is a short-term (1 month) variation of the Palmer Drought Severity Index (PDSI). The PDSI is effective for monitoring long-term drought (12 months minimum) by integrating surface air temperature, the soil-water-balance (SWB) model and potential plant evapotranspiration. Using a short-term index helps identify brief episodes of drought that cause soil moisture stress in crops and the causal effects of rapid dry spells on crop yields.

The advantages of this method are that it quickly and cheaply assesses drought based on a single observation of climatic conditions and immediately delivers the corresponding payoff. From a farmer's perspective, this weather-based insurance policy reduces liquidity stress because it improves the waiting time between the financial impact of the drought and the insurer's indemnity payment. Moreover, this insurance contract offers economic gain not only to crop producers, but to all economic agents in the value chain of Saskatchewan crop production that are affected indirectly by drought spell as well.

From an insurer's perspective, transaction costs are minimized by devoting fewer financial resources to assessment of margin loss. A crop insurance program with an underlying weather-based index avoids the issues of adverse selection and moral hazard that lead to crop insurance market failure. Since the payoff is triggered by a climatic index observation rather than an estimated profit margin shortfall, the producer is not prompted to alter inputs (e.g., use of pesticides) to potentially manipulate actual production history for seeking future higher insurance claims (Mieno, Walters et Fulginiti, 2018). In addition, adverse selection is minimized with a weather-based framework, as the distribution of the weather index is well known and can be estimated using corrected and gridded climatic data for any specific climatic station. Also, a level of flexibility in the contract design would allow the farmer to select the combination of climatic station and observed month that best fits the situation of their insured land. Thus, the farmer's premiums can be adjusted accordingly as distributions of weather realizations are observed with increasing precision driven by technological progress.

A major drawback of weather-based derivatives is the presence of an inherent basis risk. That is, a farmer's income loss might not be fully compensated by the triggered payment if there is an imperfect correlation in the yields-index relationship. An imperfect correlation can result from the insurance contract design itself, the geographical distance between the climatic station and the farmer's field, or poor selection of insurance policy specifications by the farmer. The presence of basis risk explains the low demand for weather-based insurance products by crop farmers (Elabed et al., 2013). In addition, farmers may not have the training to assess the probability of future drought-induced losses or to estimate the potential economic gain in hedging crop production with an index-based insurance contract (Barnett, Barrett et Skees, 2006). For this reason, the insurance policy's capacity to assess basis risk will be central to its sustainability.

This paper is structured as follows: the next section will present a literature review of challenges and opportunities in weather-based insurance, followed by presentation of the data, methodology and crop-yield relationship analysis. We will then present an insurance contract that is simulated based on this relationship and assess its hedging effectiveness by evaluating the basis risk. Finally, a discussion on the viability of such an insurance contract based on a geographical and temporal perspective will be followed by the conclusion.

Literature review

I. Background

i. Business Risk Management programs

Agriculture is one of the oldest economic sectors in Canadian history, and one long paired with immigration policy, as it was a key economic sector in European colonization of the vast territory now known as Canada. Federal crop programs for improved settler welfare began as early as 1887 and were designed to study the adaptation of European crops to the Canadian climatic environment. Over the last century, these programs supporting farmers adapted as Canadian agriculture grew and faced several challenges. Wartime demands, drought and flood hazards, extended bug infestations, provincial tax policy involvement and the evolution of economic philosophy have shaped present-day federal-provincial agriculture support programs. These programs continue to evolve by integrating new concerns such as environmental protection, integration of new productivity-oriented technologies, and national food safety.

Presently, there is much focus on managing risks for agriculture businesses. In 2007, the Canadian federal, provincial and territorial ministers of agriculture agreed to adopt Growing Forward, a market-driven vision for Canada's agriculture, agri-food, and agri-based products industry in every region of the country. As a result, new business risk management programs replaced the former Canadian Agriculture Income Stabilization (CAIS) program (Schmitz, 2008). Currently, under the Canadian Agricultural Partnership (CAP) agreement, Business Risk Management (BRM) tools include a suite of programs: AgriInsurance, AgriInvest, AgriStability, and AgriRecovery. These federal-provincial cost-shared programs offer financial capital to stabilize farmers’ margins when they suffer significant shortfalls due to climatic or non-climatic events.

AgriInsurance stabilizes a producer's income by minimizing the economic effects of primarily production losses caused by high intensity and unpredictable climatic hazards. This program is administered by the individual provinces to better match producers’ weather risk insurance needs. Some provinces offer both a collective and an individual insurance policy (e.g., Quebec) while others (e.g., Saskatchewan) offer a variety of plans and allow producers to select the one that best fits their situation. Typically, the producers cover 40% of the tab and the federal and provincial governments share the other 60% in addition to the administrative costs.

AgriInvest is a producer-government program designed to guide farmers in using their savings to manage small income declines and make investments to manage risk and improve market income. Each year, a producer can deposit up to 100% of their Allowable Net Sales (i.e., gross sales of allowable commodities minus allowable purchased inputs) and receive a matching government contribution of 1% of this amount. The farmer can then withdraw funds at any time to smooth income or invest in business development.

AgriStability protects producers from large declines in their farming income caused by production loss, increased costs or market conditions. Incomes and expenses relative to all commodities produced on the farm are used to calculate a 5-year Olympic average reference margin. This program offers a direct payment of 70 cents per dollar lost under a 70% reference margin for the season. Offered on a federal-provincial 60/40 cost-share basis, the provinces administer this program for each specific agriculture business environment.

AgriRecovery provides targeted, disaster-specific programming when the assistance needed is beyond the scope of programs like AgriStability. This program is designed to offer additional help in case of an extreme natural disaster with significant negative impacts and extraordinary costs beyond the producer's capacity. (Ker et al., 2017) recognized that AgriRecovery is rarely triggered, and as contributing factors, pointed to a lack of clarity around what defines a natural disaster and the requirement that relief be initiated by request of a provincial or territorial government.

All of the programs cited above are administered by the provinces and territories. For example, the Saskatchewan Crop Insurance Corporation (SCIC) supplies several agricultural risk management policies for wildlife damages, livestock price insurance and crop insurance. In a specific effort to manage climate risk, the SCIC offers 3 weather-based insurance programs: Forage Rainfall (FRIP), Corn Rainfall (CRP) and Corn Heat Unit (CHU) insurance. FRIP insures precipitation levels for grazing pasturelands based on a monthly weighted cumulative precipitation level, with a payout of 2.5% liability for each percentage point below 80% of normal precipitation that is recorded at a farmer-selected weather station. Premiums are shared 40-60 between the producer and governments and are calculated based on the weather station's historical precipitation records.

Claims under the CRP are based on weighted average precipitation models. Claims are triggered if rainfall at a selected weather station falls below 80% of normal and offer progressive payment rates between 3.5% and 100% of the amount covered if rainfall falls below 32% of normal levels. The CHU program insures against yield losses due to cold temperatures in summer and is triggered by the selected weather station's registration of lower levels of heat units. This program framework offers claims of 4% of liability for every percentage point the cumulative heat units fall below 95% of the normal level for the selected station from May 15th to the first frost day past July 1st.

These programs are framed to be flexible for farmers who based on experience have better knowledge of the relationship between rainfall levels or heat units and crop yields. For instance, the producer is asked to choose one weather station within 100 kilometers that registers climatic conditions as closely as possible to the climatic observations on their insured land. In addition, the producer must select monthly precipitation weighting options for the cumulative rainfall index to match the program claim computation and crop-specific fragile growth stages. Lastly, the farmer can choose the level of coverage and number of acres that best fits their insurance needs. Thus, premium rates are calculated using the weather station's historical precipitations or heat unit data and the weighting option selected by the producers.

ii. Effectiveness of Business Risk Management Tools

The effectiveness of AgriStability has been assessed in the literature through quantitative analysis and survey methodology studies. Schaufele et al. (Schaufele, Unterschultz et Nilsson, 2010) evaluate its effectiveness with a simulated model applied to cow-calf production income hit by a catastrophic price drop of 60% to 80% versus a baseline scenario. They found that all producers, regardless of their utility function or risk aversion level, were better off if they participated in the program. They recognized that the program fees paid by the producer are disconnected from their respective risk profile, which implies that gains in expected producer benefits are largely due to implicit subsidies in the AgriStability program. Thus, these authors concluded that this program is feasible as a disaster risk management tool largely due to Canadian taxpayers' contributions even if the direct payment is only distributed one year after application to the program.

(Abbasi, 2014) critiques the performance of the AgriStability program for farmers in Kindersley and Maidstone, SK, citing the complexity of the required paperwork, the difficulty of classifying eligible income and expense items, and a lack of predictability in the amounts receivable for indemnities. Study participants identified the use of a reference margin as a major shortfall because diversified farms wouldn't have any income shortfall substantial enough to trigger payment. Finally, delays between a climatic drought episode and recovery payment can be extended over a full year which is inconvenient for liquidity issues and risk management efficiency.

Jeffrey & al. (Jeffrey, Trautman et Unterschultz, 2017) examine the effects of BRM programs targeting the financial situation and environmental stewardship practices of a representative farm in Alberta. These novel incentives, known as Beneficial Management Practices (BMPs), are publicized as management practices that reduce environmental risk in farm operations. Since BRM programs are not tied with any environmental factors, there is concern about how they could incite the adoption of such practices. Moreover, BRM programs can increase returns for crop land, thus increasing the opportunity cost of adopting BMPs which typically reduce the area available for farming. As a result, these authors conclude that BRM programs decrease the incentive to adopt BMPs. (Hailu et Poon, 2017) studied the relationship between technical production efficiency and government program payments for Ontario beef operations using BRM program administrative data. These authors found a significant negative relationship between BRM payments and production efficiency, which suggests that less efficient farmers may receive a higher payout per dollar of revenue. This means that the BRM programs themselves limit the incentive to increase productivity through investment and innovation.

In light of these findings, (Slade, 2020) proposed 4 recommendations for further modifications to Canadian BRM programs. This author argues that the objectives of such programs aren't as clearly defined as they might be if they were intended to stabilize farmer incomes or offer disaster relief capital when needed. Thus, he first suggests a two-step procedure to amend BRM programs: 1) Clearly define the actual objectives through public consultation; and 2) Underwrite policies that are centered on filling these objectives to please political lobbies. Additionally, he recommends separation of risk management and income stabilization in BRM programs by setting insurance premiums closer to their actuarially fair prices. De-subsiding BRM premiums would decrease the participation rate, but income support with direct payment would steer participation in AgriInsurance and AgriStability towards risk management intentions rather than income stabilization. His third recommendation is to replace AgriStability with whole-farm revenue insurance. Whole-farm revenue insurance supplies a hedging feature against output prices whereas AgriStability focuses both on outputs and input prices in estimating margin declines. A major advantage is that reporting external revenue is less resource-consuming then evaluation of a margin. The author's fourth and final recommendation suggests changing the AgriStability formula to encourage private insurance instruments that cover previously uninsured risks. Since AgriStability is margin-based insurance, any private insurance payoff could decrease a margin shortfall, thus reducing the probability of triggering AgriStability payments, or reduced them as a result. Moreover, as having multiple insurance contracts could incite crop yields shortfall rather than high yield performance, such incentives bring additional moral hazard concerns.

In summary, BRMs are recognized as effective within the theoretical framework of the academic literature. However, they appear to be somewhat less effective from the farmers' perspective due to a major drawback related to paperwork and poor complementarity with real risk management tools, formal or informal. Therefore, the need to cover production yields directly could be an improvement, as margin coverage discourages innovation and increases moral hazard in farmers' behavior.

II. Risks in agriculture

Agriculture is a sector that must cope with a high degree of uncertainty due to working with living things. Both animal and vegetal species face diverse risks throughout the year: diseases, weather, pests and wildlife threats. Along with these production risks, producers face exogenous market challenges from price fluctuations, commodity tariffs, shortage of agricultural employees and access to new technologies. These threats fuel revenue uncertainty since outcomes are not known in advance, thus creating a need for risk management tools that reframe uncertainty as risk.

Risk and uncertainty are defined in various ways in the literature, but Knight (Watkins, 1922) proposed an early, well-accepted distinction: in risk, the outcome is unknown, but the probability distribution function governing the outcome is known; in uncertainty, both the outcome and probability distribution are unknown. Thus, with risk the chance taken is objective, whereas with uncertainty, it is subjective (de Groot et Thurik, 2018). A hundred years later, this distinction is still crucial to understanding the potential benefits of risk management activities in terms of cutting through subjective bias with objective facts and creating value for stakeholders by stabilizing farm operation revenue.

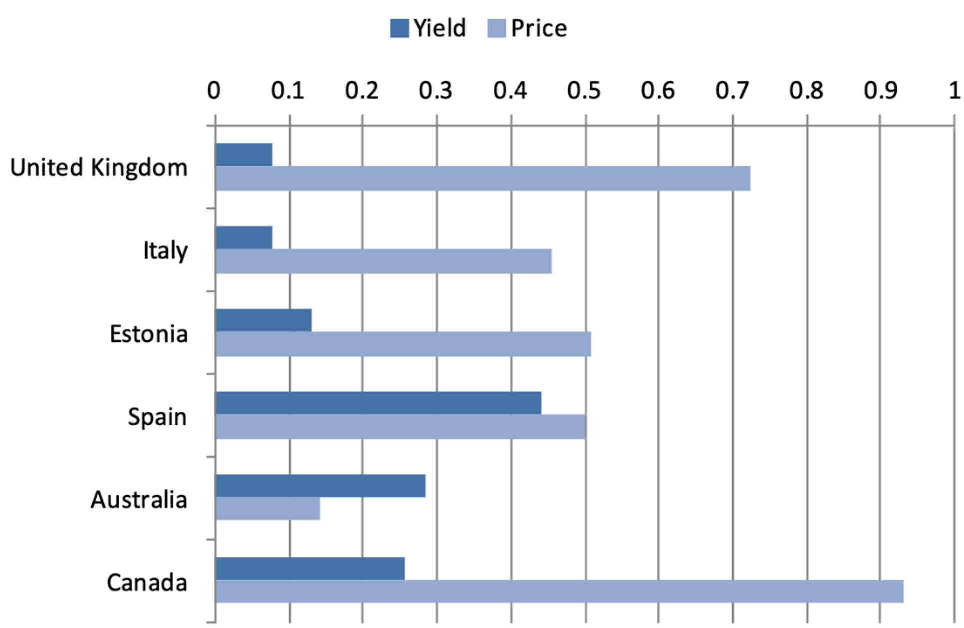
Before monitoring uncertainty using risk management practices in agriculture, we must identify how risk can affect a producer’s income. Income from crop production is a function of the volume of grain sold and the price, known as a spot price, or a price settled by forward contracts. (Hardaker et al., 2004) proposed several sources of risk in agriculture: market risk, institutional risk, counterpart risk and production risk.

i. Market risk

The main sources of market risk for Canadian crops are related to prices and exchange rates, both of which farmers perceived as having a higher potential for major financial impacts on farm operations than weather (Antón, Kimura et Martini, 2011). Market risk is the most significant risk for a producer because it impacts both the input and output sides of the operation. Thus, a high worldwide level of grain production can add downward pressure on commodity price and can threaten the viability of a crop producer's farm operation characterized by high fixed production costs, largely for fuel and fertilizers. If the Canadian dollar appreciates against other international currencies, Canadian grain exportation could decrease from this economic disadvantage.

Antón and al. drew several conclusions in regard to correlation dynamics in the Canadian crop business. First, they found that the price-yield correlation for wheat and barley were mostly negative in Canada, so that the farmer benefits from a natural hedging between price and yields. That said, when price is up, yields are down, and vice-versa, so that lost income due to the price effect is offset by the volume effect to stabilize the income received. They also estimated the correlation of yields and prices across farmers and across crop species. They found that correlations between crop returns were relatively weak, and therefore, that revenue diversification with crop culture rotation is another strategy for managing price risk. Price correlations among Canadian farmers were extremely high (>0.9) in comparison to farmers in other grain-producing countries. In addition, the correlation of wheat yield across farms is low, suggesting that it is possible to geographically diversify. These two main findings suggest that price risk is systemic across farmers, but production risk is less correlated, and diversification may be possible.

FIGURE II: CORRELATION OF YIELD AND PRICE ACROSS FARMERS



Source: Antón and al. (2011)

ii. Institutional risk

Institutional risk includes all unpredictable actions undertaken by foreign or domestic institutions that harm crop revenue stability. Foreign political actions against domestic exportations due to national protectionism can reduce price tariffs by discouraging purchase of a country's products. The numerous ecological groups fighting for reduction of pesticides, chemicals or antibiotics in food production also impose financial stress on producers who need to adapt farm operation activities to address new consumer preferences.

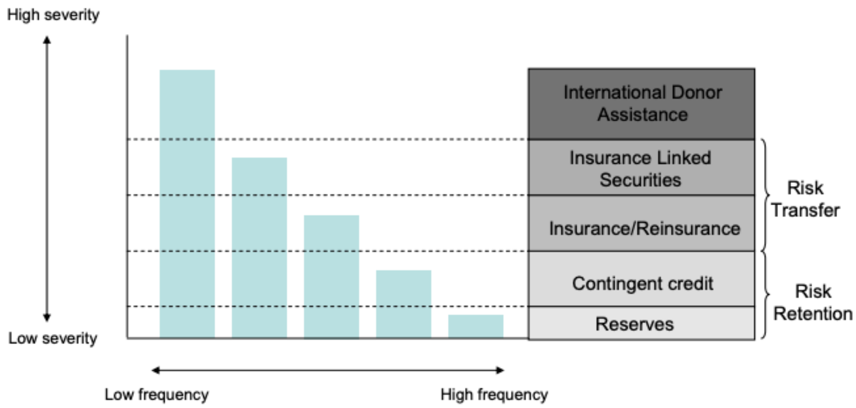
iii. Counterpart risk

Counterpart risk refers to any risks associated with doing business with other partners in the farm operation business. From contractual partners who sign agreements facilitating supply-chain process operations to the financial risks of debt and equity funding, counterpart risk is unique to each producer. While counterpart and institutional risks are still defined as uncertain from the farmer perspective since the probability distribution of tariff wars or financial and economic crises are unknown, production and market risk can be assessed and hedged using many tools such as insurance, natural diversification, off-farm revenues or the use of derivatives.

iv. Production risk

Production risk is associated with unpredictable events such as climatic hazard, disease or crop performance. Assessment of production risk is as complex as the relationship between crops and nature. Production risk is, to a large degree, influenced by the weather, but it is possible to separate this risk into multiple layers with specific risk management strategies. (Ghesquiere et Mahul, 2010) proposed a top-down response approach to natural disaster. The main objectives of this approach are to identify the levels of frequency and severity for various potential natural hazards and to build a suitable risk management strategy balancing risk retention, risk transfer and international donor assistance.

FIGURE III: CLIMATIC RISK LAYERS WITH SPECIFIC RISK MANAGEMENT STRATEGIES



Source: Ghesquiere and Mahul, 2010

As illustrated in Fig. 3, the risk retention layer includes highly frequent events with low severity of impact, such as a small drought episode or an occasional poor performance in crop yield. This layer, characterized as non-catastrophic risk, is managed by maintaining a reserve of financial capital or use of contingent credit by governments. Farmers can adopt several informal strategies to protect against this area of risk: using crop species adapted to have higher resistance to drought, diversifying farm income with other kinds of production or off-farm income sources, and saving a reserve of capital to smooth consumption under favorable or non-favorable climatic conditions. Risk transfer strategies are used for natural disasters with high severity but low frequency. This layer of catastrophic risk can be managed with risk management strategies including private-public partnerships, insurance backed by an international reinsurer, or use of catastrophe bonds (Kunreuther et Heal, 2012). Catastrophic risks have a systematic characteristic when they hit multiple farm incomes across a large geographical area. This systematic risk exposes an insurance company to significant financial losses and requires a reinsurer to transfer risk to the international market. Importantly, the demand for traditional catastrophic risk insurance is surprisingly low, as the probability of such events is wrongly estimated by farmers to be nil, rather than low (Barnett, Barrett et Skees, 2006).

This paper focuses on hedging non-catastrophic risk for crop producers. Weather derivatives can be purchased independently by crop producers to cover non-catastrophic risk in the retention layer and hedge loss of income. By their nature, weather derivatives are more suited for this layer of risk because their payout frequency is better matched to the frequency of this kind of income shortfall. In addition, current AgriStability programs are better suited to the catastrophic layer of risk that happens infrequently but requires more resources to properly assess the margin impact and offer suitable compensation.

III. Derivatives

The weather-based insurance contract presented in this paper is based on a long-put option derivative framework. To offer a better understanding of weather-based insurance contract, we first presented the concept of a financial derivative. The next section is concluded with an introduction to a payoff structure for a put option on a stock price that will be reused with the weather-based insurance framework.

i. Definition

A derivative is a financial instrument whose value is determined by the price of an agreed-upon underlying asset or set of assets and how the payoff is framed relative to this price. This underlying asset can take several forms: commodities, currencies, bonds or corporate stocks. Derivatives can be customized for a specific deal and traded over-the-counter (OTC) with another party or standardized and traded on the Chicago Mercantile Exchange (CME).

(Hodgkins, 2014) generalized three main characteristics of derivatives. First, a derivative is unique in that no assets change hands in the transaction – rather, it's a contract between two counterparties that offers the right, but not the obligation, to sell or buy the underlying assets at a pre-defined price. This agreement, known as an option, gives the opportunity for the involved parties to come to an agreement on a future settled price based on each individual's view of the future. The second characteristic is that derivatives payouts are based on uncontrollable future events, happenings, or occurrences. Both agents must use public and private information to estimate the probability of all possible outcomes in order to make a judgment call. Finally, derivatives have a zero-sum settlement. In essence, the loss of one is offset by the gain of the other; no overall value is created but a transfer of wealth occurs between the parties based on the outcome of the underlying asset. To sum up, a derivative can be initiated by two parties with divergent views who are willing to engage a contract that could benefit either of their views, the options contract makes this agreement official.

In agriculture, futures contracts, forward contracts and options are well-implemented derivatives for managing price risk. In a futures contract, the purchaser assumes the obligation to purchase and receive the underlying asset on the contract's expiry date. The seller of a futures contract assumes the obligation to supply and deliver the underlying asset on the expiry date. A forward contract is a customized contract between two parties to buy or sell an asset at a specified price at a future date. The main difference between the two is their standardized form in regard to quantity and quality. Futures contracts facilitate high volume trading. Forward contracts are traded over-the-counter with specific conditions negotiated by both parties for specific purposes. Options contracts offer the right, but not the obligation, to buy or sell a futures contract of a stated commodity at a given strike price on or before the expiration date. In the agriculture business as in other forms of business, three main purposes drive the use of derivatives: arbitrage, speculation and hedging.

ii. Arbitrage

Arbitrage is a financial strategy where an investor locks in risk-free profit by taking advantage of a disparity of prices in different markets. The easiest arbitrage strategy is called "cash and carry". This strategy consists of simultaneously selling a futures contract on an asset and buying the asset itself, but with each valued at a different price. In the case of stock, an investor could buy a stock at $50 and sell a futures contract for a price of $75. If the investor keeps the stock and delivers it at the end of the futures contract, they lock in a $25 profit. However, in this simple example, many investors could see the same disparitie and systematically sell the futures contract, putting downward pressure on the contract price that would converge to the stock price until both are even. From this example, we can see that arbitrage activity tends to eliminate price disparities by themselves, and arbitrage opportunities as a result. The no-arbitrage hypothesis is one of the 3 fundamental assumptions of Arbitrage Pricing Theory (APT) developed by the economist Stephen Ross in 1976.

iii. Speculation

By its nature, a derivative instrument can be seen as a speculative investment process since the two parties each have a view of the future, and this view is a judgment call on whether the value of the underlying asset will increase or decrease. Investors seeking protection against inflation or diversification in a market uncorrelated with the equity market can enter into a derivative contract in the commodity market without even buying the commodity itself, speculating only on the derivative price without needing to hedge this position on an asset. Some will argue that this speculation can cause additional pressure on the asset price on the demand side, an argument based on the no-arbitrage theory. In the agricultural industry, derivative instruments applied to commodity futures contracts are suspected to have increased the volatility of commodity prices, disconnecting them from the fundamental economics (Baffes et Haniotis, 2010)

However, the literature is divided into two camps in terms of the significant causal relation of speculation on commodity price fluctuations since the financial crisis of 2008, when many noncommercial traders took a long position in the commodity market, inducing upward pressure. (Trostle, 2012) argues that speculator activities add liquidity to a market and risk-seekers are necessary to counterpart the risk-adverse, explaining upward prices by pointing to fundamental price drivers such as weather-related shortfall in supply, diversification of row crop usage into bio-fuel industries, or emerging demand from Asian countries. On the other hand, some argue that the individual investors seek returns for their investments, but collectively, artificially induce price pressure in the cash market though the derivative futures market (Etienne, Irwin et Garcia, 2018). Consequently, although derivatives are considered a good instrument to increase liquidity and add diversification to asset managers' portfolios, the causality between them and price fluctuations is empirically demonstrated.

iv. Hedging

Finally, derivatives were originally used for hedging as risk transferring tools and risk managing tools. Using derivatives to manage risk allows a party to transfer the risk to a counterparty willing to bear the risk under remuneration or able to manage it via diversification or risk transfer to another agent. It is important to specify that in such agreements, the risk still exists, but exposure to the risk is transferred to a counterparty in exchange for remuneration. Risk transferring is the insurance company process in which a premium is paid in exchange for an indemnity if a disaster occurs. For instance, a catastrophe bond is a debt instrument that raises capital in exchange for an interest payment, where the face value is reimbursed at maturity or used for funding the disaster relief force should disaster occur. With the same hedging feature, a weather-based parametric insurance contract will offer compensation according to the level of the index, thus providing coverage against climatic hazards.

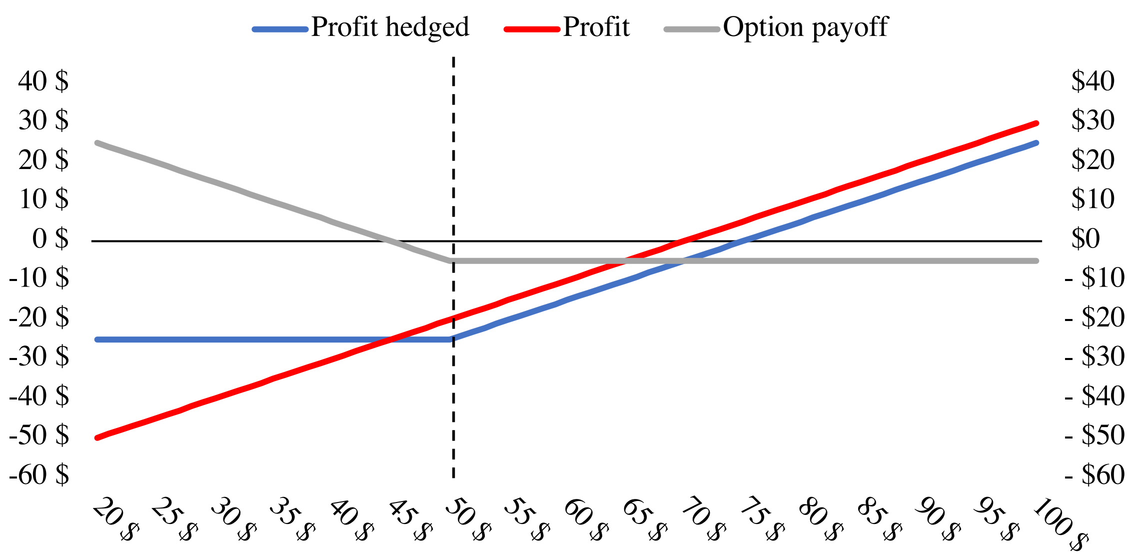
v. Payoff structure

Understanding the intuition behind a derivative makes it easier to understand the index-based parametric insurance product. However, there is a well-known distinction between the underlying index, i.e., the price of a stock and the climate index. In the first case, the profit generated by a financial derivative is the difference between the strike and the price at the time the option is exercised. In an insurance context based on a climatic index, it is important to evaluate the elasticity of grain yields with respect to the index in order to estimate an adequate compensation, i.e., one that covers the loss of income.

An investor can use a put option as price risk management for an investment in a stock priced at $70 with a three-month investment horizon. The investor is risk-adverse and wants to hedge his position in case the economic environment turns out to be unfavorable, so he buys a put option at $5 giving them the right, but not the obligation, to sell the stock at a strike price of $50 three months later. If the stock price closes under the strike price (put option is in-the-money), the investor can sell his stock at $50, limiting his loss to $25 ($20 of capital + $5 of option premium), as illustrated by the blue line in Fig. 4.

An investor can't be certain of future economic conditions, so they need to consider what the returns on an investment would be in a favorable or an unfavorable economic environment. In the example above, for the hedged position the loss is minimized to $20 while the potential future gain is infinite, and in the unhedged position, the investor can lose their initial investment ($70) while the potential future gain is still infinite. The important point here is that risk management doesn't guarantee revenue but rather, stabilizes revenue through the favorable and unfavorable economic environments a business may face by exchanging payment of a premium in favorable states for a payoff in unfavorable states.

FIGURE IV: FINANCIAL PUT OPTION PAYOFF STRUCTURE



In financial terms, an investor is said to have a long position when they expect to benefit from an upward movement (bullish) in the value of the underlying asset, and to have a short position when they expect to benefit from a downward position (bearish). Initially, our investor has a long position on the stock since they seek a favorable economic environment that should increase the stock valuation. The investor purchases a long position on a put option because they benefit from an increased option value when there is a downward stock price movement. As a result, their final position is composed of a long position on the stock price and a long position on a put option valuation.

The purpose of this paper is to hedge production risk against a downward yield realization with a long-put position on a weather-based insurance contract with a similar payoff structure. The closing stock price is substituted with the Palmer Z-Index as the underlying index, and the y-axis observation is that crop yields are subject to decrease when the climatic environment is unfavorable. The insurance contract stabilizes revenue through favorable and unfavorable climatic environments based on the same logic as we see with financial derivatives and favorable or unfavorable economic conditions. The return on a financial option is intrinsically linear due to the nature of the contract, i.e. the difference between the strike and the spot price. However, since the relationship between crop yields and weather conditions can take different forms, the specification in the econometric analysis need to account for this distinction. For this paper, we simplify the model by assuming that the relationship is linear with a break point at strike of 0.

IV. Weather-based derivatives

i. Literature

The first derivative was traded in 1997, when an OTC contract embedded a weather risk option in a power contract with Aquila Energy Corporation. Since then, the volume of trade has increased exponentially. The El Niño winter of 1997-1998 was widely publicized, alerting corporations who chose to hedge their earnings from significant decreases in value due to significant meteorological hazards. Since then, use of a weather-based derivatives framework has been assessed in the literature in various contexts: agriculture business (Musshoff, Odening et Xu, 2009), low income countries (Barnett et al., 2008), the construction industry (Alzarrad, Moynihan et Vereen, 2017), the wine industry (Seccia, Santeramo et Nardone, 2016), and revenue smoothing in the golf business (Leggio, 2007).

Perez-Gonzalez et Yun (2010) demonstrate that the use of weather derivatives as an active risk management policy does have an effect on a firm's value, offering four notable conclusions. First, firms that are highly exposed to weather volatility have significantly lower valuations, less debt financing and less dividend-paying policies. Second, weather exposure susceptibility before 1997 is a strong predictor of derivatives use after 1997, and the firms previously highly exposed are two to three times more likely to use derivatives. Third, the use of derivatives leads to an economically important and statistically robust increase in firm value; these authors found a significant increase of at least 6% in market-to-book ratio for firms using derivatives. Fourth, hedging leads to more aggressive financing policies and higher investment levels since the smoothed cash flows increase debt capacity by reducing distress costs or other financial friction. The authors concluded that those whose earnings were exposed to weather-risk consequences before 1997 saw an increase in value after adopting a weather-based strategy to stabilize income.

With weather-based derivatives, the underlying is not an stock price, but an uncontrollable climatic index. This index offers a serious advantage over traditional insurance since it reduces asymmetric information between the insured and the insurer, and transaction costs are lower because the insurer doesn't need to deploy resources to assess the damage to be covered (Barnett et al., 2008). Moreover, weather derivatives are simple in form, standardized and easy to understand, and therefore available to all kinds of buyers for the purpose of adding liquidity to cashflow management – unlike insurance contracts that are complex, non-liquid and unique to each insured party (Adaletey et al., 2020).

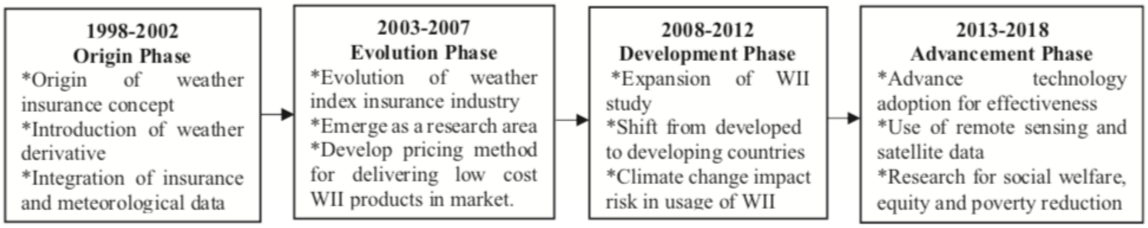
Singh and Agrawal (2019) review the academic literature on agriculture risk management with weather index insurance (WII), with a broad and integrative approach. Based on a 20-year body of literature beginning in 1998, their study examines 158 academic articles with quantitative and qualitative approaches, to identify four main development phases of weather risk management as follows:

The Origin Phase (2003-2007) is so named because this was the period when the WII domain first evolved, both as an actuarial industry and an academic field. Primarily, the focus was on developing insurance contracts based on heating degree-days (HDD), a metric to monitor the energy consumption required for growing crops, as a predictive index for estimated yields. This index was believed to be correlated enough to be used as an underlying index in an insurance policy. As awareness of global warming grew, researchers wondered how such a tool could still be effective in a climate change environment. Finally, studies of actuarial interest in pricing techniques concluded that these weather-based contracts offer a low-cost substitute for informal risk management strategies for smoothing income through unfavorable climatic environments.

The Development Phase (2008-2012) is characterized by the international expansion of the academic field in developing and developed countries such as China, India, Germany, the United States and Kenya. Quantitative study assessed what made farmers from poor backgrounds or economic situations willing or unwilling to pay WII contract premiums. As a result, the main focus was to study challenges in the usage of WII that would explain the low level of insurance demand observed by researchers. Finally, as attention to climate change increased in academic fields, researchers further studied the impact of climate change in poor countries with a focus on poverty trap mitigation, microfinance economic integration and the role of government as a premium subsidy supplier.

The Advanced Phase (2013-2018) explored new opportunities for weather-based insurance contracts as artificial intelligence was applied to large datasets of meteorological data and satellite image observations, enabling creation of the normalized difference vegetation index (NDVI). The focus was on increasing effectiveness in weather-yield relationship monitoring with robust predictive models, in order to improve the commercial viability of index-based insurance policies, which were plagued by a principal limitation: basis risk. In addition, WII effectiveness was assessed with human factor perspectives such as social protection, welfare impact, poverty reduction and social equity. Further, questions were raised in regard to the use of public funds to subsidize premiums in developing countries.

FIGURE V: WEATHER-BASED AGRICULTURE INSURANCE LITERATURE DEVELOPMENT PHASES



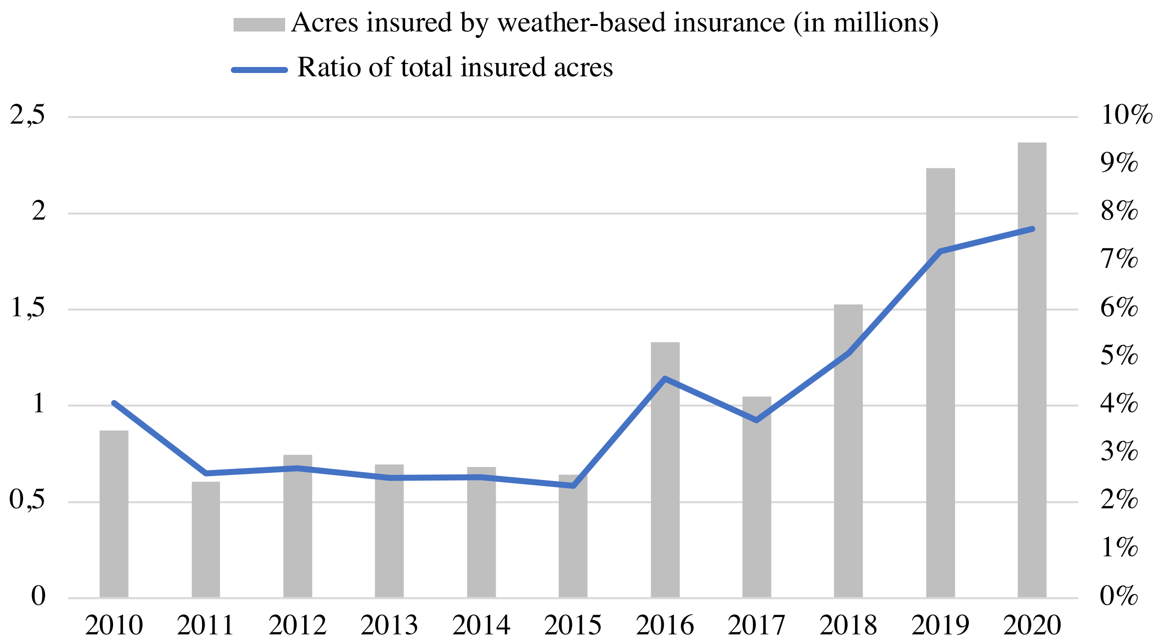
Source: Singh and Agrawal, 2019

This paper aims to contribute to the advancement phase through its identification of the potential of using the Palmer Z-Index as an underlying index for a crop insurance policy. Using a novel index is justified by the need to address drought episode impacts with a better monitoring index. As a result, this index with a short-term monitoring timespan will better fit the current need for an insurance tool that hedges farmers' incomes against short drought episodes.

ii. Weather-based derivatives usage in Saskatchewan

In 2020, the SCIC reported a total of 31 million insured acres of which more than 2.2 million acres were insured by weather-based programs. We see an upward trend in the total insured acres with weather-based programs even if the lands insured under such programs represent only 8% of the total insured lands.

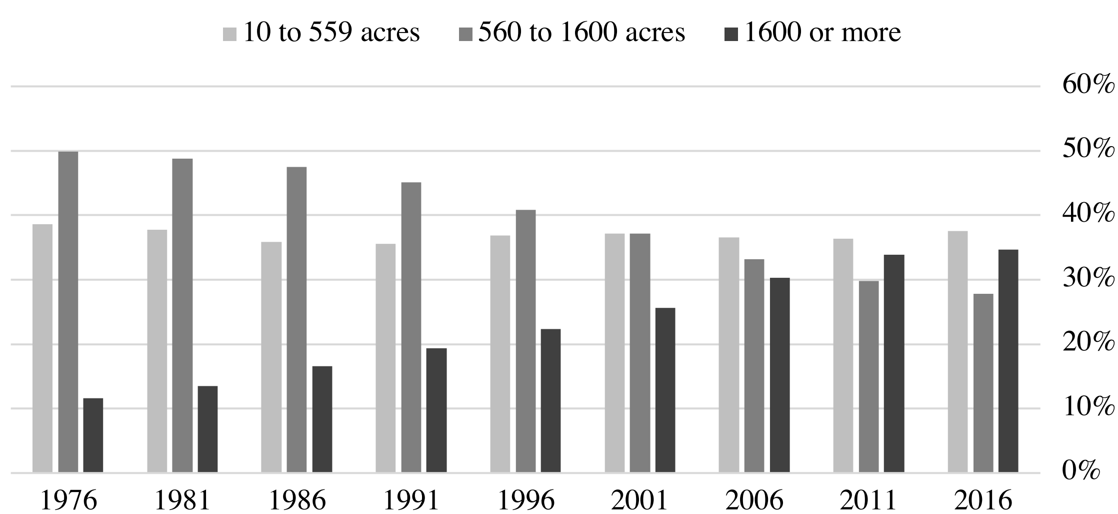
FIGURE VI: ACRES INSURED BY THE SASKATCHEWAN CROP INSURANCE CORPORATION



Source: Saskatchewan Crop Insurance Corporation (SCIC)

Khan, Rennie et Charlebois (2013) produced a first overview of the weather risk management practices of Saskatchewan's grain producers through an online survey interviewing 397 randomly selected producers. They found that 78 percent of respondents confirmed financial losses due to weather-related hazards within the previous three years. From a logistic regression estimating the decision to hedge their production with an insurance contract and/or usage of weather options, they found a significant positive relationship with the size of the farm operations, a non-significant relationship with the age of the owners and a significantly higher usage of risk management tools for cereal grain producers, oil seed producers and seed growers. They found that fewer than 10 percent of respondents used weather derivatives while 77 percent used insurance contracts, the majority of which (90%) were offered by the SCIC. When asked why they don't use weather derivatives, 57 percent of respondents said they were not aware of this risk managing tool and 34 percent said they lacked the knowledge they would need to use derivative products properly. The authors concluded that there would be a potential economic benefit for the agricultural sector and the province if the government worked to improve farmers' ability to use weather derivatives as a complement to existing insurance programs. Noting the possibility of bias due to the survey only being offered online, the authors suggested that the proportion of options-skilled farmers may be higher in those that are skilled with computers and add some positive bias to their final conclusions.

FIGURE VII: PROPORTIONS OF FARMS BY LAND SIZE IN SASKATCHEWAN



Source: Statistics Canada, table 32-10-0156-01

Since 1976, the overwhelming trend in agriculture has been toward fewer but larger farms, with the proportion of Saskatchewan farmers owning more than 1600 acres of land ballooning from 11%

in 1976 to 35% in 2016. Accordingly, as Khan and al. (2013) found a significant relationship between farm size and the use of weather-based derivatives, there is potential for increased use of weather-based derivatives driven by this trend.

V. Basis Risk

The hedging power of weather-based derivatives is dependent on a perfect correlation between yield losses and the climatic index. Since this correlation isn't perfect, the effectiveness of hedging is evaluated by minimizing the degree at which the payoff doesn't perfectly cover losses from the occurrence of a climatic hazard. This risk is the basis risk (Turvey, 2001). The weather-crop relationship is far more complex than a curvilinear function, as crop yields can respond differently to soil moisture, wind exposure or pest infestations from year to year, resulting in a farmer receiving a higher or lower payment than their observed yield shortfall. In the first situation, this upside risk would increase the magnitude of payout but also increase the premium cost for the insured. In the second situation, the downside risk of a lower payment would increase exposure to loss. Both kinds of risk hide the overinsurance or underinsurance effects that would impact the effectiveness of weather-based insurance and accordingly, the demand for weather-based insurance (Teh et Woolnough, 2018). Joshua Woodard et Garcia (2007) introduced basis risk in weather derivatives, breaking it down into three categories: local, geographic and product basis risk.

i. Local basis risk

Local basis risk refers to occasions when the underlying index registered at a given climatic station and the crop fields insured are in the same geographical area but somehow, real climatic conditions in the fields are more severe. Musshoff, Odening et Xu (2009) observed that the risk-reducing effect of weather-based derivatives decreases as the distance between the hedged field and the climatic station increases. They estimated that the level of correlation between the estimated yield and observed yield varied from 0.80 to 0.99 when the climatic station registering the rainfall sum index was 40 kilometers from the farm.

ii. Geographic basis risk

Geographic basis risk refers to the risk of using a non-local weather derivative instrument to hedge a specific event. It is the extent of the local risk when the underlying index cannot be monitored in the local area for some reason (e.g., lack of technology, financial resources, inaccessible land, etc.). In such cases, the underlying index is sourced from a nearby city or is calculated based on the spatially weighted average of several nearby stations. This risk can be increased by the presence of micro-climates that characterize a small geographic area with a higher probability of extreme weather events. Norton, Turvey et Osgood (2012) compared insurance payouts at nearby locations based on differences in the distance between stations and differences in altitude, longitude and latitude. They concluded that geographic differences were a poor predictor of payouts, but the presence of payout triggered by nearby station was a strong predictor. Thus, using multiple stations in a single contract as a ''risk portfolio'' structure would strongly reduce geographic basis risk for a single location.

iii. Product basis risk

In addition, product basis risk may remain if a weather-based derivative contract is not properly specified with respect to the relationship between yield and index due to the derivatives design itself. For instance, Conradt, Finger et Bokusheva (2015) compared a weather-based insurance design featuring a quantile regression with a traditional standard regression to estimate the index-yield relationship on a 31-year timeseries of wheat yields at 41 separate farms in Northern Kazakhstan. Quantile regression is more suitable for outlier-contaminated, non-normally distributed and skewed yield data that has a non-linear dependency with a climatic index. The authors showed that quantile regression is much more powerful in conditioning the index-yield relationship and that this addition leads to a higher risk reduction for a more efficient contract design since the design focuses on the actuarial calculations on the lower tails of income distribution. On the other hand, Farooq, Hussain et Siddique (2014) and Dalhaus, Musshoff et Finger (2018) and found a significant contribution to hedging effectiveness by adding phenology—the study of periodic events in biological life influenced by seasonal variations in climate—as criteria in an insurance contract. Their studies aimed to find the occurrence date at which grain enters the anthesis, flowering and grain-filling stages when it is crucially sensitive to drought stress, and to establish the derivative payoff based on the index observation at this date. They showed that weather-based insurance using Yearly Phenology Reporters—a publicly provided open dataset of plant growth stage occurrence dates, increased risk-averse farmers' expected utility and reduced financial exposure to drought risk. Thus, a weather derivatives framework based on a better index-yield estimation technique and better index observation timing can minimize temporal and product basis risk by increasing the measurement of correlation between the yields and the index (Zhang et al., 2010).

The literature on basis risk is extensive and many other studies could have been included in this paper. However, product basis risk is in essence the most important risk remaining in this insurance policy, because it is the result of all basis risk plaguing the insurance product. If the design is wrongly specified in regard to the distance between the insured land and the climatic station, the timing of the drought relative to the most fragile crop growing stages, the climatic index itself or the econometric methodology that estimates the payoff, there is no chance that the product will correspond to the coverage needed. Thus, as an initiative to improve climatic risk management by reducing the product basis risk, this paper presents an insurance policy with an original framework featuring a climatic index monitoring drought over a short period of time close to the insured area.

VI. The Palmer Z-Index

In agriculture, weather-based insurance based on rain levels and/or temperature exposure is commonly used to assess the duration and severity of the impacts of climate hazards such as drought or floods on yields. table 1 presents several weather indices used in the literature to assess drought spells. Some of these have been used in weather-based insurance policies and their effectiveness in reducing risk has been demonstrated in the literature (Štulec, Petljak et Bakovic, 2015). The choice of the Palmer Z-Index as the underlying index is based on the analysis of Quiring et Papakryiakou (2003). These authors tested multiple curvilinear regression-based crop yield models for 43 crop districts in the Canadian prairies cultivating Canada Western Red Spring wheat using 4 different established drought indexes: The Palmer Drought Severity Index (PDSI), the Palmer Z-Index, the Standardized Precipitation Index (SPI) and the NOAA Drought Index (NDI). They concluded that the Palmer Z-Index was the most appropriate index for predicting spring wheat yields during crop seasons from 1920 to 1999 when significant moisture stress occurred in presence of agricultural drought.

TABLE I: SUMMARY OF WEATHER INDICES IN LITERATURE

Index	Description	Reference
Palmer Deficit Index & Z-Index	Precipitation and temperature analyzed in a water balance (PDSI and PHDI) model; comparison of meteorological and hydrological drought across space and time	(Palmer, 1965)
NOAA drought index	Dry spell defined as an 8-week period in which average precipitation falls below 60% of normal precipitation based on the most recent 30-year period	(Strommen et Motha, 2019)
Standardized precipitation index (SPI)	Allows measurement of droughts and wet spells in terms of precipitation deficit, percent of "normal," probability of no exceedance, and SPI at multiple simultaneous timescales with potentially different behavior in any of them	(McKee, Doesken et Kleist, 1993)
Vegetation Condition Index	Satellite AVHRR radiance; measures "health" of vegetation	(Kogan, 1995)
Drought Monitor	Integrates several drought indices and ancillary indicators in a weekly operational drought-monitoring map product	(Svoboda, 2000)
Growing degree-days (GDD)	Amount of heat units used to estimate the growth and development of crops in the growing season.	(McMaster et Wilhelm, 1997)
Cumulative rainfall index	Sum of daily precipitations on a weekly, monthly, or crop season time scale. Drought spells defined as a departure from the average	(Turvey, 2001)
Multi-index drought (MID) model	The MID model was developed to combine the strengths of various drought indices for agricultural drought risk assessment	(Sun, Mitchell et Davidson, 2012)

i. Definition

Heim (2002) reviewed all drought indexes introduced in the United States since the 19th century and identified the work of Palmer (1965) as a central index developing a water-budget-based approach to drought. The main advantage of the Z-Index over the three others is the non-memory-based process of the computation; the monthly observation indicates the drought intensity for each unique month without smoothing for moisture observation for up to 3, 6, or 12 past months in alternatives tested by Quiring et al. (2003). Since crops are fragile on a timescale of 2 to 3 weeks, a month-long drought is enough to cause an irreversible decrease in crop yield. Using a metric calculated by a memory-free process ensures a well-specified and consistent pattern between the cause and the effects of a sudden and short-term drought on grain yields susceptible to short periods of moisture stress. The Palmer Z-index reports any departures of the weather of a particular month from the average moisture climate for that month, regardless of the climatic conditions observed in the previous month (Heim, 2002). This index is a continuous variable that can register eight classifications of climatic conditions ranging from extreme drought to extremely wet, as illustrated in table 2.

TABLE II: Z-INDEX DROUGHT CLASSIFICATION

Index value	Classification
-4.00 or less	Extreme drought
-3.00 to -3.99	Severe drought
-2.00 to -2.99	Moderate drought
-1.00 to -1.99	Mild drought
-0.50 to -0.99	Incipient dry spell
0.49 to -0.49	Near normal
0.50 to 0.99	Incipient wet spell
1.00 to 1.99	Slightly wet
2.00 to 2.99	Moderately wet
3.00 to 3.99	Very wet
4.00 or more	Extremely wet

Source: Palmer (1965)

Palmer's objective was to create a computed index that would evaluate departures from the normal average levels of moisture specific to this region. Time independence was another challenge that Palmer attempted to address by adding weighting factors to the index. Thus, May and September departures from normal precipitation levels could be -60 mm and -20 mm respectively but still computed as a Z-index value of -1. Accordingly, the index needs to be geographically independent since soil characteristics and available water capacity (AWC) create different retention rates which alter the volume of water stored in the soil and available for growing crops. With time and geographical independency, the Palmer Z-Index offers a measurement of the abnormality of recent weather for a region, the opportunity to compare current conditions with a historical perspective, and a spatial and temporal comparison with historical droughts (MacKerron, 2005).

The Z-Index is derived from a soil/moisture balance algorithm based on various soil and temperature variables such as daily air temperature and precipitation data, soil moisture storage, runoff and potential evapotranspiration (PE). Soil moisture storage is defined as two soil layers, surface layer Ls and underlying layer Lu, where Ls, at a thickness of 25 mm, needs to be saturated so that water can reach Lu. Runoff happens when both layers are saturated. Potential evapotranspiration—water lost to the atmosphere by transpiration from living plant surfaces (Rind et al., 1990), —is computed using the Thornthwaite (1948) method, where water is extracted from the surface layer Ls when monthly evapotranspiration exceeds monthly precipitation. Finally, the evapotranspiration of the underlying layer Lu depends on the underlying layer of soil, potential evapotranspiration and the combined levels of water in both layers (Quiring & Papakryiakou, 2003).

Dai, Trenberth et Qian (2004) derived a monthly dataset of the Palmer Drought Severity Index (PDSI), from which the Z-Index is derived as a memory-free process, from 1870 to 2002 for some parts of China, the former Soviet Union, Mongolia, and Illinois in the United States. They found that the PDSI is significantly correlated with the soil moisture content to a depth of 1 meter in the warming season ($r = 0.5$ to 0.7), and that correlation was higher in late summer and lower in spring since the impact of snow on soil moisture isn't taken into account in the index calculation. In Illinois, the correlation between monthly mean soil moisture content and the model-computed PDSI and Z-Index were 0.58 and 0.72 respectively at a depth of 0.9 meters.

ii. Limitations

However, Karl (1986) have identified some drawbacks to use of the Z-Index that can be outlined as follows: the Z-Index evaluates the available flow of water in a given month but doesn't take into account the water stock already available. In fact, the Z-Index doesn't account for snowfall, snow cover or frozen ground available for soil moisture storage in spring melt periods. Moreover, the index is sensitive to the AWC of a soil type so comparing climate divisions may be too general without soil characteristics. Thus, the division into two layers of soil for the water balance computation is an oversimplification.

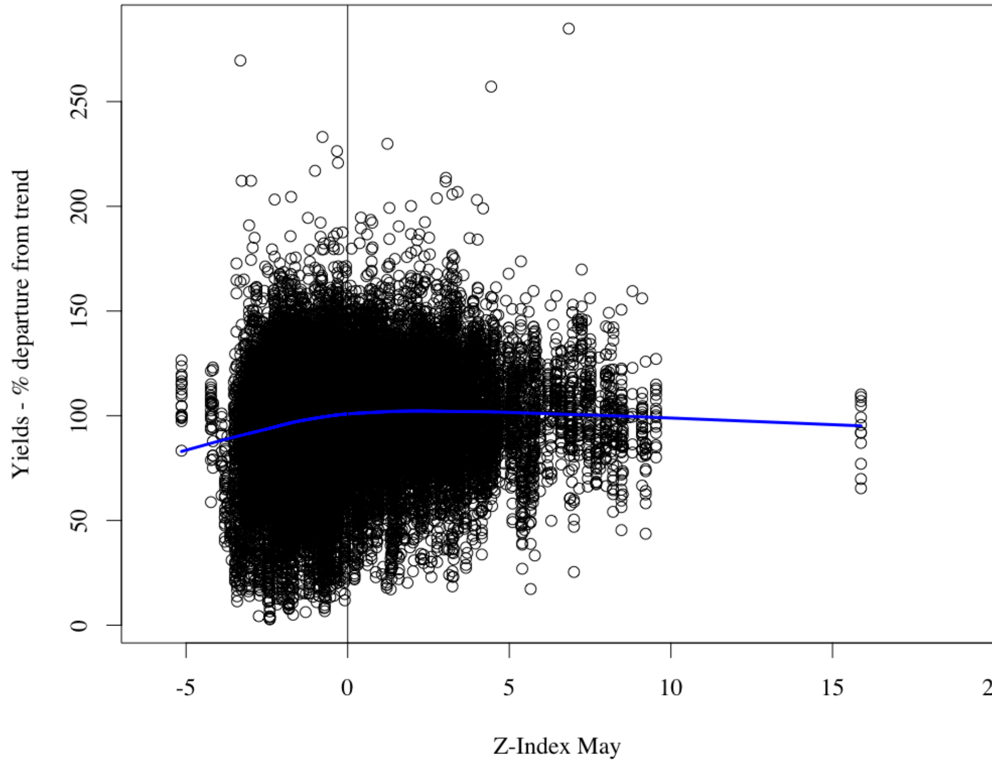
iii. Application

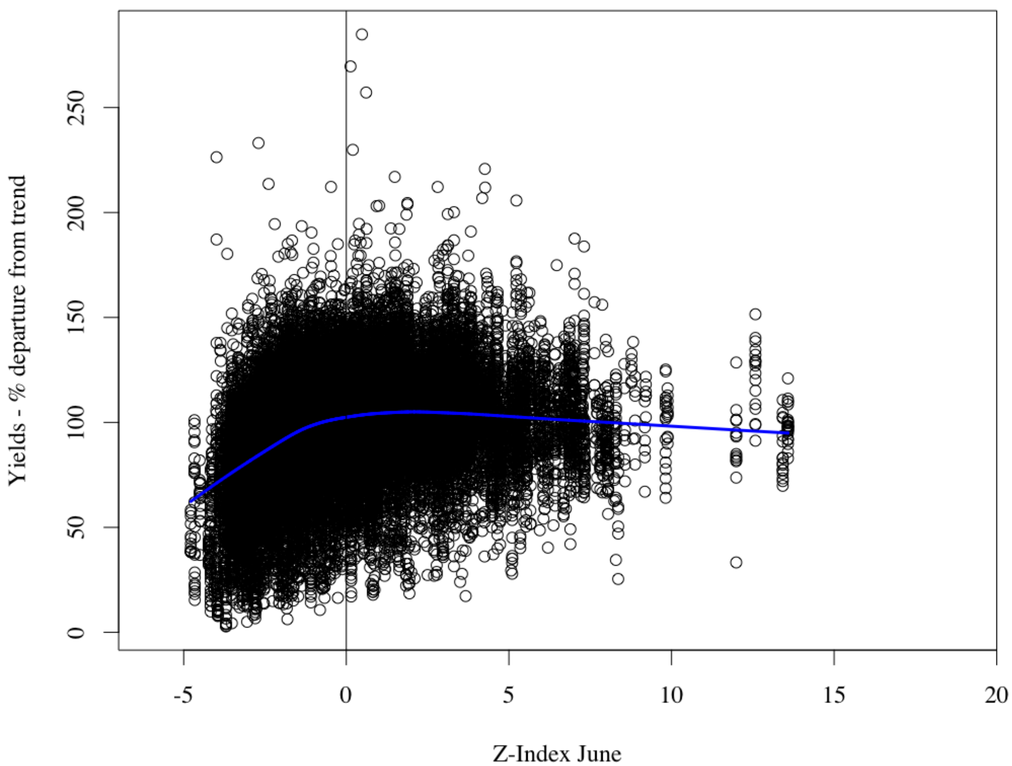
Despite all the drawbacks and limitations of the Z-Index, this index is used with several other indices that form a complementary index to capture a period of drought. Sun, Mitchell et Davidson (2012), presented the MID model: an operational model framework combining the strengths of the Palmer Z-Index and various others drought indexes to assess drought impacts on 6 growth stages of spring wheat in the Canadian Prairies. The prediction accuracy of this model is better than or occasionally equal to using a single drought index because it overcomes some of the deficiencies in the individual indices to evaluate all factors affecting crop sensitivity to soil moisture. Moreover, the authors conclude that adding drought indices that incorporate the groundwater recharge period (underground water available before the crop season) are useful for early drought risk detection. In fact, adding this component is particularly useful in arid regions where a weak groundwater recharge period means that above-normal precipitation levels will be needed to obtain practicable soil moisture. The MID index is more suited to arid regions in the southern prairies as it tends to increase its precision with multiple observations of a more varied precipitation pattern. The accuracy of prediction of yields based on the MID index is improved as the growing season progresses and is maximized in June and the beginning of July when the spring wheat growth process enters the crucial water-sensitive stages of heading and soft dough.

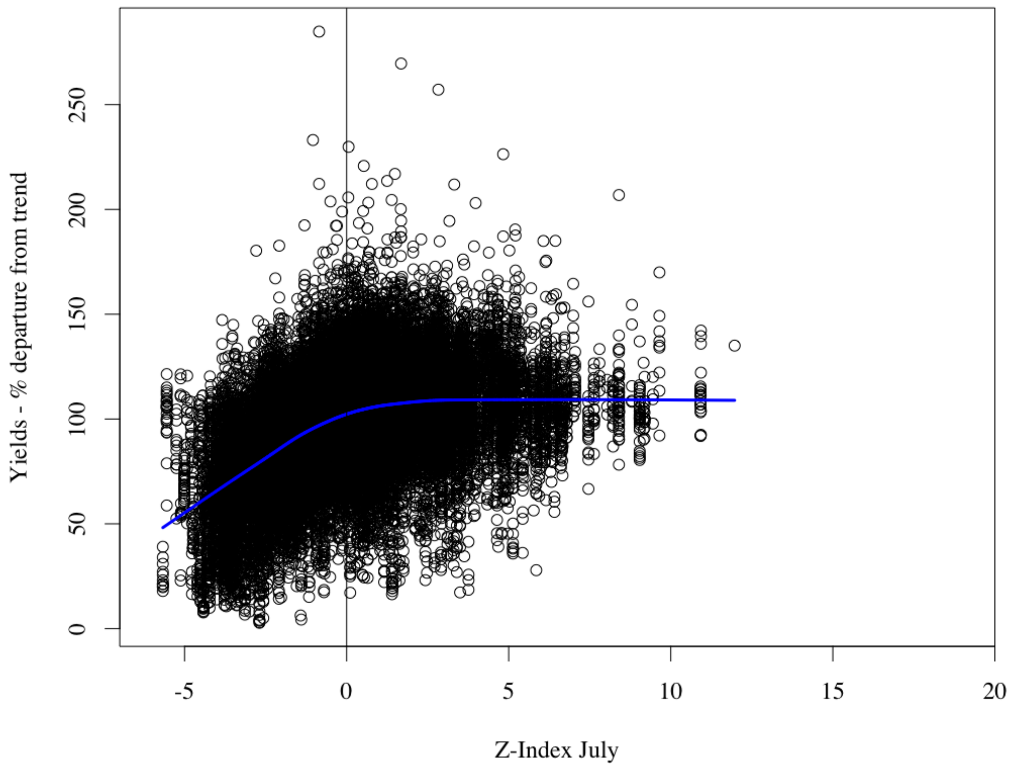
iv. Yield-Index relationship

Fig. 8 illustrates the short-put relationship between Z-Index observations and crop yields that is the focus of this paper. The left axis represents crop yields interpreted as departures from the normal, with the ratio of observed yields on the trend estimated by a locally weighted regression. In abscise is the Z-Index observation for each month of the growing season. Then, the short-put relationship is clearly illustrated by the blue line in the graphs. From a visual inspection, we can hypothesize that the short-term relationship estimated for the month of July would be the model with the highest predictive power since the shape of the "hockey stick" is well illustrated.

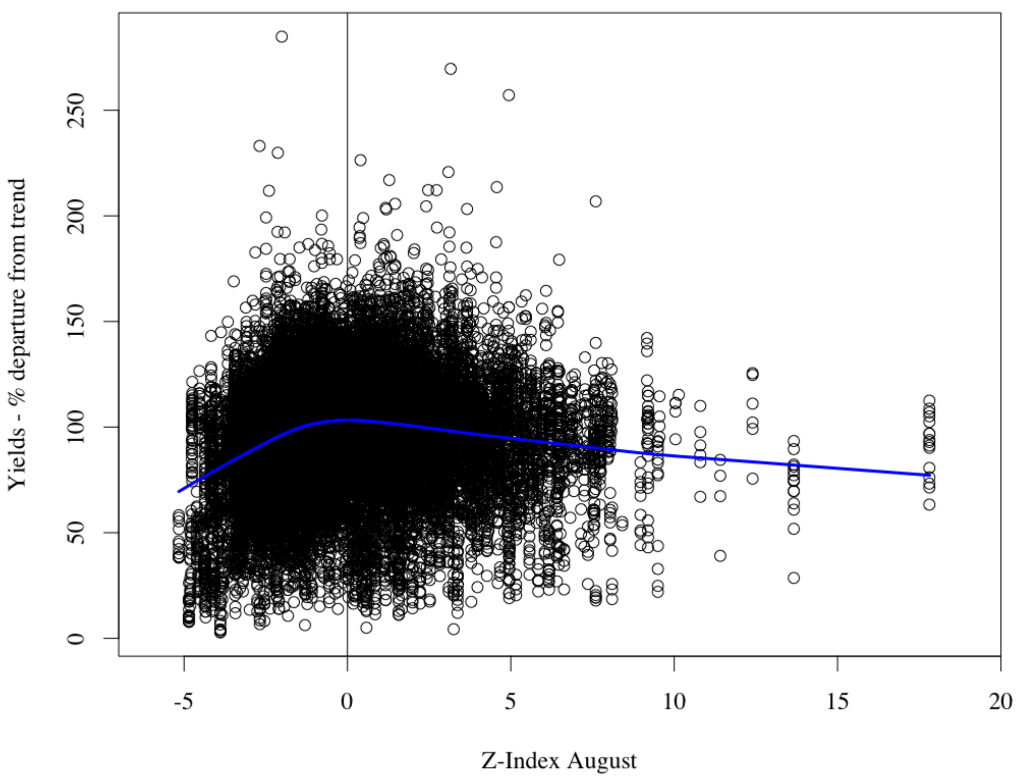
FIGURE VIII : SHORT-PUT RELATIONSHIP BETWEEN Z-INDEX OBSERVATIONS FROM 36 CLIMATIC STATIONS AND CROP YIELDS (WHEAT, OATS, BARLEY, CANOLA) FROM 144 RM







Yields - % departure from trend
Z-Index July



Yields - % departure from trend
Z-Index August

Methods

The next section will focus on the methodology used to estimate the short-put relationship, to define an insurance policy inspired from a long-put option, and to estimate the effectiveness and cost of this insurance policy. The descriptive data on the yields and Z-Index will be presented along with the methodology that couples rural municipalities with their respective climatic stations. Lastly, equations to estimate the short-put relationship will be presented, followed by the results.

I. Data

Time series of crop yields were acquired from the Saskatchewan Ministry of Agriculture. These series are estimations from crop reporters and yields declared by individual farms centralized by the Saskatchewan Crop Insurance Corporation (SCIC) for insurance purposes from 1951 to 2019. All yields are expressed in bushels per acre on a yearly basis and reported on a rural municipality (RM) scale, which is the closest available observation level to a farm-scale perspective. Yield performance is recorded if there is a minimum of 2 producers harvesting 400 acres minimum each. Since many RMs have missing values in their data, we selected RMs that have at least 65 years of yields for spring wheat, oats and barley productions, and at least 50 years for canola (generalized canola production started in 1975). Of 296 potential rural municipalities, we were able to acquire yield records for 144 in an unbalanced panel dataset. Spring wheat, oats, barley and canola are classified as spring-sown grains, which complete their life cycle in the summer season. These crops would typically be seeded by mid-April to mid-May and would reach maturity after a life cycle of 80-100 days. Finally, they would be harvested in late August or early September before the first frost of autumn would damage the plants and reduce yields. Thus, we would define the growing season as the period of time from May 1st to August 31st.

Table 3 presents descriptive data on crop yields in bushels per acre, i.e., on a level basis. At first, we can see that wheat and barley are the most represented in the data, while oats and canola are less represented at 96 and 70 RMs evaluated, respectively, and a smaller number of observations. There is a significantly smaller number of observations for canola since there were few RMs harvesting it during a shorter sample period of 1975 to 2019.

TABLE III : CROP YIELDS IN BUSHELS PER ACRE (BU./AC.)

Grain	Number of RM	Observations	Min	Mean	Max
Spring wheat	144	9920	1	27.34	70.20
Oats	96	6527	1	52.49	155.80
Barley	140	9609	1	41.11	102.70
Canola	74	3856	3	24.44	56.69

The Palmer Z-Index observations were gathered from the AgroClimate division of Agriculture and Agri-Food Canada (AAFC) for 36 climatic stations on a monthly basis from 1938 to 2019, and no calculation was required to obtain the index. Covering the entire southern Saskatchewan area, the map in Fig. 10 illustrates the climatic stations in blue with their corresponding RM locations in orange. From the distribution of Z-Index observations for all 36 climatic stations used, we can see that dry or wet soil conditions are both likely to happen for each month of the growing season since the proportion of the Z-Index below 0 is around 0.5. However, the minimums around -5, maximums higher then 11 and skewness near 1 (except in July where skewness is 0.56) inform us that these distributions are positively skewed, so there is more weight on the left side of the distribution. This implies that dryer conditions (Z-index < 0) happen as often as wetter conditions but are less diffuse. In other words, dry episodes are likely to be registered between -4 and -1 but wet spells are registered between 1 and 10, thus are more diversified in regard to their intensity. A kurtosis of around 3 for August means that distribution is normal while other distributions have thinner tails.

TABLE IV: DESCRIPTIVE STATISTICS Z-INDEX

Month	% obs. < 0	Min	Mean	Max	Std. dev.	Skew.	Kurtosis
May	0.57	-5.14	0.08	15.88	2.30	1.10	1.87
June	0.52	-4.78	0.24	13.58	2.55	0.95	1.52
July	0.49	-5.67	0.17	11.97	2.38	0.56	0.65
August	0.56	-5.16	0.03	17.81	2.40	1.10	2.78

FIGURE IX: Z-INDEX MONTHLY DISTRIBUTION FOR 36 CLIMATIC STATIONS

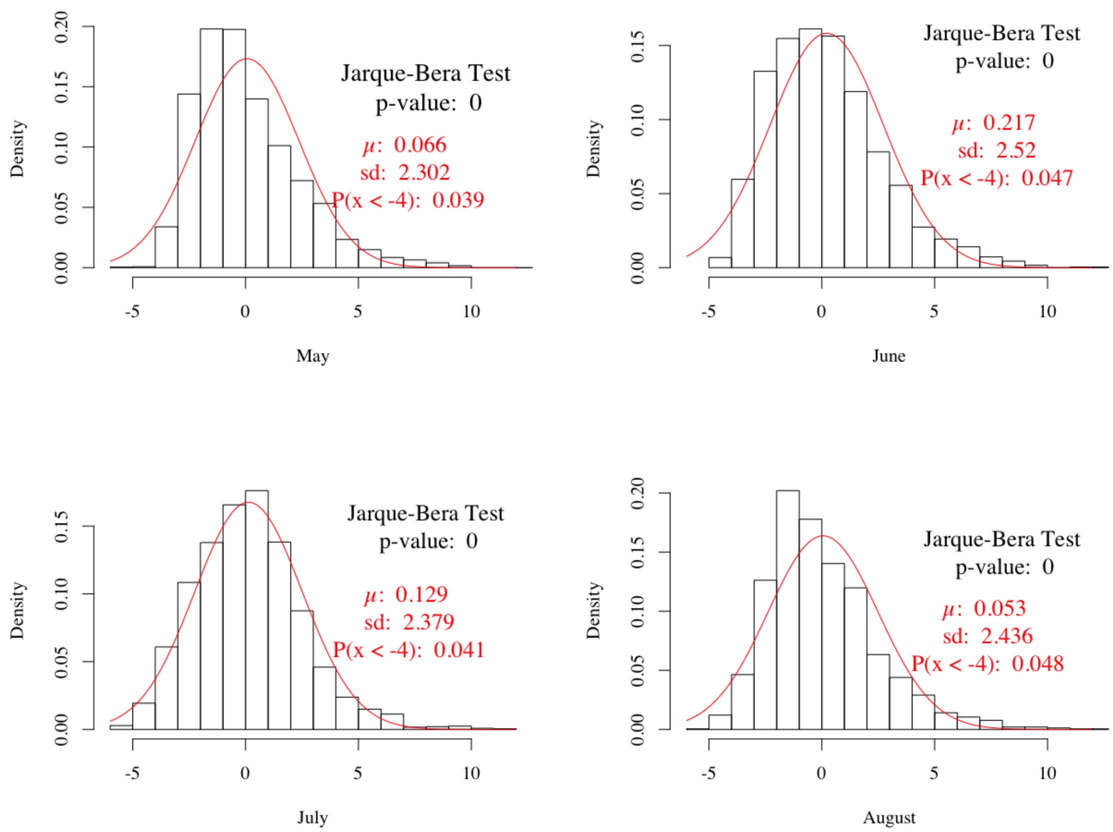


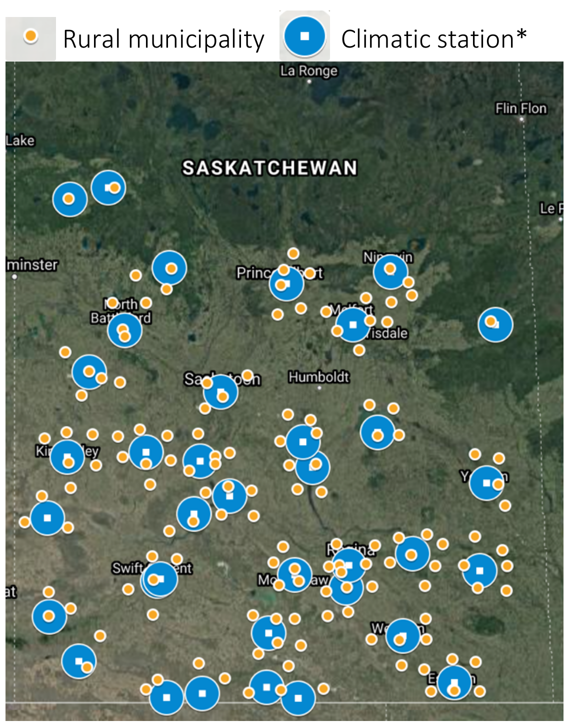
Fig. 9 shows the distribution of the Z-Index for each month of the growing season for all 36 climatic stations. Thus, these graphs aggregate all Z-Index observations independently without taking into account any geospatial correlation, while it certainly exists. However, it offers a global representation of Saskatchewan climatic conditions over a 69-year period.

The Jarque-Bera test assesses whether the Z-Index observations are not normally distributed. In each month, the null hypothesis of normal distribution is rejected. This can be explained by a simple observation of the graph where a left truncation seems to limit the lower tail to -4. The red line illustrates a fitted normal distribution in the data with the corresponding mean and standard error estimated. Since we seem to have a left-hand limit of -4, we estimate the probability of observing the Z-Index below -4. Recall that a Z-Index of -4 is defined as an extreme drought, so that any Z-Index observation at this threshold will be categorized as a catastrophic drought spell. Therefore, the probability of observing a catastrophic drought spell at one of the 36 climatic stations is around 4-5%.

II. Coupling rural municipalities and climatic stations

To estimate crop yield departures due to a drought episode, we must identify the closest climate station that recorded a climatic condition as identical as possible to the field conditions. AAFC furnished the geolocation coordinates with the climatic station data, and the geolocation coordinates for the rural municipalities were gathered using Google Geocode Service. This methodology is based on the idea that a rural municipality will be named after an associated major city or village. Then the distance between each RM and climatic station is computed using the great-circle distance equation: the length of the shorter arc of the great circle joining two points. Finally, based on Musshoff, Odening et Xu (2009), climate stations and RMs less than 40 kilometers apart were coupled to minimize local basis risk. This level of disaggregation of crop yields associated with a weather station within 40 kilometers aims to more accurately replicate a farmer's actual situation as compared to other research with higher levels of disaggregation [Quiring et Papakryiakou (2003); Vedenov Vedenov et Barnett (2004)]. As a result, we based our study on a total of 144 rural municipalities, 36 climatic stations, and 4 crops, amounting to a total of 474 relationships studied.

FIGURE X: COUPLING RURAL MUNICIPALITIES AND CLIMATIC STATIONS



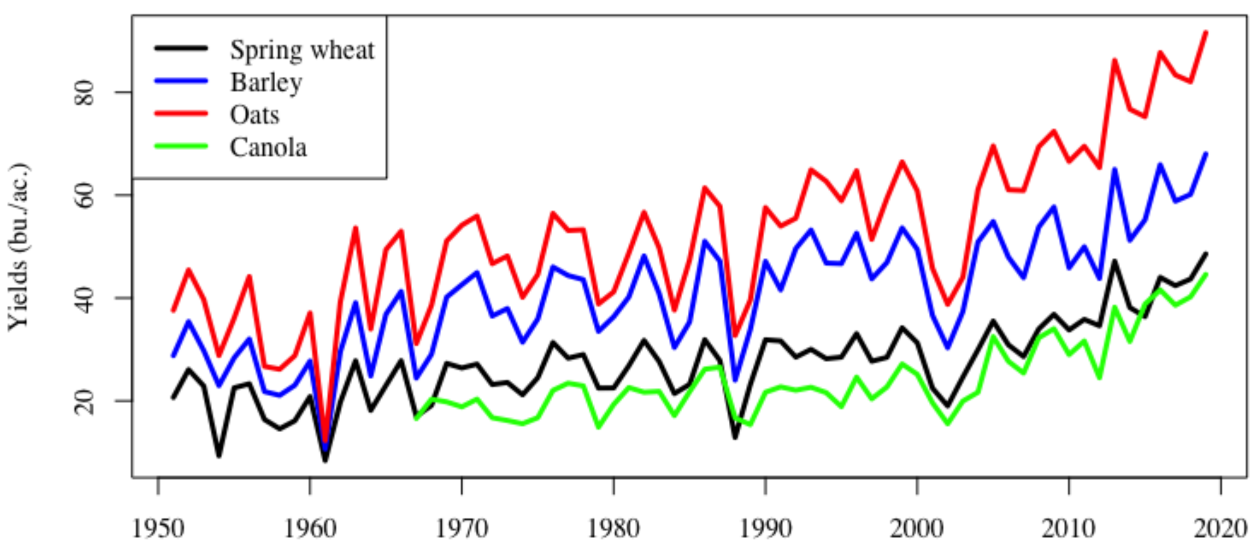
The blue circle does not represent the 40 km coupling scope used

III. Analysis

i. Detrending

A detrending technique is important because poor specification of a trend will directly bias evaluation of the drought impact as a departure from a poorly specified normal situation. The detrending technique is central to our analysis because it will produce a yield reference from which the departure will be evaluated. Technological evolution is recognized in the literature in many agronomics fields (genetics, engineering, soil manipulation techniques, etc.) causing yields to increase over time. Thus, the objective is to see how a drought would impact yields even if technological progress increases the magnitude of yields. It is obvious that the implementation of technological development has not been at the same pace for all RMs, thus we must individually assess each RM's trends. In addition, we can see in Figure 11 that an acceleration is observed in the yield trend that must be taken into account in the detrending yield technique. In regard to the Z-Index timeseries, trend estimations with OLS regressions were not statistically significant for each month. Therefore, detrending is not necessary.

FIGURE XI: RURAL MUNICIPALITIES' MEAN YIELDS PER CROP PRODUCTION



Lu, Carbone et Gao (2017) compute several techniques commonly used in the agricultural literature to isolate a trend from a time series. Comparing simple linear regression, second order polynomial regression, centered moving average, locally weighted regression and spline smoothing, they concluded that a locally weighted regression is best for simulation of a trend in a time series. Locally weighted regression involves a regression model based on a weighted least squares method that uses a local point of interest and assigns more weight to neighboring points and less weight to points farther away. The locally weighted regression R function Lowess was applied for this paper. The delta (d) was set to 1 and the f parameter (neighborhood size) was set to .5 to allow a level of smoothness enough to keep a trend design as suggested by Cleveland (1979).

After yields are detrended so that the mean is stable for all periods, we must control for heteroscedasticity caused by increased yield level over time. In other words, crop yield variance increases with the productivity shock of technological progress. The need for homoscedastic variance is essential for interpretation of drought impact independent of time and the technological environment. To compare 1960's drought to drought in or 2003, we need to compare the drought-impacted yields to the specific expected mean yields at these times. Lu, Carbone et Gao (2017) tested a multiplicative and an additive decomposition to evaluate a yield's departure from the normal. The additive decomposition supposes that the trend is subtracted from the time series so that the residuals are defined as a departure from normal expressed in bushels per acre. But as the magnitude of yields increases due to technological advances, the difference between the trend and the observed yields increases, making it impossible to compare drought events across time. For instance, a departure from the normal of 10 bu./ac., when compared with estimated trends of 17 bu./ac. in 1951 and 39 bu./ac. in 2019, would not have the same impact on a farmer's business operation. Thus, we need to use a ratio that can be compared across time.

Using a multiplicative decomposition, the standardized yields are the ratio between the yield and the trend, thus yields are now interpreted as a ratio from the normal that can be compared across time. Fig. 12 and Fig. 13 illustrate standardized yields obtained from the additive and multiplicative decomposition models respectively. From a visual inspection, we can see that additive decomposition resulted in heteroscedasticity while a multiplicative decomposition model removed it.

FIGURE XII: ADDITIVE DECOMPOSITION YIELDS - DEPARTURE FROM TREND IN LEVEL

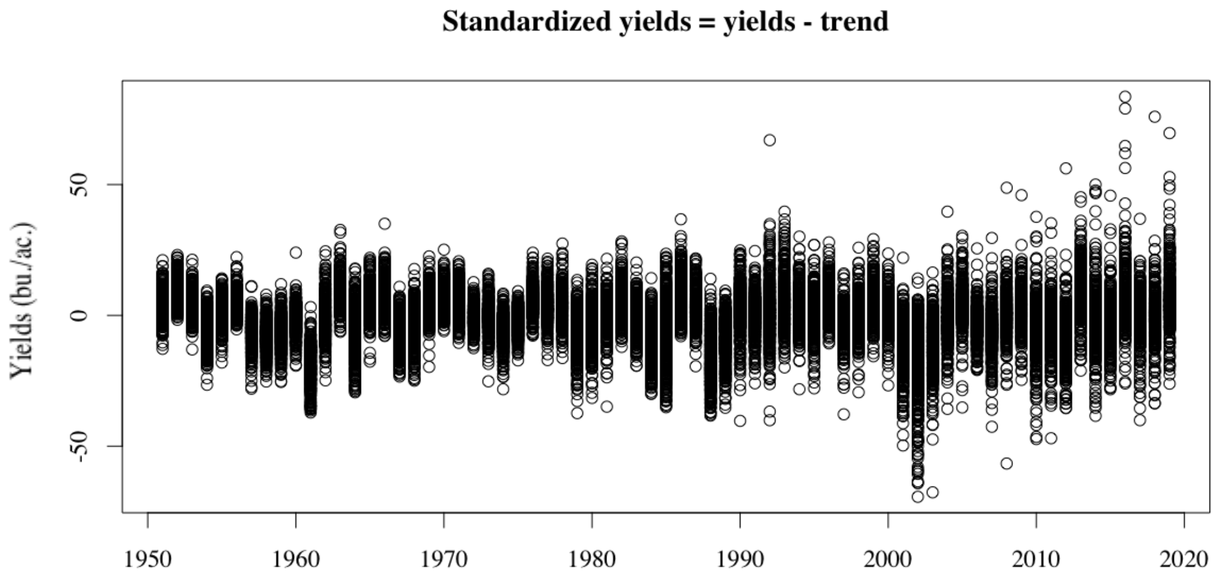


FIGURE XIII: MULTIPLICATIVE DECOMPOSITION YIELDS - DEPARTURE FROM TREND IN RATIO

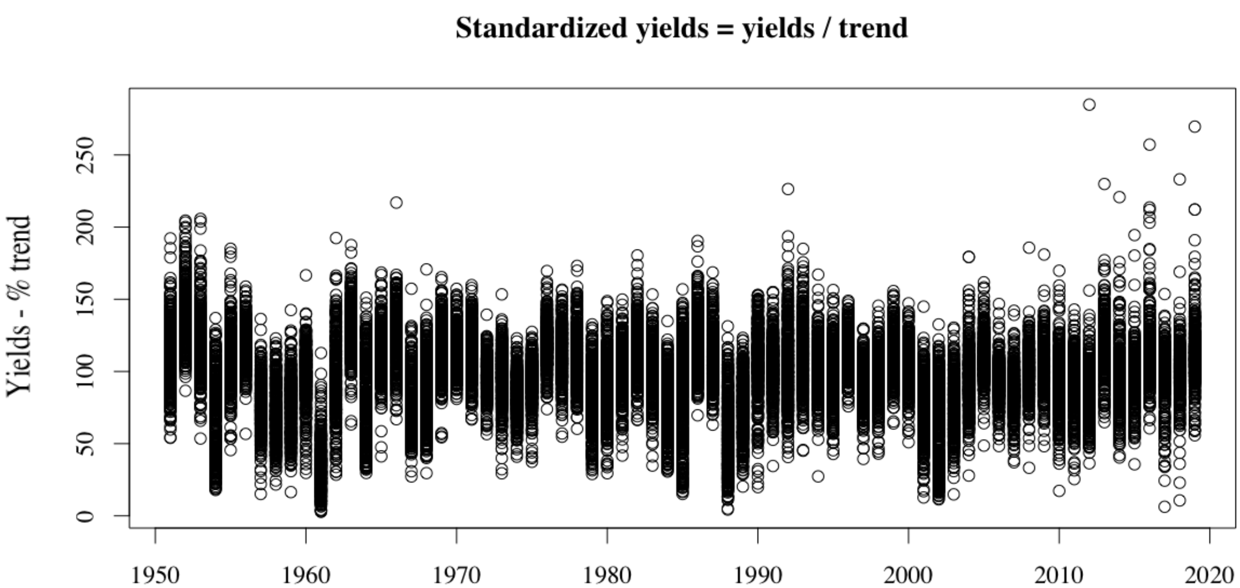
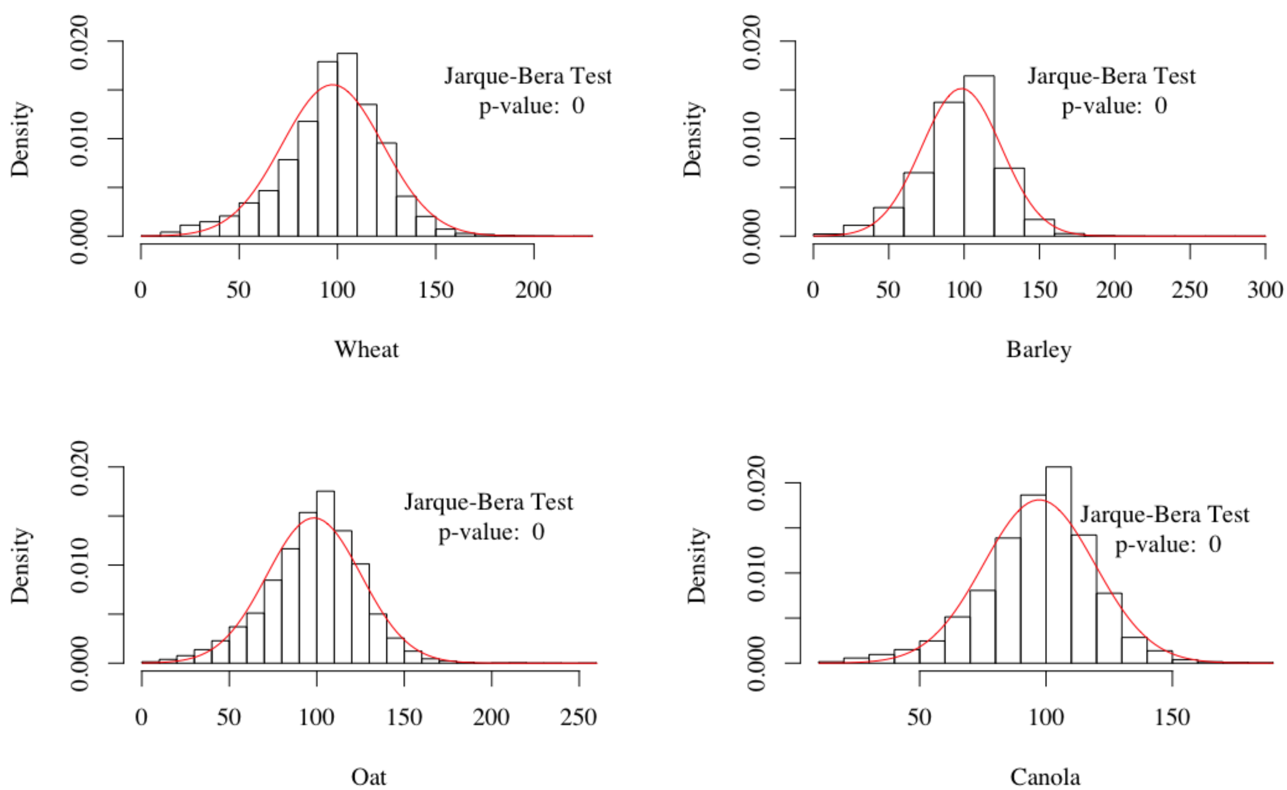


Table 5 summarizes the descriptive statistics of the standardized yields from the multiplicative decomposition. The mean hovers at around 98% with similar standard deviations of around 22-27. With skewness between -0.43 and -0.24 and positive kurtosis between 0.88 and 1.03, we can conclude that the distribution of detrended yields is symmetric with thinner tails then a normal distribution. The Jarque-Bera test for normality is rejected for each crop, confirming this.

TABLE V: DESCRIPTIVE STATISTICS - STANDARDIZED YIELDS (% TREND)

Grain	Number of RMs	Observation	Min	Mean	Max	Std. dev.	Skew.	Kurtosis
Spring wheat	144	9920	4.33	97.48	229.86	25.69	-0.43	0.88
Oats	96	6527	2.80	98.42	257.15	26.95	-0.24	0.87
Barley	140	9609	3.86	98.26	284.84	26.35	-0.28	1.03
Canola	74	3856	12.83	97.32	186.66	22.03	-0.43	0.93

FIGURE XIV: STANDARDIZED YIELD (% TREND) DISTRIBUTIONS BY CROP



ii. Model

The main contribution of this paper is to identify the ''short put'' relationship between an index reflecting drought conditions and crop yields on a rural municipality scale. This relationship is estimated using yields expressed in bushels per acre (Equations 1 & 2) and standardized yields expressed in departures from the trend (Equation 4 & 5). Here, the trend is estimated with a locally weighted regression that captures the yield for each combination of RM and crop individually as explained above.

Equation (1) is the first model to estimate the short-put relationship. Each variable is specified with 3 sub elements: t refers to the year of observation between 1951 and 2019, i is the identity of the RM, and c is the crop harvested. On the right side is the Z-Index observed for a chosen month, a dummy variable set to 1 when the Z-Index is higher than the strike S, and 0 otherwise, a fixed effect for each RM i, a fixed effect for each crop c and the residual. Thus, ν_{i} & τ_c are the fixed effects added to take into account non-observed individual characteristics for the RMs and crops.

The inflection point is set to the theoretical 0 mean of the Z-Index, where a negative Z-Index is computed for observed dry conditions and a positive Z-Index indicates wet conditions. $\hat{\beta}_1$ is a yield's elasticity to climatic conditions, while $\hat{\beta}_2$ is a specific yield's elasticity for Z-Index values above 0. The hypothesis of this model is to test if the estimated coefficients β_1 and β_2 are inverse values, and then subtract $\hat{\beta}_2$ from $\hat{\beta}_1$ to find a slope of 0 for positive values of the Z-Index. In other words, if $\hat{\beta}_1$ = - $\hat{\beta}_2$ is statistically not rejected, we have an inflexion point at Z-Index = 0, therefore the short put relationship is relevant.

$$yield_{t,i,c} = \beta_1 * Z_{Index_{t,i}} + \beta_2 * \left[I\left(Z_{Index_{t,i}} > 0\right)\right] * Z_{Index_{t,i}} + \beta_3 * trend_{\mathrm{t,i,c}} + \nu_i + \tau_c + \varepsilon_{t,i,c} \quad (1)$$

In Equation 2, an interactive dummy is added to evaluate the efficiency of the short-put relationship when catastrophic drought spells occur. From the Palmer Z-Index, an observation less than or equal to -4 represents an extreme drought, therefore a catastrophic event.

$$yield_{t,i,c} = \beta_1 * Z_{Index_{t,i}} + \beta_2 * \left[I\left(Z_{Index_{t,i}} > 0\right)\right] * Z_{Index_{t,i}} + \beta_3 * trend_{\mathrm{t,i,c}} + \beta_4 * \text{Catastrophe}\left[I\left(Z_{Index_{t,i}} < -4\right)\right] * Z_{Index_{t,i}} + \nu_i + \tau_c + \varepsilon_{t,i,c} \quad (2)$$

In contrast, Equation 4 & 5 uses standardized yields based on the yield-trend ratio which refers to the multiplicative decomposition residuals explained above. Thus, heteroscedasticity caused by increased yields over time is naturally eliminated, and elasticities are now expressed in percentage points from the trend.

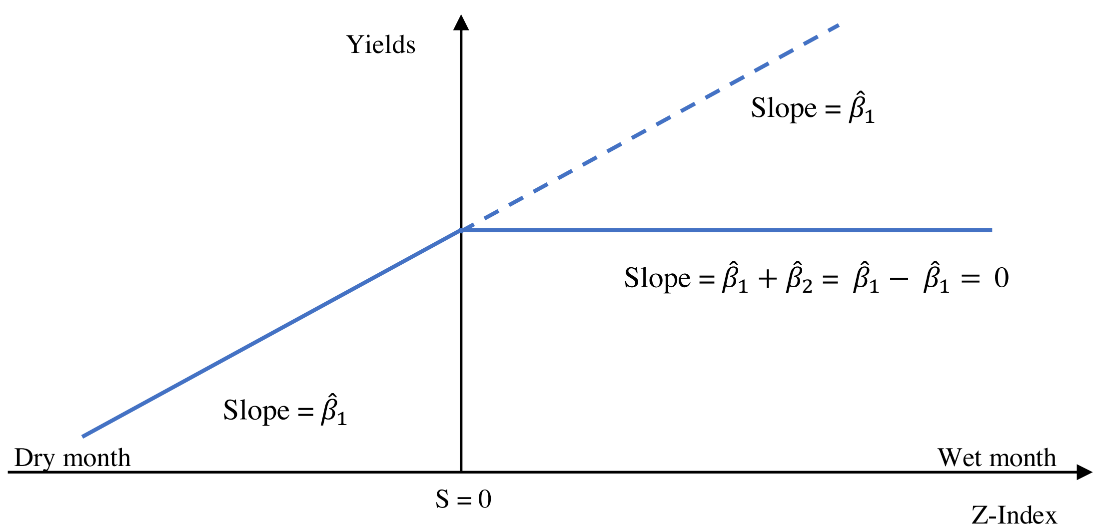
$$standardized\ \ yield_{t,i,c} = \frac{yield_{t,i,c}}{trend_{\mathrm{t,i,c}}} * 100 \quad (3)$$

$$standardized\ yield_{t,i,c} = \beta_1 * Z_{Index_{t,i}} + \beta_2 * \left[I\left(Z_{Index_{t,i}} > \mathrm{S}\right)\right] * Z_{Index_{t,i}} + \nu_i + \tau_c + \varepsilon_{t,i,c} \quad (4)$$

$$\underline{5}standardized\ yield_{t,i,c} = \beta_1 * Z_{Index_{t,i}} + \beta_2 * \left[I\left(Z_{Index_{t,i}} > \mathrm{S}\right)\right] * Z_{Index_{t,i}} + \beta_3 * \text{Catastrophe}\left[I\left(Z_{Index_{t,i}} < -4\right)\right] * Z_{Index_{t,i}} + \nu_i + \tau_c + \varepsilon_{t,i,c} \tag{5}$$

The main distinction between Equations 1 & 2 and Equation 4 & 5 is the specification of the yields in regard to the trend. In Equations 1 & 2, the trend is added as a regressor in the equation, and this specification refers to the additive decomposition seen above. The presence of heteroskedasticity is controlled with White's robust estimator. In this case, the elasticities are expressed in bushels per acre.

FIGURE XV: SHORT-PUT THEORETICAL VISUALIZATION



The panel data regression with multiple fixed effects is performed using the felm() function in R (Cameron, Gelbach et Miller, 2006). Since we have panel data, we add some fixed effects for the RM and for the crop. The fixed effect associated with the RM allows the models to add some non-observed individual characteristics for each firm. This fixed effect would capture idiosyncratic characteristics in the relationship between the yield and index for each RM. An identical fixed effect across all RMs would suggest a homogenous yield-index relationship and a no such idiosyncratic components are not relevant. As for the crop, we have an individual crop fixed effect that allows the model to add some non-observed crop characteristic relationships to the Z-Index such as sensitivity or resistance to drought.

Results

I. Model estimation

Farooq, Hussain et Siddique (2014) explain that grain has distinct growth stages in each month of production, with different levels of sensitivity to drought-related water stress. Since we have monthly Z-index observations, the short-put relationship is estimated using a Z-Index observation of each month of the growing season to see when drought episodes impact yields more severely. Quiring and Papakryiakou (2003) summed monthly Z-Index values from May to August and achieved an overall crop season Z-Index observation. This methodology has a major limitation: a very dry month with a negative value can be offset by a wet month with a high positive value, resulting in a false normal despite extreme climate conditions in both months. Thus, the short-put relationship was estimated for each month of the growing season individually and for all months together. Then an F-test was computed to evaluate the null hypothesis that all estimated coefficients in regard to the Z-Index variables summed to zero. P-values for these tests are shown in the results.

Figs. 6 and 7 present the results in levels, which means that the estimated elasticities are the variations in bushels per acre with an additional Z-Index unit. In contrast, Figs. 8 and 9 present elasticities in ratios, so the estimated coefficients are expressed in percentage points from the RM-crop specific trend. From Fig. 6, we can see that the trend, estimated by the locally weighted regression, is statistically significant, and suggests that technological progress on average increases yields by 1 bu./ac. per year. From the R^2 criteria, this trend seems to explain 71% of the crop yield's variation over the years. This result is consistent in Models I-V as well, even when controlling for a catastrophic dry month.

TABLE VI : EQUATION 1 RESULTS (BU./AC.)

	.	1-I	1-II	1-III	1-IV	1-V
Trend	0.99 ***	0.95 ***	1.00 ***	0.97 ***	0.95 ***	1.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Z-Index May		-0.00	1.30 ***			
		(0.08)	(0.08)			
I(Z-Index May > 0)		-0.13	-1.36 ***			
		(0.10)	(0.10)			
Z-Index June		1.61 ***		2.92 ***		
		(0.10)		(0.11)		
I(Z-Index June > 0)		-2.05 ***		-3.21 ***		
		(0.13)		(0.15)		
Z-Index July		3.01 ***			3.39 ***	
		(0.09)			(0.09)	
I(Z-Index July > 0)		-2.56 ***			-3.07 ***	
		(0.13)			(0.11)	
Z-Index August		0.13				1.88 ***
		(0.08)				(0.08)
I(Z-Index August > 0)		-0.86 ***				-2.62 ***
		(0.11)				(0.10)
Obs.	29912	29912	29912	29912	29912	29912
R^2	0.71	0.78	0.72	0.74	0.77	0.72
Adj -R^2	0.71	0.78	0.72	0.74	0.77	0.72
F-test $\sum \beta = 0$ (p-value)	NA	0.00	0.17	0.00	0.00	0.00

TABLE VII: EQUATION 2 RESULTS (BU./AC.)

	2-I	2-II	2-III	2-IV	2-V
Trend	0.95 ***	1.00 ***	0.97 ***	0.95 ***	1.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Z-Index May	0.05	1.36 ***			
	(0.08)	(0.08)			
I(Z-Index May > 0)	-0.19	-1.44 ***			
	(0.10)	(0.10)			
Catastrophe I(Z-Index May < -4)	-1.72 **	-1.76 ***			
	(0.64)	(0.25)			
Z-Index June	1.55 ***		2.80 ***		
	(0.10)		(0.11)		
I(Z-Index June > 0)	-1.98 ***		-3.06 ***		
	(0.13)		(0.15)		
Catastrophe I(Z-Index June < -4)	0.96 ***		1.58 ***		
	(0.18)		(0.19)		
Z-Index July	3.06 ***			3.38 ***	
	(0.10)			(0.09)	
I(Z-Index July > 0)	-2.64 ***			-3.06 ***	
	(0.13)			(0.11)	
Catastrophe I(Z-Index July < -4)	-0.29			0.03	
	(0.17)			(0.18)	
Z-Index August	0.13				1.59 ***
	(0.07)				(0.10)
I(Z-Index August > 0)	-0.86 ***				-2.28 ***
	(0.10)				(0.12)
Catastrophe I(Z-Index August < -4)	0.13				1.30 ***
	(0.17)				(0.17)
Obs.	29912	29912	29912	29912	29912
R^2	0.78	0.72	0.74	0.77	0.73
Adj -R^2	0.78	0.72	0.74	0.77	0.72
F-test $\sum \beta = 0$ (p-value)	0.00	0.10	0.00	0.00	0.00

TABLE VIII: EQUATION 4 RESULTS (% TREND)

	4-I	4-II	4-III	4-IV	4-V
Z-Index May	0.27	3.92 ***			
	(0.20)	(0.22)			
I(Z-Index May > 0)	-0.50	-3.87 ***			
	(0.26)	(0.24)			
Z-Index June	4.59 ***		8.45 ***		
	(0.27)		(0.32)		
I(Z-Index June > 0)	-5.64 ***		-9.03 ***		
	(0.36)		(0.41)		
Z-Index July	8.63 ***			10.04 ***	
	(0.28)			(0.28)	
I(Z-Index July > 0)	-7.60 ***			-9.38 ***	
	(0.32)			(0.29)	
Z-Index August	0.96 ***				5.95 ***
	(0.22)				(0.28)
I(Z-Index August > 0)	-3.37 ***				-8.34 ***
	(0.29)				(0.33)
Obs.	29912	29912	29912	29912	29912
R^2	0.29	0.03	0.13	0.24	0.06
Adj -R^2	0.28	0.02	0.12	0.23	0.05
F-test $\sum \beta = 0$ (p-value)	0.00	0.69	0.00	0.00	0.00

TABLE IX: EQUATION 5 RESULTS (% TREND)

	5-I	5-II	5-III	5-IV	5-V
Z-Index May	0.43 *	4.08 ***			
	(0.20)	(0.23)			
I(Z-Index May > 0)	-0.69 **	-4.07 ***			
	(0.26)	(0.25)			
Catastrophe I(Z-Index May < -4)	-4.76 **	-4.66 ***			
	(1.79)	(0.51)			
Z-Index June	4.47 ***		8.13 ***		
	(0.27)		(0.33)		
I(Z-Index June > 0)	-5.50 ***		-8.65 ***		
	(0.36)		(0.41)		
Catastrophe I(Z-Index June < -4)	2.21 ***		4.12 ***		
	(0.47)		(0.60)		
Z-Index July	8.84 ***			10.08 ***	
	(0.29)			(0.28)	
I(Z-Index July > 0)	-7.91 ***			-9.43 ***	
	(0.34)			(0.31)	
Catastrophe I(Z-Index July < -4)	-1.16 *			-0.15	
	(0.45)			(0.50)	
Z-Index August	0.93 ***				5.05 ***
	(0.21)				(0.33)
I(Z-Index August > 0)	-3.32 ***				-7.26 ***
	(0.29)				(0.40)
Catastrophe I(Z-Index August < -4)	0.72				4.03 ***
	(0.53)				(0.55)
Obs.	29912	29912	29912	29912	29912
R^2	0.29	0.03	0.13	0.24	0.06
Adj -R^2	0.29	0.02	0.13	0.23	0.06
F-test $\sum \beta = 0$ (p-value)	0.00	0.92	0.00	0.00	0.00

Therefore, we have 5 regression models which each have a different specification regarding the month chosen for the Z-Index observation. From the adjusted-R^2 criteria, which explains how well the model fits the data even with different numbers of explanatory variables, we prefer Models I, IV and III. Model I show the yield regressed for the entire growing season Z-Index observations where, except for the month of May, all other months are statistically significant. This result suggests that droughts can impact yields at all growing stages except for the early growth stages. With $\hat{\beta}_1 > 0$ and $\hat{\beta}_2 < 0$ being statistically significant in Models II to V, we can assume that the short-put relationship is present for all months of the growing season. In contrast with the other models, only Model II doesn't reject the null hypothesis that the sum of estimated coefficients equals 0.

Both of these results suggest that the short-put relationship is relevant for all months, but the relationship between the Z-Index and the yields is not arbitrary for dry climatic observations and two conclusions can be drawn. If $\hat{\beta}_1 - \hat{\beta}_2 > 0$ (Equation 4-IV), the relationship between the yield and index is positive, and if $\hat{\beta}_1 - \hat{\beta}_2 < 0$ (Equation 4-III), the relationship is negative. The former would mean that wetter climatic observations are associated with increased yield whereas in the latter they would be associated with decreased yield. Model I also contribute to this conclusion. This implies that an excess of water can be positively or negatively related to crop production. In further analysis, the addition of an explanatory variable to control for the level of irrigation would clarify this conclusion. Moreover, since the Z-Index doesn't take into account soil moisture level caused by snow melt in early spring, adding this information in a further analysis could increase the predictive power of this model.

As for the catastrophic dummy variable added in Equation 2 and 5, the results were in contradiction with our initial hypothesis that yields would decrease significantly under catastrophic dry conditions. Independently of the model estimated, the latter conclusion seems to be the same. First, catastrophic dry climatic situations decreased yields in Model II as we initially expected, but then increased yields in Models III and V. Considering that the observation percentages of the Z-Index below -4 varies between 0.1% and 2.1% depending on the month, it is a very small sample which is a recognized problem in risk management when little observation in the tails of the density functions limits the ability to assess the climatic impacts of these events.

For the insurance policy simulation, based on the null hypothesis rejection criteria, we would have chosen Model II because the short-put relationship is statistically significant, but it has poor explanatory power with the lower adjusted-R^2. Therefore, we chose Models III and IV. From this result, we can suppose that an additional decrease in the Z-Index in July (June) would decrease the yields by 10.04 (5.95) percentage points with a 1% level of confidence. From the R^2 criteria, we will use the month of July as the underlying index for the insurance contract since it appears to be the month where drought conditions had higher impact on yields with the higher adjusted R^2.

II. Insurance contract

The following section will introduce a theoretical weather-based insurance contract and its hedging effectiveness by assessing the level of basis risk inherent to the insurance contract. Then, the payoff structure will be presented for a specific RM, Swift Current, and the insurance cost policy for all 144 RMs will be presented.

i. Definition

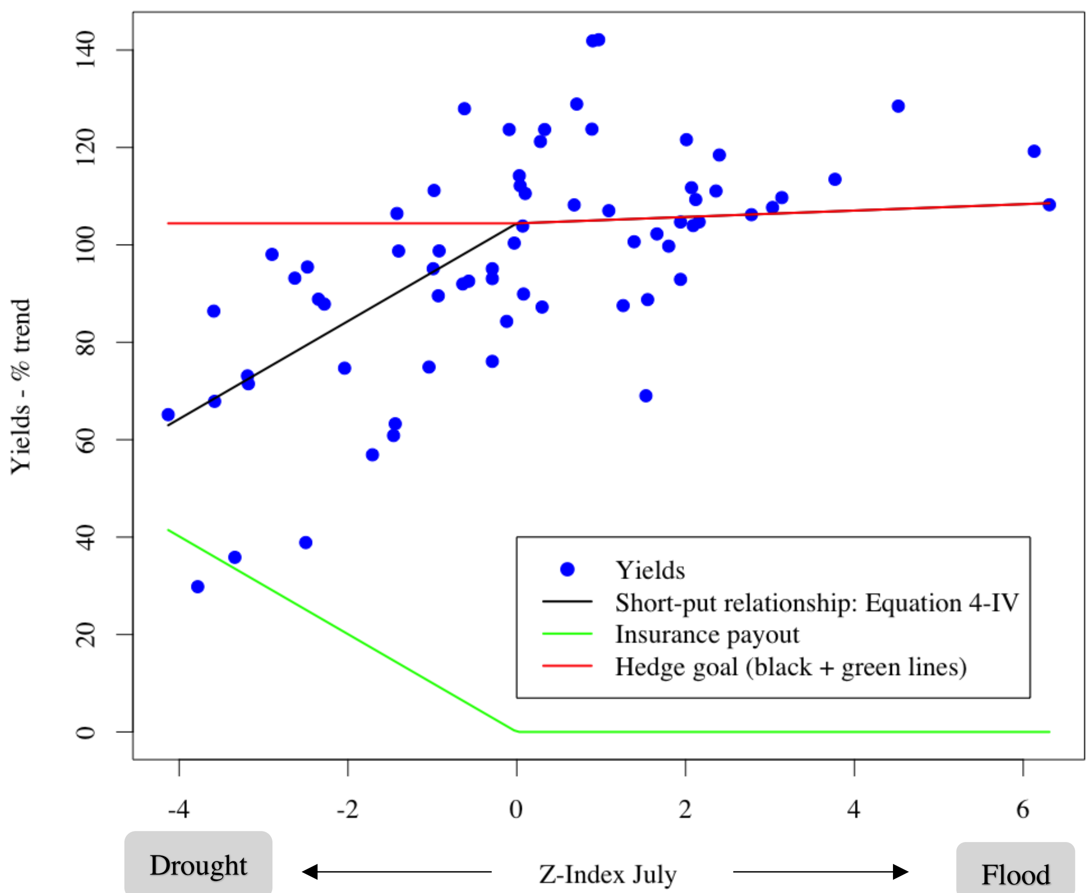
The design of weather derivatives is possible if the risk covered meets specific conditions. Barnett, Barrett et Skees (2006) and Charpentier (2008) proposed several criteria for a risk to be insurable:

1. Legal insurability: the occurrence of claims associated with the risk need to follow a random process. The acts of nature are uncontrollable for both the insured and insurer, so that no behavioral change relative to indemnity requests induces issues of moral hazard.
2. The average severity of cost and average frequency should be identifiable and calculable, and the maximum loss should not be a threat to insurer solvency, but if so, a reinsurance company must be available to transfer systemic risk to other geographical areas or to international mutualization of risk.
3. There must be a large number of roughly homogenous, independent exposure units so that the law of large numbers can apply, and claims are independent and identically distributed. Moreover, this act of nature must affect insured agents identically, so there is not adverse selection where the different risk profiles are used to compute premiums.
4. The premiums must be economically feasible and regulated by the law of supply and demand through an existing market in which an equilibrium price arises.

ii. Payoff structure

The payoff structure is based on the results of Equation 4-IV since it is the equation with the highest predictive power in regard to the R^2 criteria. Fig. 16 presents the payoff structure, the estimated yields and the hedge objective for the rural municipality of Swift Current. At first sight, we can see that yields decrease when the Z-Index decreases, with a catastrophic yield of 30% in 1985 when the Z-Index was near -4 (extreme drought). In the opposite direction, we can see yields 40% higher than the trend when the conditions are slightly wet with a Z-Index of around 1. The black line represents the short-put relationship estimated by Equation 4-IV, where the slopes are $\widehat{\beta_1} = 10.04$ and $\widehat{\beta_2} = -9.38$ with a 1% level of confidence. Thus, this relationship is characterized by two dynamics: positive when the Z-Index is under 0, and nearly null (randomly distributed) when the Z-Index is above 0. Since the statistic test rejected the null hypothesis of inversed coefficients, it is not possible to conclude that the relationship is randomly distributed for positive values of the Z-Index.

FIGURE XVI: JULY-BASED INSURANCE POLICY PAYOUT FOR SPRING WHEAT PRODUCTION IN SWIFT CURRENT



From the estimation of model 4-IV, we develop a payoff structure inspired by a long-put option. In other words, the indemnity compensates the yield lost so that the level of outcome equals a yield realization when climatic conditions are characterized as normal. This hedged yield objective will be set as the estimated yield when the Z-Index equals zero, so the intercept is estimated by the RM individual fixed effect $\hat{v}_i$. The green line shows the payoff by unit of the Z-Index with a slope equal to $\hat{\beta}_1$ and the red line is the extrapolated fixed effect coverage objective when the payoff is triggered.

Before simulating the hedged position with the payoff structure, several parameters need to be set between the insurer and the insured so that the payoff structure, illustrated with the green line, is agreed to by both sides. These settings include the location of the climatic station, the month of observation, the strike level under which the payoff is triggered, the payoff per unit of index and the reference margin used to compute the payoff. In this case, this contract is a European option, where the payoff can be triggered only at the end of July. The alternative would be an American option, where the payoff would be triggered at any time during the month of July as long as the Z-Index is below 0. Obviously, such a framework can't be used by practitioners, since we need the observations for the whole month of July to adequately assess a drought situation.

TABLE X: JULY-BASED INSURANCE CONTRACT FOR SWIFT CURRENT

Insurance contract	
RM	Swift Current
No.	137
Climate Sation	Swift Current CDA
ID	4028060
Distance	5,06 km
Index	Z-Index
Month	July
Strike	0
Option type	European put
Tick size	10.04 % points per index unit
Reference	Locally weighted OLS trend

Table. 10 presents a standard European put option contract, and its application to the Swift Current rural municipality. The payoff is triggered if the Z-Index observed at the end of July is below the strike 0. If it is triggered, the payoff would be a monetary equivalent of 10.04% of the normal level of production per unit of the Z-Index. For instance, if the Z-Index should fall to -3, the payoff would be as calculated as (6) shows.

$$Payout_{i,t,c} = Max\left[0 - \left(\mathrm{Z}_{\mathrm{Index}_{i,t}}\right), 0\right] * \hat{\beta}_1 = Max[0 - (-3), 0] * 10.04 = 30.12\ \%\ \text{points} \quad (6)$$

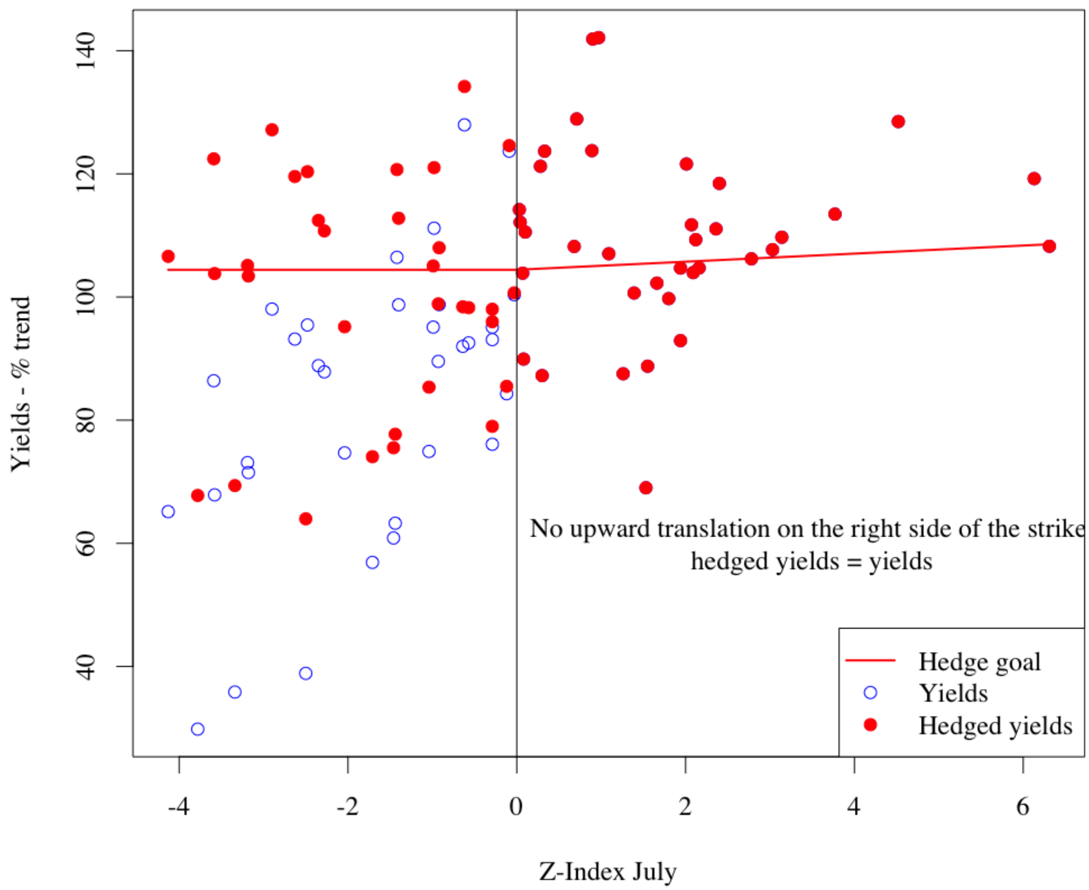
Thus, the insurer will have to compensate the farmer for up to 30.12% of their normal production level. For the insurance coverage simulation, this single contract will be extended to all 144 rural municipalities where only the climatic station and the fixed effect will change, and results will be presented in a portfolio perspective where an insurer would cover all RMs in the sample.

iii. Insurance coverage simulation

The insurance coverage simulation is intended to evaluate the disparity between the payoff and the shortfall in observed yields. In other words, the objective is to evaluate the remaining basis risk for a unique standardized insurance policy hedging all combinations of RM and crop from drought spells. To achieve this, we have simulated the hedged position from the contract specified above for all rural municipalities in the sample. The hedged position is defined as the sum of the yields and the payoff. Then, we compute the difference between the hedge goal and the yields hedged to evaluate how the payoff overshoots or undershoots the objective.

In Fig. 17, we can see the historical yields illustrated with blue dots and the hedged position from the simulation with red dots. On the right side of the horizontal line at the strike level 0, the yields don't change as there is no payoff triggered when the Z-Index is positive. On the left side, you can see the upward translation of the historical yields to the hedged position. This upward movement is the payoff from the insurance contract, which is higher as the Z-Index values worsen. As a result, some yields are perfectly hedged, on the red line, others are over-hedged, above the red line, and others are under-hedged, below the red line. For instance, the catastrophic level of yields around 30% is up to 60%, but there is a 40% uninsured that the insurer must bear. To sum up, from the graph we can see that the farmer is better off in the hedged position than the initial position since the yields are lifted up as the Z-index decreases without taking account of transaction cost. However, there is still disparity between the red line (objective) and the red dot (simulated) in the payoff hedging effectiveness that needs to be assessed to evaluate the remaining level of basis risk.

FIGURE XVII: JULY-BASED HEDGED POSITION FOR SPRING WHEAT PRODUCTION, SWIFT CURRENT



iv. Insurance policy cost

Now that we have simulated the payoff contract, it is possible to present the cost for the insurer, i. e., the monetary compensation equivalent to the long-put option payoff in $ per acres insured. To estimate the cost to the insurer as estimated by (7), the payout from (6) will be multiplied by the normal yield; i. e., the locally weighted estimated trend, and a long-term mean price. In the Fig. 18 and 19, we present the distributions of the monetary payoff delivered to the RMs for each crop.

$$Policy\ cost\left(\frac{\$}{ac.}\right) = Payout(\%) * trend_{i,t,c}\left(\frac{bu.}{ac}\right) * historical\ average\ price\left(\frac{\$}{bu.}\right) \quad (7)$$

FIGURE XVIII: JUNE-BASED (EQUATION 4-III) INSURANCE POLICY COST

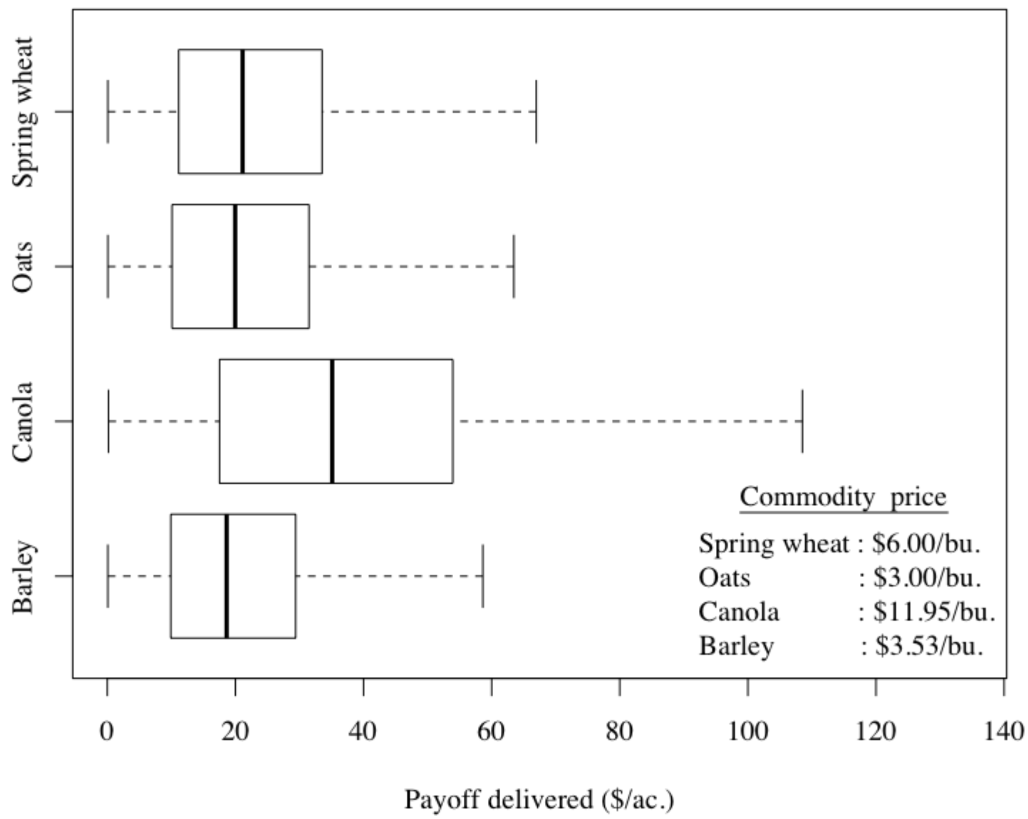
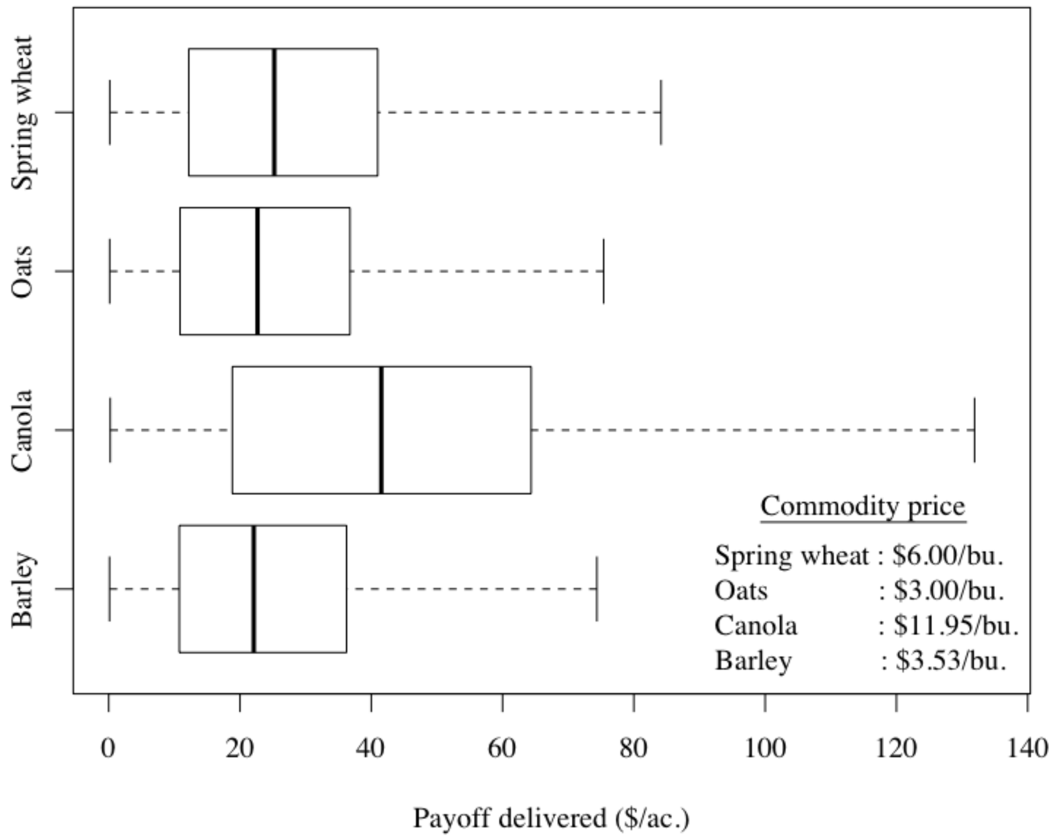


FIGURE XIX: JULY-BASED (EQUATION 4-IV) INSURANCE POLICY COST



v. Estimation of basis risk

Equation (8) present the calculation of the hedged position (red dot) for the rural municipality *i* at time *t* for the crop *c*. Since the yield-index correlation isn't perfect, some disparity remains and that is the remaining basis risk as showed by (9).

$$Hedged\ yields_{i,t,c}(\%) = \ yield_{i,t,c} \ + \ \ payout_{i,t,c} \tag{8}$$

As the aim is to offer a compensation high enough that the hedged position equals a reference yield, which is the yield realized when climatic conditions are characterized as normal from the Z-Index observation. As such, the hedged goal is defined as the individual RM's fixed effect.

$$\begin{gathered} Basis\ risk_{i,t,c}(\%) = Hedged\ yields_{i,t,c} \ - Hedge\ goal_{i,t,c} \\ Basis\ risk_{i,t,c}(\%) = (yield_{i,t,c} + \ \ payout_{i,t,c}) \ - \hat{v}_{i,c} \end{gathered} \tag{9}$$

The basis risk calculated by (9) would be interpreted as the yield departure from the normal that is not compensate by the insurance policy through the hedged position. A negative basis risk implies that the hedged objective isn't entirely covered (hedged position under the hedge goal) and a positive basis risk would imply overshooting the hedged objective (hedged position above hedge goal). A greater shortfall can be explained by higher climate stress or other events such as insect infestation or another biological crop disease causing effects that are not taken into account in this model. Also, lower-than-expected yield shortfall can be explained by a difference in the drought level monitored at the climatic station and the drought level actually occurring at the crop field even if this local basis risk is minimized by the short distance between the station and the field.

FIGURE XX: JUNE-BASED BASIS RISK: SPREAD BETWEEN HEDGE GOAL AND HEDGED YIELDS (BU./AC.)

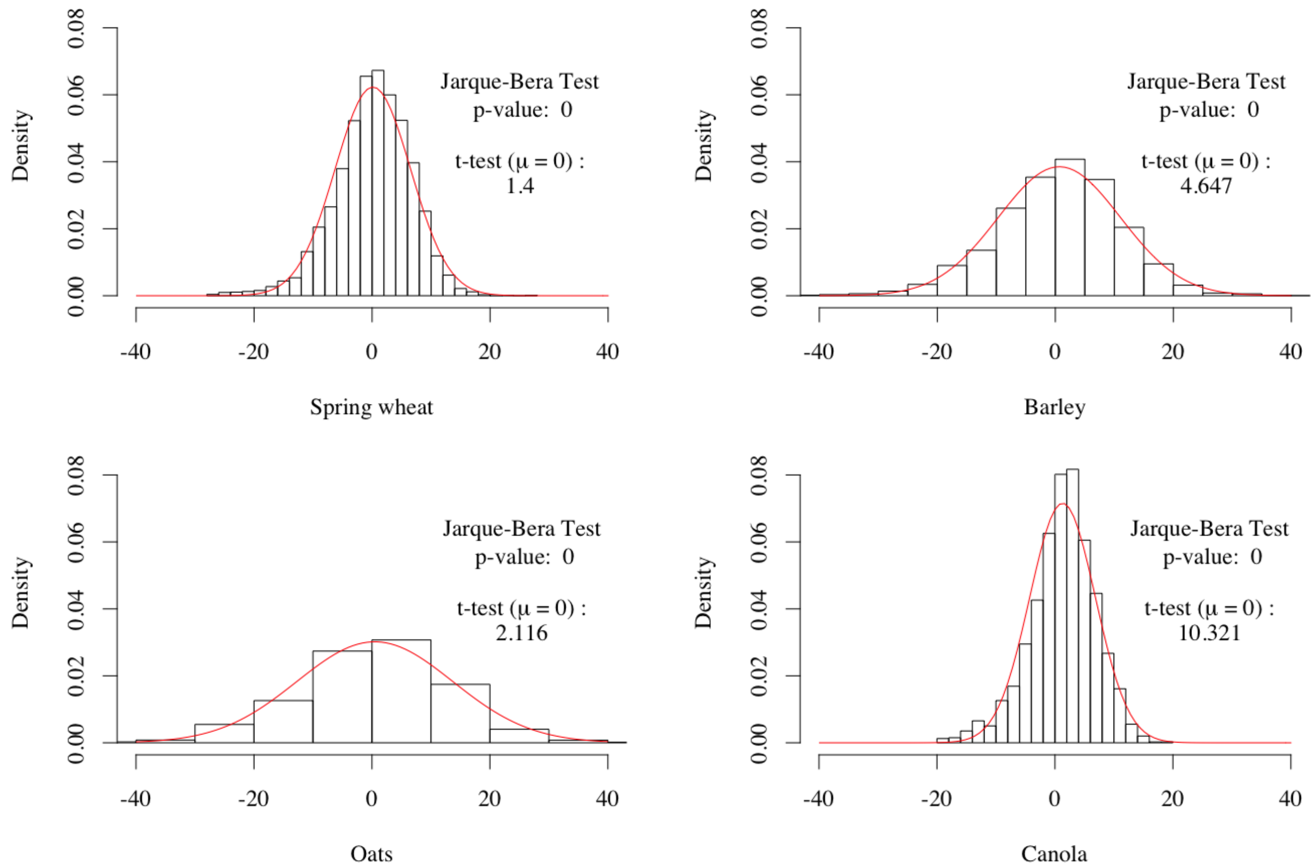
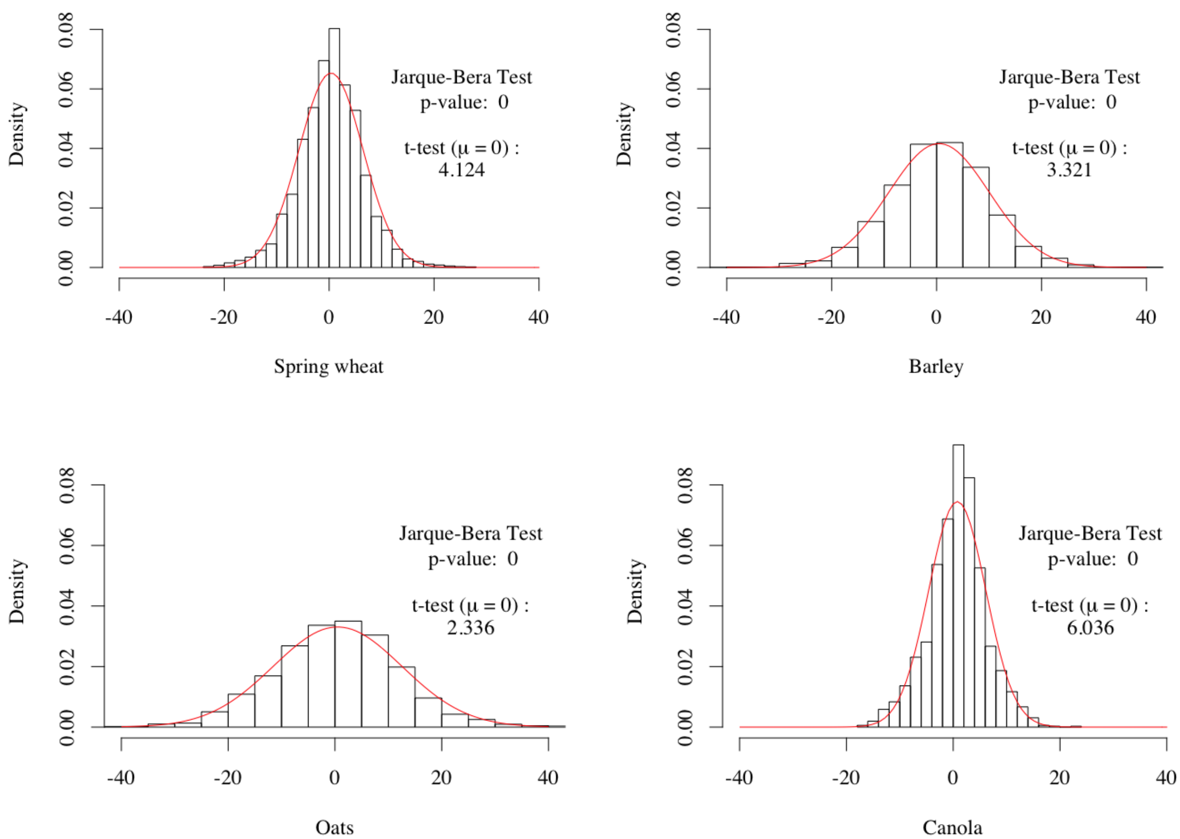


FIGURE XXI: JULY-BASED BASIS RISK: SPREAD BETWEEN HEDGE GOAL AND HEDGED YIELDS (BU./AC.)



Figs. 20 and 21 show the distributions of basic risk in bushels per acre for the 4 productions and the 2 months used for the insurance contract. The normality of the distributions is rejected at a 1% confidence level by the Jarque-Bera test. In addition, the calculated t-statistics allow us to conclude that the null hypothesis that the average basis risk is zero is rejected at a 1% confidence level except for the oat and wheat production for the June contract. In addition, the distributions for barley and oat production are more sagging, suggesting that basis risk may be taking on larger extreme variables due to two tails of denser distributions than a normal distribution. In the appendix, two descriptive tables show an excess of positive kurtosis for each distribution, confirming this statement.

In addition, basis risk means above 0 and negative skewness for all distributions support two dynamics for the performance of a single insurance policy to cover these 4 productions. To begin with, this insurance policy would over-insure the loss of yield on average. In other words, the difference between the hedged yields and the coverage objective is positive on average, so an insurer would deliver higher compensation than necessary to restore income affected by a drought to a level of income corresponding to a normal climatic situation.

Moreover, the presence of negative skewness implies a higher left-tail distribution suggesting that the negative basis risk is more prominent, which can be explained by the presence of catastrophic weather risk that requires a risk management strategy complementary to the insurance contract defined in this paper. Figs. 24 and 25 support this suggestion by introducing the impacts of catastrophic drought periods recognized in the literature.

The basis risk estimated in ratio by (9) can be estimated in bushels per acre when multiplied by the trend previously estimated by the lowess regression and multiplied by the price of the commodity in dollars per bushel to obtain the basis risk on a monetary basis per acre of land insured with Equation 10. Thus, this monetized basic risk is the missing payout for the farmer to reach an income level under normal climatic conditions. Since the prices of each crop are different, it allows the insurer to better understand the effectiveness of the insurance contract in terms of dollars per insured hectare. Finally, it is useful to express it in dollars because insurance services offer the possibility of insuring a flexible number of acres at a premium already defined in dollars per acre.

$$Basis\ risk_{i,t,c}\left(\frac{\$}{ac.}\right) = Basis\ risk_{i,t,c}(\%) * trend_{i,t,c}\left(\frac{bu.}{ac.}\right) * price\left(\frac{\$}{bu.}\right) \quad (10)$$

FIGURE XXII: JUNE-BASED INSURANCE POLICY: BASIS RISK ($/AC.)

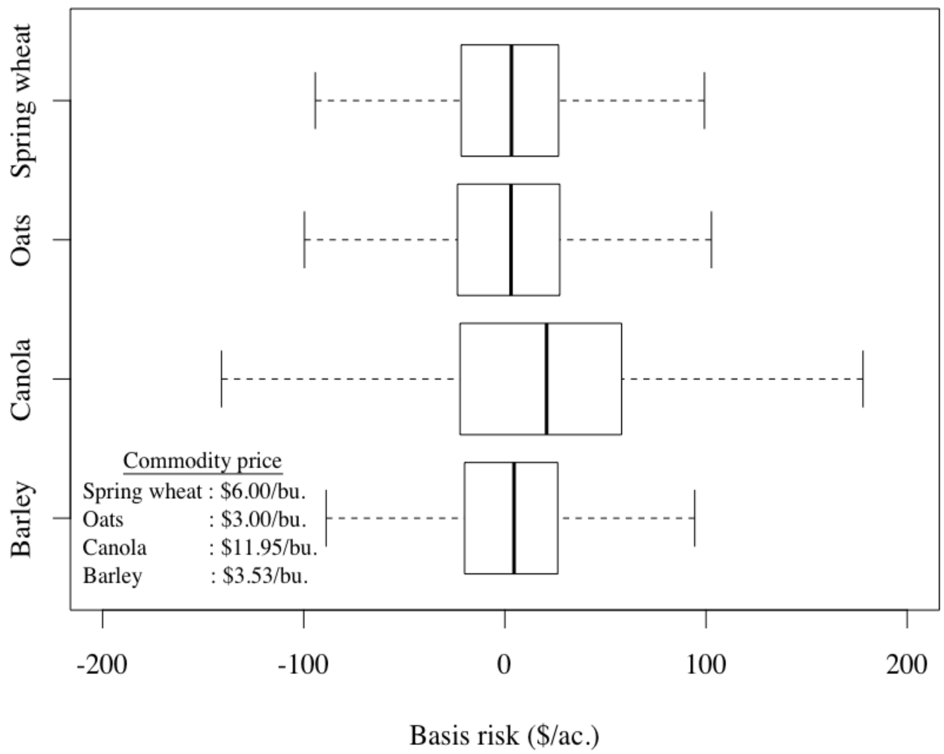


FIGURE XXIII: JULY-BASED INSURANCE POLICY: BASIS RISK ($/AC.)

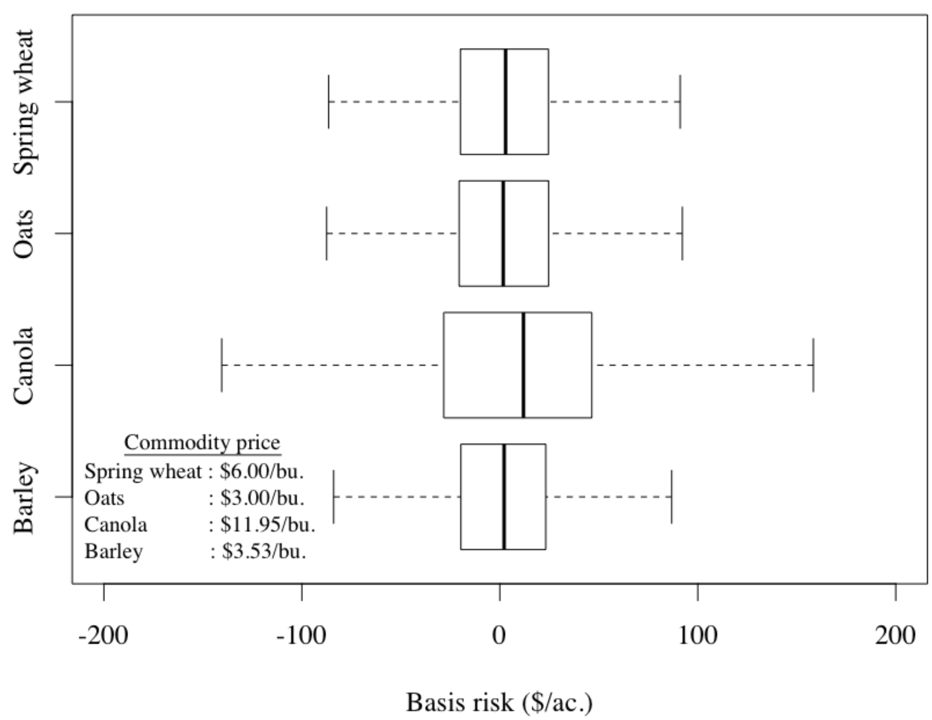


Fig. 22 and 23 presents the basis risk expressed in dollar per acres as defined by (10). Historical average prices were used to simplify the analysis. First, the simulated contract covers barley production more effectively since the extremes are narrower than the others. In addition, the performances of the insurance policy for oat and spring wheat productions are, with the maximum and minimum being around 100 dollar per insured acre. The average basis risk of the insurance policy for canola is not centered on 0, meaning the contract is not adequate to this production. In fact, because the average basis risk is positive, the contract would over-hedge the shortfall of income and cost. In the appendix, a table shows the models estimation of (4) by crop, and the estimated elasticity for canola production is less than half the estimated elasticities of other crops. These figures support the need for a specific weather-based insurance policy for canola production.

TABLE XI: JUNE-BASED INSURANCE POLICY: BASIS RISK ($./AC.)

Crop	Min	Mean	Max	Std. Dev,	Skew.	Kurtosis
Spring wheat	-166.89	0.75	158.13	38.42	-0.52	0.94
Oats	-183.49	1.45	248.79	39.67	-0.02	1.67
Barley	-153.43	2.41	177.66	36.57	-0.26	0.69
Canola	-238.34	15.45	219.83	66.64	-0.51	0.71

TABLE XII: JULY-BASED INSURANCE POLICY: BASIS RISK ($./AC.)

Crop	Min	Mean	Max	Std. Dev.	Skew.	Kurtosis
Spring wheat	-144.00	2.16	156.18	36.64	-0.04	1.03
Oats	-163.93	1.49	226.77	36.19	0.22	1.69
Barley	-153.00	1.64	197.11	33.83	-0.03	0.85
Canola	-207.84	9.11	263.49	64.02	-0.12	0.57

In Figs. 24 and 25, we can see the rural municipalities average basis risk in bu./ac. We can see that the three major droughts reported in 1961, 1988 and 2001-2003 by Bonsai et Wheaton (2005) significantly decrease the mean of the basis risk. In addition, the climatic impact seems to be less important in years where climatic conditions are not characterized as catastrophic. This observation illustrates how this contract could be effective to hedge against low intensity, high probability events while high intensity, low probability events seem to have a systematic impact on all RM in the sample. Further research could study the combination of systematic and idiosyncratic components in the basis risk.

FIGURE XXIV: JUNE-BASED INSURANCE POLICY - MEANS OF BASIS RISK ACROSS RURAL MUNICIPALITIES SIGNIFICANTLY AFFECT BY CATASTROPHIC DROUGHTS

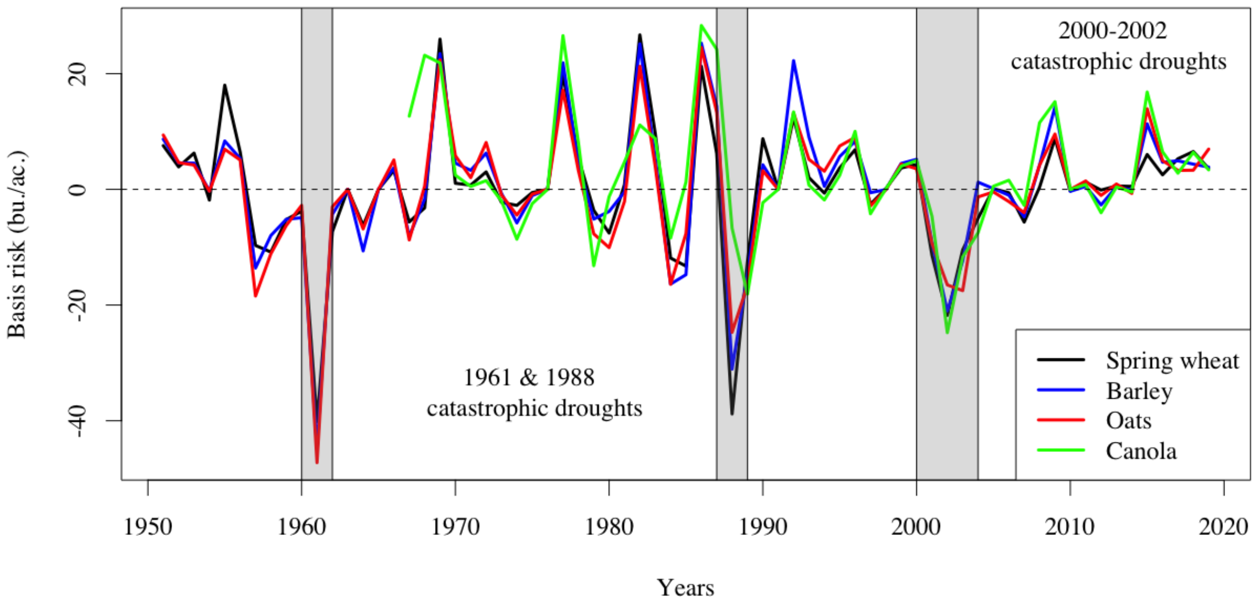
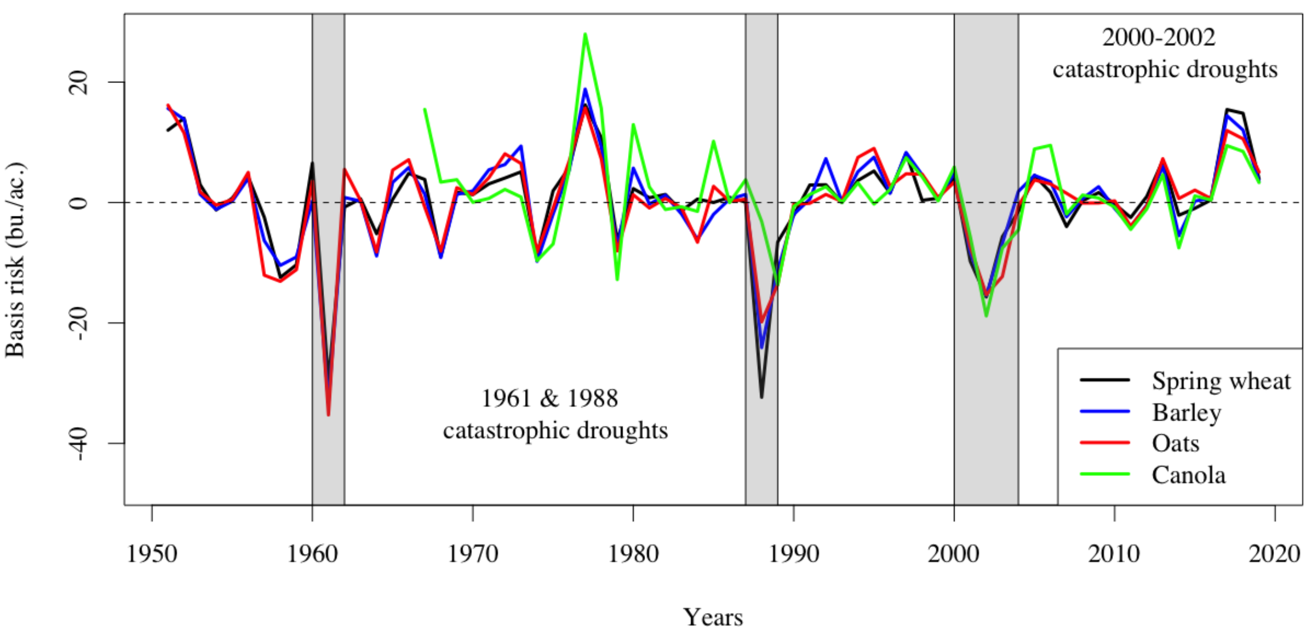


FIGURE XXV: JULY-BASED INSURANCE POLICY – MEAN OF BASIS RISK ACROSS RURAL MUNICIPALITIES SIGNIFICANTLY AFFECT BY CATASTROPHIC DROUGHTS



III. Temporal analysis

A recent surge in literature tends to assess the necessity of trimming historical periods to compute premiums and assess weather risk evolution over time. Those in favor of such methodology argue that agricultural conditions, technological environments, awareness of the role of soil moisture and use of pesticides differ through the decades. Technological progress may take the form of linear or exponential increases in individual RM yield production, since progress took place under different paces. Thus, this increasing yield performance is also reflected in the variability of the yields over time. Moreover, one can argue that recent climatic hazard occurrences induced by climate change are another source of heteroscedasticity, since yield variability should be directly impacted by these increased catastrophic events. Thus, a major challenge arises when estimating yield distributions generated by non-stationary data progress influenced by climate change and technological developments. To take this dynamic into account, some argue that in order to find a stationary data-generating process it is useful to select smaller samples of time.

Joshua D. Woodard (2014) assessed the impacts of sample period length and sampling variability in weather on yield risk estimation using a farm-level dataset in the Midwestern United States: ‘’Estimates generated under the weather experienced over the 1980-2009 period are found to be—for all practical purposes—very similar to those generated when accounting for weather over the longer period of 1895-2009 [p.3]’’. The result suggested little added value attributed to a trimmed dataset after 30 years of data.

In opposition, Shen, Odening et Okhrin (2017) contribute to this long-time debate by developing a data-driven approach based on a local parametric approach. The designed algorithm focuses on finding an optimal interval of homogeneity where a local parametric model with constant parameters fits the data. The model is tested backward to identify structural changes between two homogenic subsets caused by technological development. The model, applied on large numbers of American counties with winter wheat, corn, soybean and cotton yields, selected manageable subsets ranging from 20 to 30 years where the estimated coefficient of means and variance were stationary. Additionally, Liu et Ker (2019) used distributional tests and an out-of-sample retain-code rating game to evaluate the economic benefits of trimming yields data to estimate premium rates. Distributions of yield data seem to change enough to justify the use of 25-year periods with statistically significant and more accurate premium rates.

Following the literature, we trimmed the yield data into three sets of 25 years. From estimation of model (4), we can see that the first hypothesis of equally inverse values for the estimated coefficient seems to hold for the 3 data samples. However, there is a decrease in predictive power as R2 decreases through the generations, that could be explained by the fact that the yields' resistance to drought tends to increase with technological progress (e.g., due to genetic development, better use of soil, better machinery, etc.). In fact, the elasticity of yields to the Z-Index begins at 14% in 1951-1974, lowers to 10% in 1975-1996 and hits an even lower point of 6% between 1997 and 2019. This result supports the hypothesis that the entire historical data sample is irrelevant since the relationship between the Z-Index and the yield shortfall seems to change over a period of 69 years. Moreover, it seems that the usage of trimmed time series allows the model to not reject the null hypothesis of the inverse estimated coefficient. This relationship is statistically significant in the 1975-1996 period for the June-based policy and 1951-1974 for the July-based policy.

Factors highlighted in the literature such as better use of agricultural soil techniques, improved plant genetics or informal risk management behavior can explain this decrease in predictive power over the years. From an insurer's perspective, this dynamic where the elasticity of yields to the climate index decreases is important because it illustrates the importance of truncating the panel in order to better estimate future claims and premiums.

TABLE XIII: JUNE-BASED SHORT PUT ESTIMATION THROUGH DATA SUBSETS (EQUATION 4-III)

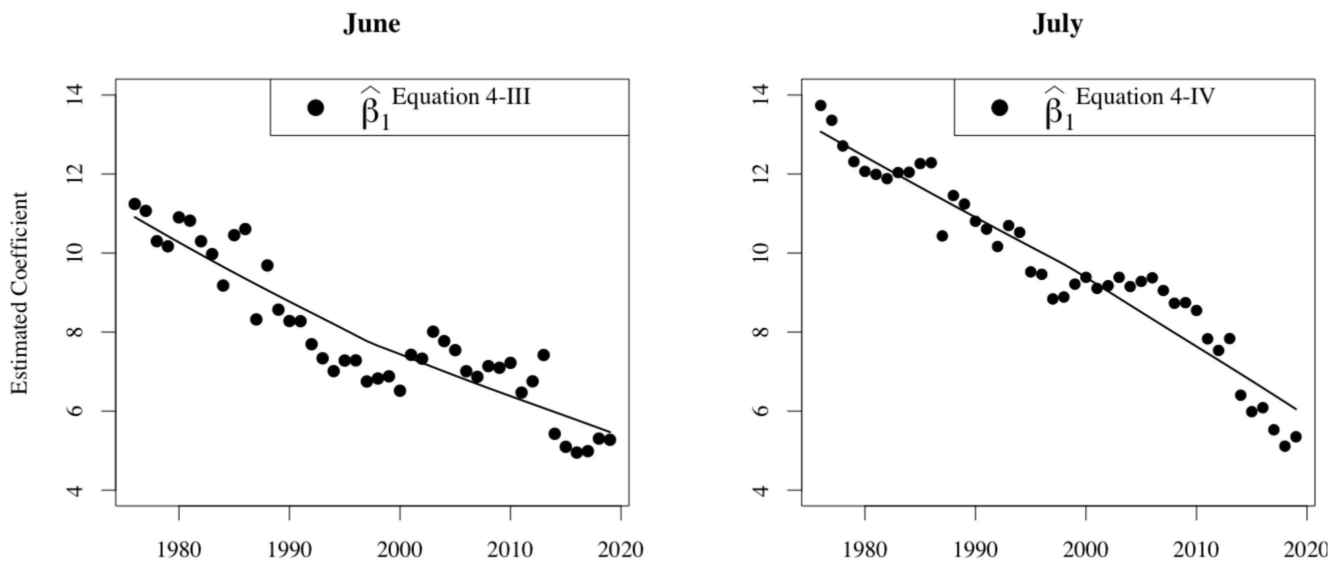
	Total	2019 - 1997	1996 - 1975	1975 - 1951
Z_Index_June	8.45 ***	5.45 ***	6.57 ***	11.76 ***
	(0.32)	(0.41)	(0.46)	(0.40)
I(Z-Index June > 0)	-9.03 ***	-6.23 ***	-6.38 ***	-11.08 ***
	(0.41)	(0.52)	(0.60)	(0.63)
Obs.	29912	10291	10426	9649
R^2	0.13	0.07	0.08	0.27
Adj -R^2	0.12	0.05	0.07	0.26
F-test $\sum \beta = 0$ (p-value)	0.00	0.00	0.39	0.04

TABLE XIV: JULY-BASED SHORT PUT ESTIMATION THROUGH DATA SUBSETS (EQUATION 4-IV)

	Total	2019 - 1997	1996 - 1975	1974 - 1951
Z-Index July	10.04 ***	5.70 ***	9.79 ***	13.67 ***
	(0.28)	(0.39)	(0.50)	(0.38)
I(Z-Index July > 0)	-9.38 ***	-4.97 ***	-8.09 ***	-13.11 ***
	(0.29)	(0.50)	(0.60)	(0.60)
Obs.	29912	10291	10426	9649
R^2	0.24	0.12	0.28	0.35
Adj -R^2	0.23	0.11	0.26	0.34
F-test $\sum \beta = 0$ (p-value)	0.00	0.00	0.00	0.14

To further visualize the weakening relationship between the Z-Index and the yields, we perform the looped estimations of (4) on the month of June and July with moving periods of 25 years long. Since we have a dataset running from 1951 to 2019, we have 43 estimations of the yield's elasticity to episodes of drought. The graph shows how the relationship decreases from 0.14 for the period ending in 1974 to 0.56 for the period ending in 2019. Showing this relationship through a graph can help us to visualize the linear trend of this dynamic. Technological progress seems to increase yield production by bushels per acre, but it also increases crop resistance (elasticity) to climatic hazard. From an insurer's perspective, prime valuation should be adjusted accordingly with an expected payout of 5 percentage points ($\widehat{\beta_\iota}$ estimated on a subset of 25 years running from 1994 to 2019) instead of 10 percentage points ($\widehat{\beta_\iota}$ estimated on the 69 years dataset from 1950 to 2019) for each additional Z-Index unit if we take into account temporal dynamics. the $\widehat{\beta_\iota}$ estimated on a subset of 25 years running from 1994 to 2019.

FIGURE XXVI: ESTIMATED YIELDS-INDEX ELASTICITIES ON 25-YEAR MOVING DATA SUBSET (EQUATION 4-III AND 4-IV)

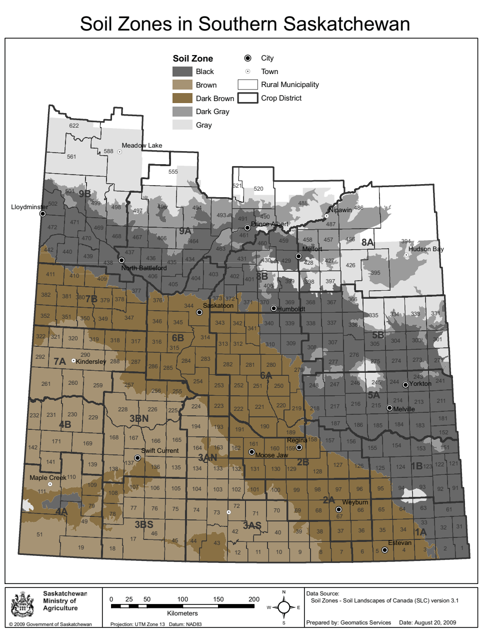


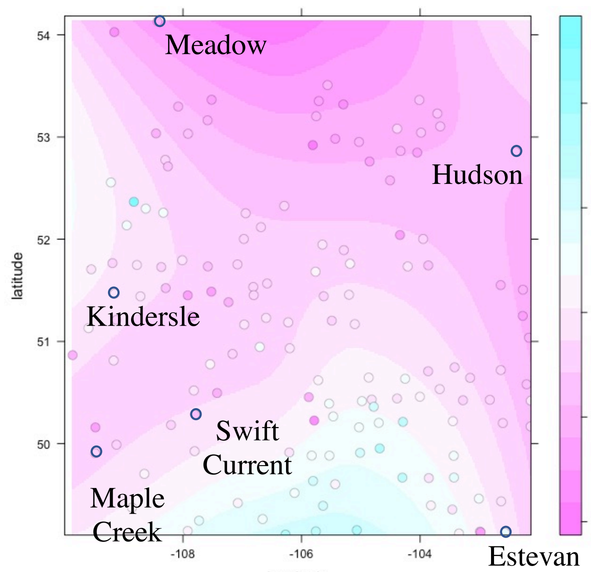
IV. Spatial Correlation

In this model, fixed effects are added to access the individual characteristics of each rural municipality. The fixed effect of the rural municipality is the level of yields at the intercept. Recall that our Z-Index strike is set to 0, which is characterized as normal climatic conditions. In Fig. 27, we locate each fixed effect on a heat map using the latitude and longitude of each rural municipality. On the right side of the map, a color gradation shows a maximum value of 111 and a minimum value of 102 which can be interpreted as the individual estimated yields in ratio with the trend when the July Z-Index computation equals 0, monitoring normal climatic observations at this point.

Even if the economic interpretation doesn't help us to understand which areas tend to be more productive at equal Z-Index values, it informs an insurer that the spatial location of the insured is important and therefore that an identical insurance contract for all Saskatchewan farmers could not be effective. As such, even if the soil characteristics are captured in the Z-Index, the spatial correlations appear to follow soil zones in the province. These results are consistent with Sun, Mitchell et Davidson (2012) who found significant spatial variation across the prairies, especially between western and eastern Saskatchewan. Presence of a river shore, delimited by a fuzzy black line on the soil zone map, does not affect the geographic correlation with a flood risk or better water availability that would impact an RM's individual fixed effect as fig. 39 suggests.

FIGURE XXVII: GEOGRAPHICAL DISTRIBUTION RM' FIXED EFFECT FROM EQUATION 4-IV





Discussion

This paper aims to answer the following research question: is it possible to establish a relationship between climate and grain yields and conceptualize a single insurance coverage to cover the yields of 4 distinctive crop productions during climatic hazards? To do so, an econometric analysis estimated a short-put relationship between spring wheat, oat, barley and canola yields and the Palmer's Z-Index climate index over the period 1951 to 2019 for 144 rural municipalities in Saskatchewan. This estimated relationship is used to establish an insurance-type policy which pays an indemnity depending on the realization of this index. This contract offers a payout comparable to a long-put financial option that provides, a hedge income equal to an income achieved under weather conditions characterized as normal for a given weather station.

The outcome of this paper shows that the short-put relationship exists although it is not statistically significant. In fact, hypothesis testing rejects the null hypothesis that it exists in its theoretical shape, but it does appear to exist in practice. This theoretical relationship consists of a positive relationship for negative values of the Z-Index, and an arbitrary relationship for positive values of the Z-Index. The rejection of this assumption is mostly due to the fact that there is still some form of relationship either positive or negative between yields and wetter than normal moisture conditions (positive Z-Index values) from the month selected to estimate the relationship.

From a farmer's perspective, this ''hockey-stick'' shaped relationship is intuitively understood considering that drought risk and flood risk requires different management strategy since they affect crop yields asymmetrically. First, irrigation techniques to manage the amount of water in the soil due to snow, rain and runoff are particularly effective. Therefore, it is under farmer capability to manage the optimal amount of water for plant growth, as long as there are no rivers or lakes that could flood this land. In regard to drought, this risk is particularly difficult to manage physically, since deploying an extensive water supply network on agricultural land costs and requires a of infrastructure. Therefore, agricultural producers are working with agronomists, machinery manufacturers and climate forecasters to adapt to these dry periods. Through plant genetics or soil manipulation techniques that preserve a high level of moisture retention, they manage to produce interesting yields despite the fact that some drought episodes drastically influence soil moisture levels.

Given that the risk of drought remains the technically hard to manage, especially in agricultural areas subject to water stress, this thesis aims to cover this risk through an insurance contract.

Furthermore, the payment is designed to provide an amount sufficient to raise the farm income level to a situation qualified as average in terms of yields realization when climate conditions are also normal. Since the crop season expand from May to August, the insurance policy is based on Z-Index observations in July, as this is the model specification that generates the highest explanatory power compared to models using other months. In addition, the month of July is recognized by Sun, Mitchell et Davidson (2012) as the crop stages of filling and tillering, a phase of grain growth recognized by the precariousness of grains during drought periods. Furthermore, the July-based insurance policy performs as well as the model including all months of the growing season suggesting that establishing the insurance contract on the month of July would be sufficient to hedge farms income from drought related crop yields decrease.

In addition, the simulation of the insurance hedging capability for June-based and July-based policy gives similar conclusions. First, the effectiveness of this product is measured by the amount of basis risk inherent in this insurance scheme. Indeed, Figure 30 shows that this insurance contract is not as effective in covering oat and barley yields as it is for spring wheat and canola. However, the basis risk is centered at 0, which suggests that, on average, this risk is null. However, most statistical tests reject the null hypothesis of a mean centered to zero for the basis risk distribution for the June-based and July-based insurance policy.

The basis risk was minimized in the methodology design by setting the distance between the rural municipality and the climate station to 40 kilometers. However, there is still a risk considering that the municipalities have different sizes, whose presence of microclimate can influence the sensitivity of the estimate. In addition, this insurance product is conceptualized to cover yields against high frequency and low intensity droughts. Thus, there remains a possibility of catastrophic droughts hitting the fields, which this insurance contract might not be able to cover. Based on the aggregated monthly Z-Index observations distribution function of the 36 climate stations used in this paper, the probability that an extreme drought (Z-Index < -4) will occur is estimated at 4%. Thus, the payout triggered when Z-Index reach -4 will not sufficiently hedge crop yields shortfall, leaving the producer to bear the remaining spread. As a result, AgriRecovery type program would be relevant to for his completeness with the insurance contract presented in this paper in regard to catastrophic related yields shortfall.

A further limitation of the policy is a Z-Index characteristic regarding the fact that the index calculations does not account for snowmelt in May in the calculation. Thus, it would be appropriate to add an explanatory variable that could account for the amount of water accumulated in the soil during snowmelt to better specify the model. This explanatory variable could control for the amount of water already present in the fields during seeding, whereas the Z-Index only evaluates the water supply over a short period of time.

Therefore, it is important to evaluate a respective short-put relationship for each crop species hedged. In Figure 43 in Annexes, the estimated coefficients for July-based relationship are roughly the same for wheat, oats and barley production but quite different for canola. Given canola is a very different crop specie, a crop-specific insurance contract would be preferable, considering that the current one is far too generous with a 10.03% per unit of Z-Index indemnity with the simulated insurance contract versus 5.83% per unit of Z-Index decreasing observations.

The improvement of crop resistance to drought shown in the temporal analysis caused the slope of the short put relationship to flatter on the periods. Thus, the need to estimate the yield elasticity to drought with a subset of data, 25 years was used in this case, increase the effectiveness of the policy. The coefficients are then estimated with drought episodes hitting crop fields with the same technological environment then actual hedged fields. However, a lack of historical data by trimming the subset to 25 years implies a loss of catastrophic drought related observations, decreasing the explanatory power of the model as a result.

The physical location of the field is another crucial parameter that must be considered when estimating the elasticity of crop yields to drought events for two reasons. First, the soil composition can have specific water retention characteristic that influence the drought impact on yields. Even if this parameter was controlled in the calculation of the Z-index itself because it is an input to the index, there is a specific soil-crop combination independent of the moisture conditions that affects yield performance that must be take into account. Then, the second issue is spatial correlation among rural municipalities with comparable organic soil composition will be affect differently than RMs with others soil composition as shown in the spatial analysis. For an insurer's perspective, level of monetary payoff needed to hedge income must be adjusted to take into account difference yields performance caused by different soil composition. At a higher level when multiple rural municipalities are hedged in the same or different areas, a spatial correlation analysis give a possibility to adapt the risk management strategy if droughts impact rural municipality on an individual basis, named as idiosyncratic risk here, or on an area basis, called systematic risk. Illustrated by the heatmap above, south-east RMs (light blue) shows geographical similar fixed effect which informs an insurer that a unique insurance policy specific for this area could be implemented to hedge drought related yield shortfalls.

Therefore, the elasticity of yields to drought should be estimated using a subset of data whose temporal and geographic observations best match the specific characteristics of the agricultural field to construct an adequate insurance contract. Thus, the insurance contract designed in this article, a single insurance policy to cover 4 crop species produced by 144 rural municipalities spread over a large area such as the Saskatchewan Prairies, is not adequate since temporal, geographic and crop specificities must be taken into account to limit the remaining basis risk.

Conclusion

As the literature highlights, the use of weather-based derivatives in Saskatchewan has the potential to grow in the coming years. With the expectation of increasing drought frequency due to climate change, hedging tools centered on the threat itself can supply a better suited strategy. To ensure the development of these tools with farmers, resources need to be deployed to increase farmers' derivatives skills and awareness of potential economic gain. In Saskatchewan, 78% of crop producers have seen damages from weather in the past three years but less then 10% have taken advantage of weather-based derivatives. In fact, alongside the BRMs programs already in place to hedge catastrophic risk (high intensity and low probability), there is a need for a non-catastrophic risk management tool to help farmers stabilize crop revenue in all climatic conditions.

Based on a financial derivative framework, a weather-based derivatives contract is well suited to offer this complementary protection. First, they are known to be less afflicted by adverse selection and moral hazard since the underlying index is uncontrollable for both insurer and insured. Moreover, weather index realizations density can be precisely estimated with historical meteorological data, and this field of study is on the edge of several developments with incoming remote sensing, satellite images and machine learning (Singh et Agrawal, 2019). Therefore, the increasing capacity for estimating index-yield crop relationships would minimize basis risk and lower the cost of assessing damages. On the other hand, the hedging effectiveness of such tools is reliant on the correlation between crop yield shortfalls and the underlying index monitoring drought intensity. Due to geographical issues, insurance product issues or temporal issues, this imperfect correlation implies the presence of basis risk that can reduce the demand for such products. In addition, the probability of suffering a loss for which the contract does not trigger a payment is another drawback that needs to be assessed to better understand the viability of these products.

This paper examined the following research question: can a single weather-based insurance policy hedge 4 crop productions from 144 rural municipalities spread across the Saskatchewan Prairies from drought spells? The answer to this question has two folds: YES, because an insurable short-put relationship between the weather observations and yields shortfall exists, and NO because a single insurance contract does not account for temporal, geographical and species issues at specific location. Thus, relying on weather observations to trigger a payment is a possible design, but additional information on the specific location must be added to understand the real impact function of climate physical risk on yields realization.

The outcome of this paper shows that the short-put relationship exists although it is not statistically significant. In fact, hypothesis testing rejects the null hypothesis that it exists in its theoretical shape, but it does appear to exist in practice. This theoretical relationship consists of a positive relationship for negative values of the Z-Index, and an arbitrary relationship for positive values of the Z-Index. The rejection of this assumption is mostly due to the fact that there is still some form of relationship either positive or negative between yields and wetter than normal moisture conditions (positive Z-Index values) from the month selected to estimate the relationship.

Among a panoply of indices measuring the weather, the Palmer Z-Index was chosen for its demonstrated capacity to correctly estimate yields (Quiring & Papakryiakou, 2003). In addition, this index has the advantage of estimating a drought over a short period of time, which is more consistent with the short-term relationship between weather and grain yield than an index using up to 12 previous months in its calculations. Even if the Z-Index does not take snow cover and runoff into account, there is little evidence to suggest this is an issue in the case of humid land, however, it may have a slight impact for arid soil as the latter benefits from this snow as water storage. Thus, the Z-Index developed by Palmer (1965) is still used now as a component of Drought Monitoring programs that centralize drought metrics to increase precision and predictability, and this index is used as the underlying index of an insurance contract to hedge spring wheat, barley, oats and canola yields against drought episodes.

The transformation of a practical question (danger) into a technical problem (risk) is analogous to the strategy to cancel the well-known Knightian distinction between uncertainty and risk (Knight, 1921). In this case, unknown and unknowable danger can (must) become quantified risk, enabling the fulfilment of the Cartesian ideal of prediction, management and control (Funtowicz, 2020). An essential feature of this operation is trust in the power of science and technology to shelter us from the unknown and the unknowable. When this belief is weakened or absent, the Risk Society regresses into the 'Uncertainty Society'; fresh mechanisms of protection emerge, some resembling those of other civilizations in human history.

This index is now a component of a larger approach; the Drought Monitor attempts to evaluate drought severity by assessing the total environmental moisture status using all available drought indicators integrated into one standardized form. As drought index development is still ongoing with newly available satellite images (Demisse *et al.*, 2011) and datamining analysis (Gandhi et Armstrong, 2016), real-time techniques will increase precision in the geographical extent evaluation of drought and the causal impacts on various species of grain.

Annexe

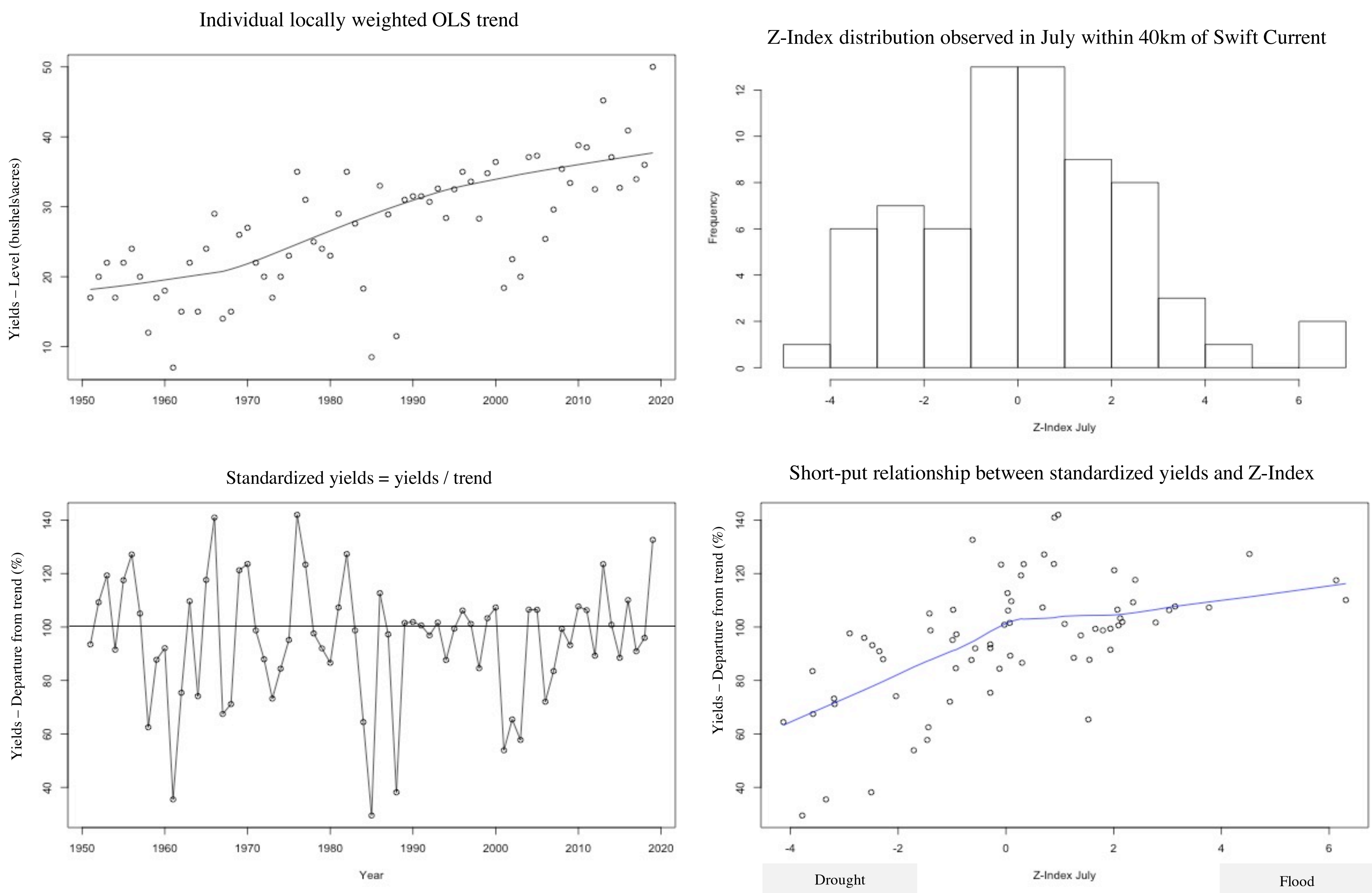
TABLE XV: EQUATION 4-III ESTIMATIONS BY CROP – ELASTICY OF STANDARDIZED YIELDS TO DROUGHT FROM 1951 TO 2019

	Total	Spring wheat	Barley	Oats	Canola
Z-Index June	8.45 ***	8.88 ***	9.35 ***	9.09 ***	3.47 ***
	(0.32)	(0.29)	(0.32)	(0.45)	(0.41)
I(Z-Index June > 0)	-9.03 ***	-9.14 ***	-10.44 ***	-8.91 ***	-4.59 ***
	(0.41)	(0.41)	(0.43)	(0.61)	(0.51)
Obs.	29912	9920	9609	6527	3856
R^2	0.13	0.15	0.14	0.16	0.03
Adj -R^2	0.12	0.14	0.13	0.14	0.01
F-test $\sum \beta = 0$ (p-value)	0.00	0.13	0.00	0.45	0.00

TABLE XVI: EQUATION 4-IV ESTIMATIONS BY CROP - ELASTICY OF STANDARDIZED YIELDS TO DROUGHT FROM 1951 TO 2019

	Total	Spring wheat	Barley	Oats	Canola
Z-Index July	10.03 ***	9.99 ***	10.56 ***	11.38 ***	5.83 ***
	(0.28)	(0.28)	(0.28)	(0.36)	(0.42)
I(Z-Index July > 0)	-9.38 ***	-9.56 ***	-9.73 ***	-10.58 ***	-5.01 ***
	(0.29)	(0.30)	(0.32)	(0.43)	(0.51)
Obs.	29912	9920	9609	6527	3856
R^2	0.24	0.24	0.26	0.28	0.11
Adj -R^2	0.23	0.22	0.25	0.27	0.09
F-test $\sum \beta = 0$ (p-value)	0.00	0.02	0.00	0.00	0.01

FIGURE XXVIII: Swift Current visualization of the short-put relationship scheme



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R Code

```
# Regressions Equation (1)

1-I <- felm(yields ~ trend + Z_Index_May + Z_Index_May_I + Z_Index_June + Z_Index_June_I + Z_Index_July + Z_Index_July_I + Z_Index_August + Z_Index_August_I | rm + grain | 0 | rm,DF_vf)

1-II <- felm(yields ~ trend + Z_Index_May + Z_Index_May_I | rm + grain | 0 | rm, DF_vf)

1-III <- felm(yields ~ trend + Z_Index_June + Z_Index_June_I | rm + grain | 0 | rm, DF_vf)

1-IV <- felm(yields ~ trend + Z_Index_July + Z_Index_July_I | rm + grain | 0 | rm, DF_vf)

1-V <- felm(yields ~ trend + Z_Index_August + Z_Index_August_I | rm + grain | 0 | rm, DF_vf)

# Regressions Equation (2)

2-I <- felm(yields ~ trend + Z_Index_May + Z_Index_May_I + Z_Index_June + Z_Index_June_I + Z_Index_July + Z_Index_July_I + Z_Index_August + Z_Index_August_I + Catastrophe_May + Catastrophe_June + Catastrophe_July + Catastrophe_August| rm + grain | 0 | rm,DF_vf)

2-II <- felm(yields ~ trend + Z_Index_May + Z_Index_May_I + Catastrophe_May | rm + grain | 0 | rm, DF_vf)

2-III <- felm(yields ~ trend + Z_Index_June + Z_Index_June_I + Catastrophe_June | rm + grain | 0 | rm, DF_vf)

2-IV <- felm(yields ~ trend + Z_Index_July + Z_Index_July_I + Catastrophe_July | rm + grain | 0 | rm, DF_vf)

2-V <- felm(yields ~ trend + Z_Index_August + Z_Index_August_I + Catastrophe_August | rm + grain | 0 | rm, DF_vf)
```

Regressions Equation (4)

4-I <- felm(d_yields ~ Z_Index_May + Z_Index_May_I + Z_Index_June + Z_Index_June_I + Z_Index_July + Z_Index_July_I + Z_Index_August + Z_Index_August_I + Catastrophe_May + Catastrophe_June + Catastrophe_July + Catastrophe_August| rm + grain | 0 | rm,DF_vf)

4-II <- felm(d_yields ~ Z_Index_May + Z_Index_May_I + Catastrophe_May | rm + grain | 0 | rm, DF_vf)

4-III <- felm(d_yields ~ Z_Index_June + Z_Index_June_I + Catastrophe_June | rm + grain | 0 | rm, DF_vf)

4-IV <- felm(d_yields ~ Z_Index_July + Z_Index_July_I + Catastrophe_July | rm + grain | 0 | rm, DF_vf)

4-V <- felm(d_yields ~ Z_Index_August + Z_Index_August_I + Catastrophe_August | rm + grain | 0 | rm, DF_vf)

Regressions Equation (5)

5-I <- felm(d_yields ~ Z_Index_May + Z_Index_May_I + Z_Index_June + Z_Index_June_I + Z_Index_July + Z_Index_July_I + Z_Index_August + Z_Index_August_I + Catastrophe_May + Catastrophe_June + Catastrophe_July + Catastrophe_August| rm + grain | 0 | rm,DF_vf)

5-II <- felm(d_yields ~ Z_Index_May + Z_Index_May_I + Catastrophe_May | rm + grain | 0 | rm, DF_vf)

5-III <- felm(d_yields ~ Z_Index_June + Z_Index_June_I + Catastrophe_June | rm + grain | 0 | rm, DF_vf)

5-IV <- felm(d_yields ~ Z_Index_July + Z_Index_July_I + Catastrophe_July | rm + grain | 0 | rm, DF_vf)

5-V <- felm(d_yields ~ Z_Index_August + Z_Index_August_I + atastrophe_August | rm + grain | 0 | rm, DF_vf)