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# The Impact Of Agroclimatic Variables On Crop Insurance Claims In Saskatchewan

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# THE IMPACT OF AGROCLIMATIC VARIABLES ON CROP INSURANCE CLAIMS IN SASKATCHEWAN

by

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Patrick Frimpong Manso

May 1st, 2017

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To my wife Akosua and my two boys Koby and Kojo

I love you all

**ABSTRACT**

The study investigated the impact of agroclimatic variables on the loss cost of hard red spring wheat (HRSW), durum, barely and canola in Saskatchewan. Using daily data on temperature and precipitation, we estimated the water balance or soil moisture using American Society of Civil Engineers standard reference evapotranspiration formula. Accounting for model uncertainty by using Bayesian modeling averaging (BMA), we find that loss cost is influence by monthly temperature and water balance. We find that water balance in June and August impact loss cost of the HRSW, durum, barley and canola. Depending on the crop, one percent increase June water balance, above its long-term average, decreases loss cost between 0.35 percent and 0.64 percent while a one percent increase in August water balance, above its long-term average, increases the loss cost between 0.24 percent and 0.36 percent. A one percent increase in water balance variability increases the loss cost between 0.35 percent and 0.66 percent.

Temperature also affects loss cost, depending on the crop and month. For the early stage of the growing season, a percent increase in GDD increases loss cost between 0.75 and 1.99 percent. However, at the later stages of the growing season, a one per increase in GDD decreases loss cost between 0.7 percent and 2.25 percent.

We find that BMA, in general, outperforms OLS model for out-sample-forecast. Lastly, we find that the forecasted premium rate based on weather probabilities from BMA predictors performed better than simple or 10 year moving average.

# CHAPTER 1

# INTRODUCTION

## 1.0 Background

Agricultural production is susceptible to annual weather variability. Such variability has a significant impact on the agriculture-dependent economies such as Saskatchewan. Saskatchewan, as a leader in agri-food production and export value in Canada, has 44 percent of the total cultivated farmland in Canada and a total export value of $13 billion CDN in 2015 (Saskatchewan Ministry of Agriculture, 2015). The main crops grown are canola, hard red spring wheat (HRSW), barley, durum, field peas, and lentils. Given the significant contribution of Saskatchewan agriculture to Canada's agri-food economy, changes in production emanating from climatic variability can have a significant effect on both the regional and national economy.

Variability in climatic variables such as precipitation, temperature, humidity, solar radiation, and wind speed impacts crop evapotranspiration (ET) regimes and consequently crop growth and production. The extent of crop losses is influenced by the frequency and the severity of climate variability (including extreme weather events such as drought, flood, heat stress, or frost) in the growing season Easterling et al., (2007); McKenzie & Woods, (2011).

The weather uncertainty in any of these variables poses production and financial risk to producers, government, and other stakeholders. For instance, the 2002 drought decreased crop production in Saskatchewan by 48 percent in 2 years, an estimated value of $3.6 billion in crop revenue loss. Crop insurance has been one of the risk-sharing strategies employed by governments to mitigate the impact of such catastrophic events on farm incomes. For instance, the 2002 drought resulted in a $1 billion payout to producers from Saskatchewan Crop Insurance

Corporation, SCIC. At the farm level, cash receipt declined by $652 million in 2001 and $968 million in 2002 (Kulshreshtha, 2011; SCIC 2015).

Though the purpose of crop insurance is to stabilize farm incomes from the insurer perspective, long-term financial sustainability of the crop insurance agency is equally important. Therefore, climatic variability (including the occurrence of extreme weather events such as drought, flood, frost, heat stress) is also a concern to the insurer since it signals higher premiums to stabilize their financial position. The 2002 drought increased the loss ratio to 4.79 and increased average customer premiums from $2,381 per customer to $3,604 per customer, a 51 percent increase. Since both the insured (farmer) and the insurer (SCIC) are affected, the extent to which the agroclimatic variables affect crop yield is essential for estimating crop production risk and crop insurance rate-making Woodard, (2014).

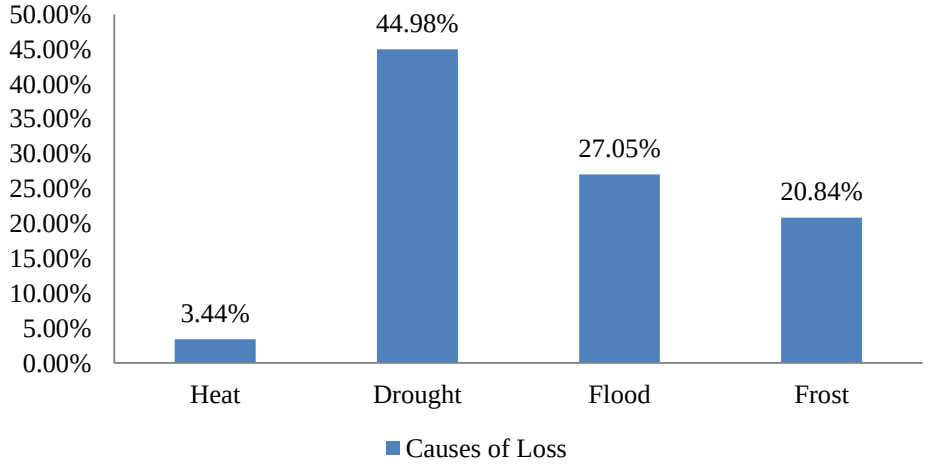
Crop ET is a measure of crop water use or water demand, and precipitation is a measure of crop water supply for non-irrigated production. It forms the basis for determining crop water requirements (Thurlow et al., 2009). An increase in temperature, wind speed, and solar radiation and a decrease in precipitation and humidity result in an increase in crop ET: water demand exceeds supply (moisture deficit) and consequently crop yields decreases. Similarly, a decrease in temperature, wind speed, and solar radiation and an increase in precipitation and humidity will increase water supply (moisture surplus), and consequently increase crop yields (Brouwer & Heibloem, 1986). Crop water usage and temperature are usually the limiting factors in crop yields. When crop water supply is sufficient for crop water demand over the growing season, crop yields are not adversely affected. However, when there is an imbalance between water supply and crop water demand, crop yields are significantly affected. For the purposes of this analysis, the difference between crop ET (demand) and precipitation (supply) is called water

balance, ignoring surface runoff and deep drainage. When crop water demand exceeds water supply for a considerable period of time, drought occurs. Conversely, when water supply exceeds demand over a considerable period of time, excess moisture or flood occurs.

Similarly, temperature above or below a critical value affects crop yield. Crop growth and development, and consequently crop yields, are inhibited if temperature exceeds a critical maximum (heat stress) or below a critical minimum (frost). For HRSW, durum, barley, and canola, the critical maximum is 30º C, and the critical minimum is -5º C. Growing degree days (GDD), an average of the daily minimum temperature and maximum temperature compared to a base temperature of 5º C, is used to measure temperature in agronomy. Therefore, crop water balance and GDD has a direct effect on crop yields, and consequently, crop insurance claims or payout.

Analysis of the historical claimants in the last 17 years showed the major causes of yield loss are drought (45 percent), flood (27.1 percent), frost (20.8 percent), and heat stress (3.4 percent) among producers of HRSW, durum, barley, and canola, as shown in Figure 1.

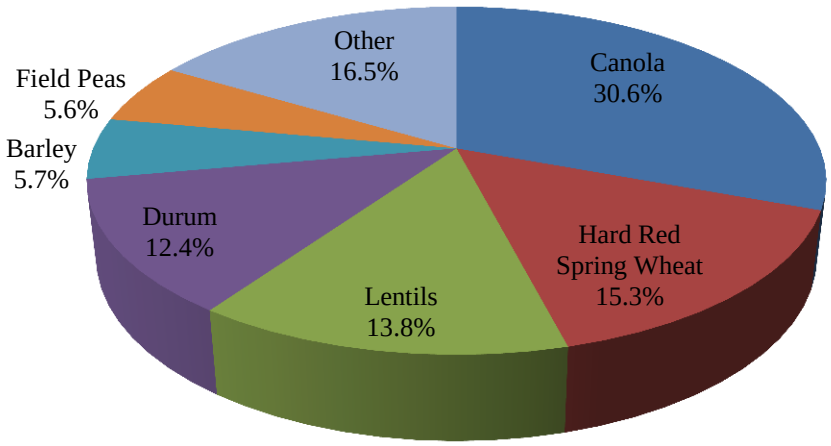
**Figure 1: Primary Cause of Yield Loss from 1998 to 2015 for Major Crops**




Source: SCIC 2016

This paper investigates the extent of water balance and GDD impact on crop insurance payouts or claims. It also used to predict crop insurance expected payouts or claims and price crop insurance risk using water balance and GDD. The major crops investigated are canola, hard red spring wheat, barley, and durum because they constitute approximately 64 percent of 2016 total insured acres in Saskatchewan as shown in Figure 2.

**Figure 2: 2016 Total Insured Acres by Major Crops**




Source: SCIC 2016

## 1.1 Purpose and Objectives

The purpose of this study is to examine the impact of agroclimatic variables on yield risk of major crops insured in Saskatchewan. In particular, we investigate the effect of variants (average and coefficient of variation) of monthly water balance and GDD on the yield risk of crops. In this study, we will use crop insurance claims, the loss cost, as our proxy for yield risk. Loss cost is the ratio of insurance claims to its exposure or liability. Loss cost is a standard measure of riskiness in actuarial analysis. High loss cost implies high risk and low lost cost implies low

yield risk. To best of our knowledge, no study has used water balance and GDD as indices to estimate the impact of climate variability on crop insurance claims in Saskatchewan.

The objective of the study is:

- To determine the relationship between loss cost of HRSW, barley, durum and canola, and variants of water balance and GDD
- Evaluate the performance of Bayesian Modeling Average (BMA), compared to standard regression (OLS), in predicting loss cost of HRSW, durum, barley, and canola.
- Estimate the weights for historical loss cost in premium rating methodology.

## 1.2 Importance of Study

This study will be beneficial to crop producers, the crop insurance agencies, commodity traders, insurance and reinsurance companies, and provincial and federal governments. The study will provide crop producers guide as the level of yield risk anticipated given the prevailing weather conditions and aid in their risk management decisions.

For the insurer such as SCIC, such information will be vital in predicting claims at the start, during, and at the end of the growing season using information such as Environment Canada's weather forecast. It will also provide an alternative means of forecasting claims instead of the current heuristic approach. The results from this study will be essential for the short-term and long-term planning and budgetary allocation decisions. Knowledge about the relationship between climate variables and loss cost will assist the insurer in assessing its reinsurance needs; evaluate its financial position and long-term program sustainability.

The study will also provide important information for the commodity traders and weather derivatives players in further understanding the impact of weather risk on crop losses. Such

information will enhance their weather-derivatives contract structuring, and understanding and estimating weather-crop losses conversion factors to develop appropriate weather-based hedging strategies.

We find that water balance in June and August impact loss cost of the HRSW, durum, barley and canola. Depending on the crop, one percent increase in June water balance decreases loss cost between 0.35 percent and 0.64 percent while a one percent increase in August water balance increases the loss cost between 0.24 percent and 0.36 percent. We also find that the impact of water balance variability on loss cost depends on the crop and month. In general, a one percent increase in water balance variability increases the loss cost between 0.35 percent and 0.66 percent.

Temperature also affects loss cost, depending on the crop and month. For the early stage of the growing season, a percent increase in GDD increases loss cost between 0.75 and 1.99 percent. However, at the later stages of the growing season, a one per increase in GDD decreases loss cost between 0.70 percent and 2.25 percent.

BMA is appropriate methodology for predicting loss cost and perform better that full model OLS. We also find that weather probabilities based on the BMA predicted values could be used to price risk in crop insurance since it outperforms the 10-year moving average and simple methods for estimating premium rates.

### 1.3 Organisation

The study is organized into six chapters. The present chapter discusses the introduction, purpose and objectives, and the importance of the study to relevant industry players. Chapter 2 reviews literature on agroclimatic based indices and their impact on crop yield and yield risk. Chapter 3

presents the study area, description and sources of data used in the study. Chapter 4 shows the theoretical framework for loss cost modeling and the empirical application of Bayesian modeling averaging (BMA) for the study. Chapter five presents the result and discussion of (BMA); compares predictive ability between BMA and OLS and then determines the appropriate weight for risk pricing. The final chapter, (6) provides a summary of the result and conclusion and policy implications of the study.

# CHAPTER 2

# LITERATURE REVIEW

## 2.0 Review of Existing Climatic Indices for Agricultural Production

There are various types of indices to capture weather variation. It can be a thermal index such as just temperature, growing degree days, heating degree days or cooling degree days. It can also be moisture index, which usually combines temperature precipitation, such as soil moisture capacity, Palmer drought severity index, moisture deficit, water stress index or moisture index (Sauchyn and Kulshreshtha, 2008; Bornn & Zidek, 2012). Other indices include Standardized precipitation index (SPI), Crop Moisture Index (CMI), Surface Water Supply Index, Percent of Normal, Palmers Drought Index, Deciles (Hayes, 2014) and, Reconnaissance Drought Index (RDI) Tigkas & Tsakiris, (2013). See Heim Jr, (2012) for a complete review of drought indices. However, the Palmer's Z Index is widely accepted and considered the most appropriate measure of drought indices particularly in Saskatchewan even though the calculation is complex and long series of data is not readily available (Wheaton et al., 2008; Quiring & Papakryiakou, 2003).

Therefore most studies used direct temperature and/or precipitation at fixed calendar periods as a proxy for crop moisture or ET. They include daily precipitation and/or daily temperature (He, et al., 2013; Kutcher et al., 2010; Warland & Brandt, 2010); monthly precipitation and/or monthly temperature or growing degree days as in Meng et al., (2016); An & Carew, (2015) and Robertson et al., (2013); or temperature and precipitation for entire growing season as in An and Carew, (2015) and Robertson et al., (2013). Other variables such as the number of days that temperature exceeds the critical maximum (An and Carew, 2015) and cumulative hour of crop exposure to temperature interval (Robertson et al., 2013: Schlenker & Roberts, 2008).

Changes in temperature and precipitation affect the potential ET and soil moisture. Therefore, the accurate measure of climatic variability, necessary for estimating the appropriate impact on crop yield risk, should include other agri-climate variables such as duration of solar radiation, elevation of the location, wind speed, air humidity (Dixon et al., 1994; McKenzie & Woods, 2011). Some studies such as Chipanshi et al., (2015); Bornn & Zidek, (2012) and (Sun et al., 2011) used ET based models, such as water deficit index, palmers z-index, and multi-drought indices, to estimate the impact of agroclimatic variables on crop yields and/or risk. However, Penman-Monteith (PM) models such as the reference ET equation, developed by American Society of Civil Engineers (ASCE), provides sufficient accuracy for crop production models compared to other ET models (Maule et al., 2006). ASCE ET based model is adaptable, reproducible, comprehensible, standardized, universally accepted, and provides alternative estimation for missing variables such as humidity, wind speed, and sun radiation. By using ASCE ET, it allows us to consolidate important agroclimatic variables into one variable to reduce the dimensionality of covariates.

Therefore the study will use daily crop ET based on the ASCE standardized reference ET equation. This model uses other climate variables such as wind speed, solar radiation, air humidity, longitude, and latitude because such variables improve the accuracy of the estimates. Calculating ET models that include as many variables as possible performs better than parsimonious ET models (Dixon et al., 1994 and Maule et al., 2006). Maule et al.,(2006) compared ASCE ET to six alternative ET models in the Canadian Prairies and concluded the ASCE-ET or similar models that incorporate temperature, humidity, solar radiation, and wind speed perform better than alternative published ET models such as Linacre ET, Hargreaves ET, and Baier-Roberston ET. To the best of our knowledge, no study has used the ASCE-ET based to

model for crop insurance claims, particularly in Saskatchewan. This may be due to the recency of the ASCE-ET model (the full report was released in 2005). Also, conversion of reference ET to crop ET requires crop coefficients which are usually obtained through field experiments conducted over period of time. Crop coefficients in Saskatchewan are not readily available. Our research was based on unpublished crop coefficients obtained from Alberta.

## 2.1 Impact of Weather on Crop Yields and Risk

The majority of literature in crop yield models, particularly in Saskatchewan or Canadian prairie, uses raw agroclimatic variable mainly temperature and/or precipitation, at various time periods. In attempt to capture the plant growth stage, these variables are grouped by certain periods of time such as daily as in He et al., (2013) and Kutcher et al., (2010); monthly and in Meng et al., (2016); An and Carew, (2015); Robertson et al., (2013) or the entire growing season as in An and Carew, (2015); Robertson et al., (2013) and Isik & Devados, (2006). Other studies have also included variables in an attempt to capture extreme weather events (An and Carew, 2015; Robertson et al., 2013; Schlenker & Roberts, 2008). However, these studies usually ignore the prevailing environment conditions such as humidity, wind speed and solar radiation, their interrelations among the climate variables and the underlying plant physiological process.

ET based models that attempt to incorporate these limitations are also limited. Few studies have used ET based models such as water deficit index (Chipanshi, et al., 2015; Bornn & Zidek, 2012 and palmer's z-index Sun et al., 2011; Beach et al., 2010 and Coble et al., 2011) to estimate the impact of agroclimatic variables on crop yields and/or yield risk. ET models require intensive data, and their calculation is complex. In addition, most of the ET based models are calculated by a third party; therefore, they are not easily customizable to the geographic demarcation of the

variable of interest. For instance, the palmer's z-index is calculated by the census agricultural region which is different from the risk zones demarcation of SCIC.

The impact of agroclimatic variables on the yield and risk of crops depend on the crop type, type of agroclimatic variable and timing of the variable (Beach et al., 2010). Generally, there is a positive relationship between total precipitation over the growing season and the yields of crop yields. Most studies indicate a positive relationship between crop yields and monthly precipitation in the growing seasons or over the entire growing season. Whether the relationship is significant or not depends on the type month and type of crop. Precipitation in May and June and sometimes in the pre-season is critical in crop yields (An & Carew, 2015; (Kutcher et al, 2010; Robertson et al., 2013; Van Kooten, 1992 and Deschenes & Greenstone, 2007). However, the relationship between yield risk and precipitation could be negative (Meng et al., 2016; Carew et al., 2009).

Temperature has a negative impact on crop yields beyond the critical maximum temperature (Deschenes & Greenstone, 2007; Schlenker & Roberts, 2008). For wheat, barley, and canola, Robertson et al., (2013) and Meng et al., (2016) report that the critical temperature is generally around 30ºC Temperatures beyond these values adversely affect crop yields. A degree increase results in a 7 percent loss in canola yields, 5.5 percent for wheat and 3.8 percent for corn (An & Carew, 2015 Lobell et al., 2011. However, Isik & Devados,(2006) showed an elastic relationship between temperature and wheat and barley yield risk. One percent increase in temperature results in 1.22 percent and 1.11 percent decrease in barley and wheat yield risk, respectively. In Saskatchewan, Meng et al., (2016), reports that September GDD reduces the yield risk of canola and spring wheat while July GDD increases the variability of these crops. June GDD, however,

increases the variance of only spring wheat. Similarly, Carew et al., (2009) indicated a negative marginal product of precipitation and temperature on spring wheat yield risk.

The closest research to this study is by Meng et al., (2016) who studies the impact of monthly temperature, precipitation and days of heat stress on yield and risk of canola and spring wheat. However, this study differs from their research and other research in the following ways.

None of these studies have used the water balance that is based on ASCE standardized reference ET model. This model uses other climate variables such as wind speed, solar radiation, air humidity, elevation, longitude, and latitude to improve the accuracy of estimates Dixon et al., (1994). Solar radiation, air temperature, wind speed and humidity affect crop water demand and usage. The effect of these variables on water balance is shown in Table 1.

**Table 1: Impact of Climatic Factors on Crop Water Needs**

| **Climatic Factor** | **Crop Water Need** | |
|---|---|---|
| | High | Low |
| Temperature | Hot | Cool |
| Humidity | Low(dry) | High (humid) |
| Wind speed | Windy | Little Wind |
| Sunshine | Sunny(no clouds) | Cloudy(no sun) |

Source: FAO, 1986

Most of these studies used aggregate yield data of voluntary producers as reported by Statistics Canada. Such information usually suffers response bias and lack of data validation,; therefore, the final data may not be representative of Saskatchewan producers. This study, on the other hand, uses a unique dataset from crop insurance clients or producers. These producers are mandated to report their yields, and field adjusters verify such yields for accuracy and reliability. Therefore, the loss cost information is a true reflection of the risk of the majority of Saskatchewan producers.

Also, most of these studies used standard multiple regression models (Basso et al., (2013) at a specified set of predictor variables. For a high dimensional data, model selection and detailed examination of regression outputs becomes overwhelming and inefficient. For instance, for over 40 covariates, the data analyst has to examine carefully $2^{40}$ potential models to identify the best fit. Common approaches such the subset selections based on adjusted $R^2$, Mallow's $C_p$ criterion, is inefficient and misleading because it penalises models with more covariates. In addition, model selection based on Alkaike information criterion (AIC), Bayesian information criterion (BIC) or even prediction sum of squares (PRESS) are inefficient; daunting with large number of covariates and selects a single "best" model. Similarly, automatic variable selection technique such as the "Best" subset algorithms, stepwise regression (forward selection or backward elimination) usually result in a single best model; can be tedious and long; can produce suboptimal model. As Kutner et al., (2004) noted that "Most important for good model building is the recognition that no automated procedure will always find the "best" model, and that, indeed, there may exist several regression models whose appropriateness for the purpose at hand needs to be investigated." Such approach ignores uncertainty in the model choice and can result in model misspecification, over-confident inferences and predictions due to estimation bias, (Draper, 1995). In addition, such regression approach could omit important variables that theoretically should be included. An example of model selection problem in yield risk modeling is apparent in Coble et al., (2011) where indeed the choice of best model indicates statistically insignificance of the explanatory variables. Other methods such as principal components analysis (PCA) could be used to reduce dimensionality and combine correlated variables. However, interpreting such results within the context of the loss cost modeling could be problematic.

To address such model uncertainty, we will be using Bayesian modeling average (BMA). BMA helps to determine models or set of covariates with a high likelihood of explaining the data generating process of the dependent variable. The final "best" model is a posterior probability weighted-average of all the models. BMA uses all the possible models as "best" model instead of one single model. Therefore final coefficient of each predictor variable (posterior distribution mean) is based on weighted average of all possible models. Also, it provides the posterior inclusion probability of each covariate, essentially determining the relative importance of each covariate on the dependent variable. Using the inclusion probabilities, BMA helps to determine which explanatory variables to include in the model specification. To the best of our knowledge, this study is the first to use loss cost information, water balance and BMA technique to estimate the impact of weather on yield risk in Saskatchewan. The next chapter describes the sources of data and variables used in the loss cost modeling. It also provides a brief description of the Saskatchewan and SCIC.

# CHAPTER 3

# DATA

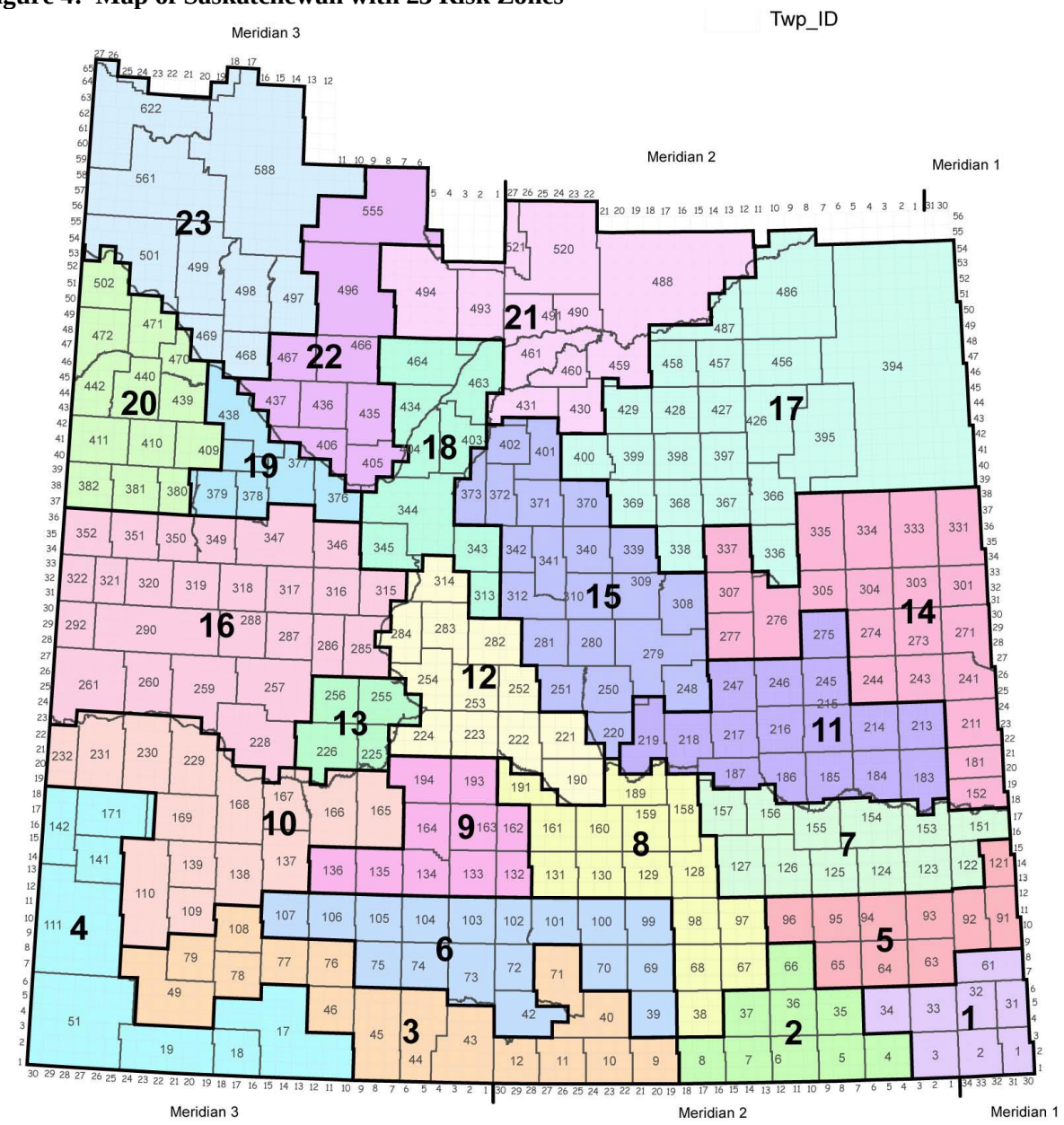
## 2.0 Study Area

Saskatchewan (Figure 3) is one of the provinces in the Canadian prairies with agriculture as one of the primary industries. It consists of 44 percent of agriculture land in Canada. SCIC is a provincial Treasury Board Crown Corporation in Saskatchewan, Canada. It was established in 1961 with the responsibility of developing, managing and offering agricultural risk management programs such as production insurance in Saskatchewan, Canada. The production insurance provides protection to producers against yield loss emanating from multi-perils. These perils include drought, flood, hail, snow, wind, lightning, hurricane, tornado, accidental fire, wildlife damage, and insect, rodents and/or plant disease across the province. This Multi-peril Crop Insurance Program guarantees producers a minimum yield and quality.

In 2015, SCIC had a total liability or exposure of $4.8 billion in Canadian dollars, a total premium of approximately $489 million, paid approximately $265 million in claims and insured approximately 26.2 million acres of agricultural land (2015/2016 Annual Report). SCIC insures approximately 46 crops with canola, HRSW, durum, and barley as the major crops in terms of liability and insured acres. In 2016, canola, HRSW, durum and barley consisted of 64 percent of the total insured acres. These crops are distributed across the province of Saskatchewan. To ease in program administration, SCIC divides the province into 23 homogenous risk areas (Figure 4). The implicit assumption is that the risk of producers in a given risk area is similar primarily due to similar agroclimatic conditions. Consequently, the loss cost (pure premium) and other important insurance variables for each crop are calculated by these risk areas.

**Figure 3 Map of Saskatchewan**

**Figure 4: Map of Saskatchewan with 23 Risk Zones**




Canada

Government of Saskatchewan

SCIC SASKATCHEWAN CROP INSURANCE CORPORATION

Growing Forward

Source: SCIC, 2016

## 3.0 Dependent Variable Measurement and Data Source

The loss cost (LC) is defined as the ratio of insurance claims or indemnity to the total exposure or risk or liability. It is a measure of the riskiness of a crop. High LC indicates high risk and low LC indicates low risk. The claims of each insured are calculated based on his/her actual yield, coverage level chosen and their long-term yield or guarantee. For a given year, claims are paid if actual yield is below coverage (product coverage level and long-term yield) but no claims if the actual yield higher than coverage. Producers have the option to choose their coverage level. SCIC offers coverages in 50 percent, 60 percent, 70 percent and 80 percent. For a given producer, the claim or indemnity is calculated as

$$I_{nt} = \max\left(0, c\bar{y}_{nt} - \left(y_{nt}(Weather, Trend)\right)\right) \times p_t \times A_t \qquad (1)$$

Where $I_{nt}$ is the total indemnity or claims for year t, customer *n*, in \$. $c$ is the base coverage level it can be 50, 60, 70 or 80 percent.$\bar{y}_{nt}$ is the long-term average annual yield (kg/ac) in year for customer, *n*. $y_{nt}(Weather, Trend)$in kg/ac. The yield function also depends on agroclimatic variables that will be discussed later**.** $p_t$ is the price of insured crop in \$/kg in year ,t.$A_{nt}$is the total insured acres at time *t* and customer *i*.

The total exposure or liability per acres is calculated as:

$$L_{nt} = c\bar{y}_{nt} \times p_t \times A_{nt} \qquad (2)$$

Therefore the loss cost ratio for a given crop for all insured in a given risk zone, z. is given

$$\text{as} LCR_{zt} = \frac{\sum_{n=1}^{N} I_{nt}}{\sum_{n=1}^{n} L_{nt}} \qquad (3)$$

Data on historical claims were obtained from SCIC database. This database contains customer level information on liability, indemnity, premium, insured acres and risk area of the insured crop for each crop since 1973. The indemnity and liability were aggregated at the risk zone level for each year. The indemnity and liability were then restated to reflect the program changes that have occurred for each crop. The historical loss cost is simply the ratio of restated indemnity to restated liability as shown in equation 3. In rare occasions where the loss cost exceeds the unity, the loss cost is capped at 1.

### 3.1 Explanatory Variable Selection and Data

The explanatory variables required for the study are the agroclimatic variables during the growing season. These are: Monthly water balance from May to September; Monthly risk or variability of water balance from May to September; Monthly growing degree days from May to September; Monthly risk or variability of growing degree days; Number frost days; Number of excessive heat days; Year to capture technological trend and Spatial Risk Heterogeneity

Calculations of these agroclimatic variables require daily weather data on precipitation, minimum temperature, maximum temperature, elevation, longitude, latitude among others. These weather data were obtained from three main sources: SCIC weather data, Environment Canada weather data and Natural Resources Canada (NRC) interpolated data. The NRC used ANUSPLIN software to interpolate relevant weather variables. ANUSPLIN uses thin-plate smoothing splines that incorporate the spatial and temporally varying dependence on ground elevation, to interpolate relevant weather variables Hopkinson et al., (2011).

In all there are 545 weather stations where some are defunct, relocated and some still existing. For each weather station, the order of data source importance is SCIC supplemented by

Environment Canada data and then Natural Resource Canada. Base on the location of the weather, using the latitudes and longitudes, each weather station is assigned to the risk area. Weather stations that are not located on arable lands were excluded. The resulting database is the daily precipitation, minimum temperature, maximum temperature from 1960 to 2016 for all the weather stations.

### 3.1.1 *Calculation of Monthly Water Balance*

Water balance is used to measure water availability or unavailability for crop growth and development. Precipitation, site specific characteristics, and temperature impacts water balance. To calculate the water balance for each month in the growing season, we used the following methods.

*Calculation of Daily Reference Evapotranspiration:* For each weather station, the daily reference evapotranspiration based on the American Society of Civil Engineers' standardized formula as indicated in Appendix 1.

*Calculation of Crop Evapotranspiration*: The next step is to calculate the crop evapotranspiration since evapotranspiration differs by crop. The crop evapotranspiration is calculated as:

$$ET_c = K_{co} \times ET_{rs} \qquad (4)$$

Where $ET_c$ is the crop evapotranspiration in mm per day.$K_{co}$ is crop co-efficient. $ET_{rs}$ is standardized reference evapotranspiration. Crop co-efficient was obtained from Ted Harms, Soil and Water Specialist with Alberta Agriculture and Forestry. The crop coefficient is based on the field experiment, Ted fitted 5$^{th}$ polynomial model for field evapotranspiration. we adopted the same crop co-efficient due to geographical similarities between Saskatchewan and Alberta in

terms of agri-climate patterns and soil characteristics rainfall pattern. The co-efficient is shown in Table 1. Therefore, the crop evapotranspiration is calculated as

$$ET_c = \alpha + \sum_{q=1}^{4} \beth_q ET_{rs}{}^q \qquad (5)$$

<u>*Calculation of daily water balance for each weather station:*</u> The daily water balance for station *s* and daily *d*, is calculated as the difference between daily precipitation (P) and crop evapotranspiration (ET).

$$WB_{s,d} = P_{s,d} - ET_{c,s,d} \qquad (6)$$

<u>*Calculation of daily water balance by Risk zone:*</u> For each risk zone, z, the daily water balance (WB) is calculated as the average of the water balance for all weather stations in the risk zone, z.

$$WB_{z,d,t} = \sum_{s=1}^{S} WB_{s,d,t} / \sum_{s=1}^{S} W \qquad (7)$$

Where W denotes the number weather stations in a risk zone. With the daily water balance for each risk zone,z,. The next stage is to calculate the aggregate water balance by month.

<u>*Calculation of monthly water balance by risk zone and year:*</u> If N denotes the last day of the month, the monthly water balance for risk zone, *z*, and year, *t*, then the cumulative water balance for month m is calculated as:

$$WB_{z,t,m} = \sum_{d=1}^{N} WB_{z,d,t} \qquad (8)$$

We obtain the water balance each for May, June, July, August and September from 1960 to 2016.

### 3.1.2 *Calculation of Variability of Water Balance*

The water balance also has distribution. It is necessary to capture this distribution into the loss cost model. In this study, we use the coefficient of variation a measure of the risk or variability of the water balance for each risk zone, month and year. The coefficient of variation of the water balance in risk zone, z, year, t, and month m is calculated as the ratio of the standard deviation to mean water balance:

$$CVWB_{z,t,m} = \sqrt{\left(WB_{z,d,t} - \overline{WB_{z,d,t}}\right)^2} \Big/ \overline{WB_{z,d,t}} \qquad (9)$$

### 3.1.3 *Calculation of the monthly GDD*

Similar to the monthly water balance calculation, the monthly GDD is calculated first by calculating the daily GDD for each weather station. Daily GDD is calculated as

$$GDD_{w,d}(Tmean_{w,d}) = \begin{cases} Tmean_{w,d} - 5 & if\ Tmean_{w,d} > 5℃ \\ 0 & if\ Tmean \leq 5℃ \end{cases} \qquad (10)$$

Where $Tmean_{w,d}$ is the mean temperature calculated as average between minimum and maximum temperature. The daily GDD for risk zone is then calculated as the average of the daily GDD for weather stations in the risk zone. The daily GDD is then summed over the number of days in the month to get the monthly GDD for each risk zone and year.

### 3.1.4 *Calculation of GDD variability*

The variability of GDD for each risk zone and year is calculated as the ratio of the standard deviation of daily GDD to mean of daily GDD for that risk zone and year.

$$CVGDD_{z,t,m} = \sqrt{\left(GDD_{z,d,t} - \overline{GDD_{z,d,t}}\right)^2} \Big/ \overline{GDD_{z,d,t}} \qquad (11)$$

### 3.1.5 *Measurement of Technological Impacts*

Technological advancement in farm agronomic practices, varieties and technology in farm machinery is expected to impact crop yield risk significantly. As technology improves crop yields, we expect a negative impact on loss cost. That is high yielding extreme water and/or heat resistant varieties can decrease the loss cost. Technology is captured as linear time trend in the model.

### 3.1.6 *Measure of Frost*

The long stretch of cold in the growing season affects crop insurance claims. We expect a positive relationship between frost and loss cost. We included a dummy variable to indicate days with temperature below 5° Celsius in the growing season. The total number of frost days or frost index is captured in the model as:

$$FI = \sum_{gs=1}^{N} I\{Tmin_{i,t} < -2°\text{C}\} \qquad (12)$$

### 3.1.7 *Measurement of Excessive Heat*

Heat stress over a significant period of time affects crop growth and development. Similarly, we expect a positive relationship between heat stress and loss cost. We include a dummy variable to indicate the number of days of temperature above 30° Celsius in the growing season. The total number of heat stress days is captured as:

$$HI = \sum_{gs=1}^{N} I\{Tmax_{i,t} > 30°\text{C}\} \qquad (13)$$

### 3.1.8 *Site specific Characteristics*

Producers on the same risk zone are offered the same gross premium (premium before discount or surcharge). However, premium offered differ by risk zone. SCIC inherently assumes risk

homogeneity for each risk zone. It will therefore be necessary to capture spatial differences (if any) in risk as assumed by the insurer. We used a dummy variable for each risk zone to capture the potential spatial heterogeneous risk.

# CHAPTER 4

# METHODS AND MODEL

## 4.0 Theoretical Framework

Crop insurance is usually used to mitigate downside risk. From the insurer perspective, the cost of the risk (premium) should reflect the inherent yield risk of the insured. One measure of the cost of risk in standard actuarial literature is the loss cost. Loss cost is the ratio of the indemnity or claims to liability or exposure. In this study, the loss cost ratio is used as a proxy for yield risk. Woodard, (2014), states the strong positive correlation between expected loss cost and yield risk. The loss cost ratio is a function of crop yield distribution which in turn is influenced by agroclimatic variables. The nature (frequency and severity) of the loss cost is largely influenced by weather and climate and their variability on crop yields and technological progress. The expected conditional loss cost ratio therefore can be expressed as:

$$E(LCR|x) = \frac{\int_0^\infty Max(0, E(Y|x).\theta - y.f(y)dy)}{\int_0^\infty \mathrm{E}(Y|x).\theta} \qquad (14)$$

where $E(LCR|\boldsymbol{x})$ is the expected loss cost condition on $\boldsymbol{x}$ covariates.$\theta$ is the coverage level.$\mathrm{E}(Y|\boldsymbol{x})$ is the crop yield function

Since the expected loss cost is influenced by the distribution of weather variables, technological progress, the E (LCR) for given location, *t*, and location, *i* ,can estimated empirically as:

$$E(LCR_{it}) = f(Climate_{it}, Technology_{it}, Location\ Characteristic) + \varepsilon_{it} \qquad (15)$$

## 4.1 Empirical Model

As stated earlier, we used technological improvements, the number of frost days in the growing season, the number of excessive heat days and variants of water balance (WB) and growing

degree days (GDD) while accounting for site specific characteristics, to model the expected loss cost. The full model is

$$LCR_{it} = \alpha + \phi Time_{it} + \sum_{m=5}^{9} \beta_m WB_{it} + \sum_{m=5}^{9} \gamma_m CVWB_{it} + \sum_{m=5}^{9} \delta_m GDD_{it} + \sum_{m=5}^{9} \tau_m CVGDD_{it} + \omega \sum_{gs=1}^{N} I\{Tmean_{i,t} < -2\} + \varphi \sum_{gs=1}^{N} I\{Tmax_{i,t} > 30\} + \sum_{i=1}^{22} \psi_i RZ_i + \epsilon_{it} \quad (16)$$

where $LCR_{it}$ is the loss cost ratio at location *i*, and year *t* . $WB_{it}$ is the water balance at location *i*, and year *t* for each month *m* (May=5, June=6, July=7, August=8, September=9).$CVWB_{it}$ is the coefficient of variation of water balance at location *i*, and year *t* for each month *m* (May=5, June=6, July=7, August=8, September=9). $GDD_{it}$ is the growing degree days at location *i*, and year *t* for each month *m* (May=5, June=6, July=7, August=8, September=9).$CVGDD_{it}$ is the coefficient of variation of growing degree days at location *i*, and year *t* for each month *m* (May=5, June=6, July=7, August=8, September=9).$I\{Tmin_{i,t} < -2\}$ is an indicator variable for frost in the growing season (May 1 to September 30) at location *i*, and year *t*. $I\{\boldsymbol{Tmax}_{i,t} > 30\}$ is an indicator variable for heat stress in the growing season (May 1 to September 30) at location *i*, and year *t* .$RZ_i$ is the riskzone dummy for site characteristics

### 4.1.1 *Bayesian Modeling Averaging (BMA)*

A standard linear model with loss cost ratio as dependent variables and $\boldsymbol{X}$ covariates typically express as:

$$LCR = \alpha_k + X_k \beta_k + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I) \quad (17)$$

Given the large set of covariates (44 variables), there is uncertainty on the choice of covariates that truly reflect the expected loss cost ratio. Typically a stepwise, forward or backward regression could be used in the covariate selection. However, such regression approach could

result in inefficiency and omit important variables that theoretically should be included. One recommended approach to deal with such model of uncertainty is Bayesian modeling averaging Steel, (2016). BMA calculates all the combinations of independent variables and construct a weighted average of all the models.

Let us assume that for our dataset D, there are $\mathcal{M} = \{\mathcal{M}_k, k = 1,2, \ldots\ldots K\}$ potential models

Following (Hoeting, Madigan, Raftery, & Volinsky, 1999), assuming the loss cost ratio is given as LCR, then the posterior distribution of LCR given the dataset D

$$pr(\theta|LCR, X) = \sum_{k=1}^{K} p(\theta|\mathcal{M}_k, LCR, X)\, p(\mathcal{M}_k|X, LCR) \qquad (18)$$

$p(\theta|\mathcal{M}_k, LCR, X)$ is posterior distribution of the coefficients given the model $\mathcal{M}_k$

$p(\mathcal{M}_k|X, LCR)$ is the posterior probability that $\mathcal{M}_k$ is the correct model, given that one of the models is correct. The BMA posterior distribution of LCR is the weighted average of the posterior distribution of the LCR under each of the models, weighted by their posterior model probabilities.

The posterior model probability of $\mathcal{M}_k$ is given by

$$p(\mathcal{M}_k|LCR, X) = \frac{p(LCR|\mathcal{M}_k, X)p(\mathcal{M}_k)}{\sum_{k=1}^{K} p(LCR|\mathcal{M}_s, X)p(\mathcal{M}_s)} \qquad (19)$$

$p(\mathcal{M}_k)$ is the prior model probability; $p(LCR|\mathcal{M}_k)$ is the marginal likelihood of model $\mathcal{M}_k$. This obtained by integrating over the unknown parameters.

$$p(LCR|\mathcal{M}_k) = \int p(LCR|\theta_k, \mathcal{M}_k)p(\theta_k|\mathcal{M}_k)\mathrm{d}\theta_k \qquad (20)$$

where $\theta_k$is the vector of parameters of model $\mathcal{M}_k$. $p(LCR|\theta_k, \mathcal{M}_k)$ is the likelihood $\theta_k$ under model $\mathcal{M}_k$. $p(\theta_k|\mathcal{M}_k)$ is the prior density of $\theta_k$ under model $\mathcal{M}_k$

The posterior mean and variance is therefore calculated for the model parameter say $\beta_1$:

$$E(\beta_1|LCR) = \sum_{k=0}^{K} \hat{\beta}_1^k p(\mathcal{M}_k|LCR) \quad (21)$$

and variance

$$Var(\beta_1|LCR) = \sum_{k=0}^{K} \left(Var[\beta_1|LCR, \mathcal{M}_k] + \hat{\beta}_k{}^2\right) p(\mathcal{M}_k|LCR) - E(\beta_1|LCR)^2 \quad (22)$$

where

$$\hat{\beta}_{\boldsymbol{k}} = E(\beta_k|LCR, \mathcal{M}_k)$$

BMA averages the parameter estimates over the entire potential models using posterior model probability as weights. In addition, the posterior inclusion probabilities shows which covariates should be included in the final model. This approach can ensure a good predictive ability than standard OLS approach (Hoeting et al., 1999).

### 4.1.2 *Empirical Estimation of Loss Cost Model*

The BMA model for loss cost ratio was estimated for HRSW, durum, barley, and canola. The "BMA" package version 3.18.6 in R software was used in the estimation process.

Equation 16 was transformed into ratio by dividing each variable by their respect overall average to allow ease of interpretation and conceptualisation. This approach is consistent (Paulson & Hart, 2006) and (Zhang, 2008) where crop yields were related to agroclimatic index such as accumulated cooling degree days or precipitation by ratios. In this way, the parameter estimates can be interpreted as a percentage change in loss cost above or below the long-term loss cost due to 1 percent increase in the agroclimatic index above its long-term average. Consequently, the Equation 3 was transformed to

$$\widehat{LCR_{zt}} = \alpha + \phi Time_{zt} + \sum_{m=5}^{9} \beta_m \widehat{WB_{zt}} + \sum_{m=5}^{9} \gamma_m \widehat{CVWB_{zt}} + \sum_{m=5}^{9} \delta_m \widehat{GDD_{zt}} + \sum_{m=5}^{9} \tau_m \widehat{CVGDD_{zt}} + \omega \sum_{gs=1}^{N} I\{Tmean_{z,t} < -2\} + \varphi \sum_{gs=1}^{N} I\{Tmax_{z,t} > 30\} + \sum_{z=1}^{22} \psi_z Z_z + \epsilon_{zt} \quad (23)$$

where $\widehat{LCR_{\iota z}}$ = is the ratio of the loss cost at riskzone *z*, and year *t* to the average loss cost. $\widehat{WB_{\iota z}}$ is the ratio of water balance to the average water balance at riskzone *z*, and year *t* for each month *m* (May=5, June=6, July=7, August=8, September=9). $\widehat{CVWB_{\iota z}}$ is the ratio coefficient of variation of water balance at riskzone *z*, and year *t* to the average coefficient of variation of for each month *m* (May=5, June=6, July=7, August=8, September=9) balance. $\widehat{GDD_{\iota z}}$ is the ratio of growing degree days at riskzone *z*, and year *t* to average growing degree for each month *m* (May=5, June=6, July=7, August=8, September=9). $\widehat{CVGDD_{\iota z}}$ is the ratio of coefficient of variation of GDD at riskzone *z*, and year *t* to average coefficient of variation of GDD for each month *m* (May=5, June=6, July=7, August=8, September=9)

The next chapter presents the results and discussion of the study. It starts with descriptive statistics of the variables used in the study. It then presents and discusses the result of the BMA analysis. We then compared the predictive ability of BMA model by comparing out-sample forecast for BMA and OLS model and determined the premium rate based on probabilities from the BMA predicted loss cost.

# CHAPTER 5

# RESULTS AND ANALYSIS

## 4.2 Introduction

This chapter presents a descriptive statistics of the variables and results of the BMA analysis by crop. We also looked at the predictive ability of the BMA model compared to the already existing approach for forecasting loss cost for years 2010 to 2015. The BMA results are based on R package "BMA" while the prediction is based on R package "BMS" because we encountered a challenge of using "BMA" to conduct predictions. A comparison of the posterior mean and posterior inclusion probabilities is not significantly different between these two softwares.

In addition, we backcasted historical loss cost to 1960 and then assigns weight to the historical loss experience in an attempt to improve the premium rate setting process. For each crop we looked at the descriptive statistics, BMA model results, develop an index to assign appropriate weight to historical loss cost experience and calculated premium rate based on the relative probabilities of the predicted loss cost.

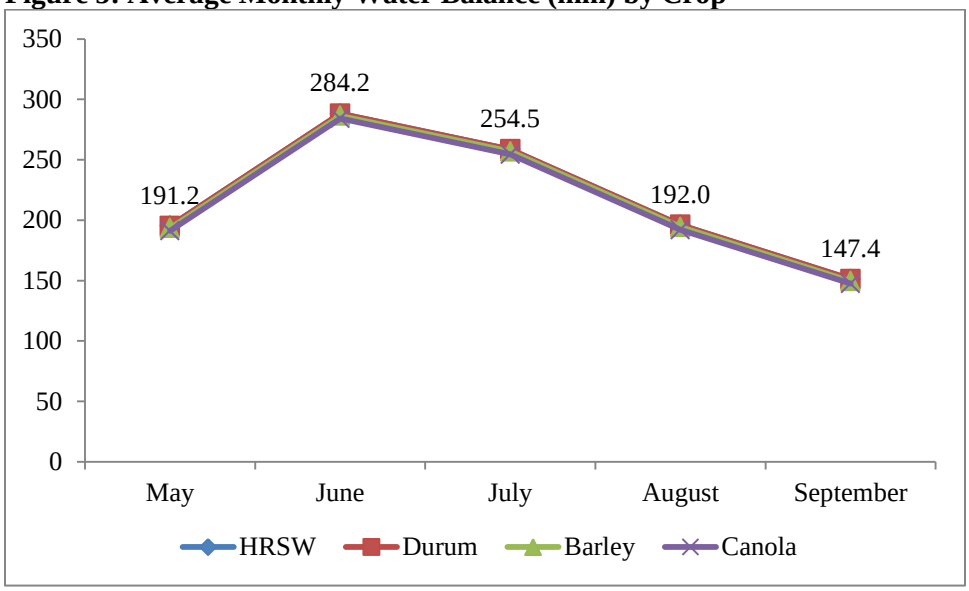
## 5.1 Exploratory Analysis

The full descriptive is shown in Appendix 3 to Appendix 6. The average loss cost is 8.8 percent for HRSW, 10.1 percent for durum, 12.1 percent for barley and 14.8 percent for canola. The average number frost days in a growing season is five days and the average number excessive heat days is 11. However, we did not capture when such extreme temperature occurs during the growing season.

The average cumulative water balance, an indication of water availability for crop use, is high in June and July, coinciding with heading and flowering stage in the crops development where

water use is high. The lower water balance in August and September also coincides with low water requirement in the yield formation and ripening stage.

**Figure 5: Average Monthly Water Balance (mm) by Crop**

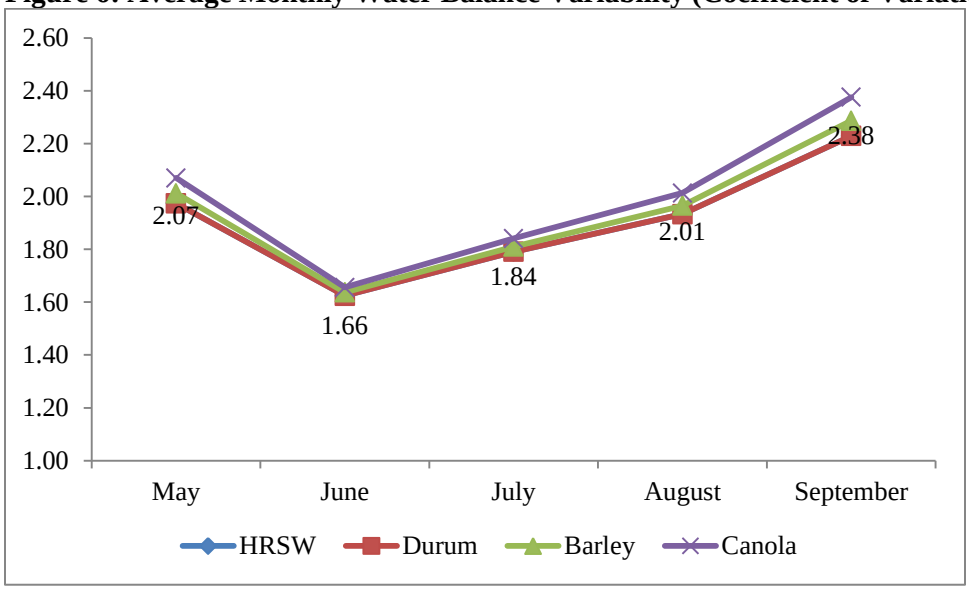



Water balance variability is not significantly different among the crops as indicated in Figure 6.

Generally, water availability is variable in May, become more stable in June and then variability increases in the months July, August, and September.

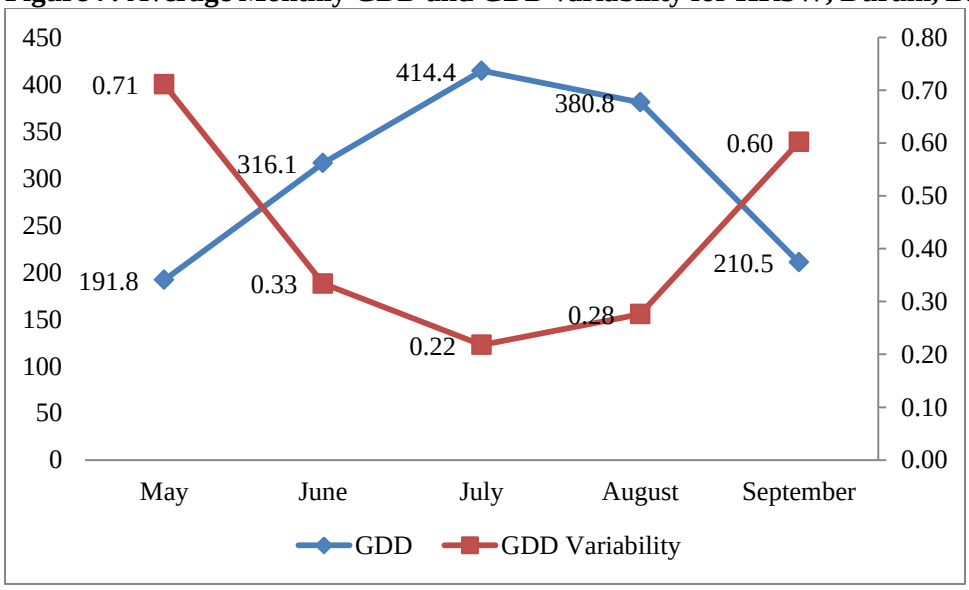
The summary of the average GDD and its variability is shown Figure 7. In May, average monthly GDD is approximately 191.8º C, then increases to 316.1º C in June, and the highest in July of 414.4 ºC and then begins to drop to 380.87 ºC in August and then 210.5 ºC in September. The monthly GDD appears to have an inverse relationship with the average monthly GDD. The variability remained low in July (where average GDD is high) and high at May and September when average GDD is low.

**Figure 6: Average Monthly Water Balance Variability (Coefficient of Variation) by Crop**




The variability of GDD also remained relatively low in June, July, and August, indicating stable temperature in these periods of the critical crop growth and development. The high values in the May and September variability is reasonable given the usually fluctuating temperatures from transitioning from spring to summer and summer to fall.

**Figure 7: Average Monthly GDD and GDD variability for HRSW, Durum, Barley and Canola**



## 5.2 BMA Results and Analysis

This section analyzes the impact of agroclimatic variables on the loss cost of HRSW, durum, barley and canola using BMA. The full results are in Appendix 8 for hard red spring wheat, Appendix 9 for durum, Appendix 10 for barley and Appendix 11 for canola. Each table includes the posterior inclusion probability (PIP) for each covariate, BMA posterior distribution mean for each parameter estimates, BMA posterior distribution standard deviation, and the best five models based on the BIC which is fairly close the uniform information priors (UIP). Each of the models has the number of covariates selected, $R^2$, the BIC and the posterior probability of being the correct model. The posterior inclusion probability shows the probability that the parameter estimate of the covariate is not zero among the possible models.

A summary of the results as indicated in Table 2 show that the posterior distribution mean of covariates with the probability of inclusion greater than or equal 70 percent. The choice of 70 percent is arbitrary. However, we believe that 70 percent is appropriate given the high dimensionality of the covariates.

Technological improvements such as improved crop varieties, production techniques, and management practices decrease the loss cost of barley and canola by 0.02 percent and 0.03 percent, respectively. In other words, technological improvement increases crop yields and decreases risk and therefore lowers the probability of yield claim position. This result is consistent with Woodard, (2014) and McCarl et al., (2008) who find that expected loss cost (yield risk) decreases with increasing trend.

**Table 2: Posterior Distribution Mean for Variables (PIP >=0.7) HRSW, Durum, Barley and Canola**

| Variable | HRSW | Durum | Barley | Canola |
|---|---|---|---|---|
| Intercept | -6.72 | -5.64 | 34.39 | 54.82 |
| Trend | 0.00 | 0.00 | -0.02 | -0.03 |
| Water Balance Ratio in June | -0.53 | -0.64 | -0.42 | -0.35 |
| Water Balance Ratio in July | 0.00 | 0.00 | -0.22 | 0.00 |
| Water Balance Ratio in August | 0.31 | 0.36 | 0.24 | 0.30 |
| Water Balance Variability Ratio in June | 0.38 | 0.00 | 0.00 | 0.00 |
| Water Balance Variability Ratio in July | 0.00 | 0.35 | 0.49 | 0.00 |
| Water Balance Variability Ratio in September | 0.66 | 0.00 | 0.00 | 0.00 |
| GDD Ratio in May | 1.68 | 1.65 | 1.41 | 0.75 |
| GDD Ratio in July | 1.65 | 0.00 | 1.99 | 1.85 |
| GDD Ratio in August | -2.25 | -1.98 | 0.00 | 0.00 |
| GDD Ratio in September | -1.19 | -0.70 | -1.11 | 0.00 |
| GDD Variability in July | 0 | 0 | 0.82 | 0 |
| GDD Variability Ratio in August | 0.00 | 0.00 | 0.00 | 0.82 |
| GDD Variability Ratio in September | 0.91 | 0.00 | 0.00 | 0.00 |
| Number Frost Days | 0.13 | 0.13 | 0.12 | 0.07 |
| Number of Heat Stress Days | 0.07 | 0.06 | 0.05 | 0.06 |

The results indicate that water balance ratio in May and September is not a significant predictor of the loss cost of HRSW, durum, barley and canola. This result is inconsistent with Meng et al., (2016), who determined that May precipitation decreases the yield risk of both spring wheat and canola. However, Cabas et al., (2010) found that May precipitation is not a significant statistical predictor of the yield risk of corn, soybean and winter wheat. Precipitation may be a significant predictor of yield variability; however, its impact may be neutralized by the water demand for such crop. Water balance ratio in June (August) decreases (increases) the loss cost of all crops. One percent increase in June water balance above its average decreases the loss cost of hard red spring wheat, durum, barley and canola by 0.53 percent, 0.64 percent, 0.42 percent and 0.35 percent, respectively. Alternatively, one percent decrease in June water balance above its average increases the loss cost of these crops by such magnitudes. However, one percent increase in August water balance above its average increase increases the loss cost by 0.31 percent for

HRSW, 0.36 percent for durum, 0.24 percent for barley and 0.30 percent for canola. The result is consistent Meng et al., (2016) who found a negative relationship between June precipitation and yield risk of HRSW and canola but positive relationship between August precipitation and yield risk. Cabas et al., (2010) found positive relationship August precipitation and corn yield risk. Water balance in July only affects barley loss cost. One percent increase in the water balance above its average decreases the loss cost by 0.22 percent. The results are expected given that June is the critical period of the plant growth, where water use is essential. High water availability above the normal ensures the crop gets required water for its growth. Consequently the likelihood of crop loss or lower yield necessary to trigger claims in minimized. McKenzie and Woods (2011) noted that water usage is critical in June and July for cereals including barley. If moisture is insufficient, crop losses can occur. In August, however, crop water use is lower at the pod development and ripening stage. Thus an increase in water availability above the normal can affect the quality of harvested yield. Since SCIC pays for both quantity and quality related losses, such a situation can increase insurance claims.

The impact of water balance variability depends on the month and crop. For instance, June and September water balance variability impacts the only loss cost of HRSW and July water balance variability impact durum and barley loss cost. The more variable the water balance the higher the loss cost. One percent increase in June water variability above its long-term increases loss cost of HRSW by 0.38 percent. Similarly, one percent increase in the July water balance variability above its average increases the loss cost of durum and barley by 0.35 percent and 0.49 percent above their long-term loss cost, respectively. Finally, one percent increase in water balance variability in September increase loss cost of HRSW by 0.66 percent. A more variable water balance affects the stability and continuous supply of soil moisture necessary for growth

and development. These consequently affect crop yield and quality and could lead to high claims.

Temperature affects crop yield and consequently crop loss cost. Temperature effect depends on the month and type of crop. In general, the loss cost of all the crops is positively influenced by May GDD. A one percent increase in May GDD increases the loss cost by 1.68 percent for HRSW, 1.65 percent for durum, 1.41 percent for barley and 0.75 percent for canola. This result is inconsistent with Meng et al., (2016) and Cabas et al., (2010) who found a negative relationship between May GDD and yield risk of HRSW, canola, corn and soybean. July temperature positively influences the loss cost of barley and canola while August temperature negatively influences the wheat crops . September GDD negatively affect only the cereals (HRSW, durum and barley). July GDD only influences the loss cost of HRSW, barley and canola. A one percent increase in July GDD increases the loss cost of HRSW, barley and canola by 1.65 percent, 1.99 percent, and 1.85 percent, respectively. The result is consistent with Meng et al., (2016) who determined that May, July and September GDD are significant predictors of canola yield risk. On the other hand, a percent increase in August GDD increases the loss cost of HRSW and durum by 2.15 percent and 1.98 percent, respectively. A one percent increase in September GDD increases the loss cost of HRSW, durum, and barley by 1.19 percent, 0.7 percent and 1.11 percent, respectively. This result reemphasizes that while right amount of temperature is critical in seed germination in the early growth stage, it is equally important in the latter part of the growing season for crop ripening and harvesting. The relationship between July, August and September GDD is consistent with Meng et al., (2016).

Temperature variability also affects the loss cost of HRSW, barley and canola. One percent increase in the variability of the GDD in August increases loss cost of canola by 0.82 percent.

Also, a one percent increase in the GDD variability in July increase the loss cost of barley by 0.82 percent. Similarly, a one percent increase in September GDD variability increases the loss cost of HRSW by 0.91 percent. McCarl et al., (2008) found similar relationships between variability in temperature and yield risk for corn and sorghum. They reported that a degree increase in temperature variability increases the yield risk of corn and sorghum by 0.14 percent and 0.026 percent, respectively.

The number of frost days and heat stress also impact the loss cost. A day of frost (temperature below -5 degrees C) increases the loss cost by 0.13 percent for HRSW, 0.13 percent for durum, 0.12 percent for barley and 0.07 percent for canola. Similarly, a day of heat stress (temperature greater 30 degrees) increases loss cost by 0.07 percent for HRSW, 0.06 percent in durum, 0.05 percent for barley and 0.06 percent for canola. However, the timing of frost or heat stress in the growing season is equally important. A frost in the latter stage of the growing season will affect crop quality, and increase insurance claims, more than in the early stage of the growing season. Similarly, heat stress in the early stage of the growing season will impact crop yield and increase insurance claims more than a heat stress in the latter stage of the growing season.

We find that water balance in June and August impact loss cost of the HRSW, durum, barley and canola. Depending on the crop, one percent increase June water balance decrease loss cost between 0.35 percent and 0.64 percent while a one percent increase in August water balance increases the loss cost between 0.24 percent and 0.36 percent. We also find that the impact water balance variability depends on the crop and month.  In general, a one percent increase in water balance variability increases the loss cost between 0.35 percent and 0.66 percent.

Temperature also affects loss cost, depending on the crop and month. For the early stage of the growing season, a percent increase in GDD increases loss cost between 0.75 and 1.99 percent. However, at the later stages of the growing season, a one percent increase in GDD decreases loss cost between 0.70 percent and 2.25 percent.

We also find that the number of frost or heat stress days affect loss cost for all the crops. A day of frost increases the loss cost between 0.07 percent and 0.13 percent. Similarly, a day of heat stress increases the loss cost between 0.05 percent and 0.07 percent.

### 5.3 Comparison of Predicted Values between BMA and Regression Techniques

To validate the efficiency and predictive ability, we compared the predicted values for the BMA (Appendix 8 to Appendix 11) to the full model multiple regression (OLS) as shown in Appendix 7. We calculated the root mean square error (RMSE) (shown in Appendix 12) and mean absolute error (MAE) (shown in Appendix 13) for out-of-sample (2010 to 2015) data for each risk zone and crop. Lower RMSE or MAE indicate high predictive accuracy. A summary of the results is shown in Table 3.

**Table 3: RMSE of OLS and BMA techniques**

| | RMSE | | MAE | |
|---|---|---|---|---|
| | BMA | OLS | BMA | OLS |
| **HRSW** | 6.51% | 7.80% | 4.62% | 5.48% |
| **Durum** | 11.51% | 11.78% | 7.78% | 7.95% |
| **Barley** | 8.81% | 8.97% | 6.33% | 6.35% |
| **Canola** | 7.80% | 9.86% | 4.41% | 5.52% |

In general, the BMA consistently performs better than full model OLS in terms of forecasting loss cost for both criteria. However, for some crops and risk zones, OLS outperforms BMA using RMSE criteria. In 12 (11) of 23 risk zones, OLS performs better than BMA for durum

(barley). Conversely, BMA performs better than OLS in 20 (21) of the 23 risk zone for HRSW (canola). The result is consistent with Bornn and Zidek (2012), who reported that Bayesian methods have lower optimal prediction error than OLS for wheat yield in Canadian Prairies using RMSE. In 18 and 20 risk zones for HRSW and canola, respectively, BMA had a better predictive ability when MAE is used. However, for durum and barley, only 13 and 10 risk zones show better predictive accuracy for the BMA. The conclusion is than BMA models could be most appropriate to forecast lost cost for HRSW and canola. However, for durum and barley lost cost modeling, OLS methodology could still compete. Thus, BMA methodology could be considered in modeling loss cost in crop insurance and other agricultural risk modeling in further understanding of the underlying factors influencing choice decisions.

### 5.4 Crop Insurance Risk Pricing using BMA Predicted Values

The objective premium rate in crop insurance is to reflect the expected value of future costs. Consequently, most Crop Insurance Agencies uses a simple average or moving average for the aggregate historical loss cost experience. For instance, in the US, the pure premium is calculated as the simple average of the historical loss cost experience (Rejesus et al., 2015). However, using simple averages implicitly assumes equal weight for each historical loss cost. That is the probability of occurrence of the loss cost follows a uniform distribution. Loss cost is largely driven by weather events, which may not be uniformly distributed. Using simple average, loss cost from exceptional bad year (such as 2002) is given the same weight as the good experience such as 2013 crop year. Catastrophic events are infrequent and should be assigned lower weights compared than “normal” or typical events. However, to determine the accurate weight of catastrophic and rare events, we need a long series of data to capture all possible potential weather outcomes. As Rejesus et al., (2015) noted that “information about the probabilities of

different weather events will better captured using a very long climate data series." Moreover, using moving averages, not only assigns equal weight but also suffer year-over-year fluctuations especially when an extreme value is removed or included.

We used the predicted loss cost ratio from the BMA to estimate a weather index distribution to aid in risk pricing. The concept is similar to Cobel et al., (2013) and Rejesus et al., (2015) except that we used a fixed number of bins instead of variable bins. Using the BMA technique, we estimated predicted values for pre-crop insurance years (that is pre-1975) to obtain a 56 (1960-2015) years of data. We then conducted a histogram for the predicted loss cost for each crop. We use the relative probabilities from the histogram to assign weights to the actual historical loss cost experience. The estimated probabilities by crop is indicated in Appendix 14. As Coble et al., (2013) noted, the histogram approach is simple, straightforward and easy to implement than using kernel densities or parametric distributions. We then calculated the premium from 2010 to 2015 (out-of-sample data) using the weighted probabilities, 10-year moving average, and simple average methods. There is a one-year lag for data used. For instance, for 2010 premium rate, we use data up to 2009. So for the simple average, we used data from 1975 to 2009; for 10-year moving average we used (2000 to 2009) and for weather probability, it is the weighted average of loss cost from 1975 to 2009. For each crop, we the calculate the RMSE by risk zone as indicated Appendix 15. Table 4 is a simple average of RMSE across risk zones for each crop.

**Table 4: RMSE Comparison of WP, 10 Year Moving Average and Simple Average for HRSW, Durum, Barley and Canola**

| | WP | 10-Year MA | Simple Average |
|---|---|---|---|
| HRSW | 5.79% | 6.84% | 6.75% |
| Durum | 8.69% | 10.42% | 10.08% |
| Barley | 7.31% | 7.45% | 9.08% |
| Canola | 7.86% | 8.60% | 12.18% |

As shown in Table 4, weather probabilities approach performs better than 10-year moving average and simple average. This indicates, on the average, the weather weighted average is an accurate predictor of premium rate than the current averaging methodologies employed by most crop insurance agencies. However, across risk zones, other simple averaging performs better than weather probabilities. Weather probability-based premium rate outweigh other methods in 14 of 23 risk zones for HRSW, 18 of 23 risk zone for durum, 11 of 23 risk zones for barley and 13 of the 23 risk zones for canola.

We agree with Rejesus et al., (2015) that weather probability-based approach is feasible to estimate accurate premium rate and should be considered for competing models in crop insurance rating methodology in Canada. By incorporating weather into the premium rating methodology, the premium rate can adjust and respond the climate variability and change particularly when the weights are reviewed periodically. In addition, by using weather weights, it provides a scientific justification of assigning weight to historical loss experience, thus removing human judgment as such the choice data duration to be used. Moreover, weather weights can provide essential information to reduce information asymmetry such as moral hard and adverse selection.

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# CHAPTER 6

## SUMMARY AND CONCLUSIONS

The study looked at the impact of agroclimatic variables on the yield risk of major crops grown in Saskatchewan. The loss cost calculated as the ratio of indemnity to liability, was used as a proxy for yield risk. The climatic variables considered are temperature, crop water availability, frost days and heat stress days. Crop water availability was developed using ASCE standard method for reference evapotranspiration. This approach ensures more climatic variables such as sun radiation; wind speed and humidity are included in the loss cost modeling. The temperature was measured in growing degree days, a standard measure temperature in crop yield models. The distribution of the monthly distribution (average and coefficient of variation) of these variables was used in the loss cost models. We also included the number of days of frost and temperature in the growing season.

In general, the impact of these agroclimatic variables depends on the crop, the month and type of agroclimatic variable. We find that water balance in June and August impact loss cost of all crops. Depending on the crop, one percent increase in June water balance decrease loss cost between 0.35 percent and 0.64 percent while a one percent increase in August water balance increases the loss cost between 0.24 percent and 0.36 percent. We also find that the impact of water balance variability depends on the crop and month. In general, a one percent increase in water balance variability increases the loss cost between 0.35 percent and 0.66 percent.

Temperature also affects loss cost, depending on the crop and month. Conversely, high temperature (above normal) in the early part of the growing season increases loss cost while in the latter part decreases losses. In the early stage of the growing season, a percent increase in

GDD increases loss cost between 0.75 and 1.99 percent. However, at the later stages of the growing season, a one per increase in GDD decreases loss cost between 0.7 percent and 2.25 percent. High temperature could damage the crop in its early stage but such temperature may be necessary for ripening and harvesting in the later stage.

The number of frost days and heat stress in the growing season affected all crops. In general, frost impacts the loss cost more than heat stress. We also find that the number of frost or heat stress days affect loss cost for all the crops. A day of frost increases the loss cost between 0.08 percent and 0.14 percent. Similarly, a day of heat stress increases the loss cost between 0.04 percent and 0.08 percent.

The study also looked at the predictive power of the BMA approach used compared to the standard and OLS approach using RMSE. The result indicates that BMA has better predictive accuracy than full model OLS. However, the performance differs by risk zone and crop. In some risk zone, we observed OLS performs better than BMA. The implication is that BMA can be considered in the crop yield risk modeling particularly when agroclimatic variables are used as explanatory variables..

The study also estimated the weight that should be assigned to each year's loss cost for risk pricing and premium rate calculation. By using a longer series of data to estimated weights, the study can improve the actuarial credibility and statistical validity of the premium rates. We find the weather probabilities perform better than 10 year moving average or simple average. This approach presents a more scientific and justifiable approach to assigning weights to historical loss cost instead of average (where each loss cost is assigned equal probability of occurrence).

The study has implication for climate change and potential impact on the operations of crop insurance agency and government efforts to mitigate production risk. By disaggregating data into monthly values, it ensured that there quantitative estimates of the impact of critical months on crop production losses. In addition the study further buttresses that temperature has a higher impact on the loss cost than precipitation or any other agroclimatic variable, consistent with Lobell and Burke (2008) and Meng et al., (2016). The results from this study can be used to develop appropriate weather-based (temperature, precipiation, solar radiation, or humidity) insurance program for crop producers to reduce information asymmetry such as moral hazard and adverse selection.  The pricing of crop insurance risk using the weather probabilities ensures climatic change and weather variability is reflected in cost of risk transferred to producers.

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**Appendix 1: Calculation of Reference Evapotranspiration**

This appendix is based on ASCE-EWRI (2005) calculation of reference evapotranspiration $ET_{ref}$, the data required, equations and process to calculating reference evapotranspiration based on the ASCE-Penman-Monteith $ET_{ref}$. The reference evapotranspiration is requires data on air temperature, humidity, solar radiation and wind speed. Humidity, solar radiation and wind speed are based ASCE-EWRI recommendations for missing values. The standardized reference ET is calculated as:

$$ET_{ref} = \frac{0.408\Delta(R_n - G) + \gamma\frac{C_n}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + C_d u_2)} \qquad (24)$$

where $ET_{ref}$ is tall ($ET_r$) reference crop evapotranspiration [mm day$^{-1}$]. $R_n$ is the net radiation at the crop surface [MJ m$^{-2}$ day$^{-1}$]. G is the soil heat flux density at the soil surface [MJ m$^{-2}$ day$^{-1}$]. T is the mean daily air temperature at 1.5 to 2.5-m height [°C]. $u_2$ is the mean daily wind speed at 2-m height [m s$^{-1}$],$e_s$ is the mean saturation vapor pressure at 1.5 to 2.5-m height [kPa]; for daily computation, value is the average of $e_s$ at maximum and minimum air temperature. $e_a$ is the mean actual vapor pressure at 1.5 to 2.5-m height [kPa]. $\Delta$ slope of the vapor pressure-temperature curve [kPa °C$^{-1}$].$\gamma$ psychrometric constant [kPa °C$^{-1}$]. $C_n$is the numerator constant for reference type and calculation time step (1700). $C_d$is the denominator constant for reference type (0.38) .

**Calculation Psychrometric and Atmospheric Variables used in the equation**

*Mean Air Temperature (T)*: For the standardized method, the mean air temperature, T, for a daily time step is preferred as the mean of the daily maximum and daily minimum air temperatures rather than as the average of hourly temperature measurements to provide for consistency across all data sets.

$$T_{mean} = \frac{T_{max}+T_{min}}{2} \qquad (25)$$

where: $T_{mean}$= daily mean air temperature [˚C], $T_{max}$= daily maximum air temperature [˚C]. $T_{min}$= daily minimum air temperature [˚C].

*Atmospheric Pressure (P)*: The mean atmospheric pressure at the weather site is predicted from site elevation using a simplified formulation of the Universal Gas Law:

$$P = 101.3\left(\frac{293-0.0065z}{293}\right)^{5.26} \qquad (26)$$

where: P = mean atmospheric pressure at station elevation z [kPa]. and z = weather site elevation above mean sea level [m].

*Latent Heat of Vaporization (λ)*: The value of the latent heat of vaporization, $\boldsymbol{\lambda}$, varies only slightly over the ranges of air temperature that occur in agricultural or hydrologic systems. For $ET_{ref}$, a constant value of $\lambda$ = 2.45 MJ kg$^{-1}$ is recommended. The inverse of $\lambda$ = 2.45 MJ kg$^{-1}$ is approximately 0.408 kg MJ$^{-1}$.

*Psychrometric Constant (γ)*:The standardized application using $\lambda$ = 2.45 MJ kg$^{-1}$ results in a value for the psychrometric constant, γ, that is proportional to the mean atmospheric pressure:

$$\gamma = 0.000665P \qquad (27)$$

where: P has units of kPa and $\gamma$ has units of kPa $^{\circ}C^{-1}$.

*Slope of the Saturation Vapor Pressure-Temperature Curve (Δ)*: The slope of the saturation vapor pressure-temperature curve, Δ, is computed as:

$$\Delta = \frac{2503\exp(17.27T/T+273.3)}{(T+237.3)^2} \qquad (28)$$

where Δ = slope of the saturation vapor pressure-temperature curve [kPa $^{\circ}C^{-1}$]. and $T_{mean}$= daily mean air temperature [°C].

*Saturation Vapor Pressure ($e_S$)*: The saturation vapor pressure ($e_S$) represents the capacity of the air to hold water vapor. For calculation of daily ET , $e_s$ is given by:

$$e_s = \frac{e^0(T_{max})+e^0(T_{min})}{2} \qquad (29)$$

where: $e^0(T)$= saturation vapor pressure function [kPa]. The function to calculate saturation vapor pressure is:$e^0(T) = 0.618exp\left(\frac{17.27T}{T+237.3}\right)$where: vapor pressure is in units of kPa and temperature is in $^{\circ}C$.

*Actual Vapor Pressure ($e_a$ )*: Actual vapor pressure ($e_a$) is used to represent the water content (humidity) of the air at the weather site. The actual vapor pressure is calculated from calculated from measured dew point temperature.

$$e_a = e^0(T_{dew}) = 0.618exp\left(\frac{17.27T_{dew}}{T_{dew}+237.3}\right) \qquad (30)$$

We assumed dew point temperature ($T_{dew}$) as daily minimum air temperature ($T_{min}$).

*Net Radiation ($R_n$ )*: Net radiation ($R_n$) is the net amount of radiant energy available at a vegetation or soil surface for evaporating water, heating the air, or heating the surface. $R_n$ includes both short and long wave radiation components:

$$R_n = R_{ns} - R_{nl} \qquad (31)$$

where: $R_{ns}$ = net short-wave radiation, [MJ $m^{-2}$ $d^{-1}$] (defined as being positive downwards and negative upwards). $R_{nl}$ = net outgoing long-wave radiation, [MJ $m^{-2}$ $d^{-1}$] (defined as being positive upwards and negative downwards). $R_{ns}$ and $R_{nl}$ are generally positive or zero in value.

Net Solar or Net Short-Wave Radiation ($R_{ns}$ ): Net short-wave radiation resulting from the balance between incoming and reflected solar radiation is given by:

$$R_{ns} = (1 - \alpha)R_s \qquad (32)$$

where: $R_{ns}$ = net solar or short-wave radiation [MJ $m^{-2}$ $d^{-1}$]; $\alpha$ = albedo or canopy reflection coefficient, is fixed at 0.23; $R_s$ = incoming solar radiation [MJ $m^{-2}$ $d^{-1}$].

The calculation of ET uses the constant value of 0.23 for albedo for daily and hourly periods. It is recognized that albedo varies somewhat with time of day and with time of season and latitude due to change in sun angle.

*Net Long-Wave Radiation ($R_{nl}$)*: Net long-wave radiation, is the difference between upward long-wave radiation from the standardized surface ($R_{lu}$) and downward long-wave radiation from the sky ($R_{ld}$), so that $R_{nl} = R_{lu} - R_{ld}$. The following calculation for daily $R_{nl}$ follows the method of Brunt (1932, 1952) of using vapor pressure to predict net emissivity:

$$R_{nl} = \sigma\, f_{cd}\left(0.34 - 0.14\sqrt{e_a}\right)\left[\frac{T_{Kmax}^4 + T_{Kmin}^4}{2}\right] \qquad (33$$

where: $R_{nl}$ = net long-wave radiation [MJ m$^{-2}$ d$^{-1}$]; $\sigma$ = Stefan-Boltzmann constant [4.901 x 10$^{-9}$ MJ K$^{-4}$ m$^{-2}$ d$^{-1}$], $f_{cd}$ = cloudiness function [dimensionless] (limited to $0.05 \leq f_{cd} \leq 1.0$). $e_a$ = actual vapor pressure [kPa]. $T_{K\ max}$ = maximum absolute temperature during the 24-hour period [K]. (K =°C + 273.16); $T_{K\ min}$ = minimum absolute temperature during the 24-hour period [K] (K =°C + 273.16).

For daily timesteps, $f_{cd}$ is calculated as:

$$f_{cd} = 1.35\frac{R_s}{R_{so}} - 0.35 \qquad (34$$

where: $R_s/R_{so}$ = relative solar radiation (limited to $0.3 \leq R_s/R_{so} \leq 1.0$). $R_s$ = measured or calculated solar radiation [MJ m$^{-2}$ d$^{-1}$]. $R_{so}$= calculated clear-sky radiation [MJ m$^{-2}$ d$^{-1}$]. The ratio $R_s/R_{so}$ represents relative cloudiness and is limited to $0.3 < R_s/R_{so} \leq 1.0$ so that $f_{cd}$ has limits of $0.05 \leq f_{cd} \leq 1.0$.

*Clear-Sky Solar Radiation ($R_{so}$)*: Clear-sky solar radiation ($R_{so}$) is used in the calculation of net radiation ($R_n$). Clear- sky solar radiation is defined as the amount of solar radiation ($R_s$) that would be received at the weather measurement site under conditions of clear-sky (i.e., cloud-

free). The ratio of $R_s$ to $R_{so}$ in the equation for $R_n$ is used to characterize the impact of cloud-cover on the downward emission of thermal radiation to the earth's surface. Daily $R_{so}$ is a function of the time of year and latitude. $R_{so}$ is also impacted by station elevation (affecting atmospheric thickness and transmissivity), the amount of precipitable water in the atmosphere (affecting the absorption of some short-wave radiation), and the amount of dust or aerosols in the air.

$$R_{so} = (0.75 + 2 \times 10^{-5} z) R_a \quad (35$$

z = station elevation above sea level [m].

*Extraterrestrial Radiation for 24-Hour Periods ($R_a$ )*: Extraterrestrial radiation, $R_a$, defined as the short-wave solar radiation in the absence of an atmosphere, is a well-behaved function of the day of the year, time of day, and latitude. It is needed for calculating $R_{so}$, which is in turn used in calculating $R_n$. For daily (24-hour) periods, $R_a$ can be estimated from the solar constant, the solar declination, and the day of the year:

$$R_a = \frac{24}{\pi} G_{sc} d_r [\omega_s \sin(\varphi) \sin(\delta) + \cos(\varphi) \cos(\delta) \sin(\omega_s)] \qquad (36$$

$R_a$ = extraterrestrial radiation [MJ $m^{-2}$ $d^{-1}$], $G_{sc}$ = solar constant [4.92 MJ $m^{-2}$ $h^{-1}$]. dr = inverse relative distance factor (squared) for the earth-sun [unitless]. $\omega_s$ = sunset hour angle [radians]; $\varphi$ = latitude [radians]. and $\delta$ = solar declination [radians].

The latitude,$\varphi$, is positive for the Northern Hemisphere and negative for the Southern Hemisphere. The conversion from decimal degrees to radians is given by:

$$Radians = \frac{\pi}{180} (decimal\ degrees) \qquad (37)$$

and $d_r$ and $\delta$ are calculated as:

$$d_r = 1 + 0.033cos\left(\frac{2\pi}{365}J\right) \qquad (38)$$

$$\delta = 0.409sin\left(\frac{2\pi}{365}J - 1.39\right) \qquad (39)$$

$$\omega_s = arccos[-\tan(\varphi)\tan(\delta)] \qquad (40)$$

*Soil Heat Flux Density (G):*Soil heat flux density is the thermal energy utilized to heat the soil. G is positive when the soil is warming and negative when the soil is cooling. The magnitude of the daily, weekly or ten-day soil heat flux density, G, beneath a fully vegetated grass or alfalfa reference surface is relatively small in comparison with $R_n$. Therefore, it is ignored so that: $G_{day} = 0$.

$G_{day}$ = daily soil heat flux density [MJ $m^{-2}$ $d^{-1}$].

*Wind Speed:*Wind speed varies with height above the ground surface. For the purposes of this analysis, I used a value of 2 $ms^{-1}$ for an agricultural setting. This value is based on an average computed from over 2000 weather stations around the globe.

**Appendix 2: Crop Co-efficient For Selected Crop**

| Crop Name | $\alpha$ | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_1$ |
|---|---|---|---|---|---|
| Hrsw | -1.924845167% | 0.264100497% | 0.000010480% | -0.000000223% | 0.0000000000357% |
| Durum | -1.913969450% | 0.264007918% | 0.000010683% | -0.000000223% | 0.0000000000298% |
| Barley | 4.216950033% | 0.150838398% | 0.000488784% | -0.000000869% | 0.0000000002491% |
| Canola | 8.700000000% | 0.713000000% | -0.001970000% | 0.000002300% | -0.0000000009630% |

Source: Tim Harms, Alberta Agriculture and Forestry, 2016

**Appendix 3: Descriptive Statistics of Agroclimatic Variables and Loss Cost for Hard Red Spring Wheat**

| | | | Raw Data | | | | Transformed Data | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Month** | **# of Obs** | **Mean** | **Std Dev** | **Min** | **Max** | **Std Dev** | **Min** | **Max** |
| **Cumulative Water Balance (mm)** | May | 805 | 195.2 | 135.2 | 8.090 | 976.6 | 0.693 | 0.0415 | 5.004 |
| | June | 805 | 288.1 | 155.2 | 35.95 | 993.5 | 0.539 | 0.125 | 3.449 |
| | July | 805 | 258.6 | 159.6 | 16.38 | 1,001 | 0.617 | 0.0633 | 3.871 |
| | August | 805 | 196.0 | 133.8 | 12.69 | 873.9 | 0.683 | 0.0647 | 4.458 |
| | September | 805 | 151.1 | 111.8 | 5.162 | 689.9 | 0.740 | 0.0342 | 4.566 |
| **Water Balance Variability** | May | 805 | 1.974 | 0.524 | 1.034 | 5.525 | 0.265 | 0.524 | 2.798 |
| | June | 805 | 1.624 | 0.396 | 0.874 | 3.538 | 0.244 | 0.538 | 2.178 |
| | July | 805 | 1.791 | 0.507 | 0.864 | 4.212 | 0.283 | 0.482 | 2.352 |
| | August | 805 | 1.933 | 0.497 | 1.019 | 4.120 | 0.257 | 0.527 | 2.131 |
| | Sept | 805 | 2.229 | 0.631 | 0.875 | 4.476 | 0.283 | 0.392 | 2.008 |
| **Cumulative GDD** | May | 805 | 191.8 | 50.15 | 75.39 | 341.9 | 0.261 | 0.393 | 1.783 |
| | June | 805 | 316.1 | 48.08 | 199.0 | 545.1 | 0.152 | 0.630 | 1.724 |
| | July | 805 | 414.4 | 47.40 | 300.8 | 565.4 | 0.114 | 0.726 | 1.364 |
| | August | 805 | 380.8 | 64.17 | 216.8 | 547.1 | 0.169 | 0.569 | 1.437 |
| | Sept | 805 | 210.5 | 51.90 | 92.05 | 365.2 | 0.247 | 0.437 | 1.735 |
| **GDD Variability** | May | 805 | 0.711 | 0.201 | 0.346 | 1.406 | 0.283 | 0.486 | 1.979 |
| | June | 805 | 0.334 | 0.0741 | 0.150 | 0.613 | 0.222 | 0.450 | 1.835 |
| | July | 805 | 0.218 | 0.0378 | 0.127 | 0.349 | 0.174 | 0.583 | 1.604 |
| | August | 805 | 0.276 | 0.0693 | 0.116 | 0.589 | 0.251 | 0.420 | 2.138 |
| | Sept | 805 | 0.602 | 0.175 | 0.258 | 1.193 | 0.290 | 0.428 | 1.981 |
| **Lost Cost (%)** | | 805 | 0.0880 | 0.142 | 0 | 0.965 | 1.613 | 0 | 10.96 |
| **Risk Zone** | | 805 | 11.88 | 6.65 | 1.00 | 23.00 | | | |
| **Number of Frost (<-5)** | | 805 | 4.026 | 3.991 | 0 | 21 | | | |
| **Number of Excessive Heat (>30)** | | 805 | 10.99 | 8.620 | 0 | 42 | | | |
| **Year** | | 805 | 1,992 | 10.11 | 1,975 | 2,009 | | | |

**Appendix 4: Descriptive Statistics of Agroclimatic Variables and Loss Cost for Durum**

| | | | Raw Data | | | | Transformed Data | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Month** | **# of Obs** | **Mean** | **Std Dev** | **Min** | **Max** | **Std Dev** | **Min** | **Max** |
| **Cumulative Water Balance (mm)** | May | 805 | 195.1 | 135.2 | 8.087 | 976.6 | 0.693 | 0.0414 | 5.005 |
| | June | 805 | 288.1 | 155.2 | 35.95 | 993.5 | 0.539 | 0.125 | 3.449 |
| | July | 805 | 258.6 | 159.6 | 16.38 | 1,001 | 0.617 | 0.0633 | 3.871 |
| | August | 805 | 196 | 133.8 | 12.69 | 873.9 | 0.683 | 0.0647 | 4.459 |
| | September | 805 | 151.1 | 111.8 | 5.159 | 689.9 | 0.740 | 0.0341 | 4.566 |
| **Water Balance Variability** | May | 805 | 1.974 | 0.524 | 1.034 | 5.527 | 0.265 | 0.524 | 2.799 |
| | June | 805 | 1.624 | 0.396 | 0.874 | 3.538 | 0.244 | 0.538 | 2.178 |
| | July | 805 | 1.791 | 0.507 | 0.864 | 4.212 | 0.283 | 0.482 | 2.352 |
| | August | 805 | 1.933 | 0.497 | 1.019 | 4.121 | 0.257 | 0.527 | 2.132 |
| | Sept | 805 | 2.229 | 0.631 | 0.875 | 4.476 | 0.283 | 0.392 | 2.008 |
| **Cumulative GDD** | May | 805 | 191.8 | 50.15 | 75.39 | 341.9 | 0.261 | 0.393 | 1.783 |
| | June | 805 | 316.1 | 48.08 | 199 | 545.1 | 0.152 | 0.630 | 1.724 |
| | July | 805 | 414.4 | 47.4 | 300.8 | 565.4 | 0.114 | 0.726 | 1.364 |
| | August | 805 | 380.8 | 64.17 | 216.8 | 547.1 | 0.169 | 0.569 | 1.437 |
| | Sept | 805 | 210.5 | 51.9 | 92.05 | 365.2 | 0.247 | 0.437 | 1.735 |
| **GDD Variability** | May | 805 | 0.712 | 0.2 | 0.319 | 1.403 | 0.281 | 0.448 | 1.970 |
| | June | 805 | 0.334 | 0.0738 | 0.152 | 0.558 | 0.221 | 0.455 | 1.674 |
| | July | 805 | 0.218 | 0.0384 | 0.124 | 0.352 | 0.177 | 0.569 | 1.620 |
| | August | 805 | 0.276 | 0.0696 | 0.0971 | 0.564 | 0.252 | 0.352 | 2.044 |
| | Sept | 805 | 0.603 | 0.178 | 0.277 | 1.224 | 0.296 | 0.459 | 2.031 |
| **Lost Cost (%)** | | 781 | 0.101 | 0.155 | 0 | 1 | 1.513 | 0 | 9.861 |
| **Risk Zone** | | 805 | 11.88 | 6.65 | 1.00 | 23.00 | | | |
| **Number of Frost (<-5)** | | 805 | 4.026 | 3.991 | 0 | 21 | | | |
| **Number of Excessive Heat (>30)** | | 805 | 10.99 | 8.62 | 0 | 42 | | | |
| **Year** | | 805 | 1,992 | 10.11 | 1,975 | 2,009 | | | |

**Appendix 5: Descriptive Statistics of Agroclimatic Variables and Loss Cost for Barley**

| | | | Raw Data | | | | Transformed Data | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Month** | **# of Obs** | **Mean** | **Std Dev** | **Min** | **Max** | **Std Dev** | **Min** | **Max** |
| **Cumulative Water Balance (mm)** | May | 805 | 193.4 | 135.2 | 6.355 | 974.9 | 0.699 | 0.0329 | 5.040 |
| | June | 805 | 286.4 | 155.2 | 34.30 | 991.8 | 0.542 | 0.120 | 3.463 |
| | July | 805 | 256.9 | 159.6 | 14.73 | 999.4 | 0.621 | 0.0573 | 3.890 |
| | August | 805 | 194.3 | 133.8 | 11.01 | 872.1 | 0.689 | 0.0567 | 4.489 |
| | September | 805 | 149.4 | 111.8 | 3.443 | 688.2 | 0.748 | 0.0231 | 4.608 |
| **Water Balance Variability** | May | 805 | 2.012 | 0.557 | 1.042 | 6.542 | 0.277 | 0.518 | 3.251 |
| | June | 805 | 1.637 | 0.400 | 0.888 | 3.568 | 0.244 | 0.542 | 2.180 |
| | July | 805 | 1.810 | 0.518 | 0.870 | 4.259 | 0.286 | 0.480 | 2.353 |
| | August | 805 | 1.965 | 0.518 | 1.026 | 4.498 | 0.264 | 0.522 | 2.289 |
| | Sept | 805 | 2.287 | 0.662 | 0.886 | 5.109 | 0.289 | 0.387 | 2.234 |
| **Cumulative GDD** | May | 805 | 191.8 | 50.15 | 75.39 | 341.9 | 0.261 | 0.393 | 1.783 |
| | June | 805 | 316.1 | 48.08 | 199.0 | 545.1 | 0.152 | 0.630 | 1.724 |
| | July | 805 | 414.4 | 47.40 | 300.8 | 565.4 | 0.114 | 0.726 | 1.364 |
| | August | 805 | 380.8 | 64.17 | 216.8 | 547.1 | 0.169 | 0.569 | 1.437 |
| | Sept | 805 | 210.5 | 51.90 | 92.05 | 365.2 | 0.247 | 0.437 | 1.735 |
| **GDD Variability** | May | 805 | 0.712 | 0.202 | 0.327 | 1.398 | 0.284 | 0.460 | 1.963 |
| | June | 805 | 0.334 | 0.0733 | 0.140 | 0.642 | 0.219 | 0.418 | 1.922 |
| | July | 805 | 0.218 | 0.0385 | 0.119 | 0.351 | 0.176 | 0.547 | 1.609 |
| | August | 805 | 0.276 | 0.0687 | 0.120 | 0.574 | 0.249 | 0.435 | 2.078 |
| | Sept | 805 | 0.601 | 0.176 | 0.265 | 1.144 | 0.292 | 0.441 | 1.904 |
| **Lost Cost (%)** | | 805 | 0.121 | 0.162 | 0 | 0.963 | 1.338 | 0 | 7.945 |
| **Risk Zone** | | 805 | 11.88 | 6.65 | 1.00 | 23.00 | | | |
| **Number of Frost (<-5)** | | 805 | 4.026 | 3.991 | 0 | 21 | | | |
| **Number of Excessive Heat (>30)** | | 805 | 10.99 | 8.620 | 0 | 42 | | | |
| **Year** | | 805 | 1994 | 11.26 | 1975 | 2013 | | | |

**Appendix 6: Descriptive Statistics of Agroclimatic Variables and Loss Cost for Canola**

| | | | Raw Data | | | | Transformed Data | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **Month** | **# of Obs** | **Mean** | **Std Dev** | **Min** | **Max** | **Std Dev** | **Min** | **Max** |
| **Cumulative Water Balance (mm)** | May | 805 | 191.2 | 135.2 | 4.127 | 972.8 | 0.707 | 0.0216 | 5.088 |
| | June | 805 | 284.2 | 155.2 | 32.01 | 989.6 | 0.546 | 0.113 | 3.483 |
| | July | 805 | 254.5 | 159.7 | 12.09 | 997.2 | 0.627 | 0.0475 | 3.918 |
| | August | 805 | 192.0 | 133.9 | 8.504 | 870.0 | 0.697 | 0.0443 | 4.531 |
| | September | 805 | 147.4 | 111.8 | 1.486 | 686.2 | 0.758 | 0.0101 | 4.655 |
| **Water Balance Variability** | May | 805 | 2.070 | 0.638 | 1.048 | 8.925 | 0.308 | 0.506 | 4.312 |
| | June | 805 | 1.656 | 0.407 | 0.909 | 3.611 | 0.246 | 0.549 | 2.181 |
| | July | 805 | 1.841 | 0.539 | 0.878 | 4.347 | 0.293 | 0.477 | 2.361 |
| | August | 805 | 2.013 | 0.565 | 1.034 | 5.251 | 0.280 | 0.514 | 2.608 |
| | Sept | 805 | 2.376 | 0.783 | 0.897 | 8.248 | 0.329 | 0.377 | 3.471 |
| **Cumulative GDD** | May | 805 | 191.8 | 50.15 | 75.39 | 341.9 | 0.261 | 0.393 | 1.783 |
| | June | 805 | 316.1 | 48.08 | 199.0 | 545.1 | 0.152 | 0.630 | 1.724 |
| | July | 805 | 414.4 | 47.40 | 300.8 | 565.4 | 0.114 | 0.726 | 1.364 |
| | August | 805 | 380.8 | 64.17 | 216.8 | 547.1 | 0.169 | 0.569 | 1.437 |
| | Sept | 805 | 210.5 | 51.90 | 92.05 | 365.2 | 0.247 | 0.437 | 1.735 |
| **GDD Variability** | May | 805 | 0.710 | 0.196 | 0.349 | 1.295 | 0.276 | 0.492 | 1.824 |
| | June | 805 | 0.335 | 0.0735 | 0.151 | 0.581 | 0.220 | 0.450 | 1.736 |
| | July | 805 | 0.218 | 0.0387 | 0.124 | 0.345 | 0.178 | 0.569 | 1.583 |
| | August | 805 | 0.278 | 0.0712 | 0.101 | 0.567 | 0.256 | 0.364 | 2.040 |
| | Sept | 805 | 0.602 | 0.177 | 0.287 | 1.143 | 0.294 | 0.476 | 1.898 |
| **Lost Cost (%)** | | 781 | 0.148 | 0.213 | 0 | 1 | 1.424 | 0 | 6.752 |
| **Risk Zone** | | 805 | 11.88 | 6.65 | 1.00 | 23.00 | | | |
| **Number of Frost (<-5)** | | 805 | 4.026 | 3.991 | 0 | 21 | | | |
| **Number of Excessive Heat (>30)** | | 805 | 10.99 | 8.620 | 0 | 42 | | | |
| **Year** | | 805 | 1,992 | 10.11 | 1,975 | 2,009 | | | |

**Appendix 7: Regression Results of Loss Cost Model for hard red spring wheat, durum, barley and canola**

| VARIABLES | (1)<br>HRSW | (2)<br>Durum | (3)<br>Barley | (4)<br>Canola |
|---|---|---|---|---|
| Trend | 0.00850* | 0.00707 | -0.0212*** | -0.0304*** |
| | (0.00485) | (0.00469) | (0.00376) | (0.00500) |
| Water Balance Ratio in May | -0.00569 | 0.0119 | -0.125** | -0.0492 |
| | (0.0841) | (0.0932) | (0.0589) | (0.0709) |
| Water Balance Ratio in June | -0.408*** | -0.557*** | -0.443*** | -0.303*** |
| | (0.117) | (0.114) | (0.0933) | (0.103) |
| Water Balance Ratio in July | 0.0377 | -0.0412 | -0.219*** | -0.0458 |
| | (0.0758) | (0.0807) | (0.0587) | (0.0707) |
| Water Balance Ratio in August | 0.303*** | 0.350*** | 0.243*** | 0.325*** |
| | (0.0903) | (0.0842) | (0.0676) | (0.0817) |
| Water Balance Ratio in September | -0.128* | -0.00778 | 0.0708 | 0.00206 |
| | (0.0692) | (0.0638) | (0.0497) | (0.0700) |
| Growing Degree Days Ratio in May | 2.306*** | 2.356*** | 1.680*** | 1.305*** |
| | (0.314) | (0.294) | (0.249) | (0.326) |
| Growing Degree Days Ratio in June | 0.992 | 0.601 | 0.652* | 0.0323 |
| | (0.676) | (0.536) | (0.363) | (0.533) |
| Growing Degree Days Ratio in July | 2.863*** | 1.952** | 2.778*** | 2.731*** |
| | (0.871) | (0.765) | (0.605) | (0.657) |
| Growing Degree Days Ratio in August | -1.364** | -0.911 | 0.802* | 1.260** |
| | (0.615) | (0.613) | (0.436) | (0.565) |
| Growing Degree Days Ratio in September | -1.136*** | -1.219*** | -1.150*** | -0.707** |
| | (0.256) | (0.270) | (0.211) | (0.285) |
| Ratio of Water Balance Variability in May | -0.0514 | 0.0742 | -0.272* | 0.151 |
| | (0.217) | (0.193) | (0.157) | (0.186) |
| Ratio of Water Balance Variability in June | 0.583*** | 0.420** | 0.111 | 0.420** |
| | (0.210) | (0.184) | (0.146) | (0.188) |
| Ratio of Water Balance Variability in July | 0.497** | 0.573*** | 0.457*** | 0.114 |
| | (0.225) | (0.190) | (0.150) | (0.191) |
| Ratio of Water Balance Variability in August | 0.0806 | -0.0218 | -0.0412 | -0.0947 |
| | (0.207) | (0.197) | (0.161) | (0.219) |
| Ratio of Water Balance Variability in September | 0.724*** | 0.432*** | 0.200* | 0.0904 |
| | (0.166) | (0.155) | (0.119) | (0.131) |
| Ratio of Growing Degree Days Variability in May | 0.805*** | 0.610** | 0.0730 | 1.010*** |
| | (0.302) | (0.301) | (0.213) | (0.321) |
| Ratio of Growing Degree Days Variability in June | 0.920*** | 0.688** | 0.521** | 0.740*** |
| | (0.307) | (0.268) | (0.214) | (0.267) |

| VARIABLES | (1)<br>HRSW | (2)<br>Durum | (3)<br>Barley | (4)<br>Canola |
|---|---|---|---|---|
| Ratio of Growing Degree Days Variability in July | 0.990*** | 0.753*** | 0.805*** | 0.302 |
| | (0.315) | (0.264) | (0.213) | (0.249) |
| Ratio of Growing Degree Days Variability in August | 0.430** | 0.171 | 0.285* | 1.045*** |
| | (0.208) | (0.222) | (0.169) | (0.213) |
| Ratio of Growing Degree Days Variability in September | -0.110 | -0.682** | -0.126 | -0.522** |
| | (0.243) | (0.285) | (0.192) | (0.214) |
| Riskzone 2 Dummy | 0.240 | 0.0571 | 0.370 | 0.445 |
| | (0.295) | (0.245) | (0.244) | (0.332) |
| Riskzone 3 Dummy | 0.517* | 0.205 | 0.544** | 0.518* |
| | (0.311) | (0.278) | (0.226) | (0.274) |
| Riskzone 4 Dummy | 0.547 | 0.429 | 0.460* | 0.508 |
| | (0.350) | (0.330) | (0.261) | (0.427) |
| Riskzone 5 Dummy | 0.434 | 0.394 | 0.204 | 0.326 |
| | (0.288) | (0.250) | (0.180) | (0.220) |
| Riskzone 6 Dummy | 0.122 | -0.178 | 0.290 | 0.465 |
| | (0.275) | (0.238) | (0.223) | (0.381) |
| Riskzone 7 Dummy | 0.544* | 0.435* | 0.483*** | 0.565** |
| | (0.280) | (0.235) | (0.180) | (0.236) |
| Riskzone 8 Dummy | 0.280 | -0.0938 | -1.59e-05 | 0.317 |
| | (0.263) | (0.220) | (0.181) | (0.257) |
| Riskzone 9 Dummy | 0.0290 | -0.0813 | 0.509** | 0.0294 |
| | (0.271) | (0.228) | (0.219) | (0.238) |
| Riskzone 10 Dummy | 0.152 | -0.121 | 0.187 | 0.279 |
| | (0.258) | (0.228) | (0.213) | (0.286) |
| Riskzone 11 Dummy | 0.687** | 0.595** | 0.517*** | 0.562** |
| | (0.293) | (0.231) | (0.195) | (0.255) |
| Riskzone 12 Dummy | 0.447 | 0.267 | 0.718*** | 0.431** |
| | (0.281) | (0.208) | (0.199) | (0.207) |
| Riskzone 13 Dummy | 0.399 | -0.0782 | 0.672*** | 0.291 |
| | (0.289) | (0.248) | (0.216) | (0.226) |
| Riskzone 14 Dummy | 0.694** | 0.739** | 0.240 | 0.518** |
| | (0.334) | (0.326) | (0.245) | (0.263) |
| Riskzone 15 Dummy | 0.501* | 0.343 | 0.358** | 0.217 |
| | (0.285) | (0.221) | (0.178) | (0.203) |
| Riskzone 16 Dummy | 0.432 | 0.284 | 0.215 | 0.392* |
| | (0.298) | (0.267) | (0.192) | (0.218) |
| Riskzone 17 Dummy | 1.144*** | 0.703** | 0.482** | 0.542** |
| | (0.335) | (0.298) | (0.213) | (0.248) |

| VARIABLES | (1)<br>HRSW | (2)<br>Durum | (3)<br>Barley | (4)<br>Canola |
|---|---|---|---|---|
| Riskzone 18 Dummy | 0.430 | 0.358 | 0.340* | 0.145 |
| | (0.291) | (0.276) | (0.206) | (0.207) |
| Riskzone 19 Dummy | 0.418 | 0.476* | 0.694*** | 0.437** |
| | (0.286) | (0.268) | (0.195) | (0.214) |
| Riskzone 20 Dummy | 0.772** | 0.795*** | 0.628*** | 0.545** |
| | (0.316) | (0.286) | (0.228) | (0.243) |
| Riskzone 21 Dummy | 1.094*** | 0.931*** | 0.436* | 0.541** |
| | (0.345) | (0.341) | (0.231) | (0.267) |
| Riskzone 22 Dummy | 0.743*** | 0.962** | 0.522** | 0.634** |
| | (0.283) | (0.384) | (0.232) | (0.252) |
| Riskzone 23 Dummy | 1.329*** | 0.851** | 0.927*** | 1.022*** |
| | (0.380) | (0.349) | (0.277) | (0.299) |
| Total Number Frost in Growing Season | 0.105*** | 0.109*** | 0.118*** | 0.0477*** |
| | (0.0225) | (0.0202) | (0.0158) | (0.0182) |
| Total Number Excessive Heat in Growing Season | 0.0522*** | 0.0532*** | 0.0371*** | 0.0533*** |
| | (0.0152) | (0.0149) | (0.0110) | (0.0144) |
| Constant | -25.77*** | -20.05** | 35.61*** | 52.61*** |
| | (9.871) | (9.561) | (7.682) | (10.01) |
| Observations | 805 | 805 | 805 | 805 |
| R-squared | 0.453 | 0.436 | 0.582 | 0.408 |
| Adjusted R-squared | 0.421 | 0.403 | 0.557 | 0.373 |

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Appendix 8: Summary of BMA output of Loss Cost Ratio for HRSW**

| Variable | p!=0 | EV | SD | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|---|---|---|
| Intercept | 100 | -6.72 | 9.29 | -1.97 | -4.55 | -4.13 | -2.14 | -3.53 |
| Water Balance Ratio in June | 100 | -0.53 | 0.11 | -0.58 | -0.48 | -0.49 | -0.58 | -0.56 |
| GDD Ratio in May | 100 | 1.68 | 0.38 | 1.49 | 1.44 | 1.48 | 1.50 | 1.94 |
| GDD Ratio in August | 100 | -2.25 | 0.49 | -2.32 | -1.94 | -2.05 | -2.33 | -2.16 |
| GDD Ratio in September | 100 | -1.19 | 0.29 | -1.07 | -1.55 | -1.60 | -1.04 | -1.09 |
| Number Frost Days | 100 | 0.13 | 0.02 | 0.14 | 0.13 | 0.13 | 0.14 | 0.12 |
| Number Heat Stress Days | 100 | 0.07 | 0.01 | 0.07 | 0.05 | 0.06 | 0.07 | 0.06 |
| Water Balance Ratio in August | 99.8 | 0.31 | 0.08 | 0.31 | 0.28 | 0.29 | 0.31 | 0.31 |
| Water Balance Variability Ratio in September | 99.8 | 0.66 | 0.18 | 0.62 | 0.64 | 0.68 | 0.66 | 0.64 |
| GDD Variability Ratio in September | 89.7 | 0.91 | 0.43 | 1.04 | 0.97 | 0.97 | 1.06 | 1.16 |
| GDD Ratio in July | 79.5 | 1.65 | 1.05 | 1.60 | 2.48 | 2.46 | 1.62 | 1.84 |
| Water Balance Variability Ratio in June | 70.2 | 0.38 | 0.29 | 0.55 | 0.49 | . | 0.59 | 0.55 |
| Ratio GDD Variability in June | 48.4 | 0.38 | 0.46 | . | 1.04 | 1.12 | . | . |
| GDD Variability Ratio in May | 30.8 | 0.23 | 0.39 | . | . | . | . | 0.69 |
| Water Balance Ratio in September | 27.7 | -0.05 | 0.09 | . | -0.19 | -0.19 | . | . |
| GDD Ratio in June | 24.3 | 0.29 | 0.55 | . | 1.27 | 1.31 | . | . |
| Risk zone 17 | 24.1 | 0.12 | 0.24 | . | . | . | 0.52 | . |
| Trend | 17.9 | 0.00 | 0.00 | . | . | . | . | . |
| Risk zone 23 | 15.6 | 0.08 | 0.20 | . | . | . | . | . |
| Risk zone 21 | 8.1 | 0.03 | 0.13 | . | . | . | . | . |
| Ratio of Water Balance Variability in July | 5.7 | 0.02 | 0.10 | . | . | . | . | . |
| Risk zone 11 | 0.2 | 0.00 | 0.01 | . | . | . | . | . |
| Risk zone 22 | 0 | 0.00 | 0.00 | . | . | . | . | . |
| nVar | | | | 11 | 14 | 13 | 12 | 12 |
| r2 | | | | 0.408 | 0.422 | 0.417 | 0.412 | 0.412 |
| BIC | | | | -348.07 | -347.32 | -347.14 | -347.06 | -346.93 |
| post prob | | | | 0.041 | 0.028 | 0.026 | 0.025 | 0.023 |

**Appendix 9: Summary of BMA output of Loss Cost Ratio for Durum**

| | p!=0 | EV | SD | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|---|---|---|
| Intercept | 100 | -5.64 | 10.86 | 0.67 | -22.37 | 0.21 | 0.55 | -0.05 |
| Water Balance Ratio in June | 100 | -0.64 | 0.10 | -0.66 | -0.63 | -0.65 | -0.62 | -0.65 |
| Water Balance Ratio in August | 100 | 0.36 | 0.08 | 0.36 | 0.35 | 0.35 | 0.38 | 0.34 |
| GDD Ratio in May | 100 | 1.65 | 0.24 | 1.57 | 1.72 | 1.54 | 1.53 | 1.62 |
| GDD Ratio in August | 100 | -1.98 | 0.42 | -2.08 | -2.14 | -1.97 | -2.01 | -1.91 |
| Frost Days | 100 | 0.13 | 0.01 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 |
| Heat Stress Days | 100 | 0.06 | 0.01 | 0.06 | 0.06 | 0.06 | 0.07 | 0.06 |
| GDD Ratio in September | 98.0 | -0.70 | 0.26 | -0.61 | -0.71 | -0.59 | -0.64 | -0.67 |
| Water Balance Variability Ratio in July | 69.5 | 0.35 | 0.28 | 0.51 | 0.56 | 0.46 | . | 0.49 |
| Water Balance Variability Ratio in June | 44.1 | 0.20 | 0.26 | . | . | 0.43 | 0.50 | . |
| GDD Variability Ratio in July | 27.4 | 0.17 | 0.32 | . | . | . | . | 0.57 |
| Trend | 26.4 | 0.00 | 0.01 | . | 0.01 | . | . | . |
| Water Balance Variability Ratio in September | 12.8 | 0.04 | 0.12 | . | . | . | . | . |
| GDD Variability Ratio in September | 9.7 | -0.04 | 0.16 | . | . | . | . | . |
| GDD Ratio in July | 7.0 | 0.09 | 0.35 | . | . | . | . | . |
| GDD Variability Ratio in May | 6.8 | 0.03 | 0.15 | . | . | . | . | . |
| Risk zone 22 | 5.0 | 0.02 | 0.09 | . | . | . | . | . |
| Risk zone 21 | 3.6 | 0.01 | 0.07 | . | . | . | . | . |
| Risk zone 11 | 2.5 | 0.01 | 0.06 | . | . | . | . | . |
| Risk zone 20 | 0.6 | 0.00 | 0.02 | . | . | . | . | . |
| GDD Variability Ratio in June | 0.5 | 0.00 | 0.02 | . | . | . | . | . |
| Risk zone 14 | 0.5 | 0.00 | 0.02 | . | . | . | . | . |
| | | | | | | | | |
| nVar | | | | 8 | 9 | 9 | 8 | 9 |
| r2 | | | | 0.38 | 0.38 | 0.38 | 0.38 | 0.38 |
| BIC | | | | -328.1 | -327.5 | -327.3 | -327.1 | -326.4 |
| post prob | | | | 0.091 | 0.069 | 0.06 | 0.055 | 0.04 |

**Appendix 10: Summary of BMA output of Loss Cost Ratio for Barley**

| Variable | p!=0 | EV | SD | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|---|---|---|
| Intercept | 100 | 34.39 | 7.49 | 35.22 | 34.15 | 33.96 | 35.11 | 33.27 |
| Trend | 100 | -0.02 | 0.00 | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 |
| Water Balance Ratio in June | 100 | -0.42 | 0.07 | -0.42 | -0.42 | -0.42 | -0.43 | -0.41 |
| Water Balance Ratio in August | 100 | 0.24 | 0.05 | 0.23 | 0.24 | 0.24 | 0.24 | 0.24 |
| GDD Ratio in May | 100 | 1.41 | 0.17 | 1.38 | 1.40 | 1.42 | 1.40 | 1.41 |
| GDD Ratio in July | 100 | 1.99 | 0.45 | 1.87 | 1.92 | 1.97 | 1.92 | 2.04 |
| GDD Ratio in September | 100 | -1.11 | 0.15 | -1.13 | -1.10 | -1.08 | -1.11 | -1.05 |
| GDD Variability Ratio in July | 100 | 0.82 | 0.21 | 0.84 | 0.80 | 0.79 | 0.83 | 0.79 |
| Frost Days | 100 | 0.12 | 0.01 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 |
| Heat Stress Days | 100 | 0.05 | 0.01 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Water Balance Variability Ratio in July | 99.6 | 0.49 | 0.14 | 0.48 | 0.51 | 0.49 | 0.46 | 0.53 |
| Water Balance Ratio in July | 99.5 | -0.22 | 0.06 | -0.23 | -0.22 | -0.21 | -0.23 | -0.20 |
| Risk Zone 1 | 51.4 | -0.21 | 0.24 | . | -0.40 | -0.43 | . | -0.41 |
| Risk zone 8 | 40.1 | -0.16 | 0.22 | . | . | -0.40 | -0.38 | . |
| Risk zone 23 | 35.7 | 0.14 | 0.21 | . | . | . | . | 0.39 |
| Risk zone 12 | 21.7 | 0.07 | 0.16 | . | . | . | . | . |
| Water Balance Variability in September | 17.2 | 0.04 | 0.11 | . | . | . | . | . |
| Risk zone 13 | 9.3 | 0.03 | 0.10 | . | . | . | . | . |
| Water Balance Ratio in May | 6.1 | -0.01 | 0.02 | . | . | . | . | . |
| GDD Variability Ratio in June | 3.6 | 0.01 | 0.05 | . | . | . | . | . |
| Water Balance Ratio in September | 2.3 | 0.00 | 0.01 | . | . | . | . | . |
| Risk zone 19 | 1.5 | 0.00 | 0.03 | . | . | . | . | . |
| GDD Variability Ratio in August | 1.3 | 0.00 | 0.02 | . | . | . | . | . |
| Water Balance Variability Ratio in May | 0.4 | 0.00 | 0.01 | . | . | . | . | . |
| nVar | | | | 11 | 12 | 13 | 12 | 13 |
| r2 | | | | 0.548 | 0.552 | 0.555 | 0.551 | 0.555 |
| BIC | | | | -565.61 | -565.38 | -565.37 | -564.77 | -564.36 |
| post prob | | | | 0.079 | 0.07 | 0.07 | 0.052 | 0.042 |

**Appendix 11: Summary of BMA output of Loss Cost Ratio for Canola**

| Variable | p!=0 | EV | SD | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|---|---|---|
| Intercept | 100 | 54.82 | 9.86 | 53.73 | 52.82 | 50.36 | 57.57 | 52.90 |
| Trend | 100 | -0.03 | 0.00 | -0.03 | -0.03 | -0.03 | -0.03 | -0.03 |
| Water Balance Ratio in June | 100 | -0.35 | 0.09 | -0.35 | -0.33 | -0.38 | -0.39 | -0.33 |
| Water Balance Ratio in August | 100 | 0.30 | 0.07 | 0.29 | 0.29 | 0.31 | 0.30 | 0.28 |
| GDD Variability Ratio in August | 100 | 0.82 | 0.18 | 0.83 | 0.82 | 0.85 | 0.81 | 0.84 |
| Frost Days | 100 | 0.07 | 0.02 | 0.07 | 0.06 | 0.07 | 0.09 | 0.06 |
| Heat Stress Days | 100 | 0.06 | 0.01 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |
| GDD Ratio in July | 97.1 | 1.85 | 0.64 | 2.06 | 2.24 | 1.66 | 1.87 | 2.11 |
| GDD Ratio in May | 79.4 | 0.75 | 0.48 | 1.04 | 1.10 | 0.99 | 0.56 | 1.01 |
| GDD Variability Ratio in May | 66.6 | 0.53 | 0.43 | 0.77 | 0.84 | 0.77 | . | 0.77 |
| GDD Variability Ratio in June | 62.9 | 0.37 | 0.33 | 0.60 | 0.64 | . | 0.60 | 0.55 |
| Water Balance Variability Ratio in June | 23.3 | 0.09 | 0.18 | . | . | . | . | 0.34 |
| Risk zone 23 | 21.1 | 0.10 | 0.22 | . | 0.49 | . | . | . |
| GDD Ratio in September | 12.5 | -0.05 | 0.14 | . | . | . | . | . |
| Risk zone 9 | 8.2 | -0.03 | 0.12 | . | . | . | . | . |
| Water Balance Ratio in May | 8.1 | -0.01 | 0.04 | . | . | . | . | . |
| Risk zone 1 | 5.7 | -0.02 | 0.10 | . | . | . | . | . |
| Water Balance Variability Ratio in May | 5.4 | 0.01 | 0.07 | . | . | . | . | . |
| Risk zone 18 | 0.8 | 0.00 | 0.03 | . | . | . | . | . |
| Risk zone 15 | 0.6 | 0.00 | 0.02 | . | . | . | . | . |
| | | | | | | | | |
| nVar | | | | 10 | 11 | 9 | 9 | 11 |
| r2 | | | | 0.378 | 0.383 | 0.372 | 0.371 | 0.381 |
| BIC | | | | -315.47 | -314.58 | -313.93 | -313.46 | -312.87 |
| post prob | | | | 0.12 | 0.077 | 0.056 | 0.044 | 0.033 |

**Appendix 12: RMSE Comparison of the Out-of-Sample Prediction of BMA and OLS by crop and risk zone**

| | HRSW | | Durum | | Barley | | Canola | |
|---|---|---|---|---|---|---|---|---|
| Risk Zone | **BMA** | **OLS** | **BMA** | **OLS** | **BMA** | **OLS** | **BMA** | **OLS** |
| 1 | 6.02% | 5.84% | 10.32% | 11.34% | 10.18% | 9.89% | 6.29% | 5.63% |
| 2 | 7.33% | 7.52% | 8.96% | 8.99% | 10.00% | 9.94% | 11.63% | 12.41% |
| 3 | 7.58% | 8.94% | 11.38% | 10.35% | 9.12% | 9.33% | 12.77% | 13.36% |
| 4 | 7.96% | 9.57% | 9.02% | 10.82% | 7.54% | 8.50% | 10.93% | 11.49% |
| 5 | 4.58% | 6.13% | 12.69% | 13.25% | 8.91% | 9.38% | 6.17% | 6.79% |
| 6 | 4.58% | 4.63% | 5.84% | 5.12% | 6.44% | 6.64% | 8.84% | 7.35% |
| 7 | 3.85% | 4.67% | 13.44% | 13.22% | 9.78% | 9.86% | 6.17% | 7.63% |
| 8 | 4.84% | 5.48% | 6.21% | 5.43% | 6.00% | 5.42% | 7.05% | 28.55% |
| 9 | 4.27% | 3.90% | 7.39% | 5.90% | 4.28% | 5.57% | 4.32% | 6.62% |
| 10 | 6.62% | 6.53% | 8.41% | 6.11% | 6.93% | 5.61% | 7.35% | 8.27% |
| 11 | 4.04% | 5.87% | 12.01% | 11.41% | 8.82% | 8.79% | 3.99% | 5.01% |
| 12 | 5.42% | 6.69% | 11.82% | 12.95% | 6.44% | 7.65% | 3.03% | 4.47% |
| 13 | 6.28% | 8.01% | 6.75% | 5.00% | 4.47% | 5.56% | 4.72% | 7.76% |
| 14 | 5.12% | 6.07% | 14.68% | 14.21% | 16.02% | 15.89% | 8.10% | 8.19% |
| 15 | 4.13% | 5.94% | 12.31% | 12.93% | 7.56% | 7.37% | 2.90% | 3.44% |
| 16 | 5.63% | 6.02% | 6.67% | 5.66% | 8.38% | 7.36% | 5.14% | 7.40% |
| 17 | 8.11% | 11.73% | 11.44% | 11.88% | 14.34% | 14.39% | 6.69% | 7.79% |
| 18 | 4.93% | 5.93% | 9.39% | 9.18% | 6.27% | 5.18% | 3.35% | 3.54% |
| 19 | 9.04% | 9.21% | 12.00% | 13.16% | 9.51% | 10.30% | 6.55% | 11.01% |
| 20 | 5.17% | 6.72% | 25.99% | 25.19% | 5.30% | 6.32% | 3.91% | 6.63% |
| 21 | 6.88% | 9.83% | 8.62% | 12.17% | 7.04% | 6.94% | 4.47% | 4.91% |
| 22 | 8.76% | 9.46% | 8.54% | 11.77% | 7.40% | 6.90% | 4.11% | 6.04% |
| 23 | 11.75% | 15.09% | 13.50% | 15.42% | 11.55% | 13.08% | 6.71% | 10.74% |
| Average | **6.51%** | **7.80%** | **11.51%** | **11.78%** | **8.81%** | **8.97%** | **6.85%** | **9.86%** |

**Appendix 13: MAE Comparison of the Out-of-Sample Prediction of BMA and OLS by crop and risk zone**

| | HRSW | | Durum | | Barley | | Canola | |
|---|---|---|---|---|---|---|---|---|
| Risk Zone | **BMA** | **OLS** | **BMA** | **OLS** | **BMA** | **OLS** | **BMA** | **OLS** |
| 1 | 5.05% | 4.77% | 8.79% | 9.07% | 7.28% | 6.58% | 4.46% | 3.97% |
| 2 | 6.56% | 6.87% | 7.65% | 8.00% | 8.82% | 8.69% | 9.03% | 10.04% |
| 3 | 6.33% | 7.06% | 9.69% | 8.50% | 6.58% | 7.12% | 9.64% | 10.20% |
| 4 | 6.22% | 7.49% | 8.20% | 9.35% | 6.87% | 7.57% | 8.25% | 8.73% |
| 5 | 3.34% | 4.55% | 8.54% | 9.52% | 7.61% | 7.36% | 4.42% | 5.01% |
| 6 | 3.41% | 3.31% | 5.17% | 3.86% | 5.50% | 5.14% | 6.67% | 5.39% |
| 7 | 2.73% | 3.52% | 8.35% | 8.21% | 7.52% | 7.43% | 4.60% | 6.04% |
| 8 | 3.79% | 4.17% | 4.91% | 3.95% | 4.84% | 4.11% | 5.22% | 15.36% |
| 9 | 3.57% | 2.77% | 6.39% | 5.02% | 3.78% | 5.02% | 2.91% | 3.75% |
| 10 | 4.83% | 4.56% | 6.85% | 4.31% | 5.16% | 4.12% | 4.91% | 5.19% |
| 11 | 3.27% | 4.83% | 7.84% | 7.04% | 6.92% | 6.82% | 2.91% | 3.79% |
| 12 | 3.84% | 4.07% | 7.52% | 7.88% | 4.71% | 5.52% | 1.54% | 2.18% |
| 13 | 4.56% | 5.70% | 4.50% | 3.39% | 3.84% | 4.33% | 3.04% | 4.34% |
| 14 | 4.14% | 5.04% | 10.79% | 11.70% | 11.05% | 10.66% | 5.33% | 5.31% |
| 15 | 3.25% | 4.04% | 7.59% | 8.27% | 5.45% | 5.13% | 2.09% | 2.60% |
| 16 | 4.29% | 4.47% | 5.34% | 4.34% | 7.17% | 6.05% | 3.16% | 4.08% |
| 17 | 5.64% | 9.37% | 6.90% | 7.98% | 9.46% | 9.47% | 5.15% | 5.67% |
| 18 | 4.34% | 5.09% | 6.33% | 6.81% | 5.82% | 4.98% | 1.76% | 2.17% |
| 19 | 5.54% | 5.47% | 9.47% | 9.98% | 6.29% | 7.17% | 3.68% | 5.48% |
| 20 | 2.45% | 3.46% | 14.77% | 14.02% | 3.40% | 4.01% | 2.34% | 3.41% |
| 21 | 4.77% | 7.11% | 6.44% | 9.69% | 5.13% | 5.21% | 3.54% | 3.80% |
| 22 | 5.59% | 6.29% | 6.67% | 10.32% | 4.94% | 4.65% | 2.50% | 3.48% |
| 23 | 8.70% | 12.09% | 10.35% | 11.73% | 7.49% | 8.83% | 4.36% | 7.07% |
| Average | **4.62%** | **5.48%** | **7.78%** | **7.95%** | **6.33%** | **6.35%** | **4.41%** | **5.52%** |

**Appendix 14: Weather Probabilities of Loss Cost by Crop**

| *Loss Cost* | HRSW | Durum | Barley | Canola |
|---|---|---|---|---|
| **0.000%** | 0.13817 | 0.11145 | 0.11977 | 0.14858 |
| **1.116%** | 0.03969 | 0.02844 | 0.02733 | 0.01920 |
| **2.232%** | 0.04962 | 0.03613 | 0.02974 | 0.01753 |
| **3.348%** | 0.06031 | 0.04535 | 0.02331 | 0.02003 |
| **4.465%** | 0.05191 | 0.04689 | 0.04260 | 0.03339 |
| **5.581%** | 0.04809 | 0.05995 | 0.03617 | 0.03088 |
| **6.697%** | 0.05038 | 0.05227 | 0.03859 | 0.03422 |
| **7.813%** | 0.03969 | 0.03920 | 0.05627 | 0.04007 |
| **8.929%** | 0.04962 | 0.05304 | 0.04662 | 0.02671 |
| **10.045%** | 0.05038 | 0.05380 | 0.03457 | 0.03339 |
| **11.161%** | 0.04351 | 0.06149 | 0.04502 | 0.03255 |
| **12.277%** | 0.05267 | 0.05457 | 0.03617 | 0.03422 |
| **13.394%** | 0.03511 | 0.03766 | 0.04421 | 0.03255 |
| **14.510%** | 0.03664 | 0.04151 | 0.04260 | 0.03589 |
| **15.626%** | 0.03130 | 0.03305 | 0.03055 | 0.02922 |
| **16.742%** | 0.03053 | 0.02921 | 0.02974 | 0.03088 |
| **17.858%** | 0.02901 | 0.02998 | 0.02894 | 0.03088 |
| **18.974%** | 0.01832 | 0.02229 | 0.03215 | 0.03422 |
| **20.090%** | 0.02061 | 0.02921 | 0.01688 | 0.02922 |
| **21.207%** | 0.01374 | 0.01998 | 0.01367 | 0.02504 |
| **22.323%** | 0.02137 | 0.01460 | 0.02251 | 0.02337 |
| **23.439%** | 0.00763 | 0.01076 | 0.01125 | 0.02337 |
| **24.555%** | 0.00840 | 0.01153 | 0.01849 | 0.01836 |
| **25.671%** | 0.01069 | 0.00922 | 0.02170 | 0.02003 |
| **26.787%** | 0.00687 | 0.00769 | 0.01608 | 0.02087 |
| **27.903%** | 0.00992 | 0.01076 | 0.02331 | 0.02504 |
| **29.019%** | 0.00458 | 0.00461 | 0.00804 | 0.02170 |
| **30.136%** | 0.00611 | 0.00538 | 0.01768 | 0.02003 |
| **31.252%** | 0.00534 | 0.00538 | 0.01367 | 0.02170 |
| **32.368%** | 0.00458 | 0.00538 | 0.01286 | 0.01503 |
| **33.484%** | 0.00382 | 0.00846 | 0.01206 | 0.01169 |
| **34.600%** | 0.00534 | 0.00615 | 0.01367 | 0.01586 |
| **35.716%** | 0.00763 | 0.00615 | 0.01125 | 0.01503 |
| **36.832%** | 0.00153 | 0.00461 | 0.00804 | 0.01169 |
| **37.949%** | 0.00534 | 0.00154 | 0.00804 | 0.00835 |
| **>39.065%** | 0.00153 | 0.00231 | 0.00643 | 0.00918 |

**Appendix 15: RMSE of Weighted Probabilities (WP), 10-Year Moving Average and Simple Average by Crop and Risk Zone**

| | HRSW | | | Durum | | | Barley | | | Canola | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **WP** | **10 Year Moving** | **Simple Average** | **WP** | **10 Year Moving** | **Simple Average** | **WP** | **10 Year Moving** | **Simple Average** | **WP** | **10 Year Moving** | **Simple Average** |
| 1 | 5.85% | 4.13% | 4.83% | 8.92% | 9.18% | 9.09% | 7.56% | 7.86% | 8.23% | 7.01% | 3.67% | 10.25% |
| 2 | 4.29% | 5.62% | 6.51% | 7.04% | 7.05% | 8.64% | 4.90% | 4.53% | 11.16% | 8.59% | 7.70% | 19.27% |
| 3 | 6.40% | 6.11% | 6.75% | 6.08% | 5.50% | 6.39% | 9.16% | 9.50% | 11.12% | 11.57% | 14.06% | 15.10% |
| 4 | 4.52% | 5.03% | 7.60% | 5.03% | 5.66% | 8.98% | 9.52% | 10.21% | 11.58% | 8.06% | 12.44% | 16.81% |
| 5 | 6.05% | 6.03% | 6.35% | 12.05% | 12.53% | 13.06% | 6.04% | 6.51% | 7.80% | 7.35% | 4.21% | 12.27% |
| 6 | 4.31% | 3.93% | 4.74% | 4.58% | 3.62% | 5.08% | 7.18% | 7.02% | 9.51% | 7.39% | 7.85% | 17.48% |
| 7 | 6.34% | 4.65% | 5.93% | 12.63% | 13.13% | 13.10% | 6.73% | 6.08% | 8.27% | 7.67% | 4.35% | 12.56% |
| 8 | 6.34% | 6.48% | 5.94% | 8.97% | 10.17% | 9.32% | 5.45% | 4.22% | 7.26% | 7.87% | 6.18% | 14.79% |
| 9 | 4.70% | 4.86% | 5.97% | 5.18% | 5.38% | 7.00% | 6.60% | 5.50% | 9.90% | 6.59% | 9.75% | 11.67% |
| 10 | 4.28% | 3.89% | 5.14% | 3.16% | 4.16% | 5.14% | 5.20% | 4.08% | 8.38% | 7.25% | 8.17% | 15.01% |
| 11 | 5.70% | 5.91% | 6.69% | 11.86% | 13.90% | 12.77% | 6.37% | 5.36% | 6.78% | 7.52% | 4.54% | 11.62% |
| 12 | 5.27% | 5.97% | 6.38% | 11.18% | 12.79% | 11.64% | 7.65% | 6.29% | 12.33% | 8.15% | 8.10% | 13.34% |
| 13 | 4.16% | 6.32% | 7.97% | 4.66% | 4.01% | 6.90% | 6.49% | 8.30% | 11.69% | 6.94% | 11.20% | 13.39% |
| 14 | 6.06% | 4.50% | 5.91% | 13.35% | 14.96% | 13.61% | 10.60% | 11.34% | 10.66% | 7.32% | 5.50% | 8.95% |
| 15 | 5.17% | 6.65% | 5.80% | 10.60% | 12.01% | 10.94% | 5.84% | 5.26% | 7.22% | 6.44% | 4.02% | 7.71% |
| 16 | 4.87% | 8.32% | 6.39% | 4.42% | 8.82% | 6.94% | 4.76% | 6.96% | 7.19% | 8.51% | 12.25% | 13.10% |
| 17 | 5.91% | 8.29% | 8.96% | 10.31% | 13.05% | 11.57% | 9.57% | 9.32% | 9.59% | 7.72% | 5.61% | 8.89% |
| 18 | 5.80% | 8.25% | 6.66% | 9.49% | 11.90% | 9.96% | 6.74% | 7.44% | 7.94% | 7.37% | 8.29% | 8.34% |
| 19 | 5.95% | 10.07% | 7.06% | 7.87% | 9.94% | 7.57% | 8.67% | 9.20% | 8.99% | 8.28% | 12.36% | 9.89% |
| 20 | 6.09% | 9.91% | 6.61% | 21.98% | 21.04% | 22.06% | 7.00% | 9.68% | 8.19% | 6.93% | 12.50% | 8.40% |
| 21 | 6.71% | 11.57% | 8.58% | 5.80% | 13.52% | 11.74% | 6.53% | 6.96% | 5.59% | 6.50% | 9.90% | 8.37% |
| 22 | 8.33% | 8.58% | 7.27% | 8.32% | 14.35% | 10.83% | 8.86% | 8.92% | 7.83% | 9.32% | 12.27% | 10.40% |
| 23 | 10.03% | 12.13% | 11.24% | 6.32% | 12.94% | 9.58% | 10.78% | 10.84% | 11.74% | 10.48% | 12.79% | 12.55% |
| | **5.79%** | **6.84%** | **6.75%** | **8.69%** | **10.42%** | **10.08%** | **7.31%** | **7.45%** | **9.08%** | **7.86%** | **8.60%** | **12.18%** |