University of Alberta

A Spatial Model of Agricultural Land Use with Climate Change for the Canadian Prairies

by

Susan M. Robertson

A thesis submitted to the Faculty of Graduate Studies and Research
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
in
Agricultural and Resource Economics

Resource Economics and Environmental Sociology

Spring 2012
Edmonton, Alberta

Abstract

Climate change is expected to drive major changes in agricultural production around the world, but estimates of the economic impact of these changes for Canadian agricultural production have been inconsistent. Most models use aggregate temperature data such as average temperature or growing degree days. This research shows that a novel approach that measures the marginal effect of exposure to specific temperatures in defined ranges improves yield forecasting. These novel temperature variables are incorporated into a production function to forecast yields for winter wheat, spring wheat, durum, barley, fall rye, oats, canola and flax. A spatial linear programming model in which gross margins are maximized is run for three scenarios: no climate change, a small increase in average temperature, and a large increase in average temperature. The model is calibrated to output from 2005 to 2010 and then run from 2011 to 2050. The model predicts that with a small increase in emissions, there will be a net increase in producer surplus to Canadian farmers, with wheat and canola dominating the landscape. This is similar to the current landscape; however, most crops migrate further north and west from their current range. As well, spring wheat acreage declines in favour of winter wheat, largely due to the higher yields for winter wheat. However, with a large increase in emissions, by 2050 the dominant crops in the landscape are barley and winter wheat, driven by changes in precipitation and temperature. The implications for Canadian agricultural production achieved by a spatially disaggregated model are a departure from the results of other modelling approaches and should be tested against a greater variety of behavioural assumptions and price conditions. Further study can help identify if crops other than those included here will become more prevalent. A major shift in the type of crops grown in the region would have implications for global food prices and food security.

Acknowledgements

In 2000 I began an undergraduate degree and quickly decided my goal would be to complete a doctorate. As a mature student, this would be a serious challenge. However, it is now 12 years later and I have finally arrived; it is time to thank those without whom I would not have succeeded.

This thesis would not have been completed without the generous intellectual contributions of Dr. Jim Unterschultz, without whom the original research idea and most of the content would not have evolved into its current form, and Dr. Scott Jeffrey, without whom the models would have never been finished. In addition, Dr. Jeffrey's editorial support has been invaluable. I would also like to acknowledge Drs. Peter Boxall and Marty Luckert, who were instrumental in the development of the research ideas. I extend my appreciation to Drs. Jim Vercammen and Varghese Manaloor, who both contributed substantially to the final version of this document. I have arrived at this point due to the support of my fellow graduate students, friends and family. In particular, I would like to acknowledge the particular support of Joan Robertson, Mary and Wes Nicol, Claudia Schmidt, Judy Hatt, Kierstin Hatt, Helen Banks, Jana Strakova, Jesse Cole, Zoia Komirenko, Danni Sturko, Sven and Melanie Anders, Chris Lyon, Lisa Anderson, Laura Mousseau, and the other denizens of 557C, Jeewani Fernando, Yingchun Dai and George Danso. As well, the support of my new colleagues at IDRC has been invaluable over the past year, and I extend my thanks to the 4th floor and all of the Agriculture and Food Security team. I extend my appreciation to the Manitoba Agricultural Services Corporation and the Agricultural Financial Services Corporation of Alberta for the use of proprietary data without which this research could not have been conducted. Finally I would like to thank Genome Canada, Genome Prairie and Genome Alberta for their generous funding for this research.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.0 Introduction

Agricultural land use decisions determine aggregate output of major crops, and major shifts in land use signal major structural changes in agricultural production. Agricultural land allocation decisions are based on the relative profitability of the various crop alternatives, which is itself a function of output prices, input prices, yields, and the policy environment. Input prices are determined exogenously to individual land use decisions, and Canadian producers are price takers in the international agricultural markets. Thus, selecting a mix of crops that will produce the highest expected gross margin stream, given fixed inputs, is a key element of the profitability equation that farmers can control directly. Considering their production constraints, farmers choose inputs so as to maximize profits.

Even if farmers consistently optimize input usage, yields are still variable from year to year due to fluctuations in environmental variables. Environmental variables can include soil quality, which does not change substantially from year to year, and weather, which does. In fact, weather is the main input into crop production humans cannot control, which suggests that a solid understanding of crop yield as a function of temperature and precipitation is important for predicting land use decisions in agriculture with climate change, and subsequently, aggregate supplies of cereal grains and oil seeds. In particular, extreme temperatures such as heat waves, droughts, or cold spells, may have an impact on yields. Even exposure to a single day of heat above the plant's tolerance level may have a significant impact. It has been agreed upon by the majority of experts that climate is changing, which will expose crops to higher average temperatures and increased or decreased overall precipitation levels as well as potentially increased variability of temperatures (Natural Resources Canada 2004). Thus, with climate change, the weather inputs into crop production are expected to change in substantial ways in the future, even if other crop yield function parameters remain static.

It is challenging to estimate the relationship between crop yields and weather because that relationship can change in one of two ways. First, technical change is expected to shift the yield function through the development of new seed varieties that are better adapted to the Canadian environment. Thus, even if weather variables such as temperature and precipitation do not change, yields should increase due to research efforts. For example, Dr. Brian Fowler at the University of Saskatchewan heads a research program to improve the cold tolerance of cereal grains.

The overarching purpose of this program is to analyse land use and land use change in the Canadian prairies with climate change. This research project has been broken down into two main components, each driven by a specific and related research question. The first question is how do temperatures affect yields of major Canadian prairie crops? The second question is, given improved knowledge of the effect of temperature on yield, how will changes in climate affect agricultural land allocation in the Canadian prairies at the regional level?

In studies of agricultural production, the treatment of weather variables is often *ad hoc*, with little to no reference to previous studies or theoretical support for a particular approach. The lack of published references regarding the appropriate treatment of temperature variables is a reflection of the lack of theoretically or empirically supported approaches that will provide consistent and unbiased results.

Schlenker and Roberts (2006 and 2008; SR hereafter) show that there is a relationship between daily maximum temperature whereby yields increase with exposure to temperatures up to a certain point, above which yields decrease for cotton, corn and soybeans in the United States. They use daily minimum and maximum temperatures to estimate the number of hours that a crop is exposed to heat over the growing season. The SR approach to incorporating daily weather variables is novel as most modeling approaches have used either average temperature or growing degree days (GDD). A linear relationship between temperature and yield is often assumed, such that an increase in temperature is always assumed to increase yields.

However, neither average temperatures nor GDD incorporate the potential for temperatures above some critical maximum to exhibit different, and potentially negative, marginal effects on yield than is the case for temperatures below this critical value. Statistically, averaging monthly or daily weather temperature variables eliminates the effect of particularly high or low temperatures on yields. GDD calculations eliminate the effect of temperatures above some exogenously determined value, and simulations produce results based on parameters derived from separate studies, or from historical data which are not typically validated with out-of-sample data.

Thus, SR’s approach is better suited to capture the effect of the extremes, both warm and cold, on crop yields. This section provides an overview of the methods used to incorporate weather in yield analyses.

The research undertaken in this thesis is an application of SR's methods to the Canadian prairies for major crops including wheat, canola, barley, flax and oats, with extensions to land use change analysis under climate change scenarios. Not only will the effect of summer temperatures and precipitation be examined for all crops noted above, but a separate analysis will be undertaken to examine the effect of winter weather on yields of fall-planted crops.

Once the appropriate means to derive weather variables for yield forecasting are determined, these improved forecasts are used in an analysis of agricultural land use and land use change in the Canadian provinces of Alberta, Manitoba and Saskatchewan. These three provinces comprise the Canadian Prairies and contain the largest significant agricultural region in the country and one of the most important agricultural production regions in the world. A change in agricultural production in this region can provide insights into changes in global agricultural production. There are a variety of approaches to modeling economic impacts of climate change, but not all incorporate land use or land use change. Of those that do, spatially explicit models can capture the micro-level impacts of weather. However, spatial models have not commonly been used, likely because of the complexity of the data required.

1.1 Objectives and Hypotheses

The objectives of the research are:

i. to estimate the effect of extreme daily temperatures during the growing season on yields in Alberta, Saskatchewan and Manitoba for the following major Canadian cereal and oilseed crops: winter wheat, spring wheat, canola, durum, barley, oats, flax, and spring and fall rye;

ii. to test the accuracy of out-of-sample yield forecasting for three aggregate temperature variables: monthly average, GDD and the SR method;

iii. to estimate the effects of temperatures during the winter season (in particular January and February) on yields of winter wheat and fall rye in the Canadian Prairies;

iv. to incorporate improved yield estimates into a model of land use allocation between competing agricultural uses in which both the production function and weather inputs are unchanged from the historical dataset; This scenario constitutes a short-run outcome, which is used to validate the model against current agricultural land use data; and

v. to estimate agricultural land use allocation under an assumption of climate change, as modeled by changes in average daily temperatures, and

The hypotheses that will be tested are as follows:

i. The temperature variables as formulated by SR provide better out-of-sample forecasting estimates than the GDD or monthly average temperature approaches.

ii. Using the temperature variables as formulated by SR, the selected grains and oilseeds exhibit a positive response to temperature variables in the lower ranges and a negative response to temperature variables in the higher ranges such that a critical maximum temperature can be defined beyond which yields decrease.

iii. Using the SR approach, the selected grains and oilseeds exhibit a negative yield response to temperatures below a critical minimum.

iv. Greater snow depth in January and February are associated with higher yields due to reduced winterkill for fall-seeded crops.

v. Variability of snow depth in March and April has a statistically significant effect on yields of winter wheat and fall rye, with deeper snow depth being associated with higher yields.

vi. A critical minimum temperature beyond which yields of winter wheat and fall rye exhibit a non-linear response can be identified such that exposure to temperatures above this point will have a positive effect on yield and exposure to temperatures below this point will have a negative effect on yield.

vii. Climate change will induce an increase in the acreage allocated to drought-tolerant crops.

viii. Substitution towards crops that produce higher yields and away from crops with lower yields will occur as climate shifts change growing conditions.

ix. The spatial distribution of crops will respond to climate change, with heat tolerant crops being found further north as temperatures increases.

1.2 Methods and Data

The methods used to respond to the questions and test the hypotheses outlined above require first an estimate of a production function with spatially disaggregated yield data as a function of locally observed weather. The land use analysis will proceed by incorporating the production functions to incorporate improved yield forecasting in a linear programming model.

Economic analyses of climate change and agriculture generally fall into one of two categories: an econometric model of either production or profit, or a hedonic model in which land values are a function of weather. Examples of these will be explored further in Chapter 2. Hedonic functions do not specify the land use activities that influence land values, and are therefore not useful to respond to the research questions identified above. Therefore a production function approach is used, a simplified version of reality in which yields are a function of weather, time and site-specific characteristics. Farm management choices are assumed to be constant. This production function is incorporated into a spatial linear programming model in which gross margins (price * yield – variable costs) are maximized across a grid of cells, each10 km^2 in size. Further explanation and contextualization of these choices is found in Chapter 2.

The data required for the production function are first, yields at a spatially disaggregated level, and weather information. The yield data for nine crops were obtained at the county or rural municipality level from the Alberta Agriculture Financial Services Corporation (AFSC), the Manitoba Agricultural Services Corporation (MASC) and the Government of Saskatchewan. Weather data were obtained from Environment Canada's database of climate stations. Each weather station has data for a different subset of the entire time series from 1965 to 2007. Relevant data available are rainfall, precipitation, snow fall, maximum temperature and minimum temperature.

The linear programming model incorporates input and output prices. Output prices are available at the provincial level from Statistics Canada. Input prices are available for different soil zones for different crops from the Governments of Alberta, Saskatchewan and Manitoba.

Climate change analyses require information on base period temperatures and rainfall to which changes in average temperature and rainfall are compared. These data (including estimates of monthly average temperatures for the base period of 1961 to 1990 as well as the forecasted values for 2011 to 2050) were obtained from the Canadian Institute for Climate Change, an organization run through the University of Victoria (CICS 2007). GIS maps of the estimates of new minimum and maximum temperatures, and of precipitation levels are available monthly for a select number of climate change scenarios.

1.3 Contribution to Knowledge

With competition for agricultural output for biofuels, food, and fibre, the potential for the Canadian Prairies to contribute to these industries raises several important questions. Can agriculture in the Canadian prairies supply inputs for a biofuels industry? What will happen to the price of food for Canadian consumers? Will Canadians eat more imported foods? What kind of risk management programs should the Canadian government provide for Canadian farmers? These are important policy issues that should be answered with the best available information. This information should include estimates of how anticipated changes in the climates of Alberta, Saskatchewan and Manitoba will affect agricultural output. Finally, such information should incorporate the marginal effects of increased temperatures.

This study contributes information on the marginal effect of different ranges of heat on the most important Canadian crops in the Canadian Prairies – winter wheat, spring wheat, durum, canola, flax, rye, oats, and barley. In the studies reviewed in Chapter 2, other than those of SR, Canadian and American studies have used averaged weather data or assumed critical temperature ranges in which the plant yields respond positively to temperature. This study will contribute important new information on yield responses to weather variables by increasing the quality of the weather dataset used, using daily minimum and maximum temperature data rather than average temperature data. No assumptions are made about the critical maximum and minimum temperatures to which crops will respond. Thus, the need to use averaged weather data is eliminated. Insights into how crop acreages shift in response to climatic variables are, therefore, a valuable contribution to future study of the behaviour of the Canadian agricultural sector under climate change.

As well, this study provides a new and important source of critical information about how agricultural land could be allocated as yields shift due to climate change. It contributes an improved approach to climate change analysis because of the use of detailed daily climate data compiled from Environment Canada's (2008) database of daily weather observations. It also contributes a first attempt to understand the land use implications of weather effects on fall-planted crops. The study builds on the methods of SR, but incorporates a land use and land use change analysis, absent from the SR analyses. This study also contributes spatial detail in the analysis of the distribution of agricultural production of various cereal and oilseed crops that is absent from the majority of analyses that have been conducted. The combination of detailed spatial data on crop choices combined with the detailed weather input data is novel. If the results of this analysis are consistent with other research approaches, then the additional data and time required to process this data into spatially explicit variables is not justified. If, however, the results of this analysis are inconsistent with other approaches, then the spatially-explicit approach employed here may provide insights that cannot be obtained using aggregated yield and/or weather data.

1.4 Organization of the thesis

This thesis is organized in six chapters. The second chapter provides an overview of the relevant literature on climate change analysis in agriculture, land use and land use change, and the incorporation of climate variables into these types of analysis. Chapter 3 provides an empirical test of three temperature variables as predictors of yield: average temperatures, growing degree days and the approach modeled after SR. This is followed by an application of the methods determined by of the analysis in Chapter 3 to provide improved yield forecasting. Chapter 4 consists of an analysis of yields of fall-seeded crops as a function of winter weather. Chapter 5 provides a land use analysis using a spatial linear programming model developed specifically for this thesis. Chapter 6 provides a summary of the work described above.

Chapter 2: Modeling land use and agricultural production with climate change: a review of the literature

2.0 Introduction

In Chapter 1, the research regarding land use and land use change under assumptions of climate change was outlined. In order to contextualize the research and to integrate theory and method, it is necessary to understand the types of research that have been conducted to analyse climate change and agricultural production, land use, land use change and climate change, and finally, the different approaches to incorporating climate variables into standard economic analyses. According to Briassoulis (2000, Section 5.1), there is no general theory of land use change, as the drivers are specific to each situation, and context dependant since methods vary by discipline and research question; Therefore, there is no single approach to modeling land use change that is appropriate for all circumstances.

Briassoulis (2000) divides land use change models into four categories: econometric and statistical models, spatial interaction models, optimization models, and integrated models. Spatial interaction models examine the effect when a land use in one zone has an effect on a land use in a contiguous zone, capturing interaction effects. GIS models that use spatially explicit data, but do not model the interaction between regions, do not qualify as spatial interaction models. However, they constitute a special category of optimization models. Integrated models contain characteristics of more than one of the above approaches.

This chapter provides a review of land use and land use change models in the climate change literature. Section 2.1 provides an overview of the modeling approaches used to estimate the impacts of climate change on agricultural production. These generally use production or profit functions, or hedonic models. Section 2.2 contains an overview of agricultural land use models with respect to climate change, often based on simulation models, including spatial optimization models. Section 2.3 contains a review of the methods used to incorporate climate data into yield estimates. There are three approaches most commonly used; the growing degree day (GDD), average temperatures and daily temperatures for crop simulation models. These are compared to a new method introduced by Schlenker and Roberts (2006) which is a form of adjusted GDD.

2.1 Modeling the Impacts of Climate Change with Econometric Models

Early attempts to capture the economic impacts of climate change, which did not generally attempt to specifically capture land use or land use change, capture aggregate changes in production that could be attributed to climate change. These are often partial equilibrium models, which are good at modeling detailed agronomic processes and farm level detail, and as such are particularly appropriate for modeling short term and localized effects of climate (van der Werf and Peterson 2007). These models focus on the specific technologies of agriculture or forestry, and allow more detailed modeling of spatially disaggregated data. As well, these models allow spatially heterogeneous effects to be analyzed.

The models used to capture the impacts of climate change on agricultural output are usually either production functions or profit functions. A second family are the so-called "Ricardian" or hedonic models, which capture the impact of climate change on land values, from which the impacts on agricultural production are inferred.

2.1.1 Production or Profit Function Models

The earliest approach to estimating the impact of climate change was to use a production function. Production functions for specific crops were modeled as a function of climatic variables; the changes in yield were aggregated to extrapolate economic impacts for specific crops. The profit function approach is similar in that it measures the economic impacts of climate change for a specific crop, but now as a function of input and output prices as well as weather. Table 2.1 provides a summary of selected papers that use production or profit functions.

Gay *et al*. (2006) model the production of coffee in Veracruz, Mexico, as a function of mean seasonal temperature and mean seasonal precipitation as well as economic variables including local and international coffee prices. The results show a 34 percent reduction in coffee yields and the likelihood that coffee would not be profitable in the year 2020, largely due to the temperature effect.

Table 2.1: Summary of selected papers that incorporate temperature data in yield estimates

Authors / Year	Location	Temperature treatment	Type of Model
Gay *et al.* 2006.	Mexico	Seasonal average and variance	Production function
Schlenker and Roberts. 2006 and 2008.	United States	Daily minimum and maximum, cumulative exposure calculated.	Production function
Deschênes and Greenstone. 2007.	United States	Growing degree days	Profit function
Haim *et al.* 2008.	Israel	Simulated daily data	Production Function
Lobell and Ortiz-Monasterio. 2007	Mexico California	Simulated daily data and monthly average temperature	CERES incorporated into a production function
Brassard and Singh. 2008	Quebec	Simulated daily data	CERES incorporated into a production function

Deschênes and Greenstone (2007) consider the effect of random year over year variation in temperatures to study the effect of climate change on agriculture. Looking for an alternative to hedonic models, they instead use profit as the dependent variable because profit can reflect year-over-year variations in weather where land values tend not to fluctuate sufficiently to capture this effect. Using a profit function approach, weather is incorporated by using a GDD calculation. This model imposes a short run assumption of non-substitutability between crop. The results are then compared to those for hedonic models in which such substitutability is endogenized. The authors calculate the marginal impact of weather on profit to calculate the profit elasticity of weather. They assume that in the long run this value tends to zero.

Haim et al. (2008) model the impacts of climate change on dryland wheat and cotton production in Israel using a production function with agronomic inputs. The authors used temperature projections from 2070 to 2100. Yield estimates were then used to calculate net revenues (total revenue less total cost) as a function of the price of water, nitrogen, and other input costs, as well as output price. Net revenues were found to be a function of precipitation and temperature. Net revenues for wheat were found to be negative under extreme climate change, but potentially positive with moderate climate change. Net revenues were found to be negative for cotton in both scenarios.

Schlenker and Roberts (2006 and 2008) use a simplified production function in which yield is a function of exposure to temperature and precipitation to estimate the marginal effect of weather. The climate variables are described in more detail in Section 2.3.4. They model yields for rice, corn and soybeans, and find a non-linear relationship between yield and heat. Yields increase until a critical maximum temperature is reached. Exposure to temperatures above this critical maximum reduces yields. The authors aggregate the yield impacts across production in the United States to estimate economic impacts. Given that there is no attempt to include land use or crop substitution impacts, the authors acknowledge that this estimate likely overstates the negative impacts forecasted, as is typical of the production or profit function approaches.

There are a variety of packaged simulation models used for yield estimates which can then be incorporated into production functions. One approach is the use of crop yield simulation packages such as CERES for wheat. For example, Brassard and Singh (2008) use a crop simulation models CERES, CROPGRO and SUBSTOR to examine the impacts of CO_2 fertilization effects and longer growing season due to increased temperatures on yields for potatoes, wheat, soybeans and maize, for seven agricultural regions of Quebec. All inputs except for climate are held constant between the base period and the future periods, implying that farmers are not making adaptive adjustments to their management practices.

2.1.2 Ricardian or Hedonic Models

The production function approach has not been used as often in recent years and has been overtaken in popularity by the hedonic approach. These are models in which the value of land is a function of the characteristics of the land. In order to capture climate change, temperature variables are calculated for parcels of land, which then are used to estimate the impact of temperature on land values. Land values are a proxy for the productive capacity of the land, which is implicitly assumed to be allocated to the highest value use. This approach is also known as a Ricardian model after Ricardo, who theorized that land rents provided a proxy for land values and the production that occurred on that land (Mendelsohn, Nordhaus and Shaw 1994). Schlenker, Hanemann and Fisher (2005) note that the results of the Ricardian approach received significant attention because the results of the analyses were at odds with those of previous approaches. The Ricardian approach is designed to overcome the bias in the production function approach, which implicitly ignores crop-substitution. Thus, they note that previous studies had in general overestimated the economic impact of climate change on agriculture, as farmers switch away from poorly performing crops to those with higher yields under new climatic conditions (Mendelsohn, Nordhaus and Shaw 1994). Table 2.2 shows a summary of hedonic models used to estimate the economic impacts of climate change on agriculture.

Table 2.2: Selected papers that use hedonic models to examine the impacts of climate change

Authors / Year	**Location**	**Temperature treatment**
Mendelsohn and Reinsborough. 2007.	Canada and the United States	Monthly average
Wang *et al.* 2009.	China	Monthly average
Weber and Hauer. 2003.	Canada	Deviations from mean temp, Jan, Apr, Oct, Jul
Schlenker *et al*. 2004.	United States	Monthly average derived from daily data
Mendelsohn, Nordhaus and Shaw. 1994	United States	For rainfall and temperature, monthly average derived from a weighted regression from all weather stations within 500 miles of the district for January, July, April and October only.
Reinsborough. 2003	Canada	Monthly climatic norms for 1961 to 1990

Mendelsohn, Nordhaus and Shaw (1994) examine the effects of climate change on agricultural production for the United States, comparing a production function approach to a Ricardian approach. The model is run twice, once for 1982 and again for 1978, using an average of the daily average temperature and rainfall for January, April, July and October, and the square of each of these, in the regression. The model is re-run with gross profit (total revenue less average cost) as the dependent variable. The result is that the economic impact calculation using the production function approach is approximately 20 times that of the Ricardian approach. Given that the analysis is based on a static estimate of the marginal impact of climate, the model may not be robust over time but the authors note that the marginal impacts of the variables as described were similar in the two "snapshot" years chosen. It is unclear whether or not this result could be used for forecasting; the economic impact estimates come from multiplying the marginal effect of weather on land values by the estimated climate impacts measured in degrees (temperature) and inches (rainfall).

Reinsborough (2003) uses a Ricardian model and finds that the climate change expected over the next few decades will have a negligible effect on Canadian agriculture. She notes that as production function approaches hold land use allocations constant, they provide a lower bound for benefit estimates. The Ricardian model, where crop switching takes place but transaction costs for crop switching are not incorporated, is interpreted as an upper bound on potential benefits. The Ricardian approach bypasses the yield estimates that were required for the production function efforts because land values are a function of the characteristics of the land rather than of the specific crops produced. While crop switching is assumed,neither the crops grown, nor the changes in the crops chosen, are not identifiable in the model. Reinsborough (2003) notes the confidence intervals around the results are large, making accurate interpretations of the results difficult. She concludes that potential increases in land values are small at best and highly uncertain. Building on this work, Mendelsohn and Reinsborough (2007) use a Ricardian model to compare land values in the United States and Canada based on climatic variables and find that Canadian land values are more sensitive to precipitation than temperature, with the opposite effect occurring in the United States.

Weber and Hauer (2003) provide an estimate of the economic impacts of climate change in Canada using a similar hedonic approach. They use GIS data to intersect Census of Agriculture data from 1996 with Census of Canada data from 1996 with soils and climate data for a 10 km^2 grid. Climate data consist of climate norms from 1961 to 1990 for the mid-point of December to February, March to May, June to August and September to November. The result is a set of 3,665 observations from which they estimate a standard hedonic model. The effects on agricultural land values from a one degree increase in average temperatures are examined. Consistent with previous studies, a warming of temperatures is predicted to increase land values. However, warmer temperatures are offset by drier climates and rapid maturation of grain crops, and these impacts are not modeled. The relative gain in land values is found to be highest for the prairies and lowest in the coastal regions of Canada, although positive in all regions across the country.

Ricardian models are common in the climate change literature because the data that can be used to estimate them are flexible, and both land use values and climatic data are readily available. They implicitly allow substitution between economic activities, which make them an improvement over the production function models used previously. Using long range climate predictions, Deschênes and Greenstone (2007) compared the results of a hedonic estimate with a production function and found that the hedonic model was sensitive to parameter values. They conclude this lack of robustness is not adequately represented in discussions of most hedonic models. Schlenker, Hanemann and Fisher (2005) suggest that adding irrigation amounts to precipitation variables may correct omitted-variable bias in the estimator. Using a Ricardian model, they find that the results become more robust across weighting schemes and models in the United States once irrigation is included as an explanatory variable.

The above discussion relates to “traditional” Ricardian models. Structural Ricardian models allow for the examination of specific adaptation choices as subsets of the full adaptation implicit in the approach. An example of this is one in which the hedonic model is run conditional on specific choices of livestock in Africa (Seo et al., 2008). These models allow the examination of specific adaptations but are limited to different scenarios introduced by the researcher with specific behavioural assumptions, and as such do not allow a full exploration of exogenously determined adaptations.

2.2 Modeling Impacts of Climate Change by Simulating Land Use Change

The Ricardian models provided the ability to incorporate crop substitution but Deschênes and Greenstone (2007) note that the approach provides unreliable estimates due to sensitivity to variations in control variables, sample size and weighting. In the Ricardian approach, substitution towards higher value activities is implicit. However, it does not allow for policy planning by estimating the changes in specific activities such as acreage planted to a specific crop, although the structural Ricardian approach allows testing of assumptions about some of these possible adaptations. Table 2.3 shows a sampling of studies that model the impact of climate change on agricultural land use.

Briassoulis’ (2000) definition of simulation models includes optimization models. One of the benefits of a simulation approach is the ability to model unprecedented circumstances such as technical change or shifts in climate. For these situations, no historical data exists so in order to predict into the future using assumptions about what will come, simulation modelling is an appropriate choice. Simulations also allow estimates of the trade-offs between different policy options (Verburg and Lesschen 2006).

Table 2.3: Selected papers that incorporate temperature data in simulations of agricultural land use

Authors / Year	Location	Temperature treatment	Land Use Model
Arthur and Abizadeh. 1988.	Western Canada	Derived annual average; Temperatures dictate planting dates; yields are a function of moisture deficits only	Simulation
Mooney, Jeffrey and Arthur. 1991.	Canadian Prairies	Climate normals (average)	Linear programming
Felkner. 2009.	Thailand	Daily data generated from a distribution	Spatial simulation model
Kaiser et al. 1993.	American mid-west	Monthly averages	Multi-stage mathematical programming
Rosenzweig and Parry. 1997.	International	Daily data –average or min/max not indicated	Crop yield simulation model
John, Pannell and Kingwell. 2005.	Australia	Stochastic weather; full explanation in Kingwell *et al*., 1990.	Farm level Linear programming

Arthur and Abizadeh (1988) use a simulation model to explore the impact of climate change on agricultural output in western Canada. The simulation model uses a profit function that incorporates a production function with yield as a function of standard climate change predictions, weather, seeding date, soil moisture, yield, crop choice, and sectoral effects. The model is run for various sections of the Canadian prairies.

John, Pannell and Kingwell (2005) describe a farm-level linear programming model known as MUDAS that estimates changes to farm management practices under assumptions of climate change in Australia. The model incorporates a discrete stochastic representation of weather. With this model, farmers make decisions to optimize output after observing weather conditions; Specifically, in the region in Australia modeled, farmers make decisions based on observed rainfall rather than anticipated rainfall. The full explanation of the stochastic treatment is found in a Government of Australia grey literature document by Kingwell *et al.* (1991) that is not publically available, and thus is not reviewed.

Economic simulations include optimization models where land use outcomes are compared based on changes to economic variables. Optimization models use mathematical algorithms to optimize an objective function subject to constraints. The objective function commonly represents cost, utility, or profit, or, as in the case described below, producer and consumer surplus. Constraints can include a limited resource base such as land or some other input, financial constraints such as a limited budget, and any other situationally relevant constraint. Aggregate farm modeling is an outgrowth of farm-level modeling that became possible due to an increase in computing power in the 1980s (Klein and Narayan 1992).

While the allocation of agricultural land may not have spatial dependencies, it can have a temporal dependency in that the choice of crop grown in a given year is based on the crop grown in the previous year or years. To capture this effect in an optimization model, Rousevell *et al*. (2003) include rotational penalties to reduce yields of crops that occur in less than optimal combinations year-over-year. The model is used to estimate how agricultural land use responds to climate change in two regions of the United Kingdom using farm level models to simulate land use decisions that are aggregated at the regional level.

One commonly used optimization model used in the Canadian agricultural sector is CRAM – the Canadian Regional Agricultural Model. CRAM is a static non-linear programming model that maximizes both consumer and producer surplus given constraints by choosing an optimal output level (Klein *et al*. 1996). It is used in conjunction with a variety of biological and agronomic models (AAFC 2011) and as such falls into the classification of integrated models, as defined by Briassoulis above. Production is driven by demand for agricultural goods. CRAM's production is broken down by regions at five levels: national, east and west, provincial, shipping ports, and crop regions. CRAM contains 55 crop regions and 10 livestock regions and contains baseline data for 2010 and 2006 only (UNFCC, 2011). Agriculture and Agri-Food Canada has used it to analyze policy options for greenhouse gas mitigation, for example, but note that the scale of economic data make it less appropriate for modeling smaller scale ecological phenomena (AAFC 2011a).

Aggregation by region is also used in a partial equilibrium model, FARM (The Agricultural Regional Model), also used in Canada. FARM has less disaggregation in the data than CRAM, grouping production into western and eastern Canada only (Le Roy *et al*. 2007). CRAM and FARM use regional data rather than data at the county/municipality level and as such are far coarser treatments for spatially explicit yields than the SR approach (Le Roy *et al*. 2007). Neither does weather explicitly affect output in either modeling approach. Examples where these models have been used to estimate the impacts of climate change on agricultural land use have not been found.

Spatial modeling includes linear or non-linear programming models, goal programming, and cellular automata programming techniques. Goal programming is a type of optimization model where targets are included, based on policy objectives or dictated by research on bio-physical/ecological relationships. Cellular automata techniques include various ways to define neighbourhood relationships for models where there are interactions between spatial units. Non-linear programming is one type of simulation modeling where a quadratic objective function can be defined; one common application is for trade relationships where both supply and demand from each region can be incorporated.

Spatial economic models are based on the theories of von Thunen, who used land rent to describe a theoretical city state with concentric circles of land reflecting different land use activities. High rent activities such as vegetable growing are in the inner circle, while lower rent activities such as grain growing, take place in the outer circle (Nelson 2002). In modern studies von Thunen's ideas underlie the Ricardian/hedonic analysis of Mendelsohn, Nordhaus and Shaw (1994), discussed above, and models that optimize profits on a particular parcel of land such as the mathematical programming models discussed above, including CRAM.

Spatial models are appropriate when one of two phenomena is present in the dataset. The first is spatial heterogeneity. Spatial heterogeneity reflects the spatial distribution of attributes, where the average value at the aggregate level introduces inaccuracies in the data. The second problem spatial models can address is spatial dependencies, which occur when the land use of two adjacent parcels is interrelated (Florax *et al*. 2002). Agricultural land use with climate change exhibits spatial heterogeneity as the climate impacts are different in different regions of the Prairies.

When dealing with spatial models, it is important to consider the scale of the dataset and of the analysis. Verburg and Lesschen (2006) note three issues related to scale:

- Land use decisions are the result of the decisions made at various scales, from individual to local and regional.
- Aggregation of small-scale spatial data using an averaging process does not lead to accurate representation of these processes. As suggested by the above bullet point, small scale behaviour (i.e., at the land owner level) is not equivalent to regional behaviour (i.e., average land owner behaviour at a regional level).
- Observations are restricted by the extent and resolution of the measurement of data. Extent is the scope, or size, of the region studied, and resolution is the distance between observations. Researchers are often limited to data of a certain scale, regardless of how well that scale represents the processes or decisions being modeled.

Statistical estimates of land use are sensitive to scale. For example, models that are run at the regional level are subject to distortion of heterogeneity through regional aggregation of spatial data (Gellrich and Zimmermann 2007; Verberg and Lesschen 2006). This is known as the Modifiable Area Unit Problem (MAUP) (Gellrich and Zimmermann 2007). In fact, using aggregate data under-estimates yield variability at the field level (Popp, Rudstrom and Manning 2005). The MAUP suggests that the smallest scale possible as dictated by the data is appropriate. When fine-scale data representing ecological relationships are averaged to create spatially aggregate versions of the dataset, substantial aggregation errors are introduced (Verberg and Lesschen 2006).

Spatial effects can be modeled using spatial econometrics or spatial simulation models. Spatial econometric techniques deal with econometric issues specific to spatial data, such as the colinearity created by spatial homogeneity between contiguous parcels of land, for example (Anselin 1988). One way to approach linear programming (LP) is to use spatially explicit data to generate variables. When there is no spatial interaction to the model (as discussed in Briassoulis 2000, above), an optimization model is often used. The models discussed below are summarized in Table 2.4, and do not necessarily model climate change but rather provide a sampling of various approaches to incorporating spatial information in land use analysis. All of the selected examples use linear programming.

Table 2.4: Selected examples of linear programming modeling with spatial data

Authors / Year	Location	Purpose
Arthur and Abizadeh. 1988.	Canadian Prairies	Climate change in the Canadian Prairies
Campbell et al., 1992.	Antigua	Crop diversification strategies
Yang and Weersink.	Ontario	Environmental goods and services
Mooney and Arthur. 1990.	Manitoba	Climate change in Manitoba

As discussed above, Arthur and Abizadeh (1988) estimate the economic effects of climate change with a linear programming model for Manitoba and by multiplying acreage seeded by prices by yields for Alberta and Saskatchewan, on the basis that crop choices have traditionally been more limited in these provinces. Depending on the climate change assumptions used, the province, and the method of processing weather data, results indicate increases in all crop outputs, decreases in all crops except wheat or barley, or no sensitivity at all. Because of the limitations of the climate change model used, and because of the use of daily average weather data, these results are less than definitive. No attempt was made to investigate changes in land use due to climate change in this case.

Campbell *et al.*'s (1992) paper, which uses a linear programming model with spatial data and GIS, has been used as a template for many other spatially-explicit land use change studies. The authors consider the options for Antigua to expand agricultural production beyond the traditional export crop of sugarcane, as this market had been gradually collapsing. While this is not a climate change study, the methods used have influenced the methods used to study climate change using spatial methods. The GIS is used to generate variables which are then fed into a nation-wide LP model. The results of the LP model are fed back into the GIS to examine spatial variation in land allocation decisions. GIS data included current land use/crop, landholder type, province, water supplies, land use categories, proximity to water, etc. The LP model uses local demands for agricultural production as a constraint and then minimizes the costs of producing those commodities either through local production or through imports. The model measures potential output based on non-stochastic elements only, such as soil quality and land tenure systems.

Yang and Weersink (2005) use spatially explicit data and a linear programming model to minimize costs of implementing riparian buffers. Yields in the model are calculated spatially as a function of land characteristics such as soil types and slope. The yields are reported from empirical observation as point data with spatial coordinates, so actual yields to use in the econometric regression are interpolated from these observed point data. Then a cost minimization linear program was built to examine the spatial distribution of riparian buffs. Again, weather as a stochastic element is not a key ingredient in the simulation of these land use allocations.

Another model using a linear programming approach to estimate the effects of climate change on agriculture in Manitoba was run by Mooney and Arthur (1990). Constraints on the model include land availability, feed requirements of the livestock sector, and rotational constraints. Spatial distributions of results are estimated by calculating relative effects in different parts of the province based on land values. This model allowed the introduction of new crop alternatives under different climate scenarios, using yield data obtained from other geographic regions, primarily the north-central and north-eastern United States.

2.3 Incorporating Climate Data into Yield Estimates

If researchers wish to better examine the impact of climate change on agricultural land use, then the manner in which the climatic data are incorporated into the modeling approach is critical. Capturing the marginal impacts of exposure to temperature is of particular relevance. The purpose of this section is to outline methods used for incorporating shifts in weather patterns. Weather is often excluded from agricultural production functions due to spatial and temporal heterogeneity. Researchers in the past have assumed that a production function captures all non-weather variability in production. Therefore, the error term in a given production function was assumed to capture all weather-related impacts (Goetz 1993). However, this approach can be too simplistic as weather represents an important source of risk in agricultural analysis. If weather is not included, models are mis-specified with regards to risk. Just and Pope (1978) formulated a production function that incorporated weather variability in order to address this form of mis-specification. In a Just-Pope production function, yield, Y, is a function of inputs, X, and variance of yield, Z. Z can then be formulated to include weather. Equation 2.1 shows a generic specification of this approach.

$$Y = f(\boldsymbol{X}) + h(\boldsymbol{Z}) + e \qquad [2.1]$$

The econometric reason for the use of temperature in the Just-Pope production function is to prevent bias in the estimators, rather than to capture specific weather effects. No guidance is provided on how to aggregate such complex heterogeneous weather datasets across time and/or space.

The production function shown above requires weather as an input to variance. While weather could be included in any production function, the question of how to do so is unclear. Tables 2.1 – 2.3 contain descriptors of the climate variables used in various studies noted in the tables. These treatments can be grouped into four types. The first is the use of daily minimum and maximum values for crop yield simulations. The second is the calculation of average values, either seasonal or monthly. The third is the calculation of growing degree days (GDD). The fourth is a refinement of the GDD method that breaks the heat units up into specified temperature ranges, formulated by Schlenker and Roberts (2006 and 2008).

2.3.1 Daily Minimum and Maximum Temperatures

The first method used to incorporate climate variables in climate change models is to use daily minimum and maximum temperature for crop yield simulation models. There are a wide variety of simulation models used to predict crop yields in agricultural/agronomic models such as a standardized yield simulation models such as CERES. CERES is considered a well-validated simulation model for wheat yield prediction (Rosenzweig and Tubiello 1996). In these models, complex physiological processes are modeled, requiring complex input data. Often derived daily data are used in these models, where monthly or seasonal averages are used to derive a daily value for minimum and maximum temperature. Alternatively, the mean and variance of daily minimum and maximum temperatures are used to select estimates of daily values from the distribution, but for a selected region, which are then used to estimate yield across regions. For example, Brassard and Singh (2007) use the absolute difference between weighted average daily temperatures and projected temperatures under climate change to analyze yield changes for wheat, maize, potatoes and soybeans. Crop models CERES, CROPGRO and SUBSTOR were used to simulate yields as a function of solar radiation, minimum and maximum temperature and precipitation.

Schlenker and Roberts (2008) indicate that one of the potential issues with simulation modeling is that parameters within the model are taken from various sources, any of which may be built on incompatible assumptions. As well, simulation models are built using data from a particular region and then are not usually validated against out-of-sample data (Schlenker and Roberts 2008). In one exception, Lobell and Ortiz-Monasterio (2007) compare the results of the simulation model with those from an econometric model of wheat yields. In order to make the comparison, monthly average minimum and maximum temperatures are used in the econometric regression. They find that the simulation model produces results within three percent of those of the econometric model. If, in fact, average values do not capture the effect of extreme temperatures, then it follows that the simulation model is also not adequately capturing the effects of extreme temperatures.

2.3.2 Average Temperatures

The most common approach to modeling climate change is to use an average temperature. Sometimes this is done seasonally and sometimes this is done monthly. Sometimes these are referred to as temperature normals; temperature normals are average temperatures taken over a specified period. For modelers using any of the standard climate change models, such as the Canadian General Circulation Model (CGCM), these seasonal or monthly climate normals are available as a baseline, calculated from 1961 to 1990. Researchers often choose this specific form of average temperature to be consistent with pre-existing datasets.

In an early study of climate change and agriculture, Arthur and Abizadeh (1988) use monthly average temperature data and compare two procedures used to estimate daily temperature values. First, a process based on the shape of a *sine* wave is used to estimate hourly temperature distributions for each day in the model. An alternative distribution assumption of uniformity of temperature throughout the day is also tested. The results were interpolated to the nearest of the 188 prairie weather stations, and weather station data from 1961 to 1985 were then interpolated to determine the average daily temperature for forty districts in western Canada. This derived average daily temperature is the weather variable included in their study. Note that an assumption of a linear relationship of yield to weather is implicit in this formulation of the weather component.

Bootsma and McKenney have been involved in a series of climate change impact studies for Atlantic Canada. Bootsma, Gameda and McKenney (2005), for example, report on the results of a regression of yields as a function of climate. Impacts are forecasted through climate change scenarios generated by versions of the CGCM. They use monthly temperatures from various weather stations, interpolated to daily averages values using an algorithm first presented in 1943 by Brooks (cited by various authors mentioned throughout this paper, including Arthur and Abizadeh 1988, discussed above). These weather data are then averaged out over a year. Yields are assumed to have a linear relationship with temperature.

Wang *et al*. (2009) use monthly average temperature and precipitation from 1951 to 2001 from 751 climate stations to conduct a Ricardian analysis of the effect of climate change on land values in China. They avoid interpolation of the climate data across the study region, which avoids data integrity issues introduced by interpolation but reduces the size of the dataset for analysis.

The average temperature approach is common, and was likely used in the past because it both easily available and requires as little as a single variable to incorporate into analyses. However, it is less than optimal for climate change applications because it cannot capture the effects of increasingly higher temperatures on output. A warm summer and a cool summer can have the same average temperature depending on variance. The GDD, as described in the next section, is an improvement over average temperatures, at least theoretically.

2.3.3 GDD

One alternative to the use of average temperature is the use of GDD. Taken from agronomic literature, a growing degree day is an estimate of the time a crop is exposed to heat within an exogenously determined range. The range often starts at 0 ºC and can include up to the highest observed temperature, although a critical maximum temperature is often imposed. The exogenous range varies by crop and variety (McMaster and Wilhelm 1997). The approach has the advantage of being relatively simple to calculate and the flexibility of being able to incorporate a variety of different assumptions about crop behaviour.

Larsen *et al*. (2001) use a Just-Pope production function (discussed above), which includes past variance of yield as a predictor of future yield, where variance is a function of temperature. They calculate GDD by using the cumulative daily temperature over 60 °F between May 1 and October 31. Regardless of how high the daily temperature actually rises, yields are assumed to increase. Thus, Larsen *et al*. (2001) implicitly assume a linear relationship between yield and temperature above 60 °F.

Deschênes and Greenstone (2007) use county level daily temperatures to calculate GDD to estimate the effect of an increase in temperature in their study of the effects of climate change on Canadian agricultural output. Growing season degree days are calculated using the critical temperature range of 46.6 – 89.6 °F. Here, instead of assuming increasing yields with increasing heat, the authors assume that exposure to heat above an assumed critical maximum has no effect on yield, and that the critical maximum is the same for all crops modeled. Similar implicit assumptions are also made for the critical minimum temperature.

The GDD approach, as noted above, is at least theoretically an improvement over average temperatures in capturing marginal effects of higher temperatures. A hotter summer has a higher GDD value as would a summer with a longer growing season. However, the marginal effects of exposure to various temperatures are assumed to be identical, and exposure to temperatures outside the range captured in the calculation (defined by the researcher) is assumed to have a marginal effect of zero. The following section provides an overview of a method developed to further refine temperature variables for analysis that incorporates such variable marginal effects.

2.3.4 Schlenker and Roberts

A fourth approach to aggregating temperature data has been explored by Schlenker and Roberts (2006, 2008) (SR hereafter). SR use a detailed daily dataset containing minimum and maximum daily temperature. They use an algorithm to estimate hourly temperature for each day, and calculate how many hours crops were exposed to each increment in temperature level as shown in Equation 2.2. Note that other inputs such as fertilizers, land management decisions, etc., are not captured in the model, and thus are assumed to be constant. This is consistent with the scenario described above in Brassard and Singh (2008). The unvarying characteristics are captured by the dummy variable for location and technological change with a time trend variable. SR show that in the United States, corn, soybean and rice exhibit a non-linear relationship with temperature; Yields are shown to increase until a critical maximum temperature is reached, found to be between 29 and 32 ºC. Yields are shown to fall with exposure to temperatures above these levels.

$$y_{itpj} = f(\boldsymbol{DEG_{xtj}}, \boldsymbol{D_{jt}}) \qquad [2.2]$$

Where:

y_{itpj} is yield for crop i in year t in pixel p in district j.

$\mathbf{DEG}_{xtpj}$ is the number of hours at degree range x in pixel p[1] in year t in district j.

$\boldsymbol{D}_{jt}$ is a vector of district dummies for districts j and rainfall data for district j in year t.

Often, the derivation of the temperature data for a region is a complex process involving interpolation, algorithms and calculations. Every additional manipulation can introduce error so as the complexity of derivation process increases, the confidence in the data integrity falls. There is a fundamental trade-off in manipulating spatial data between maintaining data integrity and maintaining degrees of freedom (Wang *et al*. 2007).

SR manipulate the observed temperature data from weather stations to obtain values that have been interpolated across time and space. They use weather stations with complete datasets to estimate missing temperature values. These weather-station-level datasets are then interpolated across the landscape to form a 2.5 square mile grid of pixels, each with individual weather values. From this exercise, they achieve a large data set from which to conduct their analysis of yield response to extreme weather. The trade-off is that the interpolated values are less precise than the observed values, and the data exhibits greater co-linearities as weather in spatially proximal cells will be highly correlated. The alternative is to use fewer but more precise observations. If degrees of freedom are not a concern for the estimation of accurate coefficients, the second approach may be preferred.

SR estimate their model with a randomly selected 85 percent of the sample, using the remaining 15 percent out-of-sample observations for model validation. SR’s approach provides a departure from the standard empirical perspective on aggregate yield

[1] Spatial data is represented either as polygons or as rasters. Raster maps, used here, are made up of rasters or pixels, each of which represents a specific tract of land.

responses to weather events. The SR approach incorporates marginal response to exposure to high temperatures, which is something that the average temperature or GDD approaches do not do.

Because climate change is anticipated to increase the mean temperature in western Canada (Natural Resources Canada 2004, viii), neither the use of average temperature or a GDD calculation is particularly well suited to the study of climate change. Averaging temperatures removes the impact of the extremes by offsetting higher temperature values with lower ones, eliminating the marginal impact of both extremes. The value of GDD increases with heat, as warm days contribute more to GDD than cool days, but the number of warmer days is not tracked. For both average temperature and GDD, the marginal effect of an extra day or hour of exposure to a higher temperature is not captured.

Another potential problem is that exposure to heat above some critical temperature over the course of the growing season can damage crop growth, rather than increase it. To capture these non-linear effects, it would be necessary to know at what temperatures yields begin to decline and by how much. The GDD approach either eliminates the effects of temperature above a critical maximum, effectively assuming a neutral effect on yield, or assumes no critical maximum, implicitly assuming a linear increase in yield for all increases in temperature. If, in fact, these effects matter, then GDD models that do not capture them are mis-specified and could be subject to bias in the estimators. In addition, the marginal effect of additional exposure to higher temperatures is not captured.

2.4 Summary

A wide variety of methods have been used to examine land use and land use change in agriculture and many of these have been adapted for climate change. Most commonly used has been the Ricardian or hedonic model that uses land values as a proxy for the value of production on a particular plot of land, as predicted by physical characteristics of that land, including weather. However, it has been shown that small changes in assumptions or parameters can have major changes on the model outputs, making interpretation of the results complicated.

Alternatively, linear programming models and spatial LP models have been used for ecosystem service valuation studies but less often for climate change studies. However, this approach combines the ability to incorporate spatial heterogeneity with profit seeking behaviour in a way that allows spatial shifts in land use patterns for specific crops to be demonstrated. A full discussion of the model developed to examine land use changes in the Canadian Prairies is found in Chapter 5. It is based on the discussion of spatial LP models found above.

It has been shown that the treatment of weather in climate change analyses has been *ad hoc*. The use of average temperatures is common, likely because this approach is straightforward. The majority of the applications for which average temperature is used, the marginal impact of temperatures at the extremes of the range are not important. However, for the examination of climate change, these effects are critical. The use of GDD captures better the effect of the extreme temperatures on yield but does not allow for the estimation of potential non-linear effects of higher temperatures that may in fact reduce yield rather than increase it. The weather treatment developed by Schlenker and Roberts (2006, 2008) is an adaptation of the GDD approach that allows for both non-linearities and improved capture of extreme temperature effects. As such, it is potentially an improvement over previously used temperature treatments. Researchers who do include weather explicitly in climate change models have incorporated it in an *ad hoc* manner due to lack of empirical evidence to support specific approaches. Thus the next chapter presents a comparison of average temperature with GDD and the Schlenker and Roberts approach described above with empirical evidence of out-of-sample performance for yield estimates.

Chapter 3: Estimating Yield Response to Temperature for Major Crops in the Canadian Prairies

Estimating the correct relationship between weather and yields for [these] major crops is a critical first step before more elaborate models can be used to estimate how crop choices, food supply and prices might shift in response to climate change. These models will give biased results if the underlying relationship between weather and yields is modeled incorrectly

Schlenker and Roberts 2008, p. 1

3.0 Introduction

To improve yields per hectare, farmers can adopt new management practices, optimize input use, or upgrade equipment, but are nonetheless at the mercy of the weather. In a good year, the impact of the farmer's management choices on yield is optimized. However, regardless of crop management decisions, if the weather is sufficiently adverse, yields may be so low that the cost of harvesting exceeds the revenue to be made from the sale of the crop. To save money, the farmer may opt not to harvest, resulting in an effective yield of zero. Modeling the effect of weather is an important element in the study of agricultural output, and is essential to predicting the effect of climate change on agricultural productivity and associated land use changes.

As discussed in Chapter 2, in the literature of climate change and agriculture, the choice of the temperature variables used is not justified in any of the research reviewed with the exception of the work by Schlenker and Roberts (discussed further below). Climate variables may be found in production functions, which then may form part of a profit function. Production or profit models may feed into a larger simulation model that forecasts behaviours into the future. The hedonic model approach is also commonly used to estimate aggregate impacts of climate change on land use values as a proxy for changes in production.

The temperature treatments used most often are average temperatures or growing degree days (GDD). However, average temperatures do not capture the impact of extremely high or extremely low temperatures as these tend to cancel each other out. A standard GDD variable does not differentiate between exposure to high and low heat. Because exposure to different temperatures contributes equally to the value of the GDD, there is an implicit assumption that the marginal effects of all temperatures in the defined range are equal. Outside of the defined range of temperatures the implicit marginal effect of temperature on yields is zero. Thus, the marginal impact of temperatures in the high range is not captured by this approach either and it is assumed that exposure to temperatures of 30 °C and above will occur more frequently with climate change. A third approach, based on the work of Schlenker and Roberts (2006 and 2008) (hereafter denoted SR), uses a modified GDD. The GDD approach is to calculate a *single* variable of exposure to *aggregate heat* during a defined period. The SR approach is to calculate a *series* of variables of exposure to *specific increments of heat* during a defined period. The goal of this chapter is to identify an appropriate formulation for weather data in basic production functions by comparing the performance of the SR approach to average temperature and GDD in estimating out-of-sample yield forecasts. The results of this analysis will subsequently be used to examine the effect of climate change on agricultural land use decisions in western Canada.

3.1 Objectives

The purpose of this chapter is compare two common approaches and one novel approach to aggregating weather data, and to establish empirically which one produces better out-of-sample estimations: average temperature, GDD, and the SR approach. Further, responses to temperature using the most appropriate temperature variable are estimated.

The objectives of this chapter are:

i. To estimate the effect of extreme daily temperatures during the growing season on yields for the following major Canadian cereal and oilseed crops: winter wheat, spring wheat, canola, durum, barley, oats, flax, and spring and fall rye, in Alberta, Saskatchewan and Manitoba, and
ii. To test the accuracy of out-of-sample forecasting for three aggregate temperature variables: monthly average, GDD and the SR method.

The hypotheses that will be tested are:

i. The use of more precise temperature observations with fewer degrees of freedom will prove sufficient for the purposes of analysis of yield response to extreme temperature; a modified approach to the SR method with fewer observations but lower colinearity in the data will provide comparable results to the SR method.

ii. The temperature variables as formulated by SR will provide better out-of-sample forecasting estimates than the GDD or monthly average temperature approaches.

iii. Using temperature variables as formulated by SR, the selected grains and oilseeds will exhibit a positive response to temperature variables in the lower ranges and a negative response to temperature variables in the higher ranges such that a critical maximum temperature can be defined beyond which yields decrease, as SR found for corn, soybeans and rice in the United States.

iv. Using the SR approach, the selected grains and oilseeds will exhibit a negative yield response to temperatures below a critical minimum.

3.2 Description of the Model and Data

As discussed in Chapter 2, there are various ways in which to measure the economic impact of climate change on agricultural production, ranging from econometric estimations of production or profit functions and spatial optimization models, as well as the hedonic model approach. What all these approaches have in common is the need to incorporate temperature variables. It is known that yield, and therefore profit, are a function of farmer choices, moisture and heat. Any of the approaches reviewed in Chapter 2 require weather as an explanatory variable if the impact of climate change is to be captured. Ideally, the approach should capture the marginal impact of temperatures at the high end of the range because these are increasingly likely to occur due to changes in climate. Temperatures in the mid-30s (ºCelsius) and above are hypothesized to have a different marginal impact than temperatures in the mid-20s (º Celsius).

Prior to the interest in examining climate change, modeling such marginal impacts was not a priority. In fact, rather than incorporating weather in production functions, it was assumed that the functional form of the estimate captured all human-controlled impacts and that everything else, (i.e., weather) was captured by the error term (Goetz 1993). With increasing interest in climate change related applications, it has become more important to identify temperature formulations that best capture marginal yield effects over various temperature ranges. The purpose of this chapter is to provide empirical evidence of the effectiveness of three options for modeling temperature, based on out-of-sample forecasting. Weather data will be incorporated into a basic production function in which all crop management decisions are assumed to be captured by the constant in the econometric estimate. This is consistent with the assumptions described in Chapter 2, in which farmers' adaptive choices are assumed away. Thus, the production function estimated here, in its simplest possible form, is yield as a function of weather.

This section describes the methods used to analyze the effect of exposure to summer temperatures on crop yields. The general model takes the form shown in Equation 3.1, where the natural log of yields, *y*, for crop *i* in year *t*, is a function of temperature ($\boldsymbol{TEMP}$) in ºC, total seasonal rainfall in mm (*RAIN*), a vector of district dummies, ***D***, and a time trend, *T*.

$\boldsymbol{TEMP}$ may contain a single variable or a vector of temperature variables, described further below. While there is no theoretical reason to use the natural log of yields, the method introduced by SR tested the approach with natural log of yields for the United States. In this chapter, their method is adapted for the Canadian context and therefore their model format is followed. Bolding an element in an equation signals those elements that are vectors, while non-bolded elements are scalars.

$$y_{ijt} = \alpha_i + \boldsymbol{\beta_{ikt}TEMP_{kt}} + \vartheta_{itk}RAIN_{tk} + \boldsymbol{\gamma_{ij}D_j} + \delta T_i + \varepsilon_i{}^2 \qquad [3.1]$$

The growing season is assumed to be April 15 to August 31. This is assumed to encompass the full growing season in the region, which can start as early as late April or as late as early June. Regardless of how late the growing season begins, it must end before winter begins in the Prairie regions. Harvesting begins in September and is usually complete by the end of October. In regions where crops are not planted until later in the season, the $\boldsymbol{TEMP}$ variable(s) is (are) correlated with shorter growing seasons.

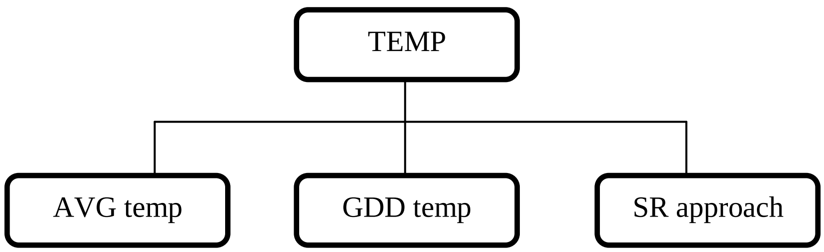
Figure 3.1 summarizes the three forms of the variable ($\boldsymbol{TEMP}$) that are calculated, and for which out-of-sample forecasting is compared. The first variant of $\boldsymbol{TEMP}$ uses an average monthly temperature calculation for each month in the growing season. This variable is correlated with the length of the growing season as, in a cooler spring, the average temperature for April and May will be substantially lower and thus proxy the effect of a shorter growing season. The second variant uses a cumulative GDD calculation. The GDD is a summation of the total number of hours in a specified range of temperature during the growing season. In a year when the spring weather is cooler, the total GDD value is lower because there are fewer hours spent in the specified temperature range. Thus, GDD is also correlated with the length of the growing season and may proxy the effect. The third variant follows SR, and is a modified GDD. The aggregate GDD value is broken down into smaller temperature "buckets," capturing only the number of hours a

---

[2] Weather station *k* is located in district *j* and there may be multiple weather stations in each districty for a given year.

crop is exposed to a series of specific, defined temperature ranges for the duration of the growing season. Instead of one aggregate variable to be used as an explanatory variable in a production function, many variables are generated, depending on how the temperature ranges are defined. The number of hours of exposure to temperatures less than freezing can be captured, for example, which endogenizes the length of the growing season more thoroughly than either of the other two approaches. As discussed in Chapter 2, average temperature and GDD are the most commonly used approaches to incorporating temperature in production or profit functions, or land use analyses. Here, the SR approach is compared to these formulations.

Figure 3.1: Overview of the approaches used to model temperature



3.2.1 Calculating the temperature variables

Three different versions of a temperature variable are calculated and used in alternative yield model formulations; average daily temperature, growing degree days (GDD), and the SR approach. Average temperature is calculated as shown in Equation 3.2. T_{nmk}^{max} and T_{nmk}^{min} are the maximum and minimum temperatures for the n^{th} day of the m^{th} month for the k^{th} weather station, where d is the number of days in the month. The monthly value is the average of the average daily maximum and minimum temperatures. For the average temperature approach, the vector ***TEMP*** contains five variables, one for each month of the growing season.

$$\boldsymbol{TEMP_{mkt}} = \frac{\sum_{n=1:d} T_{nmk}^{max} \big/ d + \sum_{n=1:d} T_{nmk}^{min} \big/ d}{2} \qquad [3.2]$$

Equation 3.3 shows the calculations for the GDD treatment of the temperature variable, where T_{nmk}^{max} and T_{nmk}^{min} are as above, and B is a baseline temperature below which it is assumed no growth occurs, and the hours in the defined range are summed over the growing season. The growing season is $n = 1 \ldots d$ days long. Refinements to the basic model are commonly applied to improve forecasting ability. If the daily average temperature ((T_{nmk}^{max}+T_{nmk}^{min})/2) is less than the base temperature, then the GDD for that day is equal to zero. Alternatively, if either T_{nmk}^{max} or T_{nmk}^{min} is less than the base, they are reset equal to the base in order to prevent negative values for GDD for a particular day from skewing the results (McMaster and Wilhelm 1997). Here, neither adjustment is made, as it is also possible to treat the first part of the equation as a simple daily average (McMaster and Wilhelm 1997). Theoretically, this does allow for negative GDD. Here, GDD calculations were made for B = {0, 5, 10} °C, as these are commonly applied base values found in the literature. *TEMP* contains only one variable for each year for this version of the model.

$$TEMP_{kt} = \sum_{n=1-d}\left(\frac{T_{nmk}^{max}+T_{nmk}^{min}}{2} - B\right) \qquad [3.3]$$

The SR approach differs from the first two approaches in terms of how temperature is modeled. In particular, hours of exposure to different levels of temperature through the growing season are used. This approach requires that the hourly temperature be estimated for each day of the growing season. The process used for this estimation is described below in Section 3.3.3. The hourly temperature estimates are converted to binary variables, DEG_{xkmnh}, which are the occurrence of temperature x at the h^{th} hour on the n^{th} day of the m^{th} month for the k^{th} weather station during the growing season. Here, "x" represents 1°C temperature intervals/increments, from 0 °C to 40 °C, with $x = 1, 2, \ldots, 40$ corresponding to intervals (0, 0.9), (1.0, 1.9) … (39.0, 39.9) with the values in parentheses being the interval lower and upper bounds, in °C. If, at a particular hour on a particular day in a particular month, the estimated hourly temperature is in interval x, the value of *DEG* for that interval is equal to 1; otherwise, it is set equal to 0. In addition, one variable captures all hours over 40 degrees, as multicollinearity was found in the data in this range. Observations of temperatures below 0 °C were dropped from the vector to prevent additive multicollinearity between variables; the total number of hours in the growing season is constant across observations, but the total number of hours above 0 °C is not.

To obtain the temperature values in the *TEMP* vector for the yield model, the individual *DEG* values are aggregated (i.e. summed) over hours, days and months. In particular, each element $TEMP_x$ is calculated as shown in Equation 3.4.

$$TEMP_x = \sum_m \sum_{n=1-d} \sum_{h=1-24} DEG_{xkmnh} \qquad [3.4]$$

The variable $TEMP_x$ represents the cumulative hours of exposure to the x^{th} temperature interval over the course of the growing season for station k in year t. The vector $\boldsymbol{TEMP_x}$ in this version of the model contains 41 variables for all x from 0 to ≥40 ºC for station k in year t.

3.2.2 Description of the analysis

Typically, no weather station has a complete set of observations for the full time period between 1965 and 2007. Spatial or inter-temporal interpolation is required to obtain a balanced panel data set such that there are no missing weather observations. SR use methods to interpolate the incomplete weather data across time and space to create a balanced panel data set for the United States, then interpolating weather data to create a 2.5 x 2.5 mile grid covering the continental United States. SR's basic unit of observation is this 2.5 square mile pixel from this grid. Using data from weather stations that were only in operation for a subset of the total period means that the data from these stations may in some way be biased, or not be representative of the climate in the region at the time in question. Interpolation of potentially biased data can exacerbate data integrity problems by compounding the biases (Jeffery *et al.* 2001). Interpolation of the weather data into a map grid of pixels is not undertaken here.

The yield data are available at the county/district level. The weather data used are at the weather station level. Each station, k, is located in a district, j, and is matched up with yield data available for that district using GIS. The interpolation process used by SR resulted in a much larger dataset from which to run the regression analysis but with greater multicolinearity in the data due to spatial homogeneity, and potentially introduced weather data integrity degradation. Here, the choice is made to use a smaller dataset (maximum potential observations around ten thousand rather than in the millions), but fewer potential problems with data integrity or multicolinearity due to spatial homogeneity by using the weather station as the unit of measure.

The following sections outline the datasets used in the analysis, created using the weather station, with its available weather data and the associated yield from the district in which it is located. Weather stations were plotted on a map using GIS. The yield, temperature and rainfall data were then intersected with the weather station data, possible because the GIS software allows all the data to be located in physical space. A total of 13,332 observations were obtained using this method, each fixed at a point in space representing the location of the weather station, the associated weather measured at that station and the yield in the district in which the station is located. Some districts contain no weather stations so by default the yield data for these districts were excluded from the analysis. Some districts, in particular in Alberta where the districts are larger, contain multiple weather stations. For these, multiple observations of weather are used to predict the yield observations for that district, as each weather station with its independent weather observations form a separate observation, even though those in the same district contain the same yield data.

Table 3.1: District average recorded lowest and highest yields and average (kg/ha) in the Canadian Prairies for selected crops, 1965-2007.

Crop	High Yield	Year	Low Yield	Year	Mean Yield
Winter wheat	5,346.0	2004	46.0	1988	2589.9
Spring wheat	4,588.7	2005	80.9	1988	1991.2
Durum wheat	4,917.4	1990	73.0	2002	1859.3
Oats	4,364.9	1992	44.7	1980	1911.2
Barley	5,000.0	2003	97.4	2002	2377.5
Spring rye	4,395.9	2003	96.0	2001	1209.3
Fall Rye	4,226.8	2007	125.8	1988	1589.3
Flax	2,502.2	2004	5.8	2002	976.7
Canola	2,913.5	2005	12.7	2002	1201.5

3.2.3 Yield data

Crop yield data are obtained from crop insurance corporations in the cases of Alberta and Manitoba, and from the Government of Saskatchewan. Data are obtained, at the county/municipal district/rural municipality level, for winter wheat, spring wheat, durum wheat, canola, fall rye, spring rye, oats, flax, and barley. These crops are selected because they constitute approximately 85 percent of field crop production in the Canadian Prairie provinces, according to the 2006 Census of Agriculture. The selected crops also comprise approximately 82 percent of total field crop land allocation (Statistics Canada 2010a). As such these crops capture major agricultural land allocation for cropping in the region. Alberta yield data are available from 1978 to 2007 because yield values prior to 1978 were self-reported and are not in use because they are less unreliable. For Saskatchewan and Manitoba, yield data are available from 1965 to 2007. Table 3.1 shows the highest and lowest individual yield observations, by crop, in the dataset. Yield data from irrigated lands are excluded as agriculture in the region is almost entirely dryland, with the exception of specific areas in southern Alberta. Rye yield data from Manitoba are excluded from the analysis because they are not separated into fall rye and spring rye. There are a low number of spring rye observations available in the analysis as, in fact, this particular crop is not that common in the region; the data show that fall rye is more popular.

3.2.4 Temperature data

Daily minimum and maximum temperature data were obtained from Environment Canada for 2,371 climate stations scattered across Alberta, Saskatchewan and Manitoba. The dataset covers 1960 to 2007, from April 14 to September 1 of each year. Data from 1965 to 2007 were used, except for stations in Alberta because there are no yield data prior to 1978, as noted above. Stations with data missing for an entire month between May through August were removed from the dataset. Many weather stations that operate in the summer only have data for the second half of April, and these were included, as data are only needed from April 14 onwards. Observations were removed for years where a) there were more than 10 days of missing data, or b) there were more than three consecutive days of data missing. The remaining missing temperature data were interpolated either spatially or intertemporally. If another weather station in the district for that date has available data, then the assumption was made that the values for those two stations were identical for that observation. If no data were available for the same date, the missing values were interpolated from the temperature data from the day prior to and following that date by taking a simple average of the two adjacent dates.

Table 3.2 shows the total number of climate stations in the Canadian Prairies with usable data and provides a summary of the total number of stations that operated during the period from 1965 to 2007. Each station was operational for a different range of the total years covered, some for one or two years, some for the whole range. The number of climate stations with usable data was approximately 36 percent of the total stations in Alberta, 39 percent in Manitoba, and 25 percent in Saskatchewan. The total weather dataset contains daily observations of weather for each of these stations as described further below.

Table 3.2 Climate Stations in Western Canada: 1965 to 2007

	Total Stations 1965-2007	Stations with Summer Data 1965-2007	Percent of Total
Manitoba	499	199	39 %
Saskatchewan	606	197	25 %
Alberta	1,242	451	36 %

In order to estimate the effect of extreme temperature on yield, it is important that sufficient examples of crop exposure to heat over 30 °C are found in the dataset. Figures 3.2a-3.2c show the distribution of temperature by month for April to August for Saskatchewan, Alberta and Manitoba. The frequency count was calculated using the daily maximum temperature value from 1965 to 2007 (1978 to 2007 for Alberta), and represents the total occurrences of each 1 °C increment of recorded daily maximum temperature for all weather stations across the landscape for the entire period.

The highest temperature in the weather dataset is 44 °C. As shown in the temperature distributions in Figures 3.2a-3.2c, maximum temperatures above 30 °C are common and above 40 °C less common, but daily maximums between 30 and 35 °C occurred up to 1000 times in July in Saskatchewan and Manitoba from 1965 to 2007, and up to 700 times in Alberta in the period from 1978 to 2007. Sufficient occurrences of temperatures in the higher ranges are assumed, therefore, to exist in the dataset for a yield response to such temperatures to be analysed econometrically.

Figure 3.2a: Frequency[3] of maximum daily temperatures for Saskatchewan 1965-2007

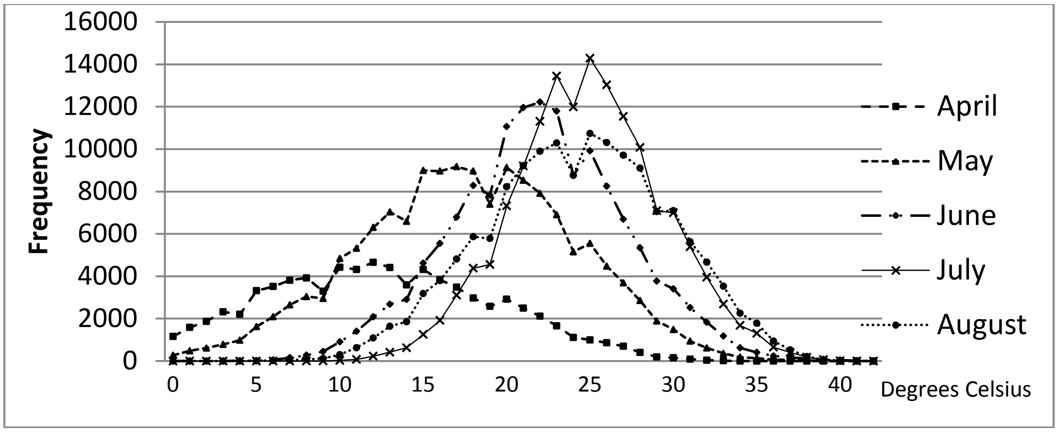


Figure 3.2b: Frequency of maximum daily temperatures for Alberta 1978-2007

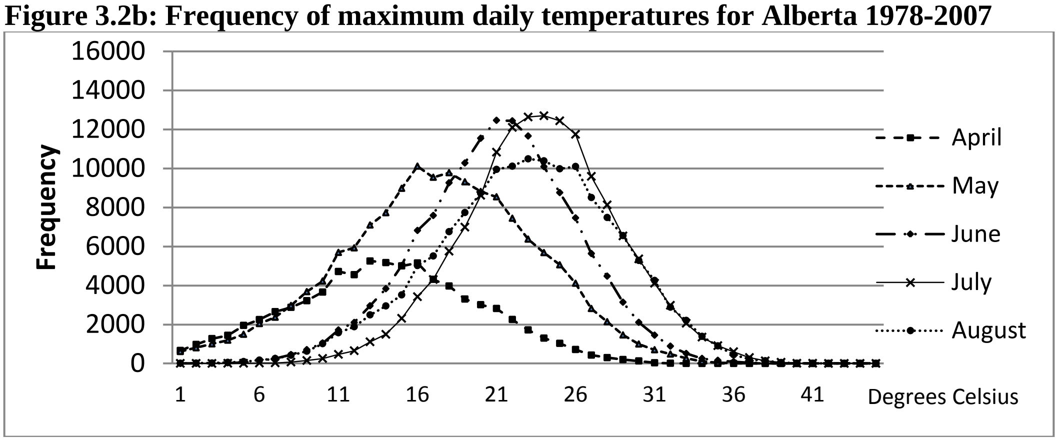
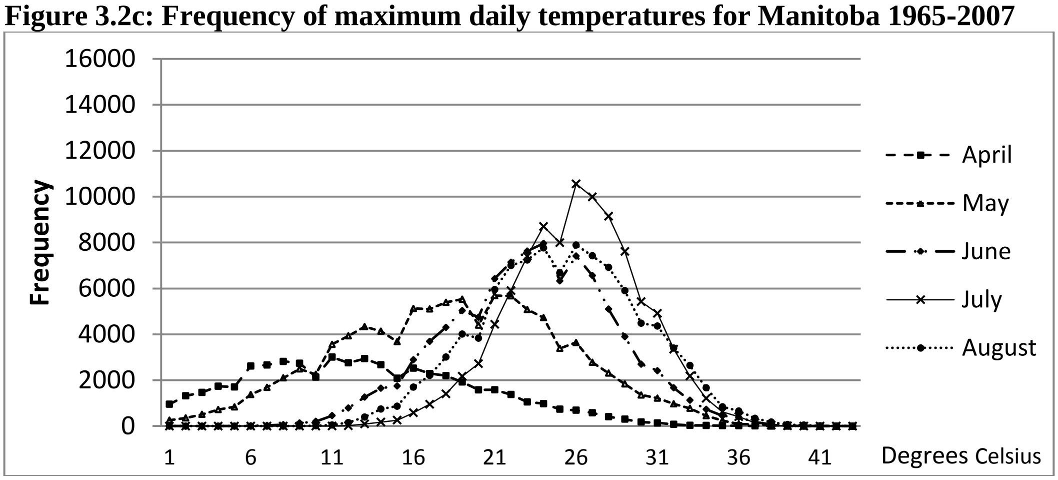


Figure 3.2c: Frequency of maximum daily temperatures for Manitoba 1965-2007



(Environment Canada 2008)

[3] Frequency refers to the number of days from 1965 to 2007 each temperature was recorded as the daily maximum in any of the weather stations used in the analysis.

Latitudes in the northern parts of the Canadian prairies experience more daylight hours in the summer than those in the southern parts, which has an impact on yields. Sunrise and sunset tables for one year were collected from the US Naval Observatory (2009) for each district from April 14 to August 31 to account for the effect of variations in daylight hours on crop yield; 2009 was the current year at the time of data collection, and was used as the base year; the same tables are used for each year. Although actual times fluctuate by several minutes per year, the year-over-year fluctuations were assumed to be economically insignificant. The dataset of daily minimum and maximum temperatures is combined with daily sunrise and sunset times to estimate hourly temperatures for each day of the growing season from 1965 to 2007 using a heat distribution function described by Cesaraccio et al. (2001), shown in Equations 3.5a-3.5c.

Each day is divided into three sections, with an associated equation to calculate hourly temperature. The first section (Equation 3.5a) covers sunrise (H_n) until four hours before sunset, which is assumed to be the time of maximum temperature (H_x). The second section (Equation 3.5b) covers the period from four hours before sunset (H_x) to sunset (H_o). Finally, the third section (Equation 3.5c) covers from sunset (H_o) until sunrise on the following day (H_p). H_x is the time at which maximum temperature (T_x) occurs, and H_n is the time at which minimum temperature (T_n) occurs, by assumption.

$$T(t) = T_n + \propto \sin\left[\left(\frac{t-H_n}{H_x-H_n}\right)\frac{\pi}{2}\right] \qquad \text{for} \qquad H_n < t < H_x \qquad [3.5a]$$

$$T(t) = T_o + R\sin\left[\left(\frac{\pi}{2} + \frac{t-H_x}{4}\right)\frac{\pi}{2}\right] \qquad \text{for} \qquad H_x < t < H_o \qquad [3.5b]$$

$$T(t) = T_o + b\sqrt{t-H_o} \qquad \text{for} \qquad H_o < t < H_p \qquad [3.5c]$$

Where:

$T(t)$ = value of $T = f(t)$, where $t = 1{:}24$
T_n = minimum daily temperature
T_x = maximum daily temperature
T_p = minimum temperature on the following day

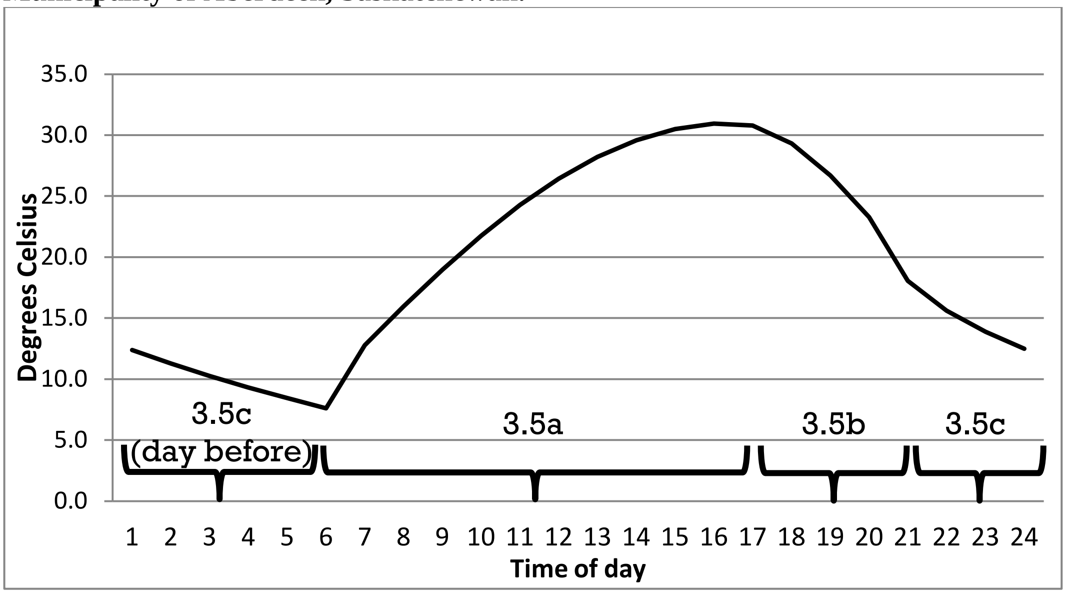
$T_o = T_x - c(T_x - T_p)$ where
c = 0.39 as calibrated by the authors based on California data.
$\alpha = T_x - T_n$
H_n = time of minimum temperature, assumed to be sunrise
H_o = time of sunset

H_x = time of maximum temperature, assumed to be four hours before sunset

$H_p = H_n + 24$ $R = T_x - T_o$ $b = \frac{T_p - T_o}{\sqrt{H_p - H_o}}$

Figure 3.3 shows the hourly temperatures for August 12, 1989 in the district of Aberdeen, SK. The parentheses indicate the equation that was applied for each portion of the day. Equation 3.5c is used for temperatures from the previous day, with the estimated temperature falling until it reaches the daily minimum at the time of sunrise, here shown to be approximately 6:00 am. Equation 3.5a is used to estimate increasing temperatures from sunrise until four hours before sunset; the time of sunset is shown here as approximately 9:00 pm, so the time of maximum temperature is assumed to occur at approximately 5 pm. Equation 3.5b is used to model falling temperatures from the time of maximum temperature until sunset, and then Equation 3.5c is used to estimate temperatures falling further, based on the minimum temperature recorded on the following day. For the date in question in Figure 3.3, the minimum temperature is shown to be around 7 °C, with the maximum temperature being approximately 31 °C. The temperature then is estimated to fall to approximately 15 °C by midnight.

Figure 3.3: Estimated hourly temperatures on August 12, 1989 For the Rural Municipality of Aberdeen, Saskatchewan.



3.5a Cesaraccio et al.'s (2001) equation for temperature from sunrise to time of maximum temperature
3.5b Cesaraccio et al.'s (2001) equation for temperature from time of maximum temperature to sunset
3.5c Cesaraccio et al.'s (2001) equation for temperature from time of sunset to sunrise on the following day

3.2.5 Rainfall data

Precipitation data are also taken from the Environment Canada database of weather station observations, in the form of daily rainfall measured in mm. These data are then summed over the entire growing season between the dates of April 15 – August 31, consistent with the growing season defined earlier. Data were available for both rainfall and total precipitation, which includes rainfall, snowfall and any other kind of precipitation that occurred. However, rainfall data were selected because it was assumed that the marginal effect of snowfall, or ice pellets or any of these other forms of precipitation, during the growing season would be separable from the marginal effect of rainfall on yield. While observations with missing data points are eliminated as described above for missing temperature data, remaining missing rainfall data are assumed to be zero for any given day, functionally assuming that there was no rainfall for that day. The calculation implies that rainfall data may be systematically lower than actual rainfall. This approach is assumed to produce minimal distortion of the data because the region is semi-arid, with total annual precipitation between 750 and 1500 mm per year. The probability that rainfall > 0 is assumed to be acceptably close to zero for any given day.

Table 3.3 shows summary statistics for rainfall. The lowest cumulative rainfall for any growing season is 19.1 mm, and the maximum on record is 709.4 mm. Average annual rainfall during the growing season ranges from 225.2 mm to 269.3 mm. Drought conditions occur when rainfall falls below average for extended periods of time, so the cumulative rainfall data reflect periods of drought where seasonal rainfall fell well below the average. The differences in observations between different crops occur because the crops are grown in different geographical ranges. For example, winter wheat has a different minimum rainfall observation than spring wheat because spring wheat is grown across the entire Prairie region but winter wheat is found mostly in the south; the weather data for each crop are pulled from a different subset of the weather stations.

Table 3.3: Summary statistics for cumulative rainfall (mm) in the Canadian prairies, by crop.

Crop	Minimum	Year	Maximum	Year	Mean
Winter Wheat	34.5	1988	638.2	2004	259.7
Spring Wheat	19.1	1988	709.4	2005	266.6
Durum	34.5	1978	596.6	1975	246.2
Oats	19.1	1980	709.4	1992	268.2
Barley	19.1	2002	709.4	2003	267.8
Fall Rye	19.1	1988	596.6	2007	239.9
Spring Rye	71.1	2001	488.7	1978	225.2
Flax	19.1	2002	626.2	2004	259.8
Canola	34.5	2002	709.4	2005	269.3

3.2.6 Comparing Temperature Variable Performance

Three versions of the model were run for each of the nine crops to compare out-of-sample forecasting. Average temperature, GDD and the DUM model, after SR, were run. The SR model is nicknamed “DUM” after the process of converting each hourly temperature observation to a dummy variable. Each model contains up to 344 district dummies, 41 temperature variables, one variable for rain and a time trend. There are up to 12,333 observations, based on availability of yield data and temperature data for each crop for each district for each year. One model is run for each of the nine crops for each temperature treatment, using a randomly selected 85 percent of the data. The resulting coefficients were used to generate estimates of yield for the 15 percent of the observations that were not used in the regression analysis. These out-of-sample forecasts were evaluated for predictive accuracy by comparing the root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and adjusted MAPE for the forecasted yield for each crop. The adjusted R^2 for each model is reported as well. The RMSE is the square root of the average of the squared values of the forecast errors; this approach weights larger errors more heavily. The MAE is the average of the absolute values of the forecast errors; this approach keeps the weighting of each error in the calculation in line with the absolute value of the error. The MAPE is the average of the absolute values of the errors in percentage terms; if the cost of the error is more closely related to the percentage error rather than the value of the error, this approach is used. However, because the observed value is used for the percentage calculation, it can result in under-forecasting. The adjusted MAPE uses the average of observed and forecasted values as the base for calculating the percentage error, which corrects for this problem (all as described in Kennedy 2003, 361).

The measurement tools described above are used collectively to provide an overview of the forecasting strength of each temperature treatment across a number of types of testing and crops. A model that provides superior forecasting than the alternatives by one or more of these measures provides robust evidence of superior forecasting overall. The size of the full dataset and the dataset used in each regression is reported in Table 3.4. The remaining observations are used in the out-of-sample forecasting accuracy predictions.

Table 3.4: Total sample and sub-sample size for parameter estimates used in out-of-sample forecasting

	Total Observations	Observations used in the Estimate	Percent of Total
Spring wheat	12,332	10,430	0.846
Winter Wheat	1,934	1,642	0.849
Durum Wheat	5,600	4,763	0.851
Oats	12,333	10,491	0.851
Barley	12,579	10,707	0.851
Spring Rye	327	269	0.823
Fall Rye	4,667	3,938	0.844
Flax	7,755	6,565	0.847
Canola	10,776	9,141	0.848

3.3 Results

Each model is tested for heteroskedasticity and autocorrelation using White and Breusch-Pagan-Godfrey tests and a Durbin Watson test for autocorrelation. The Durbin-Watson test shows no evidence of autocorrelation but the White and Breusch-Pagan-Godfrey tests show heteroskedasticity in each one of the models. This is corrected by using a heteroskedastic-consistent covariance matrix. In this section, the results of the out-of-sample predictions are provided. The best-fit model is tested for the assumption of non-separability of weather effects. If an hour of exposure to degree *x* in April or May has the same effect as an hour of exposure to degree *x* during July or August, then the assumption of non-separability of weather effects across months in the growing season is supported. As well, the temperature effects found by the preferred model are described.

3.3.1 Comparison of Temperature Treatments

Adjusted R^2 statistics are reported for each model. High adjusted R^2 indicates increased explanatory power over observed variations in the dataset; Low RMSE, MAE and MAPE values indicate high forecasting accuracy, here tested on out-of-sample data. Results are reported in the GDD case for $B = 10$ only, where B is the base temperature as defined in Section 3.3.1; changing the value of B only changes the size of the constant in the estimation results. The results of out-of-sample forecasting, as summarized in Table 3.5, indicate that the Schlenker and Roberts dummy approach ("*DUM PLUS*") outperforms all the other approaches for all crops, with the exception of canola and spring rye, where it is at least comparable to the next best alternative. Coefficients for the *AVG, AVG PLUS, GDD,* and *GDD PLUS* models are provided in Appendix A.

The SR approach implicitly assumes that an hour of exposure to a specific temperature in April produces the same effect as an hour of exposure to that same temperature in any other month of the growing season. SR tested this assumption and found that the non-separability assumption was supported with the American dataset. For the Canadian dataset, the assumption is tested by separating the data into monthly values, as shown in Equation 3.6. The vectors $\boldsymbol{RAIN_{mkt}}$ and $\boldsymbol{TEMP_{xmkt}}$ denote the weather exposure in month m for station k in year t. Note that there is an extra subscript to indicate monthly weather rather than seasonal as was found in the previous version of this equation.

$$y_{ijt} = \alpha_i + \boldsymbol{\beta_{imkt}}\boldsymbol{TEMP}_{mkt} + \boldsymbol{\vartheta_{imkt}}\boldsymbol{RAIN}_{mkt} + \boldsymbol{\gamma_{ij}}\boldsymbol{D_j} + \delta T_i + \epsilon_t \qquad [3.6]$$

A t-test is performed on the null hypothesis that the coefficients for each one degree increment in temperature are equal for different months, as shown in Equation 3.7. Here, the coefficients for hours of exposure are tested such that the null hypothesis is that the coefficient for year *t* for station *k* for $TEMP_x = 0$ for month = April is equal to the coefficient for year *t* for station *k* for $TEMP_x = 0$ for month = May, June and July or August. Thus, *m* and *r* represent April through August, where $m \neq r$. The process is repeated for all values of x from 0 to 40, and again for all monthly values of $\boldsymbol{\vartheta}_{\boldsymbol{mkt}}$ to test the separability assumption for rainfall.

$$H_0\colon\ \beta_{ixmkt} = \beta_{ixrkt} \qquad [3.7]$$

Where t-statistics are greater than ~2.0, the null hypothesis should be rejected. The corresponding P-value will be below 0.05, which indicates that the probability that the null hypothesis is true is less than 5 percent. This indicates that for these degree increments, exposure to temperature has statistically different effects in different months. The separability assumption is also tested for rain coefficients between months. Appendix B contains a summary of the t-test results with an X indicating the tests for which the P-Value is less than or equal to 0.05 indicating that the null hypothesis of non-separability is rejected. In general, non-separability doesn't hold, except for temperatures above 35 ºC; nor does it hold for rain variables across months, implying homogeneous effects of exposure to heat above this temperature.

In addition, equivalence of coefficients for variables for each month was collectively tested for all variables in each month using a series of F-tests, as shown in Equation 3.8 The values for *m* and *r* are the months April through August, and each element in the vector represents the range of temperature from *x = 0, 1, …40plus* ºC. The results of these tests indicated that for coefficients for all the temperature variables for each month, the null hypothesis of equality is rejected. The P-values on the F-tests are all 0.000, indicating a less than 1 percent probability that the coefficients are collectively equal between months.

$$H_0\colon \begin{bmatrix} \beta_{imkt0} \\ \vdots \\ \beta_{imkt40} \end{bmatrix} = \begin{bmatrix} \beta_{irkt0} \\ \vdots \\ \beta_{irkt40} \end{bmatrix} \text{ where } m \neq r \qquad [3.8]$$

The results of the F-tests indicate that non-separability does not hold for the Canadian dataset, and the results of the t-tests indicate that there is only limited support for the non-separability assumption. In general, August is statistically different from other months, as is often the case for April. Temperatures over 35 ºC are shown to be non-separable. Rainfall has a statistically different effect on yields depending on the month in which the precipitation occurred. An alternative version of the model is formed, using the same temperature values as before, but replacing the seasonal rainfall values with monthly rainfall values. These alternative models are denoted by "*AVG PLUS*", "*GDD PLUS*" and "*DUM PLUS*" in Table 3.6 (see also Figure 3.5). The variable $RAIN_{tk}$ becomes $\boldsymbol{RAIN_{mtk}}$.

Figure 3.4: Overview of modeling approaches incorporating temperature; two variants each model incorporating monthly rainfall values ("*PLUS*")

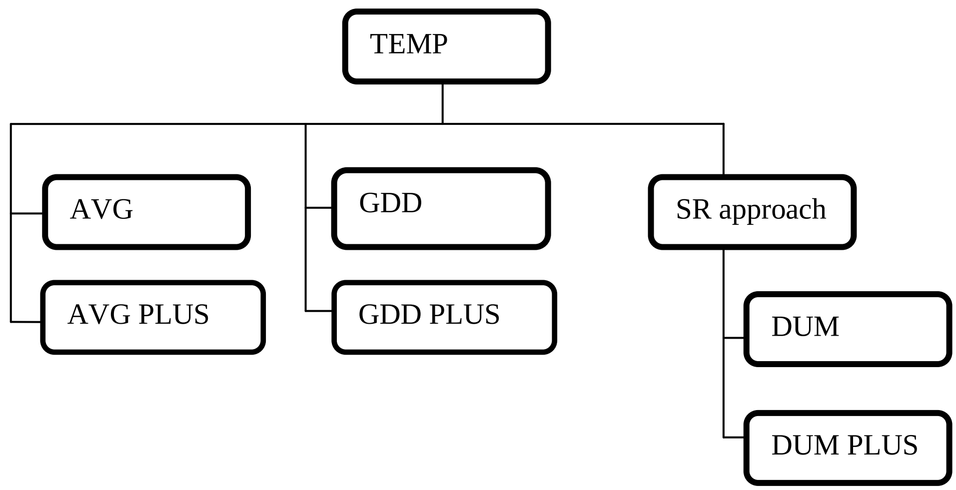


Table 3.5: Measures of out-of-sample forecasting for major crops in the Canadian prairies.[4]

WINTER WHEAT

	RMSE	MAE	MAPE	ADJ MAPE	ADJ R2
AVG	0.338	0.232	0.032	0.031	**0.533**
GDD	0.357	0.245	0.034	0.033	0.470
DUM	0.343	0.240	0.033	0.032	0.504
AVG PLUS	0.343	0.240	0.033	0.032	0.544
GDD PLUS	**0.326**	**0.224**	**0.031**	**0.030**	0.501
DUM PLUS	0.328	0.226	**0.031**	**0.030**	**0.522**

SPRING WHEAT

	RMSE	MAE	MAPE	ADJ MAPE	ADJ R2
AVG	0.294	0.215	0.029	0.029	0.369
GDD	0.302	0.220	0.030	0.030	0.322
DUM	0.286	0.208	**0.028**	**0.028**	0.393
AVG PLUS	0.288	0.212	0.029	0.029	0.388
GDD PLUS	0.294	0.217	0.030	0.029	0.353
DUM PLUS	**0.280**	**0.206**	**0.028**	**0.028**	**0.417**

DURUM

	RMSE	MAE	MAPE	ADJ MAPE	ADJ R2
AVG	0.357	0.259	0.036	0.035	0.402
GDD	0.372	0.266	0.037	0.036	0.361
DUM	0.360	0.261	0.036	0.036	0.423
AVG PLUS	0.360	0.261	0.036	0.036	0.320
GDD PLUS	0.354	0.257	0.036	0.035	0.286
DUM PLUS	**0.344**	**0.251**	**0.035**	**0.034**	**0.456**

CANOLA

	RMSE	MAE	MAPE	ADJ MAPE	ADJ R2
AVG	0.387	0.250	0.039	**0.037**	0.328
GDD	0.401	0.260	0.040	0.038	0.290
DUM	0.380	**0.248**	**0.038**	**0.037**	0.363
AVG PLUS	0.380	**0.248**	**0.038**	**0.037**	0.341
GDD PLUS	0.384	0.250	0.039	**0.037**	0.306
DUM PLUS	**0.378**	0.250	0.039	**0.037**	**0.372**

[4] Bolded entries indicate those that rank the highest for that measure.

FLAX

	RMSE	MAE	MAPE	ADJ MAPE	ADJ R2
AVG	0.417	0.298	0.047	0.046	0.267
GDD	0.426	0.303	0.048	0.046	0.239
DUM	0.420	0.295	0.047	**0.045**	0.279
AVG PLUS	**0.414**	0.297	0.047	**0.045**	0.279
GDD PLUS	0.419	0.300	0.047	0.046	0.264
DUM PLUS	**0.414**	**0.293**	**0.046**	**0.045**	**0.295**

FALL RYE

	RMSE	MAE	MAPE	ADJ MAPE	ADJ R2
AVG	0.348	0.255	0.036	0.036	0.349
GDD	0.362	0.261	0.037	0.036	0.305
DUM	0.351	0.255	0.036	0.036	0.356
AVG PLUS	0.351	0.255	0.036	0.036	0.380
GDD PLUS	**0.337**	**0.251**	**0.035**	**0.035**	0.356
DUM PLUS	0.338	**0.251**	**0.035**	**0.035**	**0.390**

SPRING RYE

	RMSE	MAE	MAPE	ADJ MAPE	ADJ R2
AVG	0.444	0.331	0.052	0.051	0.606
GDD	0.518	0.386	0.061	0.059	0.542
DUM	0.451	0.336	0.053	0.051	0.636
AVG PLUS	**0.426**	**0.309**	**0.048**	0.047	0.616
GDD PLUS	0.471	0.350	0.055	0.054	0.585
DUM PLUS	0.430	0.327	0.051	**0.050**	**0.648**

BARLEY

	RMSE	MAE	MAPE	ADJ MAPE	ADJ R2
AVG	0.323	0.228	0.031	0.666	0.334
GDD	0.339	0.241	0.033	0.667	0.277
DUM	0.319	0.225	**0.030**	0.667	0.361
AVG PLUS	0.331	0.237	0.032	**0.031**	0.340
GDD PLUS	0.341	0.245	0.033	0.032	0.294
DUM PLUS	**0.314**	**0.222**	**0.030**	0.667	**0.372**

OATS

	RMSE	MAE	MAPE	ADJ MAPE	ADJ R2
AVG	0.353	0.250	0.035	0.034	0.334
GDD	0.361	0.256	0.036	0.035	0.295
DUM	0.340	0.242	0.034	0.033	0.383
AVG PLUS	0.350	0.249	0.035	0.034	0.352
GDD PLUS	0.357	0.253	0.035	0.035	0.323
DUM PLUS	**0.337**	**0.238**	**0.033**	**0.033**	**0.403**

* RMSE = root mean squared error
* MAE = mean average error
* MAPE = mean absolute percentage error
* ADJ MAPE = mean absolute percentage error of the average of the actual and predicted values
* ADJ R2 = Adjusted R^2

✕ AVG = Average temperature model
✕ GDD = growing degree days model
✕ DUM = Schlenker and Roberts model using dummies to calculate total exposure to months
✕ AVG PLUS = Average temperature model with cumulative monthly rainfall
✕ GDD PLUS = growing degree days model with cumulative monthly rainfall
✕ DUM PLUS = Schlenker and Roberts using cumulative exposure to temperature for the season and with cumulative monthly rainfall

The results of the F and t-tests suggest that a model with monthly cumulative values could potentially provide additional information over a model with seasonal temperatures. However, with 41 temperature variables in each month rather than 41 per season, degrees of freedom are reduced by up to 168 (41 temperature variables X 4 extra months of temperature data, and 1 precipitation variable x 4 extra months) for each regression. In the seasonal regression for canola, there are 41 temperature coefficients, 1 rain coefficient, and 327 district dummies (369 total), while for winter wheat there are 41 temperature coefficients, 1 rain coefficient and 177 district dummies (219 total). To add an additional 168 coefficients to the canola data results in a total of 537 coefficients, while winter wheat would require 387 coefficients[5].

A least squares estimate of a parameter is unbiased asymptotically (Greene 2003, 68). While the number of observations in a sample required to produce unbiased estimates is unknown, more observations are preferred to fewer observations. A model may require, for example, ten observations to produce enough variation in the dataset for each

[5] This is a maximum as in some months, observations of all temperatures in the range are not observed.

unbiased coefficient. If this assumption were true, the canola model would require over 5,370 observations, and winter wheat would require over 3,870 to produce unbiased coefficients. While sufficient canola data exist to maintain this many degrees of freedom, there are, based on this criteria, insufficient data to ensure unbiased estimators for winter wheat.

Therefore, estimating the models with monthly cumulative temperature values for winter wheat, with just under 2,000 observations for 223 coefficients and spring rye, with 327 observations for 91 coefficients, is potentially problematic. Increasing the number of coefficients by 41 x 4 = 164 to include a temperature variable for each month increases the number of coefficients to be estimated to 495 for winter wheat and 255 for spring rye. As these two models do not have ten observations per parameter in Model 1, a monthly model is not undertaken. This is based on the assumption that at least ten observations per parameter is a reasonable minimum for unbiased parameter estimates.

Model 1

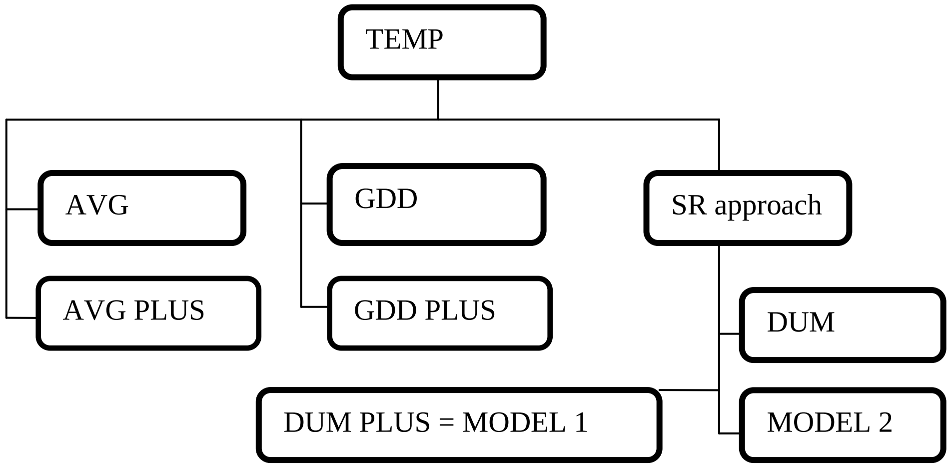
$$y_{ijt} = \partial_i + \boldsymbol{\beta_{ikt}TEMP}_{kt} + \boldsymbol{\vartheta\beta_{imkt}RAIN}_{mkt} + \boldsymbol{\gamma_{ij}D_j} + \delta T_i + \epsilon_i \qquad [3.9a]$$

Model 2

$$y_{ijt} = \partial_i + \boldsymbol{\beta_{imkt}TEMP}_{mkt} + \boldsymbol{\vartheta_{imkt}RAIN}_{mkt} + \boldsymbol{\gamma_{ij}D_j} + \delta T_i + \epsilon_i \qquad [3.9b]$$

Equation 3.9a and 3.9b are different in one respect only; the subscript *m* on the ***TEMP*** variable and its associated coefficient in Equation 3.9b is not there in Equation 3.9a. Equation 3.9a is Model 1 as shown in Figure 3.4, with temperature variables cumulative for the growing season for all temperature variables. Model 2, has temperature variables that are cumulative for each month in the growing season. The rest of the variables are identical.

Figure 3.5: Overview of the modeling approaches for temperature: Comparing seasonal and monthly temperature values



To determine if Model 2 is capturing statistically different information from Model 1, a J-test is run. This test is used to determine if Model 2 is statistically equivalent to Model 1. The J-test uses the predicted values from Model 1 as an explanatory variable for Model 2, and vice versa. If the predicted value variable from Model 1 is statistically significant in Model 2, and vice versa, then the models are shown to provide statistically significantly different information (Greene 2003). However, if the new variable in Model 2 is statistically insignificant, then the first model is does not provide any new information to the second model, or vice versa. If the predicted values from Model 2 are significant as a variable in Model 1 then Model 2 is said to provide information that is statistically different from Model 1.

$$y_{itj} = \alpha_i + \boldsymbol{\rho_{im} PRE_{i2}} + \boldsymbol{\beta_{ikt} TEMP_{kt}} + \boldsymbol{\vartheta_{ktm} RAIN_{ktm}} + \boldsymbol{\gamma_{ij} D_j} + \delta T_i + \varepsilon_i \qquad [3.10a]$$

$$y_{itj} = \alpha_i + \boldsymbol{\rho_{is} PRE_{i1}} + \boldsymbol{\beta_{iktm} TEMP_{ktm}} + \boldsymbol{\vartheta_{iktm} RAIN_{ktm}} + \boldsymbol{\gamma_{ij} D_j} + \delta T_i + \varepsilon_i \qquad [3.10b]$$

The predicted value generated for Model 2 is denoted PRE_2, and for Model 1, PRE_1. Each model is run with predicted values of the alternate model as an explanatory variable, as shown in Equations 3.10a and 3.10b. The coefficient of the predicted value variable from Model 1, PRE_1 is statistically insignificant as a predictor of yield in Model 2 for all crops except canola and oats. Results are summarized in Table 3.6.

Table 3.6: Results of the J test between Model 1 and Model 2 for variable *PRE*

Crop	P-Value for PRE_1 in Eq. 3.10b	P-Value for PRE_2 in Eq. 3.10a
Winter wheat	*N/A*	*N/A*
Spring Wheat	0.218	0.000
Durum	0.277	0.000
Canola	0.044	0.000
Flax	0.373	0.000
Fall Rye	0.224	0.000
Spring Rye	*N/A*	*N/A*
Barley	0.314	0.000
Oats	0.011	0.000

The predicted value variable from Model 2, PRE_2, is, however, statistically significant in Model 1 for each crop. In fact, including the predicted values from Model 2 in Model 1 produces results where other variables show no explanatory power at all, with P-values above 0.900 for all district fixed-effect dummy variables. The J-test results indicate, therefore, that Model 2 provides information that is not captured in Model 1, but the reverse is, in general, not true. Therefore, Model 2 is shown to provide additional information from Model 1. Further comparison of the behaviour of the two models is provided in Section 3.4.2 and 3.4.3.

3.3.2 Temperature Responses with Model 1

Model 1 is run for winter wheat, spring wheat, durum, barley, oats, spring rye, fall rye, canola, and flax in order to generate the results shown above. The size of the dataset used in the analysis is indicated in Table 3.4; the full dataset is used rather than the 85 percent subset. Rain data are aggregated by month rather than by season, as indicated by the model results reported in Section 3.3.1, indicating that the coefficients are not statistically equal between months.

Appendix C provides the results of the regression for Model 1 (Figure 3.6, Equation 3.9a). Yields for all major crops grown in the Canadian prairies exhibit negative marginal effect of exposure above temperatures that range from 28 ºC to 34 ºC, depending on the crop. These values, shown in Table 3.7, are an indication of heat tolerance for exposure to temperatures below a crop-specific critical maximum. Oats are the least tolerant to heat, with yield decreases occurring for every hour of exposure to heat above 28 ºC. Fall rye is the most heat tolerant, with yield decreases occurring only above 34 ºC. Spring wheat increases yields until the critical temperature of 29 ºC is reached, and for every hour of exposure above 29 ºC, yield decreases by 0.06 percent. Canola yields increase until 29 ºC is reached, but every hour of exposure to 29 ºC reduces yields by 0.08 percent, based on the coefficients for temperature variables over 29 ºC for these crops.

Table 3.7: Critical Maximum temperatures identified with the seasonal model following Schlenker and Roberts (2006, 2008)

Crop	Critical Minimum	Critical Maximum
Winter wheat	5 ºC	29 ºC
Spring Wheat	5 ºC	29 ºC
Durum wheat	5 ºC	29 ºC
Oats	5 ºC	28 ºC
Barley	4 ºC	28 ºC
Spring rye	5 ºC	30 ºC
Fall rye	5 ºC	34 ºC
Flax	5 ºC	30 ºC
Canola	3 ºC	29 ºC

It is notable that for fall rye in particular, yields increase to approximately 29 or 30 ºC, then show no significant negative yield effects until the temperature goes over 34 ºC. Thus, fall rye is heat tolerant in that the plant is able to sustain (but not increase) yields at higher temperatures even though these higher temperatures would damage other crops. However, should the heat rise high enough, even fall rye succumbs, and yields decrease at temperatures over 34 ºC.

One of the hypotheses of this chapter is that a critical lower temperature would be identified, such that marginal yields will be negative for exposure to temperatures below a critical minimum and increase for exposure to temperatures above this critical minimum. Often, 5 ºC is chosen as the base temperature in a GDD calculation, for example, because below 5 degrees no growth is assumed to have occurred. The existence of critical minimum temperatures is not as well-supported by Model 1. Negative coefficients are found from 3 to 5 ºC, depending on the crop, summarized in Table 3.7. However, the coefficients for variables for exposure to temperatures between 0 and 5 ºC fluctuate between positive and negative values. At least one of the positive values is statistically significant at least 5 percent for each crop. Thus, while the effect of temperature at or below 5 ºC is shown to be statistically insignificant (or statistically equal to 0) or negative, there is also evidence of growth below 5 ºC. Potentially, the assumption of non-separability of temperature effect between the months of the growing season may be obscuring differences of effects that are heterogeneous between months. Model 1, with the combination of seasonal temperature variables and monthly rainfall, explains approximately 30 – 60 percent of the variation in yield in a given year, as exhibited by the adjusted R^2 values for each regression.

3.3.3 Temperature Responses with Model 2

It was shown in Section 3.3.1 that Model 2 provides additional information that is not captured in Model 1. Model 2 is not run for winter wheat and spring rye because the number of coefficients estimated is assumed to be too great for the number of observations available for the estimate.

Results for Model 2 for the remaining crops are shown in Appendix D. For durum, flax and fall rye, critical maximum temperatures range from 23 to 26 ºC in April, 19 to 26 ºC in May, 34 to 35 ºC in June, 34 to 37 ºC in July, and 37 to 42 ºC in August. Results are summarized in Table 3.8, along with critical minimum temperatures in Table 3.9. Critical minimum temperatures range from 5 to 16 degrees in April or May, but no critical minimum temperatures are evident in June, July and August. While exposure to temperatures near zero in these months is lower than in April and May, it is hypothesized that the plant is well enough established to survive cooler temperatures by June. This likely explains the results, coupled with the fact that cooler temperatures are less common in these months.

Table 3.8: Critical maximum temperatures for Model 2, with monthly cumulative temperature and rain.

Crop	April critical maximum	May critical maximum	Jun critical maximum	Jul critical maximum	Aug critical maximum
Spring wheat	30 ºC	34 ºC	29 ºC	N/A	40 ºC
Durum wheat	24 ºC	19 ºC	35 ºC	34 ºC	38 ºC
Canola	32 ºC	32 ºC	34 ºC	N/A	38 ºC
Flax	26 ºC	26 ºC	35 ºC	35 ºC	42 ºC
Fall rye	23 ºC	20 ºC	34 ºC	37 ºC	37 ºC
Barley	31 ºC	34 ºC	31 ºC	N/A	38 ºC
Oats	30 ºC	36 ºC	N/A [6]	N/A	38 ºC

Table 3.9: Critical minimum temperatures for Model 2, with monthly cumulative temperature and rain.

Crop	April critical minimum	May critical minimum	Jun critical minimum	Jul critical minimum	Aug critical minimum
Spring wheat	7 ºC	5 ºC	10 ºC	N/A	N/A
Durum wheat	5 ºC	15 ºC	N/A	3 ºC	N/A
Canola	5 ºC	5 ºC	N/A	N/A	N/A
Flax	7 ºC	14 ºC	N/A	1 ºC	N/A
Fall rye	5 ºC	16 ºC	N/A	1 ºC	N/A
Barley	5 ºC	N/A	8 ºC	N/A	N/A
Oats	5 ºC	N/A	N/A	N/A	N/A

[6] N/A indicates that no critical minimum or maximum was found in the results.

Results shown in Appendix D indicate that the coefficients for summer temperatures are highly significant and negative for all temperatures for canola, oats, barley and spring wheat. Condition indices (see Kennedy 2003, 213) calculated for the temperature variables for these crops indicate strong multicolinearity.

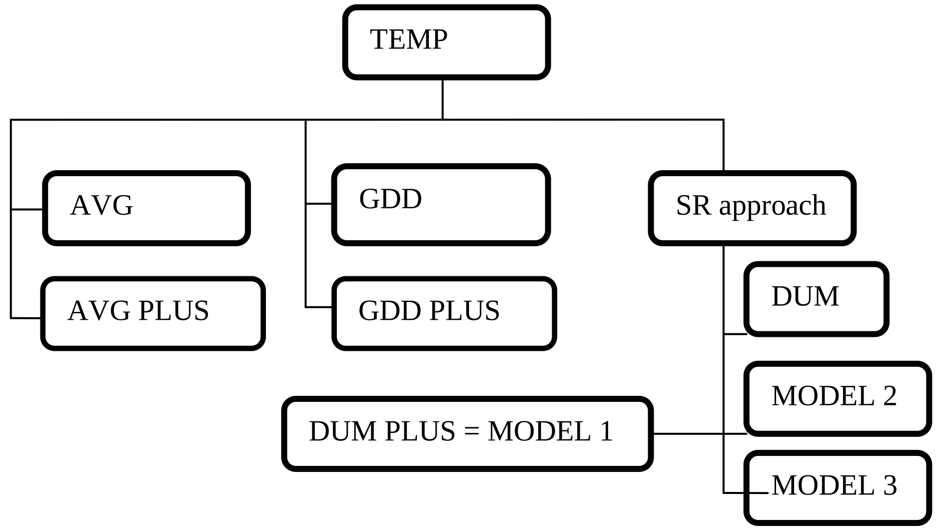
3.3.4 Temperature Responses with Model 3

Model 2 produces results for canola, barley, oats and spring wheat that are strongly influenced by multicolinearity in the data. Therefore, a model that aggregates some of the variables is used to address this problem. A third model is run for these four crops alone. Variations on variable combinations are tested; the result is a model that uses combined data for temperature in June, July and August above 30 ºC, and monthly values for all other variables (Equation 3.11, Figure 3.5). Equation 3.11 is identical to the Model 2 equation. The difference is that now *m*= *April*, *May*, *June*, *July* and *August* for temperatures below 30 ºC. For temperatures above 30 ºC, *m = April, May, June-July-August*. Under these conditions, critical maximum temperatures in April are found to be 24 ºC for all four crops, 25 ºC for spring wheat and canola, and 26 ºC for barley and oats in May. For June, July and August, the critical maximum temperature is shown to be 35 ºC for spring wheat and barley, and 36 ºC for canola and oats. For all crops here, statistical significance of variables above 34 ºC is often very low, above 10 percent, indicating that crop growth is close to zero. The results of this model are found Appendix E on page 190.

Model 3

$$y_{ijt} = \partial_i + \boldsymbol{\beta_{imkt}} \boldsymbol{TEMP}_{mkt} + \boldsymbol{\vartheta_{imkt}} \boldsymbol{RAIN}_{mkt} + \boldsymbol{\gamma_{ij}} \boldsymbol{D_j} + \delta T_i + \epsilon_i \qquad [3.11]$$

Figure 3.6 Overview of modeling approaches, aggregating certain monthly temperature variables to prevent multicolinearity in the data



Critical minimum temperatures are found to range from 7 to 12 ºC in April and May, and are not found at all in June, July and August, although some coefficients below 2 ºC are not significant at 1 percent. A summary of the critical temperatures is found in Tables 3.10 and 3.11.

The results reported in the above section, with regards to minima in particular, do not result in a clear signal. This is due to negative coefficients above a certain temperature and positive ones below (or vice versa in the low temperatures). Therefore, the reported results should be interpreted as signalling potential critical maxima or minima, rather than proof of the same.

Table 3.10: Critical maximum temperatures for spring wheat, canola, oats and barley from Model 3 using monthly cumulative temperature, combined above 30 degrees C for June, July and August.

Crop	April critical maximum	May critical maximum	Jun/Jul/Aug critical maximum
Spring Wheat	24 ºC	25 ºC	35 ºC
Canola	24 ºC	25 ºC	36 ºC
Oats	24 ºC	26 º	36 ºC
Barley	24 ºC	26 º	35 ºC

Table 3.11: Critical minimum temperatures for spring wheat, canola, oats and barley from Model 3 using monthly cumulative temperature, combined above 30 degrees C for June, July and August.

Crop	April critical minimum	May critical minimum	Jun critical minimum	Jul critical minimum	Aug critical minimum
Spring Wheat	7 ºC	14 ºC	N/A	N/A	N/A
Canola	12 ºC	13 ºC	N/A	N/A	N/A
Oats	12 ºC	5 º	N/A	N/A	N/A
Barley	12 ºC	5 º	N/A	N/A	N/A

3.4 Discussion and Conclusions

The objectives for this chapter were to estimate the effect of extreme daily temperatures during the growing season on yields for major Canadian cereal and oilseed crops, including winter wheat, spring wheat, canola, durum, barley, oats, flax, and spring and fall rye, in Alberta, Saskatchewan and Manitoba, and to test the accuracy of out-of-sample forecasting for three aggregate temperature variables: monthly average, GDD and the dummy (SR) approach. It was hypothesized that the SR approach would provide better out-of-sample forecasting than average temperature or GDD temperature variables. The SR approach was predicted to indicate that marginal impacts of exposure to different temperatures are not equal, in both the higher temperature ranges and the lower temperature ranges experienced in the Canadian Prairies.

Model 2 (Equation 3.9b), using monthly aggregate temperature and rainfall values outperforms Model 1, with seasonal aggregation of temperature values. However, in Model 2, multicolinearity in the data resulted in unexpected signs and significance for many of the variables. A solution to this problem was tested by combining variables for June, July and August above 30 ºC; the result is Model 3. The SR approach provides evidence that crops in the Canadian prairies are sensitive to temperatures in the 25-30 ºC range in April and May, but are able to withstand temperatures of up to 35 or 36 ºC in June, July and August. Evidence for critical minimum temperatures is less clear, but the signs of the coefficients, taken from the variables that exhibit the highest significance, indicate that critical minimum temperatures exist. These range from 5 to 14 ºC in April and May and are not a factor in June, July and August. It is thought that perhaps by June, the plant is well established enough to withstand temporary exposure to cool temperatures. However, colinearity in the data in the more detailed Models 2 and 3 mean that interpretation of the coefficients is difficult and that in fact, Model 1 may be more reliable.

It was assumed that it would be possible to analyze marginal yield responses with a small dataset built on the weather station as the unit of observation rather than the large dataset of pixels representing the area studied, as was done by SR. The hypothesis that using temperature observations at the station level rather than the interpolation of these observations across a landscape provides sufficient degrees of freedom for temperature/yield analysis is partially supported. For crops such as spring wheat with over 12,000 observations in the dataset, degrees of freedom appear not to be an issue.

However, the results for spring rye and winter wheat are considered potentially suspect, with less than 10 observations to estimate each coefficient. However, the results are consistent across all crops, regardless of degrees of freedom. In general, then, using weather stations as the unit of measurement for temperature data appears to be sufficient under most circumstances.

The analysis of crop yield as a response to temperature is useful because major studies of climate change have often relied on average temperatures, but these have shown to be unsuited to capturing the marginal effects of different temperatures. This analysis has clearly demonstrated that the SR approach, as shown in Models 1 and 2, is superior in capturing these effects. The results provide empirical evidence to select appropriate approaches to aggregate temperature in the study of climate change and Canadian agricultural land use in the Prairie Provinces.

The results of this analysis show that yield responses to various temperature ranges are positive for mid-range temperatures but, for each, there is a critical maximum temperature beyond which, marginal impacts on yield are negative for major crops in the Canadian Prairies. However, there is tension in the approach between the level of detail that can be modeled and colinearity in the data. The SR-inspired approach to aggregating temperature data is the approach that will be used to forecast crop yields for western Canada under climate change scenarios taken from the Canadian Institute for Climate Change. Yields will be predicted under standard climate change scenarios by changing the mean values of temperature and rainfall. Under these changed climatic conditions, predictions will be made about land use decisions in the Canadian Prairies. The results of the analysis have important implications for policy discussions related to biofuels and food production over the next decades. Chapter 4 provides an application of the DUM PLUS (SR, Model 1) approach to analysis of fall seeded crops and winter climate, while Chapter 5 provides an application of the DUM PLUS approach to land use, land use change and climate change for the provinces of Manitoba, Saskatchewan and Alberta to the year 2050.

Chapter 4: Estimating yield responses to winter temperatures in the Canadian prairies for fall-seeded crops

4.0 Introduction

In Chapter 3, it was demonstrated that the SR approach to incorporating weather variables produced better out-of-sample forecasts than using average temperatures or growing degree days (GDD) for major spring-seeded crops grown in the Canadian Prairies. The purpose of this chapter is to apply the results of Chapter 3 to a similar problem related to yields of fall-seeded crops. While summer temperatures are normally used as predictors of yield, researchers at the University of Saskatchewan Crop Development Centre suggested that winter temperatures and snowfall may have a significant impact on yields of fall-seeded crops (pers. comm.). In the Canadian Prairies, winter wheat and fall rye are seeded in September or October each year and require eight to twelve weeks of growth with exposure to gradually falling temperatures to "harden off" sufficiently to survive the winter.

Full acclimatization is typically achieved by mid-November, and survival of the seedling is a function of sufficiently warm soil temperature as this is the predictor of the temperature at the crown of the plant (Fowler 2002). While yields of fall-seeded crops are a function of summer temperatures, it is thought that the yield effects of winter climate can be isolated. This chapter tests the hypothesis that air temperatures, in particular in the coldest winter months of January and February, and snow, can proxy the effect of soil temperature on yields for fall-seeded crops. It is possible that not only will snow depth will have a statistically significant relationship with yields, but the variance of snow depth may also exhibit a similar relationship. In this chapter, yield responses for two fall-seeded crops are analyzed as a function of climatic conditions in the previous winter.

4.1 Objectives

The objective of this chapter is to estimate the effects of temperatures during the winter season (in particular January and February) on yields of winter wheat and fall rye in the Canadian Prairies. These months are chosen because it is hypothesized that the depth of the winter pack in these months is indicative of the level of insulation provided to the crop over the winter months, and thus deeper snow packs could provide a proxy measure for warmer soil temperatures due to improved insulation.

The hypotheses that will be tested are:

i. Greater snow depth in January and February are associated with higher yields due to reduced winterkill for fall-seeded crops.

ii. Variability of snow depth in March and April will have a statistically negative effect on yields of winter wheat and fall rye.

iii. It will be possible to discern a critical minimum temperature beyond which yields of winter wheat and fall rye exhibit a non-linear response. It is hypothesized that exposure to temperatures above this point will have a positive effect on yield and exposure to temperatures below this point will have a negative effect on yield.

4.2 Description of the Model

In Chapter 3, the effects of temperature and rainfall on yields for winter wheat and fall rye were examined. However, unlike spring-seeded plants, these two crops are planted in the fall of the previous year and thus begin re-sprouting on existing root systems much earlier compared to spring-seeded crops. While fall temperatures can affect the "hardening off" needed for the seedlings to survive the winter, much of the winter kill is potentially due to exposure to extreme cold in the two coldest months of the winter, which are January and February (Fowler 2002). Snow pack depth can provide insulation for the seedlings, and potentially mitigate the impact of extremely cold temperatures, which the Canadian prairies can dip below the -30 °C on a regular basis. While ideally, the model would include both winter climatic variables and summer variables, the size of the weather dataset, described below, for the winter climatic variables is much smaller than is available for summer climatic variables. This limits the number of coefficients that can be estimated. The approach outlined attempts to identify an efficient analysis that makes best use of the data available for the winter months while incorporating the SR approach to aggregating temperature.

Chapter 3 provided empirical evidence that the Schlenker and Roberts (2006, 2008) (hereafter SR) approach to aggregating temperature effects produces improved out-of-sample forecasts for yield than the average temperature or GDD approaches. However, the SR approach requires more data from which to calculate the weather variables and more observations from which to estimate the marginal effects of each increment in temperature. The effect of winter weather on the yields of winter wheat and fall rye are examined using monthly cumulative exposure to temperature. The general form of the winter model is shown in Equation 4.1. The natural log of yields, *y*, for crop *i* in year *t* in district *j*, are a function of exposure to temperature from 0 °C to -40 °C in 1 degree increments for weather station *k* in district *j* in year *t*, district dummies $\boldsymbol{D}$, a time trend, *T* and snow. While the $\boldsymbol{TEMP}$, $\boldsymbol{SNOW}$, $\boldsymbol{D}$ and *T* data are the same across crops, the marginal effect is different for each crop, which is why there is a subscript *i* on each of the coefficients but not on the variable itself. This is consistent with the model formulation in Chapter 3. The format of the temperature variables is cumulative from January to April, following Model 1 from Chapter 3, because the data indicated colinearity in monthly aggregations. Following the format of Chapter 3, bolded elements in the equation are vectors while non-bolded elements are scalars.

$$y_{itj} = \delta_i + \boldsymbol{\beta_{ikt} TEMP_{kt}} + \boldsymbol{\gamma_{ikt} SNOW_{kt}} + \boldsymbol{\gamma_{ij} D_j} + \alpha_i T_{it} + \varepsilon_t \qquad [4.1]$$

It is assumed that the majority of winterkill occurs during the months of January and February, although much of the damage may occur in March and April. By May, the danger from extreme cold to fall-seeded crops has usually receded. Data for September through December were not included in the model because the crop does not generally enter dormancy until late in this period. Thus, the data from these months was assumed to be a poor predictor of winterkill.

The yields in Equation 4.1, as in Chapter 3, are in natural log format. The vector $\boldsymbol{TEMP}$ contains cumulative temperature exposure to temperatures from 0 to minus 40 °C (and below) for the months of January to April in three degree increments. Data that can be included in the the $\boldsymbol{SNOW}$ vector include both the mean and variance of snow depth for January to April. It is hypothesized that snow depth in January and February are key to the winterkill rate for winter crops such as winter wheat and fall rye. As well, the variance of snowpack, particularly in April, is hypothesized to be an important predictor of yield in the subsequent summer. Variance of snow pack is potentially an indicator of the consistency of the insulating effect of snow pack depth. If the variance is low, the snow pack was relatively consistent, providing consistent insulation to the plant. If the variance is high, the snow pack fluctuations infer that the insulation benefits from the snow pack were inconsistent. However, if in fact warmer temperatures result in lower winterkill, this could also mean that there were frequent warm temperatures during the winter months, which might result in less damage to winter wheat and fall rye seedlings. The choice of the variables in the ***SNOW*** vector is discussed further below.

4.2.1 Yield data

Yield data are as in Chapter 3, taken from provincial crop insurance organizations in Alberta and Manitoba and from the Government of Saskatchewan. As with the analysis discussed in Chapter 3, yield data were available from 1965 to 2007 for Saskatchewan and Manitoba and from 1978 to 2007 for Alberta. Only data from 1978 and later were selected for all three provinces. Yields for fall rye and winter wheat are reported in kg/ha at the district or rural municipality level. Yields for these fall-seeded crops are only reported for those districts in which they are grown, and intersected with available weather data using GIS. Thus, appropriate coverage of weather stations is not an issue in the analysis as only those stations with available and relatively complete data were used.

When weather conditions are sufficiently adverse, winterkill for these crops is 100 percent, and the fields are re-sown in the spring. This means that the yield data do not reflect the conditions in which full winterkill occurs because there is no way in the dataset to identify years where fall-seeded crops fail in the dataset; the dataset will not reflect a relationship between very poor weather and extremely low yields (for example, when there is complete winterkill).

4.2.2 Temperature data

Minimum and maximum temperatures and snow depth data are obtained from the Environment Canada database of weather stations, as described in Chapter 3. Sufficient winter data for the years 1978 to 2007 are available for 72 stations in Manitoba, compared to 199 for summer data. In Alberta, the number of stations with sufficient data for the summer analysis is 451, but there are 126 with sufficient data in the winter, which is about 10 % of the total operational stations during the whole period. Saskatchewan has approximately 40 fewer stations with sufficient data in the winter as compared to the summer. Table 4.1 summarizes the availability of weather station data. The smaller number of stations in the winter weather dataset reflects the smaller geographic region in which the winter crops are grown as well as the smaller number of weathers stations that are operating over the winter for the period of 1978 to 2007. Thus, as with Chapter 3, the base unit of each observation is the weather station k located in district j with weather observations in year t, regressed on yield for crop i.

Table 4.1 Climate Stations in Western Canada: Totals from 1978 to 2007

	Total Stations 1978-2007	Stations with Winter Data 1978-2007
Manitoba	499	72 (14%)
Saskatchewan	606	154 (25%)
Alberta	1242	126 (10%)

Missing temperature data are treated as described in Chapter 3, but missing snow depth data are assumed to be the same as the day before and day after. For up to 10 days of missing data, values are interpolated from the values taken from the day before and day after the missing data. This is based on the assumption that if there were 70 cm of snow on Day 1 and on Day 8, there were likely 70 cm of snow for all the days between. Where more than 10 days of data are missing, or where no data are available for the first or last day from which to interpolate values, the data for that year and that station are not included in the final dataset. There were many observations of winter weather data where full months of data were missing in each year. An alternate approach to interpolating missing data could, therefore, increase the potential size of the dataset for analysis.

Minimum and maximum temperature data are used to calculate the number of hours of exposure to temperatures from -1 to -40 °C, using the same method as described in Chapter 3. To prevent additive colinearity in the data, temperatures from -0.9 °C and above are excluded. Condition indices were generated that diagnosed the presence of multicolinearity in the data between temperature variables from January to April. Combinations of temperature data are tested to reduce the multicolinearity, and the resulting variables contain three degree increments in temperature for the winter season, defined as January 1 to April 30. The ***TEMP*** variables are, therefore, organized in three degree increments, from -1 to -3 °C, which incorporates all temperatures from -1.0 degrees to -3.9 °C, and from -4 to -6.9 °C, down to -37.0 to -39.9 °C. All temperatures below -40 °C were treated as a single variable. A total of 16 temperature variables are therefore used in the analysis.

Figure 4.1a: Average number of hours in each 1 degree increment from 1978 to 2007 for winter wheat[7]

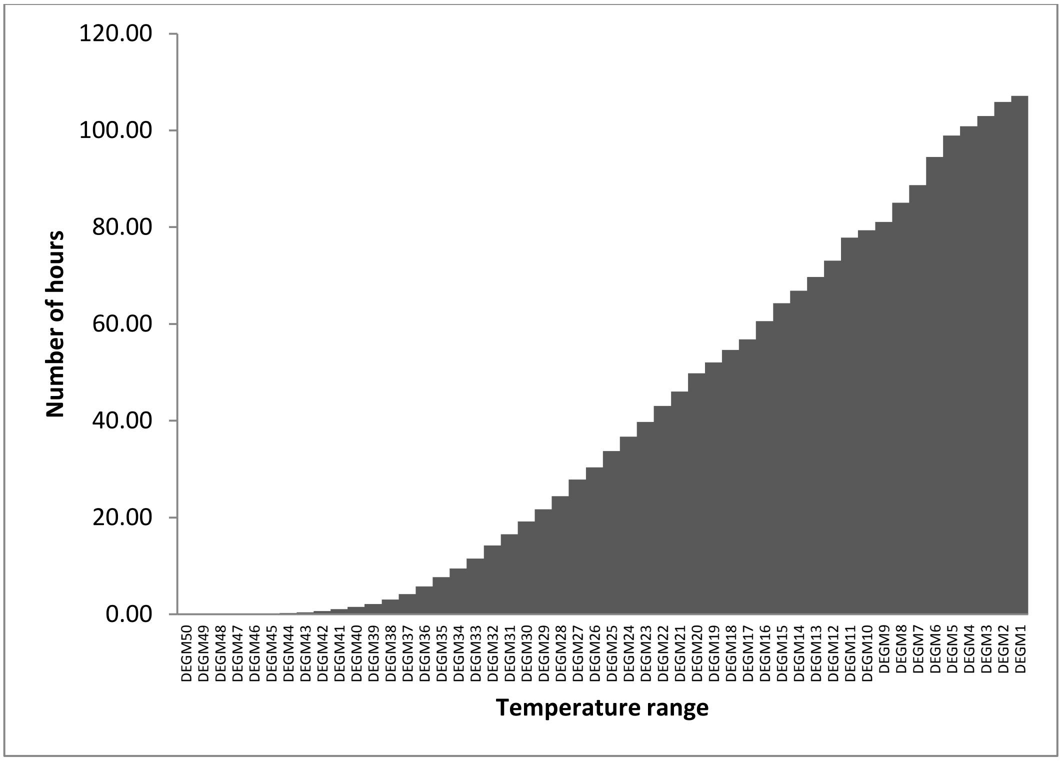
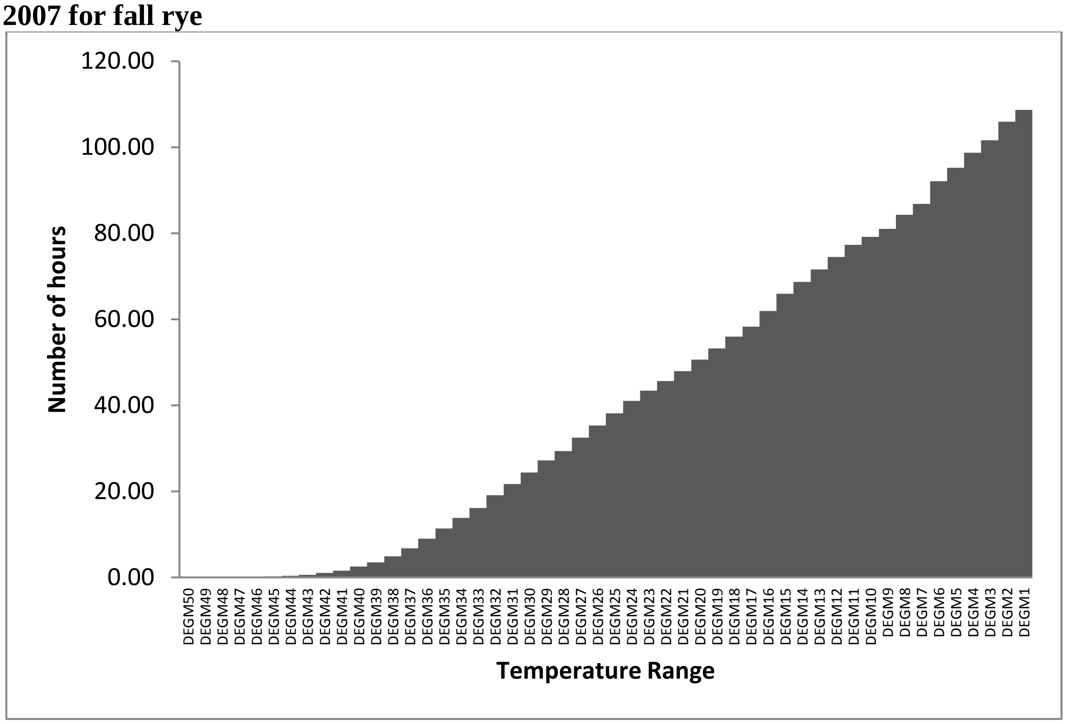


Figure 4.1b: Average number of hours in each 1 degree increment from 1978 to 2007 for fall rye



[7] DEG_{MX} = the number of hours between X ºC and X.9 ºC where X = -1 to -50.

Figure 4.1c: Minimum and maximum observations for winter wheat; number of hours at each 1 degree increment of temperature from -1 to -50 ºC from January to April 1978 to 2007

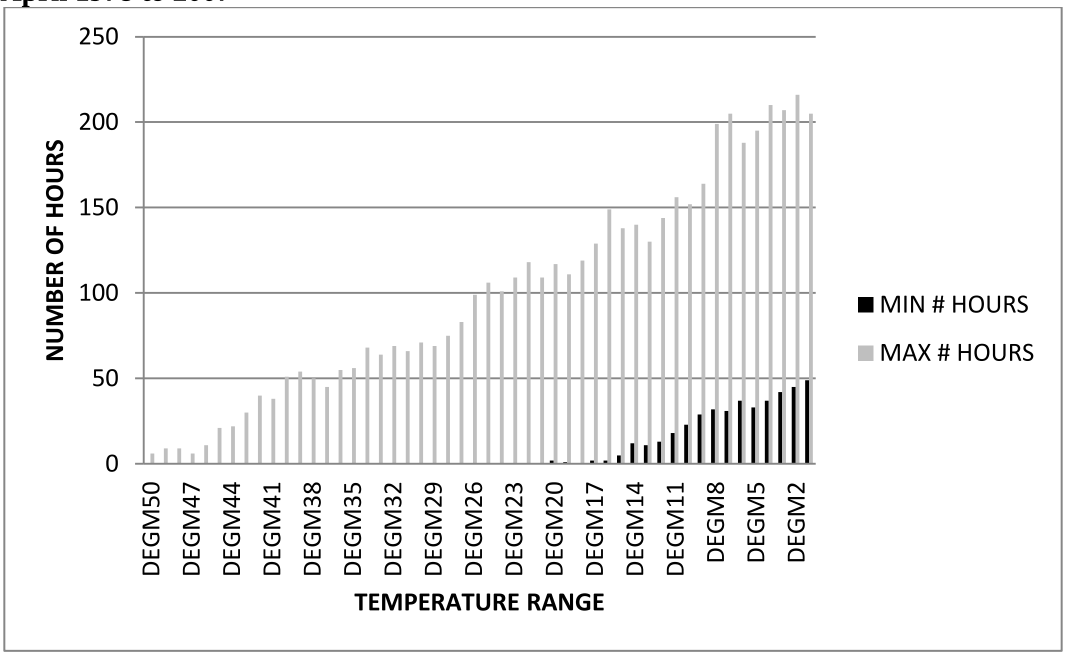
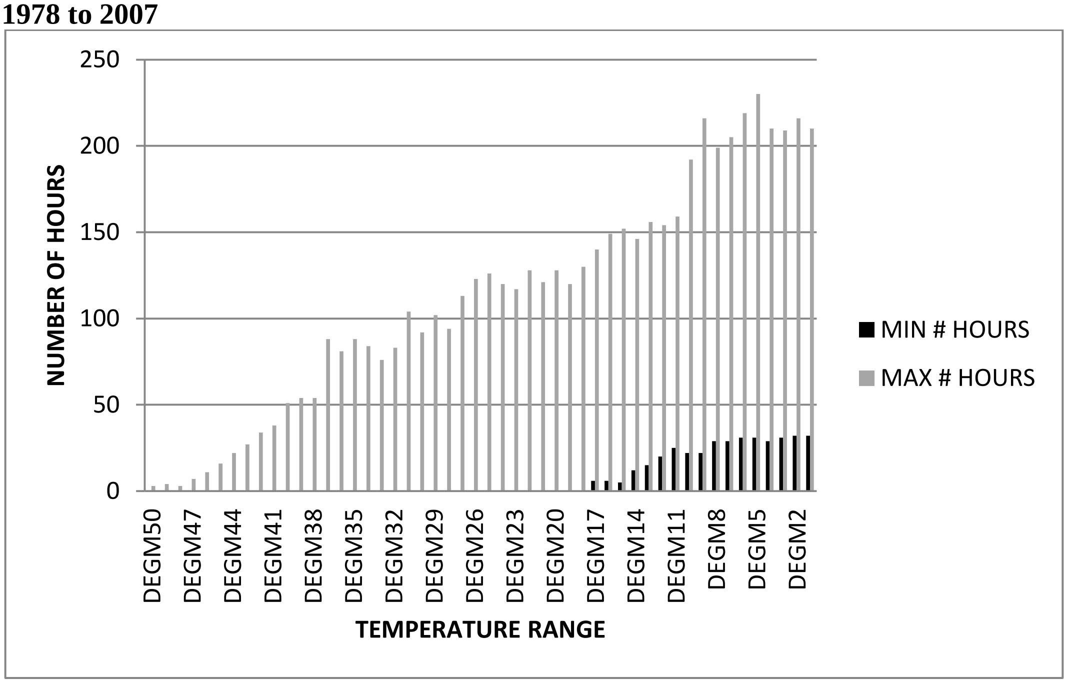


Figure 4.1d: Minimum and maximum observations for fall rye; number of hours at each 1 degree increment of temperature from -1 to -50 ºC from January to April 1978 to 2007



Figures 4.1a through 4.1b show the frequency of weather observations in the dataset for winter wheat and fall rye. The average number of hours observed in each single degree increment of temperature is consistent between the two crops, with about 125 – 150 hours on average of time between -1 and -0 °C. The average number of hours spent between -50 and -49 °C is close to zero.

Figures 4.1c and 4.1d show the minimum and maximum observed number of hours at each temperature for each day from January to March from 1978 to 2007. Figure 4.1c shows that the number of hours spent at -2 ºC ranged from a minimum of 50 hours to a maximum of 200 hours in the dataset for winter wheat. Figure 4.1d shows that for fall rye, the number of hours spent at -2 ºC ranged from around 30 hours up to over 200 hours. It is also shown that in each year the temperature reached -16 °C at least once, as the minimum number of hours is greater than 0. However, for temperatures below -16 ºC are experienced as the lowest temperature in the dataset, there are years in which the temperature does not dip this low. The minimum number of hours spent at these temperatures is 0. The maximum number of hours spent at -50 ºC is greater than 0, indicating that at least once in the time period, temperatures fell this low. As with the summer model in Chapter 3, sufficient observations of colder temperatures are therefore assumed to allow analysis of the marginal effects on crop yields.

4.2.3 Snow depth and variance data

The ***SNOW*** vector described in Equation 4.1 could contain either snow depth, snow variance, or both variables. One of the variables available in the Environment Canada database is daily snow depth in cm. From these data, the average and variance of snow depth are calculated for each weather station *k*. Table 4.2 provides summary statistics for winter snow depth, showing that the mean of average snow depth in January and February is 39 cm in regions where winter wheat is grown and 39.6 in regions where fall rye is grown. Daily snow depth data were used to calculate average monthly snow depth such that the average snow depth for station *k* for month *m* in year *t*, $\overline{SDEPTH}_{kmt}$, is the sum of daily snow depth divided by the number of days in the month, as shown in Equation 4.2. The average of this value found in the data used in the analysis from 1978 to 2007 is shown in Table 4.2 and averages from 2 -3 cm in April to approximately 20.5 cm in February.

$$\overline{SDEPTH}_{kmt} = \frac{\sum_{n=1:d} SDEPTH_{knt}}{d} \qquad [4.2]$$

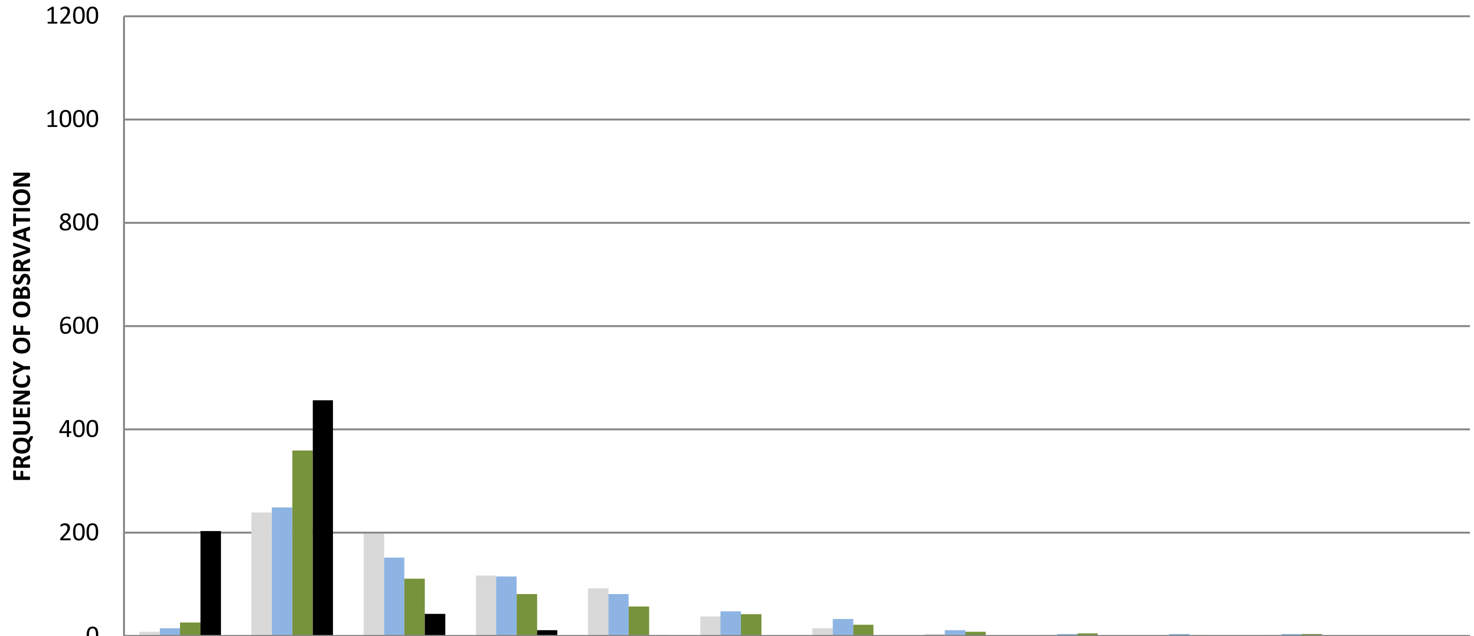
Figures 4.2a and 4.2b show the frequency of observed monthly average snow depth variables. In each month, for every weather station in the dataset, snow depth is most commonly between 0 and 10 cm. There are four observations of snow depth up to 1 m in depth in February and March in the dataset for winter wheat, but not for fall rye. The mean values shown in Table 4.2 were used to calculate variance of snow depth in each month. The frequency of variance observations are shown in Figures 4.2c and 4.2d.

The summaries indicate that February has the most snow on average throughout the region, with lowest variance, and therefore the most stable snow pack depth. This is consistent with generally consistently cold temperatures throughout the region for the month of February. April has generally less snow and less variance in snow pack depth because in many years by mid-April the snow pack has disappeared. March, on the other hand, may be cold and snowy, and may be warm with melting snow packs. It can also fluctuate back and forth between spring and winter conditions. Thus, the relatively high variance of snow depth in March with the relatively low average snow pack depth calculated from the dataset is consistent with observed patterns.

Table 4.2: Average observation of average snow depth by month (in cm) in the datasets from 1978 to 2007

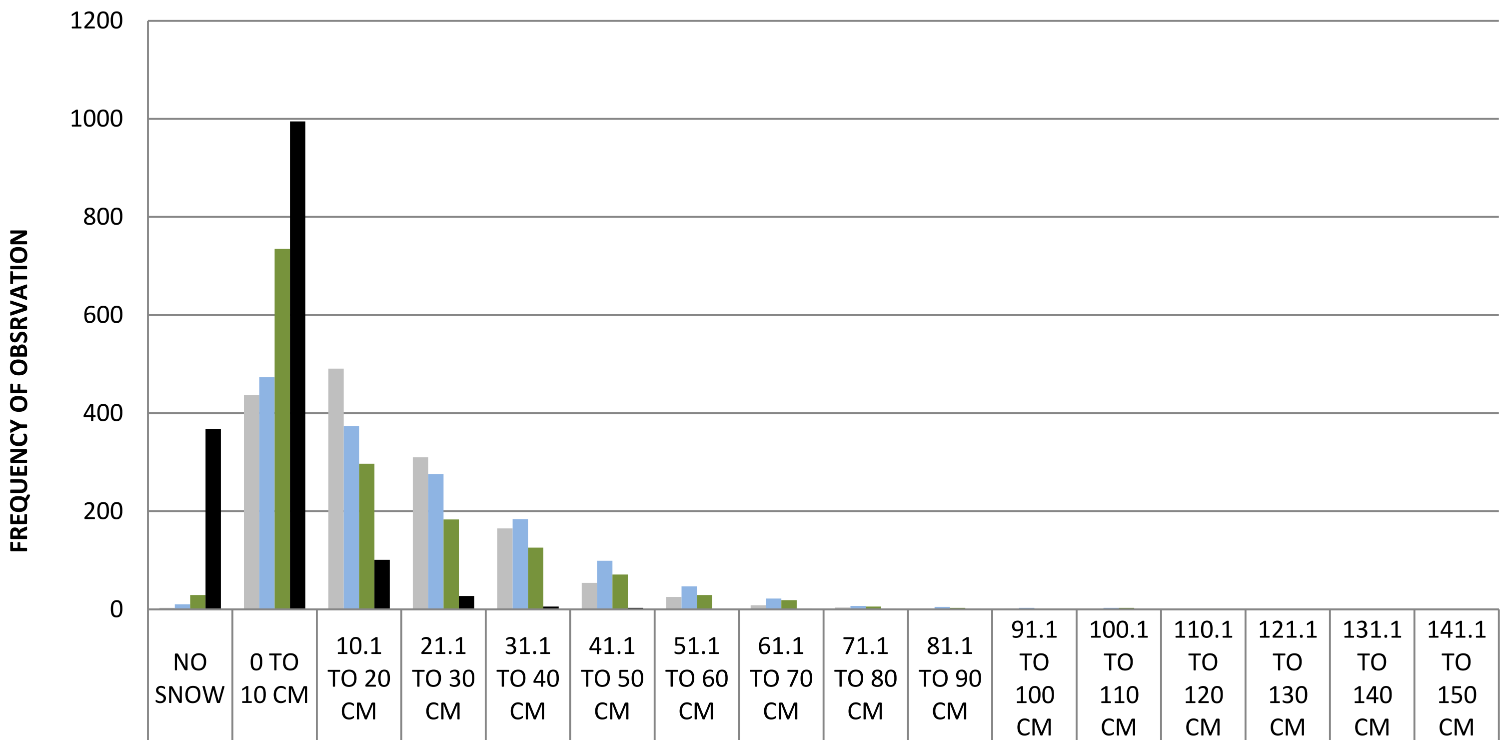
	JAN	FEB	MAR	APR
WINTER WHEAT	18.6	20.4	16.0	2.6
FALL RYE	18.6	20.5	15.6	3.1

Figure 4.2a: Frequency of observed average snow depth by month for winter wheat in cm from 1978 to 2007, all weather stations



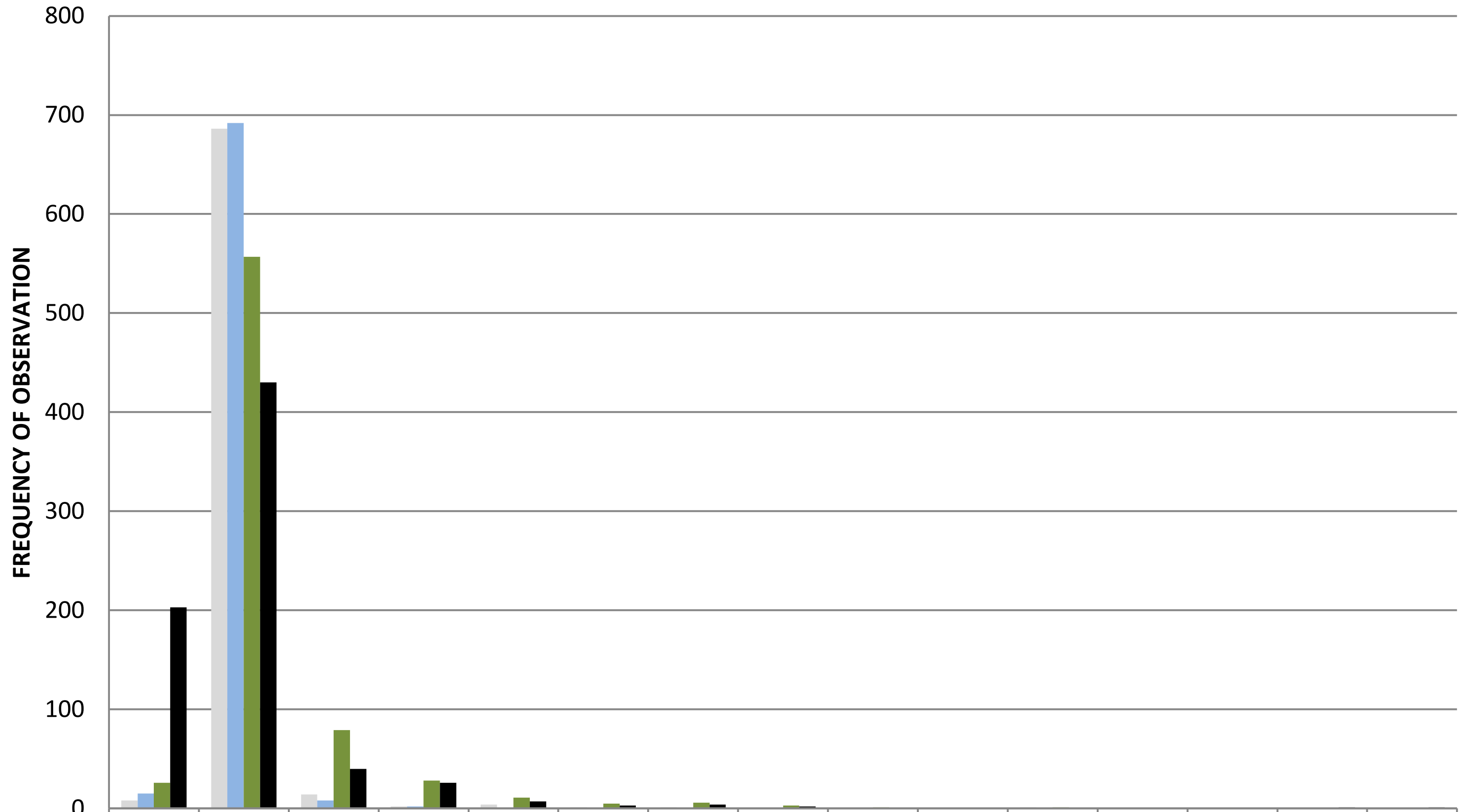
	NO SNOW	0 TO 10 CM	10.1 TO 20 CM	21.1 TO 30 CM	31.1 TO 40 CM	41.1 TO 50 CM	51.1 TO 60 CM	61.1 TO 70 CM	71.1 TO 80 CM	81.1 TO 90 CM	91.1 TO 100 CM	100.1 TO 110 CM
JAN	8	239	198	117	92	38	15	4	2	1	2	1
FEB	15	249	152	115	81	48	33	11	4	4	4	0
MAR	26	359	111	81	57	42	22	8	5	2	4	0
APR	203	456	43	11	2	0	0	1	0	1	0	0

Figure 4.2b: Frequency observed of average snow depth by month for fall rye in cm from 1978 to 2007, all weather stations



	NO SNOW	0 TO 10 CM	10.1 TO 20 CM	21.1 TO 30 CM	31.1 TO 40 CM	41.1 TO 50 CM	51.1 TO 60 CM	61.1 TO 70 CM	71.1 TO 80 CM	81.1 TO 90 CM	91.1 TO 100 CM	100.1 TO 110 CM	110.1 TO 120 CM	121.1 TO 130 CM	131.1 TO 140 CM	141.1 TO 150 CM
JAN	3	437	491	310	165	54	25	8	4	2	2	1	1	1	0	0
FEB	10	473	374	276	184	99	47	22	7	5	3	3	0	0	0	1
MAR	29	735	297	183	126	71	29	19	6	3	1	3	1	0	0	0
APR	368	995	101	27	6	3	0	2	1	1	0	0	0	0	0	0

Figure 4.2c: Frequency of observed variance of snow depth by month for winter wheat in cm from 1978 to 2007, all weather stations



	0 VARIANCE	0.1 TO 100	100.1 TO 200	200.1 TO 300	300.1 TO 400	400.1 TO 400	500.1 TO 600	600.1 TO 700	700.1 TO 800	800.1 TO 900	900.1 TO 1000	1000.1 TO 1100	1100.1 TO 1200	1200.1 TO 1300	1300.1 TO 1400
JAN	8	686	14	2	4	1	1	0	0	0	1	0	0	0	0
FEB	15	692	8	2	0	0	0	0	0	0	0	0	0	0	0
MAR	26	557	79	28	11	5	6	3	1	0	1	0	0	0	0
APR	203	430	40	26	7	3	4	2	0	0	0	0	0	1	1

Figure 4.2d: Frequency of observed variance of snow depth by month for fall rye in cm from 1978 to 2007, all weather stations

	0 VARIANCE	0.1 TO 100	100.1 TO 200	200.1 TO 300	300.1 TO 400	400.1 TO 400	500.1 TO 600	600.1 TO 700	700.1 TO 800	800.1 TO 900	900.1 TO 1000	1000.1 TO 1100	1100.1 TO 1200	1200.1 TO 1300	1300.1 TO 1400	1400.1 TO 1500	1500.1 TO 2000	2000.1 TO 2500	2500.1 TO 5500
JAN	6	1448	32	11	4	1	1	0	0	0	1	0	0	0	0	0	0	0	0
FEB	14	1472	17	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MAR	30	1250	146	40	18	7	6	2	2	1	0	0	2	0	0	0	0	0	0
APR	369	948	86	49	19	11	8	6	1	1	0	0	1	1	2	0	1	0	1

4.2.4 Description of the analysis

The combination of available yield data and weather data for the winter period provides a total of 718 observations for the winter wheat analysis and 1,504 for fall rye. This reflects the smaller geographic area in which winter wheat is found compared to fall rye in the Canadian Prairies and the more limited geographical area in which these crops are grown in general. The analysis for winter wheat using summer climatic data contained 1,934 observations, while the count for fall rye was 4,667. Overall the size of the datasets has decreased by 62 percent for winter wheat and by 67 percent for fall rye.

Variations on the model using temperature data from January and February, or January to April are tested, aggregated seasonally (as with Model 1 from Chapter 3) or monthly (as with Model 2 from Chapter 3). Colinearity in the data dictated the seasonal aggregation in 3 °C increments, as discussed above.

Snow depth and snow variability are highly colinear between January and April. Therefore, only one of these variables could be used in the analysis. The use of January and February snow data is tested against the use of snow data for January to April or January and February and April. A model was run using snow depth and another with snow variance. Comparison of the adjusted R^2 and other measures of model performance (such as the maximum of the likelihood function) indicates that a model with snow variance has improved statistical significance than a model with snow depth. Therefore, the model was run as shown in Equation 4.3 – this equation is identical to the general form of the model shown in Equation 4.1 above with the exception of the $\boldsymbol{SNOW}$ variable which has now been defined further as the variance of snow depth, $\boldsymbol{SVAR},$ for each month *m* from January to April in year *t* at station *k*.

$$y_{itj} = \delta_i + \boldsymbol{\beta_{ikt}TEMP_{kt}} + \boldsymbol{\rho_{iktm}SVAR_{ktm}} + \boldsymbol{\varphi_{ij}D_j} + \alpha_i T_t + \varepsilon_i \quad [4.3]$$

Potentially, an interactive variable between snow depth and colder temperatures would provide more insights into the effect being picked up by the model. However, models were tested in which interactions proved to be less informative than the models that are reported here. However, these variables in combination with explanatory variables not used here might provide further insights.

4.3 Results of the Winter Model for Winter Wheat and Fall Rye

The following sections provide an overview of the results of the models run for winter temperature data as discussed above. The next section provides a review of the winter wheat results, and the following section provides an overview of the fall rye results.

4.3.1 Winter Wheat

The model run for winter wheat is shown in Equation 4.2, ***TEMP*** contains cumulative exposure to temperatures from 0 to minus 40 ºC for January through April, in three degree increments. ***SVAR*** contains snow depth variance for January through April. ***D*** contains dummies for each rural municipality/county.

The coefficients for Equation 4.3, found in Appendix F[8], on snow depth variance for January and March are positive, while the coefficients are negative for February and April. Only January and February coefficients are significant at least at a 10% level of significance. As well, the coefficients are smaller by a factor of 10 for March and April, suggesting that snow depth variance in January and February are more important than late winter snow depth variance. The temperature coefficients are negative and significant at warmer temperatures. There are more coefficients that are positive and significant at colder temperatures.

This suggests that the colder the air temperature is during the winter months, the lower the winterkill and the higher the yield the following growing season for winter wheat. This is the opposite of the hypothesized result that exposure to cooler temperatures would result in a non-linear effect, with yields decreasing as temperatures fall. However, the results indicate that, if anything, exposure to temperatures below the critical level results in *increasing* yields rather than *decreasing* yields around ever cooler temperatures. The tipping point appears to be between –22 and –28 ºC, based on the significance and sign of the coefficients for these variables. The adjusted R^2 for this model is 0.457.

4.3.2 Fall Rye

The fall rye analysis proceeds exactly as for the winter wheat analysis, following Equation 4.3. The adjusted R^2 for the fall rye model is 0.247, indicating that winter weather explains less of the variability of yield for fall rye than for winter wheat. Snow variance is shown to have a positive impact on yield except in April, where the coefficient is negative and significant at 1 percent.

[8] Appendix F does not include the dummy variable coefficients for each district.

There is no discernable pattern in the coefficients for temperature, as shown in Appendix F. In the colder ranges measured, coefficients are either positive or negative, and some of both are significant at 10 percent or lower. In the warmer ranges, some coefficients are positive and some are negative but only the negative ones are significant at 10 percent or lower. This suggests the same effect found for winter wheat, where a critical minimum temperature somewhere around -25 to -28 ºC, exists. Exposure to temperatures above this critical minimum during the winter months would then decrease yields, and exposure to temperatures below this critical minimum would have no effect or increase yields.

4.4 Discussion and conclusions

The analysis is undertaken because it was hypothesized that snow depth and air temperature in the coldest months of the Canadian Prairie winter could serve as a proxy for soil temperature. Soil temperature is the known variable that predicts winter kill for fall-seeded crops. There are several elements interacting here; soil temperature predicts winter kill but this does not necessarily translate into soil temperatures functioning as an accurate predictor of yields.

Three hypotheses were tested in this chapter. The first was that greater snow depth in January and February would produce higher yields for winter wheat and fall rye in the subsequent growing season. Testing various model specifications resulted in snow depth being rejected as a variable as it was not significant on its own and because colinearity with snow variance was found. Thus, this hypothesis is not supported by the results of the analysis.

It was also hypothesized that variability of snow depth in March and April would have a statistically significant impact on yields of winter wheat and fall rye. Variability of snow depth is not statistically important for either crop in March and strongly significant (at 1% or lower) for fall rye in April. Thus, the results indicate that variability of snow pack in the late spring may have an impact on rye yields. This is likely directly related to the length of the growing season. Where the snow pack has melted by April, the variance is 0 and strongly correlated with an early growing season and higher yields. Where the early spring is cool, there can be significant snow pack on the fields until late April or early May. In this case, the variance of snow pack depth would also be low, but correlated with a late growing season and lower yields.

The hypothesis that fall rye and winter wheat will exhibit a non-linear response to a critical minimum winter temperature is partially supported, but in an unexpected way. Winter temperature appears to be positively correlated with yield of fall rye and winter wheat, provided that temperatures stay below a critical minimum of approximately minus 31 ºC; on average, crops spend between 25 and 35 hours in these temperature ranges each year. This conclusion is better supported by the winter wheat results than by the fall rye results. It is reasonable to assume that winter kill and yield at the end of the growing season are related but somehow the link between soil temperature and air temperature and snow pack is less clear.

When winter kill is extremely high due to adverse conditions over the winter, the fields are re-sown in the spring with alternate crops that will mature before the end of the growing season. Data for fall-seeded crops that fail completely are not captured in the dataset; therefore it is difficult to know to what extent the yield dataset over-states yields in any given year.

Climate data availability in the winter months is lower from that of the summer months, reducing degrees of freedom in the analysis. Aggregating over three degree increments here, and using only one snow variable over five months, plus the constant, time trend and district dummy variables, a total of 154 coefficients were estimated for the winter wheat model and 157 for rye. The winter wheat dataset has 718 observations and fall rye 1,504; both fail the rule of thumb test of 10 observations per coefficient discussed in Chapter 3, although fall rye is close. While this rule of thumb cannot be used to determine whether or not there is sufficient data, it does encourage the question to be asked. Thus, it is possible that asymptotic unbiasedness of the estimators was not achieved. This can only be tested by repeating the analysis with a larger dataset.

This chapter provides an opportunity to use temperature in an empirically sound way to test a theory about the way that fall-seeded crops respond to climate. Researchers at the University of Saskatchewan are attempting to increase cold tolerance in winter wheat, arguing that such fall-seeded crops are more environmentally beneficial than spring seeded crops, require reduced pesticide applications, and provide improved duck and other wildlife habitat in the spring. Introducing increased cold tolerance traits for fall-seeded crops can provide an opportunity for these crops to be grown in a much wider range. Currently, winter wheat is grown most often in southern Saskatchewan, Alberta and Manitoba. The model tested here provides limited support for the hypothesis that winter temperatures in the coldest months of the year, along with snow depth and variance of snow depth, can serve as predictors of the subsequent year's yields. However, it would seem that either the specification used here, or the small size of the data set, is insufficient to provide clear answers.

A different model specification, one which incorporates temperatures and snow fall data from September through December, as well as temperature and rainfall data from the subsequent growing season, could be tested for improved performance. However, a model that incorporates these variables would (at least) double the number of coefficients and many weather stations (in particular in Alberta) only operate in the summer. The number of weather stations with sufficient data to estimate yield as a function of both winter *and* summer climate variables is more limited, potentially, than those available for winter alone. Incorporating observations from 1956 to 1977 from Saskatchewan and Manitoba would also increase the degrees of freedom available for the estimate. However, it may be that the approach outlined in this chapter is impractical given the quantity of data available from which to run the analysis. If sufficient data are identified, a model that incorporates fall weather as well as winter weather may enable a more robust result to be obtained.

Chapter 5: Agricultural Land Use Change in Western Canada with Climate Change

5.0 Introduction

One of the objectives specified in Chapter 1 is to estimate the impacts of climate change on agricultural land use in the Canadian Prairies. Chapter 2 provided an overview of the literature on land use with respect to climate change. Notably, economic impacts are commonly measured with Ricardian models, but, as discussed in Chapter 2, the robustness of such models has been debated. Climate factors are often confounded with soil characteristics and other physical characteristics, resulting in confounding variables. Also, the omitted variable bias is difficult to quantify (Deschênes and Greenstone 2007). A model that will allow the estimation of agricultural land use changes from shifts in climate should use spatial data, provide the ability to predict future yields and be able to accommodate both supply side impacts as well as demand side changes that affect price. Such a model would allow the estimation of total welfare impacts of climate change in the Canadian Prairies, disaggregated by region or district, as well as provide some insights into shifts in spatial patterns of agricultural land use allocation. The purpose of this chapter is to build a model to analyze spatial trends in land use patterns for agriculture under various climatic conditions, using highly disaggregated spatial data.

Chapter 3 provided an estimate of the impact of temperatures during the growing season on crop yields for nine major Canadian crops, demonstrating that calculating cumulative exposure to temperature at different heat levels provides improved yield forecasting over average temperature or growing degree day approaches. Having an improved estimate of the relationship between yields and temperature is a launching point for estimating the impacts of changes in the economic and ecological environment in which the crops are grown. One anticipated shift is a change in the distribution of temperature due to climate change, with increased average temperature, accompanied by changes in the distribution of rainfall across western Canada.

Schlenker and Roberts (2008) make predictions of the impact of climate change for American agricultural production. However, they do so under the assumptions that production patterns are stable and that aggregate impacts are scaled up from changes in yield without any adaptive behaviour on the part of farmers. Implicitly, no substitution between crops occurs. The purpose of this chapter is to address the question of spatial shifts in crop production under climate change, while incorporating crop substitution. Section 5.1 presents a summary of the objectives of this chapter, and Sections 5.2 and 5.3

provide an overview of the model developed to examine land use change in the Canadian Prairies. The remainder of the chapter is dedicated to exploring the results of the analysis.

5.1 Objectives and hypotheses

The objectives of this chapter are:

i. To incorporate improved yield estimates into a study of land use allocation between competing agricultural uses in which both the production function and weather inputs are unchanged from the historical dataset. This scenario constitutes a short-run outcome, which is used to validate the model against current agricultural land use data.

ii. To estimate agricultural land use allocation under an assumption of climate change occurring, as modeled by changes in average daily temperatures.

iii. To demonstrate a linear programming approach that can capture the essential economic impacts of climate change on agricultural land use allocations in the Canadian Prairies.

The hypotheses that will be tested during the land use change analysis phase of the project are:

i. Climate change will induce an increase in the acreage allocated to drought-tolerant crops.

ii. Substitution towards crops that produce higher yields and away from crops with lower yields will occur as growing conditions change.

iii. The spatial distribution of crops will respond to climate change, with heat tolerant crops being found further north as temperatures increases.

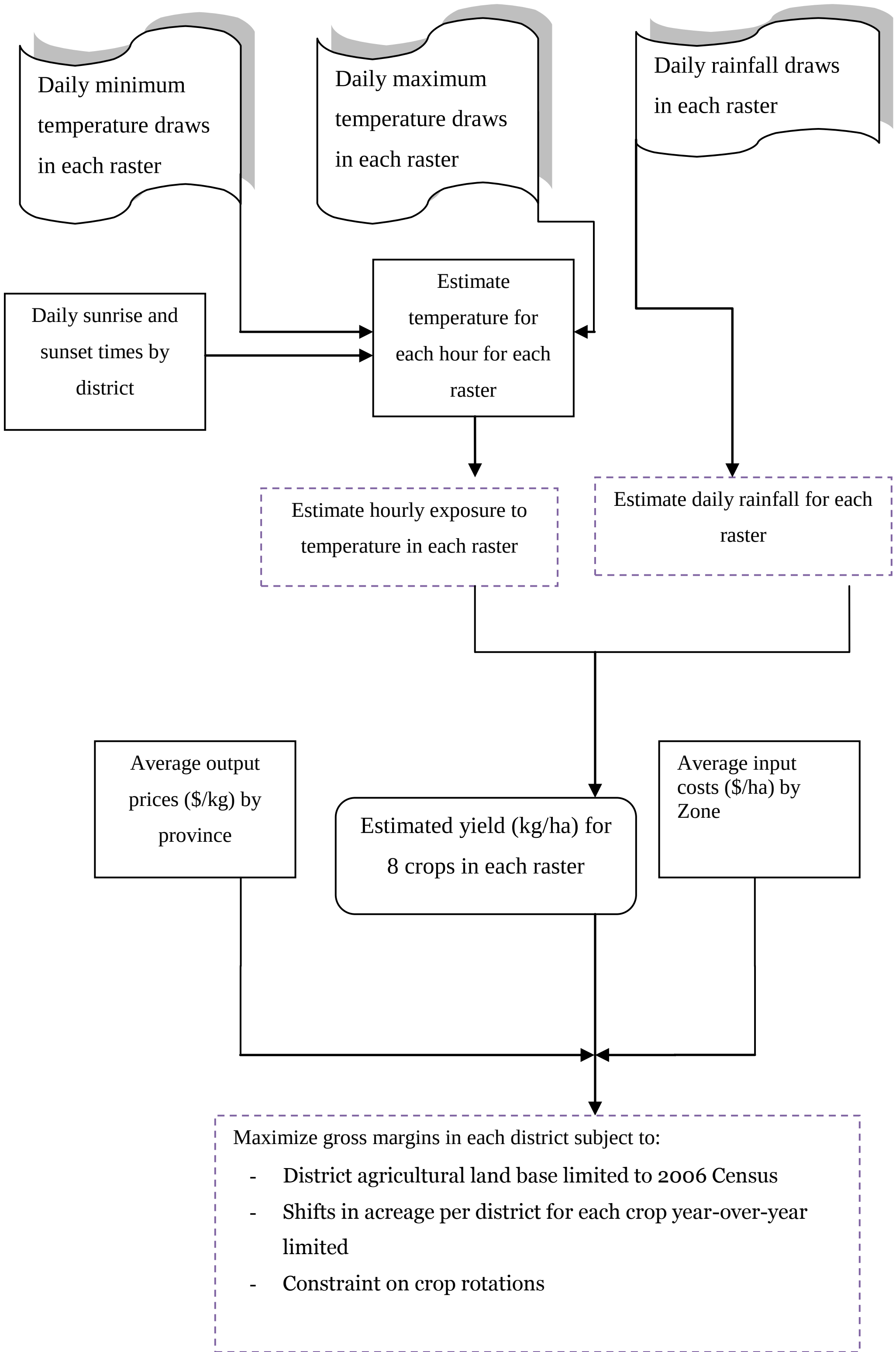
iv. The spatial distribution of crops will respond to changes in the distribution of rainfall patterns.

5.2 Model Description

As discussed in Chapter 2, there are several approaches to land use modeling that can be employed to examine the economic impacts of climate change. The most common modeling approach is the Ricardian, or hedonic model. However, as noted in Chapter 2, these models are sensitive to parameter values and therefore may not be sufficiently robust. Hedonic models commonly assume spatial homogeneity, which can lead to biased estimators (Deschênes and Greenstone 2007). A second commonly used option is a simulation model; often a math programming model that incorporates behavioural choices as well as economic and physiological restrictions. The third main option is to use specialized simulation software such as CERES that simulates yields for specific crops. CERES, however, cannot be used to simulate economic behaviour. In Chapter 2, a comparison of crop simulation models and production functions with average temperatures as explanatory variables for yield predictions showed that these approaches are statistically equal. In Chapter 3 it was shown that the use of the modified GDD as first shown by Schlenker and Roberts (2006) (hereafter termed the SR approach) provides improved yield predictions over average temperatures. Thus, crop simulation models such as CERES are not ideal for simulating the economic impact of climate change.

A model that incorporates spatial heterogeneity is appropriate for the study of weather effects as these effects will differ between the eastern and western regions of the Prairies, from the north to the south, and from the south-western region on Saskatchewan (which is particularly hot and dry) to the rest of the Prairies. The model used here allows for the use of the SR approach to estimate yield predictions and a dynamic spatial linear programming (LP) model to simulate supply responses to climate change. This approach provides the ability to model both physiological/agronomic constraints as well as economic behavioural constraints. In a single period, the LP model estimates yield under specified climate conditions, and maximizes gross margins. The model is run for each rural municipality/county from 2005 to 2010 using simulated weather draws from the base period. The model is then run over 40 years from 2011 to 2050 for two climate change scenarios as well as once with no change in climate, with dynamic links to enforce shifting restrictions on total hectares of land allocated to each crop within each district.

Figure 5.1: Model Overview, Static Elements



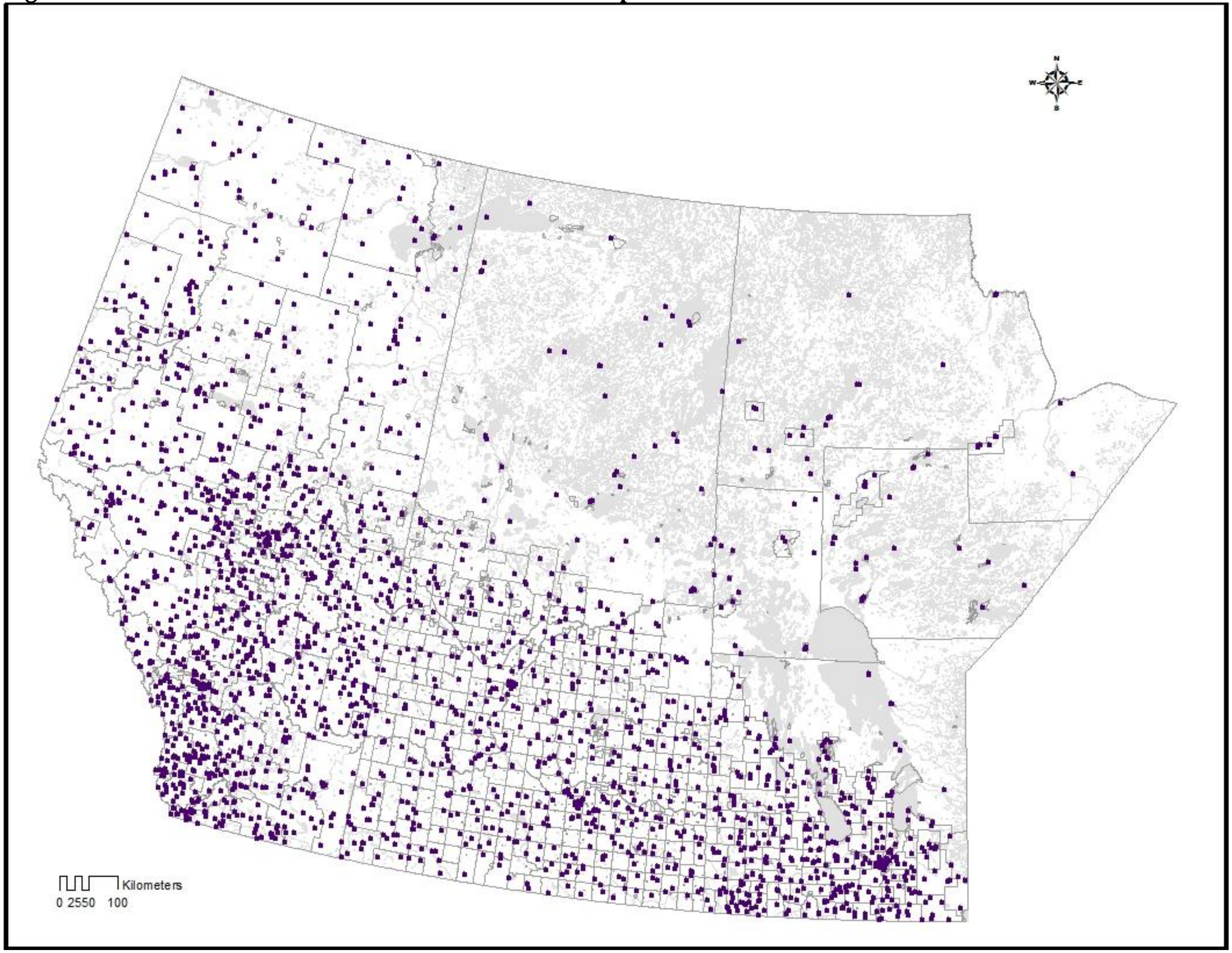
These are (1) a base scenario with no climate change, (2) a low emissions climate change scenario (B1) and (3) a high emissions climate change scenario (A1B). The low emissions scenario produces emissions that are higher than current, but the lowest emissions forecasted by climate specialists under assumptions of significant mitigative behaviours across the global economy. The high emissions scenario forecasts emissions based on a "business as usual" approach in which few if any mitigative behaviours are adopted. The LP model includes dynamic links to impose behavioural restrictions year-over-year. These restrictions provide proxies for real-world land use decisions based on crop rotations. Increased green house gas emissions of carbon dioxide (for example) result in increased temperatures and changes to rainfall patterns as a result of changes to the air and ocean currents globally. The B1 scenario predicts a smaller increase in temperatures and the A1B scenario predicts a larger increase in temperatures globally. The localized effects of these shifts for both temperature and rainfall are outlined in Appendix J, as the global averages obscure local effects that may differ from the global average in both size and direction. This is to say that local temperatures and rainfall may either rise or fall, depending on the location relative to shifts in air currents, for example.

Figure 5.1 provides an overview of a single period of the model. Historical spatial weather data are used to calculate average and variance data for each variable for each pixel in the study region. The model optimizes gross margin for each cell subject to restrictions that are applied at the district level. The 2006 Census of Agriculture is used to validate the model, as is discussed further below. The 2006 Census dictates initial land use decisions and creates the base years for the path-dependent choices that occur subsequently. Changes to average weather are taken from climate change scenarios and new land use impacts are estimated.

5.2.1 Estimating Yield: Simulating weather conditions

The purpose of this section is to outline the process by which daily temperature and precipitation data are used to generate yield estimates for each of the crops modeled. The process begins with historical data taken from weather stations throughout the region. These are transformed into a spatial dataset of maps that contain information on the minimum and maximum temperatures and on rainfall for each day in the growing season. These data are used to calculate an average value for each variable, and a variance, in the cells or "rasters" on the map, each of which represents a specific geographical area. Using MatLab's tool, tests of best-fit distributions are performed because draws on the

Figure 5.2: All weather stations in the Canadian Prairies operational between 1961 and 1990.



distribution will be used in the linear programming model to simulate weather conditions. Independent draws on the distribution of weather in each cell result in widely diverging draws between adjacent cells; these draws are adjusted using a Cholesky decomposition[9] of a correlation matrix. Because the number of cells in the final grid was too large to follow the adjustment procedure for all cells simultaneously, draws are instead adjusted between cells grouped according to the eco-regions[10] in which they are located. These adjusted draws are used to calculate the number of hours of exposure to temperatures at different ranges, which in turn are used to generate yield estimates for each crop for each year of the model by following the methods of Chapter 3. However, none of the models developed there are used here.

The first step of the process described above is to generate maps for the three climate variables (minimum and maximum temperature, and rainfall) for the study area. Weather stations collect weather data across the Canadian Prairies. These observations become part of a database, managed by Environment Canada, of all empirically observed weather. Weather stations may operate for a portion of the year only (most commonly the summer months) and very few have been in operation for the full base period. Minimum and maximum temperature and daily rainfall data were obtained for 1961 to 1990 for all weather stations in the provinces of Alberta, Saskatchewan and Manitoba because these are the base years used in the climate change model from which to compare shifts in future climate.

Each weather station across the study region was plotted as a point datum using ArcView GIS, as shown in Figure 5.2. Weather data from 1961 to 1990 were uploaded to the mapping software where daily weather observations were joined to the weather station from which it was originally captured. For each day in the growing season, defined as April 15 to August 31, plus one day at either end (139+2 =141 days[11]), weather stations with no maximum temperature data for that day for were filtered out. Of the remaining weather stations, each contains a data point that indicates the maximum temperature for that day at that site.

---

[9] The Cholesky decomposition assumes a normal distribution; this is discussed further below.
[10] Eco-regions are regions characterized by common vegetation and soils (reference) and represent the realization of climate. As such they provide a proxy for environmental variation across the study region.
[11] The data from the day before and the day after the growing season are required for Equations 3.5a through 3.5c as discussed in Chapter 3.

One of the standard options in ArcView for interpolation called kriging is used to generate maps that show estimated maximum temperature values across the study area. Kriging is an algorithm to estimate the maximum temperatures for all the physical spaces between the point data observations. The kriging process assumes a trend pattern such that if, in a given region, temperatures increase as one moves across the landscape in a particular direction, the highest temperature estimated in “hot spots” can exceed the highest temperature observed. The same can occur for downward trends and the lowest estimated values in “cold spots” can be lower than the lowest observed temperature.

The result from the kriging process is a raster map, or map of cells, each of which represents a specific location in the study area. Each cell represents 10 km^2, and the matrix of cells, in rows and columns, represents the geographical region covered by the interpolation process. As noted in Chapter 2, spatial modeling should take place on the same scale as the phenomenon being modeled. Weather could be modeled at a smaller scale than shown here but this scale was chosen as the smallest practical size that allowed the model to be run with relatively manageable processing times. The resulting data can be exported in ASCII file format and manipulated as a text data file. The process was repeated for each day of the growing season for each year in the base period from 1961 to 1990. It was repeated again for minimum temperature observations starting with April 14, 1961 and ending with September 1, 1990.

A similar procedure was used for rainfall observations. The process proceeded as described for minimum and maximum temperatures but a different interpolation algorithm was used. Using the kriging interpolation method for rainfall values resulted in negative rainfall values in certain areas. Instead of kriging, an algorithm called natural neighbour was used. The natural neighbour algorithm assumes that the trends across the landscape are bounded by the highest and lowest observed data points. This results in rainfall estimates that are bounded by zero (no rainfall) and the highest recorded rainfall for that day.

The interpolation processes described above produced 4,230 (=141 days x 30 years) maps for each climate variable, or 12,690 maps (=4,230 maps x 3 variables) in total. The extent, or geographical area, covered by each map varies because the subset of weather stations with valid data for each day is slightly different. As well, the algorithm used to generate the temperature maps produced maps with different extents than those used for rainfall. The output maps for rainfall are still made up of cells that represent the same 10 km^2 areas of land but these output maps do not cover the same geographical extent as the kriging process. Kriging interpolation produces rectangular matrices and natural neighbour interpolation does not, as an artifact of the specifics of the different algorithms. The next stage of the process is to harmonize the extent of each of the maps and to identify non-agricultural land so that it can be excluded from the economic analysis.

The extent of the map for which a full set of climate variables was obtained was determined to contain 156 columns and 122 rows of cells. From this extent, non-agricultural land was identified. Specifically, hydrological and municipal maps were used to identify cells that are mostly water or urban developments. National parks and First Nations reservations were also identified and coded as non-agricultural land. While First Nations reservations may contain a significant amount of agricultural land, data for these areas were not available and they are, therefore, not included in the analysis.

Originally, data from weather stations in British Columbia, Ontario and the North West Territories were not obtained which meant that observations of climate variables outside the geographic areas of Alberta, Manitoba and Saskatchewan could not be used in the interpolation process. As an artifact of this decision, the weather maps that were generated truncate the northern portions of Manitoba, Saskatchewan and Alberta, and some of the mountain regions in the west of Alberta. In Figure 5.3, the regions north of Lake Winnipeg in Manitoba, north of Prince Albert National Park in Saskatchewan, and the north-east corner of Alberta can be identified as Canadian Shield. These are the areas that are characterized by many thousands of lakes, both small and large, which are of no particular interest in this examination of agricultural land use.

In Alberta, a land zone rule is in place that designates land for forestry and agriculture. The “green” zone is land in the north allocated primarily to forestry, although oil sands production and other industrial activities take place there. The “white” zone is allocated primarily to agricultural production. Some of the “white zone” is excluded from the study area by the truncation described above, and some of the “green zone” is included. The amount of agricultural activity on the land base studied was defined by the amount of crop land in each district according to the 2006 Census of Agriculture, rather than by these government-imposed zones. Crop land is minimal in the green zone so the impact on the final extent is minimal. There is an exception in the region around Grande Prairie, where some crop land was truncated and this should be taken into consideration when reviewing results for that region. Manitoba and Saskatchewan do not have similar zoning regulations in place, and have no agricultural land in their northern regions as they consist largely of Canadian Shield.

The map shown in Figure 5.3 consists of a grid of 19,032 cells in 156 columns and 122 rows. Each cell contains a value of “0” for the parcels of land that have no agricultural land and a “1” for those that do. In Figure 5.3, the 0s have no colour and the 1s are shaded. In order to harmonize the extents of each of the 12,690 climate variable maps that were generated, each of the interpolated daily weather maps was multiplied by the map shown in Figure 5.3. This is a mathematical operation option in ArcView which allows mathematical manipulation of the values in the individual cells using the various maps as variables. Thus, the maps function as large matrices of data that can be manipulated as a unit. Output maps that result from these mathematical operations have an extent that matches the input map with the smallest extent; the map shown in Figure 5.3 contains the extent that contains values for all the climate variables, which is equal to or smaller than any of the individual maps. The series of 12,690 climate variable maps with different extents were, therefore, transformed into a series of 12,690 maps with identical extents. Figure 5.4 shows one example of an output map, showing the maximum temperature recorded on July 15, 1975. The highest temperatures of the day were between 32 and 36 °C, in the southern regions of Saskatchewan and Manitoba.

Of the 19,032 cells in this final extent, 7,727 consist of agricultural land that is of interest in the analysis. These cells contain daily temperature or rainfall values; the rest contain zeros. All of the cells were carried forward in the analysis to preserve the placement of each cell in the extent. This means that once the linear programming analysis is complete, the results can be accurately mapped back onto the landscape from which the climate values were generated because the dataset generated preserves the exact order in which the cells are found in the extent. From this set of climate variable maps, average values were calculated using 30 years of data from 1961 to 1990 for each variable for each day. This results in 423 (=141 days x 3 variables) maps with average values for the base period. Using these mean values, base period variances are also calculated, resulting in another 423 maps.

Figure 5.3: Area used in the simulation model

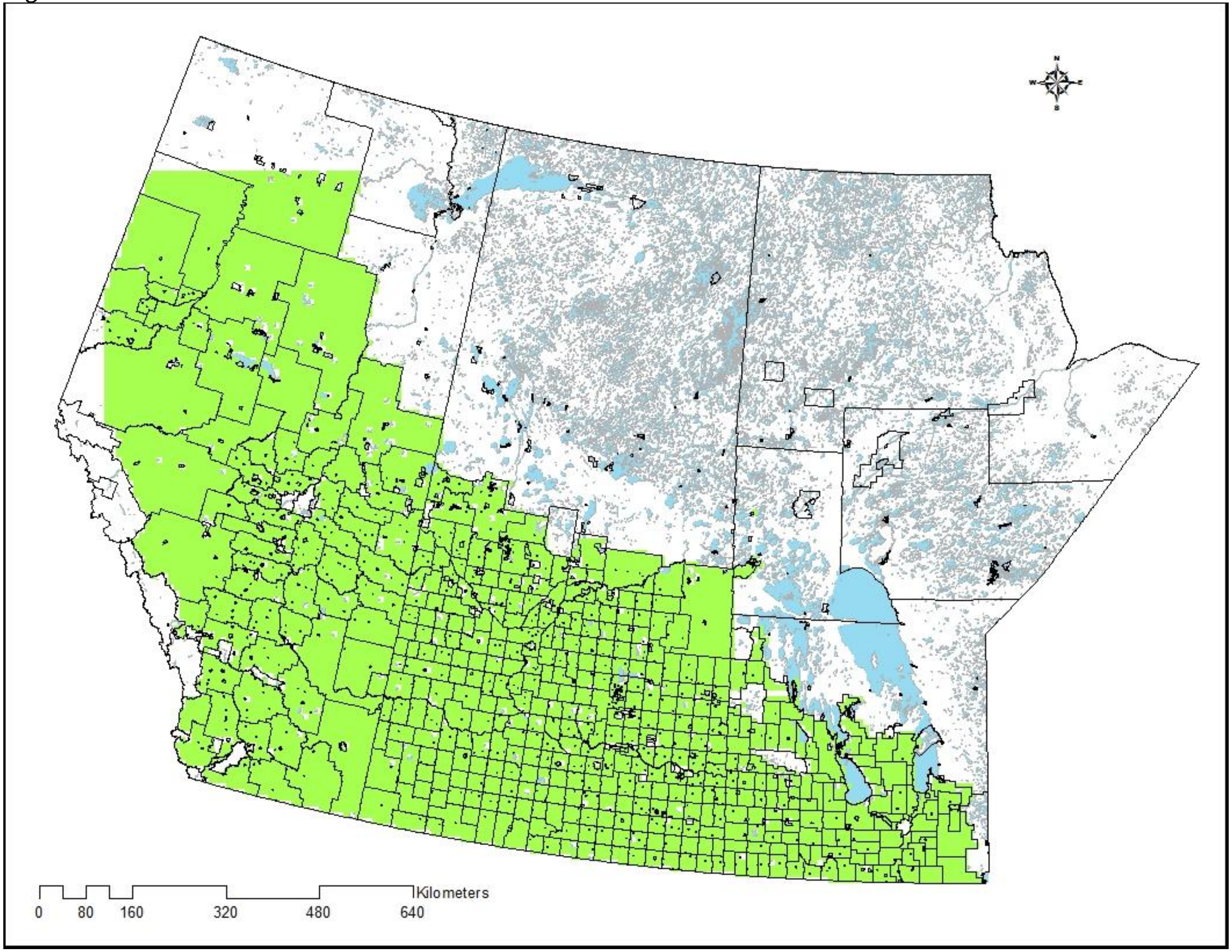
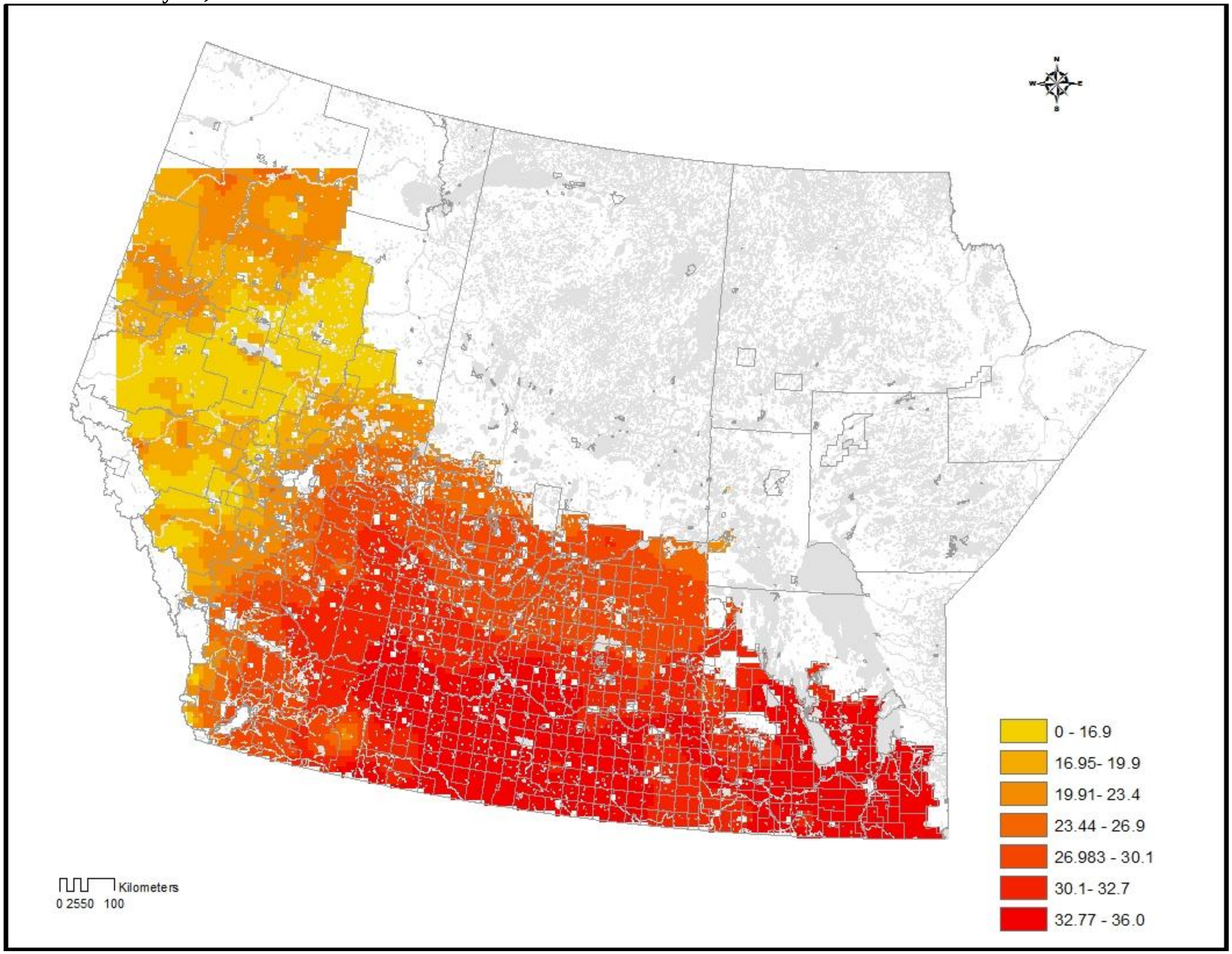


Figure 5.4: Example of maximum temperature (°C) map generated by interpolation of weather station observations; Data here is from July 15, 1975



Ultimately, draws on the distribution of the climate values will be used to generate daily minimum and maximum temperature and rainfall estimates. In order to take these draws, the best-fit distribution for the variables must be determined. While it was impractical to test for best fit distributions across 141 days of the growing season and three variables and all 19,032 cells, a selection of cells were tested. Cells were randomly selected from early, mid and late season and from north, mid-range and southern regions for each variable. This process was repeated for a year taken from the beginning of the base period, the middle and again towards the end of the base period. Normal distributions were the best fit in the highest proportion of the temperature maps (both minimum and maximum), and second best fit in the majority of the rest. . Because normal distributions have infinite tails, there exists the possiblity of extremely high or extremely low temperature draws. However, since the marginal effects of all temperatures of 35 °C and above are assumed to be homogeneous, it is assumed that these draws would not affect the analysis in any significant way. As well, correlation for spatial heterogeneity (described below) will adjust these draws such that the extremes are eliminated. Thus, for each cell (r) in a temperature map, a normal distribution around the calculated mean ($\overline{X}_r$) and variance (σ_r) is assumed. For rainfall, a lognormal distribution was the best-fit distribution identified by the same sampling procedure.

5.2.2 Estimating Yield: Spatial and Temporal Correlation

Independent draws, taken from each cell for temperature and rainfall, are not correlated, but the observed values are highly correlated spatially. Draws of a maximum temperature of 8 °C cannot be observed in one cell and 32 °C in a contiguous cell on a land-base that is no further than 10 km away, but independent draws would allow this type of pattern to emerge. Likewise, rainfall should be correlated with maximum temperatures and with minimum temperatures. The procedure below outlines the process used to obtain correlation-adjusted draws for each of the three variables for each day, which will prevent unrealistically different draws from occurring. Temporal correlation would capture the effect of several hot days in a row. However, given the approach used here the temperature data are aggregated across the season and so it is not possible to capture the effect of this type of weather pattern. Therefore, no attempt to address temporal correlation was made. The process described below for spatial correlation could have been applied to temporal correlation. However, doing so would have reduced the variation in the weather patterns such that extreme weather draws would be much less likely. Given that these are the phenomena that this study intended to examine from the outset, correlating temporal draws would have been unproductive.

The process begins with correlation of each of the three variables in a single cell. This is followed by addressing spatial correlation for each variable between cells. The most commonly applied solution to adjusting independent draws for correlation is the Cholesky decomposition method. This is a known solution to transform independent standard normal draws into correlated standard normal draws. In a typical example of the application of the Cholesky decomposition, Wang (2008) uses the decomposition method in a Monte Carlo simulation by correlating stochastic draws to simulate options prices responding to similar market shocks. The essence of the method is to construct an upper triangular matrix, A, such that $C = A^T A$ where C is the correlation matrix and A can be defined as the "square root" of C (Kennedy 2003, 545). The Cholesky decomposition is an algorithm for calculating A from any positive definite matrix, and is a standard function in most statistical software packages (including MatLab). Equation 5.1 shows the independent draw ($\widehat{\boldsymbol{X}}$) is equal to the average ($\overline{\boldsymbol{X}}$) plus an error term. Independent draws in the vector $\widehat{\boldsymbol{X}}$ multiplied by **A** produces correlated draws ($\widetilde{\boldsymbol{X}}$) as shown in Equation 5.2 where *r* and *q* are different cells in the district.

$$\widehat{\boldsymbol{X}}_{\boldsymbol{rt}} = \overline{\boldsymbol{X}}_{\boldsymbol{r}} + \boldsymbol{\epsilon}_{\boldsymbol{r}} \qquad [5.1]$$

$$\widetilde{\boldsymbol{X}}_{\boldsymbol{qt}} = \widehat{\boldsymbol{X}}_{\boldsymbol{qt}}{}' * \boldsymbol{A} \qquad [5.2]$$

The first step is to measure the correlation between minimum temperature, maximum temperature and rainfall, and adjust the independent draws for correlation. The second step is to take independent draws for the maximum temperature values, and correlate those independent draws and then repeat the process for minimum temperature draws and for rainfall draws. First, pair-wise correlation coefficients were obtained between average variable values for maximum temperature, minimum temperature and rainfall from 1961 to 1990 for a single cell r, defined below, such that $\rho_{r,q}$ is the 3 x 3 spatial correlation matrix between $\{T_{max,rt}, T_{min,rt}, R_{rt}\}$ where t = 1961 … 1990.

The definition of spatial correlation can vary. Anselin (1988) provides various definitions for spatial relationships for contiguous cells, which could include those above, below, right and left (rook pattern) or including the cells it shares corners with diagonally (queen pattern). It is possible to define which cells are related and to calculate correlations and adjusted draws for each group. Adjusted draws for a given cell could be re-adjusted as many as four times (rook pattern) as an adjustment is made for each of the four cells against which it abuts. It is better to make all the adjustments simultaneously to reduce computation time. Using the Cholesky decomposition approach, it is theoretically possible to adjust every independent draw for a given day with every other independent draw for temperature in the entire dataset simultaneously to produce a dataset of correlated draws. However, an attempt to perform this operation in MatLab resulted in extremely large correlation matrices. Larger matrices are less likely to be positive definite as there is no theoretical reason why a correlation matrix must fit this criteria. As well, MatLab has restrictions on the size of the matrices that can be used for calculations. A matrix that could adjust an entire day's worth of spatial correlations, capturing all correlated effects was, in the end, too large for the software to handle. It is unknown if another software package might alleviate this constraint.

Another option that was explored was to calculate draws for contiguous cells pair-wise, one pair at a time. Once the correlations for two contiguous cells had been calculated and the draw for the second cell adjusted, the process could be repeated for cells 2 and 3, where the draw of the third cell is adjusted based on the draw in the second. Each cell would, therefore, only be adjusted once. This approach proved to be workable, but was also impractical to run due to long computational times.

A third solution was found by dividing the research area into zones. A random draw is taken for each of the three variables for one cell in the first zone, and the independent draws for the three variables are correlated for that single cell using the Cholesky decomposition method as described above. The method does not adjust the draw for the first variable in the correlation matrix, but adjusts all other draws such that they are simultaneously correlated with the first draw and with each other. The next step is to take a draw for the first cell in each of the other zones for maximum temperature; these draws are adjusted using the Cholesky decomposition using spatial correlation between the cells as described above. A temperature shock is calculated for that cell in each zone such that $DRAW_{rzt} - AVG_{rzt} = SHOCK_{zt}$ for $r_z = 1$, where r is the first cell in the zone, z is the zone and t is the year. The SHOCK value that is generated for each z is then applied to each of the other cells such that $AVG_{qzt} + SHOCK_{zt} = DRAW_{qzt}$ in zone z for $q_z = 1 \ldots R_z$, where q is not the first cell in the zone and R_z is the number of cells in that zone. The process is repeated for minimum temperature and again for rainfall. The result is that the only independent draw for a given day is in the first cell for maximum temperatures as the Cholesky decomposition method correlates all other draws to this first value.

Correlation is measured between average values rather than observed values because correlation between average values is assumed to be higher than it would be for observed values but using a higher correlation value results in correlation-adjusted values that are closer together than if a lower value had been used. The method produced such tight correlation values for minimum and maximum temperatures that the correlated values were always very close together, no more than 2 to 4 ºC apart. To allow for greater variation between daily minimum and maximum temperatures, the correlation between these two variables is assumed to be 0[12]. The correlation matrix for maximum temperature, minimum temperature and rainfall for that first cell is shown in Table 5.1, below (the correlation between minimum and maximum temperature of 0.953 was changed to 0 by assumption). Spatial correlation between pairs of contiguous cells R_r and R_q is found to be consistently over 0.9, with many pairs showing correlations of over 0.99. Spatial correlations for rainfall and minimum temperature were similar in value to the correlations found for maximum temperature.

Table 5.1: Correlation in the first cell between minimum temperature, maximum temperature and rainfall

	MAX	**MIN**	**RAIN**
MAX	1	0.953	0.042
MIN		1	0.261
RAIN			1

In order to divide the region into zones, soil zones were considered, as these are commonly used in the agricultural production economics literature. Black soil zones are found in the mid-latitudes of the three provinces, with grey and brown soils found to the south and north. Soil zones proved to be hard to find in GIS format; however, maps of Canada's Eco-Regions were available from Agriculture and Agri-Food Canada (2008). Table 5.2 shows the groupings of Eco-Regions into the ten zones that were used here. These resulting zones closely resemble soil zones, but are more disaggregated, in

[12] Other correlation values were tested and proved to be too restrictive because they produced daily minimum and maximum temperature draws that were consistently only a few degrees apart, which is an unrealistic outcome. Thus, assuming values of the correlation coefficient that were greater than zero did not solve the problem described.

particular in Northern Alberta. Soils are divided into grey, brown, dark brown and black. Figure 5.5 shows the ten zones that were aggregated from the various eco-regions and their distribution in the study region. A shock was generated for minimum and maximum temperature draws for each day in the growing season for each of these zones using the Cholesky decomposition approach. The zone-level shock was applied to each cell in that zone. Thus, a shock of + 2.3 °C, based on the adjusted draw for the first cell in the zone, translates into a shock of 2.3 °C was applied to each of the other cells in that zone for that variable. Zone 11 is shown on the map but was dropped from the analysis because it consists of the continental divide, which is mountainous non-agricultural land.

The yield estimates for each crop is based on a single draw of minimum and maximum temperature, and rainfall, for each day of the growing season. A more rigorous approach would be to use Monte Carlo procedures whereby yields are calculated based on a number of weather draws, and the average yield in the resulting distribution used. One could likely achieve the same effect by using the average values for each of the three variables to estimate crop yield. However, this process would eliminate the variation and occurrences of higher temperatures that the model was designed to capture. As well, the time required to generate yield estimates based on the Monte Carlo process described above precluded the use of this approach.[13]

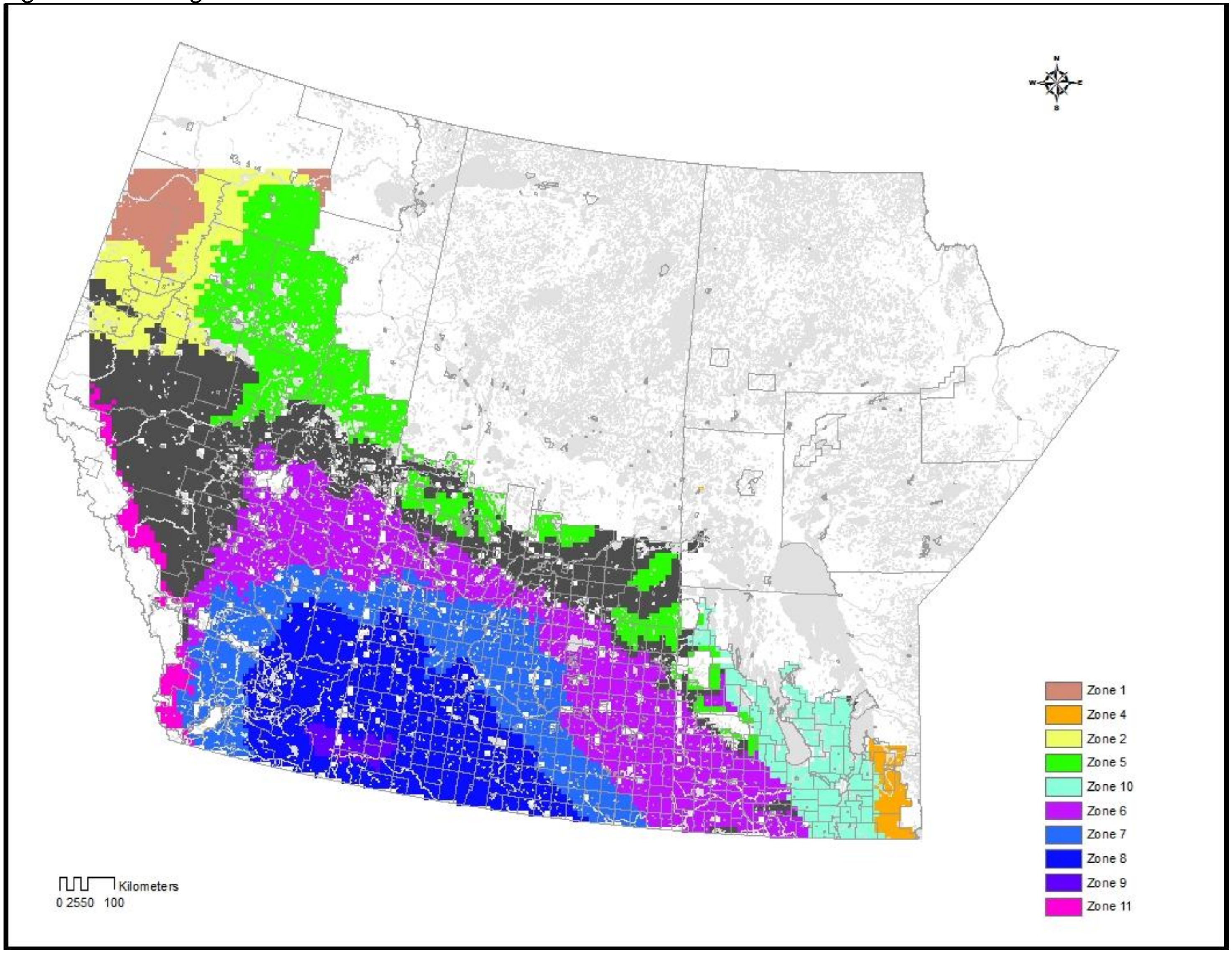
[13] Each "run" takes approximately 2.5 hours per loop. To calculate annual yield estimates for a 40 year time horizon would take approximately 25 hours.

Table 5.2: Zones used in the study as defined by Eco-Regions

Zone	Number of cells	Proxy for soil zone	Eco-region number	Eco-region name
Zone 1	233	Grey	137	Clear Hills Upland
			136	Slave River Lowland
			64	Northern Alberta Uplands
Zone 2	460	Grey	138	Peace Lowland
Zone 3	1757	Black	45	Maguse River Upland
			65	Northern Alberta Uplands
			69	Tazin Lake Upland
			70	Kazan River Upland
			71	Selwyn Lake Upland
			87	Athabasca Plain
			89	Hayes River Upland
			143	Western Boreal
			145	Western Alberta Upland
			148	Mid-Boreal Lowland
			149	Boreal Transition
			163	Southwest Manitoba Uplands
			215	Coastal Hudson Bay Lowland
			216	Hudson Bay Lowland
Zone 4	87	Black	88	Churchill River Upland
			90	Lac Seul Upland
			91	Lake of the Woods
Zone 5	922	Brown	142	Wabasca Lowland
			139	Mid-Boreal Uplands
Zone 6	1640	Black	156	Aspen Parkland
Zone 7	1063	Dark Brown	157	Moist Mixed Grassland
			158	Fescue Grassland
Zone 8	1284	Brown	159	Mixed Grassland
Zone 9	77	Dark Brown	160	Cypress Upland
Zone 10	466	Black	155	Interlake Plain
			162	Lake Manitoba Plain

(Source: adapted from AAFC 2011b)

Figure 5.5: Eco-regions of the Canadian Prairies



Source: adapted from AAFC 2011b.

5.2.3 Estimating Yield: Temperature Coefficients

Chapter 3 outlines the model that generates the coefficients used to calculate the yield from the adjusted rainfall and temperature draws described above. The process of calculating yields from all 41 temperature variables (as specified in Model 1 in Chapter 3) proved to be a time consuming process for all 7,727 cells with temperature data over 141 days in the growing season. As well, the data in Model 1 show signs of colinearity in the variables in the range of 35 ºC and higher, as well as in the lower temperature ranges below 5 °C. A decision was made to use a version of Model 1 with fewer coefficients, which reduced computation time from ~ 5 hours per loop to ~ 2.5 hours per loop by aggregating the temperature observations into fewer temperature buckets, which simultaneously address colinearity issues encountered in Chapters 3 and 4. In other words, a simplified version of Model 1 from Chapter 3 is used.

The model used to estimate yield is shown below in Equation 5.3. Hours of exposure to temperatures from 0 to 5 ºC are in the first ***TEMP*** variable. Exposure to hours between 6 and 8 ºC up to 33 to 35 ºC are in three-degree "buckets," and all hours of exposure to temperatures over 36 ºC are in a final bucket. The total number of temperature coefficients in the ***TEMP*** vector is thus reduced from 41 down to 12. Daily rainfall estimates in the vector ***RAIN*** are aggregated monthly, as per the Model 1 specification; there are, therefore, five variables in this vector. Various specifications for the time trend are tested; Model 1 from Chapter 3 resulted in highly elevated yield estimates by 2050 for a variety of crops. The model used here is tested with various time trends specified as T, T^2, T^3 and T^4, or no time trend, in isolation or in combination, to determine which specification produces the most stable yield forecasts, defined as those that do not tend towards zero or above 10,000 kg/ha and above over time. Equation 5.3 shows the model as used for canola, spring wheat, oats, barley, and flax. For durum, winter wheat and fall rye, where any time trend resulted in highly distorted yield forecasts, the time trend was dropped. These models are run with no time trend. Regardless of the time trend variant used, all yield forecasts trended to values that were either extremely high (in the 100,000s of kg/ha) or extremely low (10s of kg/ha) for all crops if modeled past 2050. The final models were run for $t = 2011 \ldots 2050$ for all crops to prevent these unrealistic yield estimates from affecting the results. The coefficients estimated using the model specifications shown above are shown in Table 5.2.

Table 5.2: Estimated Coefficients for the Crop Yield Models

	WWHT		SPRWHT		DURUM		CANOLA		FLAX	
CONSTANT	7.6014	***	6.4353	***	5.5977	***	4.8642	***	4.9143	***
TIME	NA		0.00875	***	NA		0.00994	***	0.00987	***
APRRAIN	0.00278	***	0.00068	***	0.00102	***	-0.00029		-0.00023	
MAYRAIN	0.00233	***	0.00097	***	0.00156	***	0.00060	***	0.00059	***
JUNRAIN	0.00095	***	0.00109	***	0.00235	***	0.00115	***	0.00113	***
JULRAIN	-0.00099	***	0.00018	***	0.00137	***	0.00131	***	0.00130	***
AUGRAIN	-0.00077	***	-0.00105	***	-0.00124	***	-0.00087	***	-0.00087	***
DEG0_5	0.00020		0.00028	***	0.00093	***	0.00046	***	0.00045	***
DEG6_8	-0.00051	**	0.00017	**	-0.00004		0.00023		0.00021	
DEG9_11	0.00101	***	0.00054	***	0.00098	***	0.00067	***	0.00063	***
DEG12_14	-0.00055	**	0.00049	***	0.00071	***	0.00059	***	0.00054	***
DEG15_17	0.00046	**	0.00029	***	0.00077	***	0.00063	***	0.00063	***
DEG18_20	0.00017		0.00023	***	0.00054	***	0.00052	***	0.00057	***
DEG21_23	-0.00036		0.00026	***	0.00053	***	0.00058	***	0.00057	***
DEG24_26	-0.00072		0.00034	***	0.00035	**	0.00063	***	0.00061	***
DEG27_29	-0.00036		0.00017		0.00008		0.00107	***	0.00100	***
DEG30_32	-0.00058		-0.00059	***	0.00013		-0.00015		-0.00021	
DEG33_35	-0.00085		-0.00334	***	-0.00138	***	-0.00231	***	-0.00230	***
DEG36P	0.00206	**	-0.00045		0.00025		-0.00087	*	-0.00087	*
ADJUSTED R2	**0.4838**		**0.4114**		**0.3898**		**0.2983**		**0.2994**	
NUM OBS	**1934**		**12,333**		**5,600**		**7,755**		**7,755**	

	FALLRYE		BARLEY		OATS	
CONSTANT	6.2196	***	6.2124		6.0194	***
TIME	NA		0.01017		0.00878	***
APRRAIN	0.00118	***	-0.00006		0.00023	
MAYRAIN	0.00259	***	0.00017		0.00073	***
JUNRAIN	0.00175	***	0.00042		0.00121	***
JULRAIN	0.00055	***	0.00047		0.00095	***
AUGRAIN	-0.00147	***	-0.00108		-0.00095	***
DEG0_5	0.00042	***	0.00042	***	0.00038	***
DEG6_8	0.00037	**	0.00033	***	0.00000	
DEG9_11	0.00024		0.00076	***	0.00085	***
DEG12_14	0.00057	***	0.00056	***	0.00057	***
DEG15_17	0.00048	***	0.00048	***	0.00055	***
DEG18_20	0.00015		0.00050	***	0.00039	***
DEG21_23	-0.00013		0.00055	***	0.00042	***
DEG24_26	-0.00027		0.00060	***	0.00037	***
DEG27_29	0.00096	***	-0.00020		-0.00040	**
DEG30_32	0.00011		-0.00064	***	-0.00112	***
DEG33_35	-0.00213	***	-0.00288	***	-0.00322	***
DEG36P	-0.00144	***	-0.00007		0.00048	
ADJUSTED R2	**0.3220**		**0.3651**		**0.3932**	
NUM OBS	**4,667**		**12,580**		**12,335**	

*** significant at 1 %
** significant at 5%
* significant at 10%

Table 5.2 Continued

Where:

TIME	a time trend variable
APRRAIN	Total simulated rain in April in mm
MAYRAIN	Total simulated rain in May in mm
JUNRAIN	Total simulated rain in June in mm
JULRAIN	Total simulated rain in July in mm
AUGRAIN	Total simulated rain in August in mm
DEG0_5	Total hours of exposure to degrees 0.0 to 5.9 ºC from April 15 to August 30
DEG6_8	Total hours of exposure to degrees 6.0 to 8.9 ºC from April 15 to August 30
DEG9_11 etc	as DEG6_8

$$\hat{Y}_{itr} = \alpha_i + \boldsymbol{\beta_i TEMP_{rt}} + \boldsymbol{\delta_i RAIN_{rt}} + \vartheta T_i + \boldsymbol{\gamma D_j} + \epsilon_i \quad [5.3]$$

One potential problem that may arise from the process to generate the coefficients listed above stems from the fact that each of these crops is responding to the same climatic shocks. Therefore, the error terms between the models should be correlated. Running the models independently, as was done, does not account for this correlation in the error terms. An unbalanced panel model or a seemingly unrelated regression (SUR) approach can address the issue, but neither approach was practical given the size of the dataset and the fact that each crop yield estimate is based on a different subset of the total climate observations. Thus, it is possible these yield estimates are uncorrelated when the empirical observations would be correlated, leading to distortion in the results. It is important to be aware of this potential issue when interpreting the output of the model.

5.2.4 Calculating Gross Margins

The process described above allows for the calculation of the total monthly rainfall in each cell, and the total number of hours the crop was exposed to each 3ºC increment in temperature. The model parameters derived as noted above, are then used to estimate yields for winter wheat, spring wheat, durum, barley, oats, canola, flax, and fall rye. Spring rye is excluded because the crop is the smallest of those modeled previously in terms of acreage. As noted in Chapter 3, the small size of the dataset used in the analysis meant that the results of the model developed are less “reliable” in a statistical context.

Gross margin per ha for each crop are calculated using the yield estimates calculated as described above, and average output prices from 2005 to 2010. Thus, the assumption is made that relative prices are held constant. Prices used are shown in Table 5.3 and were taken from the Statistics Canada database and adjusted for inflation using the CPI for 2010.

Table 5.3 Average crop output prices, 2005 to 2010 ($/1000 kg, real values 2010)

	Winter Wheat	Spring Wheat	Durum	Canola	Flax
Alberta	196.37	227.00	364.73	382.40	144.47
Saskatchewan	185.94	222.30	363.88	395.79	142.54
Manitoba	201.94	215.26	362.32	399.87	156.94

	Rye	Barley	Oats
Alberta	135.62	143.43	196.37
Saskatchewan	125.45	139.94	185.94
Manitoba	129.50	155.16	201.94

Source: Statistics Canada 2010b.

Table 5.4: Average Input Variable Costs by Zone for 2010 ($/ha, real values 2010)

ZONE	WWHT	SPRWHT	DURUM	CANOLA	FLAX
Zone 1	256.24	284.78	284.78	301.47	252.50
Zone 2	256.24	284.78	284.78	301.47	256.24
Zone 3	382.95	345.73	414.43	408.51	297.29
Zone 4	382.95	345.73	414.43	408.51	297.29
Zone 5	192.37	234.47	240.66	245.50	278.96
Zone 6	382.95	345.73	414.43	408.51	297.29
Zone 7	221.83	266.75	271.72	347.44	267.62
Zone 8	192.37	234.47	240.66	245.50	278.96
Zone 9	221.83	266.75	271.72	347.44	267.62
Zone 10	382.95	345.73	414.43	408.51	297.29

ZONE	FRYE	BARLEY	OATS
Zone 1	170.87	275.54	237.93
Zone 2	170.87	275.54	237.93
Zone 3	255.36	312.33	287.29
Zone 4	255.36	312.33	287.29
Zone 5	140.68	221.93	195.89
Zone 6	255.36	312.33	287.29
Zone 7	160.05	259.04	222.87
Zone 8	140.68	221.93	195.89
Zone 9	160.05	259.04	222.87
Zone 10	255.36	312.33	287.29

(Sources: listed below)

Table 5.4 shows a summary of the input costs used in the model. Manitoba produces input cost estimates for all eight crops (Manitoba Ministry of Agriculture, Food and Rural Affairs 2011) for eastern and western Manitoba, both in the black soil zone. Saskatchewan produces input costs for winter wheat for all soil zones and for spring wheat, durum, barley, oats, flax, canola, grown in the black, brown and dark brown soil zones (which correspond roughly to Zone 8 (brown), Zone 7 (dark brown) and Zones 3 and 6 (black) (Saskatchewan Ministry of Agriculture 2008). Note that no input costs for fall rye are available for Saskatchewan. Alberta provides input costs by crop and by soil zone, but does not include every crop in every soil zone (Alberta Agriculture and Rural Develop-ment 2011).

Table 5.2 shows the soil zones that correspond approximately to each of the ten zones defined for the analysis. However, values for certain specific crops for certain soil zones were not available. To obtain these missing data, the following process was followed. Data for spring wheat were available for every zone for each province and were thus used as the base for the calculation. For each soil zone, input costs are calculated as a percentage of the input cost for spring wheat. First, the average value of the input costs for available soil zones is calculated for each crop. This ratio of this value divided by the input costs for wheat in this soil zone, *p*, is calculated. This value is used to generate the value of the input cost for crop X in the each soil zone such that the input cost is equal to (*p* x *input costs* for wheat).

The final gross margin (π) calculation for crop *i* in year *t* for cell *r* is shown in Equation 5.4, below. Yields are measured in kg/ha, which multiplied by output price in $/kg produces gross revenues in $/ha. From these are subtracted input costs in $/ha for the final gross margin estimate for each crop for each cell.

$$\pi_{itr} = (\frac{\$_P}{kg_{itr}} x \ \frac{kg_{itr}}{ha}) - \frac{\$_C}{ha} \qquad [5.4]$$

5.2.5 Incorporating Climate Change

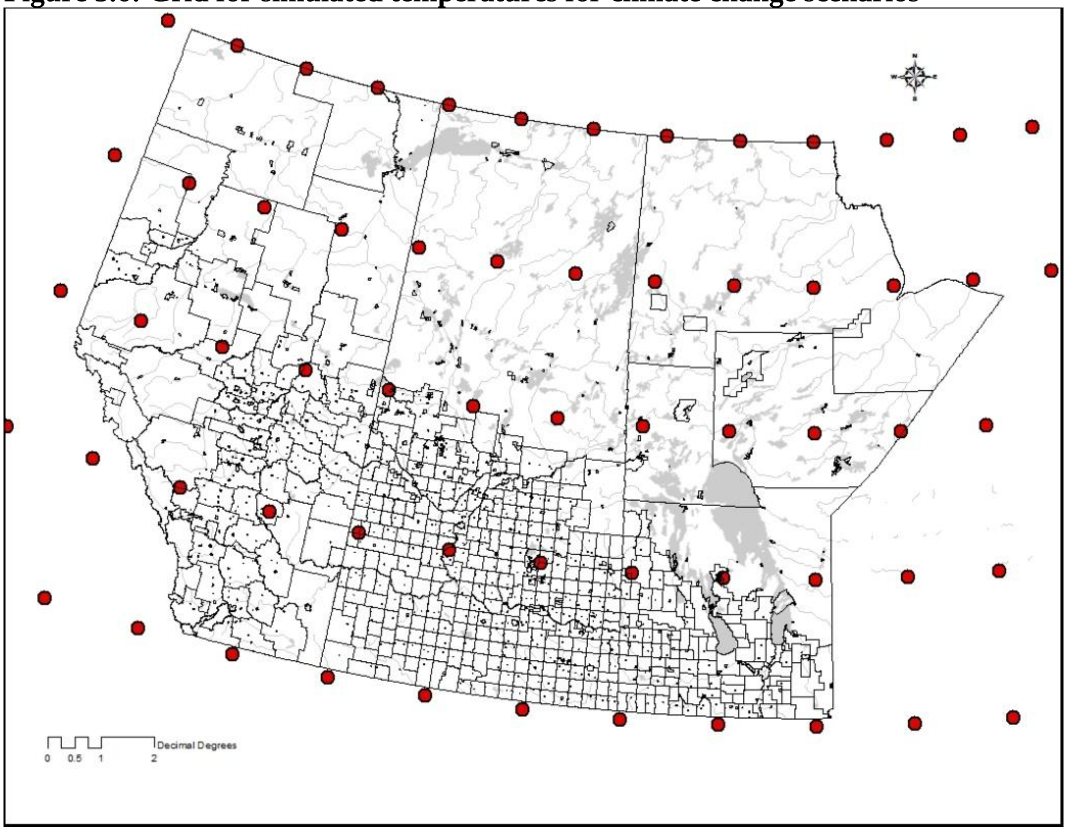
This section describes the methods used to incorporate the estimated impact of climate change on the average temperatures used in the model. The Canadian Regional Climate Model (CRCM) V4.2 monthly data (aet run) has been generated and supplied by the Ouranos Climate Simulation Team via the Canadian Centre for Climate Modeling and Analysis (CCCma)'s data distribution Web page (Canadian Centre for Climate Modeling and Analysis 2010). The data available for this model are monthly average minimum and maximum temperatures and a monthly average value for daily rainfall for 1961 to 2100. The values for of 1961 – 1990 are observed data during this period. Two climate change scenarios that are available are the B1, and A1B scenarios, described below. These are standard scenarios used in climate change modeling around the world and have well known implications for relative emissions and shifts in temperature among climate change modellers.

The B1 scenario describes a future with the least amount of emissions and minimum temperature shifts. It represents a future with a high level of environmental and social consciousness combined with a globally coherent approach to a more sustainable development. The B1 scenario assumes increases in emissions from emissions observed in the base period, but is the lowest estimate of the increases that may occur. A1B is the scenario with the highest emissions, and thus the highest levels of temperature shifts. In this scenario, the current distinctions between "poor" and "rich" countries eventually dissolve. There is a strong commitment to market-based solutions but no single source of energy is dominant. Appendix J shows snapshots of the changes to daily maximum temperature, minimum temperature and rainfall for July in 2025 and 2050. Average daily maximum temperatures rise as much as 10 ºC across the region with scenario A1B, and daily rainfall for July falls as much as 2 mm per day in the central regions but could go up as much as 0.55 mm per day in the south-eastern corners of Manitoba and in the mountains.

The data are provided for a grid across the landscape, as shown in Figure 5.6. In a process that mirrors the production of the daily variable maps, maps were produced for each monthly value (in the growing season) for each variable for the full base period from 1961 to 1990 (5 months x 30 years x 3 variables = 450 maps) and again from 2011 to 2050 (5 months x 40 years x 3 variables = 600 maps). However, the exercise discussed in Section 5.3.1 produced daily average and variance values from which the independent draws were taken, and the process described here produced monthly average values only. The monthly shock to the average maximum temperature for 2011 was calculated as the monthly value for 2011 less the average value for that month in the base period. Thus, the shock due to climate change for maximum temperature for April 2011 was the predicted average maximum temperature for April 2011 minus the average maximum temperature for April from 1961 to 1990.

For each climate change scenario, the daily average variable values were adjusted using the shock generated for the appropriate month. Thus, if for 2011, in scenario A1B, the predicted increase in average value for a particular cell is 2.3 ºC for the month of May, then the average daily maximum temperature value for each day in May was increased by 2.3 ºC for that cell. The daily values for each month in each year of the simulation were adjusted according to the change in the average value for that month for that year. This process was repeated for the minimum temperature and rainfall variables. Note that there are no changes made to climate variable variances as there are no simulation forecasts on these data in any of the standard climate forecast models from which the changes to average temperature were drawn. The result is a new daily average and original variance from which to take daily climate draws for temperature and rainfall variables. These new daily averages change for each year of the climate scenarios. Examples of the shocks to the average value used in the model for each scenario are found in Appendix J.

Figure 5.6: Grid for simulated temperatures for climate change scenarios



5.3 The Dynamic Linear Programming Model

The Schlenker and Roberts (2006, 2008) approach to estimating economic impacts from climate change introduced a new and improved method for incorporating climate variables into production function estimations. The production function approach to estimating economic impacts of climate change does not allow for any substitution between crops; this is the main critique of the production function approach. The usual approach to estimating economic impacts of climate change on agriculture has been to aggregate changes in land values across the landscape with a hedonic model or to aggregate changes in the value of production with a production function approach. The model described here simulates substitution effects between the crops modeled using a linear programming simulation approach by simulating supply responses to climate change. It does not incorporate the option of land moving in or out of crop production[14], or land moving from crop production to livestock grazing (or vice versa), or land shifting between agriculture and alternative land uses such as urban development, forestry or mining. The model does not incorporate the possibility of different crops, such as drought tolerant canary seed, chick peas, lentils and dry field peas, being grown much more widely in the region. Neither does it include price effects. It can, however, given these constraints, allow an estimation of the effects of climate change on producer surplus.

The model is described below in Equation 5.6 to 5.12, with explanations below.

$$Max \sum_i \ [((\bar{P}_{ip} * \hat{Y}_{itr}) - C_{iz}) * HA_{itj}], \forall\, j \qquad [5.5]$$

Subject to:

$$\sum_i HA_{itrj} \ \leq 10{,}000, \ \forall\, r \qquad [5.6]$$

$$\sum_r \sum_i HA_{irtj} \leq CA_j\,, \ \forall\, j \qquad [5.7]$$

$$if \ \sum_i HA_{ir2005} = 0 \ \ then\, HA_{irt} = 0\, for\; t > 2005, \ \ \forall\, r \qquad [5.8]$$

For $\boldsymbol{t} \ \leq \mathbf{2006}$;

$$\sum_i HA_{irtj} \leq \sum_i (CA_{ij} * \left(1 + c_{ip}\right)), \forall\, j \qquad [5.9a]$$

$$\sum_i HA_{irtj} \geq \sum_i (CA_{ij} * (\tfrac{1}{1+c_{ip}})), \forall\, j \qquad [5.10a]$$

For $\boldsymbol{t} \ \geq \mathbf{2006}$:

$$\sum_i HA_{ijt} \leq \sum_i (HA_{ijt-1} * \left(1 + c_{ip}\right)), \forall\, j \qquad [5.9b]$$

$$\sum_i HA_{ijt} \geq \sum_i (HA_{ijt-1} * (\tfrac{1}{1+c_{ip}})), \forall\, j \qquad [5.10b]$$

Variables

HA hectares

[14] This assumption does not preclude the model from leaving crop land idle.

Parameters

$\bar{P}$	mean price, 2005 to 2010
$\hat{Y}$	estimated yields in kg per ha
C	input costs
CA	hectares of land recorded under the 206 Canadian Census of Agriculture for each crop
c	coefficient of variation of historical acreage from 1961 to 1990
HA_{it-n}	land allocations for crop *i* in years *t-n* become parameter values in the dynamic restrictions

Subscripts

t	year
j	district
i	crops in the choice set
p	province
z	zone
r, *q*	cells in the grid
n	lagged number of years

Equation 5.5 is the objective function, in which the model maximizes gross margins from crop production for each district *j* by choosing the number of hectares to allocate to each crop *i* where $i = 1 \ldots 8$, for year *t*. Each district has R_j cells, and crops are allocated to cells $r_j = 1 \ldots R_j$. Equation 5.6 restricts the total crop land in each cell *r* in year *t* for all crops *i* to 10,000 ha, which is the physical limit of the size of the cell at 10 km^2. Equation 5.7 restricts the total crop land in each district *j* for year *t* for all crops *i* to the amount specified in the 2006 Census of Agriculture. The census total for 2006 includes all crops, including these not modeled here. Thus, the model should over-predict acreage for all crops in the first five years of the model to expand the production to include lands on which crops not included in the model were grown. These include fallow land, hay, dried field peas, corn, soybeans, switch grass, canary seed, potatoes, and other crops that are currently only grown in specific regions of the study area.

Equation 5.8 is a restriction to prevent cropland from rotating between cells. The assumption is made that the best available croplands are chosen in *t* = 2005, and the remaining lands are allocated to other uses including forestry, livestock grazing, etc. Costs of transitioning between land-use categories are assumed to be prohibitive. Thus, in the first iteration of the model, 2005, the best croplands are used to optimize the model. Restriction 5.9 ensures that the subset of all possible agricultural land that is chosen in the first iteration is held constant throughout the modeling period. If the sum of the land allocated to all crops *i* in cell *r* is zero in 2005, then the yields for all crops in cell *r* for *t* >

2005 are assumed to be 0. Effectively, no new cells can move into crop production for the duration of the simulation once they have been chosen in the first year of production. While acreages could have been set to zero, it was simpler to incorporate the values of the restriction into the restriction matrix to set yield equal to zero instead.

Equation 5.9 and 5.10 are dynamic restrictions that limit the land base for a given crop from moving more than one coefficient of variation away (+/-) from the previous year's total land base per crop. The coefficient of variation is the ratio of the standard deviation of acreage over the average acreage. If the coefficient of variation is 0.5, then acreage of the crop can fluctuate between 1.5 times the acreage of the previous year and 1/1.5 =0.666 of the previous year's acreage. The coefficient of variation is chosen instead of the variance of acreage because it provides parameters in percentage terms rather than absolute values terms. The equations produce upper and lower bounds to the shifts in total production of crop i in district j from year t to year $t+1$. The coefficient of variation is between 0 and 1, so $(1+c)$ produces an upper bound that is c percent above the acreage in $t-1$, where $(1/1+c)$ is always less than 1, and produces a lower bound that is that is c percent below the acreage in $t-1$.

The use of the coefficient of variation means that the size of the shifts are comparable between crops, which have total acreages and shifts in absolute value of acreage at very different scales. Version 5.9a and 5.10a are used for the first two years of the model (t = 2005, 2006), in which total acreage for crop i in district j must be within one coefficient of variation from the total recorded acreage for crop i for district j in the 2006 Census of Agriculture. Versions 5.9b and 5.10b are used for t > 2006, where the total land in crop i for district j for year t cannot move more than one coefficient of variation above or below the total land in crop i for district j for year $t-1$.

A single iteration of the model contains individual optimizations for $j = 1 \ldots 474$, as there are 474 districts in the final model. The model is run from 2005 to 2010, and then validated against observed data for that period. The validated model is then run from 2005 to 2050 for a total of 46 repetitions of the entire model for the base scenario (no climate change), for B1 (low emissions) and for A1B (high emissions). The model output for each year t is a table with the total allocation in ha for crop i in cell r.

5.3.1 Validating Model Output

In this section, the exercises used to validate the model outputs, and to calibrate the model inputs are outlined. The first task is to compare the estimated yields for each crop to the observed yields for those crops for 2005 to 2010. Empirical data are available for this period, and can be compared to estimated values produced by the model. Figure 5.7 shows the ratio of observed yields to estimated yields, each averaged over the 2005 to 2010 period for each crop. It is worth noting that the estimated values come from simulated temperature draws from the 1961 to 1990 base period and not on actual temperature observations from 2005 to 2010. Observed yields are, of course, a product of actual temperatures from 2005 to 2010 and not those of the whole base period. Therefore, some variation between observed yields and estimated yields is to be expected, although the inclusion of the time trend corrects for some of these variances. Winter wheat, durum and fall rye show observed average values that are approximately 50% of the

Figure 5.7: Ratio of observed/estimated average yields, 2005 to 2010

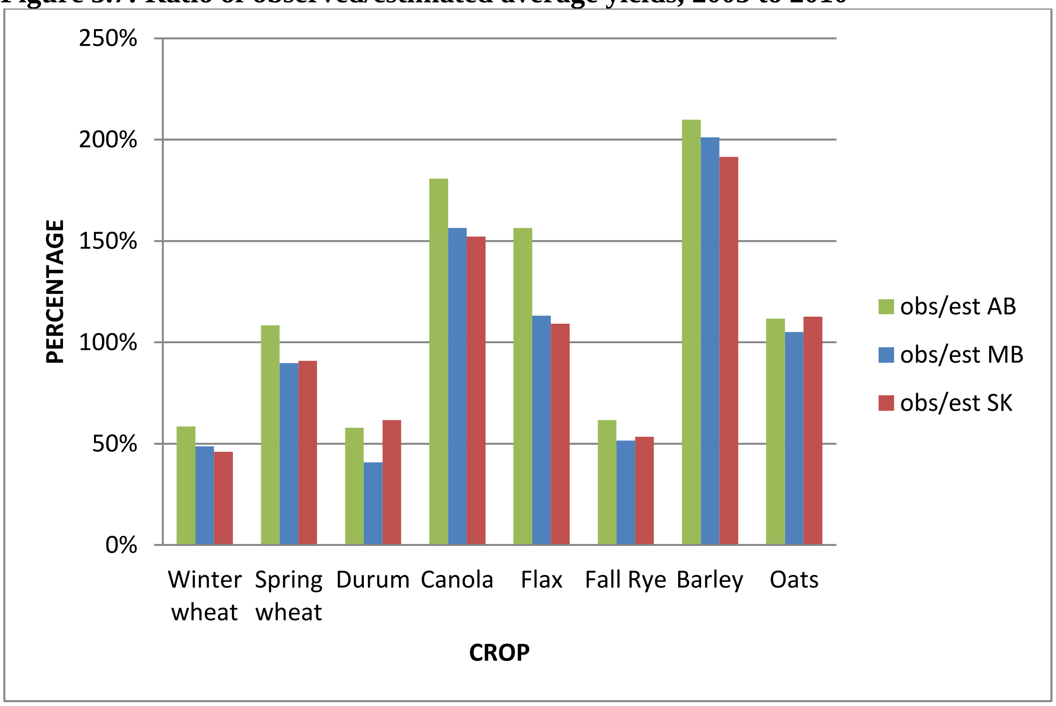
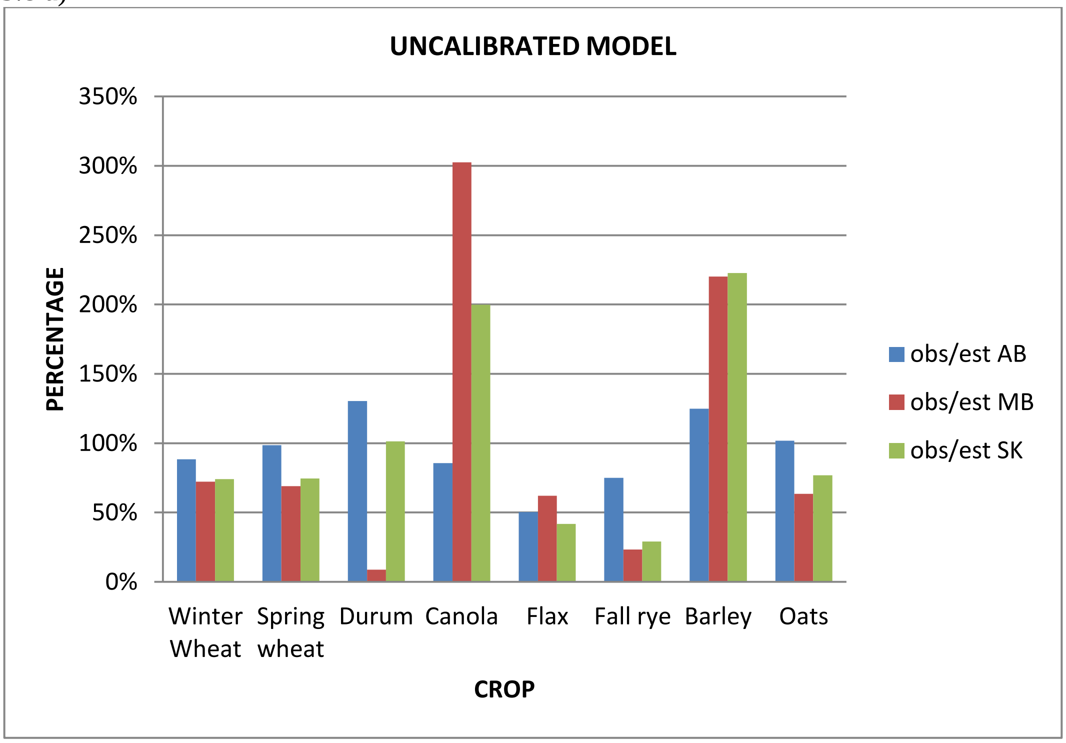
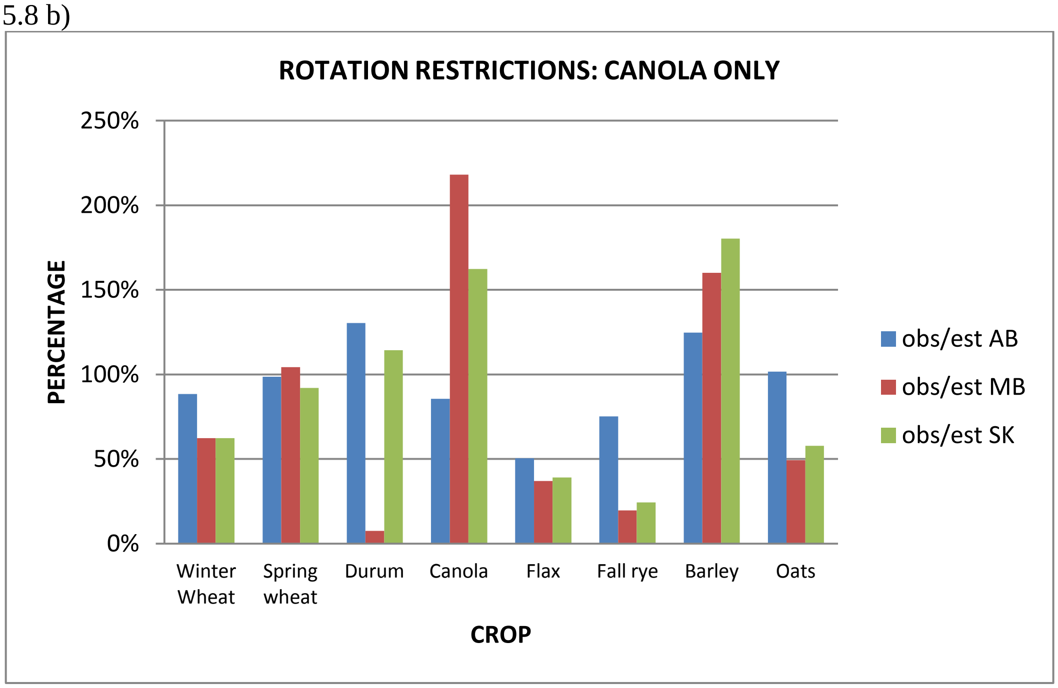


Figure 5.8: Ratio of observed to estimated percentage of total cropland for various forms of the LP model, averaged from 2005 to 2010

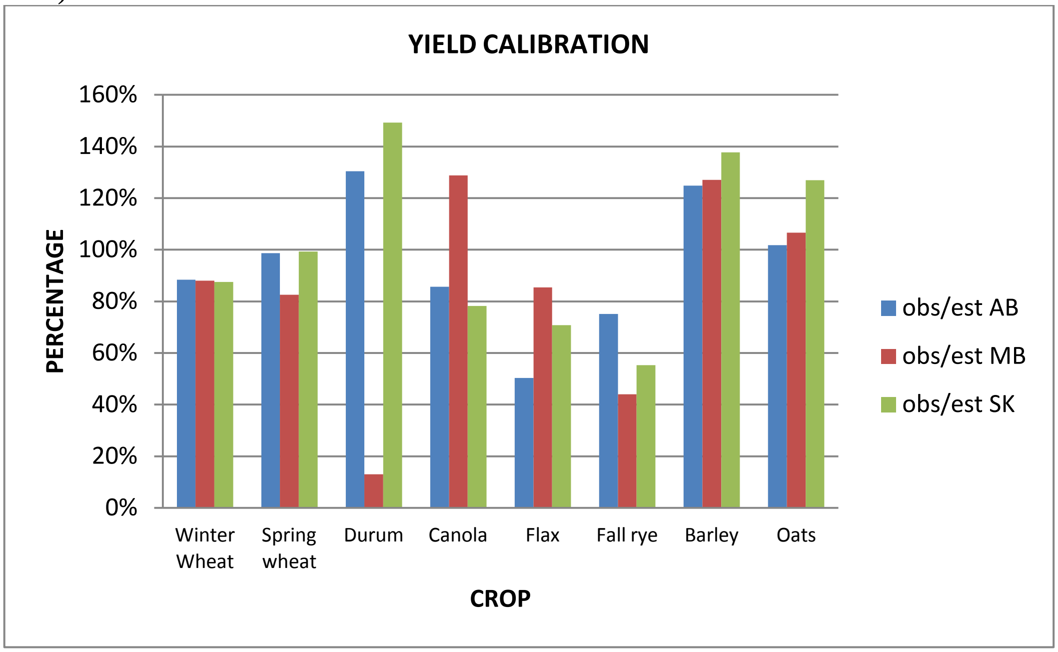
5.8 a)



5.8 b)



5.8 c)



estimated averages, while observed average canola yields are about 150% of the estimated yields. Barley shows observed average values that are almost 200 % of the estimated average value. The ratios of observed yields to estimated yields are fairly consistent between provinces, with observed yields in Alberta, in general, higher than those of the other two provinces in the simulation. It is worth noting that these results are likely highly sensitive to output prices, discussed further below.

An uncalibrated version was compared to one in which a restriction was applied to simulate crop rotations such that canola could only be grown once every four years. This restriction was found to be too constricting to the model behaviour as the total amount of cropland in production decreased substantially, even without climate change. Figure 5.8b shows that this approach underestimates barley and canola, while underestimating winter wheat, flax, fall rye and oats.

A version was run in which no rotational restrictions applied but yields were adjusted by a factor determined by the ratio of observed to predicted yields, as shown in Figure 5.7. Model performance was compared using the ratio of observed to estimated percentage of total crop land for each crop, averaged from 2005 to 2010. The results are shown in Figure 5.8a through 5.8c, above. It is shown that the uncalibrated model produces estimates of land use that overestimates land allocations to flax and fall rye and underestimates those to canola and barley by as much as 300 % for canola in Manitoba.

The model that uses adjustments to the yield estimates produces the land use allocation patterns that are, in aggregate, closest to the observed values. The calibration that produced the best result was one in which yield adjustments were made, by multiplying the yields by the adjustment factor shown in Table 5.4. These adjustment factors are based on the ratio of observed to estimated yield as discussed above in Figure 5.7. For example, the observed over estimated ratio of canola yields is approximately 140%, so a yield adjustment factor of 1.4 is applied to the estimated yield to align it more closely with observed yields.

Aggregate results for the study region are shown in Figures 5.9-5.10 for the uncalibrated model versus the calibrated version. Note that total acreage increases and then stabilizes. This is because the model does not incorporate crops other than the eight modeled but the land base in the cells selected is larger than is needed to allocate sufficient land for these specific crops. Thus, the model adds more land to the defined land base until all available land in the selected cells is in use for the modeled crops. Flax and fall rye are still over-represented, but by a smaller margin. Canola is still under-represented, but again, by a smaller margin.

Table 5.5: Adjustment factors by crop to calibrate the model as the approximate ratio of observed / estimated crop yields from 2005 to 2010

CROP	YIELD ADJUSTMENT FACTOR
Canola	1.4
Barley	1.8
Durum	0.6
Winter Wheat	0.6
Fall Rye	0.6
Oats	N/A
Flax	N/A
Spring Wheat	N/A

Figure 5.9: Total acreage of all crops, base scenario with yields calibrated as per Table 5.4

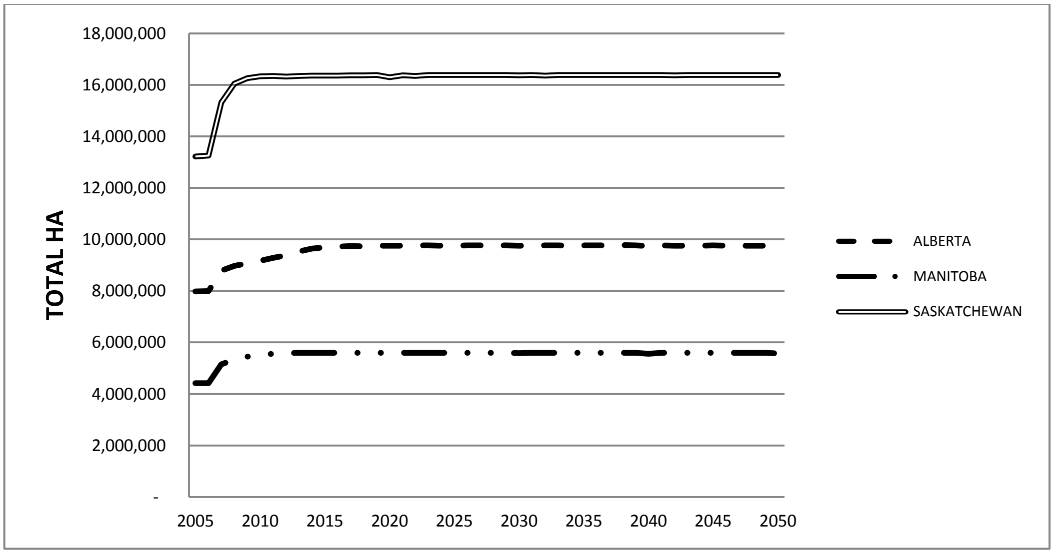
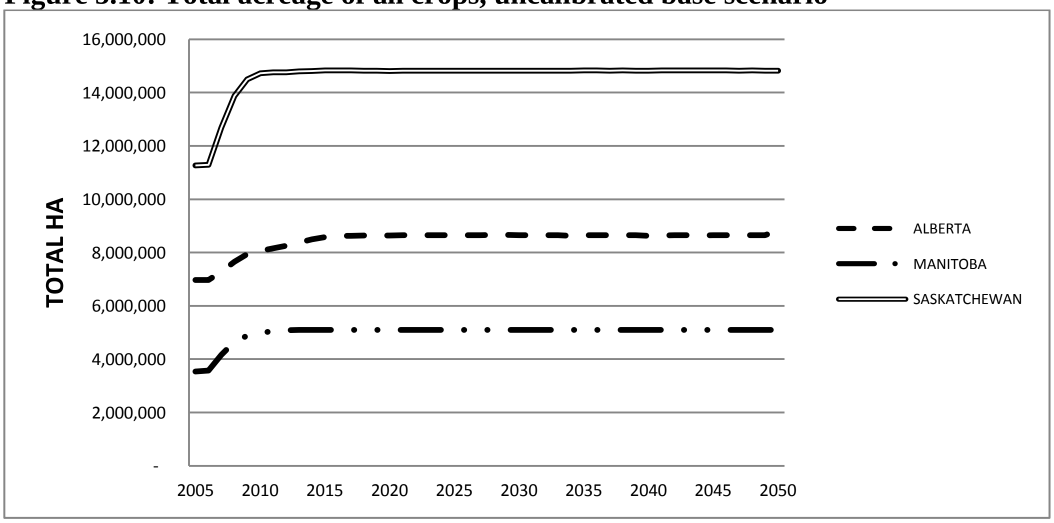


Figure 5.10: Total acreage of all crops, uncalibrated base scenario



5.4 Results

Aggregate results are presented first, which allow an overview of trends in crop production that affect all districts and regions. Following this, spatial shifts in production are reviewed. This is followed by a discussion of the results in relationship to the model specifications and parameters and contextualization of output.

5.4.1 Aggregate Results

Figures 5.11 to 5.13 show aggregate crop allocations under each model using the calibrated model. The base model, shown in Figure 5.11 and Table 5.5, produces an agricultural landscape that is dominated by canola and wheat, although it is winter wheat rather than spring wheat that is chosen. Otherwise, there are no major fluctuations of acreage over time.

Aggregate results for scenario B1 are shown in Figure 5.12 and Table 5.5. B1 is the climate change scenario with the lowest level of emissions increases, and lowest estimated temperature shifts. In this scenario canola and winter wheat acreages increase. Given that the base model overestimates winter wheat, acreage for this crop is likely overstated here as well. The biggest change from the base scenario is the increase in winter wheat acreage in exchange for an almost equal drop in spring wheat acreage.

Table 5.5 and Figure 5.13 show the results for the A1B model, which constitutes the highest increases in emissions scenario. Here production of all crops falls immediately with the exception of winter wheat and barley. Over time the production of winter wheat also begins a gradual decline. However, winter wheat acreages do not approach those found in the B1 model or the base scenario. In the A1B scenario, acreages for all crops except winter wheat fall very quickly, and winter wheat begins a steady decline starting around 2035. However, acreages for barley begin a steady increase starting around 2025. This is likely due to a combination of warmer temperatures and lower rainfall. The A1B model shows dramatically different crop choices from the base model or the B1 model.

The A1B scenario constitutes the highest emissions modeled and thus the greatest increases in temperatures. While Scenario B1 shows no major changes in the land base chosen for the eight crops modeled compared to the base period of 2005 to 2010, Scenario A1B does. In Scenario A1B, there is a loss of approximately 6 million ha of land in Saskatchewan, 2 million in Manitoba and 1 million ha in Alberta (see Figure 5.16). This is likely due to major increases in temperature and decreases in precipitation, resulting in a lower gross margins for the crops modeled. Maps showing the distribution of the changes in rainfall and temperature are shown in Appendix J.

Figures 5.14 to 5.16 show the total land in agriculture from all crops modeled for each of the three provinces in the base scenario. In Figures 5.14 and 5.15, for the base model and scenario B1, total acreage increases by approximately 2 million ha. This is accounted for by the fact that the total agricultural land available in the model is greater than the sum of the land allocated to the eight crops modeled. However, in Figure 5.16, total acreage of land allocated to these eight crops falls between 2010 and the 2020s. Acreage then increases gradually; Figure 5.13 indicates this is due to an increase in barley acreage primarily.

Table 5.6: Total ha ('000s) by crop by scenario

YEAR BASE	Winter Wheat	Spring Wheat	Durum	Canola	Flax	Fall Rye	Barley	Oats	Total
2005	383	8,553	1,689	7,249	1,113	283	4,123	2,213	25,612
2010	1,054	9,913	2,267	12,389	982	559	2,507	1,349	31,020
2025	9,688	7,207	2,293	10,359	606	424	856	297	31,730
2050	8,858	5,505	1,126	14,116	512	281	1,044	263	31,705
B1	**Winter wheat**	**Spring Wheat**	**Durum**	**Canola**	**Flax**	**Fall Rye**	**Barley**	**Oats**	**Total**
2025	10,490	3,342	5,469	9,020	456	2,093	579	263	31,712
2050	18,040	1,539	2,244	8,339	434	414	478	219	31,707
A1B	**Winter wheat**	**Spring Wheat**	**Durum**	**Canola**	**Flax**	**Fall Rye**	**Barley**	**Oats**	**Total**
2025	4,711	1,416	476	209	247	206	2,796	252	10,313
2050	4,531	980	333	168	211	226	13,448	217	20,114

Figure 5.11: Aggregate annual land use allocations by crop, base model from 2005 to 2050

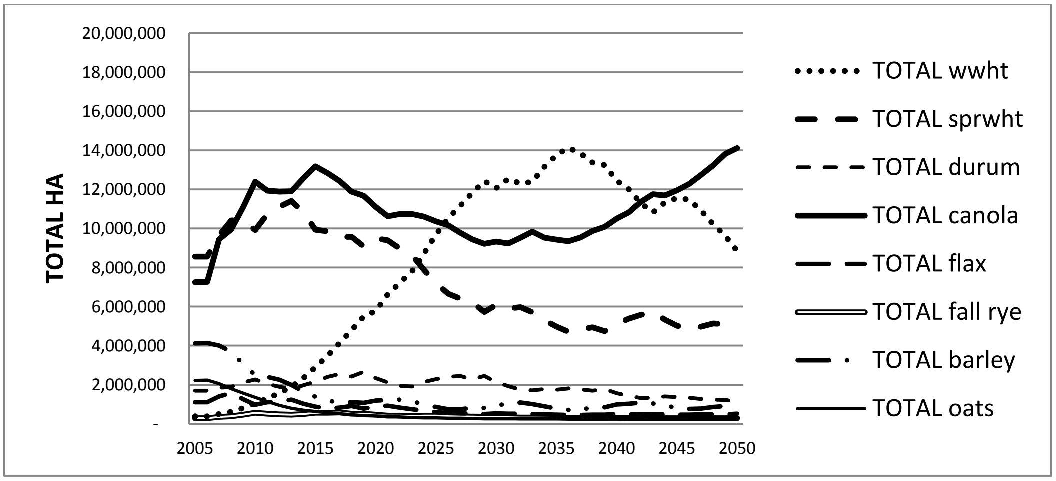


Figure 5.12: Aggregate annual land use allocations by crop, Scenario B1 (low emissions) from 2005 to 2050

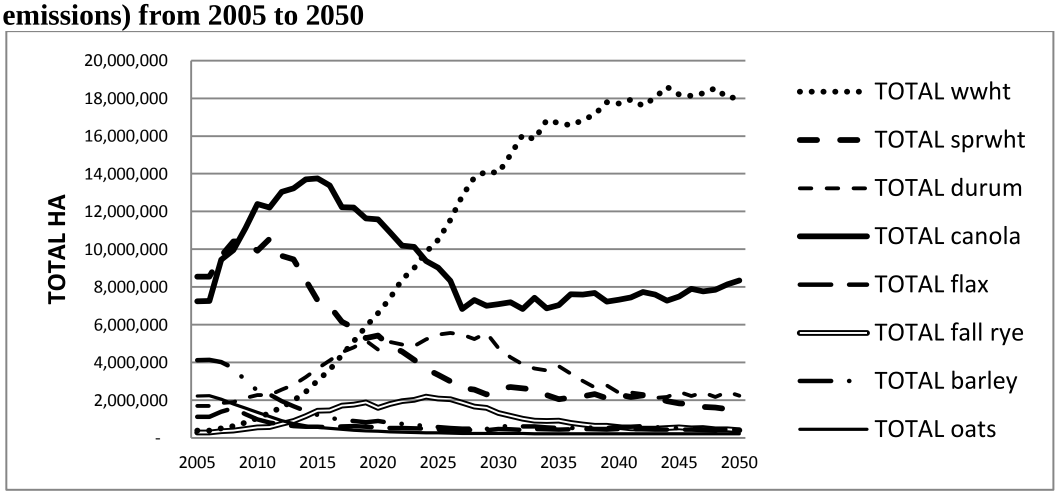


Figure 5.13: Aggregate annual land use allocations by crop, Scenario A1B (high emissions) from 2005 to 2050

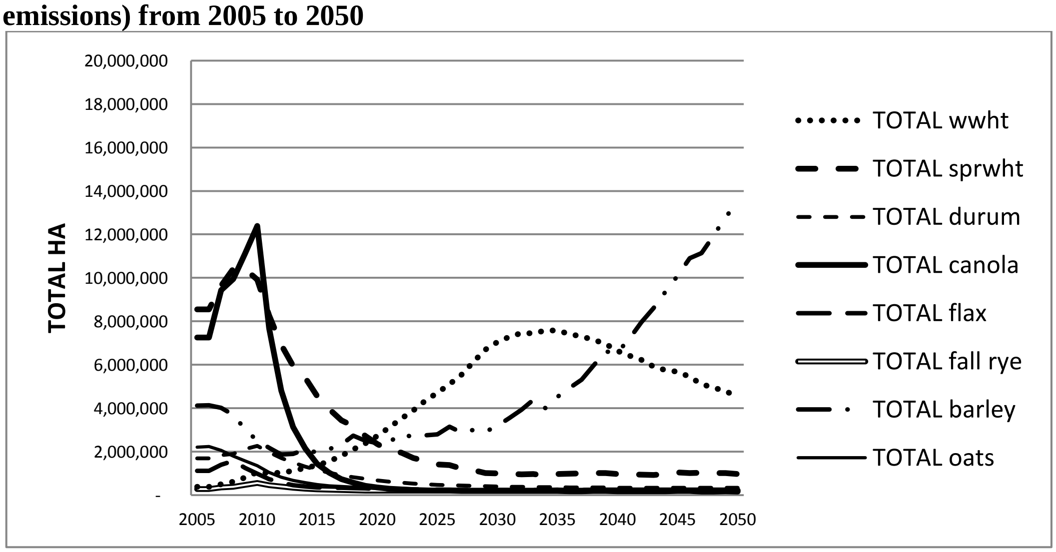


Figure 5.14: Total annual acreage by province, base model from 2005 to 2050

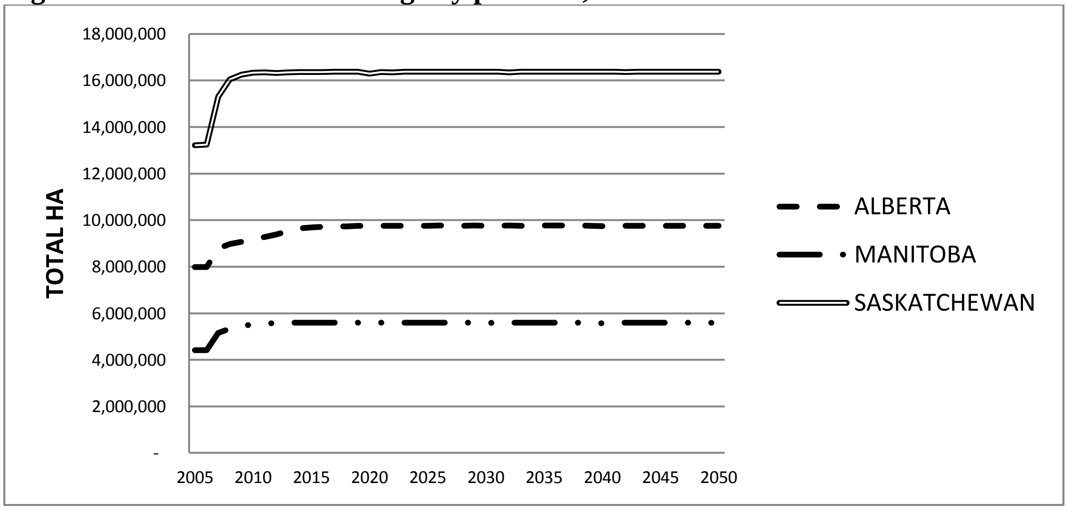


Figure 5.15: Total annual acreage by province, B1 scenario from 2005 to 2050

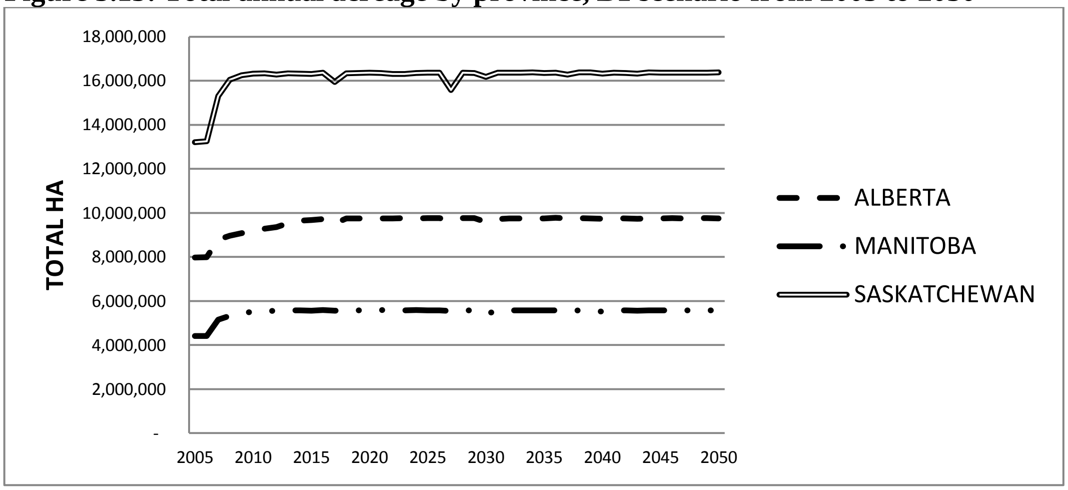
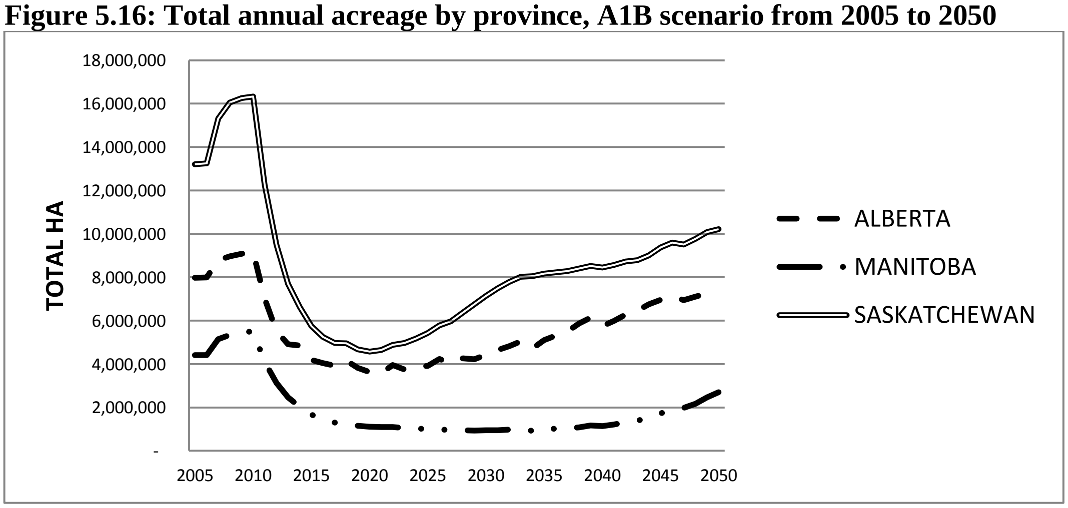


Figure 5.16: Total annual acreage by province, A1B scenario from 2005 to 2050



Figures 5.17 to 5.24 in Appendix G show that the distribution of crops around the region as observed for the years 2005 and 2010. Figure 5.19 shows the dominant crop choice in each cell, which is indicative of shifting land use patterns for the base model in 2010; the crop mix is very similar to the 2005 map shown in Figure 5.17, but with less canola overall than in 2005, largely dominated by spring wheat and durum, with some barley and oats. By 2025, shown in Figure 5.21, the spring wheat has been replaced by winter wheat, particularly in Manitoba whereas the south-west corner of Saskatchewan is largely growing durum. By 2050, shown in Figure 5.23 almost all the spring wheat has been replaced by winter wheat, as has some of the durum.

Figures 5.25 to 5.28 in Appendix H show the same maps for the B1 scenario. Figure H1 shows that for the B1 scenario, the dominant crop choices on the map for 2025 are primarily canola and some durum, particularly in the central regions of Saskatchewan. Small pockets in the southerly areas of Saskatchewan and Alberta show fall rye as well. By 2050, shown in Figure H3, winter wheat has become much more dominant throughout the region. Some durum remains in the central regions of Saskatchewan, and canola is found on the outer range of what is now the black soil zone.

Figures I1 to I4 in Appendix I shows the same information for the A1B scenario. In 2025, shown in Figure I1, the dominant crops are barley in the western regions of Saskatchewan, with spring wheat in the black soil zone. Manitoba has largely moved into winter wheat production with some spring wheat, and Alberta is largely dominated by barley with winter wheat in the south. By 2050, shown in Figure I3, the dominant crop has shifted to barley across the region although there is winter wheat found in the Grande Prairie region and interspersed in central Saskatchewan. These results may resemble the agricultural landscape found further south in the United States, in Kansas and other mid-west states where dryland agriculture is found.

It is noteworthy that the cropland in Alberta responds to heat and moisture stresses in the B1 scenario, but these conditions have a relatively minor impact on Saskatchewan and Manitoba. This is likely because Manitoba is predicted to see increases in daily rainfall along with increases in daily average temperatures, which will likely lead to improved growing conditions for many crops. Figure J1 through J2 show the changes in maximum temperature for Scenario B1 in 2025 and 2050. The maximum temperature in 2025 increases by up to 3.5 ºC in 2025 in the eastern and western portions of the province, while the average maximum temperature falls by up to 0.1 ºC in the central regions of Saskatchewan. Figure J2 and J3 show the changes in the average minimum temperature for July in 2025 and 2050 for Scenario B1. In 2025, the average daily minimum temperature in July rises by up to 8.5 ºC, while in 2050, the minimum temperature rises by up to 2.5 ºC. Saskatchewan is already a semi-arid region with rain-fed agriculture and many of the crops that are grown, in particular in the southern grey soil zone, are already fairly drought-tolerant. Figures J5 and J6 show the changes in rainfall for July for 2025 and 2050 for Scenario B1. In 2025, average daily rainfall falls by up to 2.1 mm throughout Saskatchewan and central Alberta, while increasing by up to 0.1 mm in Manitoba. By 2050, the average daily rainfall in July falls by up to 1.9 mm throughout the Saskatchewan and Alberta, while increasing up to 1.3 mm in Manitoba.

The effects of Scenario A1B on minimum and maximum temperature and rainfall for July in 2025 and 2050 are shown in Appendix J, Figures J7 and J8. Maximum temperature is expected to rise by up to 3.3 ºC in the southern parts of the study region, while falling by as much as 3.3 ºC in the northern regions and in Manitoba by 2025 (Figure J7). However, by 2050 the maximum temperature is expected to rise by up to 10.9 degrees across the region (Figure J8). Minimum temperature is expected to increase by up to 1.6 ºC throughout the region except in Manitoba, where it could fall as much as 1.2 ºC by 2025 (Figure J9). By 2050, the minimum temperature is expected to rise by up to 7.5 ºC across the region (Figure J10). Average daily rainfall in July of 2025 is expected to fall by up to 1.9 mm across the region, except for the far south east corner of Manitoba (Figure J11), while by 2050, the south east regions of Saskatchewan and Manitoba are anticipated to see a fall by 1.9 mm in the average daily rainfall, while the southern part of Alberta and the mountains may see increases by up to 0.55 mm per day.

The crops modeled generally migrate northwards, as described above, with low emissions climate change scenarios. However, the ongoing decreases in moisture become more wide-spread, including most of the Manitoba growing region by 2050 under the high emissions scenario, A1B. This trend, coupled with an increase in average temperatures in July of 10 °C are the most likely drivers of the geographical shifts in agricultural production in the area.

5.4.2 Impact of Climate Change on the Spatial Distribution of Crop Acreages

The most striking aspect of the spatial impact of climate change is that there is very little impact on the spatial distribution of the crops modeled, but rather that the total acreage allocated to most of these crops falls. Appendix G contains output maps showing concentrations of acreage for each crop for the base model for 2005, 2010, 2025 and 2050. Appendix H shows the results for each crop for 2025 and 2050 for scenario B1 and Appendix I shows the results for scenario A1B. These maps show that, for the most part, crops are grown in the same regions where they are currently found. The distributions of for each crop for 2005 in the base model are based on the 2006 Census of Agriculture and are therefore represent observed phenomena (Figures 5.17 and 5.18a-5.18h). However, a comparison with the output maps for the base model in 2010 (Figures 5.19 and 5.20a – 5.20h) does not reveal major differences in the distribution of crops across the landscape, although the concentrations have begun to shift. Durum and winter wheat, for example, are predicted to be produced in higher concentrations further west and north of their 2005 range, which for both are largely the southern parts of Saskatchewan.

Durum expands northwards into central Saskatchewan until changes in climatic variables push total acreage down. In the base scenario, durum acreage occurs largely in the south-eastern regions of Saskatchewan in the grey soil zone, although by 2010 it is showing higher concentrations in the brown zone (Figure 5.20c). The B1 scenario 2025 (Figures 5.25 and 5.26c) shows durum growing in higher concentrations throughout what is currently the black soil zone and in much lower concentrations in the grey soil zone. In 2050, the B1 scenario continues to show higher concentrations of durum in central Alberta, in the regions between Calgary and Edmonton, in particular (Figure 2.28c). In the A1B scenario, the highest concentrations of durum are to be found, once again, in the south-eastern regions of Saskatchewan (Figure I4c).

Flax is found primarily in the brown soil zones in the base model for 2005 and 2010, although the total flax acreage is falling (Figures G2e and G4e). However, under the low emissions scenario (B1), flax acreage has moved north into what is now the black soil zone by 2025 (Figure H2e). By 2050 (Figure H4e), in both climate change scenarios, total acreage has fallen but distribution has not changed from the B1 scenario in 2025.

5.4.3 Changes to Producer Surplus

Producer surplus is the difference between input costs and output prices at the margin, or the area above supply and below market price; gross margin is a calculation of this amount. Table 5.6 shows the total gross margins by crop by year by scenario for 2005, 2010, 2025 and 2050. All values are cited in Canadian dollars (CAD), at 2010 real levels. The base model predicts a rise in gross margins for agriculture in the Canadian Prairies by 2025, largely driven by an increase in the gross margin of winter wheat to just over $38 billion. However, by 2050, most of these benefits have disappeared, although agriculture has still increased overall from just under $3 billion to $15.3 billion.

The B1 model shows a total net value for agricultural production of $40 billion by 2025 driven by increases in winter wheat, durum, canola and fall rye. As with the base model, these gross margins are lower for 2050, at a total of $32 billion. The gains over 2005 stem from winter wheat valued at $26 billion, canola, valued at $2.3 billion and durum at $2.1 billion. This overall increase comes despite a decrease in gross margin of $1 billion from spring wheat. That the model shows negative gross margins for any of the crops for the entire region is indicative that restrictions on fluctuations in acreage for any given crop are binding; else these acreage values would be set to 0 to increase profits.

The A1B model shows a net gain for agriculture in 2025 of $0.4 billion, with net losses in the production of spring wheat, durum, canola, flax, fall rye, barley and oats. Only winter wheat shows positive gross margins in 2025, hence the overwhelming choice of winter wheat as the crop of choice in the model. By 2050, winter wheat and spring wheat show positive gross margins, but the other crops are all showing negative gross margin. The gross margins of agricultural production for all three provinces in 2050 for this scenario is $-0.281 billion. However, the base model tended to overstate winter wheat as a crop choice so these results are likely overstated with respect to winter wheat. On the other hand, the negative gross margin values are likely too low as farmers will likely switch out to more profitable crops that were not modeled here. Thus, the net change in producer surplus is likely higher than stated as the crop substitution effect is likely higher than the overstated winter wheat effect. It is notable that spring wheat is shown as having positive margins but has less acreage than barley, which has negative gross margins. It is worth noting that the numbers cited here are single year values, rather than net present values of the stream of gross margins over time. While barley experienced positive gross margins in 2049, winter wheat shows positive gross margins for several years leading up to 2050.

Therefore, the local effects must be highly variable where gross margins are highly profitable in specific areas in order to produce the aggregate patterns shown here.

The analysis shown here reinforces the interpretation of the results discussed above. Climate change renders the growing of the majority of common crops in the Canadian Prairies economically infeasible. The model selects for those crops that are drought tolerant as best it can, showing increases in profits from winter wheat and durum, for example. It is possible that winter wheat is shown to be an economically superior choice with climate change because the length of the growing season would favour early spring growth and snow pack from the winter months may provide additional moisture. It would be interesting, therefore, to examine winter snow pack data in combination with summer data to estimate yields for fall-seeded crops to gain a better understanding of these relationships. While the model incorporates technical change as a time trend for almost all the crops, it is excluded for fall rye, winter wheat and durum as a stable time trend that did not skew yield values into unrealistic values until 2050 could not be found.

The model was run in full with the rotational restrictions on all crops, on canola only and compared to the one reported above. Even with these different behavioural assumptions included in the model, the results are similar. The difference is that with rotational restrictions, the total acreage allocated to these eight crops falls in scenario A1B relative to the base model, and does not recover. The crop leading the increase in total acreage is barley. While actual acreage responds to agronomic conditions such as crop rotations, and farmer needs such as animal feed, this model does not incorporate such behaviours. A farm-level model may be a better means to further analyze specific behavioural assumptions associated with the model developed here. However, the results are robust across a number of assumptions, which increases the robustness of the results reported above. The implications of the results are that in the short run, farmers may enjoy significant increases in profits due to climate change but that within approximately 50 years these benefits will have eroded away, likely due to increases in temperatures and decreases in water availability. If these results were confirmed by additional analysis using this spatially disaggregated approach, it would have major implications for policy regarding farm credit, risk management and insurance, income stabilization programs, etc. As such, the approach suggests that the spatial disaggregation approach does provide additional insights that merit further study.

Table 5.7: Gross Margins ('000$) by crop by year

BASE	WINTER WHEAT	SPRING WHEAT	DURUM	CANOLA	FLAX	FRYE	BARLEY	OATS	TOTAL
2005	329,770	1,559,624	649,495	159,371	108,168	90,573	- 174,222	175,904	2,898,684
2010	1,882,929	5,157,778	4,194,986	717,495	1,011,890	1,108,845	- 62,786	601,745	14,612,882
2025	19,916,579	1,621,918	13,182,521	20,134	700,260	2,919,557	- 5,610	51,000	38,406,359
2050	13,226,163	226,108	1,610,011	19,474	147,577	40,793	7,298	20,735	15,298,159

B1	WINTER WHEAT	SPRING WHEAT	DURUM	CANOLA	FLAX	FRYE	BARLEY	OATS	TOTAL
2025	20,039,001	1,635,816	11,141,651	4,255,870	211,548	2,923,213	- 10,645	36,327	40,232,780
2050	26,800,685	541,899	2,125,109	2,311,164	125,374	157,073	- 3,991	7,007	32,064,320

A1B	WINTER WHEAT	SPRING WHEAT	DURUM	CANOLA	FLAX	FRYE	BARLEY	OATS	TOTAL
2025	862,368	-48,308	-95,836	-18,561	-20,168	-17,039	-239,525	-18,742	404,188
2050	836,162	38,673	-62,518	-14,614	-15,562	-16,652	-1,033,621	-13,004	-281,137

5.4 Discussion and conclusions

Understanding the behaviour of the base model is important to in order to fully interpret the behaviour of the climate change scenario simulations. Total acreage, as shown in Table 5.7, increases in the base model for all three provinces, and then remains largely constant for the base model and for Scenario B1. However, in Scenario A1B, total acreage drops off to less than half of the 2005 acreage by 2025. By 2050, the acreage in Alberta has recovered, but in Manitoba the acreage remains about half the level in 2005. Acreage in Saskatchewan increases from 2025 to 2050, but not to the full amount seen in 2005. The downward trend in acreages in Scenario A1B is likely due to decreased rainfall combined with increased temperatures throughout the region, although there is nothing in the spatially disaggregated results to explain why Alberta recovers more fully than the other two provinces.

Table 5.8: Total ha of cropland ('000s) by scenario by province

BASE	Alberta	Manitoba	Saskatchewan	Total
2005	7,982	4,411	13,212	25,606
2010	9,173	5,520	16,327	31,021
2025	9,759	5,592	16,337	31,728
2050	9,754	5,575	16,377	31,706
B1[15]	**Alberta**	**Manitoba**	**Saskatchewan**	**Total**
2025	9,761	5,582	16,368	31,712
2050	9,752	5,576	16,377	31,706
A1B	**Alberta**	**Manitoba**	**Saskatchewan**	**Total**
2025	3,903	989	5,421	10,314
2050	7,195	2,697	10,222	20,114

[15] The starting acreage for the B1 and A1B scenarios is that for 2010 using the base scenario for all crops.

The most likely driver in the changes in production in the region is reduced rainfall, with concomitant reductions in yield. Warmer temperatures, in the presence of adequate moisture, generally result in higher yields. Scenario B1 shows that Manitoba's main producing regions may see an increase in rainfall with mild climate change, but in the A1B scenario, by 2050, this advantage is largely dissipated with reductions of almost 2 mm of rainfall per day (or about 300 mm per growing season) across all three provinces.

The implications of the model are clear that the future for spring wheat, durum, barley, oats, fall rye, flax, and canola is questionable, assuming that the climate change predictions are accurate. The future for winter wheat, in contrast, shows economic promise. The model is not implying that there will be no agriculture in the Canadian Prairies, but rather that its face will change substantially. A further version of this model could be run with drought-tolerant crops such as canary seed, chick peas, lentils, sunflowers, etc., all of which are grown as niche crops in various regions in the Prairies.

The objectives of this chapter were to incorporate improved yield estimates into a study of land use allocation between competing agricultural uses in which both the production function and weather inputs are unchanged from the historical dataset. The second purpose of the chapter was to estimate agricultural land use allocations under the assumption that climate change has occurred, thus changing the average daily temperature. It is clear that under a wide variety of weather conditions, canola continues to be profitable for farmers in the Canadian prairies, and that with climate change; feed grains will become more economically competitive than they currently are.

There were several hypotheses that were tested in this chapter. First, it was hypothesized that climate change would induce an increase in the acreage allocated to drought-tolerant crops. It turned out that using the linear programming model made it harder to make direct linkages between land use and specific climate trends. This is an area where further analysis would provide greater insights. However, increased climate change did increase the acreage of barley and oats and rye, with winter wheat becoming more prominent under the most extreme scenario (A1B); crops that are more drought tolerant than canola and flax.

A second hypothesis that was tested was that acreages would exhibit a positive own-gross margin effect. Because prices were held constant, all changes in gross margin came from changes in yield. The increased acreages for barley and oats, and the decrease in acreages for spring wheat are due to changes in yields. Thus, the hypothesis that acreages are exhibiting a positive own-gross margin effect is supported.

A third hypothesis was that the spatial distribution of crops would respond to climate change, with heat tolerant crops being found further north as temperatures increase. The region in which the dominant crops of flax and canola is found further north, along the border with the Canadian Shield, which would tend to support the hypothesis. Another hypothesis that was posed is that the spatial distribution of crops will respond to changes in rainfall patterns. Both hypotheses are supported in the growth of range for durum and winter wheat in particular, and to some extent flax in the earlier periods and lower levels of climate change. The hypothesis that cropping patterns will respond to changes in rainfall was highly supported by the collapse of agricultural land allocated to any of the crops modeled.

There are many ways in which this research could be expanded. First, restrictions that proxy crop rotations could be incorporated and tested. Restrictions that are close to current practices may unnecessarily impose a short term assumption on the model, which, with constant input and output prices, already has many. The second way to continue the research is to incorporate demand analysis, such that different price paths that reflect different scenarios with respect to the use of biofuels, agricultural production in other countries, trends in food consumption patterns, etc., could be modeled. The third follows from the second, in which input price trends could be modeled, taking into consideration long term trends in fuel and fertilizer costs. Lastly, incorporation of crops that may be grown in higher concentrations or with a larger geographic distribution throughout the Prairies could be included, in particular those that are known for their drought tolerance. Should the inclusion of all or any of these elements produced similar results to the current model, it would increase confidence in the validity of the results reported here. Given that temperatures are predicted to increase, the marginal effect of increased exposure to warmer temperatures is a critical component to capturing the full impact of climate change on overall production.

Chapter 6: Summary and Conclusions

6.0 Introduction

Forecasts of the economic impact of climate change on Canadian agricultural production have been, at best, indeterminate with both the potential for gains and/or losses being predicted by previous studies (for example, Reinsborough 2003). Some predicted results have confidence intervals that range from negative to positive values, providing even less insights for farmers and policy makers as we begin to live with climate change. However, the aggregate impact of climate change is the sum of a myriad of local impacts, while the models used to analyze these impacts have usually been large scale with spatially aggregated weather data. The purpose of this research project was to look at small-scale weather impacts on small-scale agricultural production and to aggregate these small-scale effects in order to better estimate impacts of climate change on agricultural activity.

A number of objectives were outlined at the beginning of this thesis. The first was to estimate the marginal effect of extreme daily temperatures during the growing season on yields for the following major Canadian cereal and oilseed crops: winter wheat, spring wheat, canola, durum, barley, oats, flax, and spring and fall rye, in Alberta, Saskatchewan and Manitoba. In order to achieve this objective, three different types of temperature variables were tested for out-of-sample predictive accuracy: average temperature, growing degree days (GDD) and the method developed by Schlenker and Roberts (2006 and 2008, hereafter SR). The second objective was to apply the temperature variables with the best performance to an analysis of the effect of winter temperatures on yields for two common fall-seeded crops in the Canadian Prairies: fall rye and winter wheat. The particular focus was on the effect of snow fall and temperature in January and February. The temperature variables with the best performance were also incorporated into a study of agricultural land allocation between competing crop choices, in which the production function and weather inputs are unaffected by climate change.

The results of this short run econometric model were used to calibrate the land use model, which were then re-run under two climate change scenarios, one in which there is a small increase in emissions, and one in which there is a large increase in emissions. These scenarios are called B1 and A1B, respectively, and form part of a standard set of tools used for discussion of climate change and its impact on various ecosystems. This final analysis uses a spatial linear programming model with more spatial disaggregation than is commonly found in the economic literature on climate change and agriculture. It was noted in Chapter 2 that it is important to model spatial effects at the scale at which they occur in nature, which this spatial linear programming model was designed to capture.

Hypotheses that were tested for this thesis include the supposition that the use of more precise temperature observations with fewer degrees of freedom will prove sufficient for the purposes of analysis of yield response to extreme temperature. This is a departure from the approach used by SR, who created a 10 square mile grid that covered the continental USA, thus ensuring that sufficient degrees of freedom existed to include a large number of explanatory variables. The approach used here is a modified approach to the SR method that uses weather stations as the unit of measure resulting in fewer observations. The smaller number of observations is offset by lower spatial colinearity in the dataset and it is thought that this approach will provide comparable results to the SR method. The results of the analysis support this hypothesis.

The second hypothesis tested is that the temperature variables broken down by range, as formulated by SR will provide better out-of-sample forecasting estimates than the GDD or monthly average temperature approaches. As well, it is hypothesized that using these temperature variables to explain yield, the grains and oilseeds modeled will exhibit a positive response to temperature variables in the lower observed ranges and a negative response to temperature variables in the higher observed ranges such that a critical maximum temperature can be defined beyond which yields decrease, as SR found for corn, soybeans and rice in the United States. In addition, it is postulated that using the SR approach, the selected grains and oilseeds will exhibit a negative yield response to temperatures below a critical minimum.

The process began by empirically testing three different temperature treatments. The analysis requires an estimate of the effect of temperatures on yields, but the most common approaches, averaging temperatures or calculating GDD, cannot capture the marginal effect of various temperature ranges. Given that temperatures are predicted to increase, the marginal effect of increased exposure to warmer temperatures is a critical component to capturing the full impact of climate change on overall production. The approach modeled after SR proved to provide improved out-of-sample yield forecasts than either of the other two methods examined. Critical maxima were found to exist in the 29-34 °C range for all crops modeled, which are in the same range as those indentified by SR for cotton, corn and soybeans, although these three crops exhibit negative growth above 31°C. The ranges identified by SR are often assumed in the literature (for example in a GDD calculation), but justification for the assumption is not generally offered. Evidence of critical minima was limited at best in the empirical results.

Applying the results of the analysis to fall-seeded crops, it was postulated that increased snow depth in January and February will be associated with higher yields due to reduced winterkill for fall-seeded crops. In addition, the variability of snow depth in March and April was predicted to have a statistically significant effect on yields of winter wheat and fall rye. It was also predicted that a critical minimum temperature beyond which yields of winter wheat and fall rye exhibit decreasing marginal yields would be identified such that exposure to temperatures above this point will have a positive effect on yield and exposure to temperatures below this point will have a negative effect on yield. However, the combination of winter snow depth and winter temperatures did not provide particularly insightful results into the analysis of yields for fall rye and winter wheat. It was hypothesized that a dataset with winter temperatures, snow depth and summer temperatures and rainfall could provide potentially more interesting results. However, colinearity in the data and the small size of the winter climate data set prohibited this approach from being attempted. The results of this analysis were indeterminate and further exploration of the research question was limited by availability of data.

The spatial linear programming model was developed to test the hypothesis that climate change will induce an increase in the acreage allocated to drought-tolerant crops, and that acreages for a specific crop should increase in all provinces when gross margin for that crop increases (positive own-gross margin effect), and vice versa. It was predicted that the spatial distribution of crops will respond to climate change, with heat tolerant crops being found further north as temperatures increases, and that the spatial distribution of crops will respond to changes in the distribution of rainfall patterns. These hypotheses are supported by the empirical results.

Yield forecasts for eight crops to 2050 were calculated using changes in climate for a base case scenario with no climate change, a low emissions prediction (B1) and a higher emissions prediction (A1B). The low emissions scenario assumes that many economic behaviours changing to allow emissions to be mitigated by new technologies, but emissions are still higher than in the base scenario. The A1B scenario assumes that very few adaptive technologies will evolve and that almost no emissions reductions behaviours will be adopted. Therefore, this is the highest emissions scenario available.

These forecasted yields were incorporated into a spatial dynamic linear programming model where the gross margin on production of eight crops is maximized. Yield estimates under scenario A1B are much lower than yield estimates with the base case and the B1 scenario. Negative gross margins for most of these crops result in a gradual reduction in acreage to spring wheat, durum, canola, flax, oats and fall rye. The range of the crops modeled generally moved northward and westward with low emissions increases but under large increases in emissions, all but winter wheat and barley would no longer be commonly grown. These two crops are found in the landscape under the driest conditions modeled and these are generally more drought tolerant.

Modeling climate change is a complex process that incorporates both socio-economic and geo-physical characteristics. However, while the standard models produced by the Canadian Centre for Climate Modeling allow some analysis of climate risk they do not provide much of a basis for modeling climate uncertainty. If the models are wrong, the results of this analysis are also wrong. It is difficult to model the "unknown unknowns" that may affect the results of climate change analysis. However, these climate models represent the best effort to use what is known to predict the future.

The results of the analysis presented here are a departure from the general aggregated analyses. In Chapter 2, several studies were summarized, including those by Weber and Hauer (2003) and Reinsborough (2003) showed that either the impacts of climate change on Canadian agriculture were either very small or have confidence intervals around zero. The fact that the results of the analysis presented here are different suggests that modeling micro-scale effects is important to climate change analysis, and that models that fail to do so result in "average" impacts that are not a true aggregation of these micro-scale effects. The model developed here requires additional refinement in order to improve the confidence in the results. An analysis that incorporates demand factors as well as one in which price effects are modeled (for both input and output prices) with similar results would dramatically improve the robustness of the model results. Still, the results reported here are robust across a number of different behavioural assumptions.

The results of the analysis suggest that major changes are coming for agricultural production in Western Canada. These changes comprise a shift away from crops that require more water to those that do not. The changes would likely be slowed by price effects so the impact may not be felt for another 30 to 50 years, but the types of production that are typical of the arid mid-west of the United States may a model of what will come for the Canadian Prairies. Research by Weber and Hauer (2003) or Reinsborough (2003) suggest that the economic impacts of climate change for Canadian farmers are highly uncertain. But these are large scale models that do not attempt to incorporate the full spatial and/or temportal heterogeneity that exists across the Prairie landscape. The results of this model suggest that in the short run and with small increases in emissions, Prairie farmers will see significant benefits that can be garnered from increased production of drought tolerant grains like winter wheat and from barley. However in the longer run, the spatial models outlined here predict a decline in the profitability of production of the crops modeled, leaving barley and winter wheat dominating the landscape. The model does not include price effects, and these could slow the rate of change, as declining production for all crops across such a wide scale will result in price increases, which changes the gross margin equation. However, if governments around the world decide to tackle climate change by increasing fuel charges (for example) there will be a significant rise in input costs for fuel, fertilizer, etc., as well as in the transportation costs of such food to markets. Eventually, such input costs must rise regardless of government policy, as fossil fuels become scarcer. However, the challenge will then be to transition to a more sustainable form of energy which also implies rising input costs for farmers on a wide scale basis. Further modeling can provide insights into the relative strengths of the various scenarios for future food and fuel prices.

6.1 Limitations of the Research

The model using the SR approach described in Chapter 2 performed better than average temperature or GDD in the basic formulations for each type of variable. It was shown in Chapter 3 that the SR approach was not particularly useful in analyzing the behaviour of fall-seeded crops using winter temperatures formulated. However, under these circumstances, an approach that uses average temperatures and summer data might provide more interesting insights. As well, average maximum temperature, and alternative formulations of the GDD variable could be tested for out-of-sample forecasting against the performance of a wide variety of functional forms for the SR approach. Only three variations of the SR approach were tested here but the potential number of variants is much larger.

The land use model incorporates yield variation over time but is otherwise a short run model in which no adaptive behaviour is incorporated. As such the results of the model as described constitute a "worst-case scenario," as it is most likely that farmers would adopt crops not shown modeled here, improve land management practices, utilize irrigation where sufficient water is available, among many other possibilities. Improved varieties would be developed with increased drought tolerance – indeed much current research is already focused on this issue. In addition, land would move out of cropping and into one of many alternate uses, including livestock grazing, forestry, urban development, etc., the results shown represent short-run adaptation by producers in the Prairie region..

6.2 Future Directions

The results of the land use analysis have shown that the approach described here provides significantly different results from the Ricardian, profit or production fuctions approaches described in Chapter 2. This justifies further effort to incorporate many elements that are missing as described above in Section 6.1. A model that incorporates a variety of different crops other than those included here would provide further insights into the productive capacity for crops of predicted climate conditions. A model that incorporates land shifting between cropping and other agricultural land uses, or between agricultural and non-agricultural land uses such as forestry would be important extensions to the model.

In addition, the production function used here is basic, with yields as a function of weather only. A farm-level model in which spatial homogeneity is assumed and in various management choices can be modeled would allow the short term behavioural constraints that were imposed here to be relaxed. The production functions using the SR-type weather variables explains 30 to 60 percent of the variability in yield year over year, which implies that farmer choices explains the other 40 to 70 percent of the variability. Modeling these choices would provide additional insights into the types of adaptations that farmers can expect to make over the coming decades.

The model shown here does not incorporate any elements of risk. Further specifications that use expected gross margins rather than actual gross margins would further elucidate the types of adaptive measures that farmers may have to make in the coming decades. Finally, the current model does not incorporate any potential demand effects of climate change; that is, effects on demand and thus market prices for the crops considered in the analysis. Another potential area of further research, therefore, would be to explicitly incorporate demand relationships into the analysis (i.e., consider consumer surplus).

6.3 Summary

In this chapter, an overview of the research described in the first five chapters has been provided. The yield functions fed into the development of a spatially disaggregated linear programming model with highly detailed weather variables that are used to simulate future weather conditions to 2050. The modeling approach reported here is relatively novel in that it requires highly disaggregated spatial data and sufficient time to run. If the results of the model were akin to those produced by researchers cited above and others, then it would not add much value to the debate. However, the modeling approach does produce significantly different results, and with specific implications for how, where and potentially when farmers in the Canadian Prairies will be affected by climate change. These results have strong implications for government support programs, crop insurance, extension and research programs, etc., because the *status quo* will not serve the needs of the farming community if these results are accurate.

REFERENCES

AAFC. 2011a. *Environmental Sustainability of Canadian Agriculture: Agri-Environmental Indicator Report Series – Report No. 3.* Online at < http://www4.agr.gc.ca/AAFC-AAC/display-afficher.do?id=1311268301821&lang=eng>.

AAFC. 2011b. A National Ecological Framework for Canada. GIS Data. Online at <http://sis.agr.gc.ca/cansis/nsdb/ecostrat/gis_data.html>.

Alberta Ministry of Agriculture and Rural Development. 2011. *Average Farm input prices for Alberta.* <http://www.agric.gov.ab.ca/app21/farminputprices>.

Anselin, L. 1988. *Spatial Econometrics: Methods and Models*. London,UK: Kluwer Academic Publishers.

Arthur, L.M. and F. Abizadeh. 1988. Potential effects of climate change on agriculture in the prairies. *Western Journal of Agricultural Economics* 13: 216-224.

Barten, A.P and C.Vanloot. (1996) Price dynamics in agriculture: an exercise in historical econometrics. *Economic Modelling* 13, 315-331.

Bootsma, G. and McKenney, **D.** 2005. Impacts of potential climate change on selected agroclimatic indices in Atlantic Canada. *Canadian Journal of Soil Science* 85(2): 345-357.

Brassard, J-P. and Bhawan S. 2008. Impacts of climate change and CO2 increase on agricultural production and adaptation options for Southern Quebec. *Mitigation and Adaptation Strategies for Global Change* 13(3): 241-265.

Briassoulis, H. 2000. Analysis of Land Use Change: Theoretical and Modeling Approaches. Regional Research Institute, University of West Virginia. Online only at <http://www.rri.wvu.edu/WebBook/Briassoulis/contents.htm>.

Campbell, J. C., J. Radke, J. T. Gless and R. M. Wirtshafter. 1992. An application of linear programming and geographic information systems: cropland allocation in Antigua. *Environment and Planning A* 24:535-549.

CICS. 2007. Canadian Climate Impact Scenarios. Online at: <http://www.cics.uvic.ca/scenarios/index.cgi>.

Canadian Centre for Climate Modeling and Analysis. 2010. CRCM 4.2. Online at <http://www.cccma.ec.gc.ca/data/crcm423/crcm423_aev_sresa2.shtml>.

Cesaraccio, C., D. Spano, P. Duce and R. L. Snyder. 2001. An improved model for determining degree-day values from daily temperature data. *International Journal of Biometeorology* 45: 161-169.

Deschênes, O.and M. Greenstone. 2007. The economic impacts of climate change. Evidence from agricultural output and random fluctuations in weather. *American Economic Review* 97(1): 354-385.

Environment Canada. 2008. Canadian Daily Climate Data (CDCD). Downloadable database. Available online at < http://www.climate.weatheroffice.ec.gc.ca/prods_servs/index_e.html>.

Felkner, J., K.Tazhibayeva and R. Townsend. 2009. Impact of climate change on rice production in Thailand. *American Economic Review* 99(2): 205-210.

Florax, R. J. G. M., R. L. Voortman and J. Brouwer. 2002. Spatial dimensions of precision agriculture: a spatial econometric analysis of millet yield on Sahelian coversands. *Agricultural Economics* 27, 425-443.

Fowler, D. 2002. Winter Wheat Production Manual. Crop Production Center, University of Saskatchewan. Online at <http://www.usask.ca/agriculture/plantsci/winter_cereals/Winter_wheat/contents.php>.

Gay, C., F. Estrada, C. Conde, H. Eakin and L. Villers. 2006. Potential impacts of climate change on agriculture: A case study of coffee production in Veracruz, Mexico. *Climate Change* 79(3-4): 259-288.

Gellrich, M. and N. Zimmerman. 2007. Investigating the regional-scale pattern of agricultural land abandonment in the Swiss mountains; a spatial statistical modelling approach. *Landscape and Urban Planning* 79: 65-76.

Goetz, R. U. 1993. Land allocation under consideration of weather-induced crop yield variations: Decision support by a crop yield simulation and risk analysis model. *European Review of Agricultural Economics* 20(2): 199-221.

Govindasamy, R. and S. Jin. 1998. Fresh sweet corn acreage response in the selected states of the USA. *Applied Economic Letters* 5: 555-557.

Greene, W. H. 2003. *Econometric Analysis*. Fifth Edition. Upper Saddle River, NJ: Prentice Hall.

Haim, D., M. Schechter and P. Berliner. 2008. Assessing the impact of climate change on representative field crops in Israeli agriculture: A case study of wheat and cotton. *Climate Change* 86 (3-4):425:440.

Jeffery, S. J., J. O. Carter, . B. Moodie and A. R. Beswick. 2001. Using spatial interpolation to construct a comprehensive archive of Australian climate data. *Environmental Modeling and Software* 16, 309-330.

John, M., D. Pannell and R. Kingwell. 2005. Climate change and the economics of farm management in the face of land degradation: dryland salinity in western Australia. *Canadian Journal of Agricultural Economics* 53: 443-459.

Just, R. E. and R. D. Pope. 1979. Production function estimates and related risk considerations. *American Journal of Agricultural Economics* 61: 276-284.

Kaiser, H. M., S. J. Riha, D. G. Rossiter and D. S. Wilks. 1992. Agronomic and Economic Impacts of Gradual Global Warming: A preliminary Analysis of Midwestern Crop Farming. In *Economic Issues in Global Climate Change,* John M. Reilly and Margot Anderson, eds. Boulder: Westview Press, pp. 91-116.

Kennedy, Pr. 2003. *A Guide to Econometrics* Fifth Edition. Cambridge MA: MIT Press.

Kingwell, R. S., D. A. Morrison, and A. D. Bathgate. 1990. *MUDAS: Model of an Uncertain Dryland Agricultural System*. Western Australian Department of Agriculture, Misc. Publication 17/91.

Klein, K., B. Freeze and A. M. Walburger. 1996. Economic Returns to Yield Increasing Research on Wheat in Western Canada. *Canadian Journal of Agricultural Economics* 44: 207-218.

Klein, K. and S. Narayan. 1992. Farm level models: A review of developments, concepts and applications in Canada. *Canadian Journal of Agricultural Economics* 40: 351-368.

Larsen, J. A., E. C. Jaenicke, R. K. Roberts and D. D. Tyler. 2001. Risk effects of alternative winter cover crop, tillage, and nitrogen fertilization systems in cotton production. *Journal of Agricultural and Applied Economics* 33: 445-457.

Le Roy, D. G., K. Klein and L. Nii Arbenser. 2007. An evaluation of economic models to provide policy advice in response to the BSE crisis in Canada. *Canadian Journal of Agricultural Economics* 55(4): 551-564.

Lobell, D. B. and J. Ivan Ortiz-Monasterio. 2007. Impacts of day versus night temperatures on spring wheat yields: a comparison of empirical and CERES model predictions in three locations. *Agronomy Journal* 99(2): 469-477.

Manitoba Minister of Agriculture, Food and Rural Initiatives. 2011. Guidelines for estimating crop production costs. <http://www.gov.mb.ca/agriculture/financial/farm/caf00s03.html>.

McMaster, G. S. and W. W. Wilhelm. 1997. Growing degree days: One equation, two interpretations. *Agricultural and Forestry Meteorology* 87(4): 291-300.

Mendelsohn, R. and M. Reinsborough. 2007. A Ricardian analysis of US and Canadian farmland. *Climatic Change* 81: 9-17.

Mendelsohn, R., W. D. Nordhaus and D. Shaw. 1997. The impact of global warming on agriculture: a Ricardian analysis. In *The Economics of Global Warming*, Tom Tietenberg, editor. Cheltenham, UK: Elgar, pp. 118-136.

Mooney, S. and L. M. Arthur. 1990. The impacts of climate change on agriculture in Manitoba. *Canadian Journal of Agricultural Economics* 38(4): 685:694.

Mooney, S., S. Jeffery and L. M. Arthur. 1991. Economic impacts of climate change on crop production in the Canadian prairies. *Canadian Journal of Agricultural Economics* 39(4): 793-794.

Natural Resources Canada. 2004. *Climate Change Impacts and Adaptation: A Canadian Perspective.* Edited by Donald Lemmen and Fiona Warren. Report M174-2/2004E. Online at <http://adaptation.nrcan.gc.ca/perspective/index_e.php>.

Nelson, G. C. 2002. Introduction to the special issue on spatial analysis for agricultural economists. *Agricultural Economics* 27, 197-200.

Popp, M., M. Rudstrom and P. Manning. 2005. Spatial yield risk across region, crop and aggregation method. *Canadian Journal of Agricultural Economics* 53, 103-115.

Reinsborough, M. 2003. A Ricardian model of climate change in Canada. *Canadian Journal of Economics* 36: 21-40.

Rosenzweig, C. and F. Tubiello. 1996. Effects of changes in minimum and maximum temperature on wheat yields in the central US. A simulation study. *Agricultural and Forest Meteorology* 80: 215-230.

Rosenzweig, C. and M. Parry. 1997. Potential impact of climate change on world food supply. Chapter 6 in *The Economics of Climate Change,* Tom Tietenberg, ed. Cheltenham, UK: Elgar pp.118-136.

Rounsevell, M. D. A., J. E. Annets, E. Audsley, T. Mayr and I. Reginster. 2003. Modelling the spatial distribution of agricultural land use at the regional scale. *Agriculture, Ecosystems and Environment* 95, 465-479.

Saskatchewan Ministry of Agriculture. 2008. Crop Planning Guides. <http://www.agriculture.gov.sk.ca/crop-planning-guides>.

Schlenker, W. and M. Roberts. 2006. Nonlinear effects of weather on corn yields. *Review of Agricultural Economics* 28: 391-398.

Schlenker, W. and M. Roberts. 2008. Estimating the impact of climate change on crop yields: the importance of non-linear temperature effects. NBER Working Paper 13799, Colombia University: NBER.

Schlenker, W., W. M. Hanemann.and A. C. Fisher. (2005) Will US Agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. *The American Economic Review* 95, 395-406.

Schlenker, W., W. Hanemann and A. C. Fisher. 2004. *The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions*. Department of Agricultural & Resource Economics, UC Berkeley, Department of Agricultural & Resource Economics, UC Berkeley, Working Paper Series: 1003.

Seo, S. N. And R. Mendelsohn. 2008. Measuring impact and adaptations to climate change: a structural Ricardian model of African livestock management. *Agricultural Economics* 38: 151-165.

UNFCC. 2011. Compendium on methods and tools to evaluate impacts of, and vulnerability and adaptation to, climate change. CRAM. Online at <http://unfccc.int/adaptation/nairobi_work_programme/knowledge_resources_and_publications/items/5351.php>.

US Naval Observatory. 2009. Sun or Moon Rise/Set Table for one year. <http://www.usno.navy.mil/USNO/astronomical-applications/data-services/rs-one-year-world> .

van der Werf, E. and S. Peterson. 2007. Modeling linkages between climate policy and land use: an overview. Kiel Working Paper 1323. Kiel Institute for the World Economy, Kiel, Germany.

Verburg, P.H.and .J.P.Lesschen. (2006) Agriculture, climate and future land use patterns: potential for a simulation-based exploration. In: Anonymous *Agriculture and Climate Beyond 2015*, pp. 5-32. Netherlands: Springer.

Wang, J., R. Mendelsohn, A. Dinar, J. Huang, S. Rozelle, and L. Zhang. 2009. The impact of climate change on China's agriculture. *Agricultural Economics* 40(3): 323-337.

Wang, JR-Yan. 2008. Variance reduction for multivariate Monte Carlo simulation. *The Journal of Derivatives* 16(1): 7-28.

Weber, M. and G. Hauer. 2003. A regional analysis of climate change impacts on Canadian Agriculture. *Canadian Public Policy* 29: 163-180.

Yang, W.and A.Weersink (2004) Cost-effective targetting of riparian buffers. *Canadian Journal of Agricultural Economics* 52, 17-34.

DATA SOURCES

Weather data by weather station

Environment Canada. 2008. Canadian Daily Climate Data (CDCD). Downloadable database. Available online at < http://www.climate.weatheroffice.ec.gc.ca/prods_servs/index_e.html>.

Crop Yields by District

Saskatchewan Ministry of Agriculture

Alberta Agriculture Financial Services Corporation

Manitoba Agriculture Services Corporation

2006 Census of Agriculture

Statistics Canada. 2010a. Census of Agriculture, Tables 4.7-1 and 4.4-1. Online at <http://www.statcan.gc.ca/pub/95-629-x/2007000/4182415-eng.htm#reported>.

Crop Statistics

Statistics Canada. 2010b. Table 10010: Metric units (ha) total seeded area, output prices to 1985, yield per ha. Table 20043: output prices, monthly from 1984.

Input Costs

Saskatchewan Ministry of Agriculture. 2008. Crop Planning Guides. <http://www.agriculture.gov.sk.ca/crop-planning-guides>.

Manitoba Minister of Agriculture, Food and Rural Initiatives. 2011. Guidelines for estimating crop production costs. <http://www.gov.mb.ca/agriculture/financial/farm/caf00s03.html>.

Alberta Ministry of Agriculture and Rural Development. 2011. *Average Farm input prices for Alberta.* <http://www.agric.gov.ab.ca/app21/farminputprices>.

Climate Change Data

Canadian Centre for Climate Modeling and Analysis. 2010. CRCM 4.2. Online at <http://www.cccma.ec.gc.ca/data/crcm423/crcm423_aev_sresa2.shtml>.

Sunrise and Sunset Times

US Naval Observatory. 2009. Sun or Moon Rise/Set Table for one year. <http://www.usno.navy.mil/USNO/astronomical-applications/data-services/rs-one-year-world> .

Eco-Regions

AAFC. 2011b. A National Ecological Framework for Canada. GIS Data. Online at <http://sis.agr.gc.ca/cansis/nsdb/ecostrat/gis_data.html>.

APPENDIX A: AVG, AVG PLUS, GDD and GDD PLUS model results.

This section contains results for the models that test the average and GDD temperature treatments. One asterisk (*) indicates significance at 10%, two asterisks (**) indicates significance at 5% and three (***) indicates significance at 1%.

Variable Name	**Variable Description**
CONSTANT	The constant in the equation
TIME	Time trend, calculated as YEAR – 1964
APRIL RAIN	Total cumulative rainfall from April 15 to April 30, in mm
MAY RAIN	Total cumulative rainfall for May
JUNE RAIN	Total cumulative rainfall for June
JULY RAIN	Total cumulative rainfall for July
AUGUST RAIN	Total cumulative rainfall for August
APRIL AVG	Average daily temperature for April 15 to April 30
MAY AVG	Average daily temperature for May
JUNE AVG	Average daily temperature for June
JULY AVG	Average daily temperature for July
AUGUST AVG	Average daily temperature for August
GDD 10	Growing degree days from April 15 to August 30 with a 10 degree Base
RAIN	Total cumulative rainfall from April 15 to August 30
Adj R2	The adjusted R^2 statistic from the regression analysis
N OBS	The number of observations in the regression analysis

Model AVG: monthly average temperature, seasonal rainfall.

	Winter wheat		Spring wheat		Durum		Canola		Flax	
Constant	7.76830	***	7.9365	***	8.118	***	7.35480	***	7.10280	***
Time	0.01643	***	0.00860	***	0.00687	***	0.01484	***	0.01020	***
RAIN	0.00073	***	0.00070	***	0.00131	***	0.00048	***	0.00094	***
April AVG	0.04091	***	0.01345	***	0.01713	***	0.01527	***	0.00869	***
May AVG	-0.06211	***	-0.00836	***	-0.01983	***	0.00951	***	0.00138	
June AVG	-0.03234	***	-0.03149	***	-0.02183	***	0.00002		0.00813	**
July AVG	-0.02186	***	-0.03288	***	-0.04811	***	-0.04874	***	-0.05047	***
August AVG	0.03315	***	0.01655	***	0.01691	***	-0.00076		0.02487	***
Adj R2	**0.533**		**0.369**		**0.402**		**0.328**		**0.267**	
n OBS	**1,642**		**10,430**		**4,763**		**10,776**		**7,755**	

	Fall Rye		Spring Rye		Barley		Oats	
Constant	7.86300	***	8.4911	***	8.5062	***	8.2256	***
Time	0.01048	***	-0.01235	**	0.01078	***	0.00968	***
RAIN	0.00107	***	0.00276	***	0.00043	***	0.00109	***
April AVG	0.00559	**	0.04496	***	0.00989	***	0.00816	***
May AVG	-0.03028	***	-0.05441	***	0.00731	***	0.00355	
June AVG	-0.04156	***	-0.05236	***	-0.01420	***	-0.01738	***
July AVG	-0.01422	***	-0.05137	**	-0.06018	***	-0.05654	***
August AVG	0.01898	***	0.02959	***	0.00939	***	0.01068	***
Adj R2	**0.349**		**0.606**		**0.334**		**0.334**	
n OBS	**4,667**		**327**		**10,707**		**10,491**	

Model AVG PLUS: monthly average temperature, monthly rainfall.

	WWHT		SPRWHT		DURUM		CANOLA		FLAX	
CONSTANT	7.8321	***	8.1025	***	8.3037	***	7.4034	***	7.1974	***
TIME	0.01763	***	0.00841	***	0.00717	***	0.01500	***	0.00994	***
APRIL RAIN	0.00296	***	0.00118	***	0.00256	***	0.00129	***	0.00023	
MAY RAIN	0.00192	***	0.00152	***	0.00187	***	0.00182	***	0.00139	***
JUNE RAIN	0.00047	**	0.00125	***	0.00222	***	0.00036	***	0.00133	***
JULY RAIN	0.00013		0.00042	***	0.00129	***	0.00048	***	0.00147	***
AUGUST RAIN	0.00068	***	-0.00046	***	-0.00088	***	-0.00034	***	-0.00033	**
APRIL AVG	0.03346	***	0.01250	***	0.02061	***	0.01243	***	0.00785	***
MAY AVG	-0.05375	***	-0.00849	***	-0.02381	***	0.01185	***	0.00053	
JUNE AVG	-0.02850	***	-0.02937	***	-0.01605	***	0.00025		0.00662	*
JULY AVG	-0.03330	***	-0.03332	***	-0.04546	***	-0.04810	***	-0.04256	***
AUGUST AVG	0.03284	***	0.00581	***	-0.00196		-0.00589	***	0.01415	***
ADJ R2	**0.544**		**0.388**		**0.320**		**0.341**		**0.279**	
NUM OBS	**1,642**		**10,430**		**4,763**		**9,141**		**6,507**	

CONSTANT	FRYE		SRYE		BARLEY		OATS	
TIME	8.0458	***	8.5834	***	8.4216	***	8.3871	***
APRIL RAIN	0.01093	***	-0.01141	***	0.01068	***	0.009406	***
MAY RAIN	0.00109	***	0.00488	*	0.00069	***	0.001048	***
JUNE RAIN	0.00303	***	0.00568	***	0.00091	***	0.001581	***
JULY RAIN	0.00136	***	0.00272	***	0.00066	***	0.001682	***
AUGUST RAIN	0.00066	***	0.00169	**	0.00059	***	0.001314	***
APRIL AVG	-0.00063	***	0.00224	***	-0.00047	***	-0.00044	***
MAY AVG	0.00068		0.03749	***	0.00927	***	0.007866	***
JUNE AVG	-0.02778	***	-0.04328	**	0.00705	***	0.002186	
JULY AVG	-0.04151	***	-0.05278	***	-0.01332	***	-0.01602	***
AUGUST AVG	-0.01539	***	-0.05526	**	-0.05622	***	-0.05044	***
ADJ R2	0.00872	***	0.01774		0.00152		-0.00376	*
NUM OBS	**0.380**		**0.616**		**0.340**		**0.352**	
	3,968		**269**		**10,707**		**10,491**	

MODEL GDD: seasonal GDD, seasonal rainfall.

	Winter wheat		Spring wheat		Durum		Canola		Flax	
Constant	7.20970	***	7.2399	***	7.28860	***	6.67650	***	6.767	***
Time	0.01761	***	0.00884	***	0.00727	***	0.01382	***	0.01016	***
RAIN	0.00059	***	0.00080	***	0.00135	***	0.00071	***	0.00100	***
GDD	-0.00015	**	-0.00019	***	-0.00032	***	-0.00003		0.00009	**
Adj R2	**0.470**		**0.322**		**0.3613**		**0.290**		**0.239**	
Num. OBS	**1,642**		**10,430**		**4,673**		**10,776**		**7,755**	

	Fall Rye		Spring Rye		Barley		Oats	
Constant	7.25050	***	7.05360	***	7.5786	***	7.3236	***
Time	0.01153	***	-0.01188	*	0.01004	***	0.00910	***
RAIN	0.00100	***	0.00314	***	0.00062	***	0.00126	***
GDD	-0.00043	***	-0.00033		-0.00016	***	-0.00020	***
Adj R2	**0.305**		**0.542**		**0.277**		**0.295**	
Num. OBS	**4,667**		**327**		**10,707**		**10,491**	

MODEL GDD PLUS: Seasonal GDD, monthly rainfall.

	WWHT		SPRWHT		DURUM		CANOLA		FLAX	
CONSTANT	7.2755	***	7.2959	***	7.3358	***	6.6869	***	6.8195	***
TIME	0.01716	***	0.00851	***	0.00735	***	0.01391	***	0.00986	***
APRIL RAIN	0.00240	***	0.00094	***	0.00167	***	0.00076	***	-0.00007	
MAY RAIN	0.00258	***	0.00175	***	0.00212	***	0.00207	***	0.00132	***
JUNE RAIN	0.00052	**	0.00147	***	0.00217	***	0.00043	***	0.00141	***
JULY RAIN	0.00006		0.00075	***	0.00181	***	0.00099	***	0.00197	***
AUGUST RAIN	-0.00036		-0.00068	***	-0.00100	***	-0.00015		-0.00056	***
GDD 10	-0.00027	***	-0.00028	***	-0.00041	***	-0.00006	**	0.00002	
ADJ R2	**0.501**		**0.353**		**0.286**		**0.306**		**0.264**	
NUM OBS	**1,642**		**10,430**		**4,763**		**9,141**		**6,507**	

	FRYE		SRYE		BARLEY		OATS	
CONSTANT	7.3172	***	6.9265	***	7.4496	***	7.3991	***
TIME	0.01180	***	-0.01002	*	0.01003	***	0.008874	***
APRIL RAIN	0.00167	***	0.00571	**	0.00031		0.000689	***
MAY RAIN	0.00297	***	0.00796	***	0.00107	***	0.001759	***
JUNE RAIN	0.00158	***	0.00339	***	0.00081	***	0.001826	***
JULY RAIN	0.00073	***	0.00290	***	0.00119	***	0.001829	***
AUGUST RAIN	-0.00144	***	0.00008		-0.00058	***	-0.00048	***
GDD 10	-0.00056	***	-0.00049	*	-0.00020	***	-0.00028	***
ADJ R2	**0.356**		**0.585**		**0.294**		**0.323**	
NUM OBS	**3,968**		**269**		**10,707**		**10,491**	

APPENDIX B: SEPARABILITY TEST RESULTS

This appendix provides a summary of the cross-month t-tests of coefficient equivalency from Model 2. Equation 3.7 indicates that the null hypothesis is that the coefficients for crop i for month r or m for station k for x = . Boxes marked with an X are those where the results indicate that the probability that the null hypothesis is true is less than 5%. These are months and crops for which weather effects are statistically different.

$$H_0:\ \beta_{ixmkt} = \beta_{ixrkt} \qquad [3.7]$$

The months of the test are shown in the left column for each test, and the crops along the top of each test. The test results are shown for each 1 ºC temperature variable that was run in Model 2.

DEG1

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X			X	X	X			
April=June									
April=July		X		X					
April=August		X		X	X	X	X		
May=June									
May=July		X		X					
May=August		X		X	X	X	X		
June=July									
June=August		X		X	X				
July=August		X		X	X		X		

DEG2

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X								X
April=June							X	X	X
April=July									
April=August		X		X	X	X	X		
May=June							X	X	
May=July									
May=August		X		X	X	X	X		
June=July									
June=August		X		X	X	X	X		X
July=August									

DEG3

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May					X			X	
April=June	X							X	
April=July		X							
April=August		X		X	X	X	X		
May=June					X			X	
May=July		X		X					
May=August		X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X	X	X	X		

DEG4

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May			X	X					X
April=June							X	X	
April=July									
April=August	X	X		X	X	X	X		
May=June								X	
May=July									
May=August		X		X	X	X	X		
June=July									
June=August		X		X	X	X	X		
July=August		X		X		X			

DEG5

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X								
April=June						X		X	
April=July		X							
April=August	X	X	X		X	X	X		
May=June						X		X	
May=July		X							
May=August	X	X	X		X	X	X		
June=July		X							
June=August		X	X		X	X	X	X	
July=August		X	X		X		X		

DEG6

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May									
April=June								X	X
April=July		X							
April=August	X	X	X	X	X	X	X		
May=June		X			X			X	
May=July		X		X					
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X		
July=August		X		X	X	X	X		

DEG7

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May		X		X	X	X			
April=June						X		X	
April=July		X							
April=August		X		X	X	X	X		
May=June								X	
May=July		X							
May=August		X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X			X		

DEG8

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May		X		X	X	X	X		
April=June								X	X
April=July		X							
April=August	X	X		X	X	X	X	X	X
May=June		X			X			X	X
May=July		X		X					
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X		
July=August		X		X		X	X		

DEG9

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X								
April=June								X	
April=July		X							
April=August	X	X		X	X	X	X		
May=June								X	
May=July		X							
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG10

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May					X				
April=June						X		X	
April=July		X							
April=August	X	X		X	X	X	X		
May=June	X		X					X	
May=July		X		X					
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG11

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May									
April=June	X							X	
April=July		X							
April=August	X	X		X	X	X	X		
May=June	X							X	
May=July		X							
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG12

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May				X	X				X
April=June	X					X	X	X	X
April=July		X							
April=August	X	X		X	X	X	X	X	
May=June	X							X	
May=July		X							
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG13

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May			X				X		
April=June								X	
April=July		X							
April=August		X		X	X	X	X		
May=June								X	
May=July		X							
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG14

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May		X	X		X		X	X	X
April=June		X			X		X	X	
April=July		X							
April=August		X		X	X	X	X		
May=June								X	
May=July		X							
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X	X	X	X		

DEG15

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X		X						
April=June					X			X	
April=July		X		X					
April=August	X	X		X	X	X	X		
May=June	X				X			X	
May=July		X							
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG16

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X								
April=June					X			X	
April=July		X							
April=August		X		X	X	X	X		
May=June					X			X	
May=July		X							
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG17

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X						X	X	
April=June					X				
April=July		X							
April=August		X		X	X	X	X	X	
May=June	X								
May=July		X							
May=August	X	X		X	X	X	X	X	
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X	X	

DEG18

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X			X					
April=June								X	
April=July		X							
April=August		X		X	X	X	X		
May=June								X	
May=July		X		X					
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG19

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X								
April=June								X	
April=July		X		X					
April=August		X		X	X	X	X		
May=June								X	
May=July		X		X					
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG20

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X		X	X	X		X	X	
April=June					X		X	X	
April=July		X		X					
April=August		X		X	X	X	X		
May=June	X							X	
May=July		X							
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG21

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X				X				X
April=June								X	
April=July		X							
April=August		X		X	X	X	X		
May=June								X	
May=July		X		X					
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG22

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May		X	X						X
April=June		X						X	
April=July		X		X					
April=August	X	X		X	X	X	X		
May=June								X	
May=July		X		X					
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG23

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	X							X	
April=June							X	X	
April=July		X		X					
April=August		X		X	X	X	X	X	
May=June	X							X	
May=July		X		X					
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG24

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May			X						X
April=June			X					X	X
April=July		X							
April=August		X	X	X	X	X	X	X	
May=June								X	
May=July		X							
May=August	X	X	X	X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG25

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May					X	X		X	X
April=June						X		X	X
April=July		X							
April=August		X		X	X	X	X	X	
May=June	X							X	
May=July		X							
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X	X	X	X		

DEG26

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May									
April=June								X	
April=July		X							
April=August	X	X		X	X	X	X		
May=June	X					X		X	
May=July		X							
May=August	X	X	X	X	X	X	X	X	
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG27

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May			X	X					
April=June		X							
April=July		X							
April=August		X		X	X	X	X		
May=June	X								
May=July		X							
May=August	X	X		X	X	X	X		
June=July		X		X					
June=August		X				X	X		
July=August		X		X		X	X		

DEG28

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May					X				X
April=June					X			X	X
April=July		X							
April=August		X		X	X	X			
May=June								X	
May=July		X		X					
May=August		X		X	X	X	X		X
June=July		X		X					
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG29

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May									
April=June								X	X
April=July		X		X					
April=August		X				X	X		
May=June									
May=July		X		X					
May=August	X	X		X	X	X	X		
June=July		X							
June=August		X		X	X	X	X		
July=August		X		X		X	X		

DEG30

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May	*								X
April=June								X	X
April=July		X							
April=August		X			X	X	X		X
May=June			X					X	
May=July		X							
May=August		X		X	X	X	X	X	
June=July		X							
June=August		X		X	X	X	X	X	
July=August		X		X		X	X		

DEG31

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May		X		X	X			X	X
April=June								X	X
April=July		X							
April=August		X		X	X	X			X
May=June		X		X			X		
May=July		X		X			X		
May=August		X				X			
June=July		X							
June=August		X		X	X	X	X		
July=August		X		X		X	X		

DEG32

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May		X		X	X		X		X
April=June				X			X		X
April=July				X			X		
April=August		X		X	X	X	X		X
May=June									
May=July		X							
May=August		X		X	X	X	X		
June=July									
June=August		X		X	X	X	X		
July=August		X		X		X	X		

*Here due to multicolinearity DEG30 plus is counted for winter wheat in April and May

DEG33

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May		X							
April=June		X							
April=July									
April=August		X				X			
May=June				X	X				
May=July		X		X					
May=August		X				X			
June=July		X							
June=August		X		X	X	X			
July=August		X		X		X	X		

DEG34

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May									
April=June									
April=July		X							
April=August		X							
May=June		X							
May=July		X							
May=August		X		X		X	X		
June=July		X							
June=August		X		X	X	X			
July=August		X		X		X			

DEG35

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May									
April=June									
April=July									
April=August									
May=June		X			X		X		
May=July		X					X		
May=August									
June=July									
June=August		X		X	X	X	X		
July=August		X	X	X		X	X		

DEG36

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May							X		
April=June							X		
April=July							X		
April=August							X		
May=June									
May=July		X							
May=August						X			
June=July									
June=August		X			X	X			
July=August		X			X	X	X		

DEG37

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May									
April=June									
April=July									
April=August									
May=June									
May=July									
May=August						X	X		
June=July									
June=August						X			
July=August		X	X	X	X				

DEG38

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May									
April=June									
April=July									
April=August									
May=June									
May=July									
May=August					X				
June=July									
June=August					X				
July=August					X				

DEG39

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May									
April=June									
April=July									
April=August									
May=June						X			
May=July									
May=August				X		X	X		
June=July									
June=August									
July=August									

DEG40p

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May									
April=June									
April=July									
April=August									
May=June						X		X	
May=July						X		X	
May=August								X	
June=July									
June=August									
July=August		X							

RAIN

	winter wheat	spring wheat	durum	barley	oats	flax	canola	fall rye	spring rye
April=May		X			X	X		X	
April=June					X	X	X		
April=July					X				
April=August		X	X	X	X				X
May=June		X						X	
May=July		X						X	X
May=August		X	X	X	X	X	X	X	
June=July		X	X			X	X		X
June=August		X	X	X	X	X			X
July=August		X	X	X	X	X	X		X

APPENDIX C: MODEL 1 RESULTS (seasonal cumulative temperature and monthly cumulative rainfall.)

This section contains results for Model 1. One asterisk (*) indicates significance at 10%, two asterisks (**) indicates significance at 5% and three (***) indicates significance at 1%.

Variable Name	Variable Description
CONSTANT	The constant in the equation
TIME	Time trend, calculated as YEAR – 1964
APRRAIN	Total cumulative rainfall from April 15 to April 30, in mm
MAYRAIN	Total cumulative rainfall for May
JUNRAIN	Total cumulative rainfall for June
JULRAIN	Total cumulative rainfall for July
AUGRAIN	Total cumulative rainfall for August
DEG0	Total number of hours of exposure from April 14 to August 30 between 0.0 ºC and 0.9 ºC
DEG1	Total number of hours of exposure from April 14 to August 30 between 1.0 ºC and 1.9 ºC
DEG2 … DEG 39	As above for DEG0 and DEG1 but for temperatures from 2.0 to 2.9 ºC up to 39.0 to 39.9 ºC
DEG40P	Total number of hours of exposure from April 14 to August 30 from 40.0 ºC and above
Adj R2	The adjusted R^2 statistic from the regression analysis
N OBS	The number of observations in the regression analysis

	Spring Wheat		Durum Wheat		Winter Wheat		Canola		Oats		Barley		Flax	
Constant	5.7658	***	3.33460	***	5.12420	***	4.88500	***	5.45310	***	5.61080	***	4.53190	***
Time	0.00879	***	0.00890	***	0.01838	***	0.01367	***	0.00884	***	0.01013	***	0.00978	***
AprRain	0.00054	***	0.00102	***	0.00198	***	0.00043	*	0.00006		-0.00016		-0.00036	
MayRain	0.00097	***	0.00132	***	0.00202	***	0.00115	***	0.00075	***	0.00019	*	0.00058	***
JunRain	0.00104	***	0.00195	***	0.00022		-0.00009		0.00118	***	0.00038	***	0.00110	***
JulRain	0.00017	**	0.00124	***	-0.00033		0.00030	***	0.00094	***	0.00047	***	0.00131	***
AugRain	-0.00097	***	-0.00130	***	-0.00036		-0.00054	***	-0.00088	***	-0.00100	***	-0.00076	***
DEG0	0.00156	***	0.00310	***	0.00154		0.00094	**	0.00220	***	0.00175	***	0.00315	***
DEG1	0.00048		0.00189	***	0.00275	***	0.00013		0.00028		0.00073	**	0.00008	
DEG2	0.00074	**	0.00170	***	0.00117		0.00095	**	0.00086	**	0.00099	***	-0.00009	
DEG3	-0.00003		0.00156	***	-0.00061		-0.00027		0.00005		-0.00013		0.00022	
DEG4	0.00005		0.00107	**	-0.00009		0.00011		0.00031		-0.00008		0.00068	
DEG5	-0.00046	*	-0.00006		-0.00009		0.00004		-0.00032		0.00009		-0.00015	
DEG6	0.00087	***	0.00150	***	0.00119		0.00076	**	0.00077	***	0.00062	**	0.00087	**
DEG7	0.00035		0.00043		0.00075		0.00053	*	0.00010		0.00058	**	0.00019	
DEG8	0.00060	***	0.00125	***	0.00172	***	0.00066	***	0.00095	***	0.00077	***	0.00032	
DEG9	0.00056	***	0.00124	***	0.00028		0.00100	***	0.00065	**	0.00111	***	0.00109	***
DEG10	0.00059	***	0.00072	**	0.00065		0.00068	***	0.00075	***	0.00061	***	0.00086	**
DEG11	0.00086	***	0.00194	***	0.00127	**	0.00075	***	0.00132	***	0.00116	***	0.00122	***
DEG12	0.00056	***	0.00148	***	0.00023		0.00025		0.00064	***	0.00058	***	0.00071	**
DEG13	0.00086	***	0.00166	***	0.00023		0.00088	***	0.00096	***	0.00075	***	0.00077	**
DEG14	0.00042	**	0.00052	*	-0.00021		0.00074	***	0.00062	***	0.00064	***	0.00051	
DEG15	0.00062	***	0.00107	***	0.00060		0.00060	***	0.00059	***	0.00081	***	0.00132	***
DEG16	0.00020		0.00147	***	0.00046		0.00022		0.00059	***	0.00050	***	0.00054	*
DEG17	0.00061	***	0.00138	***	0.00230	***	0.00080	***	0.00105	***	0.00067	***	0.00076	**
DEG18	0.00033	*	0.00096	***	0.00006		0.00064	***	0.00070	***	0.00054	***	0.00065	**
DEG19	0.00034	**	0.00097	***	-0.00031		0.00092	***	0.00053	***	0.00059	***	0.00051	*

	Spring Wheat		Durum Wheat		Winter Wheat		Canola		Oats		Barley		Flax	
DEG20	0.00049	***	0.00120	***	0.00226	***	0.00089	***	0.00061	***	0.00091	***	0.00125	***
DEG21	0.00021		0.00085	***	0.00007		0.00069	***	0.00030		0.00047	***	0.00085	***
DEG22	0.00027		0.00113	***	0.00058		0.00035		0.00034	*	0.00058	***	0.00050	*
DEG23	0.00054	***	0.00117	***	0.00054		0.00099	***	0.00104	***	0.00075	***	0.00071	**
DEG24	0.00063	***	0.00130	***	0.00007		0.00122	***	0.00076	***	0.00103	***	0.00132	***
DEG25	0.00019		0.00081	**	0.00015		0.00069	***	0.00017		0.00046	**	0.00038	
DEG26	0.00047	**	0.00047		0.00061		0.00020		0.00051	**	0.00050	**	0.00063	*
DEG27	0.00073	***	0.00173	***	0.00144	**	0.00031		0.00101	***	0.00073	***	0.00113	***
DEG28	0.00024		0.00058		0.00021		0.00015		-0.00026		0.00006		0.00102	**
DEG29	-0.00056	*	-0.00023		-0.00042		-0.00088	**	-0.00097	***	-0.00098	***	0.00085	*
DEG30	-0.00056		-0.00005		-0.00020		-0.00049		-0.00069		-0.00082	*	-0.00049	
DEG31	-0.00090	*	0.00058		-0.00126		-0.00080		-0.00231	***	-0.00106	**	-0.00033	
DEG32	0.00099	*	0.00191	**	0.00072		0.00073		0.00123	*	0.00148	**	0.00132	
DEG33	-0.00035		0.00092		0.00082		-0.00136		-0.00018		-0.00007		0.00048	
DEG34	-0.00242	***	-0.00106		-0.00412		-0.00187		-0.00268	***	-0.00171	*	-0.00452	***
DEG35	-0.00434	***	-0.00104		-0.00471		-0.00321	*	-0.00423	***	-0.00457	***	0.00119	
DEG36	-0.00672	***	-0.00379		0.01058	**	-0.01070	***	-0.00978	***	-0.00775	***	-0.00346	
DEG37	-0.00632	*	-0.00582	*	-0.00754		-0.00483		-0.00351		-0.00481		-0.00894	*
DEG38	-0.01068	**	-0.00781		0.00340		-0.00834		-0.00337		-0.01064	*	-0.00723	
DEG39	0.00594		0.00823		0.00689		0.01962	*	0.01527	*	0.01351	*	0.00259	
DEG40P	-0.01688	**	-0.01412	*	0.01871		0.00615		-0.00531		-0.01137		-0.00814	
ADJ R2	**0.4242**		**0.3445**		**0.522**		**0.3612**		**0.4032**		**0.3769**		**0.3102**	
Nobs	12,332		5,600		1,642		10,776		12,333		12,579		7,755	
Ncoef	387		295		223		373		390		391		359	

	Fall Rye		Spring Rye	
Constant	5.67580	***	1.96950	
Time	0.01168	***	-0.00631	
AprRain	0.00102	***	0.00375	**
MayRain	0.00230	***	0.00549	***
JunRain	0.00121	***	0.00374	***
JulRain	0.00039	***	0.00180	**
AugRain	-0.00146	***	0.00043	
DEG0	0.00200	***	0.00351	
DEG1	0.00107	*	0.00044	
DEG2	0.00115	*	0.00680	***
DEG3	0.00015		-0.00089	
DEG4	0.00078		0.00420	*
DEG5	-0.00108	**	-0.00064	
DEG6	0.00090	*	0.00183	
DEG7	0.00092	**	0.00165	
DEG8	0.00117	***	0.00186	
DEG9	0.00039		0.00241	
DEG10	-0.00039		0.00194	
DEG11	0.00020		-0.00198	
DEG12	0.00096	***	0.00296	*
DEG13	0.00060	*	-0.00120	
DEG14	0.00060	*	-0.00093	
DEG15	0.00089	**	0.00383	***
DEG16	0.00048		0.00681	***
DEG17	0.00098	***	0.00124	
DEG18	-0.00001		-0.00100	
DEG19	0.00047		0.00217	

	Fall Rye		Spring Rye	
DEG20	0.00038		0.00253	**
DEG21	-0.00042		0.00226	
DEG22	0.00035		0.00124	
DEG23	-0.00009		0.00023	
DEG24	0.00045		0.00246	*
DEG25	-0.00073	*	0.00170	
DEG26	-0.00062		-0.00407	**
DEG27	0.00089	**	0.00265	
DEG28	0.00050		0.00238	
DEG29	0.00030		0.00247	
DEG30	0.00043		0.00028	
DEG31	-0.00115		-0.00288	
DEG32	0.00203	**	0.00308	
DEG33	0.00064		-0.00309	
DEG34	-0.00051		0.00611	
DEG35	-0.00512	**	-0.02259	***
DEG36	-0.00231		0.02451	**
DEG37	-0.01026	**	-0.01902	
DEG38	-0.00958		-0.02851	
DEG39	0.00521		-0.04116	
DEG40P	-0.03660	***	n/a	
ADJ R2	**0.3939**		**0.6671**	
Nobs	4,667		327	
Ncoef	264	[16]	91	

[16] The coefficients for the district dummies are not reported to due to conserve space.

APPENDIX D: MODEL 2 RESULTS (Monthly cumulative temperature and monthly cumulative rainfall)

This section contains results for Model 2. One asterisk (*) indicates significance at 10%, two asterisks (**) indicates significance at 5% and three (***) indicates significance at 1%.

Variable Name	Variable Description
CONSTANT	The constant in the equation
TIME	Time trend, calculated as YEAR – 1964
APRIL RAIN	Total cumulative rainfall from April 15 to April 30, in mm
MAY RAIN	Total cumulative rainfall for May
JUNE RAIN	Total cumulative rainfall for June
JULY RAIN	Total cumulative rainfall for July
AUGUST RAIN	Total cumulative rainfall for August
APRDEG0	Total number of hours of exposure from April 14 to April 30 between 0.0 ºC and 0.9 ºC
APRDEG1	Total number of hours of exposure from April 14 to April 30 between 1.0 ºC and 1.9 ºC
APRDEG2 … APRDEG 39	As above for DEG0 and DEG1 but for temperatures from 2.0 to 2.9 ºC up to 39.0 to 39.9 ºC
APRDEG40P	Total number of hours of exposure from April 14 to April 30 from 40.0 ºC and above
MAYDEG0	Total number of hours of exposure for May between 0.0 ºC and 0.9 ºC
MAYDEG1	Total number of hours of exposure for May between 1.0 ºC and 1.9 ºC
MAYDEG2 … MAYDEG 39	As above for DEG0 and DEG1 but for temperatures from 2.0 to 2.9 ºC up to 39.0 to 39.9 ºC
MAYDEG40P	Total number of hours of exposure for May from 40.0 ºC and above
JUNDEG0 to JUNDEG40P	As above, but for June
JULDEG0 to JULDEG40P	As above, but for July
AUGDEG0 to AUGDEG40P	As above, but for August
Adj R2	The adjusted R^2 statistic from the regression analysis
N OBS	The number of observations in the regression analysis

Variable	Spring Wheat		Durum		Canola		Oats	
Adjusted R2	**0.473**	**0.498**	**0.395**	**0.434**	**0.413**	**0.352**	**0.477**	
Time	0.0081	***	0.0077	***	0.0132	***	0.0084	***
AprRain	0.0008	***	0.0014	***	0.0010	***	0.0005	**
MayRain	0.0011	***	0.0015	***	0.0014	***	0.0009	***
JunRain	0.0009	***	0.0018	***	-0.0001		0.0011	***
JulRain	0.0001	*	0.0011	***	0.0001		0.0007	***
AugRain	-0.0004	***	-0.0004	**	-0.0002	**	-0.0005	***
AprDeg0	0.0012	***	0.0030	***	0.0013	**	0.0016	***
AprDeg1	0.0001		0.0024	***	0.0000		-0.0002	
AprDeg2	0.0013	***	0.0022	***	0.0023	***	0.0013	**
AprDeg3	0.0003		0.0017	**	-0.0001		-0.0008	
AprDeg4	-0.0001		0.0018	***	0.0004		-0.0003	
AprDeg5	-0.0007		-0.0015	*	-0.0002		-0.0012	**
AprDeg6	0.0005		0.0021	**	0.0011	*	0.0003	
AprDeg7	-0.0007		0.0001		0.0005		-0.0013	**
AprDeg8	0.0001		0.0020	**	-0.0010	*	-0.0013	**
AprDeg9	0.0006		0.0015	*	0.0012	**	0.0004	
AprDeg10	0.0004		0.0005		0.0008		-0.0002	
AprDeg11	0.0009	*	0.0019	**	0.0011	*	0.0006	
AprDeg12	0.0003		0.0017	**	-0.0002		-0.0011	*
AprDeg13	0.0021	***	0.0036	***	0.0029	***	0.0015	**

Variable	Spring Wheat	Durum	Canola	Oats
AprDeg14	0.0022 ***	0.0028 ***	0.0026 ***	0.0029 ***
AprDeg16	0.0007	0.0026 **	0.0005	0.0011
AprDeg17	0.0012 *	0.0005	0.0017 **	0.0023 ***
AprDeg18	-0.0022 ***	-0.0004	-0.0004	-0.0009
AprDeg19	0.0006	0.0012	0.0006	0.0013
AprDeg20	0.0032 ***	0.0056 ***	0.0033 ***	0.0028 ***
AprDeg21	0.0005	0.0010	0.0012	-0.0004
AprDeg22	0.0025 **	0.0016	0.0010	0.0012
AprDeg23	0.0016	0.0023	0.0046 ***	0.0025 *
AprDeg24	-0.0018	-0.0035 *	0.0000	0.0000
AprDeg25	-0.0003	0.0055 **	0.0024	-0.0012
AprDeg26	-0.0014	-0.0011	-0.0026	-0.0054 **
AprDeg27	0.0042 *	0.0102 ***	0.0047	0.0024
AprDeg28	0.0020	-0.0072	0.0037	-0.0075 **
AprDeg29	0.0021	0.0032	-0.0007	0.0002
AprDeg30	-0.0022	-0.0048	-0.0103	-0.0108 *
AprDeg31	-0.0137 *	0.0108	-0.0019	-0.0196 **
AprDeg32	-0.0339 **	-0.0387 **	-0.0586 ***	-0.0612 ***
AprDeg33	-0.0379 **	0.0200	-0.0190	-0.0210
AprDeg34	-0.0240	-0.0626	0.0045	-0.0076
AprDeg35	-0.0174	-0.0136	-0.0250	-0.0134
AprDeg36	-0.0819 **	-0.0629	-0.1735 ***	-0.0516

Variable	Spring Wheat		Durum		Canola		Oats	
MayDeg0	0.0019	***	0.0022	**	0.0011	*	0.0035	***
MayDeg1	0.0003		0.0003		0.0006		0.0011	*
MayDeg2	0.0001		-0.0002		-0.0003		0.0007	
MayDeg3	-0.0002		0.0000		-0.0006		0.0012	**
MayDeg4	0.0001		-0.0004		-0.0002		0.0009	**
MayDeg5	-0.0008	**	-0.0012	*	-0.0010	**	-0.0001	
MayDeg6	0.0011	***	0.0014	**	0.0005		0.0017	***
MayDeg7	0.0002		0.0001		0.0000		0.0008	*
MayDeg8	0.0010	***	0.0020	***	0.0013	***	0.0017	***
MayDeg9	-0.0002		-0.0008		-0.0002		0.0003	
MayDeg10	0.0000		-0.0003		0.0000		0.0010	**
MayDeg11	-0.0002		0.0007		-0.0005		0.0010	**
MayDeg12	-0.0006	*	-0.0010		-0.0004		0.0005	
MayDeg13	0.0004		-0.0006		-0.0003		0.0012	***
MayDeg14	-0.0004		-0.0008		0.0001		0.0004	
MayDeg15	0.0001		-0.0005		0.0008	*	0.0014	***
MayDeg16	0.0002		0.0012	*	0.0001		0.0014	***
MayDeg17	0.0000		0.0008		0.0001		0.0012	***
MayDeg18	0.0009	**	0.0006		0.0023	***	0.0022	***
MayDeg19	0.0002		-0.0003		0.0009	*	0.0013	***
MayDeg20	-0.0011	***	-0.0010		-0.0001		0.0002	
MayDeg21	0.0006		-0.0001		0.0004		0.0018	***
MayDeg22	0.0003		0.0015	**	0.0004		0.0013	**

Variable	Spring Wheat		Durum		Canola		Oats	
MayDeg24	0.0005		-0.0004		0.0007		0.0005	
MayDeg25	-0.0003		-0.0004		0.0001		0.0006	
MayDeg26	-0.0013	*	-0.0033	***	-0.0015		-0.0008	
MayDeg27	0.0012		0.0017		-0.0015		0.0016	*
MayDeg28	-0.0006		-0.0020		0.0007		0.0001	
MayDeg29	0.0003		-0.0016		-0.0015		-0.0009	
MayDeg30	-0.0028	**	-0.0012		0.0000		-0.0010	
MayDeg31	0.0039	**	0.0011		0.0027		0.0002	
MayDeg32	0.0011		0.0038		-0.0019		0.0018	
MayDeg33	0.0004		0.0004		0.0017		0.0033	
MayDeg34	-0.0039		-0.0029		-0.0024		0.0003	
MayDeg35	0.0083		0.0091		0.0162	**	0.0085	
MayDeg36	-0.0013		0.0105		-0.0137		-0.0126	
MayDeg37	-0.0144	*	-0.0150		-0.0256	**	-0.0154	*
MayDeg38	-0.0099		-0.0494	**	-0.0242		0.0052	*
MayDeg39	-0.0034		0.1582	***	-0.0683		0.0148	
MayDeg40	-0.0118		-0.1546		0.0116		-0.0270	
MayDeg41	0.0620		0.1275		0.0667		0.0744	
MayDeg42	0.1311	*	0.1588		n/a		-0.0061	
MayDeg43	n/a		n/a		n/a		n/a	
MayDeg44	n/a		n/a		n/a		n/a	

Variable	Spring Wheat	Durum	Canola	Oats
JunDeg0	-0.0011	0.0076	0.0034	0.0004
JunDeg1	-0.0008	0.0059	-0.0062 **	-0.0022
JunDeg2	-0.0006	0.0047	-0.0006	-0.0010
JunDeg3	-0.0027	0.0040	-0.0027	-0.0035
JunDeg4	-0.0023	0.0021	-0.0033	-0.0013
JunDeg5	-0.0008	0.0053	-0.0009	-0.0016
JunDeg6	-0.0012	0.0021	-0.0021	-0.0030
JunDeg7	-0.0002	0.0026	-0.0009	-0.0013
JunDeg8	-0.0015	0.0022	-0.0011	-0.0020
JunDeg9	-0.0007	0.0025	-0.0015	-0.0010
JunDeg10	-0.0005	0.0060 *	-0.0013	-0.0004
JunDeg11	0.0003	0.0056	-0.0001	0.0001
JunDeg12	-0.0003	0.0040	-0.0012	-0.0010
JunDeg13	0.0003	0.0051	0.0001	-0.0001
JunDeg14	-0.0013	0.0029	-0.0013	-0.0016
JunDeg15	-0.0015	0.0026	-0.0021	-0.0021
JunDeg16	-0.0016	0.0041	-0.0015	-0.0021
JunDeg17	-0.0012	0.0038	-0.0010	-0.0015
JunDeg18	-0.0012	0.0035	-0.0016	-0.0016
JunDeg19	-0.0008	0.0041	-0.0005	-0.0013
JunDeg20	-0.0008	0.0039	-0.0007	-0.0011
JunDeg21	-0.0011	0.0035	-0.0014	-0.0015
JunDeg22	-0.0013	0.0038	-0.0015	-0.0013

Variable	Spring Wheat		Durum		Canola		Oats	
JunDeg24	-0.0009		0.0041		-0.0010		-0.0005	
JunDeg25	-0.0016		0.0031		-0.0020		-0.0026	
JunDeg26	-0.0009		0.0024		-0.0009		-0.0012	
JunDeg27	-0.0014		0.0046		-0.0010		-0.0001	
JunDeg28	0.0001		0.0044		-0.0010		-0.0003	
JunDeg29	-0.0017		0.0014		-0.0006		-0.0026	
JunDeg30	-0.0021		0.0041		-0.0030		-0.0013	
JunDeg31	-0.0039	**	0.0033		-0.0039		-0.0049	**
JunDeg32	-0.0015		0.0028		0.0013		-0.0001	
JunDeg33	-0.0014		0.0047		0.0022		-0.0009	
JunDeg34	-0.0064	**	0.0019		-0.0020		-0.0034	
JunDeg35	-0.0174	***	-0.0033		-0.0113	**	-0.0191	***
JunDeg36	-0.0118	**	-0.0049		-0.0070		-0.0101	*
JunDeg37	-0.0113		-0.0113		-0.0051		-0.0074	
JunDeg38	-0.0073		-0.0024		-0.0063		-0.0027	
JunDeg39	0.0034		0.0194		0.0185		0.0069	
JunDeg40	-0.0041		-0.0137		-0.0090		-0.0056	
JunDeg41	0.0213		0.0029		0.0373		-0.0059	
JunDeg42	-0.1486	***	-0.1908	***	0.1282		-0.1259	***
JunDeg43	0.0773		-0.2214	*	0.0557		0.3298	*
JunDeg44	0.0294		0.3192	***	-0.1175		-0.0672	

Variable	Spring Wheat		Durum	Canola	Oats
JulDeg0	-0.0174	*	0.0087	-0.0200	-0.0092
JulDeg1	-0.0099		0.0009	-0.0079	-0.0060
JulDeg2	-0.0081		0.0144	-0.0003	0.0049
JulDeg3	-0.0211	***	-0.0009	-0.0145	-0.0104
JulDeg4	-0.0077		0.0149	-0.0077	-0.0023
JulDeg5	-0.0159	***	0.0028	-0.0123	-0.0048
JulDeg6	-0.0148	***	0.0004	-0.0110	-0.0060
JulDeg7	-0.0141	***	0.0051	-0.0120	-0.0058
JulDeg10	-0.0144	***	0.0018	-0.0117	-0.0056
JulDeg11	-0.0136	***	0.0043	-0.0100	-0.0044
JulDeg12	-0.0130	***	0.0060	-0.0122	-0.0048
JulDeg13	-0.0141	***	0.0046	-0.0117	-0.0054
JulDeg14	-0.0138	***	0.0035	-0.0107	-0.0055
JulDeg15	-0.0140	***	0.0025	-0.0108	-0.0053
JulDeg16	-0.0145	***	0.0035	-0.0114	-0.0047
JulDeg17	-0.0139	***	0.0052	-0.0106	-0.0045
JulDeg18	-0.0139	***	0.0047	-0.0114	-0.0050
JulDeg19	-0.0144	***	0.0041	-0.0114	-0.0059
JulDeg20	-0.0139	***	0.0039	-0.0107	-0.0051
JulDeg21	-0.0145	***	0.0027	-0.0115	-0.0064
JulDeg22	-0.0145	***	0.0027	-0.0121	-0.0063

Variable	Spring Wheat		Durum	Canola		Oats	
JulDeg24	-0.0141	***	0.0034	-0.0110		-0.0056	
JulDeg25	-0.0136	***	0.0036	-0.0108		-0.0052	
JulDeg26	-0.0134	***	0.0037	-0.0115		-0.0048	
JulDeg27	-0.0141	***	0.0040	-0.0119		-0.0056	
JulDeg28	-0.0150	***	0.0032	-0.0127		-0.0066	
JulDeg29	-0.0159	***	0.0028	-0.0140	*	-0.0077	
JulDeg30	-0.0151	***	0.0019	-0.0125		-0.0073	
JulDeg31	-0.0153	***	0.0028	-0.0129		-0.0086	
JulDeg32	-0.0128	***	0.0041	-0.0100		-0.0045	
JulDeg33	-0.0178	***	0.0015	-0.0167	*	-0.0084	
JulDeg34	-0.0177	***	-0.0011	-0.0129		-0.0106	
JulDeg35	-0.0195	***	-0.0035	-0.0177	*	-0.0109	
JulDeg36	-0.0232	***	-0.0010	-0.0273	***	-0.0186	
JulDeg37	-0.0190	**	-0.0013	-0.0174		-0.0107	
JulDeg38	-0.0099		0.0067	-0.0098		0.0087	
JulDeg39	-0.0269		0.0171	-0.0574		-0.0132	
JulDeg40	-0.0069		0.0262	0.0508		0.0693	**
JulDeg41	-0.0303		-0.0138	0.0158		-0.0273	
JulDeg42	-0.0180		-0.0730	-0.0481		-0.0208	
JulDeg43	-0.1621	***	-0.0659	-0.1017		-0.1556	**
JulDeg44	-0.0245		0.0391	0.0195		0.0411	

Variable	Spring Wheat		Durum		Canola		Oats	
AugDeg0	0.0116	***	0.0003		0.0117	***	0.0152	***
AugDeg1	0.0098	***	0.0016		0.0089	***	0.0089	***
AugDeg2	0.0101	***	0.0018		0.0116	***	0.0108	***
AugDeg3	0.0117	***	0.0070	**	0.0135	***	0.0108	***
AugDeg4	0.0101	***	0.0002		0.0108	***	0.0097	***
AugDeg5	0.0099	***	0.0019		0.0117	***	0.0095	***
AugDeg6	0.0108	***	0.0040		0.0123	***	0.0113	***
AugDeg7	0.0097	***	0.0000		0.0105	***	0.0095	***
AugDeg8	0.0114	***	0.0031		0.0128	***	0.0118	***
AugDeg9	0.0111	***	0.0023		0.0122	***	0.0109	***
AugDeg10	0.0109	***	0.0028		0.0119	***	0.0114	***
AugDeg11	0.0105	***	0.0025		0.0103	***	0.0106	***
AugDeg12	0.0111	***	0.0043	*	0.0125	***	0.0117	***
AugDeg13	0.0097	***	0.0022		0.0111	***	0.0102	***
AugDeg14	0.0099	***	0.0007		0.0110	***	0.0102	***
AugDeg15	0.0108	***	0.0037		0.0112	***	0.0104	***
AugDeg16	0.0099	***	0.0014		0.0105	***	0.0103	***
AugDeg17	0.0108	***	0.0016		0.0115	***	0.0111	***
AugDeg18	0.0102	***	0.0007		0.0110	***	0.0102	***
AugDeg19	0.0101	***	0.0010		0.0115	***	0.0105	***
AugDeg20	0.0109	***	0.0022		0.0113	***	0.0108	***
AugDeg21	0.0111	***	0.0032		0.0121	***	0.0111	***
AugDeg22	0.0110	***	0.0032		0.0113	***	0.0107	***

Variable	Spring Wheat		Durum	Canola		Oats	
AugDeg24	0.0114	***	0.0040	0.0129	***	0.0110	***
AugDeg25	0.0106	***	0.0031	0.0122	***	0.0106	***
AugDeg26	0.0106	***	0.0024	0.0111	***	0.0108	***
AugDeg27	0.0113	***	0.0030	0.0117	***	0.0110	***
AugDeg28	0.0102	***	0.0006	0.0117	***	0.0091	***
AugDeg29	0.0100	***	0.0006	0.0107	***	0.0094	***
AugDeg30	0.0094	***	0.0010	0.0117	***	0.0097	***
AugDeg31	0.0092	***	0.0031	0.0098	***	0.0078	***
AugDeg32	0.0105	***	0.0037	0.0106	***	0.0111	***
AugDeg33	0.0113	***	0.0039	0.0094	***	0.0098	***
AugDeg34	0.0112	***	0.0037	0.0093	***	0.0098	***
AugDeg35	0.0111	***	0.0043	0.0124	***	0.0110	***
AugDeg36	0.0104	***	0.0026	0.0041		0.0067	*
AugDeg37	0.0057		0.0018	0.0058		0.0091	*
AugDeg38	0.0050		-0.0044	-0.0052		-0.0014	
AugDeg39	0.0316	***	0.0009	0.0373	***	0.0368	***
AugDeg40	-0.0095		0.0006	-0.0424		-0.0183	
AugDeg41	0.0519		0.0476	0.1338	***	0.0573	
AugDeg42	-0.0098		-0.0135	-0.0373		0.0108	
AugDeg43	-0.0071		-0.0238	-0.0373		-0.0338	
AugDeg44	0.0093		0.0486	0.0960		0.0333	

Variable	Barley		Flax		Fall Rye	
Adjusted R2	9.0175	***	-21.2350	***	-8.4336	
Time	0.0103	***	0.0095	***	0.0100	***
AprRain	0.0004	*	-0.0001		0.0006	*
MayRain	0.0005	***	0.0007	***	0.0021	***
JunRain	0.0003	***	0.0012	***	0.0006	***
JulRain	0.0001	*	0.0006	***	0.0004	***
AugRain	-0.0004	***	-0.0004	**	0.0000	
AprDeg0	0.0013	***	0.0015	**	0.0009	
AprDeg1	0.0005		-0.0005		0.0002	
AprDeg2	0.0021	***	0.0007		0.0016	**
AprDeg3	-0.0005		0.0007		-0.0005	
AprDeg4	-0.0008	*	0.0013	*	-0.0003	
AprDeg5	-0.0007		-0.0003		-0.0009	
AprDeg6	0.0002		0.0018	**	0.0008	
AprDeg7	-0.0005		-0.0009		0.0011	
AprDeg8	0.0000		0.0003		0.0015	*
AprDeg9	0.0005		0.0008		0.0017	*
AprDeg10	0.0007		-0.0008		0.0002	
AprDeg11	0.0009	*	0.0015		0.0006	
AprDeg12	-0.0005		-0.0006		0.0004	
AprDeg13	0.0016	***	0.0028	***	0.0013	
AprDeg14	0.0016	***	0.0002		0.0024	**

Variable	Barley		Flax		Fall Rye	
AprDeg16	0.0008		0.0021	*	0.0016	
AprDeg17	0.0006		-0.0001		0.0012	
AprDeg18	-0.0026	***	0.0001		-0.0036	**
AprDeg19	0.0015	*	-0.0002		0.0027	*
AprDeg20	0.0013		0.0006		0.0048	***
AprDeg21	0.0006		0.0026	*	-0.0004	
AprDeg22	0.0022	**	0.0005		0.0000	
AprDeg23	0.0022	*	-0.0001		-0.0023	
AprDeg24	0.0000		0.0023		-0.0012	
AprDeg25	0.0002		-0.0042		-0.0073	**
AprDeg26	-0.0028		-0.0013		-0.0091	**
AprDeg27	0.0059	**	0.0076	**	0.0023	
AprDeg28	-0.0009		-0.0049		-0.0095	
AprDeg29	0.0055		0.0110	**	-0.0070	
AprDeg30	-0.0021		-0.0136	*	-0.0217	*
AprDeg31	-0.0161	**	-0.0095		-0.0316	*
AprDeg32	-0.0567	***	-0.0251		0.0093	
AprDeg33	-0.0217		-0.0224		-0.0428	
AprDeg34	0.0212		0.0043		0.0072	
AprDeg35	-0.0244		0.0334		n/a	
AprDeg36	-0.0301		-0.0794		n/a	

Variable	Barley		Flax		Fall Rye	
MayDeg0	0.0029	***	0.0048	***	0.0020	**
MayDeg1	0.0007		0.0006		0.0013	
MayDeg2	-0.0001		-0.0006		0.0000	
MayDeg3	0.0005		-0.0002		0.0007	
MayDeg4	0.0007	*	0.0007		0.0007	
MayDeg5	-0.0001		0.0000		-0.0015	**
MayDeg6	0.0011	***	0.0017	**	0.0008	
MayDeg7	0.0009	**	0.0018	***	0.0013	*
MayDeg8	0.0016	***	0.0022	***	0.0023	***
MayDeg9	0.0002		0.0011	*	0.0002	
MayDeg10	0.0006		0.0005		-0.0009	
MayDeg11	0.0003		0.0011	*	0.0009	
MayDeg12	0.0001		0.0000		0.0002	
MayDeg13	0.0010	***	0.0020	***	0.0005	
MayDeg14	0.0004		-0.0003		-0.0013	
MayDeg15	0.0011	***	0.0021	***	0.0007	**
MayDeg16	0.0007	*	0.0016	**	-0.0002	
MayDeg17	0.0006		0.0005		0.0011	
MayDeg18	0.0016	***	0.0014	**	0.0011	
MayDeg19	0.0009	**	0.0003		0.0006	
MayDeg20	0.0000		0.0000		-0.0014	*
MayDeg21	0.0015	***	0.0000		-0.0013	

Variable	Barley		Flax		Fall Rye	
MayDeg22	0.0009	*	0.0025	***	0.0015	*
MayDeg24	0.0010	*	0.0020	**	0.0012	
MayDeg25	0.0004		0.0020	*	-0.0013	
MayDeg26	-0.0006		-0.0013		-0.0031	**
MayDeg27	0.0023	***	0.0016		0.0036	**
MayDeg28	0.0007		-0.0005		-0.0033	*
MayDeg29	0.0006		0.0011		0.0025	
MayDeg30	-0.0027	*	0.0011		-0.0063	**
MayDeg31	0.0047	***	-0.0030		0.0083	**
MayDeg32	0.0007		0.0011		0.0076	
MayDeg33	0.0039		0.0051		-0.0011	
MayDeg34	-0.0014		-0.0130	**	-0.0099	
MayDeg35	0.0051		0.0161	*	0.0001	
MayDeg36	-0.0019		0.0139	*	0.0169	
MayDeg37	-0.0137		-0.0100		0.0083	
MayDeg38	0.0032		-0.0143		-0.0305	
MayDeg39	-0.0060		-0.1047		-0.0043	
MayDeg40	0.0028		0.0581		-0.0235	
MayDeg41	0.0155		0.1340		0.1132	
MayDeg42	0.1145		0.0633		0.2580	**
MayDeg43	n/a		n/a		n/a	
MayDeg44	n/a		n/a		n/a	

Variable	Barley		Flax		Fall Rye	
JunDeg0	0.0003		0.0024		0.0072	
JunDeg1	-0.0003		0.0071		0.0133	***
JunDeg2	0.0019		0.0036		0.0118	***
JunDeg3	-0.0017		0.0006		0.0117	***
JunDeg4	-0.0014		0.0021		0.0120	***
JunDeg5	0.0009		0.0079	***	0.0122	***
JunDeg6	-0.0008		0.0021		0.0113	***
JunDeg7	0.0005		0.0052	**	0.0122	***
JunDeg8	-0.0003		0.0042	*	0.0105	***
JunDeg9	0.0003		0.0032		0.0127	***
JunDeg10	0.0006		0.0038		0.0139	***
JunDeg11	0.0008		0.0042	*	0.0113	***
JunDeg12	0.0003		0.0037		0.0133	***
JunDeg13	0.0010		0.0040	*	0.0131	***
JunDeg14	-0.0006		0.0034		0.0126	***
JunDeg15	-0.0005		0.0035		0.0111	***
JunDeg16	-0.0003		0.0021		0.0109	***
JunDeg17	-0.0003		0.0038		0.0123	***
JunDeg18	0.0004		0.0032		0.0118	***
JunDeg19	0.0004		0.0038		0.0115	***
JunDeg20	0.0004		0.0049	**	0.0121	***
JunDeg21	-0.0001		0.0039		0.0116	***
JunDeg22	0.0002		0.0041	*	0.0122	***

Variable	Barley		Flax		Fall Rye	
JunDeg24	0.0008		0.0048	**	0.0132	***
JunDeg25	-0.0006		0.0033		0.0098	***
JunDeg26	0.0006		0.0050	**	0.0106	***
JunDeg27	-0.0001		0.0039		0.0087	***
JunDeg28	0.0012		0.0049	**	0.0151	***
JunDeg29	-0.0012		0.0059	**	0.0098	***
JunDeg30	-0.0007		0.0020		0.0136	***
JunDeg31	-0.0039	**	0.0025		0.0069	**

JunDeg32	0.0020		0.0089	***	0.0099	***
JunDeg33	-0.0003		0.0080	**	0.0062	*
JunDeg34	-0.0027		-0.0008		0.0070	
JunDeg35	-0.0138	***	0.0047		-0.0099	
JunDeg36	-0.0115	**	-0.0056		0.0132	*
JunDeg37	-0.0084		-0.0123		0.0100	
JunDeg38	-0.0134		-0.0110		0.0055	
JunDeg39	0.0169		0.0086		0.0313	**
JunDeg40	-0.0080		0.0039		-0.0167	
JunDeg41	0.0008		-0.0218		0.0412	
JunDeg42	-0.1557	***	-0.0951		-0.0308	
JunDeg43	0.1239		-0.1270		0.0583	
JunDeg44	0.1248		0.0587		-0.1225	

Variable	Barley		Flax	Fall Rye
JulDeg0	-0.0191	**	0.0275	0.0120
JulDeg1	-0.0077		-0.0119	-0.0135
JulDeg2	-0.0023		0.0074	0.0109
JulDeg3	-0.0151	***	0.0145	0.0060
JulDeg4	-0.0069		0.0092	0.0090
JulDeg5	-0.0112	**	0.0090	0.0042
JulDeg6	-0.0120	***	0.0057	0.0067
JulDeg7	-0.0106	**	0.0083	0.0047
JulDeg8	-0.0108	**	0.0082	0.0034
JulDeg9	-0.0104	**	0.0093	0.0062
JulDeg10	-0.0114	***	0.0090	0.0051
JulDeg11	-0.0092	**	0.0092	0.0044
JulDeg12	-0.0101	**	0.0093	0.0077
JulDeg13	-0.0114	***	0.0076	0.0056
JulDeg14	-0.0101	**	0.0091	0.0073
JulDeg15	-0.0103	**	0.0081	0.0066
JulDeg16	-0.0101	**	0.0092	0.0055
JulDeg17	-0.0104	**	0.0089	0.0067
JulDeg18	-0.0107	**	0.0096	0.0056
JulDeg19	-0.0112	**	0.0089	0.0063
JulDeg20	-0.0102	**	0.0090	0.0054
JulDeg21	-0.0115	***	0.0082	0.0047
JulDeg22	-0.0116	***	0.0077	0.0046

Variable	Barley		Flax		Fall Rye	
JulDeg24	-0.0113	***	0.0088		0.0046	
JulDeg25	-0.0107	**	0.0084		0.0062	
JulDeg26	-0.0106	**	0.0078		0.0056	
JulDeg27	-0.0113	**	0.0087		0.0060	
JulDeg28	-0.0123	***	0.0084		0.0057	
JulDeg29	-0.0136	***	0.0080		0.0058	
JulDeg30	-0.0124	***	0.0073		0.0047	
JulDeg31	-0.0126	***	0.0081		0.0060	
JulDeg32	-0.0098	**	0.0088		0.0053	
JulDeg33	-0.0139	***	0.0046		0.0074	
JulDeg34	-0.0143	***	0.0009		0.0043	
JulDeg35	-0.0175	***	-0.0015		0.0012	
JulDeg36	-0.0220	***	-0.0035		0.0039	
JulDeg37	-0.0160	*	-0.0036		-0.0060	
JulDeg38	-0.0053		-0.0034		-0.0021	
JulDeg39	-0.0220		0.0023		0.0174	
JulDeg40	-0.0065		0.0596		-0.0343	
JulDeg41	-0.0048		-0.0819		-0.1091	
JulDeg42	0.0086		0.1585	**	-0.0309	
JulDeg43	-0.1579	**	-0.0969		0.0017	
JulDeg44	-0.0245		-0.0421		-0.1477	*

Variable	Barley		Flax		Fall Rye	
AugDeg0	0.0107	***	0.0203	**	0.0016	
AugDeg1	0.0082	***	0.0232	***	0.0052	
AugDeg2	0.0071	***	0.0159	***	0.0025	
AugDeg3	0.0083	***	0.0281	***	0.0029	
AugDeg4	0.0074	***	0.0288	***	0.0058	
AugDeg5	0.0074	***	0.0219	***	0.0015	
AugDeg6	0.0079	***	0.0257	***	0.0033	
AugDeg7	0.0073	***	0.0215	***	0.0031	
AugDeg8	0.0096	***	0.0256	***	0.0049	*
AugDeg9	0.0082	***	0.0252	***	0.0011	
AugDeg10	0.0080	***	0.0238	***	0.0021	
AugDeg11	0.0081	***	0.0237	***	0.0041	
AugDeg12	0.0087	***	0.0251	***	0.0043	
AugDeg13	0.0068	***	0.0224	***	0.0016	
AugDeg14	0.0073	***	0.0241	***	0.0020	
AugDeg15	0.0076	***	0.0254	***	0.0036	
AugDeg16	0.0071	***	0.0233	***	0.0034	
AugDeg17	0.0083	***	0.0245	***	0.0018	
AugDeg18	0.0070	***	0.0236	***	0.0017	
AugDeg19	0.0076	***	0.0240	***	0.0012	
AugDeg20	0.0086	***	0.0255	***	0.0026	
AugDeg21	0.0083	***	0.0267	***	0.0028	
AugDeg22	0.0083	***	0.0246	***	0.0030	

Variable	Barley		Flax		Fall Rye	
AugDeg24	0.0089	***	0.0251	***	0.0037	
AugDeg25	0.0083	***	0.0237	***	0.0029	
AugDeg26	0.0080	***	0.0249	***	0.0026	
AugDeg27	0.0087	***	0.0249	***	0.0049	*
AugDeg28	0.0077	***	0.0245	***	0.0013	
AugDeg29	0.0072	***	0.0232	***	0.0028	
AugDeg30	0.0066	***	0.0238	***	0.0033	
AugDeg31	0.0061	***	0.0222	***	0.0021	
AugDeg32	0.0086	***	0.0240	***	0.0042	
AugDeg33	0.0078	***	0.0236	***	0.0035	
AugDeg34	0.0084	***	0.0214	***	0.0048	
AugDeg35	0.0074	***	0.0298	***	0.0003	
AugDeg36	0.0069	***	0.0292	***	0.0053	
AugDeg37	0.0051		0.0226	***	-0.0042	
AugDeg38	-0.0026		0.0239	***	0.0000	
AugDeg39	0.0291	***	0.0453	***	0.0022	
AugDeg40	-0.0205		0.0331		-0.0290	
AugDeg41	0.0666	**	0.0859	**	0.0727	*
AugDeg42	-0.0108		-0.0218		-0.1445	*
AugDeg43	0.0040		-0.0167		0.0726	
AugDeg44	0.0279		0.0485		0.0112	

APPENDIX E: MODEL 3 RESULTS

This section contains results for Model 3. One asterisk (*) indicates significance at 10%, two asterisks (**) indicates significance at 5% and three (***) indicates significance at 1%.

Variable Name	**Variable Description**
CONSTANT	The constant in the equation
TIME	Time trend, calculated as YEAR – 1964
APRIL RAIN	Total cumulative rainfall from April 15 to April 30, in mm
MAY RAIN	Total cumulative rainfall for May
JUNE RAIN	Total cumulative rainfall for June
JULY RAIN	Total cumulative rainfall for July
AUGUST RAIN	Total cumulative rainfall for August
APRDEG0	Total number of hours of exposure from April 14 to April 30 between 0.0 ºC and 0.9 ºC
APRDEG1	Total number of hours of exposure from April 14 to April 30 between 1.0 ºC and 1.9 ºC
APRDEG2 … APRDEG39	As above for DEG0 and DEG1 but for temperatures from 2.0 to 2.9 ºC up to 39.0 to 39.9 ºC
APRDEG40P	Total number of hours of exposure from April 14 to April 30 from 40.0 ºC and above
MAYDEG0	Total number of hours of exposure for May between 0.0 ºC and 0.9 ºC
MAYDEG1	Total number of hours of exposure for May between 1.0 ºC and 1.9 ºC
MAYDEG2 … MAYDEG39	As above for DEG0 and DEG1 but for temperatures from 2.0 to 2.9 ºC up to 39.0 to 39.9 ºC
MAYDEG40P	Total number of hours of exposure for May from 40.0 ºC and above
JUNDEG0 TO JUNDEG29	As above for April and May
JULDEG0 to JULDEG29	As above for April and May
AUGDEG0 to AUGDEG29	As above for April and May
JJADEG30 to JJADEG40P	Cumulative total hours for June, July and August for 30 to 30.9 ºC up to 40 ºC and above
Adj R2	The adjusted R^2 statistic from the regression analysis
N OBS	The number of observations in the regression analysis

Variable	Spring Wheat		Canola		Oats		Barley	
Adj. R2	**0.463**		**0.390**		**0.429**		**0.482**	
Trend	0.0081	***	0.0133	***	0.0084	***	0.0103	***
AprRain	0.0008	***	0.0010	***	0.0006	***	0.0004	*
MayRain	0.0011	***	0.0014	***	0.0008	***	0.0005	***
JunRain	0.0008	***	-0.0001		0.0011	***	0.0003	***
JulRain	0.0002	**	0.0001		0.0008	***	0.0002	***
AugRain	-0.0004	***	-0.0002	*	-0.0005	***	-0.0004	***
AprDeg0	0.0015	***	0.0013	**	0.0019	***	0.0016	***
AprDeg1	0.0002		0.0000		-0.0001		0.0006	
AprDeg2	0.0014	***	0.0022	***	0.0013	**	0.0021	
AprDeg3	0.0003		-0.0001		-0.0007		-0.0004	
AprDeg4	-0.0001		0.0004		-0.0003		-0.0008	*
AprDeg5	-0.0007		-0.0002		-0.0012	**	-0.0007	
AprDeg6	0.0005		0.0011	*	0.0003		0.0002	
AprDeg7	-0.0007		0.0004		-0.0013	**	-0.0006	
AprDeg8	0.0000		-0.0010	*	-0.0013	**	-0.0001	
AprDeg9	0.0006		0.0011	*	0.0003		0.0005	
AprDeg10	0.0003		0.0006		-0.0003		0.0007	
AprDeg11	0.0010	**	0.0011	*	0.0008		0.0009	*
AprDeg12	0.0003		-0.0003		-0.0011		-0.0005	
AprDeg13	0.0022	***	0.0031	***	0.0017		0.0018	***
AprDeg14	0.0024	***	0.0027	***	0.0030		0.0017	***
AprDeg15	0.0014	**	0.0013	*	0.0017		0.0019	***
AprDeg16	0.0007		0.0004		0.0011		0.0008	
AprDeg17	0.0016	**	0.0019	**	0.0026		0.0009	
AprDeg18	-0.0023	***	-0.0005		-0.0009		-0.0026	***
AprDeg19	0.0008		0.0005		0.0015		0.0016	**
AprDeg20	0.0034	***	0.0033	***	0.0031		0.0014	
AprDeg21	0.0006		0.0012		-0.0004		0.0006	
AprDeg22	0.0026	**	0.0013		0.0014		0.0024	
AprDeg23	0.0014		0.0043	***	0.0023		0.0021	
AprDeg24	-0.0020		-0.0001		-0.0003		-0.0001	
AprDeg25	-0.0002		0.0022		-0.0012		0.0002	
AprDeg26	-0.0011		-0.0021		-0.0052		-0.0027	
AprDeg27	0.0044		0.0046		0.0026		0.0062	**
AprDeg28	0.0016		0.0036		-0.0077		-0.0014	
AprDeg29	0.0039		0.0003		0.0016		0.0068	
AprDeg30	-0.0015	*	-0.0102		-0.0098		-0.0013	
AprDeg31	-0.0126	**	-0.0018		-0.0182	**	-0.0154	**

Variable	Spring Wheat		Canola		Oats		Barley	***
AprDeg33	-0.0347		-0.0216		-0.0184		-0.0191	
AprDeg34	-0.0203		0.0064		-0.0045		0.0252	
AprDeg35	-0.0163		-0.0206		-0.0116		-0.0225	
AprDeg36	-0.0831	*	-0.1703	***	-0.0543		-0.0300	
MayDeg0	**0.0017**	***	**0.0012**	*	**0.0034**	***	**0.0028**	***
MayDeg1	**0.0003**		**0.0006**		**0.0012**	*	**0.0007**	
MayDeg2	**-0.0001**		**-0.0004**		**0.0006**		**-0.0002**	
MayDeg3	**-0.0002**		**-0.0006**		**0.0013**	**	**0.0005**	
MayDeg4	**0.0001**		**-0.0001**		**0.0010**	**	**0.0008**	*
MayDeg5	**-0.0009**	**	**-0.0010**	**	**-0.0001**		**-0.0001**	
MayDeg6	**0.0012**	***	**0.0005**		**0.0017**	***	**0.0011**	***
MayDeg7	**0.0002**		**0.0000**		**0.0008**	*	**0.0009**	**
MayDeg8	**0.0009**	***	**0.0013**	***	**0.0017**	***	**0.0016**	***
MayDeg9	**-0.0002**		**-0.0003**		**0.0003**		**0.0002**	
MayDeg10	**0.0000**		**0.0000**		**0.0010**	**	**0.0005**	
MayDeg11	**-0.0002**		**-0.0004**		**0.0010**	**	**0.0003**	
MayDeg12	**-0.0006**	*	**-0.0004**		**0.0006**		**0.0001**	
MayDeg13	**0.0004**		**-0.0003**		**0.0012**	***	**0.0010**	***
MayDeg14	**-0.0004**		**0.0002**		**0.0004**		**0.0004**	
MayDeg15	**0.0000**		**0.0007**		**0.0013**	***	**0.0011**	***
MayDeg16	**0.0003**		**0.0003**		**0.0015**	***	**0.0007**	*
MayDeg17	**0.0001**		**0.0002**		**0.0013**	***	**0.0006**	
MayDeg18	**0.0009**	**	**0.0023**	***	**0.0022**	***	**0.0017**	***
MayDeg19	**0.0002**		**0.0010**	*	**0.0013**	***	**0.0009**	**
MayDeg20	**-0.0012**	***	**-0.0002**		**0.0000**		**-0.0002**	
MayDeg21	**0.0003**		**0.0004**		**0.0016**	***	**0.0013**	***
MayDeg22	**0.0003**		**0.0005**		**0.0013**	**	**0.0010**	**
MayDeg23	**0.0007**		**0.0006**		**0.0009**		**0.0011**	**
MayDeg24	**0.0002**		**0.0005**		**0.0003**		**0.0008**	
MayDeg25	**-0.0003**		**-0.0001**		**0.0005**		**0.0003**	
MayDeg26	**-0.0011**		**-0.0014**		**-0.0006**		**-0.0004**	
MayDeg27	**0.0013**		**-0.0014**		**0.0018**	**	**0.0025**	***
MayDeg28	**-0.0005**		**0.0007**		**0.0002**		**0.0008**	
MayDeg29	**0.0006**		**-0.0016**		**-0.0007**		**0.0007**	
MayDeg30	**-0.0027**	**	**0.0001**		**-0.0010**		**-0.0026**	*
MayDeg31	**0.0040**	***	**0.0031**		**0.0004**		**0.0049**	***
MayDeg32	**0.0008**		**-0.0014**		**0.0018**		**0.0007**	
MayDeg33	**0.0000**		**0.0014**		**0.0031**		**0.0035**	
MayDeg34	**-0.0053**		**-0.0037**		**-0.0013**		**-0.0029**	
Variable	**Spring**		**Canola**		**Oats**		**Barley**	

	Wheat							
MayDeg37	-0.0119		-0.0242	**	-0.0133		-0.0115	
MayDeg38	-0.0130		-0.0246		0.0011		0.0009	
MayDeg39	-0.0170		-0.0724		0.0024		-0.0144	
MayDeg40P	0.0233		0.0188		0.0060		0.0145	
JunDeg0	0.0122	***	0.0151	***	0.0133	***	0.0090	***
JunDeg1	0.0075	***	0.0009		0.0056	**	0.0047	**
JunDeg2	0.0064	***	0.0055	**	0.0058	***	0.0064	***
JunDeg3	0.0046	***	0.0040	**	0.0037	*	0.0031	**
JunDeg4	0.0050	***	0.0030	*	0.0057	***	0.0032	***
JunDeg5	0.0065	***	0.0054	***	0.0055	***	0.0055	***
JunDeg6	0.0060	***	0.0043	***	0.0040	***	0.0038	***
JunDeg7	0.0070	***	0.0054	***	0.0056	***	0.0051	***
JunDeg8	0.0056	***	0.0051	***	0.0049	***	0.0042	***
JunDeg9	0.0064	***	0.0048	***	0.0060	***	0.0049	***
JunDeg10	0.0068	***	0.0050	***	0.0066	***	0.0052	***
JunDeg11	0.0077	***	0.0062	***	0.0072	***	0.0055	***
JunDeg12	0.0069	***	0.0051	***	0.0060	***	0.0049	***
JunDeg13	0.0075	***	0.0064	***	0.0069	***	0.0056	***
JunDeg14	0.0059	***	0.0050	***	0.0055	***	0.0040	***
JunDeg15	0.0057	***	0.0043	***	0.0049	***	0.0041	***
JunDeg16	0.0056	***	0.0048	***	0.0049	***	0.0043	***
JunDeg17	0.0060	***	0.0054	***	0.0055	***	0.0043	***
JunDeg18	0.0060	***	0.0047	***	0.0054	***	0.0050	***
JunDeg19	0.0064	***	0.0059	***	0.0058	***	0.0050	***
JunDeg20	0.0065	***	0.0056	***	0.0059	***	0.0050	***
JunDeg21	0.0061	***	0.0050	***	0.0054	***	0.0044	***
JunDeg22	0.0060	***	0.0048	***	0.0058	***	0.0048	***
JunDeg23	0.0063	***	0.0047	***	0.0054	***	0.0047	***
JunDeg24	0.0063	***	0.0052	***	0.0064	***	0.0054	***
JunDeg25	0.0056	***	0.0044	***	0.0044	***	0.0040	***
JunDeg26	0.0063	***	0.0054	***	0.0058	***	0.0052	***
JunDeg27	0.0059	***	0.0054	***	0.0070	***	0.0046	***
JunDeg28	0.0074	***	0.0053	***	0.0068	***	0.0059	***
JunDeg29	0.0056	***	0.0049	***	0.0044	***	0.0034	***

Variable	Spring Wheat		Canola		Oats		Barley	
JulDeg0	0.0188	***	0.0141	**	0.0127	*	0.0091	*
JulDeg1	0.0111	**	0.0125	**	0.0064		0.0089	*
JulDeg2	0.0098	***	0.0158	***	0.0158	***	0.0123	***
JulDeg3	-0.0012		0.0044		0.0015		0.0006	
JulDeg4	0.0108	***	0.0103	***	0.0088	***	0.0080	***
JulDeg5	0.0032	**	0.0060	***	0.0069	***	0.0043	***
JulDeg6	0.0041	***	0.0066	***	0.0052	***	0.0031	**
JulDeg7	0.0051	***	0.0062	***	0.0058	***	0.0048	***
JulDeg8	0.0045	***	0.0077	***	0.0053	***	0.0042	***
JulDeg9	0.0053	***	0.0073	***	0.0074	***	0.0048	***
JulDeg10	0.0048	***	0.0064	***	0.0059	***	0.0040	***
JulDeg11	0.0056	***	0.0082	***	0.0071	***	0.0061	***
JulDeg12	0.0060	***	0.0059	***	0.0066	***	0.0051	***
JulDeg13	0.0051	***	0.0066	***	0.0063	***	0.0040	***
JulDeg14	0.0053	***	0.0075	***	0.0060	***	0.0053	***
JulDeg15	0.0051	***	0.0073	***	0.0062	***	0.0050	***
JulDeg16	0.0045	***	0.0068	***	0.0068	***	0.0052	***
JulDeg17	0.0052	***	0.0075	***	0.0070	***	0.0049	***
JulDeg18	0.0052	***	0.0068	***	0.0065	***	0.0046	***
JulDeg19	0.0047	***	0.0067	***	0.0055	***	0.0041	***
JulDeg20	0.0053	***	0.0075	***	0.0065	***	0.0051	***
JulDeg21	0.0045	***	0.0066	***	0.0051	***	0.0037	***
JulDeg22	0.0046	***	0.0060	***	0.0052	***	0.0037	***
JulDeg23	0.0054	***	0.0070	***	0.0067	***	0.0040	***
JulDeg24	0.0050	***	0.0071	***	0.0060	***	0.0041	***
JulDeg25	0.0055	***	0.0074	***	0.0063	***	0.0047	***
JulDeg26	0.0057	***	0.0066	***	0.0067	***	0.0047	***
JulDeg27	0.0051	***	0.0064	***	0.0060	***	0.0042	***
JulDeg28	0.0043	***	0.0055	***	0.0051	***	0.0032	***
JulDeg29	0.0034	***	0.0042	***	0.0040	***	0.0019	*

Variable	Spring Wheat		Canola		Oats		Barley	
AugDeg0	-0.0027		0.0004		0.0029		0.0005	
AugDeg1	0.0020		0.0030		0.0023		0.0027	
AugDeg2	0.0029	*	0.0061	***	0.0048	**	0.0020	
AugDeg3	0.0044	***	0.0076	***	0.0045	**	0.0031	**
AugDeg4	0.0032	**	0.0054	***	0.0037	**	0.0025	**
AugDeg5	0.0025	**	0.0060	***	0.0032	**	0.0023	*
AugDeg6	0.0036	***	0.0066	***	0.0052	***	0.0028	***
AugDeg7	0.0025	**	0.0048	***	0.0033	**	0.0022	**
AugDeg8	0.0043	***	0.0071	***	0.0057	***	0.0045	***
AugDeg9	0.0040	***	0.0064	***	0.0048	***	0.0032	***
AugDeg10	0.0038	***	0.0062	***	0.0053	***	0.0030	***
AugDeg11	0.0033	***	0.0045	***	0.0045	***	0.0030	***
AugDeg12	0.0039	***	0.0068	***	0.0055	***	0.0035	***
AugDeg13	0.0024	**	0.0054	***	0.0039	***	0.0017	*
AugDeg14	0.0027	***	0.0053	***	0.0040	***	0.0022	**
AugDeg15	0.0037	***	0.0056	***	0.0042	***	0.0025	***
AugDeg16	0.0027	***	0.0048	***	0.0041	***	0.0020	**
AugDeg17	0.0036	***	0.0058	***	0.0049	***	0.0031	***
AugDeg18	0.0030	***	0.0053	***	0.0040	***	0.0019	**
AugDeg19	0.0030	***	0.0059	***	0.0044	***	0.0026	***
AugDeg20	0.0037	***	0.0056	***	0.0046	***	0.0034	***
AugDeg21	0.0039	***	0.0064	***	0.0049	***	0.0032	***
AugDeg22	0.0037	***	0.0055	***	0.0045	***	0.0031	***
AugDeg23	0.0034	***	0.0062	***	0.0056	***	0.0033	***
AugDeg24	0.0042	***	0.0071	***	0.0049	***	0.0038	***
AugDeg25	0.0034	***	0.0064	***	0.0044	***	0.0031	***
AugDeg26	0.0033	***	0.0053	***	0.0045	***	0.0028	***
AugDeg27	0.0042	***	0.0061	***	0.0049	***	0.0036	***
AugDeg28	0.0029	***	0.0059	***	0.0028	**	0.0025	***
AugDeg29	0.0025	**	0.0054	***	0.0031	**	0.0019	*

Variable	Spring Wheat		Canola		Oats		Barley	
JJADeg31	**0.0029**	***	**0.0042**	***	**0.0022**		**0.0016**	
JJADeg32	**0.0050**	***	**0.0067**	***	**0.0061**	***	**0.0049**	***
JJADeg33	**0.0034**	***	**0.0038**	**	**0.0041**	***	**0.0026**	**
JJADeg34	**0.0023**	*	**0.0038**	**	**0.0023**		**0.0020**	
JJADeg35	**-0.0004**		**0.0018**		**0.0000**		**-0.0016**	
JJADeg36	**-0.0014**		**-0.0042**		**-0.0033**		**-0.0034**	
JJADeg37	**-0.0012**		**0.0003**		**0.0018**		**-0.0010**	
JJADeg38	**-0.0002**		**0.0008**		**0.0075**		**-0.0137**	
JJADeg39	**0.0155**	*	**0.0200**	*	**0.0155**	*	**0.0264**	***
JJADeg40P	**-0.0100**		**0.0082**		**-0.0043**		**-0.0076**	

APPENDIX F: WINTER MODEL RESULTS

This section contains results for Model 3. One asterisk (*) indicates significance at 10%, two asterisks (**) indicates significance at 5% and three (***) indicates significance at 1%.

Variable descriptions

Constant	The model constant
Time	Time trend, = YEAR – 1977
JanSV	Variance of snow depth for January
FebSV	Variance of snow depth for February
MarSV	Variance of snow depth for March
AprSV	Variance of snow depth for April
Win1_3	Total hours from January 1 to April 30 from -1 to -3.9 °C
Win4_6 to Win37_39	Total hours from January 1 to April 30 from -4 to 6.9 °C and -37 to *39.9 °C
Win40P	Total hours below -40 °C between January 1 and April 30
Adj R2	Adjusted R2 statistic for the regression
nObs	The number of observations in the analysis
nCoef	The number of coefficients that were estimated, including the number of district dummies

	Winter Wheat		Fall Rye	
Constant	8.186	***	7.6907	***
Time	0.01354	***	0.01063	***
JanSV	0.00039	**	0.00027	*
FebSV	-0.00075	*	0.000001	
MarSV	0.00010		0.00006	
AprSV	-0.00008		-0.00010	***
Win1_3	-0.00095	***	-0.00028	
Win4_6	-0.00015		-0.00047	**
Win7_9	-0.00035		0.00044	*
Win10_12	-0.00059	*	-0.00080	***
Win13_15	-0.00011		-0.00026	
Win16_18	0.00026		0.00019	
Win19_21	-0.00085	*	0.00018	
Win22_24	0.00009		0.00034	
Win25_27	-0.00178	***	-0.00112	***
Win28_30	0.00104	*	-0.00053	
Win31_33	-0.00072		0.00092	*
Win34_36	0.00033		0.00032	
Win37_39	-0.00114		-0.00171	**
Win40p	0.00181	*	0.00099	*
Adjusted R2	**0.457**		**0.247**	
N Obs	**718**		**1504**	
N Coef	**154**	[17]	**157**	

[17] Coefficients for the district dummies are not reported to conserve space.

APPENDIX G: Acreage concentrations by crop, selected years, Base Model

Figure G1: Base model 2005, highest acreage per cell

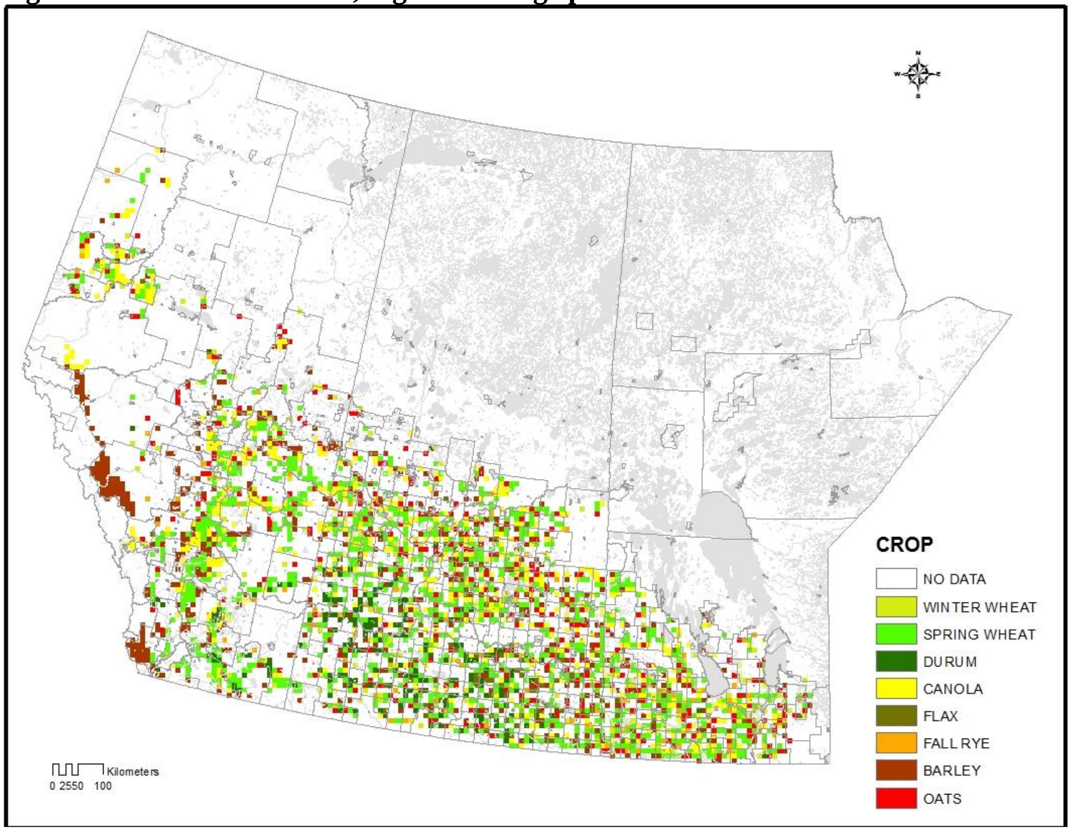


Figure G2: Base Model 2005

Figure G2a Base Model Winter wheat 2005

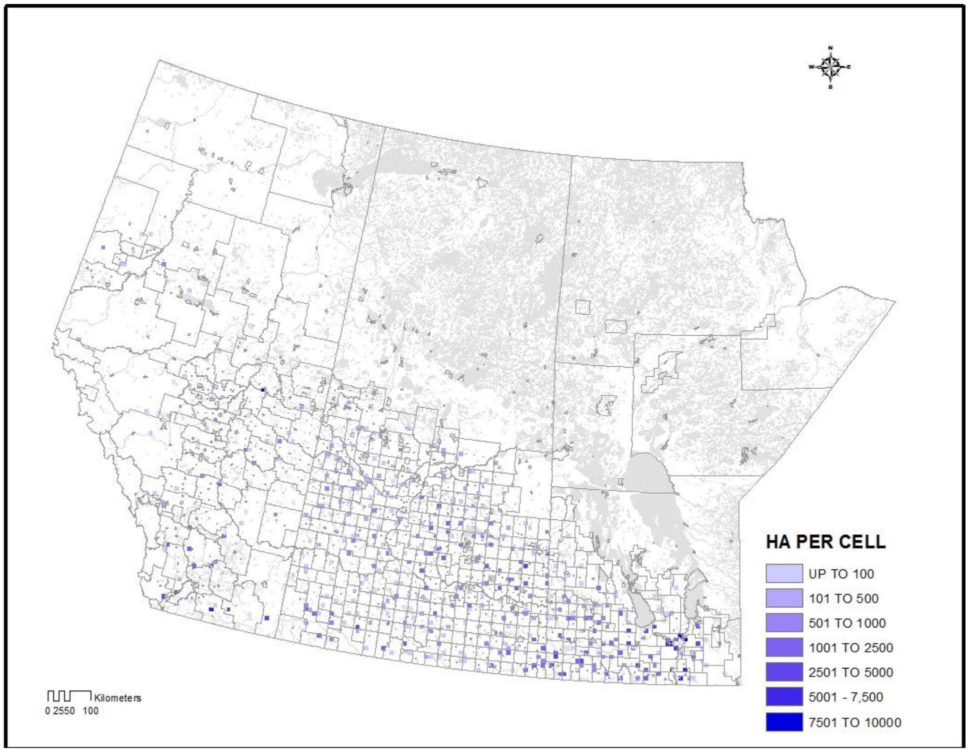


Figure G2b Base Model Spring Wheat 2005

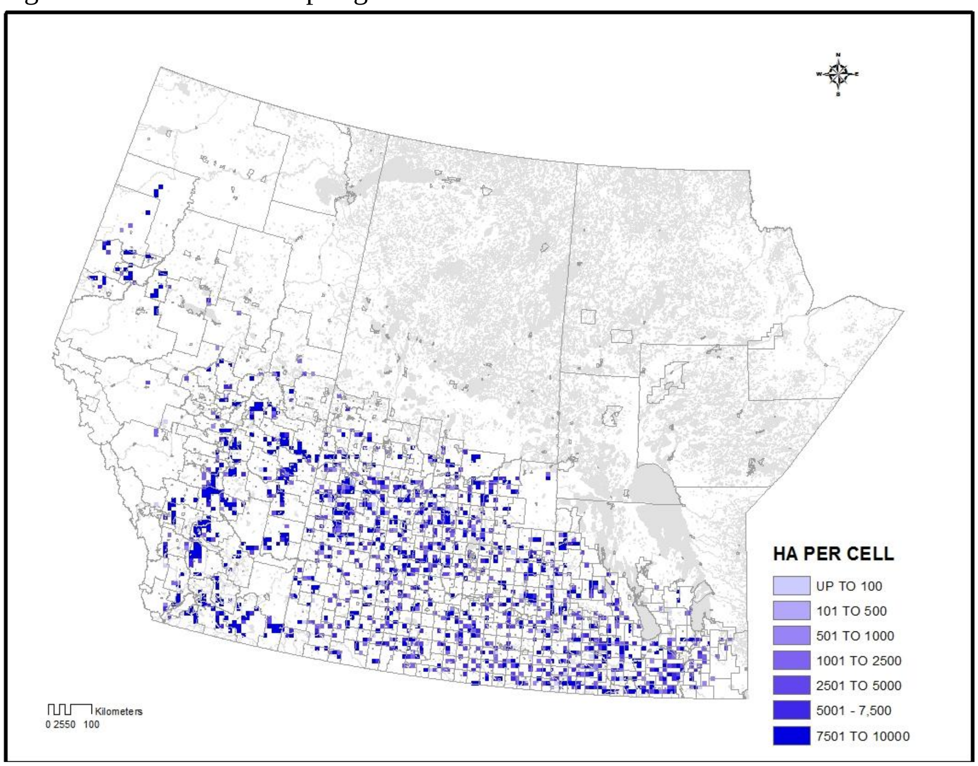


Figure G2c Base Model Durum Wheat 2005

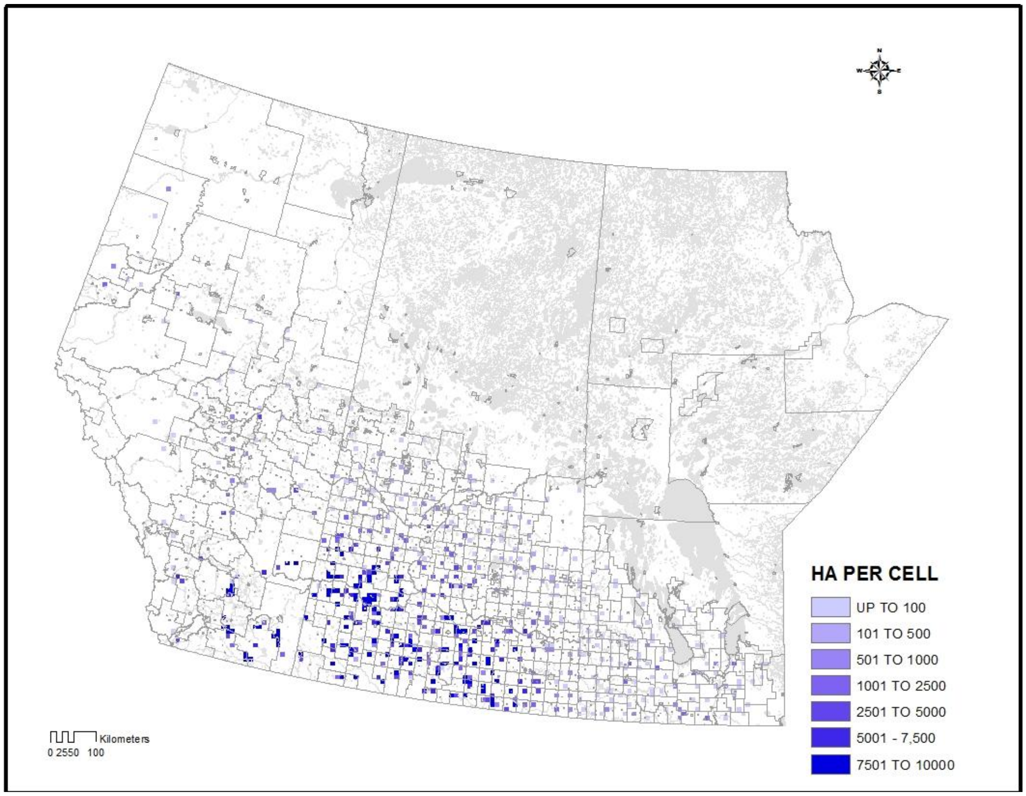


Figure G2d Base Model Canola 2005

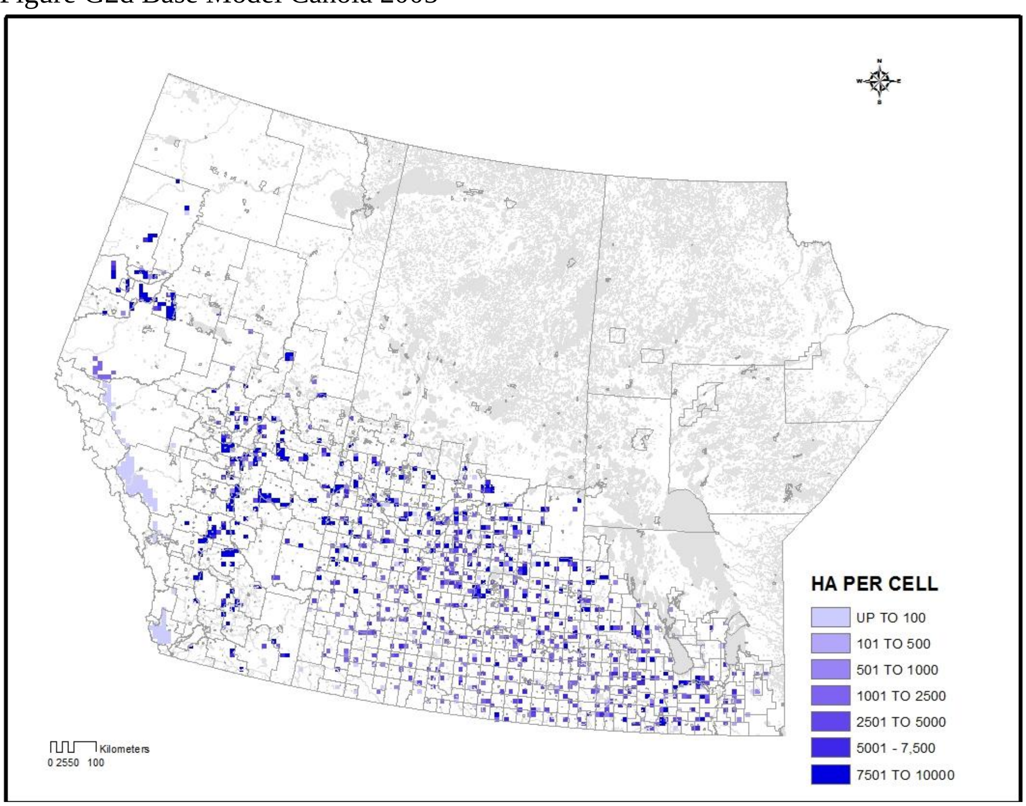


Figure G2e Base Model Flax 2005

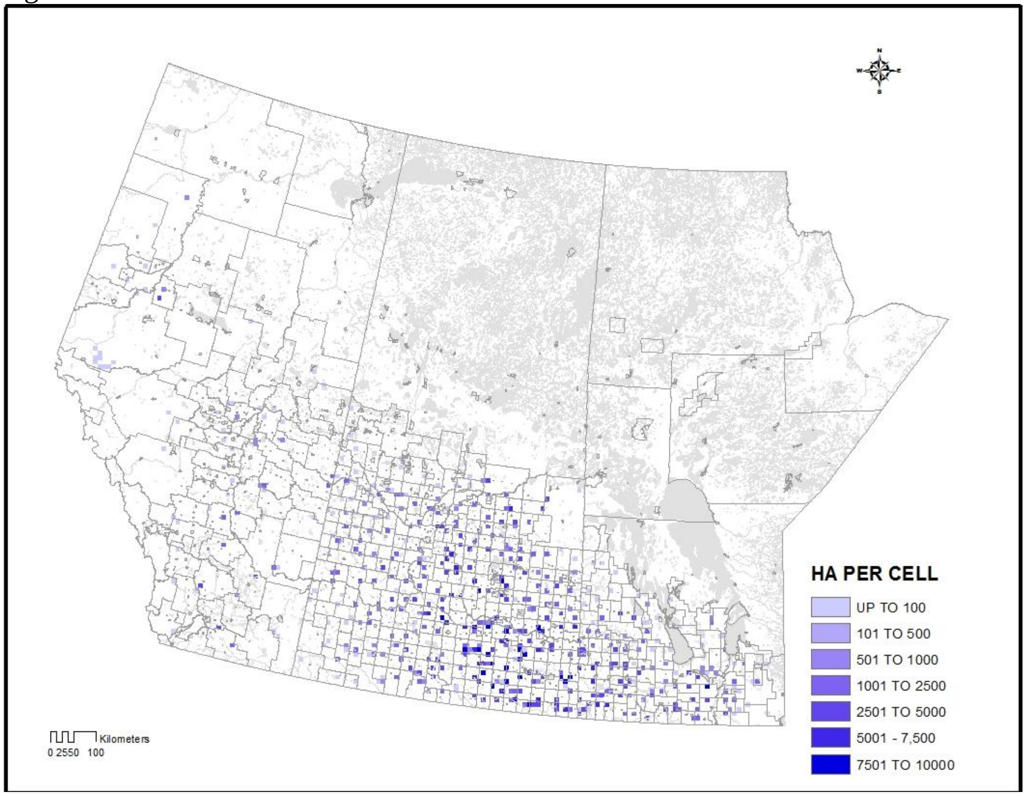


Figure G2f Base Model Rye 2005

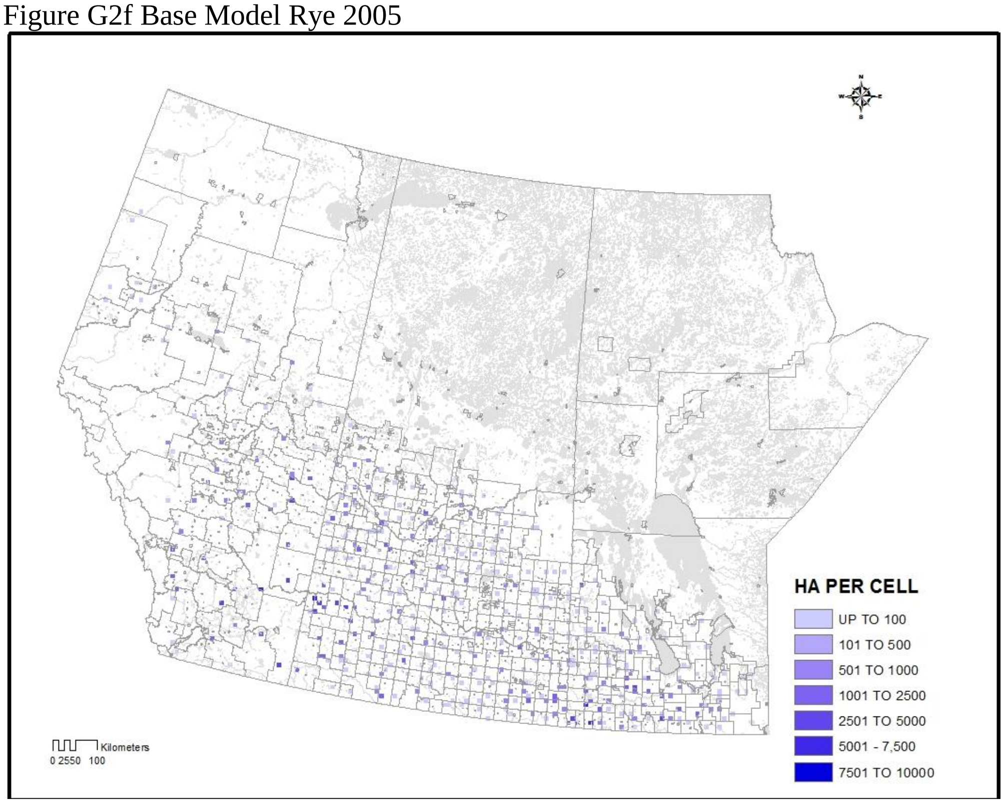


Figure G2g Base Model Barley 2005

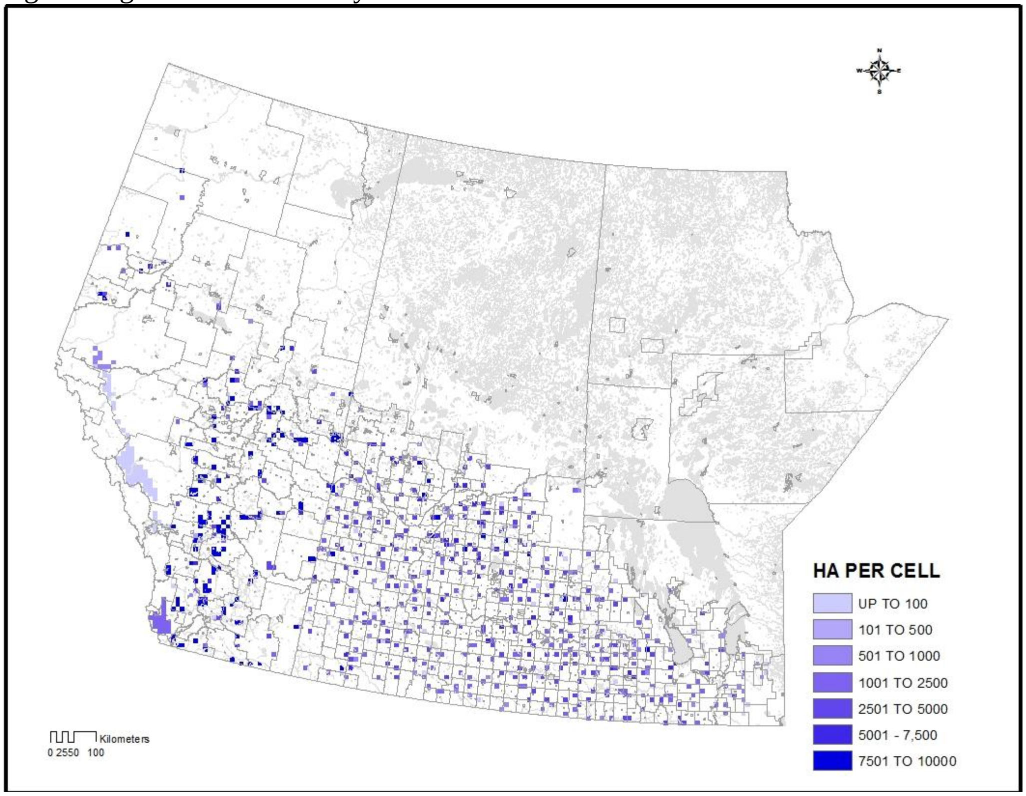


Figure G2h Base Model Oats 2005

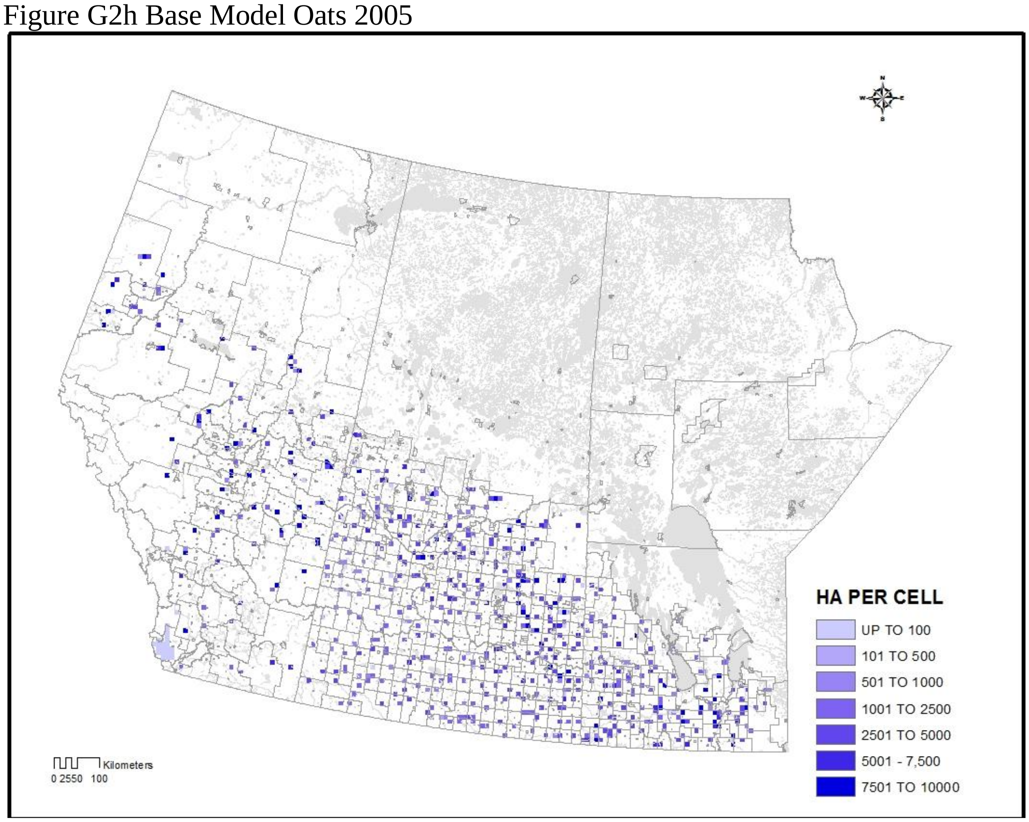


Figure G3: Base Model 2010, highest acreage per cell.

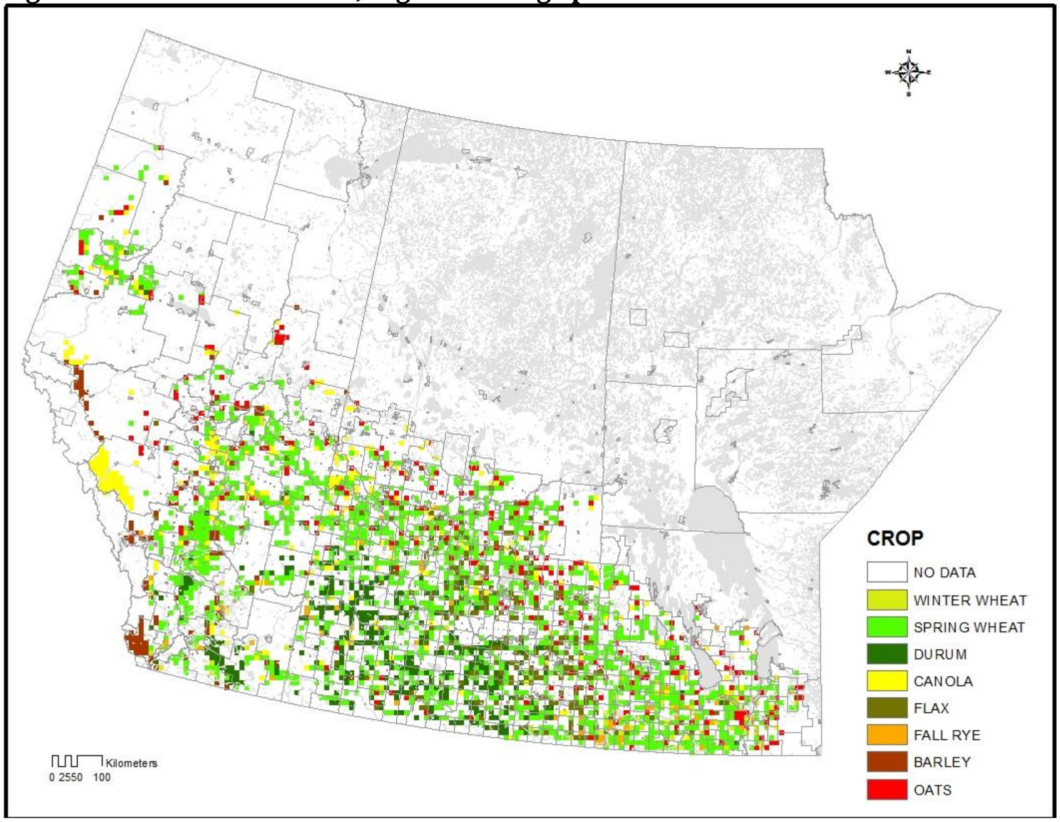


Figure G4 Base Model 2010

Figure G4a Base Model Winter Wheat 2010

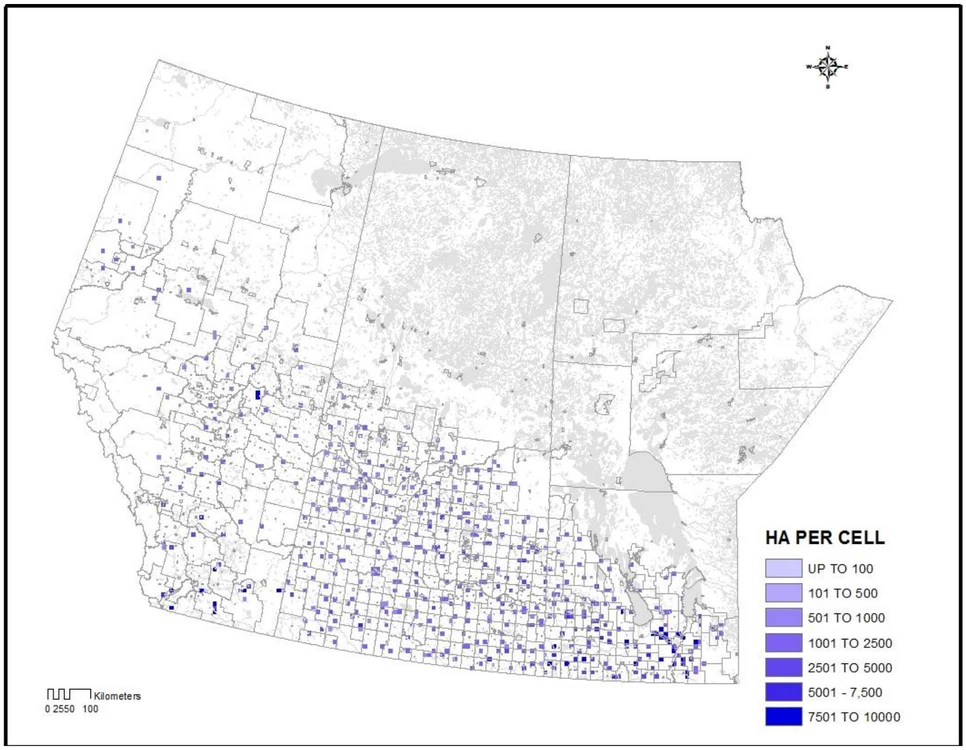


Figure G4b Base Model Spring Wheat 2010

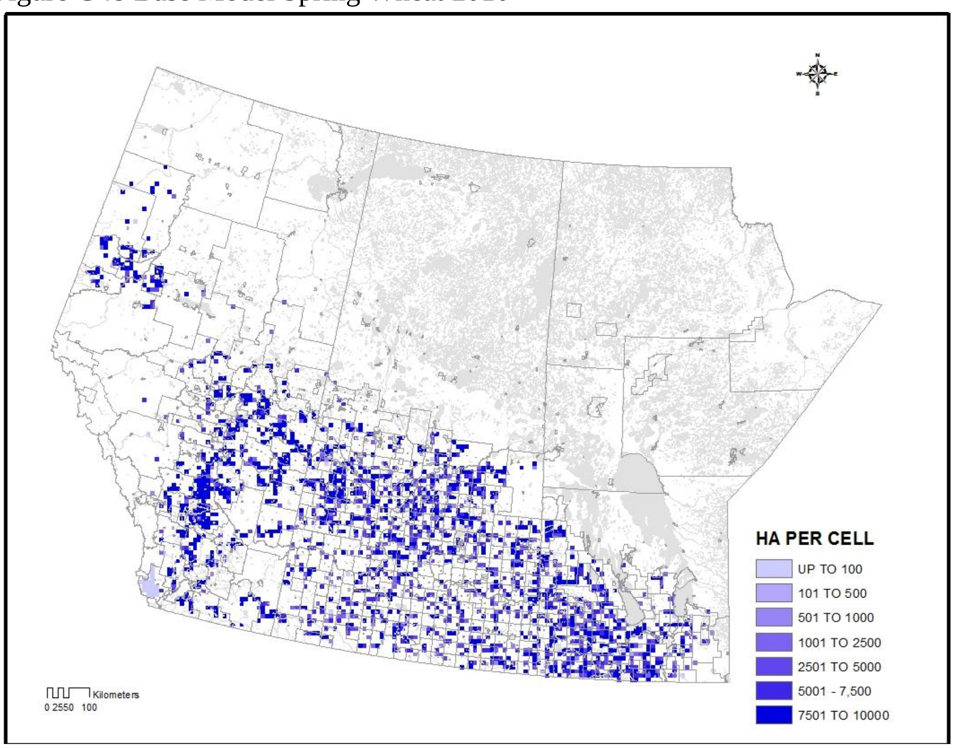


Figure G4c Base Model Durum Wheat 2010

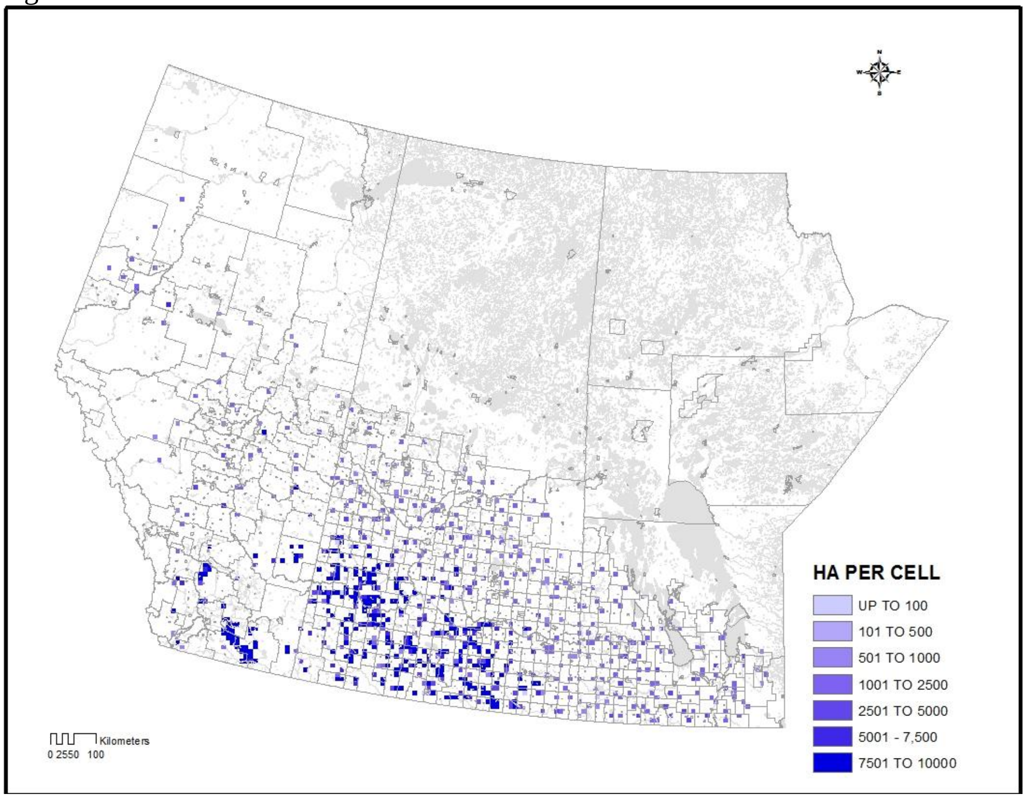


Figure G4d Base Model Canola 2010

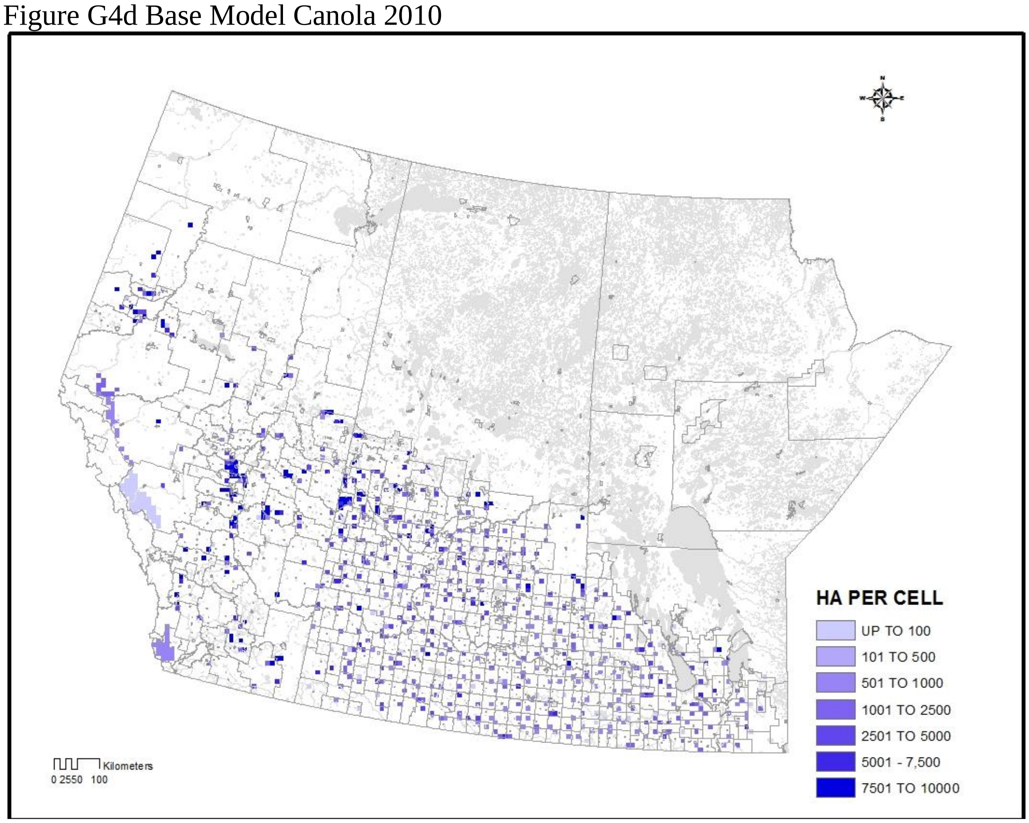


Figure G4e Base Model Flax 2010

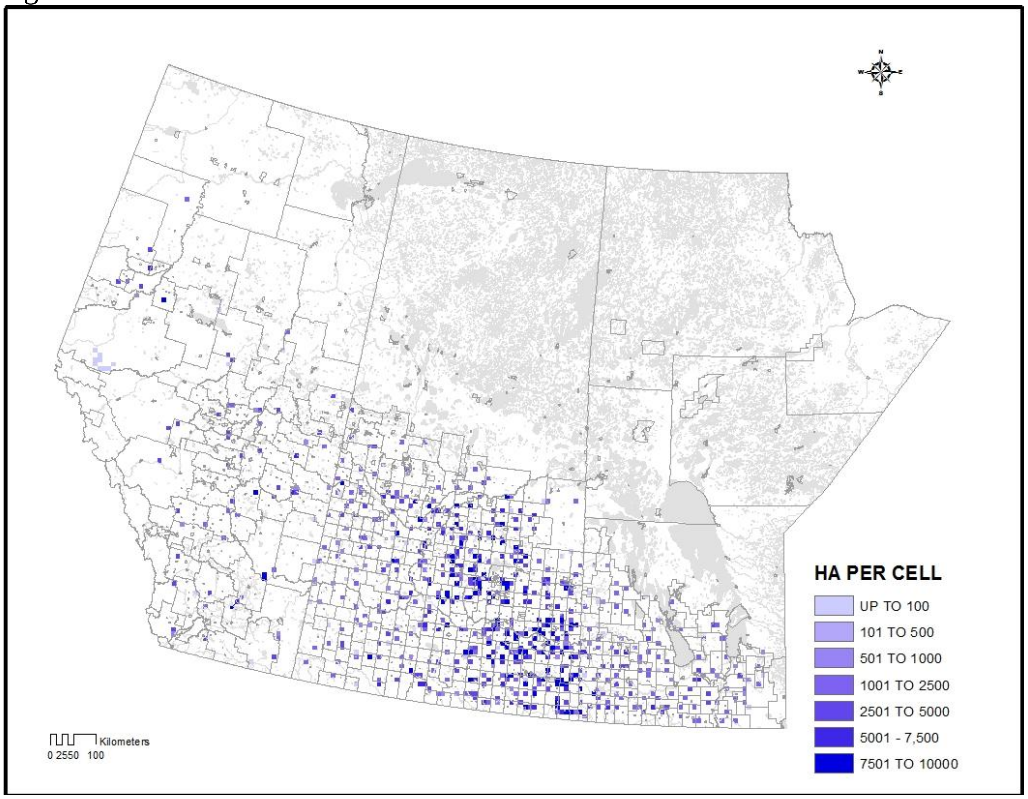


Figure G4f Base Model Rye 2010

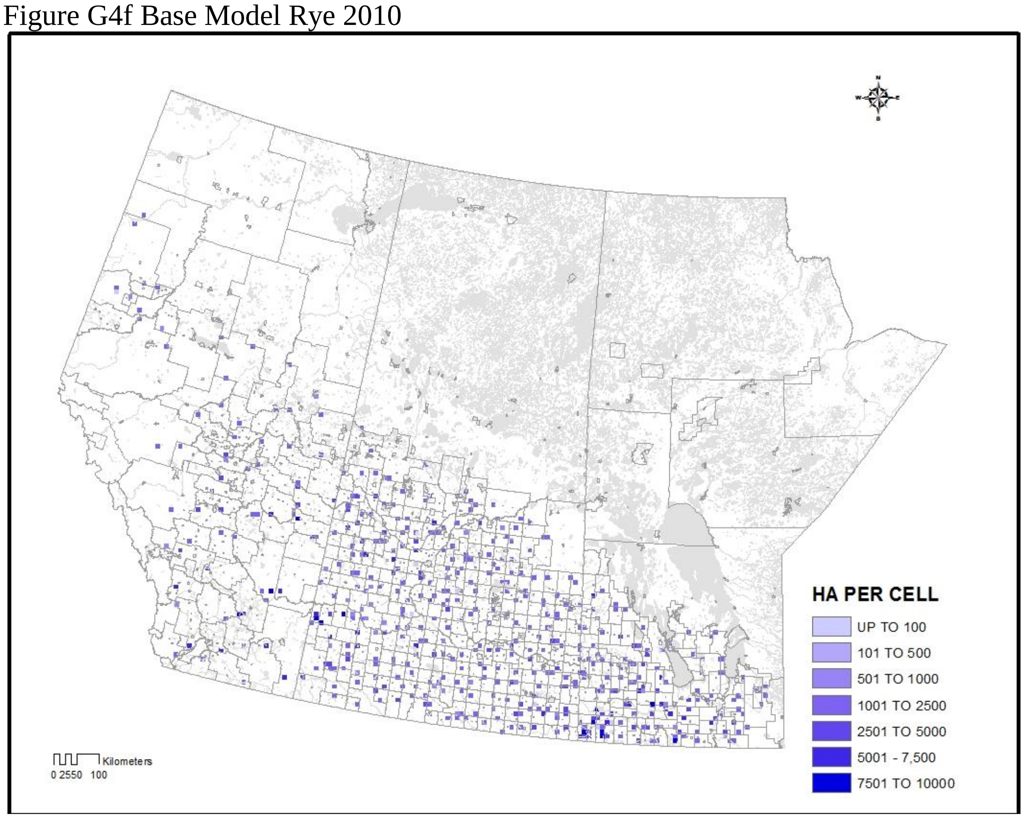


Figure G4g Base Model Barley 2010

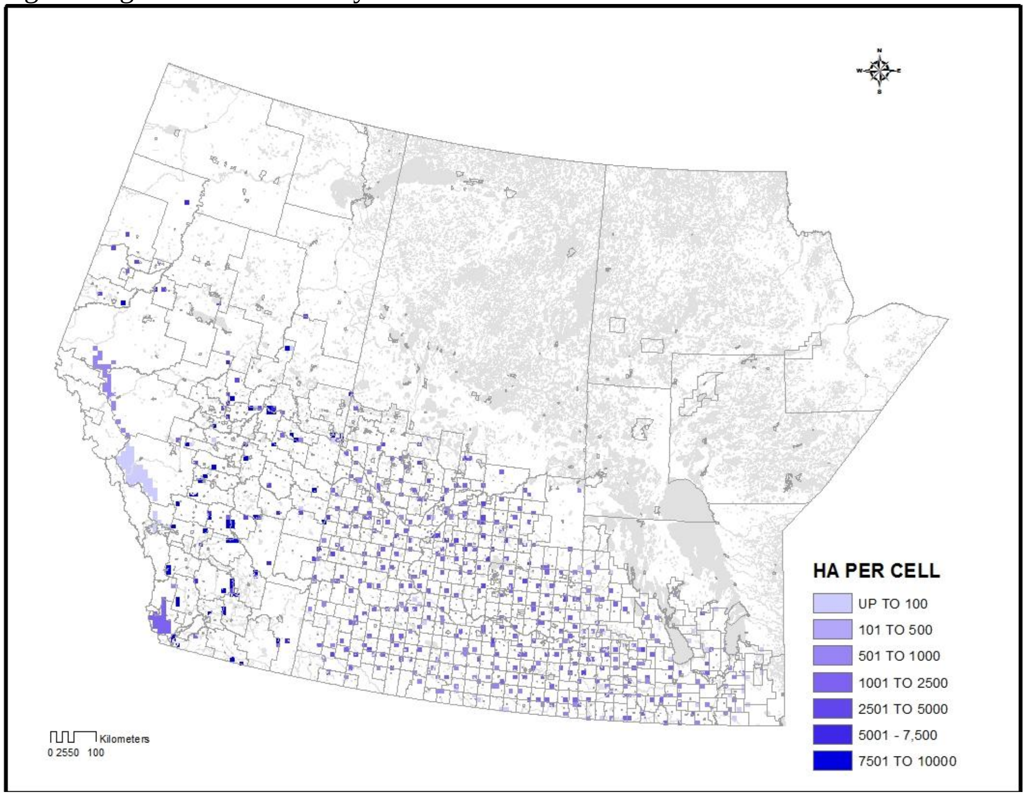


Figure G4h Base Model Oats 2010

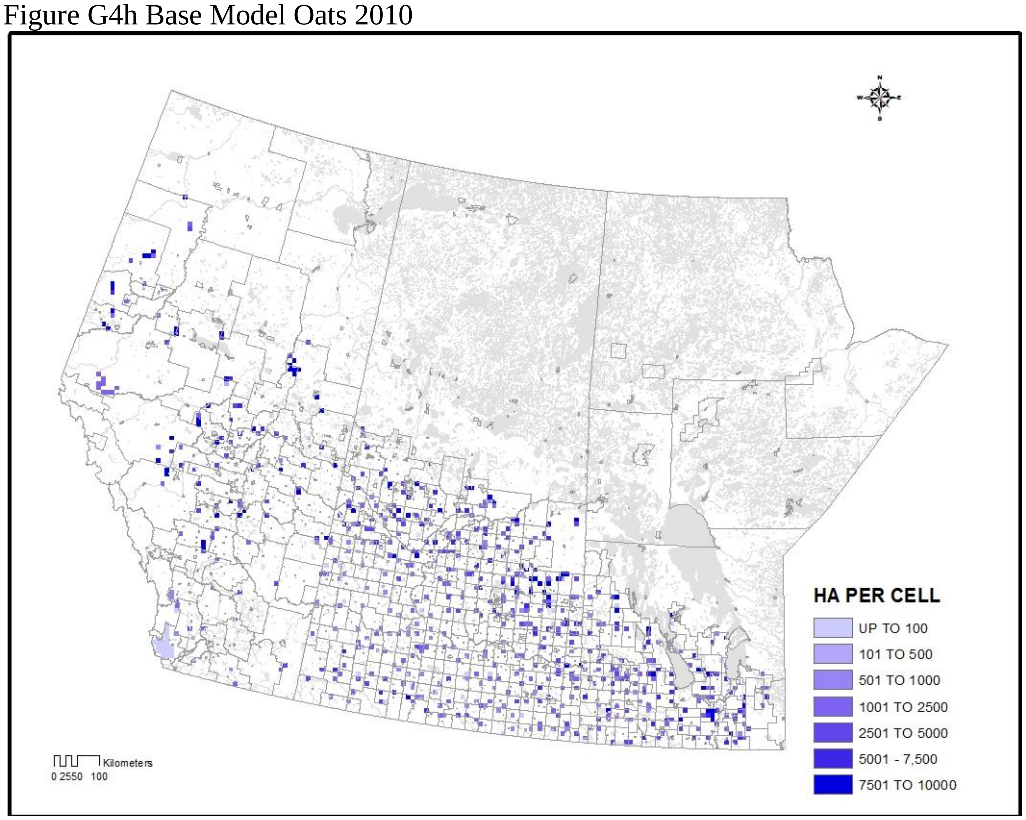


Figure G5: Base Model 2025, highest acreage per cell

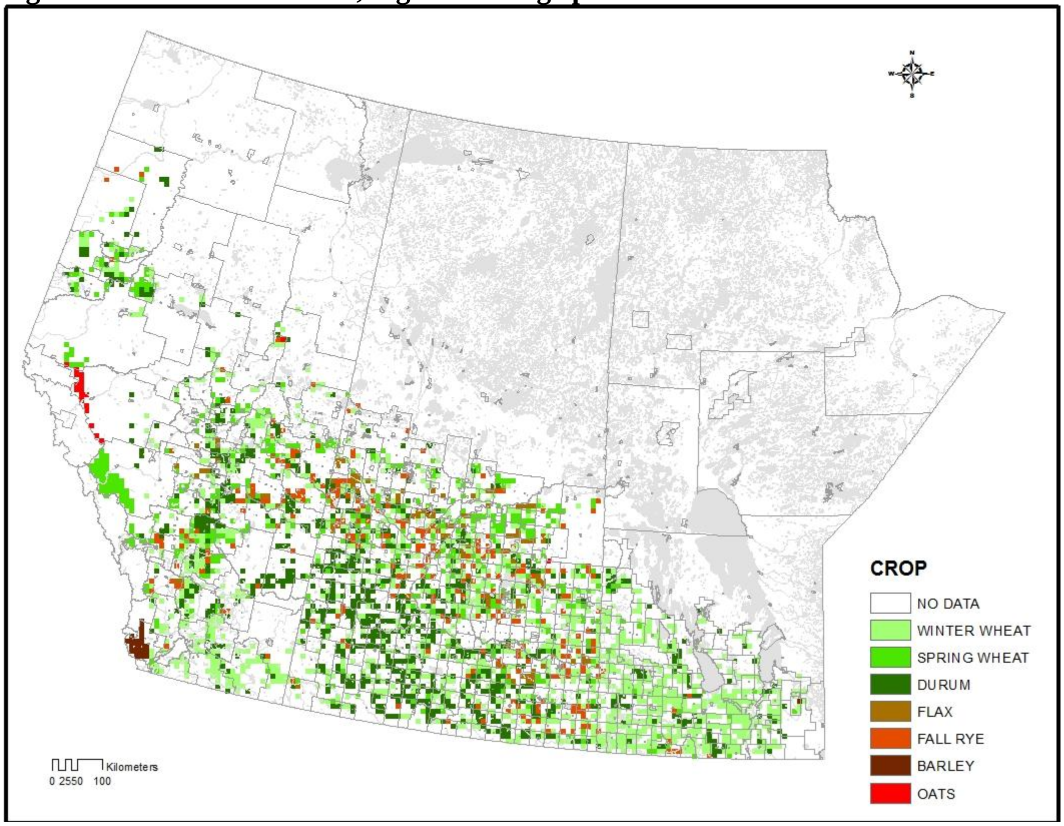


Figure G6 Base Model 2025

Figure G6a Base Model Winter Wheat 2025

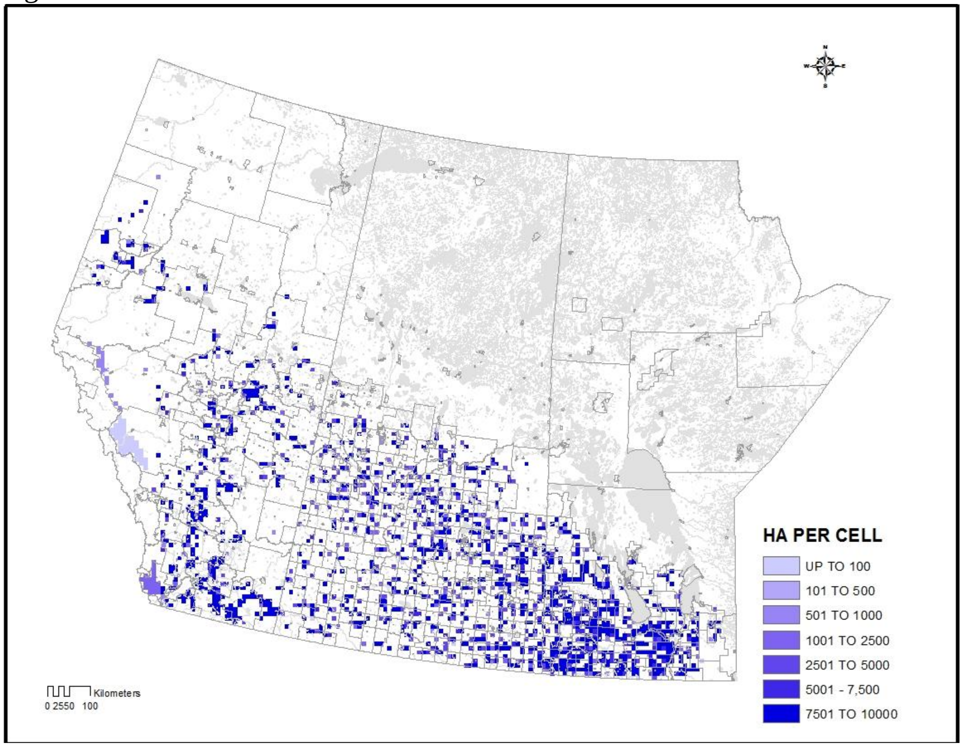


Figure G6b Base Model Spring Wheat 2025

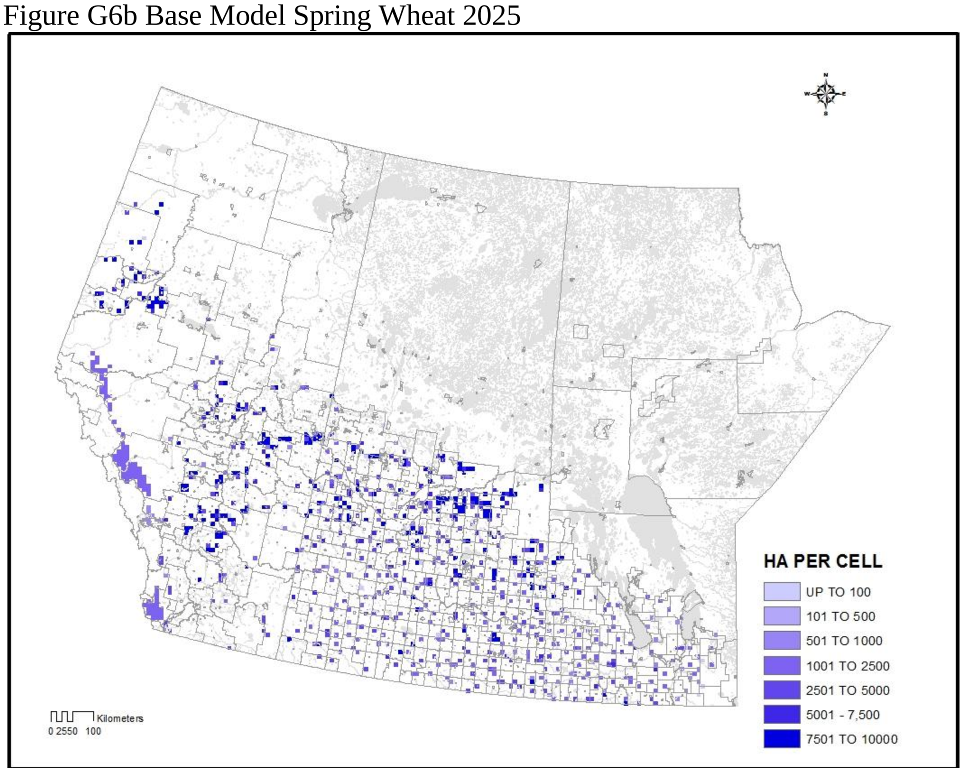


Figure G6c Base Model Durum Wheat 2025

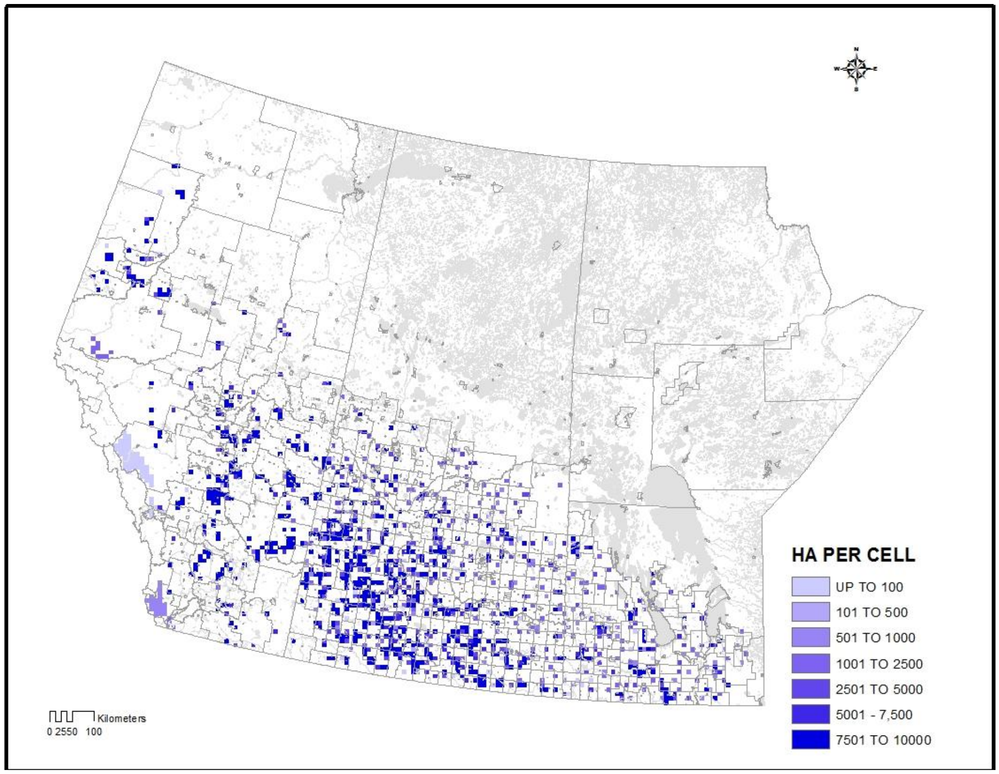


Figure G6d Base Model Canola 2025

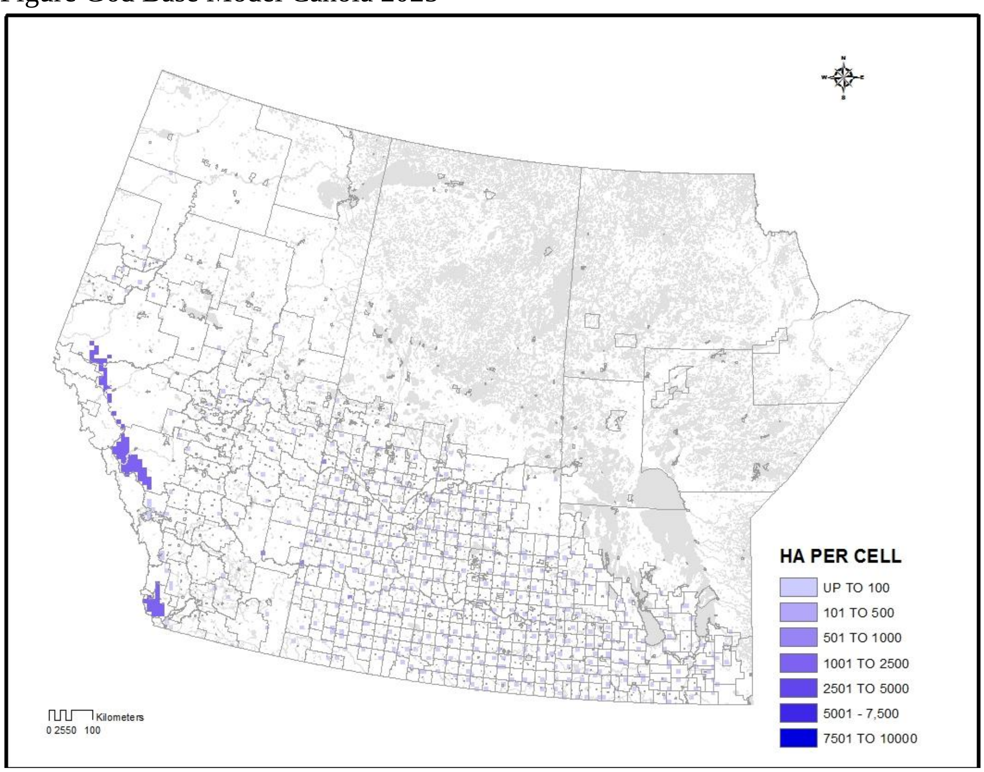


Figure G6e Base Model Flax 2025

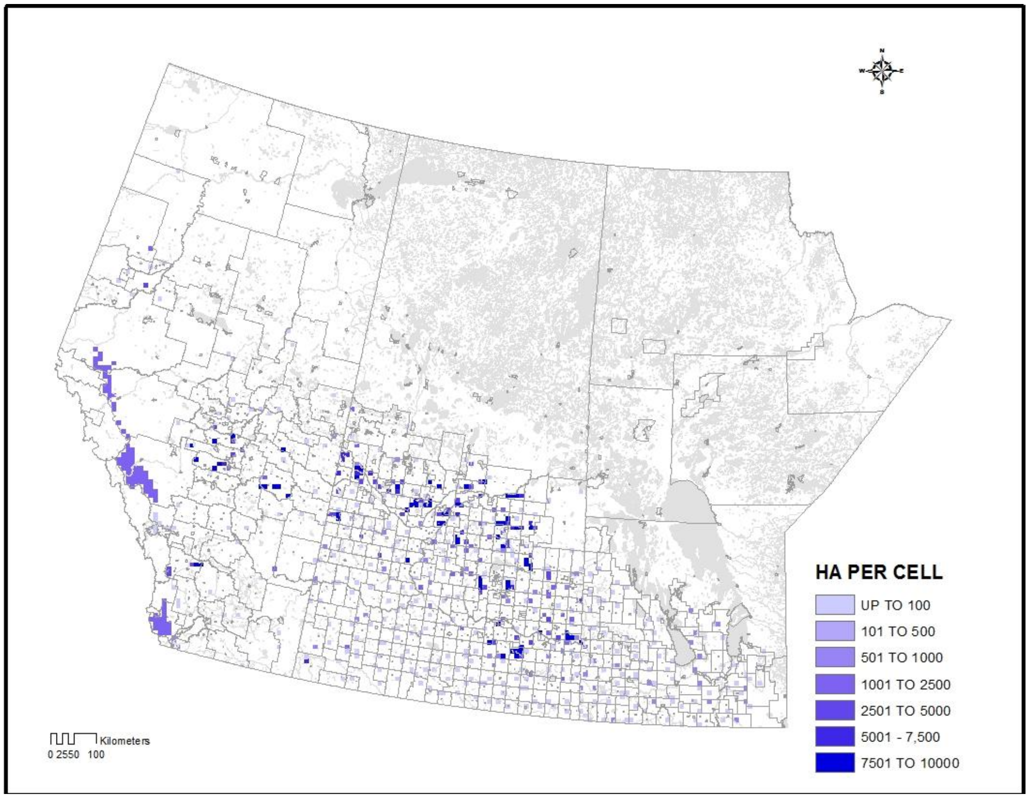


Figure G6f Base Model Fall Rye 2025

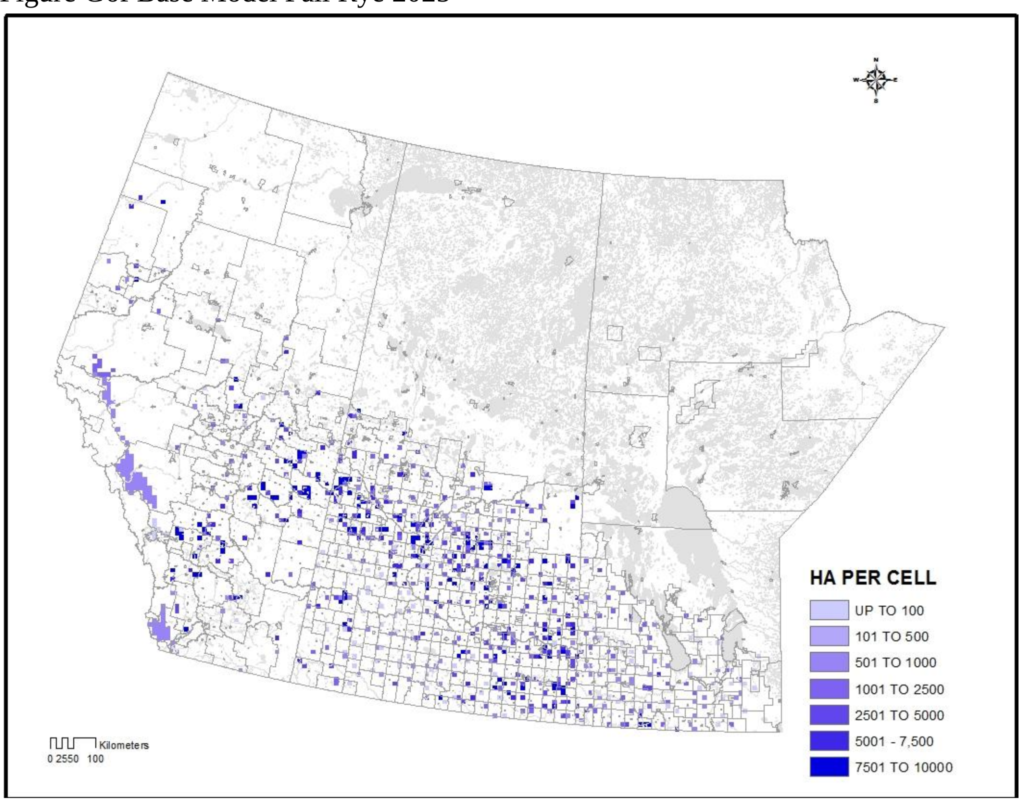


Figure G6g Base Model Barley 2025

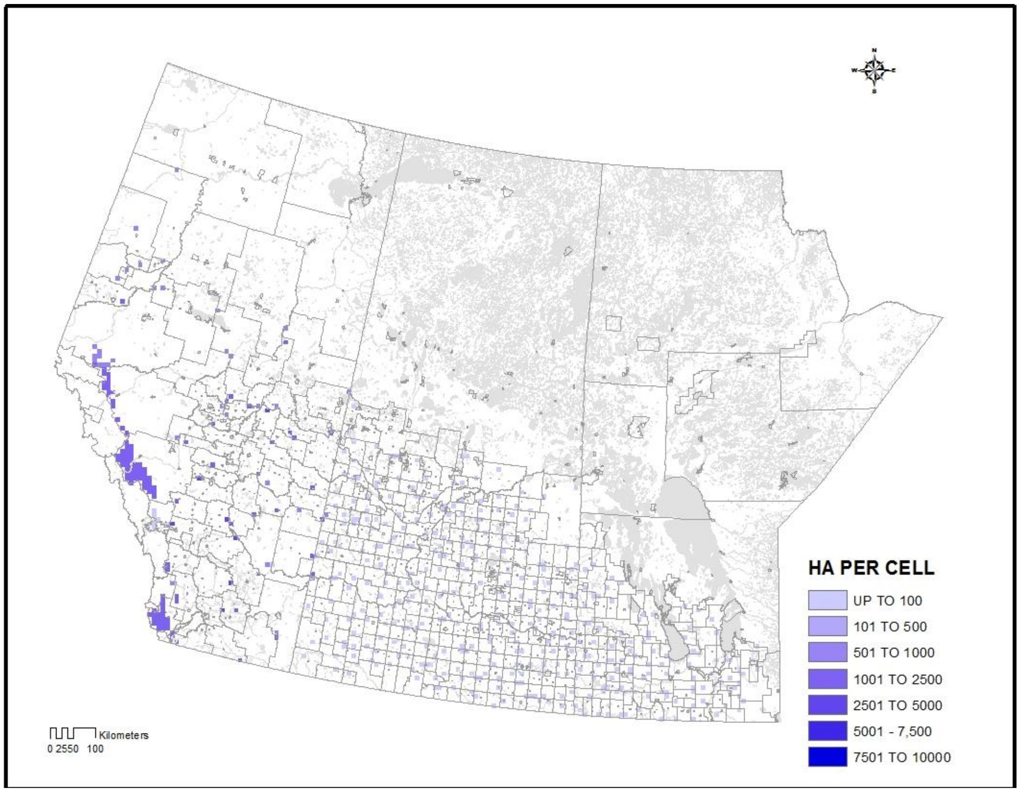


Figure G6h Base Model Oats 2025

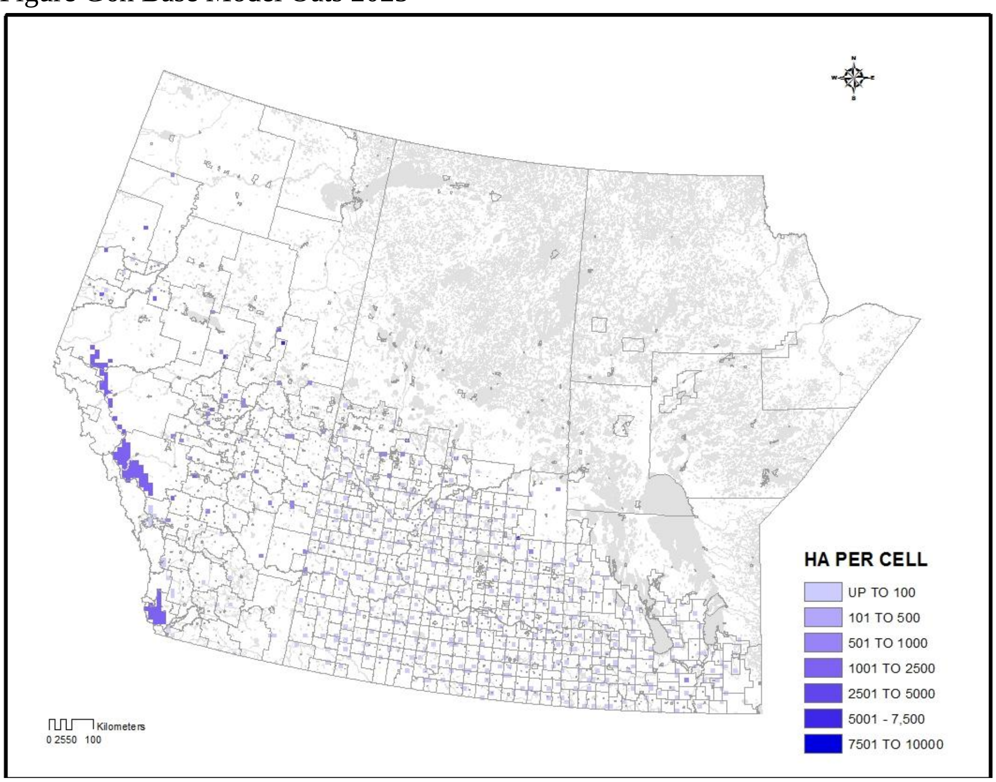


Figure G7: Base Model 2050, highest acreage per cell

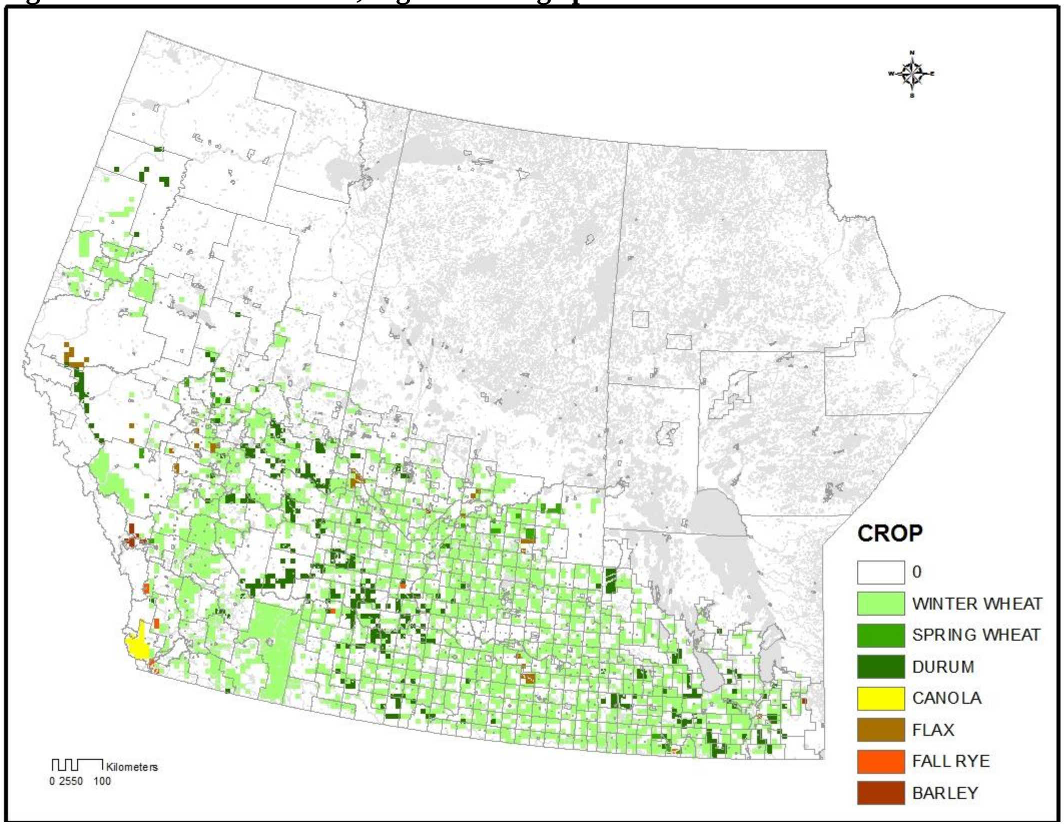


Figure G8 Base Model 2050

Figure G8a Base Model Winter Wheat 2050

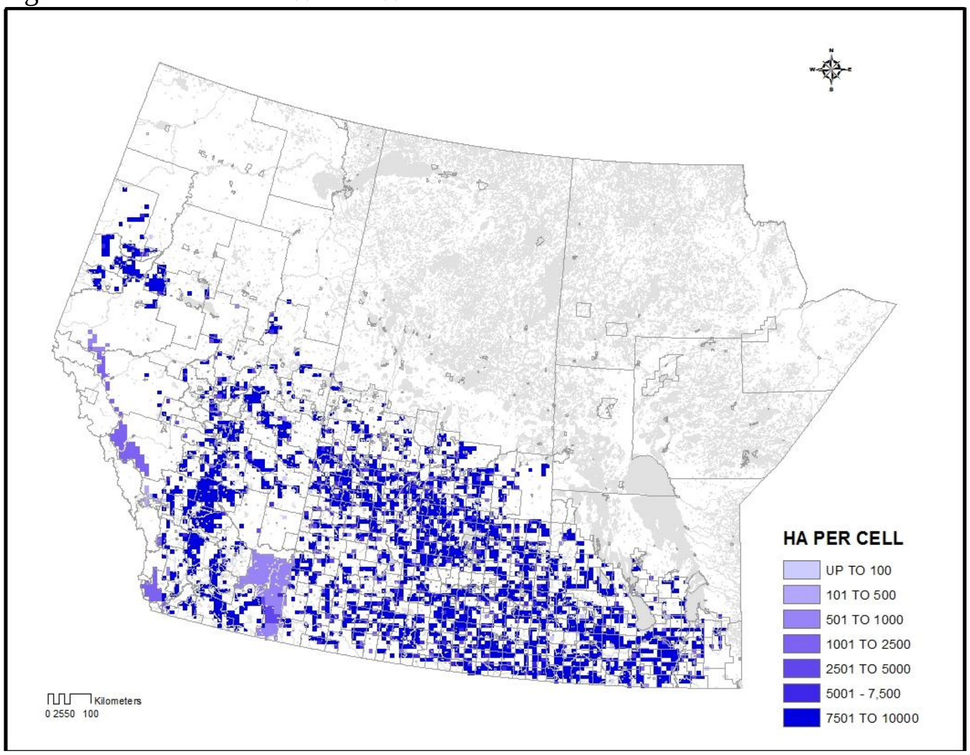


Figure G8b Base Model Spring Wheat 2050

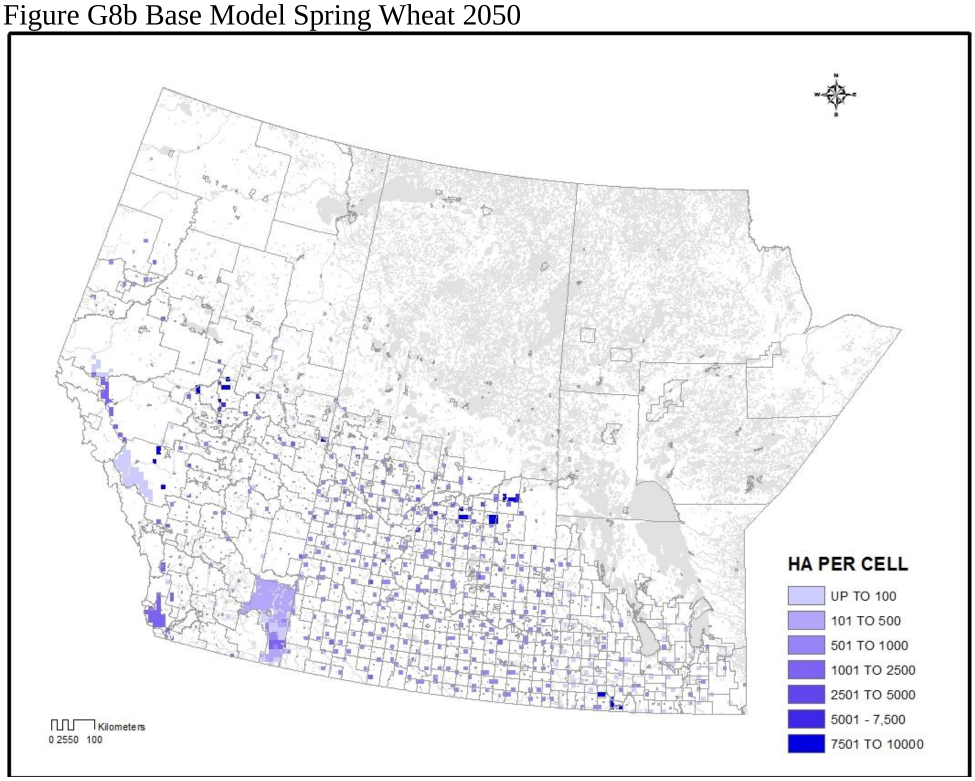


Figure G8c Base Model Durum 2050

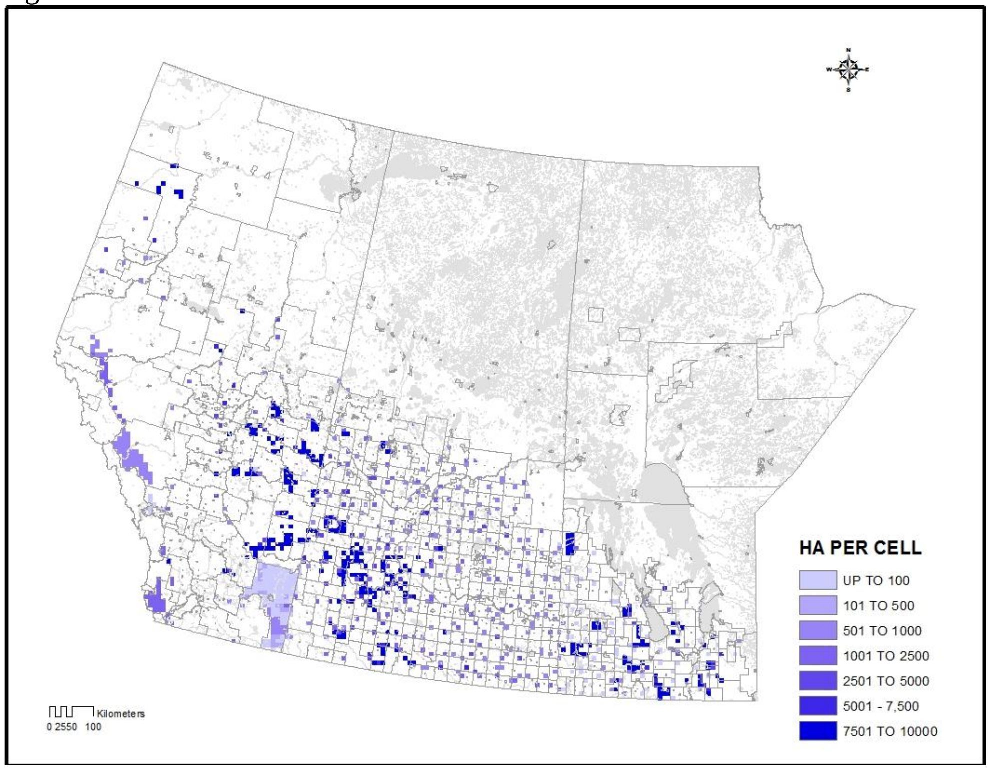


Figure G8d Base Model Canola 2050

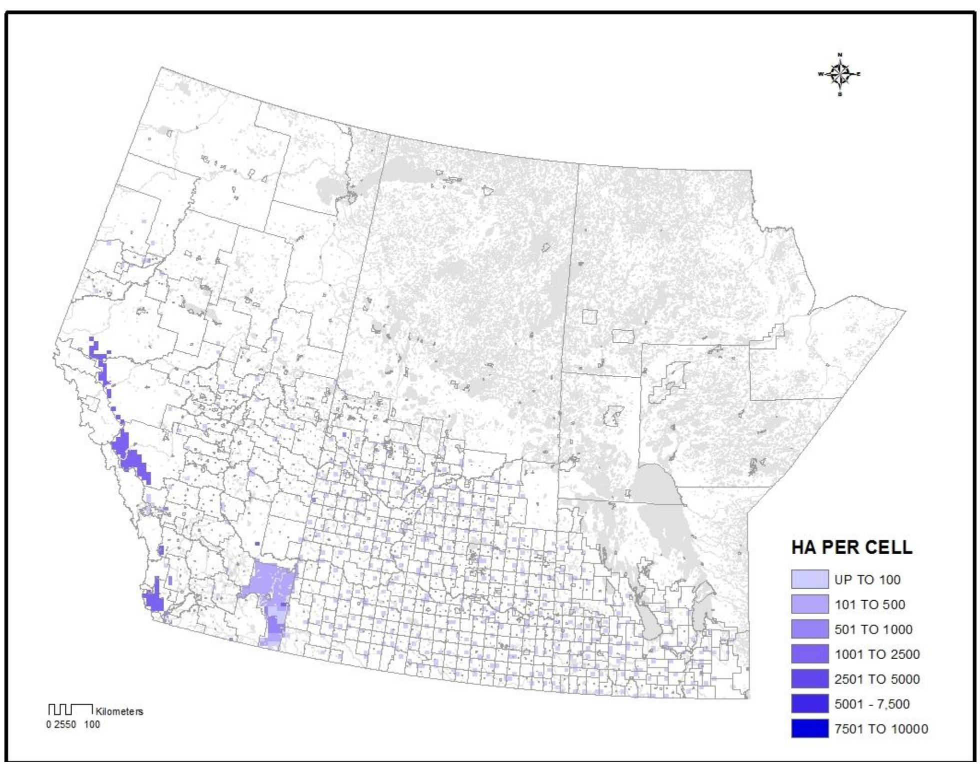


Figure G8e Base Model Flax 2050

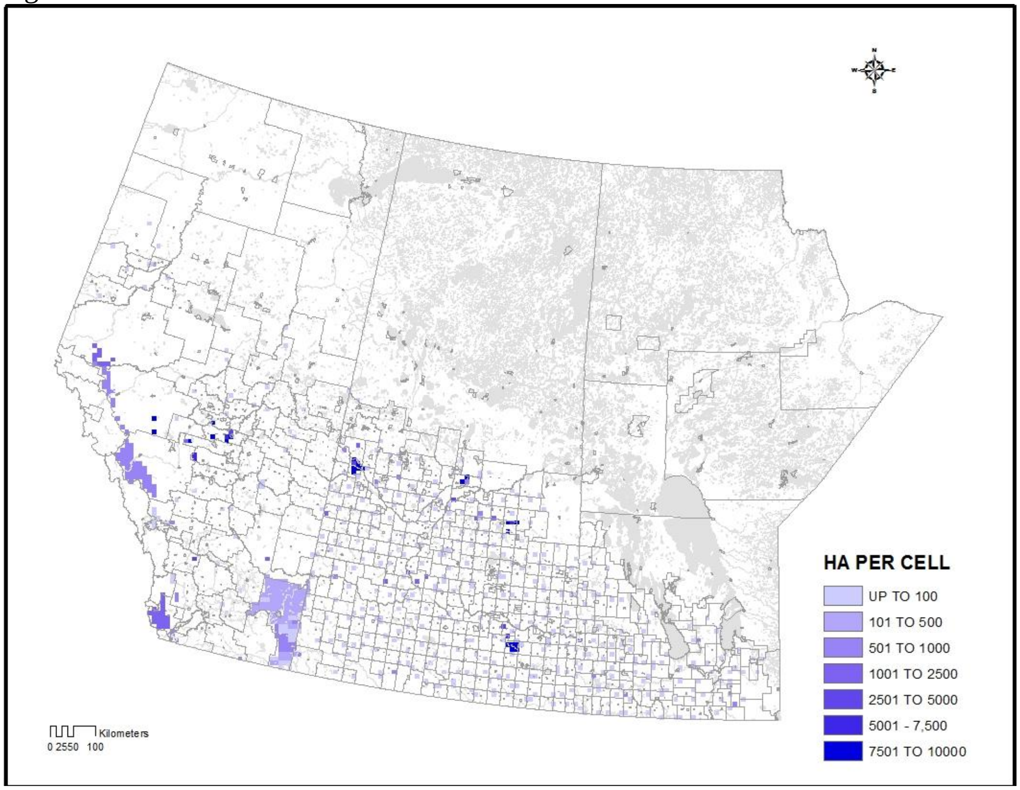


Figure G8f Base Model Rye 2050

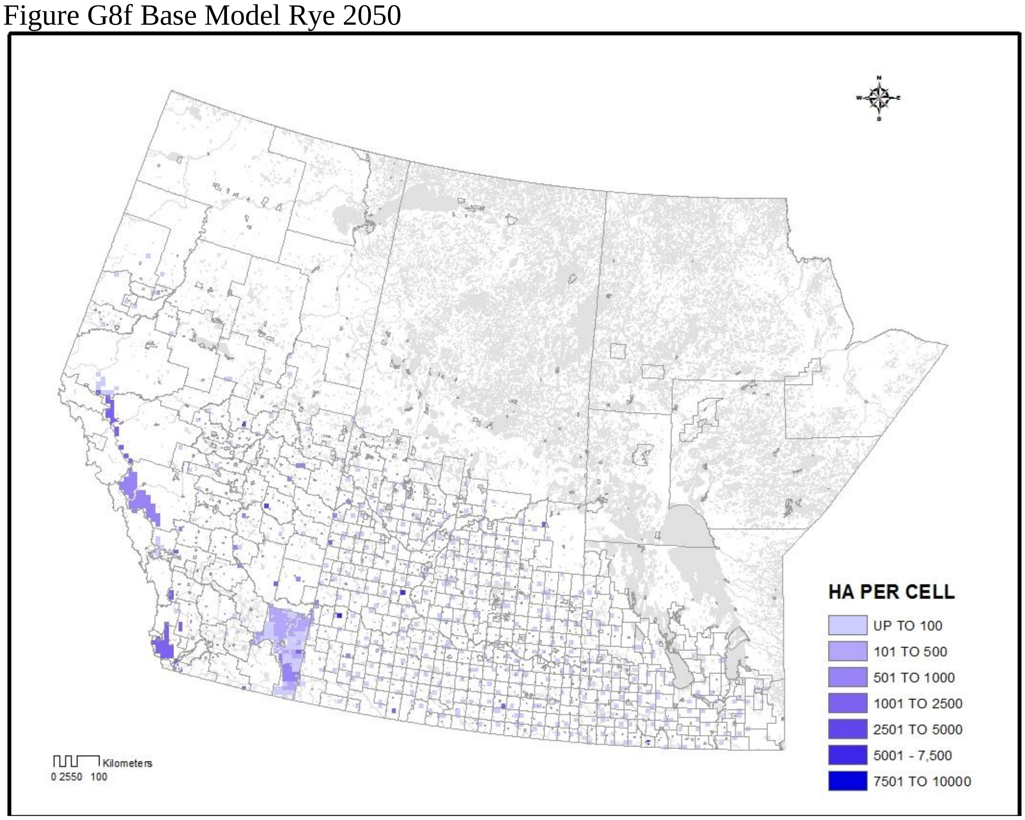


Figure G8g Base Model Barley 2050

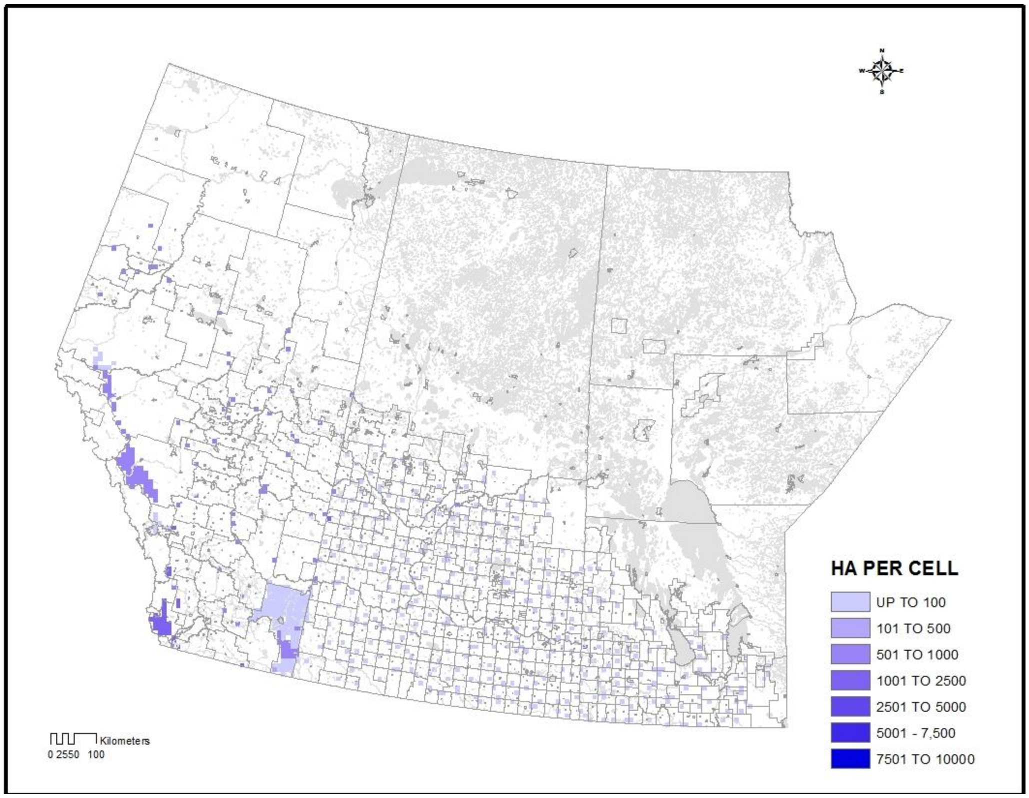
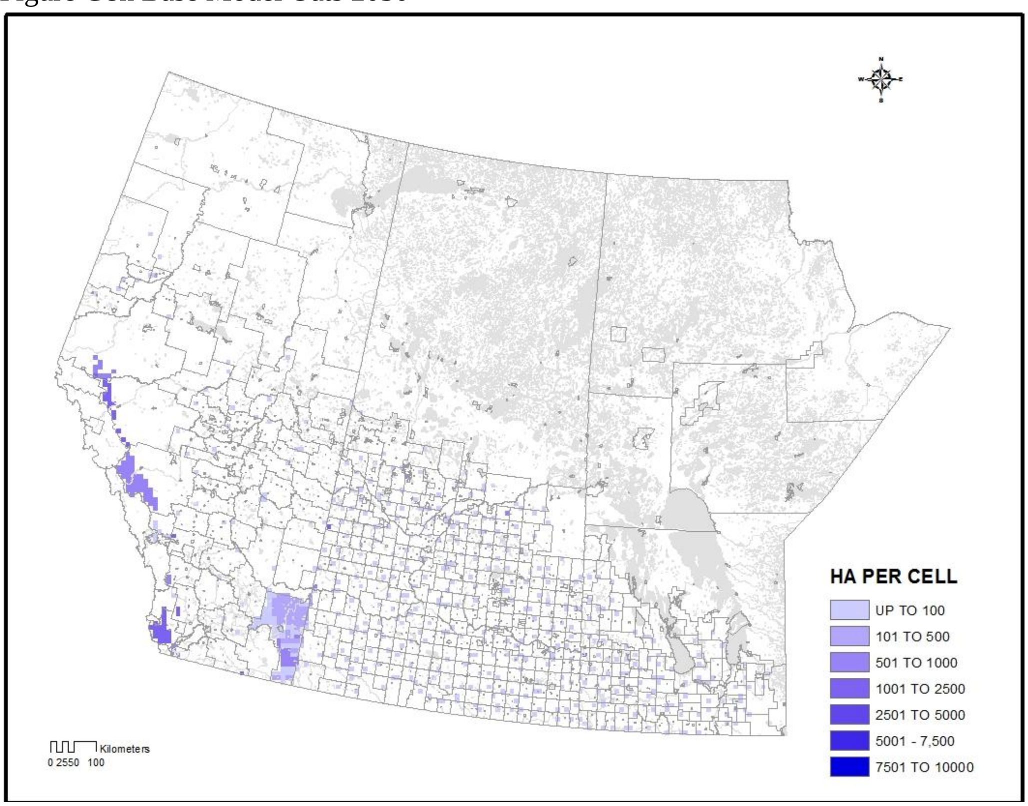


Figure G8h Base Model Oats 2050



APPENDIX H: Model B1 acreage concentrations by crop, selected years

Figure H1: Model B1 2025, highest acreage per cell

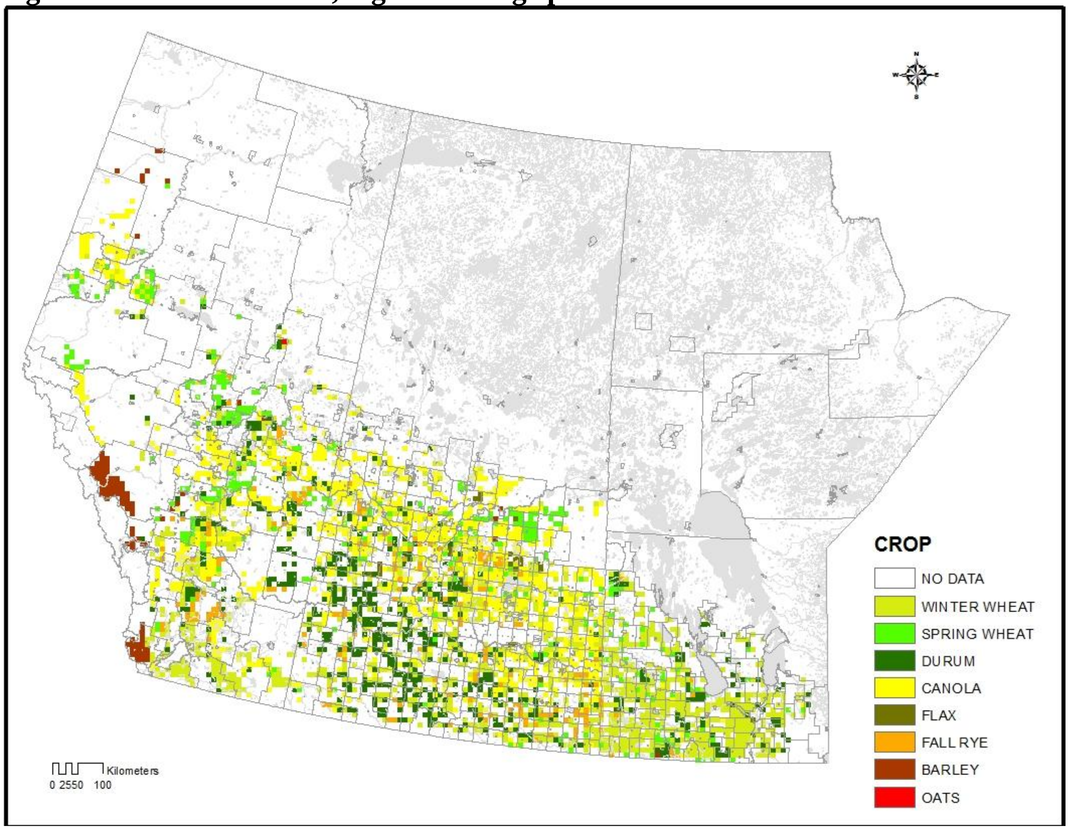


Figure H2 Model B1 2025

Figure H2a Model B1 Winter Wheat 2025

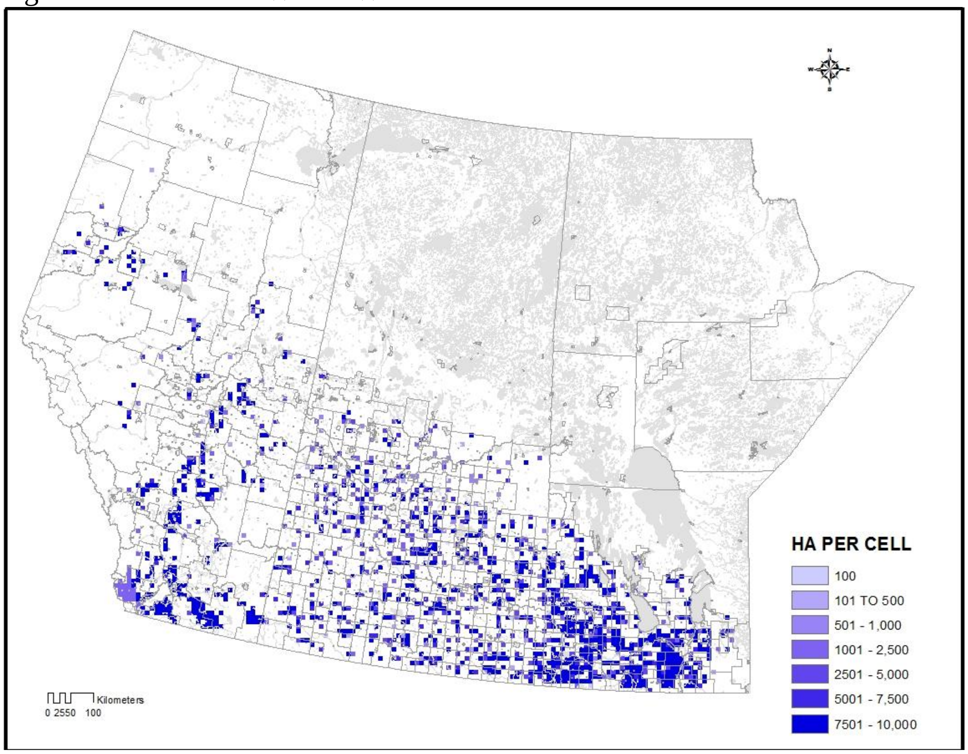


Figure H2b Model B1 Spring Wheat 2025

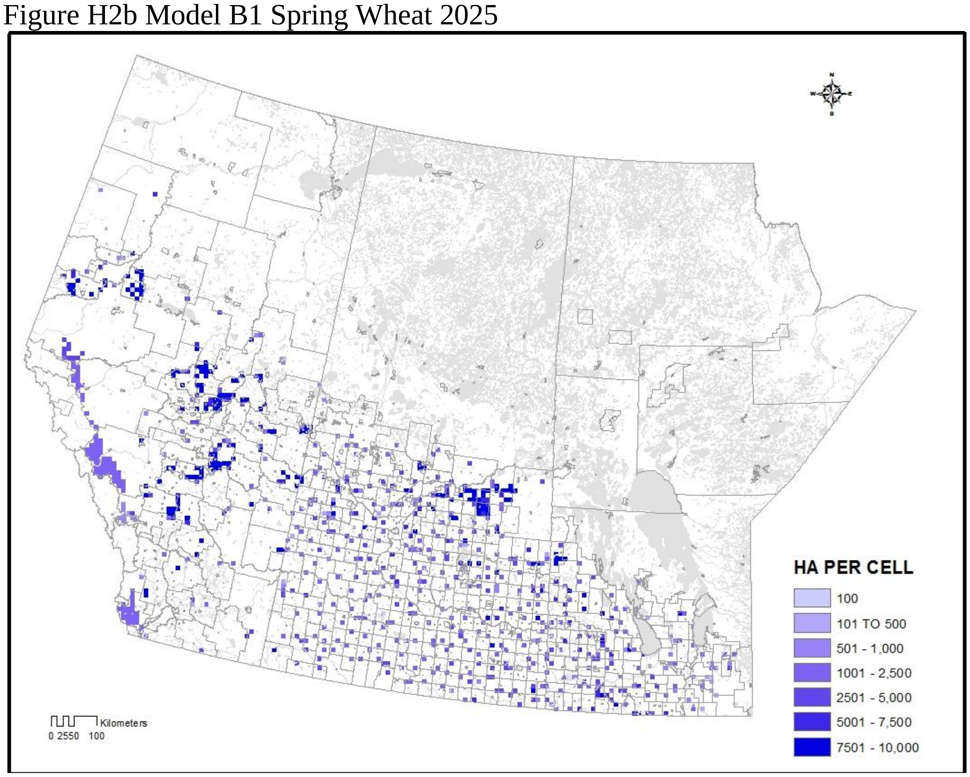


Figure H2c Model B1 Durum 2025

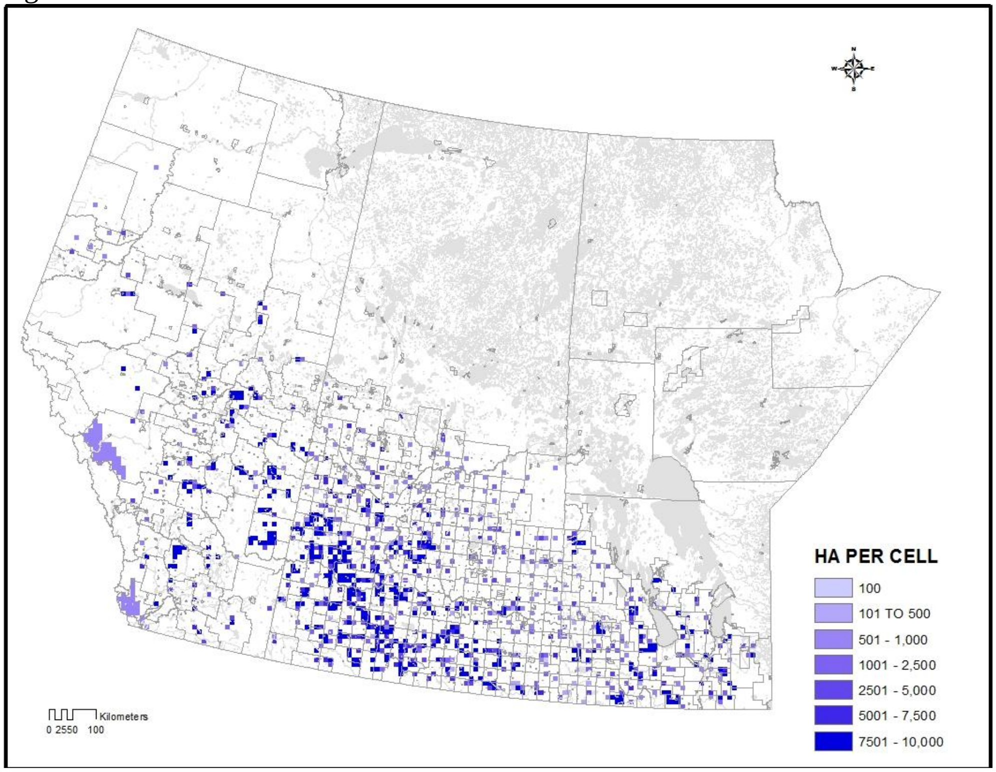


Figure H2d Model B1 Canola 2025

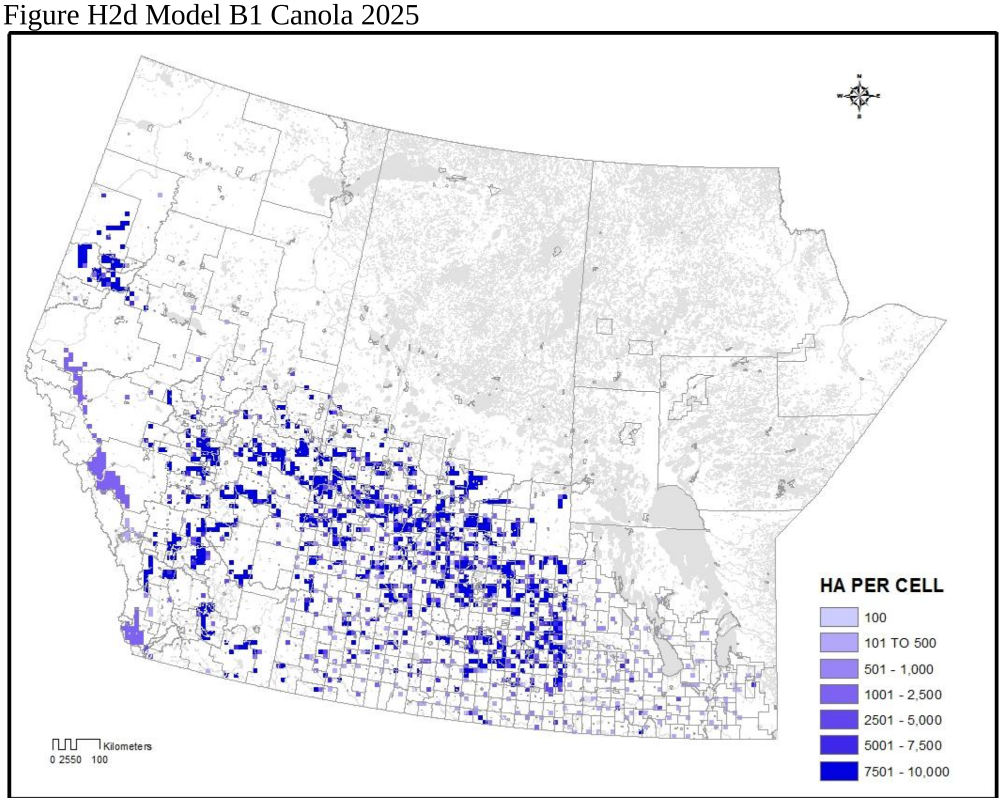


Figure H2e Model B1 Flax 2025

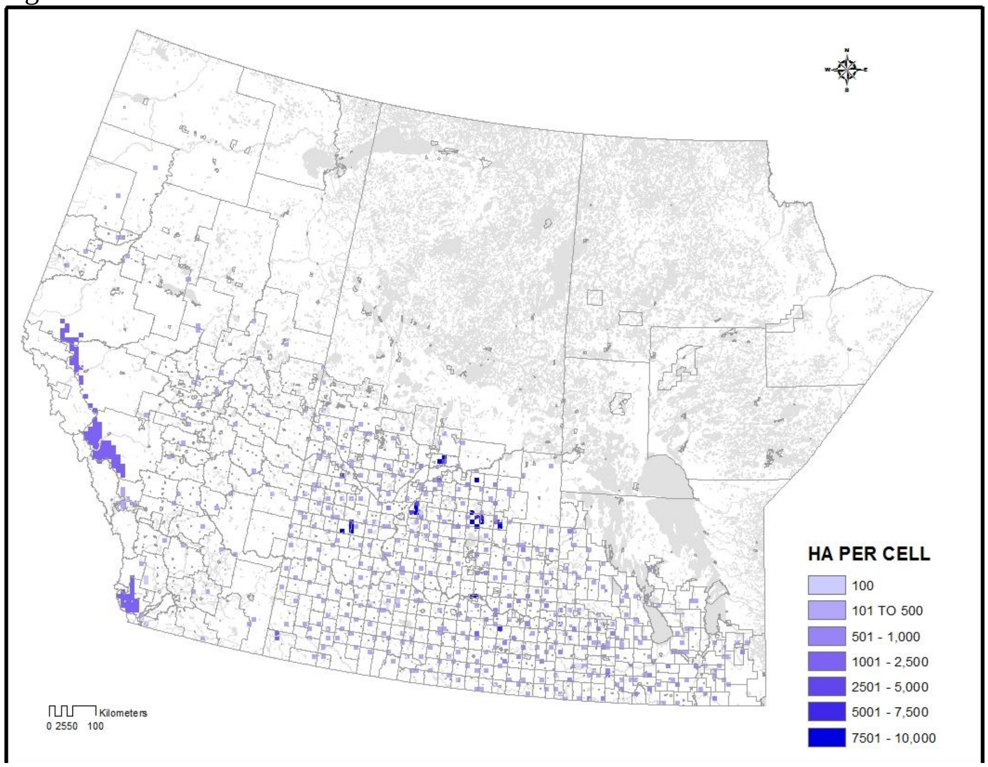


Figure H2f Model B1 Fall Rye 2025

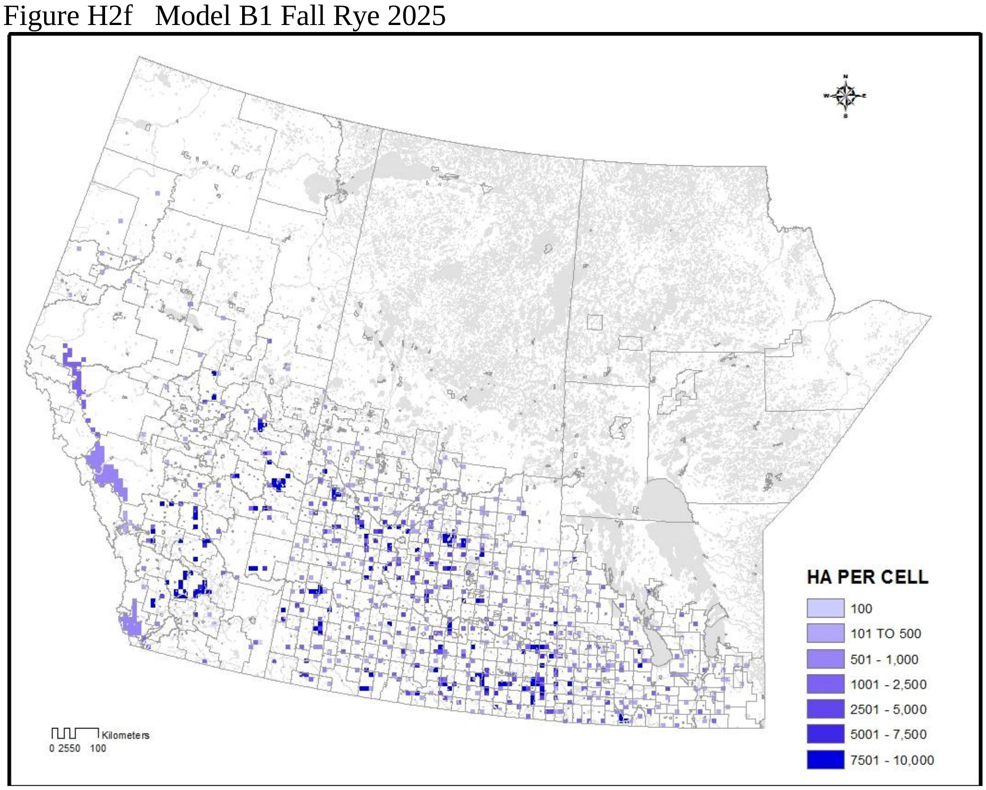


Figure H2g Model B1 Barley 2025

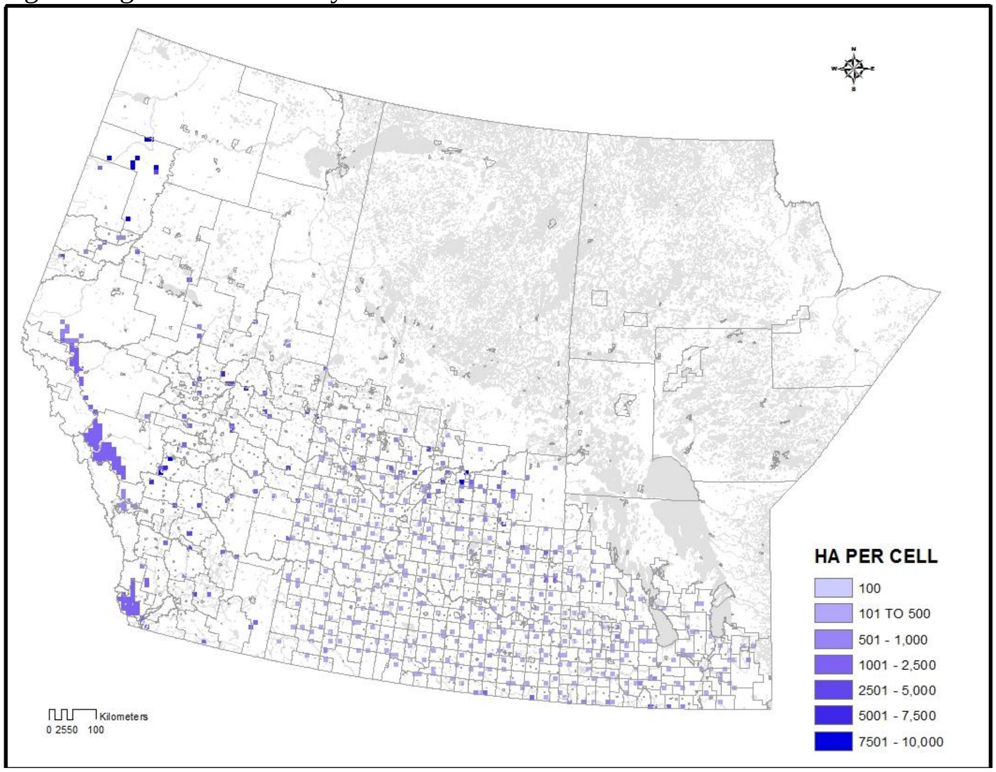


Figure H2h Model B1 Oats 2025

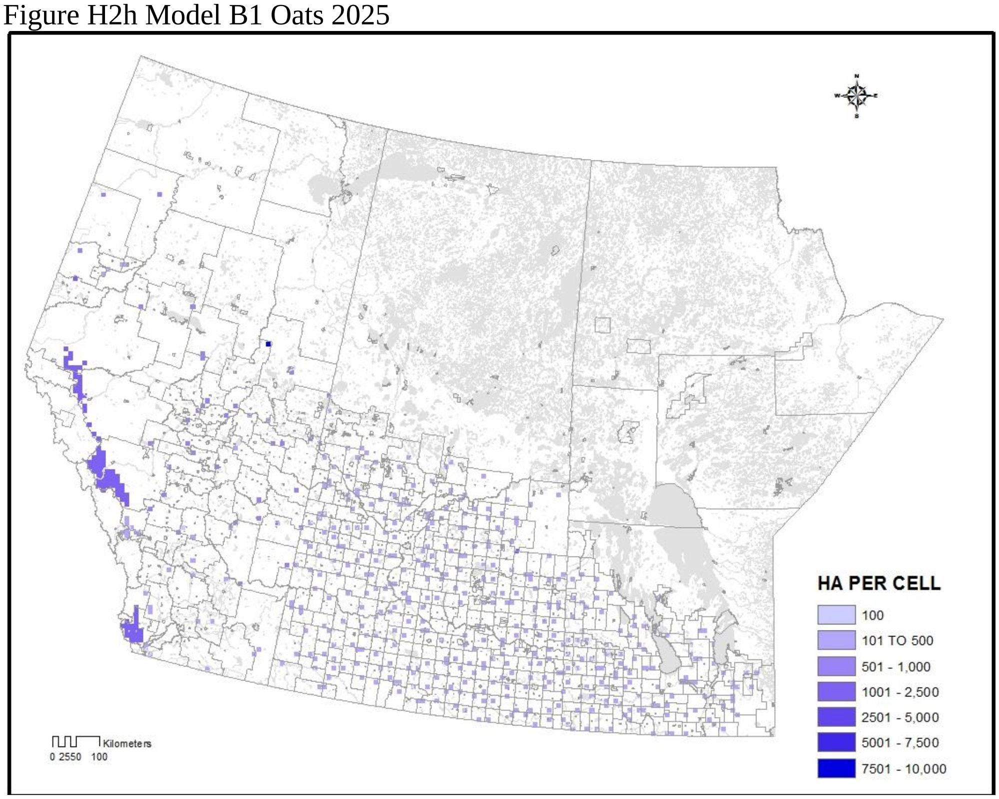


Figure H3: Model B1 2050, highest acreage per cell

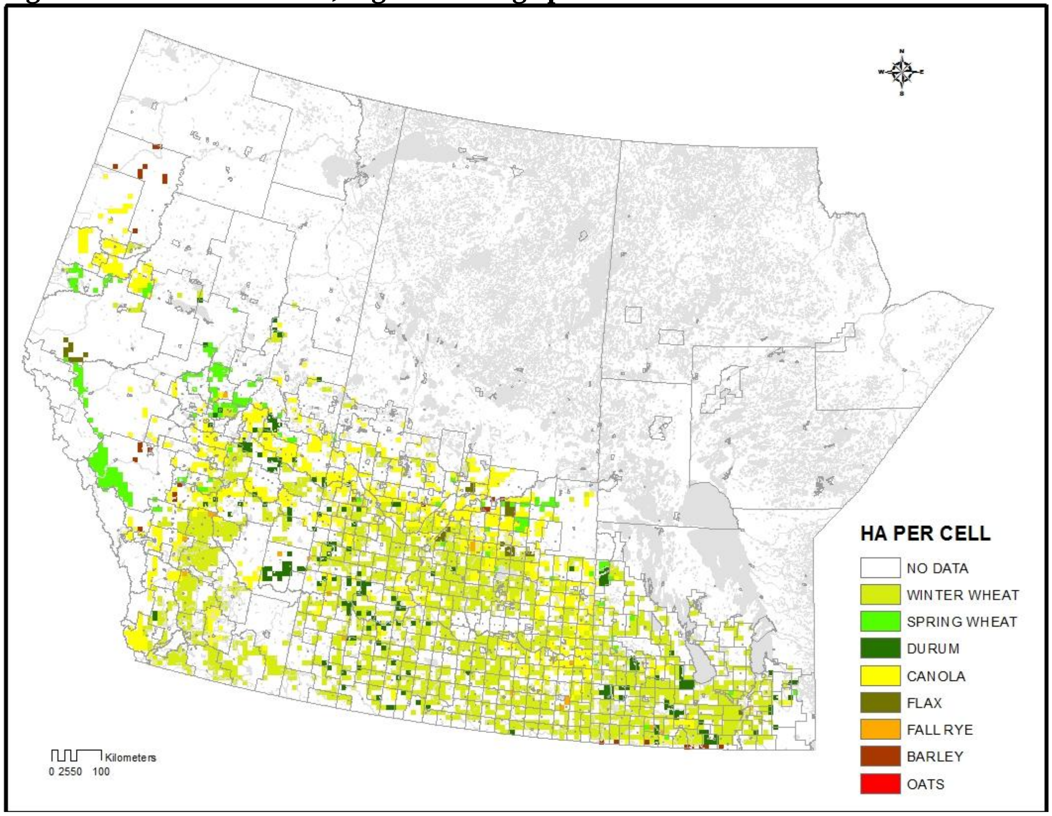


Figure H4: Model B1 2050

Figure H4a Model B1 Winter Wheat 2050

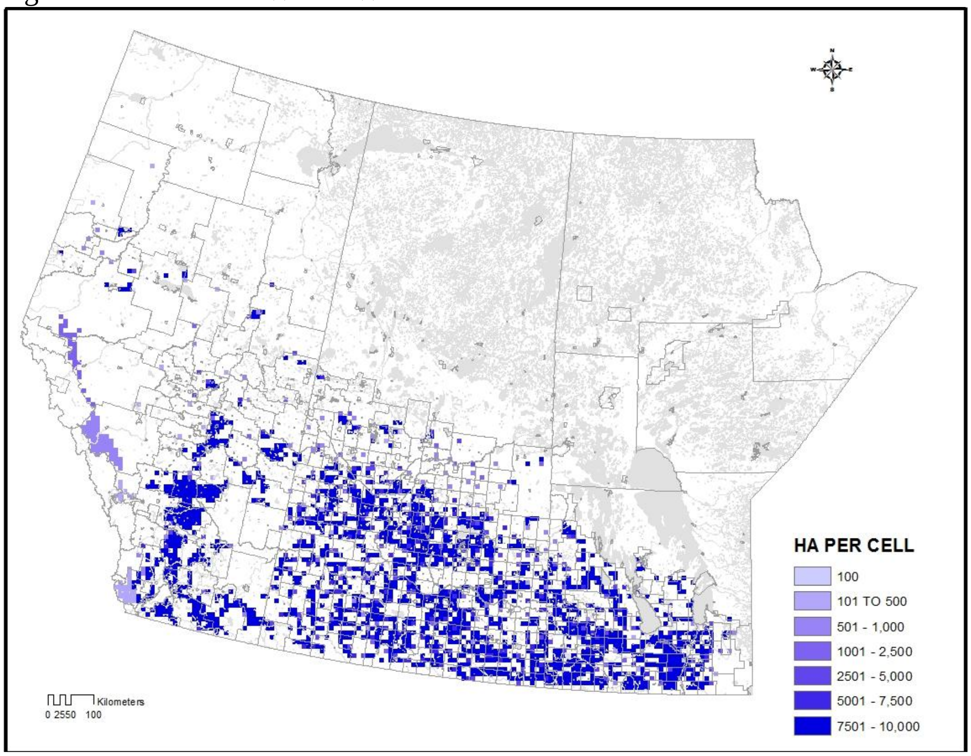


Figure H4b Model B1 Spring Wheat 2050

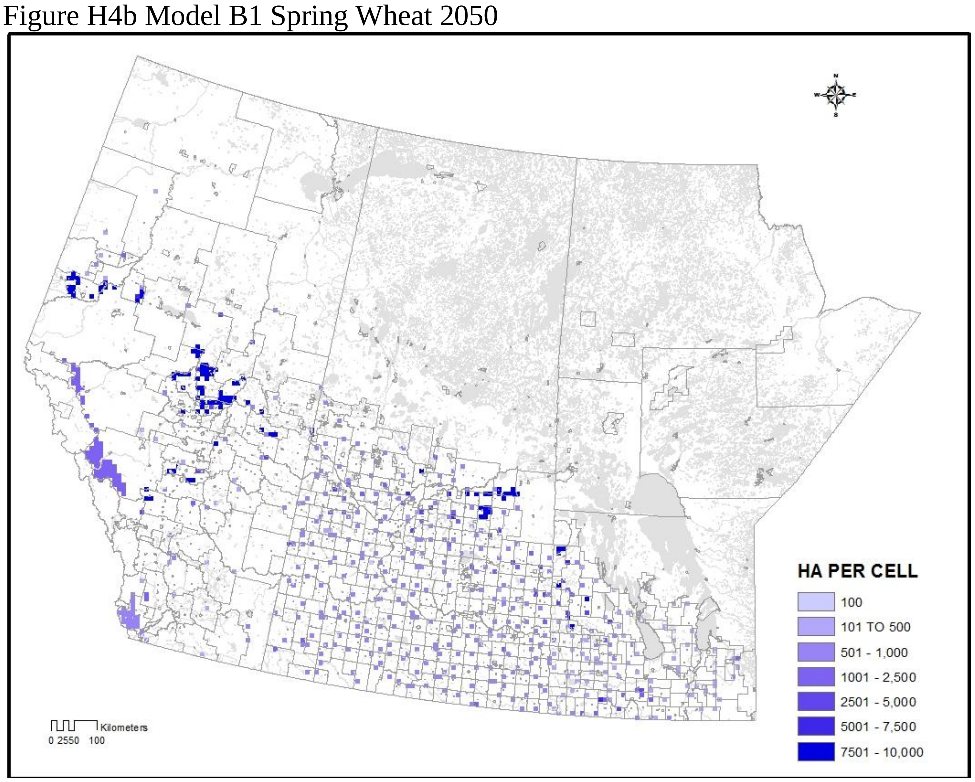


Figure H4c Model B1 Durum 2050

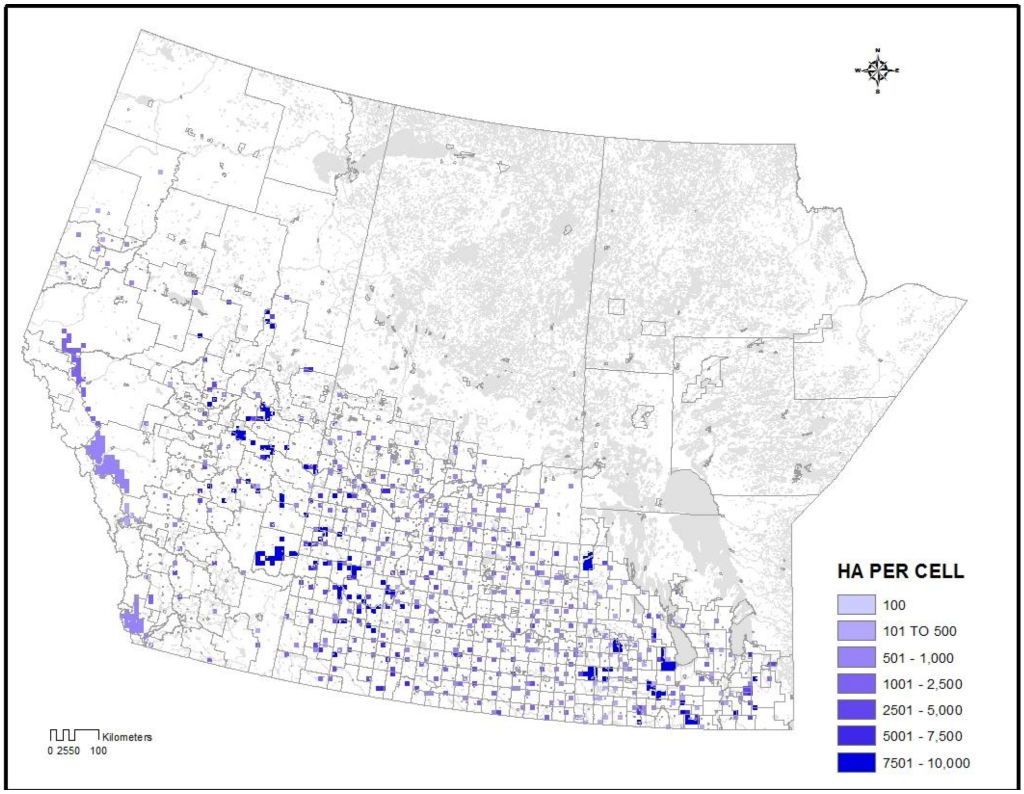


Figure H4d Model B1 Canola 2050

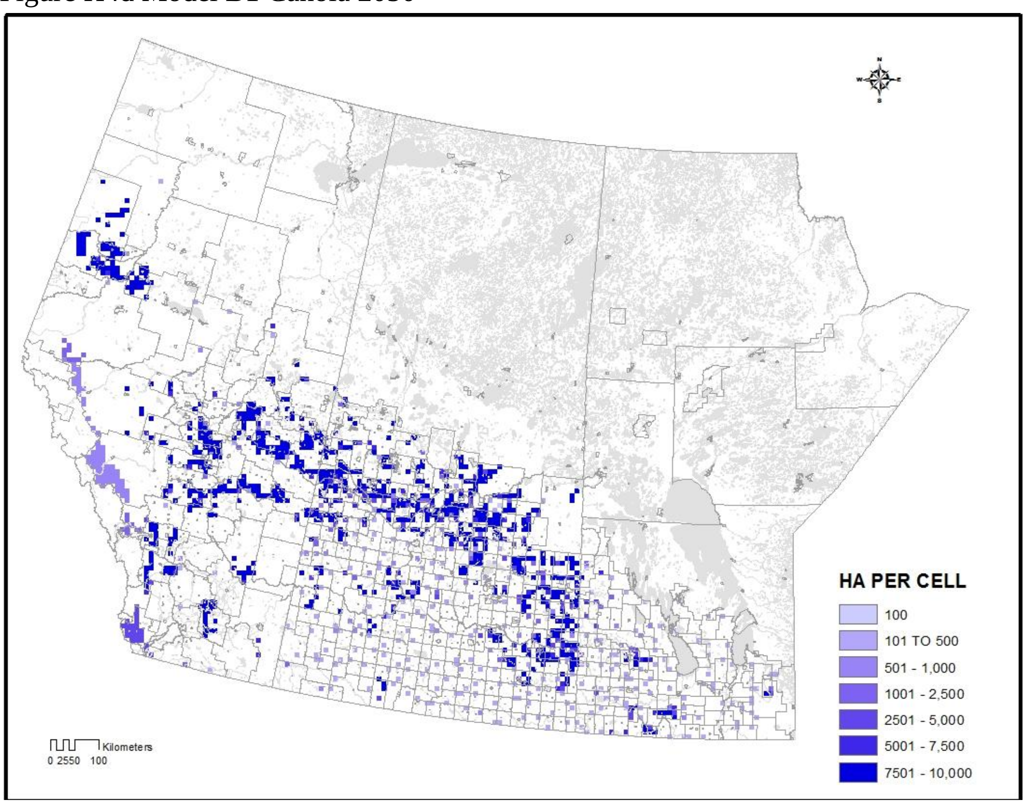


Figure H4e Model B1 Flax 2050

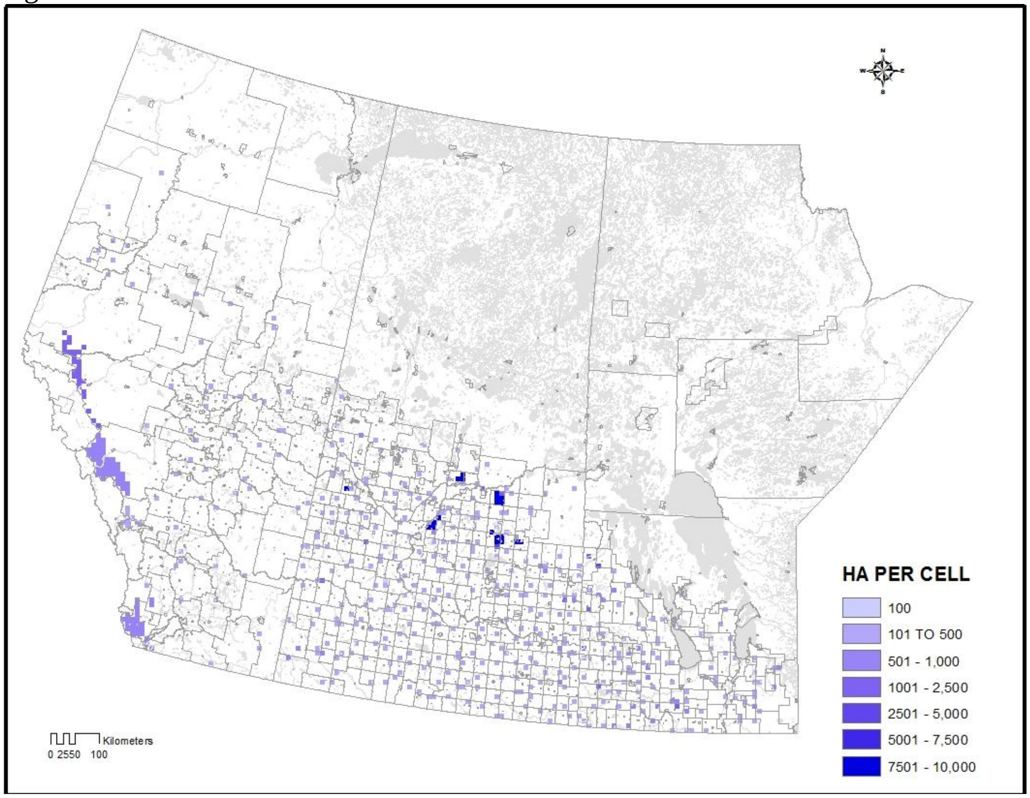


Figure H4f Model B1 Rye 2050

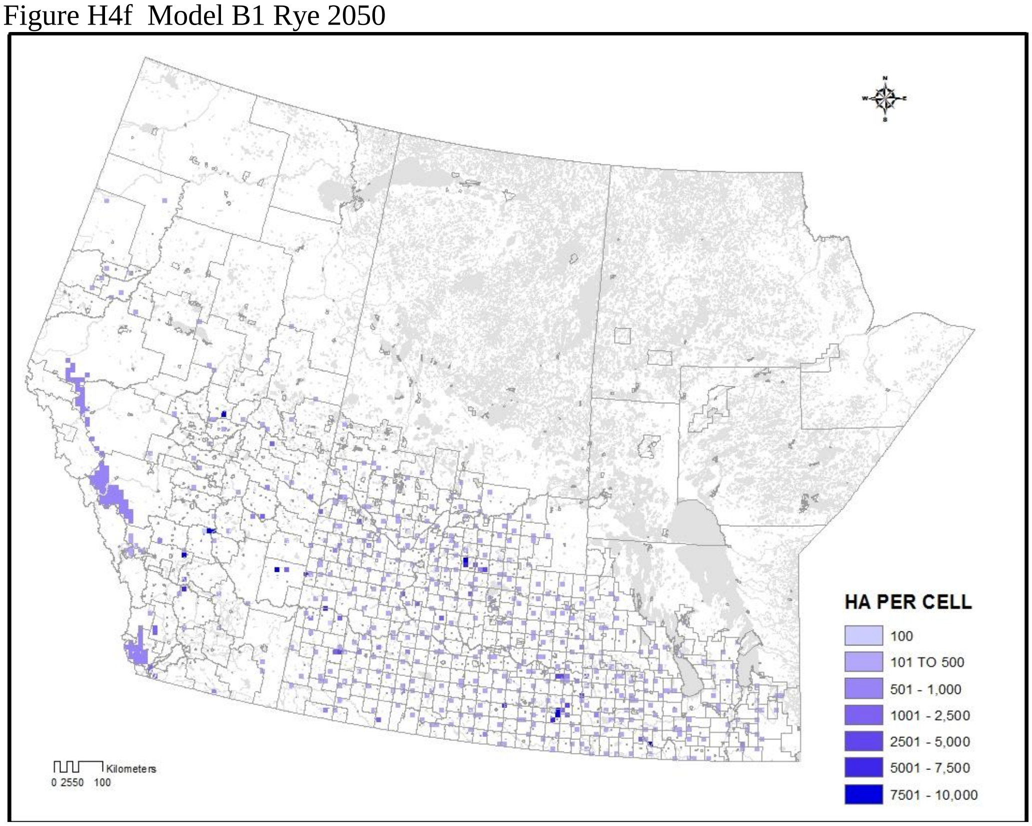


Figure H4g Model B1 Barley 2050

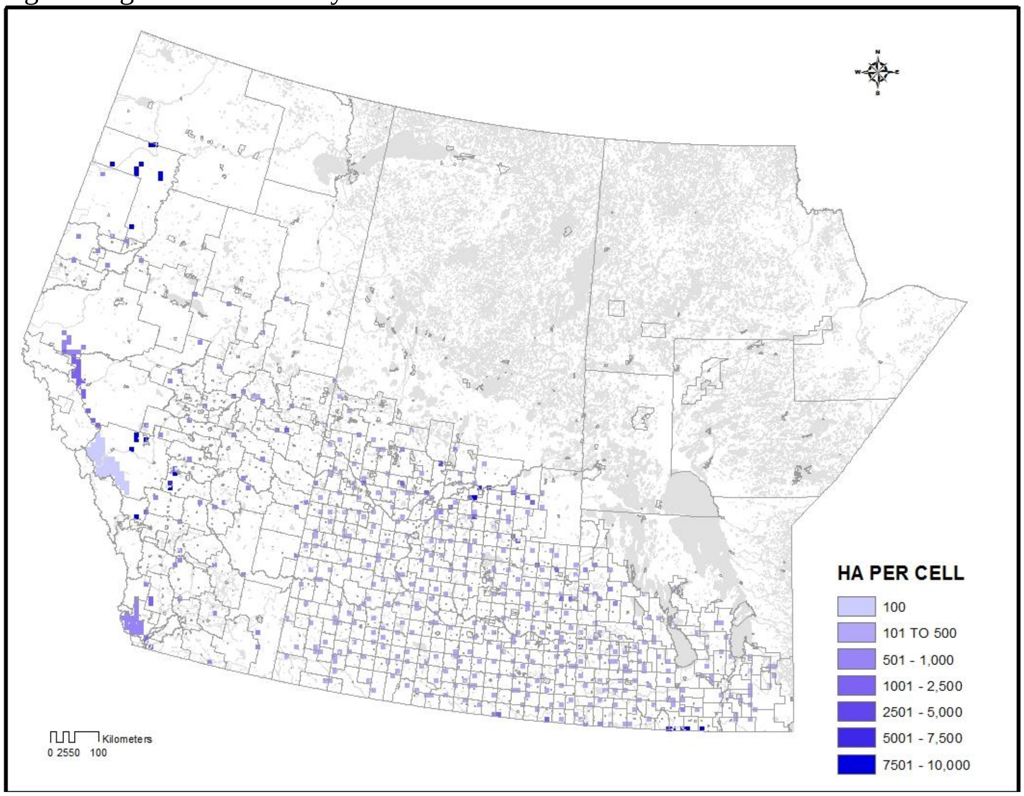
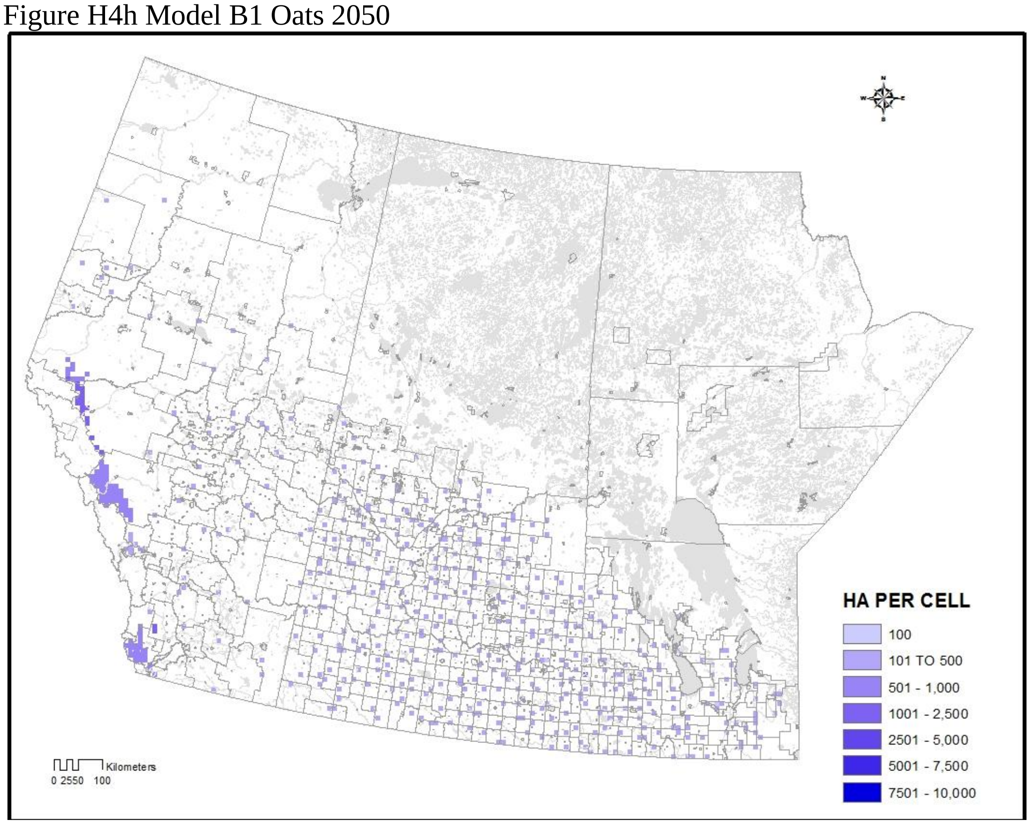


Figure H4h Model B1 Oats 2050



APPENDIX I: Model A1B acreage concentrations by crop, selected years

Figure I1: Scenario A1B 2025, highest acreage per cell

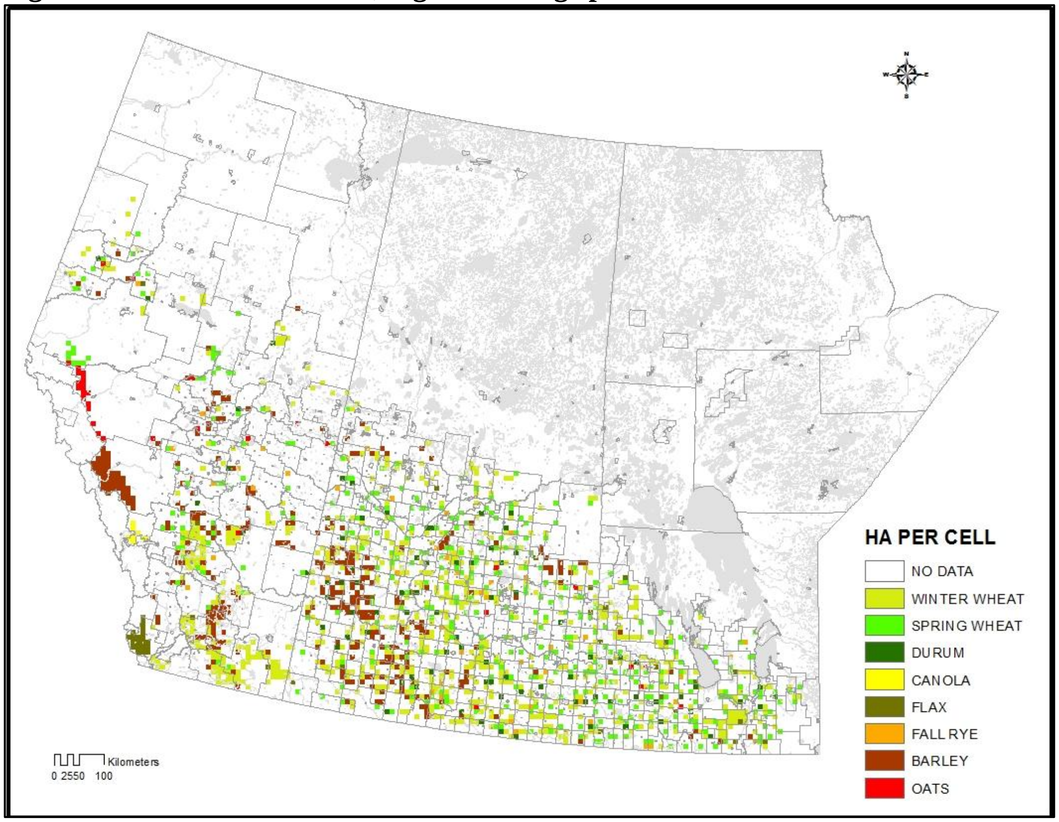


Figure I2: A1B 2025

Figure I2a A1B Winter Wheat 2025

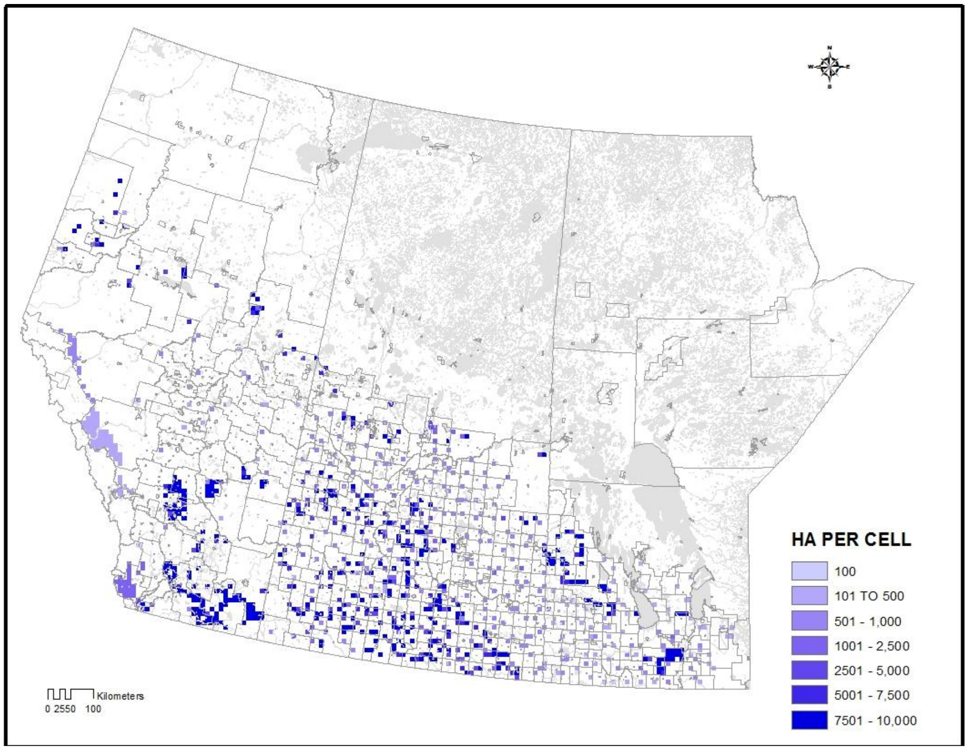


Figure I2b A1B Spring Wheat 2025

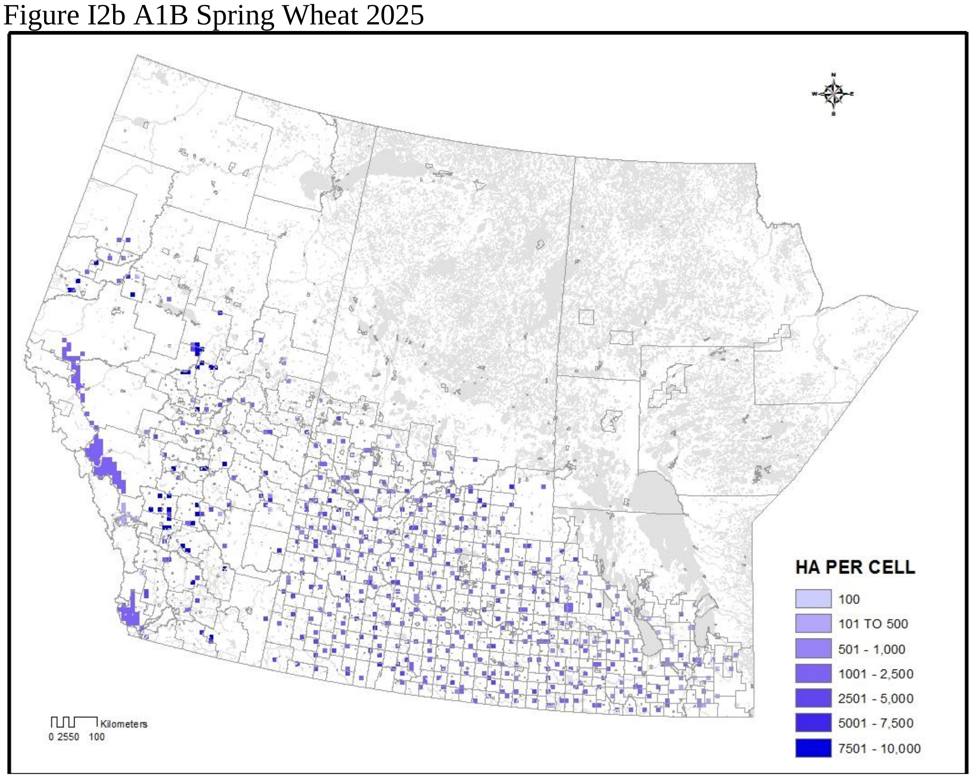


Figure I2c A1B Durum 2025

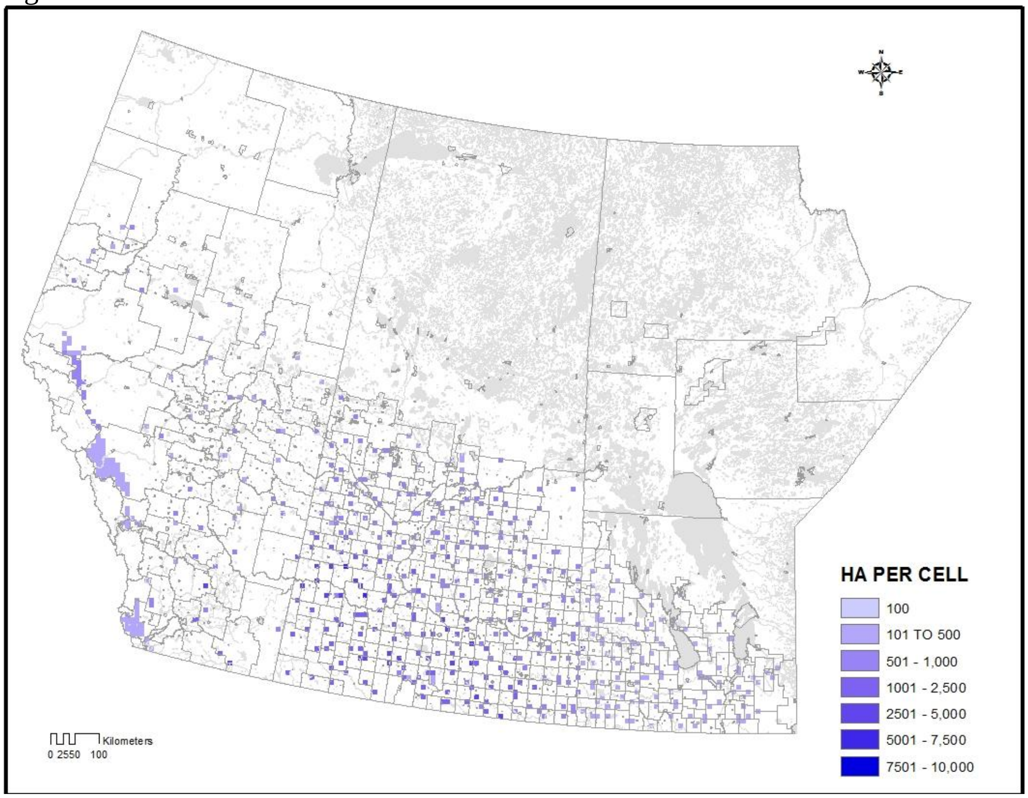


Figure I2d A1B Canola 2025

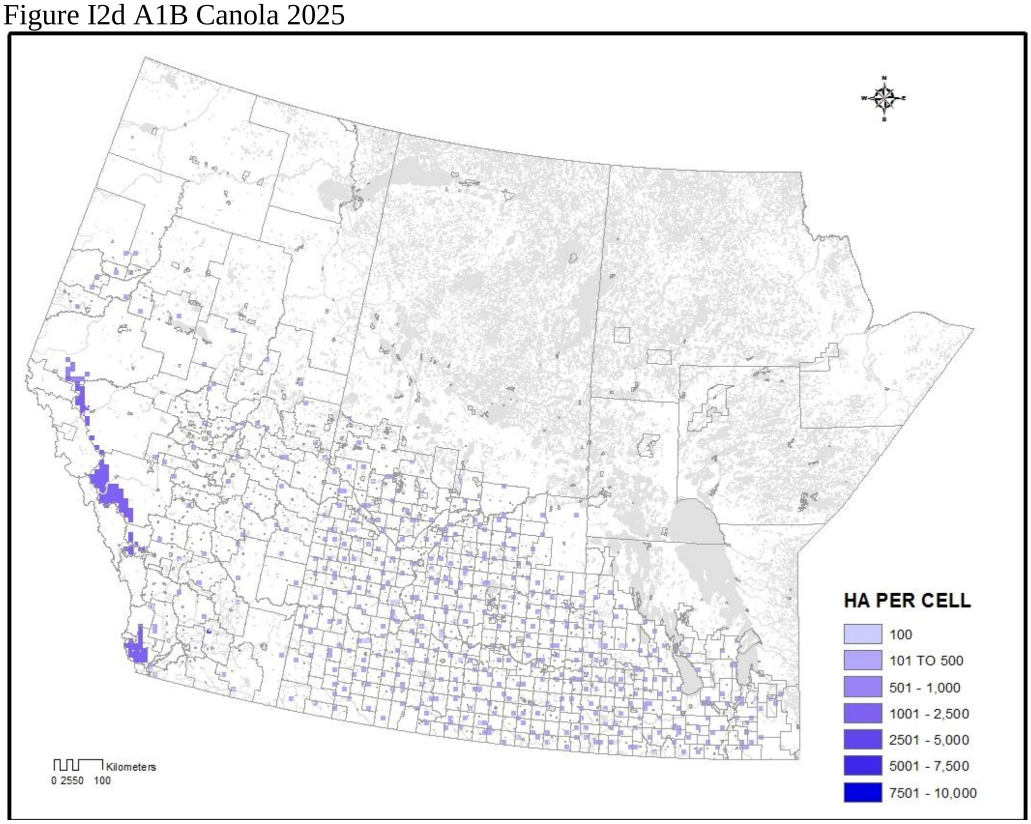


Figure I2e A1B Flax 2025

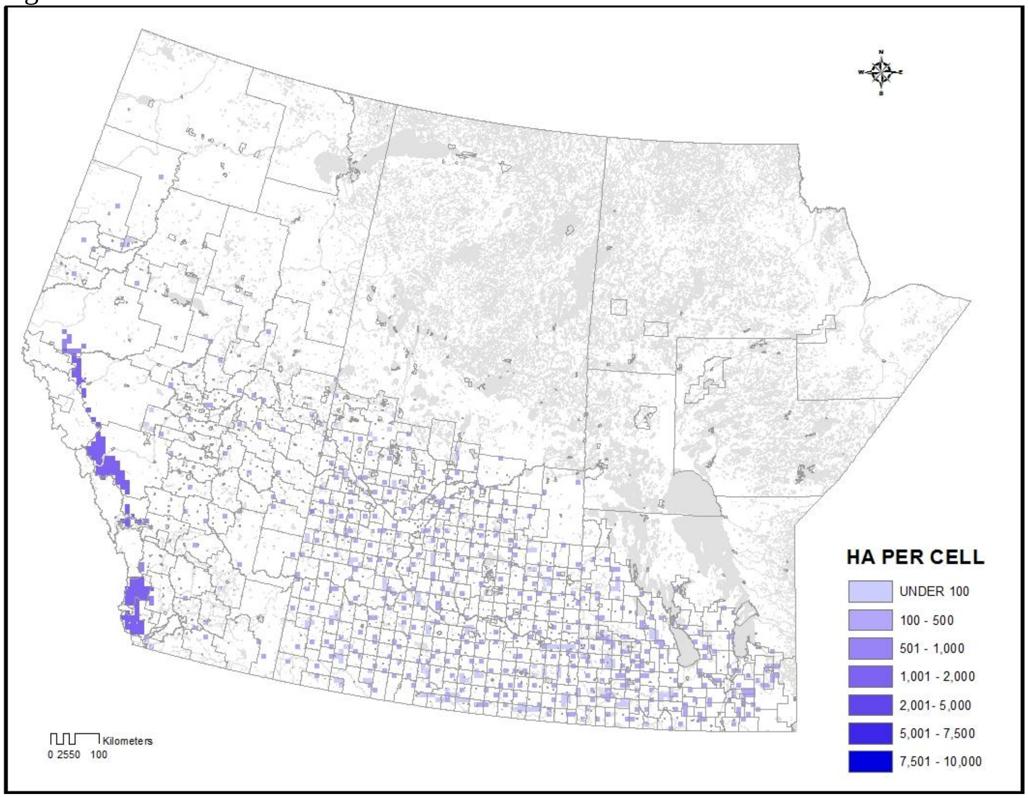


Figure I2f A1B Fall Rye 2025

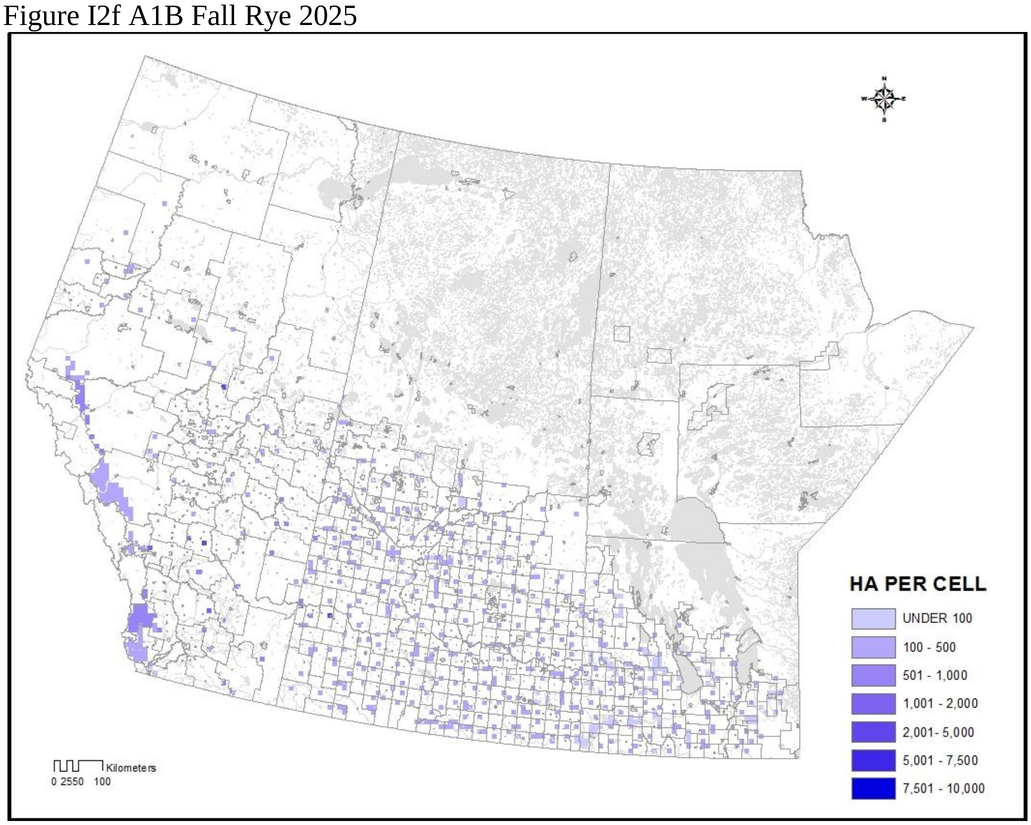


Figure I2g A1B Barley 2025

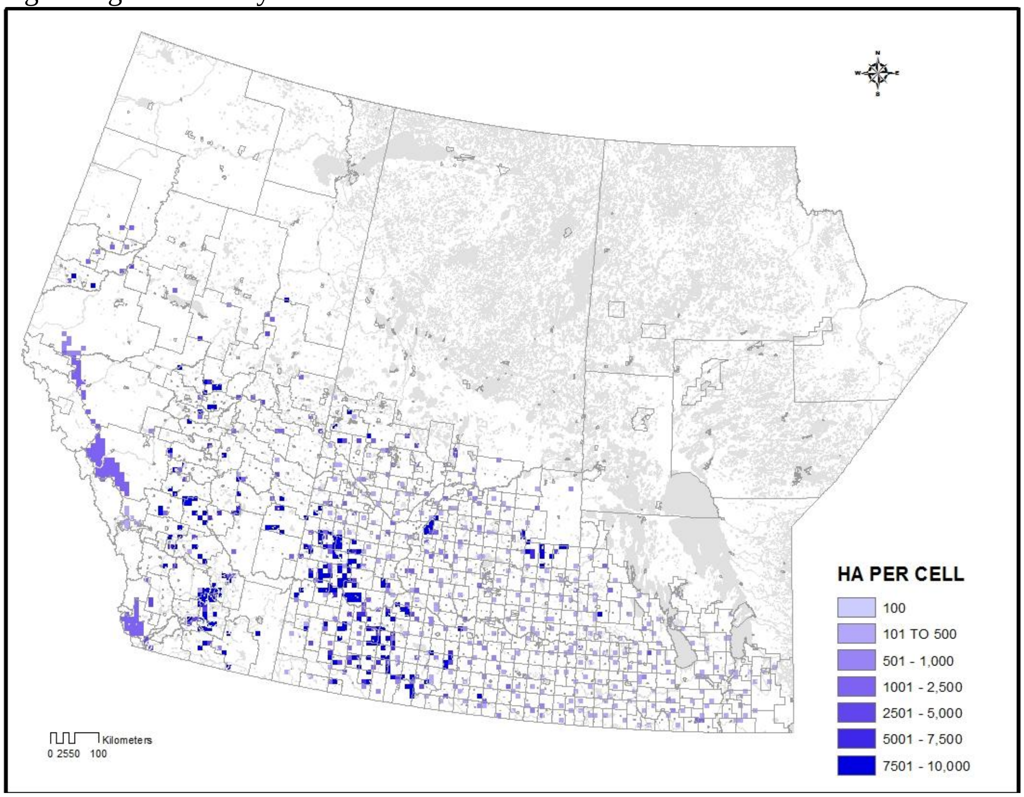


Figure I2h A1B Oats 2025

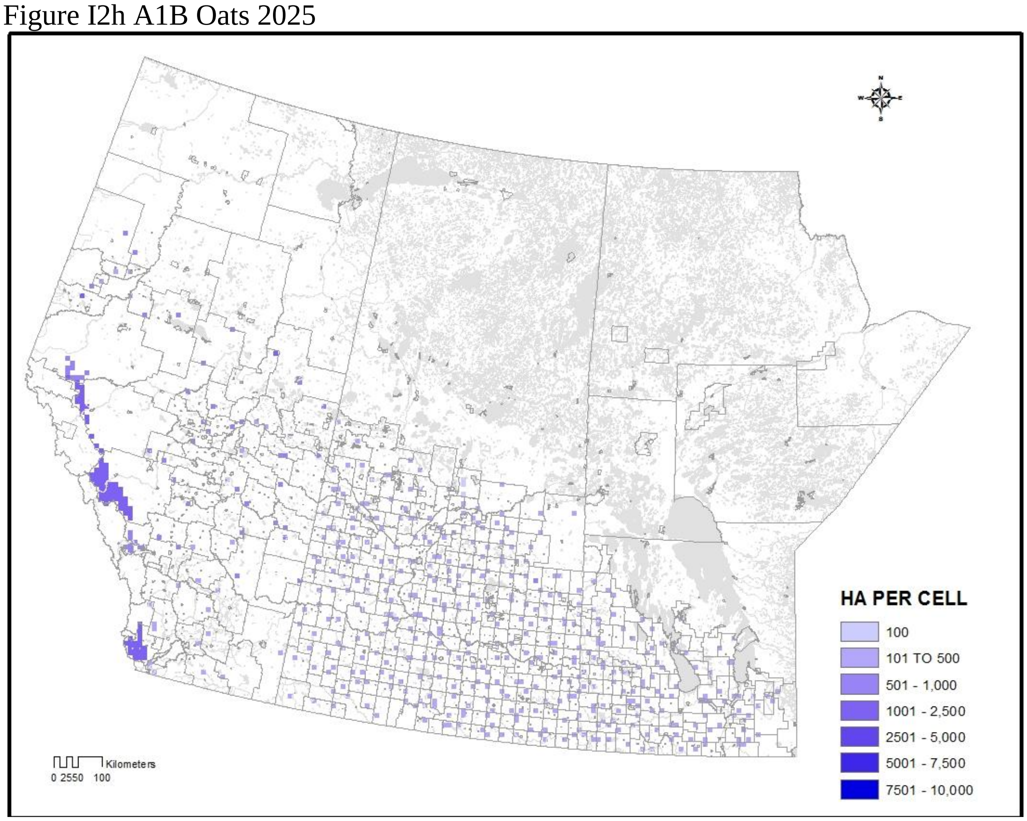


Figure I3: A1B 2050, highest acreage per cell

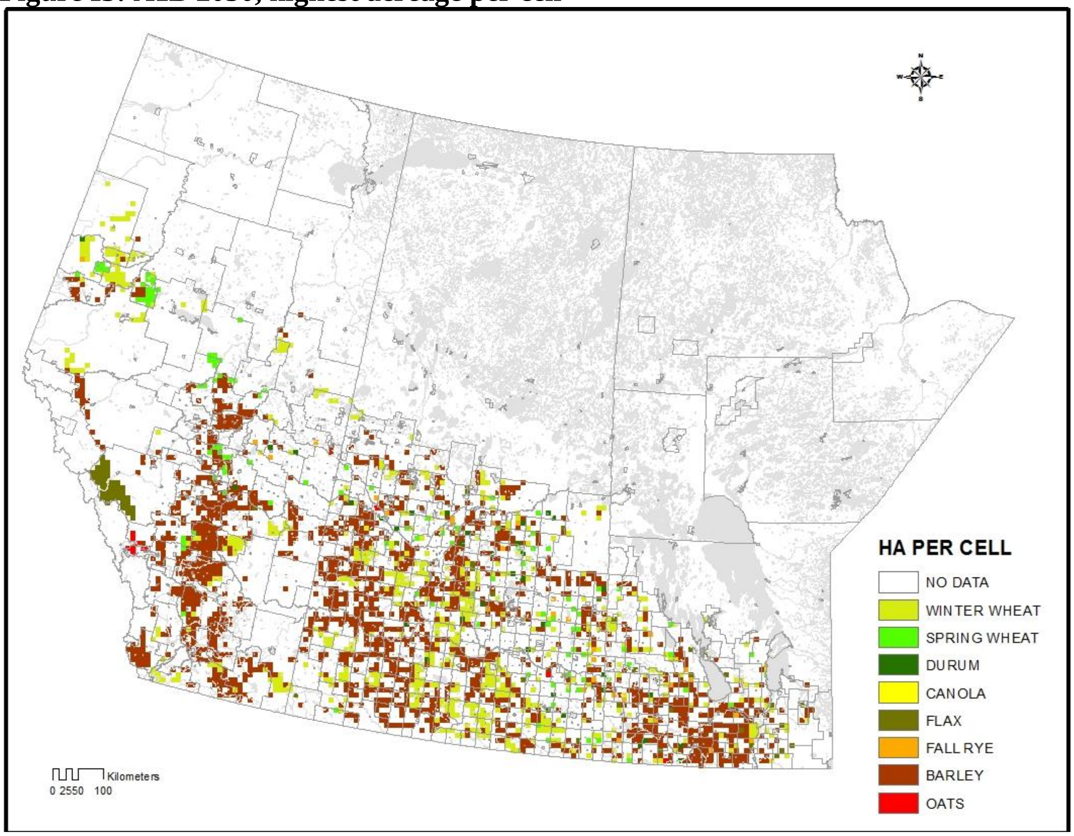


Figure I4: Model A1B 2050

Figure I4a A1B Winter Wheat 2050

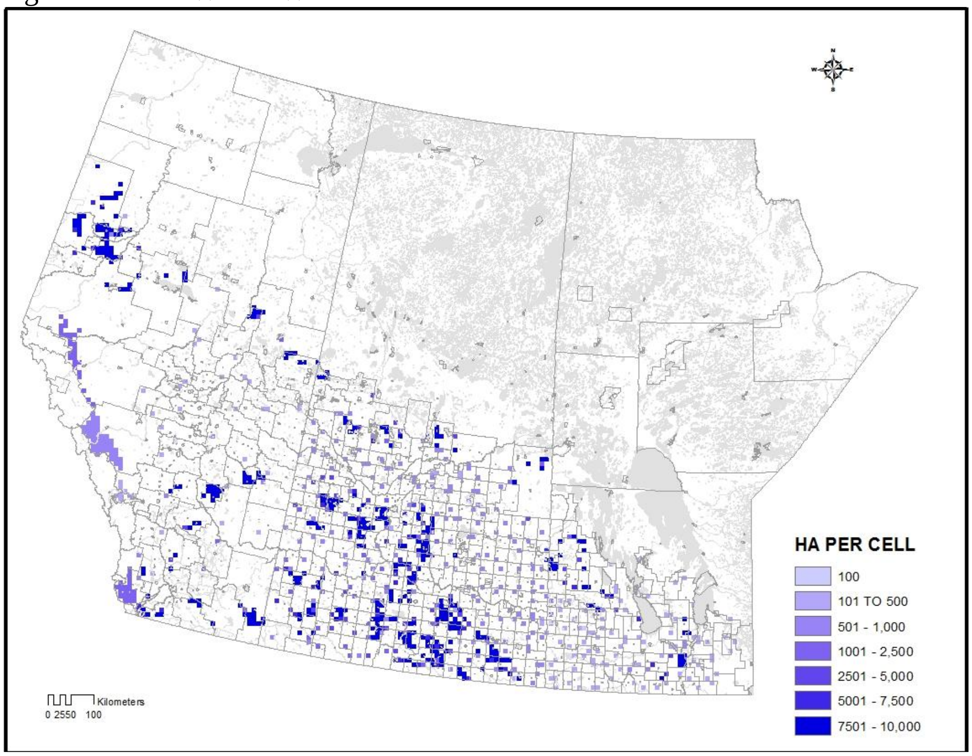


Figure I4b A1B Spring Wheat 2050

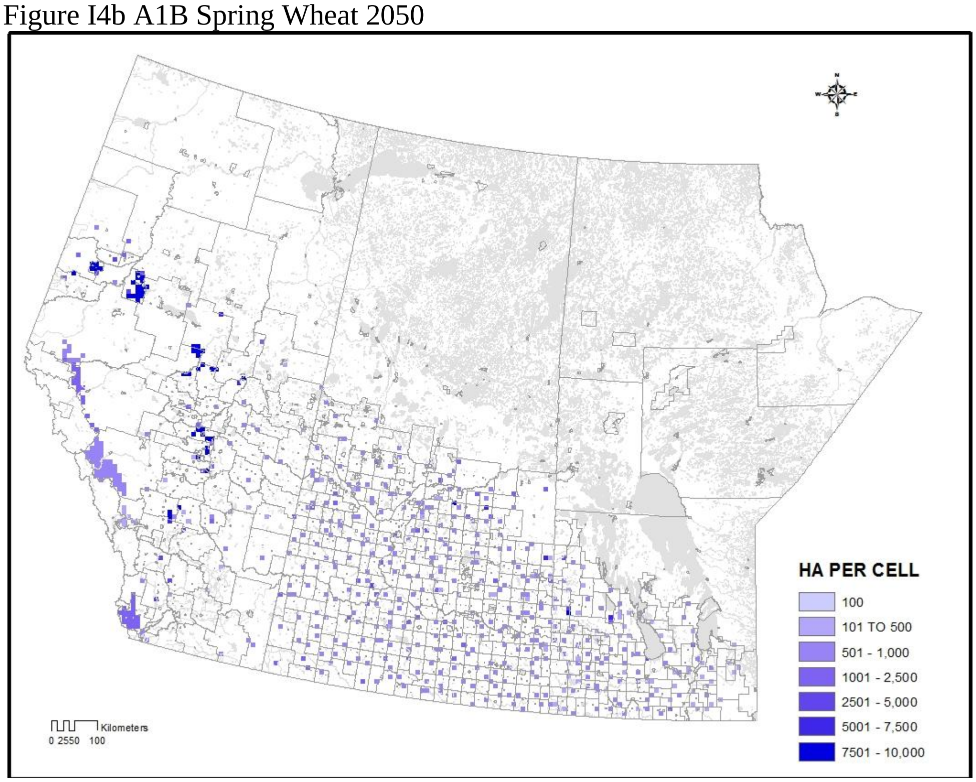


Figure I4c A1B Durum 2050

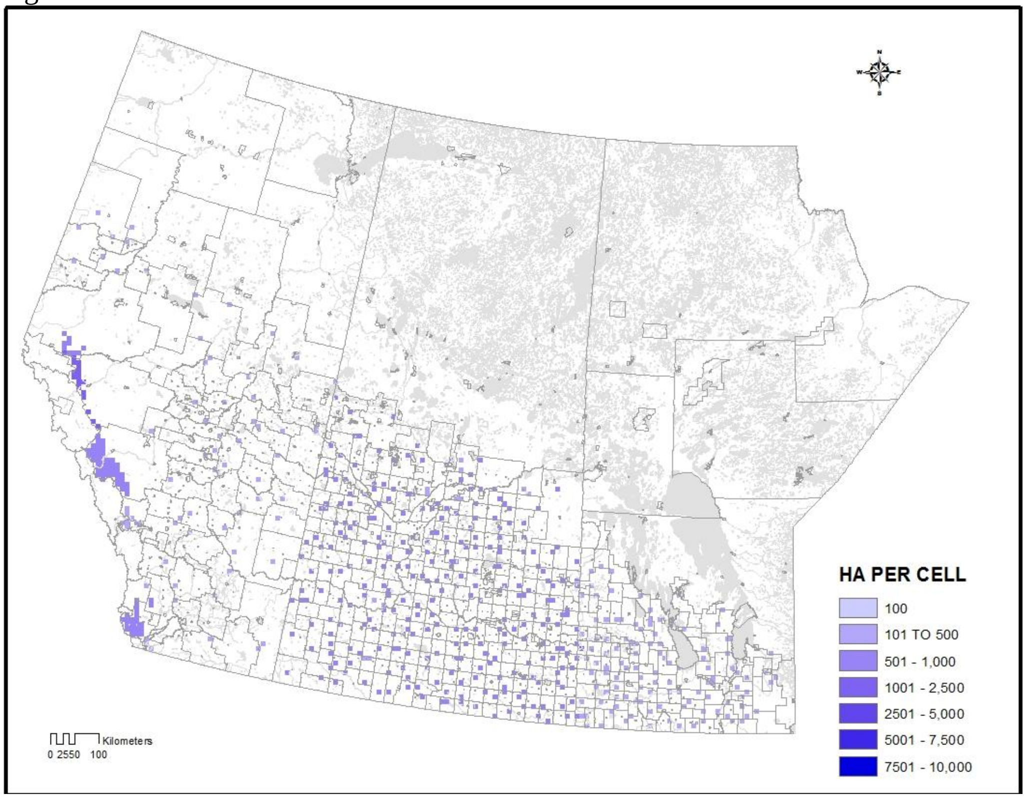


Figure I4d A1B Canola 2050

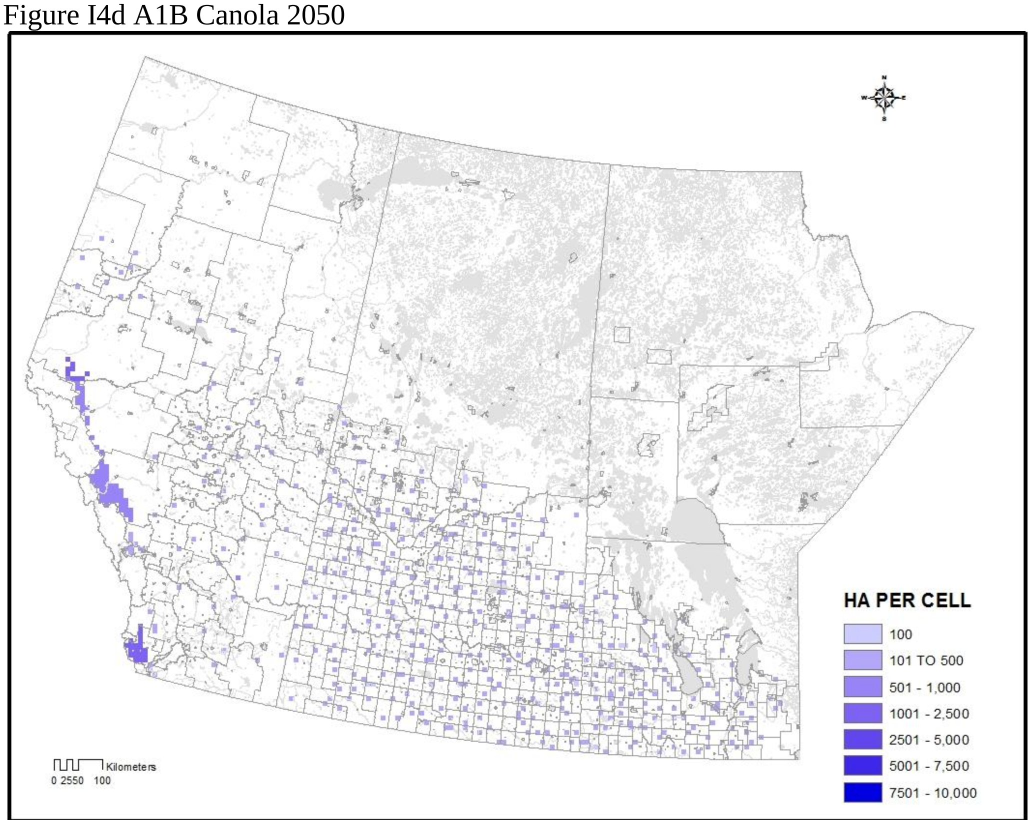


Figure I4e A1B Flax 2050

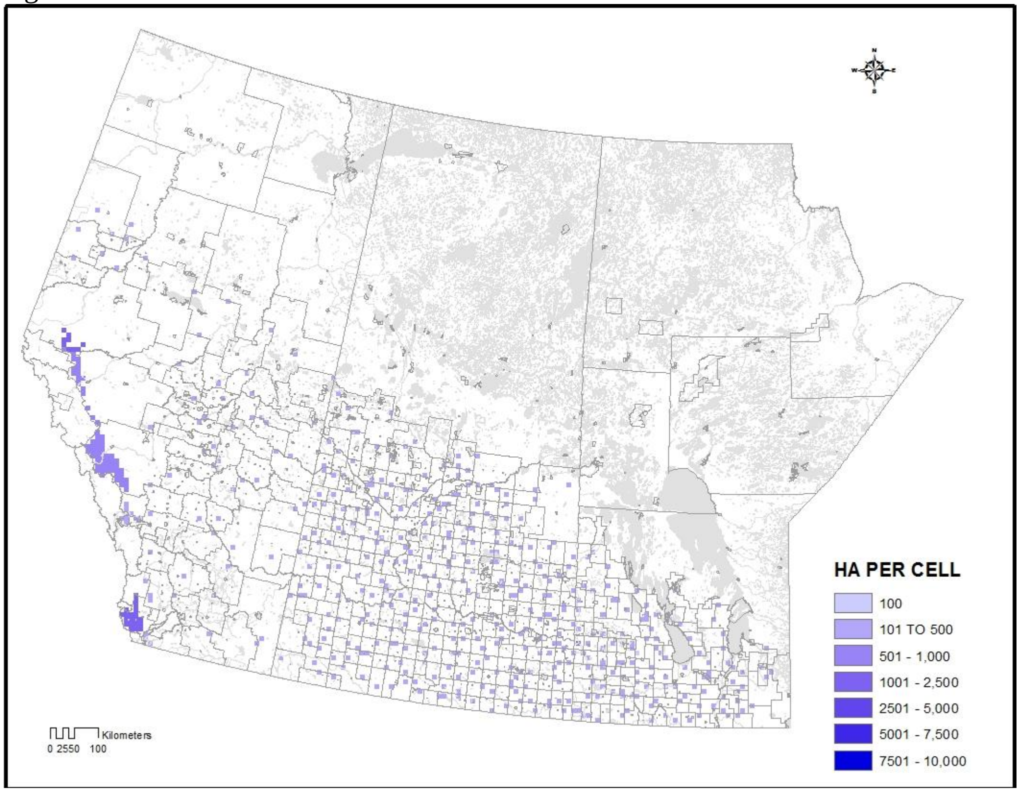


Figure I4f A1B Fall Rye 2050

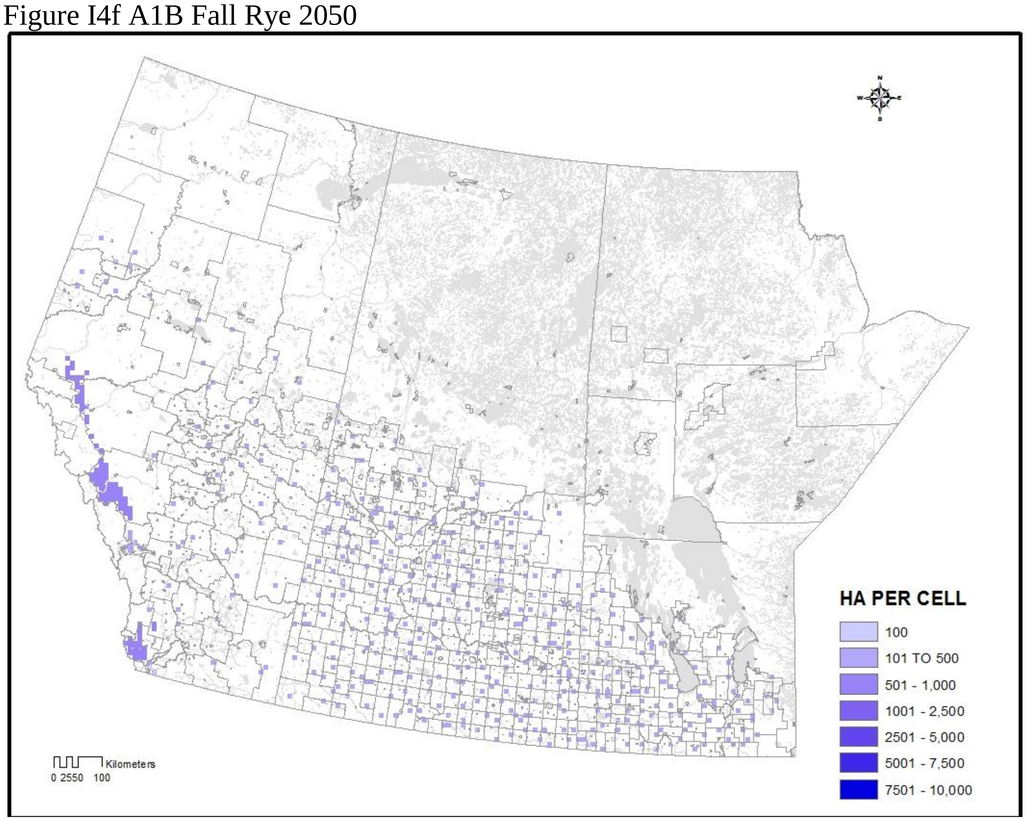


Figure I4g A1B Barley 2050

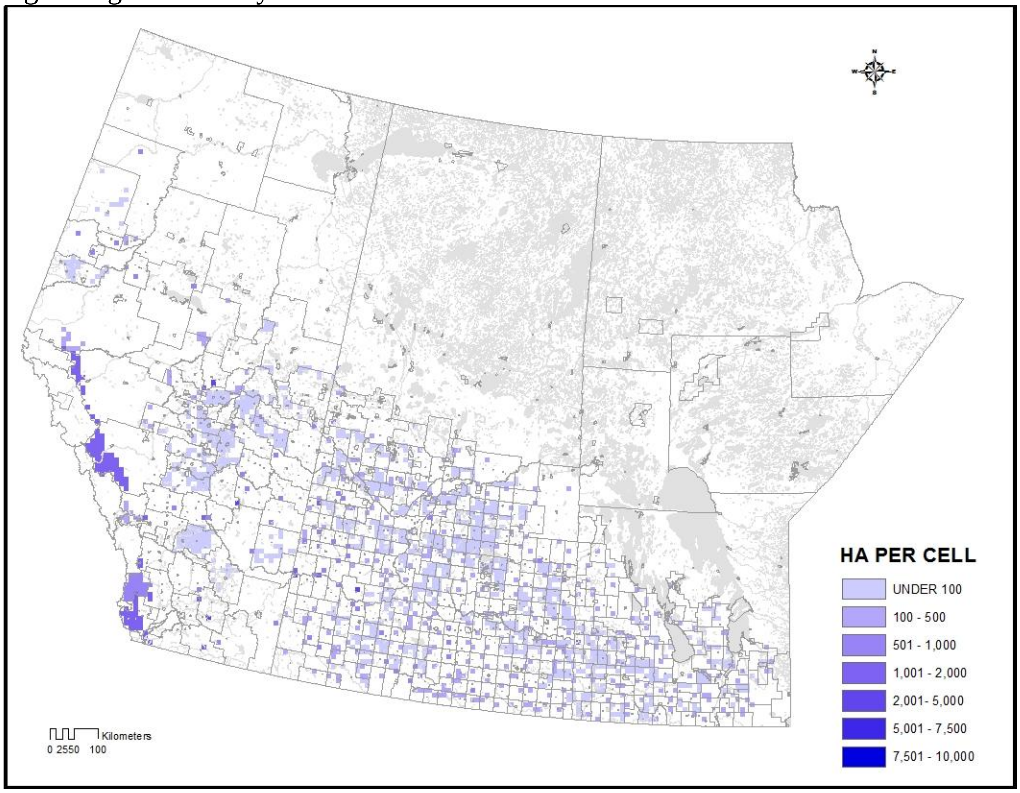
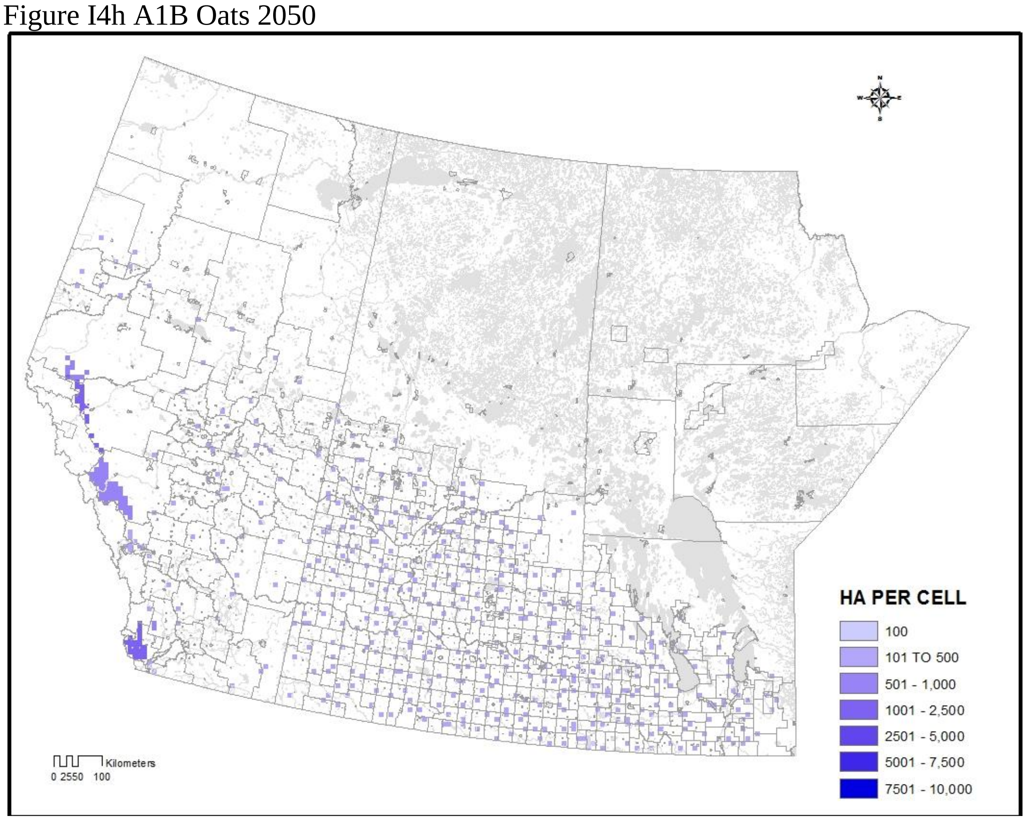


Figure I4h A1B Oats 2050



APPENDIX J: Changes to average climate variables for scenarios B1 and A1B

Figure J1: Change in daily average maximum temperature, July 2025, B1 scenario (low emissions)

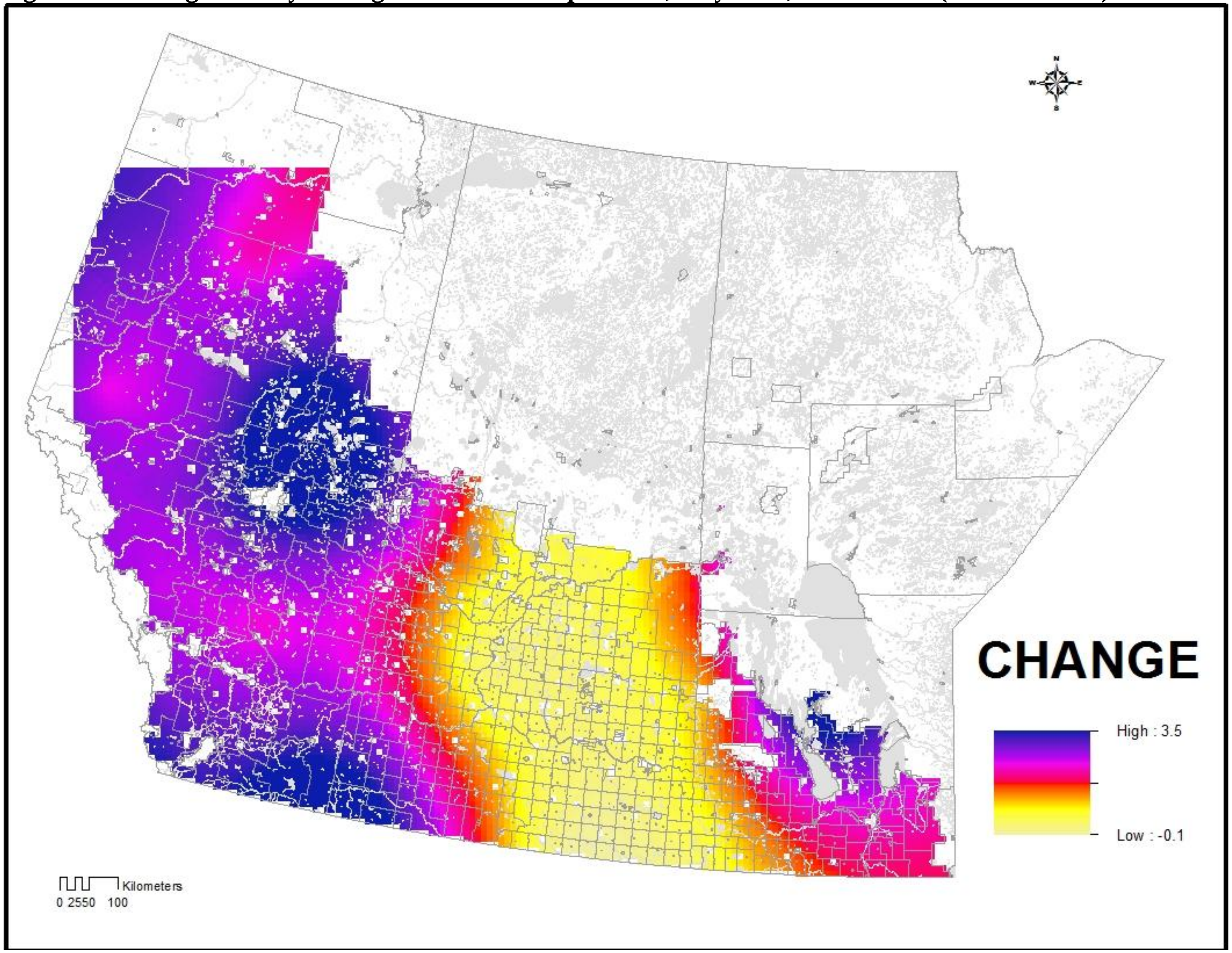


Figure J2: Change in daily average maximum temperature for July 2050, B1 scenario (low emissions)

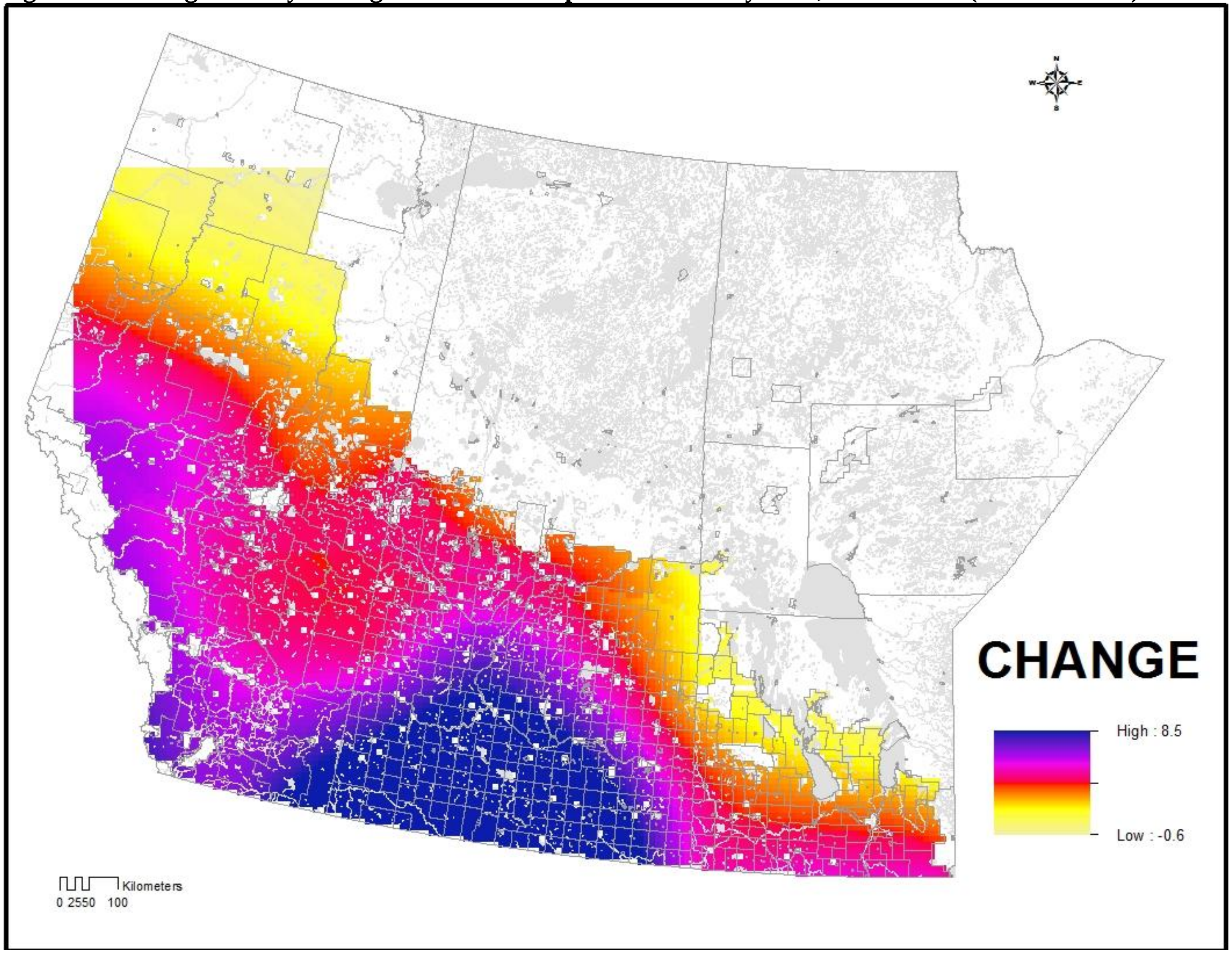


Figure J3: Change in daily average minimum temperature for July 2025, B1 scenario (low emissions)

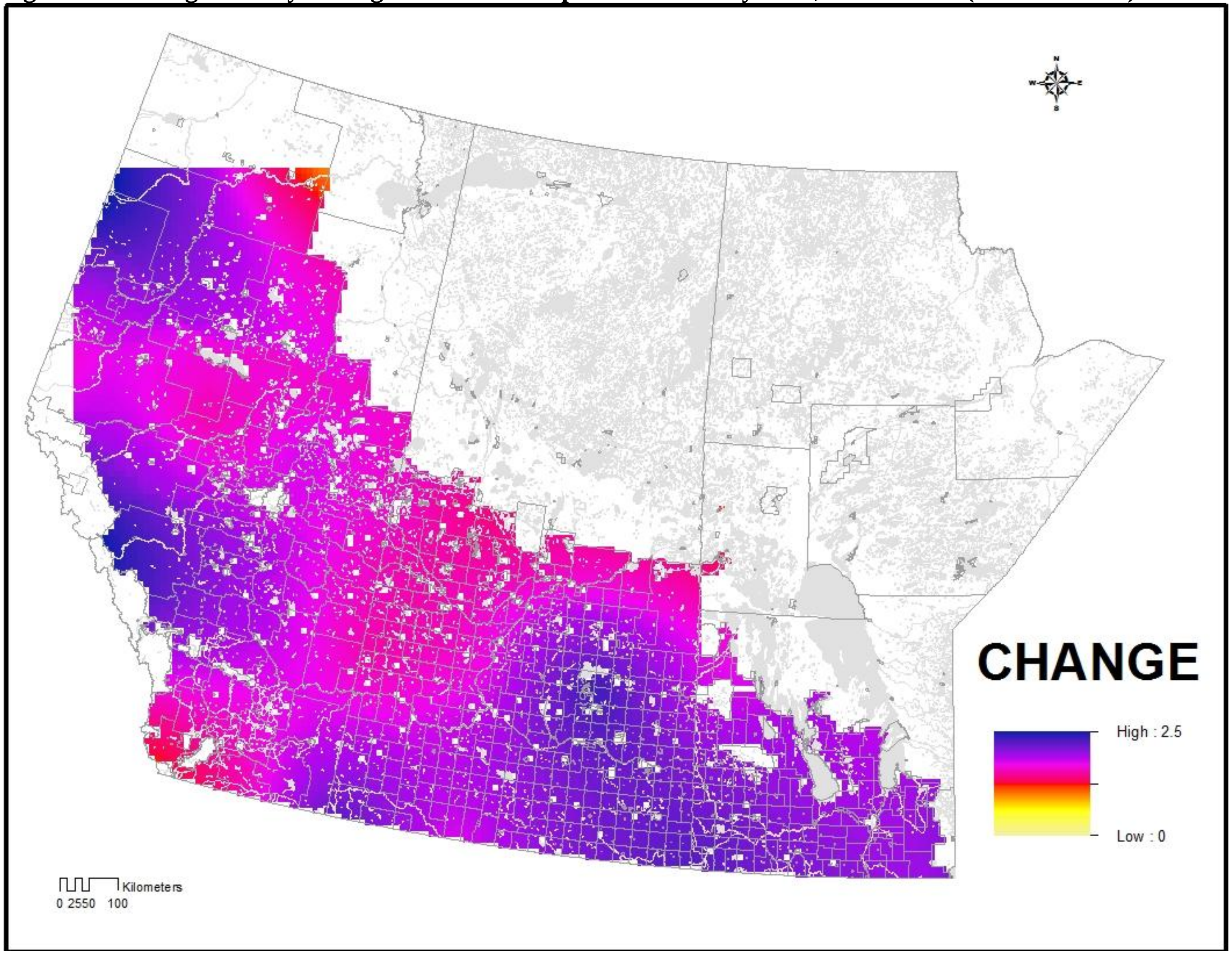


Figure J4: Change in daily average minimum temperature for July 2025, B1 scenario (low emissions)

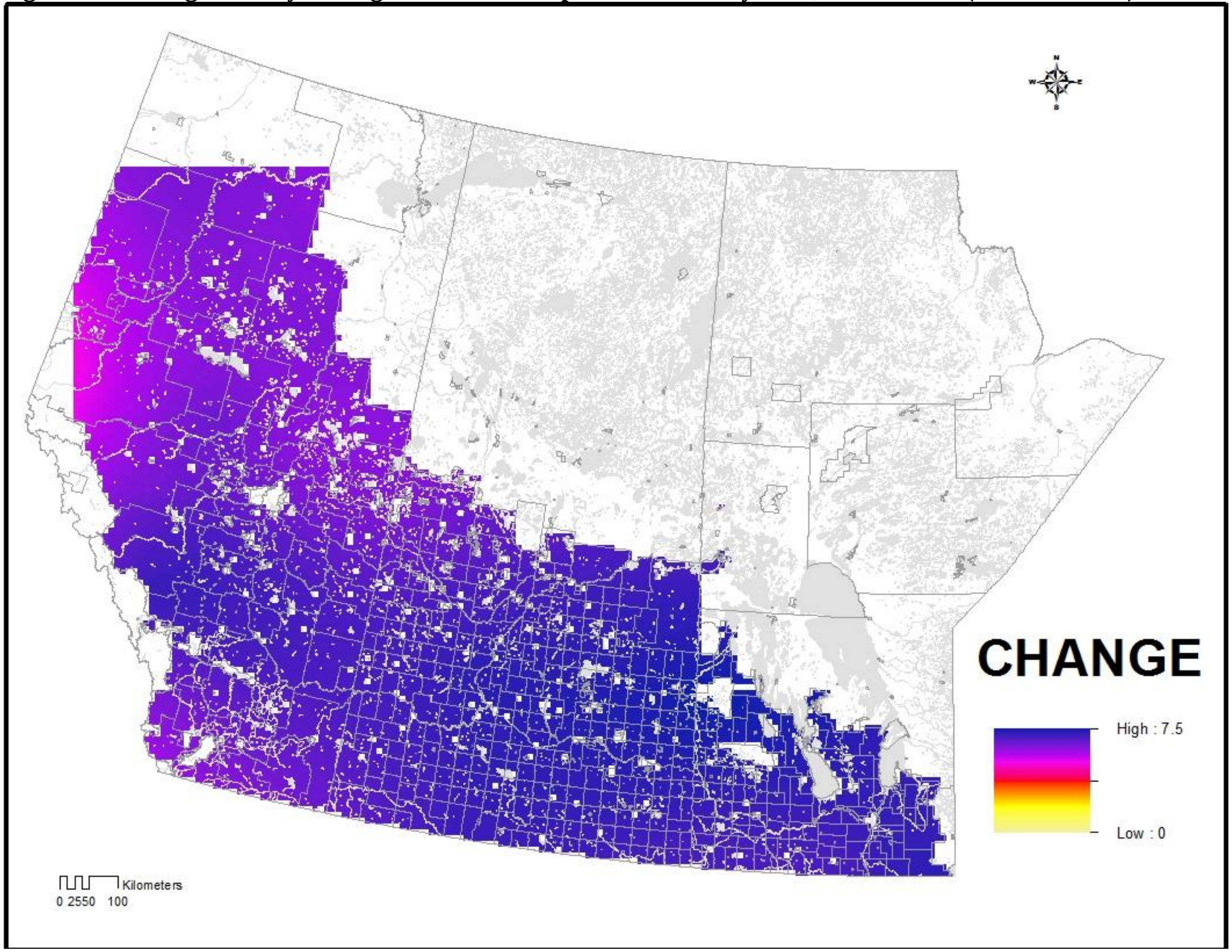


Figure J5: Change in daily average rainfall for July 2025, B1 scenario (low emissions)

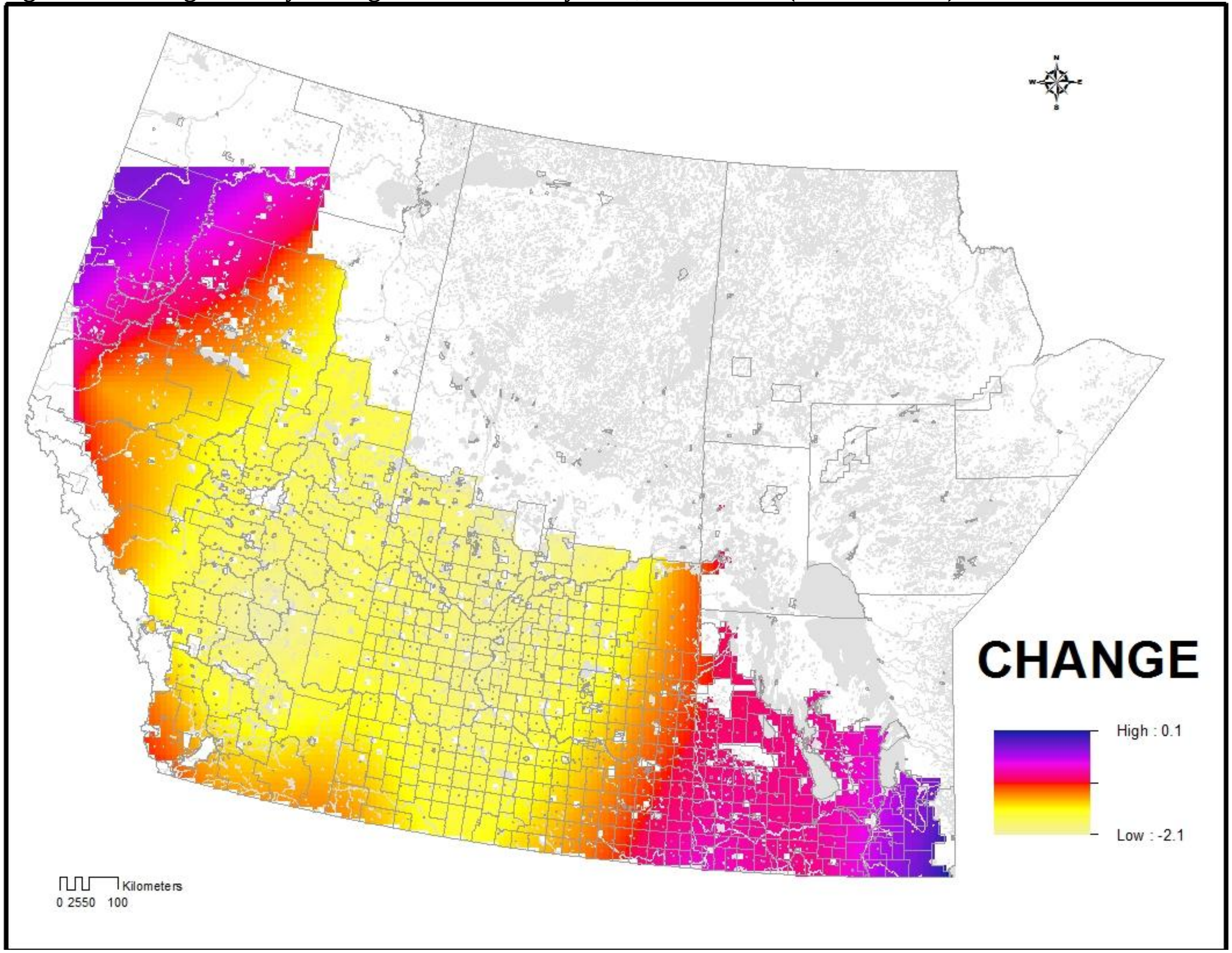


Figure J6: Change in daily average rainfall for July 2050, B1 scenario (low emissions)

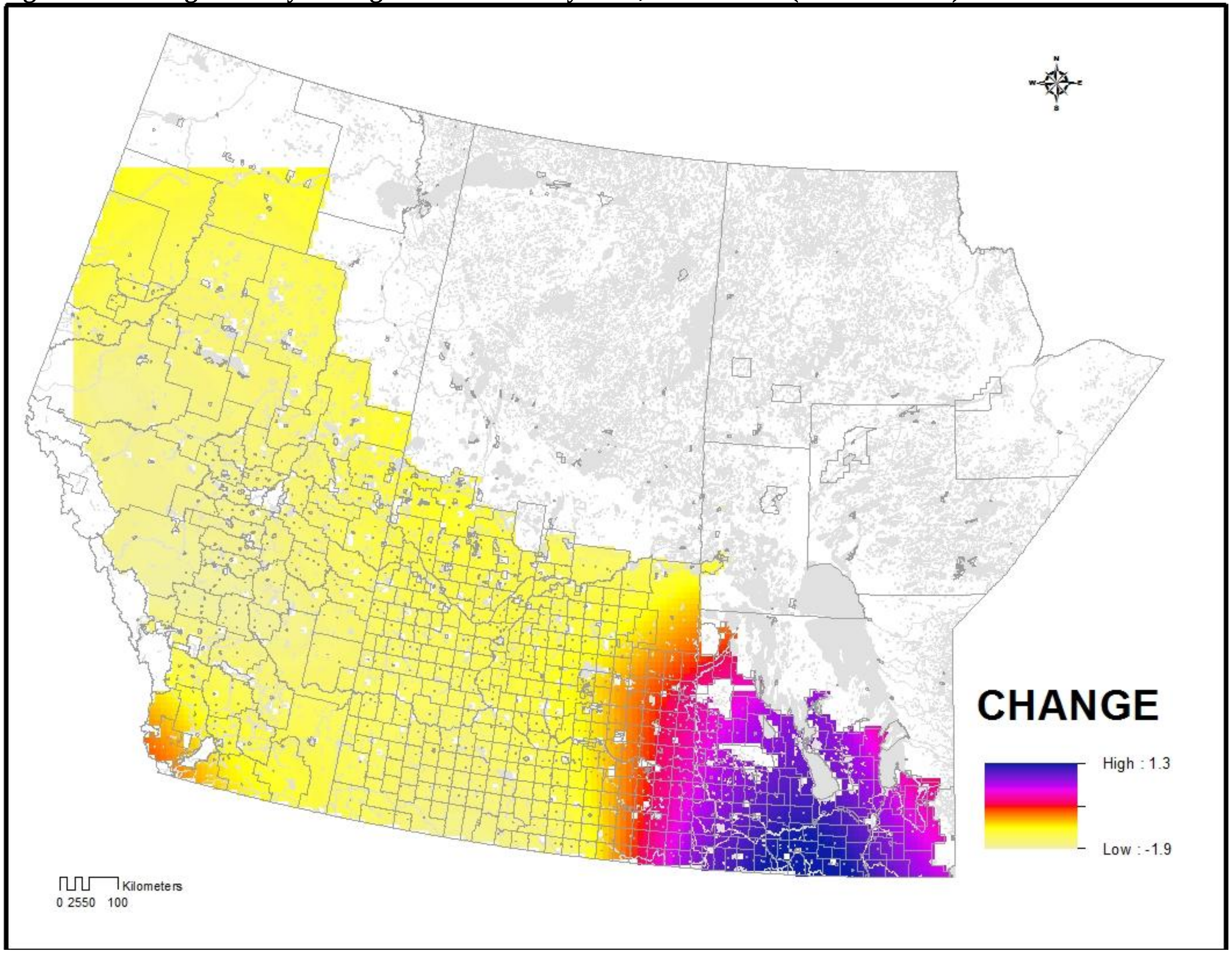


Figure J7: Change in daily average maximum temperature for July 2025, A1B scenario (high emissions)

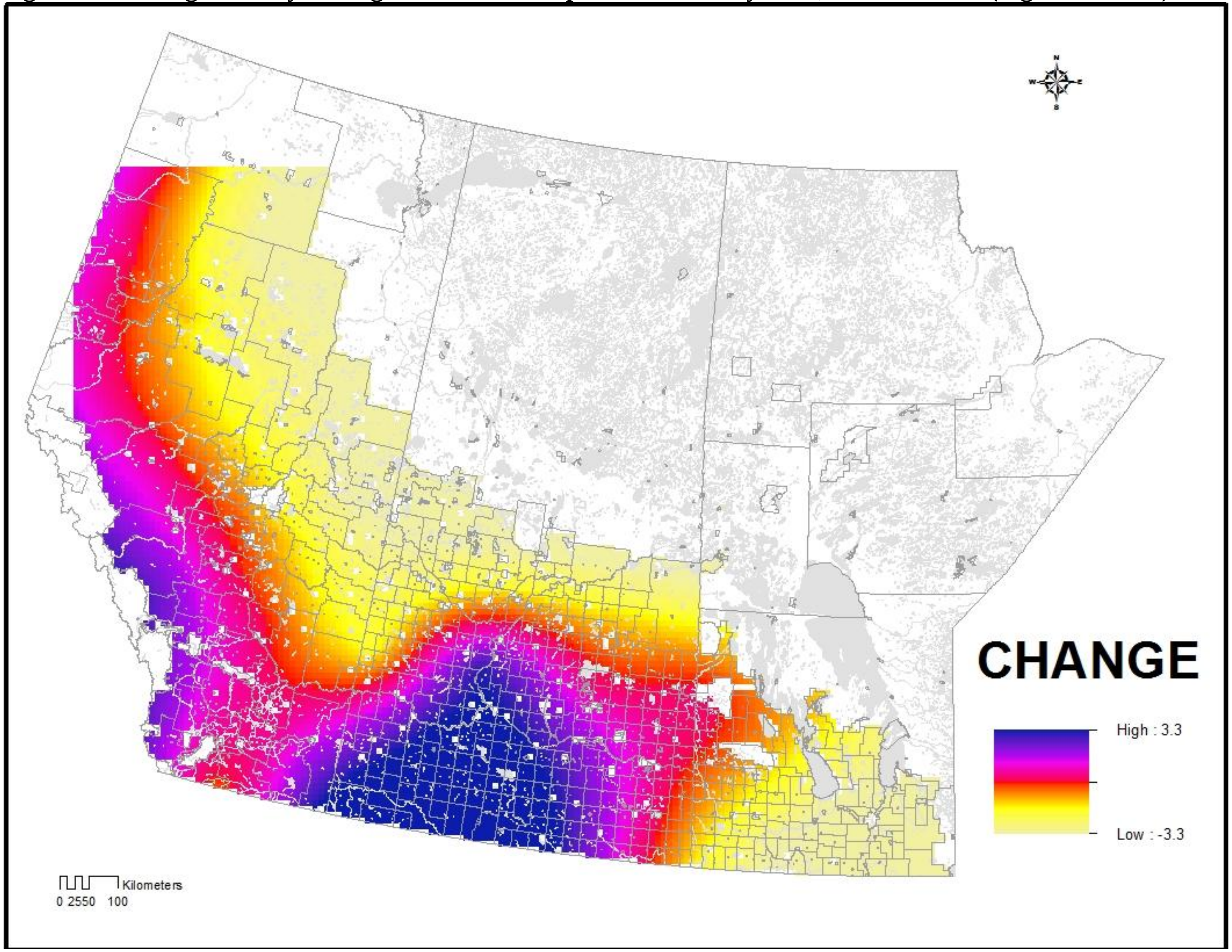


Figure J8: Change in daily average maximum temperature for July 2050, A1B scenario (high emissions)

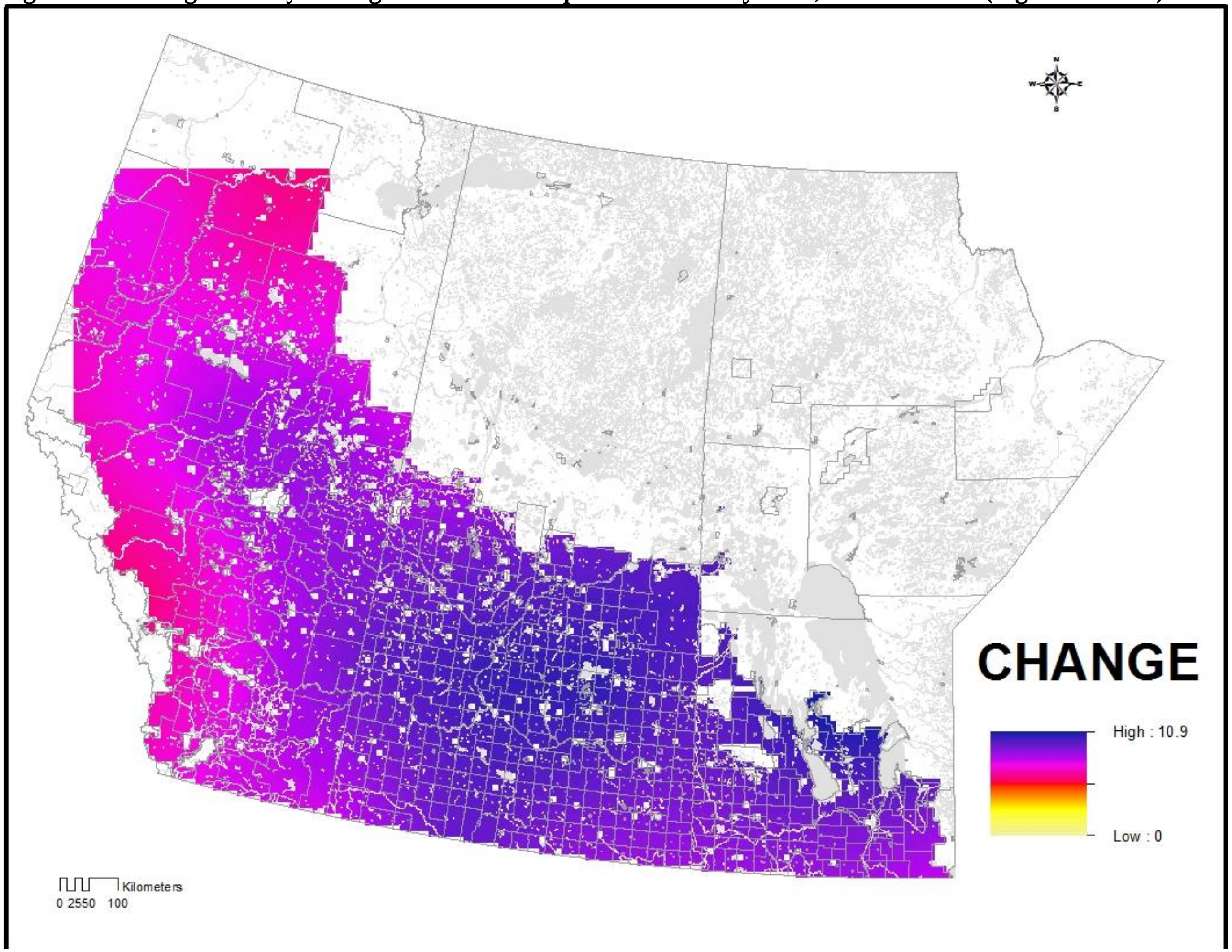


Figure J9: Change in daily average minimum temperature for July 2025, A1B scenario (high emissions)

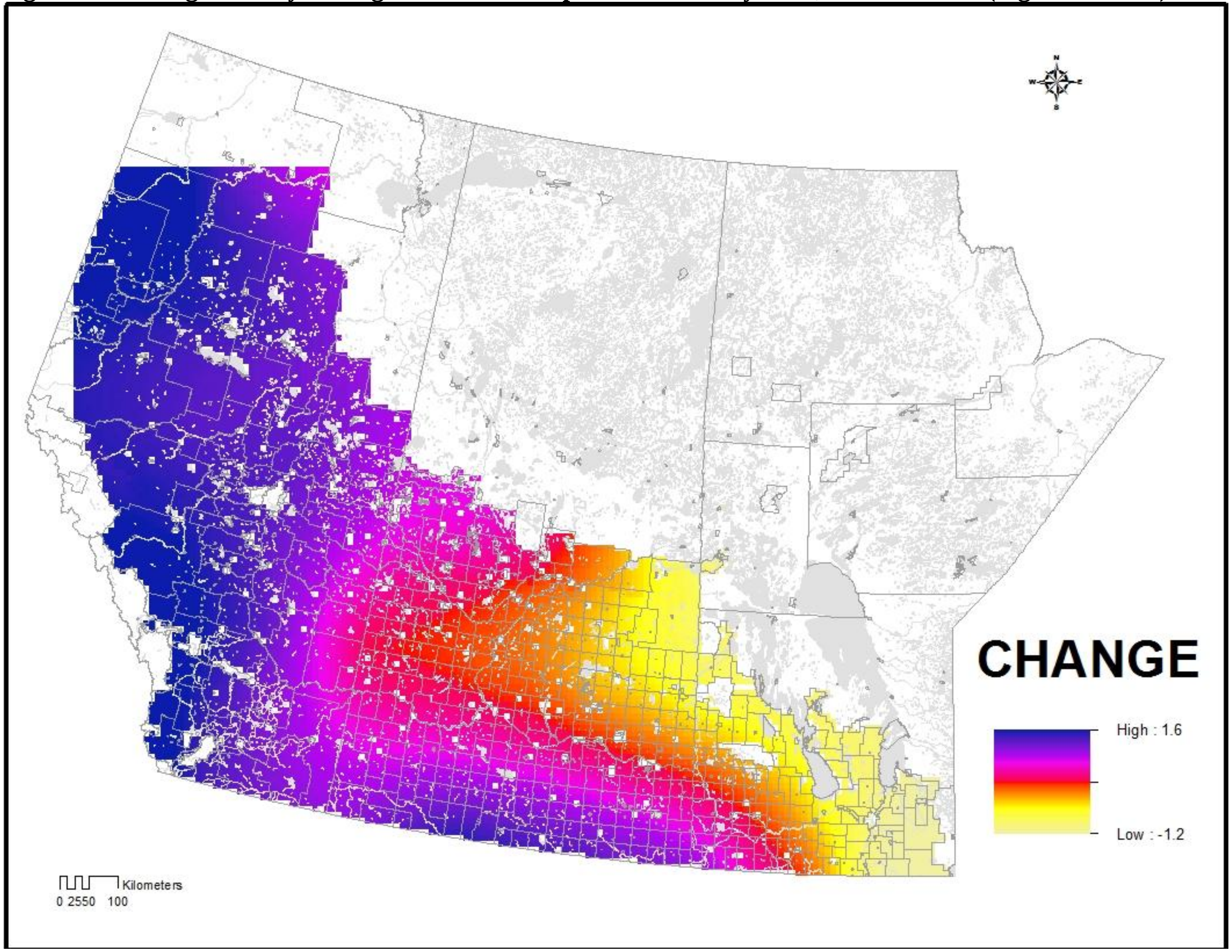


Figure J10: Change in daily average minimum temperature for July 2050, A1B scenario (high emissions)

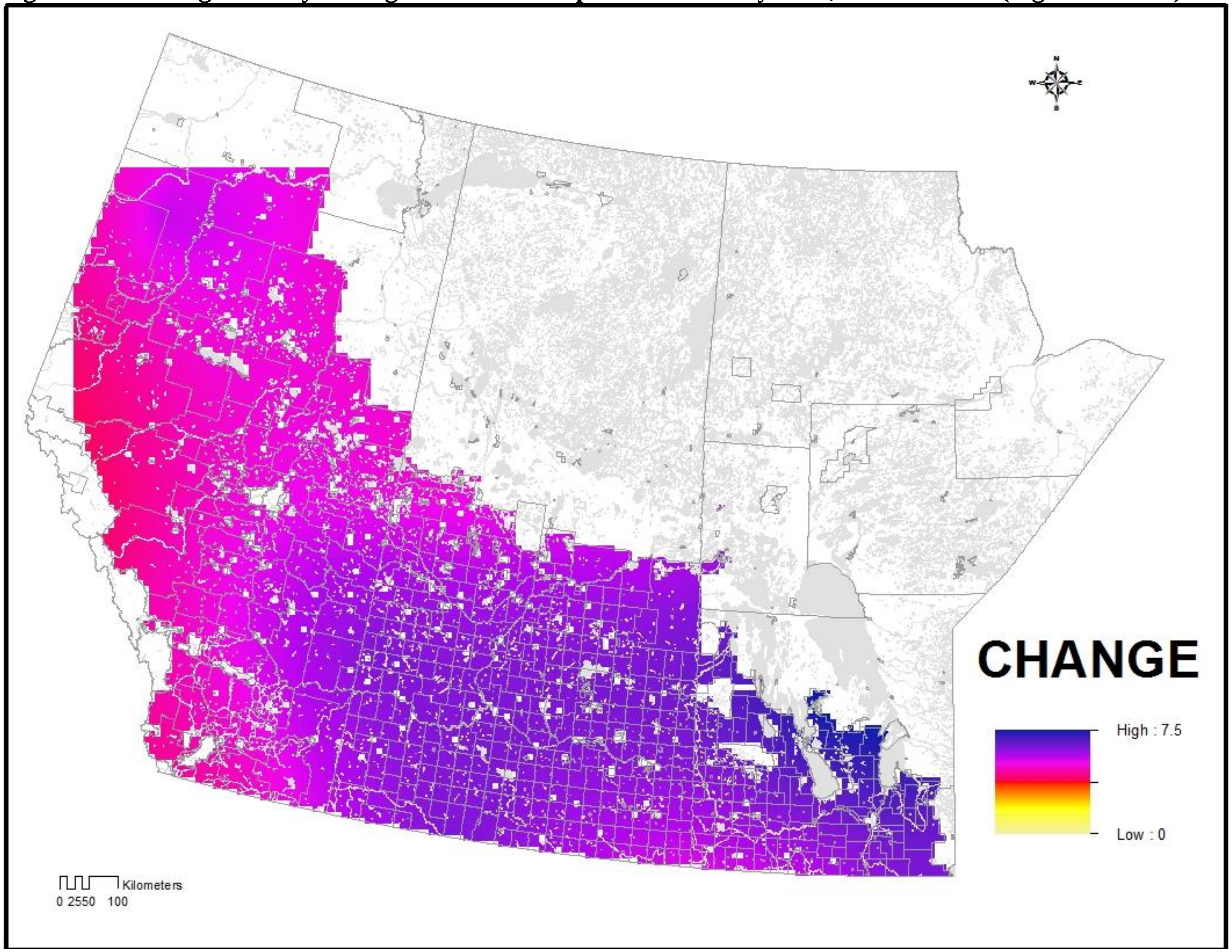


Figure J11: Change in the daily average rainfall for July 2025; A1B scenario (high emissions)

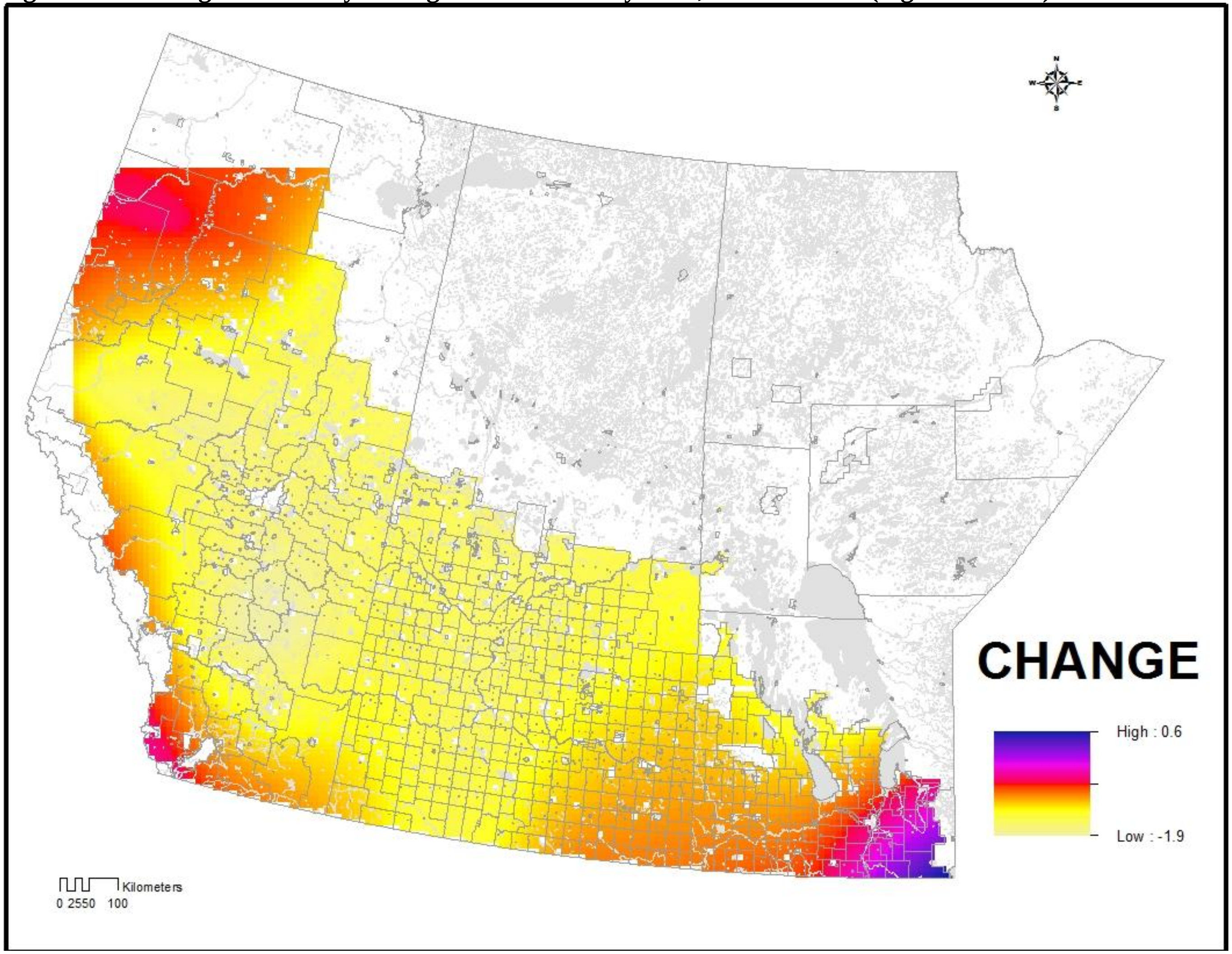


Figure J12: Change in the daily average rainfall for July 2050; A1B scenario (high emissions)