Canadian Journal of Soil Science
Revue canadienne de la science du sol

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Journal:	<i>Canadian Journal of Soil Science</i>
Manuscript ID	CJSS-2016-0075.R2
Manuscript Type:	Article
Date Submitted by the Author:	07-Feb-2017
Complete List of Authors:	Lychuk, Taras; Agriculture and Agri-Food Canada, Brandon Research and Development Centre Moulin, Alan; Agriculture and Agri-Food Canada, Brandon Research and Development Centre Izaurrealde, Cesar; University of Maryland at College Park, Geographical Sciences; University of Maryland Lemke, Reynald; Agriculture & Agri-Food Canada, Saskatoon Research and Development Centre Johnson, Eric; University of Saskatchewan, Plant Sciences Olfert, Owen; AAFC, Brandt, Stewart; Northeast Agricultural Research Foundation, ;
Keywords:	Climate change, Model bias, Agricultural inputs and cropping diversity, Growing season precipitation, Growing degree days

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Climate Change, Agricultural Inputs, Cropping Diversity, and Environmental Covariates in Multivariate Analysis of Future Wheat, Barley, and Canola Yield in Canadian Prairies, a Case Study

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Received:

Accepted:

ABSTRACT

Canada's grain and oilseed production in the Canadian Prairies may be affected by climate change, but the impact of input and diversity has not been assessed relative to projected variability in precipitation and temperature. This study assessed wheat, canola, and barley yield simulated with the Environmental Policy Integrated Climate model for historical weather and future climate scenarios in the context of agricultural inputs and cropping diversity at Scott, Saskatchewan, Canada. Variation of future yield was explored with recursive partitioning in multivariate analyses of inputs, cropping diversity, future growing season precipitation (GSP) and growing degree days (GDD). Agricultural inputs significantly affected wheat yield, but not barley or canola. Wheat yield was highest under reduced and lowest under organic inputs. The combination of input and diversity accounted for about one third of variation in future wheat yield and about 10 % for barley. Most of the variability in yield was correlated with GSP in May-July and GDD in April-June and August-September. Future growing season maximum and minimum temperatures increased by 1.06 and 2.03°C, respectively, and 11% in future GSP. This study showed how input management and reduced tillage maintained or improved yield, in the context of increased temperature due to climate change.

Short Title: Lychuk et.al. (2017) Climate change, management, diversity, and environment affect crop yield

Key words: Climate change, model bias, agricultural inputs and cropping diversity, growing season precipitation, growing degree days, recursive partitioning analysis

Abbreviations

GCM – Global Climate Model; RCM – Regional Climate Model; EPIC – Environmental Policy Integrated Climate Model; PA – Partitioning Analysis; ACS – Alternative Cropping System Study; GSP – Growing Season Precipitation; GDD – Growing Degree Days; GS – Growing Season; ORG - organic input; RED - reduced input; HI - high input; LOW - low diversity; DAG - diversified annual grains; DAP - diversified annual perennials.

Climate change is evident from trends in global oceanic and atmospheric temperature data, declines in snow and ice cover and other physical indicators (Easterling et al. 1997; Rayner et al. 2003; Stroeve et al. 2007). Climate is changing in Canada at an unprecedented rate. Between 1948 and 2007, average temperatures increased by more than 1.3°C, with year 2010 being 3.0°C above normal, which makes this year the warmest on record since nationwide records began in 1948 (McBean and al. 2012). Mean precipitation across Canada increased by about 12% during this period, and on average, the country experienced about 20 more days of rain relative to the 1950s with an increasing number of extreme floods, storms, and droughts (McBean and al. 2012; O'Riordan et al. 2013).

Agriculture in Canada will be influenced by the effects of climate change in the coming decades (Kulshreshtha and Wheaton 2013). The Canadian Prairies significantly influences Canada's economy and produces the majority of grains and oilseeds in Canada (Martz et al. 2007). In 2009, the area seeded to spring wheat in Canada was 6.8 Mha, of which approximately 6.7 Mha (98.5%) was in Western Canada (Agriculture and Agri-Food Canada 2010). Canola production is also concentrated in the Canadian Prairies and accounts for 99% of total seeded area in Canada (Casseus 2009). Barley production in the Canadian Prairies accounted for about 95% of total barley production in Canada (Statistics Canada 2015). As climate change progresses, average annual and seasonal temperatures in the Prairies will rise and precipitation regimes will change by 2050. Extreme precipitation events are expected to increase in frequency (Sauchyn and Kulshreshtha 2008). In previous research, precipitation was the most important factor affecting yield based on an 18-yr rotation study at the Agriculture and Agri-Food Canada experimental farm in Scott, SK (Lychuk et al. 2017). Hence, the fluctuations in frequency and

rates of precipitation will undoubtedly have an important impact on agricultural production in the Prairies.

Historical and future climate scenarios from regional models have been used to test hypotheses concerning the impacts of climate change on agricultural production and water resources (Rosenberg 1992). In the past, researchers have used global climate models (GCMs) to evaluate the potential changes caused by climate change on agriculture (Parry et al. 1999; Reilly et al. 2003; Reilly and Schimmelpfennig 1999; Rosenberg 1992). The scale of previous studies, (Luo and Lin 1999; Reilly and Schimmelpfennig 1999; Webster et al. 2003) with national and global climate models was too coarse to assess climate change impacts in detail (Gates 1985). Thomson et al. (2005) showed that regional agriculture will be affected by climate change with consequences for regional, national, and global food production. Regional impacts of climate change may not be quantified at coarse resolutions [e.g. 100 to 400 kilometers (Alley 2007)] of most GCMs. Resolution at this scale is problematic as GCMs were unable to capture the effects of local dynamics due to factors such as complex topography, which modulates the models' climate signal on the regional, sub-regional and local levels (Rawlins et al. 2012). Regional Climate Models (RCMs) simulate temperature and precipitation at finer scales (~ 50 km) and are relevant to the regional and sub-regional levels. Detailed topography and finer-scale atmospheric dynamics are assessed at higher spatial resolutions with RCMs. Combinations of global and regional models, often referred to as multi-RCM-GCM ensembles in climate change, are used to quantify uncertainties associated with different RCM projections (Khaliq et al. 2014). These multi-RCM and GCM ensembles are now available for North America through the North American Regional Climate Change Assessment Program (NARCCAP) (Mearns et al. 2012;

Mearns et al. 2009). The objective of the NARCCAP project was to run each RCM with National Center for Environmental Prediction (NCEP) reanalysis followed by two GCMs under the A2 scenario for the Intergovernmental Panel on Climate Change (IPCC's) Special Report on Emissions Scenarios (SRES) (Mearns et al. 2012; Mearns et al. 2009; Mearns et al. 2013) at a spatial resolution of 50 km. Under the A2 emissions scenario, global population will rise to more than 10 billion people by 2050. The projected atmospheric CO₂ concentrations are expected to reach 575 by the middle of the 21st century and 870 by its end. The NARCCAP program provides high-resolution future climate scenarios data for most of the North America continent using RCMs nested within GCMs as their boundary conditions (Mearns et al. 2012; Mearns 2007, updated 2012).

The Environmental Policy Integrated Climate (EPIC) model (Gassman et al. 2005; Izaurrealde et al. 2012; Williams 1995) has been successfully used in the past to estimate impacts of climate change on crop yields in different regions of the world (Asseng et al. 2015; Costantini et al. 2005; Izaurrealde et al. 2006; Lychuk et al. 2014; Lychuk 2014; Meki et al. 2013)). Lychuk et al. (unpublished data) evaluated EPIC's simulation of yields of wheat, barley, and canola as a function of agricultural input and cropping diversity on 18-yr Alternative Cropping System (ACS) rotation study at Agriculture and Agri-Food Canada (AAFC) Research Farm in Scott, SK. Wheat, barley, and canola simulated over the long-term, were significantly related to experimental yield data (1995 – 2013) for the three crops. Input, diversity, and environmental covariates such as precipitation and temperature were correlated with yield ($R^2 = 0.74$ to 0.98) in the simulations.

The first objective of this study was to assess crop yield as affected by agricultural input systems and diversified rotations in simulations with future projections of climate GSP and GDD, with exploratory analyses based on recursive partitioning. The second objective of this study was to compare simulations, with the EPIC model, of wheat, barley, and canola yields for historic (1971 – 2000) and future (2041 – 2070) climate scenarios with regards to the bias in climate projections which would affect simulated yield.

MATERIALS AND METHODS

Climatic Input Data and Simulations

Data from historical databases, RCMs and their driving GCMs, were used to design and conduct simulations (Table 1). In this paper, RCM simulations are referred to as 'RCM_GCM', where RCM stands for the acronym of the RCM and GCM for driving boundary condition of the global climate model (Monette et al. (2012) and Khaliq et al. (2014)). For example, CRCM simulations driven by the CGCM3 global climate model will be referred to as CRCM_CGCM3. Historic (1971 – 2000) and future (2041 – 2070) scenarios, for each RCM_GCM pair (Table 1) were simulated with climatic 3-hourly data for maximum and minimum temperatures, precipitation, solar radiation, relative humidity, and wind speed obtained from the NARCCAP database in Mearns (2007, updated 2012) for four RCMs and associated GCMs.

We used historical (1971 - 2000) weather and 1994 - 2013 tillage, soil properties and crop management operations from the ACS study at Scott and applied past (1971 - 2000) and future (2041 - 2070) projections from RCM x GCM ensembles (Table 1) to simulate the effects of

historic (1971 - 2000) and future (2041-2070) climate scenarios on wheat, barley, and canola yields and compare yield for each crop, and level of input and diversity. We also compared ensemble model averages between future and historic $\text{NO}_3\text{-N}$ leaching losses and CO_2 emissions. We employed the “business as usual” approach, i.e. we assumed that the tillage, fertilizer, and pesticide application rates, as well as other relevant field operations remain exactly the same for the past and future projections as they were during field study (1994-2013). This approach allowed us to assess changes in crop yields due to climate change independent of other factors.

Maximum and minimum daily temperatures and daily precipitation data for 1971 - 2000 were obtained from the Environment Canada (Environment Canada 2014) weather station at Scott; solar radiation data were estimated from sunshine hours simulated by the EPIC model. We derived daily means from the archived 3 hourly NARCCAP climate data. Simulations using historic weather data were conducted for a CO_2 concentration of 344 ppmv. The future weather simulations were conducted with a CO_2 concentration of 560 ppmv. The starting point for future simulations was year 2041 when significant climate change effects were predicted for the late 2030's to the early 2040's (IPCC 2007; IPCC 2014).

Details of experiments for past and future climate simulations are available at the NARCCAP Web site at <http://www.narccap.ucar.edu> and <http://www.narccap.ucar.edu/data/rcm-characteristics.html> for the individual descriptions of RCMs (Mearns et al. 2012). The regional distribution and deviations from the historical baseline of air temperatures and precipitation were predicted with four combinations of RCM and GCM models (Table 2). Description of the model bias, calculation of average, uncertainty range, and reliability of regional climate change via the

“Reliability Ensemble Average” (REA) method and their results are provided in the Appendix section.

The 1994 – 2013 Alternative Cropping System (ACS) Rotation Study

Eighteen years of crop yield, soils and meteorological data from the Alternative Cropping System (ACS) study were used to validate and calibrate the EPIC model. The ACS experiment was established in 1994 and completed in 2013 at the Agriculture and Agri-Food Canada Research Farm at Scott, Saskatchewan (52°22'N; 108°50'W; elevation 713 m). The soil was a Dark Brown Chernozem (coarse-loamy textured mesic Typic Haploboroll, US Soil Classification) (Table 3) developed from modified glacial till (Clayton and Ellis 1952) with slopes from 1 to 3%. Soil properties, cropping systems, and operational schedules for the ACS study are summarized below.

Nine cropping systems, each 6 years in length, were initiated in 1995. Nine combinations of three input management strategies were applied to three levels of cropping diversity (Table 4). The three input levels were: (1) organic (ORG, based on weed control with tillage, and non-chemical pest management and nutrients to reflect practices used by organic growers); (2) reduced (RED, employed no-till practices and integrated long-term management of pests and nutrients based on soil test recommendations); and (3) high (HI, used pesticides “as required” and fertilizers based on soil test recommendations, with tillage). The three diversity levels were: (1) low crop diversity system (LOW, wheat, oilseed and fallow or green manure based rotations);

(2) diversified annual grains system (DAG, diverse cereal, oilseed and pulse crops); and (3) diversified annual perennial systems (DAP, mix of grain and forage crops).

The experimental design was a split-plot with four replications. Input level, crop diversity and crop phase were the main, sub, and sub-sub plots, respectively. The area of the experimental site was 16 ha, and dimensions of each subplot were 40 m x 12.8 m.

For LOW crop diversity (Table 4) the crop sequence was green manure (GM) (partial fallow) – wheat (*Triticum aestivum* L.) – wheat – GM (partial fallow) – mustard (*Brassica juncea* L.) – wheat for ORG input, and canola (*Brassica napus* L.) for RED and HI inputs. Partial fallow was managed with lentil (*Lens culinaris* Medik.) in all three cycles of green manure (GM) under ORG input. Under the RED input, GM partial fallow was the first phase while chemical-fallow was the second. Under HI input, tillage fallow was in both fallow phases. For DAG under ORG input, the crop sequence was GM (partial fallow) – wheat – field pea (*Pisum sativum* L.) – barley (*Hordeum vulgare* L.) – GM (partial fallow) – mustard. In the first two six-year cycles, barley was underseeded to sweet clover (*Melilotus officinalis* L.) and following green manure fallow was sweet clover when it established. Under RED and HI inputs for DAG, the crop sequence was canola – fall rye (*Secale cereale* L.) – pea – barley – flax (*Linum usitatissimum* L.) – wheat. For DAP under ORG input, the crop sequence was mustard (canola under RED and HI inputs) – wheat – barley – alfalfa (*Medicago sativa* L.) – alfalfa – alfalfa.

Fertilizer, cultural and crop protection practices for the study were described by Brandt et al. (2010). In summary, crops were seeded at recommended rates in HI and at 33% higher rates in

ORG and RED systems to reduce herbicide inputs. Wheat and barley were straight-cut and canola was swathed prior to harvest with a Wintersteiger (Wintersteiger AG, Ried, Austria) small-plot combine from the center of experimental plots, at the full-ripe stage (early to mid-September). Fertilizer was applied at or before seeding based on soil test recommendations, but in HI system the same rate was applied to all replicates of each treatment, while in RED system, the rate varied across replicates based on soil test values for each plot (Brandt et al. 2010). In-crop weed control in HI systems utilized recommended herbicides at recommended rates based on weed populations while the ORG systems were harrowed in crop (Saskatchewan Ministry of Agriculture 1994 - 2013).

EPIC Model

The EPIC model was originally developed in 1984 to quantify the effects of erosion on soil productivity. It evolved into a single-farm biophysical process model that can simulate crop/biomass production, soil processes, and interactions based on detailed farm management and climate data (Gassman et al. 2005; Williams 1995). The EPIC model simulates growth and development of more than 100 plant species including all major crops, grasses, and legumes, as well as some trees (Izaurrealde et al. 2012). However the model does not simulate plant disease or weed populations. According to Izaurrealde et al. (2006) and Williams (1995) EPIC converts a fraction of the daily photosynthetically active radiation into plant biomass, thus using the concept of radiation-use efficiency to simulate crop growth. Vapor pressure deficits and atmospheric CO₂ concentration affect crop yield. The most severe of the daily stress indices for water, temperature, N, P and aeration is used to reduce potential plant growth and crop yield. Stress

factors for soil strength, temperature, and aluminum toxicity are used to adjust potential root growth (Izaurrealde et al. 2006; Jones et al. 1991). Crop yields are estimated by multiplying the above ground biomass at maturity (determined by accumulation of heat units or specified harvest date) by a harvest index (economic yield divided by above ground biomass) for the particular crop (Easterling et al. 1996).

Daily weather can be input from historical records or estimated from precipitation, air temperature, solar radiation, wind, and relative humidity. Parameters for EPIC simulations include soil layer depth, texture, bulk density, and carbon (C) concentration. Mixing of nutrients and crop residues within the plow layer are calculated in the tillage submodel in EPIC. Users of the EPIC model have successfully validated the model in many regions of the world under different management environments, climates, and soils including the USA, Canada, Colombia, Italy, China, and other countries (Apezteguia et al. 2009; Costantini et al. 2005; Lychuk et al. 2014; Thomson et al. 2006; Tubiello et al. 2000). The EPIC model was described in detail by Gassman et al. (2005); further information on EPIC algorithms and an in-depth description of the model are in Izaurrealde et al. (2006).

Recursive Partitioning Analysis

Methods of multivariate analyses have been widely used in ecological analysis and modeling, including climate change (Anderson 2000; Bienhold et al. 2012; Borcard et al. 1992; Diniz-Filho et al. 2009; Dray et al. 2012; Gobin 2010; Hall et al. 1999; Peres-Neto et al. 2006; Qian et al. 2009). Recursive partitioning analysis (PA) is a multivariate form of exploratory analysis,

conducted with other analyses such as partial least squares Grayson et al. (2015). The advantage of PA, particularly in climate change research, is that it accounts for variation due to continuous or categorical (nominal or ordinal) variables in exploratory data analysis. Statistical methods such as principal component analysis are best suited to continuous, normally distributed data (Jolliffe 2003; Mardia et al. 1979; Rummel 1988). Partitioning analysis is a type of exploratory modeling, which usually leads to further analysis employing additional modeling methods. The goal of exploratory modeling is to identify factors in the model with the strongest relationship with the response (Grayson et al. 2015). Partition analysis has also been successfully used in numerous climate change studies, which involved analysis of precipitation and temperature (Hijmans et al. 2005), biodiversity loss as a result of climate change (Garavito et al. 2015), effects of climate change on mixed-conifer forest growth (Hurteau et al. 2014), analysis of rainfall distributions in global circulation models (Schnur and Lettenmaier 1998) and other studies.

In our research, we utilized the decision tree approach, a variant of PA. The algorithm for decision tree induction is referred to as the top-down induction of decision trees, using a divide-and-conquer, or recursive partitioning, approach (Williams 2011). The decision tree is generally presented with the root at the top and the leaves at the bottom. The tree splits from single trunk into two or more branches, which split until the terminal node is reached. Each split, which can include a branch, root, or leaves, is referred to as a node. In the decision tree approach, the factor columns (X s) can be either continuous or categorical (nominal or ordinal). If an X is continuous, then the splits (partitions) are created by a cutting value. The sample is divided into values below and above this cutting value. In case of categorical X , the sample is divided into two groups of

levels. The response column (Y) can also be either continuous or categorical (nominal or ordinal). If Y is continuous, then the decision tree platform fits means. In the case of a categorical Y variable, the fitted value is a probability. In either case, the split is chosen to maximize the difference in the responses between the two branches of the split (SAS Institute Inc 2013). The procedure for node splitting is based on the LogWorth statistic, which is reported by split. LogWorth is calculated as follows:

$$-\log_{10}(p\text{-value}) \quad (1)$$

where the adjusted p -value is calculated in a complex manner that takes into account the number of different ways splits can occur. This calculation is unbiased compared to the unadjusted p -value, which favors X s with many levels, and the Bonferroni p -value, which favors X s with small numbers of levels (SAS Institute Inc 2013). Further details on the method are discussed in a white paper “Monte Carlo Calibration of Distributions of Partition Statistics” found on the JMP website www.jmp.com Partitioning analysis is more robust to non-normalities in data distribution compared to other types of analyses, such as principal component analysis, which works best for continuous, normally distributed data.

Statistical Analysis

All statistical analyses were done with JMP[®], Version 12.0.0 (SAS Institute Inc 1989-2015). Comparisons for yield, GSP, and GDD were made between: (1) historic (1971 – 2000) and future (2041 – 2070) scenario runs for each RCM_GCM pair and (2) between observed historical (1971 – 2000) baseline weather and future (2041 – 2070) scenarios for each RCM_GCM pair. Simulated variables, based on the ensemble model average and 1971-2000 weather, were compared using a paired *t* test. Year was considered as a random effect for analysis of variance (ANOVA) of crop yield, with agricultural input as a main fixed effect and cropping diversity as a subplot in a replicated split plot design. Data were analyzed with a MIXED model (ANOVA), and an analysis of covariance (ANCOVA) in JMP. Treatment effects were declared significant at $P < 0.05$. Yield was also analyzed as a dependent variable in recursive PA (decision tree method in JMP) with the independent variables input and diversity, GSP and GDD for each month from April to August. Partition analysis was used to identify covariates (GSP and/or GDD) used in the ANOVA and ANCOVA prior to analysis. Growing season precipitation by month and GDD were included or excluded as covariates in the appropriate ANOVA/ANCOVA for crop yield based on the results of PA analysis. Analyses addressed temporal autocorrelation (Loughin et al. 2007), by including GS precipitation and GS temperature as covariates to account for random variations in yield associated with environmental factors in the future climate scenarios. Taylor diagrams were calculated in R v 3.0.2 (R Core Team 2013). Box and whisker diagrams (SAS Institute Inc. Cary NC, 1989-2015) were plotted with JMP[®].

RESULTS AND DISCUSSION

Effects of Agricultural Inputs and Cropping Diversity on Crop Yield in the Context of Future GSP and GDD

Wheat, barley and canola yield simulations predicted from model ensemble averages were influenced by fixed effects and environmental covariates such as precipitation and GDD (Table 5) in partition analysis. Combined GDD in April and July accounted for more than 40 percent of variation in wheat yield, with GSP in April and May accounting for 14 percent of variation. Agricultural input and cropping diversity combined accounted for about 40 percent of variation in wheat yield. Combined agricultural input and cropping diversity accounted for 10 percent of variation in future barley yield, with GDD in April, GSP in May and June being primary yield defining factors. June GDD was the most important factor affecting future canola yield, accounting for almost 80 percent in yield variation, while agricultural input and cropping diversity were not significant yield predictors.

Agricultural input and cropping diversity were significant, in the analysis of variance for simulated wheat yield for three of the seven models and for the model ensemble average (data not shown). Differences in wheat yield due to input, accounted for a significant proportion of variability in both PA (Table 5) and ANOVA (Table 6), similar to ensemble average analysis for future climate change scenarios. Reduced and HI input systems increased wheat production relative to ORG production based on combined analysis of variance of fixed effects, with GSP and GDD as covariates on future wheat, barley, and canola yield for each RCM_GCM pair (Fig. 1) and by the ensemble average (Fig. 2, Table 5). Increased wheat yield was attributed to the lower number of tillage operations, and fertilizer management in the RED and HI systems which

optimized nutrient inputs and conserved soil moisture particularly during periods with high daily temperatures relative to the ORG system. Lafond et al. (2006) reported similar results for spring wheat grown in conservation tillage on cereal stubble where yields were 7.4% higher compared to conventional tillage in a 12-yr crop rotation study on a Black Chernozem at Indian Head Saskatchewan. Diversity significantly affected wheat and canola yield for the WRFG_CGCM3 future scenario, which is attributed to soil moisture as affected by chemical fallow in the LOW and fall rye in the DAG systems. However, the effect of diversity was not consistent for all scenarios. Improved soil moisture conservation and optimized nutrient inputs in RED, compared to ORG and HI systems, appear to be more suited to agriculture affected by climate change in the Canadian Prairies as reflected by higher yields for the three crops. Furthermore, we speculate that agronomic management in the RED system reduced energy inputs and labor, and likely had lower operational costs compared to the HI but were higher than under ORG systems, based on the previous results on the ACS reported by Zentner et al. (2011). Simulated cumulative average 2041 - 2070 nitrate leaching was lowest under the RED system in DAG diversity (18 kg ha^{-1}) and increased available N and wheat production relative to cropping diversity in the ORG system. Similar results were reported by Malhi et al. (2009), Lipiec et al. (2011); Malhi et al. (2011); Stoddard et al. (2005) who concluded that no-till management, relative to conventional tillage, can reduce nitrate leaching due to increased nutrient-use efficiency, especially for cereal crops. For the ACS study, Malhi et al. (2009) reported that the RED system appeared to store more of the excess N as soil organic matter during dry cycles and may be easier to manage in order to keep N supplies while avoiding large leaching losses. Simulated CO_2 emissions from microbial respiration were lowest under HI and RED systems in LOW diversity (1926 kg ha^{-1} and 2039 kg ha^{-1}) and were correlated with increased nutrient-use efficiency relative to ORG.

Nitrate-N leaching simulated with the ensemble model average was significantly higher than for 1971-2000 weather (35 kg ha^{-1} vs. 25 kg ha^{-1} , paired t test). The same trend was significant in simulations which compared future and historical CO_2 emissions resulting from microbial respiration (2254 kg ha^{-1} vs. 2206 kg ha^{-1} , paired t test). This suggests that changing climate will affect environmental quality in the Canadian Prairies.

Input, diversity and monthly GSP and GDD based on the model ensemble average significantly affected future yield in analysis of variance (Table 6) and in PA (Table 5). Growing season precipitation in May accounted for the greatest variation in future wheat yields, followed by agricultural input, GSP in June, GDD in August, April GSP, April GDD, and August GSP (Table 6). Diversity did not affect future wheat yield. Future wheat yields were significantly higher in RED relative to ORG, but not between other input systems (Fig. 2). Barley yield was numerically highest in the RED system, though neither agricultural input nor cropping diversity was significant for future yield.

The greatest variation in future barley yield was due to April GDD, followed by May GSP, May GDD, June GSP, September GSP, and September GDD (Table 6). Although agricultural input and cropping diversity explained 10% of variation in barley yield in the PA, these effects were not significant in the ANOVA. Similar research by Peltonen-Sainio et al. (2011) found that increased early-season precipitation raised the yield of spring cereals. Furthermore, Klink et al. (2014) found that higher winter and early spring precipitation may enhance spring barley yields at some sites but reduce them at others in the Northern Plains of the US and Canada. Effects of temperature varied across the sites by enhancing yields due to the positive effects of reduced

May and June maximum temperature and increased April precipitation at some sites (Klink et al. 2014).

Future canola yield was highest under the RED system, though neither agricultural input nor cropping diversity were statistically significant. The most significant factors influencing canola yield were June GDD, followed by April GDD, September GDD, and September GSP (Table 6). Kutcher et al. (2010), also showed that GS temperature had greatest impact on canola yield in Saskatchewan, followed by GSP for canola grown during 1970 – 2000.

Effects of Climate Change on Future Crop Yield

Observed Historical Baseline (1971-2000) and RCM_GCM Driven (2041-2070) Yield Comparisons

Crop yield was affected by future climate scenarios relative to historical data, though results varied between RCM_GCM models. Yield, simulated in future climate scenarios based on the ensemble model average, increased by 2.7% for wheat, 3.5% for barley, and 9.9% for canola, and by 4.05% for combined crops, relative to simulated historical yield (Table 7). However, these differences were not statistically significant. Ensemble averages and REA methods identified overall trends due to climate change, though individual models contributed to bias in these analyses.

Crop yield increased for three climate scenarios (CRCM_CGCM3, RCM3_CGCM3, RCM3_GFDL) and decreased under four scenarios based on the analysis by crop (Fig. 3a,b,c). The highest increases in crop yield occurred in three models with the greatest increases in future

GSP (Table 7 and Table 8). Relative to yield simulated with historical weather data, future crop yield was highest under the CRCM_CGCM3 future climate scenario for wheat, barley, and canola by 59, 63, and 55%, respectively and by 57% for the mean combined yield of all three crops (Tukey HSD test, $P < 0.05$). Wheat, barley, and canola yield was lowest under the WRFG_CCSM future scenarios by 69, 62, and 66% respectively while combined yield was 66% lower relative to yield simulated with historical weather (Tukey HSD test, $P < 0.05$). These yield differences were related to several factors simulated by the models. The most important factors were GSP in May, June, and July and GDD in April, May, June, August and September. Simulated GSP in April, May, June, and July (2041-2070) for the majority of RCM_GCM pairs was significantly higher than historical (1971-2000) data (Table 8) and resulted in higher crop yields for the CRCM_CGCM3, RCM3_CGCM3, and RCM3_GFDL pairs. Future yield decreased in four scenarios, due to daily heat extremes related to increases in future GS maximum temperature. These daily heat extremes may offset the benefits of additional precipitation in these scenarios.

The monthly average GSP for all climate scenarios was significantly higher compared to the historical means (Tukey HSD test, $P < 0.05$), except for August and September (Table 8). July replaced June as the month with the greatest amount of GS precipitation for the three highest yielding RCM_GCM pairs (CRCM_CGCM3, RCM3_CGCM3, and RCM3_GFDL) and the ensemble model average. Precipitation was also higher in July than June when historical data were compared for the period for (1905-1996) and that for 1980-1996 in the Canadian Prairies (Bonsal et al. 1999). Future GDD (2041-2070) in June and July for all RCM_GCM pairs were significantly higher than historical values (1971-2000), except for the RCM3_GFDL and RCM3_CGCM3 pairs (Tukey HSD test, $P < 0.05$). Similarly, simulated GDD (2041-2070) for

April, August and September were significantly higher than historical values (1971-2000) for half of the RCM_GCM pairs.

Combined GDD for all pairs were significantly higher than historical values (1971 – 2000) for the months of April, June, and July; non-significant for May, and significantly lower for the months of August and September. Crop yield was correlated with the increase of GDD in April, June, and July due to climate change, though the correlation was lower than that for GSP (Table 8).

RCM_GCM Driven Historical (1971-2000) and Future (2041-2070) Yield Comparisons

Simulated crop yield varied due to temperature and precipitation predicted by RCM_GCM pairs for historical (1971 - 2000) and climate change (2041-2070) scenarios (Fig. 3a,b,c). Historical yield was greater than the CRCM_CCSM, HRM3_GFDL, WRFG_CCSM, and WRFG_CGCM3 pairs and lower than the CRCM_CGCM3 simulations. Two models (RCM3_CGCM3 and RCM3_GFDL) over predicted yield, and their errors were smallest varying between 8 to 16%. These two models best predicted historical yield using observed (1971-2000) weather data, and are recommended for future research on yield analysis in this region.

Variability in predicted yield was attributed to fluctuations in temperature and precipitation caused by fluid physics processes in the driving GCM, which was set as a boundary condition for each RCM pair. Wheat, barley, and canola yield simulated for 2041 – 2070 increased by 33.7, 34.5, and 34% respectively, relative to predicted yield for historical (1971-2000) climate data derived from combined RCM_GCM pairs (Fig. 3d). Smith et al. (2013) simulated a 44 to 71% increase in spring wheat yield in the DNDC model under future climate scenarios for other locations in the Canadian Prairies. Yield increases were associated with a longer GS, CO₂

fertilization, and increased precipitation under future climate scenarios. Qian et al. (2016a) and Qian et al. (2016b) also simulated spring wheat yield with the DSSAT model for scenarios with increased atmospheric CO₂ concentrations at 11 locations in the Canadian Prairies. Yield increased between 10 to 37% relative to historical wheat yield, due to elevated CO₂ level and increased GS precipitation. In our study, crop yield increased in association with higher GS precipitation, increased GS minimum air temperature and greater number of GDD in future climate scenarios. The remaining variation in future simulated crop yield was attributed to CO₂ fertilization effect from increased atmospheric CO₂ concentration. Sensitivity analysis of a simulated CO₂ fertilization effect is beyond the scope and objectives of this paper.

Simulated wheat, canola and barley yields increased in simulations of climate change, similar to other analyses reported in the literature. Mooney and Arthur (1990) showed that climate change will benefit agriculture in Manitoba by lengthening the GS and increasing heat units. Higher rates of photosynthesis and radiation use efficiency increased yield of C₃ crops due to climate change and CO₂ fertilization for C₃ crops in this study. Similar results were reported by Easterling et al. (2007) who concluded that yield at mid- to high- latitudes may increase by 10-15% due to rising CO₂ levels, and a global average temperature increase of 1-2°C relative to 1980-1999. Furthermore, Porter et al. (2014) determined that global warming may increase yields and expand the growing season and acreage of agricultural crops at high latitudes including Canada. In our study, simulated yield increased in conjunction with a rise of as much as 2°C for minimum air temperature, an extended growing season (Table A1, REA method), and an increase in average precipitation by 11%. Robertson et al. (2013) reported marginal yield increases for wheat and canola below a critical level of 29°C for wheat and canola, and 28°C for

barley in the Canadian Prairies. Critical minimum temperatures were 5°C for wheat and barley, and 3°C for canola. None of the RCM_GCM pairs in this study predicted average increases in maximum GS temperature beyond 25.2°C, and five out of seven RCM_GCM pairs predicted an increase in average future GS minimum temperatures above 5°C. Increases in simulated future yield for all three crops were attributed to these changes. Only two model pairs, CRCM_CCSM and CRCM_CGCM3 predicted a decrease in future GS minimum temperatures to 4.6°C and 3.8°C, respectively.

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CONCLUSIONS

Wheat, barley, and canola yield at the study site is expected to increase by about 30% due to increases in monthly GSP and GDD due to climate change, and input management to a lesser extent. Recursive partitioning identified GSP and GDD as key factors which affected crop yield. In addition to quantifying future temperature and precipitation associated with climate change, agricultural input and cropping diversity also accounted for a significant proportion of variation in yield. Furthermore, the model bias reliability ensemble average analysis (REA method) showed that the magnitude of seasonal change for GS temperature and precipitation exceeded historical variability, and affected crop yield at the research site. At the study site, maximum and minimum GS temperatures will increase by 1.06 and 2.03°C respectively, from historical normals to projections for the period from 2041 to 2070. Growing season precipitation will increase by 11% from historical normals. Growing season precipitation in May accounted for the greatest variation in future wheat yield, April GDD for barley, and June GDD for canola. Input and diversity accounted for about one third of variation in future wheat yield and about 10 percent for barley. Diversity of crop rotations did not affect yield under future climate scenarios with the exception of one climate scenario for wheat and canola. Reduced tillage and input management will influence crop yield and mitigate the effects of climate change and seasonal variability of temperature and precipitation. Furthermore, reduced input systems may provide producers with an adaptive strategy for climate change in the area of the study.

ACKNOWLEDGEMENTS

The authors wish to thank Dr. S. McGinnis (North American Regional Climate Change Assessment Program's NARCCAP; NCAR/UCAR) for providing the data used in this paper and for technical assistance with data management. The North American Regional Climate Change Assessment Program is funded by the National Science Foundation (NSF), the US Department of Energy (DOE), the National Oceanic and Atmospheric Administration (NOAA), and the US Environmental Protection Agency Office of Research and Development (EPA). The authors are grateful to anonymous reviewers for their critical and constructive reviews. We also thank Dr. A. Glenn (AAFC Brandon Research and Development Centre) for internal review of the manuscript. Dr. T. Lychuk was supported by a post-doctoral fellowship from Agriculture and Agri-Food Canada under Growing Forward 2.

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Fig. 1 Growing season average maximum (A), minimum (B) temperatures (°C) and precipitation (C) (mm) over the present (1971-2000, rectangles with vertical lines) and future (2041-2070, striped rectangles) periods for each of the seven RCM_GCM pairs. The observed 1971 – 2000 climate normal value for temperature and precipitation is shown by non-colored rectangle. Models are listed in Table 1. Error bars represent standard error of the mean.

Fig. 2 Effect of input system (organic – ORG; reduced – RED; high – HI) on mean wheat, barley, and canola yield for the future (2041 – 2070) simulation period predicted by the model ensemble average. Means within each crop followed by the same letter do not differ at $P = 0.05$, based on Tukey's HSD. Error bars represent standard error of the mean.

Fig. 3 Average simulated yield of wheat (A), barley (B), canola (C) and combined yield of all three crops (D) over the present (1971-2000, rectangles with vertical lines) and future period (2041-2070, striped rectangles) for each of the seven RCM_GCM pairs (A, B, C) and the ensemble model average (D). Simulated historical yield using observed 1971 – 2000 weather is shown by non-colored rectangle. Models are listed in Table 1. Error bars represent standard error of the mean.

Fig. A1 Taylor diagrams for maximum and minimum air temperature, and precipitation showing standard deviation (°C (temperature) / mm gr. season⁻¹ (precipitation)), RMSE (°C (temperature) / mm gr. season⁻¹ (precipitation)), and correlation between the observed (1971 – 2000) and simulated variables. The RCMs and their driving GCMs are listed in Table 1. Standard deviations and RMSEs were normalized by the reference standard deviation (from the observed field). The contour of the reference standard deviation is shown with the solid line. Root mean square error was normalized and is shown in gray contours. Correlation rays are the (left) 95th and (right) 99th significance levels and are shown by dashed line.

Fig. A2 Distributions of growing season maximum (A) and minimum (B) temperature (°C) and growing season precipitation (C) (mm gr. season⁻¹) for the RCM historical predicted (1971-2000), historical observed, and future (2041-2070) periods prior to REA analysis. The sample median is represented by the line at the centre of the distribution, bounded by the 25th (1st quartile) and 75th (3rd quartile) percentiles represented by the lower and upper box boundaries. Whiskers show the 25th quantile – 1.5*(interquartile range) and 75th quantile + 1.5*(interquartile) range.

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Table 1. Meta-data for observed historical baseline (HIST, 1971 - 2000) weather and the North American Regional Climate Change Assessment Program’s (NARCCAP) Regional Climate Models (RCMs) and their driving Global Climate Models (GCMs) set as boundary conditions used in this study [adapted from Khaliq et al. (2014) Monette et al. (2012) Mailhot et al. (2012)]

RCM	Driving GCM	Acronym of GCM driven RCM simulation	Simulation period (historical/future)
1971-2000, HIST.	-	HIST.	1971 - 2000
Canadian Regional Climate Model: CRCM	Canadian Global Climate Model, version 3: CGCM3	CRCM_CGCM3	1971–2000/2041-2071
	Community Climate Model, version 3: CCSM	CRCM_CCSM	1971-1999/2041-2070
Hadley Regional Climate Model: HRM3	Geophysical Fluid Dynamics Laboratory Model: GFDL	HRM3_GFDL	1971-2000/2041-2070
Regional Climate Model 3: RCM3	GFDL	RCM3_GFDL	1971-2000/2041-2070
	CGCM3	RCM3_CGCM3	1971-2000/2041-2070
Weather Research and Forecasting Model: WRFG	CGCM3	WRFG_CGCM3	1971-2000/2041-2070
	CCSM	WRFG_CCSM	1971-2000/2041-2070

Table 2. Regional distribution of growing season (April 15 – September 15) air temperatures and precipitation under observed historical baseline (HIST, 1971 - 2000) conditions and deviations from the baseline predicted by the four regional climate models^a (RCMs) and their Global Climate Models (GCMs) as boundary conditions over the future (2041 – 2070) simulation period

GCM driven RCM simulation	Maximum daily air temperature (°C)	Minimum daily air temperature (°C)	Precipitation (mm)
1971-2000, HIST.	20.36	6.90	243.23
CRCM_CGCM3	0.07	- 0.64	83.16
CRCM_CCSM	4.85	0.58	- 36.69
RCM3_GFDL	- 4.20	1.43	206.33
RCM3_CGCM3	- 2.47	2.37	192.50
WRFG_CGCM3	1.04	2.29	- 47.90
WRFG_CCSM	1.90	2.46	- 94.60
HRM3_GFDL	2.72	4.77	61.52

^a Refer to Table 1 and text for the description of RCM_GCM pairs.

Table 3. Characteristics of the soil profile by depth increment

Property	Depth Increment					
	1	2	3	4	5	6
Lower boundary, m	0.07	0.15	0.30	0.60	0.90	1.20
Physical ^a						
Soil texture, g kg ⁻¹						
Sand	696	696	654	632	579	547
Clay	99	99	107	119	132	147
Bulk density, Mg m ⁻³	1.16	1.33	1.36	1.52	1.74	1.88
May soil temperature (5cm/10cm), °C ^b	10.93/9.92	-	-	-	-	-
Spring soil moisture, mm ^c	-	37.77	34.07	45.29	45.93	-
Harvest soil moisture, mm ^c	-	24.54	24.71	35.52	37.91	-
Organic carbon, % ^a	3.2	2.6	1.2	0.8	0.4	0.3
Chemical						
pH ^a	5.1	5.6	6.0	6.5	6.5	6.5
NO ₃ -N, kg ha ^{-1a}	-	38.42	11.78	11.93	18.84	26.14
PO ₄ -P, kg ha ^{-1a}	-	34.50	9.30	6.27	4.01	3.19
C/N ratio ^a	10.39	9.89	-	-	-	-

^a Data from A.P. Moulin and F. Selles, Agriculture and Agri-Food Canada, Brandon Research Center and Semiarid Prairie Agricultural Research Center (unpublished data)

^b Data from R. Weiss, Agriculture and Agri-Food Canada, Saskatoon, SK and Scott Experimental Farm (unpublished data)

^c Data from S.A. Brandt and R. Weiss, Agriculture and Agri-Food Canada, Saskatoon, SK and Scott Experimental Farm (unpublished data)

Table 4. Description of the nine cropping systems in the Alternative Cropping System (ACS) study^a

Diversity level ^b	Input level ^c	Crop sequence
LOW	ORG	GM ^d -Wheat-Wheat-GM-Mustard ^e -Wheat
	RED	GM ^d -Wheat-Wheat-Chem. Fallow ^f -Canola-Wheat
	HI	Fallow ^g -Wheat-Wheat-Fallow ^g -Canola-Wheat
DAG	ORG	GM-Wheat-Pea-Barley ^h -GM ⁱ -Mustard ^e
	RED	Canola-Fall rye ^j -Pea-Barley-Flax-Wheat
	HI	Canola- Fall rye ^j -Pea-Barley-Flax-Wheat
DAP	ORG	Mustard ^e -Wheat-Barley-Alfalfa ^k -Alfalfa-Alfalfa
	RED	Canola-Wheat-Barley-Alfalfa ^k -Alfalfa-Alfalfa
	HI	Canola-Wheat-Barley-Alfalfa ^k -Alfalfa-Alfalfa

^aSource: (Brandt et al., 2010)

^bLOW - low; DAG - diversified annual grains; DAP - diversified annual perennials

^cORG – organic, non-chemical pest control and nutrient management; RED – reduced, integrated long-term management of pests and nutrients utilizing chemicals and no-till practices; HI – high, pesticides and fertilizers “as required” based on conventional recommendations associated with pest thresholds and soil tests

^dGM - green manure (Indian Head Lentil) partial fallow

^eAfter the first cycle canola was replaced with mustard

^fChem. fallow - summer fallow with weeds controlled by herbicides

^gFallow - summer fallow with weeds controlled by tillage

^hBarley was under seeded to sweet clover in first two cycles

ⁱSweet clover in first two cycles

^jIn the third cycle, fall rye was replaced with soft white spring wheat

^kIn the first cycle, alfalfa and brome were under seeded to oat in the forage establishment year

Table 5. Percent of variation from partition analysis on future (2041 – 2070) mean wheat, barley, and canola yield attributed to input, diversity and monthly growing season precipitation and growing degree days as predicted by the model ensemble average

Crop	Input	Diver- sity	Effect											
			Growing season precipitation						Growing degree days					
			April	May	June	July	Aug.	Sept.	April	May	June	July	Aug.	Sept.
Wheat	27	10	10	4	-	-	-	-	20	-	2	21	-	6
Barley	7	3	7	17	15	-	-	3	30	-	8	-	-	10
Canola	-	-	1	1	-	3	-	-	-	17	78	-	-	-

Table 6. Analysis of variance of the effect of input (main plots) and diversity (sub-plots) with monthly growing season precipitation (GSP) and growing degree days (GDD) as covariates on annual wheat, barley, and canola yields, 2041–2070 as predicted by the model ensemble average

Source	df	Sum of squares	Significance
Wheat			
Input	2	3.4824668	*
Diversity[Input]	6	1.1641339	NS
GSP April	1	2.7790521	*
GSP May	1	7.3040130	*
GSP June	1	3.2246077	*
GSP July	1	0.1841447	NS
GSP August	1	2.2271927	*
GDD April	1	2.2367954	*
GDD August	1	3.1970024	*
Error	402	177.75464	
Barley			
Input	2	0.330059	NS
Diversity[Input]	3	0.213490	NS
GSP April	1	1.978353	NS
GSP May	1	16.628288	*
GSP June	1	7.444512	*
GSP September	1	4.621554	*
GDD April	1	18.143234	*
GDD May	1	8.950923	*
GDD September	1	2.442304	*
Error	240	145.80226	
Canola			
Input	1	0.1841601	NS
Diversity[Input]	4	0.1196095	NS
GSP April	1	0.8157638	NS
GSP September	1	1.6220571	*
GDD April	1	4.1250972	*
GDD June	1	9.3653332	*
GDD September	1	2.4095221	*
Error	80	28.312015	

Note: * Significant at $P < 0.05$; NS, not significant

Table 7. Comparisons between simulated historical yield (Scott 1971-2000) and future climate scenarios (2041 – 2070) predicted by the RCM_GCM pairs for wheat, barley, and canola. Models are listed in Table1.

Model	Crop grain yield, Mg ha ⁻¹			Mean combined yield of all three crops
	Wheat	Barley	Canola	
Scott 1971-2000 (historical baseline)	2.23a	2.29ab	2.01a	2.22a
CRCM_CGCM3	3.45b	3.66e	3.28b	3.50b
RCM3_CGCM3	3.41b	3.58e	3.18b	3.43b
RCM3_GFDL	3.28b	3.50e	3.25b	3.34b
CRCM_CCSM	1.92c	2.00b	1.93a	1.96c
HRM3_GFDL	1.92c	1.98b	1.97a	1.95c
WRFG_CGCM3	1.28d	1.20c	1.12c	1.23d
WRFG_CCSM	0.76e	0.70d	0.75c	0.74e
Ensemble average	2.29a	2.37a	2.21a	2.31a
Standard error of the difference ^a	0.07	0.10	0.16	0.06

Note: Letters within the same column indicate Tukey HSD mean differences at $P < 0.05$

^a Tukey HSD test standard error of the difference

Table 8. Comparisons between historical observed (Scott 1971-2000) and future (2041 – 2070) monthly growing season precipitation and growing degree days predicted by the RCM_GCM pairs. Models are listed in Table1.

Model	Growing season precipitation, mm month ⁻¹						Growing degree days					
	April	May	June	July	Aug.	Sept.	April	May	June	July	Aug.	Sept.
Scott 1971 – 2000	15.48a	38.43a	59.60a	69.04a	44.96a	16.28a	18.58a	177.42a	303.33a	372.34a	345.55a	106.45a
CRCM_CGCM3	16.47ab	68.18d	83.35c	85.25d	58.24d	13.75c	0.00g	140.32f	316.83b	415.64d	327.20d	83.75d
CRCM_CCSM	18.62bc	46.84b	48.21e	44.69g	28.97f	11.16d	11.63f	243.89e	452.11e	529.34f	429.98c	99.14b
RCM3_GFDL	23.22d	77.37e	117.55d	130.10b	70.85c	27.37b	0.00g	96.44g	309.53ab	387.14b	266.47g	63.61e
RCM3_CGCM3	25.52e	82.40f	119.51d	123.97c	75.29b	16.39a	12.21f	149.04f	302.82a	400.31c	325.95d	117.23f
HRM3_GFDL	34.10f	83.09f	71.83b	68.95a	39.05e	13.76c	137.05c	393.76b	514.25f	497.51g	283.58f	60.49e
WRFG_CGCM3	13.27g	44.70b	42.72f	56.76f	32.14f	6.22e	103.62d	304.37c	377.43c	396.04c	298.69e	102.34ab
WRFG_CCSM	9.30h	37.09a	38.74f	31.22h	21.31g	11.06d	77.95e	278.21d	388.51d	445.54e	376.17b	91.48c
Ensemble average	20.07c	62.81c	74.56b	77.28e	46.55a	14.24c	44.34b	183.28a	380.21cd	438.79e	329.72d	88.26cd
Standard error of the difference ^a	0.71	1.61	1.72	1.87	1.32	0.64	1.73	3.31	2.68	2.75	2.82	1.99

Note: Letters within the same column indicate Tukey HSD mean differences at $P < 0.05$

^a Tukey HSD test standard error of the difference

APPENDIX

Model Bias, Calculation of Average, Uncertainty Range, and Reliability of Regional Climate Change via the “Reliability Ensemble Average” (REA) Method

The reliability ensemble averaging (REA) method was used to calculate the mean, uncertainty range, and a measure of reliability of simulated changes in GS maximum, minimum temperature, and precipitation adjusted for the ensemble of available NARRCAP RCM_GCM pairs (Giorgi and Mearns (2002). Means and uncertainties were adjusted for model bias projections with the REA method, prior to comparisons of the difference between historical data and regional climate model predictions for the same time period.

The REA method is based on the use of weighted average of ensemble climate model members to calculate change (e.g. ΔT) over two time periods (Rawlins et al. 2012). This approach is based on two model reliability factors which contribute to the weighting for each model. The first factor is the ability of the model to reproduce observed historical climate. The second factor is the distance of each model's projected changes from the REA average. For example, the estimated change in maximum GS temperature T_{max} is a mean of ensemble model output:

$$\overline{\Delta T_{max}} = \frac{1}{N} \sum_{i=1}^N \Delta T_{max_i} \quad (1)$$

where N is the total number of models, the overbar indicates the ensemble averaging and Δ indicates the model-simulated change.

In the REA method, the average change $\widetilde{\Delta T_{max}}$ is the weighted average of the ensemble members,

$$\widetilde{\Delta T_{max}} = \widetilde{A}(\Delta T_{max}) = \frac{\sum_i R_i \Delta T_{max_i}}{\sum_i R_i} \quad (2)$$

where the operator $\widetilde{A}$ indicates REA averaging and R_i is a model reliability factor defined as

$$R_i = [(R_{B,i})^m \times (R_{D,i})^n]^{1/(m \times n)} \quad (3)$$

The bias component ($R_{B,i}$) is the difference between each RCM_GCM pair and observations over the 1971- 2000 historical weather period (Sobolowski and Pavelsky 2012). The distance criterion ($R_{D,i}$) measures the similarity of individual models to the REA average. Parameters m and n are defined by user and represent weights for each reliability factor. For calculations in this work, m and n are assumed to be equal to 1, which gives equal weights to each factor. However, they can be different, if there are reasons to believe that one of the two factors should have a greater weight (Giorgi and Mearns 2002). The uncertainty range around REA changes is measured using the root-mean square difference (rmsd) of the changes, $\tilde{\delta}_{\Delta T_{max}}$ with the total uncertainty range $\pm \tilde{\delta}_{\Delta T_{max}}$ or $2\tilde{\delta}_{\Delta T_{max}}$ according to the equation

$$\tilde{\delta}_{\Delta T_{max}} = \left[\frac{\sum_{i=1}^N R_i (\Delta T_{max_i} - \widetilde{\Delta T_{max}})^2}{\sum_i R_i} \right]^{1/2} \quad (4)$$

We calculated the natural variability of ε_{Tmax} and ε_{Tmin} for maximum and minimum GS temperature, and ε_{ppt} for GSP for the twentieth century, similar to calculations by Giorgi and Mearns (2002). Time series of observed weather parameters from the Environment Canada database (Environment Canada 2014) were computed for 30-yr moving averages of the series after linearly de-trending the data with least squares regression. We estimated ε as the difference between the maximum and minimum values of these 30-yr moving averages (Giorgi and Mearns 2002). Other details of natural variability estimation and the REA method are described in Giorgi and Mearns (2002).

Taylor diagrams were used to evaluate the correlation, root-mean-square difference and ratio of variances for observed and simulated data, in order to assess the models. Standard deviations and RMSEs were normalized by the reference standard deviation (from the observed field). Taylor diagrams represent multiple aspects of complex models (IPCC 2001; Taylor 2001). They provide a way of graphically summarizing and representing how closely a pattern (or a set of patterns) matches observations. The similarity between two patterns is quantified in terms of their correlation, their centered root-mean-square difference and the amplitude of their variations (represented by their standard deviations). Simulated patterns from the models that agree well with observations will lie in closest proximity to the point marked "observed" on the x-axis. These models will have relatively high correlation and low RMSEs. Models lying on the solid arc (Fig. A1) will have the correct standard deviation (Taylor, 2001).

Model Bias in Regional Climate Models

Historical GS maximum and minimum temperatures at Scott were highly correlated with model output and had similar standard deviations for the same period (Fig. A1). Data from models of precipitation were more dispersed relative to the reference standard deviation, and demonstrated greater variability than for historical weather. Similar results were reported by Giorgi and Mearns (2002); Rawlins et al. (2012); Sobolowski and Pavelsky (2012) and Tencer et al. (2014) who assessed agreements between observed and future simulated precipitation predicted by different RCM_GCM pairs. In general, weather events with low intensity and high total precipitation are underestimated by climate models (Frei et al. 2003; Kopparla et al. 2013; Maraun et al. 2010), which better capture stratiform, compared to convective, precipitation events (Giorgi et al. 1998; Mearns et al. 1995). This partly explains low variability of precipitation generated by the model ensembles (Fig. A2) for historical and future weather predicted by the RCM_GCM pairs.

Positive (model overestimates) and negative (model underestimates) biases occurred in combinations of RCM_GCM models for temperature and precipitation (Fig. 1). Compared to 1971 – 2000 historical observed weather, three of the seven RCM_GCM pairs underestimated GS maximum, minimum temperatures, and precipitation, while four remaining pairs overestimated these parameters (Fig. 1).

Cumulatively, the GSP distributions for predicted historic climate showed less variability relative to observed values (Fig. A2). This indicates reduced variability in predicted GSP compared to historical observed values, and slightly lower correlation coefficients (Fig. A1). Statistical

distributions of temperature, for simulated and observed weather, were similar (Fig. A2), with high correlation coefficients (Fig. A1). Overall, the models were somewhat less efficient in capturing trends in GSP patterns compared to the trends in GS maximum and minimum temperature.

The seven climate scenarios simulated by the RCM_GCM pairs showed differences in precipitation, maximum and minimum GS temperatures (Fig. 1). Maximum GS air temperature increased in five of the seven models while minimum GS air temperature increased in six of the seven models relative to 30-yr historical observed weather. Growing season precipitation increased in four models and decreased in three. Ensemble model mean biases were -1.56 and -0.69°C for GS maximum and minimum temperature, respectively, and 3 per cent for GSP (Table A1). Multi-model means of growing season temperature and precipitation increased by 0.2°C for maximum, 1.41°C for minimum temperature and by about 24% for precipitation (Table A1 and Figure A2) in comparisons for the present and future periods. Consequently future climate at Scott will be warmer and wetter, results which are similar to research on temperature by Smith et al. (2013) and on precipitation by Khaliq et al. (2014) in the Canadian Prairies. Furthermore, Kutcher et al. (2010) reported increases of approximately 0.01°C year⁻¹ for GS maximum temperature and 0.02°C year⁻¹ for minimum GS temperature for 1971 – 2000.

The mean change exceeded mean bias for GS minimum temperature and precipitation for multi-model means (Table A1). Variability, prior to REA-based analyses, was higher for future relative to observed GS maximum temperature and lower with respect to observed precipitation (Fig. A2 and Table A1). The biases of individual models affected multi-model mean comparisons, and

justified the use of the REA method to compare ensembles with uncertainty ranges associated with model projections. The REA method (Giorgi and Mearns 2002) adjusted means by model ensemble for comparisons of future changes in temperature and precipitation. Greater increases in GS maximum and minimum temperatures, and decreases in precipitation were observed compared to multi-model means when adjusted by REA (Table A1). The magnitude of change for temperature and precipitation in each season was well outside the range of natural variability, based on the REA analysis. Similar to our findings, Qian et al. (2016) reported a warming trend of between 3 and 4°C in 2041 – 2070 future GS maximum and minimum temperatures, and 10% increase in GSP predicted by the CanRCM4 RCM for various locations in Canadian Prairies. Khaliq et al. (2014) reported increased future seasonal precipitation for the Canadian Prairies in research on seasonal and extreme precipitation simulated by a multi-RCM model ensemble. Similarly, McGinn and Shepherd (2003) related an increase in future, relative to historic, precipitation to unchanged or increased soil-water content in the top 120 cm soil across the Canadian prairies.

Fig. A1 Taylor diagrams for maximum and minimum air temperature, and precipitation showing standard deviation ($^{\circ}\text{C}$ (temperature) / mm gr. season $^{-1}$ (precipitation)), RMSE ($^{\circ}\text{C}$ (temperature) / mm gr. season $^{-1}$ (precipitation)), and correlation between the observed (1971 – 2000) and simulated variables. The RCMs and their driving GCMs are listed in Table 1. Standard deviations and RMSEs were normalized by the reference standard deviation (from the observed field). The contour of the reference standard deviation is shown with the solid line. Root mean square error was normalized and is shown in gray contours. Correlation rays are the (left) 95th and (right) 99th significance levels and are shown by dashed line.

Fig. A2 Distributions of growing season maximum (A) and minimum (B) temperature (°C) and growing season precipitation (C) (mm gr. season⁻¹) for the RCM historical predicted (1971-2000), historical observed, and future (2041-2070) periods prior to REA analysis. The sample median is represented by the line at the centre of the distribution, bounded by the 25th (1st quartile) and 75th (3rd quartile) percentiles represented by the lower and upper box boundaries. Whiskers show the 25th quantile – 1.5*(interquartile range) and 75th quantile + 1.5* (interquartile) range.

Table A1. Ensemble mean bias, projected change with and without REA (ΔT , 2041 – 2070 minus 1971 – 2000), uncertainty range ($\pm \delta_{\Delta T}$ or $\pm \delta_P$), and estimated natural variability (ε_T or ε_P) for growing season maximum ($T_{\max}$) and minimum ($T_{\min}$) temperature and precipitation across the seven RCM_GCM pairs^a

	<i>T</i> bias	ΔT	$\pm \delta_{\Delta T}$ or $\pm \delta_P$	ε_T or ε_P
<i>T</i> max	-1.56	0.20 [1.06]	0.23	0.65
<i>T</i> min	-0.69	1.41 [2.03]	0.40	0.70
Precipitation	3.0	24.0 [11.0]	0.5	6.2

^a Temperature changes are in °C and precipitation changes are in percentage of present model amounts. Values in brackets are the regional averages from the REA method. Adapted from Rawlins et al. (2012)