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Modelling the Potential Impact of Climate Change on Agricultural Production in the Province of British Columbia

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Abstract

The goal of this research was to model the potential impact of climate change on food production, in the Fraser Valley and Peace River regions of British Columbia (BC), using historical crop yield and climate data. We identified eight indicator crops of importance for these regions of BC and utilized historical Census of Agriculture and climate data (temperature and precipitation) to model future potential impacts of climate change on agriculture. We developed three climate change scenarios for these eight indicators crops (extreme, moderate, and business as usual). Under the most extreme climate model scenario the Fraser Valley is expected to experience cooler summers and springs and wetter summers, with incremental increases in oat, blueberry and green bean yields by 2050. These same climate conditions were predicted to decrease the yields for raspberry crops by 2050, while barley and wheat crop yields remain steady. The business as usual scenario, where springs and summers are warmer and summers are wetter in the Fraser Valley, predicted increased barley, oat, wheat, and blueberry crop yields by 2050, while yields of raspberries were predicted to decrease and green bean yields are expected to be steady. Under the more conservative climate change scenario conditions, yields should remain steady for all crops, except green beans where yields will increase by 2050. Future climate conditions for the Peace River area were much different from the Fraser Valley. All three scenarios forecasted warmer and wetter springs and summers with decreased evapotranspiration and moisture deficits. These changes in climate conditions predicted declines in wheat, canola, and barley crop yields by 2050, while incremental increases in oat and dry pea crop yields could be expected by 2050.

Keywords: climate change, food production, Fraser Valley, Peace River, indicator crops, crop yields

1. Introduction

The climate has been changing over the last three decades and is expected continue to do so regardless of any mitigation strategy (Barker, 2007; IPCC, 2007). Temperatures are predicted to increase about 3–5 °C by the middle of the 21st century, while precipitation patterns (amount, seasonality, and intensity) are predicted to shift (Arnell et al., 2004; IPCC, 2007). Agriculture is a climate-dependent activity and hence is highly sensitive to climatic change and climate variability (Lobell & Field, 2007; Rivington et al., 2013). Crop yields are vulnerable to these changes in climate (Rivington et al., 2013; Thornton, Jones, Ericksen, & Challinor, 2011), which can jeopardize food security and economic sustainability that provide the necessary input for sustaining people's livelihoods (FAO, 2012; FAO, WFP & IFAD, 2012). Agriculture is a key driver of national and local economies and largely depends on what can be grown and how efficiently it can be done, taking into consideration variations in climatic trends.

A literature review of the impact of climatic trends on crop yields (Bradshaw, Dolan, & Smit, 2004; Bryant et al., 2000; Joshi, Maharjan, & Luni, 2011; Lobell, Field, Cahill, & Bonfils, 2006) indicated that changes in growing season temperature and precipitation drive annual variation in average yields (Lobell & Field, 2007; Peng et al., 2004). Crop yields are a function of dynamic, nonlinear interactions between climate, soil water, management, and the physiology of the crop (Semenov & Porter, 1995). For example, changes in the variability of temperature can greatly influence dry matter production as both high and low temperatures decrease the rate of dry matter production and, at extremes, can cause production to cease (Grace, 1988; Ingver, Tamm, Tamm, Kangor, & Koppel,, 2010). Likewise, water deficit occurring immediately before flowering can lead to pollen sterility and will result in a drastic decline in grain yield (Ingver et al., 2010; Nguyen & Sutton, 2009; Thakur, Kumar, Malik, Berger, & Nayyar, 2010). Previous research relating predicted climatic variations to crop response have offered the potential to anticipate changes in crop production early enough to adjust critical decisions (Blench, 2003; Hansen, 2002; Letson et al., 2001).

To study the implications of climate change in British Columbia (BC) agriculture we selected eight indicator crops from three different food groups (grains, fruits, and vegetables). In the grains group we chose barley, spring wheat, oat, canola, and dry peas. Grains have been documented (Joshi et al., 2011; Subedi, Gregory, Summerfield, & Gooding, 1998; Thakur et al., 2010; Willenbockel, 2012) to be very vulnerable to changes in temperature and precipitation; therefore historical data on grain yields can serve as proxy to understand future effects of variable weather conditions. Likewise, fruits such as blueberries and raspberries, as well as vegetables such as green beans are susceptible to water deficit. When water supply is limited during the vegetative and yield formation periods, plant development is usually delayed, causing non-uniform growth and minimizing yield (Glass, Percival, & Proctor, 2005; Hall & Sobey, 2013; Petrova, Matev, & Haitova, 2012). Temporal yield data from fruit and vegetable crops are also used to study the relationship between climate change and agriculture in BC.

1.2 Goal

The goal of this research is to model the potential impact of climate change on BC`s food production, as represented by historical and future crop yield projections. To meet this goal we identify indicator crops of major importance for BC and utilize temporal Census of Agriculture data, available from Statistics Canada, to identify potential impacts of climate change on agriculture. We characterize climate relationships observed over time by relating archived climate information to annual agricultural yields. To reduce redundancy produced by correlated climate predictors, we use Principal Components Analysis (PCA) to derive a new set of uncorrelated climate variables. Quantitative historical values are then used to model potential future yields for 2020 and 2050 under different climate change scenarios.

1.3 Study Area

The province of BC in western Canada spans 944 735 km^2 and has a diversity of landscapes, topography, climatic zones, and geographical features (Holland, 1976). As a result of the province's variety in landforms, agriculture and food industry are diverse. The province is divided into eight agricultural census regions (Figure 1). BC possesses unique agriculture policies directly related to local food production; in particular, the Agricultural Land Reserve (ALR) is a province-wide land preservation policy of nearly five million hectares of protected farmland where farming is encouraged and non-agricultural uses are controlled (Androkovich, Desjardins, Tarzwell, & Tsigaris, 2008; Hanna, 1997). ALR delimitation is based on soil and climate and represents 5% of BC land suitable for farming, with only 1% having the best soil with the highest capability for growing crops.

Table 1. Data summary on indicator crops

Crop	Region	Years	Source
Barley	Peace River Fraser Valley	1991-2009	November 2011 Farm Survey. Statistics Canada, Agriculture Division, Crops Section.
Spring Wheat			
Oat			
Canola	Peace River	1991-2009	November 2011 Farm Survey. Statistics Canada, Agriculture Division, Crops Section.
Dry Peas		1995-2006	
Green Beans	Fraser Valley	1961-2009	Fruit and Vegetable Survey - 3407. Table 001-0013 Area, production and farm value of vegetables, annual.
Blueberries	Fraser Valley	2002-2009	Fruit and Vegetable Survey - 3407. Table 001-0009 Area, production and farm value of fresh and processed fruits, by province, annual.
Raspberries			

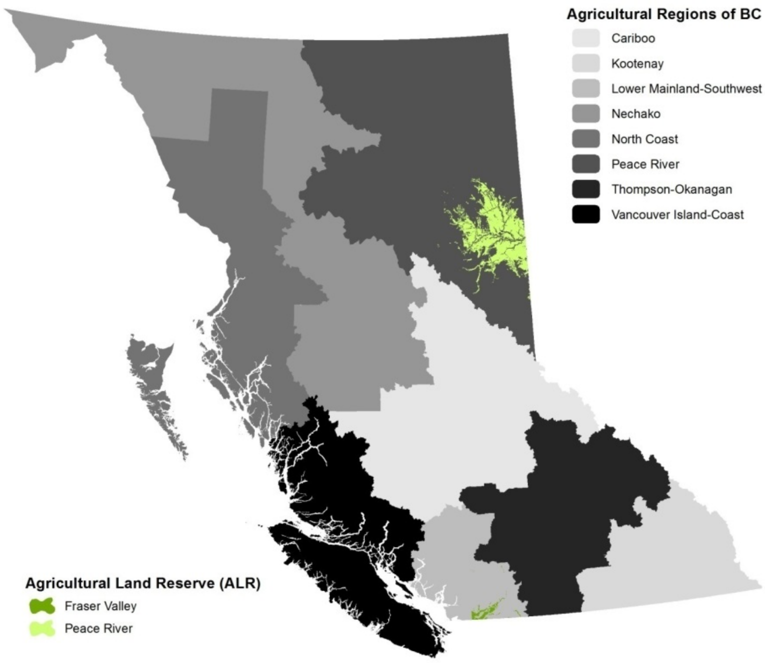


Figure 1. Map of the agricultural regions of British Columbia and the Agricultural Land Reserve of Fraser Valley and Peace River, where the indicator crops are grown.

1.4 Data

The crop yield data used in this paper were provided by Statistics Canada (Table 1). Agricultural Census data provided information on the area of farmland under cultivation for our indicator crops. Data from the farm surveys were disseminated at the provincial scale with no sub-provincial data available. Census and sample survey data were gathered by Statistics Canada from direct questionnaires supplied to farm owners in Canada. Total food production for a given product over a year is calculated by Statistics Canada using extrapolated data from sample surveys. Crop data descriptions are as follows.

1.4.1 Grains

Through Statistics Canada Field Crop Reporting Series, accurate and timely estimates of seeding intentions, seeded and harvested area, production, yield and farm stocks of the principal field crops in Canada were provided at the provincial level (Statistics Canada, 2012a). Field Crop Series data reported farms producing grains in all non-Atlantic provinces; farms were stratified by size and randomly sampled. In BC, grain crops grown in Peace River (Figure 1) were reported separately from the remainder of the province and account for 90% of total grain production excluding forage corn. A large proportion of some grain crops (e.g., oats and barley) are fed to livestock. The estimated proportion of livestock grain was removed from the production data, given that it is not be available for human consumption (Statistics Canada, 2012b).

1.4.2 Fruits and Vegetables

We used data from the annual Spring and Fall Survey of Fruits and Vegetables, conducted by Statistics Canada. Through stratified random samples this survey collected data to provide estimates of the total cultivated area, harvested area, total production, marketed production, and farm gate value of selected fruits and vegetables grown in Canada. The survey excluded farms producing only mushrooms, potatoes, and greenhouse vegetables, as well as farms that were on Indian reserves; likewise, small operations with less than one acre of fruit and less than one acre of vegetables were left out. Annual totals of production and planted area for all fruits, vegetables, and potatoes are released by Statistics Canada each year (Statistics Canada, 2012c; 2012d). Fruits and vegetables in BC are mostly grown in the Lower Mainland-Southwest area (Lower Mainland and Fraser Valley) (Figure 1).

1.4.3 Climate Data:

We used high spatial resolution topographically corrected climate information for BC sourced from the Climate Western North America database version 4.60 (CWNA) (Wang, Hamann, & Spittlehouse, 2010). CWNA utilizes the Parameter-elevation Regressions on Independent Slopes Model (PRISM) approach (Daly et al., 2008; Oregon State University, 2011) and uses up-sampling of climate models employing topography, climate stations, wind patterns, and rain shadow information to provide a continuous coverage of climate data for the province. Four datasets were used. The 49-year data spanning 1961-2009 was used to represent current climate. The three future climate scenarios were based on the Canadian Centre for Climate Modelling and Analysis (CCCma) B1, A1B, and A2 scenarios for the years 2020 and 2050. The future scenario B1 (AR4 – R4) represents the least extreme scenario, A1B (AR4 – R4) represents the business as usual scenario, and A2 (AR4 – R4) represents the most extreme scenario. Model selection was based on using the full range of possible scenarios that were available from respected institutions and were recommended by the Pacific Climate Impacts Consortium (Murdock & Splittlehouse, 2011).

2. Method

2.1 Climate variables

Selected temperature-based variables consisted of Spring and Summer mean temperature, Spring and Summer mean maximum temperature, and Spring and Summer mean minimum temperature. Hybrid climate metrics consisted of Spring and Summer climate moisture deficit and evapotranspiration. Finally, precipitation variables were Spring and Summer mean precipitation.

2.2 Principal Component Analysis

Climate variables such as temperature, precipitation, and evapotranspiration are highly correlated (Trenberth, 2005), leading to problems when applying regression techniques. After testing for correlation between the 12 climatic variables selected for this study, we used Principal Components Analysis (PCA) to derive a new set of uncorrelated climate variables in order to reduce the redundancy created by correlated predictors. PCA is a classical technique used to reduce the dimensionality of a dataset by transforming input data based on a correlation matrix into a set of linear uncorrelated eigenvalues, or principal components (PCs), equal to the number of input variables and accounts for the total variance present in the input data (Jolliffe, 2002). PCs are uncorrelated and ordered such that the k^{th} PC has the k^{th} largest variance among all PCs. The k^{th} PC can be interpreted as the direction that maximizes the variation of the projections of the data points such that it is orthogonal to the first $k-1$ PCs (Abdi & Williams, 2010; Saporta & Niang, 2010). While the first few PCs account for the greatest proportion of the data variance, the last PCs may be as interesting as the first components, since the type or the direction of the shifts are *a priori* unknown (Abdi & Williams, 2010; Jolliffe, 2002; Saporta & Niang, 2010). PCA was conducted using climate variables from the Fraser Valley and Peace River regions. A total of twelve PCs were derived from climate variables in each region.

2.3 Generalized Linear Models

The principal component scores were employed as inputs in generalized linear models (GLMs) with a gamma distribution (Husak, Michaelsen, & Funk, 2007), which were used to predict future crop yields in the Fraser Valley and Peace River regions under different climate scenarios. The gamma distribution was chosen because it is bounded at zero and this takes into account that crops are always present.

First presented by Nelder and Wedderbum (1972), GLMs are a flexible generalization of ordinary linear regression, allowing the linear model to be related to the response variable via a link function and the magnitude of the variance of each measurement to be a function of its predicted value (Gotway & Stroup, 1997; Nelder & Wedderburn, 1972). GLMs permit analyzing data from non-normal distributions and account for non-linear relationships. In this study, the final GLM for each crop was chosen using stepwise model selection based on the second-order Akaike's information criterion (AICc), which includes a bias-correction term to account for a small sample size relative to the number of model parameters (Anderson, Burnham, & Thompson, 2000; Burnham & Anderson, 2002). The model with the lowest AICc score was considered the most parsimonious, thus minimizing estimate bias and optimizing precision (Burnham & Anderson, 2002). Significant PCs retained in final GLMs were assessed to determine which climate variables were influential in the prediction of future crop yields. Forecast of future crop yields for the Fraser Valley and Peace River regions were calculated using the climate scenarios B1, A1B, and A2 and values associated with the 90% confidence interval (CI) are presented as Kg/ha.

3. Results

3.1 Principal Component Analysis

Twelve PCs were drawn from the PCA for each region (Fraser Valley and Peace River). It should be noted that a common rule of thumb for selecting the quantity of PCs is to choose the smallest number of PCs such that a chosen percentage of total variation is exceeded. For the Fraser Valley data, the first 5 PCs cover more than 93%

of the total variation in the data, while for the Peace River dataset the first 4 PCs account for over 92% of the total variation. However, if only four or five components had been chosen, it would have had a detrimental effect on the regression model given that final PCs often represent stable linear relationships between predictor variables that are of interest in climate modelling.

3.2 Generalized Linear Models

The overall variability in crop yields was high and the mean was relatively low, with a positively skewed gamma distribution. Out of the several models generated for each crop and region, a total of eleven models were selected based on their AICc. AICc values and the number of parameter (Ki) per model are reported in Table 2. The reported AICc corresponded to the lower value attained with K parameters, allowing us to determine which model among a set of models was most parsimonious.

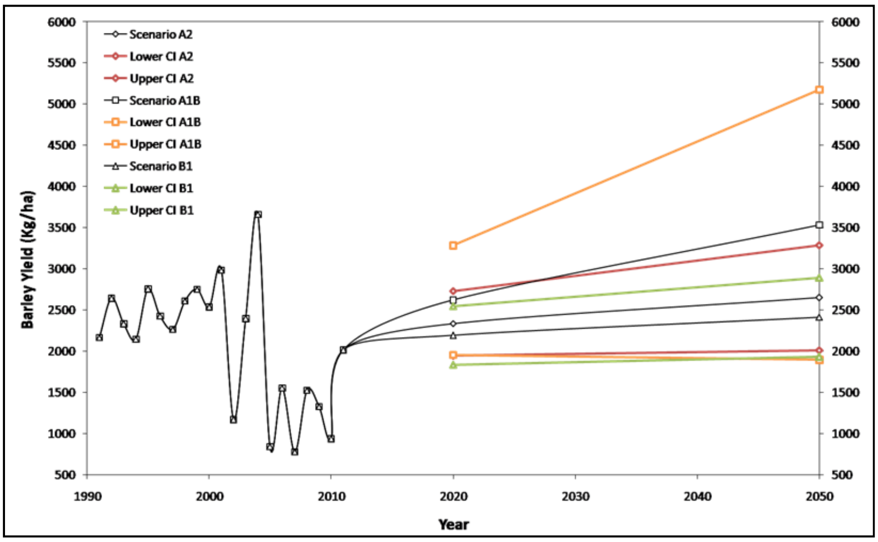
Table 2. AICc-selected models for eight different crops in the regions of Fraser Valley and Peace River. *CI* represents the 90% confidence intervals of the predictions in Kg/ha.

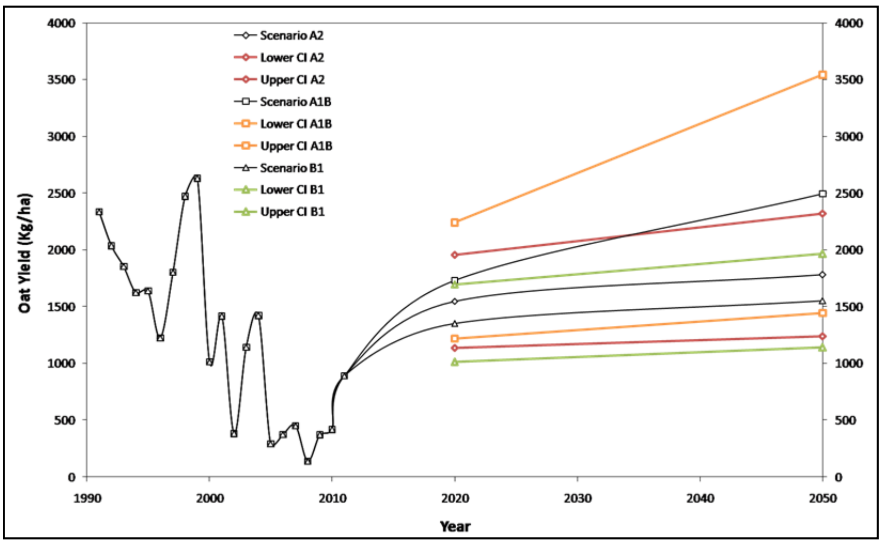
Region	Model	AICc	Scenario A2		ScenarioA1B		Scenario B1	
			***CI* 2020**	***CI* 2050**	***CI* 2020**	***CI* 2050**	***CI* 2020**	***CI* 2050**
Fraser Valley	Barley	308.12	2730.46	3286.22	3283.37	5175.11	2549.75	2894.78
			1946.16	2013.67	1958.96	1897.92	1838.76	1931.5
	Blueberry	154.79	8277.11	11152.66	11340.34	19767.94	8070.06	9606.16
			4972.32	5887.77	6020.75	6817.69	5507.2	5787.11
	Green Beans	662.82	6515.77	6816.78	6940.28	7205.26	6999.72	7828.04
			4991.5	6310.15	6478.13	6632.8	6527.3	6785.83
	Oat	306.44	1958.47	2321.59	2241.29	3543.06	1695.69	1964.69
			1138.05	1240.06	1221.11	1445.43	1011.7	1140.27
	Raspberries	157.78	6705.09	6687.44	7490.87	8353.57	7165.34	7478.56
			4906.72	4080.86	4163.05	1826.83	5145.11	4727.45
	Wheat	303.02	3187.07	3296.26	3213.95	4165.57	3008.59	3086.12
			2242.4	2214.27	2235.79	1943.45	2277.15	2264.57
Peace River	Barley	306.45	4192.23	4872.51	3458.75	3251.29	5828.67	4221.64
			2412.04	2552.77	2183.94	2027.28	2522.36	2452.89
	Canola	277.12	2043.51	2452.29	2430.58	2336.92	2346.43	2313.05
			807.86	460.14	741.19	144.72	371.7	213.47
	Dry Peas	204.44	2416.11	2901.51	2632.67	3294.33	2768.15	2881.91
			1698.82	1698.19	1496.62	974.29	1573.33	1777.48
	Oat	295.41	2902.79	3756.58	3101.85	3499.09	2834.79	3143.49
			1847.08	2064.55	1751.02	1464.07	1763.66	1894.42
	Wheat	291.97	3643.01	4113.9	3315.72	3232.31	4508.41	3653.59
			2364.98	2254.54	2053.81	1721.37	2455.48	2121.15

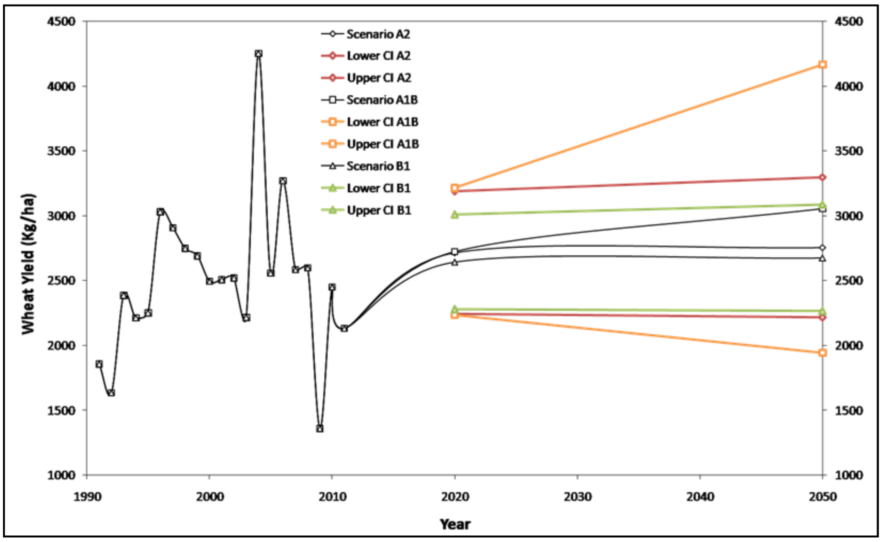
Table 3. Future trends in climate variables under different emission scenarios

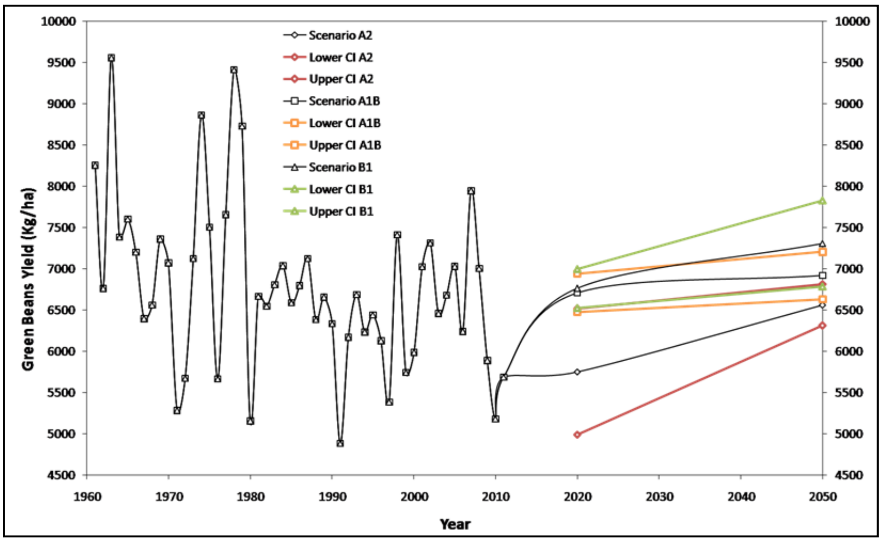
Scenario A2												
Region	**Climate change between 2009 and 2020**											
	Tmax_sp	Tmax_sm	Tmin_sp	Tmin_sm	Tave_sp	Tave_sm	PPT_sp	PPT_sm	Eref_sp	Eref_sm	CMD_sp	CMD_sm
Fraser Valley	↓	↓	↓	↓	↓	↓	↓	↑	↓	↓	↑	↓
Peace River	↑	↓	↑	↑	↑	↑	↑	↑	↑	↓	↓	↓
Scenario A1B												
Region	**Climate change between 2009 and 2020**											

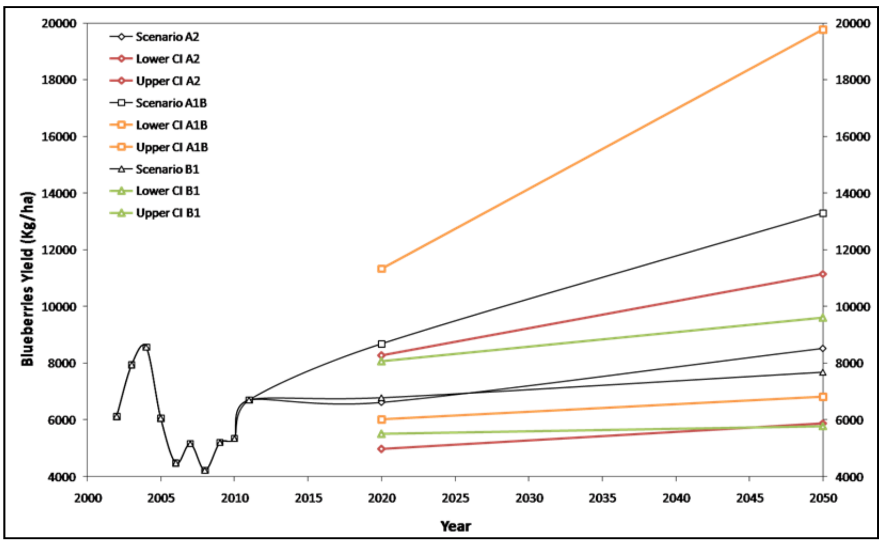
	Tmax_sp	Tmax_sm	Tmin_sp	Tmin_sm	Tave_sp	Tave_sm	PPT_sp	PPT_sm	Eref_sp	Eref_sm	CMD_sp	CMD_sm
Fraser Valley	↑	↑	↑	↑	↑	↑	↓	↑	↑	↓	↑	↑
Peace River	↑	↑	↑	↑	↑	↑	--	↑	↑	↓	↑	↓
Scenario B1												
Region	**Climate change between 2009 and 2020**											
	Tmax_sp	Tmax_sm	Tmin_sp	Tmin_sm	Tave_sp	Tave_sm	PPT_sp	PPT_sm	Eref_sp	Eref_sm	CMD_sp	CMD_sm
Fraser Valley	↑	↓	↑	↑	↑	↓	↓	↑	↑	↓	--	↓
Peace River	↑	↓	↑	↑	↑	↑	↑	↑	↑	↓	↓	↓






Wheat Yield (Kg/ha)
4500
4000
3500
3000
2500
2000
1500
1000
1990
2000
2010
2020
2030
2040
2050
Year
Scenario A2
Lower CI A2
Upper CI A2
Scenario A1B
Lower CI A1B
Upper CI A1B
Scenario B1
Lower CI B1
Upper CI B1


Green Beans Yield (Kg/ha)
10000
9500
9000
8500
8000
7500
7000
6500
6000
5500
5000
4500
1960
1970
1980
1990
2000
2010
2020
2030
2040
2050
Year
Scenario A2
Lower CI A2
Upper CI A2
Scenario A1B
Lower CI A1B
Upper CI A1B
Scenario B1
Lower CI B1
Upper CI B1


Blueberries Yield (Kg/ha)
20000
18000
16000
14000
12000
10000
8000
6000
4000
2000
2005
2010
2015
2020
2025
2030
2035
2040
2045
2050
Year
Scenario A2
Lower CI A2
Upper CI A2
Scenario A1B
Lower CI A1B
Upper CI A1B
Scenario B1
Lower CI B1
Upper CI B1

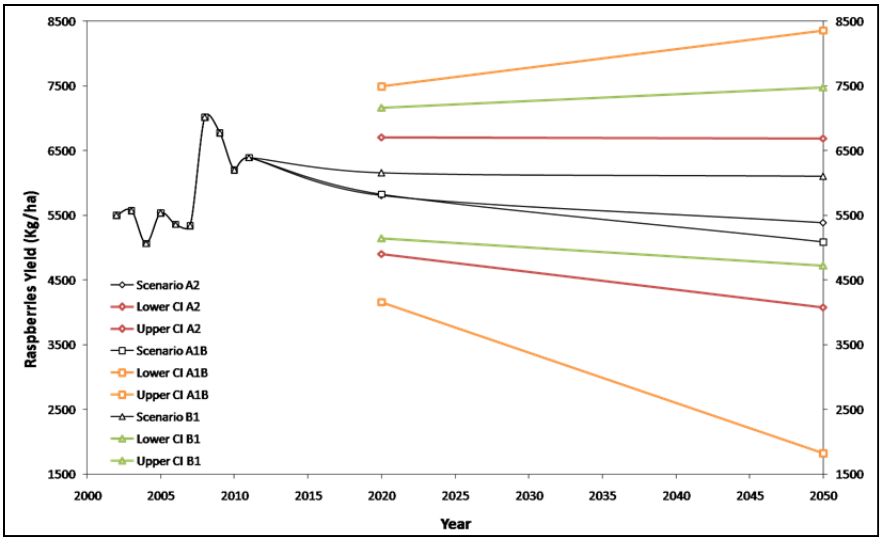
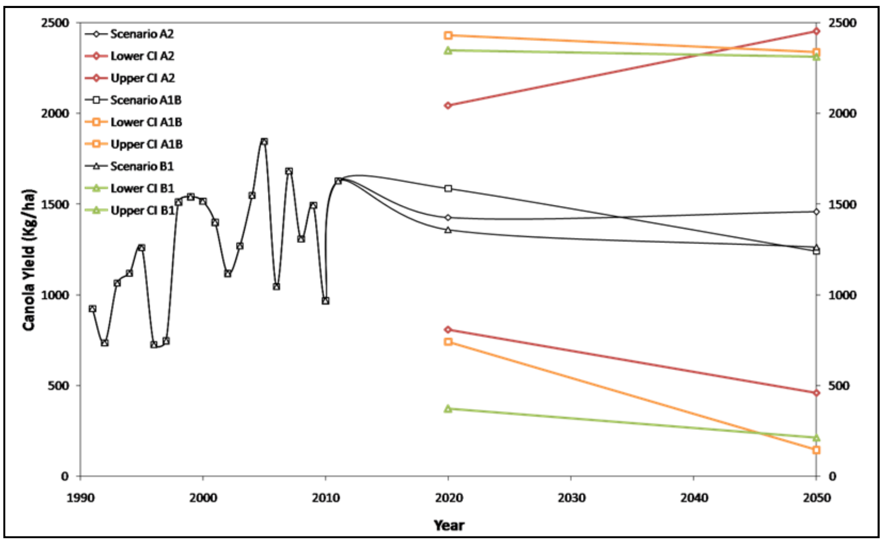
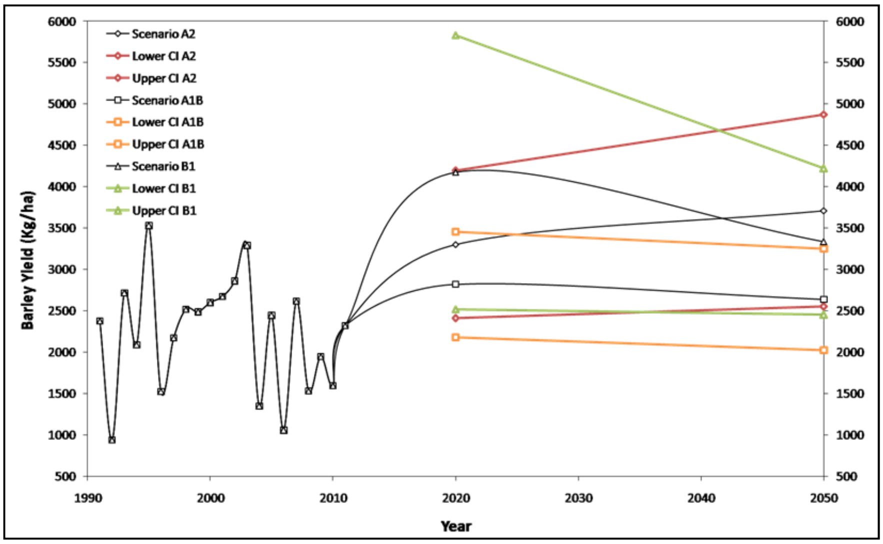


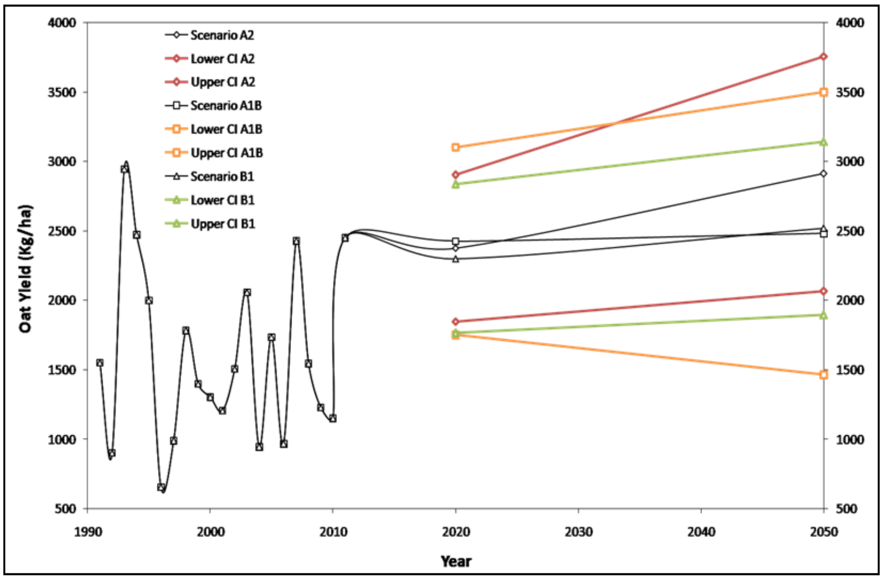
Figure 2. Past and predicted crop yields for the Fraser Valley area. Yield projections for six crops represent scenarios A2, A1B and B1. Colour lines represent upper and lower limits of a 90% confidence interval

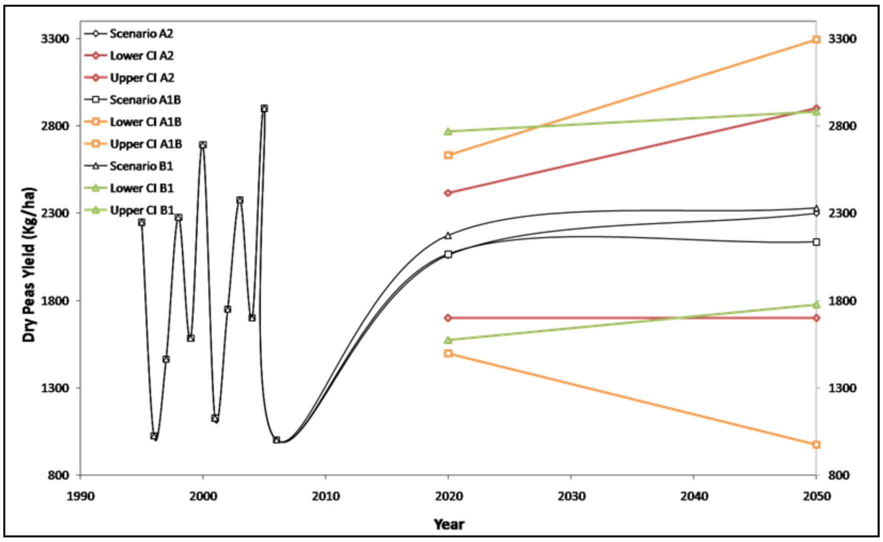
Models of climate change showed different trends for the Fraser Valley and Peace River BC under three emission scenarios (Table 3). The most extreme climate model scenario (A2) foresees, for the Fraser Valley, cooler summers and springs and wetter summers, predicting increments in oat, blueberry and green bean yields by 2050 (Figure 2). The same climate conditions are expected to affect raspberry crops by decreasing yields by 2050, while barley and wheat crop yields remain steady through time. The business as usual scenario (A1B), where spring and summers are warmer, and summers are wetter in the Fraser Valley, predicted increased barley, oat, wheat, and blueberry crop yields by 2050, while yields of raspberry crops were predicted to decrease and green bean crop yields were expected to remain stable. The more conservative climate change scenario, the B1 model, forecasts warmer and wetter springs and cooler and dryer summers for the Fraser Valley area. Crop yield predictions under the B1 scenario were all crops have steady yields, except for green bean yields, which would increase by 2050.

Future climate conditions for the Peace River area were different from the Fraser Valley (Table 3). The three scenarios (A2, A1B, B1) forecasted warmer and wetter springs and summers for the three emission scenarios, with decreased evapotranspiration and moisture deficits. These changes in climate conditions predicted declines in wheat, canola, and barley crop yields by 2050, with an increment in oat and dry pea crop yields (Figure 3).




Scenario A2
Lower CI A2
Upper CI A2
Scenario A1B
Lower CI A1B
Upper CI A1B
Scenario B1
Lower CI B1
Upper CI B1
Barley Yield (Kg/ha)
Year


Scenario A2
Lower CI A2
Upper CI A2
Scenario A1B
Lower CI A1B
Upper CI A1B
Scenario B1
Lower CI B1
Upper CI B1
Oat Yield (Kg/ha)
Year


Scenario A2
Lower CI A2
Upper CI A2
Scenario A1B
Lower CI A1B
Upper CI A1B
Scenario B1
Lower CI B1
Upper CI B1
Dry Peas Yield (Kg/ha)
Year

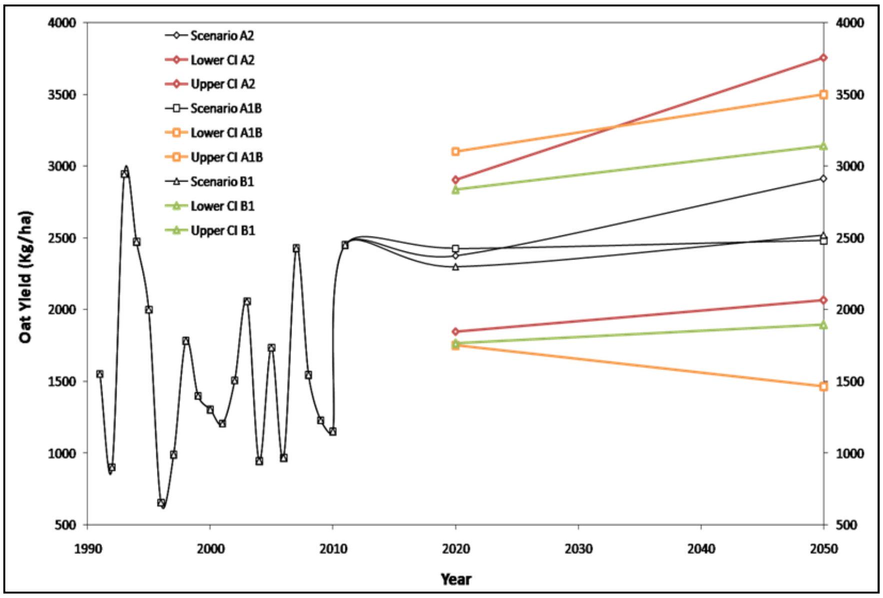


Figure 3. Past and predicted crop yields for the Peace River area. Yield projections for six crops represent scenarios A2, A1B and B1. Colour lines represent upper and lower limits of a 90% confidence interval

4. Discussion

As a result of a high correlation between our climate variable data, we generated twelve uncorrelated PCs to decrease the redundancy product of highly correlated predictors. The development of relationships between the PCs and historical dataset of crop yields allowed us to create a predictive model of yields based on future climate conditions. Despite the fact that it was hard to interpret the directionality of the relationships in our final GLM model coefficients due to the conversion of all climate variables into PCs, overall, the PCs explained a good proportion of the variance in the temperature and precipitation data. Previous studies (e.g., Challinor & Slingo, 2003) incorporating precipitation data in PCs have been found to correlate well with crop yields in other regions.

Underestimation of the uncertainty of a forecast can lead to excessive responses that are inconsistent with a decision maker's risk tolerance, while overestimating uncertainty leads to under confidence and lost opportunity to prepare for adverse conditions or to take advantage of favourable conditions. Specifically for our model, climate variability and crop yield data errors were the major sources of uncertainty in yield forecasting. Likewise, the datasets used in this study showed a lot of variability in year to year crop yields, but less variability with the climate data, creating uncertainty in the long-term forecasting, especially since some of the yield/climate sample sizes were quite small. However, by using GLM as a predictive modeling technique, we were able to forecast yields using less data than what traditional techniques would require. GLMs tend to be more robust than other predictive modeling techniques and are less susceptible to the over-fitting that may occur with small datasets (McCullagh & Nelder, 1989).

Due to confidentiality procedures with the Census of Agriculture, it was not possible to obtain the exact location of farms (Statistics Canada, 2012c). With no spatially identifiable agricultural operations and yields available, the spatial distribution of crop yields (response variable) was not comprehensive. This poses a problem when associating yield data to climate variables in heterogeneous areas. For defining the relationships between climate and crop yields we utilized mean seasonal (spring and summer) values from 1961 to 2009. The use of these datasets in large areas such as the province of BC brings the uncertainty entailed in dynamical downscaling from coarse to fine resolution. This uncertainty in the regional climate response has been documented in numerous contexts (Christensen et al., 2007; Elía et al., 2008). With respect to modelling and statistical downscaling, uncertainties are also associated with imperfect knowledge and/or representation of physical processes, limitations due to the numerical approximation of the model's equations, simplifications and assumptions in the models, and/or approaches and internal model variability (Mearns et al., 2012). Likewise, it is essential to acknowledge that the observed regional climate is sometimes characterized by a high level of uncertainty due to measurement errors and sparseness of stations, especially in remote regions such as northern BC and in regions of complex topography.

Similar to Challinor, Slingo, Wheeler, Craufurd, and Grimes (2003), our models showed that much of the inter-annual variability in crop yields can be explained simply using temperature and precipitation, and that this relationship is demonstrated at a regional scale. For most of the crops, the percent of deviance explained was over 45%. Where crops had lower deviance (e.g., Fraser Valley Green Beans, Wheat, Barley, and Oats) it is possible that they responded more to factors other than climate such as soil conditions and/or available carbon/nitrogen. Previous authors (Moen, Kaiser & Riha, 1994; Reilly et al., 2003) found that increasing within-year temperature variability had the greatest impact on yields if the growing season temperature is outside the optimum for growth. For BC it would be possible to examine whether years of low/high crop yields correlate with low/high temperature and precipitation.

Conclusion

We predicted future crop yields for eight indicator crops under three future climate change scenarios for the Fraser Valley and Peace River regions of BC. In the Fraser Valley, the three climate scenarios predicted different trends in temperature and precipitation, resulting in a range of predicted crop responses. In the most extreme scenario, cooler springs and summers along with wetter summers should result in increased yields of oats, blueberries, and green beans, with decreased raspberry yields. In contrast, the three climate scenarios all predicted warmer and wetter springs and summers for the Peace River region, resulting in predictions of increased yields for oat and dry pea crops, with decreased yields of wheat, canola, and barley crops. Our results have important implications for policy as it is easier to mitigate the potential impacts of climate change on crop yields by instituting policy on farming reform or adaptations at a regional level rather than at the local scale. Using GLMs to model future crop yields allowed us to overcome issues with small sample sizes.

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