Chapter 15

Potential Impacts of and Adaptation to Future Climate Change for Crop Farms: A Case Study of Flathead Valley, Montana

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Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/39265

1. Introduction

Greenhouse gas emissions alter carbon and hydrologic cycles, mean surface air temperature, the spatial and temporal distribution of energy, water, and nutrients, atmospheric CO_2 concentration, and the frequency and severity of storms (Adams et al., 1990; National Research Council, 2001; Reilly 2002; Wang and Schimel 2003; Smith 2004; IPCC, 2007). A major consequence of increasing greenhouse gas emissions is climate change and variability (CCV). CCV alters annual levels and intra-annual patterns of temperature, precipitation, and other climate-related variables, which can impact crop yields and the profitability of crop farming. Such impacts are likely to vary across agricultural production areas. Crop yields are projected to increase in agricultural production areas experiencing slightly higher surface air temperature and growing season precipitation, and decrease in production areas experiencing significantly higher surface air temperature, lower growing season precipitation, and inadequate irrigation water supplies (McCarthy et al., 2001). Even if future CCV causes crop yields to decrease, crop farmers may be able to reduce those negative impacts by adapting their crop enterprises and crop production systems (CPSs) (i.e., combinations of crop enterprises) to actual or expected CCV (Stewart et al., 1998; Smit et al., 2000; Walther et al., 2002; Spittlehouse & Stewart, 2003; Antle et al., 2004; Easterling et al., 2004; Inkley et al., 2004). Most previous studies of CCV impacts on agriculture: (1) focus on how CCV is likely to impact regional or national crop yields; (2) do not consider CCV impacts on net farm income; and (3) do not evaluate the extent to which adapting crop enterprises and farms to CCV reduces adverse impacts of CCV. Because crop farming is a business, crop farmers need to consider the potential impacts of CCV on their financial returns; particularly impacts on crop enterprise net returns and net farm income.

2. Objectives

The objectives of this chapter are: (1) to assess the impacts of climate change on the levels of crop enterprise net returns and net farm income (NFI) in a future period (2006–2050) relative to their levels in an historical period (1960–2005) for small and large representative farms in Flathead Valley, Montana-the study area; and (2) to determine whether adapting CPSs to future climate change in Flathead Valley results in superior or inferior levels of net farm income compared to not adapting to future climate change. Small and large representative farms use a mix of crop enterprises, farming operations, and crop acreages, and have total sizes similar to actual small and large farms in the study area.

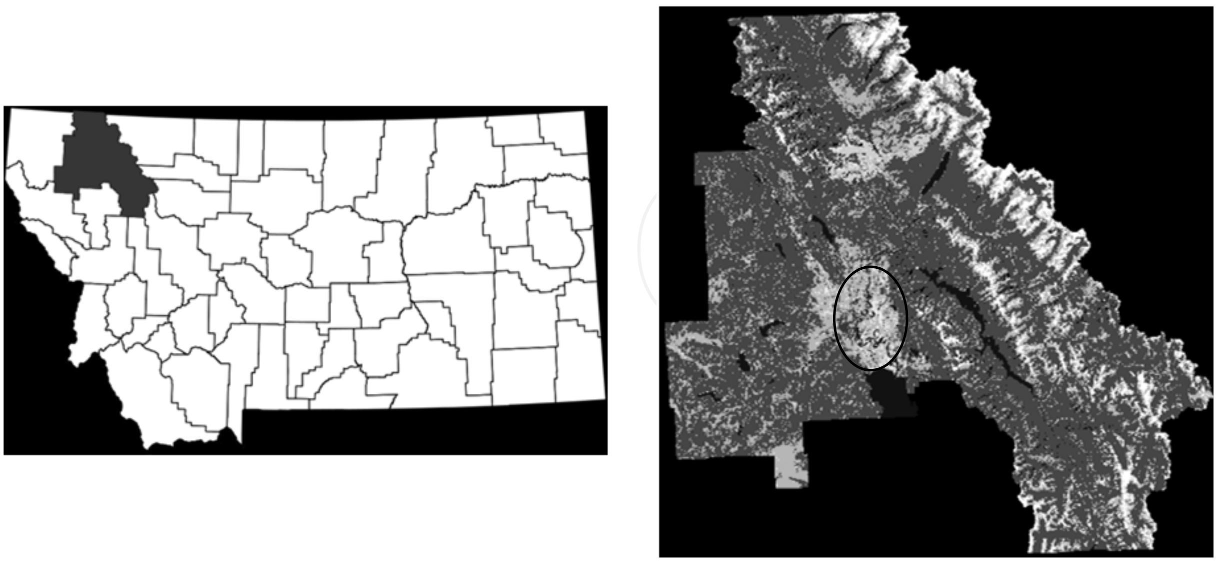
3. Previous research

Several studies have examined how climate change might affect agriculture. Reilly (2002) used the Hadley Center and Canadian climate models to estimate potential impacts of climate change on 2030-2090 crop yields for the entire US. He found that future climate change could result in: (1) higher yields for cotton, corn for grain and silage, soybeans, sorghum, barley, sugar beets, and citrus fruits; (2) higher or lower yields for wheat, rice, oats, hay, sugarcane, potatoes, and tomatoes, depending on the climate scenario; (3) large increases in average grain yields for the northern half of the Midwest, West, and Pacific Northwest; (4) depending on the climate scenario and time period, either increases or decreases in crop yields in other regions of the US; and (5) large reductions in crop yields in the South and Plains States for climate scenarios with low precipitation and substantial warming. For the Midwestern United States, Brown and Rosenberg (1997) simulated the impacts of climate change on crop yields and water use under different future climate scenarios using the Environmental/Policy Integrated Climate (EPIC) model (Williams et al., 1989). In a similar study, Izaurralde et al. (2003) used the EPIC model to evaluate the potential impacts of climate change on US crop yields, yield variability, incidence of various crop stress factors, evapotranspiration, and national crop production. That study evaluated how a baseline climate scenario for the period 1961–1990 and two Hadley Center climate scenarios for the periods 2025–2034 and 2090–2099 impact 204 representative farms. Reilly (2002), Brown and Rosenberg (1997), and Izaurralde et al. (2003) did not evaluate how future climate change is likely to impact crop enterprise net returns and NFI for representative farms as does this study. Kaiser et al. (1993) evaluated the economic and agronomic impacts of several climate warming scenarios, mainly temperature changes, on a grain farm in southern Minnesota and alternative ways to adapt the farm to those scenarios. That study did not evaluate the impacts of other climate variables, such as precipitation and atmospheric CO_2 concentration, on crop yields as does this study.

Antle et al. (1999) evaluated the impacts of climate change on crop enterprise returns in the Great Plains. That study showed: (1) with adaptation of crop enterprises to climate change, climate change and CO_2 enrichment caused mean crop enterprise return to change by -11% to +6% and variability in crop enterprise return to increase 7–25% relative to the baseline climate; and (2) without adaptation, mean crop enterprise return decreases 8–31% and variability in crop enterprise return increases 25–83% relative to the baseline climate. Antle et al. (2004) examined relative and absolute economic measures of the vulnerability of dryland grain farms in Montana to climate change with and without adaptation using data from a statistically representative sample of farm fields. That study allowed inferences to be drawn about the vulnerability of a heterogeneous population of farms to climate change with and without adaptation, and showed that when both climate change and higher atmospheric CO_2 concentrations are taken into account, average crop enterprise return was higher relative to the baseline climate for five and lower for three of the eight adaptation scenarios evaluated. Although Antle et al. (1999, 2004) evaluated the potential impacts of climate change on crop yields and crop enterprise returns, they did not consider potential impacts of future climate change on NFI as does this study.

4. Study area

Flathead Valley, Montana is the study area (Fig. 1). It is located in Flathead County. The county is approximately 13,605 km^2 in area (roughly the size of the State of Connecticut in the US) of which approximately 79% is managed by the federal government (Flathead County Planning and Zoning Office, 2009). In 2007, Flathead County had 1,094 farms with an average farm size of 93 ha. Of the 1,094 farms, 1,048 were less than 405 ha and 46 exceeded 405 ha in size. Sixty-one farms had annual sales less than \$100,000 and 1,033 farms had annual sales greater than \$100,000. In 2007, major crops grown in Flathead County in order of area harvested were spring wheat, alfalfa hay, winter wheat, other hay, barley, and canola. In 2006, cash receipts from the sale of principal agricultural commodities in Flathead County amounted to \$33.5 million (Montana Agricultural Statistics Service, 2008; National Agricultural Statistics Service, 2011).



(a) (b)

Figure 1. Location of Flathead County in Montana (a) and Flathead Valley (oval-shaped area) (b)

Daily and monthly climate data from the Creston, Montana weather station located in the Flathead Valley show that during the historical period: (1) average monthly maximum and average monthly minimum temperature for the winter months (i.e., December through February) were 0.41°C and -7.93°C, respectively; (2) average monthly maximum temperature and average monthly minimum temperature for the summer months (i.e., June through August) were 24.88°C and 8.32°C, respectively; and (3) average annual precipitation was 488 mm.

5. Methods and procedures

This section begins with an overview of the methods and procedures used to assess the potential agricultural impacts of the three climate scenarios (i.e., impact assessment) and the potential benefits of adapting CPSs for representative farms to the three climate scenarios (i.e., adaptation evaluation), and describes in detail the methods and procedures used in the impact assessment and adaptation evaluation.

5.1. Overview

The impact assessment determines the potential agricultural impacts of CO_2 emissions scenarios A1B, B1, and A2 developed by the Intergovernmental Panel on Climate Change Fourth Assessment Report (IPCC) (2007). The assessment involved: (1) specifying crop enterprises, CPSs, and soil types for small and large representative farms in Flathead Valley; (2) simulating crop yields; and (3) estimating net returns for crop enterprises and CPSs and net farm income in the historical and future periods. The adaptation evaluation determined the potential benefits of adapting CPSs for representative farms to the three climate scenarios, which involved determining: (1) whether the most dominant CPS in the historical period is different than the most dominant CPS for each climate scenario in the future period; and (2) for cases where they are different, whether the most dominant CPS for each climate scenario is superior to the most dominant CPS in the historical period.

5.2. Impact assessment

5.2.1. Specifying crop enterprises, CPSs, soils types, and representative farms

Ten crop enterprises, common to Flathead Valley, were specified for the study: spring wheat; winter wheat; oats; spring canola; spring barley; dryland (unirrigated) alfalfa; irrigated alfalfa; spring lentils; and dry (unirrigated) peas. Permanent pasture, a common forage crop enterprise in Flathead Valley, was excluded from the study because it does not produce a marketed crop. A CPS is a unique combination of crop enterprises. Two producer panels were established; one for a small representative farm (66 ha) and the other for a large representative farm (243 ha). Each panel consisted of 3-5 farmers that operated a small-scale or large-scale farm in Flathead Valley. Three CPSs were specified for each representative farm (Table 1) with the assistance of the producer panels. Two common soil types were evaluated for each crop enterprise: Creston silt loam (Ce), which is on 0–3% slopes and accounts for 3.4% of the total agricultural area in Flathead Valley; and Kalispell loam (Ke), which is on 0–3% slopes and accounts for 2.7% of the total agricultural area in Flathead Valley.

Crop enterprise	Large representative farm		
	CPS 1	CPS 2	CPS 3
Spring wheat	–	81	162
Winter wheat	81	–	–
Oats	–	–	40
Spring canola	40	–	–
Spring barley	61	61	–
Dry alfalfa	61	–	–
Irrigated alfalfa	–	61	–
Spring lentils	–	–	40
Dry peas	–	40	–
	Small representative farm		
	CPS 4	CPS 5	CPS 6
Spring wheat	–	12	8
Oats	–	8	–
Spring canola	12	8	8
Spring barley	10	–	–
Irrigated alfalfa	28	22	22
Spring lentils	–	–	12

Table 1. Hectares in crop enterprises for crop production systems (CPSs) for large and small representative farms

5.2.2. Simulating crop yields

Annual crop yields in the historical period were simulated for both soil types by inputting to the EPIC model (Williams et al., 1989) daily data on precipitation, maximum temperature (T_{max}), minimum temperature (T_{min}), relative humidity, solar radiation, and wind velocity from the Creston weather station in Flathead Valley and other sources, and field operations for crop enterprises (i.e., amount and/or timing of planting, fertilizer/pesticide use, tillage operations, and harvesting). Annual atmospheric CO_2 concentrations for the historical period were determined using the dynamic CO_2 option in the EPIC model. That option varies the annual atmospheric CO_2 concentration according to the following quadratic equation: $CO_2\ (X) = 280.33 - 0.1879X + 0.0077X^2$; where X equals the number of years between the prediction year and 1880. For example, for X = 2000 - 1880 = 120, the equation gives a CO_2 concentration in 2000 of $CO_2\ (120) = 280.33 - 0.1879 * 120 + 0.0077 * (120)^2 = 368.7$ ppm. This regression equation was estimated using the historical CO_2 record from the Mauna Loa Observatory in Hawaii (Izaurralde et al., 2006).

Annual crop yields in the future period were simulated for each climate scenario and soil type by inputting to the EPIC model daily projections of precipitation, maximum temperature (T_{max}), minimum temperature (T_{min}), relative humidity, solar radiation, and wind velocity, and annual projections of atmospheric CO_2 concentration for that climate scenario. Daily projections of precipitation and temperature were derived by applying the delta method (e.g., McGinn et al., 1999) to monthly bias-corrected, downscaled climate projections for each of the three climate scenarios. Monthly climate projections are based on the World Climate Research Program's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) (Meehl et al., 2007), which are available through the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP's Working Group on Coupled Modeling (WGCM; see http://gdo-dcp.ucllnl.org/). CMIP3 climate projections synthesize monthly temperature and precipitation data from 112 projection-specific datasets representing 16 CMIP3 climate models and the three future CO_2 emission scenarios for the period 1950-2099 (Meehl et al., 2007). In terms of which downscaled climate projection to use, the 12-km downscaled grid used in the study is the grid centered over the Creston meteorological station and the majority of the Flathead Valley. Annual CO_2 concentrations for each climate scenario were interpolated assuming linear increases in CO_2 concentration from 379 ppm in 2005 to the IPCC concentration for that scenario specified in 2100 (Table 2). The crop yield simulations take into account the fertilization effects of CO_2 concentration for the three climate scenarios.

The CMIP3 dataset does not contain monthly data on relative humidity, solar radiation, and wind velocity. Daily relative humidity and solar radiation projections were developed by applying the MTCLIM model (Hungerford et al., 1989; Kimball et al., 1997) to the daily temperature and precipitation projections for each climate scenario. Due to lack of data, daily wind velocity for each climate scenario was assumed to be the same as the corresponding daily wind velocity in the historical period. Specifically, daily wind velocity in month t+30 for each climate scenario equals the corresponding daily wind velocity in month t of the historical period.

EPIC simulates annual crop yields for the 46 years in the historical period and 45 years in the future period based on operations for each crop (i.e., amount and/or timing of planting, fertilizer/pesticide use, tillage operations, and harvesting) specified by producer panels, weather data for the historical period, and weather projections for each climate scenario in the future period discussed above. These simulated annual crop yields are referred to as raw crop yields, which are then used to extract the underlying crop yield distribution and derive 100 values of crop yields for calculating crop enterprise net returns. The parameter estimation, simulate, and CDFDEV functions in the Simulation and Econometrics to Analyze Risk (Simetar) program (Richardson et al., 2006) were used to simulate 100 values of crop yields for each period as follows. First, the parameter estimation function with maximum likelihood estimation was used to fit 16 probability distributions (i.e., Beta, double exponential, exponential, gamma, logistic, log–log, log–logistic, lognormal, normal, Pareto, uniform, Weibull, binomial, geometric, Poisson, and negative binomial) to raw crop yields for the historical period and each climate scenario in the future period. Second, the simulate function in Simetar was applied to the estimated parameters of each fitted probability distribution to simulate 100 values of crop yields for each distribution. Third, the CDFDEV function was applied to the 100 simulated crop yields for each distribution to determine the best-fitting probability distribution for crop yields. Fourth, a random sample of 100 values of crop yields was drawn from the best-fitting probability distribution was used to calculate 100 values of net returns per ha.

Scenario	Level of forcing	CO_2 concentration in 2100 (ppm)	Average increase in global temperature (°C)[a]
B1	Low	530	1.8
A1B	Medium	700	2.8
A2	High	800	3.4

[a]Mean temperature for years 2090-2099 minus mean temperature for years 1980-1989, Source: IPCC (2007)

Table 2. Description of three climate scenarios

5.2.3. Estimating net returns for crop enterprise and CPSs and net farm income

Annual net return per ha for a crop enterprise equals annual crop yield times crop price per unit of output minus total cost of production per ha. The 100 values of crop yields simulated using the procedures described in section 5.2.2, and 100 values of crop prices per unit of output and annual total cost of production per ha were used to simulate 100 values of crop enterprise net returns for the historical period and each climate scenario for the future period. The 100 values of crop prices were randomly selected from the best-fitting probability distribution for crop prices determined by applying the three Simetar functions described in section 5.2.2 to annual inflation-adjusted (base year = 2008) crop prices for the historical climate period. The 100 values of total cost of production per ha for a crop enterprise were randomly selected from triangular probability distributions. The mean of the triangular distribution equals the mean annual total cost of production per ha for that crop enterprise given by crop enterprise budgets for the study area (Table 3). Mean annual total cost of production is the sum of average variable and average fixed costs per ha. Variable cost includes the costs of seed, fertilizer, pesticides, fuel and lubricants, hired labor, and, in the case of irrigated crops, the cost of pumping and applying irrigation water. Fixed cost includes the costs of land, equipment, machinery, vehicles, and owner/operator labor. The minimum value of the triangular probability distribution was set equal to 80% of the mean and the maximum value was set equal to 120% of the mean. It was assumed that inflation-adjusted crop prices per unit of output and mean annual total cost of production per ha in the future period were the same as in the historical period. For that reason, the same 100 values of crop prices and total cost of production per ha randomly selected for a given crop enterprise for the historical period were used for the future period.

5.3. Adaptation evaluation

The dominant CPS was identified for each representative farm and period by applying the stochastic efficiency with respect to a function (SERF) criterion (Hardaker et al., 2004) for a particular risk aversion coefficient (RAC) to the 100 simulated values of net returns for the three

CPSs specified for each farm. With the SERF criterion, the dominant CPS for a representative farm is the one with the highest certainty equivalent (Hardaker et al., 2004). The latter is the payoff amount that a farmer is willing to receive in exchange for accepting the variability in NFI associated with a particular CPS. Application of the SERF criterion was based on three assumptions: (1) RACs are in the range [0,0.03], where RAC = 0 implies the farmer is risk neutral and RAC > 0 implies the farmer is risk averse (Anderson and Dillon, 1992); (2) constant absolute risk aversion, which implies that the risk premium a farmer is willing to pay to reduce income risk does not vary with the level of income; and (3) the farmer's utility function is exponential in NFI (i.e., u[NFI] = exp[-RAC * NFI]). In addition, the SERF criterion was used to determine whether the dominant CPS for a representative farm in the historical period is superior to the dominant CPS for that representative farm under each climate scenario. If the dominant CPS in the historical period is the same as the dominant CPS under a climate scenario in the future period, then adaptation to that climate scenario is not advantageous. If the dominant CPS in the historical period differs from the dominant CPS under a climate scenario (e.g., CPS_i is the dominant CPS in the historical period and CPS_j is the dominant CPS for climate scenario k) and CPS_j dominates CPS_i, then adapting CPSs to that climate scenario (i.e., switching from CPS_i to CPS_j under climate scenario k), is advantageous to the farmer.

Crop enterprise	Variable cost	Fixed cost	Total cost[d]
Spring wheat	307.54[a]	91.07[a]	398.61
Winter wheat	274.42[b]	117.74[b]	392.16
Oats	227.51[b]	129.03[b]	356.54
Spring canola	383.59[a]	57.65[a]	441.24
Spring barley	307.74[a]	91.07[ac]	398.81
Dry alfalfa	152.23[a]	95.96[a]	248.19
Irrigated alfalfa	498.67[a]	95.96[ab]	594.63
Spring lentils	247.22[b]	130.47[b]	377.69
Dry peas	253.67[b]	130.47[b]	384.13

[a]Based on crop enterprise budgets supplied by Duane Johnson, former Superintendant of Montana State University's Northwestern Montana Agricultural Research Center, Creston, MT
[b]Based on predicted 2008 crop enterprise budgets for northwest North Dakota

Table 3. Variable, fixed, and total cost for crop enterprises ($per ha in 2008 dollars)

6. Results

6.1. Impact assessment

Simulated annual crop yields for the same crop were very similar across the three climate scenarios because IPCC climate projections of monthly temperature and precipitation are very similar across the three climate scenarios. The latter occurs because the divergence in the time paths of temperature and precipitation for the three climate scenarios does not take place until the latter half of the IPCC assessment period (i.e., 2055–2100), which occurs after the future period. Because simulated yields for a given crop are very similar across the three climate scenarios and the 100 simulated crop prices and production costs for a given crop are the same across the three scenarios, crop enterprise net returns for the same crop and soil type and NFI for the same CPS and soil type are likewise similar across the three climate scenarios. For that reason, results for the future period are averages of the results for the three climate scenarios.

6.1.1. Means and standard deviations of simulated crop enterprise net returns

Means and one-standard deviation error bars for simulated crop enterprise net returns per ha are given in Fig. 2 for the historical period and Fig. 3 for the future period. Between the historical and future periods, enterprise net returns: (1) decreases by 84.3% on average for spring barley, dry canola, dry and irrigated alfalfa, oats (in Ce soil), and spring wheat (in Ce soil); and (2) increases by 44% on average for dry lentils, oats (in Ke soil), winter wheat, spring wheat (in Ke soil), and dry peas. Averaged over the nine crop enterprises and two soil types, mean simulated crop enterprise net return per ha is 24% lower in the future period than in the historical period. In summary, mean simulated net return per ha for the same crop enterprise is between 202% lower and 74% higher in the future period than in the historical period.

6.1.2. Means and standard deviations of net farm income for crop production systems

The mean and one-standard deviation error bars for simulated NFIs for the six CPSs in the historical period are shown in Fig. 4 for the historical period and Fig. 5 for the future period. Simulated NFIs for CPSs in the future period assume no adaptation to climate scenarios. As expected, for both periods, simulated NFI is higher for the large representative farm (i.e., CPS 1, CPS 2, and CPS 3) than for the small representative farm (i.e., CPS 4, CPS 5, and CPS 6). In four of the six cases in the historical period, mean simulated NFI is higher for Ke soil than Ce soil. For the historical period and large representative farm, the mean simulated NFI is highest for CPS 3 in Ce soil at $87,275 and lowest for CPS 1 in Ce soil at $65,568. For the historical period and small representative farm, mean simulated NFI is highest for CPS 6 in Ke soil at $23,612 and lowest for CPS 4 in Ce soil at $21,599. For the future period and large representative farm, the mean simulated NFI is highest for CPS 3 in Ke soil for climate scenario B1 at $40,571 and lowest for CPS 3 in Ce soil for climate scenario A2 at $14,585. For the future period and small representative farm, the mean simulated NFI is highest for CPS 6 in Ke soil for climate scenario A2 at $13,726 and lowest for CPS 5 in Ce soil for climate scenario A2 at $8,864. Mean simulated NFIs for the CPSs decrease 57% between the historical and future periods. The maximum percent decline in mean simulated NFI between the historical and future periods is 83% for CPS 3 in Ce soil for the large representative farm under climate scenario A2. The minimum percent decline in mean simulated NFI between the historical and future periods is 41.9% for CPS 6 in Ke soil for the small representative farm under climate scenario A2. In summary, mean simulated net farm income for the same CPS is between 42% and 83% lower in the future period than in the historical period.

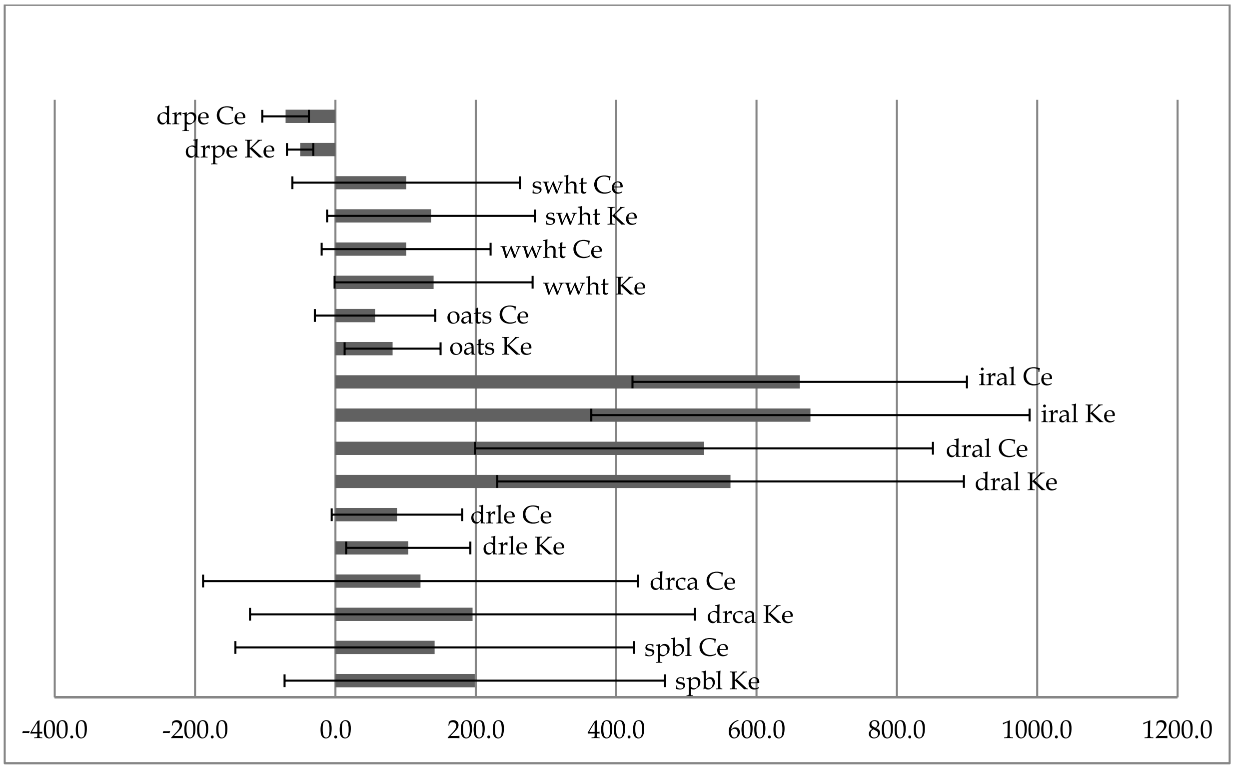


Figure 2. Means and one-standard deviation error bars for simulated crop enterprise net returns per ha (in 2008 dollars) for the historical period, by soil type (drpe is dry peas, swht is spring wheat, wwht is winter wheat, iral is irrigated alfalfa, dral is dry (unirrigated) alfalfa, sple is spring lentils, drca is dry (unirrigated) canola, and spbl is spring barley)

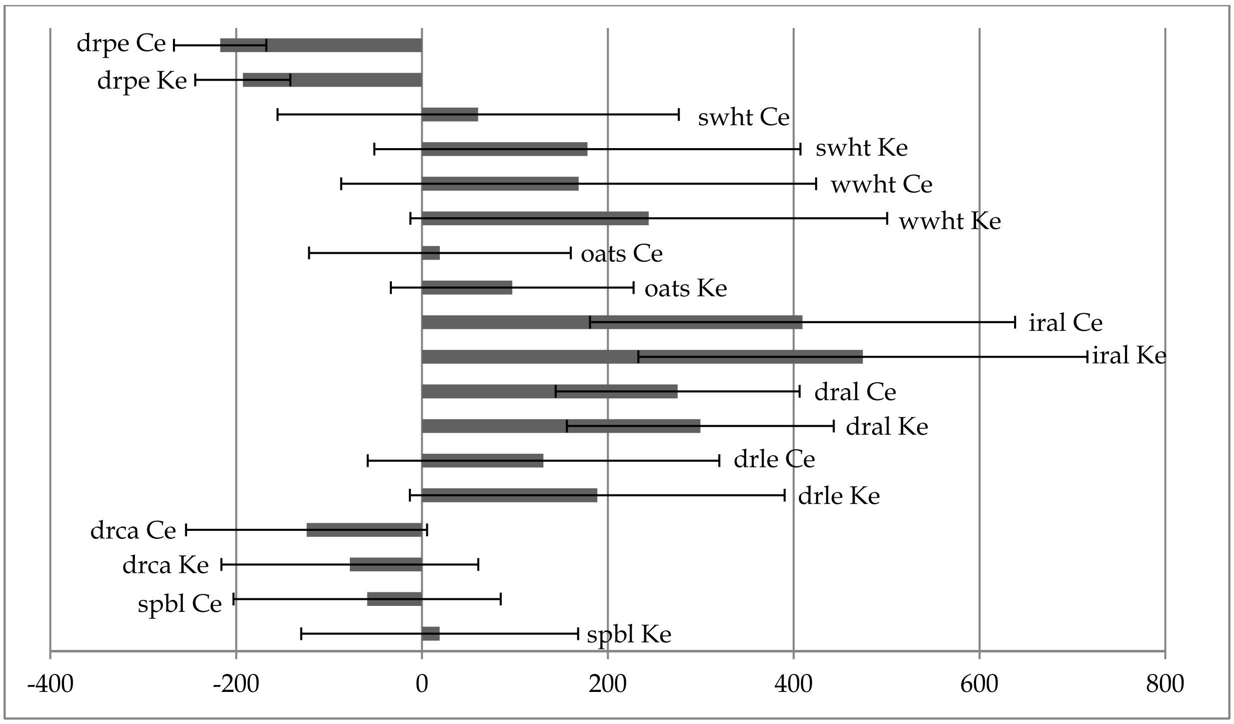


Figure 3. Means and one-standard deviation error bars for simulated crop enterprise net returns per ha (in 2008 dollars) for the future period, by soil type (crop enterprise legend given in Fig. 2)

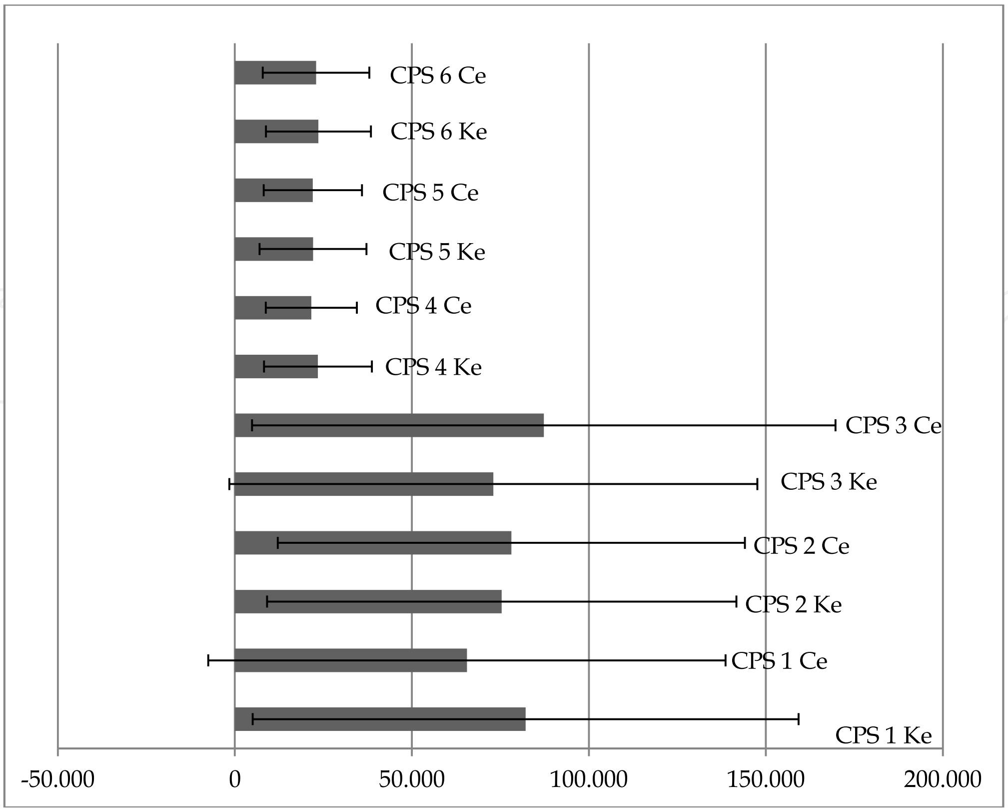


Figure 4. Means and one-standard deviation error bars for simulated net farm income in 2008 dollars for crop production systems (CPSs) in the historical period, by soil type (crop enterprises for each CPS are listed in Table 1)

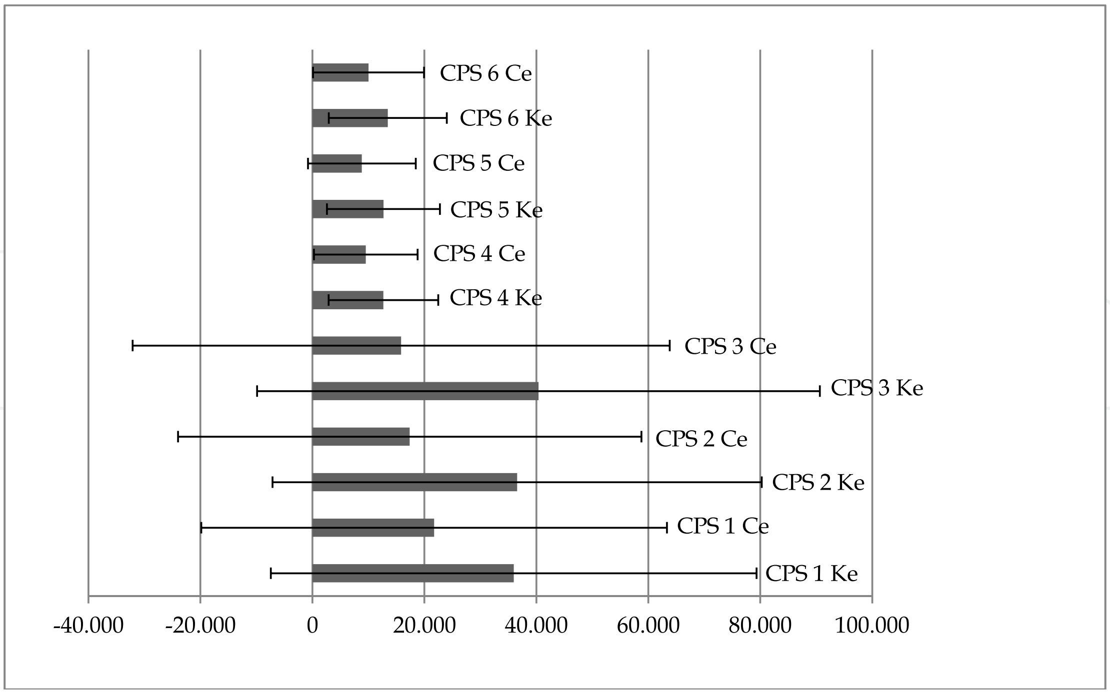


Figure 5. Means and one-standard deviation errors bars for simulated net farm income in 2008 dollars for crop production systems (CPSs) for the future period without adaptation to climate scenarios, by soil type (crop enterprises for each CPS are listed in Table 1)

6.2. Adaptation evaluation

Table 4 shows the dominant CPSs for the small and large representative farms and two soil types for the historical period and three climate scenarios. For the large representative farm: (1) CPS 2 dominates CPS 1 and CPS 3 for both soil types in the historical period and under climate scenarios A1B and A2 for the Ke soil type; (2) CPS 3 dominates CPS 1 and CPS 2 under climate scenario B1 for the Ke soil type; and (3) CPS 1 dominates CPS 2 and CPS 3 under all three climate scenarios for the Ce soil type. For the small representative farm: (1) CPS 4 dominates CPS 5 and CPS 6 in the historical period for both soil types; (2) CPS 4 dominates CPS 5 and CPS 6 under climate scenario A1B for both soil types; and (3) CPS 5 dominates CPS 4 and CPS 6 under climate scenarios A2 and B1 for both soil types. These results indicate that switching CPSs between the historical and future periods (i.e., adapting CPSs to future climate change) is optimal in eight of the twelve cases evaluated. Specifically, it is advantageous to switch: (1) from CPS 2 to CPS 3 under climate scenario B1 for the Ke soil type and from CPS 2 to CPS 1 under all three climate scenarios for the Ce soil type for the large representative farm; and (2) from CPS 4 to CPS 5 under climate scenarios A2 and B1 for both soil types for the small representative farm.

Table 5 reports the dominance relationships for CPSs for the large and small representative farms and two soil types between the historical period and three climate scenarios. Of particular interest are the dominance relationships for the cases in which the dominant CPS differs between the historical and future periods because these relationships indicate whether NFI in the historical period is superior or inferior to NFI with adaptation of CPSs to climate change. For the large representative farm: (1) CPS 2 in the historical period dominates CPS 3 under climate scenario B1 for soil type Ke; and (2) CPS 2 in the historical period dominates CPS 1 under all three climate scenarios for the Ce soil type. For the small representative farm: (1) CPS 4 in the historical period dominates CPS 5 under climate scenarios B1 and A2 for soil type Ke; and (2) CPS 5 under climate scenarios B1 and A2 dominates CPS 4 in the historical period for the Ce soil type. Combining the results in Tables 4 and 5 indicates that while adapting CPSs to future climate change reduces potential losses in NFI in eight of the 12 cases evaluated, in only three of those eight cases is NFI in the future period after adaptation to climate change superior to NFI in the historical period. Conversely, in five of those eight cases, NFI in the future period after adaptation to climate change is inferior to NFI in the historical period.

7. Conclusion

It is difficult to evaluate the potential adverse impacts of future climate change on agricultural production because of uncertainty regarding the nature and extent of future climate change and how such change is likely to influence crop yields, crop enterprise net returns, and NFIs for CPSs. Most previous studies of the agricultural impacts of climate change focus on how past climate change has influenced crop yields and/or crop enterprise net returns at the regional and/or national levels. The unique contribution of this study is that it developed a method for assessing the potential economic benefits (in terms of alleviating losses in NFI) of adapting CPSs to future climate change for representative farms in a local agricultural production area. This is an important contribution because farming is a business that requires farmers to understand the potential impacts of future climate change on NFI and determine whether adapting CPSs to future climate change alleviates negative impacts of those changes on NFI.

Averaged over the two representative farms and two soil types in Montana's Flathead Valley, simulated net return per ha for the nine crop enterprises decreases 24% and mean simulated NFI for CPSs decreases 57% between the historical and future periods. Although adapting CPSs to future climate change reduces potential losses in NFI in eight of the 12 cases evaluated here, in only three of those eight cases is NFI in the future period after adaptation to climate change superior to NFI in the historical period. Therefore, for most part, adapting CPSs to future climate change alleviates but does not eliminate the negative impacts of that change on simulated NFI. The impact assessment and adaptation evaluation methods described here can be used to determine the potential impacts of future climate change on crop enterprise net returns and NFI for representative farms and evaluate the potential economic benefits of adapting crop enterprises and CPSs to future climate change in other agricultural production areas.

Soil type	**Large representative farm**	**Small representative farm**
	Historical period	
Ke	CPS 2	CPS 4
Ce	CPS 2	CPS 4
	Climate scenario	
	A1B	
Ke	CPS 2	CPS 4
Ce	CPS 1	CPS 4
	A2	
Ke	CPS 2	CPS 5
Ce	CPS 1	CPS 5
	B1	
Ke	CPS 3	CPS 5
Ce	CPS 1	CPS 5

[a]Based on SERF method assuming a risk-averse farmer (i.e., $0.0013 < RAC \leq 0.03$)

Table 4. Dominant crop production systems (CPSs) for the historical period and each of the three climate scenarios (B1, A1B, and A2), by large and small representative farms and two soil types[a]

Soil Type	Large representative farm	Small representative farm
Ke	CPS 2 (H) $\mathcal{D}^{b}$ CPS 3 (B1)	CPS 4 (H) $\mathcal{D}$ CPS 5 (B1)
	CPS 2 (H) $\mathcal{D}$ CPS 2 (A1B)	CPS 4 (H) $\mathcal{D}$ CPS 4 (A1B)
	CPS 2 (H) $\mathcal{D}$ CPS 2 (A2)	CPS 4 (H) $\mathcal{D}$ CPS 5 (A2)
Ce	CPS 2 (H) $\mathcal{D}$ CPS 1 (B1)	CPS 5 (B1) $\mathcal{D}$ CPS 4 (H)
	CPS 2 (H) $\mathcal{D}$ CPS 1 (A1B)	CPS 4 (A1B) $\mathcal{D}$ CPS 4 (H)
	CPS 2 (H) $\mathcal{D}$ CPS 1 (A2)	CPS 5 (A2) $\mathcal{D}$ CPS 4 (H)

[a]Based on SERF method assuming a risk-averse farmer (i.e., $0.0013 < RAC \leq 0.03$)
[b]$\mathcal{D}$ indicates "dominates"

Table 5. Dominance relationships for crop production systems (CPSs) across the historical period (H) and three climate scenarios (B1, A1B, and A2), by large and small representative farms and two soil types[a]

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Acknowledgement

The research reported here was supported in part by the National Research Initiative of the USDA Cooperative State Research, Education and Extension Service, grant number 2006-55101-17129.

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