Research Article

How climatic and sociotechnical factors influence crop production: a case study of canola production

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Abstract

In most climate change research, agricultural yields are explained as a function of climatic and biophysical factors such as soil, rainfall and temperature. However, the increased use of integrated sensors, digital technologies and robotics within the agricultural sector has dramatically altered the way in which we produce food. Considering both the agriculture industry's continuing widespread technological innovation and a rapidly changing biophysical environment, there is a need to explore how sociotechnical and climatic variables interact to determine yield. In this paper, we present a regression model derived from Agriculture and Agri-Food Canada (AAFC) yield data, Environment and Climate Change Canada (ECCC) climate and land capability data, and Statistics Canada Census of Agriculture databases that include sociotechnical variables such as farms that use GIS and GPS had access to high-speed internet alongside more traditional biophysical factors to predict canola (rape seed) yields in the southern prairies of Canada. We demonstrated that about 38% of canola yield variability could be explained by temperature and rainfall during the growing season (defined as 3 months of June, July and August) and access to high-speed internet, application of chemical fertilizer, fungicides and average age of farm operators. While of a preliminary nature, our results demonstrate that a better understanding of how climatic and sociotechnical factors interact is necessary to anticipate how climate change may affect the crop yield.

Keywords Crop production · Climate change · Sociotechnical factors · Canola · Digital data

1 Introduction

The Canadian prairies are home to one of the world's most highly productive farming system that are influenced and largely constrained by various climatic conditions, particularly moisture availability and temperatures which limit growing season length [8, 36, 41]. Under the projected climate change scenarios, warmer temperatures, increased precipitation, and an increase in the intensity/frequency of extreme weather events will create large variability in weather patterns [41]. As agricultural yields are dependent on climatic conditions, this increased climatic variability is expected to impact agricultural yields. Nevertheless, the degree to which climate change may affect production both globally and on the prairies remains uncertain (e.g. [7]. This uncertainty is not only due to the complexities of climate systems and how crops will respond to global warming, but is also a result of how one assumes humans

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will react and adapt to these changing agricultural growing conditions [14].

The adaptive capacity of an agricultural system to extreme weather events is inherently stochastic and is predominately determined by a combination of social, economic and technological factors [24]. Access to education and capital [24], land-use inputs such as fertilizer [1, 4, 14, 30] and available technologies like tractors [25] have all been shown to be important in determining adaptive capacity as these factors influence the way a farmer can respond to environmental problems such as drought. Historically, however, correlations between agricultural yields and technological advancements have been challenging to quantify [13]. Despite the difficulty in quantifying the exact degree of the effect of technology, technological advancements such as GPS-guided tractors, genetically modified crops and chemical inputs have been shown to increase the productivity of farms around the globe and offer a tremendous opportunity to help increase the adaptive capacity of farmers [27, 40]. For instance, as far back as in the 1970s Lu and Quance [27] estimate that a 1% increase in research and extension expenditure will increase agricultural productivity by 0.037% over a 13-year period. The potential for more recent digital technologies to enhance adaptive capacity has also been explored [40]. Understanding the spatial differences in sociotechnical factors affecting the adaptive capacity of farms across the country will help improve Canadian agri-food policy. One lesson from this literature is that the harvest from a crop depends both the socioecological and sociotechnical systems [31]. Therefore, to better understand the opportunities and constraints caused by the combination of technological innovation and a changing climate, we need to use integrated quantitative analysis by combining both climatic and sociotechnical variables.

There are currently relatively few studies on assessing crop yields that integrate both climatic and socio-economic variables. Fraser and Simelton both present integrated crop vulnerability models at the global level [14, 35], and Antwi-Agyei et al. [4] attempt to integrate socio-economic and biophysical data to assess how climate change may affect farming in Ghana [24] and explore how global grain yields are influenced by technology. Within Canada, which is one of the world's most important food producing nations, however, relatively few empirical studies exist that explicitly draw together both socio-technical and environmental data. A few study attempts to do this by exploring corn and wheat production, but these are predominantly grown in southern Ontario and not in the prairies [6, 39]. However, among the field crops grown within the Canadian Prairie region, canola (*Brassica napus*, also known as oilseed rape) is the most valuable, contributing approximately 26.7 billion Canadian Dollars to the Canadian economy each year [28], Statistics Canada 2016. Similar to other field crops, canola yields are influenced by climate, as the crop is sensitive to extremes in temperatures and water availability (e.g. Aksouh-Harradj et al. [3, 15, 26, 41]. Identifying interactions of crop yields in canola with socio-economic variables is challenging as data on advanced technological variables (e.g. usage rates of GPS autosteer or variable rate seeding) are not readily available. This distinctive lack of data on digital technology use in agriculture makes it hard to develop sociotechnical crop yield models. However, in recent years, the Canadian agricultural census includes a limited number of questions pertaining to sociotechnical variable such as providing data on the number of farmers using GPS and GIS and the number of farms having access to internet. These data can be used as a proxy to evaluate the usage of digital technologies in agricultural production and their corresponding impact on agricultural crop yield.

In this context, the purpose of this paper is to explore how both sociotechnical and climatic variables interact to determine the yield taking an example of canola production in the prairie region of Canada. This is an important question for two reasons: (1) climate change is going to create new opportunities and constraints in Canada's prairies and (2) new technologies mean that technology, which has always been important, is set to become more important. In this paper, we assess the spatial variability of canola crop yields' sensitivity to climate and the way that farmers access to land and advanced technologies mediates the relationship between canola yield climate and land capability developing a logistic regression model.

2 Materials and methods

2.1 Crop yield data

Canola crop yield data for the southern prairies for 2010–2016 were obtained from Agriculture and Agri-Food Canada (AAFC) [2]. Reported canola yields (kg/ha) from agricultural insurance companies in Alberta, Saskatchewan and Manitoba were provided to AAFC, where the data were aggregated and interpolated from quarter section level to a township level (approximately 10 × 10 km cell) to maintain confidentiality.

2.2 Weather data

Daily temperature and precipitation data, collected by Environment and Climate Change Canada (ECCC), are available by meteorological station point locations [11]. Climatic data were averaged by month between the years of 2010–2016, for the days of the year 182–243

(1 June to August 31), the defined growing season of canola. Four variables defined as monthly mean temperature (T_{mean}), monthly maximum temperature (T_{max}), monthly minimum temperature (T_{min}) and total monthly precipitation (P_{tot}) for June, July and August were prepared. From the point-level weather data, a thematic layer for each of the variables was prepared using an interpolation technique [21].

2.3 Sociotechnical data

The socio-economic data were obtained through Statistics Canada and its census of agriculture database in the form of CSV files [37]. All census data were linked administratively to the consolidated census subdivision level. Data are available in five-year increments, are open-access, and become available the year after a census has been completed. Since the canola crop yield data are available between 2010 and 2016, we used the 2011 censuses data for this study. From this census data, socio-economic variables predicted to have the impact on crop yields were selected based on a review of the literature [1, 4, 14, 30]. These variables are presented in Table 1.

2.4 Land capability data

Land capability data were acquired through Government of Canada. Government of Canada [17] officers open access geospatial Canada Land Inventory (CLI) 1:250,000—Land Capability for Agriculture data. Based on the soil physical and chemical properties, land is divided into eight classes as per their magnitude of suitability for agricultural activities where class 1 stands for highly suitable for agricultural activities and 8 is not suitable for agricultural activities.

2.5 Data integration

Each of the canola crop yield, land capability, weather and census data sets exists in idiosyncratic formats and at different spatial scales. However, to assess the association through statistical analysis between crop yields, weather, land capability and census variables, all data need to be integrated. The objective of this paper was to understand how biophysical and sociotechnical factors might have

Table 1 Description of selected sociotechnical variables used in census

Variables	Unit of measurement	Explanation	References
Number of farms	Number	Total number of farms	Canada Census 2011
Area	Acres	Total farm area	Canada Census 2011
Farm operators	Number	Operators on all farms	Canada Census 2011
Farm operator's age	Years	Average age of farm operators	Canada Census 2011
Capital	CAD	Total farm capital	Canada Census 2011
Chemical fertilizer	Acers	Farm area under application of chemical fertilizer	Canada Census 2011
Fungicides	Acres	Farm area under fungicide application	Canada Census 2011
Lime	Acres	Farm area under lime application	Canada Census 2011
Farm Manure	Number	Number of farms producing or using manure	Canada Census 2011
Irrigated farm area	Acers	Total area of land irrigated	Canada Census 2011
Equipment Value	CAD	Value of all farm machinery and equipment	Canada Census 2011
Tractors	Number	Total number of tractors used in agricultural activities	Canada Census 2011
Trucks	Number	Total number of farm truck used in agricultural activities	Canada Census 2011
Vans	Number	Total number of vans used	Canada Census 2011
Balers	Number	Total number of balers used in agricultural activities	Canada Census 2011
Combines	Number	Total number of combiners used in agricultural activities	Canada Census 2011
Harvesters	Number	Total number of harvesters used agricultural activities	Canada Census 2011
Mowers	Number	Total number of mowers used in agricultural activities	Canada Census 2011
Irrigation equipment	Number	Total number of irrigation equipment used in agricultural	Canada Census 2011
Tillage equipment	Number	Total number of tillage equipment used in agricultural activities	Canada Census 2011
Computer	Number	Number of farms that use computers for the farm business	Canada Census 2011
Net	Number	Number of farms who has internet access	Canada Census 2011
High-speed internet access	Number	Farms having high-speed internet access	Canada Census 2011

interacted in the case of canola production in the prairie region of Canada. So, from this perspective, geographical boundaries for this study are the selected areas in Alberta, Saskatchewan and Manitoba of the prairie region (as shown in Fig. 1), where grid cell level (approximately 10 × 10 km cell) of canola crop yield data in kg/ha is available. This is the reference layer for us to combine with weather, land capability and socio-economic data.

As mentioned above, in the weather and sociotechnical data section, we have prepared spatial layers for each of the census and weather data which allows us to integrate weather and census data together with land capability and canola crop yield data through converting all layers into 10 × 10 km grid cell and combining all of them together (For details about combining socio-economic and spatial data, please see [21–24]). This provided us with a cell that contained the sociotechnical, weather, land capability and canola yield data together. Although crop yield data varied in each cell, all the cells within a specific agricultural consolidated division had the same value for the sociotechnical variables and all the cells within a specific weather data also had the same value for weather-related variables. Similarly, all the cells within a specific land capability class also had the same value. Although this is a limitation of the study, this is inevitable when using available data but should only obscure, rather than create trends. Finally, the combined table was exported to SPSS v25 (IBM [20]) and STATA v14 (Stata [38]) for statistical analysis.

2.6 Statistical analysis

Our statistical analysis is based on the assumption that yield variability of a crop in a given location and time can be impacted by climatic, land capability and sociotechnical factors. The climatic and soil factors are the main factors, but these factors will not fully able to explain the yield variability, and we assume that the variability that is not explained by climatic factors can be explained through a set of farm- and farmer-level sociotechnical factors. For example, farm-level sociotechnical variables including fertilizers, insecticides, pesticides and different types of equipment and machinery used at various steps of farming activities and their intensity and effectiveness would have different levels of impact on yield. The efficient use of the equipment and machinery and application of farm inputs also depends on factors such as whether farmers

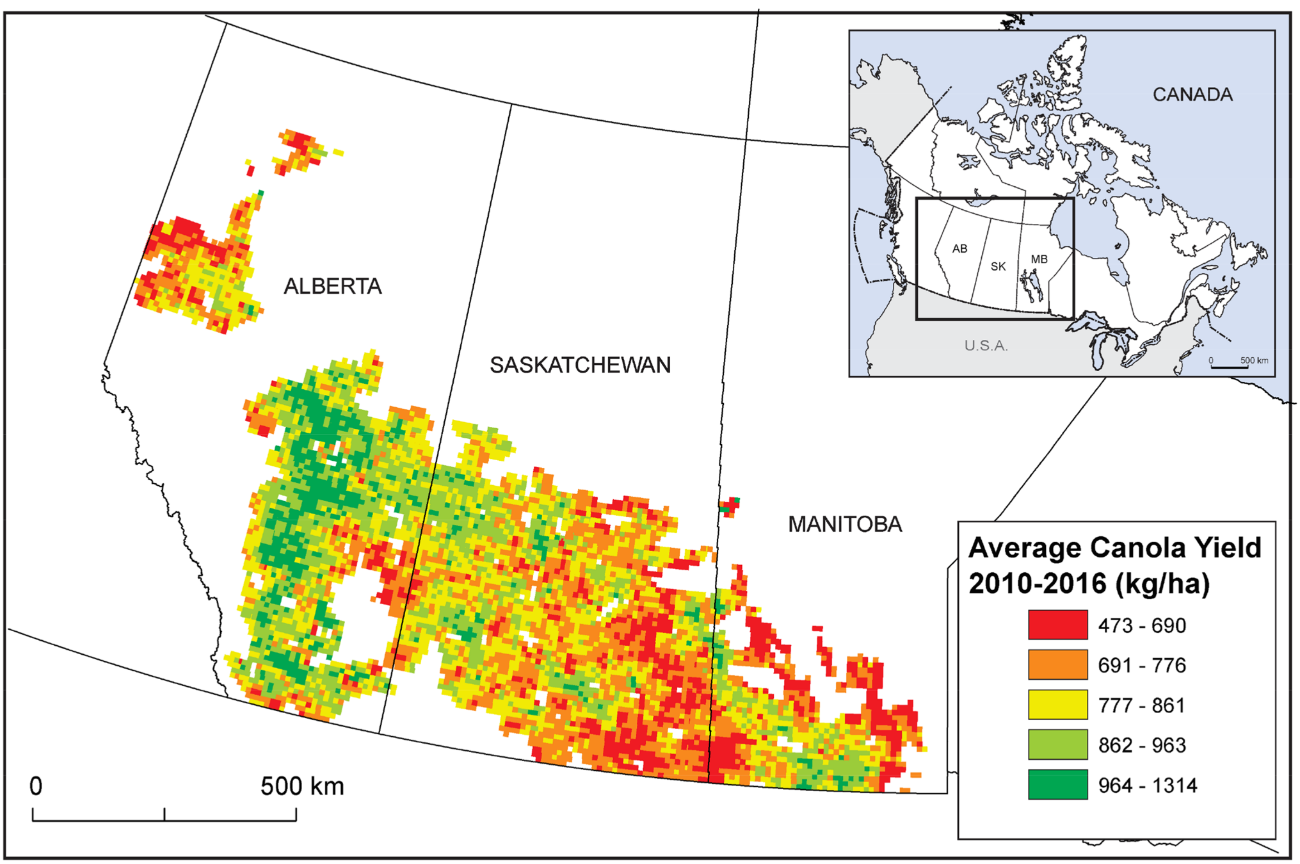

Fig. 1 Map depicting the spatial distribution of average canola crop yields (kg/ha) from 2010 to 2016 in the south of the prairie provinces of Manitoba, Alberta and Saskatchewan. (*Data Source*: Agriculture and Agri-food Canada)

get access to and use computers, internet, GPS, etc. Therefore, we hypothesize that farmers who had access to computers, global position system (GPS) and high-speed internet may be associated with high level of yields because the farmers were able to make efficient decisions on the application of farm input at the right time. To demonstrate this, we used a regression model combining some selected climatic variables like average monthly temperature and rainfall during the canola growing season together with land capability and a set of sociotechnical factors that could explain the yield variability. Next, we elaborate on the detailed description of the regression model including the assumption and preparation of variables and model run.

Average mean, minimum and maximum monthly temperature and cumulative monthly rainfall during the canola growing season period of June, July and August were used as climatic variables. A total of 12 climatic variables, three temperatures and one cumulative rainfall for each of the three months during the defined growing season were used. Doing this, we captured the weather variability [5, 34]. With respect to yield forecasting, we recognize that climate-yield forecast approach presented here is not as comprehensive of state-of-the-art yield forecast systems (e.g. [10]); however, the importance of the variables included, particularly air temperature, has been identified in previous studies (e.g. [26, 41]).

In order to select a meaningful sociotechnical factors, first of all, a correlation analysis (Table S1) was performed to assess the relation between average canola crop yield and a bunch of socio-economic variables as well as between all the socio-economic variables themselves. Based on the covariate analysis, we proceed further to select the influential sociotechnical factor that could explain the yield variability. Sociotechnical variables with a correlation coefficient greater than 0.8 [9] were combined into a single variable by using a weighted average methodology to treat the variable such that one variable would not have a disproportionate impact because of relatively large value of one variable compared to other variable. More specifically, we divided every data point by the maximum data point value of that given variable, thereby creating a standardized value of 0–1 for all variables that were then averaged together.

Next, we ran a series of stepwise regression models [19, 29] by removing the sociotechnical variables that did not show a significant association with the canola crop yields. Finally, in some cases it was necessary to also transform some sociotechnical variables to ensure commensurability. For example, originally, we had data on the acreages of farmland that applied the different types of fertilizer and limes in each consolidated subdivision. We transformed these into the "per cent of area" that used different types of fertilizer in each consolidated division by diving the acreages that used different types of fertilizer by the total areas of farmland in each consolidated subdivision. Similarly, the original data contained information on number of farms that had access to high-speed internet. We transformed this variable to the per cent of farms that had high-speed internet access in each consolidated subdivision by diving the number of farms that have access to high-speed internet by total number of farms in each consolidated subdivision. After this process, four sociotechnical variables (per cent area used chemical fertilizer, per cent of farms that had high-speed internet access, per cent areas that used fungicides and average age of farmers) were selected to assess their potential impact on canola crop yield.

3 Results

3.1 Summary results

Table 2 presents a summary statistic of canola yield, land capability, climatic and sociotechnical variables used in the regression models. Average canola yield is about 812 kg/ha, but there was big variation as yield ranges as low as 473 kg/ha to a maximum of 1314 kg/ha (Fig. 1) with a standard deviation of 107. The spatial distribution of the average canola crop yield data (2010–2016) in Alberta, Saskatchewan and Manitoba can be seen in Fig. 1. The map shows that there is a spatial clustering of canola yield, with high yields occurring in central southern Alberta, southwestern Saskatchewan and a small portion of Manitoba. The lowest average canola yields appear to occur in southeastern Saskatchewan and northern Alberta.

Climatic data represent the average values from year 2010 to 2016. Interesting trends can be noticed as the highest rainfall was in the month of June and average maximum temperature was highest in August, whereas mean and average minimum temperature was highest in July. August seems to be hottest month, but there were not big differences in terms of average maximum temperature in three months as the month-to-month difference was only about 1 °C. There was some interesting difference in terms of the average monthly temperature in the three-month canola growing season period in the study region. More variation was observed with respect to monthly average temperature compared to average monthly maximum temperature. The difference between June and July's temperature was about 2 °C. With respect to average minimum temperature, there was relatively bigger differences, as average monthly minimum temperature of June was about 2 °C, whereas average minimum temperature in the month of July was about 6 °C.

Table 2 Descriptive statistics

Parameters	Mean	Std. deviation
Yield (kg/ha)	812.62	107.77
Land capability		
(8 classes: 1 for highly suitable for agricultural activities and 8 is not suitable for agricultural activities)	3.66	1.44
Climatic factors		
Average temperature in June (degree centigrade)	15.27	1.08
Average temperature in July (degree centigrade)	17.89	1.29
Average temperature in August (degree centigrade)	17.04	1.33
Maximum temperature in June (degree centigrade)	28.31	1.37
Maximum temperature in July (degree centigrade)	30.71	1.64
Maximum temperature in August (degree centigrade)	31.02	2.37
Minimum temperature in June (degree centigrade)	2.37	1.17
Minimum temperature in July (degree centigrade)	6.03	1.43
Minimum temperature in August (degree centigrade)	3.61	1.60
Precipitation in June (millimetres)	78.20	24.44
Precipitation in July (millimetres)	63.51	21.93
Precipitation in August (millimetres)	49.16	17.02
Sociotechnical factors		
Application of chemical fertilizer (% area)	40.58	16.92
Application of fungicides (% area)	9.52	10.04
Access to high-seed internet (% farms)	45.83	9.94
Average age of the farm operators (years)	53.77	11.28

With respect to sociotechnical variable, the average age of farm operator was about 54 years which indicates relatively mature farm operators were in canola farming business. About 41% of the area was under chemical fertilizer and 46% of farms had access to high-speed internet. About 10% of the farm area was under the use of fungicides. With respect to model result, approximately 38% of variation of the canola crop yield (Table 3) was explained by the explaining variable used in our model.

3.2 Detailed results

3.2.1 Association between temperature, precipitation and canola crop yields

Our study found a strong association between weather variables and canola crop yield in the Canadian prairies, where the mean, minimum and maximum temperature and total rainfall during the month of June, July and August were found to be highly significant ($p < 0.001$) as given in Table 3. The association between precipitation in the months of June, July and August and temperature with canola yield from our finding were closely related to the previous findings by Kutcher et al. [26]. Kutcher et al. [26] found that canola crops are most sensitive to high temperatures in late June, to early July, as these are the months canola plants are flowering. Furthermore, the positive effect of the increased precipitation in the month of July and August shows how precipitation may offset the negative effect of temperature on flowering canola, through transpiration [26]. Overall, our model shows that canola crop yield increases with increasing average temperature in June and August, but yield decreases with the increasing average temperature in July. With respect to minimum temperature, our model shows that yield decreases with the decrease in the minimum temperature, particularly in June and July. With respect to maximum temperature, the month of August seems more sensitive as increasing maximum temperature in August will have a negative impact to canola crop yield. It could be because late July to beginning of August is the flowering time of canola. Our model shows that increasing rainfall during the month of July and August seems to increase canola yield. Specifically, our model estimates that a 1-mm increase in rainfall during the month of July will result in yield improvement of 1.2 kg of canola per ha.

3.2.2 Association between sociotechnical variables and canola crop yields

Our analysis found the number of farms which used digital and modern technology (such as farms that had access to high-speed internet, the acreage of areas used chemical fertilizer, percentage of area under fungicides), and the age

Table 3 Regression coefficients of the best-fit model for explaining the canola crop yield variability by climatic and sociotechnical variables in canola-producing region of Canada

Parameters	Coefficients	Coefficients std. error	Standardized coefficients beta	*t*	Sig
Constant	854.784	6.103		140.049	.000
Land capabilities (8 classes: 1 for highly suitable for agricultural activities and 8 is not suitable for agricultural activities)	−4.071	.161	−.055	−25.317	.000
Average temperature in June (°C)	23.389	1.095	.237	21.365	.000
Average temperature in July (°C)	−139.992	1.545	−1.695	−90.582	.000
Average temperature in August (°C)	134.451	1.502	1.682	89.535	.000
Minimum temperature in June (°C)	8.891	.550	.116	16.159	.000
Minimum temperature in July (°C)	5.190	.539	.080	9.635	.000
Minimum temperature in August (°C)	−19.742	.368	−.440	−53.636	.000
Maximum temperature in June (°C)	−4.488	.329	−.049	−13.648	.000
Maximum temperature in July (°C)	6.068	.459	.081	13.219	.000
Maximum temperature in August (°C)	−20.365	.459	−.303	−44.331	.000
Precipitation in June (mm)	−1.308	.016	−.293	−83.105	.000
Precipitation in July (mm)	1.227	.017	.247	74.139	.000
Precipitation in August (mm)	.208	.022	.032	9.513	.000
Application of chemical fertilizer (% of area used chemical fertilizer)	.271	.020	.043	13.467	.000
Application of fungicides (% of area used fungicides)	3.551	.036	.337	98.703	.000
Access to high-speed internet (% of farms)	.165	.002	.252	87.187	.000
Average age of the farm operators (years)	.389	.023	.037	17.158	.000

R Square .378 F = 5134.827 sig.000

of farm operators (that is assumed to be related to technology which were found to be highly significant ($p < 0.001$) as given in Table 3. Overall, our model produces intuitively obvious results as canola crop yield increases with increasing the access to high-speed internet, the amount of land under chemical fertilizer and the percentage of areas with the application of fungicide. It also indicated that canola crop yield has a positive association with the experience of farmers. However, sociotechnical variables are widely divergent in the strength of their predictive power. When comparing the absolute magnitude of each variable, large differences in the predictive power are observed because of the differences in the unit of measurement used. It is more prudent to compare these coefficients with the standardized beta coefficient as given in Table 3. Based on the standardized beta coefficients, we found that there are major differences between sub-categories of sociotechnical variables. Technological factors such as access to high-speed internet have greater predictive power than management practices such as fertilizer application.

4 Discussion

Overall, this paper makes a contribution to our understanding of the interaction between sociotechnical and environmental factors and how this interaction determines crop yield. Better understanding this interplay between social and environmental factors is necessary to help ensure global food security in the next generation. For instance, it is well known that we need to produce 70% more food by 2050 to ensure that we produce enough for the rising human population [12, 16]. Equally, it seems that agri-food systems are on the verge of a technological revolution and that the application of novel technologies to farming will be as significant in pushing yields as the Green Revolution was in the last century [32, 33]. How we meet the challenge of feeding the future by harnessing the potential of new technologies will require significant research on how social and technical factors interact. In particular, in this paper, we assessed the association between sociotechnical variables related to agricultural technology, climate variables, and canola yield in the prairie region of Canada. Through a regression modelling approach, we found that selected climate and sociotechnical variables explain approximately 38% of the variation in canola yield. In summary, through our modelling approach approximately 38% of variation in canola crop yield in the Canadian prairies could be attributed to a variety of climatic and sociotechnical variables.

The finding from our model was consistent with the past literature. The association between precipitation in the months of June, July and August and temperature with the canola yield was closely related to previous findings by Kutcher et al. [26]. Kutcher et al. [26] found that canola crops are most sensitive to high temperatures in late June to early July, as these are the months canola plants are flowering, which is consistent with the negative effect of the mean temperatures in July [26]. Furthermore, the positive effect of the increased precipitation in the month of July shows how precipitation may offset the negative effect of temperature on flowering canola, through transpiration [26]. Since our climatic model results are consistent with the literature, we postulate that there is an upper-bound limit in the predictive power of simple climatic models utilizing temperature and precipitation. As a result, the remaining variation in yield predictions may be best explained by other social, economic and cultural variables. With rapidly accelerating technological change, we argue one important and potentially overlooked variable could be sociotechnical.

Lastly, a considerable portion of the crop yields' distribution still was left unexplained despite the inclusion of climate and sociotechnical factors. Overall, the predictive power of our model may be improved by adding other variables that have been found to impact agricultural productivity, such as soil type and moisture [8, 18]. Additionally, clustering regions of the prairies via a climate sensitivity index, identifying areas of high and low sensitivity and then comparing how sociotechnical variables vary across these clusters may result in a more sensitive model. Determining the individual effect each sociotechnical variable has on crop yield using single linear regressions comparing model results may clarify contradictory relationships and each variable's individual influence on canola crop yield.

5 Conclusion

In summary, the use of digital technologies appears to have some impact on canola crop yields in the southern Canadian prairies. Combining temperature and precipitation during three-month period of canola growing season and four sociotechnical variables were able to explain about 38% of canola yield in the Canadian prairies. Our findings serve as a stepping stone to provide agricultural producers and policy makers with recommendations of which sociotechnical variables are most influential on canola crop yield.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interests.

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