Methodology Summary

Climate impacts on credit risk in agriculture: A tool for agricultural lenders to assess projected risks from a changing climate

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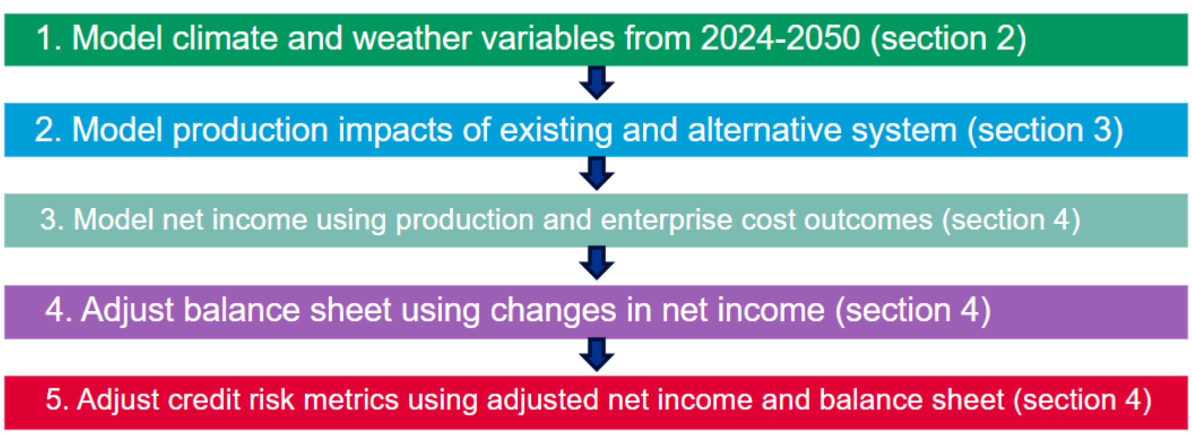
1. Methodology overview

Climate change poses business risks to farmers and lenders through warmer seasons, shifting rainfall patterns, and extreme heat. Agricultural lenders can help manage these risks by supporting investments in adaptation strategies such as transitioning to more climate-resilient crops and improving soil health.

The goal of this project was to help agricultural lending institutions (also referred to as ag lenders) in the U.S. Midwest and Canadian Prairies assess physical climate-related risks to their portfolio of row crop farming customers and compare the impacts of one potential climate change adaptation measure: alternative crop rotations. This assessment was completed by projecting changes in crop yields using the results of a trusted climate change model and biophysical crop models that predict crop yields from changes in weather or management. We then applied the changes in crop yields to crop budgets, whole farm budgets and credit risk metrics to model the financial and credit risk impacts from projected changes in the climate. Figure 1 below outlines these modelling steps. The results of the project will help agricultural lenders assess individual and portfolio-level risks from climate change and inform their strategies to support farmer customers in making investments that help them adapt to climate change.

Figure 1: Outline of our modelling approach



We've divided this paper into sections describing the climate, crop production and financial analysis datasets and methods used, with examples that should help readers understand the inputs to the web tool and the full dataset.

Maladaptation risk

It is important to avoid maladaptation when considering strategies to adapt to climate change. Maladaptation occurs when actions to adapt to changing conditions in the short-term backfire and make things worse in the long-term, such as temporary adaptive measures that could unintentionally increase farmers' vulnerability to additional climate risks in the future. For example, increasing groundwater consumption in a water-limited region to compensate for variable rainfall can accelerate the depletion of water resources and make farming of any kind more difficult in the long-run. Evaluating potential climate-related risks and identifying adaptation solutions will help agricultural lenders mitigate these risks and support their farmer customers' long-term success.

2. Climate modelling

According to the United Nations, climate change refers to the long-term shifts in temperature and weather patterns. Decades of scientific research have concluded that human activities that are emitting Greenhouse Gas Emissions (GHGs) into the atmosphere are causing the climate to change since the accumulation of GHGs in the atmosphere traps heat that would otherwise have left our atmosphere. This accumulation of GHGs in the atmosphere affects the temperature of our atmosphere, ocean water, and alters many biophysical systems on the planet. Climate change models use the best available earth and atmospheric science to project how changes in GHG concentrations in the atmosphere will change the climate and weather in the future. In the case of agriculture, climate model results can be applied to crop yield models to evaluate how changes in projected future climate conditions will affect crop yields. The CESM2 model described below generated the foundational climate change inputs that we used to evaluate climate change impacts on crop production and farm financial and credit risk performance.

Our modelling approach spans 2024-2050. 2050 was selected as the end of the time horizon since the project's agricultural finance institution advisors specified that later projections are less relevant to their business model and farmer relationships.

2.1 The CESM2 model

We used the CESM2 climate change model to project the climate and weather conditions through 2050. CESM2 is the newest iteration of the Community Earth System Model (CESM), an open-source, comprehensive model used in simulations of the Earth's historical, present, and future climates. It works at a 1-degree spatial resolution and covers the period 1850-2100 under CMIP6 historical and SSP3-7.0 future radiative forcing scenarios. The SSP3-7.0 scenario assumes a world that increases in nationalism and regional economic conflict that prevents comprehensive climate action.[1] This scenario is meant to be a "middle of the road" scenario between the worst case and more optimistic scenarios. As Danabasoglu et al., (2020) detail, CESM2 uses a combination of different oceanic and atmospheric initial states than those in CESM1, creating ensemble spreads that have several new technical and scientific capabilities; including a more realistic representation of Greenland's ice sheet, improved representation of clouds and rain, and the addition of wind-driven waves on the model's ocean surface, among others. Outputs of the CESM models are widely used in climate and land use research, including the CMIP6 model intercomparison project.

2.2 How we used the CESM2 data

For our research, we used 50 members (referred to as SMBB) of the Large Ensemble (LENS2) CESM2 Community Project. Model ensembles allow researchers to combine different models — or in this case, forms of the CESM2 model — to assess the certainty in model projections of future climate. The 50-member SMBB we used here combines different oceanic and atmospheric initial states to create an ensemble. While the CESM2 model provides simulations for the 2016-2100 period, we kept the observations through 2050 to match the overall project's time horizon of interest.

Each CESM-LENS2 member provides bias-corrected observations for daily precipitation (mm), solar radiation (MJ/m^2-day), maximum and minimum temperatures (°C) at the native resolution of 1°. For an example of peer-reviewed work using this approach for crop modeling studies, see Glotter and Elliott (2016).

3. Crop yield modelling

The primary impact of climate change on farm financial performance is through weather impacts on crop production. Changes in temperatures, precipitation, growing season length and many other environmental variables affect how well crops grow and the final crop yield of a farm. We modelled the impacts of climate change on future crop yields using two scenarios. The first scenario, called "current system", uses the Decision Support System for Agrotechnology Transfer (DSSAT) model to simulate crop yields under future climate conditions for corn, soybean, sorghum, canola, spring wheat and pea crops grown under typical current management practices and technologies (including seed varieties). The "current system" scenario is used as the basic scenario throughout the web tool. The second scenario, called "current system plus historical yield trend", utilized official historical crop yield data from the regions of interest to generate a scenario where projected future yields under the "current system" were adjusted for recent (2014-2023) yield trends. The objective of the "current system" scenario was to help assess how

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[1] Riahi, Keywan; van Vuuren, Detlef P.; Kriegler, Elmar; Edmonds, Jae; O'Neill, Brian C.; Fujimori, Shinichiro; Bauer, Nico; Calvin, Katherine; Dellink, Rob; Fricko, Oliver; Lutz, Wolfgang (2017-01-01). "The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview". *Global Environmental Change*. **42**: 153–168.

current systems will perform given expected changes to climate, while the “current system plus historical yield trend” scenario aims to incorporate recent yield increase rates, where they are detected, to the simulations of the “current system” to create a future scenario where current rates are sustained through 2050. A more detailed description of each approach is provided below.

The crop yield step of our model generates a mean yield for each permutation of county/census division, crop, and year for both yield scenarios. These yields are also averaged across the 50 ensembles, or iterations, of the CESM LENS2 model for each permutation. While this averaging is important to represent the 50 iterations of the model, it smooths out the projections. In reality, yields will likely vary significantly between years (as it has in the past) while following the trend that the averaged results demonstrate.

Given the additional complexities in modeling and quantifying the economics of irrigation over large areas for several crops, simulations were only generated for rainfed crops.

3.1 Simulating current cropping systems with DSSAT

Biophysical crop simulation models are quantitative representations of how a crop grows when exposed to environmental and management conditions, using insights from agronomy and plant physiology. DSSAT simulates the growth and development of a crop as it responds to specific management practices and to the changes in weather, soil, water, carbon, and nitrogen that take place under the cropping system over time (Jones et al., 2003). In use since the 1980’s, DSSAT is one of the most widely used crop models, able to simulate over 42 crops. DSSAT has been used for a wide range of topics from impacts of changing single-genes on crop performance, to on-farm precision management and in regional assessments of impacts of climate change on agriculture (for more see here).

We used the parallel System for Integrating Impacts Models and Sectors (pSIMS) framework to apply the CESM-LENS2 climate model outputs to the DSSAT biophysical crop model. The pSIMS framework allows for efficient implementation of large-scale assessments of climate vulnerabilities, impacts, and adaptations across multiple sectors and at unprecedented scales (Elliott et al., 2014). The pSIMS framework has been used extensively with DSSAT (named pDSSAT in the literature) to study climate change and global food security, for crops such as corn, wheat, rice and soybean (e.g. Jagermeyr et al., 2020).

3.2 DSSAT inputs and parameters

The following inputs were used to simulate the production of the selected crops (corn, soybeans, sorghum, canola, spring wheat and peas):

• **Climate data:** CESM LENS2 data described in the Climate Data Modelling section was applied to the DSSAT model to evaluate crop production under future climate and weather conditions.

• **Soil data:** the Global Soil Dataset for use in Earth System Models (GSDE) provides soil information such as soil particle-size distribution, organic carbon, and nutrients. It provides quality control information in terms of confidence level at a 30'' grid for eight vertical layers to a depth of 7.5 ft (2.3 m). The GSDE is based on the Soil Map of the World and various regional and national soil databases, including soil attribute data and soil maps (Shangguan et al., 2014).

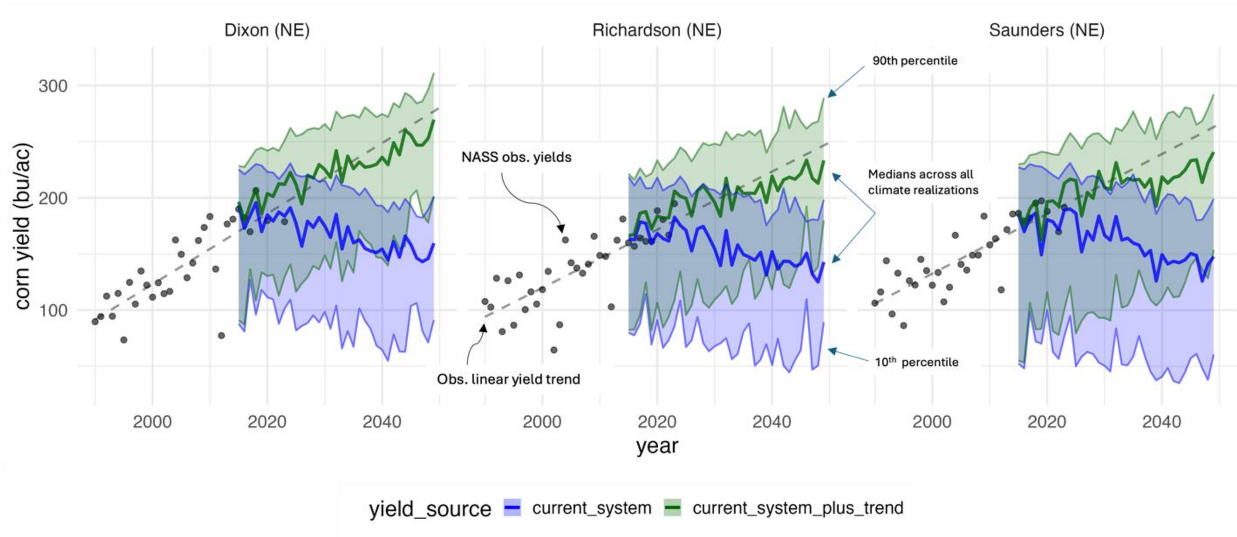
• **Crop inputs:** Sowing dates and densities, nitrogen fertilization levels, and cultivars simulated in the DSSAT model were derived from a range of sources including extension and trade publications, and peer-reviewed modeling studies (full list available upon request). Overall, sowing dates were chosen to reflect the ranges of sowing dates and densities for each crop in their respective region, while N-fertilization was set to cover usual ranges used under non-limiting conditions.

3.3 Crop yield scenarios

For all crops in the study, reported yield data from recent history (2000-2023) were used to ensure that simulations were capturing yield dynamics correctly. County-level USDA National Agricultural Statistics Service (USDA-NASS) accessed via the tidyUSDA R package were used for corn, soybean and sorghum. StatsCan Small Area Data Region yields were used for Canadian canola, spring wheat and pea yields at the level of Census Divisions. All yield data was represented in bushels per acre, using 56 lb (corn, sorghum) or 60 lb bushel weights (soybean, canola, wheat, peas).

The "current system plus historical yield trend" scenario was created by extracting linear trends from recent historical yield time series in each crop and area (U.S. county and Canadian Census Division). We used the following algorithm to extract trends: fit a simple linear regression to each geography (counties in the US or small area data regions in Canada) that had at least 8 years of yield data, with observed official yields as the response variable and year as the explanatory variable. If the year coefficient was significant at the $P < 0.1$ level, the yearly bushel per acre increase expected with each year was added to the DSSAT simulated "current system" scenario yields in each year through 2050, to estimate the impact of observing the current yield improvement trends through the study horizon. In cases where yield data was absent, or a negative or non-significant yield trend was detected, no yearly increase was added to the DSSAT simulation results. Figure 2 below shows the historical yield data, "current system" scenario results, and "current system plus historical trend" scenario results for three Nebraska counties.

Figure 2: Examples of yield scenarios



4. Farm financial and credit risk modelling

The impacts of changing climate and weather conditions on crop yields described in the previous section ultimately affect a farm's revenue, net returns and over time can impact their credit risk. The final stage of our modelling projects the financial and credit risk performance of farms based on the projected changes in crop yields through 2050. It is critical to understand that costs of crop production, net returns, and farm-level financial factors, such as income sources and land tenure, vary widely among producers and regions, making it impossible to effectively model every permutation of farm characteristics and financial performance. These factors are also estimated differently by government agencies and non-government researchers, which adds to the difficulty in conducting broad-scale economic analyses of this sort. Given these caveats, we sought to use the most complete, well-documented, consistent and granular sets of public data to evaluate the impacts of climate change on farm financial and credit risk performance. The sources and approaches used are described in the subsections below. We used U.S. county-level data when possible and Census Division (or equivalent) level in Canada.

4.1 Overall approach to financial and credit risk modelling

We modelled the financial and credit risk performance of farms under changing climate and crop yield outcomes by generating farm economic scenarios and crop rotation scenarios that were applied to artificially created "farms" with different locations, farm sizes, and current day credit risk. Projected farm financial performance and credit risk results were generated for each combination of scenarios and farm characteristics.

Farm financial performance was evaluated through total farm revenue and total farm net returns. Debt-to-asset ratio was used as a proxy measure of credit risk. It is one of the metrics used in agricultural lending institutions' risk models.

We began by generating crop enterprise budgets for each crop and region (described further in section 4.2) using publicly available information on costs of production and crop prices received. These crop enterprise budgets played the role of translating changes in crop yield into per acre changes in gross revenue and net returns.

We then generated coarse categories of farm size in each state and province, based on recent data from the US Midwest and Canadian Prairies. The goal was to generate acreage ranges in each area of interest that reflect recent trends in average farm size. The farm sizes were used to turn per acre gross revenue and net return figures to total farm gross revenue and net returns.

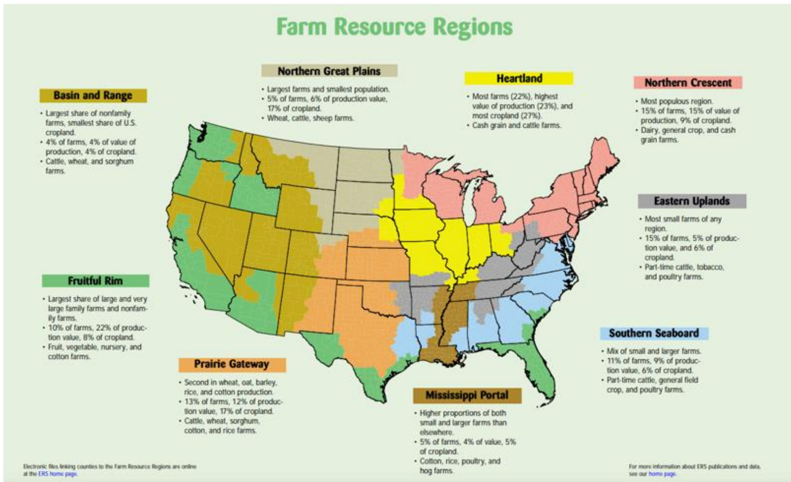
The total farm financial outcomes were modelled for the conventional rotations including a 50/50 corn-soybeans acreage split in the U.S. states and 50/50 canola-wheat acreage split in Canadian provinces. They were also modelled for the climate adaptation rotations including a 25/50/25 corn-soybean-sorghum acreage split in the U.S. states and an equal canola-wheat-pea acreage split in Canadian provinces.

The final step to turn farm financial performance into credit risk metrics included generating farm balance sheets that could be stressed by annual total farm net returns. We used publicly available farm financial balance sheet data to generate low-, medium-, and high-credit risk farm categories for each state and province. Total farm net return results from the previous step were added to the assets on the farm balance sheet while debt was held constant. Debt-to-asset ratio, an important credit risk metric for agricultural lending institutions, was derived from the farm balance sheet and adjusted as net returns change the total assets of the farm. The changes in debt-to-asset ratio were derived for each starting credit risk profile, farm size, crop rotation, county, and economic scenario combination. The following sections describe the data inputs, assumptions and methodology in further detail.

4.2 Cost of production, prices received and balance sheet data.

For the U.S., crop cost of production and returns data were obtained from the USDA's Economic Research Service, which provides detailed data by Farm Resource Regions (Figure 3).

Figure 3: USDA Farm Resource Regions for ERS data

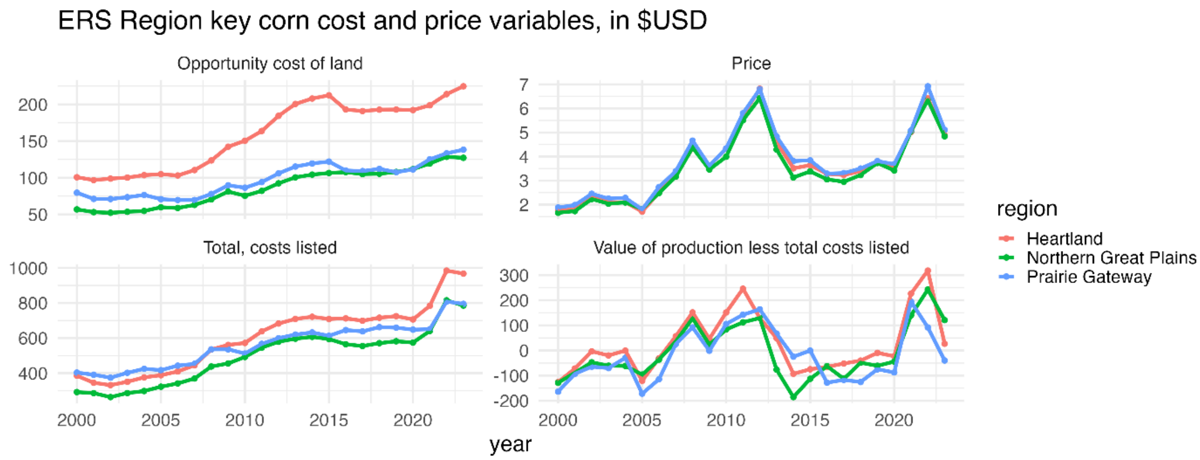


Source: *Farm Resource Regions*

Counties across Iowa, Nebraska and South Dakota span the Heartland, Prairie Gateway and Northern Great Plains ERS Farm Resource Regions. While significant variability exists within Farm Resource Regions, the cost of production was consistent with other similar, more detailed sources, such as the University of Nebraska Extension. To provide more granularity, land-rent and tenure costs from ERS budgets were adjusted using county-level rental costs obtained from USDA National Agricultural Statistics Service (USDA-NASS). Using the ERS "opportunity cost of land" variable as a baseline, we estimated county-level deviations from the ERS-defined land cost. Average rental rates within each state and ERS region were calculated using the USDA-NASS cropland rental rates. The county-level deviations from these calculated averages were then applied to the ERS baseline for each region and state. USDA-NASS data was also used to provide state-level average yearly prices received.

Figure 4 shows key metrics from the ERS dataset for the ERS regions of interest, including the opportunity cost of land, total costs listed and commodity price for corn. The value of production less total costs listed is also presented, illustrating that in most years the value received for corn production is less than the total costs.

Figure 4: ERS region key corn cost and price data



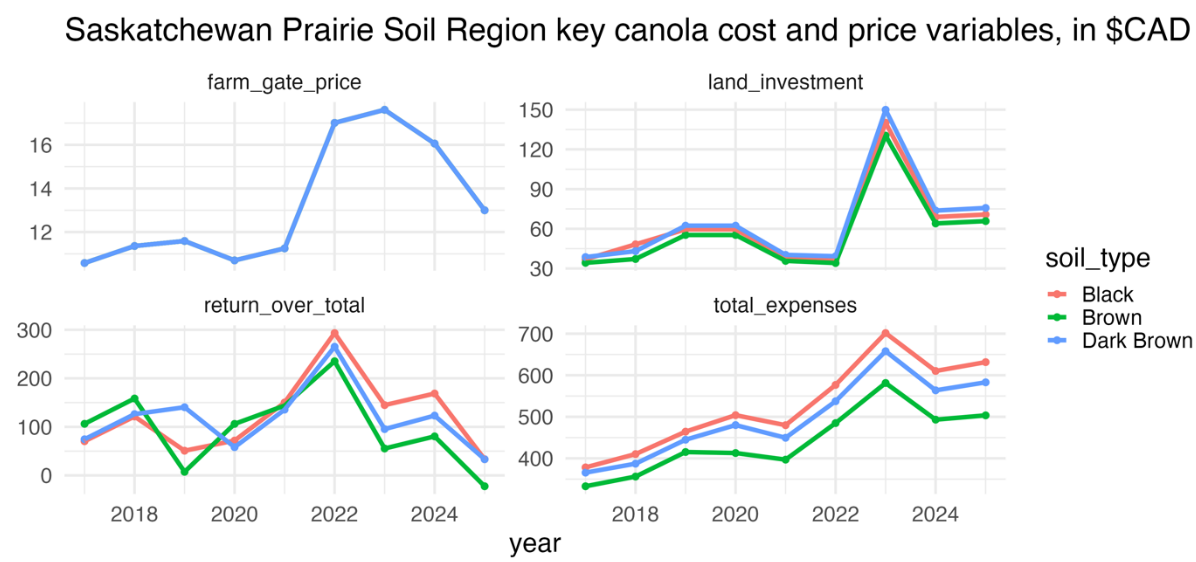
Farm-level balance sheet data was obtained from the University of Minnesota's FINBIN database, which provides financial benchmark data for producers and researchers from real farms. From this resource, we were able to query total asset, debt and debt-to-asset ratios of the 20th, 50th, and 70th percentiles of producers reporting in the states of interest, for different farm sizes. These percentiles were chosen to represent low, medium, and high starting credit risk profiles for the example farms. Users of the web tool can download the dataset and update these inputs based on their own criteria. The table below has the final values used for Nebraska, as a sample.

Table 1: Sample balance sheet figures for Nebraska

state	farm size (category)	area (ac)	risk_profile	total_assets (USD)	total_debt (USD)	debt-to-asset ratio
Nebraska	sizeSmall	1000	riskHigh	1,291,253	710,189	0.55
			riskLow	4,188,128	586,338	0.14
			riskMedium	3,084,599	740,304	0.24
	sizeMedium	2000	riskHigh	3,020,921	1,691,716	0.56
			riskLow	6,548,113	1,440,585	0.22
			riskMedium	5,741,173	1,607,528	0.28
	sizeLarge	4000	riskHigh	5,260,686	2,156,881	0.41
			riskLow	12,658,693	1,898,804	0.15
			riskMedium	9,934,260	1,986,852	0.20

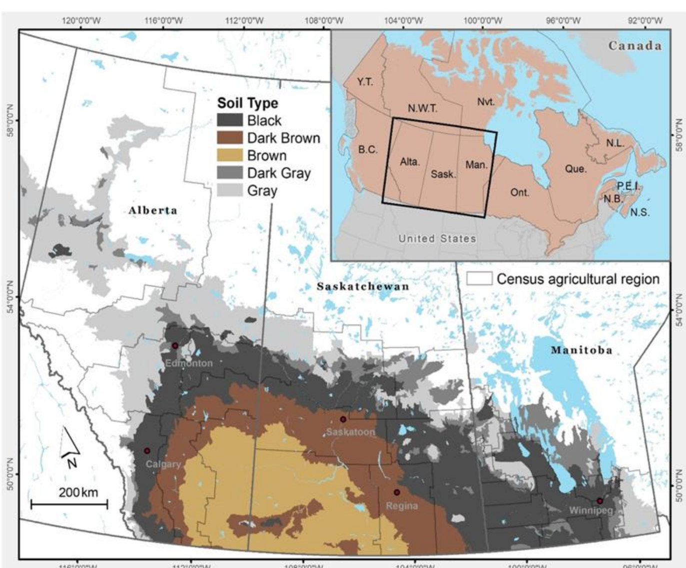
In Canada, crop cost of production was obtained from the Saskatchewan Government's Crop Planning Guide and Crop Planner (see sample of that date in Figure 5 below). Besides being a single, consistent data set that held data for all crops of interest, it provided crop budgets for the three major Canadian Prairie Soil Types (Brown, Dark Brown and Black) (Figure 6 below).

Figure 5: Key canola prices and production costs by soil type



Source: Saskatchewan Government's Crop Planning Guide and Crop Planner

Figure 6: Canadian soil type map



Source: Canadian Prairie Soil Types

We took the prices from the Saskatchewan Crop Planning guide and Crop Planner to represent those of the soil types in Alberta since these soil types dominate agricultural areas of the remaining Prairie provinces. In a few minor areas, soils classified as Gray within our Census Divisions of interest were applied the budgets for the Black soil types, which are adjacent to the Gray soil types in each Province. Crop prices received data was obtained from StatsCan.

Farm-level balance sheet data for Canada was obtained from StatsCan's Farm financial survey. We used the average values reported in the Farm financial survey, and inputs from experts to set limits that matched reasonable risk categories to generate similar risk scenarios to those generated for the U.S. The table below shows the final values used for Saskatchewan as an example. A full table with values for all provinces is available for download.

Table 2: Sample balance sheet variables in Saskatchewan

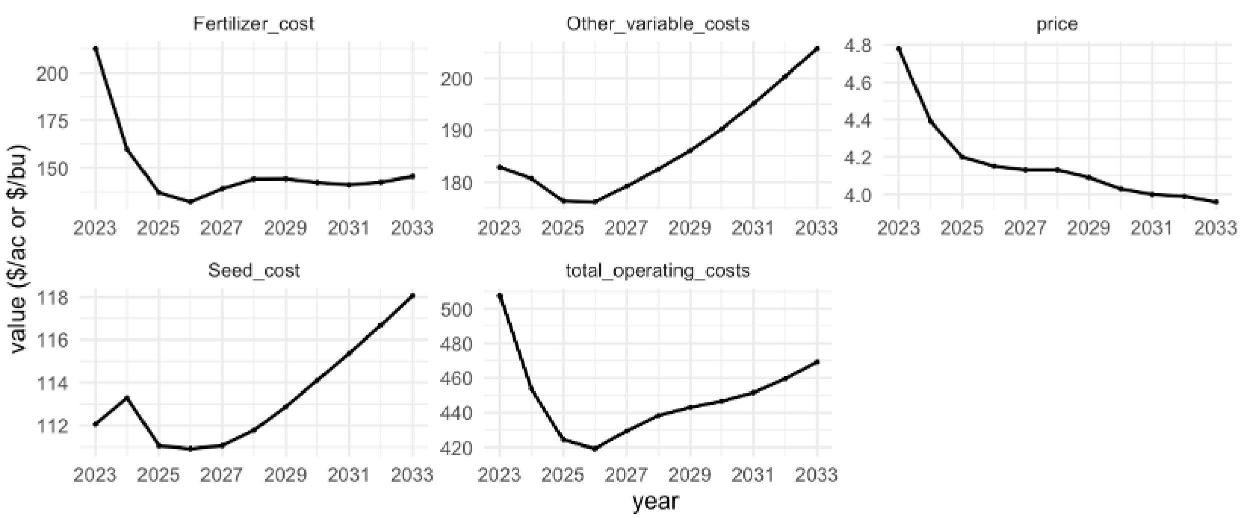
province	farm size (category)	area (ac)	risk_profile	total_assets (CAD)	total_debt (CAD)	debt-to-asset ratio
Saskatchewan	sizeSmall	700	riskLow	1,931,672	328,881	0.17
			riskMedium	1,931,672	822,204	0.43
			riskHigh	1,931,672	1,052,421	0.54
	sizeMedium	1400	riskLow	3,863,344	657,763	0.17
			riskMedium	3,863,344	1,644,407	0.43
			riskHigh	3,863,344	2,104,841	0.54
	sizeLarge	2800	riskLow	7,726,688	1,315,526	0.17
			riskMedium	7,726,688	3,288,814	0.43
			riskHigh	7,726,688	4,209,682	0.54

All cost of production, budgets and financial figures used were corrected for inflation, set to 2023 values for both USD and CAN.

4.3 Farm profitability scenarios.

Large between-year, and between-farmer variability exists in enterprise and farm-level costs, as well as in prices received and in access to government support. Consequently, setting single cost, price received, and government economic support levels is challenging. Using the cost and price received sources described above, we first adjusted all costs and prices for inflation to reflect 2023 dollars. We then obtained the 20th, 50th (median) and 70th percentiles of the distributions of the costs and prices since 2013, and combined them to create the following profitability scenarios: *medium profitability*, which combined the cost and price medians, representing our "average scenario". The *low profitability* scenario combined high costs of production (70th percentile), and low prices received (20th percentile), while the *high profitability* scenario combined low costs of production (20th percentile) with high prices received (70th percentile). We generated an additional "*realistic future"* scenario for the U.S. that applies the University of Missouri's Food and Agriculture Policy Research Institute's (FAPRI) 2024 U.S. Agricultural Market Outlook Report economic scenario. The report provides median expected changes in crop variable costs of production and prices received through the 2033-2034 season. We included FAPRI's projections to represent a dynamic economic projection that represents an agricultural economy with changing costs and prices over time. This differs from our other scenarios that keep costs of production and crop prices static over time. To incorporate expected median changes in costs and commodity prices, we calculated the yearly percent change in each variable compared to the 2023 baseline provided, and applied it to our own variable costs and prices received through 2034. For the period between 2035 and 2050, the values were kept at 2034 levels. Figure 7 below presents a sample of the data for corn.

Figure 5: Costs of production and prices received for U.S. corn according to FAPRI 2024 projections



The web tool is built around the *medium profitability* scenario, but data for the remaining scenarios is available to download. Table 3 below shows the *high, medium, and low profitability* scenarios for US corn. Profitability scenarios for all other crops are also available for download.

Table 3: Profitability scenarios for US corn

ERS_region_name	profitability_scenario	total_cost (USD/ac)	price_received (USD/bu)
Heartland	high	557	4.1
Heartland	low	630	2.7
Heartland	medium	594	3.4
Northern Great Plains	high	452	4.1
Northern Great Plains	low	505	2.8
Northern Great Plains	medium	479	3.4
Prairie Gateway	high	510	4.1
Prairie Gateway	low	567	2.8
Prairie Gateway	medium	539	3.4

4.4 Critical assumptions.

As described before in section 4.3 for costs of production and crop prices, to generalize our work across varied geographies and cropping systems, our team made a series of assumptions to perform the farm-level financial modeling.

Crops farmed: In each area of interest, we modeled the predominant row-crop systems currently in use, namely corn-soybean in the U.S. Midwest, and canola-wheat in the Canadian Prairies. We also included an additional crop in each region that could provide production and financial resilience under future climate conditions, based on existing literature: grain sorghum in the U.S. and field pea in Canada. While many other crops could have been chosen as an alternative additional crop to include in typical rotations, the crops chosen met two key criteria deemed important: they are already grown in each region of interest, which means there are already well developed management and technological practices developed for their production, and the necessary agronomic and economic data necessary for us to incorporate them in the study exists. They are also crops that work well together, creating benefits for the soils and main cash crops grown in the regions already. For an example for pea benefits in Canada, see Gill (2018), and for sorghum in the U.S., see Sindelar et al. (2016).

Land rent costs: We followed the approach taken by the ERS to generate the Commodity and Returns dataset used, which sets land values in cost-of-production accounts at its rental value. This represents either the actual rent paid by producers who lease land or the opportunity cost for those who own it. Using the opportunity cost of land variable in the ERS dataset, we identified crop-specific land costs in the U.S. and further tailored these estimates to each county as described in section 4.2. In Canada, we utilized the land rental rates provided in the budget, which were different for each Prairie Soil type.

Insurance payments: While insurance payment vary by geography, crop and farmer risk appetite, we set a basic payment calculated using a five-year rolling yield mean, triggered at 85% of the five-year mean. In other words, the insurance payment equates to adding the difference in bushels between modeled and the 5-year average yields, when yields fall below 85%. This approach allowed us to add a proxy to the Yield Protection product offered by USDA's Risk Management Agency. We applied this payment for all farm types, crops, profitability and risk scenarios in both countries.

Off-farm income: Off-farm income, including revenue from jobs off the farm, was not included in the customers' revenue. While off-farm income and other government payments are critical farm economic components, estimating baseline values that could be incorporated was outside of the scope of the study. Hence, all changes in revenue are solely due to changes in crop sales and insurance payments, if triggered.

Total debt and interest rates: For simplicity, we assumed total debt remained constant, and that interest rates remained stable. Rates in Canada were set at 6.25%, and those in the US at 6.75%.

Changes in assets: We assume that changes in total assets are solely driven by changes in net income. In years with negative net income, total assets are assumed to decrease accordingly.

4.5 Farm financial modeling approach.

With set typical costs of production, prices received and farm financial metrics, and defined profitability and risk scenarios, we calculate farm financial performance over time based on future climate-driven yield changes. Using the baseline data for 2023, we perform the following operations sequentially for each geography × farm size × crop × yield scenario × profitability scenario (only a portion of these scenarios are shown in the web tool while the others are included in the full dataset):

1) Calculate revenue per acre, by multiplying the prices received ($/bu) by the modeled yield (bu/ac). Revenue was calculated with and without an estimated insurance payment.

2) Operating income per acre was calculated by subtracting total costs of production and land rental cost per acre from the revenue per acre calculated in step 1.

3) Net income per acre was calculated by subtracting interest payments on debt from operating income. Interest payments per acre were estimated by multiplying the total debt by the prevailing interest rate and then dividing by the farm size. Net income per farm was then calculated by summing the net income per acre for each crop, weighted by its respective acreage on the farm.

4) Total assets were then calculated each year from 2024, using the prior year's total assets plus the current year's net income (which are often negative).

5) The debt-to-asset ratio was then calculated by dividing the total debt by the total assets, assuming that the debt level remains constant over the projection period.

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