Carbon footprint analysis of Saskatchewan and Canadian field crops and comparison to international competitors

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N_2O – Nitrous oxide

GHG – Greenhouse gas

LCA – Life cycle assessment

ISO – International Organization for Standardization

GIFS – Global Institute for Food Security

U. S. – United States

LCI – Life cycle inventory

CRSC – Canadian Roundtable for Sustainable Crops

N – Nitrogen

IPCC – Intergovernmental Panel on Climate Change

NIR – National Inventory report

CSIRO – Commonwealth Scientific and Industrial Research Organization

EFs – Emissions factors

CALDC – Canadian Agrifood Life-Cycle Data Centre

CO_2 – Carbon dioxide

DM – dry matter

P – Phosphorous

K – Potassium

S – Sulfur

NASS – National Agricultural Statistics Service

RU – Reconciliation unit

C – Carbon

1. Introduction

The production of commodity field crops, including non-durum wheat, canola, and field peas, makes a large contribution to the Canadian agricultural economy (Agriculture and Agri-Food Canada, 2022a). Beginning in 2019, the COVID-19 pandemic caused major disruptions throughout many global agricultural supply chains (Arita et al., 2022; Brewin, 2021; Malone et al., 2021). These challenges were further exacerbated by drought and other extreme weather events occurring throughout Canada, particularly in 2021 (Statistics Canada, 2021a). Nonetheless, production of principal field crops continues to be a significant economic driver for the Canadian agriculture and agri-food sector (Government of Canada, 2022).

A large portion of field crops produced in Canada are exported to international markets, making Canada a major contributor to international commodity field crop markets (LMC International, 2020; Pulse Canada, 2021; Statistics Canada, 2022a) (LMC International, 2020; Pulse Canada, 2021; Statistics Canada, 2022a). Within Canada, much of the production of these crops is concentrated in the Prairie provinces (Government of Canada, 2022) and, in particular, the province of Saskatchewan (Agriculture and Agri-Food Canada, 2022b).

On a global scale, international commodity crop markets are increasingly conditioned by evolving expectations and requirements regarding sustainability attributes (see, for example, Mazzocchi et al., 2021; Okpiaifo et al., 2020; Tobi et al., 2019, etc.). This trend is being driven by increasing consumer awareness of, and preference for, sustainably sourced food products (Noor et al., 2022; Xie et al., 2021; Yadav et al., 2022). As this trend continues, it will become increasingly valuable for agri-food producers to develop an in-depth understanding of the environmental impacts of and mitigation opportunities for the products they produce, potential priority areas along supply chains to target for sustainability improvement efforts, and how their environmental impacts compare to those of their competitors.

In the context of international field crop markets, there is the potential for large differences in environmental impacts per unit of crops produced in different regions throughout the world. These differences may be driven by a number of factors, including regional differences in soil, climate, and management practices (Abdalla et al., 2016; Kajsa et al., 2019). Field-level nitrous oxide (N_2O) emissions (a major source of greenhouse gasses (GHGs) in agriculture), for example, may be impacted by the type and application method for nitrogenous fertilizers, soil water content, nitrogen availability in soils (Van Zandvoort et al., 2017), as well as other management and climate conditions (Hassan et al., 2022; Kuang et al., 2021). These differences may be even more pronounced when considering “life cycle” (i.e., supply chain) impacts occurring upstream of farm-level production processes. Regional differences in field-level fertilizer-use efficiency (Q. Liu et al., 2021), for example, may be compounded by regional differences in the impacts characteristic of fertilizer production (Gong et al., 2022; Kakanis, 2021; Ouikhalfan et al., 2022).

To support rigorous assessment of, and differentiation between, the environmental impacts of internationally traded crop products, it is necessary to use life cycle thinking-based assessment tools (Pelletier, 2015). Such tools allow for transparent and reproducible assessment of the cumulative resource demands and environmental burdens associated with the complete supply chain of a product or service. Among such tools, life cycle assessment (LCA) is the most widely utilized. It has already been applied to a number of agri-food production systems both within Canada (Bamber et al., 2022; Dias et al., 2017; Pelletier, 2017; Turner et al., 2022, etc.) and internationally (Hietala et al., 2021; Masuda, 2016; Pelletier et al., 2014; Schmidt Rivera et al., 2017, etc.). Use of LCA and derivative methods is supported by internationally accepted, standardized methodological reference norms, including the ISO14040 and 14044 series for LCA (ISO, 2006a, 2006b), and ISO14067 (ISO, 2018) for carbon footprinting.

Currently, it is estimated that one third of total anthropogenic GHG emissions are attributable to food systems (Crippa et al., 2021). Within Canada, the agricultural sector is responsible for 8% of total direct GHG emissions and a much larger share of "life cycle" (i.e. supply chain) emissions. Direct agricultural emissions in Canada have increased 26% over the past thirty years (Flemming et al., 2021). Identification of key drivers of GHG emissions within Canadian agriculture, and comparison of emissions with those of products from international competitor countries are therefore vital to: (a) developing an in-depth understanding of the sustainability challenges facing the Canadian field crop sector, along with areas for improvement; and (b) potential opportunities or liabilities with respect to competing on the basis of sustainability attributes.

On this basis, the Government of Saskatchewan and the Global Institute for Food Security (GIFS) commissioned a study to enable comparing the carbon footprints of three key crops grown in Saskatchewan and other Canadian provinces (canola, non-durum wheat, and dry field peas) to those same crops grown by a subset of international competitors (Australia, France, Germany, and the United States) on a rigorous, transparent, and methodologically consistent basis. The results of this study will be used to support sustainability policy initiatives in both domestic and international contexts. The current document reports the methods for and results of this study.

2. Methods

Development of carbon footprint models for the crop-region combinations of interest followed a staged approach. In brief, stage 1 comprised a data mining and quality assessment exercise to identify sufficiently credible/rigorous data to support model development, and to select among available data sources. The outcome of stage 1 was a report describing the methods, data sources, and results of the data quality assessment and selection process. This report was subsequently shared with the Government of Saskatchewan and GIFS (stage 2) for consultation prior to proceeding to the modelling stage. Finally, in stage 3, carbon footprint models were developed for each of the crop-region combinations, and comparisons made between the GHG emissions associated with each.

2.1 Crop-region combinations included

In total, 16 crop country combinations were proposed by the study commissioners for inclusion in this analysis (table 1). Specifically, this included canola, non-durum wheat, and field peas grown in Saskatchewan, Canada (average including Saskatchewan), Australia, France, Germany, and the U.S. These combinations were selected by the Government of Saskatchewan because they represent priority field crops (i.e., on the basis of value and volume) for comparison with international competitors. In 2020, Canada was the largest producer of each of these three crops across all of the regions considered except for non-durum wheat production, of which the U.S. produced the most (table 2). Estimates of non-durum wheat production are not available for France and Germany as neither data provided by FAOstat (2021) nor made available through each countries' respective national statistical offices (Destatis, 2022; INSEE, 2022) separate estimates of durum- and non-durum wheat production. However, Groth et al. (2020) indicate that production of durum wheat in Germany is limited and that approximately 80% of durum wheat in Germany is imported. Similarly, 5 year average data from 2012-

2016 indicate that durum wheat production in France averages approximately 1.91 million tonnes, representing about 5% of wheat produced in France during the same time period (FAOstat, 2021; FranceAgriMer and Arvalis, 2017).

An additional differentiation of importance is between spring and winter wheat. Spring and winter wheat differ in terms of when seeds are sown and grain is harvested. Spring wheat is sown in spring, and grain is harvested in the fall, whereas winter wheat seeds are sown in the fall and grain is harvested in the subsequent spring/summer. In Canada, the majority of non-durum wheat produced (i.e., ~90%) is spring wheat (Statistics Canada, 2022b). In Australia, the majority of wheat produced is also spring wheat, although there is increasing interest in production of winter wheat due to the rising frequency of drought conditions in the fall in Australia (Cann et al., 2019; Shackley et al., 2022). In contrast, spring wheat represents only ~25% of U.S. wheat production (USDA, 2022a), and the majority of wheat grown in Germany and France is also winter wheat (Canal et al., 2017; Macholdt and Honermeier, 2017).

Table 1. Crop-region combinations included in this analysis. Green fill represents combinations included, while grey fill represents crop-region combinations excluded.

	Canola	Non-Durum wheat	Dry field peas
Saskatchewan			
Canada			
Australia			
France			
Germany			
U.S.			

Table 2. Production estimates for each crop in the regions included in this analysis. Recent estimates of non-durum wheat production are not available for France or Germany.

	Production (tonnes)		
	Canola	Non-Durum wheat	Field peas
Saskatchewan	10,025,036[a]	9,881,930[a]	1,903,690[a]
Canada	18,595,379[a]	26,185,750[a]	3,651,020[a]
Australia	3525412[b]	23,352,042[b]	/[c]
France	3,918,400[d]	34,050,960[e]	612,000[d]
Germany	3,565,800[d]	21,755,200[e]	273,400[d]
U.S.	/[c]	46,994,164[f]	720,005[f]

[a] 5 year average (2018-2022) as reported by Statistics Canada, table 32-10-0359-01 (Statistics Canada, 2022)

[b] 5 year average (2017-2021) as reported the Australian Bureau of Statistics (ABARES, 2022)

[c] Crop-region combination not included in this analysis

[d] 5 year average (2018-2022) as reported by EU Oilseed and Protein Crops (European Commission, 2022a)

[e] 5 year average (2018-2022) as reported by Eurostat (European Commission, 2022b)
[f] 5 year averagefrom (2018-2022) as reported by USDA NASS (USDA-NASS, 2022)

2.2 Identification of potential data sources

Calculation and comparison of carbon footprints across the crop-region combinations required the identification and compilation of data of sufficient quality to characterize crop management practices, soil/climate conditions, inputs, emissions and yields in each region. Specifically, data from the following categories are required for inclusion in all crop-region models:

- Yield
- Seed inputs
- Nutrient inputs/soil amendments including lime, manure, N fertilizers, P fertilizers, K fertilizers, and S fertilizers
- Pesticide inputs including herbicides, fungicides, and insecticides
- Energy use for irrigation
- Energy use for field activities
- Transportation of field inputs
- Post-harvest energy use
- Field level fluxes including direct and indirect N_2O emissions from N inputs, CO_2 emissions from lime and urea, and soil carbon changes from land use or management changes.

The following data points were excluded due to lack of relevance to the carbon footprints of field crop production:

- Infrastructure is excluded due to trivial contributions to GHG emissions when taken over the lifespan of the infrastructure
- Field level methane emissions from application of manure to agricultural fields are excluded, as field level emissions are negligible (Uddin et al., 2020), and calculation of them is not included in the IPCC methods (IPCC, 2019).

Such data may be derived from various sources that differ in their scope, coverage, and quality. Potential sources include publicly-available and commercial life cycle inventory (LCI) databases, other publicly available databases such as those provided by national and international statistics agencies, peer-reviewed scientific literature, and reputable grey literature sources produced by governments and industry groups. Sources were only included if they presented quantitative values for the inventory data. They were excluded if they presented the sources of the inventory data without including the values.

All of the countries of interest have developed country-specific, publicly available LCI databases (Figl and Kusche, 2021; Fritter, 2020; Grant, 2016; Koch and Salou, 2016; USDA-National Agricultural Library, 2014), which provide varying degrees of sectoral coverage. In addition to these country-specific databases, Moreno Ruiz et al. (2021) and van Paassen et al. (2019) were also searched. Each of these databases were first searched to determine if they included complete LCI datasets representative of each crop-region combination. To be considered, data sets had to be available as unit process data sets, rather than aggregated system process data sets. System process data sets were excluded because they represent the complete inventory of elementary flows associated with the supply chains of products, rather than as a set of linked processes with product flow inputs and outputs. Because of this, no individual LCI data points can be sourced, no modifications can be made to the data sets (i.e., changing electricity grid mixes to more appropriate mixes, etc.), and all granularity is lost with respect to the contributions to GHG emissions arising from the different life cycle stages of crop production.

Searches of peer reviewed scientific literature were also performed to identify possible sources that may provide data of higher quality. All fields searches in the Web of Science database were used with the keywords “life cycle assessment” OR “life cycle inventory” OR “life cycle analysis” OR “carbon footprint” OR LCA OR LCI in combination with terms representing each region-crop pairing. Region terms were used that represented both the name of the region itself, as well as the nationality attributable to that region (i.e., Canada OR Canadian, France OR French, etc.), except for searches using the term Saskatchewan. Multiple possible synonyms were used to represent each crop in each search to ensure complete coverage of the peer reviewed literature. The terms pea OR pulse OR legume were used to search for literature related to field peas. The terms wheat OR “spring wheat” OR “winter wheat” were used to search for literature related to wheat. The terms canola OR rape OR rapeseed were used to search for literature related to canola. No temporal boundaries were placed on these literature searches, because any potential data derived from these literature searches was subsequently assessed for data quality as described in section 2.3.

Grey literature from government and industry groups were similarly consulted to identify potential sources of high-quality data. Grey literature sources were identified through internet and website searches of each region’s statistical databases and government agricultural departments. These included Statistics Canada and Agriculture and Agri-food Canada, the Australian Bureau of Statistics and Department of Agriculture, Fisheries and Forestry, the French National Institute of Statistics and Economic Studies and Ministry of Agriculture and Food, the German Federal Statistics Office and Federal Ministry of Food and Agriculture, and the United States Census Bureau and Department of Agriculture. These sources were searched for agricultural census data, and any data related to production volumes and yields, land use, field activities and management practices, irrigation, or inputs of fertilizers and crop protection products. Additional searches were also performed to identify potential sources from industry groups representing field crop farmers in each region. These included the Canadian Roundtable for Sustainable Crops (CRSC), the Canola Council of Canada, the Canadian Canola Growers Association, Grain Growers of Canada, Western Canadian Wheat Growers, Pulse Canada, Saskatchewan Pulse Growers, Grain Growers and Grain Producers of Australia, the Grains Research and Development Corporation, the Australian Oilseeds Federation, L’Association générale des producteurs de blé, the French Federation of Oilseed and Protein Crop Producers, Terres Inovia, ADEME, Union zur Förderung von Oel und Proteinpflanzen, the German Grain Club, the National Association of Wheat Growers and National Wheat Foundation, and the American Pulse Association.

It must be noted that data sets sourced from different LCI databases and literature sources may not be methodologically consistent due to differences in reporting guidelines, modelling protocols, and submission criteria (Turner et al., 2020). For example, land use changes and land occupation are modeled differently between Moreno Ruiz et al. (2021) and van Paassen et al. (2019). Therefore, it was necessary that all relevant data identified from the source documents be extracted and remodeled on a methodologically consistent basis to enable rigorous comparisons between results.

2.3 Data quality assessment

Following the identification of potential data sets and/or individual data points in LCI databases, peer-reviewed literature, and grey literature sources, all data points were screened using established LCI data quality screening methods to determine the quality of data available for modeling inputs to each cropping system. Data quality criteria were defined in accordance with the pedigree matrix defined by Ciroth et al. (2016) (Table 3), with specific modifications (described below) as appropriate to the goals of the current analysis. The pedigree matrix provides a semi-quantitative method for assessing the quality of individual data points relative to the overall data quality goals of the analysis being performed. Each score in the pedigree matrix is associated with an additional uncertainty factor that combines with base sectoral uncertainty factors for each data point to generate the overall uncertainty distribution for that data point (Table 4), in accordance with equation 1 in Ciroth et al. (2016). The use of a pedigree matrix for assessing data quality allows for assessment of parameter uncertainty, an important contributor to uncertainty in LCA studies (Bamber et al., 2019).

Table 3. Default pedigree matrix for assessing data quality (Ciroth et al., 2016).

Reliability	Completeness	Temporal correlation	Geographical correlation	Further technological correlation	Quality Score
Verified data based on measurements	Representative data from all sites relevant for the market considered, over and adequate period to even out normal fluctuations	Less than 3 years of difference to the time period of the data set	Data from area under study	Data from enterprises, processes and materials under study	1
Verified data partly based on assumptions or non-verified data based on measurements	Representative data from > 50% of the sites relevant for the market considered, over an adequate period to even out normal fluctuations	Less than 6 years of difference to the time period of the data set	Average data from larger area in which the area under study is included	Data from processes and materials under study (i.e. identical technology) but from different enterprises	2
Non-verified data partly based on qualified estimates	Representative data from only some sites (<< 50%) relevant for the market considered or > 50% of sites but from shorter periods	Less than 10 years of difference to the time period of the data set	Data from area with similar production conditions	Data from processes and materials under study but from different technology	3
Qualified estimate (e.g. by industrial expert)	Representative data from only one site relevant for the market considered or some sites but from shorter periods	Less than 15 years of difference to the time period of the data set	Data from area with slightly similar production conditions	Data on related processes or materials	4

Reliability	Completeness	Temporal correlation	Geographical correlation	Further technological correlation	Quality Score
Non-qualified estimates	Representativeness unknown or data from a small number of sites and from shorter periods	Age of data unknown or more than 15 years of difference to the time period of the data set	Data from unknown or distinctly different area (North America instead of Middle East, OECD-Europe instead of Russia)	Data on related processes on laboratory scale or from different technology	5

Table 4. Default pedigree matrix uncertainty factors (Ciroth et al., 2016).

Score	Reliability	Completeness	Temporal Correlation	Geographical Correlation	Technological Correlation
1	1	1	1	1	1
2	1.05	1.02	1.02	1.01	1.05
3	1.1	1.05	1.1	1.02	1.2
4	1.2	1.1	1.2	1.05	1.5
5	1.5	1.2	1.5	1.1	2

When assessing the quality of yield data, the definitions associated with each data quality score for temporal correlation were altered to better reflect the potential for inter-annual variability in crop yields. Currently, the standard pedigree matrix as defined by Ciroth et al. (2016) assigns the highest quality score to data points for which there is less than 3 years of difference in the time periods of the study and the data set, with data quality decreasing as data sets get older. Use of this system, however, assumes that data are representative of discrete moments in time, or periods of time that do not span data quality rankings. This is inappropriate when assessing data quality for yield estimates due to the potential for inter-annual variability in yields. Inter-annual yield variability may be high for canola (Takashima et al., 2013; Taylor et al., 2013; Torriani et al., 2007), wheat (Fischer et al., 2022; Hoffmann et al., 2018; Liu et al., 2019), and field peas (Fuhrer and Chervet, 2015). This is a particularly salient issue for Canadian yield data, as 2021 yields for all three of the crops included in this analysis were drastically reduced due to widespread drought across the Canadian prairie provinces in 2021 (Agriculture and Agri-Food Canada, 2021). Similar reductions in yield were also experienced for a number of crops around the world in 2021 (USDA, 2022b). Given the potential for interannual variability in yields, alterations have been made to the temporal correlation row of the pedigree matrix for assessment of yields as detailed in table 5.

Table 5. Alternative pedigree matrix definitions for assessment of the quality of yield estimates used in the current analysis.

Temporal correlation – Score definition	Data quality score
5+ year average with last year less than three years prior	1
3 year average with last year less than three years prior OR 5+ year average with last year 3-6 years prior	2
3 year average with last year 3-6 years prior OR 5+ year average more than 6 years prior	3

1 year value less than 6 years prior OR 3+ year average more than 6 years prior	4
1 year value more than 6 years prior	5

An additional change was also made to the pedigree matrix with respect to the assessment of reliability for each data point. In the default pedigree matrix, verified data based on measurements are assigned the highest quality score while non-verified estimates are assigned the lowest quality score. In the context of this analysis, however, verified measurements of farm level inputs and outputs should not be considered as the highest quality data unless replicates are taken from a sufficiently large sample of farms to be nationally representative. This is often not the case, particularly in the context of field-level emissions, such as nitrogenous emissions released from application of N fertilizers to agricultural fields (Klimczyk et al., 2021). Rather, well defined mathematical relationships are often used for estimation of field-level nitrogenous emissions at large scales, such as whole countries (Yeluripati et al., 2015). Many different models exist for the estimation of field-level nitrogenous emissions that may vary in their geographic scope, complexity, and types of nitrogenous emissions covered. These include the IPCC models which may be used to represent globally generic emissions using Tier 1 methods and default emissions factors or nationally-resolved emissions using Tier 2 methods and regionalized emissions factors (IPCC, 2019). These models are widely accepted, as evidenced by their use in the National Inventory Reports (NIRs) of each country included in this analysis (CCNUCC, 2022; Environment and Climate Change Canada, 2022; Federal Environment Agency, 2022; Government of Australia, 2022; U.S. Environmental Protection Agency, 2022). In some cases, farm input data are also modeled, particularly when measured data are unavailable. This is the case, for example, in the Australian canola carbon footprint report prepared by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) in which N fertilizer inputs are modeled based on equations from a previously developed calculator (Eady, 2017).

Taking into account the preferability of modeled data in estimating emissions at the national scale, and the potential for the use of modeled data for farm level inputs, the following changes were made to the reliability column of the pedigree matrix. First, nationally-resolved modelled emissions (such as those calculated using IPCC Tier 2 methods) were given a reliability score of 1 because these are the highest quality data practically available for modeling at the national scale. Generically modeled emissions (such as those calculated with IPCC Tier 1 methods) were given a reliability score of 2. Similarly, modeled inventory data were given a reliability score of 2. In all cases, reliability scores may be further decreased if the model inputs included in the data set themselves receive lower reliability scores. Finally, measured input and emissions data from a single or a small number of field sites (i.e., <10) or experimental sites were given a score of 4 for reliability, as these measures are poorly fit for use at the national scale.

When models were used to calculate LCI data points (e.g., N_2O emissions calculated using the IPCC methodology), the specificity of the emission factors (EFs) were assessed in combination with the geographical representativeness of the data entered into the model (e.g., N fertilizer application rate, etc.). The lowest geographical representativeness between the data entered into the model and the EF specificity was used as the limiting factor in assigning the pedigree score. For example, if the N fertilizer application rate was representative of the region under study, but a global EF for N_2O emissions was used (e.g., IPCC Tier 1), the value for N_2O emissions was assigned a geographical representativeness score of 2, representing “average data from larger area in which the area under study is included”. If the EF used was representative of a different region (not globally representative), then scores of 3, 4, or 5 were assigned depending on the similarity of production conditions in that region to the region under study. In general, if a combination of sources were used for one data point (or several sources listed generally and the specific source for each data point was not indicated), then the pedigree scores were assigned based on the lowest quality source (table 6).

Table 6. Alternative pedigree matrix definitions for assessment of reliability.

Reliability – Score definition	Score
Verified data based on measurements from a large number of sites, such as survey data OR nationally-resolved emissions models, such as IPCC Tier 2	1
Verified data partly based on assumptions or non-verified data based on measurements OR generic emissions models, such as IPCC Tier 1	2
Non-verified data partly based on qualified estimates	3
Qualified estimate (e.g. by industrial expert) OR measured inputs and emissions from a single or small number of field or experimental sites (i.e., <10)	4
Non-qualified estimates	5

Changes were also made to the pedigree matrix with respect to the assessment of completeness for each data set. The pedigree matrix defined by Ciroth et al. (2016) assigns the lowest data quality score for completeness when the representativeness of the data set is unknown. However, in a review of Canadian agri-food LCI data sets for population of the Canadian Agri-food Life-Cycle Data Centre (CALDC), Turner et al. (2020) found that only a small portion (i.e., ~7%) of data sources presented information regarding the percentage of the supply covered by the sample used in dataset generation. Therefore, the absence of information regarding representativeness of data sets was expected to be the norm during this data mining exercise. For this reason, unknown or unreported data set representativeness was instead assigned a completeness score of 3, representing the average data quality score on the pedigree matrix, and <50% of the supply covered (Table 7). Additionally, the definition for a completeness score of 4 was expanded to include data derived from recommendations (i.e., from crop-growing manuals, etc.). Recommendations were assigned a score of 4 because they are not explicitly representative of any of the supply; however, it was assumed that recommendations are based on relevant metrics that inform the practices performed by farmers. The definitions for completeness scores of 1, 2, and 5 were unchanged.

Table 7. Alternative pedigree matrix definitions for assessment of completeness in terms of percentage of supply covered.

Completeness – Score definition	Data quality score

Representative data from all sites relevant for the market considered, over and adequate period to even out normal fluctuations	1
Representative data from > 50% of the sites relevant for the market considered, over an adequate period to even out normal fluctuations	2
Representative data from only some sites (<< 50%) relevant for the market considered or > 50% of sites but from shorter periods, or representativeness of data unreported	3
Representative data from only one site relevant for the market considered or some sites but from shorter periods, or data derived from recommended practices (i.e., crop growing manuals, etc.)	4
Representative data from a small number of sites and from shorter periods	5

Finally, the definition associated with a score of 1 for geographical correlation was slightly modified. Except for Saskatchewan, this analysis focused on national-level carbon footprint models of each crop-region pairing. In some cases, however, data sets were found which were representative of a smaller region within a country, such as a province or state in Australia and the U.S., or a specific region in France or Germany. According to the standard definitions in the pedigree matrix, such data points would be given a geographical correlation score of 3 as they are not nationally representative. However, this assumes an equal distribution of agricultural activities within each country being modelled, which is often not the case. Within Australia, for example, the provinces of New South Wales and Western Australia produce much larger amounts of agricultural products than do the provinces of Victoria, Queensland, South Australia, or Tasmania (ABARES, 2022). For this reason, data sets representative of smaller areas within the regions being modeled were given geographical correlation scores of 1 if they corresponded with important production regions. Importantly, however, the percentage of supply covered was still taken into account in assessing completeness, meaning that although data sets may receive higher scores for geographical correlation, they were still scored accordingly based on the percentage of overall supply covered for completeness.

In some cases, the definitions associated with different data quality scores in the pedigree matrix were too general to adequately assess data quality. For this reason, some interpretations of data quality definitions were required to be better able to more systematically assess data quality. Specifically, for the reliability category, data that were either published in a database or in peer reviewed literature were considered to be verified data, and hence to align with the reliability definitions for scores of 1 and 2. In some cases, interpretation was also required for temporal correlation in instances in which older data were extrapolated forward in time (i.e., data representative of 2000-2005 extrapolated forward to 2021). In these cases, temporal correlation was assessed in accordance with the final year of the original data set date range, plus an additional credit to represent the modifications made to the data set. A data set originally representative of the time period 2000-2005 extrapolated to 2021 would therefore be given a temporal correlation score of 4 rather than 5. If the documentation for a dataset did not indicate the years of representativeness, it was assumed that the data were from 5 years prior to the publication of the original source describing the methods of data collection. This provided a conservative estimate of the length of time from data collection to publication.

Importantly, in making these changes to the pedigree matrix, only the definitions associated with different data quality scores were altered. The contributions to data quality uncertainty associated with each data quality score in each category have not been altered from those presented in table 4 (from Ciroth et al. (2016)).

2.4 Choice of best fit data sets for crop-region models

Once all potential data points were assigned data quality scores for their reliability, completeness, and temporal, geographic, and technological correlation, decisions had to be made regarding which of the identified sources were of the highest quality for use in model development. This choice was done through calculation of the amount of uncertainty that would be introduced into the models through the use of each specific data source. The total uncertainty associated with each of these data points from each potential source was calculated, taking into account the pedigree matrix score for each data point and associated uncertainty contribution (Tables 3 and 4). According to Ciroth et al. (2016), total uncertainty may be calculated using the equation

$$U_T = exp\left(\sqrt{(lnU_b)^2 + \sum_i (lnU_i)^2}\right)$$

where U_t represents total uncertainty, U_b represents basic uncertainty, and U_i represents the additional uncertainty factors from pedigree matrix scores. U_t represents the total geometric standard deviation of the uncertainty distribution of each inventory data point, from which Monte Carlo samples would be drawn during uncertainty propagation (Bamber et al., 2019). U_b represents the contribution to total geometric standard deviation that may be derived from the range of collected measurements for a specific data point, such as those collected from a sample of farmers (Turner et al., 2022). U_t therefore represents the contribution to total uncertainty derived from the pedigree matrix entries associated with each data point (Ciroth et al., 2016). Since the raw data used in the calculation of each data point in each source was not available, U_b was assumed to be equal to a base value of 1 for all data points. As a result of this assumption, the U_b term drops out of the total uncertainty calculation because $\ln(1) = 0$. Each value for U_t is therefore representative of contributions to uncertainty related only to the pedigree matrix entries for each data point. Using this method, all calculated uncertainty values were within the boundaries of $1.00 \leq U_t \leq 2.52$, as these values represent the minimum and maximum values of equation 1 (i.e. representing pedigree matrix entries of all ones and all fives, respectively).

Once uncertainty values were calculated for each data point from each identified data source, the calculated uncertainty values for data points representing the same inputs for each crop/country combination were compared to identify the data point/source which is of the highest quality (i.e., that will introduce the least amount of uncertainty into the final results). The choice of best fit data for modelling each data point for each crop-region combination therefore took into account these overall data quality scores. For the choice of data representing fertilizer and pesticide inputs, two options were possible for use as a data source: the combination of nutrient or total pesticide inputs with the distribution of types of fertilizers or pesticides applied, or the use of data characterizing the amounts of specific fertilizer and pesticide types. In these cases, the data chosen was that which had the lowest overall uncertainty score (i.e., highest overall data quality). Similarly, data on energy use related to field or post-harvest activities may be characterized by the total energy use, or the combination of energy use per activity and activity data (i.e., number of passes, etc.). For manure, data can be represented as the total amount of manure applied per total ha of harvested crop, or as the percent of crop receiving manure and the amount of manure applied per ha of crop receiving manure. The data with the highest overall quality was also chosen for these data points.

For field-level emissions and soil carbon changes, the available data points were also compared against a potential scenario of using the best available input data in conjunction with the best practices for emissions modelling. For this study, IPCC Tier 2 methods for modelling direct and indirect N2O emissions, IPCC Tier 1 methods for modelling CO_2 emissions from lime and urea, and IPCC Tier 2 methods using the data available in the each country's NIR for soil carbon changes were considered to be best practices (IPCC, 2019). These methods are in line with those applied for calculation of GHG inventories in each country's NIR, and are internationally recognized (IPCC, 2019). This choice is also in line with the guidelines for assessment of environmental performance of animal feed supply chains provided by UN FAO LEAP (FAO, 2016), the most relevant guidance document from the partnership as the crops included in this analysis may be key contributors to livestock feeds (Begna et al., 2021; Cordeiro et al., 2022; Pembleton et al., 2016).The data quality for these scenarios was compared against the best available data points for these emissions from the identified sources. Therefore, for some crop-country combinations, the best available data for emissions may come from the best available data for fertilizer inputs, re-modelled using IPCC best practices (i.e. rather than coming directly from any of the identified data sources).

In instances of equivalent uncertainty scores for specific data points, data points coming from data sets from which other data points were already selected were preferentially selected based on the higher likelihood of methodological consistency in the generation of the data points.

2.5 Carbon footprint methodology

2.5.1 Intended applications, audience, and practitioners

The intended audience of this study includes a number of governmental and industry stakeholders both within Canada, and internationally. These stakeholders include GIFS, the Government of Saskatchewan, as well as relevant representatives of the various countries to which comparisons are made in this report. The results of this study are intended to be used to draw meaningful comparisons between the relative carbon footprints of major commodity field crops grown within Saskatchewan, Canada, and countries representing major competitors in international markets. These results may also be used to identify potential hotspots within the supply chains for major agricultural products in Canada that may serve as priority targets for future GHG mitigation efforts.

2.5.2 Functional unit

Results for each crop-region combination are reported according to a functional unit of one kilogram of product (i.e., wheat grain, canola seed, and dry field peas) at farm gate.

2.5.3 System boundaries

The system boundaries for this analysis included all relevant material, energy, and emissions flows associated with production of commodity field crops in each of the crop-region combinations. These included farm-level inputs of fertilizers, plant protection products, seed, and energy for irrigation, field activities, and post-harvest activities (i.e., product drying). All on-farm activities were considered as foreground processes, while all processes occurring upstream of the farm were considered as background processes. Transportation of material inputs to the field was also considered. The geographical, temporal and technological boundaries were intended to be representative of actual contemporary production conditions in Saskatchewan, Canada, Australia, France, Germany, and the United States as possible. Section 2.5.6 lists the sources for each data point and their associated data quality scores relative to this overarching goal.

2.5.4 Cut-off criteria and exclusions

Across all three crops, material inputs and associated GHG emissions attributable to production and maintenance of infrastructure were excluded as they generally make small contributions (i.e., <5%) to life cycle GHG emissions compared to combustion of fuel during use (Biswas et al., 2008; Bortolini et al., 2014; Meisterling et al., 2009). These impacts decrease further when amortized against total crop production over the lifespan of the infrastructure (Ghamkhar et al., 2022), which may be up to 30 years for some machinery (Lips, 2017). Additional crop and crop-country based exclusions were also made, as detailed below.

2.5.4.1 Canola

Data taken from van Paassen et al. (2019) for modeling canola production in Canada and Australia included small inputs of pig and poultry manure to each system. These inputs were excluded from calculation of life cycle GHG emissions for these two systems. Exclusion of manure inputs from average canola production systems in each country is in line with manure input values reported by Alcock et al. (2022). Additionally, exclusion of manure from the Canadian production system is in line with the updated canola carbon footprint report produced for the CRSC ((S&T)2 Consultants Inc., 2021a) which indicate that, on a production-weighted basis using best available data, only ~2% of harvested canola area in Canada receives an application of manure. Additionally, there are no data available on manure application rates, nor the types of manure applied, which could significantly affect amounts of nutrients applied. Similarly, exclusion of the indicated manure inputs to Australian canola production systems is in line with previous carbon footprint analyses of Australian canola production performed by Eady (2017), who indicate that animal manure is not applied to broad-acre cropping (i.e., large-scale field-crop) soils in Australia.

Data taken from van Paassen et al. (2019) also include small amounts of lime as inputs to both Saskatchewan, and Canadian canola production systems. These inputs, and associated CO_2 emissions from the application of lime to agricultural fields are excluded from this analysis in line with the updated canola carbon footprint report produced for the CRSC ((S&T)2 Consultants Inc, 2021a). This report indicates that no publicly available information characterizing agricultural lime use in Canada has been released within the last 20 years, and that, based on Canadian NIRs, there is a low average emissions rate from agricultural lime use in Canada. Inputs of lime to Saskatchewan and Canadian canola systems have therefore been excluded.

Inputs of energy for irrigation of Australian canola crops were excluded. This is in line with previous work done by Eady (2017), which indicates that only a small portion of Australian canola is irrigated, based on customized statistics received from the Australian Bureau of Statistics specifically for their study. While Eady (2017) indicates that a large portion of canola production in Tasmania is irrigated, Tasmania represents only a very small percentage of total Australian canola production (i.e., ~0.1%) (ABARES, 2022).

2.5.4.2 Wheat

Similar to canola, inputs of lime and associated emissions were excluded from Saskatchewan and Canadian wheat production systems for the same reasons as previously described. Unlike canola, however, inputs of manure from van Paassen et al. (2019) were not excluded from the Canadian wheat production model. The updated carbon footprint report for Canadian wheat production produced for the CRSC indicates that reconciliation units 17 and 19 in Ontario have data available regarding manure application rates, and significant wheat production ((S&T)2 Consultants Inc., 2021b). However, neither manure application rates, nor types of manure applied are reported, so types and amounts indicated by van Paassen et al. (2019) were used instead. For Saskatchewan, manure inputs were still excluded, since RUs 17 and 19 are in Ontario.

2.5.4.3 Field peas

Lime and manure inputs and associated emissions were excluded from Saskatchewan and Canadian pea production systems since the CRSC reports indicated that they excluded them due to low impacts ((S&T)2 Consultants Inc, 2021b), despite the values indicated in van Paassen et al. (2019) for lime and manure application to Canadian peas. Bamber et al (2020a) also did not report any lime or manure application to Canadian peas, based on survey responses from farmers. Irrigation was excluded for Saskatchewan and Canadian pea production systems, since all sources were in agreement that there is no significant amount of irrigation taking place. Irrigation was also not included for German peas since van Paassen et al (2019) did not include any inputs of energy use for irrigation, although Nemecek (2007a) did indicate an input of irrigation water.

2.5.5 Allocation methods

2.5.5.1 Manure

Manure inputs to fields were generated from animal production systems, where the animals ate crops that were originally fertilized using synthetic fertilizers. Therefore, the nutrients present in manure originated from synthetic fertilizer production processes. Based on this reasoning, manure inputs were modelled as these original synthetic fertilizer production processes, rather than as a co-product of animal production systems. This removes the need for allocation between manure and all other co-products of these animal production systems. However, the nutrients present in the manure were considered recycled materials since they contributed to the growing of the first round of crops (that fed the animals), then the second round of crops (that are receiving the manure). A 50/50 allocation of upstream impacts between the first use and second, recycled use of nutrients was assumed, in line with recommendations from AFNOR (2011).

2.5.5.2 Wheat grain and straw

Wheat cultivation results in two co-products – wheat grain and wheat straw. While canola (Iqbal et al., 2016; Karan and Hamelin, 2021; MacWilliam et al., 2014; Rothardt et al., 2021; Umbers and Watson, 2021; Vinzent et al., 2017; Wang et al., 2020) and pea residues (Bahl and Pasricha, 2000; Marschner et al., 2004; Walley et al., 2007; Wang and Sainju, 2014) are commonly left on fields and/or incorporated into soils, a portion of wheat straw is harvested and removed from fields to be used in other processes. Therefore, wheat grain and straw are considered to be co-products of wheat production systems. ISO guidelines present a hierarchy of methodologies for dealing with processes that produce multiple co-products. First, it is recommended that allocation be avoided by taking a system expansion approach. If such an approach is infeasible and allocation is unavoidable, ISO guidelines dictate that impacts should be allocated between co-products first according to an underlying biophysical relationship between co-products, and, if not possible, according to some other relationship such as relative economic value (ISO, 2006a).

The first step in developing allocation factors for wheat grain and straw was determining the proportion of straw that is removed from agricultural fields – that is, the proportion of above-ground crop residues that are a co-product. High quality, crop-specific information regarding amounts of crop residues baled are not available from any of the countries included the current analysis. Estimates in the literature regarding wheat straw removal rates for each country vary significantly (i.e., from 15% - 85% of residues removed) (Brosowski et al., 2020; Broster and Walsh, 2022; Fix and Tynan, 2011; Juneja et al., 2013; Lafond et al., 2009; Li et al., 2012b; Lokesh et al., 2019; Weiser et al., 2014). Unfortunately these sources only provide estimates of straw removal rates, without taking into account the proportion of area from which residues are removed. Calculation of total straw removed per kg of wheat therefore required estimates of removal rates, as well as crop area from which residues are removed.

In the absence of high quality, consistently calculated data regarding the total amount of residues removed per region, a standardized rate of residue removal has been applied to all regions. This standardized rate is calculated based on data for Saskatchewan, which indicates: total non-durum wheat area in Saskatchewan in 2021 (Statistics Canada, 2022b); total area from which crop residues were removed in Saskatchewan in 2021 (Statistics Canada, 2021b); and an average residue removal rate for Saskatchewan of 34.5% (Lafond et al., 2009). For all wheat production models it was therefore assumed that 8.3% of wheat straw was removed from fields, reflecting 34.5% of straw removed from 24.1% of non-durum wheat area (Lafond et al., 2009; Statistics Canada, 2021b, 2022b). Given the high degree of variability in estimates of wheat straw removal rates this assumption was the subject of sensitivity analyses. One key drawback of this approach is that it is based on the assumption that all land from which straw was removed in Saskatchewan is used for production of non-durum wheat (i.e., assuming that straw is only removed from non-durum wheat fields). While this assumption is tenuous, in the absence of crop-specific information regarding areas from which residues are removed it is unavoidable. The limitations of this assumption are further discussed in the limitations section.

Following identification of the amounts of straw co-produced with grain, it was necessary to choose an allocation method for partitioning impacts between co-products. LCI data for wheat cultivation were sourced from a variety of databases, reports, and literature sources which varied in their allocation principles. In some cases, co-production of wheat straw was ignored, and all impacts were allocated to production of wheat grain ((S&T)2 Consultants Inc., 2021a, Munoz et al. 2013), which is an approach that is not consistent with the ISO 14044 standard for life cycle assessment. When impacts were allocated between co-products both mass (i.e., Doran-Browne et al., 2015; Li et al., 2012a; Naudin et al., 2014) and economic (i.e., Eady et al., 2012; Nguyen et al., 2012; Van Middelaar et al., 2013) allocation principles were commonly applied. In some cases, allocation factors were instead defined based on measures of relative chemical energy content between grain and straw. Pelletier et al. (2010) allocate between wheat and straw based on gross chemical energy content, but do not present the allocation factors used. Similarly, Nordborg et al. (2014) also allocate based on gross chemical energy content, but this allocation step is done at the ethanol production plant rather than on-farm, so allocation is between wheat grain and the co-product distiller's dried grains with solubles. Data from Van Paassen et al. (2019) include allocation factors for wheat straw and grain based on gross chemical energy content. Finally, Buchspies and Kaltschmitt (2018) discuss the use of lower heating values as a basis for allocation, but only apply this principle to bioethanol production and not on farm, instead allocating all impacts to production of wheat grain.

While economic allocation between wheat grain and straw has been commonly applied in the literature, strong arguments have been made against its use (Pelletier and Tyedmers, 2011) on the basis that economic value bears no relationship to and fundamentally misrepresents the actuals flows of resources and emissions characteristic of industrial activities. For this reason, economic allocation was not used in this analysis, and allocation factors were instead defined based on underlying biophysical relationships, consistent with the ISO allocation hierarchy (ISO, 2006a). Arulnathan et al. (2022) provide an in-depth discussion of the use of external- or internal-causality in choice of biophysical relationships used as a basis for allocation between co-products. In doing so, they provide a strong argument for the use of chemical energy content as an underlying biophysical basis upon which to define allocation factors, as the amounts of energy present in co-products should roughly reflect the relative proportions of input energy used in production of each co-product, while other relationships, such as mass, may not (Arulnathan et al., 2022).

Both mass, and energy-based allocation methods were examined for their appropriateness to use in this analysis. To generate mass allocation factors between grain and straw, the percent of straw removed for each country was multiplied by the estimates of total above-ground biomass for each country (see section 2.5.8.3), and the proportions of total co-produced mass were used as allocation factors. Definition of energy-based allocation factors accounted for two important considerations: first that estimates of the relative energy contents of wheat grain and straw were available in consistent units for calculation of allocation factors; and second that factors may be regionally resolved, as energy content of wheat grain and straw may be impacted by both varietal (Montero et al., 2016; Rodehutscord et al., 2016) and local climate and soil conditions (Hernández et al., 2019; Montero et al., 2016). Montero et al. (2016), for example, find that wheat straw produced in Baja, California has an average higher heating value of 14.86 MJ/kg DM, less than that of the higher heating value of 16.68 MJ/Kg DM predicted for wheat straw produced in China (Niu et al., 2014).

Accounting for both the necessary consistency in units and potential regional differences in energy contents, only the energy allocation factors presented by van Paassen et al. (2019) were deemed appropriate for use in this study. Both Havrysh et al. (2021) and Feedipedia (Heuzé et al., 2021, 2015) provide the necessary energy contents for calculating allocation factors, but neither provide this information on a spatially resolved basis. To calculate energy allocation factors, the values presented by Van Paassen et al. (2019) were adjusted to account for the grain and crop residue yields used in this analysis. Upon calculation of these energy-based allocation factors it was determined that the energy- and mass-based allocation factors differed very little (i.e., 0.22% - 0.25%). Given the small differences in allocation factors, mass- and energy-based allocation were considered equivalent in this analysis. The allocation factors used in this analysis were therefore based on relative mass of co-products, and are presented in Table 8. Further, a sensitivity analysis was not performed around this choice of allocation method since the differences in resulting impacts would be trivial.

Table 8. Mass allocation factors used for partitioning of impacts between wheat grain and straw in this analysis, taking into account the proportions of straw removed from fields in each region.

	Wheat grain allocation factor	Wheat straw allocation factor
Saskatchewan	0.95	0.05
Canada	0.95	0.05
Australia	0.95	0.05
France	0.96	0.04
Germany	0.96	0.04
United States	0.95	0.05

2.5.5.3 Nitrogen credit

Peas are nitrogen-fixing legume crops, which can provide an input of N for the next crop in rotation. This was modelled using system expansion and substitution. The N credit provided by peas for the next crop in rotation was modelled as an avoided input of ammonia fertilizer, reflecting the fact that the next crop in rotation would require a smaller input of N fertilizer due to the N fixed by the peas. This was modelled as ammonia since this is the simplest N fertilizer that is used as the building block for all other N fertilizer types.

2.5.6 Foreground data collection

A large number of potential data sources were identified for modeling different crop-region combinations. In total, 43 sources were accessed for canola, 57 for non-durum wheat, and 22 for field peas. These sources included complete data sets from LCI databases, as well as individual data points from peer-reviewed literature, and government and industry group publications and statistics. Overall, the identified sources included the majority of foreground data required for modeling crop-region combinations, with some minor data gaps as described in detail below. The following sections detail the best identified data for modeling each crop-region combination and associated data quality scores. Complete lists of all sources consulted for each of the three crops, the data available therein, and their associated data quality scores are appended as separate excel files. Preceding these sections, a single section is presented in which assumptions regarding manure inputs to foreground systems are described. This section is presented separately from each crop to avoid repetition between sections as the information therein is relevant for all crops receiving manure.

2.5.6.1 Manure inputs

Manure inputs were included in relevant crop-country combinations as inputs of organic fertilizers. As detailed previously in section 2.5.5.1, manure inputs were modeled as equivalent nutrient inputs from the specific crop-region combination fertilizer mix divided in half to reflect applications of synthetic fertilizers to crops fed to the animal recycled through the animals' digestive systems. The exception to this was the French pea production model in which manure inputs were the only source of applied N, and no inputs of synthetic N sources were included. Replacement of N from manure in the French pea production system therefore used the N fertilizer mix from the German pea production system. Application of this allocation principle required data regarding approximate N, P, and K contents of the manure inputs. In all cases, inputs of manure were stated to be from pigs and poultry (van Paassen et al. 2019). Exact nutrient contents of different manures are dependent on dietary compositions and the amounts of different nutrients being taken in by the animals, as well as the form in which manure is managed (Galassi et al., 2010; Horf et al., 2022). This is reflected, for example, in differences in estimates of nutrient composition of pig slurry from Saskatchewan (Government of Saskatchewan, 2022), Germany (Kuhn et al., 2018), Denmark (Sommer et al., 2014), and Czechia (Hlisnikovský et al., 2022). The following assumptions were made regarding nutrient compositions of different manures. N and P contents of pig manure for all European were assumed to be the same as those in Germany in line with Kuhn et al. (2018), and assuming pig slurry has a density of 1000 kg/m^3, within one standard deviation of average pig slurry densities as reported by Moral and Paredes (2005). K contents of pig manure for all European countries were assumed to be the same as those reported by Moral and Paredes (2005). N, P, and K contents of pig manure for Canada, and the U.S. were assumed to be the same as average values reported by the Government of Saskatchewan (2022), also assuming pig slurry has a density of 1000 kg/m^3 (Moral and Paredes, 2005). N, P, and K contents of Canadian, American, and European poultry manures were assumed to be the same as those reported by Azeez and Van Averbeke (2010). While more regionalized nutrient contents could be determined for poultry manure from North American systems based on previously reported laying hen and broiler feed compositions (Pelletier, 2008; Pelletier et al., 2014; Turner et al., 2022), the mix of manure attributable to different poultry species is unknown, making accurate calculations of appropriate manure nutrient contents difficult. Finally, nutrient contents for pig, and average nutrient contents for poultry manure for Australia were taken from the Australian Grains Research and Development Corporation (Griffiths, 2014). All assumed manure nutrient contents are reported in Table 9. Large losses of nutrients may occur during manure storage, after excretion but before manure is applied to fields (Bai et al., 2016; Tittonell et al., 2010). To take these factors into account, all assumed manure nutrient contents reported in Table 9 are contents following losses from manure storage systems. Therefore, all losses during storage are allocated to the animal production system that produced the manure, not to the crop systems currently being modelled.

Table 9. Assumed percent nutrient contents of pig and poultry manure at time of application to field

	North America		Europe		Australia	
	Pig	Poultry	Pig	Poultry	Pig	Poultry
N	0.389	3.71	0.598	3.71	1.9	3
P	0.126	1.465	0.293	1.465	2.5	2.15
K	0.168	1.795	0.226	1.795	0.7	1.3

Based on the above information, data quality scores were assigned to those flows of synthetic fertilizers included in production models to replace nutrients from manure inputs, based on the quality of the sources from which nutrient contents were obtained. Rather than providing separate scores for pig and poultry manure, scores were assigned for each manure modeled as N fertilizers, P fertilizers, and K fertilizers. In each case, data quality scores were assigned to reflect the worst data quality between the sources considered, thereby providing a conservative view of data quality related to modeling of manure inputs. Data quality scores for manure inputs to each country are presented in Tables 10-12.

Manure nutrient contents were derived from the same sources for all Canadian and U.S. crop production systems, so they all received the same data quality scores. A score of 4 was given for reliability because it is unclear how many sites were sampled in determination of pig manure nutrient contents (Government of Saskatchewan, 2022). A score of 4 was given for completeness because the assumed nutrient compositions of poultry manure are taken from a single large supplier with little relevance to the markets being modeled (Azeez et al., 2010). A score of 5 was given for temporal correlation because the data collected for determining pig manure nutrient contents were collected from 1998-2000 (Government of Saskatchewan, 2022). A score of 5 was given for geographic correlation because the information on poultry manure nutrient content is based on estimates from a company in South Africa (Azeez et al., 2010). Finally, a score of 4 was given for technological correlation because manure is being modeled as upstream synthetic fertilizer inputs – that is, this data quality score does not reflect a limitation of the sources from which nutrient contents were taken, but rather a limitation of the modeling procedure used.

Table 10. Data quality scores for manure inputs to Canadian and U.S. crop systems

	Reliability	Completeness	Temporal correlation	Geographic correlation	Technological correlation
Manure modeled as N fertilizer	4	4	5	5	4
Manure modeled as P fertilizer	4	4	5	5	4
Manure modeled as K fertilizer	4	4	5	5	4

For German and French cropping systems, a score of 4 was given for reliability as nutrient contents are derived from qualified estimates (Kuhn et al., 2018). Similarly, a score of 4 was given for completeness as both the number of sites, and their relevance to the German and French markets are unknown. A score of 5 was given to temporal correlation because estimates of pig manure K contents are from a paper published in 2005 (Moral and Paredes, 2005) without any indication of when data was collected, so it was assumed to be 5 years prior to publication data, and because estimates of poultry manure nutrient contents were from 2006 (Azeez et al., 2010). Finally, a score of 4 was given for technological correlation for the same reasons as previously described for Saskatchewan, Canadian, and U.S. cropping systems.

Table 11. Data quality scores for manure inputs to German and French crop systems

	Reliability	Completeness	Temporal correlation	Geographic correlation	Technological correlation

Manure modeled as N fertilizer	4	4	5	5	4
Manure modeled as P fertilizer	4	4	5	5	4
Manure modeled as K fertilizer	4	4	5	5	4

Finally, for Australian cropping systems, a score of 4 was given for reliability as nutrient content estimates provided by the GRDC were assumed to be based on expert opinion, as the original source from which they were derived is unavailable (Griffiths, 2014). The unavailability of this source also resulted in a score of 4 for completeness. A score of 5 was given for temporal correlation, as the estimates of manure nutrient contents are based on data collected in 1992. A score of 5 was given for geographic correlation because no explicit information was available indicating the geographic scope of the data that was collected. Finally, a score of 4 was given for technological correlation for the same reasons as previously described for Saskatchewan, Canadian, and U.S. cropping systems.

Table 12. Data quality scores for manure inputs to Australian crop systems

	Reliability	Completeness	Temporal correlation	Geographic correlation	Technological correlation
Manure modeled as N fertilizer	4	4	5	5	4
Manure modeled as P fertilizer	4	4	5	5	4
Manure modeled as K fertilizer	4	4	5	5	4

2.5.6.2 Canola data sources

Generally, data characterizing canola production systems for each crop-region combination were of relatively high quality. Of the canola combinations included, Saskatchewan canola production had the lowest data quality scores for transportation and post harvest energy use (table 13). This was driven by the relatively small number of sources (3) found that presented LCI data for canola production in Saskatchewan specifically. Of the sources considered, it was common for Saskatchewan to be presented as part of an aggregated data set representing production conditions in western Canada, rather than being presented on its own, or in a disaggregated format. There were, however, some data included for yields, herbicides, field level emissions and soil carbon changes that were of similar quality to those to be used for modeling average canola production in Canada (table 14).

Table 13 lists the data sources for each type of LCI data, and the quality of those data. A five year average (2018-2022) yield was calculated based on the yearly values from Statistics Canada (2022b). This year range was chosen since it is the most temporally up-to-date, and is sufficiently long to diminish the yield impacts of the anomalous 2021 year across all countries (Agriculture and Agri-Food Canada, 2021; USDA, 2022b). The data on fertilizer inputs came from the CRSC report, and were calculated based on the total amount of N, P, K and S indicated in the report, as well as the distribution of types of fertilizers used to supply each nutrient. Manure and lime inputs were excluded since the CRSC report indicates that they are applied in very small amounts. The total amounts of herbicide, insecticide and fungicide inputs came from the CRSC report ((S&T)2 Consultants Inc, 2021a), as well as the proportions of types (by active ingredient) of herbicides sold (used as a proxy for types of herbicides applied). The proportions of insecticide and fungicide active ingredients applied came from MacWilliam et al. (2016), since these were not indicated in the CRSC report. The N_2O emissions calculated in the CRSC reports are based on the most recent, best practices for the IPCC methodology, with region-specific Tier 2 emission factors used and scaled up to provincial and national averages. Therefore, the N_2O emission values for Saskatchewan and Canada were taken directly from the CRSC report rather than re-calculated.

Table 13. Data sources used for modeling Saskatchewan canola production, and their associated pedigree matrix scores

Data point	**Source to be used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield (and the inverse, land area)	StatsCan, table 32-10-059-10 (Statistics Canada, 2022b)	1	2	1	1	1
Seed	MacWilliam et al., (2016)	2	3	4	1	1
Fertilizers	CRSC ((S&T)2 Consultants Inc, 2021a)	4	4	1	1	1
Herbicides	CRSC ((S&T)2 Consultants Inc, 2021a)	1	1	2	3	4
All other plant protection	CRSC ((S&T)2 Consultants Inc, 2021a) inventory data with distribution of types from	4	4	5	1	1

	MacWilliam et al., (2016)					
Field activities energy use	CRSC ((S&T)2 Consultants Inc, 2021a)	2	1	1	1	1
Transportation	Distances from van Paassen et al. (2019)	2	3	4	1	2
Post harvest	CRSC ((S&T)2 Consultants Inc, 2021a)	4	5	5	5	5
Field level emissions of N2O	CRSC ((S&T)2 Consultants Inc, 2021a)	1	3	1	1	1
CO2 emissions from lime and urea	Calculated using IPCC methods and data from CRSC ((S&T)2 Consultants Inc, 2021a)	1	3	1	1	1
Soil carbon changes	CRSC ((S&T)2 Consultants Inc, 2021a)	1	1	1	1	4

Data characterizing Canadian average canola production were of relatively higher quality than the Saskatchewan-specific data (table 14). A total of five sources were identified as providing the highest quality data for all required inventory data. Notably, completeness scores for many of the data sources were assigned a value of three, indicating that they were either representative of less than 50% of Canadian canola supply, or the amount of supply was not indicated. As noted previously, a lack of reporting of the percentage of supply covered by samples used for collection of LCI data is common (Turner et al., 2020). The worst data quality score assigned for Canadian canola production was a score of 4 given to the technological correlation for the calculation of soil carbon changes. This score was assigned because the methods to be used do not differentiate between crops. However, the methods to be used are consistent with those used in calculation of the Canadian NIR (Environment and Climate Change Canada, 2022), and represent the current best practices for calculation of average soil organic carbon changes in the field crop sector.

Table 14 details the sources and quality of the data used for each LCI data category for Canadian canola production. As was done for Saskatchewan, a five year average yield (2018-2022) was calculated from Statistics Canada yearly values. Manure and lime inputs were excluded since the CRSC reports indicated that they were applied in very small amounts for Canada. Data for all other fertilizer inputs came from van Paassen et al. (2019). Some of the fertilizer inputs were listed as only “NPK compound” or “PK compound.” However for modelling upstream impacts, precise fertilizer products need to be defined. This was achieved by modelling the generic compounds as a mix of the fertilizer products also indicated by van Paassen et al. (2019), in a combination that includes the same amount of N, P, K and S nutrients. Since these fertilizer products were modelled as a proxy for the generic compounds indicated by van Paassen et al. (2019), the technological correlation for these amounts received a data quality score of 4, for related technology. The amounts of total pesticides applied came from van Paassen et al. (2019), however they do not indicate what types of herbicides, insecticides, and fungicides are applied. Therefore, the distribution of different pesticide inputs from Nemecek (2015) was used in combination with the total amounts from van Paassen et al. (2019).

Table 14. Data sources to be used for modeling Canadian canola production, and their associated pedigree matrix scores

Data point	**Source to be used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	StatsCan, table 32-10-059-10 (Statistics Canada, 2022b)	1	2	1	1	1
Seed	Alcock et al. (2022)	2	3	2	1	1
All other nutrient inputs	van Paassen et al., (2019)	2	3	2	1	4
All pesticides	amounts from van Paassen et al., (2019), types from Nemecek (2015)	2	3	3	1	1
Irrigation energy	CRSC ((S&T)2 Consultants Inc, 2021a)	2	3	3	1	1
Field activities energy use	CRSC ((S&T)2 Consultant	2	1	1	2	1

	s Inc, 2021a)					
Transportation	distances from van Paassen et al. (2019)	2	3	4	1	1
Post harvest	Alcock et al., (2022)	2	3	2	1	1
N2O emissions (direct and indirect)	CRSC ((S&T)2 Consultants Inc, 2021a)	1	3	1	1	1
CO2 emissions from lime and urea	van Paassen et al. (van Paassen et al., 2019)	2	3	2	2	1
Soil carbon changes	CRSC ((S&T)2 Consultants Inc, 2021a)	1	1	1	1	4

Data characterizing Australian canola production were of similarly high quality (table 15). In total, 12 sources were consulted to identify the best data for characterizing Australian canola production. As with the Canadian canola production data, many of the data sources for Australian canola production were assigned completeness scores of 3 for either not indicating the percentage of supply covered, or for covering less than 50% of the Australian canola supply. The highest quality data characterizing yields was the annual report of the Australian Oilseeds Federation (Australian Oilseeds Federation, 2021).This source does not directly report yield; rather, it reports total production and total land area used for growing canola in Australia, from which yields were subsequently calculated for the five-year period of 2017-2021 (no data were available for 2022). Manure was excluded from the Australian canola production model since the literature review by Alcock et al. (2022) found that no manure was applied to Australian canola. Fertilizer inputs were modelled the same way as for Canada, with data sourced from van Paassen et al. (2019), and the “NPK compound” and “PK compound” flows were modelled using a mix of the other fertilizer inputs that gave the same nutrient inputs.

Data on the total inputs of herbicides, fungicides and insecticides came from van Paassen et al. (2019), however they did not indicate what specific products or active ingredients were applied. Little information is available regarding the specific distribution of types of pesticides applied in Australian canola systems. Therefore, the following assumptions have been made regarding Australian pesticide mixes. Herbicides are assumed to be a mix of 18.36% glyphosate, and 81.64% atrazine, in line with the proportions indicated in the canola production data set from the AusLCI database (Tomkinson, 2013). Fungicides are assumed to be an equal proportion mix of foliar fungicides registered for use on canola in Western Australia for blackleg, sclerotinia stem rot, and white leaf spot (Beard and Hills, 2022), three predominant fungal diseases of canola production systems in Australia (Van de Wouw et al., 2016). Similarly, insecticides are assumed to be an equal proportion mix of registered insecticides for control of mites and aphids (GRDC, 2018), two predominant insect pests affecting Australian canola crops (Arthur et al., 2015; Ward et al., 2021).

Through data quality assessment and calculation of total uncertainty contributions from pedigree matrix entries, it was found that the use of data from van Paassen et al. (2019) for calculation of N_2O emissions resulted in lower uncertainty than would use of data from the CSIRO canola carbon footprint report (Eady, 2017), in spite of its lower completeness score (i.e., a 3 rather than a 2). This is because the data from van Paassen et al. (2019) had a much higher data quality score for temporal correlation than the data from the CSIRO report (i.e., a 1 rather than a 5). When combined with the uncertainty factors presented by Ciroth et al. (2016) the combination of scores attributable to data from van Paassen et al. (2019) resulted in a lower overall uncertainty score than that of the CSIRO report (Eady, 2017).

Table 15. Data sources to be used for modeling Australian canola production, and their associated pedigree matrix scores

Data point	**Source to be used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	Australian Oilseeds Federation Annual report (Australian Oilseeds Federation, 2021)	1	3	1	1	1
Seed	Alcock et al., (2022)	2	3	2	1	1
Lime	Alcock et al., (2022)	2	3	2	1	1
All other nutrient inputs	van Paassen et al., (2019)	1	3	2	1	4
All pesticides	total amounts from van Paassen et al., (2019), distribution from AusLCI and registered products	4	3	4	1	1

Field activities energy use	van Paassen et al., (2019)	2	3	2	1	1
Transportation	distances from van Paassen et al., (2019)	2	3	4	1	1
Post harvest	Alcock et al., (2022)	2	3	2	1	1
N2O emissions (direct and indirect)	van Paassen et al., (2019)	2	3	1	2	1
CO2 emissions from lime and urea	IPCC methods with data from Alcock et al., (2022)	2	3	2	1	1
Soil carbon changes	NIR methods (Government of Australia, 2022)	1	1	1	1	4

Data sources used for modeling French canola production are presented in table 16. These data are of similarly high quality, with the majority of data being sourced from van Paassen et al. (2019), or from Alcock et al. (2022). A total of 11 sources were consulted in identifying French canola production data. The yield value was calculated as a five year average from 2018-2022 from the EU Oilseed and Protein Crop Production report (2022a). Fertilizer data were sourced from van Paassen et al. (2019), with the same fertilizer mix proxies used for "NPK compound" and "PK compound". Manure inputs were included for France, and the amounts and types came from van Paassen et al. (2019). As described in section 2.5.5.1 (Manure allocation methods), the total nutrient contents of these manures were determined, and they were modelled as a mix of synthetic fertilizers that provide those nutrients. This was done to avoid allocating the impacts of the animal production system, and to instead include the impacts of the original production of the fertilizers that were used to fertilize the crops that fed the animals that produced the manure. As described in section 2.5.6.4, all manure data sources received poor data quality scores since some values used in the calculations came from expert opinion from over 15 years ago, including nutrient contents representative of South Africa. As was done for Canada and Australia, total amounts of herbicide, fungicide, and insecticide inputs were sourced from van Paassen et al. (2019). Information on pesticide mixes used in France were taken from Agreste (Agreste, 2022).

As with the Australian data, data from van Paassen et al. (2019) were used in the calculation of N_2O emissions, and CO_2 emissions attributable to lime and urea application despite some other sources having potential higher quality data for individual indicators. Specifically, data from Nguyen et al. (2012) received a higher completeness score than that of van Paassen et al. (2019), but received a considerably worse score for technological correlation (i.e., 5 as opposed to 1). Since poor technological correlation is the largest overall contributor to uncertainty from pedigree matrix entries (Ciroth et al., 2016) these data were associated with higher levels of uncertainty for modelling of N_2O emissions. Similarly, the method for modeling soil carbon changes used by Ben Aoun et al. (2016) resulted in lower total uncertainty than those proposed to be used here. However, they used the CERES-EGC model (Gabrielle et al., 2006), a process-based model for simulation of soil carbon dynamics. Use of process-based models requires significant expertise to properly parametrize the models, and these models generally have large context-specific data requirements making their implementation challenging (Adams et al., 2013). While the results of these models may provide more accurate estimates of soil carbon changes associated with French canola production in specific geographical/temporal contexts, the use of process-based models is outside the scope of the current analysis. Rather, use of the methods proposed herein (which are consistent with the French NIR (CCNUCC, 2022)) represent best practices for the current analysis.

Table 16. Data sources to be used for modeling French canola production, and their associated pedigree matrix scores

Data point	Source to be used	Reliability	Completeness	Temporal correlation	Geographical correlation	Technological correlation
Yield	EU Oilseed and Protein Crop production (2022a)	1	1	1	1	1
Seed	Alcock et al., (2022)	2	3	2	1	1
Lime	Alcock et al., (2022)	2	3	2	1	1
All other fertilizer inputs	van Paassen et al., (2019)	2	3	2	1	4
Manure	inputs from van Paassen et al. (2019), modelled as fertilizer inputs based on nutrient contents from Azeez and Van Averbeke (2010), Kuhn et al.	4	4	5	5	4

	(2018), and Moral and Paredes (2005)					
All pesticides	amounts from van Paassen et al., (2019), types from Agreste 2022	1	3	2	1	1
Irrigation energy	van Paassen et al., (2019)	2	3	2	1	1
Field activities energy use	van Paassen et al., (2019)	2	3	2	1	1
Transportation	van Paassen et al., (2019)	2	3	4	1	1
Post harvest	Alcock et al., (2022)	2	3	2	1	1
N2O emissions (direct and indirect)	Modeled with data from van Paassen et al., (2019)	1	3	2	1	1
CO2 emissions from lime and urea	Modeled with data from Alcock et al., (2022)	2	3	2	1	1
Soil carbon changes	NIR methods (CCNUCC, 2022)	1	1	1	1	4

Finally, data characterizing German canola production were of similarly high quality. A total of 10 sources were consulted to identify potential data for use in modeling. Fertilizers, manures and pesticides were modelled using the same methods as France. Information on the distribution of pesticides applied to German canola systems were taken from Nordborg et al. (2014). As with previous data sets, data from van Paassen et al. (2019) were used in modeling of N_2O emissions in spite of its lower completeness score than data sourced from O'Keeffe et al. (2017). The former data is of poorer quality with respect to temporal correlation, resulting in higher overall uncertainty (table 17).

Table 17. Data sources to be used for modeling German canola production, and their associated pedigree matrix scores

Data point	Source to be used	Reliability	Completeness	Temporal correlation	Geographical correlation	Technological correlation
Yield (and the inverse, land area)	EU Oilseed and Protein Crop production (European Commission, 2022a)	1	1	1	1	1
Seed	Alcock et al., (2022)	2	3	2	1	4
Lime	Alcock et al., (2022)	2	3	2	1	1
All other fertilizer inputs	van Paassen van Paassen et al., (2019)	1	3	2	1	1
Manure (modelled as fertilizer)	van Paassen et al. (2019) for amounts, based on nutrient contents from Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and Paredes (2005)	4	4	5	5	4
All pesticides	amounts from van Paassen et al., (2019), types from Nordborg et al. (2014)	2	3	3	1	1
Irrigation energy	(Nemecek, 2007b)	2	3	4	1	1
Field activities energy use	van Paassen et al., (2019)	2	3	2	1	1
Transportation	distances from van Paassen et al., (2019)	2	3	4	1	1

Post harvest	Alcock et al., (2022)	2	3	2	1	1
N2O emissions (direct and indirect)	Modeled using data from van Paassen et al. (2019)	1	3	2	1	1
CO2 emissions from lime and urea	Modeled using data from Alcock et al. (2022)	2	3	2	1	1
Soil carbon changes	Modeled using NIR methods (Federal Environment Agency, 2022)	1	1	1	1	4

2.5.6.3 Non-durum wheat data sources

Data characterizing Saskatchewan wheat production were, with few exceptions, of fairly high quality (table 18). Data for grain yield came from Statistics Canada (2020), and data for the amount of straw removed came from Lafond et al. (2009), and Statistics Canada (2022b, 2021b). The amount of straw removed was used as the co-product of wheat grain production (see section 2.5.5.2 for the methods of allocation between co-products). It was also subtracted from the amount of above-ground residue produced for calculations of N_2O emissions from crop residue (see section 2.5.8.3).

Scores of 4 for reliability and completeness were assigned to data characterizing seed and nutrient inputs, field activity energy use, transportation, and post-harvest energy use. These data were based on expert opinion or recommendations, rather than data that directly represented practices on farms. The data sourced from van Paassen et al., (2019) for Canadian seed inputs are from 2013, and for post-harvest drying energy use are from a source published in 2010. The proportion of straw removed from fields received a score of 2 for reliability, as this data was based on experimental measures investigating proportions of straw removed by common baling machinery in Saskatchewan. However, this data received scores of 4 for completeness and 5 for temporal correlation because only a small number of experimental sites were considered, and data was collected during the 2002-2005 growing seasons. Data on the total amounts of herbicides, insecticides and fungicides came from the CRSC report, as well as data on the types of herbicides applied. However, they did not report the types of insecticides and fungicides applied, therefore this information was taken from Nemecek (2015a) in combination with the total amounts from the CRSC report. The data for pesticide inputs from the CRSC report ((S&T)2 Consultants Inc., 2021b) are representative of the province of Alberta, rather than the province of Saskatchewan, or the entirety of Canada.

Similar to canola, changes in soil carbon are to be estimated using methods from the Canadian NIR (Environment and Climate Change Canada, 2022), which do not provide crop-specific estimates of soil carbon change, hence leading to the score of 4 for technological correlation.

Table 18. Data sources to be used for modeling Saskatchewan non-durum wheat production, and their associated pedigree matrix scores

Data point	**Source**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield (grain)	StatsCan, table 32-10-059-10 (Statistics Canada, 2022b)	1	2	1	1	1
Straw removed	Lafond et al. (2009)	2	4	5	1	1
Seed	CRSC report ((S&T)2 Consultants Inc., 2021b)	4	4	1	1	1
Nutrient inputs	CRSC report ((S&T)2 Consultants Inc., 2021b)	4	4	1	1	1
Herbicide inputs	CRSC report ((S&T)2 Consultants Inc., 2021b)	1	1	2	3	1
Other pesticide inputs	Total amounts from CRSC report ((S&T)2 Consultants Inc., 2021b), fungicide and insecticide types from	2	3	3	3	1

	Nemecek (2015)					
Field activity energy use	CRSC report ((S&T)2 Consultants Inc., 2021b)	4	4	1	1	1
Transportation diesel	van Paassen et al. 2019	2	3	4	1	1
Post-harvest energy use	CRSC report ((S&T)2 Consultants Inc., 2021b)	4	4	2	2	2
Direct and indirect N2O emissions	CRSC report ((S&T)2 Consultants Inc., 2021b), scaled to account for assumed residue removal rates	1	3	1	1	1
CO2 emissions from urea	Calculated using IPCC methods based on urea inputs from CRSC report ((S&T)2 Consultants Inc., 2021b)	2	3	1	2	1
Soil carbon changes	CRSC report ((S&T)2 Consultants Inc., 2021b)	1	1	1	1	4

Data characterizing Canadian-average production of non-durum wheat were also of generally high quality (table 19). Proxy data from Saskatchewan were used for calculation of the amount of wheat straw removed. Fertilizer data came from van Paassen et al. (2019) and were of relatively high quality, however they received a score of 3 for technological correlation since proxy fertilizers were modelled when van Paassen et al. (2019) indicated an application of "NPK product" and "PK product" (as described in the canola section). Similar to the Saskatchewan average data, transportation of field inputs is an area of relatively poor data quality, indicating that this should be a focus for data collection improvements during future studies. The data sourced from van Paassen et al. (2019) for Canadian seed inputs are from 2013, and the data from the CRSC report on post-harvest drying energy use are from expert opinion.

Table 19. Data sources to be used for modeling Canadian non-durum wheat production, and their associated pedigree matrix scores

Data point	Source	Reliability	Completeness	Temporal correlation	Geographical correlation	Technological correlation
Yield (grain)	StatsCan, table 32-10-059-10 (Statistics Canada, 2022b)	1	2	1	1	1
Straw removed	Lafond et al. (2009)	2	4	5	1	1
Seed	van Paassen et al. (2019)	1	3	3	1	1
All fertilizer inputs	van Paassen et al. (2019)	1	3	2	1	3
Manure inputs (modelled as fertilizers)	van Paassen et al. (2019), based on nutrient contents from Government of Saskatchewan (2022) and Azeez and Van Averbeke (2010)	4	4	5	5	4
All pesticide inputs	CRSC report ((S&T)2 Consultants Inc., 2021b),	1	3	2	2	1

	fungicide and insecticide types from Nemecek					
Irrigation energy	van Paassen et al. (2019)	2	3	2	1	1
Fuel use for field activities	van Paassen et al. (2019)	2	3	2	1	1
Transportation of field inputs	van Paassen et al. (2019)	2	3	4	1	1
Post-harvest energy use	CRSC report ((S&T)2 Consultants Inc., 2021b)	4	4	2	2	2
Direct and indirect N2O emissions	((S&T)2 Consultants Inc., 2021b) scaled to account for assumed residue removal rates	1	3	1	1	1
CO2 emissions from lime and urea	van Paassen et al. (2019)	2	3	2	2	1
Soil carbon changes	CRSC report ((S&T)2 Consultants Inc., 2021b)	1	1	1	1	4

In general, the available LCI data for Australian wheat production were of fairly high quality (table 20). The sources of data for seed, lime inputs, and transportation from van Paassen et al., (2019) are all around 10 years old at the time of writing this report. Proxy data from Saskatchewan were used for calculation of the amount of wheat straw removed. This data was collected using experimental measures from a small number of sites throughout southern New South Wales in 2014 (Broster and Walsh, 2022). The choice of data to characterize post-harvest energy inputs was difficult due to differences in final moisture content after grain drying between sources. The data on post-harvest energy use from Nemecek (2015) received the best data quality score (i.e., lowest associated uncertainty) of all the possible sources, despite being representative of processes in Switzerland rather than Australia, and being greater than 10 years old resulting in scores of 5 for completeness, and 4 for geographical correlation. However, these data are presented in terms of amount of moisture removed from the grain after drying, while data from van Paassen et al. (2019) present post-harvest energy use in terms of amount of dried grain. To avoid relying on additional sources of data to calculate the amount of moisture removed, and for methodological consistency in data sources, data on post-harvest energy use has been taken from van Paassen et al. (2019).

Table 20. Data sources to be used for modeling Australian non-durum wheat production, and their associated pedigree matrix scores

Data point	Source	Reliability	Completeness	Temporal correlation	Geographical correlation	Technological correlation
Yield (grain)	van Paassen et al. (2019)	1	3	2	1	1
Straw removed	Lafond et al. (2009)	2	4	5	3	1
Seed	van Paassen et al. (2019)	1	3	3	1	1
Lime inputs	van Paassen et al. (2019)	2	3	3	1	1
Fertilizer inputs	van Paassen et al. (2019)	1	3	2	1	3
Manure inputs	Amounts based on van Paassen et al. (2019) and nutrient contents from (Griffiths, 2014)	4	4	5	5	4
Herbicide, fungicide and insecticide inputs	total amounts from van Paassen et al. (2019), types from Nemecek	2	3	3	1	1
Irrigation energy	van Paassen et al. (2019)	2	3	2	1	1
Field activities energy	van Paassen et al. (2019)	2	3	2	1	1
Transportation	van Paassen et al. (2019)	2	3	3	1	1
Post-harvest energy use	van Paassen et al. (2019)	2	5	3	4	1
Direct and indirect N2O emissions	Modelled using IPCC Tier 2 with N input data	1	3	2	1	1

	from van Paassen et al. (2019)					
CO2 emissions from lime and urea	van Paassen et al. (2019)	2	3	2	2	1
Soil carbon changes	Modelled using NIR data (Government of Australia, 2022)	1	1	1	1	4

The data sources for French and German wheat production are similar, and have overall high quality (tables 21-22). The data from van Paassen et al., (2019) for seed and transportation of field inputs are 9 years old, and assumed to be 14 years old based on time of publication respectively, at the time of writing this report. Proxy data from Saskatchewan were used for calculation of the amount of wheat straw removed from both the French and German production systems. As with Australian wheat production, post-harvest energy use data has been taken from van Paassen et al. (2019) rather than Nemecek (2007b) for the same reason as previously described. For pesticide inputs for France, data on the total amounts of herbicides, fungicides, and insecticides were taken from van Paassen et al. (2019), and data on the specific types of plant protection products came from Agreste (Agreste, 2022) for herbicides and fungicides, and Nemecek (2007b) for insecticides. The Nemecek insecticide data were valid from 2000-2004, extrapolated to the year 2021 (without an explanation of how this was done), and thus have a data quality score of 4 for temporal correlation. Some of the herbicides and fungicides indicated by Agreste (Agreste, 2022) did not have representative background production inventories in ecoinvent, therefore they were modelled as the generic "pesticide, unspecified", which gave them a technological correlation of 4. Similarly for Germany, the types of pesticides came from Nordborg et al. (2014), and some of these pesticide types were modelled as "pesticide, unspecified". For soil carbon change for France, Muñoz et al. (2014) had data of higher quality than is achievable via modelling using the NIR values since it was modelled specifically for wheat, whereas the NIR is not crop specific. However, for consistency with the data available for all countries, we have chosen to model soil carbon changes according to the NIR model.

Table 21. Data sources to be used for modeling French non-durum wheat production, and their associated pedigree matrix scores

Data point	**Source**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield (grain)	Eurostat Database	1	1	1	1	1
Straw removed	Lafond et al. (2009)	2	4	5	3	1

Seed	van Paassen et al. (2019)	1	3	3	1	1
Lime	van Paassen et al. (2019)	1	3	2	1	1
Fertilizers	van Paassen et al. (2019)	1	3	2	1	3
Manure (modelled as fertilizers)	van Paassen et al. (2019) for amounts, based on nutrient contents from Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and Paredes (2005)	4	4	5	5	4
Herbicide and fungicide inputs	total amounts from van Paassen et al. (2019), types from Agreste (Agreste, 2022)	1	3	2	1	4

Insecticide inputs	total amounts from van Paassen et al. (2019), types from Nemecek (2007b)	2	3	4	1	1
Irrigation energy use	van Paassen et al. (2019)	2	3	2	1	1
Field activities energy use	van Paassen et al. (2019)	2	3	2	1	1
Transportation of field inputs	van Paassen et al. (2019)	2	3	4	1	1
Post-harvest energy use	van Paassen et al. (2019)	2	5	3	4	1
Direct and indirect N2O emissions	Modelled using IPCC Tier 2 methods with N input data from van Paassen et al. (2019)	1	3	2	1	1
CO2 emissions from lime and urea	van Paassen et al. (2019)	2	3	2	2	1
Soil carbon changes	Modelled using NIR values	1	1	1	1	4

	(CCNUCC, 2022)					

Table 22. Data sources to be used for modeling German non-durum wheat production, and their associated pedigree matrix scores

Data point	**Source**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield (grain)	European Commission (2022)	1	1	1	1	1
Straw removed	Lafond et al. (2009)	2	4	5	3	1
Seed	van Paassen et al. (2019)	1	3	3	1	1
Lime	van Paassen et al. (2019)	1	3	2	1	1
Fertilizer inputs	van Paassen et al. (2019	1	3	2	1	3
Manure (modelled as fertilizer inputs)	van Paassen et al. (2019) for amounts, based on nutrient contents from Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and Paredes (2005)	4	4	5	5	4
All pesticide inputs	total amounts from van Paassen et al. (2019), types from Nordborg et al. 2014	1	3	2	1	4
Irrigation energy use	van Paassen et al. (2019)	2	3	2	1	1

Field activities energy use	van Paassen et al. (2019)	2	3	2	1	1
Transportation of field inputs	van Paassen et al. (2019)	2	3	4	1	1
Post-harvest energy use	van Paassen et al. (2019)	2	5	3	4	1
Direct and indirect N2O emissions	Modelled using IPCC Tier 2 methods with N input data from van Paassen et al. (2019)	1	3	2	1	1
CO2 emissions from lime and urea	van Paassen et al. (2019)	2	3	2	2	1
Soil carbon changes	Modelled using NIR values (Federal Environment Agency, 2022)	1	1	1	1	4

The available data for wheat production in the U.S. was of high quality (table 23). The main sources for data are van Paassen et al. (2019) and the USDA LCA Commons (USDA-National Agricultural Library, 2014). In fact, the data in van Paassen et al. (2019) were taken from the USDA LCA Commons, and modified for simplicity as well as correcting reported errors in the original data. For this reason, the van Paassen et al. (2019) data were preferentially sourced over the USDA LCA Commons data when they are both indicated in the table. Proxy data from Saskatchewan were used for calculation of the amount of wheat straw removed. These data were based on qualified estimates and econometric modeling of the removal of corn stover for use in production of ethanol from lignocellulosic biomass (Juneja et al. 2103). Data for amounts and types of fertilizer inputs were taken from van Paassen et al. (2019). While higher quality data for amounts of fertilizers was available from the NASS (USDA, 2020), these numbers are only presented in terms of total nutrients applied, rather than in terms of products applied. Some data points (seed, field activities, transport and post-harvest) had lower data quality for temporal correlation since they are all almost 10 years old at the time of writing this report. Post-harvest energy use data was taken from van Paassen et al. (2019) as previously described

Table 23. Data sources to be used for modeling US non-durum wheat production, and their associated pedigree matrix scores

Data point	Source	Reliability	Completeness	Temporal correlation	Geographical correlation	Technological correlation
Yield (grain)	NASS report (USDA, 2020)	1	1	1	1	1
Straw removed	Lafond et al. (2009)	2	4	5	3	1
Seed	van Paassen et al. (2019)	2	1	2	1	1
Lime	van Paassen et al. (2019) (USDA-National Agricultural Library, 2014)	2	1	3	1	1
Manure	van Paassen et al. (2019), based on nutrient contents from Government of Saskatchewan (2022) and Azeez and Van Averbeke (2010)	4	4	5	5	4
All fertilizer inputs	van Paassen et al. (2019)/USDA LCA Commons (USDA-National Agricultural Library, 2014)	2	1	2	1	3
Herbicide, fungicide, insecticide inputs	NASS database (USDA-NASS, 2022)	1	1	1	1	4
Irrigation energy use	van Paassen et al. (2019)/USDA LCA Commons (USDA-National	1	1	2	1	1

	Agricultural Library, 2014)					
Field activities	van Paassen et al. (2019)/USDA LCA Commons (USDA-National Agricultural Library, 2014)	2	1	3	1	1
Transport of field inputs	van Paassen et al. (2019)/USDA LCA Commons (USDA-National Agricultural Library, 2014)	2	1	3	1	1
Post-harvest energy use	van Paassen et al. (2019)	2	5	3	4	1
Direct and indirect energy use	Calculated using IPCC Tier 2 methods and N inputs from van Paassen et al. (2019)	1	1	2	1	1
CO2 emissions from lime and urea	van Paassen et al. (2019)	2	1	2	2	1
Soil carbon changes	Calculated using NIR methods (U.S. Environmental Protection Agency, 2022)	1	1	1	1	4

2.5.6.4 Field pea data sources

A total of three sources were consulted for Saskatchewan, and five sources were consulted for Canadian field pea production. In contrast to both canola and non-durum wheat, both Saskatchewan and Canadian field pea production may be characterized by data of very high quality (tables 24-25). This is a result of a recently completed project by Bamber et al. (2020) for Pulse Canada. In this project, survey data was collected characterizing farm-level inputs for over 600 pea and lentil producers, including a large sample from Saskatchewan pea producers. These data were used, with few exceptions.

Specifically, data characterizing transportation of inputs to farms are taken from van Paassen et al. (2019). Data on irrigation energy for the Canadian model was taken from van Paassen et al. (2019). All other data in both the Saskatchewan and Canadian models were taken from Bamber et al. (2020), adjusted to take into account changes in yield since initial data collection. The input values for inoculant were partially based on expert opinion, therefore they received a score of 4 for both reliability and completeness. The data on types and amounts of pesticide active ingredients applied from (Bamber et al., 2020) are representative of the technology used on Canadian and Saskatchewan farms, however background production datasets for each chemical type are not available in ecoinvent. For this reason, some pesticide products were modelled using the generic “pesticide, unspecified” process. This proxy resulted in a data quality indicator of 4 for technological correlation. Importantly, data on types of pesticides applied are limited in the appended excel file which represents the processes available in ecoinvent at the time of the creation of the dataset. However, the full lists of pesticide products are available for use in the current analysis, and are presented in the appended LCI excel files. The N credit from N fixed by the peas that is made available to the next crop in rotation was calculated based on data from research in Western Canada (Barker, 2007). This source is over 15 years old, therefore it received a 5 for temporal correlation. The N credit was modelled as an avoided use of ammonia fertilizer for the next crop in the rotation, therefore it received a 4 for technological correlation due to this proxy.

Table 24. Data sources to be used for modeling Saskatchewan dried field pea production, and their associated pedigree matrix scores

Data point	**Source to be used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	StatsCan, table 32-10-059-10 (Statistics Canada, 2022b)	1	2	1	1	1
Seed	Bamber et al. (2020)	1	3	1	1	1
Inoculant	Bamber et al. (2020)	1	3	1	1	2
Fertilizer inputs	Bamber et al. (2020)	1	3	1	1	1
Pesticides	Bamber et al. (2020)	1	3	1	1	4
Field activities energy use	Bamber et al. (2020)	1	3	1	1	1
Transportation	van Paassen et al. 2019	2	3	4	1	1
Post harvest	Bamber et al. (2020)	1	3	1	1	1
N2O emissions	CRSC values scaled to N inputs from	1	3	1	1	1

(direct and indirect)	Bamber et al. (2020)					
CO2 emissions from lime and urea	Bamber et al. (2020)	1	3	1	1	1
Soil carbon changes	NIR methods (Environment and Climate Change Canada, 2022)	1	1	1	1	4
N credit	Barker (2007)	2	3	5	1	4

Table 25. Data sources to be used for modeling Canadian dried field pea production, and their associated pedigree matrix scores

Data point	**Source to be used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	StatsCan, table 32-10-059-10 (Statistics Canada, 2022b)	1	2	1	1	1
Seed	Bamber et al. (2020)	1	3	1	1	1
Inoculant	Bamber et al. (2020)	4	4	1	1	2
Fertilizer inputs	Bamber et al. (2020)	1	3	1	1	1
All pesticides	Bamber et al. (2020)	1	3	1	1	4
Irrigation energy	van Paassen et al. (2019)	2	3	2	1	1
Field activities energy use	Bamber et al. (2020)	1	3	1	1	1
Transportation	van Paassen et al. (2019)	2	3	4	1	1
Post harvest	Bamber et al. (2020)	1	3	1	1	1
N2O emissions	CRSC values scaled to N inputs from	1	3	1	1	1

(direct and indirect)	Bamber et al. (2020)					
CO2 emissions from lime and urea	Bamber et al. (2020)	1	3	3	1	1
Soil carbon changes	NIR methods (Environment and Climate Change Canada, 2022)	1	1	1	1	4
N credit	Barker (2007)	2	3	5	1	4

Data characterizing French and German field pea production are generally of high quality, with the majority of data in both cases sourced from van Paassen et al. (2019) (tables 26-27). Yield data were taken from the EuroStat database, a publicly available repository for a variety of data from European Union member states (European Commission, 2022b). For both France and Germany, post-harvest energy use could not be sourced from van Paassen et al. (2019) as it is excluded from the datasets presented. Rather, this data had to be sourced from Nguyen et al. (2012), which used data with errors corrected from Nemecek (2007e, 2007f), where it was representative of survey data originally collected from 2000-2004, and extrapolated to 2021. Similarly, inputs of synthetic N fertilizers to German pea production systems was also sourced from Nemecek (2007c), as the data available from van Paassen et al. (2019) do not include synthetic N sources, and only include N derived from pig and chicken manure application. Inputs of inoculant were modelled based on the Canadian average data from Bamber et al. (2020), since no data were available on inoculant inputs for France and Germany, but it was assumed that inoculants were used since these contribute to the N-fixing ability of peas (Clayton et al., 2004). The N credit for French and German peas was calculated based on GL-Pro (2005), which indicated that wheat grown after peas could use 20-25% less fertilizer. Therefore, the N credit was calculated as 20% of the N fertilizer amount applied to French and German wheat, and modelled as an avoided ammonia input.

Table 26. Data sources to be used for modeling French dried field pea production, and their associated pedigree matrix scores

Data point	**Source to be used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield (and the inverse, land area)	Eurostat database (European Commission, 2022b)	1	1	1	1	1
Seed	van Paassen et al. (2019)	1	3	3	1	1
Lime	van Paassen et al. (2019)	2	3	3	1	1

Inoculant	Bamber et al. 2020a	4	4	1	4	2
All other fertilizer inputs	van Paassen et al. (2019)	1	3	2	1	1
Manure inputs (modelled as fertilizers)	van Paassen et al. (2019) for amounts, based on nutrient contents from Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and Paredes (2005)	4	4	5	5	4
All pesticides	total amounts from van Paassen et al. (2019), distribution from Nemecek 2007	1	3	2	1	1
Irrigation energy	van Paassen et al. (2019)	2	3	2	1	1
Field activities energy use	van Paassen et al. (2019)	2	3	2	1	1
Transportation	van Paassen et al. (2019)	2	3	4	1	1
Post harvest	Nemecek 2007 and Nguyen 2012	2	3	4	3	2
N_2O emissions (direct and indirect)	Modeled using data from van Paassen et al. (2019)	1	3	2	1	1
CO_2 emissions	Modeled using data	2	3	3	1	1

from lime and urea	from van Paassen et al. (2019)					
Soil carbon changes	NIR methods (CCNUCC, 2022)	1	1	1	1	4
N credit	GL-Pro (2005)	1	3	5	1	4

Table 27. Data sources to be used for modeling German dried field pea production, and their associated pedigree matrix scores

Data point	**Source to be used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield (and the inverse, land area)	Eurostat database (European Commission, 2022b)	1	1	1	1	1
Seed	van Paassen et al. (2019)	1	3	3	1	1
Inoculant	Bamber et al. 2020a	4	4	1	4	2
Lime	van Paassen et al. (2019)	2	3	3	1	1
N fertilizer	Nemecek (2007f)	4	3	4	1	1
All other fertilizer inputs	van Paassen et al. (2019)	1	3	1	1	1
Manure (modelled as fertilizer inputs)	van Paassen et al. (2019) for amounts, based on nutrient contents from Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and	4	4	5	5	4

	Paredes (2005)					
All pesticides	total amounts from van Paassen et al. (2019), types from Nemecek 2007f	1	3	2	1	1
Irrigation energy	van Paassen et al. (2019)	2	3	2	1	1
Field activities energy use	van Paassen et al. (2019)	2	3	2	1	1
Transportation	van Paassen et al. (2019)	2	3	4	1	1
Post harvest	Nemecek (2007f) and Nguyen et al 2012	4	3	4	1	1
N2O emissions (direct and indirect)	Modeled with data from van Paassen et al. (2019)	1	3	2	1	1
CO2 emissions from lime and urea	Modeled with data from van Paassen et al. 2019	2	3	2	2	1
Soil carbon changes	NIR methods (Federal Environment Agency, 2022)	1	1	1	1	4
N credit	GL-Pro (2005)	1	3	5	1	4

Finally, data characterizing U.S. field pea production were of generally high quality, with most requisite data sourced from van Paassen et al. (2019) (table 28). Inoculant input data came from the Canadian average from Bamber et al. (2020a). None of the sources consulted included estimates of post-harvest energy use for U.S. field pea production. This gap was filled using data adapted from Canadian production conditions as presented by Bamber et al. (2020a). The N credit was calculated using the same source as the Canadian data, which was based on research from Western Canada (Barker 2007).

Table 28. Data sources to be used for modeling U.S. field pea production, and their associated pedigree matrix scores

Data point	Source to be used	Reliability	Completeness	Temporal correlation	Geographical correlation	Technological correlation
Yield	NASS database	1	3	1	1	1
Seed	van Paassen et al. (2019)	1	3	3	1	1
Inoculant	Bamber et al. 2020a	4	4	1	3	2
Lime	van Paassen et al. (2019)	2	3	3	1	1
All fertilizer inputs	van Paassen et al. (2019)	1	3	2	1	3
Manure inputs	van Paassen et al. (2019), based on nutrient contents from Government of Saskatchewan (2022) and Azeez and Van Averbeke (2010)	4	4	5	5	4
All pesticides	van Paassen et al. (2019)	1	3	2	1	4
Irrigation energy	van Paassen et al. (2019)	2	3	2	1	1
Field activities energy use	van Paassen et al. (2019)	2	3	2	1	1
Transportation	van Paassen et al. (2019)	2	3	4	1	1
Post harvest	Bamber et al. 2020a	1	3	1	3	1
N2O emissions (direct and indirect)	Modelled with data from Bandekar et al. (Bandekar et al., 2022)	1	3	2	1	1

CO2 emissions from lime and urea	Modelled with data from van Paassen et al. (2019)	2	3	3	2	1
Soil carbon changes	NIR Methods (U.S. Environmental Protection Agency, 2022)	1	1	1	1	4
N credit	Barker (2007)	2	3	5	3	4

2.5.7 Background data providers

The ecoinvent database version 3.8 was chosen for all background data providers. A single background data source was chosen to ensure methodological consistency for all background data. The ecoinvent database was chosen since it contains background datasets for all relevant data categories at the appropriate levels of regional specificity (country-level as well as for the province of Saskatchewan). It is also one of the most commonly used background database for LCA practitioners. Table 29 lists all providers used to model background datasets, as well as any modifications made to make them better fit for the purposes of this study. Table 30 lists all processes used in modifications. These tables were split in order to avoid redundancy, as electricity providers were changed across many of the background processes listed in table 29. In general, processes were modified to use electricity providers specific to the country or province modelled, unless otherwise indicated in the table. In some cases, production processes representing specific pesticide active ingredients are unavailable in ecoinvent v.3.8. Where possible, active ingredients have been modeled as production of active ingredients of the same chemical family. When these were not available, pesticides were modeled as unspecified.

Table 29. LCI flows, the processes used to model them from ecoinvent v.3.8, and any modifications made to those processes.

Data point	**Process (from ecoinvent v.3.8)**	**Modifications**
Seed		
Pea seed	pea seed production, for sowing | pea seed, for sowing | APOS, U - CH	electricity and pea providers changed for each region
Wheat seed	wheat seed production, for sowing | wheat seed, for sowing - RoW	electricity and wheat providers changed for each region
Canola seed	rape seed production, for sowing | rape seed, for sowing - CH	electricity and rapeseed providers changed for each region
Fertilizers (including manure modelled as upstream synthetic fertilizer production)		
Urea	urea production | urea | APOS, U – RER or RNA	electricity providers changed for each region for CA, the national average electricity mix was used since urea is produced in many Canadian provinces (Cheminfo Services Inc., 2016)
Ammonia	ammonia production, steam reforming, liquid | ammonia, anhydrous, liquid | APOS, U – RER or RNA	electricity and natural gas providers changed for each region
Ammonium nitrate	ammonium nitrate production | ammonium nitrate | APOS, U – RER or RNA	electricity providers changed for each region for CA, the national average electricity mix was used since ammonium nitrate is produced in many Canadian provinces (Cheminfo Services Inc., 2016) ammonia providers changed to regionalized ammonia providers (modifications described above)
Calcium ammonium nitrate	calcium ammonium nitrate production | calcium ammonium nitrate – RNA or RER	electricity providers changed for each region for CA, the national average electricity mix was used since ammonium nitrate is produced in many Canadian provinces (Cheminfo Services Inc., 2016) ammonia providers changed to regionalized ammonia providers (modifications described above)

Urea ammonium nitrate (UAN)	urea ammonium nitrate production | urea ammonium nitrate mix | APOS, U – RNA or RER	ammonium nitrate provider changed to regionally modified ammonium nitrate process for each region (described above) electricity providers changed for each region for CA, the national average electricity mix was used since urea ammonium nitrate is produced in many Canadian provinces (Cheminfo Services Inc., 2016)
Monoammonium phosphate (MAP)	market for monoammonium phosphate | monoammonium phosphate | APOS, U – RNA or RER	electricity providers changed for each region for CA and SK, process was modelled as taking place in AB since that is the only location of a production facility for MAP (Cheminfo Services Inc., 2016)
Diammonium phosphate (DAP)	diammonium phosphate production | diammonium phosphate | APOS, U – RNA or RER	electricity providers changed for each region ammonia providers changed to regionalized ammonia providers (modifications described above) for CA and SK, process was modelled as taking place in AB since that is the only location of a production facility for MAP (Cheminfo Services Inc., 2016), and no information was provided for production locations for DAP
Single superphosphate	single superphosphate production | single superphosphate | APOS, U - RER	electricity and phosphate rock providers changed for each region for CA and SK, process was modelled as taking place in AB since that is the only location of a production facility for MAP (Cheminfo Services Inc., 2016), and no information was provided for production locations for superphosphate
Triple superphosphate	triple superphosphate production | triple superphosphate | APOS, U - RER	electricity, phosphate rock, and phosphoric acid providers changed for each region for CA and SK, process was modelled as taking place in AB since that is the only location of a production facility for MAP (Cheminfo Services Inc., 2016), and no information was provided for production locations for superphosphate
Phosphate rock	phosphate rock beneficiation | phosphate rock, beneficiated | APOS, U - RER	electricity providers changed for each region
Potassium chloride (potash) – SK, CA, US	potassium mining and benefication | potassium chloride | APOS, U - CA-SK	electricity providers changed for each region for CA, process was modelled as SK since that is the only location for a production facility of potash, and SK was modelled as SK (Cheminfo Services Inc., 2016)
Potassium chloride (potash) – FR, DE, AU	potassium chloride production | potassium chloride | APOS, U	electricity providers changed for each region

Potassium sulfate	potassium sulfate production | potassium sulfate | APOS, U - RER	electricity providers changed for each region for CA, process was modelled as SK since that is the only location for a production facility of potassium, and SK was modelled as SK (Cheminfo Services Inc., 2016) potassium chloride providers changed for each region (SK for both SK and CA)
Ammonium sulfate	ammonium sulfate production | ammonium sulfate | APOS, U - RER	ammonia providers changed to regionalized ammonia providers (modifications described above) electricity providers changed for each region for CA, the national average electricity mix was used since ammonium sulfate is produced in several Canadian provinces (Cheminfo Services Inc., 2016)
Sulfur	natural gas production | sulfur | APOS, U - CA-AB or DE	electricity providers changed for each region for CA and SK, the AB electricity mix was used since sulfur is mainly produced in AB (Prud'homme, 2013)
Zinc	primary zinc production from concentrate | zinc | APOS, U – CA-QC	electricity and urea providers changed for each region for CA, the national average electricity mix was used since zinc is produced in several Canadian provinces, for SK the MB electricity mix was used since SK does not produce zinc and MB is the largest producer (World Atlas, 2022)
Magnesium	magnesium production, electrolysis | magnesium | APOS, U - IL	electricity provider changed to market group for electricity, high voltage | electricity, high voltage | APOS, U - CA
Lime	lime production, milled, loose | lime | APOS, U – CA-QC or CH	electricity providers changed for each region for CA, the national average electricity mix was used since lime is produced in several Canadian provinces, and SK used for SK (Vagt, 2015)
Plant protection products		
Glyphosate	glyphosate production | glyphosate | APOS, U - RER	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a) ammonia and decarbonised water providers changed for each region
Pyroxasulfone, Metolachlor	acetamide-anillide-compound production, unspecified | acetamide-anillide-compound, unspecified | APOS, U - RER	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a) ammonia, sulfur and decarbonised water providers changed for each region
Sulfentrazone, propiconazole, prothioconazole,	triazine-compound production, unspecified | triazine-	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a)

epoxiconazole, tebuconazole, metconazole, Tetraconazole, Carfentrazon-ethyl, metribuzin	compound, unspecified | APOS, U - RER	ammonia and decarbonised water providers changed for each region
Glufosinate, chlorpyrifos, Methidathion	organophosphorus-compound production, unspecified | organophosphorus-compound, unspecified | APOS, U - RER	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a) ammonia, decarbonised water and sulfur providers changed for each region
MCPA, 2,4-D, Quizalofop-ethyl	phenoxy-compound production | phenoxy-compound | APOS, U - RER	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a) ammonia and decarbonised water providers changed for each region
Bromoxynil, Azoxystrobin, Dimoxystrobin, chlorothalonil, ethaboxam	nitrile-compound production | nitrile-compound | APOS, U - RER	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a) ammonia and decarbonised water providers changed for each region
Bentazon	benzo[thia]diazole-compound production | benzo[thia]diazole-compound | APOS, U - RER	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a) ammonia, sulfur and decarbonised water providers changed for each region
Fluroxypyr, Diflufenican, Boscalid	pyridine-compound production | pyridine-compound | APOS, U - RER	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a) ammonia and decarbonised water providers changed for each region
Triallate	[thio]carbamate-compound production | [thio]carbamate-compound | APOS, U - RER	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a) ammonia, sulfur and decarbonised water providers changed for each region
Diquat	bipyridylium-compound production | bipyridylium-compound | APOS, U - RER	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a)

		ammonia, sulfur and decarbonised water providers changed for each region
Ethalfluralin, Trifluralin, Pendimethalin	dinitroaniline-compound production | dinitroaniline-compound | APOS, U - RER	electricity and ammonia providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a)
Deltamethrin, cyhalothrin-lambda, Bifenthrin, Alpha-cypermethrin, Cypermethrin, Etofenprox, Beta-Cyfluthrin, Permethrin	pyrethroid-compound production | pyrethroid-compound | APOS, U - RER	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a) ammonia and decarbonised water providers changed for each region
Atrazine	atrazine production | atrazine | APOS, U - RER	electricity and ammonia providers changed for each region
Dimethanamid-P	dimethenamide production | dimethenamide | APOS, U - RER	electricity, ammonia, sulfur and decarbonised water providers changed for each region
Napropamide	napropamide production | napropamide | APOS, U - RER	electricity, sulfur, and decarbonised water providers changed for each region
cyclic N-compound	cyclic N-compound production | cyclic N-compound | APOS, U - RER	electricity, ammonia, sulfur, and decarbonised water providers changed for each region
Metrafenone, dicamba, Propoxycarbazone, fludioxonil	benzoic-compound production | benzoic-compound | APOS, U - RER	electricity, ammonia, sulfur, and decarbonised water providers changed for each region
Flumioxazin	phthalimide-compound production | phthalimide-compound | APOS, U - RER	electricity, ammonia, urea and decarbonised water providers changed for each region
Thiram	dithiocarbamate-compound production | dithiocarbamate-compound | APOS, U - RER	ammonia and electricity providers changed for each region

Benzimidazole compound	benzimidazole-compound production | benzimidazole-compound | APOS, U - RER	ammonia, electricity, and sulfur providers changed for each region
All other active ingredients	pesticide production, unspecified | pesticide, unspecified | APOS, U - RER	electricity providers changed for each region US national electricity grids were used for US, CA and SK since the majority of pesticides used in Canada are sourced from the US (Bamber et al., 2022a) ammonia, urea, sulfur and decarbonised water providers changed for each region
Inoculant		
Peat moss	peat moss production, horticultural use | peat moss | APOS, U – CA-QC	ammonium nitrate and electricity providers changed for each region
Energy providers		
Diesel	diesel, burned in agricultural machinery | diesel, burned in agricultural machinery | APOS, U - GLO	infrastructure and machinery flows removed
Electricity	market for electricity, low voltage | electricity, low voltage | APOS, U (for each region)	processes for each region used without modifications
Light fuel oil	heat production, light fuel oil, at boiler 10kW condensing, non-modulating | heat, central or small-scale, other than natural gas | APOS, U – Europe without Switzerland	electricity providers changed for each region
Natural gas (heat)	heat production, natural gas, at boiler condensing modulating >100kW | heat, district or industrial, natural gas | APOS, U – CA-QC or Europe without Switzerland	electricity and natural gas providers changed for each region
Process steam from natural gas (electricity)	electricity production, natural gas, combined cycle power	processes for each region used without modifications

	plant | electricity, high voltage | APOS, U – for each country	
Transportation		
Truck transportation	market for transport, freight, lorry 7.5-16 metric ton, EURO4 | transport, freight, lorry 7.5-16 metric ton, EURO4 | APOS, U - RER	
N credit		
Ammonia (used as a negative input to credit the decreased use of N fertilizer for next crop in rotation due to N fixation by peas)	ammonia production, steam reforming, liquid | ammonia, anhydrous, liquid | APOS, U	regional modifications as described above

Table 30. Processes used for modification of background processes

Modifications	**Processes used for modifications**
Electricity	- market for electricity, low voltage | electricity, low voltage | APOS, U – Saskatchewan, - market group for electricity, low voltage | electricity, low voltage | APOS, U – Canada, - market for electricity, low voltage | electricity, low voltage | APOS, U – France - market for electricity, low voltage | electricity, low voltage | APOS, U – Germany - market group for electricity, low voltage | electricity, low voltage | APOS, U – United States
Pea seed	- pea seed production, for sowing | pea seed, for sowing | APOS, U | - Saskatchewan - pea seed production, for sowing | pea seed, for sowing | APOS, U | - Canada - pea seed production, for sowing | pea seed, for sowing | APOS, U | - France - pea seed production, for sowing | pea seed, for sowing | APOS, U | - Germany - pea seed production, for sowing | pea seed, for sowing | APOS, U | - United States
Wheat seed	- wheat seed production, for sowing | wheat seed, for sowing | APOS, U | - Australia - wheat seed production, for sowing | wheat seed, for sowing | APOS, U | - Canada - wheat seed production, for sowing | wheat seed, for sowing | APOS, U | - Saskatchewan

<table>
<tr><td></td><td>- wheat seed production, for sowing | wheat seed, for sowing | APOS, U | - Germany
- wheat seed production, for sowing | wheat seed, for sowing | APOS, U | - France
- wheat seed production, for sowing | wheat seed, for sowing | APOS, U | - United States</td></tr>
<tr><td>Canola seed</td><td>- rape seed production, for sowing | rape seed, for sowing | APOS, U | - Australia
- rape seed production, for sowing | rape seed, for sowing | APOS, U | - Canada
- rape seed production, for sowing | rape seed, for sowing | APOS, U | - Saskatchewan
- rape seed production, for sowing | rape seed, for sowing | APOS, U | - France
- rape seed production, for sowing | rape seed, for sowing | APOS, U | - Germany</td></tr>
<tr><td>Natural gas</td><td>- market group for natural gas, high pressure | natural gas, high pressure | APOS, U – Canada
- market for natural gas, high pressure | natural gas, high pressure | APOS, U – United States
- market for natural gas, high pressure | natural gas, high pressure | APOS, U – Germany
- market for natural gas, high pressure | natural gas, high pressure | APOS, U – Australia
- market for natural gas, high pressure | natural gas, high pressure | APOS, U – Alberta</td></tr>
<tr><td>Phosphate rock</td><td>- market for phosphate rock, beneficiated | phosphate rock, beneficiated | APOS, U – Europe
- market for phosphate rock, beneficiated | phosphate rock, beneficiated | APOS, U – United States
- phosphate rock beneficiation | phosphate rock, beneficiated | APOS, U | - Australia
- phosphate rock beneficiation | phosphate rock, beneficiated | APOS, U | - France</td></tr>
<tr><td>Phosphoric acid</td><td>- phosphoric acid production, dihydrate process | phosphoric acid, fertiliser grade, without water, in 70% solution state | APOS, U – United States
- phosphoric acid production, dihydrate process | phosphoric acid, fertiliser grade, without water, in 70% solution state | APOS, U – Rest of World
- phosphoric acid production, dihydrate process | phosphoric acid, fertiliser grade, without water, in 70% solution state | APOS, U - Europe</td></tr>
<tr><td>Potassium chloride</td><td>- potassium mining and benefication | potassium chloride | APOS, U | - Australia
- potassium mining and benefication | potassium chloride | APOS, U – Saskatchewan
- potassium chloride production | potassium chloride | APOS, U | - Germany
- potassium chloride production | potassium chloride | APOS, U | - France
- potassium mining and benefication | potassium chloride | APOS, U | - United states</td></tr>
<tr><td>Urea</td><td>- Urea production | urea | APOS, U | - Canada</td></tr>
<tr><td>Ammonia</td><td>- ammonia production, steam reforming, liquid | ammonia, anhydrous, liquid | APOS, U | - Australia
- ammonia production, steam reforming, liquid | ammonia, anhydrous, liquid | APOS, U | - United States
- ammonia production, steam reforming, liquid | ammonia, anhydrous, liquid | APOS, U | - Germany
- ammonia production, steam reforming, liquid | ammonia, anhydrous, liquid | APOS, U | - France</td></tr>
</table>

Decarbonised water	- market for water, decarbonised | water, decarbonised | APOS, U – Rest of World - market for water, decarbonised | water, decarbonised | APOS, U – United States - market for water, decarbonised | water, decarbonised | APOS, U – Germany - market for water, decarbonised | water, decarbonised | APOS, U - France
Sulfur	- market for sulfur dioxide, liquid | sulfur dioxide, liquid | APOS, U - Europe - natural gas production | sulfur | APOS, U – United States - natural gas production | sulfur | APOS, U | - Germany - natural gas production | sulfur | APOS, U | - France
Ammonium nitrate	- ammonium nitrate production | ammonium nitrate | APOS, U | - Saskatchewan - ammonium nitrate production | ammonium nitrate | APOS, U | - Canada - ammonium nitrate production | ammonium nitrate | APOS, U | - Germany - ammonium nitrate production | ammonium nitrate | APOS, U | - France - ammonium nitrate production | ammonium nitrate | APOS, U | - United States

2.5.8 Emissions modelling

2.5.8.1 Soil carbon change

The estimates of soil carbon change from each country's NIR were used. These values were calculated by dividing the total soil carbon change for each country's cropland by the total area of cropland in each country. These area-based estimates were then scaled by the yield of each crop in each country to give carbon sequestration or emission estimates per functional unit of 1 kg of crop. Apart from the differences in yield, these values are not crop specific, since the NIR reports these values for all crops. These values were used to ensure methodological consistency between countries, since detailed data were not available for all countries to perform process-based modelling at a crop-specific level. For estimates of carbon sequestration, these were calculated as inputs of CO_2 to the soil from the atmosphere, and carbon losses were modelled as emissions of CO_2 to the atmosphere from the soil.

2.5.8.2 N_2O emissions

In order to ensure methodological consistency for all crop-country combinations, the modelling practices employed in each country's NIR were used, with all deviations documented. Direct N_2O emissions were calculated in accordance with the IPCC (2019) equation 11.2 such that

$$N_2O_{direct} - N = \sum_i (F_{SN} + F_{ON})_i \times EF_{1i} + (F_{CR} + F_{SOM}) \times EF_1 + N_2O - N_{OS} + N_2O - N_{PRP}$$

where

$N_2O_{direct} - N$ represents the annual direct N_2O–N emissions produced from managed soils in kg N_2O–N year^{-1}

F_{SN} represents the amount of synthetic fertilizer N applied to soils in kg N year^{-1}

F_{ON} represents the annual amount of animal manure, compost, sewage sludge, and other organic N additions applied to soils in kg N year^{-1}

EF_{1i} represents emissions factors developed for N_2O emissions from synthetic fertilizers, organic N application, N inputs from crop residues, and mineralization of N due to losses of soil organic matter in kg N_2O-N (kg N input)$^{-1}$

F_{CR} represents the annual amount of N in above and belowground crop residues, including N-fixing crops, and from forage/pasture renewal, returned to soils in kg N year^{-1}

F_{SOM} represents the annual amount of N in mineral soils that is mineralised, in association with loss of soil C from soil organic matter as a result of changes to land use or management, in kg N year^{-1}

For Canada and Saskatchewan, the N_2O emissions estimated in the CRSC carbon footprint methodology report were used ((S&T)2 Consultants Inc., 2021a), since they are based on the Canadian NIR, calculated at a sub-regional level, then aggregated to the provincial and national scale. This includes the contribution to N_2O emissions from decomposition of crop residues left on the field which were scaled down in accordance with the percentage of crop residues assumed to be removed in wheat production systems from those values presented which assumed no removal of crop residues from wheat production systems. The Canadian and Saskatchewan emission factors presented in Table 31 are production weighted averages of the Reconciliation Unit (RU) factors presented in the CRSC reports. Since the production volumes in each RU differ by crop, the emission factors also differ due to the differences in production weighted averages. They used the same emission factors for all types of N fertilizer applied. The values for the direct N_2O emission factors for Australia, France and Germany were taken from each country's NIR (Cetipa, 2022; Commonwealth of Australia, 2022; Federal Environment Agency, 2022). The French NIR uses the IPCC Tier 1 value, whereas the Australian and German NIRs present country-specific Tier 2 values. For the United States, the NIR uses a combination of Tier 1 and Tier 3 values, with the Tier 3 values calculated using the process-based model DAYCENT(Del Grosso et al., 2001). However, they do not present crop-specific Tier 3 results for N_2O emissions, and the data are not available to use process-based models to calculate these emissions for the U.S., or other countries. Therefore, the Tier 2 EF was taken from Dusenbury et al., (2008), which was used in the LCA of US peas in rotation with wheat (Bandekar et al., 2022). This EF is representative of the Northern Great Plains region of US cropland.

Indirect N_2O emissions come from both volatilization (or gasification) of applied N as NH_3 and NO_x, and leaching as NO_3, followed by subsequent emissions of N_2O from each of these N compounds. Indirect N_2O emissions from volatilization or gasification were calculated according to equation 11.11 from IPCC (2019), such that

$$N_2O_{(ATD)} - N = \left\{ \sum_i \left(F_{SN_i} \times Frac_{GASF_i} \right) + \left[\left(F_{ON} + F_{PRP} \right) \times Frac_{GASM} \right] \right\} \times EF_4$$

Where

$N_2O_{(ATD)}$ – N represents the annual amount of N_2O – N produced from atmospheric deposition of N volatilised from managed soils in kg N_2O–N yearr^{-1}

F_{SN} represents the annual amount of synthetic fertilizer N applied to soils in kg N year^{-1}

$Frac_{GASF}$ represents the fraction of synthetic fertilizer N that volatilises as NH_3 and NO_x in kg N volatilised (kg of N applied)$^{-1}$

F_{ON} represents the annual amount of managed animal manure, compost, sewage sludge and other organic N additions applied to soils in kg N year^{-1}

$Frac_{GASM}$ represents the fraction of applied organic N fertilizer materials (F_{ON}) that volatilises as NH_3 and NO_x, in kg N volatilised (kg of N applied or deposited)$^{-1}$ with values taken from table 11.3 in IPCC (2019)

EF_4 represents emission factor for N_2O emissions from atmospheric deposition of N on soils and water surfaces, in [kg N–N_2O (kg NH_3–N + NO_x–N volatilised)$^{-1}$] with values taken from table 11.3 in IPCC (2019)

Indirect emissions of N_2O from N leaching and runoff were calculated according to equation 11.10 from IPCC (2019) for regions where leaching/runoff occurs such that

$$N_2O_{(L)} - N = \left(F_{SN} + F_{ON} + F_{PRP} + F_{CR} + F_{SOM} \right) \times Frac_{Leach-(H)} \times EF_5$$

where

$N_2O_{(L)}$–N represents the annual amount of N_2O–N produced from leaching and runoff of N additions to managed soils in regions where leaching/runoff occurs, in kg N_2O–N year^{-1}

F_{SN} represents the annual amount of synthetic fertilizer N applied to soils in regions where leaching/runoff occurs, in kg N year^{-1}

F_{ON} represents the annual amount of managed animal manure, compost, sewage sludge and other organic N additions applied to soils in regions where leaching/runoff occurs, in kg N year^{-1}

F_{CR} represents the amount of N in crop residues (above- and below-ground), including N-fixing crops, and from forage/pasture renewal, returned to soils annually in regions where leaching/runoff occurs, in kg N year^{-1}

F_{SOM} represents the annual amount of N mineralised in mineral soils associated with loss of soil C from soil organic matter as a result of changes to land use or management in regions where leaching/runoff occurs, in kg N year^{-1} calculated according to equation 11.8 in IPCC (2019)

$Frac_{Leach}$ represents the fraction of all N added to/mineralised in managed soils in regions where leaching/runoff occurs that is lost through leaching and runoff, in kg N (kg of N additions)$^{-1}$ with values taken from table 11.3 in IPCC (2019)

EF_5 represents the emission factor for N_2O emissions from N leaching and runoff, in kg N_2O–N (kg N leached and runoff)$^{-1}$ with values taken from table 11.3 in IPCC (2019)

For Canada, as per the CRSC methodology report ((S&T)2 Consultants Inc., 2021a), the IPCC Tier 1 methodology was followed for indirect N_2O emissions from volatilization. Regionalized Tier 2 values for $Frac_{LEACH}$ were taken from the CRSC methodology report ((S&T)2 Consultants Inc., 2021a), and aggregated to Saskatchewan and national level averages based on the relative proportions of production for each crop in each region. The Tier 1 value for EF_5 was used. For Australia, France, Germany and the United States, the values for $Frac_{GAS}$, $Frac_{LEACH}$, EF_4 and EF_5 were taken from each country's NIR (Cetipa, 2022; Commonwealth of Australia, 2022; Federal Environment Agency, 2022). Due to the climate conditions in Australia, no volatilization was included, and leaching was only included in regions where the climate conditions allowed it (100% of irrigated land and 20% on non-irrigated land) (Commonwealth of Australia, 2022). For Germany, the $Frac_{GASF}$ values from the NIR are both country-specific, and fertilizer type-specific. Therefore, the overall fractions for each crop were calculated based on the proportions of each type of fertilizer applied. The German $Frac_{GASM}$ values from the NIR were manure type and application method-specific. Crop-specific data were not available for the methods of manure application, therefore the generic values were used.

Table 31. Emission factors and fractions used in N_2O emissions modelling for all crops and regions.

Region	**$EF1_{FSN}$ Irrigated cropland[a]**	**$EF1_{FSN}$ Non-irrigated cropland[a]**	**$EF1_{FON}$ Dairy, feedlot, poultry**	**$EF1_{FON}$ pigs**	**$EF1_{FCR}$**	**$EF1_{FSOM}$**	**$Frac_{GASF}$ CAN**	**$Frac_{GASF}$ ammonium solutions[b]**	**$Frac_{GASF}$ urea[b]**	**$Frac_{GASF}$ ammonium phosphates[b]**	**$Frac_{GASF}$ NK and NPK fertilizers[b]**	**$Frac_{GASF}$ straight fertilizers/ single nutrient fertilizers[b]**	**$Frac_{GASM}$**	**EF_4**	**$Frac_{LEACH}$**	**EF_5**
Canada (peas)	0.0074	0.0074	0.0074	0.0074	0.0074	0.0074	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.1597	0.011
Canada (wheat)	0.0085	0.0085	0.0085	0.0085	0.0085	0.0085	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.1748	0.011
Canada (canola)	0.0077	0.0077	0.0077	0.0077	0.0077	0.0077	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.1649	0.011
Saskatchewan (peas)	0.0072	0.0072	0.0072	0.0072	0.0072	0.0072	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.1603	0.011
Saskatchewan (wheat)	0.0074	0.0074	0.0074	0.0074	0.0074	0.0074	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.1632	0.011
Saskatchewan (canola)	0.0074	0.0074	0.0074	0.0074	0.0074	0.0074	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.1636	0.011
Australia	0.0085	0.002	0.01	0.0039	0.001	0.002	-	-	-	-	-	-	-	-	0.24	0.011
France	0.01	0.01	0.01	0.01	0.01	0.01	0.06	0.06	0.06	0.06	0.06	0.06	0.147	0.01	0.25	0.0075
Germany	0.0062	0.0062	0.0062	0.0062	0.0062	0.01	0.0066	0.081	0.038	0.041	0.041	0.008	0.21	0.01	0.3	0.0075
United States	0.0021	0.0021	0.0021	0.0021	0.0021	0.0021	0.11	0.11	0.11	0.11	0.11	0.11	0.21	0.01	0.24	0.011

[a] The distinction between irrigated and non-irrigated cropland is only made for Australia

[b] The distinction between fertilizer types is only made for Germany

The input values for synthetic fertilizer and manure came from the inventory values, as described in section 2.5.6. The F_{SOM} values were calculated using the estimates of soil carbon change, as described in section 2.5.8.1. For any countries that had net carbon losses from the soil (rather than sequestration), these carbon losses were used to calculate the losses of N based on the N:C ratio of 0.1 (Cetipa, 2022; Commonwealth of Australia, 2022; Environment and Climate Change Canada, 2022; Federal Environment Agency, 2022). Inputs of N from crop residue were calculated for each crop-country combination, as described below in section 2.5.8.3.

2.5.8.3 N inputs from crop residues

Retention of crop residues on agricultural fields after crop harvesting may impart a large number of benefits to agricultural soils. Potential benefits include limiting soil water evaporation, reducing risks soil erosion by wind and water, and increases in soil carbon stocks and sequestration (Ranaivoson et al., 2017). These benefits may be offset, however, by increased emissions of N_2O resulting from microbial N mineralization and nitrification of residues, the rate of which is dependent on the N content of crop residues (Abalos et al., 2022; Chen et al., 2013). Accurate modeling of N_2O emissions therefore requires information related to crop residue yields and associated management practices, such as their removal from fields, as well as the N content of these residues. Specific assumptions made about crop residue-related management practices, yields, and N contents for each crop-country combination are detailed below.

2.5.8.3.1. Canola

Retention of canola crop residues on fields has been demonstrated to have suppressive effects on weeds (Haramoto and Gallandt, 2004; Radicetti et al., 2013), and positive impacts on nutrient uptake in proceeding crops (Arcand et al., 2014; Hirzel et al., 2022) without negatively impacting establishment, growth, or yields (Robertson et al., 2009). Canola residues were assumed to be left on the field for all countries in this analysis. Leaving residues on the field was previously identified as a best practice for canola in western Canada (MacWilliam et al., 2014), and is in line with work performed for the CRSC ((S&T)2 Consultants Inc, 2021a). In Australia, retention of canola residues on fields is in line with the most common practice for broad-acre crops (Umbers and Watson, 2021), and previous carbon footprint assessments of Australian canola (Eady, 2017). In France, it has been argued that canola crop residues are not being utilized to their maximum potential in the energy sector due to the lack of a mature market for these residues throughout the European Union (Iqbal et al., 2016; Karan and Hamelin, 2021). Finally, in Germany it is common practice to leave canola residues on the fields (Rothardt et al., 2021; Vinzent et al., 2017; Wang et al., 2020).

Following harvesting, total crop residues include both an above and belowground component, each occurring in different proportions and each with potentially different contributions to crop residue N_2O emissions due to differences in decomposition and N mineralization (Arcand et al., 2014). For the Saskatchewan and Canadian canola production models, above and belowground residue yields and N contents are taken from Thiagarajan et al. (2018), the current best available estimates of these data. Use of these values is in line with work done for the CRSC ((S&T)2 Consultants Inc, 2021a), and the Canadian National Inventory Report (Environment and Climate Change Canada, 2022).

For Australian canola production, yields, dry matter contents, and N contents are taken from the Australian NIR for oilseeds (Government of Australia, 2022), in line with previous work done by Eady

(2017). For French canola production, amounts of above and belowground residues were calculated based on values reported in the French NIR (Cetipa, 2022) assuming a dry matter content of 91%, in line with Terres Inovia (2020). N content of aboveground French canola residues was subsequently taken from Arvalis (2020a), while N content of belowground residues was taken from the French NIR (Cetipa, 2022). Yields and N contents of above and belowground residues in German canola production systems were calculated based on Vos et al. (2022), in line with the German NIR (Federal Environment Agency, 2022). A complete breakdown of assumed above and belowground crop residue yields and N contents for canola is presented in table 32.

Table 322. Assumed values for canola crop residue yields and N contents used in calculation of N_2O emissions from crop residues

	Aboveground crop residues (kg dry matter/kg yield)	Belowground crop residues (kg dry matter/kg yield)	Aboveground residues N content (kg/kg residue)	Belowground residues N content (kg/kg residue)
Saskatchewan	2.65[1]	1.35[1]	0.013[2]	0.009[2]
Canada	2.65[1]	1.35[1]	0.013[2]	0.009[2]
Australia	2.00[3]	0.64[3]	0.009[3]	0.010[3]
France	2.46[4]	0.74[4]	0.007[5]	0.009[6]
Germany	1.51[7]	0.46[7]	0.008[7]	0.010[7]

[1] Values taken from (Thiagarajan et al. (2018)

[2] Thiagarajan et al. (2018)

[3] Australian NIR (Government of Australia, 2022), table 5.I.1

[4] Calculated based on French NIR (Cetipa, 2022), assuming a dry matter content of 91% in line with Terres Inovia (2020)

[5] Arvalis (2020a)

[6] French NIR (Cetipa, 2022), table 274

[7] Calculated based on Vos et al. (2022)

2.5.8.3.2. Wheat

Retention of wheat residues on field and subsequent incorporation into agricultural soils may have beneficial effects on yields (Esther et al., 2014; Sui et al., 2015), soil nutrient dynamics and nutrient use efficiencies (Coelho et al., 2016; Hoang and Marschner, 2019; Sui et al., 2015), and soil microbiota (Chen et al., 2021; Esther et al., 2014). Incorporation of straw may also provide protective effects from wind- and water-induced soil erosion (Nelson, 2002; Yang et al., 2020), while providing farmers with an alternative management practice to burning of residues (Liu et al., 2021). Harvesting of straw residues, however, may be economically beneficial for farmers given the myriad potential uses of wheat straw, such as a feedstock for production of second generation biofuels (Hasanly et al., 2018; Suardi et al., 2020), bedding in livestock systems (Smerchek and Smith, 2020; Yesufu et al., 2020), and others (Saad Azzem and Bellel, 2022; Xie et al., 2012).

Accurate emissions modeling for wheat production systems therefore requires estimation of above and belowground residues after harvesting, the proportion of above ground residues removed from the field in the form of wheat straw, and the N contents of belowground residues, and those aboveground residues that are not removed and are rather retained on the field. Specific proportions of wheat straw removed from fields for each region have been previously described in section 2.5.5.2. For the Saskatchewan and Canadian wheat production models above and belowground residue yields and N contents are taken from Thiagarajan et al. (2018), the current best available estimates of these data. Use of these values is in line with work done for the CRSC ((S&T)2 Consultants Inc., 2021b), and the Canadian National Inventory Report (Environment and Climate Change Canada, 2022).

Residue yields and N contents for the Australian production model were calculated based on values presented in the Australian NIR (Government of Australia, 2022). French residue yields and N content of below ground residues were calculated based on values presented in the French NIR (Cetipa, 2022) assuming a dry matter content of 87.2%, in line with Arvalis (2020b). N content of aboveground residues in the French production system was taken from values presented by Arvalis (2020a). Residue yields and N contents for the German production system were calculated based on Vos et al. (Vos et al., 2022), in line with methods used in the German NIR (Federal Environment Agency, 2022). Estimation of residue yields and N contents for the American production system was more difficult as the U.S. NIR calculates these values using the process-based DAYCENT model (Del Grosso et al., 2001), application of which is infeasible for the current study. Further, only a single U.S.-specific literature source could be identified from which these values may be derived (Kemanian et al., 2007) . However, this source only presents ranges for N contents of grain and above ground biomass without presenting data related to belowground biomass or harvest indices which would be required to calculate the required data (Kemanian et al., 2007). In the absence of U.S.-specific data, Canadian data from Thiagarajan et al. (2018) have been used in proxy (table 33).

Table 333. Assumed values for wheat crop residue yields and N contents of above and belowground residues

	Aboveground crop residues (kg dry matter/kg yield)	Belowground crop residues (kg dry matter/kg yield)	Aboveground residues N content (kg/kg residue)	Belowground residues N content (kg/kg residue)
Saskatchewan	1.49[1]	0.58[1]	0.007[1]	0.015[1]
Canada	1.49[1]	0.58[1]	0.007[1]	0.015[1]
Australia	1.32[2]	0.38[2]	0.006[2]	0.01[2]
France	0.97[3]	0.46[3]	0.0066[4]	0.011[3]
Germany	0.69[5]	0.31[5]	0.006[5]	0.009[5]
United States	1.49[1]	0.58[1]	0.007[1]	0.015[1]

[1] Thiagarajan et al. (2018), assuming a dry matter content of 89.3% in line with CRSC report ((S&T)2 Consultants Inc., 2021b)

[2] Calculated based on Australian NIR table 5.I.1 (Government of Australia, 2022)

[3] Calculated from French NIR (Cetipa, 2022) using an assumed dry matter content of 87.2% in line with Arvalis (2020b)

[4] Arvalis (2020a) pg 495

[5] Vos et al. (2022) – pg 388

2.5.8.3.3. Field peas

Pulse crops, such as field peas, are often included in crop rotations due to their ability to fix N, thereby reducing requirements for synthetic fertilizers in subsequent crops (MacWilliam et al., 2014; Xing et al., 2017). Key to farmers recognising these benefits is the retention of crop residues on fields, as large amounts of N may be released during decomposition (Bahl and Pasricha, 2000; Walley et al., 2007). Retention of residues on fields may also improve the biological properties of soils (Marschner et al., 2004), and soil carbon dynamics (Wang and Sainju, 2014). Given the important role that pea crop residues play in providing benefits to subsequent crops in rotation it is assumed here that all residues are retained for the purposes of calculating N inputs from crop residues.

Yields of above and belowground residues, as well as N contents for the Saskatchewan and Canadian systems have been taken from Thiagarajan et al. (2018), the current best available estimates of these data. Use of these values is in line with work done for the CRSC ((S&T)2 Consultants Inc, 2021b), and the Canadian National Inventory Report (Environment and Climate Change Canada, 2022). These numbers assume field peas have a dry matter content of 89.3%, in line with the CRSC report ((S&T)2 Consultants Inc, 2021b). French residue yields and N content of below ground residues were calculated based on values presented in the French NIR (Cetipa, 2022) assuming a dry matter content of 87.2%, in line with Arvalis (2020b). N content of aboveground residues in the French production system was taken from values presented by Arvalis (2020a). Residue yields and N contents for the German production system were calculated based on Vos et al. (2022), in line with methods used in the German NIR (Federal Environment Agency, 2022). As with estimates of yields and N contents of wheat residues, Canadian proxy data has been used for the U.S. production system in the absence of U.S.-specific data (table 34).

Table 344. Assumed values for dry field pea crop residue yields and N contents of above and belowground residues

	Aboveground crop residues (kg dry matter/kg yield)	Belowground crop residues (kg dry matter/kg yield)	Aboveground residues N content (kg/kg residue)	Belowground residues N content (kg/kg residue)
Saskatchewan	2.28[1]	0.49[1]	0.021[1]	0.022[1]
Canada	2.28[1]	0.49[1]	0.021[1]	0.022[1]
France	0.69[2]	0.29[2]	0.0135[3]	0.008[2]
Germany	0.69[4]	0.31[4]	0.006[4]	0.009[4]
United States	2.28[1]	0.49[1]	0.021[1]	0.022[1]

[1] Thiagarajan et al. (2018), assuming a dry matter content of 89.3% in line with CRSC report ((S&T)2 Consultants Inc, 2021b)

[2] Calculated from French NIR (Cetipa, 2022)

[3] Arvalis (2020a) pg 495

[4] Vos et al. (2022) – pg 388

2.5.9 Impact assessment methods

The carbon footprint of each crop-country model was calculated using the IPCC 2021 AR6 methodology. (Cilleruelo, 2022). This method is based on the most recent Assessment Report (AR6) released by the IPCC (IPCC, 2022), which reports all characterization factor values used in calculation of global warming impacts.

2.5.10 Calculation of production weighted average global carbon footprints

As a point of comparison, global, production weighted average carbon footprints were calculated for each crop to compare with the carbon footprint results from Saskatchewan cropping systems. Global production weighted averages were calculated by determining the proportion of total production represented by each country included in the analysis, as reported in table 2. These proportions were then multiplied by the calculated impact assessment results (both with and without soil carbon change), and the products summed. Importantly, calculation of these production weighted average carbon footprints did not include the impacts attributable to Saskatchewan cropping systems. They did, however, include the impacts attributable to Canadian production systems. These production weighted average values were generated for all three crops included in this analysis.

2.5.11 Data quality and uncertainty assessment

Data quality indicators were computed for each LCI data point based on the pedigree matrix scores assigned during the data quality assessment stage (reported in tables 13-28). These pedigree matrix scores were entered into openLCA for each flow. The openLCA software was used to calculate the total uncertainty (geometric standard deviation) associated with the data quality indicators, as described in section 2.4. In addition to data quality uncertainty, the other source of uncertainty that was accounted for was the parameter uncertainty, known as the base uncertainty in openLCA. This represents the stochastic uncertainty associated with the variability in the value for each data point, rather than the quality of the data (Bamber et al., 2019). These uncertainty values were sourced from Frischknecht et al., (2005), which provides generic base uncertainty factors specific to sector or type flow (Table 35). These generic factors were used since data were collected from various sources and it was not possible to consistently calculate the variability of the data values. The uncertainty of the impact assessment results was calculated using Monte Carlo simulation, which propagates the uncertainty in the inventory data to the results to determine the overall uncertainty of the model. The Monte Carlo simulation was performed with a total of 1000 runs, which is the most common method of uncertainty propagation for agricultural LCAs (Bamber et al., 2019).

input / output group	c	p	a	input / output group	c	p	a
demand of:				**pollutants emitted to air:**			
thermal energy, electricity, semi-finished products, working material, waste treatment services	1.05	1.05	1.05	CO_2	1.05	1.05	
transport services (tkm)	2.00	2.00	2.00	SO_2	1.05		
Infrastructure	3.00	3.00	3.00	NMVOC total	1.50		
resources:				NO_X, N_2O	1.50		1.40
primary energy carriers, metals, salts	1.05	1.05	1.05	CH_4, NH_3	1.50		1.20
land use, occupation	1.50	1.50	1.10	individual hydrocarbons	1.50	2.00	
land use, transformation	2.00	2.00	1.20	PM>10	1.50	1.50	
pollutants emitted to water:				PM10	2.00	2.00	
BOD, COD, DOC, TOC, inorganic compounds (NH_4, PO_4, NO_3, Cl, Na etc.)		1.50		PM2.5	3.00	3.00	
individual hydrocarbons, PAH		3.00		polycyclic aromatic hydrocarbons (PAH)	3.00		
heavy metals		5.00	1.80	CO, heavy metals	5.00		
pesticides			1.50	inorganic emissions, others		1.50	
NO_3, PO_4			1.50	radionuclides (e.g., Radon-222)		3.00	
pollutants emitted to soil:							
oil, hydrocarbon total		1.50					
heavy metals		1.50	1.50				
pesticides			1.20				

Table 355. Basic uncertainty factors for the inherent stochasticity in combustion (c), process (p) and agricultural (a) processes, based on the sector of the activity. Source: Frischknecht et al. (2005).

2.5.12 Sensitivity analysis

Sensitivity analyses were performed to determine the sensitivity of the final results to any methodological choices that were based on assumptions, and that made significant contributions to the overall carbon footprint results. These included the choice of data sources for LCI data when the data quality was similar between multiple sources, the choice of cut-off criteria and exclusions, allocation methods for manure and wheat straw, N_2O emissions modelling, and impact assessment methods. Since sensitivity analyses are used to determine the impacts of methodological choices on results, amounts of uncertainty associated with sensitivity analysis results were not calculated.

2.5.12.1 Cut-off criteria and exclusions

Manure inputs were excluded from the canola and pea models for Saskatchewan and Canada, and the canola model for Australia, since the CRSC reports ((S&T)2 Consultants Inc, 2021b), Eady (2017), and Alcock et al. (2022) reported no manure inputs for these crop-region combinations. However, van Paassen et al. 2019 reported manure inputs for these regions. As a sensitivity analysis, the manure inputs reported in van Paassen et al. 2019 were used in the canola and pea models for Saskatchewan, Canada, and the canola model for Australia. Similarly, for Canadian and Saskatchewan canola, wheat, and peas, lime inputs were excluded since the CRSC reports ((S&T)2 Consultants Inc., 2021b,c,d) and Bamber et al. (2020a) excludes them. However, van Paassen et al. 2019 include lime inputs for Canada, therefore these were included in the model as a sensitivity analysis. Irrigation was also not included for German peas since van Paassen et al. 2019 did not include any inputs of energy use for irrigation, although Nemecek (2007) did indicate an input of irrigation, therefore this value was used as a sensitivity analysis.

2.5.11.3 Manure nutrient contents

To replace manure inputs in terms of upstream inputs of synthetic fertilizers as described in section 2.5.5.1, it was necessary to determine manure nutrient contents. Nutrient contents of manure are largely dependent on specific feed formulations and the amounts of nutrients consumed by the animal which may vary significantly across different regions. The assumed manure nutrient contents used here reflect this (table 9). To better understand the potential impacts of regional differences in estimates of manure nutrient contents on the final results, a sensitivity analysis was performed in which manure nutrient contents were assumed to be the same across all regions included in this analysis. Specifically, average values were calculated based on the assumed manure nutrient contents, and these values were applied to all systems that included manure inputs. The assumed manure nutrient contents used in this sensitivity analysis are presented in table 37

Table 36. Assumed percent nutrient compositions applied to all manure inputs in all cropping systems for sensitivity analysis

	Pig	Poultry
N	0.96	3.47
P	0.97	1.69
K	0.36	1.63

2.5.11.4 Allocation methods

Manure inputs were modelled as the original inputs of synthetic fertilizer (i.e. those that that provided the nutrients that were subsequently passed through the crops that were fed to the animals and eventually excreted in the manure used). This avoided the need for allocation between manure and other co-products of the animal production systems. However, the nutrients in the manure are recycled products since they were first used to produce the crops consumed by the livestock. Therefore, a 50:50 allocation ratio was used to model the recycling of these products, as suggested by AFNOR (2011). For the sensitivity analysis, the 0:100 and 100:0 allocation ratios also suggested by AFNOR (2011) were used, meaning that either none or all of the impacts of the fertilizer production were allocated to the manure.

Given the highly variable estimates of wheat straw removal rates observed in the literature, a sensitivity analysis was performed around the amount of straw assumed to be removed. First, a sensitivity analysis was designed in which it was assumed that 0% of straw was removed (i.e., all impacts allocation to wheat grain production), in line with assumption by ((S&T)2 Consultants Inc., 2021b). Second, analyses were performed taking into account the region-specific straw removal rates found in the literature. It was assumed that the identified rates applied to total crop residues throughout each specific region. These assumed straw removal rates were: 55% for Canada (Li et al., 2012b); 54% for Australia (Broster and Walsh, 2022); 50% for France (Lokesh et al., 2019) and the U.S. (Juneja et al., 2013); and 67.5% for Germany, representing an average value from Weiser et al., (2014) and Brosowski et al., (2020). Finally, a sensitivity analysis was also performed in which it was assumed that 85% of straw was removed in all regions, in line with the maximum possible removal rate suggested by any single source (Li et al. 2012).

In addition, during consultation with stakeholders some concerns were raised regarding the accuracy of the reported reference year for the area of land from which crop residues were baled as reported by Statistics Canada (2021b). Specifically, it is reported that the information given is taken from the Canadian Census of Agriculture performed in 2021. In the relevant question on the Census of Agriculture (i.e., question 37), it is specified that information is being collected related to crop residue baling practices in the year 2020 (Statistics Canada, 2021c). However, the published data tables list 2021 as the reference year for the information presented. Whether the published information reflects crop residue baling practices in 2021 or 2020 slightly changes the constant assumed rate at which crop residues are removed applied to all of the wheat models. For this reason, a sensitivity analysis was performed in which it was assumed that the reported data is representative of crop residue baling practices in 2020 instead of 2021. This number was then compared with the total area used for non-durum wheat production in Saskatchewan in 2020 to estimate the percentage of non-durum wheat land from which crop residues were baled (i.e., 21.1% rather than 24.1%). This number was then used in combination with the 34.5% residue removal rate from Lafond et al. (2009) to calculate the total residues removed, applied to all wheat production models.

2.5.11.5 N_2O emissions modelling

For each emission factor or fraction used in the N_2O emission calculations, a sensitivity analysis was conducted to use instead the minimum and maximum values of the ranges given. These were obtained from the NIRs or IPCC reports that reported the uncertainty associated with each factor. The Australian NIR (Government of Australia, 2022) estimated an uncertainty range of +/-55.9% for the total estimate of N_2O emissions from agricultural soils. This was not broken down to uncertainty estimates around each emission factor or fraction, therefore values of +55.9% and -55.9% of total N_2O emissions were used as a sensitivity analysis. The French NIR (Cetipa, 2022) used the generic uncertainty factors from IPCC (2019), which are a range of 0.001-0.018 for EF_1 for direct N_2O emissions from fertilizer and 0.000-0.014 for manure, and for indirect emissions a range of 0.002-0.018 for EF_4 and 0.00 to 0.02 for EF_5. For Germany, they also used the default uncertainty ranges for EF_1 and EF5, and EF_4 ranged from 0.002 to 0.05 (Vos et al. 2022). The US NIR (United States Environmental Protection Agency, 2022) reported an uncertainty range of -27% to +26% for the total estimate of N_2O emissions from agricultural soils. The Canadian NIR (Environment and Climate Change Canada, 2022) reported an uncertainty range of -36% to +52% for their estimate of total N_2O emissions from agricultural soils. In addition to this uncertainty, there was a recent publication by Liang et al., (2020) that indicates that the region-specific N_2O emission factors should be scaled by a factor of 0.28 when applied to crop residue N inputs, and by 0.84 for manure N inputs. This was not performed in the N_2O estimates from the CRSC reports used for Canada ((S&T)2 Consultants Inc., 2021a), therefore, this change was also included as part of the sensitivity analysis.

2.5.11.6 Crop residue yields and N contents

Large differences were observed in the above and below ground crop residue yields and N contents across the regions included in this analysis. Given the potentially important role that N from crop residues may play in determining field level nitrogenous emissions a sensitivity analysis was conducted to explore how these regional differences may be impacting results. Specifically, average values for above and below ground residue yields and N contents were calculated for each crop, and these values were used in calculations of the N inputs from crop residues for each crop-region combination. Above and below ground residue yields and N contents used in this sensitivity analysis are presented in table 37. Use of these alternative crop residues yields and N contents alters both the field level emissions due to differences in the N contribution made by crop residues to each system, and alters the allocation factors associated with removed crop residues in the wheat production systems. The wheat allocation factors used in this sensitivity analysis were calculated following the procedure outlined in section 2.5.5.2, using an assumed constant straw removal rate, and proportion of land from which straw is removed, representative of Saskatchewan.

Table 37. Crop residue yields and N contents used for sensitivity analysis.

	Aboveground crop residues (kg dry matter/kg yield)	Belowground crop residues (kg dry matter/kg yield)	Aboveground residues N content (kg/kg residue)	Belowground residues N content (kg/kg residue)
Canola	2.25	0.91	0.01	0.009
Wheat	1.24	0.48	0.006	0.012
Field pea	1.64	0.41	0.017	0.017

2.5.11.7 Impact assessment methods

The impact assessment method chosen was the IPCC 2021 GWP 100, which estimates the infrared radiative forcing on a 100-year timeframe. As a sensitivity analysis, we also used the IPCC 2021 GWP 500, which estimates the radiative forcing on a 500 year timeframe instead(IPCC, 2022).

3. Results and discussion

3.1 Life cycle inventory

3.1.1 Canola

Germany had the highest canola yields (3360 kg/ha), followed by France (3210 kg/ha), Canada (2145.2 kg/ha), and Saskatchewan (2118.8 kg/ha). Australia had the lowest (1387.5 kg/ha) (Table 38). Seed inputs were similar between regions, ranging from 0.001-0.003 kg/kg yield. Lime was only applied in Australia and Germany, ranging from 0.1-0.19 kg/kg. France and Germany had the highest N fertilizer application rates (0.145 and 0.14 kg/kg), and Saskatchewan and Australia had the lowest (0.057 and 0.056 kg/kg). P fertilizer application rates were fairly similar, ranging from 0.02 kg/kg in Germany to 0.031 kg/kg in Saskatchewan. K and S fertilizer rates were more variable, with K fertilizer application rates ranging from 0.00g kg/kg in Canada and Australia to 0.039 kg/kg in France, and S fertilizers ranging from 0.008 kg/kg in Australia to 0.042 kg/kg in Saskatchewan. France and Germany were the only countries with manure application to canola production. French canola received 0.334 kg/kg of pig manure and 0.101 kg/kg of poultry manure. German canola had a similar poultry manure application rate to France (0.09 kg/kg) and around a 3 times higher pig manure application rate than France (1.05 kg/kg). Total pesticide active ingredient application rates were very similar, ranging from 0.001 kg/kg in Saskatchewan to 0.002 kg/kg in all other regions.

Irrigation energy was only used for Canadian, French and German canola production, ranging from 0.007 MJ/kg in France to 0.05 MJ/kg in Germany. Australia had the highest energy use for field activities (1.791 MJ/kg), followed by Germany and France (1.21 MJ/kg), and Canada and Saskatchewan had the lowest (0.472 MJ/kg and 0.458 MJ/kg). Saskatchewan had the lowest post-harvest energy use (0.003 MJ/kg), and Germany had the most (0.32 MJ/kg). All transportation distances were assumed to be the same (30 km for manure and 50 km for all other inputs) due to lack of region-specific data. Saskatchewan, Canada and Australia have much lower amounts of inputs transported to the lack of manure application, compared to France and Germany.

Australia has the lowest N_2O emissions (1.88×10^{-4} kg/kg), due to their relatively dry climate and lack of tillage for canola. France and Germany (0.002 kg/kg) have double the N_2O emissions of Canada and Saskatchewan (0.001 kg/kg), due to higher N inputs, more field activities, and differences in soil and climate. Australia has the highest levels of field-level CO_2 emissions (0.118 kg/kg) since they have the highest inputs of lime. Germany also has lime inputs and has the second highest field-level CO_2 emissions (0.09 kg/kg). Saskatchewan, Canada and France do not have lime inputs and thus have lower field-level CO_2 emissions (0.03-0.045 kg/kg). Canadian and Saskatchewan soils are sequestering carbon (-0.225 and -0.161 kg CO_2/kg), while all other countries have net carbon emissions from soils. France and Germany have higher emissions (0.227 and 0.390 kg CO_2/kg), and Australia has lower emissions (0.046 kg CO_2/kg).

Table 38. Summary of life cycle inventory data for canola production

	Saskatchewan	**Canada**	**Australia**	**France**	**Germany**
Yield (kg/ha)	2118.8	2145.2	1387.5	3210	3360
Seed (kg/kg)	0.003	0.003	0.002	0.001	0.001
Lime (kg/kg)	0	0	0.190	0	0.10
N fertilizers (kg/kg)	0.057	0.091	0.056	0.145	0.14
P fertilizers (kg/kg)	0.031	0.030	0.029	0.027	0.02
K fertilizers (kg/kg)	0.009	0.006	0.006	0.039	0.06
S fertilizers (kg/kg)	0.042	0.015	0.008	0.003	0.01
Pig manure (kg/kg)	0	0	0	0.334	1.05
Poultry manure (kg/kg)	0	0	0	0.101	0.09
Total pesticide AI (kg/kg)	0.001	0.002	0.002	0.002	0.002
Irrigation energy (MJ/kg)	0	0.010	0	0.007	0.05
Field activities energy (MJ/kg)	0.458	0.472	1.791	1.209	1.21

	Saskatchewan	Canada	Australia	France	Germany
Post-harvest energy (kWh/kg)	0.003	0.186	0.050	0.152	0.32
Transportation (kg*km/kg)	7.081	7.204	14.483	24.506	51.58
Field-level N_2O emissions (kg/kg)	0.001	0.001	1.882E-4	0.002	0.002
Field-level CO_2 emissions (kg/kg)	0.030	0.045	0.118	0.030	0.09
Soil carbon change (kg CO_2/kg)	-0.225	-0.161	0.046	0.227	0.390

3.1.2 Non-durum Wheat

Similar to canola, Germany had the highest wheat grain yields (7360 kg/ha), followed closely by France (7090 kg/ha) (Table 39). Canada, the US and Saskatchewan had similar yields (3375, 3322, and 2986 kg/ha, respectively), and Australia had the lowest (2042 kg/ha). In addition to the grain yield, wheat also has straw as a co-product, ranging from 0.057-0.123 kg/kg). There were no lime inputs to Saskatchewan and Canadian wheat production systems. Seed inputs were fairly similar between Saskatchewan, Canada, France and Germany, ranging from 0.021-0.033 kg/kg. The US had slightly higher seed inputs (0.047 kg/kg), and Australia had the highest seed inputs (0.075 kg/kg). Australia and the US had the highest lime application rates (0.196 kg/kg and 0.124 kg/kg) due to their relatively low yields. France and Germany had 0.056 and 0.054 kg/kg lime application. N fertilizer application rates ranged from 0.037 kg/kg in Australia to 0.065 kg/kg in France. France and Germany had relatively low P fertilizer application rates (0.005-0.006 kg/kg) compared to all other regions (0.013-0.026 kg/kg). K and S fertilizer application rates were somewhat similar between regions with K rates ranging from 0.003 kg/kg in Australia to 0.006 kg/kg in Canada, France, and the US. S fertilizer application rates ranged from 0.001 kg/kg in France to 0.011 kg/kg in Saskatchewan. Saskatchewan wheat received no manure inputs. Pig manure application rates were the lowest in Australia (0.049 kg/kg), fairly similar in Canada, France, and the US (0.103-0.164 kg/kg), and highest in Germany (0.479 kg/kg). Poultry manure application rates were lowest in Canada and Australia (0.024-0.025 kg/kg), followed by France and Germany (0.042-0.046 kg/kg), with the highest application rates in the US (0.115 kg/kg). Pesticide application rates were similar between regions, ranging from 0.0002-0.001 kg/kg.

Irrigation was not performed in Saskatchewan. Where irrigation was performed, energy inputs were the lowest in Germany and the US (1.25×10^{-9}-2.86×10^{-9} MJ/kg), followed by Canada and France (0.004 and 0.002 MJ/kg), and Australia had the highest (0.015 MJ/kg). Australia and the US had the highest energy use for field activities (1.240 and 1.290 MJ/kg), followed by Canada (0.758 MJ/kg), France and Germany (0.558 and 0.565 MJ/kg), and Saskatchewan had the lowest (0.330 MJ/kg). Australia, France, Germany and the US all had the same post-harvest energy use (0.530 MJ/kg), as did Canada and Saskatchewan (0.003 MJ/kg). Like canola, all transportation distances were assumed to be 30 km for manure and 50 km for all other inputs. Germany and the US had the most inputs transported to farm (23.519 ad 20.899 kg*km/kg), followed by Australia and France (15.631 and 14.056 kg*km/kg), and Canada and Saskatchewan (6.286 and 8.895 kg*km/kg).

Australia had the lowest N_2O emissions, due to their soil, climate, and management conditions (3.11×10^{-4} kg/kg). This was followed by the US (4.87×10^{-4} kg/kg), then Saskatchewan and Canada (6.07×10^{-4} and 6.57×10^{-4} kg/kg), and France and Germany had the highest emissions (7.98×10^{-4} and 7.91×10^{-4} kg/kg). Saskatchewan, Canada, France and Germany had similar field-level CO_2 emissions (0.020-0.038 kg/kg) and the US and Australia had higher emissions (0.072 and 0.109 kg/kg). Saskatchewan and Canadian soils had net carbon sequestration (-0.078 to -0.153 kg CO_2/kg). All other soils had net CO_2 emissions, ranging from 0.031 kg/kg in Australia to 0.178 kg/kg in Germany.

Table 39. Summary of life cycle inventory data for wheat production

	Saskatchewan	**Canada**	**Australia**	**France**	**Germany**	**United States**
Yield (kg/ha)	2986.2	3374.7	2042	7090	7360	3222.0
Straw removed (kg DM/kg)	0.123	0.123	0.110	0.081	0.057	0.123
Seed (kg/kg)	0.032	0.033	0.075	0.022	0.021	0.047
Lime (kg/kg)	0	0	0.196	0.056	0.054	0.124
N fertilizers (kg/kg)	0.056	0.042	0.037	0.065	0.058	0.051
P fertilizers (kg/kg)	0.022	0.013	0.026	0.006	0.005	0.017
K fertilizers (kg/kg)	0.005	0.006	0.003	0.006	0.005	0.006
S fertilizers (kg/kg)	0.011	0.007	0.005	0.001	0.005	0.003
Pig manure (kg/kg)	0	0.103	0.049	0.151	0.479	0.164
Poultry manure (kg/kg)	0	0.024	0.025	0.046	0.042	0.115
Total pesticide AI (kg/kg)	0.001	0.001	0.001	2.13E-04	4.38E-04	2.60E-04
Irrigation energy (MJ/kg)	0	0.004	0.015	0.002	1.25E-09	2.86E-09
Field activities energy (MJ/kg)	0.330	0.758	1.240	0.558	0.565	1.290
Post-harvest energy (kWh/kg)	0.003	0.003	0.530	0.530	0.530	0.530

	Saskatchewan	Canada	Australia	France	Germany	United States
Transportation (kg*km/kg)	6.286	8.895	15.631	14.056	23.519	20.899
Field-level N_2O emissions (kg/kg)	6.07E-04	6.57E-04	3.11E-04	7.98E-04	7.91E-04	4.87E-04
Field-level CO_2 emissions (kg/kg)	0.027	0.020	0.109	0.038	0.036	0.072
Soil carbon change (kg CO_2/kg)	-0.153	-0.078	0.031	0.103	0.178	0.060

3.1.3 Peas

France and Germany had the highest yields of peas (3346 and 3200 kg/ha), followed by Saskatchewan and Canada (2235 and 2325 kg/ha), and the US had the lowest yield (1950 kg/ha) (Table 40). Saskatchewan and Canada had the lowest seed inputs (1.02×10^{-4} and 1.58×10^{-4} kg/kg), followed by France and Germany (0.042 and 0.044 kg/kg), and the US had the highest (0.072 kg/kg). Due to a lack of data availability, all inoculant inputs were assumed to be the same as the Canadian application rates on a per hectare basis, therefore all variation was due to yield differences (0.001-0.002 kg/kg). There were no lime inputs to Saskatchewan and Canadian peas. France and Germany had similar lime application rates (0.12 and 0.125 kg/kg), and the US had a higher rate (0.205 kg/kg). French peas had no synthetic N fertilizer application, and all other regions had low application rates, ranging from 2.59×10^{-4} kg/kg in Canada to 1.88×10^{-2} kg/kg in Germany. All other synthetic fertilizer application rates were also fairly low. P fertilizer application rates ranged from 1.89×10^{-2} kg/kg in Canada to 7.19×10^{-2} in the US. K application rates ranged from 1.36×10^{-3} kg/kg in Saskatchewan to 6.32×10^{-2} in the US, and S application rates ranged from 0 kg/kg in France to 2.40×10^{-3} kg/kg in Canada. Manure was not applied in Saskatchewan or Canada. Pig manure application rates ranged from 0.272 kg/kg in the US to 1.101 kg/kg in Germany. Poultry manure application rates ranged from 0.097 kg/kg in France and Germany to 0.191 kg/kg in the US. Canada had the lowest application rate of total pesticide active ingredients (9.45×10^{-4} kg/kg), followed by Saskatchewan, France and Germany (0.0012-0.0016 kg/kg), and the US had the highest (0.002 kg/kg).

France and the US were the only countries that irrigated their peas, using 0.037 and 0.064 MJ/kg, respectively. France, Germany, and the US had higher field activities fuel use (0.965-1.179 MJ/kg) than Canada and Saskatchewan (0.503-0.564 MJ/kg). Based on average moisture contents at harvest, German peas do not need to be dried. Canada had the lowest post-harvest drying energy use (8.10×10^{-4} MJ/kg), followed by Saskatchewan and the US (0.001 MJ/kg), and France had the highest (0.041 MJ/kg). As with canola and wheat, all transportation distances were assumed to be 30 km for manure inputs and 50 km for all other inputs. Since there was no manure application on Saskatchewan and Canadian peas, they had much lower transportation of inputs (1.26 and 1.30 kg*km/kg) compared to France (25.29 kg*km/kg), the US (35.83 kg*km/kg), and Germany (49.71 kg*km/kg).

Saskatchewan peas had the lowest N_2O emissions (6.80×10^{-4} kg/kg), due to their climate, soil and management conditions. Canada and France had similar N_2O emissions (7.38×10^{-4} and 7.39×10^{-4} kg/kg), followed by the US (9.19×10^{-4} kg/kg), and Germany had the highest emissions (1.30×10^{-3} kg/kg). Since there was no lime applied to Saskatchewan or Canadian peas, their field-level CO_2 emissions were much lower (2.47×10^{-4}-2.98×10^{-4} kg/kg), compared to France, Germany, and the US (5.25×10^{-2}-9.80×10^{-2} kg/kg). Canadian and Saskatchewan soils were the only regions that had net carbon sequestration (-0.162 to -0.208 kg CO_2/kg). All other regions had net CO_2 emissions from soil carbon change, ranging from 0.099 kg/kg in the US to 0.410 kg/kg in Germany. The N credit from N fixation was fairly similar across all regions (-0.004 to -0.006 kg ammonia/kg).

Table 40. Summary of life cycle inventory data for dry pea production

	Saskatchewan	**Canada**	**France**	**Germany**	**United States**
Yield (kg/ha)	2235.14	2324.59	3346	3200	1950.281
Seed (kg/kg)	1.02E-04	1.58E-04	0.042	0.044	0.072
Inoculant (kg/kg)	0.002	0.002	0.001	0.001	0.002
Lime (kg/kg)	0	0	0.120	0.125	0.205
N fertilizers (kg/kg)	3.58E-04	2.59E-04	0	1.88E-02	1.38E-02
P fertilizers (kg/kg)	2.00E-02	1.89E-02	4.42E-02	3.52E-02	7.19E-02
K fertilizers (kg/kg)	1.36E-03	3.25E-03	4.81E-02	5.02E-02	6.32E-02
S fertilizers (kg/kg)	2.08E-03	2.40E-03	0	1.56E-03	1.33E-03
Pig manure (kg/kg)	0	0	0.320	1.101	0.272
Poultry manure (kg/kg)	0	0	0.097	0.097	0.191
Total pesticide AI (kg/kg)	1.22E-03	9.45E-04	1.62E-03	1.43E-03	0.002
Irrigation energy (MJ/kg)	0	0	0.037	0	0.064
Field activities energy (MJ/kg)	0.503	0.564	0.965	1.058	1.179
Post-harvest energy (kWh/kg)	1.30E-03	8.10E-04	0.041	0	0.001
Transportation (kg*km/kg)	1.26	1.30	25.29	49.71	35.83
Field-level N_2O emissions (kg/kg)	6.80E-04	7.38E-04	7.39E-04	1.30E-03	9.19E-04

	Saskatchewan	Canada	France	Germany	United States
Field-level CO_2 emissions (kg/kg)	2.98E-04	2.47E-04	5.26E-02	5.89E-02	9.80E-02
Soil carbon change (kg CO_2/kg)	-0.208	-0.162	0.217	0.410	0.099
N credit (kg ammonia/kg)	-0.004	-0.005	-0.006	-0.005	-0.006

3.2 Life cycle impact assessment

Overall, Saskatchewan and Canadian canola, wheat, and peas, have relatively low impacts compared to the same crops produced in other countries. Throughout all the results, including sensitivity analyses, either Saskatchewan or Canadian average crops had the lowest carbon footprint except for Australian canola, which had lower impacts of production due to lower field-level N_2O emissions. However, when using the low end of the possible N_2O emission values in the sensitivity analysis, Saskatchewan canola had lower impacts than Australian canola. Changing the impact assessment method from GWP 100 to GWP 500 also changed the results so that Saskatchewan canola had lower impacts than Australia. This was due to the reduction in the impact factor for N_2O from the 100 to 500 year timeframe. Also, when the impacts of soil carbon changes were included in the carbon footprint totals, Saskatchewan and Canadian crops always had the lowest impacts since their soils have net carbon sequestration, and all other countries have net carbon losses.

In general, field-level N_2O emissions, fertilizer production, field activities, and soil carbon changes were the largest contributors to the carbon footprints of crop production. The specific contributions for each crop-region model are detailed below.

3.2.1 Canola

Best practice is to present the LCIA results and the soil carbon change impacts separately. Therefore, Figure 1 shows the carbon footprint results, excluding soil carbon changes, for canola production in Saskatchewan, Canada, Australia, France and Germany, broken down by the contribution of each major LCI data category. For Canada and Saskatchewan, the main contributors to the carbon footprint of canola production were fertilizer inputs (27%), and associated N_2O emissions (57-59%). For Saskatchewan, all N_2O emissions came from a combination of N applied in synthetic fertilizer and from crop residues, with ~55% from fertilizer and 45% from residues. There is no manure application for Canadian canola, and there are no net soil carbon losses on Saskatchewan soils that could lead to N losses. For the Canadian average, 0.01% of the N_2O emissions came from mineralization N losses due to soil carbon change. The impacts of upstream fertilizer production were predominantly due to CO_2 emissions in the upstream production of ammonia to produce N fertilizers. CO_2 from the combustion of diesel for field activities contributed 6% of the impacts. Canadian average canola production had 19% higher production than Saskatchewan, due to higher fertilizer inputs and associated N_2O emissions.

For Australia, fertilizer inputs accounted for 26% of the carbon footprint but N_2O emissions were only 11%. This is due to the very low N_2O emission factors and lack of volatilization in Australia due to its dry climate and lack of irrigation for canola. Approximately 64% of the N_2O emissions were due to fertilizer application, 26% from crop residues and 10% from soil carbon change. There was no manure application for Australian canola. Field activities accounted for 30% of Australian GHG emissions, which is much higher than the 5-6% for Canadian and Saskatchewan canola. This is because Australian canola requires higher levels of field activities, and because the overall impacts of production are lower, leading to the higher percent contribution from field activities. CO_2 emissions from lime and urea application also accounted for 24% of emissions, compared to 5-6% for Canada and Saskatchewan. This is because lime fertilizer is applied in Australia and not in Canada. Overall, Australian canola had a 19% lower carbon footprint than Saskatchewan canola (not including SOC changes), due to the significantly lower N_2O emissions. All differences between regions were statistically significant (as indicated by the separate letters above each bar on the graph).

French and German canola production systems had quite similar impacts, with 24% of impacts coming from fertilizer inputs, and 55-58% coming from field-level N_2O emissions. Fifty-one percent of N_2O emissions from French canola were from synthetic N fertilizer, 6% from manure, 22% from crop residues, and 20% from soil carbon change. For Germany, 34% of N_2O emissions came from synthetic fertilizer, 8% from manure, 14% from crop residue and 44% from soil carbon loss. Field activities accounted for 10% of the impacts of both French and German canola, and all other categories were <5%. French and German canola production had 57% and 66% higher impacts than canola production in Saskatchewan. These differences came from higher inputs of fertilizers and manure, and higher levels of field activities, despite the higher yields in Europe compared to Canada. There were also higher levels of N_2O emissions due to a combination of the higher N inputs, as well as differences in soil, climate, and management conditions.

Canadian soils are the only cropland soils that are sequestering carbon, due to a combination of soil, climate and management factors (Figure 2). The soil carbon sequestration estimates for Saskatchewan are higher than the national average, since there are some regions in Canada that do not sequester as much carbon, and some that have net CO_2 emissions. All other countries have net CO_2 emissions from their cropland soils. Germany has the highest levels of emissions, followed closely by France. This is due to the soil and climate conditions in these regions, as well as the intensity of field operations. Australia has much lower levels of CO_2 emissions, likely due to differences in soil, climate and management factors. According to the Australian NIR (Commonwealth of Australia, 2022), the majority (~70%) of the estimate soil carbon losses from cropland are due to land converted to cropland, with the remainder from cropland remaining cropland. In the most recent Australian NIR, they indicated that croplands have a small net emission of carbon, however in previous years (2016 and 2018) they have had a small net sequestration. However, these inter-annual changes are small compared to the long-term trend of decreased carbon emissions (-95%) from Australian soils from 1990-2020, due to the adoption of no-till and reduced-till practices (Commonwealth of Australia, 2022).

Including the impacts of soil carbon changes, Saskatchewan canola has the lowest life cycle GHG emissions of all regions studied (0.372 kg CO_2e/kg). Australian and Canadian canola have similar overall impacts, at ~ 42% and 47% higher than Saskatchewan. Despite the lower impacts of production for Australian canola compared to Saskatchewan and Canadian canola, Australian agricultural soils have net CO_2 emissions, whereas Saskatchewan and Canadian soils are sequestering carbon. French and German peas have much higher impacts (214% and 271% higher than Saskatchewan), since they have both higher impacts of production, and higher CO_2 emissions from agricultural soils. Both including and excluding the soil carbon changes, Saskatchewan canola has a lower carbon footprint (20-49% lower) than the weighted average of all countries included this analysis (Table 41).

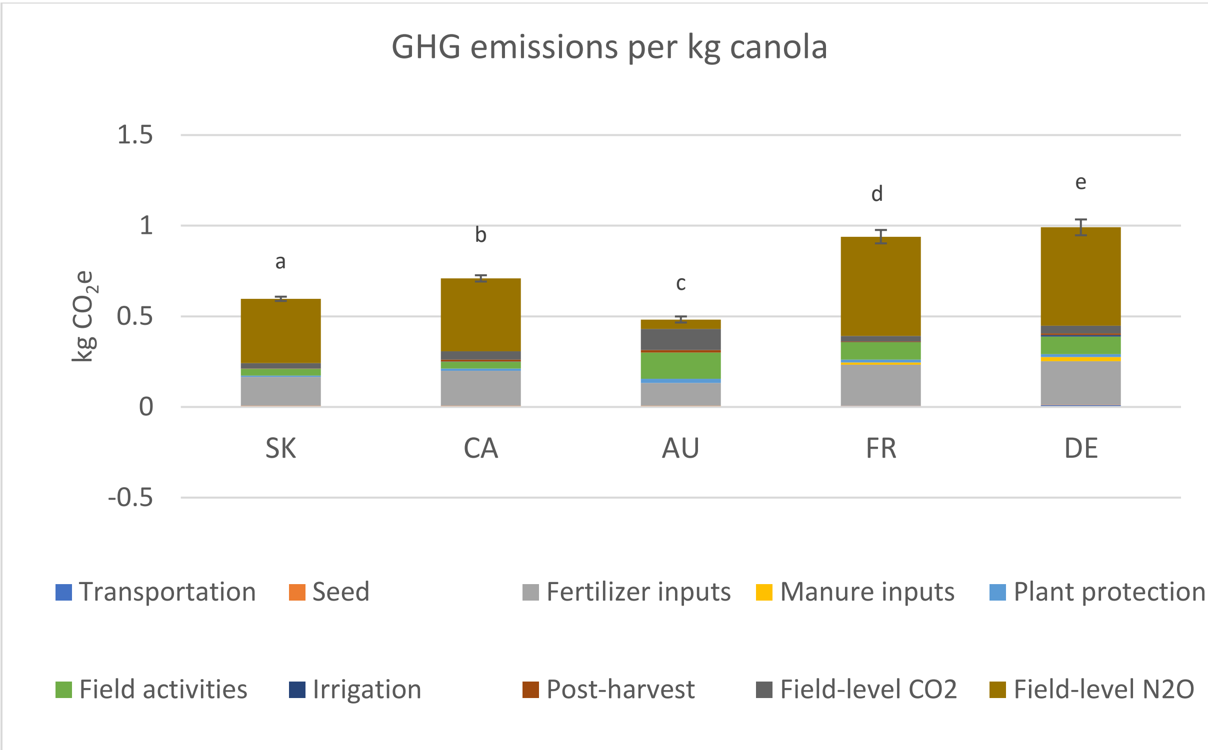

Figure 1. Contribution analysis of main LCI data categories to the overall carbon footprints (without soil carbon change) of canola produced in SK, CA, AU, FR and DE (kg CO_2e per kg canola).

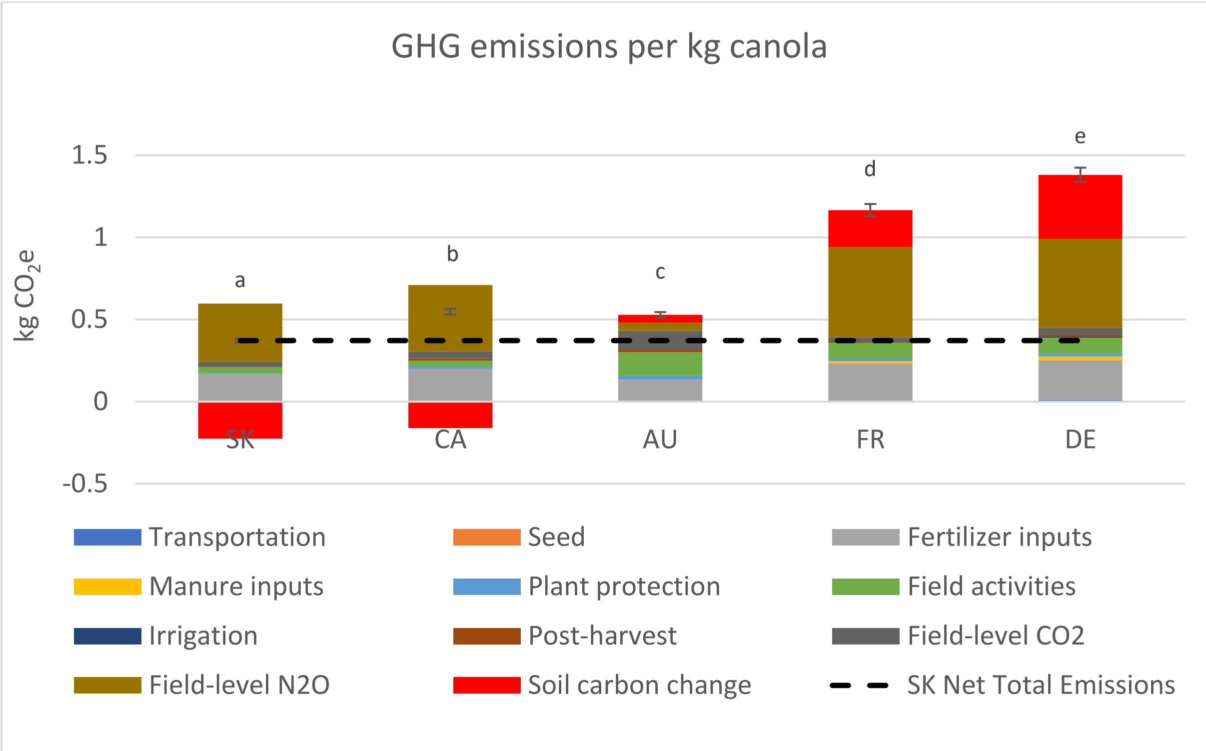

Figure 2. Contribution analysis of main LCI data categories to the overall carbon footprints (with soil carbon change) of canola produced in SK, CA, AU, FR and DE (kg CO_2e per kg canola). The dashed line represents net total emissions in SK, accounting for negative impacts from soil carbon changes.

Table 41. Global average carbon footprint values (with and without soil carbon change) compared to Saskatchewan carbon footprint values for canola production.

	Global average	Saskatchewan
kg CO_2e per kg canola (without soil carbon change)	0.747	0.597
kg CO_2e per kg canola (with soil carbon change)	0.728	0.372

3.2.2 Non-durum wheat

Figure 3 shows the LCIA results, without soil carbon change, for the production of 1 kg of non-durum wheat grain (allocated based on the mass relationship between grain and straw harvested) for Saskatchewan, Canada, Australia, France, Germany, and the United States. The results are broken down into the contributions from transportation, seed, fertilizer inputs, manure inputs, plant protection products, field activities, irrigation, post-harvest drying, and field-level CO_2 and N_2O emissions. For Canadian and Saskatchewan wheat, fertilizer inputs (22-31%) and associated field-level N_2O emissions

(47-51%) were the highest contributors to the life cycle GHG emissions. Around 65% of the N2O emissions came from synthetic N fertilizer, and 35% from crop residues. For the Canadian average, <1% came from N mineralization due to soil carbon losses, due to small regional soil carbon losses in the Eastern provinces as well as British Columbia. There were no carbon losses in Saskatchewan soils, therefore no N_2O emissions from this source. Field activities contributed 7-15% of the GHG emissions of Saskatchewan and Canadian wheat grain, and field-level CO_2 emissions from the application of urea contributed 5-7%. All other inputs and activities contributed 5% or less. Overall, the Canadian average wheat production had 5% higher impacts than Saskatchewan. All other countries had significantly higher impacts of production than Saskatchewan.

Australian wheat had 57% higher impacts than Saskatchewan wheat. The impacts of seed production were much higher in Australia than any other region (21%). This is due to the assumed land use change in Australia for the production of wheat seed, as included in Nemecek (2015). Australian peas also had higher levels of field activities than Canada and Saskatchewan, which contributed a similar proportion (17%), but were actually double the Canadian levels of energy use. Fertilizer inputs, post-harvest energy use, and field-level CO_2 and N_2O emissions all had similar percentage contributions to the overall impacts of Australian wheat (10-18%). Seventy-nine percent of the N_2O emissions for Australian wheat were due to synthetic N fertilizer application. Nine percent were from N mineralization due to soil carbon losses, 7% from crop residues, and 4% from manure inputs. All other inputs and activities contributed 1% or less to the overall carbon footprint of Australian wheat production.

French and German wheat had very similar impacts, which were 33-38% higher than Saskatchewan wheat. This was due mostly to higher field-level N_2O emissions, as well as higher post-harvest energy use. Field-level N_2O emissions were the highest contributor to the overall impacts, contributing 47-48%. Fifty percent of French N_2O emissions came from synthetic fertilizer application, 21% from soil carbon losses, 23% from crop residues and 6% from manure inputs. For German N_2O emissions, the breakdown was 47% from soil carbon losses, 32% from fertilizer inputs, 8% from manure and 13% from crop residues. Fertilizer production contributed 18% of the impacts of French and German wheat production, post-harvest energy use contributed 13-15%, and field activities 9%. Field-level CO_2 emissions from lime and urea application contributed 7% of impacts, and all other inputs and activities contributed 2% or less.

Wheat production in the US had 51% higher impacts than Saskatchewan. This is due to higher levels of field activities, post-harvest energy use, and field-level CO_2 emissions. Fertilizer production (22%) and field-level N_2O emissions (27%) were the largest contributors to the carbon footprint of US wheat. Forty-five percent of field-level N_2O emissions for US wheat came from the application of synthetic N fertilizers, 34% came from crop residues, 11% from soil carbon loses, and 9% from manure. Field activities contributed 18% of the life cycle GHG emissions of US wheat production, field-level CO_2 emissions from lime and urea contributed 13%, and post-harvest energy use contributed 11%. All other impacts and activities contributed 6% or less.

Saskatchewan soils had the highest levels of carbon sequestration per kg of wheat (Figure 4). Average Canadian soils are also sequestering carbon, albeit at a lower rate. All other regions have net carbon emissions from agricultural soils. Australia has the lowest levels of emissions, followed by the US, France, and Germany. When the impacts of soil carbon changes are included in the overall carbon footprint, Saskatchewan wheat production has the lowest impacts (0.214 kg CO_2e/kg), followed by

Canadian wheat (41% higher). All other regions have much higher impacts than Saskatchewan, since they have higher life cycle impacts of production, and have net carbon emissions from soils. Of all other regions, Australian and France have the lowest impacts (176% of Saskatchewan impacts), followed by the United States (180%). German wheat has the highest combined impacts (203% of Saskatchewan). Either including or excluding soil carbon changes, Saskatchewan wheat grain production had lower impacts (28-61% lower) than the global production weighted average of all countries (Table 42).

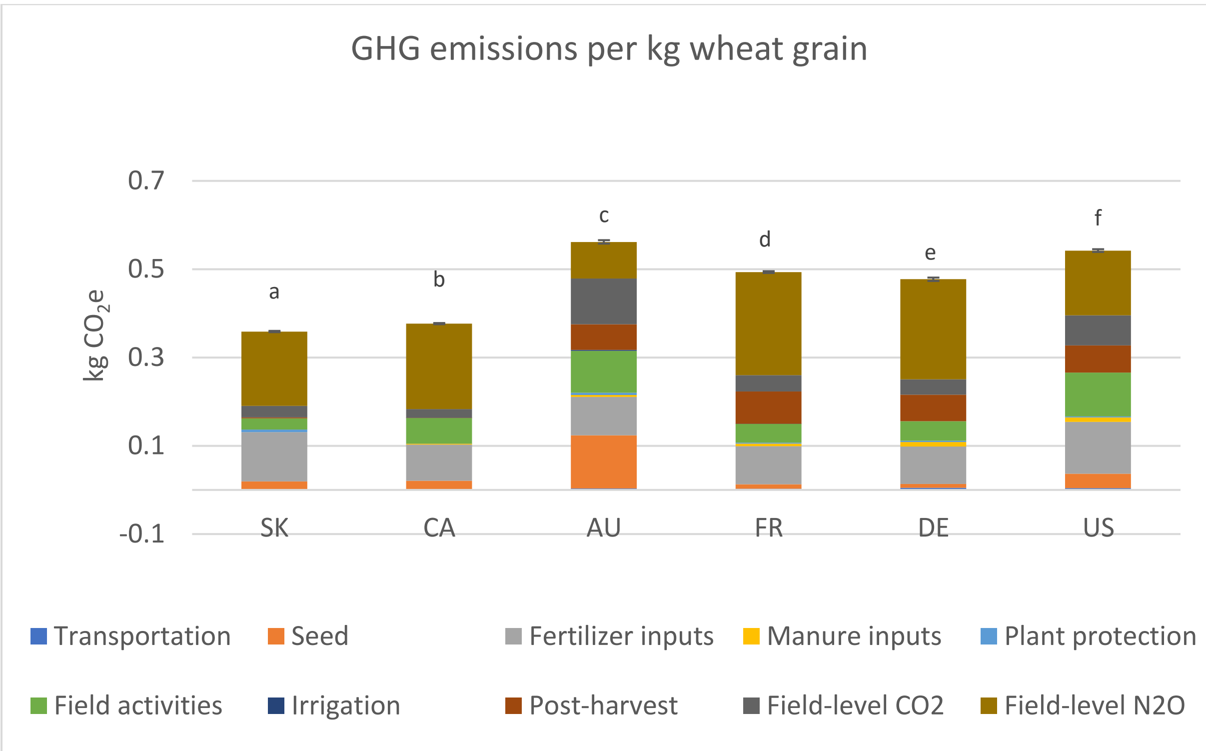

Figure 3. Contribution analysis of main LCI data categories to the overall carbon footprints (without soil carbon change) of wheat grain produced in SK, CA, AU, FR, DE, and US (kg CO_2e per kg wheat grain), using mass allocation between harvested grain and straw.

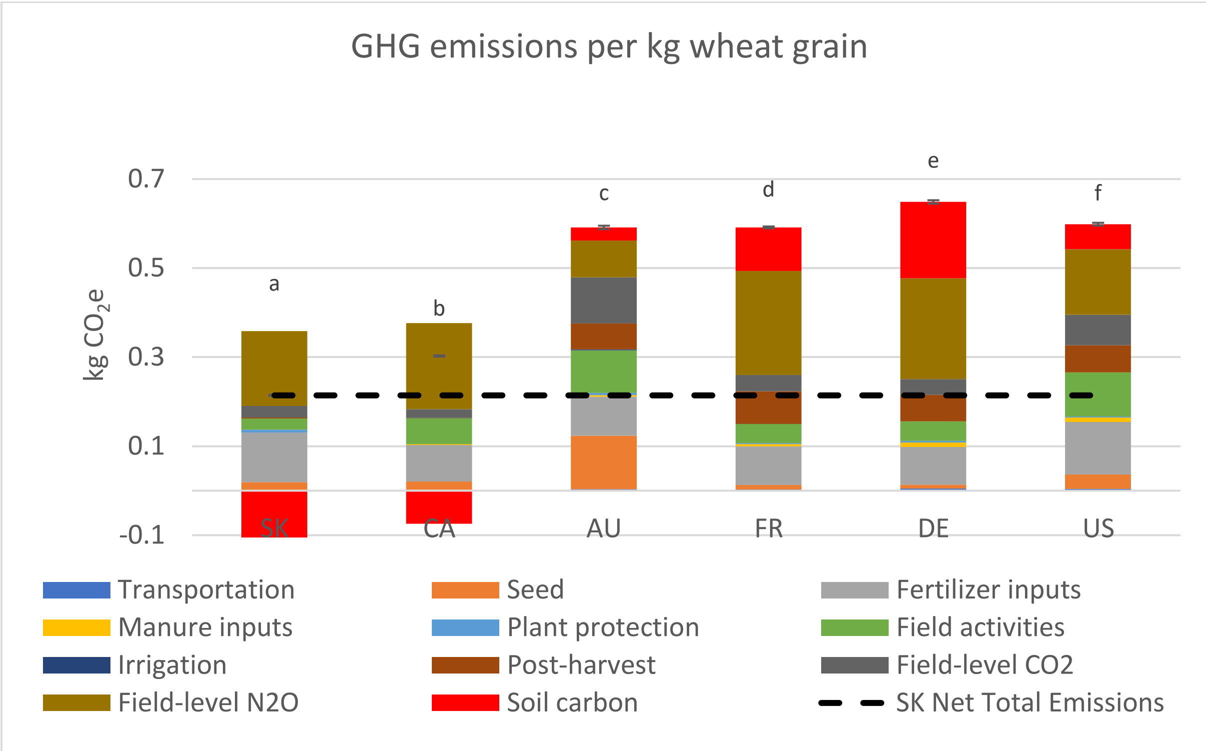

Figure 4. Contribution analysis of main LCI data categories to the overall carbon footprints (with soil carbon changes) of wheat grain produced in SK, CA, AU, FR, DE, and US (kg CO_2e per kg wheat grain), using mass allocation between harvested grain and straw. The dashed line represents net total emissions in SK, accounting for negative impacts from soil carbon changes.

Table 42. Global average carbon footprint values (with and without soil carbon change) compared to Saskatchewan carbon footprint values for wheat grain production.

	Global average	Saskatchewan
kg CO_2e per kg wheat grain (without soil carbon change)	0.497	0.359
kg CO_2e per kg wheat grain (with soil carbon change)	0.552	0.214

3.2.3 Peas

Figure 5 shows the LCIA results, without soil carbon change, for the production of 1 kg of peas for Saskatchewan, Canada, France, Germany, and the United States. The results are broken down into the contributions from transportation, seed, fertilizer inputs, manure inputs, inoculant inputs, plant protection products, field activities, irrigation, post-harvest drying, field-level CO_2 and N_2O emissions, and N credit. Peas produced in Saskatchewan have the lowest carbon footprint, followed closely by the Canadian average (7% higher). The highest contributor to the carbon footprint of Saskatchewan and Canadian pea production is field-level N_2O emissions (75-76%). Approximately 95% of the N_2O emissions are due to crop residue N inputs, and 5% from fertilizer N inputs, due to the high levels of crop residues and low synthetic fertilizer and manure application rates for peas. Field activities contributed 16-17% of the life cycle impacts for Canadian and Saskatchewan peas, and fertilizer production contributed 7-8%. The N credit, for reduced N fertilizer required for the next crop in rotation, contributed a 4% reduction in impacts. All other inputs and activities contributed 5% or less.

All differences between regions are significantly different. French peas had 70% higher impacts than Saskatchewan peas, due to higher inputs of fertilizer and manure, higher levels of field activities, and higher field-level CO_2 emissions due to the inclusion of lime application. Field-level N_2O emissions are the highest contributor to the carbon footprint of French pea production (48%). Fifty-five percent of these N_2O emissions are due to N mineralization from soil carbon loss. Twenty-nine percent are from crop residues, and 16% are from manure inputs. There were no synthetic N fertilizers applied to French peas. After N_2O emissions, field activities are the next highest contributor to the carbon footprint of French peas (18%). Fertilizer inputs and field-level CO_2 emissions from lime inputs contributed 12% each, and all other inputs and activities contributed 3% or less. The N credit contributed -3%.

German peas had the highest carbon footprint of all regions (156% of Saskatchewan peas). This was due to higher field-level N_2O emissions, as well as higher fertilizer inputs. Field-level N_2O emissions contributed 56% of the life cycle GHG emissions. Seventy-one percent of these emissions came from soil carbon losses, 13% from manure, 9% from crop residues and 7% from synthetic N fertilizer. Fertilizer production, and field activities each contributed 13% to the carbon footprint of German peas, and field-level CO_2 emissions from lime and urea application contributed 9%. All other inputs contributed 4% or less.

Pea production in the US had the second highest carbon footprint (after Germany), which was 137% of the Saskatchewan pea carbon footprint. This was due to high levels of field activities and field-level CO_2 emissions, and relatively high field-level N_2O emissions (but lower than Germany). Field-level N2O emissions were the highest contributors to the carbon footprint of US peas (43%). These emissions came from crop residues (69%), soil carbon losses (12%), synthetic N fertilizer (10%), and manure (10%). Fertilizer production and field-level CO_2 emissions from lime and urea application each contributed 17% to the overall carbon footprint of US pea production. Field activities contributed 16%, and all other inputs and activities contributed 3% or less.

Saskatchewan soils had the highest levels of soil carbon sequestration, followed by the Canadian average (Figure 6). All other countries had net carbon emissions from their agricultural soils. The US had the lowest levels of carbon emissions, followed by France, and Germany had the highest. When the impacts of soil carbon changes are combined with the LCIA results, Saskatchewan peas still have the lowest carbon footprint (0.04 kg CO_2e/kg), followed by the Canadian average (160% higher). Since all other regions already had higher impacts of production, and have much higher impacts from soil carbon change, their combined impacts compared to Saskatchewan range from 1500% higher in France to 2516% higher in Germany. When either including or excluding soil carbon changes, Saskatchewan peas had a lower carbon footprint (28-86% lower) than the global weighted average (Table 43).

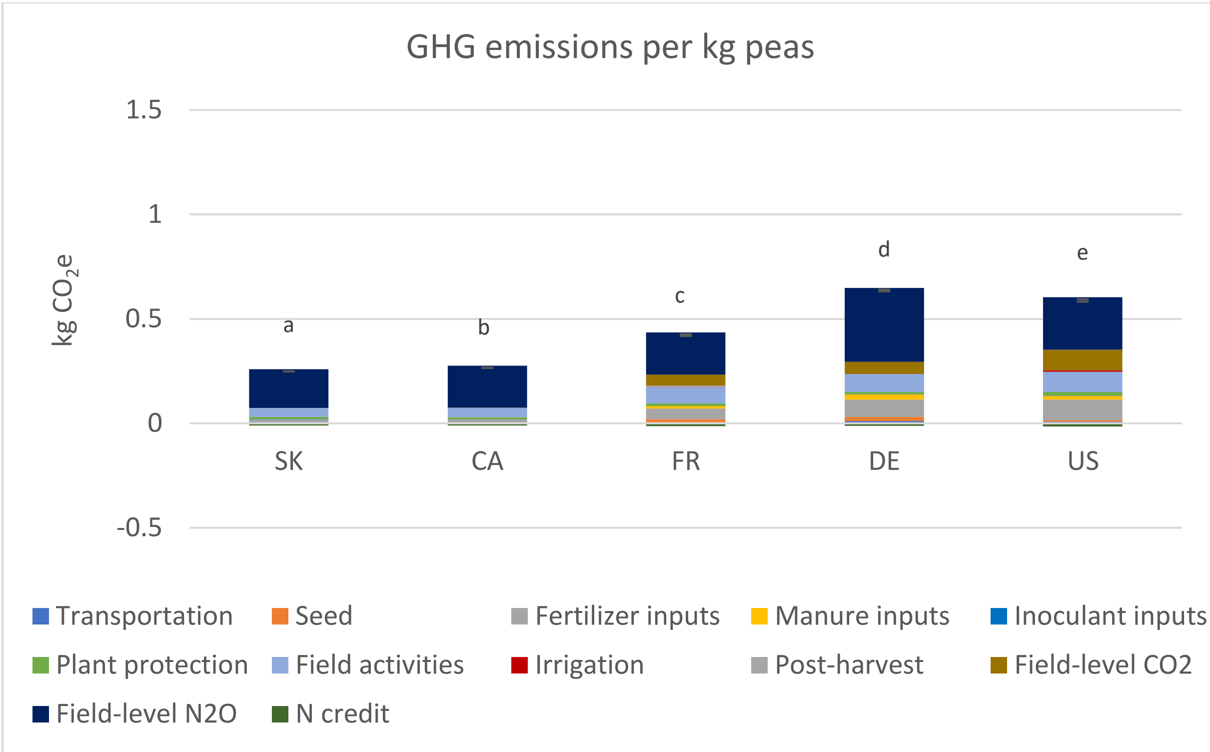

Figure 5. Contribution analysis of main LCI data categories to the overall carbon footprints (without soil carbon changes) of peas produced in SK, CA, FR, DE, and US (kg CO_2e per kg peas).

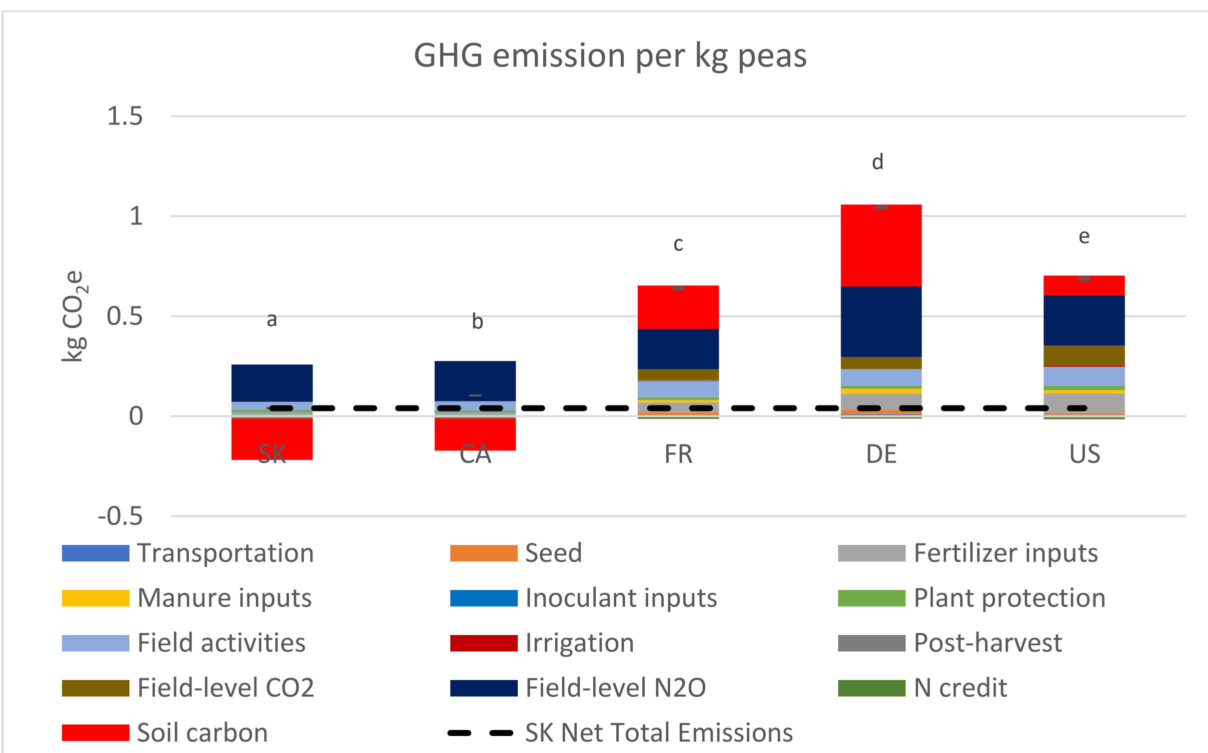

Figure 6. Contribution analysis of main LCI data categories to the overall carbon footprints (with soil carbon changes) of peas produced in SK, CA, FR, DE, and US (kg CO_2e per kg peas). The dashed line represents net total emissions in SK, accounting for negative impacts from soil carbon changes.

Table 43. Global average carbon footprint values (with and without soil carbon change) compared to Saskatchewan carbon footprint values for pea production.

	Global average	Saskatchewan
kg CO_2e per kg peas (without soil carbon change)	0.347	0.248
kg CO_2e per kg peas (with soil carbon change)	0.295	0.040

3.3 Sensitivity analysis

3.3.1 Cut-off criteria and exclusions

Including the manure inputs that were previously excluded from the analysis for Saskatchewan, Canadian, and Australian canola, and the lime inputs for Saskatchewan and Canada increased the total carbon footprint values by 1-16% (Table 44). Including the previously excluded manure and lime inputs for Saskatchewan and Canadian peas, and the irrigation input for German peas increased the total carbon footprint values from 0-36% (Table 45). Despite these changes, the relative rankings (from lowest to highest carbon footprint) of the regions did not change for either crop.

Table 44. Canola sensitivity analysis results for the inclusion of inputs excluded in the original results.

kg CO_2e/kg	**Fertilizer inputs**	**Manure inputs**	**Field-level CO2**	**Field-level N2O**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0.164	0.004	0.113	0.355	0.689	16%	2	2
CA	0.195	0.004	0.127	0.402	0.799	13%	3	3
AU	0.126	0.006	0.118	0.051	0.489	1%	1	1
FR	0.226	0.013	0.030	0.547	0.940	0%	4	4
DE	0.240	0.023	0.043	0.543	0.991	0%	5	5

Table 45. Peas sensitivity analysis results for the inclusion of inputs excluded in the original results.

kg CO_2e/kg	**Fertilizer inputs**	**Manure inputs**	**Irrigation energy**	**Field-level CO2**	**Field-level N2O**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0.024	0.005	0	0.079	0.186	0.337	36%	1	1
CA	0.022	0.005	0	0.076	0.202	0.350	32%	2	2
FR	0.051	0.012	1.91E-03	0.053	0.202	0.422	0%	3	3
DE	0.082	0.025	1.17E-06	0.059	0.354	0.636	0%	5	5
US	0.098	0.018	7.36E-03	0.098	0.251	0.588	0%	4	4

3.3.2 Manure nutrient contents

Using the same average manure nutrient contents for all countries changed the overall carbon footprint results between 0-5% across all crop-country combinations (Tables 46-48). This change altered both the manure input amounts, and the associated N_2O emissions. Due to these small changes, the relative ranking of all countries from lowest to highest carbon footprint did not change.

Table 46. Canola sensitivity analysis results for changed manure nutrient contents.

kg CO_2e/kg	Manure inputs	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0.000	0.355	0.597	0%	2	2
CA	0.000	0.402	0.709	0%	3	3
AU	0.000	0.051	0.483	0%	1	1
FR	0.016	0.551	0.947	1%	4	4
DE	0.034	0.560	1.019	3%	5	5

Table 47. Wheat sensitivity analysis results for changed manure nutrient contents.

kg CO_2e/kg	Manure inputs	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0.000	0.169	0.359	0%	1	1
CA	0.003	0.194	0.377	0%	2	2
AU	0.003	0.082	0.560	0%	6	6
FR	0.007	0.234	0.495	0%	4	4
DE	0.016	0.233	0.489	2%	3	3
US	0.011	0.153	0.548	1%	5	5

Table 48. Peas sensitivity analysis results for changed manure nutrient contents.

kg CO_2e/kg	Manure inputs	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0	0.186	0.248	0%	1	1
CA	0	0.202	0.266	0%	2	2
FR	0.016	0.207	0.431	2%	3	3
DE	0.038	0.371	0.667	5%	5	5
US	0.022	0.254	0.595	1%	4	4

3.3.3 Manure allocation methods

Changing from the 50:50 allocation method for the impacts of the production of the upstream synthetic fertilizers that provided the nutrients to the manure inputs, to the 100:0 and 0:100 allocation methods changed the results by 0-4% for all crops and countries (Tables 49-54). Allocating 0% of the impacts to the manure reduced impacts by 0-4% and allocating 100% of the impacts to manure increased impacts by 0-4%. Again, due to these small changes, the relative ranking of the countries did not change.

Table 49. Canola sensitivity analysis results for 0% allocation of recycled synthetic fertilizer impacts to manure.

kg CO_2e/kg	**Manure inputs**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0	0.597	0%	2	2
CA	0	0.709	0%	3	3
AU	0	0.483	0%	1	1
FR	0	0.926	-1%	4	4
DE	0	0.968	-2%	5	5

Table 50. Wheat sensitivity analysis results for 0% allocation of recycled synthetic fertilizer impacts to manure.

kg CO_2e/kg	**Manure inputs**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0	0.359	0%	1	1
CA	0	0.374	-1%	2	2
AU	0	0.558	-1%	6	6
FR	0	0.488	-1%	4	4
DE	0	0.467	-2%	3	3
US	0	0.532	-2%	5	5

Table 51. Peas sensitivity analysis results for 0% allocation of recycled synthetic fertilizer impacts to manure.

kg CO_2e/kg	**Manure inputs**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0	0.248	0%	1	1
CA	0	0.266	0%	2	2
FR	0	0.410	-3%	3	3
DE	0	0.611	-4%	5	5
US	0	0.570	-3%	4	4

Table 52. Canola sensitivity analysis results for 100% allocation of recycled synthetic fertilizer impacts to manure.

kg CO_2e/kg	**Manure inputs**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0	0.597	0%	2	2
CA	0	0.709	0%	3	3
AU	0	0.483	0%	1	1
FR	0.026	0.953	1%	4	4

DE	0.047	1.014	2%	5	5

Table 53. Wheat sensitivity analysis results for 100% allocation of recycled synthetic fertilizer impacts to manure.

kg CO_2e/kg	**Manure inputs**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0	0.359	0%	1	1
CA	0.005	0.379	1%	2	2
AU	0.008	0.566	1%	6	6
FR	0.011	0.499	1%	4	4
DE	0.020	0.487	2%	3	3
US	0.021	0.553	2%	5	5

Table 54. Peas sensitivity analysis results for 100% allocation of recycled synthetic fertilizer impacts to manure.

kg CO_2e/kg	**Manure inputs**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0	0.248	0%	1	1
CA	0	0.266	0%	2	2
FR	0.025	0.434	3%	3	3
DE	0.050	0.661	4%	5	5
US	0.037	0.606	3%	4	4

3.3.4 Wheat straw content and allocation methods

When 0% of the impacts of wheat production were allocated to wheat straw (i.e., 100% of impacts were allocated to wheat grain, and no straw was assumed to be removed from the field) the wheat grain carbon footprint increased by 4-7%, depending on the original assumed allocation factors (Table 55). This did not change the relative rankings of the countries. When the largest possible percent of straw (85%) was assumed to be removed as a co-product and allocated to, the impacts of wheat grain decreased by 45-61% (Table 56), and the relative rankings of wheat from Australia, Germany and US changed. Saskatchewan had the lowest carbon footprint, followed by Canada, then the United States, France, and Australia. Germany had the highest carbon footprint. Application of a slightly altered straw removal rate of 21.1% rather than 24.1% assuming data from Statistics Canada(2021b) are representative of crop residue baling practices in 2020 rather than 2021 had very minor (i.e., <1% change) impacts on the estimated carbon footprint values, and did not change the ranking of regions in terms of emissions (Table 57). Finally, when the variable rates of straw removal from the literature were used, the estimated impacts of wheat grain production decreased 30-48% (Table 58). Again, the relative rankings changed. With the variable straw removal rates, Saskatchewan had the lowest impacts, followed by Canada, the US, Germany, and France. Australia had the highest impacts. This shows the importance of transparency in allocation methods when conducting a carbon footprint analysis or life cycle assessment, as well as the need for principled approaches that are consistent with current international methodological standards. In light of the potentially influential role of assumed wheat straw removal rates, development of accurate, country-specific data is also highly desirable.

Table 55. Wheat sensitivity analysis for 0% wheat removal and allocation.

kg CO_2e/kg	**Field-level N2O**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0.182	0.382	7%	1	1
CA	0.209	0.402	7%	2	2
AU	0.088	0.592	5%	6	6
FR	0.247	0.519	5%	4	4
DE	0.237	0.497	4%	3	3
US	0.157	0.574	6%	5	5

Table 56. Wheat sensitivity analysis for 85% wheat removal and associated allocation.

kg CO_2e/kg	**Field-level N2O**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0.059	0.142	-60%	1	1
CA	0.067	0.147	-61%	2	2
AU	0.039	0.277	-51%	6	5
FR	0.120	0.269	-45%	4	4
DE	0.139	0.303	-36%	3	6
US	0.055	0.227	-58%	5	3

Table 57. Wheat straw sensitivity analysis assuming that crop residues were removed from 21.1% of land rather than 24.1% of land.

kg CO_2e/kg	**Field-level N2O**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0.170	0.362	0.81%	1	1
CA	0.195	0.380	0.82%	2	2
AU	0.083	0.566	0.66%	6	6
FR	0.235	0.496	0.63%	4	4
DE	0.228	0.480	0.52%	3	3
US	0.148	0.546	0.73%	5	5

Table 58. Wheat sensitivity analysis for variable wheat removal and associated allocation.

kg CO_2e/kg	**Field-level N2O**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0.105	0.233	-35%	1	2
CA	0.094	0.195	-48%	2	1
AU	0.081	0.375	-33%	6	6
FR	0.155	0.338	-31%	4	5

DE	0.158	0.335	-30%	3	4
US	0.078	0.305	-44%	5	3

3.3.5 N_2O emissions modelling

Modelling the N_2O emissions as the lowest possible values based on the ranges presented by each country resulted in overall reductions in the carbon footprint of canola ranging from a 6% reduction for Australia to a 53% reduction for France (Table 59). For wheat, using the lowest possible N_2O values resulted in reductions ranging from 7% for the US to 43% for France (Table 60). For peas, the reductions ranged from 12% for the US to 60% for Saskatchewan and Canada (Table 61). When using these low N_2O values, Saskatchewan canola had the lowest carbon footprints (excluding soil carbon), followed by France, Australia, and Canada. Germany had the highest. This is different from the original ranking, in which Australia was lowest, followed by Saskatchewan, Canada, France, and Germany. For wheat, the relative rankings did not change. Peas changed from Saskatchewan, Canada, France, United States, Germany, to Saskatchewan, Canada, France, Germany, United States.

Using the highest N_2O values gave increases in carbon footprint values for canola ranging from 7% in Australia to 90% in Germany (Table 62). For wheat, using the highest N_2O values resulted in increases ranging from 7% in the US to 90% in Canada (Table 63). For peas, the increases ranged from 11% for the US to 91% for Germany (Table 64). When using these high N_2O values, the relative rankings from lowest to highest for canola carbon footprint values (excluding soil carbon changes) did not change from the original ranking of Australia, Saskatchewan, Canada, France, Germany. For wheat, the rankings changed to Saskatchewan, United States, France, Canada, Australia, Germany. For peas, the rankings did not change from the original Saskatchewan, Canada, France, United States, Germany ranking.

Table 59. Canola sensitivity analysis results for lowest N_2O values in range.

kg CO_2e/kg	**Field-level N2O**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0.154	0.396	-33.68%	2	1
CA	0.174	0.481	-32.19%	3	4
AU	0.023	0.454	-5.95%	1	3
FR	0.048	0.441	-53.09%	4	2
DE	0.062	0.510	-48.52%	5	5

Table 60. Wheat sensitivity analysis results for lowest N_2O values in range.

kg CO_2e/kg	**Field-level N2O**	**Total without soil carbon**	**% change from original**	**Original ranking (lowest to highest CF)**	**New ranking (lowest to highest CF)**
SK	0.081	0.271	-25%	1	1
CA	0.093	0.276	-27%	2	2
AU	0.037	0.515	-8%	6	6
FR	0.021	0.280	-43%	4	4
DE	0.026	0.276	-42%	3	3
US	0.107	0.502	-7%	5	5

Table 61. Peas sensitivity analysis results for lowest N_2O values in range.

kg CO_2e/kg	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0.037	0.100315	-60%	1	1
CA	0.041	0.105095	-60%	2	2
FR	0.017	0.237784	-44%	3	3
DE	0.038	0.320526	-50%	5	4
US	0.183	0.520244	-12%	4	5

Table 62. Canola sensitivity analysis results for highest N_2O values in range.

kg CO_2e/kg	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0.540	0.781	31%	2	2
CA	0.612	0.919	30%	3	3
AU	0.080	0.511	6%	1	1
FR	1.057	1.450	54%	4	4
DE	1.499	1.948	97%	5	5

Table 63. Wheat sensitivity analysis results for highest N_2O values in range.

kg CO_2e/kg	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0.382	0.572	60%	1	1
CA	0.534	0.717	90%	2	4
AU	0.129	0.608	8%	6	5
FR	0.452	0.711	44%	4	3
DE	0.623	0.874	83%	3	6
US	0.185	0.580	7%	5	2

Table 64. Peas sensitivity analysis results for highest N_2O values in range.

kg CO_2e/kg	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0.281	0.344	39%	1	1
CA	0.307	0.372	40%	2	2
FR	0.390	0.610	45%	3	3
DE	0.930	1.212	91%	5	5
US	0.316	0.653	11%	4	4

3.3.6 Crop residue yields and N contents

Using the same average crop residue yield and N content for all countries changed the total carbon footprint of canola between -8 and 6% (Table 65). Due to these relatively small changes, the relative ranking of the countries did not change. For wheat, the total carbon footprint values changed by -3 to +5% and the relative rankings did not change (Table 66). For peas, the carbon footprint values changed between -12 to 28% (Table 67). This changed the relative rankings of France and the US, changing from the third and fourth lowest carbon footprints to the fourth and third, respectively.

Table 65. Canola sensitivity analysis results for crop residue yields and N contents.

kg CO_2e/kg	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0.310	0.551	-8%	2	2
CA	0.352	0.658	-7%	3	3
AU	0.052	0.483	0%	1	1
FR	0.582	0.974	4%	4	4
DE	0.606	1.054	6%	5	5

Table 66. Wheat sensitivity analysis results for crop residue yields and N contents.

kg CO_2e/kg	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0.160	0.352	-2%	1	1
CA	0.182	0.366	-3%	2	2
AU	0.085	0.567	1%	6	6
FR	0.241	0.501	1%	4	5
DE	0.251	0.499	5%	3	3
US	0.132	0.530	-2%	5	5

Table 67. Peas sensitivity analysis results for crop residue yields and N contents.

kg CO_2e/kg	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0.136	0.199	-20%	1	1
CA	0.149	0.213	-20%	2	2
FR	0.320	0.540	28%	3	4
DE	0.480	0.763	20%	5	5
US	0.181	0.518	-12%	4	3

3.3.7 Impact assessment methods

Using the GWP 500 impact assessment method instead of the GWP 100 changed the carbon footprint estimates for canola by -9% to -33% (Table 68). The decreases were mainly due to the differences in impact factors for N_2O between the two methods. The original GWP 100 method has an impact factor of 273 kg CO_2e/kg N_2O, and the GWP 500 has an impact factor of 130. The estimated impacts of the other inputs and activities also changed due to differences in impact factors for upstream N_2O and other emissions, however these changes were small compared to the change in field-level N_2O emissions. Since the impacts of Saskatchewan canola decreased more than Australian canola, Saskatchewan had the lowest carbon footprint estimate in this scenario, followed by Australia. All other relative rankings for canola remained unchanged.

For wheat, the estimated carbon footprint values decreased by 6-30% (Table 69), and peas by 27-40% (Table 70). Again, these differences were mainly due to the difference in impact factor for N_2O. The relative rankings of wheat for Saskatchewan and Canada swapped from lowest and second lowest to second lowest and lowest, respectively. The relative rankings of the other countries did not change for wheat. For peas, the country with the highest carbon footprint changed from Germany to the US.

Table 68. Canola sensitivity analysis results for GWP 500 impact assessment methods.

kg CO_2e/kg	Transportation	Seed	Fertilizer inputs	Manure inputs	Plant protection	Field activities	Irrigation	Post-harvest	Field-level CO2	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0.001	0.004	0.150	0	0.007	0.036	0.000	0.002	0.030	0.169	0.399	-33.1%	2	1
CA	0.002	0.005	0.175	0	0.012	0.038	0.001	0.011	0.045	0.192	0.479	-32.5%	3	3
AU	0.003	0.003	0.116	0	0.021	0.143	0.000	0.013	0.118	0.024	0.441	-8.6%	1	2
FR	0.005	0.001	0.210	0.014	0.012	0.096	0.000	0.003	0.030	0.260	0.633	-32.6%	4	4
DE	0.011	0.002	0.223	0.022	0.014	0.097	0.007	0.008	0.043	0.258	0.685	-30.8%	5	5

Table 69. Wheat sensitivity analysis results for GWP 500 impact assessment methods.

kg CO_2e /kg	Transportation	Seed	Fertilizer inputs	Manure inputs	Plant protection	Field activities	Irrigation	Post-harvest	Field-level CO2	Field-level N2O	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	0.001	0.014	0.104	0.000	0.006	0.104	0.000	0.002	0.026	0.080	0.338	-6%	1	2
CA	0.002	0.015	0.075	0.002	0.000	0.057	0.000	0.000	0.019	0.092	0.263	-30%	2	1
AU	0.003	0.108	0.081	0.004	0.004	0.094	0.002	0.056	0.104	0.039	0.494	-12%	6	6
FR	0.003	0.007	0.080	0.005	0.001	0.043	0.000	0.070	0.036	0.111	0.358	-28%	4	4
DE	0.005	0.007	0.078	0.010	0.003	0.043	0.000	0.057	0.035	0.108	0.346	-28%	3	3
US	0.004	0.025	0.103	0.009	0.002	0.098	0.000	0.057	0.068	0.070	0.436	-20%	5	5

Table 70. Peas sensitivity analysis results for GWP 500 impact assessment methods.

kg CO_2e/kg	Transportation	Seed	Fertilizer inputs	Manure inputs	Inoculant inputs	Plant protection	Field activities	Irrigation	Post-harvest	Field-level CO2	Field-level N2O	N credit	Total without soil carbon	% change from original	Original ranking (lowest to highest CF)	New ranking (lowest to highest CF)
SK	2.60E-04	1.274E-05	0.018	0	0.001	0.011	0.040	0	0.001	3.00E-04	0.089	-0.010	0.150	-40%	1	1
CA	2.700E-04	1.455E-05	0.018	0	0.001	0.008	0.045	0	1.60E-04	2.50E-04	0.096	-0.011	0.159	-40%	2	2
FR	0.005	0.011	0.049	0.011	0.001	0.011	0.077	1.87E-03	0.006	0.053	0.096	-0.013	0.309	-27%	3	3
DE	0.010	0.017	0.078	0.023	0.001	0.011	0.085	0	0	0.059	0.169	-0.012	0.440	-31%	5	4
US	0.007	0.008	0.090	0.016	0.001	0.016	0.095	7.10E-03	4.00E-04	0.098	0.120	-0.015	0.443	-25%	4	5

3.4 Limitations of the analysis

LCA has limitations. While the impacts of these limitations may be somewhat mitigated through performance of in-depth sensitivity analyses, as has been done here, some limitations remain. The most obvious of these is the use of secondary data sourced from LCI databases, published literature, and government and industry sources as the basis for the analyses. LCA is data intensive, and the robustness of models and associated results and interpretations are intrinsically linked to the quality of the data used in model development (Ciroth et al., 2016). While much of the data used in this analysis are of high quality, many data points were of relatively lower quality with respect to the completeness criteria, either due to small sample sizes, or a lack of reporting on the percentage of supply covered. This lack of reporting is, unfortunately, quite common in the LCA literature (Turner et al., 2020). Completeness scores could also be improved through the collection of primary data based on large, representative samples across industries. Doing so, however, would require significant effort and resources.

An additional key limitation of LCA is related to the models and assumptions used for estimation of LCI data. These include those for estimation of field level emissions, manure nutrient inputs, crop residue yields, etc. While use of modeled values is necessary given the infeasibility of primary data collection, the potential biases that may be inherent to these models should not be ignored. The impact of these biases has been taken into account through the performance of uncertainty analysis as per best practices in the LCA field (Bamber et al., 2019). This limitation is particularly evident with regards to the assumptions made around amounts of straw removed as a co-product of wheat production systems. Wheat straw is commonly used as a bedding material (Smerchek and Smith, 2020; Yesufu et al., 2020) and as forage (Ates et al., 2017; Molavian et al., 2020) for livestock systems, as well as for production of second generation biofuels (Hasanly et al., 2018; Suardi et al., 2020). Harvest and removal of wheat straw residues is therefore likely dependent on regional market forces (i.e., demands for livestock bedding/forage and biofuel feedstocks). A more in-depth exploration of the removal of wheat straw from fields, and the resulting changes in associated allocation factors, would therefore require in-depth knowledge of regional markets, or data of sufficiently high quality characterizing the proportions of harvested wheat straw diverted to each possible use. Data describing the relative size of the livestock sectors across the different regions included in this analysis could be used in proxy to scale proportions of straw removed across each country, but this scaling would be based on the fallible assumption that demand for wheat straw is driven solely by the livestock sector in each region. For example, operating with this assumption, and scaling the amount of straw baled per kilogram of wheat produced linearly, results in the conclusion that, in the U.S., 5 times more wheat straw must be baled than is produced per kilogram of wheat, based on cattle inventories from Statistics Canada (Statistics Canada, 2022c) and FAOstat (FAOstat, 2021) In the future, it is clear that greater effort must be put into accounting for production of crop residues, as well as the proportion of residues that are harvested for use in other sectors.

4. Conclusion

Production of commodity field crops is economically important in Saskatchewan as well as in Canada as a whole. Field crops produced in Canada have substantial international market share, making increasingly important contributions to global food security (Caparas et al., 2021). Given increases in societal desires for sustainably produced foods (Mazzocchi et al., 2021; Okpiaifo et al., 2020; Tobi et al., 2019), it is necessary that food system managers and stakeholders develop an in-depth understanding of the GHG emissions associated with food production systems, including key hot spots along supply chains and the comparative impacts of food products, such that sustainability improvement measures may be implemented in order to promote net-positive outcomes.

This analysis provides estimates of life cycle GHG emissions for canola, non-durum wheat, and field pea production in Saskatchewan and compares them with the emissions attributable to the same crops produced in Canada as a whole as well as in Australia, France, Germany, and the U.S. Saskatchewan and Canadian crop production systems compare favourably to their international counterparts, having the lowest and second lowest GHG emissions per kilogram of product, with few exceptions. The results generally exhibited a low degree of sensitivity to methodological choices made in the study. Key supply chain hotspots for all crop-region combinations included field level N_2O emissions and fertilizer inputs. These may serve as foci for research into potential sustainability improvement strategies.

While canola, non-durum wheat, and field peas represent an important portion of the Saskatchewan field crop sector, similar comparisons of other economically important crops should be considered in the future. These comparisons may help develop a deeper understanding of how the Saskatchewan field crop sector compares to international competitors, as well as opportunities for improvement.

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Appendix 1. Detailed results for baseline analyses

Table A 1 Detailed contribution analysis describing contributions to total GHG emissions (kg CO_2e) per kilogram of canola produced in the baseline model.

Region	Transportation	Seed	Fertilizer inputs	Manure inputs	Plant protection	Field activities	Irrigation	Post-harvest	Field-level CO2	Field-level N2O	Soil carbon change
SK	0.002	0.005	0.159	0.000	0.007	0.037	0.000	0.002	0.030	0.355	-0.225
CA	0.002	0.006	0.191	0.000	0.013	0.038	0.001	0.012	0.045	0.402	-0.161
AU	0.003	0.004	0.126	0.000	0.023	0.145	0.000	0.013	0.118	0.051	0.046
FR	0.005	0.001	0.226	0.013	0.015	0.098	0.000	0.003	0.030	0.547	0.227
DE	0.011	0.002	0.240	0.023	0.015	0.098	0.008	0.009	0.043	0.543	0.390

Table A 2 Detailed contribution analysis describing contributions to total GHG emissions (kg CO_2e) per kilogram of wheat grain produced in the baseline model.

Region	Transportation	Seed	Fertilizer inputs	Manure inputs	Plant protection	Field activities	Irrigation	Post-harvest	Field-level CO2	Field-level N2O	Soil carbon change
SK	0.001	0.018	0.111	0.000	0.006	0.025	0.000	0.002	0.026	0.169	-0.145
CA	0.002	0.019	0.081	0.002	0.000	0.058	0.000	0.000	0.019	0.194	-0.074
AU	0.003	0.120	0.087	0.004	0.005	0.095	0.002	0.058	0.104	0.083	0.029
FR	0.003	0.010	0.087	0.006	0.002	0.043	0.000	0.073	0.036	0.234	0.098
DE	0.005	0.009	0.084	0.010	0.003	0.044	0.000	0.060	0.035	0.227	0.171
US	0.004	0.032	0.118	0.010	0.002	0.099	0.000	0.062	0.068	0.147	0.057

Table A 3 Detailed contribution analysis describing contributions to total GHG emissions (kg CO_2e) per kilogram of peas produced in the baseline model.

Region	Transportation	Seed	Fertilizer inputs	Manure inputs	Inoculant inputs	Plant protection	Field activities	Irrigation	Post-harvest	Field-level CO2	Field-level N2O	N credit	Soil carbon

SK	2.70E-04	1.35E-05	0.019	0.000	0.001	0.011	0.041	0	0.001	3.00E-04	0.186	-0.010	-0.208
CA	2.70E-04	1.56E-05	0.019	0.000	0.001	0.009	0.046	0	1.70E-04	2.50E-04	0.202	-0.011	-0.162
FR	0.005	0.014	0.051	0.012	0.001	0.012	0.078	1.91E-03	0.006	0.05	0.202	-0.013	0.217
DE	0.011	0.021	0.082	0.025	0.001	0.011	0.086	0.00E+00	0.00000	0.06	0.354	-0.013	0.410
US	0.008	0.008	0.098	0.018	0.001	0.017	0.096	7.36E-03	4.10E-04	0.10	0.251	-0.016	0.099