Carbon footprint analysis of Saskatchewan and Canadian field crops and comparison to international competitors: Part 2.

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AR6 – IPCC Sixth Assessment Report
ARMS – Agricultural Resource Management Survey
BNF – Biological Nitrogen fixation
CALDC – Canadian Agri-food Life-cycle Data Centre
CO_2 – Carbon dioxide
CRSC – Canadian Roundtable for Sustainable Crops
CSIRO – Commonwealth Scientific and Industrial Research Organization
EF – Emissions factor
ERS – Economic Research Service
EU – European Union
FAO – Food and Agriculture Organization of the United Nations
GHG – Greenhouse gas
GIFS – Global Institute for Food Security
GREET – Greenhouse gases, Regulated Emissions, and Energy use in Transportation
IFA – International Fertilizer Association
IPCC – Intergovernmental Panel on Climate Change
ISO – International Organization for Standardization
K – Potassium
LCA – Life cycle assessment
LCI – Life cycle inventory
LCIA – Life cycle impact assessment
LEAP – Livestock Environmental Assessment and Performance
LULUCF – Land use, land use change and forestry
N – Nitrogen
N_2O – Nitrous oxide
NASS – National Agricultural Statistics Service
NH_3 – Ammonia
NIR – National Inventory Report
NO_3 – Nitrate
NO_x – Nitrogen oxides
P – Phosphorus
RU – Reconciliation Unit
S – Sulphur
SK – Saskatchewan
SOC – Soil Organic Carbon
U.S. – United States
UN – United Nations
UNFCCC – United Nations Framework Convention on Climate Change
USDA – United States Department of Agriculture

1. Introduction

The production of commodity field crops, including durum and non-durum wheat, canola, lentils 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). 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. Such an understanding may help field crop producers and marketers develop and maintain a competitive advantage on the basis of superior sustainability outcomes (Nassos and Avlonas, 2020; Tobi et al., 2019).

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 (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. LCA has 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 2-part study to enable comparing the carbon footprints of five key crops grown in Saskatchewan and other Canadian provinces (canola, durum and non-durum wheat, lentils, and dry field peas) to those same crops grown by a subset of international competitors (Australia, France, Germany, the United States (U.S.), Italy, the Netherlands, Russia, Ukraine and Turkey), as well as soy produced in Brazil and the U.S., on a rigorous, transparent, and methodologically consistent basis. The Canadian average, Prairie Province average, and Canada without Saskatchewan production systems were also assessed and included in the comparison. The results of this study may 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, which is the second part of the 2-part study. The methods and detailed results for part 2 are included in this document, along with the life cycle impact assessment (LCIA) results from part 1 for comparison included in the graphical results.

2. Methods

As in part 1, the development of carbon footprint models for the additional crop-region combinations of interest in part 2 followed a staged approach. In stage 1, a data mining and quality assessment exercise was carried out to determine for which of the proposed crop-region combinations sufficiently credible/rigorous data were available to support model development, and to select among available data sources. The key deliverable resulting from this first stage was a data availability and quality report detailing the potential data sources, and their associated data quality, which was used in stage 2 in consultation with the Government of Saskatchewan and GIFS to finalize a short-list of crop-region combinations for inclusion in the part 2 analysis. During the consultation stage, decisions were made regarding for which crop-region combinations data was unavailable in sufficient quality to support development of rigorous life cycle inventory models for assessment of GHG emissions. Finally, in stage 3, carbon footprint models were developed for all those crop-region combinations for which data of sufficient quality were identified, and comparisons were drawn between the GHG emissions associated with each crop-region combination. A complete, detailed account of the methodologies used throughout these stages are further detailed below.

2.1 Crop region combinations included

In total, 27 crop-country combinations were proposed by the study commissioners for inclusion in part 2 of the project (Table 1). Cells filled in yellow represent crop-region combinations included in part 1, while those filled in green represent additional combinations proposed for inclusion in part 2. Cells filled in grey were not considered for inclusion. The additional combinations for part 2 include canola grown in Canada without Saskatchewan, the Netherlands, Russia, and Ukraine, soy grown in Brazil and the U.S., non-durum wheat grown in Canada without Saskatchewan, Russia and Ukraine, lentils grown in Saskatchewan, Canada, Canada without Saskatchewan, the Canadian Prairies, Australia, Russia, Turkey, and the U.S., durum wheat grown in Saskatchewan, Canada, the Canadian Prairies, Canada without Saskatchewan, France, Italy, and the U.S., and dried peas grown in Canada without Saskatchewan, Russia and Ukraine. These combinations were selected by the Government of Saskatchewan and the Global Institute for Food Security because they represent priority field crops (i.e., on the basis of value and volume) for comparison with international competitors (Table 2).

Table 1. Crop-region combinations included in this analysis. Yellow fill represents combinations included in part 1, green fill represents additional combinations included in part 2, while grey fill represents crop-region combinations excluded.

	Canola	Soy	Non-Durum Wheat	Lentils	Durum Wheat	Dried Peas
Canada (SK)						
Canada average						
Canada (Prairie average)						
Canada (without SK)						
Australia						
Brazil						
France						
Germany						
Italy						
Netherlands						
Russia						
Turkey						
Ukraine						
United States						

Table 2. Production estimates for each crop in the regions included in this analysis.

	Production (Tonnes)					
	Canola	Soy	Non-Durum wheat	Lentils	Durum wheat	Dry field peas
Saskatchewan	10,081,396[a]	/[b]	9,892,865[a]	2,016,609[a]	4,224,450[a]	1,849,541[a]
Canada	18,612,710[a]	/[b]	26,204,144[a]	2,267,208[a]	/[b]	3,615,727[a]
Australia	3,525,411[c]	/[b]	22,952,040[d]	592,414[c]	/[b]	/[b]
Brazil	/[b]	120,738,805[e]	/[b]	/[b]	/[b]	/[b]
France	4,084,971[e]	/[b]	33,968,936[f]	/[b]	1,506,474[g]	612,000[h]

Germany	3,561,540[e]	/[b]	21,728,720[f]	/[b]	/[b]	273,400[h]
Italy	/[b]	/[b]	/[b]	/[b]	4,077,012[g]	/[b]
Netherlands	6006[e]	/[b]	/[b]	/[b]	/[b]	/[b]
Russia	2,185,124[e]	/[b]	78,908,993[e]	160,178[e]	/[b]	2,773,456[e]
Turkey	/[b]	/[b]	/[b]	354,089[e]	/[b]	/[b]
Ukraine	2,744,370[e]	/[b]	27,265,550[e]	/[b]	/[b]	698,326[e]
U.S.	/[c]	114,540,544[e]	46,994,164[i]	290,328[e]	1,660,000[j]	720,005[i]

[a] 5 year average (2018-2022) as reported by Statistics Canada, table 32-10-0359-01 (Statistics Canada, 2022)
[b] Crop-region combination not included in this analysis
[c] 5 year average (2017-2021) as reported the Australian Bureau of Statistics (ABARES, 2022)
[d] 5 year average (2017-2021) production of all Australian wheat as reported the Australian Bureau of Statistics (ABARES, 2022), minus estimates of average annual Australian durum wheat production reported by Beres et al. (2020)
[e] 5 year average (2017-2021) as reported by FAOstat (2022)
[f] 5 year average (2018-2022) production of all German and French wheat as reported by Eurostat (European Commission, 2022a) minus production of German and French durum wheat in the same time period as reported by Eurostat (European Commission, 2022a)
[g] 5 year average (2018-2022) as reported by Eurostat (European Commission, 2022a)
[h] 5 year average (2018-2022) as reported by EU Oilseed and Protein Crops (European Commission, 2022b)
[i] 5 year average (2018-2022) as reported by USDA NASS (USDA-NASS, 2022)
[j] 5 year average (2018-2022) as reported by U.S. Wheat Associates (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.

A number of the countries of interest have developed country-specific, publicly available LCI databases, which provide varying degrees of sectoral coverage. Specifically, publicly available, country-specific LCI databases have been developed for Canada (Fritter, 2020), Australia (Grant, 2016), France (Koch and Salou, 2016), Brazil (Marçal de Souza et al., 2021) and the U.S. (USDA-National Agricultural Library, 2014). Databases are currently under development in both Italy (Notarnicola et al., 2022) and Turkey (TÜBİTAK, 2021), though are not yet available for use. Neither Russia, nor Ukraine have developed national LCI databases. While the Netherlands have developed a national LCI database (Nationale Milieu Database, 2022), it was not consulted during this project because it is not publicly available. In addition, two commercial LCI databases were also searched that are not specific to any single country. The first database, described by van Paassen et al. (2019a, 2019b) is a global database that includes datasets specific to the agri-food sector, while the second, described by Moreno Ruiz et al. (2021) is a global database that includes datasets relevant to both the agri-food, and many other industrial sectors. Each of these country-specific and commercial 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 these data sets represent the inventory of elementary flows associated with the entire 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. A topic search in the Web of Science Core Collection was performed using the following query: TS=((“life cycle assessment” OR “life cycle inventory” OR “life cycle analysis” OR “carbon footprint” OR LCA OR LCI) AND (canola OR rape* OR soy* OR wheat OR lentil* OR pulse* OR legum* OR durum OR pea*) AND (Canad* OR Saskatchewan OR Australia* OR Brazil* OR France OR French OR Ital* OR Netherlands OR Dutch OR Holland OR Russia* OR Turk* OR Ukrain* OR United States OR US OR USA OR America*)). 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. The * was included as a wildcard search operator representing any group of characters, including no characters. Inclusion of this operator therefore means, for example, the term “Canad*” would return results related to “Canada”, “Canadian”, etc.

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 Brazilian institute of Geography and Statistics and Ministério da Agricultura e Pecuária, the French National Institute of Statistics and Economic Studies and Ministry of Agriculture and Food, the Italian National Statistics Institute and Ministry of Agricultural Food, and Forestry Policies, the Dutch Ministry of Agriculture, Nature and Food Quality and Statistics Netherlands, the Turkish Statistical Institute and Ministry of Agriculture and Forestry, the Ministry of Agrarian Policy and Food of Ukraine and State Statistics Service of Ukraine, and the United States Census Bureau and Department of Agriculture. Attempts were made to also access websites for the Russian National Agricultural Agency, Federal State Statistics Service, and the Ministry of Agriculture of the Russian Federation. However, due to the ongoing Russian invasion of Ukraine, these websites were inaccessible. 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 international statistics databases were also searched for information, including FAOStat, EuroStat, and the EU Oilseeds and Protein Crops database. Finally, additional searches were performed to identify potential sources from relevant industry groups representing field crop farmers in each region and national and international sustainability consortia. 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, Pulse Australia, the Australian Grains and Legumes Nutrition Council, Aprosoja Brazil, Embrapa, L'Association générale des producteurs de blé, the French Federation of Oilseed and Protein Crop Producers, Terres Inovia, ADEME, the Italian Association of Millers and National Cerealist Association, the Association of Dutch Producers of Edible Oils and Fats, Fediol, the Istanbul Cereals, Pulses, Oilseed and Products Exporters' Association, the Seed Association of Ukraine and the Ukrainian Grain Association, the National Association of Wheat Growers and National Wheat Foundation, the American Pulse Association, American Soybean Association, the Field to Market Initiative, the United Soybean Board, the U.S. Dry Pea and Lentil Council, USA Pulse, the U.S. Pea and Lentil Trade Association, the International Soybean Growers Alliance, the Roundtable for Responsible Soy Association, and the Global Pulse Confederation.

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, modeling 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 potential sources be extracted and remodeled on a methodologically consistent basis to enable rigorous comparisons between results during model development.

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 the 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
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-	Data on related processes on laboratory scale or from different technology	5

Reliability	Completeness	Temporal correlation	Geographical correlation	Further technological correlation	Quality Score
			Europe instead of Russia)		

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

Quality 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, which may be high for many of the field crops included (Takashima et al., 2013; Taylor et al., 2013; Torriani et al., 2007; Fischer et al., 2022; Hoffmann et al., 2018; Liu et al., 2019; Fuhrer and Chervet, 2015). This is a particularly salient issue for Canadian yield data, as 2021 yields were drastically reduced due to widespread drought across the Canadian Prairie Provinces (Agriculture and Agri-Food Canada, 2021). Similar reductions in yield were also experienced for a number of crops around the world in 2021 (USDA, 2022). 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	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 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 many countries 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	Quality 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	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 and the Prairie Provinces, 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 Italy. 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 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 were made regarding which of the identified sources were of the highest quality for use in model development. This choice was done through the 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 – 7). 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 can 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_i 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 modeling 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 modeling. For this study, IPCC Tier 2 methods for modeling direct and indirect N_2O emissions, IPCC Tier 1 methods for modeling 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 the United Nations Food and Agriculture Organisation Livestock Environmental Assessment and Performance (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 Tier 1 and 2 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, farmers, traders, retailers, and other interested parties. 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, dry field peas, lentils, soy, and durum wheat grain) at farm gate. This functional unit was chosen for consistency with part 1 of this project.

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 include 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 as representative of actual contemporary production conditions in Saskatchewan, Canada, Australia, France, the United States, the Netherlands, Russia, Ukraine, Brazil, and Italy 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

Of the 27 crop-country combinations proposed for inclusion in part 2 of this analysis, data were available in sufficient quality to allow for inclusion of 24 of them. Specifically, sufficiently high-quality data were not available for lentils produced in Russia and Turkey, or durum wheat produced in France. There were essentially no reliable data sources found representing Russian lentil production, and those sources that were identified often did not report specific values that could be used as LCI data. Previously, Bamber et al. (unpublished) performed a comparison of Canadian and Russian lentils for Pulse Canada using the information provided by Lee (2022), and assuming that application rates of inputs were the same as in Canada on a per hectare basis. However, this is an assumption with large implications and very little supporting evidence. Similar issues of very little data availability were encountered for Turkish lentil production. French durum wheat production was excluded due to the fact that the majority of available data reside in Agribalyse, a French national LCI database, which often does not indicate the source of many of the included data points (seed, manure, fertilizers, irrigation, and field activities), and discrepancies and inconsistencies were found in the LCI data that raised concerns around the quality of the values presented. Taking into account these issues, these three crop-region combinations were excluded from the analysis.

Across all remaining crop-country combinations, 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 and all emission sources 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

Irrigation was excluded from the Ukrainian canola production model. FAOStat (2022b) provides information on total crop land and total crop land that is actually irrigated in Ukraine on a non crop-specific basis, indicating that only ~1% of all crop land in Ukraine is irrigated. Additionally, van Paassen et al. (2019) does not include inputs of irrigation water or associated energy for Ukrainian canola. In the absence of crop-specific information to the contrary, it is therefore assumed that any irrigation water and associated energy use in Ukrainian canola production systems is negligible.

The Ukrainian State Statistics service provides a list of pesticide active ingredients applied to Ukrainian canola in 2021. This list includes 236 different pesticide active ingredients, the vast majority of which are applied in small quantities (i.e., accounting for <1% of all pesticides applied to Ukrainian canola). All pesticide active ingredients representing <1% of all pesticides applied to Ukrainian canola were excluded from the Ukrainian canola production model, leaving 21 active ingredients for inclusion, cumulatively representing approximately 77% of all pesticides applied to Ukrainian canola in 2021.

2.5.4.2 Soy

No specific exclusions were made during modeling of soy production systems.

2.5.4.3 Non-durum wheat

The Ukrainian State Statistics service provides a list of pesticide active ingredients applied to Ukrainian non-durum wheat in 2021. This list includes 257 different pesticide active ingredients, the vast majority of which are applied in small quantities (i.e., accounting for <1% of all pesticides applied to Ukrainian non-durum wheat). All pesticide active ingredients representing <1% of all pesticides applied to Ukrainian non-durum wheat were excluded from the Ukrainian non-durum wheat production model. This left 24 active ingredients for inclusion, cumulatively representing approximately 82% of all pesticides applied to Ukrainian non-durum wheat in 2021.

2.5.4.4 Lentils

No specific exclusions were made during modeling of lentil production systems.

2.5.4.5 Durum wheat

No specific exclusions were made during modeling of durum wheat production systems.

2.5.4.6 Peas

The Ukrainian State Statistics Service provides a list of 249 different pesticide active ingredients applied to other cereal and leguminous crops (used to represent peas) in 2021, the majority of which represent <1% of the cumulative pesticides applied to these crops. All pesticide active ingredients representing <1% of all pesticides applied to Ukrainian peas were excluded from the Ukrainian pea production model. This left 28 active ingredients for inclusion, cumulatively representing approximately 81% of all pesticides applied to Ukrainian peas in 2021.

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), and in line with methodologies applied in part 1 of this analysis.

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 leguminous crop 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. This applies to both non-durum and durum wheat. Therefore, wheat grain and straw are considered to be co-products of non-durum and durum 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, 2006).

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. In part 1 of this analysis, significant difficulty was encountered in finding high-quality, crop specific information detailing amounts of wheat residues baled and removed from fields, with available literature estimates ranging from 15% - 85% of residues removed from an unknown proportion of total production. Given these difficulties, a standardized wheat straw removal rate was applied to all countries representing 8.3% of non-durum wheat residues removed from field. The limitations of this assumption were discussed in detail in part 1.

Similarly, very little information could be found regarding residue removal rates for durum wheat in any of the countries included. The only durum wheat specific residue removal rate found was in Chinnici et al. (2015), who estimate that 90% of durum wheat straw produced in Sicily is left on fields. Given the lack of data on durum specific residue removal rates for other countries included, and the similarity in estimated percent removed between Chinnici et al. (2015) and the assumed removal rate used for non-durum wheat straw in part 1, it has also been assumed that 8.3% of durum wheat residues are removed from fields in each of the countries included.

Following the identification of the amounts of straw co-produced with grain, it was necessary to choose an allocation method for partitioning impacts between co-products. In part 1 of this analysis, mass and energy-based allocation methods were examined for their appropriateness to use for allocation of impacts between wheat grain and straw. In doing so, it was found that, for wheat grain and straw, allocation factors calculated based on mass and energy content of co-products vary from one another negligibly. Mass allocation was therefore used here, in line with methodological choices made in part 1 of this analysis. The allocation factors used in part 2 are presented in Table 8. As in part 1, this choice was not subject to a sensitivity analysis due to the minimal expected differences in estimated GHG emissions when using a mass- or energy-based allocation approach.

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.

	Non-durum wheat grain allocation factor	Non-durum wheat straw allocation factor	Durum wheat grain allocation factor	Durum wheat straw allocation factor
Saskatchewan	0.95	0.05	0.95	0.05
Canada	0.95	0.05	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	0.95	0.05
Russia	0.95	0.05	-	-
Ukraine	0.95	0.05	-	-
Italy	-	-	0.95	0.05

2.5.5.3 Nitrogen credit

Peas, lentils and soybeans 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, 19 sources were identified for canola, 56 for soy, 11 for non-durum wheat, 27 for lentils, 26 for durum, and 7 for peas, in addition to the previous sources from part 1 (48 sources were accessed for canola, 55 for non-durum wheat, and 26 for dry 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 include the majority of all foreground data required for modeling the crop-region combinations included in this analysis. The following sections present 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 six crops, the data available therein, and their associated data quality scores were provided as separate Excel files. Preceding these sections in the report, 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 that were bypassed through the animals' digestive systems. 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, with the exception of U.S. soy production systems, which also included inputs of cattle manure. In part 1 of this analysis, pig and poultry manure nutrient contents were identified for North America, Europe, and Australia (Table 9). Where relevant, these nutrient contents were also applied here in part 2 – for example, European manure nutrient contents were applied to manure inputs in Dutch, Russian, and Ukrainian production systems, and data quality scores were assigned accordingly.

The Ukrainian State Statistics Service listed two types of manure applied to crops: poultry, and agricultural animal manure. In line with other countries included in the analysis, the unspecified agricultural animal manure was assumed to be pig manure. This assumption is justified in light of the relative production scale of the pork industry in Ukraine, which produced more than twice as much meat than the Ukrainian cattle industry in 2021, while the Ukrainian dairy industry has experienced sharp declines in size in recent years (FAOstat, 2022a).

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[1]	3.71[2]	0.598[3]	3.71[2]	1.9[5]	3[5]
P	0.126[1]	1.465[2]	0.293[3]	1.465[2]	2.5[5]	2.15[5]
K	0.168[1]	1.795[2]	0.226[4]	1.795[2]	0.7[5]	1.3[5]

[1] Values taken from Government of Saskatchewan (2022), assuming a density of 1000 kg/m^3, within one standard deviation of the average reported by Moral and Paredes (2005)
[2] Values taken from Azeez and Van Averbeke (2010)
[3] Values taken from Kuhn et al. (2018), assuming a density of 1000 kg/m^3, within one standard deviation of the average reported by Moral and Paredes (2005)
[4] Value taken from Moral and Paredes (2005)
[5] Values taken from the Australian Grains Research and Development Corporation (Griffiths, 2014)

The inclusion of Brazilian soy in part 2 of this analysis necessitated the identification of pig and poultry manure nutrient contents representative of Brazil. A number of different sources were available from which Brazilian manure nutrient contents could be derived. Five different sources were identified as potential sources of poultry manure nutrient contents. Poultry manure nutrient contents showed relatively little variability across these different sources. N contents ranged from 2.2% - 5%, P contents ranged from 0.93% to 5.72%, and K contents ranged from 1.83% to 5.4%. Importantly, however, some of these sources gave nutrient contents of poultry litter rather than poultry manure. Poultry litter is generally composed of manure, as well as feathers and other substrates provided by farmers to allow for hens to perform a more complete suite of highly motivated behaviours. Poultry litter may therefore differ significantly in composition across different sources, as many different substrates may be provided to hens including sand, wood chips, and others (Campbell et al., 2017). Upon assessment of the data quality of different possible sources, an average value from Mendes et al. (2022) was used. This value represents poultry manure directly rather than poultry litter, and was the only source that provided a national average nutrient composition, rather than being based on production in a specific Brazilian state. Mendes et al. (2022) derived their estimates of poultry manure nutrient composition through a literature review identifying potential agricultural substrates for use in anaerobic co-digestion systems for the purposes of energy generation. Overall, estimated N contents of Brazilian poultry manure are greater, but comparable to those used for any country in part 1, while P and K contents are much higher than those used in part 1.

In contrast, a much greater degree of variability was observed in estimated nutrient contents of Brazilian pig manure. N contents ranged from 0.04% to 11.2%, P contents ranged from 0.0048% to 8.94%, and K estimates ranged from 0.0028% to 6.23%. Upon assessment of the data quality of different possible sources, values were taken from Mendes et al. (2022). This was one of only two sources to provide a national average value rather than a value derived from field trials in specific Brazilian states. N contents of Brazilian pig manure as estimated by Mendes et al. (2022) are comparable to those used for modeling Australian crops in part 1, while P estimates represent a midpoint between numbers used for modeling North American and European, and Australian crops. Estimated Brazilian pig manure K contents are slightly higher than those used for modeling Australian crops. The assumed percent nutrient contents used for modeling of pig and poultry manure inputs to Brazilian soy are reported in Table 10.

Table 10. Assumed percent nutrient contents of Brazilian pig and poultry manure at time of application to field.

	Brazil	
	Pig	Poultry
N	2.3[1]	4.19[1]
P	0.68[1]	3.50[1]
K	1.06[1]	3.93[1]

[1] Average value from Mendes et al. (2022)

For modeling of manure inputs to U.S. soy systems, Lim et al. (2023) indicate that only a small percentage of soybeans (2.3%) planted in the U.S. were treated with manure in the 2020 growing season. This number has decreased from 2012, in which the United States Department of Agriculture (USDA) Economic Research Service (ERS) Agricultural Resource Management Survey (ARMS) survey indicated that 3.2% of planted soybean area was treated with manure (USDA, 2019). When soybeans are treated with manure, Lim et al. (2023) report that the majority of manure applied to U.S. soy comes from beef and poultry systems, with smaller proportions coming from dairy and swine systems. The authors further note that cattle manure from beef and dairy operations may be stored in solid or liquid form, but do not indicate the proportions with which different storage systems are employed in the U.S. Manure nutrient contents for cattle manure used in the U.S. were therefore taken from the University of Minnesota (Wilson, 2021), who collected data on average manure nutrient contents in both liquid and solid beef and dairy cattle manure at three commercial labs from 2012-2018. Since the exact distribution of cattle manure applied to U.S. soybeans is unknown (i.e., proportions coming from solid and liquid storage systems from beef and dairy farms), an average value of these four options is used (Table 11). Manure nutrient contents identified in part 1 for North America were used for modeling of pig and poultry manure applied to American soybeans. Amounts of manure applied were calculated using data from the USDA ERS ARMS for the year 2012 (USDA, 2019), the most recent year for which numerical manure application data is available, and distribution of manure types taken from van Paassen et al. (2019).

Table 11. Assumed percent nutrient contents of American cattle at time of application to field.

	US.
	Cattle
N	0.580[1]
P	0.144[1]
K	0.451[1]

[1] Average value of beef and dairy manure stored in solid and liquid form, as taken from Wilson (2021)

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, poultry, and cattle 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. No manure nutrient content data quality scores improved between parts 1 and 2. Since data quality scores across North American, European, and Australian manure inputs were the same, these scores have been condensed into a summary table (Table 12), with in-depth explanation of these scores available in part 1. Table 13 therefore provides the data quality scores given the Brazilian manure inputs, as these represent the only new data quality scores assigned to manure inputs in part 2.

Table 12. Data quality scores for manure inputs to North American, European, and 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

For Brazilian crop systems, pig and poultry manure nutrient contents were taken from Mendes et al. (2022). A score of 2 was given for reliability as nutrient contents were taken from a bibliographic survey of potential biomass sources for use in energy generation via anaerobic digestion. A score of 3 was assigned to completeness, as it is unclear what percentage of potential pig and poultry manure available is represented by the bibliographic analysis performed. The temporal scope of the bibliographic analysis performed was not reported; however, the source was published in 2022, so the data are assumed to be representative of 5 years prior to publication data, resulting in a temporal correlation score of 3. Finally, scores of 1 were assigned to both geographic and technological correlation, as the source presents estimated national average nutrient contents of Brazilian pig and poultry manure.

Table 13. Data quality scores for manure inputs to Brazilian crop systems.

	Reliability	Completeness	Temporal correlation	Geographic correlation	Technological correlation
Manure modeled as N fertilizer	2	3	3	1	1
Manure modeled as P fertilizer	2	3	3	1	1
Manure modeled as K fertilizer	2	3	3	1	1

2.5.6.2 Canola data sources

Generally, data characterizing canola production systems for each crop-region combination were of relatively high quality, and similar quality across the Netherlands, Russia and Ukraine. Tables 14-16 list the data sources for each category of LCI data, and the quality of those data. Five year average (2017-2021) yields were calculated from FAOstat (2022) for Russia and Ukraine, and from the EU Protein and Oilseeds database (European Commission, 2022b) for the Netherlands (2018-2022 average). These year ranges were chosen to be the most temporally up-to-date, and sufficiently long to diminish the yield impacts of the anomalous 2021 year across all countries (Agriculture and Agri-Food Canada, 2021; USDA, 2022b). Data for seed and lime inputs came from van Paassen et al. (2019a) for each country. The data on fertilizer inputs came from a combination of van Paassen et al. (2019a), and FAOStat, and manure inputs were from van Paassen, and the State Statistics Service of Ukraine.

Herbicide, insecticide and fungicide inputs amounts came from van Paassen for the Netherlands and Russia. Types of herbicides, insecticides and fungicides applied in the Netherlands were taken from Schreuder et al. (2009), the most recent version of a cost of production survey for Dutch arable farming and field vegetable cultivation that is publicly available. Information on amounts and types of pesticides applied in Ukraine were taken from the Ukrainian State Statistics Service. Information on the types of pesticides applied to Russian canola could not be found. In the absence of this information, the distribution is assumed to be the same as that used in Ukraine, applied to the amounts given by van Paassen et al. (2019). Energy use and transportation data were sourced from van Paassen for all countries, except for Dutch post-harvest energy use which came from Dekker et al. (2013). However, these data have generally low data quality because they are fairly old, and often come from expert opinion or the sources are not indicated. Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices, and soil organic carbon (SOC) change data were sourced from each country's NIR, in accordance with IPCC Tier 2 methodology (however these estimates are not crop specific).

For energy use associated with canola irrigation in the Netherlands, van Paassen et al. (2019) do not include energy inputs for irrigation systems – rather, the energy inputs included in the data set specify that they are for all field activities, except for irrigation. No crop specific information is available regarding irrigation practices in the Netherlands; however, the Eurostat database (European Commission, 2022a) includes information regarding total hectares of irrigated utilized agriculture area in the Netherlands in 2016, indicating that 201,360 hectares of agricultural land were irrigated. When compared to data available from FAOstat indicating total area of agricultural land in the Netherlands in 2016, it is estimated that approximately 11.1% of all agricultural land in the Netherlands was irrigated. Given the non-trivial percentage of land that was irrigated in 2016, it seems unlikely that there are no irrigation related inputs to Dutch canola production systems, so an alternative source for irrigation energy use had to be found. Narain-Ford et al. (2021) estimate that, on average, total sprinkler irrigation water demand in the Netherlands is 144 million m^3, based on a 2016 source. This average sprinkler irrigation water demand was divided by the total irrigated utilized agricultural land in 2016 to get an average rate of water application per irrigated hectare, which was subsequently used to calculate an average rate of irrigation water application per hectare of Dutch agricultural land. This irrigation rate was used to estimate irrigation energy use using background data provided by ecoinvent (Gmunder, 2019).

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

Data point	Source used	Reliability	Completeness	Temporal correlation	Geographical correlation	Technological correlation
Yield	EU Oilseed and Protein Crop database	1	1	1	1	1
Seed	NL - van Paassen et al. 2019	1	3	3	1	1
Lime inputs	NL - van Paassen et al. 2019	2	3	3	1	1
Manure nutrients	Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and Paredes (2005)	4	4	5	5	4
NPKS fertilizers	NL - van Paassen et al. 2019	1	3	2	1	1
Total active ingredient inputs of herbicides, fungicides, insecticides	NL - van Paassen et al. 2019	1	3	2	1	1
Types and distribution of herbicides, fungicides, insecticides	Schreuder et al., (2009)	1	3	4	1	1
Irrigation energy use	Combination of Narain-Ford et al., (2021), FAOStat, and Euorstat	3	3	3	1	3

Field activities energy use	NL - van Paassen et al. 2019	2	3	2	1	1
Transportation	NL - van Paassen et al. 2019	2	3	4	1	1
Post harvest	NL - Dekker et al. 2013	4	4	4	2	1
Field level emissions of N_2O	IPCC Tier 2, with inputs from van Paassen et al. 2019	1	3	2	1	1
CO_2 emissions from lime and urea	IPCC Tier 1, with inputs from van Paassen et al. 2019	2	3	2	2	1
Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4

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

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	RU - FAOStat	1	1	1	1	1
Seed	RU - van Paassen et al. 2019	1	3	3	1	1
Lime inputs	RU - van Paassen et al. 2019	2	3	3	1	1
Manure nutrients	Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and	4	4	5	5	4

	Paredes (2005)					
NPKS fertilizers	RU - van Paassen et al. 2019	1	3	2	3	1
Herbicide, pesticide and fungicide inputs	van Paassen et al. 2019 for amounts, Ukrainian State Statistics Service for types	1	3	2	3	3
Irrigation energy use	RU - van Paassen et al. 2019	2	3	2	1	1
Field activities energy use	RU - van Paassen et al. 2019	2	3	2	1	1
Transportation	RU - van Paassen et al. 2019	2	3	4	1	1
Post harvest	RU - van Paassen et al. 2019	2	3	5	2	1
Field level emissions of N_2O	IPCC Tier 2 with inputs from van Paassen et al. 2019	1	3	2	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from van Paassen et al. 2019	2	3	2	2	1

Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4

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

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	UA - FAOStat	1	1	1	1	1
Seed	UA - van Paassen et al. 2019	1	3	3	1	1
Lime inputs	UA - van Paassen et al. 2019	2	3	3	1	1
Manure nutrients	Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and Paredes (2005)	4	4	5	5	4
NPKS fertilizers	UA - van Paassen et al. 2019	1	3	2	1	3
Herbicide, insecticide, and fungicide input amounts and types	UA - FAOStat	1	1	1	1	3
Field activities energy use	UA - van Paassen et al. 2019	2	3	2	1	1
Transportation	UA - van Paassen	2	3	4	1	1

	et al. 2019					
Post harvest	UA - van Paassen et al. 2019	2	3	5	2	1
Field level emissions of N_2O	IPCC Tier 2 with inputs from van Paassen et al. 2019	1	3	2	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from van Paassen et al. 2019	2	3	2	2	1
Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4

2.5.6.3 Soy data sources

Yield data for U.S. soy were taken from the USDA National Agricultural Statistics Service (NASS) database (USDA-NASS, 2022) (Table 17). Seed input data came from Beal et al. (2021), a peer-reviewed literature source that originally sourced their data from a combination of USDA sources and the Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) model. Lime inputs came from Knoope et al. (2018), originally sourced from national statistics. No sources were identified that directly provided LCI data for inoculant application, however Santos et al., (2019) indicated that only 15% of U.S. soy was inoculated. This was used in combination with the label rate for a common inoculant (AgTiv, 2023), and the methods for modeling inoculant used by Bamber et al. (2022b), originally taken from Alberta Agriculture and Forestry (2018). Data on the amount of manure applied to U.S. soybeans came from the USDA ERS ARMS Survey, with the breakdown of manure types from van Paassen et al. (2019). These data are rather old (from 2012, or not indicated), and do not indicate the percent of supply covered. Data on fertilizer types and amounts came from van Paassen, the USDA NASS report, and He et al. (2019). Van Paassen et al. (2019) do not indicate how old their fertilizer data are. For pesticides, the amounts of total inputs of active ingredients were sourced from the NASS report, with the breakdown of types from van Paassen et al. (2019). The van Paassen data have low quality since they did not report the source or the age of these data. Energy use and transportation data came from Beal et al. (2021), van Paassen et al. (2019), and Benavides et al. (2020). Similarly, the data sourced from van Paassen have low quality since they did not report the source or age of the data. Irrigation data were calculated based on data from Lopez et al. (2022) that indicated that 12% of soybean acres in the U.S. are irrigated, as well as the estimate from Rittler and Bykova (2022) for total water needed to grow soybeans (from all sources, including irrigation and rainfall). Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices, and SOC change data were sourced from the U.S. NIR, in accordance with IPCC Tier 2 methodology (however these estimates are not crop specific). The N credit from biological nitrogen fixation (BNF) was calculated using the equations in Barker (2007), based on research from Western Canada.

Table 17. Data sources used for modeling U.S. soy production, and their associated pedigree matrix scores.

Data point	Source used	Reliability	Completeness	Temporal correlation	Geographical correlation	Technological correlation
Yield	USDA NASS database	1	1	1	1	1
Seed	US - Beal et al. 2021	2	3	2	1	1
Lime inputs	US - Knoope et al. 2018	1	2	4	1	1
Inoculant	Santos et al. (2019) and AgTiv label rate	4	4	3	1	4
Manure amounts	US - USDA ERS ARMS Survey	1	3	3	1	1
Manure types	US - Van Paassen et al. 2019	1	3	5	1	1
Manure nutrient contents	Government of Saskatchewan (2022) and Azeez and Van Averbeke (2010)	4	4	5	5	4
NPKS fertilizer amounts	US - NASS report	1	2	1	1	1
NPKS fertilizer types	US - Van Paassen et al. 2019	1	3	5	1	1
Herbicide, insecticide, and fungicide input amounts	NASS Report	1	2	1	1	1
Herbicide, insecticide,	Van Paassen et al. 2019	5	3	5	1	1

and fungicide input types						
Irrigation energy	Lopez et al. (2022) and Rittler and Bykova (2022)	4	4	3	4	1
Field activities energy use	US - Beal et al. 2021	2	3	2	1	1
Transportation	van Paassen et al. 2019	5	3	5	1	1
Post harvest	US – Hoffman et al. 2019	4	4	5	1	1
Field level emissions of N_2O	IPCC Tier 2 with inputs from NASS report	1	3	5	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from NASS report and van Paassen et al. 2019	2	3	5	2	1
Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4
N credit	Barker et al. 2007	4	4	5	1	4

For Brazil, the majority of the inventory data were sourced from van Paassen et al. (2019) (Table 18). Some of these data points (transportation and post-harvest energy use) had somewhat low data quality due to not reporting the age of the data. Other data sources included FAOStat for yield, and Nemecek (2015) for lime, other fertilizer inputs (micronutrients other than NPKS), and pesticide types. No sources were identified that directly provided LCI data for inoculant application, however Santos et al., (2019) indicated that the majority of Brazilian soy was inoculated. This was used in combination with the label rate for a common inoculant (AgTiv, 2023), and the methods for modeling inoculant used by Bamber et al. (2022b), originally taken from Alberta Agriculture and Forestry (2018). Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices. SOC change data were sourced from van Paassen, based on their Direct Land Use Change Tool. The N credit from BNF was calculated using the equations in Barker (2007), based on research from Western Canada.

Table 18. Data sources used for modeling Brazilian soy production, and their associated pedigree matrix scores.

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**

Yield	BR - FAOStat	1	1	1	1	1
Seed	BR - Van Paassen et al. 2019	1	3	3	1	1
Inoculant	Santos et al. (2019) and AgTiv label rate	4	4	3	1	4
Lime inputs	BR - Nemecek 2015	1	3	3	1	1
Manure amounts and types	BR - Nemecek 2015	1	3	2	1	1
Manure nutrient contents	Mendes et al. (2022)	2	3	3	1	1
NPKS fertilizers	BR - Van Paassen et al. 2019	1	3	2	1	1
Herbicide, insecticide, and fungicide input amounts and types	BR - Nemecek 2015	1	3	3	1	1
Irrigation energy	BR - Van Paassen et al. 2019	2	3	2	1	1
Field activities energy use	BR - Van Paassen et al. 2019	2	3	2	1	1
Transportation	BR - Van Paassen et al. 2019	2	3	5	1	1
Post harvest	BR - Nemecek 2015	2	3	5	2	1

Field level emissions of N_2O	IPCC Tier 2 with inputs from van Paassen et al. 2019	1	3	2	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from van Paassen et al. 2019	2	3	2	2	1
Soil carbon changes	van Paassen Direct Land Use Change Tool	1	3	2	1	1
N credit	Barker et al. 2007	4	4	5	1	4

2.5.6.4 Non-durum wheat data sources

For Russian wheat production, the majority of data came from van Paassen et al. (2019) (Table 19). Most of these data points have good data quality, except for the temporal correlation of transportation and post-harvest energy use, since they did not indicate the age of these data. For yield, the data were sourced from FAOStat. The USDA raised concerns over the yields reported by Russia (as included in FAOStat), since they were considerably higher than their satellite images suggested. However, the data for Russian wheat yields reported by USDA based on their satellite images was, in fact, slightly higher than the FAO data, and only by a very small amount. Therefore, the FAO data were considered to be representative. Canadian proxy data were used for the types of pesticides applied, in combination with the country-specific values for total amounts applied from van Paassen et al. (2019). Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices, and SOC change data were sourced from the Russian NIR, in accordance with IPCC Tier 2 methodology (however these estimates are not crop specific).

Table 19. Data sources used for modeling Russian wheat production, and their associated pedigree matrix scores.

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	RU – FAOStat or RU - USDA WAP	1	1	1	1	1

Straw	Assumed same removal rate as part 1	2	4	5	3	2
Seed	RU - van Paassen et al. 2019	1	3	3	1	1
Lime inputs	RU - van Paassen et al. 2019	2	3	3	1	1
Manure amounts and types	RU - van Paassen et al. 2019	1	3	2	1	1
Manure nutrient contents	Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and Paredes (2005)	4	4	5	5	4
NPK fertilizers	RU - van Paassen et al. 2019	1	3	2	1	1
Herbicide, insecticide, and fungicide input amounts	RU - van Paassen et al. 2019	1	3	2	1	1
Herbicide, insecticide, and fungicide input types	CRSC report ((S&T)2 Consultants Inc., 2022b), fungicide and insecticide types from Nemecek	1	3	2	4	1
Irrigation energy	RU - van Paassen et al. 2019	2	3	2	1	1

Field activities energy use	RU - van Paassen et al. 2019	2	3	2	1	1
Transportation	RU - van Paassen et al. 2019	2	3	5	1	1
Post harvest	RU - van Paassen et al. 2019	2	3	5	2	1
Field level emissions of N_2O	IPCC Tier 2 with inputs from van Paassen et al. 2019	1	3	2	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from van Paassen et al. 2019	2	3	2	2	1
Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4

For Ukrainian wheat LCI data, the Ukrainian State Statistics Service data were used for manure amounts and types, and pesticide amounts (Table 20). The remainder of the data, including fertilizer data, were taken from van Paassen. The temporal data quality was low for transportation and post-harvest energy use since they did not report the age of the data. Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices, and SOC change data were sourced from the Ukrainian NIR, in accordance with IPCC Tier 2 methodology (however these estimates are not crop specific). As with canola, Ukrainian manure inputs to wheat were poultry, and assumed to be pig.

Table 20. Data sources used for modeling Ukrainian wheat production, and their associated pedigree matrix scores.

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	UA - FAOStat	1	1	1	1	1
Straw	Assumed same removal rate as part 1	2	4	5	3	2
Seed	UA - van Paassen et al. 2019	1	3	3	1	1

Lime inputs	UA - van Paassen et al. 2019	2	3	3	1	1
Manure amounts and types	UA - State Stats Service	1	3	1	1	1
Manure nutrient contents	Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and Paredes (2005)	4	4	5	5	4
NPK fertilizer types and amounts	UA - van Paassen et al. 2019	1	3	2	1	1
Herbicide, insecticide, and fungicide input amounts	UA - State Stats Service	1	3	1	1	1
Irrigation energy	UA - van Paassen et al. 2019	2	3	2	1	1
Field activities energy use	UA - van Paassen et al. 2019	2	3	2	1	1
Transportation	UA - van Paassen et al. 2019	2	3	5	1	1
Post harvest	UA - van Paassen et al. 2019	2	3	5	2	1
Field level emissions of N_2O	IPCC Tier 2 with inputs	1	3	1	1	1

	from State Stats Service					
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from State Stats Service and van Paassen et al. 2019	2	3	1	2	1
Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4

2.5.6.5 Lentil data sources

The majority of Saskatchewan and Canadian average lentil production data came from the Pulse Canada report from 2020 (Bamber et al., 2022), that was based on survey responses from ~300 Canadian lentil farmers (Tables 21-22). All data from this source were of high quality other than the inoculant data since these were based on expert opinion rather than the farmer surveys. Updated yield data were sourced from StatsCan. Irrigation was excluded from the Bamber data since it is not a common practice, but a small amount is included in the CRSC report ((S&T)2 Consultants Inc., 2022a), therefore the CRSC irrigation data were used. However, these data were from a small number of experimental sites therefore they have low data quality. Post-harvest (other than drying) data were also supplemented from CRSC data, which also had low data quality since they were assumed values based on expert opinion. Canadian transportation data came from van Paassen et al. (2019), which are based on modelled values. Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices (with the N_2O values reported in the CRSC report), and SOC change data were sourced from the CRSC report (in line with Canada's NIR), in accordance with IPCC Tier 2 methodology (however these estimates are not crop specific). The N credit from BNF was calculated using the equations in Barker (2007), based on research from Western Canada.

Table 21. Data sources used for modeling Saskatchewan lentil production, and their associated pedigree matrix scores.

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	SK - StatsCan	1	1	1	1	1
Seed	SK - Bamber et al. 2020	1	3	1	1	1

Inoculant	SK - Bamber et al. 2020	4	4	1	1	2
NPKS and other fertilizer amounts and types	SK - Bamber et al. 2020	1	3	1	1	1
Herbicide, insecticide, and fungicide input amounts and types	SK - Bamber et al. 2020	1	3	1	1	1
Irrigation energy	SK - CRSC	4	4	4	3	1
Field activities energy use	SK - Bamber et al. 2020	1	3	1	1	1
Transportation	SK - Bamber et al. 2020	4	3	1	1	1
Post harvest drying	SK - Bamber et al. 2020	1	3	1	1	1
Other post-harvest	SK - CRSC	4	3	1	5	5
Field level emissions of N_2O	SK - CRSC	4	3	1	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from Bamber et al. 2020	2	3	1	2	1
Soil carbon changes	SK - CRSC	1	1	1	1	4
N credit	Barker et al. 2007	4	4	5	1	4

Table 22. Data sources used for modeling Canadian lentil production, and their associated pedigree matrix scores.

Data point	Source used	Reliability	Completeness	Temporal correlation	Geographical correlation	Technological correlation
Yield	CA - StatsCan	1	1	1	1	1
Seed	CA - Bamber et al. 2020	1	3	1	1	1
Inoculant	CA - Bamber et al. 2020	4	4	1	1	2
NPKS and other fertilizer amounts and types	CA - Bamber et al. 2020	1	3	1	1	1
Herbicide, insecticide, and fungicide input amounts and types	CA - Bamber et al. 2020	1	3	1	1	1
Irrigation energy	CA - CRSC	4	4	4	3	1
Field activities energy use	CA - Bamber et al. 2020	1	3	1	1	1
Transportation	CA - Bamber et al. 2020	2	3	4	1	1
Post harvest drying	CA - Bamber et al. 2020	1	3	1	1	1
Other post-harvest	CA - CRSC	4	3	1	5	5
Field level emissions of N_2O	CA - CRSC	4	3	1	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from	1	3	1	1	1

	Bamber et al. 2020					
Soil carbon changes	CA - CRSC	1	1	1	1	4
N credit	Barker et al. 2007	4	4	5	1	4

For Australian lentils, the only data gaps were for inoculant inputs, pesticide types, and post-harvest (Table 23). In the absence of country-specific data on inoculant use, the same inoculant application rate as Canadian lentils was assumed, as well as the same method of modeling, originally from Alberta Agriculture and Forestry (2018). The distribution of herbicide, insecticide, and fungicide types came from Bamber et al. (2020), in combination with the crop-country specific data from van Paassen et al. (2019) on the total amounts of pesticides. The Canadian post-harvest energy use data from Bamber et al. (2020) and the CRSC report ((S&T)2 Consultants Inc., 2022a) were used as a proxy. The majority of Australian lentil data came from van Paassen et al. (2019), which had high data quality other than the temporal correlation for transportation and post-harvest, since the age of the data was not reported. Yield data came from FAOStat. Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices, and SOC change data were sourced from Australia's NIR, in accordance with IPCC Tier 2 methodology (however these estimates are not crop specific). The N credit from BNF was calculated using the equations in Barker (2007), based on research from Western Canada.

Table 23. Data sources used for modeling Australian lentil production, and their associated pedigree matrix scores.

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	AU - FAOStat	1	1	1	1	1
Seed	AU - van Paassen et al. 2019	1	3	3	1	1
Inoculant	CA - Bamber et al. 2020	4	4	1	4	2
Lime inputs	AU - van Paassen et al. 2019	2	3	3	1	1
Manure amounts and types	AU - van Paassen et al. 2019	1	3	2	1	1

Manure nutrient contents	Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and Paredes (2005)	4	4	5	5	4
NPKS fertilizer amounts and types	AU - van Paassen et al. 2019	1	3	2	1	1
Herbicide, insecticide, and fungicide input amounts	AU - van Paassen et al. 2019	1	3	2	1	1
Herbicide, insecticide and fungicide input types	CA - Bamber et al. 2020	1	3	1	4	1
Irrigation energy	AU - van Paassen et al. 2019	2	3	2	1	1
Field activities energy use	AU - van Paassen et al. 2019	2	3	2	1	1
Transportation	AU - van Paassen et al. 2019	2	3	5	1	1
Post harvest drying	CA - Bamber et al. 2020	1	3	1	4	1
Other post-harvest	CA - CRSC	4	3	1	5	5
Field level emissions of N_2O	IPCC Tier 2 with inputs from van Paassen	1	3	2	1	1

	et al. 2019					
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from van Paassen et al. 2019	2	3	2	2	1
Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4
N credit	Barker et al. 2007	4	4	5	4	4

U.S. lentil production had some data gaps and data quality issues (Table 24). The seed, pesticide, and field activity data from Bandekar et al. (2022) were based on expert opinion. In addition, the field activity information provided only mentions the absence of tillage, and does not include any other types of field activities. There are also no sources of data for post-harvest energy use, or transportation of inputs other than fertilizers. The majority of these data gaps were filled using Canadian data. The Canadian data for field activity energy use (Bamber et al. 2020), minus the amounts for tillage, were used as a proxy, as well as the Canadian post-harvest data (Bamber et al. 2020 and CRSC report). The generic transportation distance of 50km used by van Paassen et al. (2019) for all field inputs other than manure was used in this case. The data from the International Fertilizer Association (IFA) on fertilizer nutrient inputs are representative of all pulses rather than just lentils. The FAOStat data on fertilizer types are also not crop specific, however this is acceptable since these data were only used to determine the distribution of fertilizer products applied, rather than the total amounts. Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices, and SOC change data were sourced from the American NIR, in accordance with IPCC Tier 2 methodology (however these estimates are not crop specific). The N credit from BNF was calculated using the equations in Barker (2007), based on research from Western Canada. In the absence of country-specific data on inoculant use, the same inoculant application rate as Canadian lentils was assumed, as well as the same method of modeling, originally from Alberta Agriculture and Forestry (2018). Despite the small number of data gaps this dataset was still included, along with explicit documentation of its data gaps and weaknesses.

Table 24. Data sources used for modeling U.S. lentil production, and their associated pedigree matrix scores.

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	US - FAOStat	1	1	1	1	1
Seed	US - Bandekar et al. 2022	4	4	3	2	2

Inoculant	CA - Bamber et al. 2020	4	4	1	1	2
NPKS fertilizer amounts	US Fertilizer – IFA – all pulses	1	1	2	1	2
NPKS fertilizer types	US – FAOStat – all crops	1	1	3	1	3
Herbicide, insecticide, and fungicide input amounts and types	US - Bandekar et al. 2022	4	4	3	2	2
Field activities (tillage)	US - Bandekar et al. 2022 – assumed no till, others not mentioned	4	2	3	1	1
Field activities (other)	CA - CRSC	4	3	1	5	5
Transportation (fertilizer	US - Bandekar et al. 2022	1	3	2	2	2
Transportation (other)	AU - van Paassen et al. 2019	2	3	5	1	1
Post harvest drying	CA - Bamber et al. 2020	1	3	1	3	1
Post harvest other	CA - CRSC	4	3	1	4	5
Field level emissions of N_2O	IPCC Tier 2 with inputs from IFA	1	1	2	1	2
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from IFA and FAOStat	2	1	3	2	3
Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4

N credit	Barker et al. 2007	4	4	5	2	4

2.5.6.6 Durum wheat data sources

The majority of the LCI data for Saskatchewan and Canadian durum wheat were sourced from the CRSC report ((S&T)2 Consultants Inc., 2022b) (Tables 25-26). Some data points (seed, fertilizers, pesticides) had fairly low quality when the data came from expert opinions or crop budget guides, or when the data were old or of unknown age. The CRSC report did not include types of fertilizers, therefore these were sourced from a peer-reviewed literature source from an experimental site in Saskatchewan (Liu et al., 2020). The transportation data presented in the CRSC report ((S&T)2 Consultants Inc., 2022b) was only representative of transportation of grain from the field to storage, therefore the transportation values from van Paassen et al. (2019) for inputs to Canadian non-durum wheat were used as a proxy. Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices (with the N_2O values reported in the CRSC report), and SOC change data were sourced from the CRSC report (in line with Canada's NIR), in accordance with IPCC Tier 2 methodology (however these estimates are not crop specific).

Table 25. Data sources used for modeling Saskatchewan durum wheat production, and their associated pedigree matrix scores.

Data point	Source used	Reliability	Completeness	Temporal correlation	Geographical correlation	Technological correlation
Yield	SK - StatsCan	1	1	1	1	1
Straw	Assumed same removal rate as non-durum	2	4	5	3	2
Seed	SK - CRSC	4	4	5	1	1
NPKS fertilizer types and amounts	SK - CRSC	4	4	1	1	1
Herbicide, insecticide, and fungicide input amounts	SK - CRSC	1	3	5	3	3
Herbicide, insecticide, and fungicide input types	SK - Liu et al. 2020	4	4	2	1	2
Field activities	SK - CRSC	4	3	5	1	3
Transportation	van Paassen et al. 2019	2	3	4	1	2

	(Canadian non-durum wheat)					
Post harvest	SK - CRSC	4	3	1	5	5
Field level emissions of N_2O	CRSC (IPCC Tier 2)	4	3	1	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from CRSC	4	4	1	2	3
Soil carbon changes	CRSC (IPCC Tier 2 from NIR)	1	1	1	1	4

Table 26. Data sources used for modeling Canadian durum wheat production, and their associated pedigree matrix scores.

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	CA - StatsCan	1	1	1	1	1
Straw	Assumed same removal rate as non-durum	2	4	5	3	2
Seed	Prairie - CRSC	4	3	5	3	1
NPKS fertilizer amounts	Prairie - CRSC	4	3	1	3	1
NPKS fertilizer types	Prairie - CRSC	1	1	1	1	3
Total pesticide amounts	Prairie - CRSC	1	3	5	3	3
Herbicide, insecticide, fungicide types	SK - Liu et al. 2020	4	4	2	1	2
Field activities	Prairie - CRSC	4	3	5	1	3

Transportation	van Paassen et al. 2019 (Canadian non-durum wheat)	2	3	4	1	2
Post harvest	Prairie - CRSC	4	3	1	5	5
Field level emissions of N_2O	Prairie – CRSC (IPCC Tier 2)	4	3	1	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from CRSC	4	3	1	3	3
Soil carbon changes	Prairie – CRSC (IPCC Tier 2 from NIR)	1	1	1	1	4

The data sources for Italian durum wheat production rely heavily on Palmieri et al. (2017) (for seed, fertilizers, irrigation, field activities, and transportation), which are not durum specific, but state that the majority of their data are for durum (Table 27). According to the Eurostat database (European Commission, 2022a), Italy produced approximately 4.22 million tonnes of durum wheat in 2021. Based on comparisons between reported values for Italian durum production according to Eurostat, and reported values for Italian common wheat and spelt production according to FAOStat, it is estimated that approximately 60% of all Italian wheat production is durum wheat. An exact estimate of this proportion, however, cannot be reached because the FAOStat database does not differentiate between common wheat and spelt in their reported values. However, according to Özbek and Baloch (2022), spelt is no longer produced in large quantities throughout Europe as it once was. If Italian Spelt production is assumed to be negligible, then durum is assumed to represent ~60% of all Italian wheat, and this percentage may be higher in the sample of farmers used in Palmieri et al. (2017), since they indicated that in the Foggia Province, 95% of cereal crop area is durum wheat.

Yield and pesticide input amounts came from Eurostat, which is representative. Herbicide types came from Palmieri et al. (2017). However, there were no sources for fungicide and insecticide types, therefore the breakdown of types came from Evolution des pratiques (Agreste, 2022), which were representative of French durum wheat. These were used in combination with the crop-country specific values for total amounts of pesticides from Eurostat. Post-harvest energy use data came from Bux et al. (2022), which is representative of a single farm. Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices, and SOC change data were sourced from the

Italian NIR, in accordance with IPCC Tier 2 methodology (however these estimates are not crop specific). Despite the potential data quality issues, this dataset was included.

Table 27. Data sources used for modeling Italian durum wheat production, and their associated pedigree matrix scores.

Data point	Source used	Reliability	Completeness	Temporal correlation	Geographical correlation	Technological correlation
Yield	IT - EuroStat	1	1	1	1	1
Straw	Assumed same removal rate as non-durum	2	4	5	3	2
Seed	IT - Palmieri et al. 2017	1	3	4	1	2
NPKS fertilizer amounts and types	IT - Palmieri et al. 2017	1	3	4	1	2
Herbicide, insecticide, and fungicide input amounts	IT - EuroStat	1	1	3	1	1
Fungicide types	Evolution des pratiques (FR durum wheat)	1	3	2	3	1
Insecticide types	Evolution des pratiques (FR durum wheat)	1	3	2	3	1
Herbicide types	IT - Palmieri et al. 2017	4	4	4	1	1
Irrigation water	IT - Palmieri	1	3	4	1	2

	et al. 2017					
Field activities	IT - Palmieri et al. 2017	1	3	4	1	2
Transportation	IT - Palmieri et al. 2017	1	3	4	1	2
Post harvest	IT- Bux et al. 2022 – single farm	4	4	2	1	1
Field level emissions of N_2O	IPCC Tier 2 with inputs from Palmieri et al. 2017	1	3	4	1	2
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from Palmieri et al. 2017	2	3	4	2	2
Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4

The majority of LCI data for U.S. durum wheat production came from van Paassen et al. (2019) (seed, lime, fertilizer, pesticides, irrigation and field activities). Most had low data quality since van Paassen et al. (2019) did not report the source or age of the data (Table 28). Yield and S fertilizer amounts came from the NASS report (2020), which had good data quality. Manure inputs came from the USDA ERS ARMS survey, which is from 2009, but otherwise of good quality. Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices, and SOC change data were sourced from the U.S. NIR, in accordance with IPCC Tier 2 methodology (however these estimates are not crop specific).

Table 28. Data sources used for modeling U.S. durum wheat production, and their associated pedigree matrix scores.

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**

Yield	US - NASS report 2020	1	1	1	1	1
Straw	Assumed same removal rate as non-durum	2	4	5	3	2
Seed	US - van Paassen et al. 2019	5	3	5	1	1
Lime	US - van Paassen et al. 2019	5	3	5	1	1
Manure amounts	US - USDA ERS ARMS Survey	1	3	4	1	1
Manure types	US - van Paassen et al. 2019	1	3	5	1	1
Manure nutrient contents	Government of Saskatchewan (2022) and Azeez and Van Averbeke (2010)	4	4	5	5	4
NPKS fertilizer amounts and types	US - van Paassen et al. 2019	1	3	5	1	1
Herbicide, insecticide, and fungicide input amounts and types	US - van Paassen et al. 2019	5	3	5	1	1
Irrigation energy	US - van Paassen et al. 2019	5	3	5	1	1
Field activities	US - van Paassen et al. 2019	5	3	5	1	1
Transportation	van Paassen et al. 2019	5	3	5	1	1

Post harvest	US - van Paassen et al. 2019	5	3	5	1	1
Field level emissions of N_2O	IPCC Tier 2 with inputs from van Paassen et al. 2019	1	3	5	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from van Paassen et al. 2019	2	3	5	2	1
Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4

2.5.6.7 Pea data sources

The data quality for Russian and Ukrainian pea LCI data was generally good (Tables 29-30). The majority of the data points came from van Paassen et al. (2019), which has high data quality other than the temporal correlation for transportation and post-harvest since they did not report the age of the data. Yield data came from FAOStat for both countries. Inoculant is a data gap, with Lee et al. (2022) reporting the approved substances for use in Russia, but no data on application rate for either country. In the absence of country-specific data on inoculant use, the same inoculant application rate as Canadian peas was assumed, as well as the same method of modeling, originally from Alberta Agriculture and Forestry (2018).

The distribution of pesticide types for Russia came from the Canadian data (Bamber et al. 2020), in combination with crop-country specific data on application amounts from van Paassen et al. (2019). The Ukrainian State Statistics Service does not provide information on pesticides applied to field peas specifically; rather, information is provided regarding pesticide active ingredients applied to cereal and leguminous crops excluding those applied to wheat, maize, and soybeans. This distribution of active ingredients was applied to the total amounts of herbicides, insecticides, and fungicides applied to Ukrainian peas as reported by van Paassen et al. (2019), since they provide pea specific information on amounts of pesticides applied. Post-harvest data from Canada (Bamber et al. 2020) were used as a proxy for both Russian and Ukrainian peas. Values for N_2O and CO_2 emissions from nutrient inputs were calculated using IPCC Tier 1 and 2 best practices, and SOC change data were sourced from each country's NIR, in accordance with IPCC Tier 2 methodology (however these estimates are not crop specific). The N credit from BNF was calculated using the equations in Barker (2007), based on research from Western Canada.

Table 29. Data sources used for modeling Russian pea production, and their associated pedigree matrix scores.

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**

Yield	RU - FAOStat	1	1	1	1	1
Seed	RU - van Paassen et al. 2019	1	3	3	1	1
Inoculant	Bamber et al. (2020a)	4	4	1	4	2
Lime	RU - van Paassen et al. 2019	2	3	3	1	1
Manure	RU - van Paassen et al. 2019	1	3	2	1	1
Manure nutrient contents	Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and Paredes (2005)	4	4	5	5	4
NPKS fertilizer amounts and types	RU - van Paassen et al. 2019	1	3	2	1	1
Herbicide, insecticide, and fungicide input amounts	RU - van Paassen et al. 2019	1	3	2	1	1
Herbicide, insecticide, and fungicide input types	Bamber et al. (2020a)	1	3	2	3	1
Irrigation energy	RU - van Paassen et al. 2019	2	3	2	1	1
Field activities	RU - van Paassen	2	3	2	1	1

	et al. 2019					
Transportation	RU - van Paassen et al. 2019	2	3	5	1	1
Post harvest	Bamber et al. (2020a)	1	3	1	4	1
Field level emissions of N_2O	IPCC Tier 2 with inputs from van Paassen et al. 2019	1	3	2	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from van Paassen et al. 2019	2	3	2	2	1
Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4
N credit	Barker et al. 2007	4	4	5	4	4

Table 30. Data sources used for modeling Ukrainian pea production, and their associated pedigree matrix scores.

Data point	**Source used**	**Reliability**	**Completeness**	**Temporal correlation**	**Geographical correlation**	**Technological correlation**
Yield	UA - FAOStat	1	1	1	1	1
Seed	UA - van Paassen et al. 2019	1	3	3	1	1
Inoculant	Bamber et al. (2020a)	4	4	1	4	2
Lime	UA - van Paassen	2	3	3	1	1

	et al. 2019					
Manure	UA - van Paassen et al. 2019	1	3	2	1	1
Manure nutrient contents	Azeez and Van Averbeke (2010), Kuhn et al. (2018), and Moral and Paredes (2005)	4	4	5	5	4
NPKS fertilizer amounts and types	UA - van Paassen et al. 2019	1	3	2	1	1
Herbicide, insecticide, and fungicide input amounts	UA - van Paassen et al. 2019	1	3	2	1	1
Herbicide, insecticide, and fungicide input types	UA - State Statistics	1	3	1	1	3
Irrigation energy	UA - van Paassen et al. 2019	2	3	2	1	1
Field activities	UA - van Paassen et al. 2019	2	3	2	1	1
Transportation	UA - van Paassen et al. 2019	2	3	5	1	1
Post harvest	Bamber et al. (2020a)	1	3	1	4	1

Field level emissions of N_2O	IPCC Tier 2 with inputs from van Paassen et al. 2019	1	3	2	1	1
CO_2 emissions from lime and urea	IPCC Tier 1 with inputs from van Paassen et al. 2019	2	3	2	2	1
Soil carbon changes	IPCC Tier 2 from NIR	1	1	1	1	4
N credit	Barker et al. 2007	4	4	5	4	4

2.5.7 Background data providers

A single background data source (ecoinvent database version v.3.8) was chosen to ensure methodological consistency for all background data. This database 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 databases for LCA practitioners. Table 31 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 32 lists all processes used in modifications listed in Table 31 (e.g., regional electricity providers). These tables were split in order to avoid redundancy, as electricity and other regional providers were changed across many of the background processes listed in Table 31. 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 31. 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 (durum and non-durum)	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
Soybean seed	soybean seed production, for sowing | soybean seed, for sowing | APOS, U - CH	electricity and soybean providers changed for each region
Lentil seed	lentil seed production, for sowing | lentil seed, for sowing | APOS, U - GLO	electricity and lentil 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 providers changed to regionalized ammonia providers (modifications described below)
Ammonia	ammonia production, steam reforming, liquid | ammonia, anhydrous, liquid | APOS, U – RER or RNA	electricity, natural gas, and tap water 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 provider changed to regionally modified ammonium nitrate process for each region (described above)

	ammonium nitrate mix | APOS, U – RNA or RER	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) urea provider changed to regionally modified urea process for each region (described above)
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 phosphate rock providers changed to modified regional phosphate rock processes (described below)
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 providers changed to modified regional phosphate rock processes (described below)
Phosphate rock	phosphate rock beneficiation | phosphate rock, beneficiated | APOS, U - RER	electricity providers changed for each region

Potassium chloride (potash) – SK, CA, US, BR	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, NL, RU	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)
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)
Magnesium		electricity providers changed for each region for CA, the national average electricity mix was used since magnesium is produced in several Canadian provinces (Bamber et al., 2020)
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, propisochlor	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, tebuconazole, metconazole, Epoxyconazole, cyproconazole, flutriafol	triazine-compound production, unspecified | triazine-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 and decarbonised water providers changed for each region
Glufosinate, chlorpyrifos, Methidathion, Parathion, Phenyl organothiophosphate	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	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	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	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	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, promethrin	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	
carbendazim, prochloraz	benzimidazole-compound production | benzimidazole-compound | APOS, U - RER	ammonia, electricity, and sulfur providers changed for each region
2,4-dichlorophenol, 2,4-dichlorophenoxy-acetic acid 2-ethylhexyl ether, 2-methyl-4-chlorophenoxyacetic acid	2,4-dichlorophenol production | 2,4-dichlorophenol | APOS, U - RER	electricity provider changed for each region
Thiocarbamate herbicides	dithiocarbamate-compound production | dithiocarbamate-compound | APOS, U - RER	
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)	electricity grid process 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 |	electricity providers changed for each region

	APOS, U – Europe without Switzerland	
Natural gas	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
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 32. 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 group for electricity, low voltage | electricity, low voltage | APOS, U – United States - market for electricity, low voltage | electricity, low voltage | APOS, U – Netherlands - market for electricity, low voltage | electricity, low voltage | APOS, U – Russia - market for electricity, low voltage | electricity, low voltage | APOS, U – Ukraine - market for electricity, low voltage | electricity, low voltage | APOS, U – Italy - market group for electricity, low voltage | electricity, low voltage | APOS, U – Brazil
Pea (as input to pea seed)	- Russia: protein pea production | protein pea | APOS, U – RoW - Ukraine: protein pea production | protein pea | APOS, U – RoW
Wheat (as input to both	- Saskatchewan: wheat production | wheat grain | APOS, U - Canada without Quebec

durum and non-durum wheat seed)	- Canada: wheat production | wheat grain | APOS, U - Canada without Quebec - United States: wheat production | wheat grain | APOS, U – US - Russia: wheat production | wheat grain | APOS, U – RoW - Ukraine: wheat production | wheat grain | APOS, U – RoW - Italy: wheat production | wheat grain | APOS, U – RoW
Rape (as input to rape seed)	- Netherlands: rape seed production | rape seed | APOS, U – RoW - Russia: rape seed production | rape seed | APOS, U – RoW - Ukraine: rape seed production | rape seed | APOS, U – RoW
Soybean (as input to soybean seed)	- United States: soybean production | soybean | APOS, S - US - Brazil: market for soybean | soybean | APOS, U - BR
Lentil seed	- Saskatchewan: lentil production | lentil | APOS, U - CA-SK - Canada: market for lentil production | lentil | APOS, U – CA - Australia: lentil production | lentil | APOS, U – RoW - United States: lentil production | lentil | APOS, U - RoW
Decarbonised water	- market for water, decarbonised | water, decarbonised | APOS, U – Rest of World (Ukraine, Netherlands, Italy, Australia) - market for water, decarbonised | water, decarbonised | APOS, U – United States - market for water, decarbonised | water, decarbonised | APOS, U – Canada - market for water, decarbonised | water, decarbonised | APOS, U – Brazil - market for water, decarbonised | water, decarbonised | APOS, U – Russia

2.5.8 Emissions modeling

2.5.8.2 N_2O emissions

In order to ensure methodological consistency for all crop-country combinations, the modeling 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 durum and non-durum wheat production systems from those values presented which assumed no removal of crop residues. The Canadian and Saskatchewan emission factors presented in Table 33 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. Since the submission of part 1 of this report, there have been updates to the N_2O emissions methodology used in the CRSC reports ((S&T)2 Consultants Inc., 2022c). For consistency, the main results are presented with the original methodology from part 1, with a sensitivity analysis for the updated methodology (see section 2.5.12.1).

The values for the direct N_2O emission factors for Australia, the Netherlands, Russia, Ukraine, Brazil, and Italy were taken from each country's NIR (Cetipa, 2022; Commonwealth of Australia, 2022; Ministry of Environmental Protection and Natural Resources of Ukraine, 2022; Ministry of Foreign Affairs, 2020; National Institute for Public Health and the Environment, 2022; Russian Federation, 2022; The Institute for Environmental Protection and Research (ISPRA), 2022) (Table 33). The Ukrainian, Brazilian, and Italian NIRs use the IPCC Tier 1 value, whereas the Australian, Dutch, and Russian 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 U.S. 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

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

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, prairie province, and national 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, the United States, the Netherlands, Russia, Ukraine, Brazil and Italy 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; Ministry of Environmental Protection and Natural Resources of Ukraine, 2022; Ministry of Foreign Affairs, 2020; National Institute for Public Health and the Environment, 2022; Russian Federation, 2022; The Institute for Environmental Protection and Research (ISPRA), 2022; United States Environmental Protection 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% on irrigated land and 14-20% on non-irrigated land) (Commonwealth of Australia, 2022). For the Netherlands, the $Frac_{GASF}$ and $Frac_{GASM}$ values were both country-specific, as well as specific to the types of fertilizer and methods of manure application. All values used in the Russian and Brazilian NIRs for indirect N_2O emissions were default Tier 1 values. The Ukrainian NIR provided a country-specific value for $Frac_{GASF}$, and all other values were default Tier 1. The Italian NIR provided country-specific Tier 2 values for all Fracs used in indirect N_2O modeling.

Calculation of manure-related emissions according to methods used in the Dutch NIR requires information regarding manure application methods – specifically, the proportions of manure that are surface applied and incorporated. According to Fraters et al. (2021), Dutch fertilization requirements dictate that, as of February 2012, all manure must be applied using a "low-emission process". In the description of the methodology used for estimating GHG emissions in the Dutch NIR, van der Zee et al. (2022) indicate that manure may be applied using surface spreading or low-emission techniques. Given the information presented by Fraters et al. (2021), it is assumed that all manure applied in the Netherlands is done so using a low-emission technique, and none is surface spread.

Table 33. Emission factors and fractions used in N_2O emissions modeling 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	$EF1_{FCR}$	$EF1_{FSOM}$	$Frac_{GASF}$ (NH_3) ammonium sulfate[b]	$Frac_{GASF}$ (NH_3) diammonium phosphate[b]	$Frac_{GASF}$ (NH_3) calcium ammonium nitrate[b]	$Frac_{GASF}$ (NH_3) other nitrogen, phosphate and potassium fertilizers[b]	$Frac_{GASF}$ (NH_3) urea[b,d]	FracGAS (NO_x) all sources[b]	$Frac_{GASM}$ (NH_3)[b]	EF_4	$Frac_{LEACH}$	EF_5
Canada (lentils)	0.0070	0.0070	0.0070	0.0070	0.0070	0.0070	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.1569	0.011
Canada (durum)	0.0071	0.0071	0.0071	0.0071	0.0071	0.0071	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.1575	0.011
Saskatchewan (lentils)	0.0069	0.0069	0.0069	0.0069	0.0069	0.0069	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.1555	0.011
Saskatchewan (durum)	0.0069	0.0069	0.0069	0.0069	0.0069	0.0069	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.1551	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
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
Netherlands	0.007	0.007	0.013[c]	0.013[c]	0.01	-	0.113	0.074	0.025	0.045	0.054	0.012	0.24	0.01	0.13	0.0075
Russia	0.0137	0.0137	0.0137	0.0137	0.0137	0.0137	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.30	0.0075
Ukraine	0.01	0.01	0.01	0.01	0.01	0.01	0.145	0.145	0.145	0.145	0.145	0.145	0.20	0.01	0.30	0.01
Brazil	0.01	0.01	0.01	0.01	0.01	0.01	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.01	0.30	0.0075
Italy	0.01	0.01	0.01	0.01	0.01	0.01	0.0995	0.0995	0.0995	0.0995	0.0995	0.0995	0.0886	0.01	0.27	0.0075

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

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

[c] The emission factor for manure incorporated into the soil (rather than above-ground application) was used because Dutch fertilization requirements dictate manure must be applied using a "low emissions" method Fraters et al. (2021), which the Dutch NIR differentiates from surface spreading (van der Zee et al., 2022)

[d] Calculated as the average of all factors specified foe reach urea type

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.

2.5.8.1 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. For Canada, the RU-level values presented in the CRSC reports ((S&T)2 Consultants Inc., 2022d, 2022e), that were calculated based on the methods in the NIR (Environment and Climate Change Canada, 2022), were aggregated to provincial, prairie province, and national averages. 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 modeling 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. The only exception to this methodology was for Brazil. In Brazil's Fourth Biennial Update Report to the United Nations Framework Convention on Climate Change (UNFCCC) (Ministry of Foreign Affairs, 2020), no distinction is made between different land use types in their Land Use, Land Use Change and Forestry (LULUCF) section, as is done in the NIRs of all other countries, allowing for the estimation of SOC changes attributed to cropland. Therefore, instead of using this source, the estimate of CO_2 emissions from land use change from van Paassen et al. (2019b) was used. This was chosen since this dataset was also used to source other data for Brazilian soy. The CO_2 from land use change estimate in van Paassen et al. (2019b) is based on their Direct Land Use Change Assessment Tool, which is methodologically consistent with the PAS2050-1 framework, data from the FAO, and the 2019 updated guidelines for National Greenhouse Gas Inventories from the IPCC.

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 of 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). In part 1, canola residues were assumed to be left on field for all countries included in the analysis. This assumption was also applied here to canola production in Ukraine and Russia. Additional research was performed to determine if this assumption also adequately applies to Dutch canola production, as the Dutch NIR (National Institute for Public Health and the Environment, 2022) notes that there has been a decrease in the amount of crop residues left on Dutch agricultural fields over the period from 1990 to 2020. The Dutch NIR calculates emissions from crop residues according to the methodology described by van der Zee et al. (2022). This methodology notes that rates of crop residue removal, and crop specific N loads per hectare of crop residues are taken from Van der Hoek et al. (2007), which indicates that all crop residues are left on fields in Dutch canola production systems. This source also indicates that aboveground canola crop residues are associated with an N load of 42 Kg N/hectare. This value for Dutch canola crop residue N load is similar to that used by de Ruijter and Huijsmans (2019), and higher than the value of 32.5 Kg N/hectare used by Firrisa (2011), though this lower value is derived from a German-specific source from 1993 (Reinhardt, 1993). The approach to modeling emissions from Dutch canola crop residues used by the NIR is therefore followed here. Aboveground canola crop residue yields for Dutch canola production are modelled using an average value for the EU28 countries for the period 2011-2015, as presented by Garcia-Condado et al. (2019). No information could be found on belowground residue yields or N contents, so the German values from part 1 of the project are used, as calculated from Vos et al. (2022).

Little information is available on yields and N contents of above and belowground canola residues in Ukraine and Russia. Aboveground residue yields were calculated using data reported in Iqbal et al. (2016), who report aboveground canola residue stocks in Ukraine and Russia in 2016 based on unspecified literature sources. The reported values were subsequently used in combination with data from FAOstat (2021) regarding production quantities of canola in each country in 2016 to calculate aboveground crop residue yields per tonne of canola produced (1.11 tonnes/tonne for Russia, and 1.63 tonnes/tonne for Ukraine). This Ukrainian value is similar to that proposed by Jiang et al. (2019). No information is available regarding belowground canola residue yields. The Russian NIR indicates that N_2O emissions from crop residues are estimated according to the method described by Romanovskaya et al. (2002) using crop residue yields and N contents derived from literatures sources from the 70s, 80s, and 90s that are not publicly accessible. In a presentation at a meeting of the Global Council for Innovation in Rapeseed and Canola in 2017, Tuchin (2017) indicated that, since the mid 1990s, there has been a proliferation of Western genetics among the varieties and hybrids of canola in Russia, such that Western varieties now represent the majority of varieties grown. Based on this, Russian belowground crop residue yields, and N contents of above and belowground canola residues are assumed to be the same as those used for modeling Canadian canola production, proportionate to grain yields.

The Ukrainian NIR does provide an equation and the requisite variables for using the equation to estimate N inputs from crop residues. However, reporting inconsistencies in the NIR make interpretation of the equation and results it gives uncertain. To avoid potential errors due to inappropriate use of the equation, Canadian numbers were used instead. N contents of above and belowground crop residues were taken from the Ukrainian NIR. A complete breakdown of assumed above and belowground crop residue yields and N contents for canola is presented in Table 34.

Table 34. 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)
Netherlands	2.49[1]	0.46[2]	0.012[3]	0.005[2]
Russia	1.11[4]	1.35[5]	0.013[5]	0.009[5]
Ukraine	1.63[4]	1.35[5]	0.007[6]	0.012[6]

[1] Average value for EU28 countries (Garcia-Condado et al., 2019)
[2] Calculated based on Vos et al. (2022)
[3] Calculated based on Van der Hoek et al. (2007)
[4] Calculated using a combination of Iqbal et al. (Iqbal et al., 2016) and data from FAOStat (FAOstat, 2022a)
[5] Values taken from (Thiagarajan et al. (2018)
[6] Values taken from the Ukrainian NIR (Ministry of Environmental Protection and Natural Resources of Ukraine, 2022)

2.5.8.3.2 Soy

Retention of soybean residues on field may have a number of positive agronomic impacts, particularly in relation to water retention (Liu and Lobb, 2021; Salado-Navarro and Sinclair, 2009). Removal of soybean crop residues is a technically challenging process, as reviewed by Deen (2017). Further, soybeans are a relatively low-residue yielding crop, and residues are generally more brittle than those of other crops, limiting their potential usage in other economic activities. Some residues may be removed for use as livestock bedding, though this proportion is likely small and the prevalence of the practice is likely highly regionally specific (Oo, 2012). Based on this, all soybean residues were assumed to be left on fields.

For American soy residues, aboveground residue yields and N contents were calculated according to a guide to harvesting crop residues produced by the University of Nebraska (Wortmann et al., 2012), assuming 1 bushel of soybeans is 27.2 kg, in line with the U.S. NASS report (USDA NASS, 2020) (Table 35). These calculated values are consistent with aboveground residue yields and N contents reported in the literature as reviewed in Tables 3-5 of the CRSC soybean report ((S&T)2 Consultants Inc, 2022). No information could be found on belowground residue yields for American soy or N contents, so the values are taken from Thiagarajan et al. (2018).

An average value for aboveground residue yield and N contents in Brazilian soybeans was taken from Zuffo et al. (2022), who calculated the N content of soybean straw based on samples taken from experimental stations in the Mato Grosso do Sul province of Brazil. The calculated value for aboveground residue yield is consistent with the lowest end of the range of literature values as reviewed in Tables 3-5 of the CRSC soybean report ((S&T)2 Consultants Inc, 2022). No information could be found on belowground residue yields for Brazilian soy or N contents, so the values are taken from Thiagarajan et al. (2018).

Table 35. Assumed values for soy 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)
USA	1.11[1]	0.545[2]	0.0085[1]	0.011[2]
Brazil	0.78[3]	0.545[2]	0.0249[3]	0.011[2]

[1] Calculated according to Wortmann et al. (2012)
[2] Values taken from Thiagarajan et al. (2018)
[3] Values taken from Zuffo et al. (2022)

2.5.8.3.3 Non-durum 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 many 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. Estimation of the proportion of aboveground residues removed has been previously described in section 2.5.5.2.

No information could be found describing Russian wheat crop residue yields or N contents, so the same values used for Canada have been applied as taken from Thiagarajan et al. (2018) (Table 36). Estimated aboveground residue yields for Ukrainian wheat were taken from Jiang et al. (2019), who investigated the potential for crop residues to be used for power generation in Ukraine. This estimated aboveground residue yield is slightly lower than the yields used for Canadian, Australian, and American wheat, but greater than those used for German and French wheat in part 1. N contents of above and belowground Ukrainian wheat residues were calculated according to values given in the Ukrainian NIR (Ministry of Environmental Protection and Natural Resources of Ukraine, 2022), production weighted for the amount of spring and winter wheat produced in Ukraine in 2021 as reported by the Ukrainian State Statistics Service. No information could be found regarding belowground wheat residue yields, so these values were assumed to be the same as those in Canada taken from Thiagarajan et al. (2018).

Table 36. 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)
Russia	1.49[1]	0.58[1]	0.007[1]	0.015[1]
Ukraine	1.275[2]	0.58[1]	0.0045[3]	0.008[3]

[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] Value taken from Jiang et al. (2019)
[3] Values calculated based on Ukrainian NIR (Ministry of Environmental Protection and Natural Resources of Ukraine, 2022), taking into account proportions of spring and winter wheat grown in Ukraine

2.5.8.3.4 Lentils

Little information is available regarding management practices used for lentil crop residues. Alkhtib et al. (2017) note that lentil straw is a key source of livestock fodder throughout Africa, South Asia, and the Middle East. Similarly, Alberta Pulse Growers note that lentil straw may have value as a feed source for livestock, though the decision to use lentil straw this way should take into account the costs of baling and hauling, and it is suggested a nutrient analysis is performed on the straw to determine the trade-offs between using it for livestock feed compared to leaving it on the field (Alberta Pulse Growers, 2023). Retention of lentil residues on field may provide large amounts of N to subsequent crops, reducing synthetic fertilizer needs, and may be associated with improvements in soil carbon content as well (Alberta Agriculture and Forestry, 2020; Biederbeck et al., 1998). Given the potential benefits of retaining lentil residues on fields, and the lack of evidence indicating that significant amounts of lentil straw are removed for use as livestock fodder in any of the countries included in this analysis, it is assumed that all lentil residues are left on field. This assumption is also in line with previous LCA work done assessing the environmental impacts of Canadian lentil production systems for Pulse Canada (Bamber et al., 2022b).

For Saskatchewan, the Prairie Provinces, and the Canadian national average, values for crop residue mass and N contents came from Thiagarajan et al. (2018), the current best available estimates of these data (Table 37). Use of these values is in line with the Canadian NIR (Environment and Climate Change Canada, 2022). Aboveground crop residue yields for Australian lentils were calculated using an average harvest index taken from Lake and Sadras (2021), who present harvest indices for 20 different lentil varietals grown in Southern Australia. Of note, the harvest indices reported by Lake and Sadras (2021) are considerably lower than Canadian estimates of lentil harvest index. Estimates of Australian lentil harvest index range from 0.03 – 0.33, compared to a ranges of 0.22 to 0.4 (Hanlan et al., 2006), 0.36 – 0.56 (Choudhry, 2012), and 0.41 suggested by Thiagarajan et al. (2018) for Canadian lentils. In comparison, the average Australian lentil harvest index calculated from Lake and Sadras (2021) was 0.215, lower than the lowest value among ranges found for Canadian lentils. This lower harvest index results in a greater yield of aboveground crop residues per kilogram of lentils produced. The calculated aboveground residue yield for Australian lentils was greater than any of the literature values reviewed in Table 3.6 of the CRSC lentil report ((S&T)2 Consultants Inc., 2022a), which gave a maximum aboveground residue yield of 2.92. No estimates of belowground residue yields, or residue N contents could be found for Australian lentils, so the Canadian values from Thiagarajan et al. (2018) were used.

These values were deemed more appropriate for use than those found in the Australian NIR (Commonwealth of Australia, 2022) because they are lentil specific, while values from the Australian NIR are representative of all pulses.

The U.S. NIR indicates that, while burning of lentil crop residues may be common in some parts of the country, the total production area on which lentil residues are burnt is negligible (i.e., <0.5% of all productive area). Emissions related to burning of lentil crop residues has therefore been excluded here. Aboveground crop residue yields for American lentils are taken from the U.S. NIR (United States Environmental Protection Agency, 2022). The U.S. NIR does not provide information on belowground residue yields, or N contents of above or belowground lentil residues. Aboveground residue N content of American lentils was calculated using an average value from four lentil varietals grown in the Pacific northwest taken from Whitehead et al. (2000), scaled to the aboveground residue yield taken from the U.S. NIR (United States Environmental Protection Agency, 2022). While Whitehead et al. (2000) is an old source, the aboveground residue N content calculated from their data is comparable to the Canadian value in Thiagarajan et al. (2018). Belowground residue yields and N contents for American lentils are assumed to be the same as those in Canada, taken from Thiagarajan et al. (2018).

Table 37. Assumed values for lentil 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	1.38[1]	0.56[1]	0.012[1]	0.020[1]
Prairie provinces	1.38[1]	0.56[1]	0.012[1]	0.020[1]
Canada	1.38[1]	0.56[1]	0.012[1]	0.020[1]
Australia	3.65[2]	0.56[1]	0.012[1]	0.020[1]
USA	1.837[3]	0.56[1]	0.014[4]	0.020[1]

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

[2] Calculated using an average harvest index from Lake and Sadras (2021)

[3] Value from U.S. NIR (United States Environmental Protection Agency, 2022)

[4] Calculated using an average value from Whitehead et al. (2000) scaled to the residue yield taken from the US NIR

2.5.8.3.5 Durum wheat

As with non-durum wheat straw, durum wheat straw may be used for animal bedding, as well as many other potential applications. Palladino et al. (2021), for example, explore the use of durum straw bales as an insulation substrate for use in building walls, as durum straw is abundantly available in Italy, the region in which the analysis was performed. Robust data on percentages of durum wheat residues removed from fields could not be found. The same standardized residue removal rate applied to non-durum wheat residues has therefore been applied to durum wheat as well, assuming that 8.3% of all residues are removed from fields in each country.

For Saskatchewan, the Prairie Provinces, and the Canadian national average, values for crop residue yields and N contents came from Thiagarajan et al. (2018), the current best available estimates of these data. Use of these values is in line with the Canadian NIR (Environment and Climate Change Canada, 2022).

The U.S. NIR (United States Environmental Protection Agency, 2022) does not provide estimates of crop residue yields for durum wheat. Values for aboveground biomass yields in American durum production systems were taken from Dai et al. (2016), who estimate American durum wheat aboveground residue yield to be 1.22 kg kg durum^{-1}, which is slightly lower than the literature values reviewed in the CRSC report ((S&T)2 Consultants Inc., 2022b). No information could be found on belowground residue yields for American durum systems, so the Canadian values from Thiagarajan et al. (2018). This assumption is in line with those used in modeling of crop residue emissions from non-durum wheat, in which values from Thiagarajan et al. (2018) were used as well.

Estimates of Italian durum wheat residue yields varied significantly across different sources. In an analysis of biomass availability for energy production in Sicily, Chinnici et al. (2015) estimate that aboveground residue yields of Italian durum wheat are only 10% of total durum production. Using the numbers they present, an aboveground residue yield of 0.1 kg kg durum^{-1} may be calculated, while Ingrao et al. (2018) estimate that aboveground residue yields in Italian durum systems are 0.5 kg kg durum^{-1}. In both cases, these estimated aboveground residue yields are significantly lower than any of the sources reviewed in Tables 3-5 of the CRSC durum wheat report ((S&T)2 Consultants Inc., 2022b). Ingrao et al. (2019) estimate that durum wheat straw production in Sicily ranges from 1.5 – 2 tonnes per hectare of planted durum area, which, when scaled to durum wheat yields used here, gives an aboveground residue yield of 0.88 kg kg durum^{-1}, which is also much lower than all those values reported in the CRSC report. The Italian NIR (The Institute for Environmental Protection and Research (ISPRA), 2022) does not provide an estimate of durum wheat residue yields. No information could be found on belowground residue yields for Italian durum wheat production. Given the large amount of variability found in estimates of Italian durum wheat aboveground residue yields, Canadian values taken from Thiagarajan et al. (2018) are used instead. Values from Thiagarajan et al. (2018) were also used for belowground residue yields in Italian durum production.

Little information was found regarding N contents of durum wheat residues. Hirzel et al. (2020) provide an estimate of N contents of aboveground durum wheat residues produced in Chile, which is similar to the value from Janzen et al. (2003) used in the CRSC durum report. Given climatic differences between Chile and the other countries included in this analysis, Canadian estimates were deemed a better fit as proxy data for Italy and the U.S. Values for N contents of above and belowground durum wheat residues in both the U.S. and Italy were therefore assumed to be the same as those in Canada, taken from Thiagarajan et al. (2018).

Table 38. Assumed values for durum 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	1.485[1]	0.576[1]	0.007[1]	0.015[1]
Prairie provinces	1.485[1]	0.576[1]	0.007[1]	0.015[1]
Canada	1.485[1]	0.576[1]	0.007[1]	0.015[1]

USA	1.22[2]	0.576[1]	0.007[1]	0.015[1]
Italy	1.485[1]	0.576[1]	0.007[1]	0.015[1]

[1] Values from Thiagarajan et al. (Thiagarajan et al., 2018)
[2] Values taken from Dai et al. (2016)

2.5.8.3.6 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.

Previously, Bamber et al. (unpublished) performed an LCA comparing the life cycle environmental impacts of field peas grown in Canada to those of field peas grown in Russia for Pulse Canada. In that analysis, pea residue yields and N contents were assumed to be the same as those for Canada, as taken from Thiagarajan et al. (2018). As no new information could be found regarding field pea residue yields or N contents for Russia, this assumption was also used here (Table 39). The Ukrainian NIR does provide an equation and the requisite variables for using the equation to estimate N inputs from pea crop residues. However, reporting inconsistencies in the NIR make interpretation of the equation and results it gives uncertain. To avoid potential errors due to inappropriate use of the equation, Canadian numbers were used instead. Nitrogen contents of Ukrainian above and belowground pea residues were taken from the Ukrainian NIR (Ministry of Environmental Protection and Natural Resources of Ukraine, 2022).

Table 39. 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)
Russia	2.28[1]	0.49[1]	0.021[1]	0.022[1]
Ukraine	2.28[1]	0.49[1]	0.0125[2]	0.017[2]

[1] Thiagarajan et al. (2018), assuming a dry matter content of 89.3% in line with CRSC report ((S&T)2 Consultants Inc, 2021)
[2] Values taken from the Ukrainian NIR (Ministry of Environmental Protection and Natural Resources of Ukraine, 2022)

2.5.8.4 Emissions from burning of crop residues

In some cases, crop residues may be burnt on field rather than baled and removed or left on fields. Burning of crop residues may have a phytosanitary impact and may increase yields in subsequent crops (Limon-Ortega et al., 2009). Emissions associated with burning of crop residues are relevant for GHG estimates of Italian durum wheat production, as residue burning has been identified as a common practice used by durum wheat farmers in Southern Italy (Rinaldi et al., 2017; Ventrella et al., 2016). The proportion of Italian durum wheat crop residues burnt and the proportion left on the field unburnt was taken from Palmieri et al. (2017), scaled to the assumed rate of residue removal applied to each country in this analysis. This resulted in an estimate that 8.3% of durum residues were removed, 58.69% were left on field, and 33.01% were burnt on field. Emissions associated with burning of residues were calculated according to the Italian NIR (The Institute for Environmental Protection and Research (ISPRA), 2022), which is in line with the IPCC methodology, using the following equations:

$$(1)\ CH4\ emissions\ from\ biomass\ burning \\ = kg\ residues\ burnt * C\ content\ of\ residues * EF_{CH4-C} * 16/22$$

where the kg residues burnt was calculated as described above,
the IPCC default value of 0.5 was used for the C content of residues,
the IPCC default value of 0.005 was used for $EF_{CH4\text{-}C}$, and
16/22 represents the molecular ratio of CH_4-C to CH_4.

$$(2)\ N2O\ emissions\ from\ biomass\ burning \\ = kg\ residues\ burnt * N\ content\ of\ residues * EF_{N2O-N} * 44/28$$

where the kg residues burnt was calculated as described above,
the N content of residues was taken from Thiagarajan et al. (2018),
the IPCC default value of 0.007 was used for $EF_{N2O\text{-}N}$, and
44/28 represents the molecular ratio of N_2O-N to N_2O.

2.5.9 Impact assessment methods

The carbon footprint of each crop-country model was calculated using the IPCC 2021 Assessment Report (AR) 6 methodology (Cilleruelo, 2022). This method is based on the most recent 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 Prairie province and Canada without Saskatchewan carbon footprints

In addition to the Canadian and Saskatchewan results, production weighted averages were also calculated for the Prairie Provinces (including Manitoba, Saskatchewan, and Alberta), using the same regionalized data sources as the Saskatchewan models. For Canadian lentils and durum wheat, these three provinces represented the only locations of production included in the national average models, therefore the Prairie Province models were identical to the Canadian average models. Models were also calculated for Canada without Saskatchewan, as production weighted averages of all relevant Canadian provinces other than Saskatchewan, using the same (generally regionalized) data sources as the Saskatchewan and Prairie Province models. Canada without Saskatchewan models were also calculated for canola, non-durum wheat, and peas, since these were not included in part 1. All data sources and data quality were the same for the Canada without Saskatchewan models as the Saskatchewan models, except for the yield values for durum wheat. Statistics Canada provided data for 2018-2022 for the Canadian average, however to calculate the production weighted average for Alberta and Manitoba, a 4-year average (2019-2022) was used instead since Statistics Canada did not report yield or production values for Manitoba for 2018 due to unreliable data from that year. Therefore the temporal correlation was given a score of 2 rather than 1. This issue was not indicated in their estimated Canadian average yields for the same year, with no explanation of how they were calculated given the unreliable Manitoba data.

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 40). 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). In the current draft, uncertainty was calculated for canola and soy as a representative sample. Once all data are finalized, a final report with all uncertainty assessment will be completed.

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 40. 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. A sensitivity analysis was performed around the estimates of N_2O emissions for Canadian crops from the CRSC reports and Canadian NIR. Previously, sensitivity analyses were performed in part 1 for cut-off criteria and exclusions, manure nutrient contents, allocation methods, N_2O emissions modeling, crop residue yields and N contents, and impact assessment methods.

2.5.12.1 Canadian N_2O emissions modeling

There was an update to the CRSC reports ((S&T)2 Consultants Inc., 2022c) to scale the N_2O emissions from crop residue and manure N by a factor of 0.84. This was somewhat informed by the recent publication by Liang et al., (2020) that indicated 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. However, (S&T)2 Consultants Inc., (2022) instead chose to apply the factor of 0.84 to both manure (when applicable) and crop residue, rather than using the factor of 0.28 for crop residue, citing insufficient evidence for this factor. The CRSC update also included changes to the EF for synthetic N, indirect N_2O emissions, and to how irrigation impacts N_2O emissions (only relevant for Southern Alberta, since they have significant irrigation), in accordance with the Canadian NIR.

Since this update to the CRSC reports was published after the completion of part 1 of this report, the N_2O emissions for Canadian durum and lentils were also sourced from the CRSC reports prior to the update for consistency. Therefore, a sensitivity analysis was performed to assess the impacts of using the updated N_2O emission values from the updated CRSC reports. These values were similarly calculated at a sub-regional level, then aggregated to the provincial, prairie province, and national scale. Since the CRSC update still differs from the Canadian NIR, the methodology presented in the NIR was also included as an additional sensitivity analysis. These analyses were performed for all Canadian crops (including those from both parts 1 and 2 of this report).

3. Results and discussion

3.1 Life cycle inventory

Overall, there were available data with fairly high quality for most crop-country combinations included in part 2 of this project. Specifically, in addition to the data from part 1, for canola there were adequately high-quality data available for Canada without Saskatchewan, the Netherlands, Russia and Ukraine. For soy, there were data available for Brazil and the U.S. For wheat, in addition to the data from part 1, there were data for Canada without Saskatchewan, Russia and Ukraine. For lentils there were data of sufficient quality for Saskatchewan, Canada (and Prairie average), Canada without Saskatchewan, Australia and the United States. For durum wheat there were data of sufficient quality for Saskatchewan, Canada (and Prairie average), Canada without Saskatchewan, Italy, and the United States. For peas, in addition to the data from part 1, there were data of sufficient quality for Canada without Saskatchewan, Russia and Ukraine. Russian and Turkish lentil production, and French durum wheat production were excluded from the analysis due to a lack of available data of sufficient quality.

The results of this section focus on the crop-country combinations specific to part 2 of this project, with the Canadian/Saskatchewan results from part 1 duplicated in part 2 for comparison. For information on the other crop-country combinations, see the part 1 report. Summaries of the LCI data are presented in the main body of the report, and detailed LCIs are attached as Excel files.

3.1.1 Canola LCI

The Netherlands had the highest canola yields (3448 kg/ha), followed by Ukraine (2646 kg/ha), and Canada/Saskatchewan (2119-2145 kg/ha). Russia had the lowest yields (1565 kg/ha) (Table 41). Seed inputs were similar in the Netherlands (0.006 kg/kg) and Ukraine (0.007 kg/kg), and higher in Russia (0.012 kg/kg). Similarly, lime inputs were comparable in the Netherlands (0.177 kg/kg) and Ukraine (0.151 kg/kg), higher in Russia (0.256 kg/kg), and lower in Canada (0.003 kg/kg). The Netherlands had the highest rate of N and K fertilization (0.177 kg N fertilizer/kg and 0.016 kg K fertilizer/kg), with lower rates in Russia (0.016 kg N fertilizer/kg and 0.003 kg K fertilizer/kg), Ukraine (0.036 kg N fertilizer/kg and 0.007 kg K fertilizer/kg), and Canada/Saskatchewan (0.057-0.091 kg N fertilizer/kg and 0.006-0.010 kg K fertilizer/kg). Canada/Saskatchewan had the highest P and S fertilization rates (0.030-0.031 kg P fertilizer/kg and 0.015-0.042 kg S fertilizer/kg); rates in other countries were fairly similar, ranging from 0.008 kg P fertilizer/kg (Russia and Ukraine) to 0.012 kg P fertilizer/kg (Netherlands), and from 0.002 kg S fertilizer/kg (Russia and Ukraine) to 0.003 kg S fertilizer/kg (Netherlands). The Netherlands (7.50 kg/kg pig manure and 0.0085 kg/kg poultry manure) and Ukraine (0.636 kg/kg pig manure, and 2.08 kg/kg poultry manure) both had high manure inputs, with lower inputs in Russia (0.253 kg/kg pig manure, and 0.077 kg/kg poultry manure). There were no manure inputs for Canada. Total pesticide active ingredient inputs ranged from 4.03×10^{-4} kg/kg in Russia to 0.003 kg/kg in the Netherlands.

Irrigation was only used for Dutch and Albertan (Canadian) canola, using 2.20×10^{-7} MJ of energy per kg Dutch canola, and 0.01-0.023 MJ per kg Canadian and Canadian without Saskatchewan canola. Russia had the highest energy use for field activities (3.019 MJ/kg), followed by Ukraine (1.927 MJ/kg), the Netherlands (1.370 MJ/kg), and Canada/Saskatchewan (0.458-0.497 MJ/kg). A similar trend was seen for post-harvest energy use (0.094 kg/kg in Russia, 0.056 kg/kg in Ukraine, 0.011 kg/kg in the Netherlands, and 0.003 kg/kg in Canada). Transportation was highest in the Netherlands (244.14 kg*km/kg) due to the high manure inputs, followed by Ukraine (92.02 kg*km/kg), and Russia (24.73 kg*km/kg). Canada had the lowest transportation (7.08-8.43 kg*km/kg).

Russia and Canada had the lowest N_2O emissions (9.94×10^{-4} and 0.001 kg/kg) due to their relatively lower inputs of fertilizers, manure, and N emissions from soil mineralization of C. Both the Netherlands (2.65×10^{-3} kg/kg) and Ukraine (3.57×10^{-3} kg/kg) have significantly higher emissions due to higher N inputs, as well as soil mineralization from losses of soil carbon in the case of Ukraine. Since Russia has higher lime inputs, CO_2 emissions from lime and urea are highest in Russia (0.113 kg/kg), followed by Ukraine (0.076 kg/kg), the Netherlands (0.064 kg/kg), and Canada (0.03-0.045 kg/kg). The Dutch NIR reported no change in soil carbon, since all land use and management practices remained the same. According to the Russian and Ukrainian NIRs, Russian agricultural soils are on balance sequestering carbon (-0.061 kg CO_2/kg canola), and Ukrainian soils are losing carbon (0.365 kg CO_2/kg canola). Canadian soils had the highest levels of sequestration, ranging from -0.094 kg CO_2/kg in Canada without Saskatchewan to -0.225 kg CO_2/kg in Saskatchewan.

Table 41. Summary of LCI data for canola produced in the Netherlands, Russia, and Ukraine.

	Saskatchewan	**Canada**	**Prairie Provinces**	**Canada without Saskatchewan**	**Netherlands**	**Russia**	**Ukraine**
Yield (kg/ha)	2119	2145	2123	2141	3448	1565	2646
Seed (kg/kg)	0.003	0.003	0.003	0.003	0.006	0.012	0.007
Lime (kg/kg)	0	0	0	0	0.116	0.256	0.151

	Saskatchewan	Canada	Prairie Provinces	Canada without Saskatchewan	Netherlands	Russia	Ukraine
N fertilizers (kg/kg)	0.057	0.091	0.079	0.088	0.177	0.016	0.036
P fertilizers (kg/kg)	0.031	0.030	0.031	0.030	0.013	0.008	0.008
K fertilizers (kg/kg)	0.009	0.006	0.010	0.010	0.016	0.003	0.007
S fertilizers (kg/kg)	0.042	0.015	0.042	0.036	0.003	0.002	0.002
Pig manure (kg/kg)	0	0	0	0	7.50	0.253	0.636
Poultry manure (kg/kg)	0	0	0	0	0.085	0.077	2.08
Total pesticide AI (kg/kg)	0.001	0.002	0.001	0.0007	0.003	4.03×10^{-4}	4.54×10^{-4}
Irrigation energy (MJ/kg)	0	0.010	0	0.023	2.20×10^{-7}	0.000	0.000
Field activities energy (MJ/kg)	0.458	0.472	0.476	0.497	1.370	3.019	1.927
Post-harvest energy (kWh/kg)	0.003	0.003	0.003	0.003	0.011	0.094	0.056
Transportation (kg*km/kg)	7.08	7.20	8.24	8.43	244.14	24.73	92.02
Field-level N_2O emissions (kg/kg)	0.001	0.001	0.001	0.0017	2.65×10^{-3}	9.94×10^{-4}	3.57×10^{-3}
Field-level CO_2 emissions (kg/kg)	0.030	0.045	0.041	0.044	0.064	0.113	0.076
Soil carbon change (kg CO_2/kg)	-0.225	-0.161	-0.160	-0.094	0.000	-0.061	0.365

3.1.2 Soy LCI

The United States had higher soy yields (3363 kg/ha) than Brazil (3335 kg/ha) (Table 42). Seed inputs were similar in both countries (0.02-0.03 kg/kg). Brazil had higher use of inoculants than the U.S. (1.12×10^{-7} m3/kg compared to 1.67×10^{-8}). Lime application was higher in the US (0.14 kg/kg) than in Brazil (0.08 kg/kg). Fertilizer inputs were fairly similar between the two countries, with higher N fertilizer application in the US (4.86×10^{-3} kg/kg compared to 4.26×10^{-3}), higher P fertilizer application in Brazil (0.09 kg/kg compared to 0.04), the same K fertilizer application in both countries (0.05 kg/kg), and higher S fertilizer application in the US (4.15×10^{-3} kg/kg compared to 1.36×10^{-3}). The U.S. had a higher application rate of cow manure (0.10 kg/kg compared to 0), and Brazil had higher application rates of pig (0.23 kg/kg compared to 0.07) and poultry (0.04 kg/kg compared to 1.23×10^{-3}) manure. Total pesticide application was higher in Brazil (1.63×10^{-3} kg AI/kg) than in the US (7.29×10^{-4} kg AI/kg).

Energy use was fairly comparable between the two countries, with higher irrigation energy use ($9.16x10^{-4}$ MJ/kg compared to $2.07x10^{-6}$) and field activities energy use (0.94 MJ/kg compared to 0.80) in Brazil. Post-harvest energy use (0.006 kWh/kg compared to $9.76x10^{-6}$) and transportation (34.20 kg*km/kg compared to 20.54) were higher in the United States. The N credit was assumed to be the same in each country (replacing the application of $4.88x10^{-3}$ kg of ammonia per kg soy). The largest difference between the countries was the CO_2 emissions from soil carbon change, due to the large impacts of land use change for Brazilian soy. Therefore, the estimate of CO_2 emissions from soil carbon change (from land management and land use change) for Brazil was 4.67 kg CO_2/kg, compared to only 0.06 kg CO_2/kg for the US. Since SOC change also contributes to N_2O emissions, the estimate of total N_2O emissions from agricultural soils for Brazil was 0.01 kg N_2O/kg, compared to only $2.9x10^{-4}$ kg N_2O/kg for the US. Field level CO_2 emissions from lime and urea inputs were higher in the US (0.06 kg/kg compared to $3.34x10^{-3}$), due to the higher levels of inputs.

Table 42. Summary of LCI data for soy produced in the United States, and Brazil.

	United States	**Brazil**
Yield (kg/ha)	3363	3335
Seed (kg/kg)	0.03	0.02
Inoculant (m^3/kg)	$1.67x10^{-8}$	$1.12x10^{-7}$
Lime (kg/kg)	0.14	0.08
N fertilizers (kg/kg)	$4.86x10^{-3}$	$4.26x10^{-3}$
P fertilizers (kg/kg)	0.04	0.09
K fertilizers (kg/kg)	0.05	0.05
S fertilizers (kg/kg)	$4.15x10^{-3}$	$1.36x10^{-3}$
Cow manure (kg/kg)	0.10	0.00
Pig manure (kg/kg)	0.07	0.23
Poultry manure (kg/kg)	$1.23x10^{-3}$	0.04
Total pesticide AI (kg/kg)	$7.29x10^{-4}$	$1.63x10^{-3}$
Irrigation energy (MJ/kg)	$2.07x10^{-6}$	$9.16x10^{-4}$
Field activities energy (MJ/kg)	0.80	0.94
Post-harvest energy (kWh/kg)	0.006	$9.76x10^{-6}$
Transportation (kg*km/kg)	34.20	20.54
Field-level N_2O emissions (kg/kg)	$2.90x10^{-4}$	$9.69x10^{-3}$
Field-level CO_2 emissions (kg/kg)	0.06	$3.34x10^{-3}$
Soil carbon change (kg CO_2/kg)	0.06	4.67
N credit (kg ammonia/kg)	$-4.88x10^{-3}$	$-4.88x10^{-3}$

3.1.3 Non-durum wheat LCI

Ukrainian wheat (4064 kg/ha) had much higher yields than Canadian (2986-3945 kg/ha) or Russian wheat (2850 kg/ha) (Table 43). Straw removal was assumed to be almost identical (0.12 kg DM residue removed per kg yield in Russia and Canada, and 0.11 kg DM removed/kg in Ukraine). Russia had higher inputs of seed (0.05 kg/kg compared to 0.04 in Ukraine and 0.03 in Canada), and lime (0.14 kg/kg compared to 0.10 and 0). Canada had the highest inputs of fertilizers (0.041-0.056 kg N fertilizer/kg, 0.013-0.034 kg P fertilizer/kg, 0.005-0.015 kg K fertilizer/kg, and 0.007-0.014 kg S fertilizer/kg) and pesticides ($3.86x10^{-4}$-0.001 kg AI/kg). Russia, compared to Ukraine, had higher inputs of pig manure (0.14 kg/kg compared to 0.04 kg/kg), and poultry manure (0.04 kg/kg compared to 0.01 kg/kg).

As for energy use, Russia had the highest post-harvest energy use (0.053 kWh/kg) and transportation (16.71 kg*km/kg). Ukraine had the highest irrigation energy use (0.03 MJ/kg), and field activities energy use (1.25 MJ/kg). Ukraine's NIR estimated net losses of soil organic carbon (0.24 kg CO_2/kg), Russia's NIR estimated net gains of SOC (-0.03 kg CO_2/kg), and Canada had gains from 0.031 kg CO_2/kg in Canada without Saskatchewan to 0.153 kg CO_2/kg in Saskatchewan. Ukraine had the highest N_2O emissions (9.97x10-4 kg N_2O/kg), due to the N_2O emissions associated with SOC losses, as well as higher N inputs from fertilizer. Field-level CO_2 emissions from lime and urea were slightly higher in Russia (0.06 kg/kg), due to the higher levels of inputs.

Table 43. Summary of LCI data for non-durum wheat produced in Russia and Ukraine.

	Saskatchewan	**Canada**	**Prairie Provinces**	**Canada without Saskatchewan**	**Russia**	**Ukraine**
Yield (kg/ha)	2986	3375	3372	3945	2850	4064
Straw removed (kg DM/kg)	0.123	0.123	0.123	0.123	0.12	0.11
Seed (kg/kg)	0.032	0.033	0.033	0.031	0.05	0.04
Lime (kg/kg)	0	0	0	0	0.14	0.10
N fertilizers (kg/kg)	0.056	0.042	0.047	0.041	0.02	0.03
P fertilizers (kg/kg)	0.022	0.013	0.033	0.034	0.01	$3.49x10^{-3}$
K fertilizers (kg/kg)	0.005	0.006	0.015	0.013	$1.69x10^{-3}$	$3.11x10^{-3}$
S fertilizers (kg/kg)	0.011	0.007	0.014	0.012	$2.79x10^{-3}$	$1.63x10^{-3}$
Pig manure (kg/kg)	0	0.103	0	0	0.14	0.04
Poultry manure (kg/kg)	0	0.024	0	0	0.04	0.01
Total pesticide AI (kg/kg)	0.001	0.001	0.001	$3.86x10^{-4}$	$7.18x10^{-5}$	$1.20x10^{-4}$
Irrigation energy (MJ/kg)	0	0.004	0	0.015	0.02	0.03
Field activities energy (MJ/kg)	0.330	0.758	0.312	0.283	1.02	1.25
Post-harvest energy (kWh/kg)	0.003	0.003	0.003	0.003	0.053	0.036
Transportation (kg*km/kg)	6.286	8.895	7.146	6.577	16.71	10.22
Field-level N_2O emissions (kg/kg)	$6.07x10^{-4}$	$6.57x10^{-4}$	$6.94x10^{-4}$	$7.99x10^{-4}$	$7.74x10^{-4}$	$9.97x10^{-4}$
Field-level CO_2 emissions (kg/kg)	0.027	0.020	0.024	0.021	0.06	0.05

	Saskatchewan	Canada	Prairie Provinces	Canada without Saskatchewan	Russia	Ukraine
Soil carbon change (kg CO_2/kg)	-0.153	-0.078	-0.103	-0.031	-0.03	0.24

3.1.4 Lentil LCI

Saskatchewan lentils had the highest yields (1410 kg/ha), followed by Canada (1407 kg/ha), then Australia (1295 kg/ha), and the US had the lowest (1207 kg/ha) (Table 44). Inoculant application was assumed to be fairly similar across all countries (ranging from 1.00×10^{-5} m^3/kg in the US to 8.51×10^{-6} m^3/kg in Saskatchewan). Australia was the only country that applied lime (0.31 kg/kg). US lentils had 10 times the N fertilizer application rate (0.10 kg/kg) as any other country (0.01 kg/kg). P fertilizer application rates were similar across all countries, ranging from 0.02 kg/kg in the US to 0.04 kg/kg in Saskatchewan and Canada. The US also had much higher K fertilizer application rates (0.07 kg/kg compared to none in Australia, and 3.45×10^{-3} to 3.57×10^{-3} in Canada/Saskatchewan). The US also had higher S fertilizer application (8.03×10^{-3} kg/kg compared to 2.0910^{-3} in Australia and 3.11×10^{-3} to 3.14×10^{-3} in Canada/Saskatchewan). Australia was the only country to apply manure (0.08 kg/kg pig manure and 0.04 kg/kg poultry manure). Pesticide application rates were similar between countries, ranging from 1.15×10^{-3} kg AI/kg in Canada to 2.8×10^{-3} kg AI/kg in the US.

Canada was the only country to irrigate lentils (8.85×10^{-4} MJ energy use per kg). Australia used significantly more energy for field activities than other countries (1.61 MJ/kg compared to a range of 0.55 MJ/kg in Saskatchewan to 0.69 MJ/kg in Canada). Post-harvest energy use was assumed to be the same in all countries (0.014 kWh/kg). Australia had lower transportation of farm inputs than other countries (23.08 kg*km/kg compared to a range of 45.92 in the US to 51.09 in Canada).

According to each country's NIR, Canadian (and Saskatchewan) soils had a net carbon sequestration (-0.39 to -0.40 kg CO_2/kg, and Australian and US soils had net carbon emissions (0.05 and 0.16 kg CO_2/kg, respectively). The US had the highest N_2O emissions (1.02×10^{-3} kg/kg compared to 1.73×10^{-4} in Australia and a range of 3.30×10^{-4} to 3.37×10^{-4} in Canada/Saskatchewan), due to higher levels of N fertilizer application. Australia had higher levels of CO_2 emissions from lime and urea (0.15 kg/kg compared to 0.05 in the US and 0.01 in Canada/Saskatchewan), since they were the only country to apply lime.

Table 44. Summary of LCI data for lentils produced in Saskatchewan, Canada, Australia and the United States.

	Saskatchewan	Canada/Prairie provinces	Canada without Saskatchewan	Australia	United States
Yield (kg/ha)	1410	1407	1384	1295	1207
Seed (kg/kg)	0.11	0.10	0.06	0.04	0.05
Inoculant (m^3/kg)	8.51×10^{-6}	8.59×10^{-6}	8.67×10^{-6}	7.74×10^{-6}	1.00×10^{-5}
Lime (kg/kg)	0.00	0.00	0.00	0.31	0.00

	Saskatchewan	Canada/Prairie provinces	Canada without Saskatchewan	Australia	United States
N fertilizers (kg/kg)	0.01	0.01	0.00	0.01	0.10
P fertilizers (kg/kg)	0.04	0.04	0.03	0.03	0.02
K fertilizers (kg/kg)	3.57×10^{-3}	3.45×10^{-3}	1.47×10^{-3}	0.00	0.07
S fertilizers (kg/kg)	3.14×10^{-3}	3.11×10^{-3}	1.78×10^{-3}	2.09×10^{-3}	8.03×10^{-3}
Pig manure (kg/kg)	0.00	0.00	0.00	0.08	0.00
Poultry manure (kg/kg)	0.00	0.00	0.00	0.04	0.00
Total pesticide AI (kg/kg)	1.18×10^{-3}	1.15×10^{-3}	8.47×10^{-4}	2.40×10^{-3}	2.80×10^{-3}
Irrigation energy (MJ/kg)	0.00	8.85×10^{-4}	9.21×10^{-3}	0.00	0.00
Field activities energy (MJ/kg)	0.55	0.69	0.78	1.61	0.63
Post-harvest energy (kWh/kg)	0.014	0.014	0.0139	0.014	0.014
Transportation (kg*km/kg)	49.53	51.09	64.43	23.08	45.92
Field-level N_2O emissions (kg/kg)	3.30×10^{-4}	3.37×10^{-4}	4.08×10^{-4}	1.73×10^{-4}	1.02×10^{-3}
Field-level CO_2 emissions (kg/kg)	0.01	0.01	0.00	0.15	0.05
Soil carbon change (kg CO_2/kg)	-0.40	-0.39	-0.40	0.05	0.16
N credit (kg ammonia/kg)	-4.88×10^{-3}	-4.88×10^{-3}	-4.88×10^{-3}	-5.30×10^{-3}	-5.69×10^{-3}

3.1.5 Durum wheat LCI

Italy had the highest yield (3300 kg/ha), followed by the United States (2678 kg/ha), then Canada (2298 kg/ha), and Saskatchewan had the lowest yield (2262 kg/ha) (Table 45). A constant straw removal rate was assumed for all countries (0.12 kg DM/kg yield). The U.S. had a lower seed application rate than other countries (5.87×10^{-3} kg/kg compared to 0.04-0.05 kg/kg). The U.S. was the only country to apply lime (0.02 kg/kg). Italy had the highest application rate of N fertilizers (0.08 kg/kg), followed by Canada (0.07 kg/kg), Saskatchewan (0.06 kg/kg), and the U.S. had the lowest. Italy had no application of other types of fertilizers, whereas Canada and the U.S. applied P, K and S fertilizers. The US had the lowest application rates of each types of fertilizer. For P fertilizers, the US applied 1.14×10^{-2} kg/kg compared to 0.02 kg/kg in Canada/Saskatchewan, for K fertilizers the U.S. applied 8.31×10^{-4} kg/kg compared to 3.39×10^{-3} to 3.45×10^{-3} in Canada/Saskatchewan, and for S fertilizers the US applied 2.78×10^{-3} kg/kg compared to 8.44×10^{-3} in Canada and 1.05×10^{-2} in Saskatchewan. The U.S. was the only country to apply manure (0.02 kg/kg of pig manure). Italy had the lowest pesticide application rate (1.07×10^{-4} kg AI/kg, compared to 9.54×10^{-4} in Canada, 1.05×10^{-3} in Saskatchewan and 1.48×10^{-3} in the U.S.).

Canada and Italy were the only countries to irrigate their durum wheat, using 1.16×10^{-2} and 1.29×10^{-3} MJ/kg, respectively. Italy had much higher energy use for field activities than Canada and the US (2.35 MJ/kg compared to 0.43 in Canada/Saskatchewan, and 0.70 in the U.S.). Italy also had much higher energy use for post-harvest activities (0.539 kWh/kg compared to 0.011 in Canada/Saskatchewan, and 0.056 in the U.S.). Italy had the lowest transportation of farm inputs (1.18 kg*km/kg), followed by the U.S. (4.56 kg*km/kg), and Canada/Saskatchewan had the highest (7.41-7.49 kg*km/kg).

The U.S. was the only country to have net CO_2 emissions from soil carbon change (0.07 kg CO_2/kg), with net sequestration in Italy (-4.69×10^{-4} kg CO_2/kg) and Canada/Saskatchewan (-0.26 to -0.24 kg CO_2/kg). Italy had the highest N_2O emissions (9.88×10^{-4} kg N_2O/kg, compared to 3.63×10^{-4} in the U.S., 6.39×10^{-4} in Canada, and 6.11×10^{-4} in Saskatchewan), due to higher N inputs and emission factors. Italy was the only country to burn a significant proportion of crop residues, leading to emissions of 1.63×10^{-3} kg CH_4/kg. Field-level CO_2 emissions from lime and urea were fairly similar between countries, ranging from 0.03 kg/kg in the U.S. to 0.05 kg/kg in Canada/Saskatchewan.

Table 45. Summary of LCI data for durum wheat produced in Saskatchewan, Canada, the United States and Italy.

	Saskatchewan	**Canada/Prairie provinces**	**Canada without Saskatchewan**	**United States**	**Italy**
Yield (kg/ha)	2262	2298	2455	2678	3300
Straw removed (kg DM/kg)	0.12	0.12	0.12	0.12	0.12
Seed (kg/kg)	0.05	0.05	0.05	5.87×10^{-3}	0.04
Lime (kg/kg)	0.00	0.00	0.00	0.02	0.00
N fertilizers (kg/kg)	0.06	0.07	0.08	0.04	0.08
P fertilizers (kg/kg)	0.02	0.02	0.02	1.14×10^{-2}	0.00
K fertilizers (kg/kg)	3.39×10^{-3}	3.45×10^{-3}	3.77×10^{-3}	8.31×10^{-4}	0.00
S fertilizers (kg/kg)	1.05×10^{-2}	8.44×10^{-3}	5.55×10^{-5}	2.78×10^{-3}	0.00
Pig manure (kg/kg)	0.00	0.00	0.00	0.02	0.00
Poultry manure (kg/kg)	0.00	0.00	0.00	0.00	0.00
Total pesticide AI (kg/kg)	1.05×10^{-3}	9.54×10^{-4}	5.66×10^{-4}	1.48×10^{-3}	1.07×10^{-4}
Irrigation energy (MJ/kg)	0.00	1.16×10^{-2}	6.09×10^{-2}	0.00	1.29×10^{-3}

	Saskatchewan	Canada/Prairie provinces	Canada without Saskatchewan	United States	Italy
Field activities energy (MJ/kg)	0.43	0.43	0.40	0.70	2.35
Post-harvest energy (kWh/kg)	0.011	0.011	0.011	0.056	0.539
Transportation (kg*km/kg)	7.41	7.49	7.87	4.56	1.18
Field-level N_2O emissions (kg/kg)	6.11x10^{-4}	6.39x10^{-4}	7.71x10^{-4}	3.63x10^{-4}	9.88x10^{-4}
CH_4 emissions from biomass burning (kg/kg)	0.00	0.00	0.00	0.00	1.63x10^{-3}
Field-level CO_2 emissions (kg/kg)	0.05	0.05	0.075	0.03	0.04
Soil carbon change (kg CO_2/kg)	-0.26	-0.24	-0.196	0.07	-4.69x10^{-4}

3.1.6 Pea LCI

Canadian peas had the highest yields (2550 kg/ha for Canada without Saskatchewan), and Ukrainian peas (2227 kg/ha) had somewhat higher yield than Russian peas (2106 kg/ha) (Table 46). Seed and lime inputs were highest in Russia (0.07 kg seed/kg and 0.19 kg lime/kg). Inoculant inputs were assumed to be similar in all both countries (6.32x10^{-6}-6.77x10^{-6} in Canada, 5.53x10^{-6} m^3/kg in Russia, and 5.24x10^{-6} in Ukraine). Russia had the highest inputs of N fertilizer (0.08 kg/kg), S fertilizer (9.89x10^{-3} kg/kg), pig manure (0.19 kg/kg compared to 0.16 in Ukraine), and poultry manure (0.06 kg/kg compared to 0.05 in Ukraine). Ukraine had the highest inputs of P fertilizer (0.13 kg/kg), K fertilizer (0.05 kg/kg), and pesticides (1.50x10^{-3} kg AI/kg).

Russia was the only country to irrigate their peas (0.03 MJ/kg). Canada had the highest post-harvest energy use (3.16x10^{-4}-1.30x10^{-3} kWh/kg), while Russia and Ukraine were assumed to have the same (8.10x10^{-4} kWh/kg). Ukraine had the highest transportation (29.31 kg*km/kg), and field activities energy use (1.91 MJ/kg). According to each country's NIR, Russian and Canadian soils were assumed to be sequestering carbon (-0.05, and -0.108 to -0.208 kg CO_2/kg), and Ukrainian soils had net soil carbon losses (0.043 kg CO_2/kg). Field-level N_2O emissions were highest in Russia with 2.40x10^{-4} kg N_2O/kg, followed by 2.01x10^{-3} kg N_2O/kg for Ukraine, and 6.37x10^{-4}-1.08x10^{-3} in Canada/Saskatchewan. CO_2 emissions from lime and urea were similar in Russia and Ukraine, each with 0.09 kg CO_2/kg, and lower in Canada/Saskatchewan (1.88x10^{-4}-2.98x10^{-4} kg CO_2/kg). The N credit was assumed to be similar for each country, with ~0.005 kg ammonia avoided per kg peas.

Table 46. Summary of LCI data for pea production in Russia and Ukraine.

	Saskatchewan	Canada	Prairie Provinces	Canada without Saskatchewan	Russia	Ukraine
Yield (kg/ha)	2235	2325	2370	2550	2106	2227
Seed (kg/kg)	1.02x10^{-4}	1.58x10^{-4}	1.55x10^{-4}	1.97x10^{-4}	0.07	0.06

	Saskatchewan	Canada	Prairie Provinces	Canada without Saskatchewan	Russia	Ukraine
Inoculant (m^3/kg)	6.77×10^{-6}	6.75×10^{-6}	6.62×10^{-6}	6.32×10^{-6}	5.53×10^{-6}	5.24×10^{-6}
Lime (kg/kg)	0.00	0.00	0.00	0.00	0.19	0.18
N fertilizers (kg/kg)	3.58×10^{-4}	2.59×10^{-4}	2.55×10^{-4}	1.81×10^{-4}	0.08	0.03
P fertilizers (kg/kg)	2.00×10^{-2}	1.89×10^{-2}	1.86×10^{-2}	0.017	0.02	0.13
K fertilizers (kg/kg)	1.36×10^{-3}	3.25×10^{-3}	3.19×10^{-3}	0.005	0.02	0.05
S fertilizers (kg/kg)	2.08×10^{-3}	2.40×10^{-3}	2.36×10^{-3}	0.002	9.89×10^{-3}	1.74×10^{-3}
Pig manure (kg/kg)	0.00	0.00	0.00	0.00	0.19	0.16
Poultry manure (kg/kg)	0.00	0.00	0.00	0.00	0.06	0.05
Total pesticide AI (kg/kg)	1.22×10^{-3}	9.45×10^{-4}	9.27×10^{-4}	5.52×10^{-4}	2.73×10^{-4}	1.50×10^{-3}
Irrigation energy (MJ/kg)	0.00	0.00	0.00	0.00	0.03	0.00
Field activities energy (MJ/kg)	0.503	0.564	0.553	0.518	1.18	1.91
Post-harvest energy (kWh/kg)	1.30×10^{-3}	8.10×10^{-4}	8.10×10^{-4}	3.16×10^{-4}	8.10×10^{-4}	8.10×10^{-4}
Transportation (kg*km/kg)	1.26	1.30	1.28	1.28	26.18	29.31
Field-level N_2O emissions (kg/kg)	6.80×10^{-4}	7.38×10^{-4}	6.37×10^{-4}	1.08×10^{-3}	2.40×10^{-3}	2.01×10^{-3}
Field-level CO_2 emissions (kg/kg)	2.98×10^{-4}	2.47×10^{-4}	2.43×10^{-4}	1.88×10^{-4}	0.09	0.09
Soil carbon change (kg CO_2/kg)	-0.208	-0.162	-0.162	-0.108	-0.05	0.43
N credit (kg ammonia/kg)	-0.004	-0.005	-0.005	-0.005	-5.01×10^{-3}	-4.74×10^{-3}

3.2 Life cycle impact assessment

Overall, field level N_2O emissions were the main driver of the carbon footprints for most crop-country combinations. Fertilizer production and fuel use for field operations were also large contributors. When soil carbon was included, it often made large positive or negative contributions to the carbon footprint estimates. Saskatchewan crops generally had the lowest carbon footprints of all countries included in the comparison. The only exceptions to this were U.S. lentils without soil carbon, Australian canola without soil carbon, and U.S. soy compared to Saskatchewan canola (both with and without soil carbon).

The results from part 1 are included in the graphs presented in the current document to facilitate comparisons. However, detailed descriptions of the LCIA results are only presented here for the crop-country combinations that are new in part 2. See part 1 of this report for the previous crop-country combinations. See Appendix 1 for tables of the contribution analysis to the LCIA results for the baseline scenario for the crops in part 2.

3.2.1 Canola and soy LCIA

The highest contributor to the carbon footprint of Dutch canola was field-level N_2O emissions, accounting for 63% of the total (Figure 1). Of the total N_2O emissions, 47% were due to N applied as manure, 42% from synthetic fertilizer, and 11% from crop residues. The next highest contributors were the upstream production for manure inputs (11%), and fuel use for field activities (10%). Field-level CO_2 emissions contributed 6%, and all other inputs and activities contributed 5% or less. The Dutch NIR reported no soil carbon changes, therefore there are no CO_2 emissions or sequestrations associated with soil carbon. Overall, Dutch canola had 91% higher impacts than Saskatchewan canola when soil carbon was not accounted for, and 206% higher impacts when soil carbon was included.

Field-level N_2O emissions accounted for 37% of the impacts of Russian canola, of which 18% were from synthetic fertilizer, 10% from manure and 72% from crop residue. This breakdown is significantly different than the breakdown of Dutch N_2O emissions since the total amount of N_2O emissions for Russia was much lower (0.271 kg CO_2e/kg compared to 0.723 kg CO_2e/kg for the Netherlands), and Russian canola had higher amounts of crop residues and associated N inputs. After field-level N_2O, the next highest contributor to Russian canola was fuel use for field activities (33%), since Russia had approximately double the energy demand for field activities than either the Netherlands or Ukraine. Field-level CO_2 emissions from lime and urea made up 15% of the carbon footprint for Russian canola, and upstream fertilizer production was 6%. All other inputs made up less than 5%. Russian soils had net carbon sequestration, and therefore reduced the overall carbon footprint by 8%. Russian canola had 24% higher impacts than Saskatchewan canola without soil carbon, and 83% higher with soil carbon.

For Ukrainian canola, field-level N_2O emissions were also the highest contributor to the carbon footprint, accounting for 64% of impacts. This was broken down as 10% from fertilizer, 53% from manure, 16% from crop residue and 21% from N emissions from SOC loss. The next highest contributor to the carbon footprint was upstream production for manure (13%), followed by fuel use for field activities (10%). All other inputs accounted for 5% or less. CO_2 emissions from soil carbon change added an additional 24% to the overall carbon footprint. Without soil carbon, Ukrainian canola had a carbon footprint 156% higher than Saskatchewan, and with soil carbon it was 409% higher.

In addition to canola produced in other countries, Saskatchewan and Canadian canola was compared to soybeans produced in both the U.S. and Brazil. U.S. soy had 49% lower impacts than Saskatchewan canola on a per kg basis, when soil carbon was not included, and only 7% lower when soil carbon was included. On the other hand, Brazilian soy was 381% higher than Saskatchewan canola without soil carbon, or 1924% with soil carbon. In fact, soil carbon emissions from land use change are the main driver of the impacts associated with Brazilian soy. When soil carbon is included, it adds an additional 163% of impacts to the carbon footprint. This is due mostly to land use change to grow Brazilian soy. Other than soil carbon, N_2O emissions are the major driver of impacts (92%). Ninety-three percent of the N_2O emissions are due to mineralization from SOC emissions, with 5% from crop residues and <1% each from fertilizer and manure inputs. Nitrous oxide emissions are also the main driver of the impacts of U.S. soy, accounting for 26% of impacts. This is broken down as 57% from crop residues, 21% from soil carbon losses, 19% from synthetic fertilizer, and 3% from manure. The next highest contributors to the overall carbon footprint of U.S. soy are fuel use for field activities (22%), upstream fertilizer impacts (22%), and the field-level emissions of CO_2 from lime and urea application (20%). Soil carbon change contributes an additional 19% to the total carbon footprint when included.

The carbon footprint estimates for Canada, Canadian Prairie Provinces, and Russia were not significantly different from each other. All other differences were statistically significant.

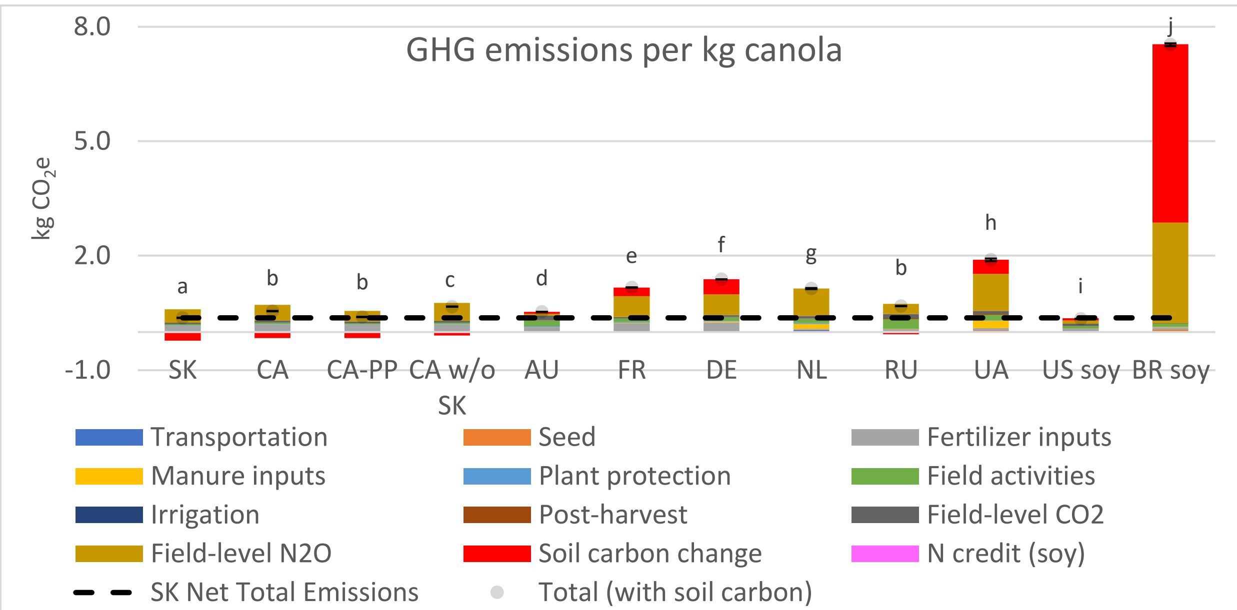

Figure 1. Carbon footprint of canola produced in Saskatchewan, Canada, Canadian Prairie Provinces, Canada without Saskatchewan, Australia, France, Germany, Netherlands, Russia and Ukraine, and soy produced in the United States and Brazil. Error bars represent standard error, and different letters indicate statistically significant differences.

3.2.2 Non-durum wheat LCIA

The highest contributor to the carbon footprint of Russian non-durum wheat is field-level N_2O emissions (45%) (Figure 2). Of this, 59% was due to N inputs from crop residues, 33% from synthetic fertilizer, and 8% from manure inputs. The next highest contributor to the carbon footprint was fuel use for field activities (17%), followed by field-level CO_2 emissions from lime and urea (13%), and upstream fertilizer production (10%). Seed inputs contributed 8%, and all other inputs contributed <3%. When soil carbon sequestration is included, it reduces the overall carbon footprint by 7%. Russian wheat has a 25% higher carbon footprint than Saskatchewan wheat when soil carbon is not included, and a 95% higher impact when soil carbon is included.

Nitrous oxide emissions are also the highest contributor to the carbon footprint of Ukrainian wheat (49%). These emissions can be attributed to mineralization from soil carbon losses (49%), synthetic fertilizer application (30%), crop residue inputs (20%), and manure application (1%). After N_2O, the next highest contributors are fertilizer production and field activities (17% each), followed by field level CO_2 emissions from lime and urea application (9%). All other inputs contributed less than 5%. When soil carbon was included, it added an additional 41% to the overall carbon footprint. Ukrainian wheat has a 55% higher carbon footprint than Saskatchewan wheat, without including soil carbon, and a 265% higher carbon footprint with soil carbon.

The carbon footprint estimates for Canada and Canadian Prairie Provinces were not significantly different from each other. All other differences were statistically significant.

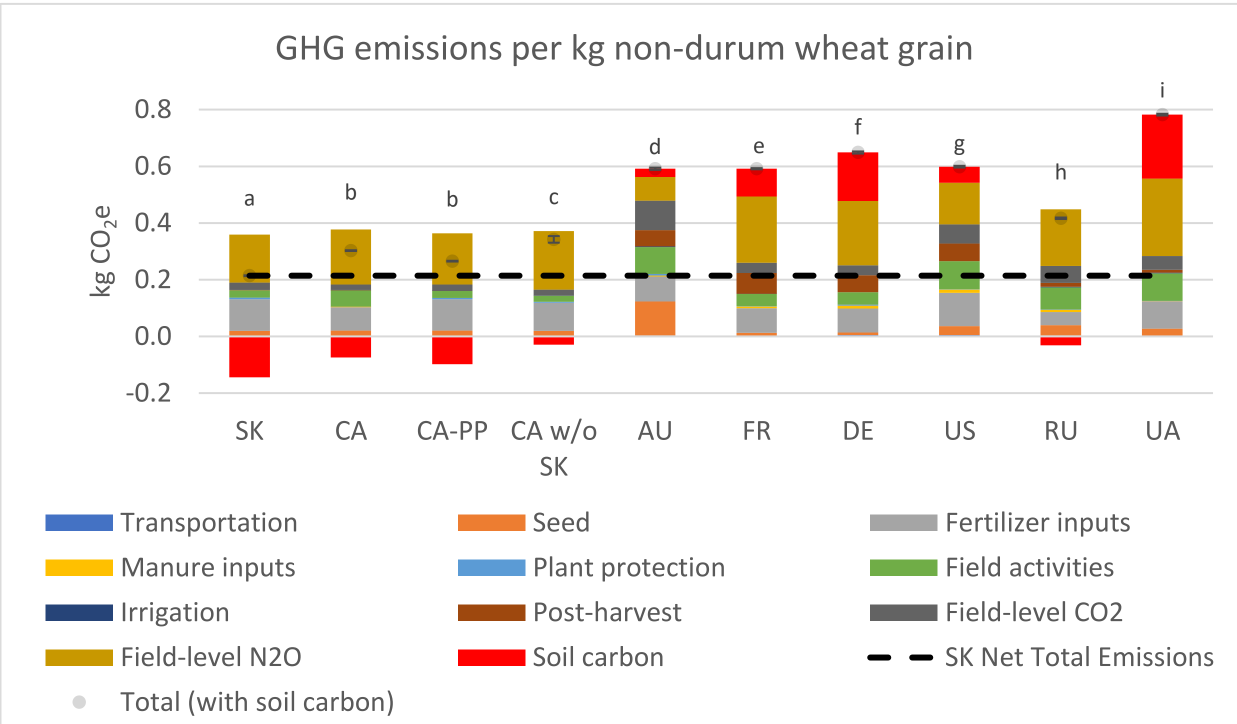

Figure 2. Carbon footprint of non-durum wheat produced in Saskatchewan, Canada, Canadian Prairie Provinces, Canada without Saskatchewan, Australia, France, Germany, United States, Russia, and Ukraine. Error bars represent standard error, and different letters indicate statistically significant differences.

3.2.3 Lentil LCIA

The highest contributor to the carbon footprint of Saskatchewan and Canadian lentils was field-level N_2O emissions (41% and 36%, respectively) (Figure 3). These emissions came from N fertilizer application (19% and 20%), and crop residues (81% and 80%). The next highest contributors were field activities energy use (20% and 22%), and upstream fertilizer production (21% and 18%). Seed contributed 10% and 17% to the carbon footprints of Saskatchewan and Canadian lentils, and all other inputs contributed 5% or less. The N credit was responsible for a 5% reduction in impacts due to the avoided production of fertilizer. Canadian soils have net carbon sequestration, therefore the soil carbon change impacts reduced the overall carbon footprint by 180% for Saskatchewan and 152% for Canada.

The Canadian average carbon footprint was 17% higher than Saskatchewan without the inclusion of soil carbon, and 24% higher with soil carbon. The Canada without Saskatchewan carbon footprint was 12% higher than Saskatchewan without soil carbon and 31% higher with soil carbon included.

Both Australian and U.S. lentils had higher impacts than Saskatchewan lentils, both without soil carbon (98% and 197% higher, respectively), and with soil carbon (376% and 562% higher). For Australia, field-level CO_2 emissions from lime and urea application had the highest contribution to the carbon footprint (34%). This is relatively high since Australian lentils have fairly high lime application in relation to their yield. The next highest contributor was from fuel use for field activities (30%), then upstream fertilizer production (12%). Field-level N_2O only accounted for 11% of the carbon footprint. Australia has the lowest N_2O emissions due to their soil, climate, and management conditions. The N_2O emissions came mostly from N inputs from crop residue (63%), as well as synthetic fertilizer (17%), manure (12%), and SOC loss (9%). After N_2O emissions, seed accounted for 7%, and plant protection for 6%. All other inputs were 2% or less. The N credit reduced the impacts by 3%, and soil carbon change added 11% to the impacts.

For U.S. lentils, N_2O emissions were again the highest contributor to the carbon footprint (42%). These impacts came from N inputs from synthetic fertilizer (44%), crop residues (39%) and mineralisation from soil carbon losses (17%). US lentils had much higher inputs of N fertilizer than Canadian or Australian lentils, as well as higher levels of soil carbon loss, leading to much higher N_2O emissions. The next highest contributor to the overall carbon footprint was upstream fertilizer production (33%), followed by fuel use for field activities and field-level CO_2 emissions from lime and urea (8% each). All other inputs contributed 5% or less. The N credit reduced impacts by 2%, and soil carbon change increased impacts by 24%.

All differences in carbon footprints were statistically significant.

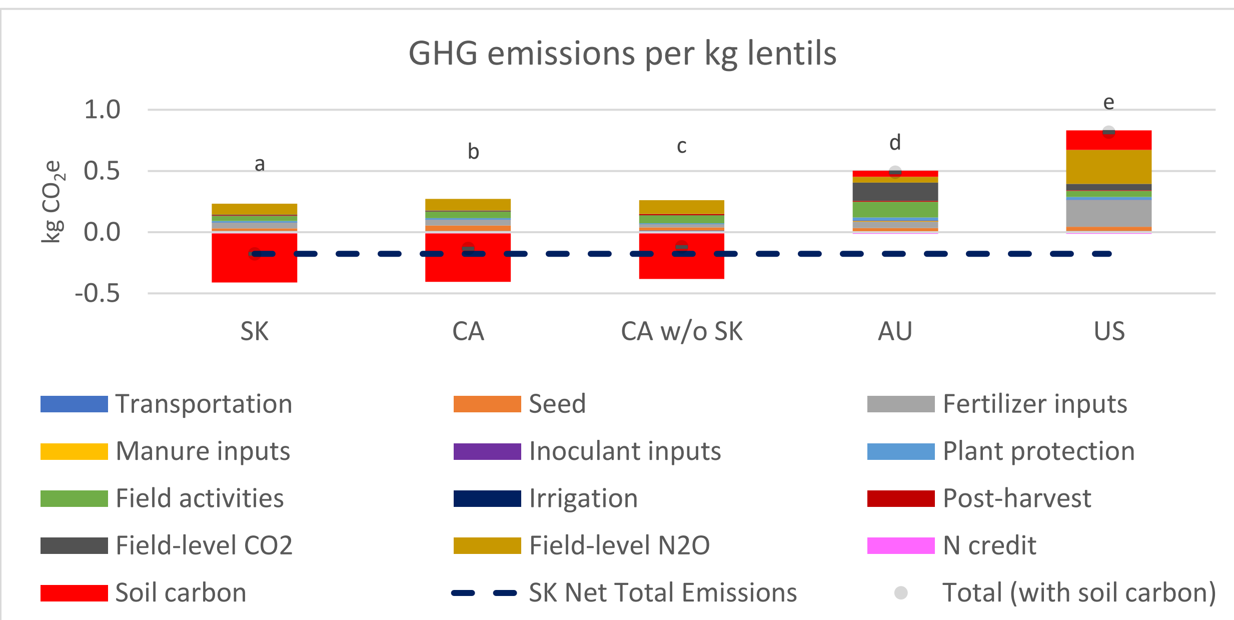

Figure 3. Carbon footprint of lentils produced in Saskatchewan, Canada (same as Prairie Provinces), Canada without Saskatchewan, Australia and the United States. Error bars represent standard error, and different letters indicate statistically significant differences.

3.2.4 Durum wheat LCIA

The highest contributor to the carbon footprint of Saskatchewan and Canadian durum wheat was field-level N_2O emissions (40-41%) (Figure 4). These emissions were attributed to N from synthetic fertilizer (64-65%) and crop residues (35-36%). The next highest contributor to the carbon footprint was upstream fertilizer production (28-29%). Field-level CO_2 emissions from lime and urea contributed 12%, field activities contributed 8%, and seed contributed 7%. All other inputs contributed 2% or less. When soil carbon was included, it reduced the overall carbon footprint by 61% for Saskatchewan, and 57% for Canada. The Canadian average carbon footprint was higher than Saskatchewan by 2% without soil carbon, and 12% higher with soil carbon. The Canada without Saskatchewan average was 19% higher than Saskatchewan without soil carbon, and 76% higher with soil carbon.

U.S. durum wheat had 29% lower impacts than Saskatchewan durum wheat when soil carbon was not included, and 123% higher impacts when soil carbon was included. Field-level N_2O emissions were also the highest contributor to U.S. durum impacts (33%), coming from N inputs from crop residues (48%), synthetic fertilizer (30%) and soil organic carbon loses (21%). Manure N inputs contributed <1% to the total N_2O emissions. After N_2O emissions, upstream fertilizer production contributed the most to the carbon footprint (28%), followed by energy use for field activities (19%). Field-level CO_2 emissions from lime and urea contributed 10%, and all other inputs contributed 5% or less. When soil carbon was included, it added an additional 24% to the overall carbon footprint.

Italian durum wheat had 112% higher impacts than Saskatchewan without soil carbon, and 435% higher impacts with soil carbon. The main reasons for these large impacts were higher energy use for field activities and post-harvest, as well as higher N_2O emissions from higher inputs of N from synthetic fertilizers, as well as burning of crop residues. Field-level N_2O emissions contributed 30% of the carbon footprint of Italian durum, 68% of which were due to synthetic N application, 28% from crop residue N incorporation into soils, and 4% from burning crop residues. The next highest contributor was energy use for post-harvest activities (23%). This was due to the unusually high amount of energy used in post-harvest for Italian durum. Field activities contributed 21%, and upstream fertilizer production contributed 13%. All other inputs contributed 5% or less. Methane from biomass burning also contributed 5% to the overall carbon footprint. When soil carbon was included, it reduced the impacts by only 0.1%.

All differences in carbon footprints were statistically significant.

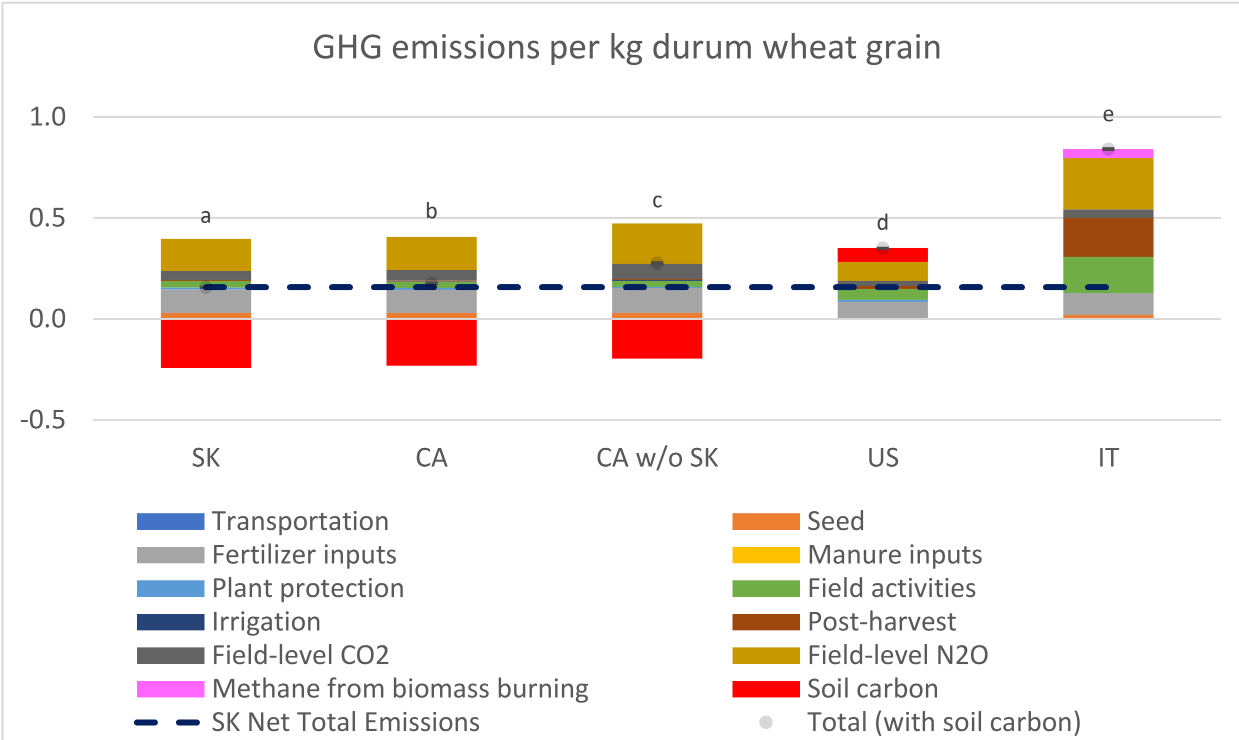

Figure 4. Carbon footprint of durum wheat produced in Saskatchewan, Canada (same as Prairie Provinces), Canada without Saskatchewan, United States, and Italy. Error bars represent standard error, and different letters indicate statistically significant differences.

3.2.5 Pea LCIA

Field-level N_2O was the highest contributor to the carbon footprint of Russian peas (63%) (Figure 5). These emissions came from N inputs from crop residues (61%), synthetic fertilizers (35%), and manure (4%). The next highest contributor was upstream fertilizer production (15%), followed by fuel use for field activities (9%), and field-level CO_2 emissions from lime and urea (8%). All other inputs contributed 3% or less. The N credit from avoided N fertilizer production reduced the carbon footprint by 1%, and soil carbon reduced it further by 4%. Overall, Russian peas had 315% higher impacts than Saskatchewan peas without the inclusion of soil carbon, mainly due to higher N fertilizer inputs and associated N_2O emissions. When soil carbon was included, the impacts of Russian peas were 2366% higher than Saskatchewan, since Russian soils had only small amounts of carbon sequestration compared to the larger amounts seen in Saskatchewan.

Ukrainian peas had slightly lower impacts than Russian peas when soil carbon was not included (299% higher than Saskatchewan peas), mostly due to slightly lower N_2O emissions than Russia. However, when soil carbon was included, Ukrainian peas had even higher impacts (3467% that of Saskatchewan), since Ukrainian soils had net carbon emissions, rather than the net carbon sequestration in Canada/Saskatchewan and Russia. The highest contributor to the carbon footprint of Ukrainian peas was field-level N_2O emissions (55%). These emissions came from N mineralization from SOC loss (44%), N inputs from crop residues (37%), synthetic N fertilizer application (15%), and manure application (3%). The next highest contributors were upstream fertilizer production and fuel use for field activities (16% each), followed by field-level CO_2 emissions from lime and urea (9%). All other inputs contributed 3% or less. The N credit reduced the carbon footprint by 1%. When soil carbon was included, it added an additional 44% to the overall carbon footprint of Ukrainian peas.

The carbon footprints for Saskatchewan and Canada without Saskatchewan, and for Canada and the Canadian Prairie Provinces, were not significantly different from each other. All other differences were statistically significant.

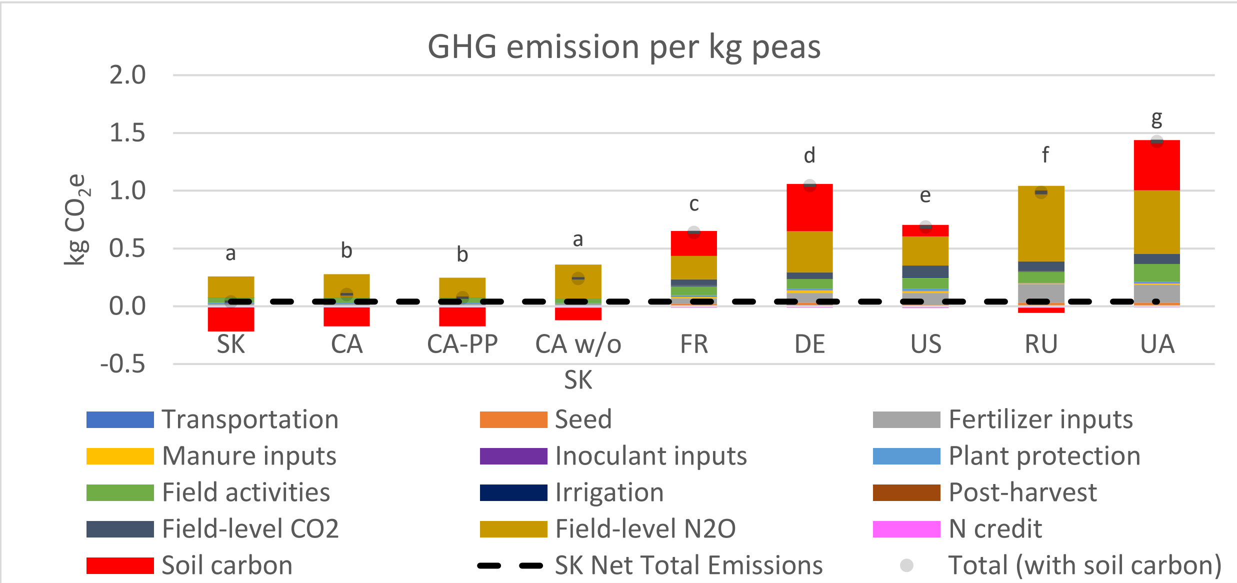

Figure 5. Carbon footprint of peas produced in Saskatchewan, Canada, Canadian Prairie Provinces, Canada without Saskatchewan, France, Germany, United States, Russia and Ukraine. Error bars represent standard error, and different letters indicate statistically significant differences.

3.3 Sensitivity analysis

3.3.1 N_2O emissions modeling

Durum wheat and lentils

The updated N_2O emissions methodology used in the CRSC report ((S&T)2 Consultants Inc., 2022c) significantly reduced the estimates of N_2O emissions from Canadian durum wheat (-33 to -40%) and lentils (-23 to -29%) (Table 47). Overall, this reduced the total carbon footprint (without soil carbon) of durum wheat by 13-16%, and of lentils by 8-12%. The methodology utilized by the Canadian NIR (Environment and Climate Change Canada, 2022) yielded further reductions in the N_2O emissions estimates (-43 to -48% from baseline scenario for durum, and -60% to -63% for lentils), since the EF for crop residues was lower. This was particularly relevant for lentils, since the majority of N_2O emissions came from N inputs from crop residues, due to high residue content and low fertilizer inputs. With the N_2O emissions calculated according to the NIR methods, the overall carbon footprints (without soil carbon) of Canadian and Saskatchewan durum and lentils were reduced by 17-19% and 21-25%, respectively, from the baseline results. The differences in N_2O emissions and resulting changes in the overall carbon footprints were large, re-enforcing the conclusion that Saskatchewan and Canadian durum wheat and lentils had the lowest impacts when soil carbon change was included. When soil carbon was not included, U.S. durum wheat still had lower impacts than Saskatchewan and Canada with all N_2O emission calculation methods.

Canola, non-durum wheat, and peas

The updated N_2O emissions methodology used in the CRSC report ((S&T)2 Consultants Inc., 2022c) significantly reduced the estimates of N_2O emissions from Saskatchewan and Canadian canola (-51 to -55%), non-durum wheat (-36 to -48%), and peas (-62 to -29%) (Table 47). In turn, this reduced the overall carbon footprint (without soil carbon) by 29-33%, 22-24%, and 47-52% for Saskatchewan and Canadian canola, non-durum wheat, and peas, respectively. Using the updated NIR methods yielded larger reductions. The N_2O emissions were 60-63%, 46-56%, and 84-87% lower than the baseline, and the overall carbon footprints were 34-37%, 27-28%, and 64-65% lower than the baseline, for Saskatchewan and Canadian canola, non-durum wheat, and peas, respectively.

These differences were large enough to change the relative ranking of Saskatchewan/Canadian canola in comparison to canola produced in other countries, as well as soy produced in the U.S. and Brazil. In the baseline scenario, U.S. soy and Australian canola had lower carbon footprints than both Saskatchewan and Canadian canola without the inclusion of soil carbon, and with soil carbon, U.S. soy still had the lowest CF, and Australian canola was higher than Saskatchewan but lower than Canadian canola. However, with both the CRSC and NIR N_2O changes, with the inclusion of soil carbon, Saskatchewan and Canadian canola had lower carbon footprints than both U.S. soy and Australian canola. Without soil carbon, U.S. soy was still lower than both Saskatchewan and Canadian canola for both sensitivity analyses. Australian canola (without soil carbon) was still lower than Canadian canola (and higher than Saskatchewan canola) with the updated CRSC methods, and was higher than both with the updated NIR methods. This highlights the importance of the methods for N_2O modelling, and in transparently reporting these methods to ensure comparisons are made robustly and without bias. For wheat and peas, Saskatchewan and Canadian crops had the lowest carbon footprints in all scenarios, clearly highlighting their low impacts of production.

Table 47. Change in estimated N_2O emissions using the updated methodology from the CRSC reports and Canadian NIR.

	Durum wheat		**Lentils**		**Canola**		**Non-durum wheat**		**Peas**	
	SK	CA	SK	CA	SK	CA	SK	CA	SK	CA
Original N_2O emission (kg/kg)	0.000522	0.000552	0.00029	0.00030	0.00130	0.00147	0.00061	0.00066	0.00068	0.00074
CRSC update										
Updated N_2O emission (kg/kg)	0.000316	0.00037	0.00021	0.00023	0.000586	0.00072	0.000319	0.000425	0.00021	0.000282
% Change in N_2O	-39%	-33%	-29%	-23%	-55%	-51%	-48%	-36%	-69%	-62%
% Change in CF (without soil carbon)	-16%	-13%	-12%	-8%	-33%	-29%	-24%	-22%	-52%	-47%
NIR update										
Updated N_2O emission (kg/kg)	0.000270	0.000317	0.000109	0.000121	0.000481	0.000592	0.00027	0.000354	8.56E-05	0.000117
% Change in N_2O	-48%	-43%	-63%	-60%	-63%	-60%	-56%	-46%	-87%	-84%
% Change in CF (without soil carbon)	-19%	-17%	-25%	-21%	-37%	-34%	-28%	-27%	-65%	-64%

4. Conclusions

Overall, field level N_2O emissions were the main driver of the carbon footprints for most crop-country combinations. Fertilizer production and fuel use for field operations were also large contributors. When soil carbon was included, it often made large positive or negative contributions to the carbon footprint estimates. Saskatchewan crops generally had the lowest carbon footprints of all countries included in the comparison. The only exceptions to this were U.S. durum without soil carbon, Australian canola without soil carbon, and U.S. soy compared to Saskatchewan canola (both with and without soil carbon). The changes made to the N_2O emissions methods in the newest version of the CRSC report and Canadian NIR made significant changes to the N_2O estimates for Canadian crops, which resulted in decreases in the overall carbon footprint. Using the updated NIR methods, Saskatchewan and Canada had the lowest carbon footprints for all crops when soil carbon was included, and only U.S. soy (compared to canola) and durum had lower carbon footprints when soil carbon was excluded.

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Appendix 1. Detailed results for baseline analyses

Table A1 Detailed contribution analysis describing contributions to total GHG emissions (kg CO_2e) per kilogram of canola (or soy) produced in the baseline model.

	Transportation	Seed	Fertilizer inputs	Manure inputs	Plant protection	Field activities	Irrigation	Post-harvest	Field-level CO2	Field-level N2O	N credit	Soil carbon change
SK	0.002	0.005	0.159	0.000	0.007	0.037	0.000	0.002	0.030	0.355	0.000	-0.225
CA	0.002	0.006	0.191	0.000	0.013	0.038	0.001	0.012	0.045	0.402	0.000	-0.161
CA-PP	0.002	0.006	0.186	0.000	0.007	0.038	0.001	0.002	0.041	0.273	0.000	-0.160
CA w/o SK	0.002	0.005	0.197	0.000	0.006	0.040	0.001	0.001	0.044	0.464	0.000	-0.094
NL	0.052	0.010	0.024	0.127	0.023	0.111	0.000	0.006	0.064	0.723	0.000	0.000
RU	0.005	0.022	0.047	0.011	0.004	0.244	0.000	0.025	0.113	0.271	0.000	-0.061
UA	0.019	0.013	0.073	0.191	0.004	0.156	0.000	0.019	0.076	0.975	0.000	0.365
US soy	0.007	0.013	0.067	0.002	0.006	0.065	1.67×10^{-7}	0.001	0.061	0.079	-0.012	0.057
BR soy	0.004	0.054	0.054	0.016	0.016	0.076	7.14×10^{-5}	2.59×10^{-6}	0.003	2.647	-0.012	4.672

Table A2 Detailed contribution analysis describing contributions to total GHG emissions (kg CO_2e) per kilogram of non-durum wheat grain produced in the baseline model.

	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
CA-PP	0.001	0.019	0.111	0.000	0.005	0.024	0.000	0.000	0.023	0.180	-0.098
CA w/o SK	0.001	0.018	0.100	0.000	0.003	0.022	0.001	0.000	0.020	0.207	-0.029
RU	0.003	0.036	0.047	0.008	0.001	0.078	0.002	0.013	0.060	0.200	-0.032
UA	0.002	0.025	0.096	0.001	0.001	0.096	0.003	0.009	0.049	0.272	0.226

Table A3 Detailed contribution analysis describing contributions to total GHG emissions (kg CO_2e) per kilogram of lentils produced in the baseline model.

	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 change
SK	0.010	0.022	0.046	0.000	0.001	0.011	0.044	0.000	0.003	0.006	0.090	-0.012	-0.399
CA	0.011	0.044	0.047	0.000	0.001	0.011	0.056	0.000	0.003	0.006	0.092	-0.012	-0.393
CA w/o SK	0.014	0.025	0.026	0.000	0.001	0.008	0.063	0.001	0.011	0.000	0.111	-0.012	-0.370
AU	0.005	0.029	0.051	0.008	0.001	0.026	0.130	0.000	0.007	0.149	0.047	-0.013	0.049
US	0.010	0.036	0.218	0.000	0.001	0.023	0.051	0.000	0.005	0.052	0.278	-0.014	0.159

Table A4 Detailed contribution analysis describing contributions to total GHG emissions (kg CO_2e) per kilogram of durum wheat grain produced in the baseline model.

	Transportation	Seed	Fertilizer inputs	Manure inputs	Plant protection	Field activities	Irrigation	Post-harvest	Field-level CO2	Field-level N2O	Methane from biomass burning	Soil carbon change
SK	0.002	0.028	0.117	0.000	0.009	0.033	0.000	0.004	0.046	0.158	0.000	-0.242
CA/PP	0.002	0.028	0.115	0.000	0.008	0.033	0.001	0.004	0.051	0.165	0.000	-0.231
CA w/o SK	0.002	0.029	0.123	0.000	0.005	0.031	0.006	0.004	0.075	0.200	0.000	-0.196
US	0.001	0.003	0.080	0.000	0.011	0.053	0.000	0.013	0.027	0.094	0.000	0.068
IT	0.000	0.021	0.105	0.000	0.001	0.180	0.000	0.194	0.040	0.256	0.043	0.000

Table A5 Detailed contribution analysis describing contributions to total GHG emissions (kg CO_2e) per kilogram of peas produced in the baseline model.

	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	2.70×10^{-4}	1.35×10^{-5}	0.019	0.000	0.001	0.011	0.041	0.00	0.001	3.00×10^{-4}	0.186	-0.010	-0.208
CA	2.70×10^{-4}	1.56×10^{-5}	0.019	0.000	0.001	0.009	0.046	0.00	1.70×10^{-4}	2.50×10^{-4}	0.202	-0.011	-0.162
CA-PP	2.70×10^{-4}	1.53×10^{-5}	0.019	0.000	0.001	0.009	0.045	0.00	1.70×10^{-4}	2.40×10^{-4}	0.174	-0.011	-0.162
CA w/o SK	2.70×10^{-4}	1.95×10^{-5}	0.019	0.000	0.001	0.005	0.042	0.000	6.54×10^{-5}	1.88×10^{-4}	0.295	-0.012	-0.108
RU	0.006	0.027	0.158	0.008	0.001	0.003	0.095	0.004	0.001	0.087	0.654	-0.012	-0.045
UA	0.006	0.025	0.154	0.013	0.001	0.012	0.154	0.000	0.000	0.088	0.550	-0.011	0.434