Life cycle assessment of impacts of eliminating chemical pesticides used in the production of U.S. corn, soybeans, and cotton

Final Report

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PROJECT INFORMATION	
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List of Acronyms

ANOVA	Analysis of Variance
APEX	Agricultural Policy/Environmental eXtender model
ARMS	Agricultural Resource Management Survey
ARS	Agricultural Research Service
CDL	Cropland Data Layer
CF	Carbon Footprint
CH_4	Methane
CO_2	Carbon Dioxide
CO_2 eq.	Carbon Dioxide Equivalent
DAP	Diammonium Phosphate
EPIC	Environmental Policy Integrated Climate (EPIC) Model
ERS	Economic Research Service
FAO	Food and Agriculture Organization of the United Nations
FRIS	Farm and Ranch Irrigation Survey
FU	Functional Unit
GHG	Greenhouse Gas
GLEAMS	Groundwater Loading Effects of Agricultural Management Systems
GWP	Global Warming Potential
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
LU	Land Use
MAP	Monoammonium Phosphate
MCS	Monte Carlo Simulation
N	Nitrogen
N_2O	Nitrous Oxide
NAL	National Agricultural Library
NASS	National Agricultural Statistics Service
NCGA	National Corn Growers' Association
NH_3	Ammonia
NO	Nitric Oxide
NPK	Nitrogen, Phosphorus, and Potassium
NRCS	Natural Resources Conservation Service
P	Phosphorus
SOC	Soil Organic Carbon
SSURGO	Soil Survey Geographic
UARC	University of Arkansas Resiliency Center
USDA	United States Department of Agriculture
USEPA	United States Environmental Protection Agency
WU	Water Use

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Executive Summary

ES 1 Introduction

The use of pesticides (fungicides, insecticides, and herbicides) is reported to prevent a substantial decrease in crop yield. The application of herbicides has also helped to reduce the amount of labor, machinery, and fuel that have been used mainly for mechanical weed control. Despite these benefits, there is the potential for some harmful effects which could arise from improper, or off-label use of pesticides.

A review of 21 crops cultivated in the US showed a rapid increase in the application of pesticides over the 48-year period of 1960-2008 (Fernandez-Cornejo et al., 2014). Pesticide use increased from 196 million pounds of active ingredients in 1960 to 632 million pounds in 1981. The significant increase in the application of pesticides was mainly due to the increased share of the planted acres treated with herbicides for weed control, e.g., the total planted acreage for corn, wheat, and soybean increased from the early 1960s to the early 1980s. The increased adoption of herbicides was also driven by price declines that improve the cost-effectiveness of herbicides relative to other pest control practices and encouraged the substitution of herbicides for labor, fuel, and machinery used in mechanical weed control.

The impacts of chemical pest control, both positive and negative, are difficult to quantify, but of increasing interest to the public (van der Werf et al., 2020). The goal of this study was to apply Life Cycle Assessment (LCA) methods to analyze the environmental impacts of chemical controls for weeds, insects, and disease for corn, soy, and cotton production in the U.S. Midwest. The purpose of the LCA was to provide Crop Life America (CLA) with quantitative assessments of the impacts of chemical pest control across the life cycle of each crop system.

ES 2 Goal and Scope

The study's primary goal was to analyze the environmental impacts of chemical controls for weeds, insects, and diseases for corn, soy, and cotton production in the U.S. Midwest. This assessment provides Crop Life America (CLA) with insight regarding the impacts of chemical pest control across the life cycle of each crop system. The environmental key performance indicators that U.S. crop producers are concerned with assessing are short-term climate change, fossil and nuclear energy use, land occupation, and water consumption. The remaining life cycle impact assessment midpoint impact categories are reported for completeness of the LCA.

The specific goals of this project are:

1. Perform an ISO 14040/4044 compliant lifecycle assessment (LCA) of impacts of production of each of the three crops under US standards of practice with and without the use of pesticides (herbicides, insecticides, and disease control):
    a. Functional Unit for corn: One kg (15.5% moisture),
    b. Functional Unit for soybean: One kg (12.5% moisture),
    c. Functional Unit for cotton: One kg of lint with seed and trash (5% moisture),
2. Identify critical stages in the supply chain for midpoint assessments for crop production with and without the use of chemical pest controls.
3. Review of report by an external expert panel in order to support comparative assertions to be disclosed to the public.

The scope of this LCA is a cradle-to-farm gate assessment of corn, soy, and cotton. This LCA focused on four mid-point impact categories of concern using IMPACT World+ for each crop:

1. Energy use (reported as *fossil and nuclear energy use*),
2. Water use (reported as *water consumption*),
3. Greenhouse gas emissions (reported as *short-term (100 year) climate change*), and
4. Land use (measured as *land occupation biodiversity*).

The full range of midpoint categories for IMPACT World+ are presented for further context but were not the focus of this LCA. The LCA analyzed each crop's production practices with and without pesticide use based on representative (archetypal) farms from across the U.S. in order to estimate the variability of production conditions and practices for corn, soybeans, and cotton. We include a sensitivity test for alternate impact assessment frameworks, which show the same pattern of results as the Impact World+ framework.

Attributional modeling was adopted since the alternative scenarios are well-defined such that there is no multifunctionality modeled in the foreground and assessing differences in background databases is beyond the scope of this study. ISO 14044 standards do not support combining multiple metrics into a single score in applications where the study commissioner will communicate comparative results to the public. Therefore, the results of this project are reported for each impact category (ISO, 2006a).

ES 2.1 Life Cycle Inventory Approach

The data collection and analysis methods developed in LCA provide a rational basis for evaluating natural resource use efficiency. The Life Cycle Inventory (LCI) for this LCA was constructed from a combination of data from county production budgets, public databases such as USDA-ARS and NASS, peer-reviewed scientific data, and simulated processes using the APEX model (Reap et al., 2008). However, finding data directly from producers at a sufficient level of detail is challenging and the counterfactual situation without pesticide use is not typically practiced. For that reason, this LCA relied on crop production simulation models using Agricultural Policy Extender (APEX) (Gassman et al., 2009) to generate inventory data to analyze agricultural management's impact at the field and watershed level.

The APEX models for corn, soy and cotton scenarios for this LCA were created to represent the dominant crop production practices across the US to evaluate the impacts, both negative and positive of the use of chemical pest controls. We simulated the field operations across 40 archetype production systems for each crop (four counties each in the top 10 producing states for corn and cotton, and no more than four counties each for the top 13 producing states for soybeans due to data availability issues), calibrated to yield based on generic production practices for the representative county. Four scenarios in addition to the baseline were simulated for this project using APEX:

1. Cover Crops,
2. No Chemical Disease Control (NoDiseaseCont),
3. No Chemical Insect Control (NoInsectCont),
4. No Chemical Weed Control (NoWeedCont).

The four scenarios were constructed with data from existing literature, and each simulates the impact an adjustment to the production practices used has on the environmental impact of crop production. In particular, the three no chemical control scenarios were calibrated using the pest pressure variables within APEX for the no chemical disease and insect control scenarios and the planting population of representative weeds for the no chemical weed control scenario. The calibration was performed on the annual yields within the simulation period to have yield penalties approximating the medium yield penalty values from the literature review.

The LCA was performed using SimaPro version 9.1.0.8 with Ecoinvent 3.6 (compiled December 2019) as the primary library from which background datasets were taken. The crop production processes were constructed based on the LCI generated from the APEX models. The Life Cycle Impact Assessment (LCIA) was performed for midpoint categories using IMPACT World+ because this framework is internationally accepted and has both global and regional characterization factors.

ES 2.2 Results

The summary results of the LCIA of eliminating chemical pest controls on corn, soy, and cotton for the four primary environmental midpoint categories show the importance of yield loss on environmental impacts (figures ES-1 through ES-3). The box plots represent the mean, upper- and lower-95 percent confidence intervals, and outlier data. Letters represent Dunn-Bonferroni post-hoc test groups.

Corn Production: The results of environmental midpoint LCIA impact categories showed consistent results across chemical pest control scenarios for U.S. corn production. The four primary impact categories (short-term climate change, fossil and nuclear energy use, land occupation-biodiversity, and water consumption) were significantly increased for the counterfactual evaluation of eliminating chemical pest control (disease, insect, and weed). The No Insect Control and No Weed Control scenarios had the largest effect on these midpoint impact categories. Adding cover crops did not significantly change impacts for any of the midpoint indicators compared to the baseline.

Soy Production: The results of environmental midpoint LCIA impact categories showed consistent results across chemical pest control scenarios for U.S. soy production. The four primary impact categories (short-term climate change, fossil and nuclear energy use, land occupation- biodiversity, and water consumption) were significantly increased for the counterfactual analysis of eliminating chemical pest control (disease, insect, and weed). Eliminating insect control had the largest effect on all midpoint impact categories. Adding cover crops did not significantly change impacts for any of the midpoint indicators compared to the baseline.

Cotton Production: The results of environmental midpoint LCIA impact categories showed consistent results across chemical pest control scenarios for U.S. cotton production. The four primary impact categories (short-term climate change, fossil and nuclear energy use, land occupation- biodiversity, and water consumption) were significantly increased for the counterfactual evaluation of eliminating chemical pest control (disease, insect, and weed). Eliminating chemical control of insects had statistically significant higher impacts across all midpoint impact categories. Adding cover crops did not significantly change impacts for any of the midpoint indicators compared to the baseline.

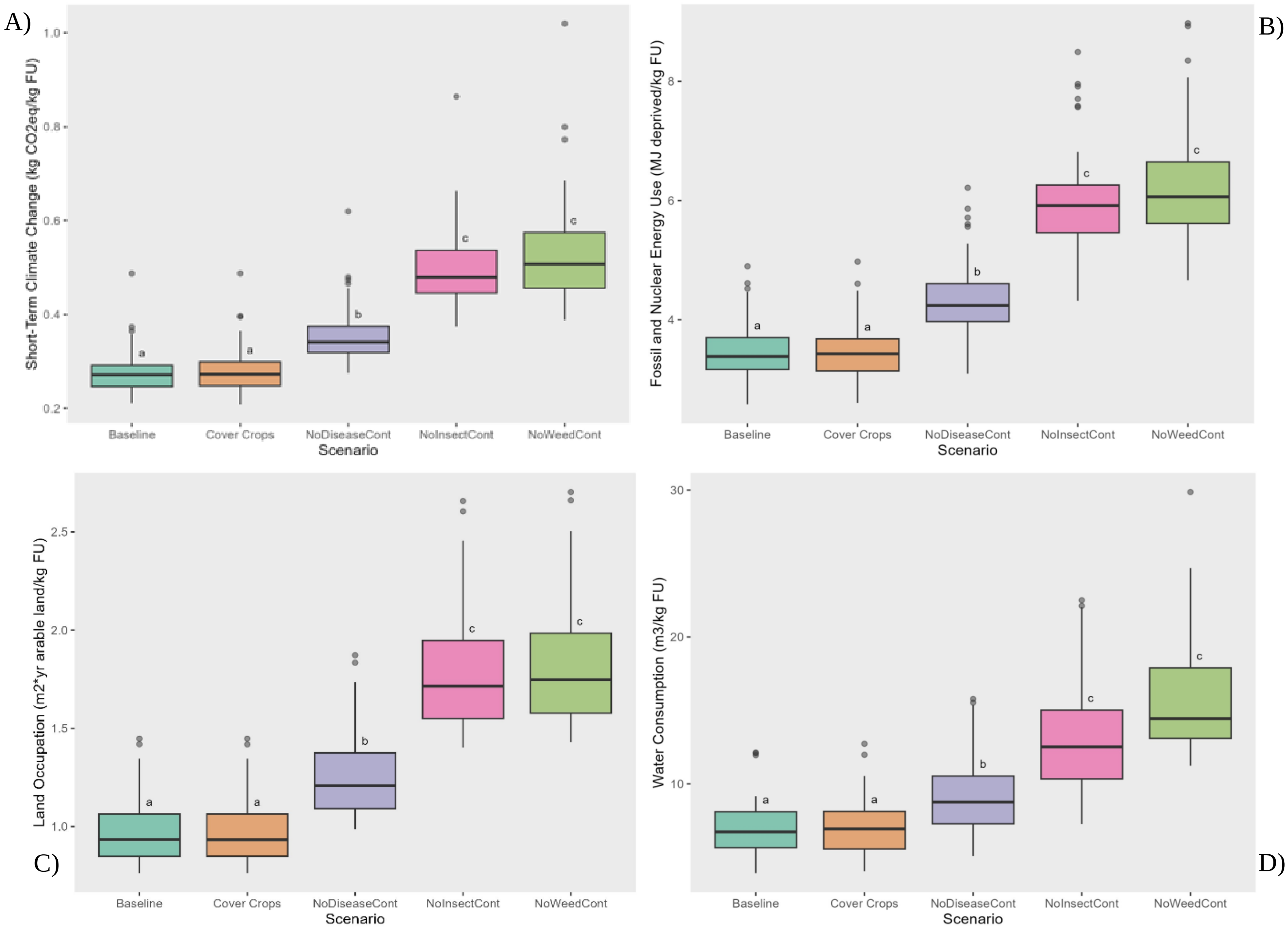

Figure ES 1: Results for Corn Impact Analysis: A) Short-Term Climate Change, B) Fossil and Nuclear Energy Use, C) Land Occupation, and D) Water Consumption. Letters represent Dunn-Bonferroni post-hoc test groups (all p values <0.05).

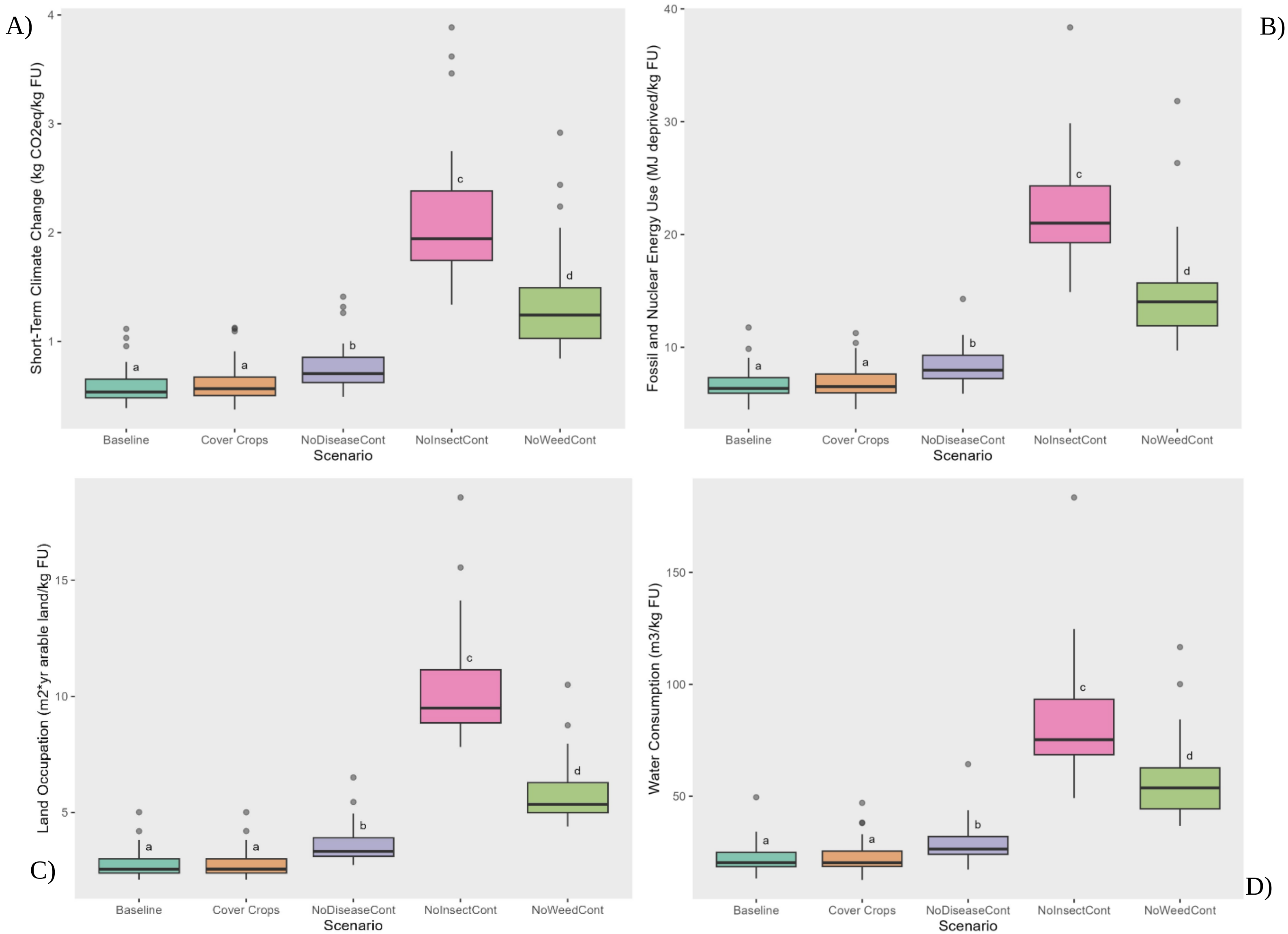

Figure ES 2: Results for Soybean Impact Analysis: A) Short-Term Climate Change, B) Fossil and Nuclear Energy Use, C) Land Occupation, and D) Water Consumption. Letters represent Dunn-Bonferroni post-hoc test groups (all p values <0.05).

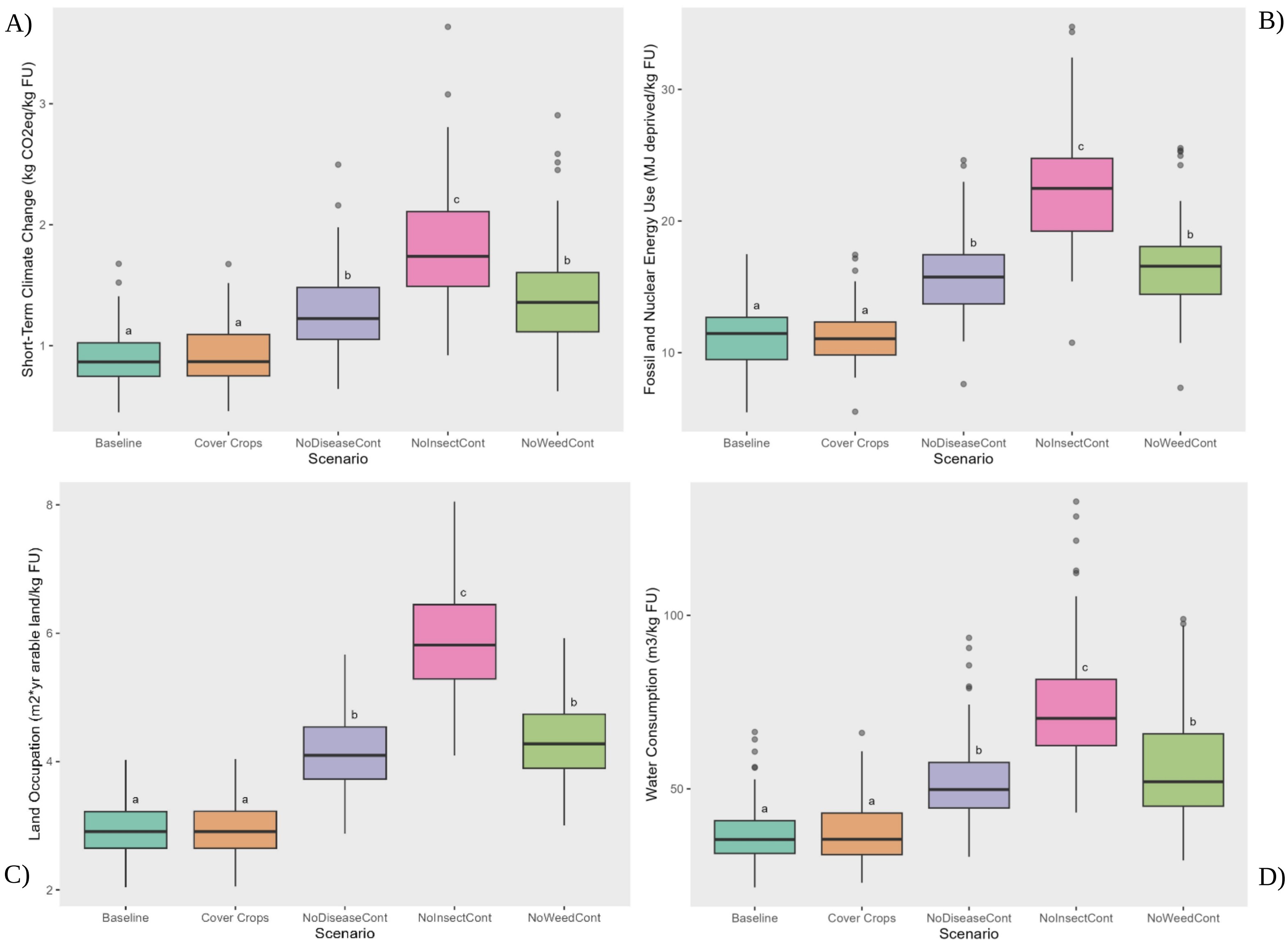

Figure ES 3: Results for Cotton Impact Analysis: A) Short-Term Climate Change, B) Fossil and Nuclear Energy Use, C) Land Occupation, and D) Water Consumption. Letters represent Dunn-Bonferroni post-hoc test groups (all p values <0.05).

ES 3 Conclusions

The results of environmental midpoint LCIA categories for corn, soy and cotton showed consistent results across chemical pest control scenarios for U.S. archetypes (Table ES 1). Producing crops without chemical disease control increased all four priority impact categories significantly ($p < 0.05$). Overall impact increases were greatest across all three crops for all four priority impact categories for insect control followed by weed control and disease control respectively. The highest increase for impact categories were for soy with no insect control (more than 3-fold), followed by soy with no weed control (more than doubled) and cotton with no insect control (doubled).

Table ES 1: Summary impacts of not using chemical pest controls across corn, soy, and cotton in the U.S., measured as percent of baseline impact.

Corn

Impact Category	Units	NoDiseaseCont	NoInsectCont	NoWeedCont
Climate change short term	kg CO_2 eq	29%*	82%	93%
Fossil and nuclear energy use	MJ deprived	26%	72%	80%
Land occupation biodiversity	m^2 arable la	29%	84%	88%
Water Consumption	m^3	30%	85%	126%

Soy

Impact Category	Units	NoDiseaseCont	NoInsectCont	NoWeedCont
Climate change short term	kg CO_2 eq	29%	258%	127%
Fossil and nuclear energy use	MJ deprived	24%	226%	116%
Land occupation biodiversity	m^2 arable la	29%	84%	88%
Water Consumption	m^3	30%	270%	153%

Cotton

Impact Category	Units	NoDiseaseCont	NoInsectCont	NoWeedCont
Climate change short term	kg CO_2 eq	44%	105%	60%
Fossil and nuclear energy use	MJ deprived	41%	100%	50%
Land occupation biodiversity	m^2 arable la	41%	100%	47%
Water Consumption	m^3	41%	101%	51%

* Meaning 29% higher than baseline scenario

Cover crop practices resulted in no significant changes from the baseline for any of the LCIA frameworks. For corn, soy, and cotton this means that all the additional inputs to produce cover crops (seed, fuel, water, cultivation, etc.) created no significant increase in environmental impacts. The advantages of cover crops for soil conservation, soil health, and water conservation are well documented and not measured in any LCIA framework. These results support the assessment that the environmental impacts of cover crops as a management practice are net positive for corn, soy, and cotton in the U.S.

Life cycle assessment of impacts of eliminating chemical pesticides used in the production of U.S. corn, soybeans, and cotton.

Final Report

1. Introduction

The use of pesticides (fungicides, insecticides, and herbicides) is reported to prevent a substantial decrease in crop yield. The application of herbicides has also helped to reduce the amount of labor, machinery, and fuel that have been used mainly for mechanical weed control. Despite these benefits, there are some harmful effects which arise from improper, or off-label use of pesticides including impacts on human health and the environment.

A review of 21 crops cultivated in the US showed a rapid increase in the application of pesticides over the 48-year period of 1960-2008 (Fernandez-Cornejo et al., 2014). Pesticide use increased from 196 million pounds of active ingredients in 1960 to 632 million pounds in 1981. The significant increase in the application of pesticides was mainly due to the increased share of the planted acres treated with herbicides for weed control, e.g., the total planted acreage for corn, wheat, and soybean increased from the early 1960s to the early 1980s. The increased adoption of herbicides was also driven by price declines that improve the cost-effectiveness of herbicides relative to other pest control practices and encouraged the substitution of herbicides for labor, fuel, and machinery used in mechanical weed control. However, by 2018 the total pesticide use had trended slightly downward (to 516 million pounds in 2018), as most of the planted acres, mainly soybean and corn were already being treated with herbicides by 1980. Between 1982-2008, there were fluctuations in pesticide usage, driven by various factors, such as changes in planted acreage, costs, weather, pesticides regulations, and the introduction of new pesticides and genetically engineered seeds. Furthermore, about 5-10% of corn, wheat, and cotton acres were reported to be treated with herbicides in 1952, which reached 90-99% of the acres planted by 1980. Of the top four most used active ingredients in 2008 (glyphosate, atrazine, acetochlor, and metolachlor), all were herbicides. The share of fungicides has remained at about 7% since 1971, down from 11-13% in the early 1960s. Other pesticides including soil fumigants, desiccants, harvest aids, and plant growth regulators, accounted for about 5-11% of the total pesticide use from 1960-1992, and increased to 17% in 2002, later declining to 13% in 2008.

Corn has been the top pesticide-using crop in the US since 1972 and received about 39% of the pesticides in 2008 (mostly herbicides). Soybeans had the next largest share in 2008, accounting for 22% of the pesticides used, again mostly herbicides. Cotton accounted for about 7% of pesticide use, mostly insecticides. For cotton, the downtrend of pesticide applications since 1972 is mainly attributed to the replacement of Dichlorodiphenyltrichloroethane (DDT) and other older insecticides with more effective products, eradication of the boll weevil, and adoption of insect resistant (Bt) cotton. The impacts of chemical pest control, both positive and negative, are difficult to quantify, but of increasing interest to the public (van der Werf et al., 2020). The goal of this study was to apply Life Cycle Assessment (LCA) methods to analyze the environmental impacts of chemical controls for weeds, insects, and disease for corn, soy, and cotton production in the U.S. Midwest. The purpose of the LCA was to provide Crop Life America (CLA) with quantitative assessments of the impacts of chemical pest control across the life cycle of each crop system.

2. Literature review

A comprehensive review of pesticide LCA literature is presented in Appendix A: Literature Review.

3. LCA methods

LCA is an accounting scheme based on scientific and engineering principles of material and energy flows and is constructed as a set of linked unit processes. Each unit process accounts for the material and energy, raw material consumption, and emissions to the environment necessary to produce a product or service. We used SimaPro software for the analysis of the Life Cycle Inventory and Life Cycle Impact Assessment[1]. We followed the standard procedure for conducting LCA as elaborated in a suite of international standards (ISO, 2006b, 2006a). ISO 14040 defines principles and frameworks and provides a clear overview of the practice, applications, and limitations of LCA to a broad range of potential users and stakeholders, including those with limited knowledge of LCA. ISO 14044 stipulates specific requirements and is designed to prepare, create, and critically review life cycle inventory (LCI) analysis. It also offers guidance on the impact assessment phase of LCA, that is, the life cycle impact assessment (LCIA) and on the interpretation of LCA results, as well as the nature and quality of the data collected.

The basic steps of an LCA are: (i) goal and scope definition, (ii) develop the life cycle inventory (LCI), (iii) conduct the life cycle impact assessment (LCIA), and (iv) interpretation of results (Figure 1). LCIA is the phase in the LCA aimed at understanding and evaluating the magnitude and significance of the potential environmental impacts of a product system. In this phase, inventory data on inputs and outputs are translated into indicators about the product system's potential impacts on the environment and the availability of natural resources. The last stage of an LCA is the interpretation of the results of the LCI and LCIA according to the goal of the study. Interpretation allows the results of each of the previous steps to be placed into the system context and to point out the key factors for environmental decision-making. In this study, the LCA methodologies were carried out in accordance with ISO 14040 and 14044 standards to comply with public reporting procedures (ISO, 2006b, 2006a). This is a third-party, full assessment report intended to support internal decision-making and comparative assertions to the public.

[1] Pré-sustainability, https://pre-sustainability.com/ 2023

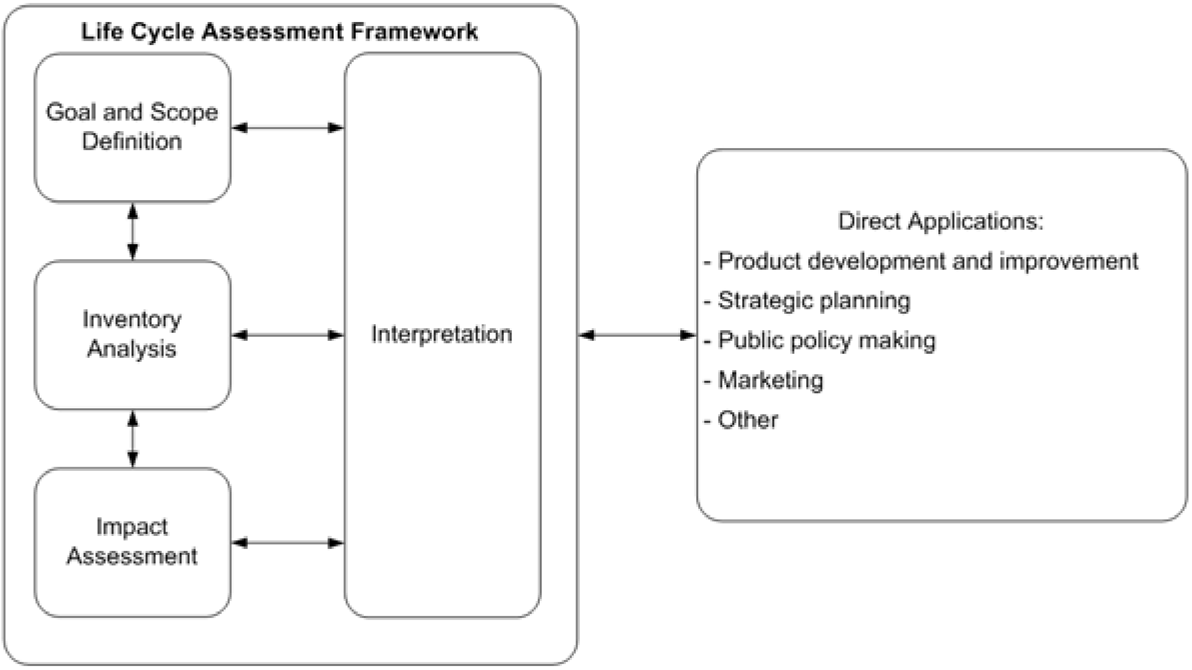

Figure 1: Stages of an LCA (from ISO 2006a).

3.1 Goal and scope definition

The study's primary goal was to analyze the environmental impacts of chemical controls for weeds, insects, and disease for corn, soy, and cotton production in the U.S. Midwest. This assessment provides Crop Life America (CLA) with insight regarding the impacts of chemical pest control across the life cycle of each crop system. The environmental key performance indicators that U.S. crop producers are concerned with assessing are short-term climate change, fossil and nuclear energy use, land occupation, and water consumption. The remaining life cycle impact assessment midpoint impact categories are reported for completeness of the LCA.

The specific goals of this project are:

1. Perform an ISO 14040/4044 compliant lifecycle assessment (LCA) of impacts of production of each of the three crops under US standards of practice with and without the use of pesticides (herbicides, insecticides, and disease control).
2. Identify critical stages in the supply chain for midpoint assessments for crop production with and without the use of chemical pest controls.

3. Review of report by an external expert panel in order to support comparative assertions to be disclosed to the public.

The scope of this LCA is a cradle-to-farm gate assessment of corn, soy, and cotton (Figure 2). The corn, soy and cotton supply chains were divided into 4 stages: (1) pre-farm supply chain; (2) planting; (3) fertilizer application, disease and pest control, irrigation; (4) harvest and drying. For each stage, a separate full inventory of inputs and emissions was created and linked to construct the cradle-to-gate system. Emissions to air water and soil include releases of greenhouse and combustion gases, chemicals in both the foreground (crop production) and background (activities upstream of on-field activities). The impact assessment was then performed for each crop using the SimaPro platform, and statistical analyses performed to provide a basis for comparison of the baseline and counterfactual scenarios.

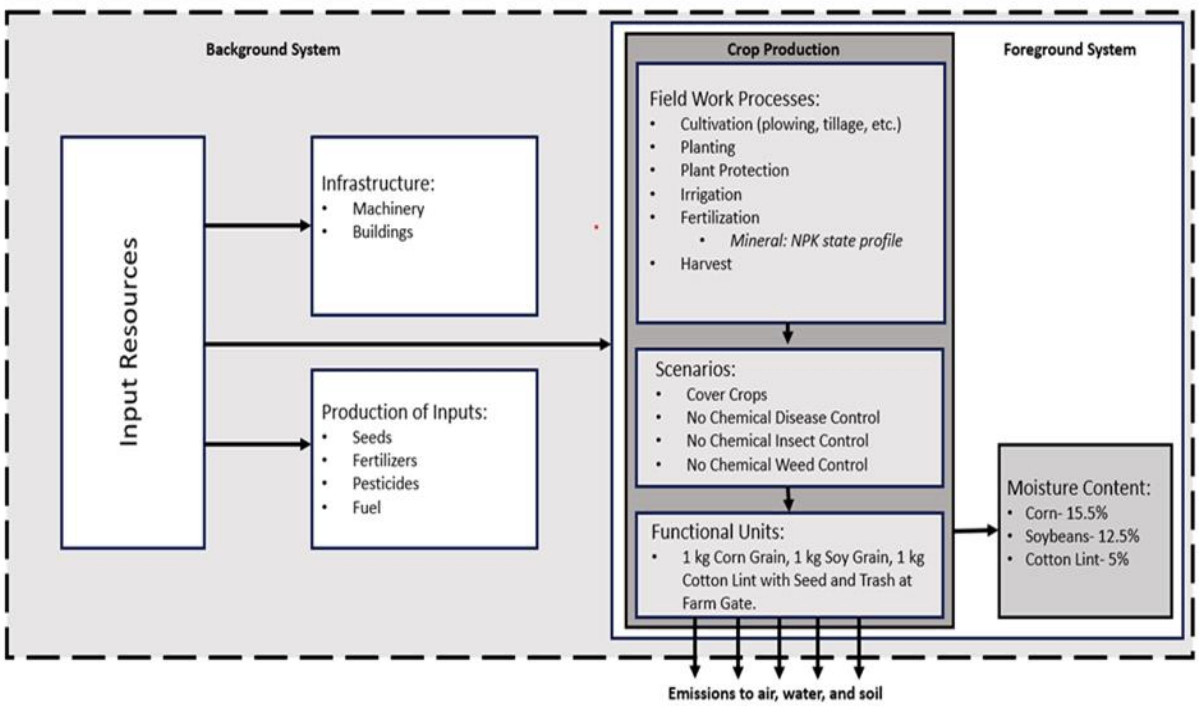

Figure 2: Systems Boundaries for Corn, Soy, and Cotton LCAs

The impact categories analyzed were midpoint impact categories using IMPACT World+ 2.0.1 for each crop, comparing production with and without pesticide use in total across the U.S. Attributional modeling was adopted since the alternative scenarios are well-defined such that there is no multifunctionality modeled in the foreground and assessing differences in background databases is beyond the scope of this study. ISO 14044 standards do not support combining multiple metrics into a single score in applications where the study commissioner will communicate comparative results to the public. Therefore the results of this project are reported for each impact category (ISO, 2006a). Because the study is intended for release to the public, the ISO review panel evaluated the analysis for conformance with the ISO series of standards that cover LCA.

3.2 Functional unit and system boundary

In LCA studies, the choice of a functional unit is defined to relate the environmental footprints of the target product(s) with respect to the quantified reference flows. No specific performance characteristics will differ between the production systems; thus, in this case, the reference flow and functional unit are equivalent and are described below.

1. Functional Unit for corn: One kg (15.5 % moisture),
2. Functional Unit for soybean: One kg (12.5 % moisture),
3. Functional Unit for cotton: One kg of lint with seed and trash (5 % moisture).

3.3 Multi-functionality

For the current systems, all multi-functional processes are in upstream input unit processes and thus already calculated in the Ecoinvent unit processes selected as inputs. Because no allocation was needed for foreground systems, the ISO requirement for sensitivity testing of modeling assumptions (i.e., choice of the solution for multi-functionality) does not apply.

3.4 Data Quality Requirements

Data of sufficient quality necessary to support the goal and scope of an LCA is a requirement. Table 1 summarizes the data quality characteristics relevant for this study; the available data is considered of sufficiently high quality to support the goal and scope.

Upstream processes for purchased inputs to the main production processes (e.g., electricity, fuel, transportation, etc.) were taken from the Ecoinvent v3.6 cut-off database. We chose the average market process for U.S. electricity. Environmental impacts associated with infrastructure (buildings, machinery, etc.) and ancillary services (banking, legal, accounting, etc.) are not included for foreground processes except when an existing Ecoinvent unit process includes background infrastructure. Background infrastructure was not excluded as testing indicated that the model was sensitive to changes in background infrastructure for some midpoint impact categories. Specifically, we noted that, for some of the toxicity impact categories, there was a notable contribution from infrastructure in the background unit processes, though only minor differences were noted in the non-toxicity impact results. Lifecycle inventory processes from the Ecoinvent database are assumed to be of adequate quality for the study.

3.5 Lifecycle Impact Assessment

As noted in the ISO standards, LCIA results are relative expressions and do not predict impacts on category endpoints, the exceeding of thresholds, safety margins, or risks. This study aims to be reasonably comprehensive in evaluation of potential environmental impacts associated with changes in pest management practices for corn, soybean, and cotton production in the US. Climate change and water resources are of significant societal concern. These two categories are thoroughly covered in this assessment. However, other categories including fossil energy consumption, land occupation, fine particulate matter formation, and aquatic eutrophication are also relevant impact categories for which high-quality data are reasonably available and are also reported. Acidification potential is generally much less of a concern today than in the 1970s and 1980s because of significant reductions in acidifying emissions associated with the Clean Air Act, and therefore is not a focus for this assessment. Human and ecotoxicity potential impacts are relevant categories included in the reporting, although not the primary focus of the study Commissioner.

Table 1: Summary of data quality assessment considered acceptable for achieving the goal and scope for the current project.

Time coverage	All primary data are contemporaneous with sufficient data available for all years within the modelled period of 2015-2020 for the model construction.
Geographical coverage	An adequate range of locations has been included covering 40 counties for each crop across the major U.S. production regions.
Technology coverage	Current Management Practices and manufacturing technologies appropriate to the systems under study have been adopted. Inputs of materials, all for conventional management in crop cultivation, were taken from the Ecoinvent database; this coverage may be dated in some instances but will be uniform across all scenarios.
Precision	The model yields were all calibrated using the methods described in section 4D to reach an acceptable level of precision to the actual field conditions in the counties being modelled.
Completeness	To our knowledge, no activities to be considered different between the compared scenarios have been excluded; thus, the data sets are considered complete
Representativeness	Models are based upon data that has been collected from the systems that they are intended to represent.
Consistency	Modelling choices and other assumptions that have been uniformly applied across all scenarios evaluated.
Reproducibility	We have included sufficient information to reproduce the study results to the extent possible.
Data sources	Data from a previous study and public sources and scientific literature were the primary data sources, coupled with APEX simulations

3.6 Data gaps

The primary input inventory flows were readily available from a range of sources as presented in the inventory section. The inventory flows for emissions were taken from the output of the APEX model. There was one class of inputs and emissions for which there were notable data gaps: the quantity of some pesticides and missing characterization factors for others.

3.6.1 Missing production dataset

Due to some gaps in the availability of production data for some of the chemicals, we elected to use a generic pesticide production flow to represent the production of all pesticides within the system In cases where a reported chemical was not the available databases, its production was included as a generic pesticide using the unit process, Pesticide, unspecified {GLO}| market for | Cut-off, U as the proxy flow. This was accomplished by calculating the average application rate in kg/yr/hectare for each state included in the study based on available NASS data and then calculating the cumulative total applied pesticides as a single flow (USDA NASS, 2022, 2019a).

3.6.2 Missing application quantity

In some instances, chemical application rates were not available for all years during the study period, so the available data was averaged, and the average was assumed for the application rate each year during the study period. To determine the environmental fate of each chemical, we examined pre-existing models of each crop system (Cooper et al., 2012). Pesticides within those models were divided by pesticide class (herbicide, fungicide, and insecticide) and average ratios for emission to water, soil, and air were calculated. These ratios were then applied to the state pesticide profiles to assign emissions of each chemical to soil, water, and air respectively (Table 2). For some states, certain chemical application rates were withheld, meaning that the NASS database showed that the chemical was applied but did not publish data on how much of the chemical was applied, resulting in data gaps. Withheld chemicals were excluded from the LCI, a complete list of withheld chemicals is presented in Appendix C: List of Chemicals with Withheld Data in the NASS Database. The impact of knowledge uncertainty for these parameters is relatively low given the variability of toxicity between chemicals. The uncertainty in toxicity characterization factors (human and environmental) is very high, so uncertainty between known and unknown pesticides applied in the baseline scenarios is anticipated to have a minor effect on comparisons of environmental impacts.

Table 2: Pesticide Emission Allocation Percentages

Crop	Class	Emissions to air	Emissions to water	Emissions to soil
Corn	Fungicide	0.05%	0.01%	99.95%
	Herbicide	9.00%	1.00%	90.00%
	Insecticide	3.17%	0.35%	96.48%
Cotton	Fungicide	19.60%	0.88%	79.52%
	Herbicide	9.00%	1.00%	90.00%
	Insecticide	9.00%	1.00%	90.00%
Soybeans	Fungicide	0.82%	0.09%	99.09%
	Herbicide	9.00%	1.00%	90.00%
	Insecticide	2.43%	0.27%	97.30%

3.6.3 Missing characterization factor

There were also some chemicals that were present in the NASS data but were not characterized in Impact World+ version 2.0.1. In these cases, proxy datasets were identified for use in the analysis from databases available in SimaPro (an LCA software platform). These proxy datasets were selected by identifying the pesticide class for each chemical with missing characterization factors, and choosing the chemical within the same class, which was available in the Ecoinvent database, that had the highest characterization factor as its proxy. In the instance where there wasn't a suitable replacement within the same chemical class, the scope of the selection was broadened until a replacement chemical that did have a characterization factor was identified. If no replacements were identified within the same mode of action, the search was further expanded to all chemicals in the same pesticide classification (herbicide, fungicide, or insecticide) if needed. These substitutions are documented in Appendix D: List of Substituted Chemicals.

3.7 Cut-off criteria

ISO 14044 provides guidance on the different strategies for simplifying the study, either by excluding less relevant product systems or reducing the amount of inventory data through the so-called cut-off rules (ISO, 2006b). The purpose of including cut-off criteria in the ISO guidelines is to allow the exclusion of inventory flows representing less than a specified threshold of the total input of unit processes. No cut off was applied in any foreground inventory. Cut-off of flows in the background Ecoinvent database are out of this project's scope as such no modification was made to the upstream components of the process flows used for this project. Any data readily obtained was not excluded from this study, and we are confident that missing data (none has been identified) will not affect the conclusions of this study. An ISO requirement regarding cut off for comparative assertion reporting is the performance of a sensitivity analysis to determine if mass, energy, or impact cut off have been met. In this study, this is not required as no foreground cut off was applied.

3.8 SimaPro Software

The LCA was performed using SimaPro version 9.1.0.8 with Ecoinvent 3.6 (compiled December 2019) as the primary library from which processes were obtained[2]. SimaPro, a life cycle and sustainability assessment software tool, developed by PRé Consultants was used for the project. The Ecoinvent database is one of the world's leading LCI databases regarding transparency and consistency. It provides documented process data for thousands of products and is frequently used as a source of information for upstream supply chain inputs. The background data sets from the Ecoinvent database (v 3.6 cut-off model) are subject to separate licensing. SimaPro was used to

[2] SimaPro by PRé Consultants, https://simapro.com/, and Ecoinvent, https://ecoinvent.org/.

link the individual stages of production, creating a supply chain model. The integrated flows of materials and energy required to produce the respective functional units were converted to impact category equivalents representative of environmental burdens-the lifecycle impact assessment stage.

3.9 Audience

For this LCA, the intended audiences are the stakeholders of CropLife America, including its member organizations, agricultural supply chain businesses, and the consuming public.

3.10 Type and Format of the Report

In accordance with the ISO requirements (ISO, 2006) the results, data, methods, assumptions and limitations from this study are presented in a transparent manner and in sufficient detail to convey the complexities, limitations, and trade-offs inherent in the LCA to the reader. This allows the results to be interpreted and used in a manner consistent with the goals of the study. This LCA has been conducted to be conformant to the ISO/TS 14071 standard for third party review.

3.11 Third-party review

The commissioner of this study is CropLife America, and it was conducted by the University of Arkansas. It is intended that the results of this study be shared with the stakeholders who have provided data in support of the project and the public. Because the results will be disseminated beyond the commissioner and practitioner, an external review was conducted. The review consisted of three rounds of comment/response during the period of time between fall 2023 and spring 2024. The review panel comments, responses, and critical review statement are presented in Appendix H: ISO Critical Review. The review panel members are:

- Tom Gloria, Industrial Ecology Consultants. t.gloria@industrial-ecology.com. An expert LCA practitioner with extensive ISO compliance review experience.
- Mike Levy, First Environment, Inc. mlevy@firstenvironment.com. An expert LCA practitioner with extensive ISO compliance review experience.
- Terrie Boguski, Harmony Environmental. <tboguski@harmonyenviro.com>. An expert LCA practitioner with extensive ISO compliance review experience.

4. Life cycle inventory

The data collection and analysis methods developed in LCA provide a rational basis for the evaluation of natural resource use efficiency. However, it is very difficult to find data at a sufficient level of detail directly from producers, further, the counterfactual evaluation without pesticides does not exist in practice. For these reasons, LCA practitioners often rely on crop production simulation models (Reap et al., 2008) such as APEX to generate inventory data used to analyze the impact of agricultural management at the field or watershed-level. For this project, mass and energy flows in archetype production systems were parameterized using APEX model parameters, calibrated to produce yields for each scenario.

4.1 Archetype Selection

Production practices for crops vary across the US based on soils, climate, market variables, and producers. In order to capture the variability in practices and life cycle impacts of crop production across the US we build upon the works of other LCA practitioners to create models of synthetic farms, called archetypes, to represent average production practices and conditions in discrete locations (Cooper et al., 2012; Kim et al., 2019).

Locations for archetype models for each crop were from the top 10 producing states for each crop, and the top four producing counties within each state, using NASS QuickStats (USDA NASS, 2022). The top four producing counties each in the top 10 producing states for corn and cotton, and no more than four counties each for the top 13 producing states for soybeans due to data availability issues served as archetypes for each crop. We constructed field-scale production models based on average production practices and conditions in each county. In the few instances where adequate production data were not available, or we deemed a county not suitable for inclusion for one of the crops, another county was selected in its place either from the same state or another top producing state. The details of crop archetypes and the LCIs created from them are presented in Appendix B: Crop Archetype Design, and maps of counties for each crop are shown in Figure 3 through Figure 5.

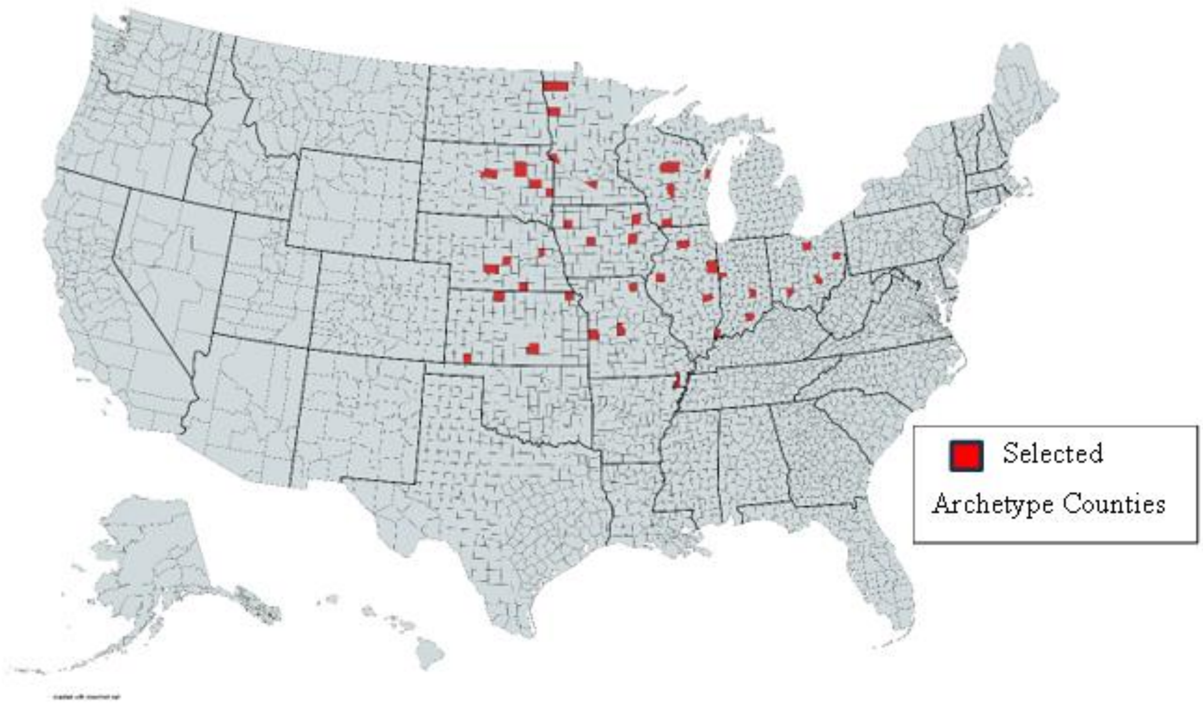

Figure 3: Archetype Locations for U.S. Corn

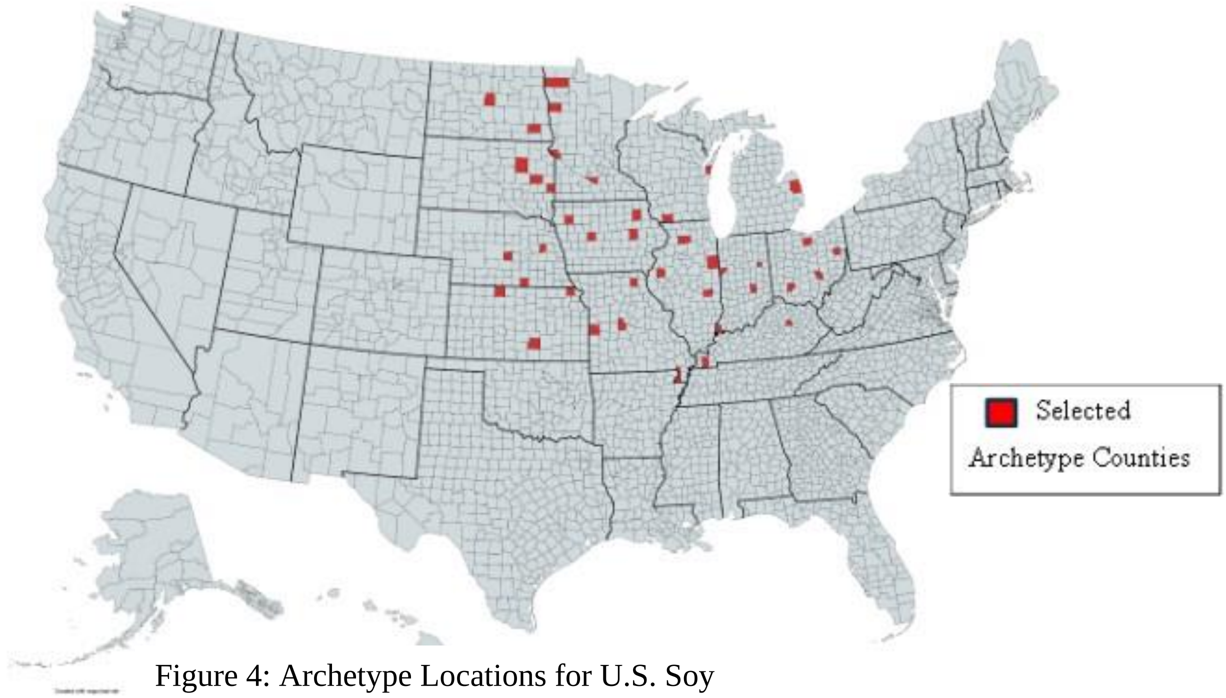

Figure 4: Archetype Locations for U.S. Soy

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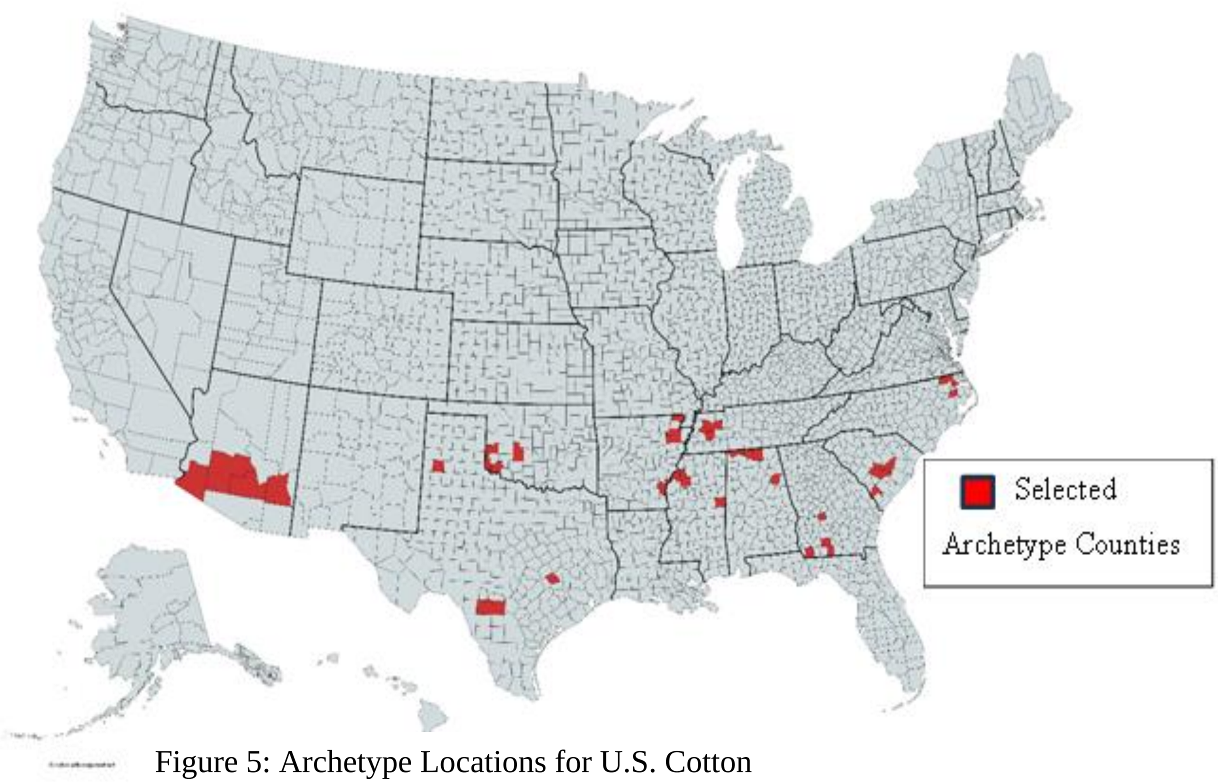

Figure 5: Archetype Locations for U.S. Cotton

4.2 APEX Archetype Model Construction Process

The Agricultural Policy Extender (APEX) model is a crop production model that is designed to simulate management practices from scales ranging from individual farms to small watersheds. The model is a combination of the Environmental Policy Integrated Climate (EPIC) and pesticide component, Groundwater Loading Effects of Agricultural Management Systems (GLEAMS), APEX uses these components to simulate land characteristics such as topography, soil type, and weather; as well as management practices such as crop rotation, tillage, land use, and chemical application. The model considers the impact of management practices on erosion, water supply, soil quality, pests, and other factors (Gassman et al., 2010). The APEX model[3] has been utilized for assessing environmental impacts of crop production and was selected for this study due to its widespread usage and modeling flexibility.

One of the strengths of the APEX model is that it is a system model that directly simulates all field operations to provide estimates of resource use, simulates soil biogeochemistry dynamics for nitrogen and carbon, and generates lifecycle inventory data for direct nitrogen emissions and carbon sequestration/loss from the soil. However, the model does not account for indirect emissions of nitrogen arising from volatilization, leaching, and runoff. The Intergovernmental Panel on Climate Change (IPCC) provides a methodology for estimating the nitrous oxide emissions from these processes which we analyzed and simulated in this study.

4.2.1 Nitrogen Modeling

Nitrous oxide (N_2O) is an important greenhouse gas emission from managed agricultural soils due to its large global warming potential. Nitrogen flux into the soil through application of fertilizers, application of manure, decomposition of crop residue, and mineralization of nitrogen in soil organic matter is important in agricultural modeling as it impacts the amount of nitrogen available for nitrification and denitrification, which in turn impacts the amount of N_2O emitted. Due to the impact of these emissions, the environmental performance of most agricultural systems is heavily influenced by the nitrogen cycle. In the context of this study, the impact observed from

[3] https://epicapex.tamu.edu/about/apex/)

these dynamics is strongly influenced by differences in crop yield, as will be shown later in this report.

Nitrogen movement through a system is controlled by several distinct processes: nitrification-denitrification, volatilization, leaching, and runoff. Each of these processes can impact the lifecycle inventory used in LCA thus influencing various impact categories such as climate change, eutrophication, and acidification. To model these interactions, many LCA practitioners utilize the IPCC methodology to evaluate soil N emissions.

The IPCC methodology for modeling soil nitrogen dynamics estimates direct N emissions from managed soils as well as indirect emissions following nitrogen volatilization, leaching, and runoff (Eggleston et al., 2006). However, the IPCC method does not account for variations in factors that influence the amount of N_2O emitted from managed soils such as soil type, management practices, and environmental conditions. The IPCC method uses a standard emission factor as a fraction of nitrogen applied.

The APEX model simulates a more complete version of the nitrogen cycle by including N inputs from the atmosphere, fertilizer applications, crop uptake, sediment transport, mineralization, immobilization, nitrification, denitrification, volatilization, leaching, surface runoff, lateral subsurface flow, and tile flow. This enables the model to make estimates of nitrogenous emissions that are more representative of site-specific conditions; however, it also requires detailed knowledge of site-specific conditions and robust calibration for each archetype being simulated which is challenging to achieve. In order to simulate the nitrogen dynamics as completely as possible we synthesized the strengths of both methods into the model.

4.2.2 APEX nitrogen balance

The model incorporates simulation of nitrogen dynamics summarized in the following equation:

$$N_{soil} = N_{init} + N_{dep} - N_{ero} - N_{wind} - N_{run} - N_{SSFo} - N_{perc} - N_{denitr} - N_{crop} - N_{vol} + N_{mfert} + N_{ofert} + N_{legu} + N_{SSFi} - N_{drain} - N_{burn} + N_{point}$$

Where Nsoil is the accumulated soil nitrogen pool; Ninit is the initial total Nsoil; Ndep is N added with rainfall; Nero is N transported with sediments; Nwind is N loss in wind erosion; Nrun is soluble N lost in runoff; NSSFo is N in subsurface flow (SSF) that leaves; Nperc is soluble N that percolates to groundwater; Ndenitr is N loss by denitrification (sum of N_2 and N_2O); Ncrop is N harvested with crop; Nvol is N loss by volatilization (NH3); Nmfert is N added with mineral fertilizer (nitrate and ammonia forms) + Nlegu is N fixed by legumes; Nofert is N added with organic fertilizers; NSSFi is N in SSF into the area; Ndrain is N in tile drainage outflow; Nburn is N burn loss; Npoint is point source soluble N load. Direct N_2O emissions are accounted in the denitrification subprogram within the APEX model.

4.2.3 Denitrification

Denitrification consists of the sequential reduction of NO_3^- to NO_2^-, NO, N_2O, and N_2. In this process NO, N_2O, and N_2 can diffuse from the soil to the atmosphere and represent a net loss of nitrogen from the soil. Denitrification does not include N loss from volatilization, leaching, or runoff. Thus, it is equivalent to direct emissions from managed soils. APEX has three denitrification computational methods including EPIC classic method(Izaurralde et al., 2006), Izaurralde's method (Izaurralde et al., 2017), and Kemanian method. Both NH_3-N and NO_3-N fertilizers result in ammonia emission and nitrate leaching, which are known to lead to secondary emissions of nitrous oxide associated with subsequent denitrification, potentially off-site which is not accounted for in the APEX denitrification subprogram. (Hergoualc'h et al., 2019).For this study we elected to use Izaurralde's method for computing direct emissions of nitrogen. (Izaurralde et al., 2017).

4.2.4 IPCC Methodology for Indirect Emissions

As the APEX model does not account for indirect emissions of N_2O, we calculated those emissions using the IPCC method (Hergoualc'h et al., 2019). We applied the IPCC emissions factors of 0.010 to the reported Nvol and 0.011 to the sum of Nrun and Nperc to represent indirect emission associated with ammonia volatilization and nitrate runoff and leaching respectively. While our estimations of direct N_2O emissions from managed soils were calculated based on IPCC tier 3 methodology, the methodology used for indirect emissions from atmospheric re-deposition of N volatilized from the soil utilized the IPCC tier 1 methodology (Hergoualc'h et al., 2019).

4.2.5 Carbon Modeling

APEX models carbon cycling through algorithms developed for EPIC (Izaurralde et al., 2006). These algorithms simulate the accumulation of carbon in soil by estimating soil carbon dynamics as a function of climate conditions, soil properties, and management practices (such as crop residue management and fertilizer applications). APEX then simulates how the flow of carbon into and out of the soil is impacted by soil moisture, temperature, erosion, tillage, soil density, leaching, and other variables (Gassman et al., 2010).

4.2.6 Data Collection

Crop production process information to support simulations was obtained from several sources. Where available, county-level data from publicly available databases and enterprise production budgets were used to construct the farm models for each archetype. Information was also requested from county extension agents in each archetypical county, but not all the extension agents were responsive to requests for information and some only provided part of the requested data. In instances where data gaps were identified, the gaps were filled by estimating appropriate values or by model calibration results.

4.2.7 Archetype Data Gaps, Assumptions, Limitations

After defining the counties to be used for construction of the archetype models, we conducted a survey of extension agents in each county. While this yielded a large amount of the required information, there were still data gaps in the definition of management practices. To fill these gaps, information was obtained from a variety of publicly available sources including enterprise production budgets, specific to the county or state, and USDA publications. Each archetype was assumed to have a single production profile (tillage, rotation, irrigation, etc.) based on the most prevalent practices for the location. Likewise, soils were also limited to one per archetype location, based on our judgement and expert opinion of the most prevalent soil type to crop production within the archetype area. These assumptions can impact the results of the simulation as the APEX model is sensitive to both practices and soil type but modeling every combination of practice and soil for each archetype is impractical. The most important assumptions for the APEX model were soil type, tillage, rotation, irrigation, N application, pesticide applications, and crop planting density which are discussed in the following sections.

4.3 APEX Input Data

Each archetype farm model was constructed using information from multiple sources from a previous LCA. We used publicly available county- and state-level data, enterprise production budgets, and information acquired through communication with county extension agents in the counties selected for modeling. We sought to prioritize archetype specific data from the surveys wherever possible for inclusion in the model. We have attempted to fill gaps in the data through other sources prioritizing publicly available county level government data, then state-wide averages from government data, national averages government data, and finally enterprise budgets.

The APEX model operates on a daily time step and is structured to be able to simulate agricultural production over decades. At the recommendation of the model developers, we run for 33 years prior to the 6-year simulation period of 2015-2020. This “spin up” step is intended to allow the model to achieve a steady state regarding soil carbon and nitrogen stocks prior to the simulation of the 6-year period of interest. Site-specific characteristics, such as topography, climate, and soil type, were accounted for in the field level simulation. Additionally, we used APEX to estimate fuel consumption based on the defined field operations, irrigation, and environmental emissions at the field scale (i.e., greenhouse gas emissions from nutrient cycling and applications).

4.3.1 Literature/Publicly Available Data:

We used publicly available data regarding regional production practices and conditions to fill in the gaps left in the models after we completed our surveys. This data was sourced from reports published by NASS, ARMS, FRIS, and the ERS for the regions and time periods of interest (USDA ERS, 2022a, 2022b; USDA NASS, 2022, 2019a, 2019b; USDA NRCS, 2022). This literature data allowed us to create archetypical LCAs examining specific production practices and the regional effects of soil types and weather.

4.3.2 Soil Type Selection

The soil type for each archetype model in APEX was selected by identifying the most common soil type underlaying the area of the archetype county where the rotation being modeled was in use (i.e., continuous corn, corn-soybean, corn-cotton, etc.). To accomplish this, we utilized SURGO soils spatial data from USDA NRCS Web Soil Survey (USDA NRCS, 2019) and crop spatial data from the USDA NASS Cropland Data Layer (CDL) (USDA NASS, 2019). We created a spatial overlay of the CDL and SURGO data for each archetype county, and then calculated the dominant soil type using only the area using the target crop rotation during the 2016 growing season. In cases where the dominant soil type was not available in the APEX database, we substituted the closest soil type in name/attribute that was available in the APEX database. This archetype approach addresses variation of impacts on crop model output from soil characteristics that are tied to climate and practices associated with the soils. The APEX model results represent more than 40 soil types for each crop. The variability of output from soil types was integrated through the model with variability of weather and production practices.

4.3.3 Electricity and Material Transportation

Direct on-farm energy use was estimated using 2015 crop production budgets produced by university extension offices (Hanna, 2015; Klein et al., 2015; Purdue Extension, 2015; Schnitkey, 2015). For transportation, one average value was estimated for the transport of materials for each crop with the inputs to crop production assumed to travel a total of 1000 km prior to use on the farm N.D.). For states where energy and transport data were not readily available, data from adjacent states was substituted (Arkansas and Arizona were substituted with data from Missouri and Colorado respectively). Average national electricity GHG emissions were used to avoid imposing geographic energy pool gradients on cropping systems and thus masking production practice impacts, as energy sources were not the focus of the LCA.

4.4 Calibration and Validation of APEX Models

Calibration and validation of the APEX crop systems models was necessary to provide confidence in the model output for use in the LCI. We used a crop model calibration optimization process to calibrate each crop baseline model using harvest biomass ratio and leaf area index to adjust the simulated yields to ±10% of the reported yield. Model validation was assessed using APEX predicted yields compared to NASS yields for each archetype county (n=40) for each year (n=6), resulting in a total of 240 validation points. Validation for corn yields resulted in a coefficient of determination (R^2) of 0.89 with a slope of 0.97 (Figure 6). Validation for soy yields resulted in an R^2 of 0.71 with a slope of 1.04 (Figure 7). Validation for cotton yields resulted in an R^2 of 0.63 with a slope of 0.93 (Figure 8). These validation data support the use of the APEX model for generation of unit process data for the LCI. The relatively low R2 for cotton reflects the diversity of production conditions where cotton is produced in the U.S., and subsequent difficulty calibrating APEX across wide variations in production conditions. However, the slope of the regression line was close to parity, justifying the use of the model output.

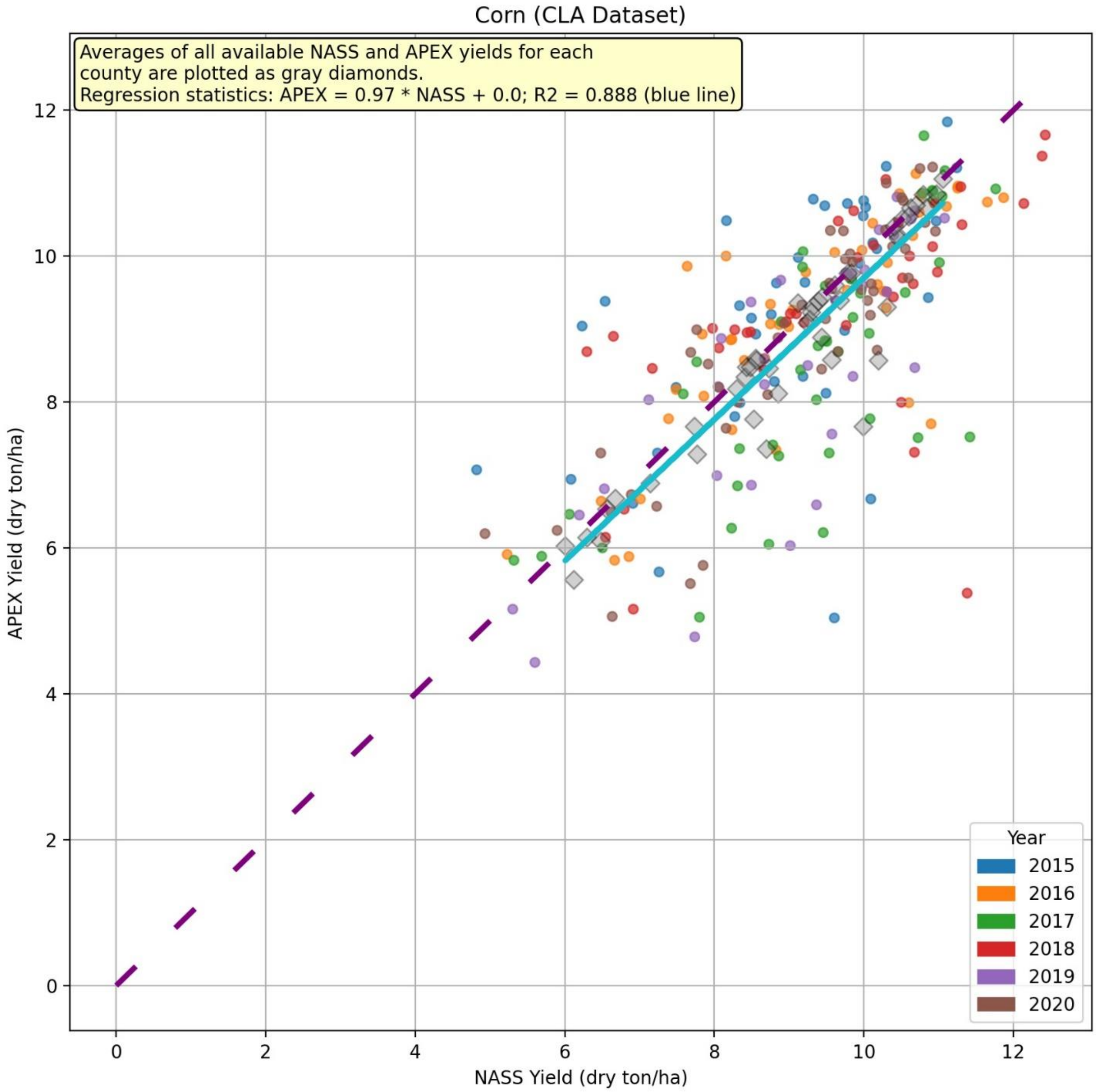

Figure 6: Parity plot of APEX corn simulated yield against NASS county yields from 2015-2020.

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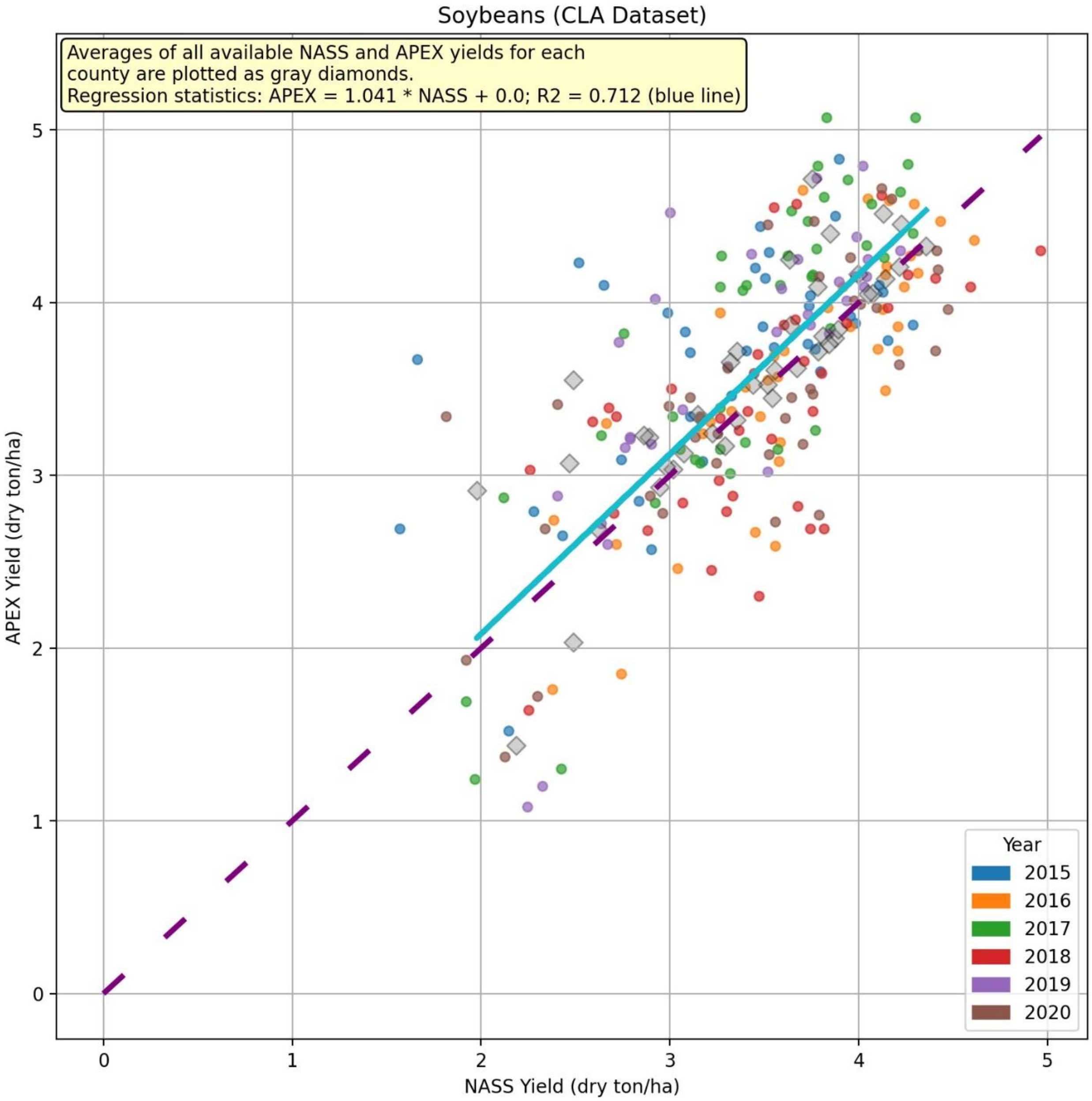

Figure 7: Parity plot of APEX soy simulated yield against NASS county yields from 2015-2020.

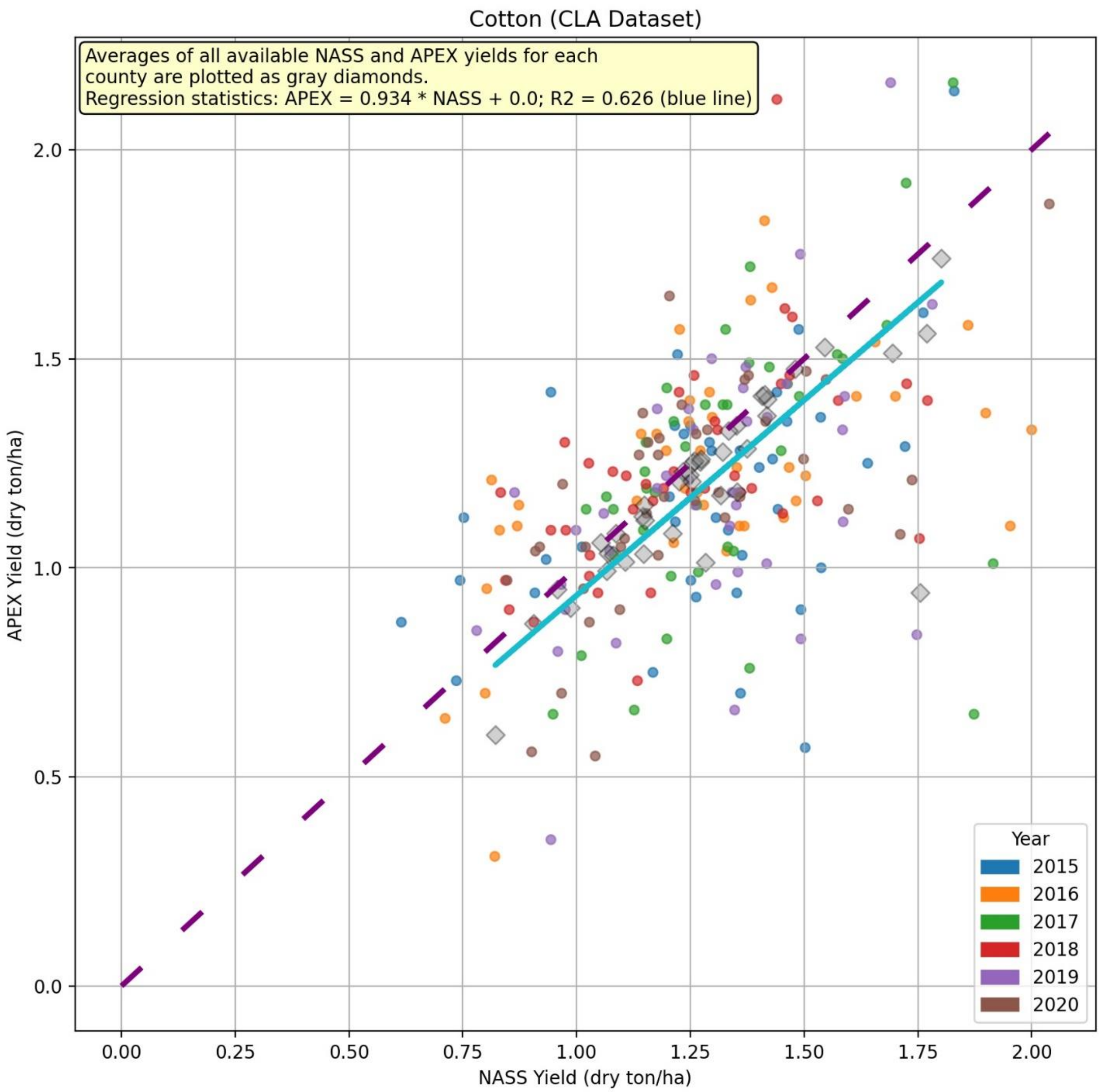

Figure 8: Parity plot of APEX cotton simulated yield against NASS county yields from 2015-2020.

4.5 Archetype Scenario Design

Four scenarios in addition to the baseline were simulated for this project using APEX:

1. Cover Crops,
2. No Chemical Disease Control (NoDiseaseCont),
3. No Chemical Insect Control (NoInsectCont),
4. No Chemical Weed Control (NoWeedCont).

Simulating these management practices in APEX provides accounting of a range of process flows beyond just the chemical components, application processes, and yield penalties. APEX crop systems model incorporates process-based simulations of soil, water, and plant dynamics that impact carbon, nitrogen, and other key processes. Yield penalties for each crop and scenario were estimated from literature reports (Table 3). For this project the medium yield penalty values for each crop and scenario were used for modeling. For the NoDiseaseCont and NoInsectCont scenarios we were unable to find literature detailing the yield impact of not using seed and foliar chemical controls simultaneously. Instead, yield penalties were estimated for the impact of not using seed treatment and foliar treatment individually and then those values were added together to approximate the impact of using neither method of chemical control. Midpoint estimates for environmental and human health metrics were computed for each scenario.

A sensitivity test was performed on the yield penalties for both corn and soybeans (the data gaps in the cotton yield data prevented adequate sensitivity testing for that crop) and indicated the models were sensitive to changes in yield penalty. For a few of the impact categories, reducing the yield penalty resulted in environmental impacts of the scenarios that were lower than the baseline scenario, which had chemical pest control, as the benefit of not having the burden of pesticide production and emissions associated with the scenario outweighed the yield penalty, but most of the impacts for corn and soybeans were higher than the baseline for all impact levels tested. Additionally, the sensitivity test showed that the impact category values for each scenario increased linearly as the yield penalty increased the low to high yield impacts. Tables showing the results of these sensitivity tests can be found in Appendix E.

The Cover Crops scenarios were constructed to simulate the impact that cover crop inclusion into the crop rotation has on the field emissions related to crop production. To do this, we introduced an additional crop between the harvesting of each crop and the planting of the next. The crops selected were chosen based on what cover crop was suggested based on expert feedback and what crops appeared most often in crop databases we obtained information from for model construction. For corn and soybeans, we selected cereal rye and for cotton, we selected winter wheat as the cover crop. The cover crop was planted shortly after the harvest of the previous crop and was terminated just prior to the planting of the next crop without being harvested so that all biomass from the cover crop was retained in the field. Potential benefits of cover crops, especially on soil health, are well documented but were not included in this LCA as these benefits of practices are not part of LCIA models.

The NoDiseaseCont scenario was constructed to simulate the impact that not using fungicides and nematicides has on the environmental performance of crop production. To accomplish this, we first removed the application of both fungicides and nematicides from field operations for all archetypes. We increased the pest damage scaling factor in the model which represents the growth rate of pest populations and determines the yield impact that pest pressure has in APEX. For the baseline archetype the value of this variable is set to 0, which represents minimal pest growth that does not affect simulated yields. For this scenario, this variable was increased until the yield loss matched estimates based on expert feedback and pesticide effectiveness data to be as representative of the counterfactual conditions. The impacts of both seed and foliar pest control were simulated by combining yield loss estimates from the literature for both pest control application methods to capture a broader picture of the influence that fungicide and nematicide usage has.

The NoInsectCont scenario was constructed to simulate the impact that not using insecticide has on the environmental performance of crop production. To accomplish this, we first removed the application of insecticide from field operations for all archetypes. We increased the pest damage scaling factor in the model which represents the growth rate of pest populations and determines the yield impact that pest pressure has in APEX. For the baseline archetype the value of this variable is set to 0, which represents minimal pest growth that does not affect yield. For this scenario, this variable was increased based on expert feedback and pesticide effectiveness data to be as representative of actual conditions as is possible. The impacts of both seed and foliar pest control were simulated by combining yield losses estimates from literature for both pest control application methods to capture a broader picture of the influence of insecticide usage.

The NoWeedCont scenario was constructed without the use of herbicides to control weeds and simulated mechanical weed control in the form of conventional tillage for all archetypes.

However, APEX does not inherently model nutrient competition from weeds very well. To account for this, we introduced two other crops, switchgrass and the common sunflower to represent grassy and broadleaf weeds, respectively, to directly compete with the primary crop for nutrients. The planting density of the weed surrogates was adjusted to reduce the six-year total yield by an amount as close to the estimated yield penalty as the model would allow. This method allowed us to capture reductions in yield due to competition as well as other less obvious effects such as how SOC, N emissions, and erosion are impacted by the presence of weeds.

Within the system boundary of the cradle-to-farm gate analysis, foreground and background emissions from corn, soybean, and cotton production were considered. Background emissions include emissions from the production and transportation of purchased materials to the farm, while the foreground includes the direct emission from the consumption of materials used on the farm. The environmental performance of crop production practices varies with location because of weather conditions and soil characteristics, which are included in the input files for the APEX model. The LCI data generated through the APEX model simulations were used for foreground modeling, while the associated background LCI was linked to the Ecoinvent database. The impact assessment was then generated from the LCI model using the SimaPro software platform. The LCI data for the upstream production of inputs to the agricultural system was sourced from Ecoinvent 3.6 (cut-off system model) database. Input and output values from the APEX process model were mapped to the SimaPro model using conversion factors to match the units used in the Ecoinvent database.

Table 3: Literature-Based Yield Penalty Range (Percent) for Corn, Soy, and Cotton Applied for Counterfactual Simulzations when Not Using Chemical Pest Controls

Pest Control System	**Corn**			**Soy**			**Cotton**		
	Low	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
Insect – Seed	3[d]	16 [a,j]	28[j]	20 [C]	33 [C]	45[h]	--	16[o]	17.5[0]
Insect – Foliar	15 [b]	30[f]	45 [d]	20 [h]	40[g, h]	60 [h]	8[L]	34[L]	40[q]
Weed – Foliar	10[e]	47[e]	83[e]	28[i]	52[i]	87[i]	--	32[m]	--
Disease - Seed	4	8[k]	12	5[c]	11[c,k]	30[c]	--	19.6[p]	21.4[p]
Disease - Foliar	6[a]	15 [a]	23 [a]	10[c]	12 [c]	13 [c]	2[n]	10[n]	20[n]

Sources	
a	Mueller, D. S., Wise, K. A., Sisson, A. J., Allen, T. W., Bergstrom, G. C., Bissonnette, K. M., ... & Wiebold, W. J. (2020). Corn yield loss estimates due to diseases in the United States and Ontario, Canada, from 2016 to 2019. Plant Health Progress, 21(4), 238-247.
b	Horikoshi, R. J., Vertuan, H., de Castro, A. A., Morrell, K., Griffith, C., Evans, A., ... & Head, G. (2021). A new generation of Bt maize for control of fall armyworm (Spodoptera frugiperda). Pest Management Science, 77(8), 3727-3736.
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d	Wechsler, S., & Smith, D. (2018). Has resistance taken root in US corn fields? Demand for insect control. American Journal of Agricultural Economics, 100(4), 1136-1150.
e	Soltani, N., Dille, J. A., Burke, I. C., Everman, W. J., VanGessel, M. J., Davis, V. M., & Sikkema, P. H. (2016). Potential corn yield losses from weeds in North America. Weed Technology, 30(4), 979-984.
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g	Koch, R. L., Potter, B. D., Glogoza, P. A., Hodgson, E. W., Krupke, C. H., Tooker, J. F., ... & Spencer, J. L. (2016). Biology and economics of recommendations for insecticide-based management of soybean aphid. Plant Health Progress, 17(4), 265-269.
h	Jensen, R. L., & Newsom, L. D. (1972). Effect of stink bug-damaged soybean seeds on germination, emergence, and yield. Journal of Economic Entomology, 65(1), 261-264.
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j	Kabaluk, J. T., & Ericsson, J. D. (2007). Metarhizium anisopliae seed treatment increases yield of field corn when applied for wireworm control. Agronomy Journal, 99(5), 1377-1381.
k	Mourtzinis, S., Marburger, D., Gaska, J., Diallo, T., Lauer, J., & Conley, S. (2017). Corn and soybean yield response to tillage, rotation, and nematicide seed treatment. Crop Science, 57(3), 1704-1712.
l	John H North, Jeffrey Gore, Angus L Catchot, Donald R Cook, Darrin M Dodds, Fred R Musser, Quantifying the Impact of Excluding Insecticide Classes From Cotton Integrated Pest Management Programs in the U.S. Mid-South, Journal of Economic Entomology, Volume 112, Issue 1, February 2019, Pages 341–348, https://doi.org/10.1093/jee/toy339
m	G.A. Constable, M.P. Bange, The yield potential of cotton (Gossypium hirsutum L.), Field Crops Research, Volume 182, 2015, Pages 98-106, ISSN 0378-4290, https://doi.org/10.1016/j.fcr.2015.07.017.
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o	Patil, B. C., Patil, S. B., Vdikeri, S. S., & Khadi, B. M. (2003, March). Effect of imidacloprid seed treatment on growth, yield, seedling vigor and biophysical parameters in cotton (Gossypium spp) genotypes. In Proc. World Cotton Res. Conf (Vol. 3, pp. 9-13).
p	National Agricultural Pesticide Impact Assessment Program (U.S.). (1993). The importance of pesticides and other pest management practices in U.S. cotton production: assessment summary (Vol. 1993). Retrieved from https://www.biodiversitylibrary.org/item/288936
q	Mohammad-Amir Aghaee and others, Evaluating Optimal Spray Timing, Planting Date, and Current Thresholds for Lygus lineolaris (Hemiptera: Miridae) in Virginia and North Carolina Cotton, Journal of Economic Entomology, Volume 112, Issue 3, June 2019, Pages 1207–1216, https://doi.org/10.1093/jee/toy407

5. Life cycle impact assessment

We adopted the impact assessment framework of Impact World+ version 2.0.1 (Agez et al., 2023; Bulle et al., 2019). This is an internationally recognized impact assessment framework, and we adopted the characterization factors without modification. The Impact World+ LCIA model includes recent methodological advances in multiple impact categories in a consistent manner with the following three characteristics:

1. Implementing the same modelling structure of fate, exposure, exposure response, and severity across ecosystem quality and human health-related impact categories,
2. Adopting the consumption/competition/adaptation functionality-based assessment for all impacts on human society generated from the loss of functional value of a resource or an ecosystem service, and
3. Offering the flexibility to represent impact scores at midpoint level or at damage level.

The full range of impact categories of the Impact World+ impact assessment model is presented in Table 4. A midpoint category represents the environmental impact that can be measured before the endpoint impact is realized (e.g., GHG emissions are a midpoint indicator for average global temperature changes) (Jolliet et al., 2003). The focus of this study was on a subset of midpoint impact categories: Short-term Climate Change, Fossil and Nuclear Energy Use, Land Occupation, and Water Consumption. The body of the report provides detailed analyses of these midpoint impact categories. The remaining midpoint categories from the Impact World+ LCIA model are reported in Appendix E: LCIA Impact Category Results and Comparisons except for land transformation which was excluded from analysis as the area occupied by the archetype models was assumed to be pre-existing agricultural land. As such, no land was converted from or to agricultural production in the LCI.

To assess the sensitivity of results to LCIA frameworks we also analyzed the models with two additional LCIA Frameworks: Environmental Footprint 3.0 and ReCiPe 2016. Environmental Footprint 3.0 (also referred to as the Product Environmental Footprint, EF 3.0, (Manfredi et al., 2012; Wu and Su, 2020). The EF 3.0 method was used rather than recently released version 3.1 (July 2022) because the EcoInvent database has not yet been updated to include the Version 3.1 reference flows. ReCiPe 2016 Him (Huijbregts et al., 2017), calculating midpoint and endpoint characterization factors for 17 midpoint categories for human health, ecosystem quality, and resource scarcity.

Table 4: List of resource, impact, and damage categories from IMPACTWorld+ 2.0.1 LCIA (Bulle et al., 2019) with the addition of water consumption impact from AWARE (Boulay et al., 2018).

Resource/impact/damage categories	**Units**	**Definitions**
Climate change long-term	kg CO_2 eq	Assessment of the contribution to global temperature potentials (GTP500), the long-term temperature increases for up to 500 years based upon IPCC 2021 AR6 characterization factors.
Climate change short-term	kg CO_2 eq	Assessment of the contribution to global warming potential (GWP100), the rate of temperature change over the first 100 years after emission based upon IPCC 2021 AR6 characterization factors.
Fossil and Nuclear Energy Use	MJ deprived	Total non-renewable (fossil) energy used.
		IMPACT World+ uses the primary energy content, as a midpoint indicator considering that it is a reasonable proxy to assess the MJ deprived per MJ consumed, under the assumption that fossil resources are mainly functional for energy purposes (Bulle et al., 2019).
Freshwater acidification	kg SO_2 eq	Acidification describes a change in acidity in the water due to atmospheric deposition of sulphates, nitrates, and phosphates. Major acidifying substances are NO_X, NH_3, and SO_2.(Jungbluth, 2024).
Freshwater ecotoxicity	CTUe[a]	Aquatic toxicity is defined as the study of the effects of a chemical substance to aquatic species which is usually determined on organisms representing the three trophic levels, i.e. vertebrates (fish), invertebrates (crustaceans) and plants (algae) (Jungbluth, 2019).
Freshwater eutrophication	kg PO_4 P lim	This factor expresses the increase in phosphorus mass per kgP discharged to aquatic environment.
Human toxicity cancer	CTUh[b]	Carcinogenic impact is based on the parameterized version of USEtox. The method considered indoor emissions and differentiated the impacts of metals and persistent organic pollutants.
Human toxicity non cancer	CTUh[b]	Human toxicity, carcinogenic impact is based on the parameterized version of USEtox for continents. The method considered indoor emissions and differentiated the impacts of metals and persistent organic pollutants.
Ionizing radiations	Bq[c] C 14 eq	Measure of the emission of radiation carrying sufficient energy to detach electrons from atoms or molecules.
Land occupation biodiversity	m2 arable la	Measure of land use and to help assess how land use affects biodiversity (Huijbregts et al., 2017)

Table 4: List of resource, impact, and damage categories from IMPACTWorld+ 2.0.1 LCIA (Bulle et al., 2019) with the addition of water consumption impact from AWARE (Boulay et al., 2018).

Resource/impact/damage categories	**Units**	**Definitions**
Land transformation biodiversity	m^2 arable la	Measure of change in land use and to help assess how land-use change affect biodiversity (Huijbregts et al., 2017)
Marine eutrophication	kg N N lim e	Expressed as the degree to which the emitted nutrients reach the marine end compartment (nitrogen considered as limiting factor in marine water) V.
Mineral resources use	kg deprived	This factor represents the fraction of material needed by future users that are not able to adapt to a full dissipation of the easily available stock. It is expressed in terms of kg of deprived resource per kg of dissipated resource (Bulle et al., 2019).
Ozone layer depletion	kg CFC 11 e	Ozone depleting substances emitted by human activity destroy the ozone layer in the stratosphere, which blocks UVB, by breaking ozone molecules into molecular oxygen through heterogeneous catalysis (Jungbluth, 2019).
Particulate matter formation	kg PM2.5 eq	Disease incidence due to kg of PM2.5 emitted. This refers to particulates ≤ 2.5 µm.
Photochemical oxidant formation	kg NMVOC[d] eq	Emissions of non-methane volatile organic compounds (NMVOC[d]).
Terrestrial acidification	kg SO2 eq	Acidification describes a change in acidity in the soil due to atmospheric deposition of sulphates, nitrates, and phosphates. Major acidifying substances are NO_X, NH_3, and SO_2. (Jungbluth, 2019).
Water scarcity	m^3 world eq	Refers to remaining water available in a watershed area after human and aquatic ecosystem demand has been met, relative to world average (Bulle et al., 2019).
Water Consumption	m^3	Refers to the total water consumed within the foreground and background systems.

[a] CTUe = The comparative toxic unit for aquatic ecotoxicity impacts (CTUe) expresses the estimated potentially affected fraction of species (PAF) integrated over time and the volume of the aquatic compartment, per unit of mass of the chemical emitted.
[b] CTUh – Comparative Toxic Unit for human (CTUh) expressing the estimated increase in morbidity in the total human population per unit mass of a chemical emitted (cases per kilogram).
[c] Bq – becquerel, SI unit for radioactivity
[d] NMVOC – non-methane volatile organic compounds

3

5.1 Climate Change

Several gaseous emissions contribute to climate change, including CO_2, CH_4, and N_2O. The concentration of GHGs is characterized as kg equivalents of CO_2 (kg CO_2-eq), i.e., the relative global warming potential of a gas compared to CO_2 (Myhre et al., 2013). Then individual equivalents are added to give the overall GHG indicator score representing the total radiative forcing potential (or global warming potential) of all GHGs released during the life cycle. However, the indicator does not consider the effects of clouds and aerosols in reflecting the sun's heat and reducing the warming. The IPCC has published extensive lists of global warming potentials for GHGs that are commonly used (Masson-Delmotte et al., 2021). To interpret this GHG indicator, the time horizon (e.g., 50, 100, or 500 years) is an important consideration. Short horizons emphasize gases with short residence times in the atmosphere, like CH_4. We have adopted the 100-year time horizon for GHG emissions for this study (short-term). Biogenic carbon is carbon that is part of the short-term (decades-long) cycling of carbon through the biogeosphere and is not specifically accounted for in this analysis. This follows the most recent IPCC guidelines, in which the emission factor for biogenic carbon is set to zero (Masson-Delmotte et al., 2021).

5.2 Fossil and Nuclear energy use

The energy use of a product, process, or service represents the direct and indirect energy inputs throughout the value chain, including the energy consumed during the extraction, manufacturing, utilization, and disposal of the raw materials. Direct energy use refers to the primary energy input required for manufacture, use, and end-of-life in the life cycle. Indirect energy use represents all inputs for purposes other than manufacturing products, such as infrastructure and equipment. As discussed in Hischier et al. (2010), energy use is split into eight categories based on the extraction of energy materials from nature. We are only considering one of the eight energy categories for this study: non-renewable fossil fuel use. The use of renewable fuels is out of the scope of this analysis.

5.3 Land occupation- Biodiversity

There are two types of land use interventions considered in LCIA: land occupation and land transformation. Land occupation refers to how land is used, and the products in this study are dominated by corn production. It is essentially the inverse of yield. Land transformation accounts for converting one type of land use to another (e.g., forest to pasture). Both are inventory items and are related to impacts on ecosystem quality and biodiversity. However, in this study, we report only land occupation (as inventory) and do not include land transformation as the majority of cropland in the United States has been under cultivation for decades. The developers of the ReCiPe method have included an assessment of the pressure on biodiversity based on the relative species richness/loss, associated with different land uses compared to a reference of annual crop production that was used in the IMPACTWorld+ version 2.0.1 method as well and is the impact metric used in this study (Huijbregts, et al. 2017).

5.4 Water consumption

The water consumption category quantifies the total water consumed by a product or process. Six elementary water flow types used in the Ecoinvent database were selected as default (Goedkoop and Huijbregts, 2013). These are Water, fresh; Water, lake; Water, river; Water, well in ground; Water, unspecified natural origin/kg; and Water, unspecified natural origin/m^3. A large quantity of water is used for cooling and processing water in most supply chains. However, 99% or more of cooling and process water is returned to the source watershed; therefore, it is not included in the inventory of water consumption. A similar situation exists for hydroelectric generation. LCA variability, uncertainty, and statistical analyses. We have also reported the AWARE method for water scarcity (Huijbregts et al., 2017).

In LCA, there are numerous sources of uncertainty (PRé Consultant Inc., 2018) that can influence the interpretation of the results and place limits on the conclusions. These sources of uncertainty include natural variability in input parameters such as fertilizer or fuel use, estimated values obtained through proxy sources (substituting a similar product for one that does not exist in available databases), or results from mathematical models which may include multi-year simulations capturing the variability of estimated parameters associated with factors such as weather or soil conditions. There are also uncertainties arising from the lifecycle impact assessment phase; however, these uncertainties are uniform across all systems compared and are not expected to significantly contribute to reported differences.

5.5 LCA variability

In this project, the uncertainty and variability in the LCA results was accounted for through the 40 archetypes analyzed for four scenarios for each of the three crops. This resulted in 40 independent LCAs for each scenario for each crop, providing an adequately robust sample size for statistical testing as described in section 6.D. This analysis is necessary for establishing defensible metrics for the comparative evaluation of alternative production systems for a given functional unit.

5.6 Model validation

The lifecycle inventory model was created using SimaPro. The Ecoinvent database (version 3.6, cutoff) was used for the LCI data for the raw and process materials used as inputs. All computational modules were documented with reference citations to external sources. Spreadsheet computations were documented with the supporting logic.

5.7 Data gaps, assumptions, and limitations

To fill data gaps in the definition of management practices, such as crop planting dates or densities, information was obtained from various publicly available sources, including sources specific to the county or state, USDA publications, and peer reviewed manuscripts. Each simulation was assumed to have a single production profile (tillage, rotation, etc.) based on the prevalent practices for the location. Likewise, the soil was limited to one per location, based on our judgment and expert opinion of the most prevalent soil type for corn production within the production county. These assumptions can impact the simulation results as the APEX model is sensitive to practices and soil type. The most important assumptions for the APEX model are soil type, tillage, rotation, N application, pesticide applications, and crop planting density.

The environmental effects under investigation in this study are intended to quantify the sustainability metrics associated with current production systems compared to counterfactual alternatives without pesticides, and an additional one for cover crops. The APEX model was assumed to simulate crop production systems consistently across the different alternatives. The benchmark system was calibrated against NASS yield and subsequently modified to represent the counterfactuals which were adjusted to match reported yield gaps.

As described in sections 3.6.1, 3.6.2, and 3.6.3, there were gaps in the available pesticide application and production data. While the missing production data and characterization factors were accounted for by substitution, there was a subset of the chemicals listed in Appendix C that we were unable to substitute as there was no application data available. These factors introduce additional uncertainty to the model, particularly within the toxicity impacts.

5.8 Statistical analyses of scenarios

Analyses of the differences between impact categories for each midpoint category for each crop were performed using R statistical software (R Core Team, 2021). The statistical analysis process was a stepwise assessment of results of each crop and associated scenarios, starting with a test of normality using the Shapiro Wilk test. The results of the scenario impact assessments (across the 40 archetypical production sites) were non-normal, so means comparison was conducted using non-parametric statistics. Non-parametric analysis of variance for each scenario set for each crop and impact category was performed using the Kruskal-Wallis test and multiple means comparisons for non-parametric data were performed using the Dunn-Bonferroni post-hoc test (see Appendix G for R code). The resulting Dunns Groupings provided a comparison of impacts at the designated level of statistical significance.

The Kruskal-Wallis test is a non-parametric statistical method used to determine whether two or more sample sets of data come from the same distribution. Within the test, the P-value determines how significant the difference between one or more of the data sets is, with P-values greater than 0.05 being determined to show no significant differences between the data sets. A secondary, paired test is required to determine which data sets are different from each other, and we selected the Dunn-Bonferroni post-hoc test for this purpose. It is a non-parametric pairwise statistical test that is typically performed after the Kruskal-Wallis test has determined that there is a significant difference between at least one pair of data sets. The Dunn-Bonferroni post-hoc test functions by comparing each pair of data sets to see if they are different and assigns each data set a letter, referred to as the Dunn significance letter, to denote the distribution it belongs to. As an example, a data set with an “a” as its Dunn letter would indicate significant difference from another data set with a “b” as its Dunn letter, but neither data set would be considered significantly different from a data set with “ab” as its Dunn letters. For this project, the Dunn significance letters are displayed in the LCIA results tables and on the box plots for individual impact categories.

6. Life cycle impact assessment results

Results of the LCIA for Impact World+ midpoint categories for each scenario are presented tabularly by crop. Graphical representation of four midpoint impact categories (GWP, fossil and nuclear energy use, land occupation, and water consumption) are presented in the report. Graphical results for all midpoint impact category comparison across scenarios are presented in Appendix E: LCIA Impact Category Results and Comparisons.

6.1 LCIA for Corn Scenarios

Midpoint impact category results of the Life Cycle Impact Assessment for corn are presented in Table 5. Box plot analyses of Short-term Climate Change, Land Occupation, Fossil and Nuclear Energy Use, and Water Consumption are provided in Figure 10 through Figure 11, respectively. The results of environmental midpoint LCIA impact categories showed consistent results across chemical pest control scenarios for U.S. corn production. The four primary impact categories (short-term climate change, fossil and nuclear energy use, land occupation/biodiversity and water consumption) were significantly increased for the counterfactual scenario when each category of chemical pest control (disease, insect, and weed) was not used. The No Insect Control and No Weed Control scenarios had the highest impact on these midpoint impact categories. Adding cover crops did not significantly change impacts for any of the midpoint indicators compared to the baseline.

The LCIA framework comparison tables and graphs for the five corn scenarios are presented in Appendix E. In general, even though the three LCIA frameworks have different impact categories, there were no significant differences in corn scenario Dunn Grouping results across the three LCIA frameworks. The environmental midpoint categories for Corn Baseline and Cover Crop scenarios for EF 3.0 and ReCiPe 2016 had the same Dunn groupings, meaning there were no differences in groupings from Impact World+. The No Disease Control scenarios for EF 3.0 and ReCiPe 2016 were grouped separately from the other four scenarios. The Freshwater Eutrophication impact category was one Dunn Group across all five scenarios in Impact World+ and showed some differences across No Insect Control and Not Weed Control in EF 3.0 and ReCiPe 2016. These minor differences are likely due to the way the two older LCIA frameworks calculate the impacts of contributions of phosphorus to streams from the APEX models. The Human Toxicity (both non-carcinogens and carcinogens) in EF 3.0 both showed significant increases in the three non-pesticide scenarios. This is due to the increased burden of the toxicity associated with energy usage for the lower-yielding scenarios.

Table 5: Life Cycle Impact Assessment of environmental midpoint impact categories for U.S. corn production comparing four production scenarios with baseline production.

Mid-point Impact Categories												
Impact Category	Units	Baseline		Cover Crops		NoDiseaseCont		NoInsectCont		NoWeedCont		P-Value
Climate change long term	kg CO_2 eq	0.26	a	0.26	a	0.33	b	0.47	c	0.50	c	2.23E-30***
Climate change short term	kg CO_2 eq	0.28	a	0.28	a	0.36	b	0.51	c	0.54	c	3.97E-30***
Fossil and nuclear energy use	MJ deprived	3.49	a	3.47	a	4.38	b	6.02	c	6.29	c	1.52E-31***
Freshwater acidification	kg SO_2 eq	2.50E-3	a	2.72E-3	a	3.60E-3	b	5.50E-3	c	6.08E-3	c	1.16E-23***
Freshwater ecotoxicity	CTUe	40.00	a	39.60	a	50.80	b	69.90	c	70.80	c	2.4E-32***
Freshwater eutrophication	kg PO_4 P lim	1.68E-4	a	2.05E-4	a	2.22E-4	a	2.82E-4	a	3.03E-4	a	0.0322**
Human toxicity cancer	CTUh	2.91E-9	a	2.90E-9	a	3.67E-9	b	5.07E-9	c	5.43E-9	c	1.42E-30***
Human toxicity non cancer	CTUh	2.60E-8	a	2.57E-8	a	3.29E-8	b	4.55E-8	c	4.69E-8	c	3.33E-32***
Ionizing radiations	Bq C 14 eq	2.06	a	2.05	a	2.64	b	3.72	c	4.12	c	2.07E-30***
Land occupation biodiversity	m^2 arable land	0.99	a	0.99	a	1.28	b	1.82	c	1.86	c	6.88E-31***
Marine eutrophication	kg N N lim eq	5.84E-4	a	6.36E-4	a	8.71E-4	a	1.38E-3	b	1.23E-3	b	2.71E-10***
Mineral resources use	kg deprived	9.12E-3	a	9.12E-3	a	1.16E-2	b	1.62E-2	c	1.82E-2	c	1.18E-30***
Ozone layer depletion	kg CFC 11 eq	5.01E-8	a	4.99E-8	a	6.19E-8	b	8.43E-8	c	5.57E-8	d	3.53E-25***
Particulate matter formation	kg PM2.5 eq	3.83E-4	a	4.19E-4	a	5.55E-4	b	8.54E-4	c	9.54E-4	c	5.36E-24***
Photochemical oxidant formation	kg NMVOC eq	9.64E-4	a	9.57E-4	a	1.23E-3	b	1.72E-3	c	1.84E-3	c	4.53E-32***
Terrestrial acidification	kg SO_2 eq	4.85E-3	a	5.42E-3	a	7.22E-3	b	1.13E-2	c	1.27E-2	c	2.4E-21***
Water scarcity	m^3 world eq	0.14	a	0.13	a	0.17	b	0.24	c	0.24	c	2.8E-28***
Water Consumption	m^3	7.03	a	7.11	a	9.15	b	13.00	c	15.90	c	7.53E-27***

Impact Values denoted are the mean and Dunn significance group letter.

Significance: ^{NS}(P>0.05), *(P<0.05), **(P<0.01), ***(P<0.001)*

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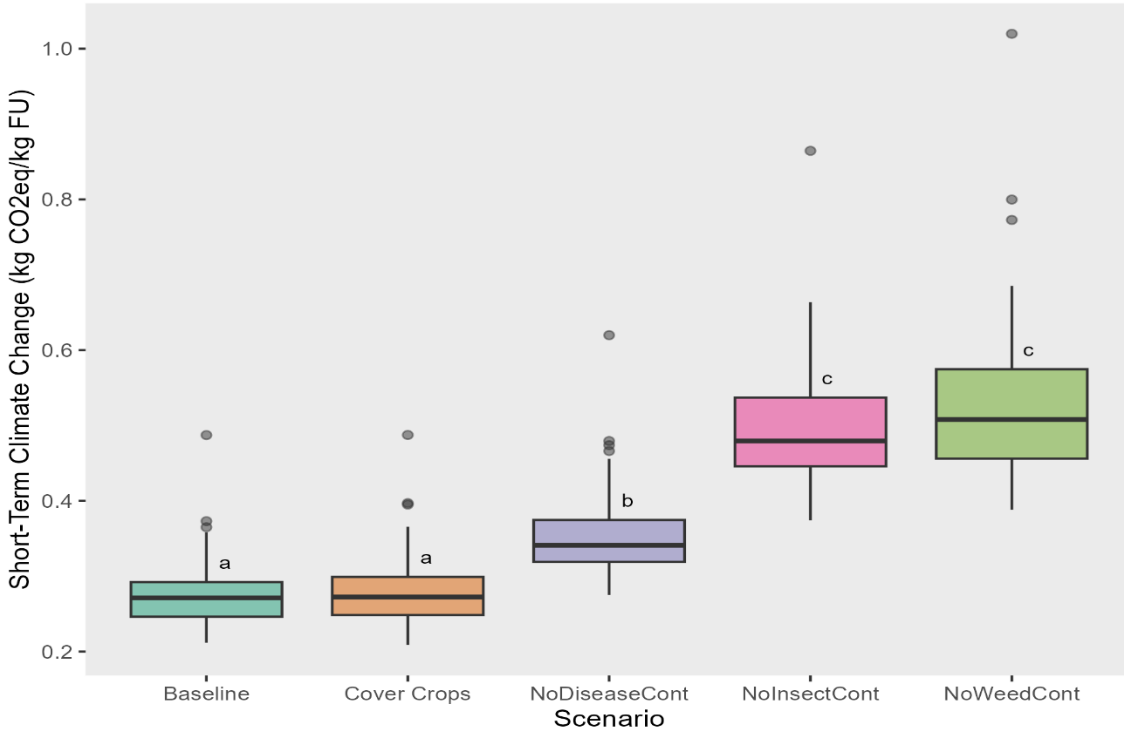

Figure 10: Box plots of corn production LCIA midpoint scenarios for Short-term Climate Change compared to Baseline.

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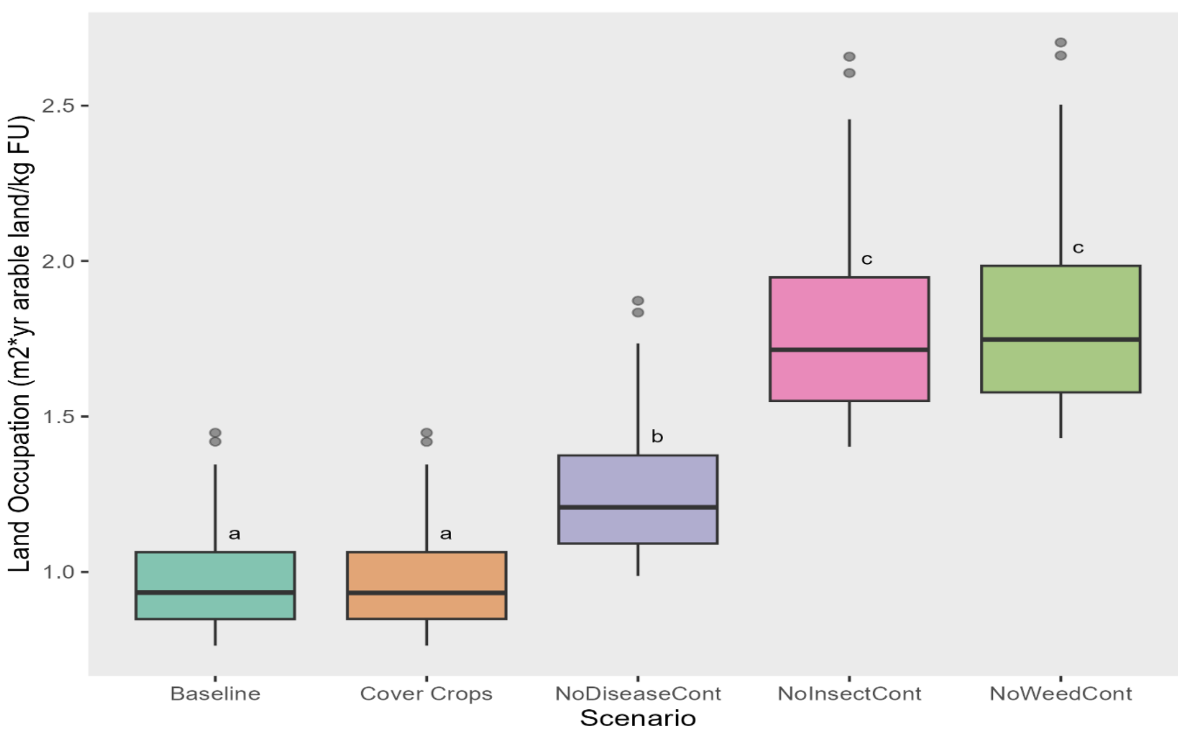

Figure 9: Box plots of corn production LCIA midpoint scenarios for Land Occupation compared to Baseline.

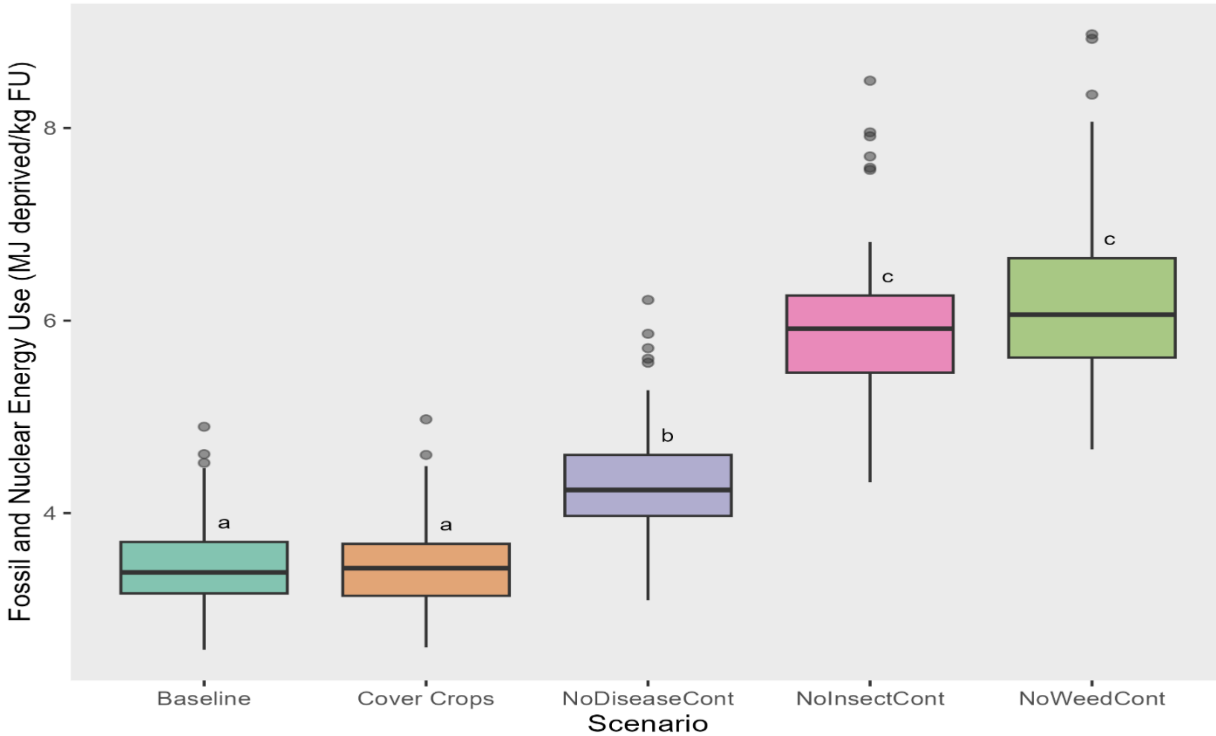

Figure 12: Box plots of corn production LCIA midpoint scenarios for Fossil and Nuclear Energy Use compared to Baseline.

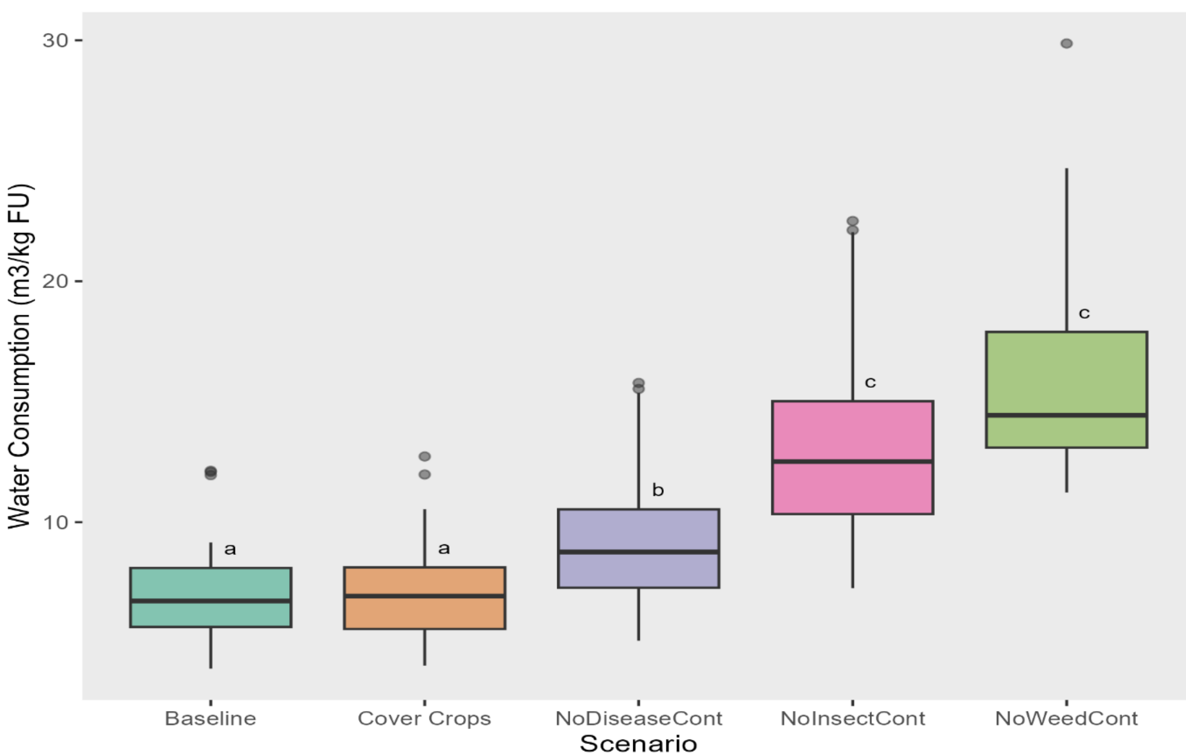

Figure 11: Box plots of corn production LCIA midpoint scenarios for Water Consumption compared to Baseline.

6.1.1 Contribution Analysis: Corn

In this section we present the contribution analysis for corn production across the five scenarios. Figure 13 and Figure 15 present the contribution analysis from various activities in supply chain for short-and long-term climate change impacts based on the Impact World+ framework. The contribution profiles are, not surprisingly, very similar because the primary difference in the characterization factors between these two categories is associated with short lived climate pollutants, primarily methane. Since there is relatively little methane emission associated with these production systems, the difference between these two categories is relatively small. The three major contributing activities in the supply chain are nitrous oxide (direct and indirect), production of nitrogen fertilizer and irrigation. The irrigation contribution is driven by the pumping energy, primarily electricity, necessary for delivery of the water to the field. Nitrogen fertilizer production and irrigation are also the dominant contributors to fossil resource scarcity (Figure 14), for similar reasons as their contribution to climate change.

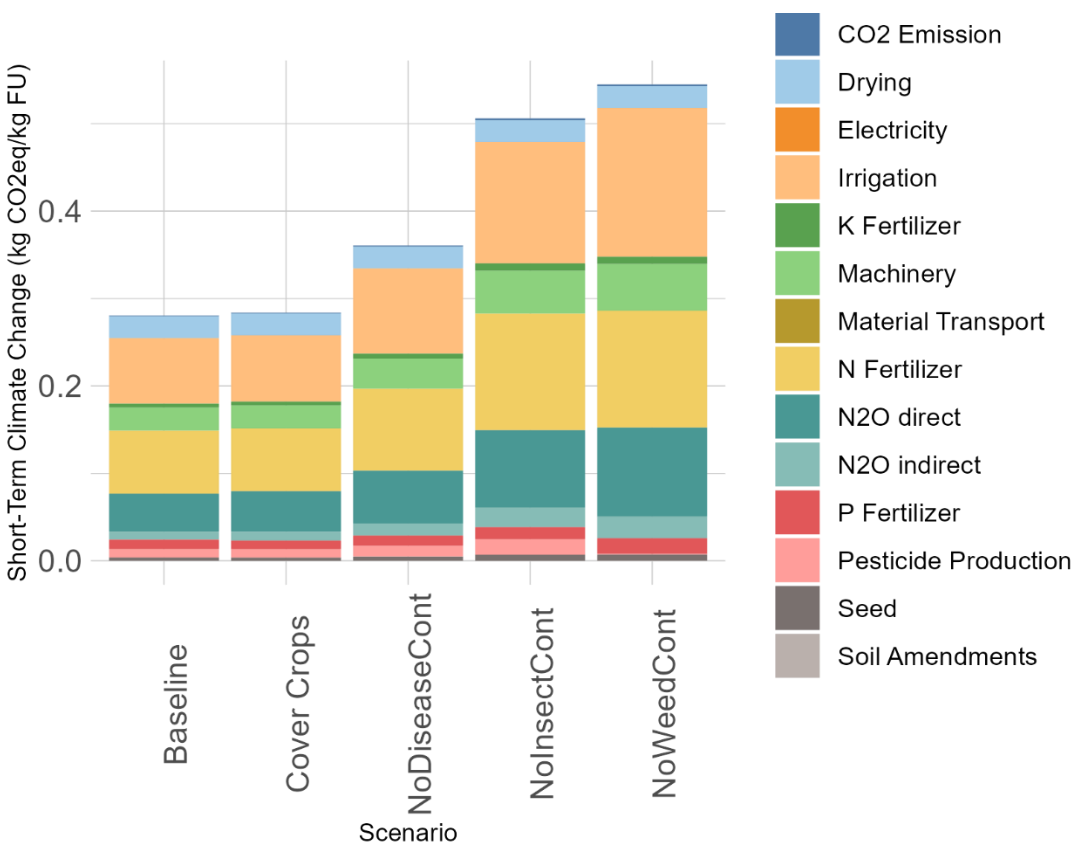

Figure 13. Short-term climate change impacts to produce 1 kg of Corn using the Impact World+ Framework.

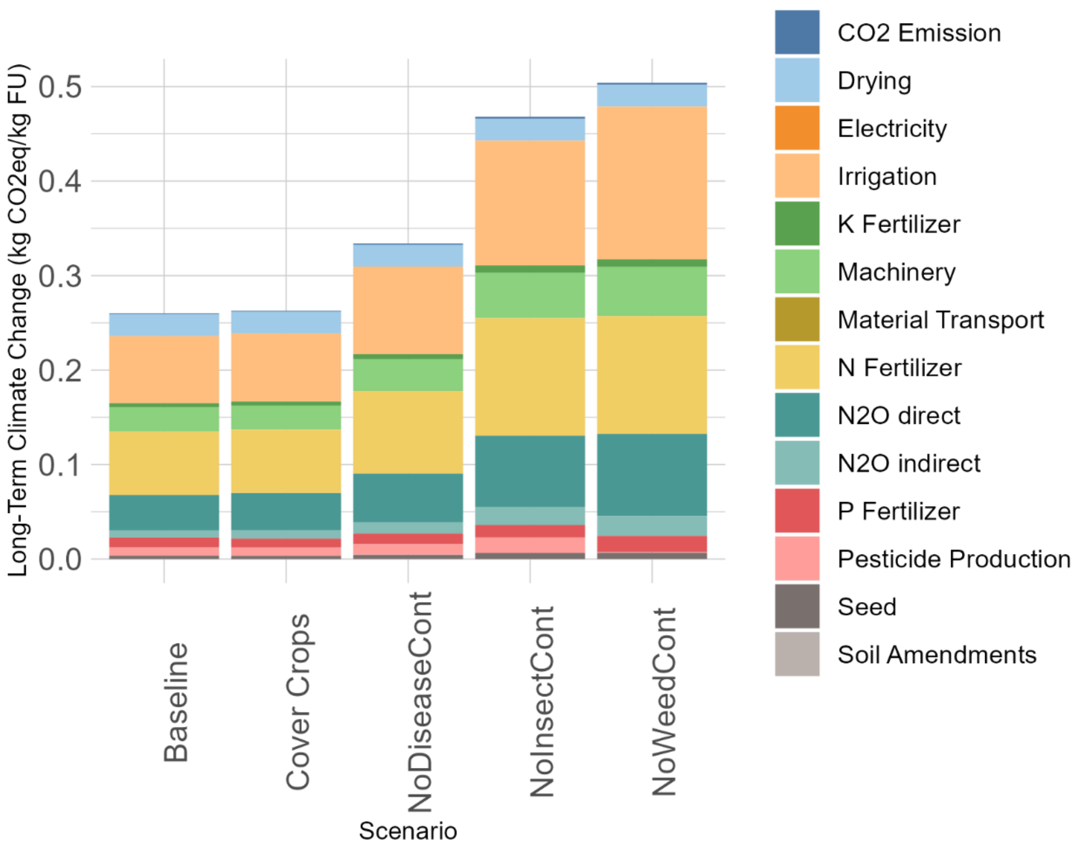

Figure 15. Long-term climate change impacts to produce 1 kg of Corn using the Impact World+ Framework.

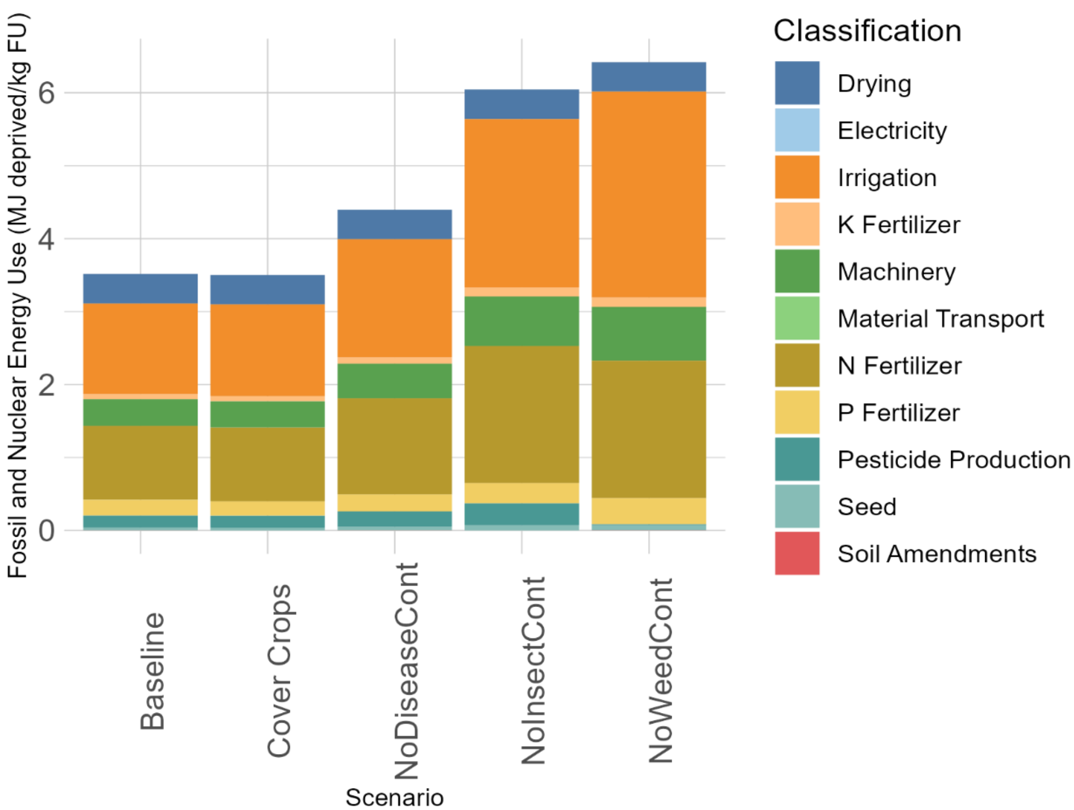

Figure 145:. Fossil And Nuclear Energy Use impacts to produce 1 kg of Corn using the Impact World+ Framework.

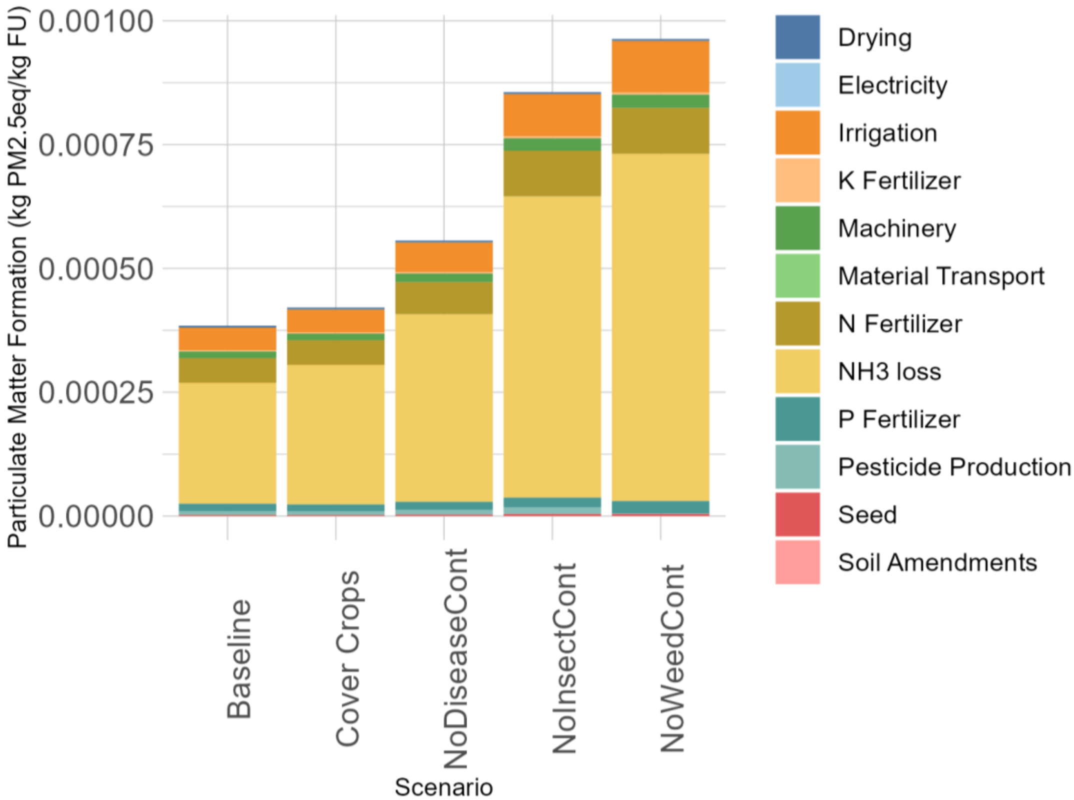

Figure 16. Particulate Matter Formation impacts to produce 1 kg of Corn using the Impact World+ Framework.

Ammonia emissions are the dominant contributor to fine particulate matter formation (Figure 16). Ammonia is also the dominant contributor to terrestrial acidification (see Appendix F: Contribution Analysis) and is a major cause of indirect nitrous oxide in the climate change categories.

Figure 17 presents the AWARE method water scarcity index for corn production. While water consumption is dominated by irrigation water consumed in the crop production phase, water scarcity is, interestingly, dominated by production of fertilizers (cooling water in manufacturing stage) and only secondarily associated with direct water consumption as irrigation water.

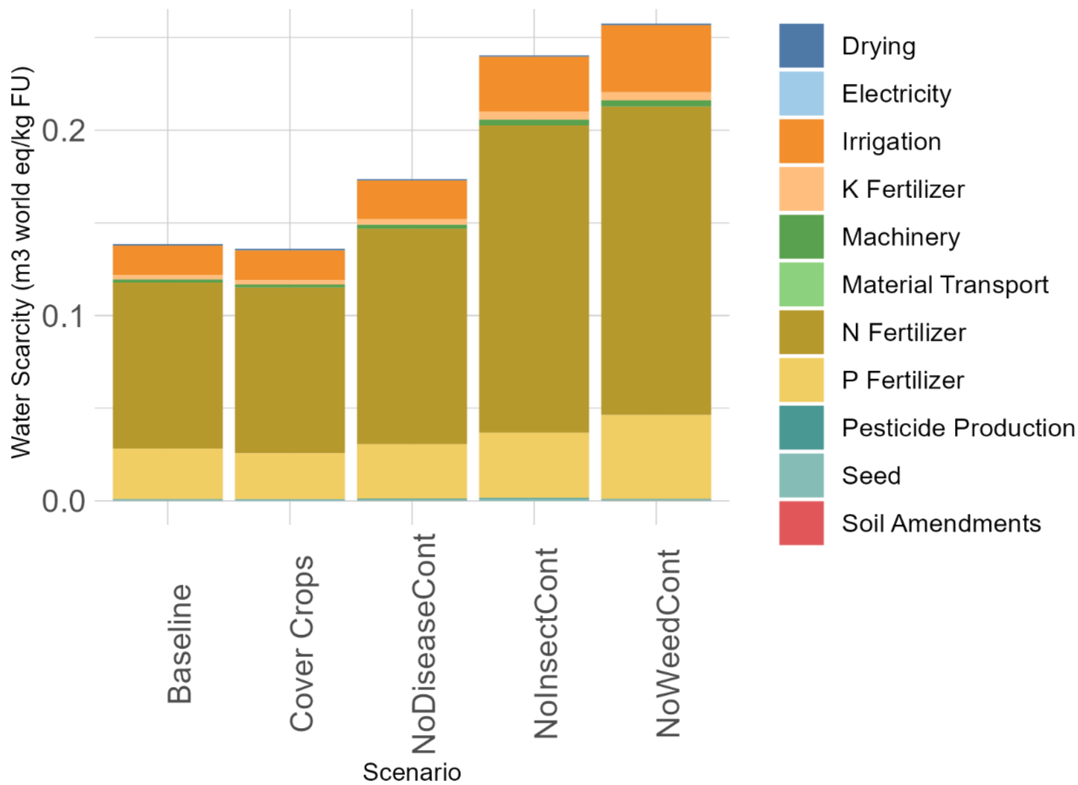

Figure 17. Water Scarcity impacts to produce 1 kg of Corn using the Impact World+ Framework.

6.1.2 LCIA Toxicity Results for Corn as an Example

Although toxicity is not a focus of this study, for completeness, and to demonstrate that there are no significant trade-offs between impact categories, we discuss in the section the human and eco-toxicity impact categories from Impact World+; we also analyzed each crop scenario with EF 3.0 and ReCiPe 2016 for sensitivity (see Appendix E: LCIA Impact Category Results and Comparisons).

It should be noted before this discussion that the ability of current LCIA frameworks to assess ecosystem or human toxicity are very limited based on the general models used. For example, the USEtox model is the dominant toxicity model for LCIA frameworks (Rosenbaum et al., 2011, 2008). Fantke et al. (2021) recommended a near-field/far-field exposure and toxicity characterization framework, for example. They recommended a probabilistic dose-response approach combined with a decision tree for identifying divergent impacts. Hou et al. (2020) pointed out that USEtox only has characterization factors for a limited number of chemicals in commercial use. Analyzing the ecotoxicity and human toxicity impacts from decisions associated with complex supply chain processes like crop production requires development of more comprehensive risk-based analytical models for hazard and exposure.

With the above caveats in mind, we note that the results for toxicity-related impact categories beyond the four primary categories of concern for the purpose of the LCA seem to be counter to expectations (Figure 18 and Figure 19) when evaluated with the Impact World+ framework. The toxicity impact categories of human toxicity – cancer, and freshwater ecotoxicity, are higher with exclusion of chemical insect and weed control. The expected result would be that taking away chemicals with known toxicities like insecticides and herbicides would reduce the life cycle toxicity of a kilogram of corn, soy, and cotton. The Impact World++ framework, for these categories, is dominated by emissions of metals Cr, Al, Cu, Zn, etc) rather than pesticides – Atrazine is the only notable contributor at around 2.5% of total for any of these 3 categories. The increases in contributions, for the counterfactual scenarios, from irrigation, nitrogen fertilizer, and machinery are all from the toxicity associated with energy used in each process (pumping water, synthesizing N fertilizer, operating machinery).

When evaluated using the ReCiPe 2016 and Environmental Footprint 3.0 frameworks (Figure 20 - Figure 23)we see different results for freshwater eco-toxicity and similar results for human carcinogenic text toxicity. The freshwater eco-toxicity in these two methods is dominated by pesticide emissions from the “corn production” which includes field emissions. The Environmental Footprint 3.0 method shows a notable decline in toxicity associated with eliminating pesticides in the “no weed control” scenario, him and despite a dominant contribution from energy production sector for irrigation that is similar to the Impact World+ results. Again, this is largely due to the different emphasis placed on pesticide versus metal emissions for the characterization factors. An additional explanatory factor is associated with the yield difference between the baseline and counterfactual scenarios. The land occupation results are direct measures of yield impacts; for corn the land required to produce one kg of corn was approximately 1 m^2 (Table 5). Without insect or weed control the amount of land required to produce one kg of corn was approximately 1.8 m^2, or nearly double. These losses occurred post-planting and cultivation, so the same quantity of inputs went into each area of land across baseline and chemical pest control exclusions.

The range of characterization factors in UseTox spent approximately 40 orders of magnitude (Rosenbaum et al., 2011, 2008), and therefore, assertions regarding differences in toxicity measures must be made with extreme caution. A rule of thumb in life cycle assessment is that if the differences between scenarios are less than approximately a factor of 1000 it is not appropriate to assert that there are significant differences between the scenarios. Thus, in this study, despite some indications of directional differences between scenarios the differences are far less than 1000-fold and therefore the practical conclusion is that there is no significant difference in the overall toxicity of the system between the baseline and counterfactual scenarios.

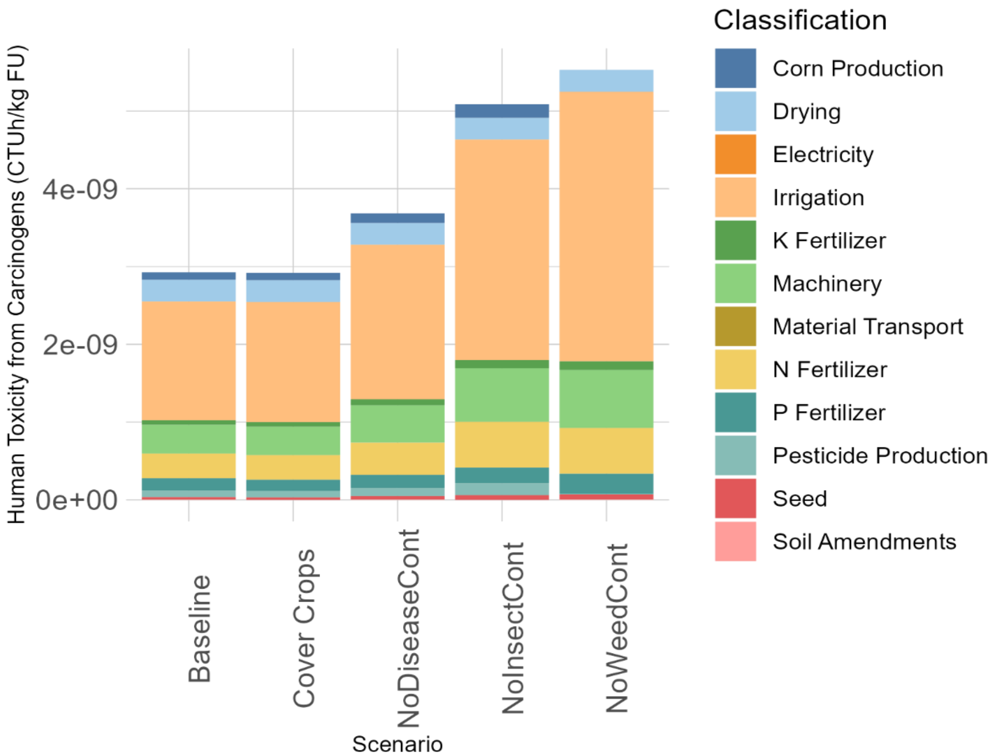

Figure 18: Impact World+ contribution chart of corn production LCIA midpoint scenarios for Human Toxicity from Carcinogens compared to Baseline.

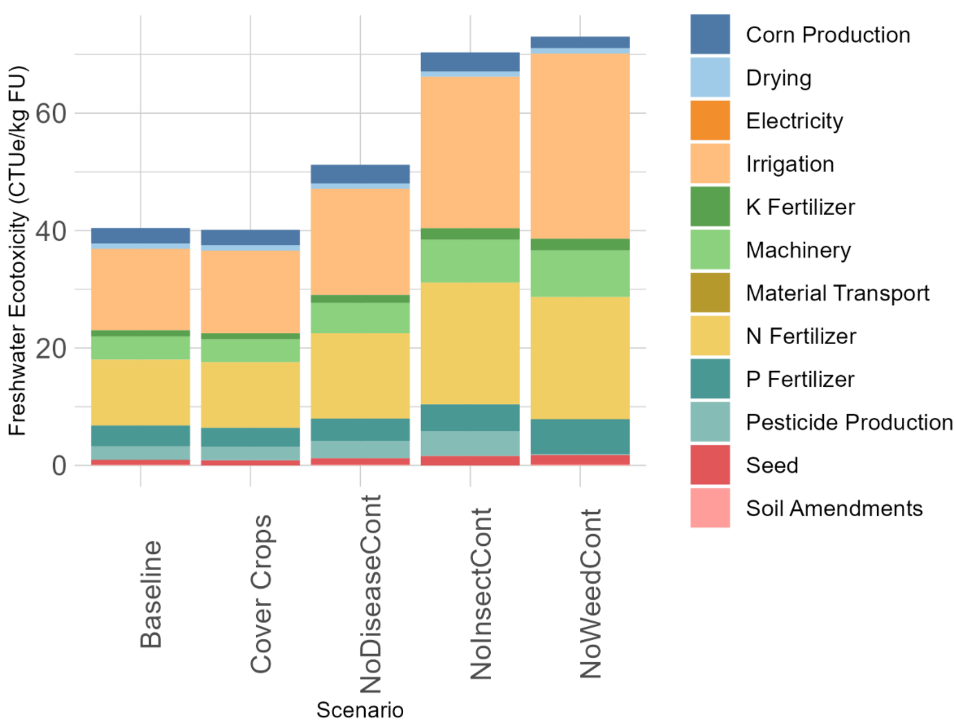

Figure 19: Impact World+ contribution chart of corn production LCIA midpoint scenarios for Freshwater Ecotoxicity compared to Baseline.

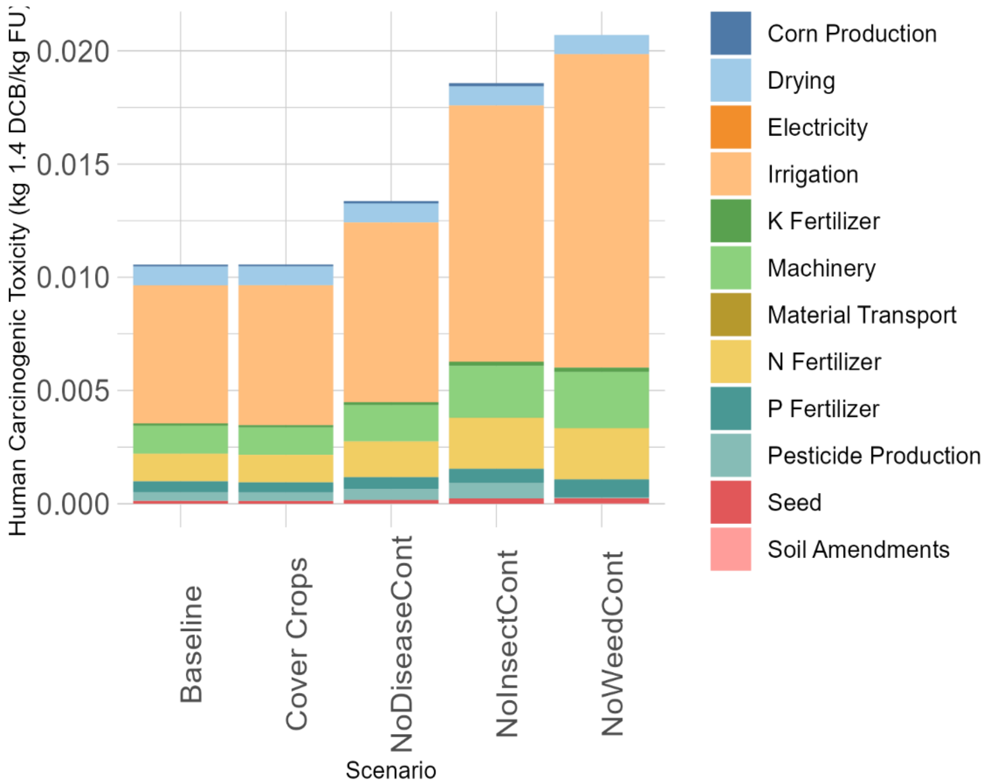

Figure 20. Human Carcinogenic Toxicity impacts to produce 1 kg of Corn using the ReCiPe 2016 (H) Framework.

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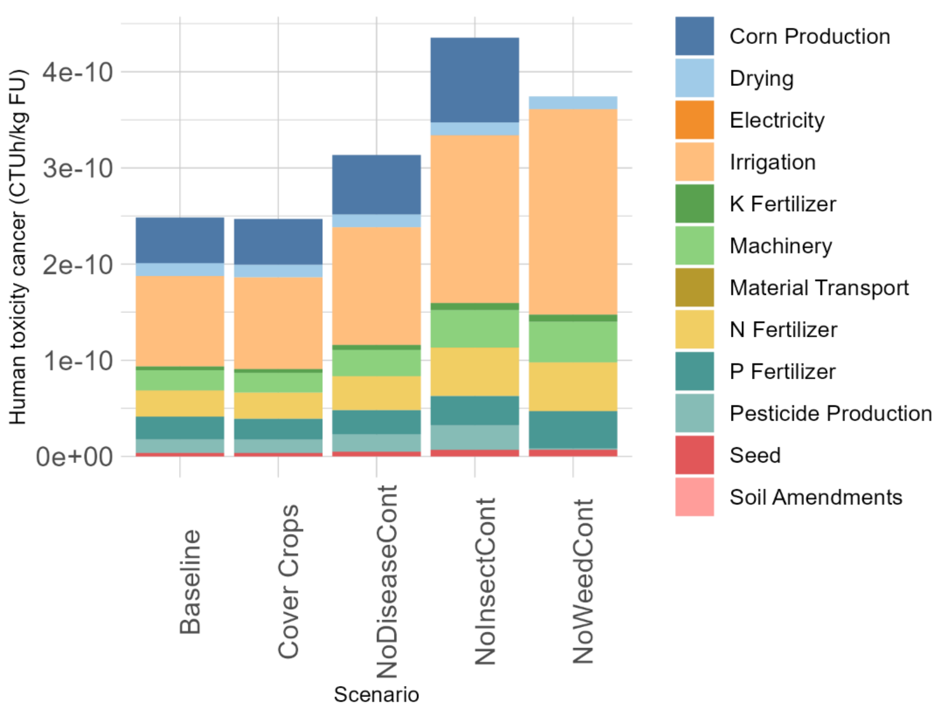

Figure 21. Human toxicity: carcinogenic- comparative toxic unit for human (CTUh) impacts to produce 1 kg of Corn using the Environmental Footprint 3.0 Framework .

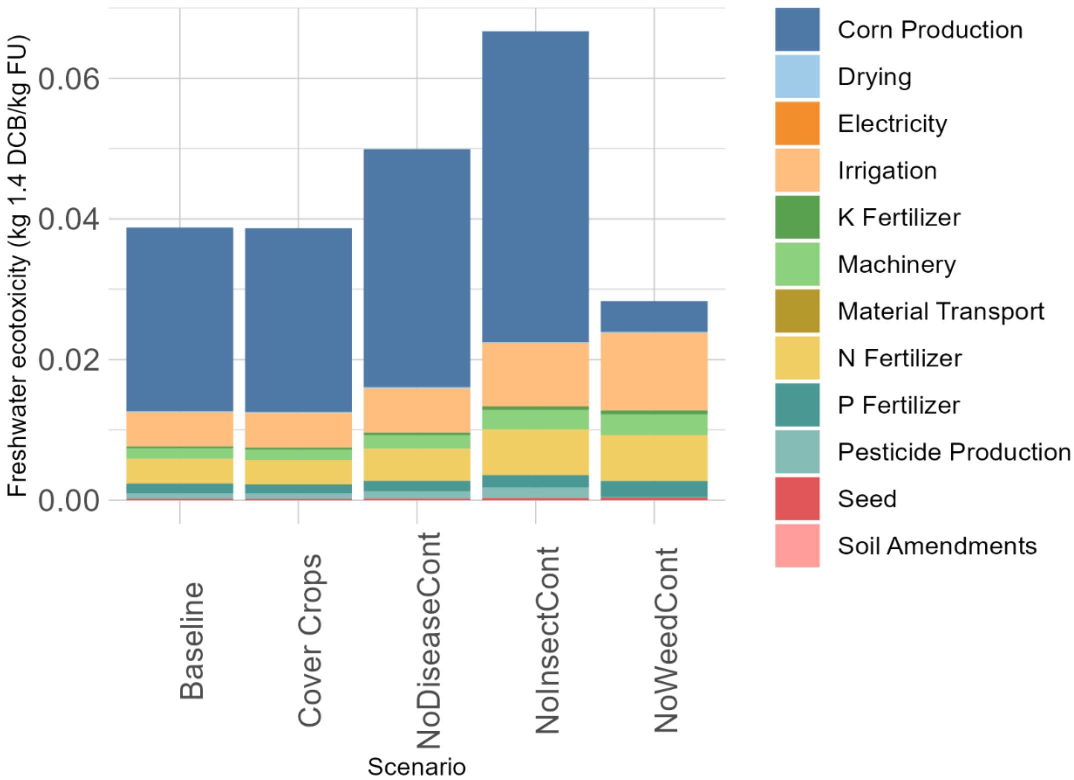

Figure 22: Ecotoxicity: freshwater - comparative toxic unit for ecosystems (CTUe) impacts to produce 1 kg of Corn using the ReCiPe 2016 (H) Framework.

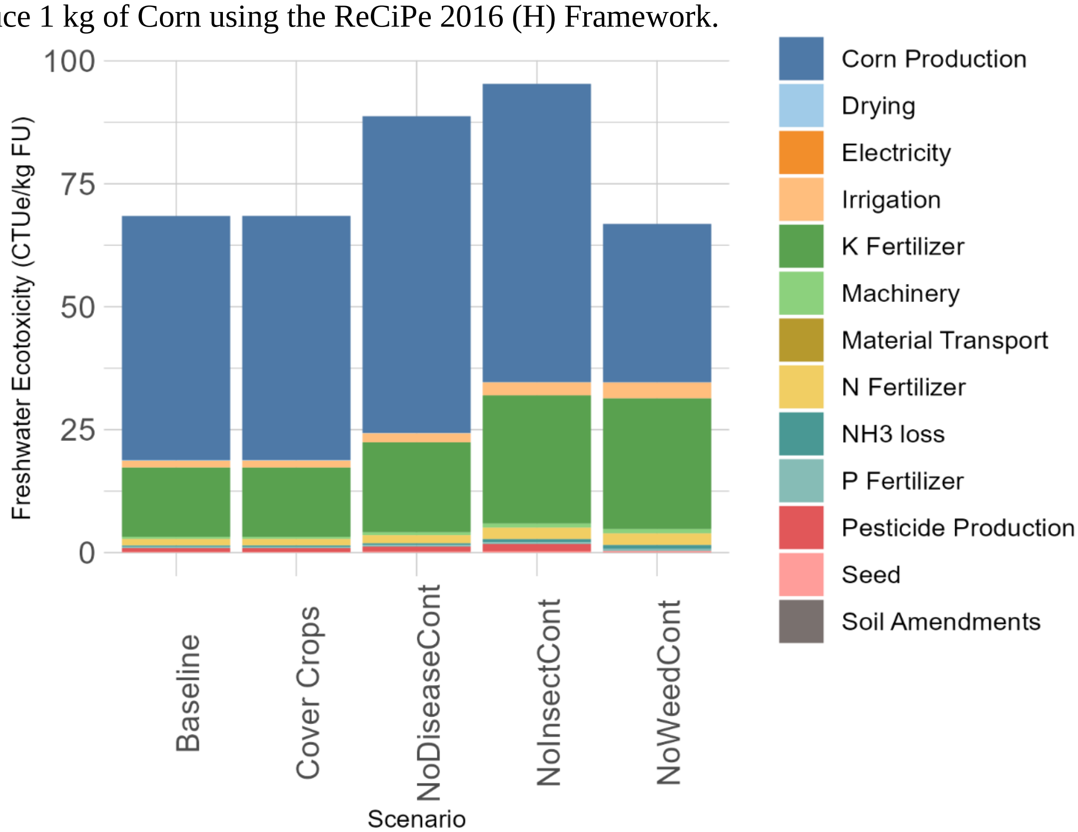

Figure 23: Ecotoxicity: freshwater - comparative toxic unit for ecosystems (CTUe) impacts to produce 1 kg of Corn using the Environmental Footprint 3.0 Framework.

6.2 LCIA for Soy Scenarios

Midpoint impact category results of the Life Cycle Impact Assessment for soy are presented in Table 6. Box plot analyses of Short-Term Climate Change, Land Occupation, Fossil and Nuclear Energy Use, and Water Consumption are provided in Figure 25 through Figure 26, respectively. The results of environmental midpoint LCIA impact categories showed consistent results across chemical pest control scenarios for U.S. soy production. The four primary impact categories (short-term climate change, fossil and nuclear energy use, land occupation- biodiversity, and water consumption) were significantly increased when each category of chemical pest control (disease, insect, and weed) were not used. Eliminating insect control had the largest effect on all midpoint impact categories. Adding cover crops did not significantly change impacts for any of the midpoint indicators compared to the baseline.

The LCIA framework comparison tables and graphs for the five soy scenarios are presented in Appendix E. In general, even though the three LCIA frameworks have different impact categories, there were no significant differences in corn scenario Dunn Grouping results across the three LCIA frameworks. The environmental midpoint categories for Corn Baseline and Cover Crop scenarios for EF 3.0 and ReCiPe 2016 had the same Dunn groupings, meaning there were no differences in groupings from Impact World+. The No Disease Control scenarios for EF 3.0 and ReCiPe 2016 were grouped separately from the other four scenarios. The Freshwater Eutrophication impact category was one Dunn Group across all five scenarios in Impact World+ and showed some differences across No Insect Control and Not Weed Control in EF 3.0 and ReCiPe 2016. These minor differences are likely due to the way the two older LCIA frameworks calculate the impacts of contributions of phosphorus to streams from the APEX models. The Human Toxicity (both non-carcinogens and carcinogens) impact category in EF 3.0 both showed significant increases in the three non-pesticide scenarios. This is due to the increased burden of the toxicity associated with energy usage for the lower-yielding scenarios.

Table 6: Life Cycle Impact Assessment of environmental midpoint impact categories for U.S. soy production comparing four production scenarios with baseline production.

Mid-point Impact Categories

Impact Category	Units	Baseline		Cover Crops		NoDiseaseCont		NoInsectCont		NoWeedCont		P-Value
Climate change long term	**kg CO_2 eq**	0.55	a	0.57	a	0.71	b	1.95	c	1.24	d	8.53E-32***
Climate change short term	**kg CO_2 eq**	0.59	a	0.62	a	0.76	b	2.11	c	1.34	d	1.65E-31***
Fossil and nuclear energy use	**MJ deprived**	6.75	a	6.98	a	8.34	b	22.00	c	14.60	d	9.57E-33***
Freshwater acidification	**kg SO_2 eq**	5.15E-3	a	5.67E-3	a	7.85E-3	b	2.53E-2	c	1.41E-2	d	9.39E-31***
Freshwater ecotoxicity	**CTUe**	87.30	a	90.20	a	108.00	b	277.00	c	182.00	d	9E-33***
Freshwater eutrophication	**kg PO_4 P lim**	4.52E-4	a	5.09E-4	a	6.02E-4	a	2.12E-3	b	1.04E-3	c	1.89E-15***
Human toxicity cancer	**CTUh**	7.14E-9	a	7.35E-9	a	9.04E-9	b	2.52E-8	c	1.55E-8	d	2.15E-32***
Human toxicity non cancer	**CTUh**	5.59E-8	a	5.83E-8	a	7.02E-8	b	1.97E-7	c	1.29E-7	d	2.29E-33***
Ionizing radiations	**Bq C 14 eq**	7.50	a	7.65	a	8.93	a	21.00	b	14.80	c	6.71E-31***
Land occupation biodiversity	**m^2 arable land**	2.78	a	2.78	a	3.61	b	10.30	c	5.81	d	5.37E-34***
Marine eutrophication	**kg N N lim eq**	1.05E-2	a	1.09E-2	a	1.87E-2	b	6.56E-2	c	1.76E-2	b	2.06E-22***
Mineral resources use	**kg deprived**	2.09E-2	a	2.16E-2	a	2.69E-2	b	7.71E-2	c	5.22E-2	d	1.2E-32***
Ozone layer depletion	**kg CFC 11 eq**	8.44E-8	a	8.64E-8	a	1.06E-7	b	2.97E-7	c	9.31E-8	a	4.75E-24***
Particulate matter formation	**kg PM2.5 eq**	8.11E-4	a	8.88E-4	a	1.24E-3	b	3.94E-3	c	2.21E-3	d	9.65E-31***
Photochemical oxidant formation	**kg NMVOC eq**	1.78E-3	a	1.87E-3	a	2.26E-3	b	6.35E-3	c	4.36E-3	d	1.7E-32***
Terrestrial acidification	**kg SO_2 eq**	1.03E-2	a	1.15E-2	a	1.64E-2	b	5.39E-2	c	2.94E-2	d	6.16E-30***
Water scarcity	**m^3 world eq**	0.14	a	0.15	a	0.17	a	0.51	b	0.35	b	4.91E-31***
Water Consumption	**m^3**	22.50	a	22.80	a	29.20	b	83.30	c	56.90	d	1.66E-31***

Impact Values denoted are the mean and Dunn significance group letter

Significance: ^{NS}(P>0.05), **(P<0.05), **(P<0.01), ***(P<0.001)*

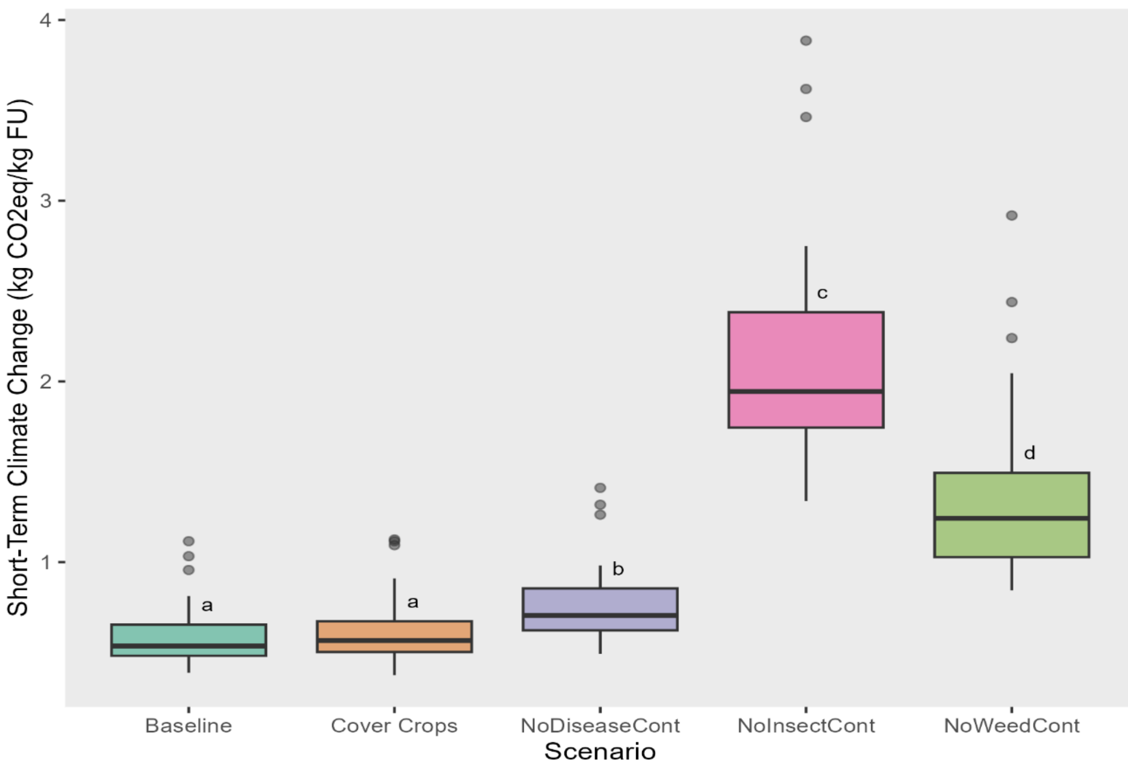

Figure 254: Box plots of soy production LCIA midpoint scenarios for Short-term Climate Change compared to Baseline.

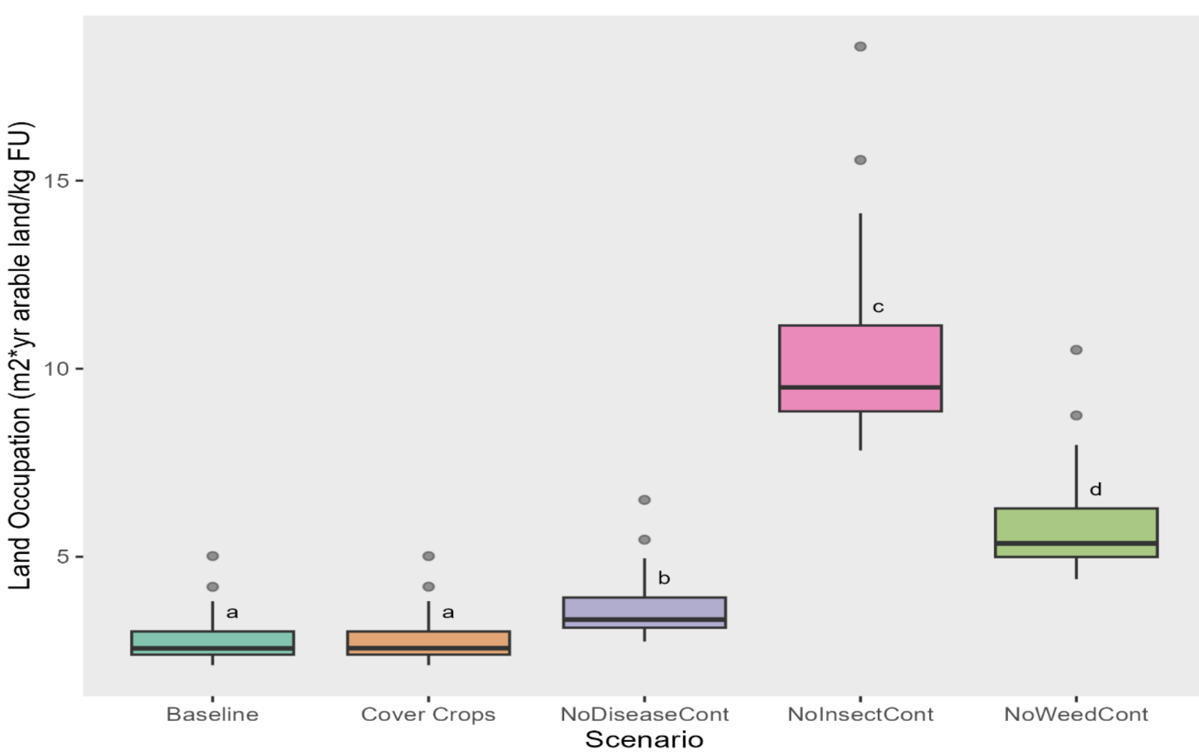

Figure 245: Box plots of soy production LCIA midpoint scenarios for Land Occupation compared to Baseline.

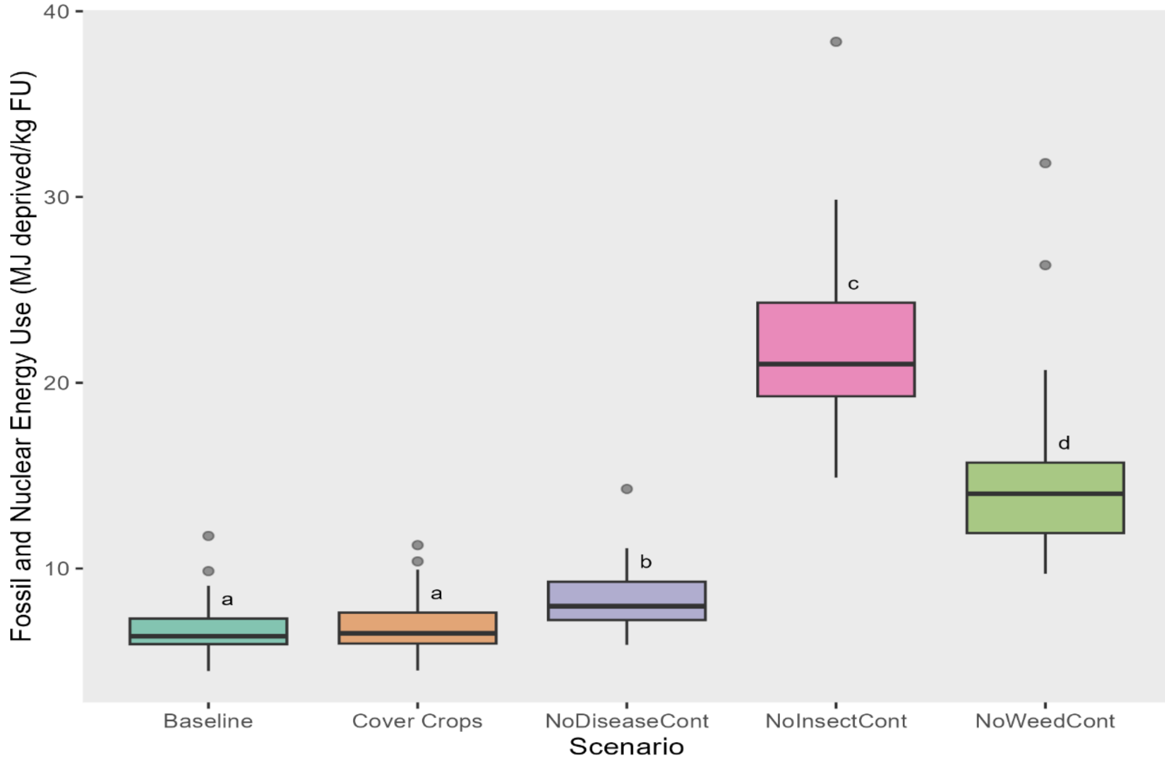

Figure 276: Box plots of soy production LCIA midpoint scenarios for Fossil and Nuclear Energy Use compared to Baseline.

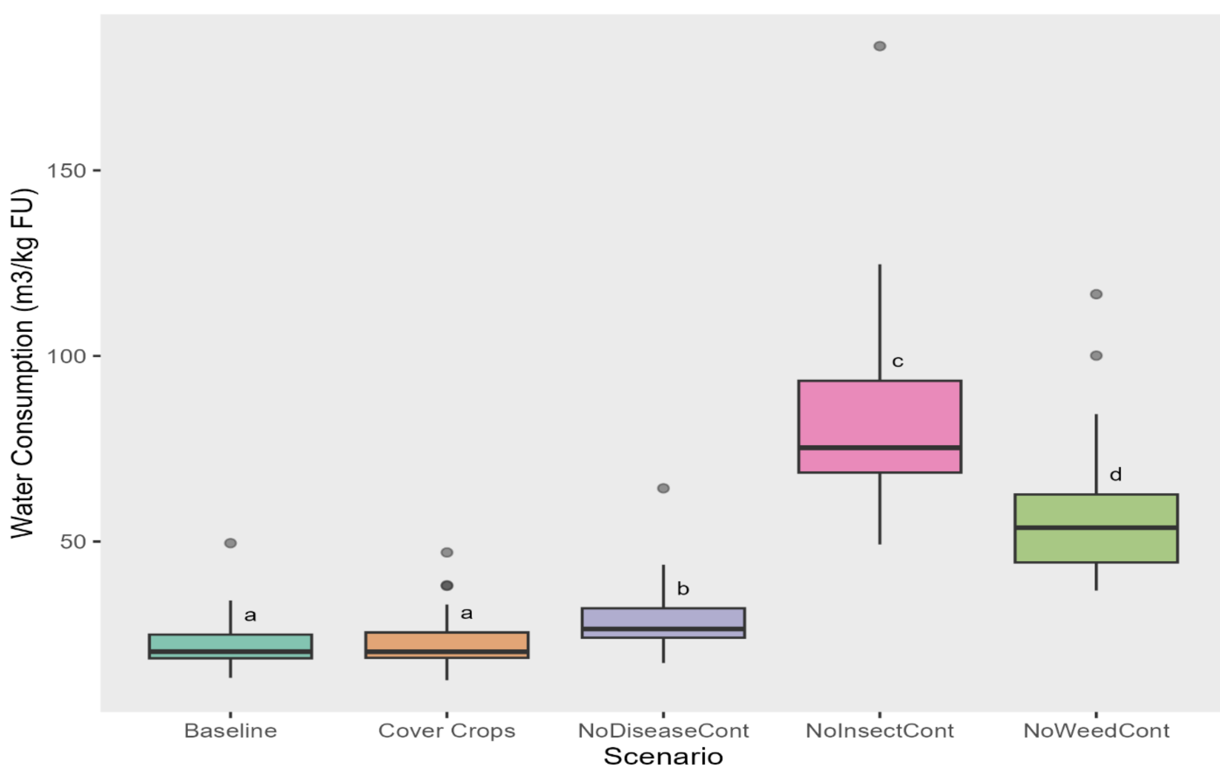

Figure 267: Box plots of soy production LCIA midpoint scenarios for Water Consumption compared to Baseline.

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6.2.1 Contribution Analysis: Soy

In this section we present the contribution analysis for soy production across the five scenarios. Figure 28 presents the contribution analysis from various activities in supply chain for long-term climate change impacts based on the Impact World+ framework. The contribution profiles are notably different from corn production due to the absence of significant nitrogen fertilizer input and the reduction in impact for the "no weed control" scenario compared to the "no insect control" scenario. This seems to be driven by differences in yield impact associated with these two scenarios.

Figure 29 shows that the dominant contributor to fossil resource use is associated with irrigation energy, differing from corn production due to the significantly lower use of nitrogen fertilizer.

Figure 30 shows a similar pattern to corn production in that ammonia emissions are the dominant contributor to particulate matter formation which is a significant contributor to human health impacts. Backspace, and as with the description for corn production also contributes to terrestrial acidification and indirect nitrous oxide emissions.

As shown in Figure 31 fertilizer production remains a dominant contributor to water scarcity despite its lower utilization and soybean production.

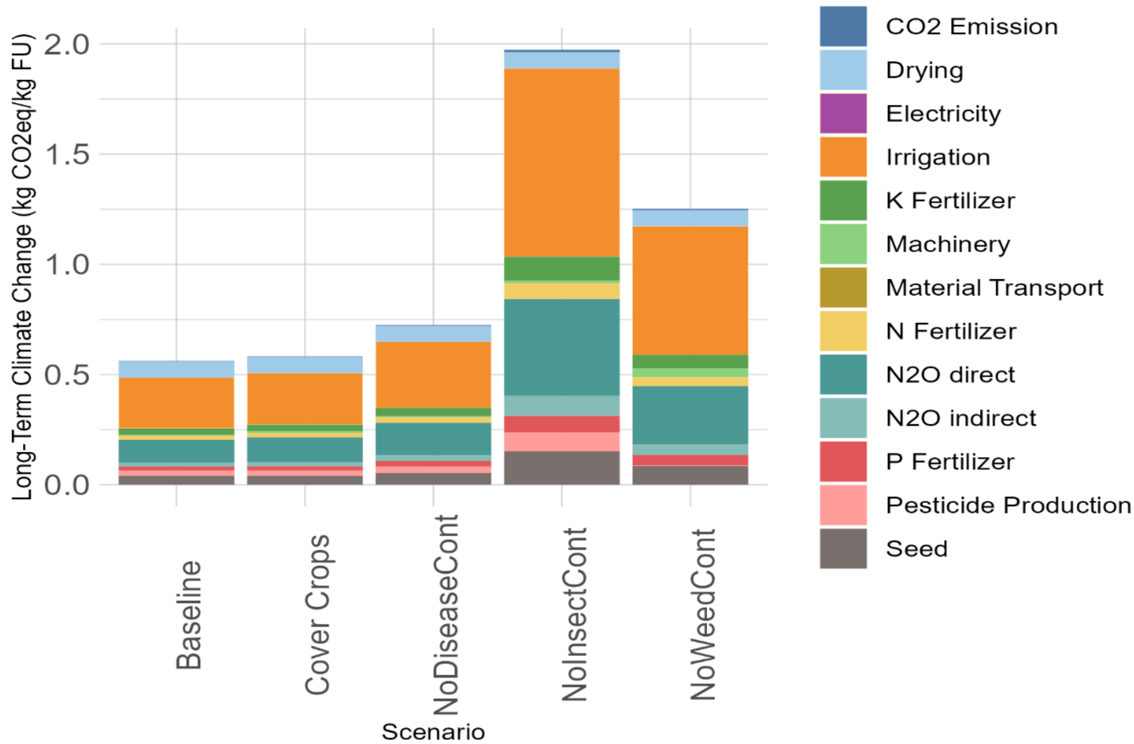

Figure 28. Climate Change: Long Term impacts to produce 1 kg of Soybean using the Impact World+ Framework.

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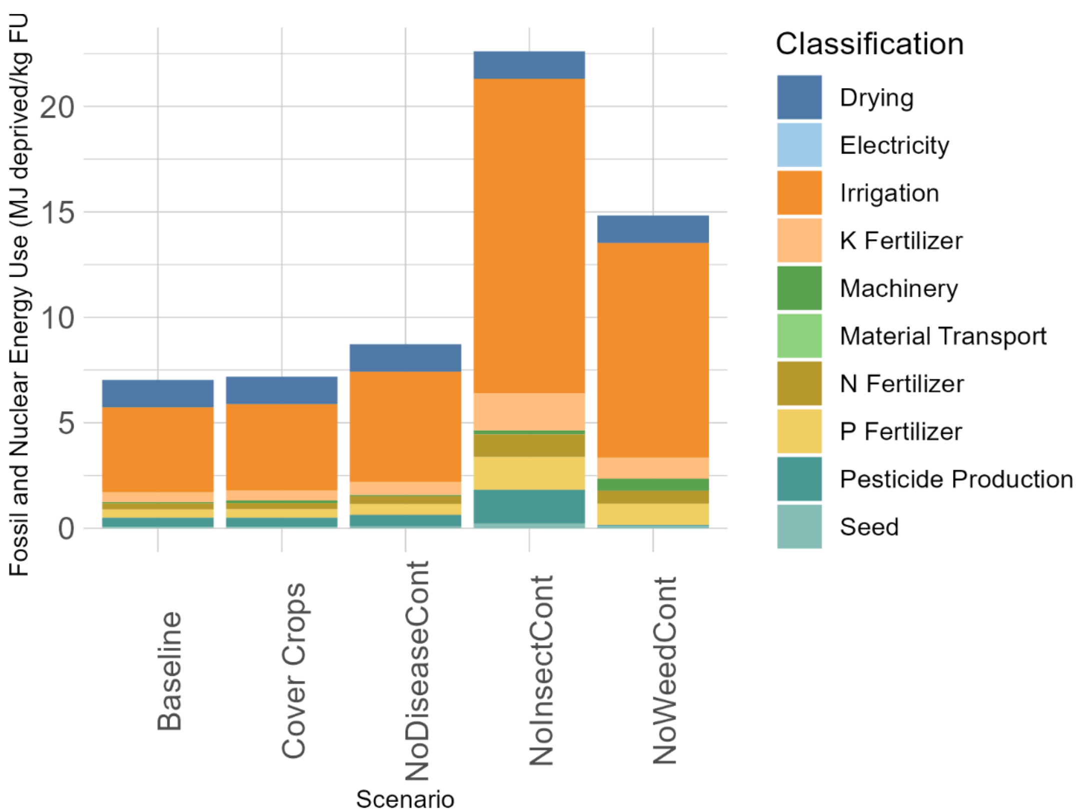

Figure 29. Fossil And Nuclear Energy Use impacts to produce 1 kg of Soybean using the Impact World+ Framework.

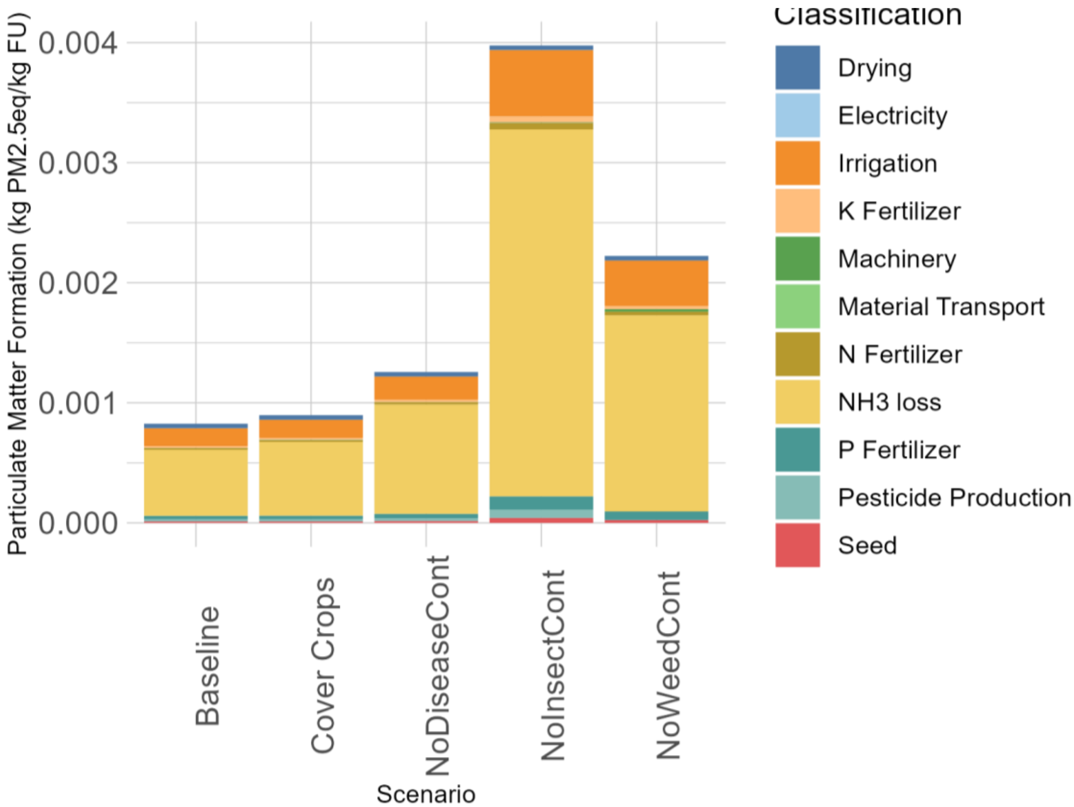

Figure 30. Particulate Matter Formation impacts for the production of 1 kg of Soybean using the Impact World+ Framework

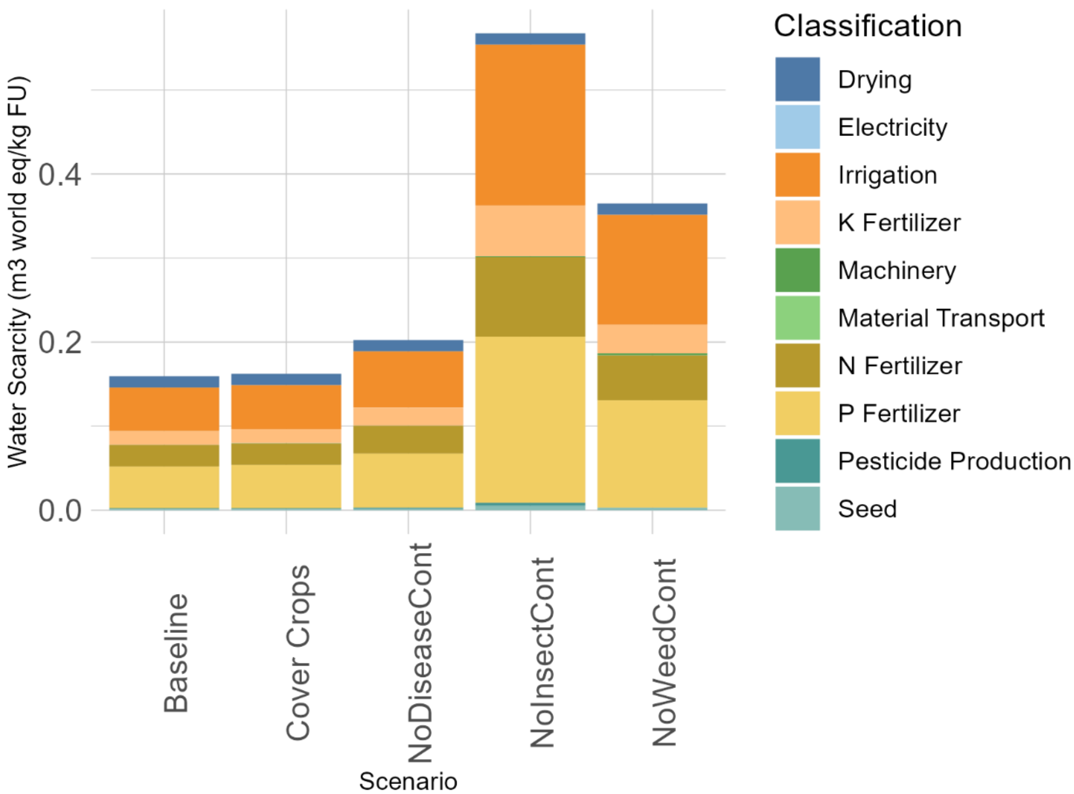

Figure 31. Water Scarcity impacts for the production of 1 kg of Soybean using the Impact World+ Framework

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6.3 LCIA for Cotton Scenarios

Midpoint impact category results of the Life Cycle Impact Assessment for cotton are presented in Table 7. Box plot analyses of Short-term Climate Change, Land Occupation, Fossil and Nuclear Energy Use, and Water Consumption are provided in Figure 32 through Figure 35, respectively. The results of environmental midpoint LCIA impact categories showed consistent results across chemical pest control scenarios for U.S. cotton production. The four primary impact categories (short-term climate change, fossil and nuclear energy use, land occupation/biodiversity and water consumption) were significantly increased when each category of chemical pest control (disease, insect, and weed) were not used. Eliminating chemical control of insects had statistically significant higher impacts across all midpoint categories. Adding cover crops did not significantly change impacts for any of the midpoint indicators compared to the baseline.

The LCIA framework comparison tables and graphs for the five cotton scenarios are presented in Appendix E. In general, even though the three LCIA frameworks have different impact categories, there were no significant differences in corn scenario Dunn Grouping results across the three LCIA frameworks. The environmental midpoint categories for Corn Baseline and Cover Crop scenarios for EF 3.0 and ReCiPe 2016 had the same Dunn groupings, meaning there were no differences in groupings from Impact World+. The No Disease Control scenarios for EF 3.0 and ReCiPe 2016 were grouped separately from the other four scenarios. The Freshwater Eutrophication impact category was one Dunn Group across all five scenarios in Impact World+ and showed some differences across No Insect Control and Not Weed Control in EF 3.0 and ReCiPe 2016. These minor differences are likely due to the way the two older LCIA frameworks calculate the impacts of contributions of phosphorus to streams from the APEX models. The Human Toxicity (both non-carcinogens and carcinogens) impact category in EF 3.0 both showed significant increases in the three non-pesticide scenarios. This is likely due to the increased burden of the toxicity associated with energy usage for the lower-yielding scenarios.

Table 7: Life Cycle Impact Assessment of environmental midpoint impact categories for U.S. cotton production comparing four production scenarios with baseline production.

Mid-point Impact Categories												
Impact Category	**Units**	**Baseline**		**Cover Crops**		**NoDiseaseCont**		**NoInsectCont**		**NoWeedCont**		**P-Value**
Climate change long term	**kg CO_2 eq**	0.85	a	0.88	a	1.22	b	1.74	c	1.35	b	2E-21***
Climate change short term	**kg CO_2 eq**	0.91	a	0.95	a	1.31	b	1.87	c	1.46	b	2.35E-21***
Fossil and nuclear energy use	**MJ deprived**	11.3	a	11.4	a	15.9	b	22.6	c	16.9	b	5.1E-25***
Freshwater acidification	**kg SO_2 eq**	8.08E-3	a	9.44E-3	a	1.29E-2	b	1.88E-2	c	1.46E-2	b	2.36E-20***
Freshwater ecotoxicity	**CTUe**	206	a	207	a	289	b	293	b	285	b	6.98E-13***
Freshwater eutrophication	**kg PO_4 P lim**	7.13E-4	a	6.24E-4	a	8.43E-4	ab	1.22E-3	b	1.10E-3	ab	3.25E-3**
Human toxicity cancer	**CTUh**	1.15E-8	a	1.16E-8	a	1.62E-8	b	2.29E-8	c	1.65E-8	b	8.49E-24***
Human toxicity non cancer	**CTUh**	1.22E-7	a	1.23E-7	a	1.71E-7	b	1.89E-7	b	1.79E-7	b	2.33E-19***
Ionizing radiations	**Bq C 14 eq**	8.96	a	9.05	a	12.60	b	17.80	c	13.40	b	8.46E-24***
Land occupation biodiversity	**m^2 arable land**	2.95	a	2.95	a	4.15	b	5.89	c	4.33	b	1.85E-30***
Marine eutrophication	**kg N N lim eq**	2.90E-2	a	2.75E-2	a	5.04E-2	bc	7.47E-2	b	4.19E-2	ac	1.50E-6***
Mineral resources use	**kg deprived**	3.81E-2	a	3.85E-2	a	5.35E-2	b	7.60E-2	c	5.70E-2	b	2.08E-22***
Ozone layer depletion	**kg CFC 11 eq**	1.44E-7	a	1.45E-7	a	2.02E-7	b	2.87E-7	c	2.13E-7	b	3.58E-27***
Particulate matter formation	**kg PM2.5 eq**	1.26E-3	a	1.47E-3	a	2.01E-3	b	2.93E-3	c	2.27E-3	b	1.57E-20***
Photochemical oxidant formation	**kg NMVOC eq**	3.50E-3	a	3.52E-3	a	4.91E-3	b	6.97E-3	c	5.18E-3	b	3.78E-17***
Terrestrial acidification	**kg SO_2 eq**	1.57E-2	a	1.90E-2	a	2.60E-2	b	3.80E-2	c	2.97E-2	b	1.28E-18***
Water scarcity	**m^3 world eq**	0.36	a	0.36	a	0.49	b	0.69	c	0.53	b	1.87E-24***
Water Consumption	**m^3**	37.9	a	38.5	a	53.5	b	76.0	c	57.4	b	1.14E-20***

Impact Values denoted are the mean and Dunn significance group letter.

Significance: ^{NS}(P>0.05), *(P<0.05), **(P<0.01), ***(P<0.001)

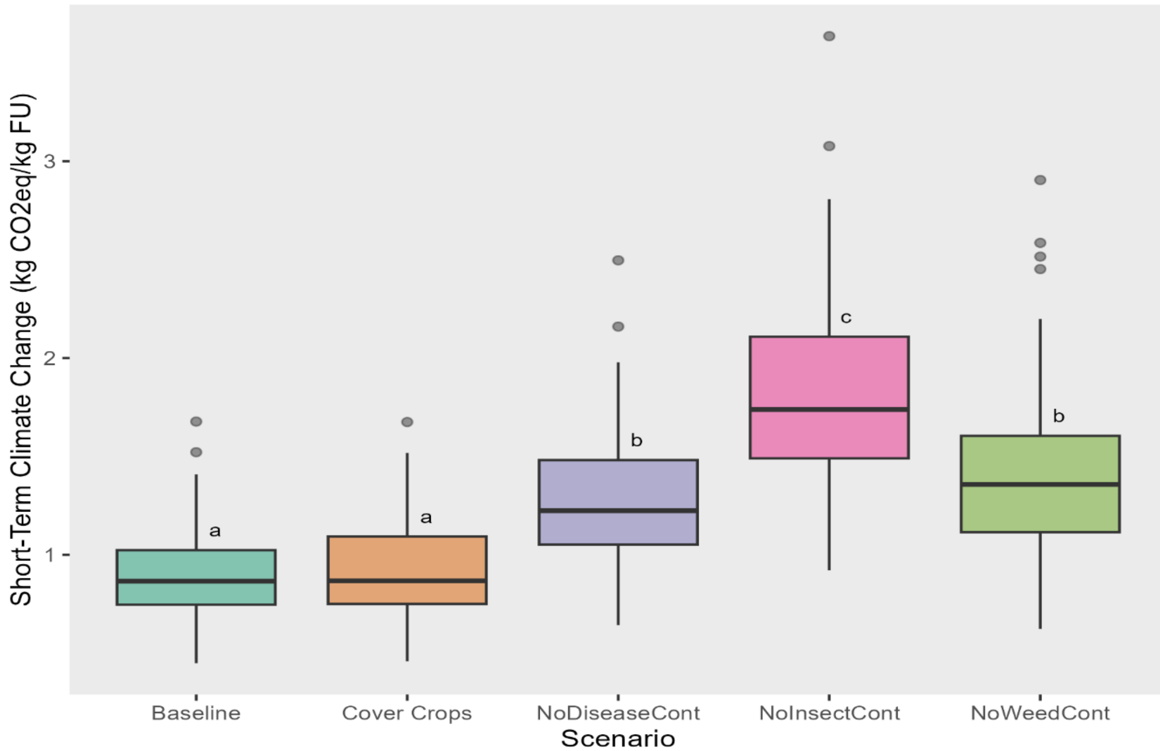

Figure 32: Box plots of cotton production LCIA midpoint scenarios for Short-term Climate Change compared to Baseline.

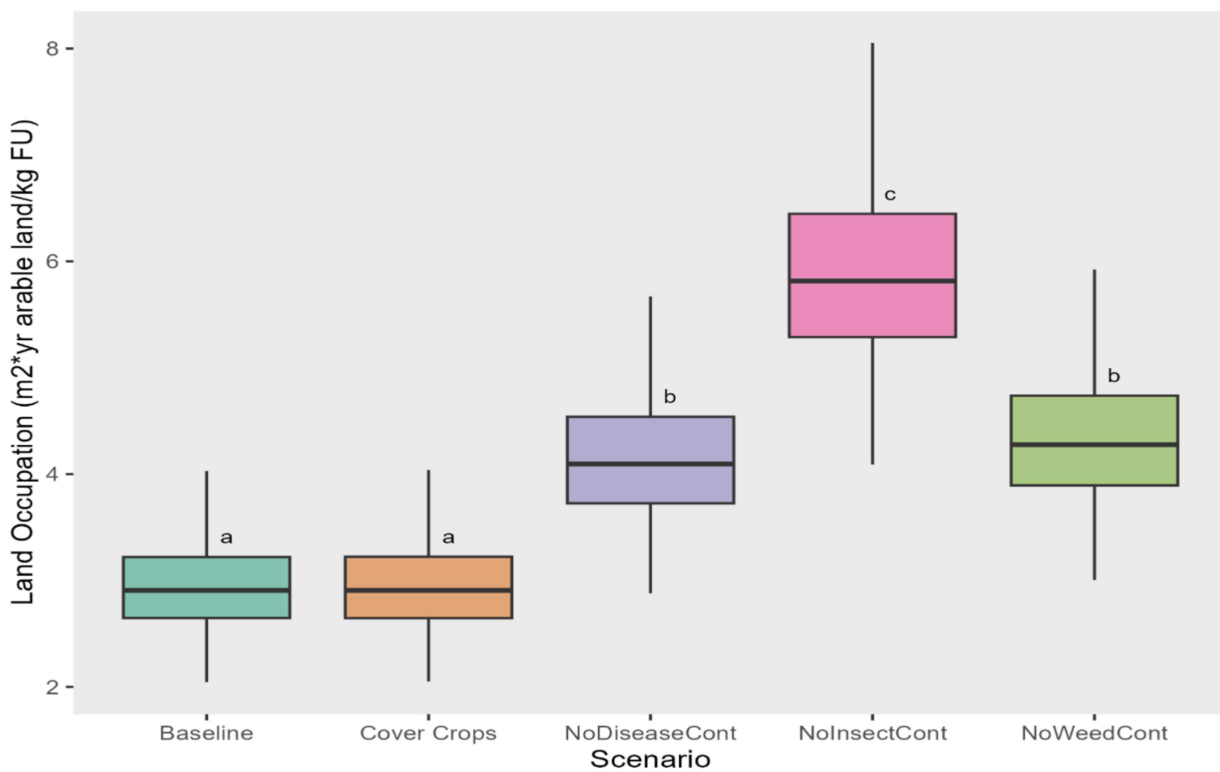

Figure 33: Box plots of cotton production LCIA midpoint scenarios for Land Occupation compared to Baseline.

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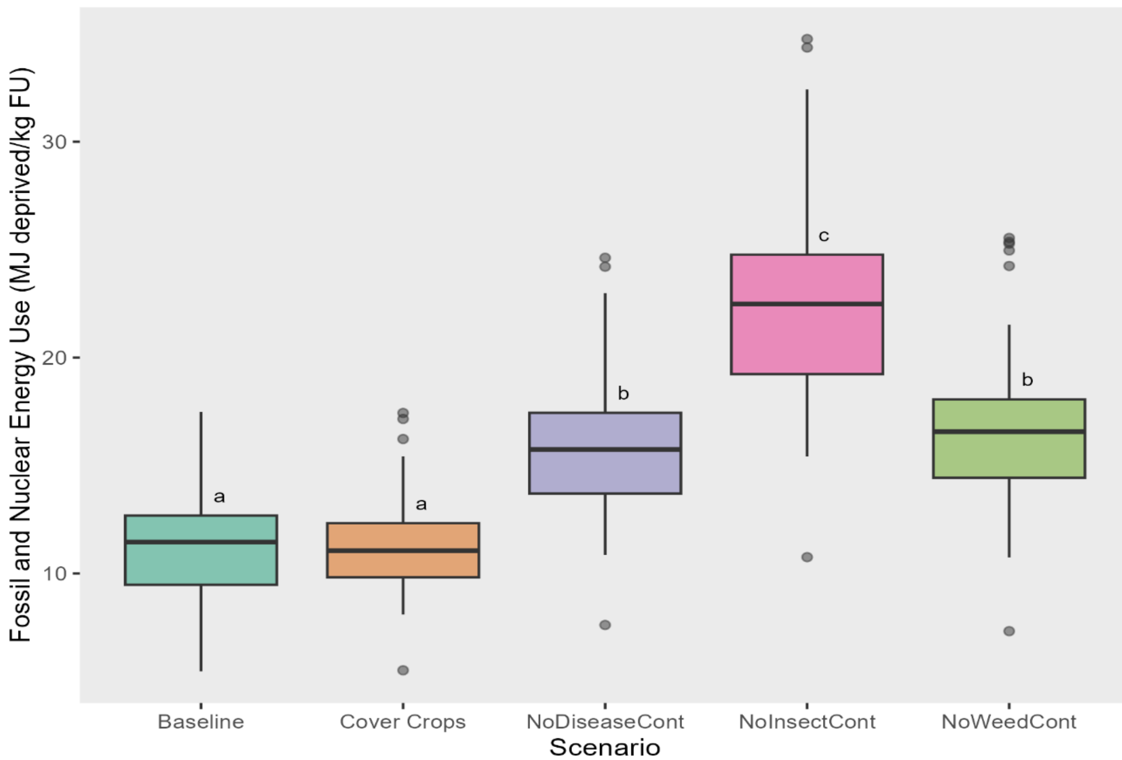

Figure 34: Box plots of cotton production LCIA midpoint scenarios for Fossil and Nuclear Energy Use compared to Baseline.

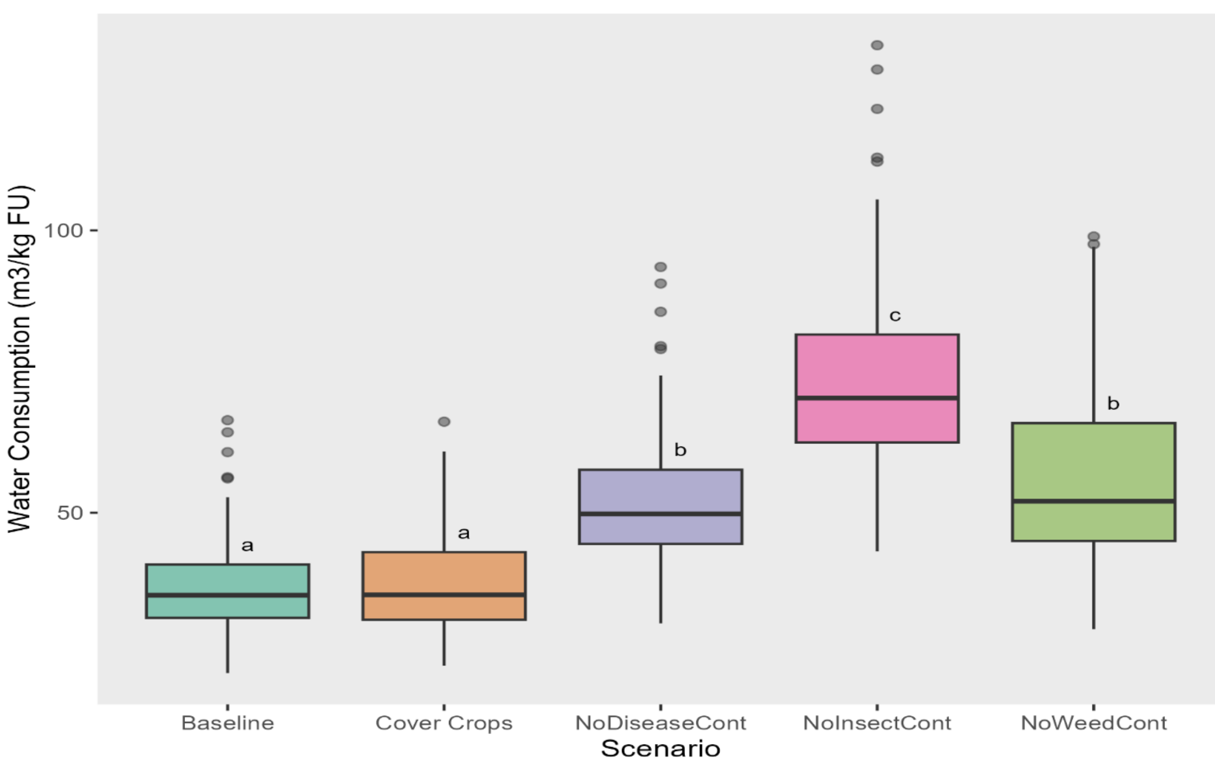

Figure 35: Box plots of cotton production LCIA midpoint scenarios for Water Consumption compared to Baseline.

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6.3.1 Contribution analysis: cotton

In this section we present the contribution analysis for cotton production across the five scenarios. Figure 36 presents the contribution analysis from various activities in supply chain for long-term climate change impacts based on the Impact World+ framework. The contribution profiles show the dominant contributing factors are energy for irrigation, fertilizer production and indirect nitrous oxide emissions associated with fertilizer application. The same contributing factors, aside from nitrous oxide emissions, are the dominant contributors to fossil resource consumption as shown in Figure 37.

Figure30 shows a similar pattern to corn production in that ammonia emissions are the dominant contributor to particulate matter formation which is a significant contributor to human health impacts. Backspace, and as with the description for corn production also contributes to terrestrial acidification and indirect nitrous oxide emissions.

As shown in Figure 38 fertilizer production remains a dominant contributor to water scarcity, with water used for irrigation as the second largest contributor.

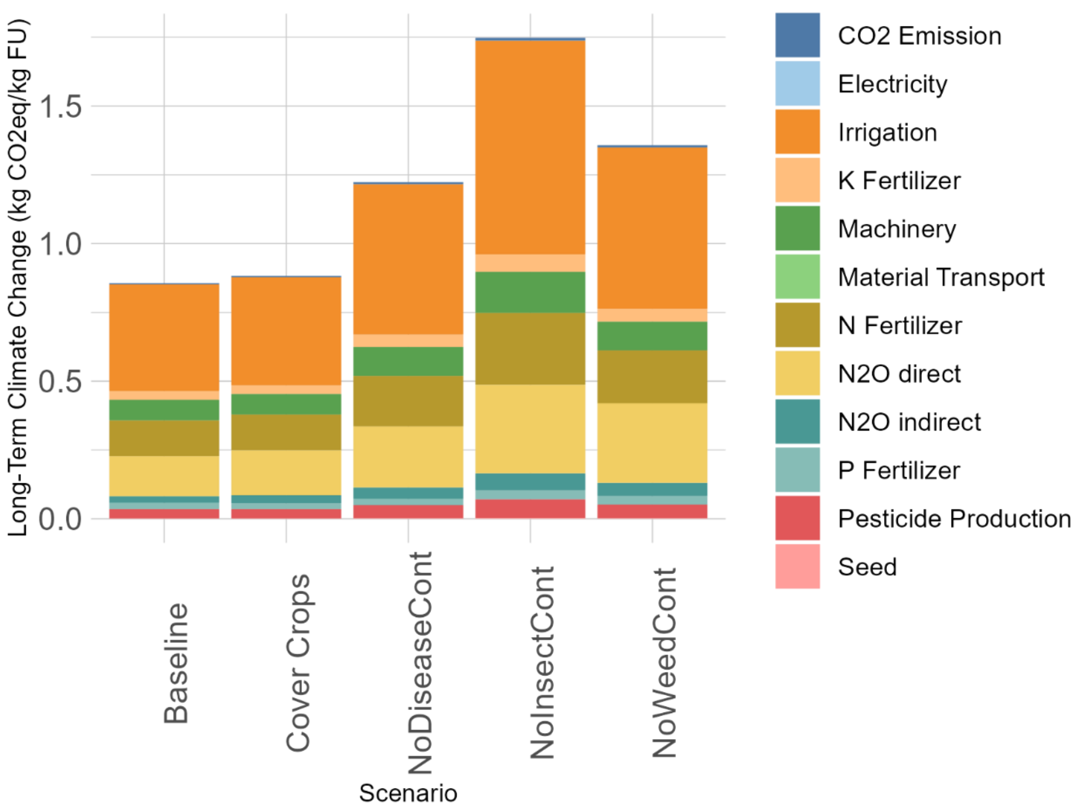

Figure 36. Climate Change: Long Term impacts to produce 1 kg of Cotton using the Impact World+ Framework.

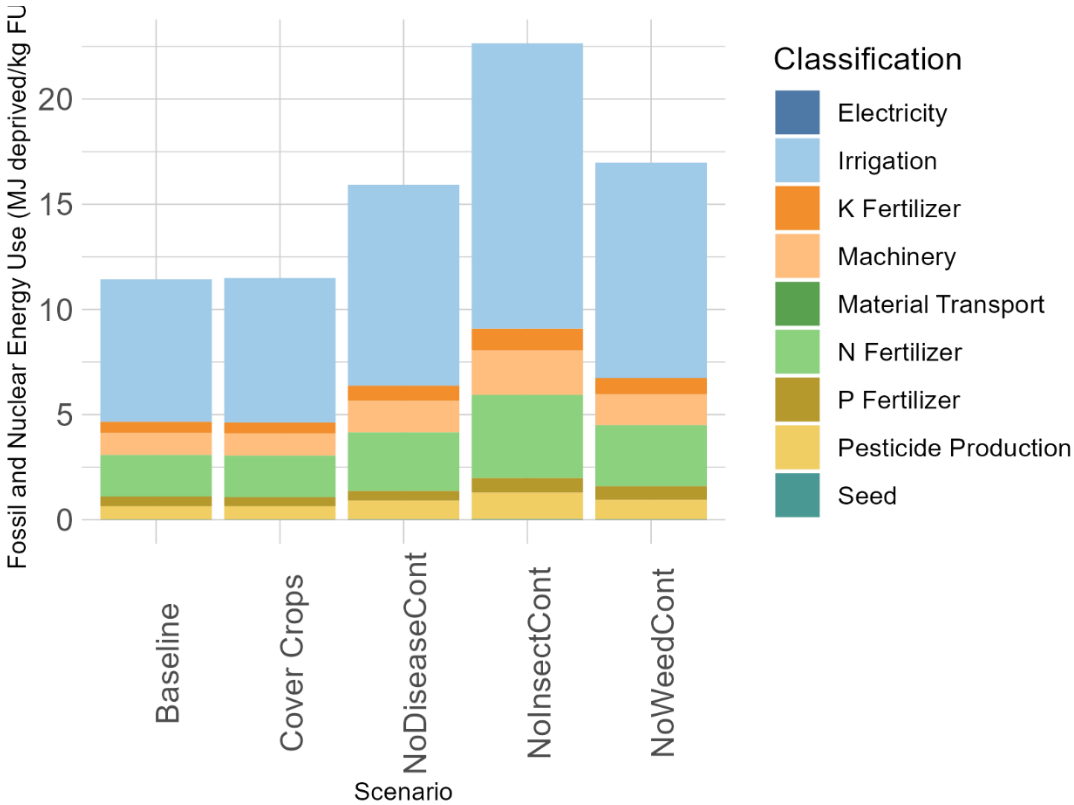

Figure 37. Fossil And Nuclear Energy Use impacts for the production of 1 kg of Cotton using the Impact World+ Framework.

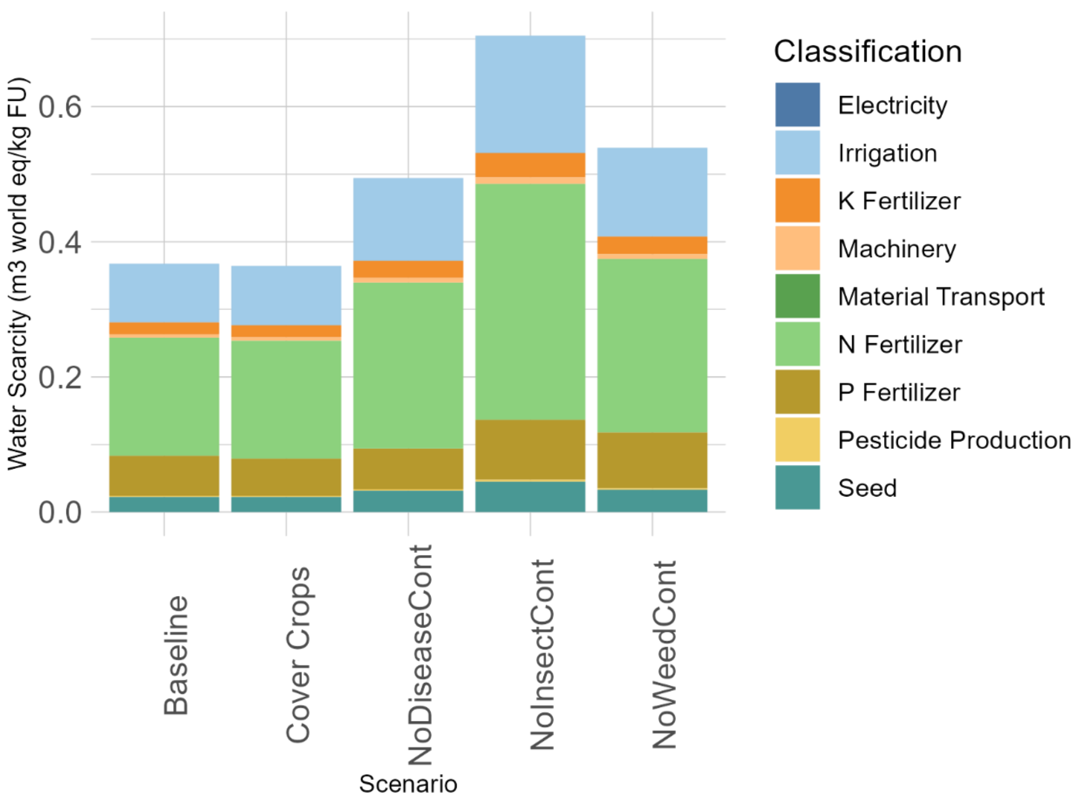

Figure 38. Water Scarcity impacts for the production of 1 kg of Cotton using the Impact World+ Framework

6.4 Completeness assessment

ISO 14040/4044 requires a completeness check to ensure that all required information and data from all activities have been used and are available for interpretation, including identification of data gaps. The system boundary and inventory are comprehensively described in the report according to the goal and scope. The LCI includes all known relevant flows for producing the functional unit. The database, Ecoinvent v3.6, cut-off system model, generally excludes services, which are also excluded from the foreground activities, as discussed in the cutoff criteria section (3.G). Generally, an input-output database would be needed to fully account for services in the supply chain. Exclusion of services can introduce a truncation error of up to 12% for climate change impacts (Font Vivanco, 2020). Although the exclusion of services may result in missing emissions, this will not affect the comparison of the alternatives in this study because all scenario systems would use the same services. The full suite of midpoint impact categories is included in Appendix E, which does not show tradeoffs between impact categories that affect the study conclusions.

6.5 LCIA Toxicity Results for Corn as an Explanation

The purpose of this LCA was to compare the life cycle impacts of exclusion of pesticide chemicals from corn, soy and cotton production in the US. The primary LCIA framework we used was Impact World+, though we also analyzed each crop scenario with EF 3.0 and ReCiPe 2016 for sensitivity (see Appendix E). The results for several impact categories beyond the four primary categories of concern for the purpose of the LCA seem to be counter to expectations. For example, corn impact categories for freshwater ecotoxicity, human toxicity – Cancer, and human toxicity non-cancer are all higher with exclusion of chemical insect and weed control. The expected result might be that taking away chemicals with known toxicities like insecticides and herbicides would reduce the life cycle toxicity of a kilogram of corn, soy, and cotton. However, this is the power of LCA. It quantifies the impacts of the entire supply chain, aggregates and allocates the impacts to the unit process (one kilogram of crop). When a production management decision is made that reduces yield but does not reduce inputs proportionally, the impact burdens from upstream of the crop are amplified accordingly. The land occupation results are direct measures of yield impacts; for corn the land required to produce one kg of corn was approximately 1 m^2 (Table 5). Without insect or weed control the amount of land required to produce one kg of corn was approximately 1.8 m^2, or nearly double. These losses occurred post-planting and cultivation, so the same quantity of inputs went into each area of land across baseline and chemical pest control exclusions. The contributions of toxicities to freshwater systems, cancer and non-cancer in humans are presented in Figures 21, 22, and 23, respectively. These examples from corn are similar across all three crops and other midpoint categories (Appendix F). Note that pesticide contribution to toxicity is the third bar component from the bottom in all the scenarios except "no week control" scenario. The relative toxicity across all scenarios from pesticide manufacturing and use were very low on a per unit production of crops basis. The increases in contributions from irrigation, nitrogen fertilizer, and machinery are all from the toxicity associated with energy used in each process (pumping water, synthesizing N fertilizer, operating machinery). However, all three LCIA frameworks use UseTox as the toxicity models. Uncertainty in UseTox can exceed 1000-fold differences for a given compound or exposure (Schenk and White, 2014). Assessment of impacts of toxicity to environmental or human endpoints would be better assessed using exposure-based toxicity risk assessment methods.

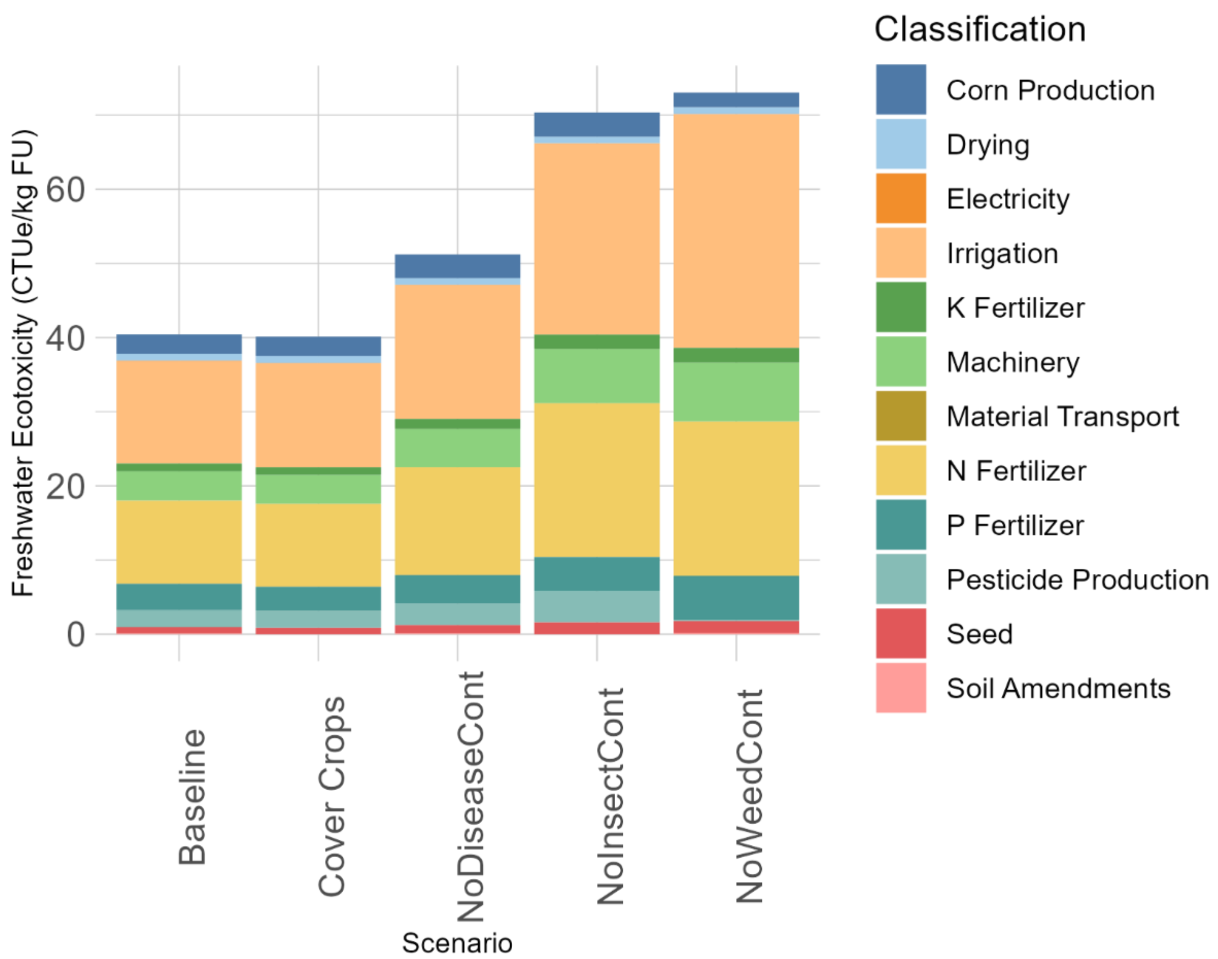

Figure 39: Contribution chart of corn production LCIA midpoint scenarios for Freshwater Ecotoxicity compared to Baseline.

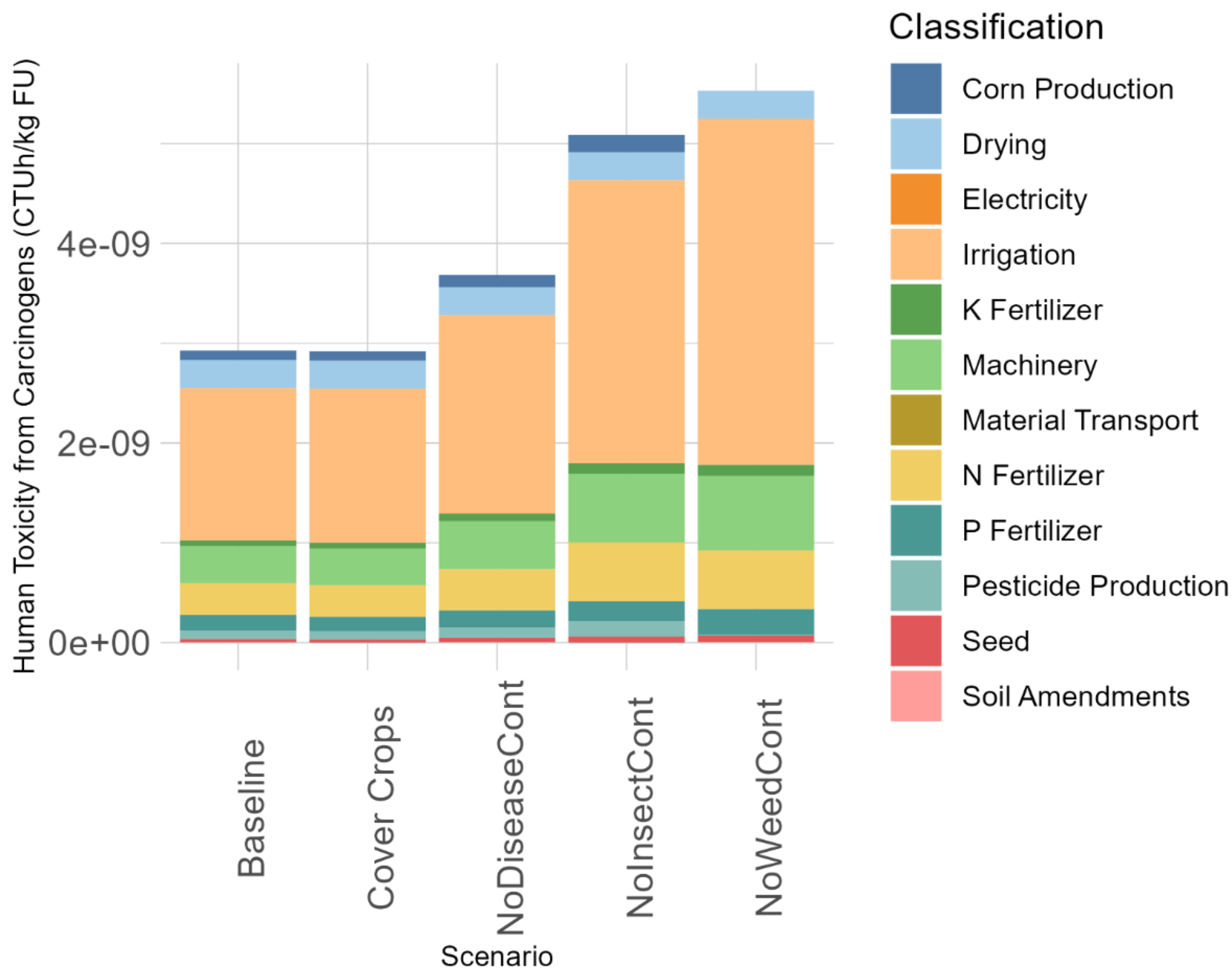

Figure 40: Contribution chart of corn production LCIA midpoint scenarios for Human Toxicity from Carcinogens compared to Baseline.

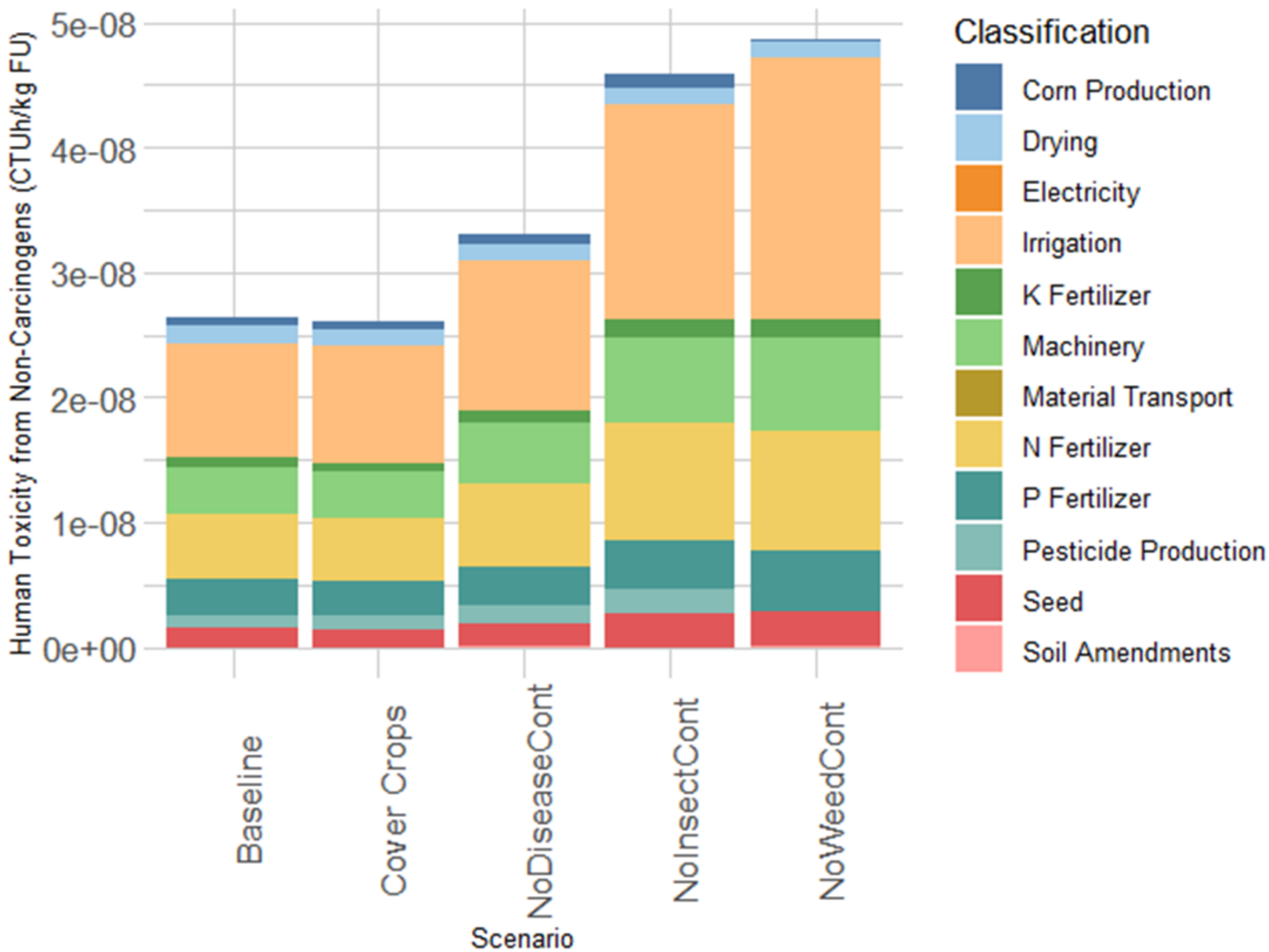

Figure 41: Contribution chart of corn production LCIA midpoint scenarios for Human Toxicity from Non-carcinogens compared to Baseline.

6.6 Consistency assessment

The consistency assessment evaluates whether assumptions, methods, and data are consistent with the study's goal and scope. Archetypal crop production operations were used for all comparative scenarios and are thus consistent and do not introduce bias to the comparison. However, there is lower temporal consistency in the Ecoinvent database, as some processes remain from as early as the 1990s. Nonetheless, this represents one of the best available data sources for background unit processes. System boundaries are also fully consistent across the compared systems.

6.7 Geographical and temporal representativeness.

This LCIA used a geographically distributed approach to archetype development to capture the range and variability of production conditions for corn, soy, and cotton. Each crop was represented by the top four producing counties in the top ten states, based on yield. The LCI data taken from the APEX models used a six-year cumulative total of yields for each crop system, capturing weather variability from 2015-2020.

6.8 Uncertainty assessment

The purpose of this assessment was to analyze the impacts of eliminating chemical pest control from major cropping systems. Uncertainty analysis was performed by representing the variability of the geographic range of production conditions (soil type, weather, local practices) for each crop in the archetype crop production models. Environmental and health impact categories were analyzed post-hoc using nonparametric analysis of archetype scenarios for each crop. Each cropping system had 40 archetype locations and six years of yield resulting in 240 estimators within each scenario. There were four scenarios for each of the three crops. The statistical analyses for sensitivity across scenarios for each impact category were significant, with $p<0.01$.

6.9 Value choices: LCIA framework.

Decisions regarding selection of supporting information, such as the use of a particular impact assessment framework can be considered value choices of the practitioner. These choices should not be determinative of the study outcomes, and thus are also subject to sensitivity testing. Here, the choice of the Impact World+ assessment framework. We have performed the complete analysis, including statistical testing for the ReCiPe 2016 Hierarchist and the Environmental Footprint 3.0 impact assessment frameworks.

As seen in Table 8 through Table 10, which report the statistical analysis for the ReCiPe 2016 (H) and Environmental Footprint 3.0, respectively for soy production. Similar results for corn and cotton are presented in Appendix E. The conclusions of this study are robust under the different impact assessment methods. The conclusions are not substantially changed either in terms of the general level of significance nor the direction and magnitude of the differences observed between the baseline and counterfactual scenarios. Thus, we conclude that the study conclusions are robust under our value choice of the life cycle impact assessment framework.

Table 8: Life Cycle Impact Assessment of ReCiPe 2016 environmental midpoint impact categories for U.S. soy production comparing four production scenarios with baseline production.

Mid-point Impact Categories

Impact Category	Units	Baseline		Cover Crops		NoDiseaseCont		NoInsectCont		NoWeedCont		P-Value
Global Warming	**kg CO_2 eq**	0.94	a	0.97	a	1.35	b	1.93	c	1.51	b	3.9E-21***
Stratospheric Ozone Depletion	**kg CFC11 eq**	9.72E-6	a	1.08E-5	a	1.48E-5	b	2.15E-5	c	1.84E-5	bc	1.78E-11***
Ionizing Radiation	**kBq Co60 eq**	5.84E-2	a	5.91E-2	a	8.20E-2	b	1.16E-1	c	8.80E-2	b	8.64E-24***
Ozone Formation- Human Health	**kg NOx eq**	2.61E-3	a	2.63E-3	a	3.66E-3	b	5.20E-3	c	3.85E-3	b	1.34E-15***
Fine Particulate Matter Formation	**kg PM2.5 eq**	3.37E-3	a	3.85E-3	a	5.28E-3	b	7.66E-3	c	5.90E-3	b	8.31E-22***
Ozone Formation- Terrestrial Ecosystems	**kg NOx eq**	2.68E-3	a	2.70E-3	a	3.77E-3	b	5.35E-3	c	3.96E-3	b	9.49E-16**
Terrestrial Acidification	**kg SO_2 eq**	1.75E-2	a	2.13E-2	a	2.91E-2	b	4.26E-2	c	3.32E-2	b	2.91E-18***
Freshwater Eutrophication	**kg P eq**	2.36E-3	a	2.00E-3	a	2.78E-3	b	4.11E-3	c	2.97E-3	bc	1.31E-08***
Marine Eutrophication	**kg N eq**	8.63E-3	a	8.13E-3	a	1.50E-2	bc	2.22E-2	b	1.24E-2	ac	1.11E-06***
Terrestrial Ecotoxicity	**kg 1.4 DCB**	5.27	a	5.28		7.38	b	9.60	c	5.08	a	9.06E-22***
Freshwater Ecotoxicity	**kg 1.4 DCB**	1.14E-1	a	1.14E-1	a	1.60E-1	b	1.99E-1	b	9.32E-2	a	6.75E-15***
Marine Ecotoxicity	**kg 1.4 DCB**	9.17E-2	a	9.21E-2	a	1.28E-1	b	1.33E-1	b	1.29E-1	b	3.37E-18***
Human Carcinogenic Toxicity	**kg 1.4 DCB**	4.38E-2	a	4.43E-2	a	6.16E-2	b	8.69E-2	c	6.52E-2	b	2.08E-23***
Human Non-Carcinogenic Toxicity	**kg 1.4 DCB**	4.17	a	4.18	a	5.87	b	2.37	c	6.09	b	8.12E-13***
Land Use	**m2a crop eq**	2.95	a	2.95	a	4.16	b	5.90	c	4.34	b	1.86E-30***
Mineral Resource Scarcity	**kg Cu eq**	8.37E-3	a	8.41E-3	a	1.15E-2	b	1.63E-2	c	1.25E-2	b	2.56E-26***
Fossil Resource Scarcity	**kg oil eq**	0.22	a	0.22	a	0.31	b	0.44	c	0.33	b	6.39E-25***
Water Consumption	**m3**	8.91E-3	a	8.92E-3	a	1.23E-2	b	1.74E-2	c	1.32E-2	b	3.44E-24***

Impact Values denoted are the mean and Dunn significance group letter.

Significance: ^{NS}(P>0.05), **(P<0.05), **(P<0.01), ***(P<0.001)*

Table 9: Life Cycle Impact Assessment of Environmental Footprint 3.0 environmental midpoint impact categories for U.S. soy production comparing four production scenarios with baseline production.

Mid-point Impact Categories												
Impact Category	**Units**	**Baseline**		**Cover Crops**		**NoDiseaseCont**		**NoInsectCont**		**NoWeedCont**		**P-Value**
Climate Change	**kg CO_2 eq**	0.61	a	0.64	a	0.79	b	2.20	c	1.39	d	2.45E-31***
Ozone Depletion	**kg CFC 11 eq**	7.96E-8	a	8.15E-8	a	1.00E-7	b	2.81E-7	c	8.65E-8	a	3.62E-24***
Ionizing Radiation	**kBq U235 eq**	6.69E-2	a	6.83E-2	a	7.96E-2	a	0.19	b	0.13	c	5.95E-31***
Photochemical Ozone formation	**kg NMVOC eq**	1.75E-3	a	1.85E-3	a	2.23E-3	b	6.26E-3	c	4.31E-3	d	1.77E-32***
Particulate Matter	**disease inc**	1.34E-7	a	1.48E-7	a	2.11E-7	b	6.91E-7	c	3.80E-7	d	3.3E-30***
Human Toxicity non-carcinogens	**CTUh**	2.08E-8	a	2.12E-8	ab	2.66E-8	bc	6.08E-8	d	3.45E-8	c	3.07E-24***
Human Toxicity carcinogens	**CTUh**	1.18E-9	a	1.19E-9	a	1.48E-9	b	4.22E-9	c	1.09E-9	a	1.62E-23***
Acidification	**mol H eq**	1.78E-2	a	1.97E-2	a	2.85E-2	b	9.37E-2	c	5.10E-2	d	9E-30***
Freshwater Eutrophication	**kg P eq**	1.74E-3	a	1.78E-3	a	2.24E-3	ab	6.49E-3	b	3.43E-3	bc	3.65E-23***
Marine Eutrophication	**kg N eq**	1.16E-2	a	1.20E-2	a	2.03E-2	b	7.05E-2	c	1.98E-2	b	4.57E-23***
Terrestrial Eutrophication	**mol N eq**	7.41E-2	a	8.26E-2	a	0.12	b	0.40	c	0.22	d	2.3E-29***
Freshwater Ecotoxicity	**CTUe**	246.00	a	246.00	a	318.00	ab	630.00	c	381.00	b	2.4E-19***
Land Use	**Pt**	143.00	a	143.00	a	185.00	b	529.00	c	299.00	d	4.73E-34***
Water Use	**m^3 deprived**	0.14	a	0.16	a	0.17	a	0.52	b	0.36	b	5.08E-31***
Fossil Resource Use	**MJ**	6.22	a	6.42	a	7.68	b	20.30	c	13.40	d	1.09E-32***
Mineral Resource Use	**kg Sb eq**	1.18E-5	a	1.30E-5	a	1.46E-5	a	4.47E-5	b	2.91E-5	c	3.51E-31***
Climate Change- Fossil	**kg CO_2 eq**	0.57	a	0.60	a	0.74	b	2.05	c	1.31	d	4.97E-31***
Climate Change- Biogenic	**kg CO_2 eq**	8.73E-4	a	9.10E-4	a	1.10E-3	b	3.04E-3	c	2.05E-3	d	5.8E-33***

Impact Values denoted are the mean and Dunn significance group letter.

Significance: ^{NS}(P>0.05), *(P<0.05), **(P<0.01), ***(P<0.001)

Table 10: Life Cycle Impact Assessment of Environmental Footprint 3.0 environmental midpoint impact categories for U.S. soy production comparing four production scenarios with baseline production.

Mid-point Impact Categories												
Impact Category	**Units**	**Baseline**		**Cover Crops**		**NoDiseaseCont**		**NoInsectCont**		**NoWeedCont**		**P-Value**
Climate Change- Land use and Land change	**kg CO2 eq**	3.71E-2	**a**	3.71E-2	**a**	4.85E-2	**b**	1.39E-1	**c**	7.83E-2	**d**	8.49E-35***
Human Toxicity Non-carcinogen organics	**CTUh**	7.90E-9	**a**	7.91E-9	**a**	1.02E-8	**ab**	1.44E-8	**b**	9.25E-9	**a**	1.25E-04***
Human Toxicity non-carcinogen inorganics	**CTUh**	6.77E-9	**a**	6.84E-9	**a**	8.71E-9	**b**	2.48E-8	**c**	1.06E-8	**d**	7.76E-32***
Human Toxicity non-carcinogen metals	**CTUh**	6.18E-9	**a**	6.52E-9	**a**	7.77E-9	**b**	2.17E-8	**c**	1.47E-8	**d**	5.07E-33***
Human Toxicity carcinogen organics	**CTUh**	9.57E-10	**a**	9.62E-10	**a**	1.20E-9	**a**	3.42E-9	**b**	5.5E-10	**c**	5.35E-29***
Human Toxicity carcinogen inorganics	**CTUh**	0	**n/a**	0	**n/a**	0	**n/a**	0	**n/a**	0	**n/a**	n/a
Human Toxicity carcinogen metals	**CTUh**	2.2E-10	**a**	2.3E-10	**ab**	2.76E-10	**b**	8.0E-10	**c**	5.4E-10	**d**	1.21E-32***
Freshwater Ecotoxicity-Organics	**CTUe**	139.00	**a**	139.00	**a**	179.00	**ab**	234.00	**b**	159.00	**a**	6.05E-05***
Freshwater Ecotoxicity-Inorganics	**CTUe**	14.50	**a**	14.60	**a**	18.90	**b**	54.20	**c**	29.00	**d**	2.73E-28***
Freshwater Ecotoxicity-Metals	**CTUe**	92.80	**a**	93.00	**a**	120.00	**b**	341.00	**c**	193.00	**d**	7.21E-27***

Impact Values denoted are the mean and Dunn significance group letter.

Significance: ^{NS}(P>0.05), *(P<0.05), **(P<0.01), ***(P<0.001)*

7. Conclusions

The goal of this LCA was to analyze the impacts of removing chemical controls for weeds, insects, and disease from production practices for U.S. corn, soy, and cotton production. To accomplish this goal, we performed an ISO 14040/14044 conformant LCA of impacts of production of each of the three crops under US standards of practice with and without the use of pesticides (herbicides, insecticides, and disease control), as well as application of cover crops.

The scope of this LCA is a cradle-to-farm gate assessment of corn, soy, and cotton (Figure 2). The corn, soy and cotton supply chains were divided into 4 stages: (1) pre-farm supply chain; (2) planting; (3) fertilizer application, disease and pest control, irrigation; (4) harvest and drying. For each stage, a separate full inventory of inputs and emissions was created and linked to construct the cradle-to-gate system. The functional units for each crop were:

1) Functional Unit for corn: One kg (15.5 % moisture),
2) Functional Unit for soybean: One kg (12.5 % moisture),
3) Functional Unit for cotton: One kg of lint with seed and trash (5 % moisture).

The LCIA framework applied to this LCA was IMPACT World+. The primary midpoint impact categories of concern by Crop Life America were the four dominant key performance indicators (KPIs) used in global assessment of sustainability of row crops: short-term climate change, fossil and nuclear energy use, land occupation and water consumption. Results for each crop were compared with baseline production impacts for each crop using archetype production practices across the U.S.

The results for U.S. archetypes of corn, soy and cotton showed consistent statistically significant increases in impacts across each scenario where chemical pest controls were excluded. Removing chemical pest management from crop production reduced yields for each crop, resulting in increased environmental impacts across the midpoint impact categories. These results are consistent with life cycle thinking, where the impact burdens on functional units are very sensitive to the efficiency of production of the product by which all impacts are assessed. Reduced yield of each crop by reducing chemical pest protection did not reduce the inputs necessary to produce those crops; the yield losses and associated impact burdens carried forward to the crop functional units. These are not inconsistent with results from similar agricultural systems where production strategies that reduce yields result in increased impacts.

Cover crop practices had no significant changes for any of the LCIA frameworks. For corn, soy, and cotton (Tables 5, 6, and 7 respectively) this means that all the additional inputs to produce cover crops (seed, fuel, water, cultivation, etc.) created no significant increase in deleterious environmental impacts. The advantages of cover crops for soil conservation, soil health, and water conservation are well documented and not measured in any LCIA framework. These results support the assessment that the environmental impacts of cover crops as a management practice are net positive for corn, soy, and cotton in the U.S.

The LCIA result for the four KPIs were summarized as percentage increases over baseline results (Table 11). The sensitivity analysis of corn and soy were analyzed for archetypes with median yields to represent sensitivity of the APEX model and LCIA to yield penalties. Producing crops without chemical pest controls increased all four priority impact categories by at least 26 percent (corn and soy fossil and nuclear energy uses for no disease control scenarios) and as much as 270 percent (soy water consumption with no insect control scenario). Overall impact increases were greatest across all three crops for all four priority impact categories for insect control followed by weed control and disease control respectively. The impacts increased as the yield penalty (low, medium, and high) increased. This is the expected behavior as the only change in the LCI for the scenarios was the yield penalty (chemical and other inventory changes were implemented for the lowest penalty and not further modified as yield penalty increased) – thus resulting in essentially constant inputs and emissions with declining yield led to a linear in category score as a function of yield. The coefficients of determination (R^2) between yield penalty and impact category score exceeded 0.90 for the four primary environmental impact categories in Table 11. These increases in environmental impacts are mostly driven by losses of yields across all three crops for all three chemical pest exclusion scenarios.

7.1 Recommendations and Limitations

This assessment shows the importance of life cycle thinking in assessing strategies to address local to global environmental challenges. The outcomes also highlight challenges with current LCIA frameworks in addressing environmental and human impacts in complex systems. Future analyses of the environmental impacts of agricultural production practices need LCIA frameworks that analyze potential beneficial impacts. These include soil conservation, soil health, habitat conservation, ecosystem services, and others.

The difficulty of finding sufficient information to perform an LCA of this scope and level of detail was the driving factor behind the usage of APEX to simulate crop production. While utilization of the APEX provided the data required to analyze the environmental impact that eliminating chemical pesticides can have, the archetype models have limitations as well. Data gaps in reported yield, pesticide application rates and environmental fates, characterization factors, and other aspects of the APEX modeling and LCI creation process had to be accounted for. The methods used to fill these data gaps are detailed in section 3.6 and 4.2.7.

As noted in our conclusions, the usage of cover crops practices did not significantly change the environmental impact of any of the three crop systems analyzed. One limitation of this study in regard to this scenario is that the APEX models used were not able to account for the pest management benefits that cover crops can provide such as the allelopathy of certain species of common cover crops or the weed suppression effects that the crop residue can have. Accounting for these aspects in future studies would provide a more complete picture of the benefits cover crops can potentially provide.

The ability of current LCIA frameworks to assess ecosystem or human toxicity are very limited based on the general models used. For example, the USEtox model is the dominant toxicity model for LCIA frameworks (Rosenbaum et al., 2011). Fantke et al. (2021) recommended a near-field/far-field exposure and toxicity characterization framework, for example. They recommended a probabilistic dose-response approach combined with a decision tree for identifying divergent impacts. Hou et al. (2020) pointed out that USEtox only has characterization factors for a limited number of chemicals in commercial use. Analyzing the ecotoxicity and human toxicity impacts from decisions associated with complex supply chain processes like crop production requires development of more comprehensive risk-based analytical models for hazard and exposure.

Table 11: Summary impacts of not using chemical pest controls across corn, soy, and cotton in the U.S., measured as percent differences from baseline impact.

Corn

Impact Category	Units	NoDiseaseCont	NoInsectCont	NoWeedCont
Climate change short term	kg CO_2 eq	29%*	82%	93%
Fossil and nuclear energy use	MJ deprived	26%	72%	80%
Land occupation biodiversity	m^2 arable la	29%	84%	88%
Water Consumption	m^3	30%	85%	126%

Soy

Impact Category	Units	NoDiseaseCont	NoInsectCont	NoWeedCont
Climate change short term	kg CO_2 eq	29%	258%	127%
Fossil and nuclear energy use	MJ deprived	24%	226%	116%
Land occupation biodiversity	m^2 arable la	29%	84%	88%
Water Consumption	m^3	30%	270%	153%

Cotton

Impact Category	Units	NoDiseaseCont	NoInsectCont	NoWeedCont
Climate change short term	kg CO_2 eq	44%	105%	60%
Fossil and nuclear energy use	MJ deprived	41%	100%	50%
Land occupation biodiversity	m^2 arable la	41%	100%	47%
Water Consumption	m^3	41%	101%	51%

* Meaning 29% higher than baseline scenario

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Life Cycle Assessment of impacts of eliminating chemical pesticides used in production of U.S. corn, soybeans, and cotton.

Appendices

Appendix A: Literature Review

Provided in electronic format.

Appendix B: Crop Archetype Design

Provided in electronic format.

Appendix C: List of Chemicals with Withheld Data in the NASS Database

Provided in electronic format.

Appendix D: List of Substituted Chemicals

Provided in electronic format.

Appendix E: LCIA Impact Category Results and Comparisons

To be provided in electronic format.

Appendix F: Contribution Analysis

To be provided in electronic format.

Appendix G: R Code for Statistical Analyses

To be provided in electronic format.

Appendix H: ISO Critical Review

To be provided in electronic format.

- Critical Review Statement -

Life cycle assessment of impacts of eliminating chemical pesticides used in the production of U.S. corn, soybeans, and cotton
Final Report

Commissioned by:	CropLife America
Conducted by:	Greg Thoma, Marty Matlock, Kyle Lawrence, Brandon Taylor, Jacob Hickman
Reviewers:	Tom Gloria – Industrial Ecology Consultants (Chair) Terrie Boguski – Harmony Environmental Pakarat Promyu – First Environment
References:	ISO 14044:2006 – Environmental Management – Life Cycle Assessment – Requirements and Guidelines ISO/TS 14071:2014 — Environmental management — Life cycle assessment — Critical review processes and reviewer competencies:Additional requirements and guidelines to ISO 14044:2006

Scope of the Critical Review

In accordance with ISO 14044:2006, section 6.1, the goal of the Critical Review was to assess whether:

- the methods used to carry out the LCA are consistent with the international standards ISO 14040 and ISO 14044,
- the methods used to carry out the LCA are scientifically and technically valid,
- the data used are appropriate and reasonable in relation to the goal of the study,
- the interpretations reflect the limitations identified and the goal of the study, and
- the study report is transparent and consistent.

As the study is intended to support comparative assertions intended to be disclosed to the public, the review was performed by a panel of independent experts following ISO 14044:2006, section 6.3.

This review statement is only valid for the specific report titled "**Life cycle assessment of impacts of eliminating chemical pesticides used in the production of U.S. corn, soybeans, and cotton Final Report**", dated March 25th, 2024, but not to any other report versions, derivative reports, excerpts, press releases, and similar documents.

The review was performed exclusively on the LCA study report. No software models were shared or requested during the review.

Critical Review process

The review was conducted by exchanging comments and responses using a review matrix based on Annex A of ISO/TS 14071:2014.

The critical review was carried out between November 11, 2023 (delivery of the first draft of the report) and April 10, 2024 (delivery of the final review statement). There were three formal rounds of comments on the report as well as email conversations in-between. A copy of the final review report containing all written comments and responses has been provided to the study commissioner along with this review statement, and shall be made available to third parties upon request.

The overall review was conducted in an equitable and constructive manner. The reviewers would like to highlight the constructive collaboration with the authors of the report. All comments were addressed and all open issues were resolved. There were no dissenting opinions held by any of the involved parties upon finalization of the review.

General evaluation

The study is well scoped, and the analysis is capable of supporting the goal of the study. It shows a high level of technical knowledge and methodological proficiency.

Conclusion

Based on the final study report, it can be concluded that the methods used to carry out the LCA are consistent with the international standard ISO 14044, that they are scientifically and technically valid, that the data used are appropriate and reasonable in relation to the goal of the study, and that the interpretations reflect the limitations identified and the goal of the study. The study report is considered sufficiently transparent and consistent.

When communicating results to third parties outside of CropLife America, ISO 14044, section 5.2 requires that a third-party report be made available to any such parties. The third-party report shall be made available by the study commissioner and should contain all required information as specified in ISO 14044, section 5.2. Any confidential or otherwise sensitive contents can be removed or blacked out prior to sharing the report with third parties.

The reviewers sign this review statement as individual experts. Their signatures do not constitute an endorsement of the study's scope or results by the affiliated organizations.

Thomas Gloria	Terrie K Boguski	Pakarat Promyu
Thomas Gloria	Terrie Boguski	Pakarat Promyu

Valid as of April 10, 2024