



Life cycle greenhouse gas emissions for irrigated corn production in the U.S. great plains

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ABSTRACT

Agricultural management practices improve crop yields to satisfy food demand of the growing population. However, these activities can have negative consequences, including the release of greenhouse gas (GHG) emissions that contribute to global climate change. To mitigate this global environmental problem, the management practices that contribute the most to system GHG emissions should be identified and targeted to mitigate emissions. Accordingly, we estimated the cradle-to-product GHG emissions of irrigated corn production under various farmer-selected scenarios at an experimental testing field in the semi-arid U.S. Great Plains. We applied a carbon footprint approach to quantify life cycle GHG emissions associated with pre-field (e.g., energy production, fertilizer production) and in-field (e.g., groundwater pumping, fertilizer application) activities within fourteen scenarios in the 2020 Oklahoma Testing Ag Performance Solutions (TAPS) sprinkler corn competition. We determined that 63% of the total GHG emission from corn production was associated with in-field activities and that agricultural soil emissions were the overall driving factor. Soil biochemical processes within agricultural soils were expected to contribute an average of $89 \pm 18 \text{ g CO}_2\text{-eq kg}^{-1}$ corn of the total $271 \pm 46 \text{ g CO}_2\text{-eq kg}^{-1}$ corn estimated from these systems. On-site natural gas combustion for agricultural groundwater pumping, pre-field fertilizer production, and pre-field energy production for groundwater pumping were the next most influential parameters on total GHG emissions. Diesel fuel, seed, and herbicide production had insignificant contributions to total GHG emissions from corn production. The model was most sensitive to the modeled GHG emissions from agricultural soil, which had significant uncertainty in the emission factor. Therefore, future efforts should target field measurements to better predict the contribution of direct soil emissions to total GHG emissions, particularly under different managements. In addition, identifying the optimal application rate of irrigation water and fertilizer will help to decrease GHG emissions from groundwater irrigated crops.

Introduction

While irrigation water and fertilizers can increase crop yields, their potential negative environmental and economic consequences should not be neglected. The U.S. Great Plains rely on agricultural irrigation water, particularly in Oklahoma where more than 1800 farms apply irrigation water to maintain crop yields in arid and semi-arid climate regions (Mehata and Taghvaeian, 2020). The expected increase in climate extremes (e.g., drought, floods) will only increase the need for groundwater resources for agriculture, yet, aquifer water levels continue to decline in areas of the state that need the water most (Field et al., 2012; McGuire, 2017). To address this issue and encourage adoption of regenerative and efficient agricultural management, Oklahoma has engaged producers in the Testing Ag Performance Solutions (TAPS) program in the panhandle region for several years (Rudnick et al., 2020). Historically, this area has focused on crop yields and nitrogen use efficiency to promote economically sustainable agriculture (Freeman et al., 2007). While the farmer competition has been assessed to understand

economic concerns surrounding the use of irrigation water and fertilizer in this region, environmental impacts (e.g., greenhouse gas (GHG) emissions) have not been previously explored. There is some precedent for considering carbon footprint reduction for irrigation efficiency (Karimi et al., 2012) and reduced tillage (Zhang et al., 2016), but site-specific life-cycle GHG emissions associated variable irrigation and fertilizer rates are lacking.

The principle GHG emissions from human activities include carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) (USEPA 2022; UNCC 2022). Greenhouse gas emissions can be reported on the basis of CO_2 -equivalents ($\text{CO}_2\text{-eq}$) when multiplying by the global warming potential of each gas. Of these principle GHGs, N_2O is almost 300 times that of CO_2 , which can make N_2O emissions of even greater concern when reported as $\text{CO}_2\text{-eq}$ despite their lower net emissions (USEPA 2022). Worldwide, agriculture is the third largest source of GHG emissions (24% of 2010 global GHG emissions) and the main source of N_2O (Cocco et al., 2018).

To understand the factors that contribute to these overall emissions and target GHG mitigation strategies, agricultural systems should be evaluated for

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their carbon footprint or life cycle GHG emissions. GHG emissions may come from pre-field processes (e.g., fertilizer production) which are associated with energy production and consumption. GHG emissions are also linked to field conditions and in-field management practices, which can significantly affect the rates of N₂O emissions from agricultural activities (Decock, 2014; Foltz and Zilles, 2019). So, quantifying and comparing the agricultural GHG emissions from various field management practices and environmental conditions is crucial to distinguish the more sustainable and less environmentally costly farming practices that enhance yield.

Several experimental and modeling approaches could be adopted to quantify agricultural GHG emissions. The Intergovernmental Panel on Climate Change (IPCC) offers a simple empirical-equation based on nitrogen (N) inputs to estimate the direct N₂O emissions from managed soils and can be used even when minimal input data is available (IPCC, 2006). Various other stages of corn production (e.g., fertilizer production) can be assessed using a carbon footprint approach to estimate life cycle GHG emissions of various pre-field and in-field factors. Although CO₂ uptake by the crop may affect the net CO₂ of the system, only positive emissions are considered here.

This research aims to quantify cradle-to-product GHG emission estimations of corn production under different fertilizer and irrigation management. This study specifically aims to (i) estimate the total GHG emissions of corn production under various rates of fertilizer and irrigation water application in Oklahoma, (ii) identify the categories that contribute most to total GHG emissions, and (iii) quantify the effects of in-field agriculture management practices on GHG emissions.

Material and methods

Study area

The study area is an interactive program titled “Testing Ag Performance Solutions” (TAPS) that is operated in Texas county, Oklahoma (Panhandle), United States. Originally started in Nebraska, TAPS was later expanded to Oklahoma to help irrigated corn and cotton producers improve water use efficiency and management (Rudnick et al., 2020). The ongoing program provides the opportunities for farmers to examine research-based improved technologies and strategies in experimental plots of the Oklahoma Panhandle before applying these approaches on their land. The TAPS field is operated with one center pivot irrigation system, although individual plots can be irrigated and fertilized at different rates, which are remotely controlled with a FieldNET variable rate irrigation system (Lindsay Irrigation, Omaha, NE, USA). In the year of consideration (2020), there were fourteen farmers controlling individual plots, such that each “field” had different farmer-selected rates of irrigation water, fertilizer application, and corn seeding (Table 1). All primary input data for the competition year are reported here and included in the supplementary material as an Excel spreadsheet.

All fields were planted to corn which typically requires soil temperature to be 55°F or more and moisture at field capacity or above maximum allowable depletion for seed germination. The irrigation amount for this crop often varies based on the environmental conditions,

Table 1

Farmer-selected application rates of irrigation water, fertilizer, and seed in each field of the 2020 TAPS competition. Herbicide application was constant (3 kg ha⁻¹) across all fields.

Field	Irrigation (m ³ ha ⁻¹)	Fertilizer (kg ha ⁻¹)	Seed (kg ha ⁻¹)
1	6662	247	14
2	6236	235	13
3	7201	269	14
4	6007	230	15
5	6998	247	14
6	7709	269	15
7	7264	342	11
8	6121	303	14
9	6845	471	13
10	5258	213	13
11	6803	297	13
12	5512	296	13

13	6502	280	12
14	6519	191	13

which are driven by rainfall received during the growing season and crop water demand. However, irrigation allocations in the Panhandle have been limited. Recommended fertilization rate for corn depends on residual nutrient status and site-specific yield goal, which was at least 15,000 kg corn ha⁻¹ at this site. Farmers often differ in their approach to application amount and frequency, as reflected in Table 1, with the goal of meeting this yield goal.

Life cycle GHG emissions

A carbon footprint was adopted to estimate the total GHG emissions from corn production under different application rates of irrigation water and fertilizer. The life cycle GHG emissions were estimated for different pre-field and in-field parameters. Pre-field GHG emissions include those from generating energy (electricity and natural gas) for irrigation, fuel production for agricultural vehicles, and producing and transportation of seeds and chemicals (i.e., fertilizers, herbicides). SimaPro (Ecoinvent) and GREET-2021 databases were used to obtain GHG emission data for pre-field processes (Table 2). The in-field GHG emissions include GHG emissions from agricultural soils, natural gas combustion from groundwater pumping, and several on-farm human activities (e.g., preparing the land, planting, applying chemical materials, harvesting). Total GHG emissions from each TAPS field were calculated as the sum of the pre-field and in-field GHG emissions. All GHG emissions were converted to CO₂-eq and normalized using the functional unit of corn yield (kg⁻¹ corn), which is considered a better estimate than unit area although less ideal that on an economic basis (Huang et al., 2019). As it is recommended to consider both economic and yield-based comparisons (Huang et al., 2019), we have included economic considerations as outlined in Section 2.8 below.

Table 2

Assumed GHG emissions from various corn production parameters based on databases and published guidance.

Parameter	GHG Emissions	Unit
Fertilizer Production ⁵	2545.89	kg CO ₂ -eq ton ⁻¹
Corn Seed Production ⁵ Herbicide	1971.14	
Production ⁵ Transportation ⁵	11,002.89	
Electricity Generation ⁶	132.69	kg CO ₂ -eq km ⁻¹ g
Natural Gas Production ⁶	712.3	CO ₂ -eq kWh ⁻¹
On-site Natural Gas Engine Combustion ⁵ Diesel	20.94	
Production ⁶	185.76	
On-site Diesel Combustion ⁵	534.2	kg CO ₂ -eq L ⁻¹
On-farm Fuel Consumption of Vehicles	2673.2	
	36.85	L ha ⁻¹

⁵: Extracted from SimaPro 9.3 (Ecoinvent) (Frischknecht et al., 2005).

⁶: Extracted from GREET-2021.

⁵: EPA Greenhouse Gas Inventory Guidance (EPA 2016).

Fuel and energy production

Fuel production for agricultural vehicles were estimated using the GREET-2021 well to pump model (GREET version 2021, Argonne National Laboratory, Argonne, IL, USA). “Conventional Diesel from Crude Oil for US Refineries Main Output: Conventional Diesel” category was considered as diesel used for agricultural vehicles fuel.

Pumping energy needed for irrigation was estimated as a function of dynamic head, groundwater discharge, pumping plant efficiency, and distribution loss (Karimi et al., 2012). The irrigation water for the field was provided through groundwater pumping from three wells, one electric and two natural gas pumps. About 75 percent of the groundwater pumping energy was natural gas and the remainder electricity. The overall pump efficiencies were assumed to be 46.9% for electric and 14.8% for natural gas pumps. The lifting height was assumed to be 60 m, based on average groundwater levels in the area (Oklahoma Water Resources Board 2022). The emissions from electricity generation for the “U.S. Central and Southern Plains Mix” was

applied for groundwater pumping using electric pumps, while those for stationary natural gas were estimated based on the GHG emissions from “NA (North American) NG from Shale and Conventional Recovery as Stationary Fuel.”

Seed and chemical production

GHG emissions from seed and chemical (i.e., fertilizer and herbicide) production and transportation of these materials to the agricultural site were estimated based on discussion with farm managers and using the Ecoinvent database within SimaPro 9.3 (Frischknecht et al., 2005). All resulting GHG emissions obtained from the Ecoinvent database were converted to CO₂-eq using global warming potentials. The fertilizer type (anhydrous ammonia) was constant between fields in the TAPS competition. Thus, fertilizer was based on “Ammonia, anhydrous, liquid {RNA}| market.” Although different corn seeds (hybrids) were used in the TAPS competition, GHG emissions from seed production were estimated based on only one type: “Maize seed, for sowing {GLO}| market for | APOS, U.” GHG emissions from herbicide production were estimated based on the “Glyphosate {GLO}| market for | APOS, U.” Based on discussion with field managers, transportation of these products was assumed to occur overland via roads and estimated based on “Transport, freight, lorry 3.5–7.5 t, euro6 {RoW}| market for transport, freight, lorry 3.5–7.5 t, EURO6 | APOS, U.” Distances were obtained directly from farm managers based on the distance nearby suppliers, all of which were local. For example, fertilizer was purchased from a local supplier within 33 miles of the experimental site.

Agricultural soils

GHG emissions from agricultural soil for each TAPS field were estimated using emission factor approach as specified in the Intergovernmental Panel on Climate Change (IPCC) guidelines (IPCC 2006). N₂O was assumed to be the dominant source of direct soil GHG emissions, so the Tier 1 IPCC model was applied to estimate direct N₂O fluxes as a function of fertilizer applied (IPCC 2006). The model was simplified by eliminating non-relevant terms (i.e., flooded rice, organic amendments, land use change) such that the N₂O emissions (kg N y⁻¹) were estimated by multiplying an emission factor (EF₁) by the sum of fertilizer applied (F_{SN}, kg N y⁻¹) and crop residues left in the field (F_{CR}, kg N y⁻¹) (IPCC 2006). The IPCC default value for EF₁ is 0.01 with an uncertainty range between 0.003 and 0.03 (IPCC 2006).

Natural gas combustion

Operation of natural gas pumps were estimated for their contribution to in-field GHG emissions from the fuel combustion process. The stationary engine emissions were estimated based on the U.S. Environmental Protection Agency Greenhouse Gas Inventory Guidance (EPA 2016). As such, emissions were estimated as a function of fuel combusted, fuel heat content, and an emission factor. The 2016 values for fuel heat content and emission factors were used in these overall emission estimates (EPA 2016).

Farm vehicle operation

GHG emissions from agricultural vehicles include those from producing diesel fuel (accounted for under pre-field) and the GHG emissions from fuel combustion (considered part of in-field). The GHG emissions from diesel combustion were estimated using GREET-2021 “Conventional Diesel from Crude Oil for US Refineries Main Output: Conventional Diesel.” The average fuel consumption for on-farm human activities was estimated from an extension report out of Minnesota (Lazarus, 2001).

Net revenue

The farmer decisions from the 2020 competition and their associated costs and generated revenue were calculated and normalized to an area basis based on individual field corn yields. Some costs were uniform between fields, such as strip tillage (\$42/acre), planting costs (\$37/ acre), and herbicide application cost (\$151/acre), all of which were estimated based on discussion with farm managers. Some costs were farmer-decision dependent, including fertilizer, irrigation, and seeding costs, which differed based on selected fertilizer, irrigation, and seeding rates for each field (Table 1). Fertilizer costs averaged \$314/acre, irrigation costs averaged \$509/acre, and seeding costs averaged \$299/acre, all estimated based on discussion with farm managers. Farmers had multiple selling opportunities and revenue was obtained from farm managers based on corn market price and market decisions. Net revenue was estimated as the sum of revenue from corn sales minus all incurred costs in the growing year, including transportation of corn grain to market. Land costs were neglected in this analysis as the farmers did not pay rent for the land used in the competition.

Uncertainty and sensitivity analyses

The main consideration in uncertainty analysis was the large uncertainty regarding the emission factor EF₁ (0.03–0.003) in estimating in-field agricultural soil emissions. The other major area of uncertainty was due to the differences in farmer decisions (various application rates of irrigation water and fertilizer) that resulted in unique GHG emission estimates for each field parameter. A Monte-Carlo uncertainty simulation with 100,000 runs per year and treatment based on variation in model inputs was adopted in R to analyze the uncertainties associated with the overall GHG emission estimates. A uniform distribution was assumed for EF₁ based on the minimum and maximum of its range. The rest of the parameters were assumed to fit normal distributions with different means and standard deviations based on variability in inputs from farmer decision-making (Table 1). We chose these variables based on known uncertainty (i.e., EF₁) and management variability (e.g., fertilizer rate, irrigation rate, yield).

Using the results of the Monte Carlo runs, Spearman’s Rank correlation was used to find the correlation coefficient (rho) between total GHG emissions and various parameters (EF₁; F_{CR}; F_{SN}; corn yield; natural gas, diesel, and pumping energy; herbicide, seed, and fertilizer production; diesel and natural gas combustion; and agricultural soil emissions). The correlation coefficients were used to assess the overall sensitivity of total GHG emissions to each tested parameter, where rho values near ±1 indicate strong correlations.

Results and discussion

Field-specific yields and revenue

Yields were measured at harvest and used in determination of net revenue based on the difference in revenue and costs from different farmer decisions (Table 3). Most fields produced at least 13,700 kg corn ha⁻¹, although a few fields severely underperformed (field 10 had only 7880 kg corn ha⁻¹) and field 11 had the overall highest yield (15,189 kg corn ha⁻¹). It should be noted that only field 11 obtained yield higher than the yield goal (15,000 kg corn ha⁻¹). Based on farmer decisions and resulting yields, net revenue averaged \$687 ha⁻¹, although field 10 generated no revenue (lost \$8 ha⁻¹) and field 14 had the highest net revenue (\$1115 ha⁻¹). Despite field 11 having the highest yield, its net revenue was lower (\$763 ha⁻¹) as it had higher fertilizer and irrigation rates compared to several other fields.

Yield-weighted life cycle GHG emissions

Total GHG emissions from the fourteen corn fields were yield-weighted and ranged from 213 to 360 (average 271 ± 46) g CO₂-eq kg⁻¹ corn (Fig. 1). The differences among yield-weighted GHG emitted from various fields were due

to different rates of irrigation water and fertilizer and their resulting differences in corn yields. The maximum GHG emissions per kilogram of corn production was estimated from field 10, which had the lowest corn yield (7880 kg corn ha⁻¹). The minimum GHG emission came from field 17, which had the lowest fertilizer application (191 kg ha⁻¹) and the second highest corn yield (14,934 kg corn ha⁻¹). This trend is to be expected, as decreased fertilizer application rates are tied to decreases in N₂O emissions and overall GHG emissions (IPCC 2006; Decock, 2014). Considering the range of uncertainty, total GHG emissions from each individual field could deviate between -24% and +56% from the average due to different values of the IPCC emission factor EF₁ (minimum of 0.003, average of 0.01, and maximum of 0.03). These extreme uncertainty ranges reveal the importance of accurate estimation on EF₁ when calculating agricultural GHG emissions.

Contributions of pre-field and in-field parameters to total GHG emissions

Total GHG emissions from corn production averaged 271 ± 46 g CO₂-eq kg⁻¹ corn, with the highest proportion (average of 171 g CO₂-eq kg⁻¹ corn or about 63%) associated with in-field GHG emissions (Table 4). This total is of a similar magnitude to other reported carbon footprints for corn (Ma et al., 2012; Cheng et al., 2015; Xu and Lan, 2017). Semi-arid regions requiring irrigation are generally expected to have higher carbon footprints, as was found in China (390 g CO₂-eq kg⁻¹ corn) (Yan et al., 2015). It is interesting to note that the proportion of GHG emissions associated with in-field management varied between fields and were not always directly proportional to fertilizer or irrigation rates. For example, field 14 had the lowest total GHG emissions (213 g CO₂-eq kg⁻¹ corn) and the highest proportion (65% of the total) were from in-field management. Meanwhile, field 10 had the highest total GHG emissions (360 g CO₂-eq kg⁻¹ corn) and only 62.5% came from in-field management. The relationship is further complicated when normalizing GHG emissions by yield (per kg corn). Thus, the influence of fertilizer and irrigation rate simultaneously impacts GHG emissions and corn yield, sometimes in opposite directions, such that total weighted GHG emissions varies. For example, field 9 had the highest fertilizer rate (471 kg ha⁻¹) and yet the proportion of those emissions from in-field management (i.e., fertilizer-induced soil N₂O emissions) were lowest (61%). Although it would be expected that fertilizer application would directly increase the in-field GHG emissions,

Table 3

Yields and net revenue for each field of the 2020 TAPS competition.

Field	Corn Yield (kg ha ⁻¹)	Net Revenue (\$ ha ⁻¹)
1	14,150	624
2	14,921	937
3	14,910	987
4	13,709	285
5	13,737	525
6	14,910	637
7	14,435	909
8	14,095	837
9	14,399	771
10	7880	-8
11	15,189	763
12	9594	220
13	14,732	1016
14	14,934	1115

ated with diesel production for agricultural vehicles (1.5 g CO₂-eq kg⁻¹ corn), followed by seed (0.77%) and herbicide (0.81%) production. The GHG emission from on-site diesel combustion from the agricultural vehicle is estimated at an average of approximately 7.5 g CO₂-eq kg⁻¹ corn. Therefore, operation of farm vehicles and equipment should not be a major focus for reducing total GHG from agriculture. Similarly, improving efficiency of seed and herbicide production should not be a focus until fertilizer production and energy production are more efficient and sustainable.

Yield impacts

As the GHG emissions were yield-weighted in this study, it was important to consider the influence of irrigation water and fertilizer application on yield. Corn yield had a strong positive polynomial

weighting GHG emissions by corn yield rewards fields with efficient fertilization rates that effectively increase yields.

Estimated GHG emitted from each parameter indicated that agricultural soils contribute the most (89 ± 18 g CO₂-eq kg⁻¹ corn or about 33%) to the total GHG emissions from corn production (Fig. 2). Denitrification and nitrification processes are two dominant pathways contributing to N₂O emissions from agricultural soils (Braker and Conrad, 2011; Kumar et al., 2020; Tian et al., 2020). Although many factors can contribute to these soil N₂O emissions, the model presented here only included fertilizer-induced emissions as predicted by IPCC. When converted to CO₂-eq emissions, the contribution of N₂O becomes significant due to its global warming potential nearly 300 times higher than CO₂ (USEPA 2022). This contrasts with the other in-field and pre-field parameters which are mostly associated with energy production and consumption and primarily produce CO₂ (USEPA 2022). This relationship is consistent with previous studies that have reported fertilizer use as a primary source of agricultural GHG emissions (Yan et al., 2015; Jat et al., 2019; Wu et al., 2022).

As fertilizer-induced soil emissions dominated total GHG production, it is likely the contributions from agricultural soils could be decreased when applying best management practices (BMPs) for fertilizer. Studies suggest BMPs for N fertilizer application considering the source of N, rate, timing, and placement in addition to other in-field practices (e.g., cover cropping) could lower GHG emissions from corn production (Snyder et al., 2009; Decock, 2014; Foltz et al., 2021).

Besides agricultural soil, other influential parameters on total GHG emissions in this study include on-site natural gas combustion for agricultural groundwater pumping (28%), fertilizer production (20%), and energy production for groundwater pumping (15%). This is consistent with a carbon footprint study from China, where fertilizer, electricity consumption for irrigation, and agricultural films were identified as the main factors contributing to carbon emissions (Huang et al., 2022). Improving overall pump efficiencies to decrease agricultural pumping energy consumption and switching the pumping energy from natural gas to electricity, specifically wind energy, where possible, could also reduce agricultural carbon footprint (data not shown).

The lowest portion (0.55%) of the total GHG emissions was associ-

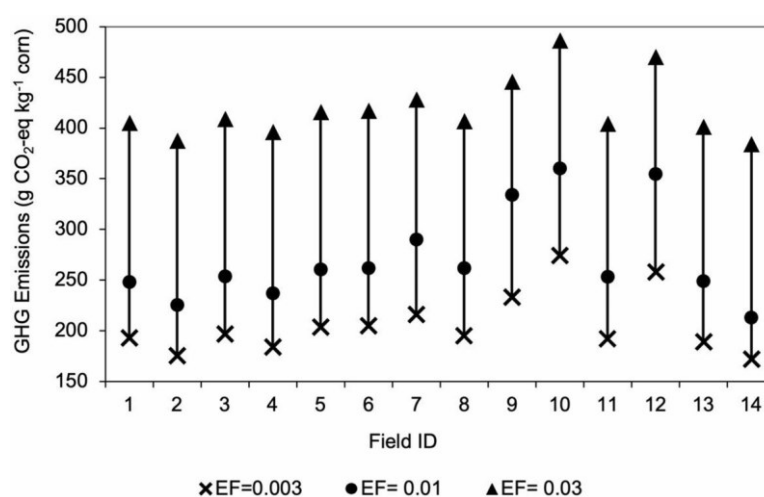


Fig. 1. Total GHG emissions in g CO₂-eq kg⁻¹ corn production from each field in the 2020 TAPS competition. IPCC emission factor (EF) values used in the ranges are reported as minimum, average, and maximum for each field.

Table 4

Pre-field, in-field and total yield-weighted GHG emissions (g CO₂-eq kg⁻¹ corn) from each field in the 2020 TAPS competition.

Field ID	Pre-Field	In-Field	Total
1	90	158	248
2	81	144	225
3	92	161	253
4	86	151	237
5	94	166	260
6	95	167	262
7	108	182	290
8	97	165	262
9	130	204	334
10	135	225	360
11	93	160	253
12	136	219	354
13	91	158	249
14	74	138	213
Ave	100	171	271

overwatering at a higher economic and environmental cost with no net gains to yield. However, the risk of falling below this critical irrigation rate is significant to yield and costs. For example, the two lowest yielding fields (10 and 12) were the highest overall emitters of GHG on a per kg corn basis. Further, these farmer's losses economically are significant, with yields well below average.

Sensitivity and uncertainty

Uncertainty in the emission factor and differences in farmer-selected field management were incorporated into Monte Carlo simulations and correlation analysis of resulting GHG emission estimates. Parameters that were most influential for GHG emissions had rho values close to ± 1 . Yield-weighted total GHG emissions were driven by emissions from agricultural soil, so it was not surprising that total emissions were most sensitive to agricultural soil emissions (Table 5). As agricultural soil emissions are strongly linked to the emission factor (EF₁), variability in

relationship with water application ($R^2 = 0.96$, Fig. 3) while it has a weak relationship with fertilizer application ($R^2 = 0.04$, data not shown). In the study year, there appeared to be an optimum irrigation rate of about 6000 m³ ha⁻¹ above which yield did not fluctuate as much with additional water. The study year was a relatively dry year with a drought starting in May 2020 (NIDIS 2022), which may also contribute to the strong connection between irrigation rate and yield. The presence of a yield plateau suggests that many fields were

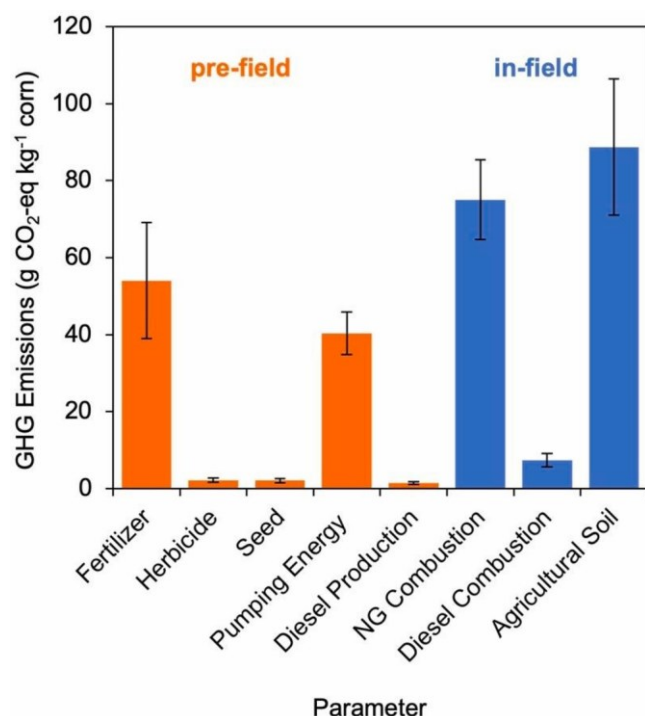


Fig. 2. Average yield-weighted GHG emissions from each process or parameter associated with irrigated corn production in the 2020 TAPS competition. Error bars show standard deviations ($n = 14$). Orange bars represent pre-field parameters, while blue bars represent in-field parameters.

this input parameter caused significant variability in the total estimated GHG emissions. While agricultural soil emissions, and more specifically the emission factor, had a strong positive correlation with total GHG emissions ($\rho = 0.87\text{--}0.97$), emissions were the least sensitive to herbicide, seed, and diesel production. Fertilizer production and fertilizer application rate (F_{SN}) both had positive correlations with total GHG emissions, but at a lower level ($\rho = 0.18\text{--}0.28$) which could be linked to the insignificant link between fertilizer application and yield discussed previously. Overall, these sensitivity outcomes indicate the importance of targeting agricultural soil when planning to reduce agricultural GHG emissions from crop production. Due to the high sensitivity of GHG emissions from crop production to EF_1 , accurate estimation of this

FCR	0.0676
F _{SN}	0.2768
EF ₁	0.8706
Corn Yield	− 0.2553
NG Combustion	0.1162
Diesel Combustion	0.0212
Fertilizer Production	0.1790
Herbicide Production	0.0041
Seed Production	0.0043
Pumping Energy	0.0610
Diesel Production	0.0060
Agricultural Soil	0.9705

emission factor is essential to reduce the uncertainty of these GHG estimations. Sustainable agriculture could be planned through a multi-objective optimization model that targets maximizing crop yield and minimizing GHG emissions.

Model uncertainty in average GHG emissions from corn production was estimated using Monte Carlo simulations based on uncertainty in EF_1 and variation of the GHG emitted from different pre-field and in-field parameters at each of the 14 TAPS fields. The model results show approximately 25 percent uncertainty in estimating total GHG emissions from corn production. Most of this uncertainty was due to uncertainty in EF_1 , which was an issue established in the literature previously (Zhang et al., 2017). It was our intention to minimize uncertainty in our total GHG emission estimates by removing uncertainty surrounding inventory data, for which we had exact input rates for fertilizer, irrigation, seeding, travel distances, yields, and costs. However, uncertainty in the direct soil emissions still dominate, which is a limitation of this study. This outcome suggests that incorporation of process-based models and direct field measurements of GHG will be necessary to improve accuracy of predictions.

Implications and recommendations

Total GHG emissions from irrigated corn production in CO₂-eq per kg corn were driven by in-field parameters, mostly as direct N₂O emissions from soil and the combustion of natural gas for groundwater pumping. Among pre-field parameters, energy production for groundwater pumping was the dominant GHG source, followed by fertilizer production. Therefore, when planning methods to reduce the GHG emissions from corn production, direct soil N₂O emissions should be closely considered first. The second area to target in decreasing overall GHG emissions from agriculture involves improving energy use efficiency such that energy-related emissions in the agricultural life cycle are decreased. Overall, it is recommended to estimate the optimum fertilizer

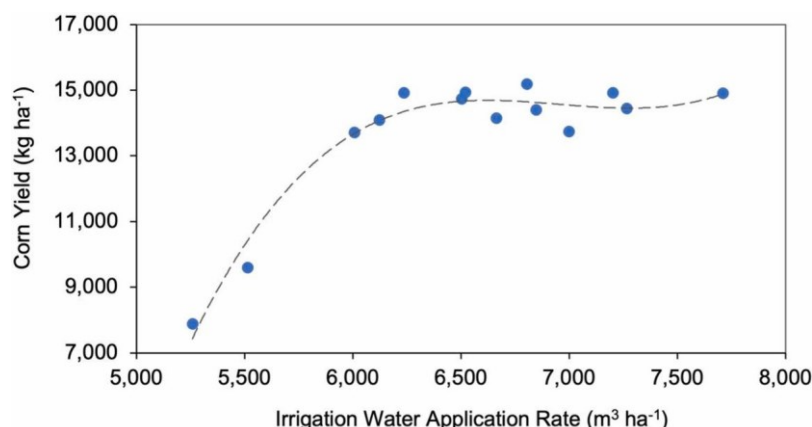


Fig. 3. Relationship between irrigation water application rate and corn yield in the 2020 TAPS competition. The polynomial relationship shown: $R^2 = 0.96$.

Table 5

Spearman's Rank correlation coefficients (ρ) between yield-weighted total GHG emissions and various parameters. Correlation coefficients greater than 0.5 are bolded to highlight strong correlations.

Variable	Total GHG Emissions
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and water application rates for specific areas that will maximize crop yield and minimize potential GHG emissions. In the efforts to improve GHG emission estimates, parameters with high uncertainty and model sensitivity (i.e., the IPCC emission factor, EF_1) should be determined for each site, as climate variability and field conditions may affect the resulting GHG emissions.

Therefore, it is recommended that direct soil emissions are measured in at least one growing season and used to validate process-based models that have been calibrated to the site with other direct field measurements, such as corn yield and soil moisture. With better estimates of in-field soil emissions, the overall GHG emissions from irrigated corn production will have greater certainty. Then, identification of optimal application rates will enable targeted policy and education to reduce overall GHG from irrigated and fertilized crops.

Conclusions

In this study, we quantified life cycle GHG emissions associated with pre-field and in-field activities within fourteen independent, farmer- selected management scenarios in the 2020 Oklahoma TAPS sprinkler corn competition. Our overall findings were as follows:

- Irrigated corn production in the U.S. Great Plains produced an average of 271 ± 46 g CO₂-eq kg⁻¹ corn across diverse, farmer- selected irrigation and fertilization scenarios.
- In-field activities represented the majority ($63 \pm 10\%$) of total GHG emission.
- Direct soil emissions (as N₂O) were the greatest source (89 ± 18 g CO₂-eq kg⁻¹ corn) of total GHG from corn production.
- On-site natural gas combustion for agricultural groundwater pumping, pre-field fertilizer production, and pre-field energy production for groundwater pumping were the next most influential parameters on total GHG emissions.
- Diesel fuel, seed, and herbicide production had insignificant contributions to total GHG emissions from corn production.
- The model was most sensitive to the modeled GHG emissions from agricultural soil, which had significant uncertainty in the emission factor.

Supplementary Material

All primary data used as inputs for modeling and resulting outputs for each of the 14 fields in the 2020 OK TAPS sprinkler corn competition are available as “OK-TAPS-2020-sprinkler-corn-competition.xlsx” for further information. The Excel file includes the following: field number, total irrigation amount, number of irrigation events, total fertilizer amount, pre-plant fertilizer amount, post-planting fertigation amount, number of fertigation events, seed, corn yield, net revenue, pre-field GHG emissions, in-field GHG emissions, and total GHG emissions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data are available in the Supplementary Material as an .xlsx file

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.envc.2023.100750.

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