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LCA FOR AGRICULTURE

Spatial greenhouse gas emissions from US county corn production

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Abstract

Purpose Stakeholders from across supply chains have been prompted to explore ways to reduce the environmental burdens of corn production. To effectively manage these environmental impacts, spatially explicit information accounting for the differences in growing conditions and production practices across the production landscape is essential, allowing for high impact intensity corn to be identified and prioritized for improvement. To support these sustainability efforts, this study examines the spatially explicit life cycle greenhouse gas emissions of US county corn production, providing the most comprehensive assessment to date.

Methods A streamlined spatial life cycle assessment is conducted, focusing on the three key hotspots of corn production for spatial differentiation at the county scale across the contiguous USA, accounting for almost 60% of total average cradle-to-farm gate impacts. Variations in nitrogen fertilization types and rates, N_2O emission rates, and irrigation emission rates are specifically revealed. Spatially distinguished hotspot inputs and related emissions are combined with static national average emission estimates from all other inputs used in corn production to gain a full picture and understand the relative contributions to total cradle-to gate impacts.

Results and discussion Results show significant variation across corn producing counties, states, and regions. High impact priority locations are highlighted and key contributors of impact for each location are illuminated, providing critical information on the spatially explicit levers to reduce impacts. Results increase the generalizability of emission estimates using expected yields to characterize emission intensity, enabling more practical integration into company supply chain sustainability assessments to align with the time horizons in which decisions are made.

Conclusions Streamlined life cycle assessment methods are an effective way to characterize spatial heterogeneity around key contributors of impact, helping deliver the necessary information for companies, stakeholders, and policy makers to target their influence to reduce these emissions through various engagement efforts.

Keywords Corn production · Green supply chain management (GSCM) · Life cycle assessment (LCA) · Spatial · Streamlined LCA

1 Introduction

Agricultural activities have been widely recognized as significant sources of environmental burden, particularly concerning contributions to greenhouse gas emissions (GHG), impaired water quality, water depletion, and biodiversity loss (Garnett 2011; Foley et al. 2011; Schaible and Aillery 2012). It is estimated that direct agricultural emissions and inputs to agriculture account for approximately 30% of GHG emissions, and are responsible for about 80 to 90% of consumptive water loss (Garnett 2011; Foley et al. 2011; Schaible and Aillery 2012). Consequently, agriculture, including both crop production and livestock production, has been identified as a significant hotspot in many supply chains along many categories of impact (Styles et al. 2012; Roy et al. 2009). In the USA, corn is the most commonly produced crop, with acres devoted to its production in almost every state, making up 40% of the world's total corn supply (Johnston et al. 2015). In the USA, corn grain is primarily used for livestock feed and fuel ethanol production, which together accounts for approximately 75% of the total demand of US corn grain (Capehart and Liefert 2017), see Fig. S1 in the Electronic Supplementary Material.

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Corn grain production is known to produce large environmental impacts, due to the large quantities of fertilizers, fuels, and electricity used in its production (Ecoinvent 2012; Hsu et al. 2010). The contribution of corn grain's impact on downstream products can have important implications for consumer-facing businesses, which are increasingly attuned to managing environmental risks via green supply chain management (GSCM) methods in order to avoid potential supply chain disruptions, current or future regulatory action, and public image issues (Smith 2013; Styles et al. 2012; Macfadyen et al. 2016; Peck 2006). As such, among GSCM agricultural improvement efforts, corn production is a significant focus, as evidenced by the 84 consumer facing companies participating in the Field to Market's Alliance for Sustainable Agriculture initiative, including General Mills, Kellogs, Pepsico, Coca-Cola, McDonalds, Walmart, Unilever, Cargill, BASF, etc. (Field to Market 2017). These efforts are supported by information from environmental life cycle assessments (LCA) representing conventional corn production practices, which help highlight the relative contribution to impact different stages of corn production. This information, however, often reflects national averages and thus lacks the spatial specificity required to most effectively address supply chain impacts due to the substantial heterogeneity that exists in crop production systems across the USA and world (Yang and Heijungs 2017).

Indeed, many studies strongly advocate for more spatially explicit environmental information for agricultural production, due to the significant heterogeneity of management practices, growing conditions, and electricity mixes used across the production landscape (Hellweg and Canals 2014; Rodriguez et al. 2014; Nitschelm et al. 2016; Dresen and Jandewerth 2012; Liska et al. 2009; Yang et al. 2012). A few studies have conducted spatial assessments at the regional or state level; for example, Liska et al. 2009) conducted a state-level assessment of corn farming and found that GHG impacts regionally varied between 37 and 65% of the impacts of corn ethanol systems. Significant heterogeneity also exists, however, at the sub-state level due to variations in the biogeochemical characteristics of the land and differences in management practices (Rodriguez et al. 2014; Liska et al. 2009). A recent study by Smith et al. (2017) more finely captures this variability by providing county-level estimates of corn GHG emissions and water consumption for the purposes of informing downstream protein and ethanol supply chains, using new models linking production and consumption systems for increased supply chain transparency. This new transparency into corn feed and ethanol supply chains and the corresponding environmental impacts enable the potential for producers to differentiate from traditional commodity markets. While the study was able to provide a cursory look at corn production heterogeneity, the study was only able to capture the county-level variability in yield, water consumption (evaporative losses), and the types of nitrogen fertilizers used (with state-level nitrogen application rates) (Smith et al. 2017) during discrete years of production, leaving significant room for improving estimates and capturing the likely range and distribution of potential impacts across space and time to increase the confidence in and effectiveness of GSCM improvement efforts.

The scarcity in environmental assessments at the sub-national and sub-state level is likely due to the substantial data requirements, time, and costs required to conduct such assessments. Streamlined life cycle assessment (LCA) methods, which focus detailed process-based analyses on the hotspot drivers of impact and limited categories of impact (Pelton and Smith 2015; Huang et al. 2009; Bala et al. 2010), can be a practical strategy to reduce the barriers to conducting these spatial assessments (e.g., time and costs to gather necessary data), allowing GSCM decisions to be better informed around key contributors of impact in impact categories relevant to the decision at hand (Rebitzer and Schafer 2009; Pelton et al. 2016). This study builds on the Smith et al. (Smith et al. 2017) study by providing a streamlined spatial LCA that more thoroughly captures the variability of corn production practices and associated GHG emissions across US corn-producing counties, providing the most comprehensive assessment to date. While other impact categories are also important to assess to understand potential environmental trade-offs and possibilities for problem-shifting, global warming potential (GWP) impacts are the focus of the study due to the current interest by companies and stakeholders and global urgency to manage climate-changing emissions (Smith 2013). The results of the study can help inform conscientious farmers, engaged downstream companies in the corn supply chain, concerned NGOs, and policy makers at multiple scales of governance, on where high GWP impact intensity corn production occurs at the county scale, enabling deployment of various intervention efforts. Such information can be used as a baseline for assessing the environmental consequences of alternative production systems and management practices and their strategic deployment across heterogeneous production regions, and can be combined with commodity transport models to link impacts and potential emission savings to downstream buyers, as was partially demonstrated in Smith et al. (2017). Most promisingly, this information can help prioritize capital resources, policies, and overall company and NGO engagement efforts for improving the associated environmental impacts of corn production. The following sections detail the methods used in the streamlined spatial assessment and the corresponding global warming potential (GWP) results across US corn-producing counties, followed by a discussion on the implications of the assessment for policy makers and GSCM decision-makers for affecting impacts.

2 Materials and methods

2.1 Hotspot assessment

Several types of material and energy inputs are used to produce corn, which can vary significantly across production locations. A national average LCA on corn reveals that nitrogen-based fertilizer application contributes to over half of all corn GHG impacts, due almost equally to the upstream manufacturing emissions and the on-field nitrous oxide emissions that result after application (see Fig. S2, Electronic Supplementary Material), representing a strong hotspot for GWP impact (Hsu et al. 2010; Ecoinvent 2012). The spatial impacts of nitrogen fertilization on corn fields are expected to be highly variable, based on the specific types of nitrogen fertilizer applied, the quantity applied, and the specific characteristics of the land in which it is applied. Regarding the type of fertilizer applied, there exists substantial variation in the manufacturing impacts across different nitrogen fertilizers types; for example, ammonium nitrate fertilizers result in an upstream impact of 9.1 kg CO_2e/kg N applied, whereas anhydrous ammonia fertilizers result in 2.1 kg CO_2e/kg N applied, see Fig. S3 (Electronic Supplementary Material). GWP impacts of irrigation, although having a relatively smaller impact contribution than the nitrogen fertilizer impacts, also has been demonstrated to have significant spatial variability (Smith et al. 2017), due to the heterogeneity in the location in which irrigation occurs and the quantity of irrigation water withdrawn. An even greater degree of variation in impacts is expected, however, with consideration of the method of application (e.g., sprinkler vs. gravity fed), the type of energy used for irrigation (e.g., electricity, natural gas, diesel, etc.), and the differences in the embedded impacts of electricity generation across the USA. Given this spatial variability and contribution to total impact, the upstream nitrogen fertilizer emissions, on-field nitrous oxide emissions, and irrigation-induced emissions are considered significant spatial hotspots of the corn production system and are therefore the focus for this streamlined assessment study, enabling almost 60% of the total average corn production GHG emissions to be captured in the spatial assessment (see Fig. S2, Electronic Supplementary Material; (Ecoinvent 2012)). The other 40% of impacts are included in the streamlined LCA assessment based on national average estimates.

Spatial variation in impacts are captured across these hotspot stages by spatially differentiating activity data (i.e., the quantity of an input or activity used in production within a geographic region, such as fertilization rates) and/or emissions data (i.e., the total emissions output associated with an activity, such as the nitrous oxide outputs from N fertilizer input). This spatial variation is based on an assortment of data sources and models, and is supplemented with national average information for the inputs not spatially investigated in order to have a full accounting of the estimated county-level impacts associated with corn grain production. The functional units investigated include a harvested acre and a bushel of corn grain. Because yields vary annually, based largely on the climatological conditions, CO_2e per bushel estimates are predicated on the expected value of yields at any given year, based on the historical probability of the yield occurring in each county for 2000–2016. This data range represents the most recent half of a climate period and spans enough years to sufficiently estimate yield probabilities for each county while covering the average activity date ranges used in the assessment. In some cases, county yield data is unavailable for the specified 2000–2016 time period, in which case, the period of 1970–2016 is instead used in order to estimate expected yields for as many counties as possible (see Equation S1 and S2, Electronic Supplementary Material). Use of expected yields enable per bushel impact estimates to be not just representative of a particular year of production, but are instead generalizable, accounting for the uncertainty of yields across years and gaining a greater likelihood for the emission factors' applicability to any given year in the short-term future. Such spatially explicit and temporally generalizable emission factors are especially useful for purposes of linking to downstream environmental assessments using annually changing downstream demand, as opposed to use of annually changing per bushel emission factors which may confound decisions for making improvements due to potential fluke yield years. The following subsections describe the inventorying and impact assessment methods used for each of the investigated hotspot categories.

2.2 Fertilizer manufacturing emissions

The embedded life cycle GHG emissions associated with use of nitrogen fertilizer accounts for approximately a quarter of total emissions based on the national average distribution of fertilizer types used and quantity applied (Ecoinvent 2012). The emissions associated with each fertilizer type are based on national average emission factors, as provided by commercial databases such as EcoInvent and GaBi thinkstep (Ecoinvent 2012; PE International 2014), using the TRACI impact assessment method, since more granular sourcing and emission factor information is unavailable. This study uses the approach taken by the Smith et al. (Smith et al. 2017) study for capturing the spatial variability in the types of nitrogen fertilizers used via the 2011 National Emissions Inventory (NEI), which provides county-level information on agricultural ammonia emissions across different fertilizer types, allowing for estimation of the distribution of nitrogen fertilizer types used across counties (EPA 2011). Although the estimates are based on the total quantity of fertilizers applied in each county across all types of N-receiving crops, it is assumed that the distribution reasonably represents the fertilizer types used in corn production.

The emissions associated with each of the fertilizer types are scaled based on the quantity of N applied per acre, which is known to vary significantly between locations due to cost considerations and soil characteristics (AAPFCO 2012; NASS 2015; NRCS 2015). This study estimates this spatial variability across corn-producing counties by using a unique interpolated estimate of total annual synthetic N used across all crops in each county, subtracting the amount of fertilizer expected for wheat, cotton, and soy production, and apportioning the remaining amount to corn production based on the proportion of corn-planted acres receiving N to all other farm-planted acres receiving N in each county (i.e., total farm acres less corn, wheat, cotton, and soy acres). This method takes into account the relative differences in application rates between the most commonly produced crops in the USA (USDA 2016a, 2016b). Such estimations for corn N application rates are necessary due to data deficiencies, as such data is not collected at these spatial scales in any census or farm survey. Other sources are also not adequate; farm budgets, for example, are developed for US regions and not specific enough for county-level estimation nor does it indicate the types (N, P, and K) and proportions of each fertilizer type used. Similarly, use of extension recommendations or precision farming algorithms are not sufficient because these would bias results toward optimal fertilizer application, an unlikely representation of corn production across all US corn-producing counties, leaving no room for identification of improvement opportunities.

Instead, the amount of fertilizer expected for wheat, cotton, and soy was estimated using state N application rates and county-level N-fertilized planted acres. The total annual N used across each county's total farm acreage is based on county average fertilizer sales data for 2007–2012 provided by the Association of American Plant Food Control (AAPFCO) and is interpolated to the proximal locations of N use by weighting the average cropping areas within and between counties, which is altogether provided by the Nutrient Use Geographic Information System (NuGIS) (Fixen et al. 2012). Regarding the planted acres, census information at the county-level is currently unavailable, although data on harvested acres is available which can be used to estimate county-planted acres, as described in Section S1 and S2 in the ESM. Regarding the total farm-planted acres (across all crop types), county-level estimates are also provided by NuGIS, which are based on USDA census crop production data (Fixen et al. 2012).

Due to a lack of higher resolution data, the USDA state-level survey data on the percent of corn, wheat, cotton, and soy acres receiving N fertilizer is applied to the respective counties to estimate the portion of N-receiving planted acres in each county for each crop. These state-level estimates are together used to estimate the portion of total farm-planted acres receiving N in each county (USDA 2016a, 2016b), as described in Section S3 of the Electronic Supplementary Material.

The resulting distribution illustrated in Fig. S4 (Electronic Supplementary Material) shows several outliers. Because these unlikely outlier rates may be a result of poor underlying data quality for some counties or using fertilizer sales as a proxy for actual application, these outliers are removed from the sample by constraining the maximum application rate to the 97 percentile—approximately 308 lbs of N per fertilized planted acre, representing a very small portion of counties. To ensure consistency with nationally reported data, the resulting county estimates of corn total N usage are scaled to the most recent national census average (2007–2010) total corn N use, which adjusts the county estimates downwards by approximately 5%. The resulting cumulative probability distribution is depicted in Fig. S5 (Electronic Supplementary Material). The estimated county total corn N use are then divided by county total harvested corn acres for the corresponding years, resulting in a unique county-level estimate of N applied per harvested corn grain acre.

Multiplying the fertilizer application rates with the percent distribution of nitrogen fertilizer types used across counties, and the respective GHG emissions per unit of N associated with each of the fertilizer types, provides a county-level estimate of fertilizer-manufacturing emissions per corn acre harvested. Dividing this by the expected county yield (bushels per acre) (see Fig. S6 and S7, Electronic Supplementary Material), results in the embedded fertilizer GHG emissions per bushel of corn produced. Figure S8a (Electronic Supplementary Material) describes the estimated N fertilizer application rates applied across US corn-producing counties, while Fig. S8b (Electronic Supplementary Material) shows the associated nitrogen fertilizer embedded GHG emissions per acre, and S8c shows the expected GHG emissions per bushel of corn produced. Shown together, these figures illustrate the different factors contributing to the intensity of carbon emissions, where some counties with high fertilization rates may appear less impactful per acre than would be expected, due to the types of fertilizers used that may have lower embedded emissions relative to others, and where counties with high yields can significantly reduce emissions intensity, such as those counties in the Midwest with relatively high fertilization rates. Since no aggregate county-level fertilizer data exists for corn (thus requiring estimation), comparing the state-weighted average fertilization rates to state-level census estimates provides a cursory level of validation. Table S1 (Electronic Supplementary Material) compares the state-weighted average fertilization rates (weighted by county average fertilized acres) to those provided by US census average 2000–2010, showing these estimates are on par with census estimates (see Electronic Supplementary Material for explanation on differences), particularly for states responsible for over 80% of the total annual corn production.

2.3 On-field N_2O emissions

While upstream nitrogen fertilizer emissions are a significant component of corn grain GWP impacts, the direct and indirect on-field nitrous oxide (N_2O) emissions associated with fertilizer use are almost equal in magnitude (ANL 2014). Direct emissions refer to the portion of nitrogen applied that directly volatilizes to N_2O. Indirect emissions refer to the portion of N that is volatilized to ammonia and nitric oxide and converts to N_2O through secondary reactions, and the portion that is derived from leaching/runoff (IPCC 2006). Most LCAs use the IPCC tier-1 method to calculate direct and indirect emissions, which applies spatially generic emission factors based on the quantity of N fertilizer applied (IPCC 2006). However, the biogeochemical characteristics, climate, and management practices of different locations significantly affect the quantities of direct and indirect emissions per unit of N applied (Ogle et al. 2014; Del Grosso et al. 2006).

This study uses direct N_2O base emission rates associated with typical rates of fertilization as derived through a combination of process-based biogeophysical models vetted by an expert panel of the USDA (Ogle et al. 2014). In particular, the USDA report uses the Denitrification and Decomposition (DNDC) model and DAYCENT model to estimate N_2O emissions from typical N application rates and the background N_2O emissions (i.e., the emissions rate when no N fertilizer is applied) for different crop types located in land resource regions (LRR) for three categories of soil classes including fine, medium, and coarse soils, while taking into account spatially explicit climatic factors (Ogle et al. 2014). Using geographic information systems (GIS) tabulate area tools, the percent of corn acres grown on 12 different soil types in each county was determined, based on the first 25 cm of soil data (PSU 2006). These 12 different soil categories were then organized into fine, medium, and coarse soil texture classes, resulting in the percent of county corn grain acres grown on each soil texture (FAO n.d.). Similarly, the portion of each LRR in each county is also determined. Together, this information was used in conjunction with the USDA base N_2O emissions rates, background emissions rates, and typical fertilization rate estimates per LRR and soil texture class to determine the respective weighted average county-level metrics. Where state or LRR emission factor data is missing from the USDA report, the IPCC tier-1 direct N_2O emission factors are used, resulting in approximately 10 kg N_2O-N/MT N. For each county's unique set of emission factors (kg N_2O-N/ha) and fertilization rates (MT N/ha), the background emission rates are subtracted from the base emission rates and divided by the fertilization rates to determine the county level N_2O-N emissions per MT of N applied. These rates are multiplied by the N_2O-N/N conversion factor and the GWP of 298, corresponding to the AR4 (IPCC 2007) and AR5 considering climate carbon-feedbacks (IPCC 2013). As a way to view the differences in rates, the weighted average emission factors are estimated for each state based on the respective total county-harvested acres, see Table S2 (Electronic Supplementary Material). The USDA report does not provide process-based indirect N_2O rates as they are still considered highly uncertain (Ogle et al. 2014), so in place of more spatially explicit factors, indirect N_2O emissions are also estimated using the IPCC tier-1 indirect emission factors (IPCC 2006). Despite this, variability in indirect N_2O emissions is still partially captured in the current study due to the differences in N application rates across counties. Multiplying these emission factors by the average quantity of N fertilizer applied per harvested acre of corn and total harvested acres, respectively and dividing by the expected yield results in the average GWP emissions from on-field N_2O per bushel of corn produced, as depicted in aggregate in Fig. S9, and separately in Figs. S10 and S11 (Electronic Supplementary Material).

2.4 Irrigation emissions

Corn is the most heavily irrigated crop in the USA (Johnston et al. 2015). While the significant variation in irrigation impacts between counties was first highlighted in Smith et al. (2017), a limitation of the study was that it only captured the spatial variation in the quantity of irrigation water consumed (i.e., blue water footprint), based on a 1998–2002 dataset, which was then paired with a generic average GREET emission factor per unit water applied. Because water consumption metrics represent only the portion of water loss, largely from evapotranspiration, the contribution of irrigation emissions presented in that study are likely underestimated and should instead be based on irrigation water withdrawal data. The current study uses irrigation water withdrawal data and captures a greater degree of spatial variability than previous estimates through the use of more recent data on applied irrigation water and the additional consideration of irrigation application method, whether water is withdrawn from groundwater or surface water sources affecting total energy requirements, the different energy sources used for irrigation, and the spatial variability of electricity emission factors, all of which are considered to be significant factors in total energy use and associated emissions of irrigation.

As demonstrated in several studies, some counties heavily irrigate while others rely solely on rain-fed sources. This variation is captured using the WATER model, which provides more recent county estimates of the average quantity of irrigation water consumed between 1998 and 2008 for corn production in the USA, as determined through the purpose-based allocation method (Chiu and Wu 2012), see Fig. S12 (Electronic Supplementary Material). These estimates, paired with the state-level USGS estimates on the return-to-withdrawal ratio, initially used in the WATER model, were used to estimate county-level irrigation water withdrawal (Chiu and Wu 2012; Wu et al. 2012).

Using the USDA Farm and Ranch Irrigation Survey (FRIS), the method of irrigation was determined for each state based on the number of irrigated corn grain acres receiving water via a pressure-system (e.g., sprinkler irrigation systems), or a gravity-fed system (e.g., furrow irrigation), see Table S3 (Electronic Supplementary Material) (USDA 2013). Energy is required to power the sprinkler irrigation systems, which can be supplied from a variety of sources. In the USA, electricity- and diesel-powered irrigation systems are most often used, although there are a small number of irrigated acres that are also powered by natural gas, LP, propane, and gasoline systems, see Table S4 (Electronic Supplementary Material) (USDA 2013). The FRIS provides state-level information on the quantity of sprinkler-irrigated acres that are powered by each type of fuel category. It furthermore describes whether water is withdrawn from groundwater or surface water sources for each fuel type. Sourcing from either groundwater or surface water determines the total amount of energy required to deliver one unit of water (e.g., m^3). In absence of more spatially explicit information, it is assumed that water withdrawn from groundwater sources (requiring deep pumps) travels an average height of approximately 61 m (i.e., the total lift). Shallow pumps on the other hand, which withdraw water from surface water sources, are assumed to travel an average height of about 35 m (Wang 2012). These assumptions are based on a survey of deep and shallow pump irrigation systems in China, due to limitations in US specific data. The resulting estimates of total energy use, using Equation S4, for each fuel category are indicated in Table S5 (Electronic Supplementary Material); electricity use estimates range between 0.28 for deep pumps and 0.16 kwh/m^3 for shallow pumps putting estimates on par with average electricity use parameters provided by Ecoinvent at .24 Kwh/m^3 (Ecoinvent 2012).

The total quantity of electricity used to satisfy irrigation demands are combined with the eGRID sub-regional electricity GHG emission factors (EPA 2017), which add an additional layer of spatial specificity to the final GHG estimates. Using geographical information system (GIS) software, each county is spatially joined to the primary eGRID sub-regional provider; while sub-regions do import power from other sub-regions, this amount ranges with substantial variation between 0 and 30% of the power supply in each of the sub-regions, meaning that most of the generated electricity is used within the respective sub-region (Diem and Quiroz 2012). In addition to the combustion emissions from electricity generation, the emission factors indicated in Fig. S13 (Electronic Supplementary Material) also include upstream emissions from fuel production and the emissions for transmissions/distribution grid-losses (EPA 2017; Diem and Quiroz 2012; PE International 2014), both of which also vary by sub-region. The upstream fuel production emissions are computed using the eGRID fuel mix portfolios for each sub-region and the associated average emission factor for each fuel type, as provided by the USLCI and PE databases (PE International 2014; NREL 2012), as indicated in Table S5 and S6 (Electronic Supplementary Material). Emissions for sprinkler irrigation systems are then summed across fuel categories and water sources, detailed in Equation S4, resulting in county estimates of irrigation induced GHG emissions. Dividing by the expected county yields results in the expected GWP emissions of irrigation per bushel of irrigated corn, as seen in Fig. S14 (Electronic Supplementary Material).

2.5 Other inputs to corn production

To capture the full impacts of corn production, a static average emission factor was applied to reflect the additional inputs used in corn farming. The emission factor of 82.7 kg CO_2e/ton of corn excludes N fertilizers, N_2O emissions, and irrigation impacts, and includes average quantities of phosphorus, potassium, lime, pesticides/herbicides, and fuel inputs used to produce a ton of corn (Hsu et al. 2010). Using the study's assumed yield of 175 bushels/acre, the emission factor is converted to kg CO_2e/acre and divided by each corn-producing county's expected yield to provide a unique but coarse estimate of emissions from these other inputs into corn production per bushel of corn supplied from each county (Fig. S15, Electronic Supplementary Material).

3 Results

Total cradle-to-gate GWP emissions on a per bushel and per harvested acre basis are presented in Fig. 1a, b, respectively, showing substantial variation across the corn production landscape. Figure 2a, b shows these emission factors from a quantile perspective, organized from the least to the most impactful growing areas. These estimates reflect the spatial variability in nitrogen fertilization (fertilizer type/emission factors and application rates), on-field nitrous oxide outputs (emission rates and application rates), and irrigation practices (water and energy use rates, fuel types, emission factors), as well as differences in the expected yields. Clearly, there are considerable differences in the distribution of impacts across the USA for the two types of emission factors, due to the relatively high and low yields experienced at different locations. On a per acre basis, for example, corn production in the Midwest is noticeably more impactful compared to other production locations, due largely to the amount and type of nitrogen fertilizers applied. However, due to the comparatively high yields indicated in Fig. S6 (Electronic Supplementary Material), emissions per bushel in the Midwest are on par with other medium to low emission intensity regions, with the exception of Nebraska and Kansas due to the additionally high

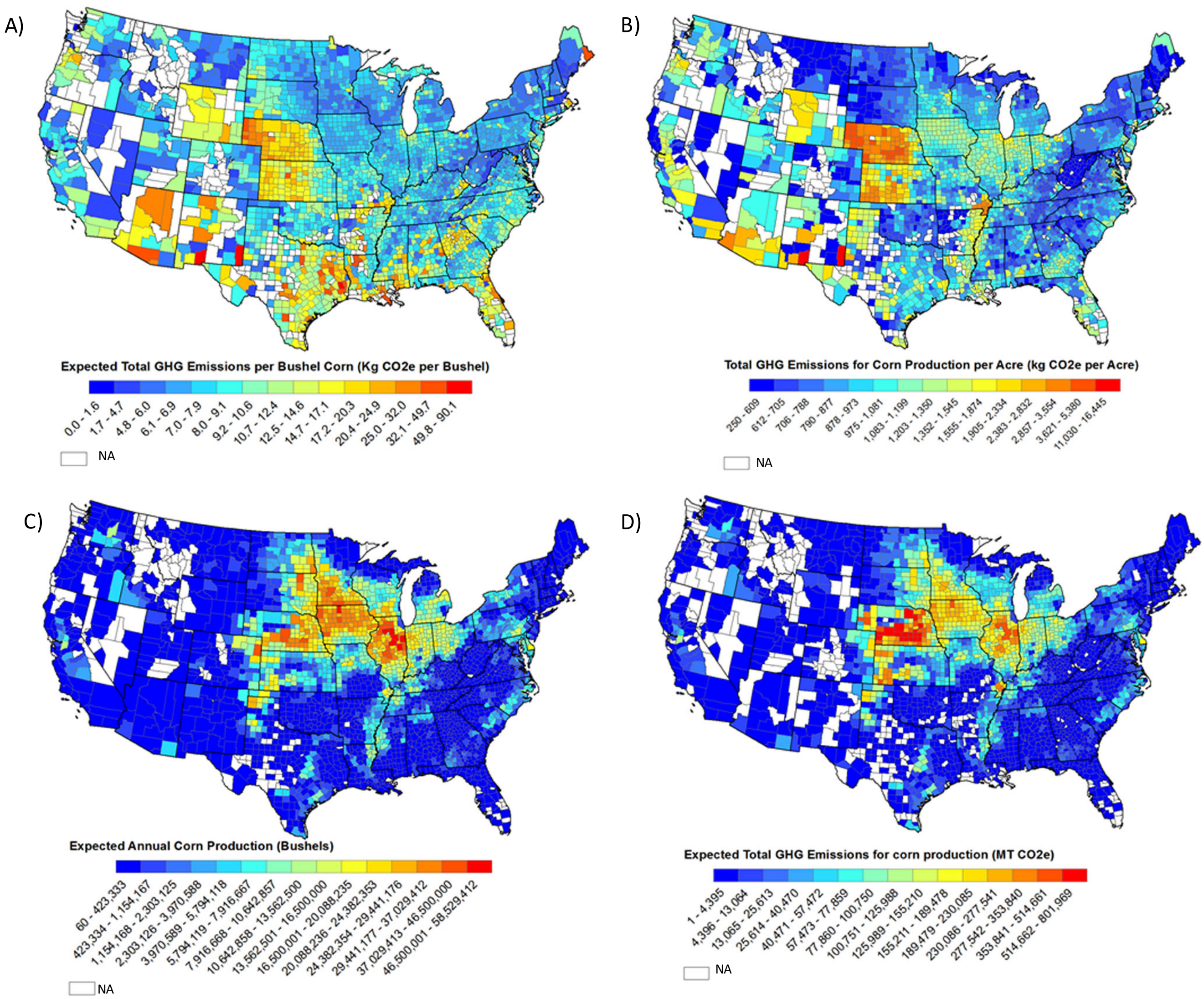

Fig. 1 **a** County corn production expected GHG emissions per bushel (kg CO_2e/bushel). **b** County corn production average GHG emissions per harvested acre (kg CO_2e/harvested acre. **c** Total expected annual yields (bushels). **d** Total expected embedded emissions from corn production (MT CO_2e)

emissions associated with irrigation. Counties in Texas, on the other hand, which have relatively low emissions per acre corn harvested, also have relatively low yields, giving rise to higher emission intensity corn on a per bushel basis compared to other production locations. Not surprisingly, county total cradle-to-farm gate GHG emissions (Fig. 1d) closely resemble the distribution of total harvested bushels of corn (Fig. 1c); however, in some instances, total embedded emissions in a county are either more or less pronounced than would be expected, due to the higher or lower associated emission factors. This is illustrated in the case of Nebraska, where, due to the large quantities of corn produced, it is expected that total corn GHG emissions would also be relatively large compared to other low corn producing regions. Total emissions are even higher than expected, however, due to the comparatively high expected emissions per bushel of corn produced in Nebraska counties. Counties in western Nebraska producing irrigated corn, for example, are expected to generate approximately four to seven times more GHG emissions than a bushel of corn produced in western Iowa counties (see Table S7, Electronic Supplementary Material). The differences are driven primarily by the higher use of irrigation water to produce corn in Nebraska (4.4 m^3/acre in Iowa vs. 610 m^3/acre in Nebraska) and the lower yields in Nebraska compared to Iowa (169 bushel/acre in Iowa vs. 159 bushels/acre in Nebraska), which overshadows the higher rates of fertilization estimated in Iowa compared to Nebraska (148 lbs N/harvested acre in Iowa vs. 139 lbs N/harvested acre in Nebraska), and the higher modeled N_2O emissions per pound of N fertilizer applied (3.5 kg CO_2e/lb. N in Iowa vs. 2.0 kg CO_2e/lb. N in Nebraska). Note that the total embedded emissions (Fig. 1d) represent the intermediate consumption-based impacts of corn

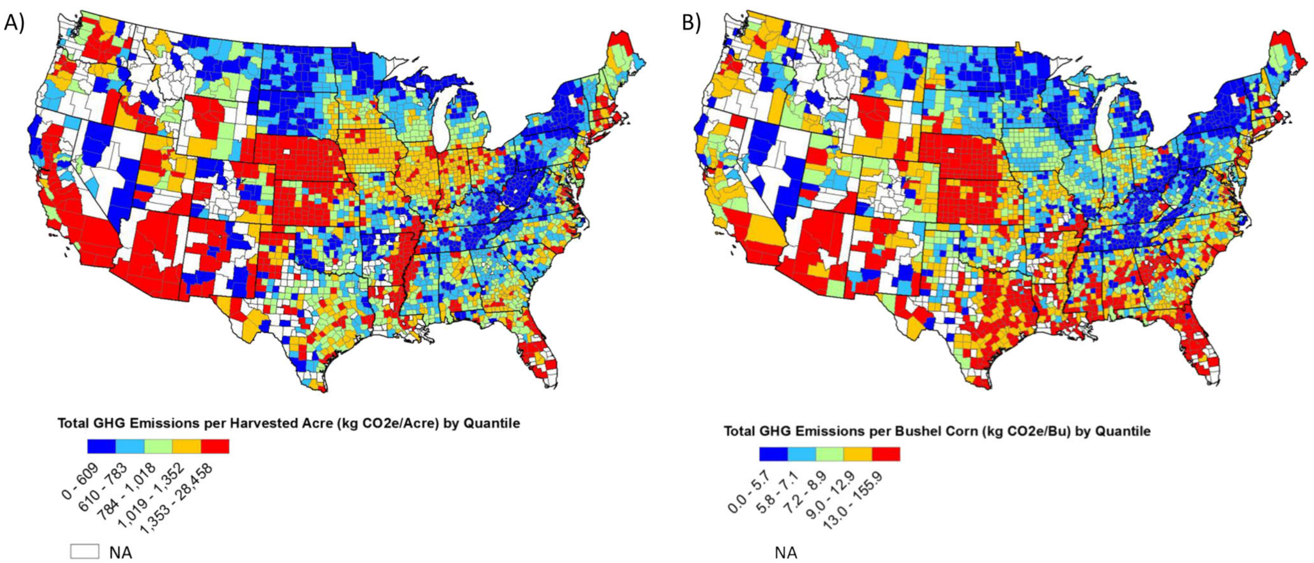

Fig. 2 Expected GHG emissions per bushel of corn production (**a**) and per harvested corn acre (**b**), organized by quantile of the least to most impactful corn producing counties

farming and is therefore embedded in the overall emissions of downstream products (e.g., livestock and biofuels), as such, care should be taken to avoid double-counting total consumption-based emissions of US agriculture.

Table S8 (Electronic Supplementary Material) shows these differences manifested in the contribution of each spatially investigated hotspot to the total GWP impacts in each state; the same hotspot contribution analysis is done for each county and is available in the accompanying data tables, providing strong indication for how to prioritize reduction efforts at relatively high spatial resolution. Table S8 (Electronic Supplementary Material) clearly show the importance of capturing the variation in these hotpots, as the differences in the contribution of each is quite different across states, propelled by the differences in the underlying county production systems. Fertilizer-related impacts, including manufacturing and on-field N_2O emissions, for example range between 8 and 90% of total estimated impacts, with irrigation emissions contributions ranging between 1 to 60% of total estimated corn emissions. The bottom-up US-weighted average indicated in the table shows a similar distribution as that estimated by Hsu et al. (2010) for the top-down national average corn impact contributions, with some key differences. While fertilizer impacts account for 51% of total impacts, on par with those shown in Fig. 4, the amount of embedded fertilizer emissions are estimated to be just a third of the total fertilizer impacts on average, with direct emissions accounting for the other two thirds, as opposed to the 50/50 distribution estimated previously. Irrigation contributions are also estimated to account for 13% of total corn impacts on average, increasing from 5% estimated by Hsu et al. (2010).

Comparing the total irrigation emissions of Nebraska to California helps reveal the importance of the type of irrigation systems employed on the contribution to total GHG emissions. Figure S12 (Electronic Supplementary Material) shows that the amount of irrigation water used to grow corn is greater in California than that used in western Nebraska, with similar amounts of yield output (Fig. S6, Electronic Supplementary Material), yet the associated emissions are substantially higher in Nebraska compared to California (see Fig. S14, Electronic Supplementary Material). The reasons for this are revealed in Tables S3, S4, and S5 (Electronic Supplementary Material), where S3 shows that California irrigated acres primarily rely on gravity-fed irrigation systems, whereas Nebraska-irrigated acres rely on sprinkler-fed irrigation systems that require power for operation, primarily from electricity and diesel fuel sources, about 53 and 28%, respectively. Of these powered systems, most are also drawing from deeper groundwater sources, about 96 and 94% respectively (see Table S4, Electronic Supplementary Material), which have higher associated energy requirements due to the greater height that water must travel (see Table S5, Electronic Supplementary Material). Diesel systems are also relatively inefficient, and the electricity emission factor for Nebraska is on the medium to high side relative to other locations (see Fig. S13, Electronic Supplementary Material). For these reasons, emissions per bushel from irrigation in Nebraska prove to be greater than emissions from California. By switching to similar irrigation systems employed by California, emissions in Nebraska could drastically improve. Future research can investigate the degree to which these changes could improve GHG results. While these overall findings are not particularly surprising and have been generally discussed in the literature, there has never before been the ability to identify the degree to which these elements and trade-offs occur and contribute to total impact intensity across the production landscape at such fine spatial scale. Such information enables identification of the activities and technologies that directly contribute to exaggerated impacts in different areas.

The US county-weighted average emission factor (weighted by total expected production) is approximately 9.0 kg CO_2e/bushel of corn harvested, corresponding to about 1339 kg CO_2e/acre harvested. On a per acre basis, the county-scale bottom-up assessment results in 29% more emissions than the top-down national average estimate provided by Hsu et al. (2010), the differences driven largely by the substantial impact that irrigation contributes in some states, compared to states in the Midwest whose impact composition bears a closer resemblance to that estimated in the Hsu et al. (2010) article (see Table S8 and S2, Electronic Supplementary Material). The estimate of 9.0 kg CO_2e/bushel is also in alignment with the recent Smith et al. (2017) study estimating 9.9 kg CO_2e/bushel using a similar bottom-up county perspective. However, by extending the spatial environmental analysis to include the other heterogeneous hotspot areas investigated in this study, a slightly wider range of variation in GHG impacts is uncovered. While the Smith et al. (2017) study finds county variation ranging from 5.7 to 14.3 kg CO_2e/bushel for the 10th–90th percentiles, the current study finds the expected percentile range to extend from 4.9 to 17.7 kg CO_2e/bushel. This study also reveals different patterns of impact across US production landscape between the two studies. Noticeably, while western South Dakota corn was shown previously to be at the highest end of the emission intensity spectrum, paling Nebraska emission intensities, the current study reveals Nebraska corn instead having overall higher intensities in emissions. This difference was previously driven by the yield differences in the two regions (South Dakota having substantially lower yields than Nebraska), the trend of which still exists in the current study but is mediated by the substantial additional impacts of irrigation in Nebraska compared to South Dakota that consider several additional important spatial considerations than just irrigation rates, as is described above.

Comparing to the Hsu et al. (2010) national average emissions per bushel estimate results in about 52% more emissions in the current study, driven largely by the lower-weighted average yield estimated in the current study compared to the Hsu et al. (2010) study, at 150 bushels/acre expected compared to 175 bushels/acre, respectively. This aspect highlights the significant influence yields on emission intensity estimates, where variability across years can be high, causing swings in emission estimates across years. This study attempts to control for this variation across years and uncertain future yields by using county-expected yields based on probabilities from historical county yield data (2000–2016), allowing for temporally generalizable estimates of emissions across years that take into account the likelihood of different yields occurring for any given year. The resulting expected emission factors are better aligned with corporate and institutional decision-relevant time-scales, for pragmatically mobilizing resources and responding to environmental supply chain information. While the approach of using expected yields allow for temporally generalizable emission estimates, future adjustment may be eventually needed in order to account for any underlying climatic, breeding, and/or GMO-propelled trends across future years that may change the yield distributions. As such, emissions per acre harvested are provided alongside emissions per expected bushels, for alternative yield estimated to be used, see accompanying data tables.

While county scale data is important for identifying sub-state locations of priority for reducing production and consumption emissions at local levels, it is also important for state and national policy makers to understand relative impacts across states in order to target policies that incentivize transitions to lower emission intensity production systems and/or management practices. Figure S16 (Electronic Supplementary Material) shows the weighted average corn production emission factors aggregated to the state and regional levels, and Fig. S17 (Electronic Supplementary Material) shows the corresponding weighted average expected yields and total expected harvested bushels. State emission factors range from 4.0 to 18.5 kg CO_2e/bushel and 562 to 2954 kg CO_2e/acre; while significant sub-state variation does exist, 95% of counties have an emission factor of less than 22 kg CO_2e/bushel and 2372 kg CO_2e/acre.

Figure 3 shows the relative and cumulative probability distributions for total emissions per acre across US counties and across each of the spatially investigated hotspot stages, showing that impacts across the different stages also widely vary, providing an indication of the magnitude of heterogeneity that exists across the production landscape when these different spatial factors are explicitly considered. Figure 4 shows the probability distributions of expected emissions per bushel across counties in each state, and is organized by the state-expected annual production quantity, including the five top producing states that produce 60% of the total annual US production, and the next five top producing states that produce 60–80% of the total annual US production. Figure S18 (Electronic Supplementary Material) shows the remaining distributions across low-producing states. Results show narrow distributions for Iowa and Illinois counties, indicating fairly consistent yields and corn production practices employed across the respective counties, which give greater confidence to state emission estimates and their generalizability to individual counties, whereas the distribution for Nebraska, Kansas, and Missouri counties are wide, having more uncertainty associated with state-level emission factors applied to the county level. These results help shed light on the states for which state-level emissions may be suitable for downscaling to county levels, and where downscaling may not be appropriate due to significant sub-state variation.

Use of expected yield values help to increase the per bushel emission factor generalizability to any given year, while the

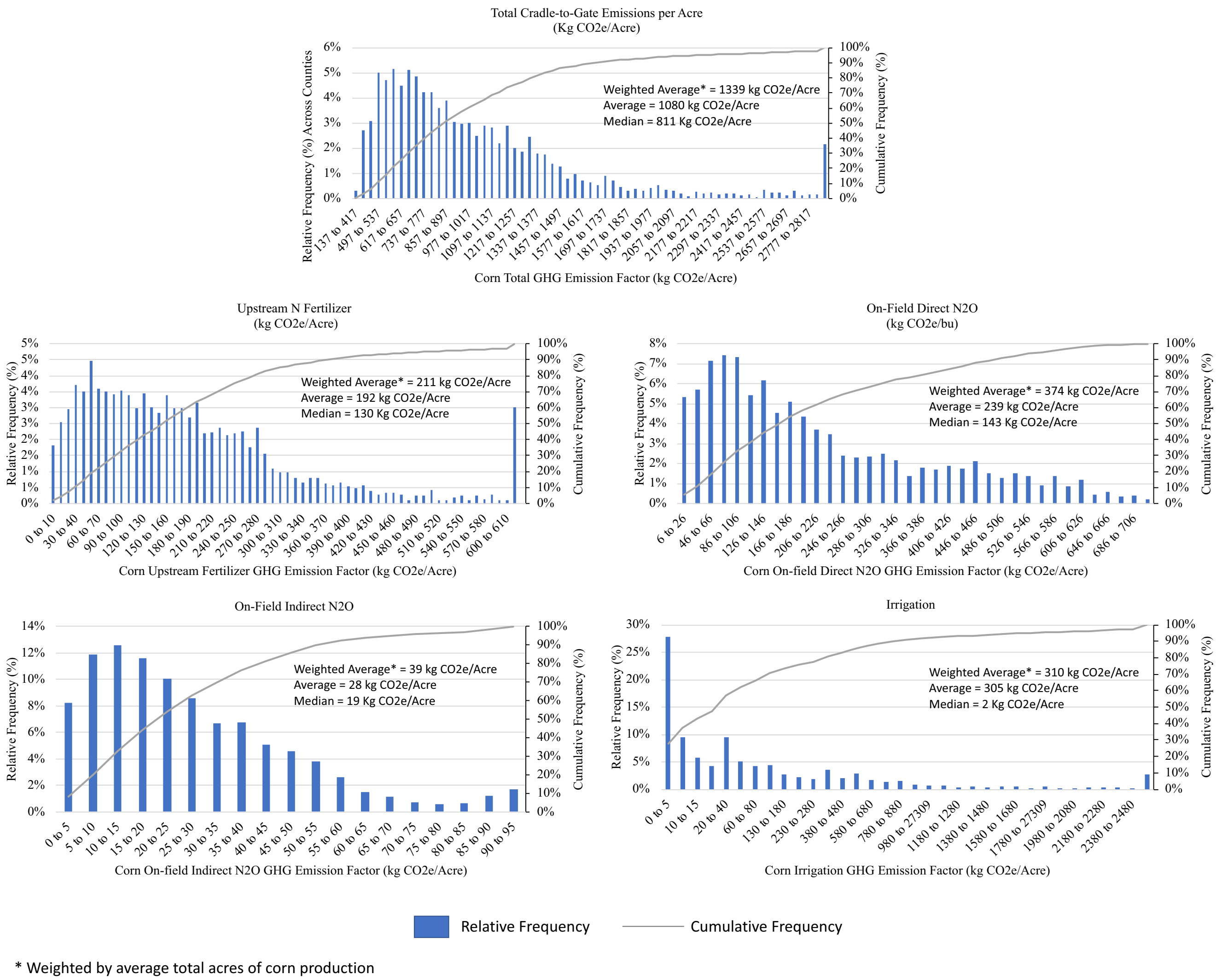

Fig. 3 Relative frequency and cumulative probability distribution of corn emission factors per acre from upstream fertilizer emissions, on-field direct, indirect N_2O emissions, irrigation emissions, and in total

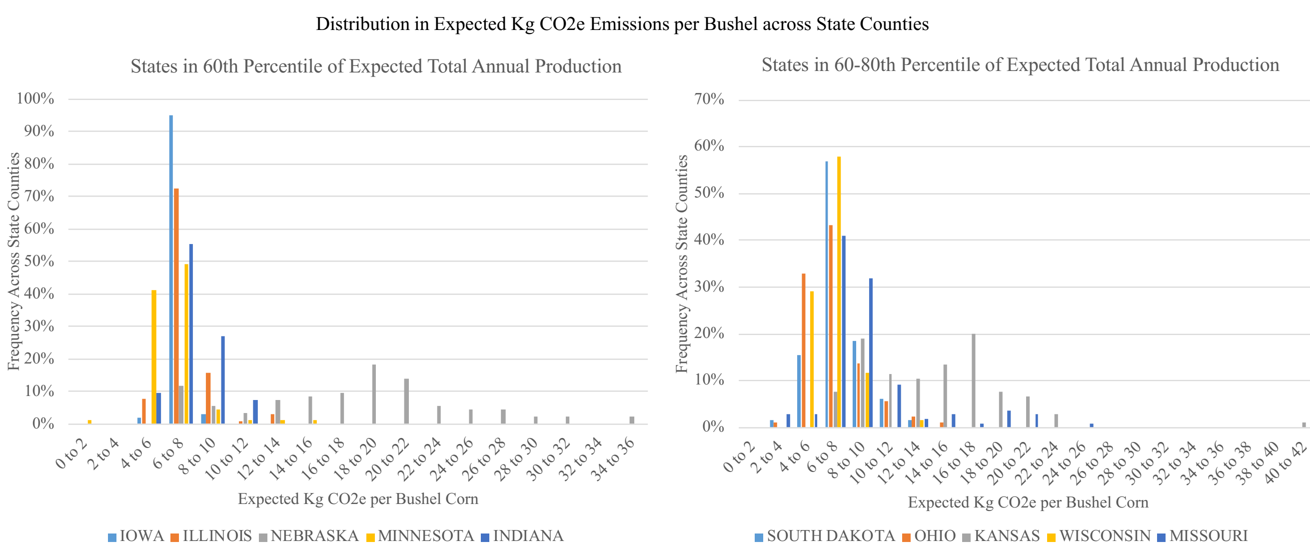

Fig. 4 Distributions in the expected GHG emissions per bushel of corn produced across each State's counties (for the years 2000–2016), including states in the top 60th percentile and 60–80th percentiles of total expected annual corn production

per acre emission estimates are likely to be naturally more stable over time due to the use of average input parameters in its estimation and the relatively established quantities and types of inputs used for corn production for a given location. Figure S7 (Electronic Supplementary Material) illustrates the variability in yields across census years for each corn-producing state, revealing higher yield variability in some states such as Missouri, and lower variability in other states, such as California, providing indication of the extent in which emissions factors can range on a year by year basis.

4 Discussion

The county-level average corn production emission factors illustrated in this study, have several useful applications for both producers and consumers of corn (through either direct or indirect use). These emission factors and corresponding life cycle inventory data serve as a baseline to compare with (1) alternative production regions and production practices to determine the environmental preferability of practices, (2) alternative climate scenarios affecting yields to understand how emissions per bushel can vary over time with the projected changes to climate across the landscape, and (3) alternative crop types with similar spatial resolution to determine the environmental effects of ingredient substitutions in different regions, particularly relevant for ethanol and feed applications. Each of these applications require additional research, but this study provides the underpinning for such assessments to go forward. Downstream buyers of corn can in turn use this current and subsequent information to understand potential risks related to regulatory action or supply shortages from changes in climate, implement environmentally preferable procurement (EPP) practices which seek to source from less impactful production areas, and to exert influence and share knowledge with upstream suppliers for improving environmental performance of high emission intensity production areas. Such information also enables differentiation of commodity markets, where corn suppliers can begin to differentiate corn supplies for better access to "green" markets, aligning with EPP practices that companies are seeking.

While EPP practices may reduce downstream impacts of particular company supply chains, through purchase of less impactful corn, the overall US corn system will continue to have the same overall total impact if no shifts or interventions in actual production practices occur. If corn demand remains relatively constant, the less impactful corn supply will be eventually exhausted and the need to consume the higher impact corn will remain. As such, public and/or private policies that influence production practices will be fundamental for reducing the overall effects of the corn production system. Downstream company buyers can work with policy makers to advocate for greater regulation to field-level practices, although significant challenges exist due to the negative public perception of these types of top-down command-control policies. Companies may also engage with NGOs, or through direct supply chain engagement to influence production practices through knowledge sharing, cost-sharing, and changes to contracts and price signals. Engagement practices such as these, while difficult, are indeed surfacing in the economy, as exemplified by the recent partnerships (e.g., Field-to-Market, Environmental Defense Fund, etc.) and commitments made by major corn buyers to reduce upstream impacts of corn supply (e.g., Smithfield Farms' 2016 GHG target to reduce supply chain emissions by 25% by 2025).

Regarding understanding the effectiveness of different alternative production practices, it will likely be difficult to separate out the noise caused by climate variability's effects on yields from the empirical effects of implementing alternative management practices on the per bushel emission factors. As such, use of biogeophysical models accounting for climate, soil properties, and field management practices to estimate the effects on crop growth will be useful for understanding the effectiveness of such alternative practices on reducing the per bushel emission factors. These estimates can then be compared to the baseline values provided in this study to determine overall effectiveness of alternative practices. Assessing alternative production practices from this perspective is essential for appropriately prescribing spatially relevant improvement strategies, rather than relying solely on per acre emissions metrics to assess effectiveness, as per acre emission factors do not consider the output side of the equation. For example, while reducing nitrogen fertilizer may be heuristically a way to reduce GHG emissions, a viewpoint that would be reinforced from the per acre perspective in many areas, there is a point at which less fertilizer may in fact reduce yields, depending on the spatially explicit conditions of production. This may lead to overall reductions in the efficiency of production, which would be reflected in the higher emissions per bushel estimates relative to conventional production practices. Use of biogeophysical models paired with projected climate scenario models will also be useful to explore the effects of alternative production practices in a changing climate and its implications on supply chain risk.

While a significant portion of the expected variation in corn impacts is captured with the current study, there are other aspects that may be useful to consider in future studies to further enhance estimates. For example, land use-change (direct and indirect) emissions have been identified as a potentially large source of additional emissions (Searchinger et al. 2008; Wright and Wimberly 2013; Plevin et al. 2010), an aspect that will be highly variable across production regions depending on the previous land use category and the amount of land converted (Lark et al. 2015). While "direct" land use change results from the direct conversion of land to produce additional corn, "indirect" land use change emissions occur when land used for food (corn feed) is instead used for fuel (ethanol), where international market forces indirectly result in other lands being converted to meet food demand. Such estimation of indirect land use change impacts therefore requires that the downstream use is known for corn grown in a particular area, which in turn requires an inter-regional commodity flow transport model as well as computable general equilibrium models for understanding production and consumption dynamics. Information on land use change emissions (direct or indirect) could lead to spatially targeted policies (public or private) that seek to minimize land use change, particularly from areas with high carbon sequestration value, such as forests and grasslands. N_2O emission estimates can also be further improved in future studies through use of biogeophysical models implemented at the county-level for characterizing N_2O per N applied, to estimate both direct and indirect emissions, instead of relying on the aggregate land resource regions and IPCC tier 1 factors. Additionally, information on manure additions on top of synthetic N inputs could provide an even better estimation of N_2O emissions at county scales. Finally, incorporating differences in lime application rates may also improve GHG emission estimates, which on average account for 18% of total emissions (Hsu et al. 2010) and may be highly variable across production regions due to differences in soil pH needs, which could be potentially captured in future studies upon data availability. Additional spatial variation may be captured by accounting for differences in phosphorous and potassium fertilizers, pesticides/herbicides, as well as differences in other on-farm fuel use (excluding energy used for irrigation), although this latter aspect may vary minimally on a per acre basis due to the relatively standard needs for planting and harvesting.

The significant variation in the degree that the different hotspots contribute to GHG emissions across the production landscape underlines the importance of spatial hotspotting efforts, and like with traditional LCAs, need to become the focus for improved data collection and analysis. As high-resolution spatial heterogeneity is increasingly woven into LCAs, knowing where that spatial variation is largest and where the inputs or impacts are more homogeneous can help direct GSCM and policy-making cost-constrained efforts. It is these areas too, where the research community and government data collection agencies should communicate the data needs to allow for accounting of the most important spatial variation in environmental impacts. For example, expanding USDA census and surveys to include county-scale information on fertilizer application rates, types of fertilizers applied, and percentage of acres fertilized per crop type could significantly reduce uncertainty of fertilizer-related impact estimates across agricultural commodities. Similarly, increasing the resolution of irrigation data to the county level with regard to the method, source, and power-source of irrigation for each crop type could additionally improve estimates.

5 Conclusions

Streamlined life cycle assessment methods are an effective way to characterize spatial heterogeneity around key contributors of impact, helping deliver the necessary information for companies, stakeholders, and policy makers to target their influence to reduce these emissions through various engagement efforts. Despite the potential room for improvement, the emission factors specified in this study provide decision-makers with high spatial resolution information for prioritizing high impact corn production areas and practices, and enable future assessments to build off of such baseline data to identify effective alternative practices that reduce impacts. Additionally, these improved estimates can be connected with downstream supply chains, assuming a degree of transparency in the locations of demand, as illustrated in Smith et al. (Smith 2017), in order to provide better estimates of organizational impacts specific to particular supply chains. As such, the county GHG emission per bushel results of this assessment have been incorporated in the $FoodS^3$ tool for aggregating upstream impacts to downstream suppliers (www.foodscube.umn.edu) and is available for public use and exploration (also see ESM for emission factor data tables).

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