Journal of Cleaner Production 242 (2020) 118465

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Spatially and temporally explicit life cycle global warming, eutrophication, and acidification impacts from corn production in the U.S. Midwest

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ARTICLE INFO

Article history:
Received 21 October 2018
Received in revised form
28 June 2019
Accepted 16 September 2019
Available online 17 September 2019

Handling Editor: Giovanni Baiocchi

Keywords:
Environmental sustainability
Corn production
Life cycle analysis
Environmental impacts
US Midwest
Spatiotemporal variability

ABSTRACT

The demand for biobased products, such as food, fuel, and chemicals, has been continuously increasing. Meanwhile, agricultural production, serving as the primary stage of biobased products, is one of the largest contributors to greenhouse gas (GHG) emissions and nutrient releases. Environmental impacts of agricultural production influenced by farming practices, soil properties, and climate conditions, are often site-specific and time dependent. Although assessing spatially and temporally explicit environmental releases and impacts are required to inform a sustainable trajectory for agricultural production, such analyses are largely lacking. This study provides site-specific analysis of on-farm and supply chain emissions from corn production to demonstrate the spatio-temporal variability of environmental impacts in the U.S. Midwest states. Using process-based life cycle assessment (LCA) and the physically-based Environmental Policy Integrated Climate (EPIC) agroecosystem model, we estimated county-level life cycle environmental release inventories from corn production in 12 U.S. Midwest states for the period of 2000–2008. Based on the Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) impact assessment model, we quantified the corresponding life cycle global warming (GW), eutrophication (EU) and acidification (AD) impacts of corn. The results show that life cycle GW, EU and AD of corn production varied by factors of 4.2, 83.7 and 10.6, respectively, across the Midwest counties over the nine-year span (2000–2008). Life cycle GW impacts of producing 1 kg of corn ranged from −6.4 in Franklin County, Illinois to 20.2 kg CO_2-eq. in Perkins County, South Dakota. The life cycle EU impacts also spanned over a wide range of 0.99 g in Morton County, Kansas to 82.9 g N-eq. in Leelanau County, Michigan, whereas life cycle AD impacts ranged from 1.3 in Clermont County, Ohio to 100.7 g SO_2-eq. in Perkins County, South Dakota. Moreover, trade-offs existed among life cycle GW, EU and AD impact categories for corn production. The spatial variation analyses showed that key contributors were the different soil types, precipitation, elevation and the amounts of fertilizers applied. These findings provided critical insight into spatio-temporal variations of life cycle environmental impacts of corn production and identified spatial hotspots and top contributors for improving environmental performances of corn production.

1. Introduction

The concerns about the environmental impacts of corn agriculture in the United States (U.S.) are growing with continuously increasing food, feed, and fuel demands. Corn is the primary animal

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https://doi.org/10.1016/j.jclepro.2019.118465

Abbreviations

GHG	Greenhouse gases
GW	Global Warming
EU	Eutrophication
AD	Acidification
CO_2-eq	Carbon Dioxide equivalent
N-eq	Nitrogen equivalent
SO_2-eq	Sulfur Dioxide equivalent
LCA	Life Cycle Assessment
EPIC	Environmental Policy Integrated Climate
TRACI	The Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts

feed grain in the U.S. and serves as an important feedstock for a multitude of food and industrial products including starch, sweeteners, ethanol, and others (USDA, 2017a). Globally, the U.S. is the largest producer and exporter of corn. At least 87% of the U.S. corn was produced from 12 Midwest states in 2008 (USDA, 2017d). Corn production in the Midwest has been linked with an array of environmental concerns such as greenhouse gas (GHG) emissions (Kim et al., 2009, 2014), acidification (Hunter et al., 2011; Van Breemen et al., 1984), and eutrophication (Galloway et al., 2003; Landis et al., 2007; Smil, 2000). Therefore, quantitative assessment of environmental impacts caused by corn production in the Midwest is critical to sustainable development of agribusinesses.

The life cycle assessment (LCA) approach allows quantification of environmental and human health impacts over the entire life cycle of a product or system (ISO, 2006a; ISO, 2006b). Although different life cycle assessment frameworks have been used for analyzing life cycle environmental impacts of agricultural products (Castanheira and Freire, 2013; Fallahpour et al., 2012; Kim et al., 2009; Sinistore et al., 2015), county-level LCA of corn production capturing on-farm emissions of carbon (C), nitrogen (N), and phosphorus (P) in the entire Midwest is still lacking. The majority of existing LCAs of corn production were conducted at coarse spatial scales, such as country (Urban and Bakshi, 2009), region (Adom et al., 2012), and state (Feng et al., 2010; Kim and Dale, 2004) levels. However, the coarse-level LCA studies are insufficient to describe the spatial heterogeneity of the environmental impacts of corn production and limited in supporting location sensible decisions. Several studies (Kim and Dale, 2005, 2008; Tabatabaie et al., 2018a) have focused on global warming impacts of corn production in particular counties in the Midwest. Despite offering county-specific analyses, the geographical coverage of these studies (Kim and Dale, 2004, 2005; Kim et al., 2014; Tabatabaie et al., 2018a) is limited to draw generalizable conclusions across the mid-western U.S. County-level analyses are required to identify spatial hotspots, as well as examine geographic patterns (among counties and states) throughout the Midwest region.

Additionally, the magnitudes of C, N, and P released into the environment from agriculture often depend on time-varying factors such as climate or farming management practices (i.e. application of fertilizers and crop rotations), requiring assessment of multiple years. For instance, temporal variation in precipitation and temperature have shown to be associated with increases in nutrient runoff and GHG emissions (Anyamba et al., 2014; Karmakar et al., 2016). However, studies explicitly comparing the temporal variation while capturing the dynamics of on-farm C, N and P releases across multiple counties and years are lacking. Previous corn LCA studies have examined environmental impacts based on a few years (Adom et al., 2012; Smith et al., 2017), while others were based on average values of multiple years or based on emission factors (Kim and Dale, 2004, 2005; Kim et al., 2009; Pelton, 2019). Therefore, the multi-year analyses including on-farm C, N and P emissions are necessary to understand the inter-annual variability and pinpoint the temporal hotspots for life cycle environmental impacts of corn production in the Midwest.

Furthermore, the relative influences of weather, soil and farming practices to the life cycle environmental impacts of corn production are rarely addressed in previous LCA studies. Previous studies in the Midwest suggested that significant variations in life cycle environmental impacts of corn production (Kim et al., 2009; Landis et al., 2007; Pelton, 2019; Smith et al., 2017; Tabatabaie et al., 2018a) were caused by variation in weather, soil and farming practices. Built upon spatially and temporally explicit life cycle data, further analyses capable of ranking the relative influences of weather, soil, elevation, and farming practices on life cycle environmental impacts are needed. Such analyses will aid stakeholders in understanding the interplays among weather, soil, elevation and farming practices on life cycle impacts, therefore supporting the design of location- and time-sensitive mitigation strategies (Haasnoot et al., 2013; Tabatabaie et al., 2018b).

To fill in these three aforementioned knowledge gaps, this study estimated county-level life cycle global warming, eutrophication and acidification from corn production in Midwest for 9 years, through combining Environmental Policy Integrated Climate (EPIC) model and process-based life cycle assessment. While the EPIC modeling provides county-specific simulations of on-farm C, N and P fluxes, LCA tracks the impacts throughout the whole supply chains of corn production. Coupling EPIC and LCA models enables to investigate both supply-chain and site-specific environmental impacts of corn production across the whole Midwest, through incorporating detailed information, such as soil characteristics, weather conditions, and farming practices (Zhang et al., 2015). Based on the county-level estimates over 9 years, the study further examined the spatial and temporal variations in life cycle environmental impacts of corn production. Subsequently, spatial variance analysis was performed to examine the relative influences of weather, soil, elevation and farming management practices parameters on variability of life cycle environmental impacts.

2. Material and methods

In this study, life cycle assessment (LCA) framework was applied to analyze the global warming (GW), eutrophication (EU), and acidification (AD) impacts of corn production in the U.S. Midwest. LCA follows the International Organization for Standardization (ISO) standards, which are internationally recognized technical evaluation standards for environmental impact assessments (ISO, 2006a; ISO, 2006b). This study focused on the life cycle environmental impact categories of GW, EU and AD due to data availability and emergent needs of supporting sustainable development decisions for corn based bio-products, such as biofuels and food (Pimentel et al., 2009).

2.1. Goal and scope definition

The three main goals of this study consisted of: (1) improving the spatial resolution of life-cycle environmental impacts of global warming, eutrophication and acidification in corn agriculture in 12 states in the Midwest U.S.; (2) examining the spatiotemporal patterns of life-cycle environmental impacts based on multi-year assessment over a large geographic region; and (3) identifying key climate and environmental factors contributing to the environmental impacts over the 9-year span.

Geographically, this study focused on the Midwest states of the

U.S., including Indiana, Illinois, Iowa, Kansas, Missouri, Minnesota, North Dakota, South Dakota, Ohio, Wisconsin, Michigan, and Nebraska, since these twelve states were responsible for over 87% of the U.S. corn production in Year (2008) (USDA, 2008). Due to data availability, life cycle environmental impacts of corn production were analyzed for 9 years from 2000 through 2008.

The system boundary of this study consisted of two subsystems. The background subsystem, which encompassed all supply chain activities for agricultural processes included the productions of seeds, agrochemicals (e.g. fertilizers, pesticides and limestone), fuel, electricity and agricultural machinery (i.e. tractors, harvesting equipment, etc.). The foreground subsystem included on-site agronomic operations, such as tillage, application of fertilizers, pesticides and limestone and water irrigation, as well as associated direct field emissions resulting from on-farm activities (Fig. 1).

Transportation of agrochemicals from regional storehouses or production sites to the farm were excluded from the assessment because the locations of regional storehouses were not available. Also, a few LCA studies, which have included transportation of all agrochemicals to the farms, concluded that the contributions of transporting agrochemicals were minimal from life cycle perspectives (Kim and Dale, 2005; Landis et al., 2007). The functional unit of the analysis was 1 kg of corn grain. The mass-based functional unit of kilogram was chosen as it is an internationally comparable unit, facilitating the comparison of results with other studies.

2.2. Life cycle inventory (LCI)

This study included LCI from two subsystems: 1) the EPIC model simulations, which captured site-specific on-farm carbon, nitrogen and phosphorus releases under various climate and environmental conditions (Section 2.2.1), and 2) the environmental releases from upstream supply chain activities, which was tracked through the process-based LCI. The environmental releases from both supply chain and on-farm emissions were compiled through combining EPIC and LCI datasets. The inputs and data sources for creating process-based life cycle inventory of corn production are listed in Table S2 in the Supplemental Information (SI).

2.2.1. Foreground inventory

EPIC model simulations. The EPIC model is an agroecosystem model capable of simulating impacts of agricultural management on key biophysical and biogeochemical processes, such as plant growth and development, water balance, C and nutrient cycling, soil erosion, and greenhouse-gas emissions (Izaurralde et al., 2006; Williams et al., 1995). A spatially-explicit modeling system was developed and tested (Zhang et al., 2010, 2015) to use EPIC for simulating yields and environmental impacts of major crop rotations in the US Midwest. In this study, the EPIC based geospatial modeling framework was adapted to simulate carbon, water, nitrogen and phosphorus cycling and associated on-site environmental releases at the county level.

2.2.2. Background inventory

Input parameters. Corn yield and application rates of fertilizers, pesticides, and lime usage data of twelve US Midwest states were obtained from the U.S. Department of Agriculture National Agricultural Survey Statistics (NASS) at the county and state levels for the period of 2000–2008 (USDA, 2017d). To process pesticide data, we only included herbicides information for our analysis since most usage data are available from most of the states. We excluded insecticides since over 80% of the usage information has been withheld by agencies to avoid disclosing information for individual farms, as previously highlighted (Yang, 2015; Yang et al., 2017). Fungicides were not included due to data limitation. We chose the most commonly used herbicides for corn production in the Midwest, which is consistent with previous corn LCA studies (Kim et al., 2009; Landis et al., 2007). State-level diesel usage data was obtained from previous literature derived from nine Midwest states (Shapouri et al., 1995). Environmental releases from the supply chain activities (such as production of agrochemicals and seedlings, or fuel use) were retrieved from the Ecoinvent v3.1 database (Wernet et al., 2016).

County-level water used for corn irrigation (m^3) were obtained from previous literature (Pelton, 2019; Smith et al., 2017). The percentages of water applied to corn farms and water withdrawals from groundwater and surface water were obtained from USDA

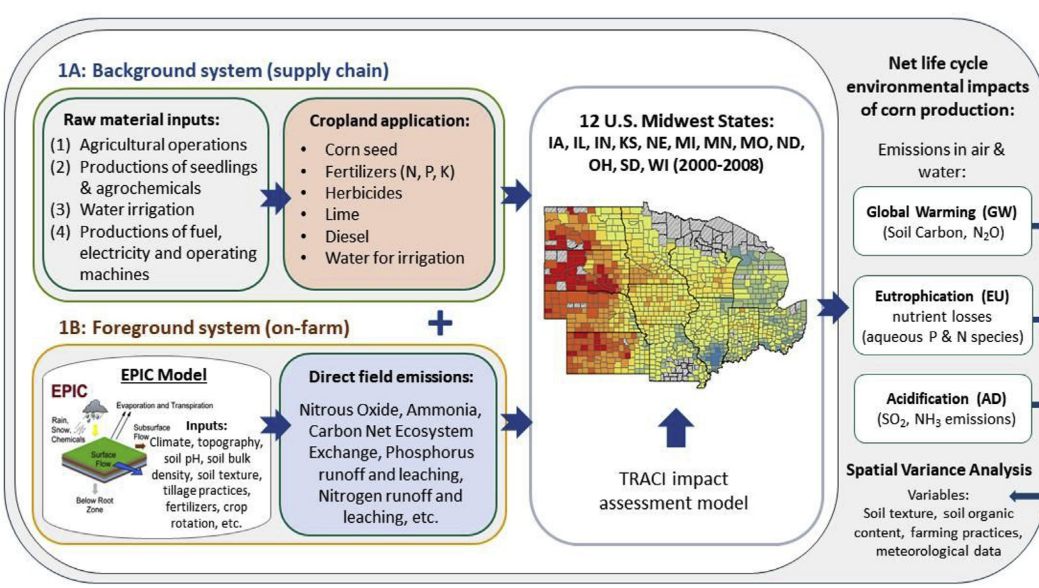

Fig. 1. System boundaries of cradle-to-farm gate of corn production in the US Midwest, 2000–2008. The system boundary includes both agronomic activities and supply chain materials. The diagram depicts the Life Cycle Inventory (LCI) of the background system with supply chain information (1A) and the foreground system with on-farm emissions based on EPIC model simulations (1B). Herbicides and fertilizers included in the analysis were: a) Herbicides: Atrazine, Dicamba, Glyphosate, S-Metolachlor, 2,4-D; and b) Fertilizers: Urea, Diammonium Phosphate, Ammonia, Triple Superphosphate, Potassium Chloride, Ammonium Nitrate (Source for EPIC model image: www.iiasa.ac.at).

Farm and Ranch Irrigation Survey (FRIS) for each state (USDA, 2017c; USGS, 2005). To estimate the electricity used for irrigation for deep pump (61m from groundwater) and shallow pump (35 m from surface water), we retrieved the emissions factor from the GaBi database (PE_International, 2014).

2.3. Life cycle impact assessment (LCIA)

The characterization factors reported by the Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) assessment model version 2.1 were used to conduct life cycle impact assessment. TRACI, developed by the US EPA, is an environmental impact assessment tool widely used in North America for over decades by various LCIA practitioners and researchers for life cycle impact assessment analyses (Bare, 2011). The life cycle GW, EU, and AD of corn production were expressed with units of kg CO_2-eq. kg corn^{-1}, kg N-eq. kg corn^{-1} and kg SO_2-eq. kg corn^{-1}.

Following the formulas in previous literature (Huang et al., 2013; Kim and Dale, 2004), the summation of agricultural foreground (A) and background (B) systems provided the life cycle impacts of corn production (equations can be found in the SI). The life cycle GW, EU and AD impacts of corn equals to the life cycle impacts of foreground (on-farm) and background (supply chain) emissions, as depicted in Fig. 1. County-level simulated on-farm environmental emissions were quantified based on nitrogen and carbon releases with its respective characterization factors (CFs) and molecular weights, as shown in equations S1 and S2 in the SI. County-level estimated supply chain emissions were quantified based on its corresponding CFs, as shown in equations S3-S7. The same equations were used to calculate the three impacts categories using their respective CFs, as listed in Tables S3 and S4.

2.4. Spatial variance analysis

2.4.1. Geographical detector

Geographical detector analyses were conducted by counties to estimate the potential influences of soil characteristics, climatic conditions, topography, and farming management practices on life-cycle environmental impacts. Geodetector, developed by Wang et al. have previously been used to address similar research questions to this study (Wang et al., 2010), including the assessment of potential influences of environmental factors on ecological impacts (Du et al., 2016), health outcomes (Fei et al., 2015; Huang et al., 2014) and environmental performances for policy implications (Wu et al., 2016).

Geodetector utilizes the spatial variance analysis approach to measure the degree of variation among different geographical strata. Each selected variable or dataset (e.g. precipitation, temperature) represents a geographical stratum. To determine the degree of environmental and climatic factors contributing to life-cycle environmental impacts, the geographical strata of county-level life cycle environmental impacts (e.g. GW, EU, and AD) was compared with the geographical strata of environmental and climate factors (e.g. soil type, weather, farming practices) through q-values (Huang et al., 2014). As depicted in Eqs. (1)–(3), q-values can measure the strength and consistency of spatial stratified heterogeneity among different strata based on variances. The spatial variance (q-values) is determined by:

$$q = 1 - \Sigma^{L}{}_{S=1}\ (N_S \times \sigma_S^2)\ /\ (N_T \times \sigma_T^2) = 1 - SSW/SST \qquad (1)$$

where the within sum of squares (SSW):

$$SSW = \Sigma^{L}{}_{S=1}\ \Sigma^{Nh}{}_{i}\ (y_{Si} - \bar{y}_S)^2 = \Sigma^{L}{}_{S=1}\ N_S \times \sigma_S^2 \qquad (2)$$

and the total sum of squares (SST):

$$SST = \Sigma^{N}{}_{i}\ (y_{Ti} - \bar{y}_T)^2 = N_T \times \sigma_T^2 \qquad (3)$$

Where the study areas are composed of N units (12 states) and stratified into h = 1, 2, … L stratum (number of counties). S represents each state and T represents the entire 12 states. Therefore, N_S represents the number of counties within each state and σ_S^2 or $(y_{Si}-\bar{y}_S)^2$ represents the variance of life-cycle environmental impacts and the determinant variables within that state. N_T denotes the total number of counties in the 12 Midwest states, σ_T^2 or $(y_{Ti}-\bar{y}_T)^2$ represents the variance of the environmental impacts and the determinant variables over the entire twelve Midwest states. The i represents the value of unit i in stratum h (life-cycle environmental impact value in each county).

Based on the variances, the q values were estimated within 0−1 (Eq. (1)). The greater the q value, the stronger association between the analyzed strata (e.g. strata of GW versus strata of climatic conditions). In contrast, the lower the q value, the weaker association between the analyzed strata. The variables with greater q values were interpreted as having greater association and influence on life-cycle environmental impacts. All variables were tested for statistical significance. The statistical significance of the algorithms was measured by the Calinski-Harabasz pseudo F-statistics ($F = \sigma_S^2/\sigma_T^2$) and the null hypothesis (Ho: $\sigma_S^2 = \sigma_T^2$) was tested by measuring the statistical difference between the variances (Calinski and Harabasz, 1974). Further details regarding spatial stratified heterogeneity is described in a previous study (Wang et al., 2016).

2.4.2. Data sources

Monthly meteorological data such as precipitation (in mm) and mean temperature (°C) between 2000 and 2008 were extracted from the National Oceanic and Atmospheric Administration (NOAA) and categorized into four seasons (Summer (June-August), Spring (March-May), Fall (September-November) and Winter (December-February)). In each county, we collected climate data from several monitoring stations and averaged to the county level (NOAA, 2017). County-level data on the different soil types (percent of clay, sand, and silt) and soil organic matter (percent) were obtained from the USDA's Soil Survey Geographic (SSURGO) database based on the averages of areas with soil data available in each county (USDA, 2017b). County-level tillage information (fraction of conventional tillage and no tillage) were obtained from the USDA and the Conservation Technology Information Center (CTIC, 2019). The county-level information about the amount of nitrogen and phosphorus fertilizers used (lbs) were estimated based on data from the NASS and corn planted areas (USDA, 2017d; USGS, 2006). Elevation data (m) was obtained from the U.S. Geological Survey (USGS) National Elevation Dataset (NED) at the county-level (USGS, 2017). Detailed information about data sources can be found in Table S5 in the SI.

These parameters were chosen based on previous studies assessing the influences of environmental conditions on agricultural production (Anyamba et al., 2014; Dendooven et al., 2012; Schoof and Robeson, 2016) as well as the scientific relevance of the environmental conditions on crop production (Bouwman, 1996; Paustian et al., 1997). These variables were examined for normality using the Proc Univariate procedure in SAS 9.4 (SAS-Institute, 2015). The mean temperature, soil organic content, and fertilizer (P and N) uses were log transformed due to the skew distribution and corrected for normality.

3. Results and discussion

3.1. Geographic variability in life-cycle environmental impacts

The life cycle GW impacts of corn among Midwest counties ranged from −6.4 in Franklin County, IL to 20.2 kg CO_2-eq. kg corn^{-1} in Perkins County, SD. Such significant variability in life cycle GW impacts was driven by the differences in on-farm nitrous emissions, fertilizer application, and soil carbon change, which were the key contributing processes to life cycle GW impacts. On-farm nitrous oxide (N_2O) emissions and GHG emissions from nitrogen fertilizer production were the dominating positive contributors to global warming for the 9-year span (Fig. 2). On-farm N_2O emissions (13–19%) and GHGs from nitrogen fertilizer production (5–9%) together accounted for 18–28% of the net GW impacts, varying from 0.04 to 3.9 kg CO_2-eq. kg corn^{-1}. Moreover, soil carbon changes, ranging from −7.3–16.9 kg CO_2-eq. kg corn^{-1}, offset GHGs by 69–81% of the net life-cycle GW impacts. Our county-level results showed that using the average values of life cycle environmental impacts of a state to represent the life cycle environmental impacts of a county within that state can cause significant errors (Fig. 3). For example, the GW impacts of corn production in Perkins County, SD reached up to 20.2 kg CO_2-eq. in 2002, which far exceeded the average GW impacts in SD, equaling to 1.31 kg CO_2-eq. kg corn^{-1}.

The life cycle EU impacts of corn at the county-level spanned from 0.99 to 82.9 g N-eq. kg corn^{-1}, varying up to a factor of 83.7. Leelanau County, MI exhibited the highest impacts of 82.9 g N-eq. kg corn^{-1}, while Morton County, KS presented the lowest impacts of 0.99 g N-eq. kg corn^{-1}. The spatial pattern of life cycle EU impacts reflects the spatial distribution and magnitudes of on-farm nutrient releases, since nutrient leaching and runoff were the leading contributors to EU throughout the Midwest, accounting for 70–97% of the total EU. Phosphorus (44%) and nitrogen (2%) leaching accounted for 46% of the net EU. Moreover, phosphorus (18%) and nitrogen (25%) runoff contributed to 43% of the total EU. Additionally, manufacturing phosphorus fertilizers accounted for ~8% of the total EU impacts.

The life cycle AD impacts of corn production throughout the Midwest varied from 1.3 in Clermont County, OH to 100.7 g SO_2-eq. kg corn^{-1} in Perkins County, SD. On-farm NH_3 releases (70–83%) and emissions associated with production of nitrogen and phosphorus fertilizers (10–30%) were the dominating contributors to the net AD throughout the 12 Midwest states. This indicates that nitrogen related sources were the major contributors to acidification (Fig. 2). Moreover, pesticides and irrigation also contributed to 2% and 1% of the total AD, respectively. The overall spatial trends across the years suggest that the AD impacts are largely explained by on-farm NH_3 emissions and corn yield. For example, Perkins County, SD, which exhibited the highest AD impacts, had the lowest corn yield of 282.4 kg/ha in 2002, compared to the average corn yield of 4738.2 kg/ha in South Dakota in that same year. Furthermore, Perkins County emitted 84.9 g SO_2-eq. kg corn^{-1} of on-farm NH_3, while the average NH_3 emissions in SD was 6.1 g SO_2-eq. kg corn^{-1}. The combination of low yield and high on-farm NH_3 in Perkins County, SD resulted in its high life cycle AD impacts.

3.2. Temporal variability in life-cycle environmental impacts

The life cycle environmental impacts for Midwest counties were not consistent across the assessed nine years. We observed the highest median GW impacts of 1.2 kg CO_2-eq. kg corn^{-1} in year 2006 in North Dakota, whereas the lowest median impacts of −1.6 kg CO_2-eq. kg corn^{-1} were shown in 2001 in that same state. The highest GW impacts were mainly attributed to the high on-farm CO_2 efflux reaching up to 1.0 kg CO_2-eq. kg corn^{-1}, as well as on-farm nitrous oxide emissions and manufacturing of nitrogen fertilizers. In contrast, CO_2 sequestration reached down to −1.8 kg CO_2-eq. kg corn^{-1} in 2001, which was 2.8 kg CO_2-eq. kg corn^{-1} lower than the value of year 2006.

The life cycle EU impacts also exhibited inter-annual fluctuations (Fig. 4). We observed the highest median value of 22.2 g N-eq.

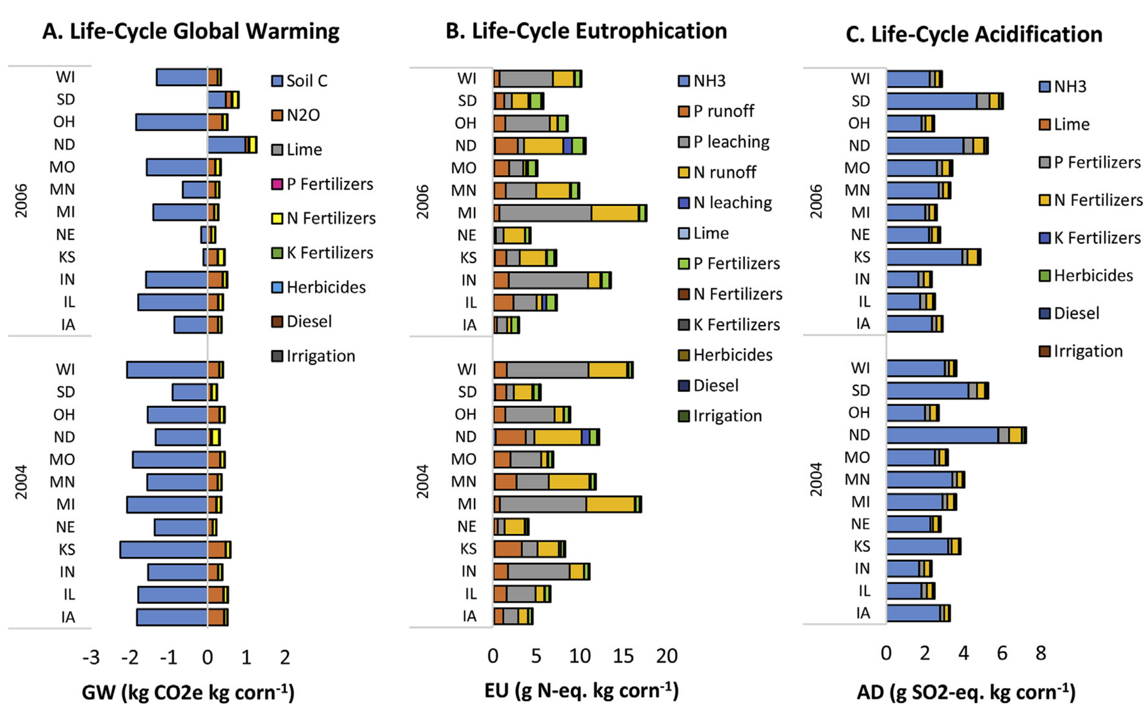

Fig. 2. Average state-level life cycle environmental impacts in 12 US Midwest states: A) global warming; B) eutrophication; and C) acidification for Years 2004, 2006. Years 2004, 2006 were selected to represent the impact categories. Due to space limitation, the results for the remaining years are reported in the supplemental information.

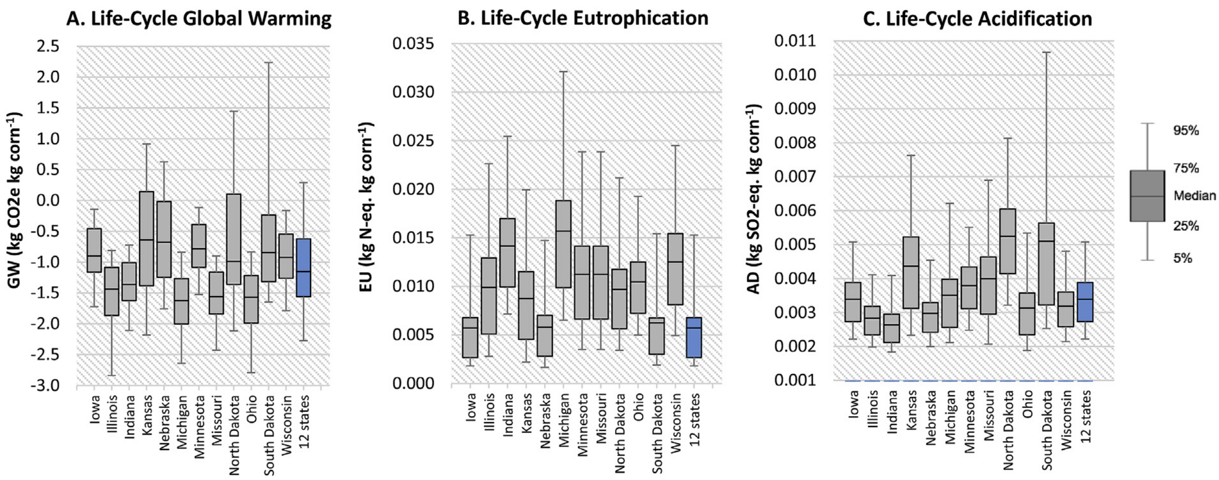

Fig. 3. Box plots representing statistical distributions of multi-year (2000–2008) county-level life-cycle environmental impacts of corn production by state. The box plots in blue represent the aggregate distribution of 12 Midwest states. Box plots show 5%, first quartile, median, third quartile, and 95% values per each state of the pertaining environmental impacts. The impact categories of A) global warming (ranging from −6.4–20.2 kg CO_2-eq. kg corn^{-1}); B) eutrophication (ranging from 0.99 to 82.9 g N-eq. kg corn^{-1}); and C) acidification (ranging from 1.3 to 100.7 g SO_2-eq. kg corn^{-1}) are shown. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

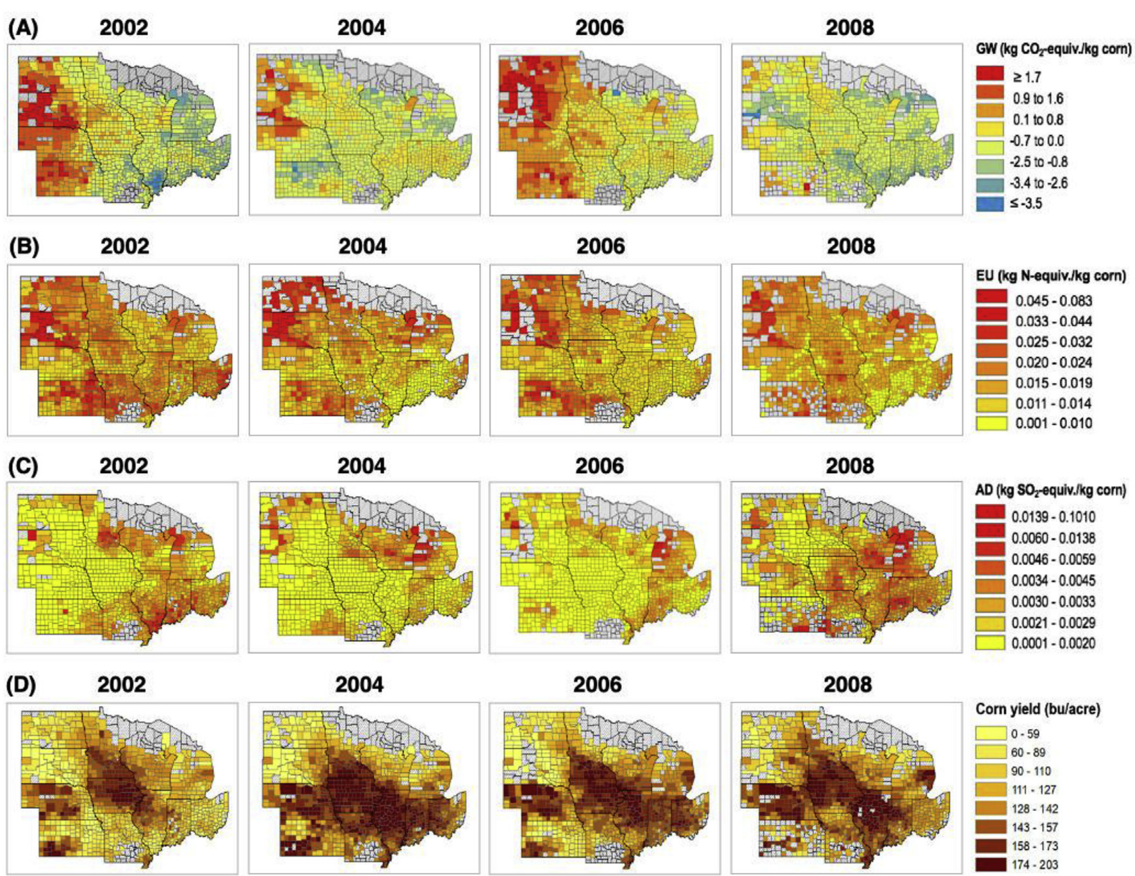

Fig. 4. Maps showing county-level life cycle environmental impacts of corn production in 12 US Midwest states between 2000 and 2008. A) Global warming (kg CO_2-eq. kg corn^{-1}), B) eutrophication (kg N-eq. kg corn^{-1}), C) acidification (kg SO_2-eq. kg corn^{-1}), and D) corn yield (bushels/acre). Years 2002, 2004, 2006 and 2008 were selected to represent the variation in environmental impacts throughout the years.

kg corn^{-1} in Michigan in year 2001, whereas significantly lower value of 9.6 g N-eq. kg corn^{-1} was shown in year 2005. The inter-annual fluctuations were caused by the variation in on-farm nutrient emissions and fertilizer applications. For example, on-farm nutrient releases in 2001 was almost twice as high as 2005. The phosphorus leaching and nitrogen runoff in Michigan in 2001 reached 14.3 and 7.3 g N-eq. kg corn^{-1}, respectively. Instead, the phosphorus leaching and nitrogen runoff in Michigan in year 2005 were only 6.6 and 2.8 g N-eq. kg corn^{-1}, respectively.

Similarly, life-cycle AD impacts varied significantly throughout the 9-year period. The highest median AD impacts reached up to 6.6 g SO_2-eq. kg corn^{-1} in year 2004, in North Dakota whereas these impacts declined by 1.5-folds in year 2008. The differences in AD impacts were caused by the variation in on-farm NH_3 emissions and manufacturing fertilizers. In year 2004, on-farm NH_3 emissions in ND state exhibited up to 5.8 g SO_2-eq. kg corn^{-1} and 1.3 g SO_2-eq. kg corn^{-1} from producing fertilizers. Comparing with 2004, on-farm NH_3 emissions declined by 1.6-folds in year 2008. The contributions of time-variant factors such as precipitation and fertilizers to the inter-annual variability in environmental impacts are explained in Section 3.3.

3.3. Contributions of weather, soil conditions, farming practices and topographic characteristics to environmental impacts

Spatial variance analyses (SVA) shown in Table 1 indicate that precipitation, soil types, the amounts of nitrogen and phosphorus fertilizers applied, and elevation were significant contributors to the life-cycle environmental impacts, as described in Sections 3.3.1-3.3.3.

3.3.1. Weather

SVA results suggest that year-to-year variation and uneven distribution of precipitation (i.e. wide variation ranging from 0 to 349 mm in monthly averages across different counties) were significantly associated with the variations in life-cycle environmental impacts. Such findings regarding the effects of rainfall variability on GHG fluxes agreed well with other studies. Studies have reported that excessive rainfall impedes C sequestration due to the flooded soil surface, potentially reducing corn yield and influence the overall magnitude of GHG emissions (Parton et al., 2015; Schoof and Robeson, 2016; Tabatabaie et al., 2018a). Moreover, rainfall has shown to contribute to EU impacts, potentially due to P and N leaching and surface runoff from fertilizers. For AD impacts, precipitation was also a significant contributor and these findings aligns well with a study conducted in Western Australia (Dolling, 1992; Dolling et al., 1993), where increased rainfall led to increased acidification (kmol H+ per hectare per year) due to potential nitrate leaching from fertilizers (Helyar et al., 1990).

3.3.2. Soil characteristics

The results indicate that the geographic variation of certain soil types contributes to GHG emissions, nutrient releases, and acidification, based on q-values ranging from 0.9 to 1.0 for the different soil types (Table 1). Previous studies have reported that coarse textured-soils, such as sandy soil types, can facilitate leaching of nitrates (NO_3) and nitrogen, as well as nitrogen losses (NH_3) due to volatilization. For instance, sandy soil types have shown to be more susceptible to phosphorus leaching due to lower phosphate binding capacity to soil organic portion (Amery and Vandecasteele, 2015). In contrast, finer textured-soils, such as clay soil types that tend to retain more water, often resulted in higher N_2O emissions due to higher nitrification and denitrification rates (Adler et al., 2012).

3.3.3. Farming practices and topography

Spatial variance analyses found that the application of fertilizers were significant contributors to GW, EU and AD impacts in certain

Table 1
Spatial variance results of life cycle environmental impacts of GW, EU, and AD against soil characteristics, weather conditions, elevation, and farming practices during the period of 2000–2008. The bolded q values in the table represent results that were statistically significant. Statistical significance was determined based on F-distributions and denoted based on $\alpha = 0.05$.

	N fert[a]	P fert[a]	Elev	Type of soil			SOC	NT	CT	PRCP				TEMP			
				Clay	Sand	Silt				Spr	Sum	Fall	Wint	Spr	Sum	Fall	Wint
GW																	
2000	0.93	0.92	0.97	0.97	0.98	0.99	0.43	0.19	0.16	0.96	0.96	0.96	0.98	0.89	0.81	0.92	0.90
2001	0.93	0.92	0.97	0.98	**0.99**	**0.99**	0.67	0.33	0.24	0.99	0.99	0.99	0.96	0.96	0.88	0.89	0.96
2002	0.95	0.94	**0.99**	0.99	**0.99**	0.98	0.65	0.33	0.35	**0.99**	**1.00**	0.97	0.99	0.92	0.96	0.91	0.98
2003	0.98	0.98	**0.99**	**0.99**	**0.99**	0.96	0.58	0.32	0.58	0.93	**0.99**	**1.00**	**0.99**	0.97	0.88	0.96	0.98
2004	0.95	0.98	0.99	0.99	**1.00**	0.99	0.61	0.24	0.61	0.96	**1.00**	0.98	**1.00**	0.89	0.94	0.88	0.96
2005	0.97	0.96	0.99	**0.99**	**0.99**	**1.00**	0.59	0.35	0.62	0.97	0.96	0.99	0.96	0.97	0.94	0.96	0.89
2006	**0.99**	0.98	**1.00**	**1.00**	**1.00**	0.98	0.60	0.33	0.29	0.87	0.88	0.90	0.77	0.93	0.91	0.88	0.94
2007	0.96	0.96	0.99	0.97	**0.99**	**0.99**	0.70	0.33	0.70	**1.00**	**1.00**	**1.00**	0.98	0.97	0.94	0.90	0.97
2008	0.93	0.96	0.97	0.99	**0.99**	0.97	0.63	0.25	0.27	0.93	0.91	0.91	0.94	0.44	0.68	0.53	0.44
EU																	
2000	0.94	0.93	0.97	0.95	0.98	0.99	0.60	0.19	**0.30**	0.96	0.98	0.96	0.97	0.87	0.79	0.89	0.87
2001	0.96	0.91	0.95	0.99	**0.99**	**1.00**	0.79	0.23	0.79	**1.00**	**0.99**	0.99	0.98	0.83	0.92	0.90	0.96
2002	**0.99**	**0.98**	0.96	0.98	**0.99**	**0.99**	0.79	0.30	0.39	0.98	**1.00**	0.98	**1.00**	0.96	0.99	**0.99**	**0.99**
2003	0.98	0.96	0.98	0.98	**1.00**	**0.99**	0.69	0.30	0.81	**1.00**	**0.99**	**1.00**	0.97	0.97	0.91	0.96	0.95
2004	0.98	0.98	0.96	0.99	**0.99**	**1.00**	0.80	0.24	0.80	**1.00**	**0.99**	0.95	0.99	0.97	0.95	0.86	0.95
2005	0.97	0.97	0.94	**1.00**	**0.99**	**0.99**	0.66	0.34	0.72	0.95	**1.00**	**1.00**	0.89	0.90	0.93	0.89	0.98
2006	**0.99**	**0.99**	0.99	**0.99**	**1.00**	**0.99**	0.73	0.27	0.28	0.81	0.80	0.87	0.83	0.90	0.83	0.78	0.86
2007	0.96	0.96	0.97	**0.99**	**0.99**	0.98	0.66	0.27	0.66	0.99	**1.00**	**1.00**	0.98	0.96	0.90	0.93	0.92
2008	0.93	0.94	0.98	**0.99**	**1.00**	**0.99**	0.67	0.25	0.33	0.89	0.96	0.88	0.94	0.38	0.64	0.58	0.58
AD																	
2000	0.86	0.84	0.97	0.97	**0.99**	0.98	0.40	0.16	0.14	0.97	0.96	0.98	0.94	0.85	0.89	0.91	0.90
2001	0.94	0.93	0.98	0.95	**1.00**	0.97	0.65	0.23	0.74	**0.99**	0.96	**1.00**	0.97	0.97	0.83	0.87	0.94
2002	0.95	0.95	**0.99**	**1.00**	**1.00**	**0.99**	0.45	0.25	0.17	**0.99**	**1.00**	0.94	0.99	0.99	0.98	0.88	0.98
2003	**1.00**	**1.00**	**0.99**	**1.00**	**1.00**	**1.00**	0.38	0.26	0.38	0.84	0.99	**1.00**	0.99	0.95	0.94	0.94	0.94
2004	0.94	0.95	**1.00**	**1.00**	**0.99**	0.98	0.56	0.25	0.56	**1.00**	**1.00**	0.99	**1.00**	0.94	0.94	0.89	**0.99**
2005	0.93	0.92	**1.00**	**1.00**	**0.99**	0.98	0.57	0.27	0.57	**0.99**	0.96	0.99	0.99	0.95	0.96	0.90	0.92
2006	**1.00**	**0.99**	**1.00**	**1.00**	**1.00**	**0.99**	0.40	0.27	0.23	0.92	0.94	0.90	0.64	**0.98**	0.87	0.89	0.96
2007	0.97	0.97	0.98	**1.00**	**1.00**	**0.99**	0.59	0.28	0.59	**1.00**	**1.00**	0.99	**1.00**	0.98	0.94	0.89	0.92
2008	0.93	0.94	0.98	**0.99**	**1.00**	**0.99**	0.67	0.25	0.33	1.00	0.79	1.00	0.76	0.38	0.64	0.53	0.58

[a] Amount of fertilizers used at county-level (lbs); Abbreviations in the table: Elev: elevation; SOC: soil organic content; NT: no tillage fraction, CT: conventional tillage fraction; PRCP: precipitation; TEMP: temperature; Spr: Spring; Sum: Summer; Fall: Fall; Wint: Winter.

years. Nitrogen fertilizers are significant sources of N_2O emissions. Nitrogen fertilizers have shown to contribute to GHG emissions through volatilization and nitrification and denitrification processes in soil (Johnson et al., 2007; Ju et al., 2009; MRI, 1998; Shcherbak et al., 2014; Snyder et al., 2009; Zhang et al., 2013). LCA results suggested that about 6–10% of total life-cycle GW impacts were attributed to the production of P and N fertilizers due to the fossil fuel use and CO_2 emissions from manufacturing process. Similarly, producing phosphorus fertilizers accounted for ~8% of the total EU impacts. Moreover, several studies reported that N fertilizers, particularly ammonium nitrate and urea are known to acidify soil due to low pH concentrations, contributing to the overall AD impacts (Barak et al., 1997; Divito et al., 2011; Hickman, 2002; Karlen et al., 1994). In addition, high elevation may have contributed to GHG emissions, as air pressure decreases with increasing altitude facilitating CO_2 efflux (Grant and Pattey, 2003).

3.4. Comparison with the existing literature values in terms of magnitude and stage contributions

The median results from this study aligned with a few corn-based studies. For instance, Kim and Dale, 2005, 2008 reported negative GW results, spanning from −3.09 to −0.8 kg CO_2-eq. kg corn^{-1}, whereas other studies presented positive GW values, ranging from 0.24 to 0.56 kg CO_2-eq. kg corn^{-1} (Adom et al., 2012; Cronin et al., 2017; Grassini and Cassman, 2012; Kim and Dale, 2004; Landis et al., 2007; Pelletier et al., 2008; Smith et al., 2017; Wang et al., 2014). The results from few studies varied considerably for EU (1.3–19.6 g N-eq. kg corn^{-1}) and AD (0.3–13.0 g SO_2-eq. kg corn^{-1}) compared to the findings of this study, with whose median values are, 7.7 g N-eq. and 3.1 g SO_2-eq. kg corn^{-1}, respectively (Cronin et al., 2017; Franzese et al., 2013; Kim and Dale, 2005; Pelletier et al., 2008; Wang et al., 2014) (Fig. 5).

The discrepancy in the life cycle results was partially caused by the different selection of input parameters (e.g. types of fertilizers, pesticides). For example, this study included four different types of nitrogen fertilizers, which yielded a total of 16.8 kg CO_2-eq. per kg N applied, whereas Adom et al. (2012) included only one type of nitrogen fertilizer, yielding a total of 4.87 kg CO_2-eq. per kg N applied (Adom et al., 2012). Furthermore, Adler et al. compared the differences in carbon intensity of different N fertilizers, which ranged from 1.9 to 5.5 kg CO_2-eq. per kg N applied, explaining the significant differences in environmental impacts (Adler et al., 2012; Adom et al., 2012; Parton et al., 2015). Moreover, the number of assessed counties could be a significant source of variation in the results. For example, the results of this study for GW impacts ranged from −6.4–20.2 kg CO_2-eq. kg corn^{-1}, which were based on ~1000 counties in the Midwest. In contrast, significantly less variation was observed in other studies, ranging from −0.8 to −0.04 kg CO_2-eq. kg corn^{-1} based on 14 counties in seven states of the US Midwest (Kim and Dale, 2005, 2008).

The distinct choices of foreground LCI models provide another potential explanation for the variation in the reported life cycle results. Some studies used DAYCENT (Adler et al., 2007; Kim and Dale, 2005; Kim et al., 2009), DNDC (Tabatabaie et al., 2018a), GREET (Kim and Dale, 2004; Landis et al., 2007; Qin and Wang, 2017; Smith et al., 2017; Wang et al., 2007) and SimDen (Parajuli et al., 2017) models, which have different algorithms and capabilities of capturing environmental releases. For example, Adler et al. and Kim and Dale used the DAYCENT model to simulate fluxes of C and N in soil (Adler et al., 2007; Kim and Dale, 2005; Kim et al., 2009), which accounted for the dynamics of plant production, allocation of net primary productivity (NPP), decomposition of litter, and soil organic matter (SOC), and resulted in negative GW impacts. Other studies (Adom et al., 2012; Grassini and Cassman, 2012; Kim and Dale, 2004) used literature-based sources or the default emission factors provided by the Intergovernmental Panel on Climate Change (IPCC), which have limited capability of capturing spatially and temporally explicit environmental dynamics and processes. Estimations of environmental releases based on EPIC model used in this study were considered to be a robust model capable of simulating spatially explicit C, N, and P processes and dynamics (Zhang et al., 2010, 2015).

3.5. Implications of the study for policy making and improving environmental sustainability

The wide range of variability and discrepancies observed throughout the years and among the different states show the potential for reduction opportunities in environmental emissions. The results from this study can serve as a scientific basis to identify locations (counties) with high environmental impacts as well as key factors that contribute to the environmental impacts. Soil carbon change, nitrous oxide, on-farm N and P leaching and runoff, and ammonia were the key factors contributing to environmental impacts. In addition, spatial variance results indicate that soil types,

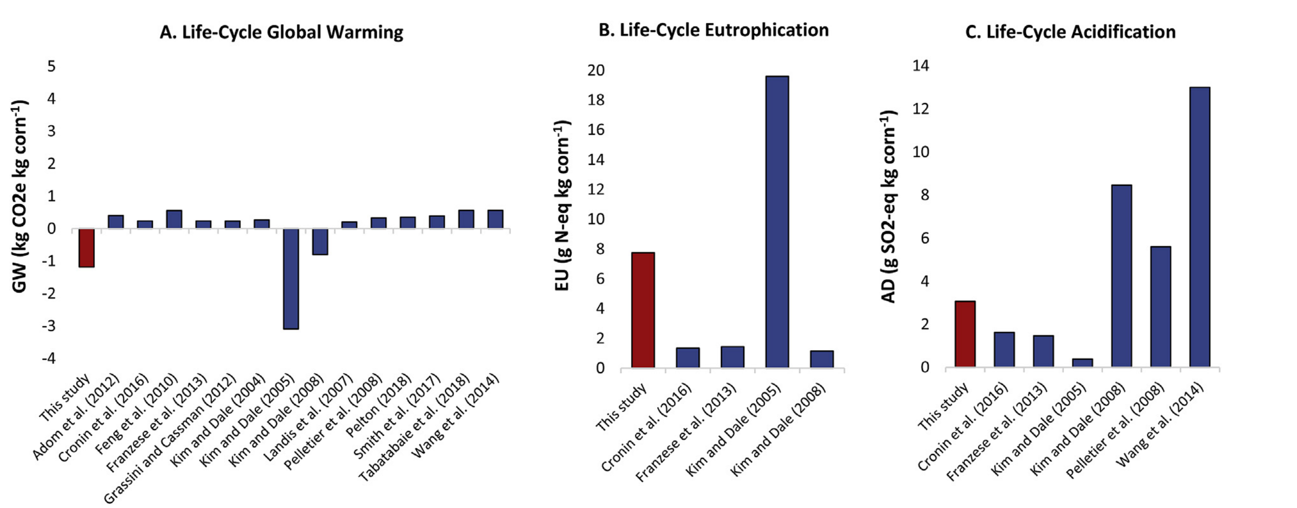

Fig. 5. Comparison of existing literature in life cycle analysis of corn production. The life-cycle environmental impact categories compared include median values of: A) global warming; B) eutrophication; and C) acidification.

as well as the amount of precipitation (particularly in the summer months (May-August)), were strongly associated with life cycle environmental impacts. Based on these findings, policies may support farmers to improve soil quality, consequently reducing environmental emissions. Concurrently, increasing awareness of climate's influence on life cycle environmental impacts may benefit farmers for effective planning of agricultural management practices in order to mitigate negative life cycle environmental impacts.

Moreover, this study suggests that trade-offs among environmental impacts existed throughout the entire Midwest states. To avoid trade-offs, remediation strategies targeting the environmental categories, where corn's impacts are particularly high, are needed. For example, counties such as Perkins County, SD exhibiting high GW (20.2 kg CO_2-eq. kg corn^{-1}) and low EU (3.7 g N-eq. kg corn^{-1}) impacts should prioritize farming practices capable of effectively reducing GHGs, such as no tillage practices (Triplett and Dick, 2008; West and Marland, 2002). Similarly, counties such as Leelanau County, MI yielding high EU impacts (82.9 g N-eq. kg corn^{-1}) and low GW impacts (-3.3 kg CO_2-eq. kg corn^{-1}) could use vegetative buffer strips for controlling nutrients and sediment load releases around farms (Costello et al., 2009; Dosskey, 2001). Nutrient removal efficiency has been estimated to reach up to 75% for nitrogen and 67% for phosphorus with appropriate buffer strip placements (Xue et al., 2014).

Furthermore, variations of life cycle environmental impacts across years provide scientific evidence for designing adaptive and dynamic policies (Haasnoot et al., 2013). Policies may be developed and adapted in response to experiences and insights over time (Swanson and Bhadwal, 2009). For example, temporary adaptions of farming practices (i.e. application of fertilizers after rain period), buffer placements targeted to more vulnerable locations for nutrient runoff (e.g. steeper elevations) and irrigation strategies based on predicted time-specific weather patterns could be suggested for reducing environmental impacts. Jointly, the results from this study highlight the importance of quantifying spatio-temporally explicit environmental impacts and identifying time- and site-specific influencing factors for improving agricultural sustainability.

4. Conclusions

This study examined the life cycle environmental impacts of corn production in the US Midwest. The life cycle analysis reports that the primary parameters contributing to the GW, EU and AD impacts were nitrous oxide and NH_3 emissions as well as on-farm nutrient releases from nitrogen and phosphorus fertilizers. The findings from this study align with previous LCA studies on corn agriculture (Kim and Dale, 2004, 2005; Landis et al., 2007). Moreover, substantial spatial and temporal variation in life cycle environmental impacts was observed throughout the years, with significantly greater variability among counties within each state, compared to the variability among states.

Spatial variance analysis provided critical information of potential agro-climatic conditions (i.e. fertilizers, precipitation) having significant influences on GW, EU and AD impacts. The inferences from this study related to agro-climatic conditions were similar to the findings of several previous studies (Boone et al., 2016; Tabatabaie et al., 2018a; Tabatabaie and Murthy, 2017), which can serve as insights for farmers, policy makers and researchers in designing future studies or developing policies.

Collectively, the findings from this study support policy makers, researchers and farmers to consider the importance of spatial and temporal explicitness in their decision-making process and analyses. This study also highlights the importance of considering key environmental and climate conditions in their analysis, since weather, farming practices and agrochemical uses often vary by geographic areas and farms. Notably, the results from this study can be particularly important for researchers to understand the significance of examining spatial heterogeneity of the environmental impacts and gain additional insights.

Acknowledgements

We would like to acknowledge the Presidential Innovation Fund for Research and Scholarship Award and the Faculty Research Award from the State University of New York at Albany for sponsoring this work. The authors would also like to thank the anonymous reviewers for their comments that improved the quality of the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.118465.

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