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Process-based modeling of soil nitrous oxide emissions from United States corn fields under different management and climate scenarios coupled with evaluation using regional estimates

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Direct emissions of soil nitrous oxide during a growing season (N_2O_{gs}) can be quantified with process-based models considering interactions between management, climate, and soil moisture when key data are available. We used an adapted "parameterized CENTURY/DAYCENT-model" ($_{p}$CENTURY) calibrated with crop growth and soil organic matter decay coefficients at the county-level for the estimation of N_2O_{gs} in the United States Corn Belt. Model estimated N_2O-emissions from corn-based biofuels scenarios considering crop rotation, fertilizer inputs, tillage, and weather were compared against meta-summary of field observations from 55 studies. Both model and meta-summary ranked N_2O_{gs}-emissions to be corn > wheat > soybean phase while model likely underestimated cover crop N_2O_{gs}-emissions. The N_2O_{gs}-emissions and the associated emission factors (EFs) were modeled and summarized to be greater after anhydrous ammonia than urea application and from conventional tilled than non-tilled fields. Modeled and observed N_2O_{gs}-emissions after organic and inorganic fertilizer amendment did not differ due to high variability associated with the treatments. However, the organic fertilizer associated EFs were greater according to meta-summary data because of N input rates. Regionalized weather scenarios indicate hotspots for N_2O_{gs}-emissions can occur where crop N uptake is limited during dry years and in eastern states also during normal or wet seasons.

Abbreviations: AA, anhydrous ammonia; AEZ, agroecological zone; CC, Continuous corn; CS, Corn-soybean rotation; CCvSCv, 2-year corn/cover crop-soybean/cover crop rotation; CSWCv, 3-year corn-soybean/winter wheat-cover crop rotation; EF, Emission factor; GHG, Greenhouse gases; GWP, Global Warming Potential; LCA, Life Cycle Analysis; N_2O_{gs}, growing season nitrous oxide; NASMD, North American Soil Moisture Dataset; $_{p}$CENTURY, Parameterized CENTURY/DAYCENT model; RFS, Renewable Fuel Standards; SOC, Soil organic carbon; SOM, Soil organic matter.

The $_p$CENTURY-derived N_2O_{gs} EFs (0.91 ± 0.19%) for counties investigated were only slightly lower than literature (1.07 ± 0.57%) or Tier-1 (1%) values. Our preliminary evaluation of regional soil moisture estimates showed reasonable agreement between monthly soil moisture estimates and the North American Soil Moisture Dataset during the growing season, but overestimation of soil moisture in winter-spring can influence the estimates of annual N_2O emissions so future work is needed to calibrate soil moisture-associated model parameters. Our work provided scenario-based estimates of climate and management impacts on soil N_2O_{gs}-emissions together with valuable spatial insights into EFs that will be improved by more accurate information of fertilizer inputs and more temporally refined model evaluation.

KEYWORDS

N_2O emissions, corn biofuel, parameterized CENTURY model, emission factor, soil moisture, meta-analytical summary

1 Introduction

Many studies attempt to quantify broad-scale agriculturally-related greenhouse gas (GHG) emissions (Mosier et al., 1998; Lokupitiya and Paustian, 2006; Yao et al., 2006; Li, 2007; Olander et al., 2013) and soil organic carbon (SOC) sequestration (Sleutel et al., 2003; Stockmann et al., 2013; Nayak et al., 2019; Paustian et al., 2019) to support policymaking and GHG accounting. Efforts have intensified in the United States with a recommitment to GHG reductions and the Paris Agreement (Rumpel et al., 2018; Guenet et al., 2021). In particular, nitrous oxide (N_2O) which has a global warming potential (GWP) that is 298 times greater than carbon dioxide (CO_2) (IPCC, 2006) has gained enormous attention that leads to research on mitigating N_2O emissions through adaptive management practices (Mosier et al., 1996; Ogle et al., 2014; Maaz et al., 2021) and quantifying environmental impacts of N_2O emissions in a future climate (Butterbach-Bahl and Dannenmann, 2011; He et al., 2018; Ma et al., 2018).

Improving the capacity to quantify agricultural N_2O emissions at the regional or national scales under various management and climate scenarios is a priority for agriculture which accounts for approximately two-thirds of the total N_2O emissions (IPCC, 2019). Broad-scale GHG inventories (Zheng et al., 2004; Rochette et al., 2008; Mazzetto et al., 2020) and life cycle analyses (LCA) have estimated soil N_2O emissions using IPCC emission factors (EFs), which is defined as the ratio between N_2O emissions and N input rates, at Tier-1 (global values) (Bouwman, 1996) or Tier-2 (regionally-specific values adjusted with covariates or classes) scales (IPCC, 2006; Hergoualc'h et al., 2019). Model-based estimates that better account for soil organic matter (SOM) dynamics and site-specific environmental and management factors (Li et al., 1992; Hansen, 2002; Gilhespy et al., 2014; Berardi et al., 2020; Del Grosso et al., 2020) are increasingly being used for valorization and GHG accounting (Crossman et al., 2013; Banger et al., 2017; Sela et al., 2017; Osmond et al., 2018). Spatially-gridded models coupled with scenario analysis provide an important opportunity to improve GHG inventories by revealing regional differences in N_2O loss resulting from site and management-specific interactions (Laville et al., 2011; Iqbal et al., 2018).

Several broad (Tesfaye et al., 2021) and national-scale studies have used process-based models (Table 1) to estimate spatial variability of soil-based N_2O emissions at fine (e.g., county) spatial resolutions in order to inform management at a meaningful spatial unit. Unfortunately, many of these studies only carried out model validation by comparison with field observations collected over a narrow range or individual site or using Tier-1 estimates, which yielded little spatial or temporal information. Considering that the high variability of growing season N_2O (N_2O_{gs}) contributes to the main challenge of N_2O quantification (Werner et al., 2007; Leip et al., 2011; Smith, 2017), Tier-2 estimates derived from strategically compiled covariates or class-based datasets are needed to generate EFs to evaluate regionalized estimates generated with process models (de Klein et al., 2020).

To effectively model N_2O emissions and the associated EFs, it is necessary to calibrate and evaluate crop growth, soil moisture and SOC (Del Grosso et al., 2011). At present, very few studies (Table 1) have calibrated key parameters or validated N-submodel outputs other than N_2O emissions. The performance of SOC-submodels has been improved by adjustment of crop growth and soil decay factors using field observations of crop yield and SOC (Meersmans et al., 2013; Kwon et al., 2017; Gautam et al., 2020). Few broad-scale studies of soil N_2O flux have evaluated soil moisture estimates or the influence of temporal weather variability on emissions even though these are key drivers of N_2O across scales (Weitz et al., 2001; Wagner et al., 2003; Butterbach-Bahl et al., 2013). Models typically rely on surrogates such as soil texture and SOM coupled with simple water budget-based method to simulate moisture patterns (Saxton and Rawls, 2006). Datasets like North American Soil Moisture Dataset (NASMD) (Quiring et al., 2016;

TABLE 1 Process-based models applied to estimate soil N_2O emissions at the national or broader scale.

Study area	Model[a]	Modeling unit[b]	Observation for calibration[c]	Sensitivity or scenario analysis[d]	Uncertainty analysis[e]	Validation	References
United Kingdom	DNDC	CL	NR[c]	C, M	MSF	Field observations of N_2O emissions with contrasting soils, crops, and fertilizers	Brown et al. (2002)
Italy	DNDC	GS	N_2O emissions from one site	S, M	MSF	Field observations of N_2O emissions from one site; IPCC estimation	Lugato et al. (2010)
New Zealand	DNDC	GS	NR	S, M	MSF	Field observations of N_2O emissions with contrasting soils; IPCC estimation	Giltrap and Ausseil (2016)
China	DNDC	CL	NR	S, C	MSF	IPCC estimation	Li et al. (2001)
China	DNDC	CL	NR	S, C, M	MSF, MC	Field observations of N_2O emissions with contrasting soils and climate conditions	Li et al. (2004)
China	DNDC	CL	Crop yield[f]	S, M	MSF	Field observations of N_2O emissions with contrasting soils and climate conditions	Chen et al. (2016)
Canada	DNDC	ER	NR	NR	NR	IPCC estimation	Smith et al. (2010)
United States	DNDC	SL	NR	S, M	MSF	IPCC estimation	Li et al. (1996)
United States	DAYCENT	CL	NR	S, C, M	MC	IPCC estimation	Del Grosso et al. (2006), Del Grosso et al. (2010)
United States	DAYCENT	CL	NR	NR	MC	Field observations of N_2O emissions with various soil and management treatments; IPCC estimation	US EPA (2021)
Europe	DAYCENT	GS	Crop yield[f]	M	MC	IPCC estimation	Lugato et al. (2017)
Global	DAYCENT	GS	NR	NR	NR	IPCC estimation	Del Grosso et al. (2009)

[a]DAYCENT, daily century; DNDC, denitrification decomposition.
[b]CL, county-level; SL, state-level; GS, gridded scale; ER, ecosystem-based region.
[c]NR , not reported.
[d]S, soil; C, climate; M, management.
[e]MSF, uncertainty analysis based on the most sensitive factors; MC, Monte-Carlo simulation.
[f]Yield reported at the modeling unit.

Yuan et al., 2021) that report uniform moisture present an opportunity to evaluate regional and temporal estimates needed for Tier-2 modeling of N_2O.

Model performance is greatly influenced by data quality, and this is particularly problematic for N fertilizer input types and rates, which are one of the most influential management factors determining N_2O (Akiyama et al., 2006; Kros et al., 2012; Eagle et al., 2017). Unfortunately, most efforts use N data reported at the state or regional level (Li et al., 1996; Del Grosso et al., 2006; Del Grosso et al., 2010). Inadequacies in the data describing N fertilizer additions to croplands that account for as much as half of direct N_2O emissions from agricultural soils, has resulted in large uncertainty in Tier-1 and 2-based estimates of soil N_2O EFs (Tian et al., 2020). A newly available United States county-level dataset for corn fertilizer N application rates (Xia et al., 2021) significantly improves N input data resolution. In addition, estimates of N_2O_{gs} must also account for the form of N fertilizers applied because chemical structure and organic and inorganic materials differ in their influence on N_2O emissions (Petersen et al., 1996; Shcherbak et al., 2014; Liu S. et al., 2017) and such differences need to be quantified to inform decision-making regarding agricultural N management. Default fertilizer coefficients commonly used in N_2O models can also be verified using compilations of field observations. The same is true for model coefficients used by N_2O models to adjust rates based on agricultural management practices. Ideally models can account for spatial interactions that can produce variable effects of practices such as reduced tillage (Chatskikh and Olesen, 2007; Mei et al., 2018), residue incorporation (Vinther et al., 2004; Li et al., 2010), fertilization and irrigation (Grant et al., 2006; Del Grosso et al., 2008; Katayanagi et al., 2012), cover crops (Farahbakhshazad et al., 2008; Abdalla et al., 2019; Muhammad et al., 2019), and crop diversification on N_2O emissions (Petersen et al., 2006;

Parihar et al., 2018). Model-derived and Tier-2 summary-based estimates of management-associated N_2O_{gs} emissions at the broad scale are critical to promoting the adoption or implementation of practices that can contribute to GHG mitigations.

Challenges for broad-scale modeling of N_2O_{gs} remain as we continue to strive to translate modeling concepts into practical tools using reproducible and transparent methods. These kinds of tools are needed to support policies like the United States. Renewable Fuel Standards (RFS) which was first launched in 2005 (Malmedal et al., 2007) and spurred development of environmental assessment and LCA of corn ethanol production (Wang et al., 2007; Hsu et al., 2010; Hong et al., 2015; Lewandrowski et al., 2020), which accounts for about two-thirds of the United States biofuel production (Birol, 2018) and has accounted for the majority of the biofuel volume required by the RFS (Bracmort, 2022). Moreover, the complexity of management impacts, as well as their interactions with weather conditions, suggest the need for broad-scale modeling to better account for scenario-based soil N_2O emissions that are representative of future climate conditions (Abdalla et al., 2010; Karimi et al., 2021; Miller et al., 2022). This work takes advantage of a 'surrogate or parameterized' version of the process-based CENTURY SOM model ($_P$CENTURY) developed by Kwon and Hudson (2010) to estimate N_2O emissions from corn-based management systems in the United States Corn Belt. The model capacity of $_P$CENTURY was expanded here to estimate county-level N_2O emissions by drawing on N and hydrology submodels from the daily version of CENTURY (DAYCENT) and improved N input datasets. The objectives of this study were to evaluate regional and temporal soil moisture estimates and compare management scenario-based estimates of N_2O_{gs}-emissions against Tier-2 meta-datasets representing dominant management practices (crop rotation, N input type, tillage) used by corn-based systems in major corn-producing states. The model was then used to simulate N_2O_{gs}-emissions under regionalized estimates of wet, dry, and average weather conditions because future climate scenarios are usually associated with pronounced changes in precipitation (Sillmann et al., 2013; Liu C. et al., 2017).

2 Materials and methods

2.1 Model expansion and simulation

This study expanded the $_P$CENTURY model (Kwon and Hudson., 2010; Kwon et al., 2013; Kwon et al., 2017) (SI: Supplementary Figure D1) by adopting the main structures and algorithms of the plant growth, water budget, soil temperature, nitrification and denitrification modules of DAYCENT (Parton et al., 1998) for N_2O modeling (SI: Supplementary Appendix SA). The resulting model simulates SOC stocks, crop biomass, soil moisture, plant available N, and soil N loss on a monthly time step. Land use and land management change scenarios were developed using a gridded SOC modeling framework developed by Kwon et al. (2020) to assess GHG emissions from corn biofuel production. The framework employs four phases of land use history described in SI: Supplementary Appendix SA. The model baseline for comparison consists of a corn-soybean rotation (***CS***), averaged tillage (USDA, 2019), and synthetic N fertilizer additions (USDA, 2018) under normal weather conditions defined by a 30-year average (1986–2015). Model inputs including soil, climate, crop, and management data (Table 2) and the model calibration process are described more fully in SI: Supplementary Appendix SB. Alternative rotation scenarios begin with the baseline conditions and consider continuous corn (***CC***) and diversified cropping systems that included a 2-year corn/rye-soybean/vetch rotation (***CCvSCv***) and a 3-year corn-soybean/winter wheat-ryegrass rotation (***CSWCv***) (Figure 1). Conventional and no-tillage scenarios were run within the baseline ***CS*** rotation. Several N input scenarios (anhydrous ammonia (***AA***), urea, animal manure) were run within diversified rotations. Finally, weather scenarios were run within the conventionally-tilled ***CS*** rotation substituted dry and wet average monthly weather conditions from the driest and wettest year observed between 1986 and 2015 at the county level. This created unique weather stress patterns for each county. The scenario-based simulation was carried out for a 6-year time period (2016–2021) in major United States corn-producing states with model inputs (Table 2) and calibration process described in SI: Supplementary Appendix SB.

2.2 Model evaluation

2.2.1 Preliminary evaluation of simulated soil moisture using NASMD observations

Model simulated soil moisture estimated within the ***CS*** scenario was compared to the NASMD dataset that includes observed volumetric water content in the 0-10 and 0–100 cm soil depths. Since $_P$CENTURY simulates soil moisture at 0-30 and 30–100 cm soil depths, a weighted average was used for 0–100 cm comparisons. The NASMD data were reported at the gridded scale (0.25°) by harmonizing soil moisture observations from 16 regional and national soil moisture monitoring networks (Xia et al., 2015a). The data were interpolated to the county-level for croplands identified by the National Land Use Dataset (Homer et al., 2007; Homer et al., 2015) to match with county-level simulations. To match with $_P$CENTURY time-step, monthly NASMD soil moisture was calculated by averaging daily values for each month

TABLE 2 Data sources for key $_{P}$CENTURY model input variables.

Category	Input variables[a]	Data sources[b]	Coverage and resolution: Temporal	Coverage and resolution: Spatial
Climate	temp, pet, ppt	CRU	Monthly from 1901 to 2012. Data was gap-filled for earlier and later periods using averages from 1901 to 1930 and 1983-2012, respectively	0.5-degree resolution worldwide. Data was resampled to 30 m resolution before being aggregated to the U.S. county level
Soil	Texture, BD, pH, SOC	UNASM	Once value in time	0.25-degree resolution worldwide. Data was resampled to 30 m resolution before being aggregated to the U.S. county level for different land use type
	Drainage class	gSSURGO		10 m for conterminous U.S. Data was resampled to the county-level by retaining the most dominant drainage class
Crop	Crop yield	NASS	Annually from 1866 to 2017. Data between 1951 and 2015 was used to gap-fill data from missing years	County-level for the U.S. where state-level data was used for gap-filling
	HI	Literature values	Separate values for early and modern agricultural periods	Nationwide by crop type
	RSR		Once value in time	
	C concentration			Nationwide by crop type with separate values for above- and below-ground biomass
	CNR		One value in time	Nationwide by crop type and separate values for crop biomass and grains
Management	Tillage and rotation type	ERS	Separate values for early and modern agricultural periods	State-level
	D_{hvst}, D_{plant}	Crop Calendar Dataset	One value in time	0.5-degree resolution worldwide. Data was aggregated to the U.S. county level for each crop type
	N_{fert}, N_{manu}	ERS/NASS/ AgC/USGS	Separate values for spin-up and model simulation period	State-level for N rates and county-level for total N inputs. Data fusion method was used in Xia et al. (2021) to derive county-level N input rates for fertilizer and manure
	T_{fert}	AAPFCO	One value in time	County-level
	Manure CNR and moisture	NRCS/AgC	One value in time	Nationwide by animal type. County-level estimates were based on proportion of animal types and the associated manure properties
	Land use history	ORNL/AgC	Separate values for the pristine period and the early and modern agricultural period	State-level

[a]BD, bulk density; CNR = C to N ratio; D_{hvst} = harvest date; D_{plant} = planting date; HI, harvest index; N_{fert} = fertilizer N application rates; N_{manu} = manure N application rates; pet = potential evapotranspiration; ppt = precipitation; RSR, root to shoot ratio; SOC, soil organic C; temp = temperature; T_{fert} = fertilizer type.
[b]AAPFCO, association of american plant and food control officials; AgC = agricultural census; CRU, climatic research unit; ERS, economics research service; NASS, national agricultural statistics service; NRCS, natural resources conservation service; ORNL, oak ridge national laboratory; UNASM, unified north american soil map; USGS = U.S. geological survey.

during the 10-year period (2003–2012) for which records were available. The comparisons were carried within agroecological zones (AEZ) that group counties with similar climate conditions (Batjes et al., 1997). Model simulated monthly soil moisture during this time period were also compared directly against NASMD observations as an evaluation of model simulated temporal pattern. Correlation between $_{P}$CENTURY anomalies ($_{P}$CENTURY minus NASMD) and key modeling factors including corn and soybean yields, soil properties, and weather were used to explore differences between modeled and measured results.

2.2.2 Comparison between model simulated soil N_2O_{gs} and a meta-analytical summary

Modeled N_2O_{gs}-emissions under the normal weather condition were evaluated with the Tier-2 meta-analytical summary of 705 observations (treatment-year combinations) of field emissions made during the growing season within major corn-producing states. Data extraction, quality control, distribution of study sites, and detailed management information of the studies are presented in SI: Supplementary Appendix SC. Soil N_2O_{gs}-emissions were simulated in $_{P}$CENTURY based on the planting and harvest dates specified by USDA (2010) and assumed to be representative for annual N_2O emissions. Then, we compared the modeled emissions with the meta-dataset to evaluate $_{P}$CENTURY's capacity to estimate changes in flux associated with management scenarios considered. The cropping comparisons include ***CC*** versus ***CS*** or ***CS***-based rotations where the 2-year corn/rye-soybean/vetch simulation was compared with observations from ***CCvSCv*** systems, and corn-soybean/winter wheat-ryegrass simulation was compared with ***CSWCv*** systems. Input comparisons included synthetic versus organic (manure, effluent, composts, residues) and anhydrous ammonia versus urea. Finally, meta-data summaries of conventional versus reduced or no-tillage, were compared against model simulated results.

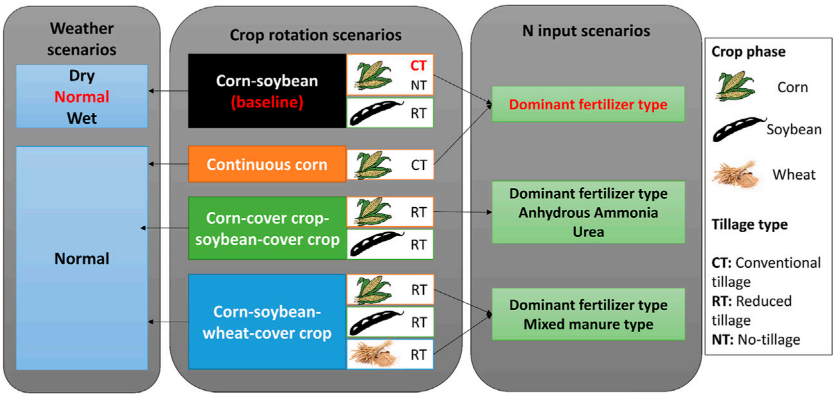

FIGURE 1
Management and weather scenarios used for $_{\mathrm{P}}$CENTURY-based simulation of soil N_2O emissions for 2016-2021 from corn fields. The baseline rotation and tillage scenario marked in red is considered the most common practice within major corn growing states in the United States The normal weather condition is defined with a 30-year average (1986–2015) before the simulation period. Dry and wet weather conditions were simulated by replacing monthly weather data inputs with the driest and wettest months between 1986 and 2015.

2.3 Estimating regional differences in soil N2O emissions from corn production

Considering future climate scenarios, growing season N_2O_{gs}-emissions were simulated for dry, normal, and wet weather scenarios at the county-level before linear regression was carried out in R (R Core Team, 2020) to describe regional differences in simulated N_2O_{gs}-emissions by AEZ and their relationships to key model inputs (N rate, precipitation, and yield) and outputs (soil moisture and plant available N).

Soil N_2O EF was calculated with Eq. 1 for different modeling scenarios and the simulation results of the baseline scenario were compared against IPCC Tier-1 estimates (both the 2006 and the revised 2019 versions) and Tier-2 meta-analytical summary. We considered the contribution of crop residue inputs for the calculation of N_2O EFs using both the modeling and the meta-analysis approach in order to align with the definition of the IPCC method.

$$\mathrm{EF} = \frac{\mathrm{N_2O\ emissions\ under\ fertilized\ treatment} - \mathrm{background\ N_2O\ emissions}}{\mathrm{Total\ organic\ and\ inorganic\ N\ inputs}} \times 100\% \quad (1)$$

3 Results and discussion

3.1 Preliminary evaluation on model simulated temporal and regional soil moisture

Our attempt to evaluate soil moisture estimates of $_{\mathrm{P}}$CENTURY is only preliminary considering that the model currently generated results at a monthly time-step which is much coarser than the actual soil moisture changes in time. However, since the evaluation of model simulated soil moisture has been largely ignored by previous broad-scale N_2O modeling work (Table 1), we hope that our preliminary efforts can lead to a more standardized, rigorous model calibration and validation scheme for future work aiming to provide spatial and temporal insights into soil N_2O modeling at the regional or national scale.

Monthly soil moisture patterns for NASMD and $_{\mathrm{P}}$CENTURY estimates were similar during the growing season (R^2 = 0.68) when monthly averages were calculated based on a 10-year time period (SI: Supplementary Figure D2). This is consistent with Xia et al. (2015b), who found agreement between warm-season soil moisture estimates (NASMD) and land-surface model simulations. Our temporal match was slightly better for whole profile (0–100 cm) comparisons than those made for the near-surface. The tendency for NASMD estimates to be drier and less variable in surface depths during winter was observed for all AEZs. This differs from Abdalla et al. (2020) where DeNitrification-DeComposition (DNDC) significantly underestimated field-scale soil moisture. The observed difference is likely due in part to the fact that NASMD data represent the 0–10 cm and not the 0–30 cm depth simulated by $_{\mathrm{P}}$CENTURY. In our study, model overestimation of soil moisture was observed during the cool season in soils with higher clay contents when a crop was not present (SI: Supplementary Table D1). Overestimation also increased with precipitation and temperature, although such trends would have been better reflected by finer simulation resolution (e.g., daily or hourly) than the current monthly time-step of the model. Greater ability to model evaporation, snow cover, and frozen status is likely to improve non-season moisture estimates (Chantigny et al., 2016).

The temporal variation in monthly soil moisture during the 10 years was moderately captured by $_{\mathrm{P}}$CENTURY (Figure 2),

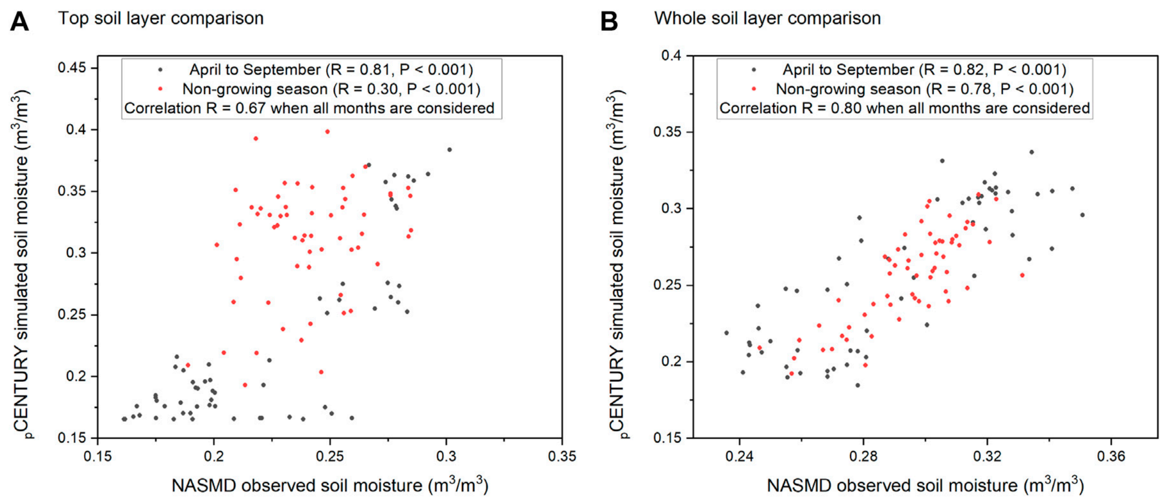

FIGURE 2
Comparison of monthly volumetric soil moisture from 2003 to 2012 estimated with $_p$CENTURY simulation and reported by the North American Soil Moisture Dataset (NASMD) for the **(A)** top and **(B)** whole soil layer. The moisture contents were calculated as corn planting area weighted-averages for the United States Corn Belt counties investigated in this study. Surface depth soil moisture was calculated at 0–30 cm for $_p$CENTURY and 0–10 cm for NASMD) observations and whole soil layer comparison was carried out at 0–100 cm depth. Pearson correlations between $_p$CENTURY and NASMD were calculated for the whole dataset and for the datasets containing corn growing season (April to September) and non-growing season observations, respectively.

with Pearson correlation between NASMD and $_p$CENTURY calculated to be 0.67 and 0.80 for the top and whole soil layers, respectively. Unfortunately, the correlation was very weak for the winter-spring non-growing season for the top soil layer (R = 0.3). It might be the case that our monthly $_p$CENTURY model was not able to fully capture the impact of precipitation or snow events in terms of their timing and duration on soil moisture dynamics. Soil moisture can be influential on inter-annual variations in soil N_2O emissions (Skiba and Smith, 2000; Smith et al., 2004; Oorts et al., 2007) so further improvement of model structure and calibration on parameters for calculating soil hydraulic properties (e.g., hydraulic conductivity, wilting point, field capacity) is needed to better simulate soil moisture dynamics. Our work did not directly compare the influence of soil moisture estimates on the accuracy of N_2O simulation. Ideally future work will investigate the influence of calibrating soil hydraulic parameters on simulated soil N_2O emissions against field measurements. Our preliminary results showed the need to focus on the evaluation using measures from non-growing season N_2O emissions because of the poor model performance on soil moisture estimates during this time period.

Spatially, while $_p$CENTURY estimates are driven by characteristics of the dominant soil type within a county, the NASMD estimates capture field-to-field variability and likely provide a better representation of average conditions. Because county-level NASMD estimates are based on extrapolations of station-based observations that may have smoothed out spatial differences, the variances of monthly soil moisture vary less than $_p$CENTURY-based estimates. Moreover, the variance of interpolated datasets can be affected by the number of samples (Beguería et al., 2016) and by the number of counties within an AEZ (Hofstra et al., 2010). Soil moisture estimates in AEZs with fewer counties and/or measuring sites are expected to be less variable.

3.2 Evaluating simulated soil N_2O emissions influenced by management factors

3.2.1 Soil N_2O_{gs}-emissions influenced by crops and rotation

Both modeled and database-derived Tier-2 estimates of N_2O_{gs}-emissions were greatest in the corn phase (2.7 ± 0.6 kg N_2O ha^{-1}) of the rotation (Table 3). The greater N inputs used to produce corn increase direct soil N_2O_{gs}-emissions (Jarecki et al., 2009; Millar et al., 2010; Nan et al., 2016). The database-derived estimates of corn phase background soil N_2O emissions (1.16 kg ha^{-1}, Table 3) are consistent with other studies (Bouwman et al., 2002; Yan et al., 2003). Reported corn N fertilizer input rates (177 kg N ha^{-1}) were only 6% lower than rates used in $_p$CENTURY scenarios (187 kg N ha^{-1}), making it possible to covert corn N_2O emissions to associated EFs for comparison of the two methods. While our EFs calculated during the growing season likely underestimate annual emissions, data

TABLE 3 Fertilizer N input rates and cumulative growing season soil N_2O emissions from $_p$CENTURY simulation and field measurements used for validation. The results are reported as model simulated county or field measured averages followed by standard deviations Different lower- and upper-case letters represent significant differences at $p < 0.05$ for corn and soybean phases, respectively.

Crop rotation[a]	$_p$CENTURY simulation		Evaluation dataset (field measurements)				
			Corn with N fertilizer inputs			Corn without N fertilizer	
	Fertilizer N rate	Cumulative N_2O	No. obs	Fertilizer rate	Cumulative N_2O	No. obs	Cumulative N_2O
	kg ha^{-1}	kgN ha^{-1}		kg ha^{-1}	kgN ha^{-1}		kgN ha^{-1}
Corn phase	187	2.68 ± 0.60	462	177	3.07 ± 1.62	79	1.16 ± 0.39
CC		2.49 c ± 0.60	188	199	3.68 a ± 1.97	27	1.40 a ± 0.24
CS		2.83 a ± 0.56	210	161	2.83 a ± 1.31	36	1.15 a ± 0.54
CCvSCv		2.72 b ± 0.57	36	159	2.24 a ± 0.86	5	0.91 a ± 0.43
CSWCv		2.86 a ± 0.57	28	193	1.81 a ± 2.45	11	0.31 a ± 0.25
Soybean phase	0	0.05 ± 0.04	122	21	0.81 ± 0.40		
CS		0.06 A ± 0.04	76		0.86 A ± 0.39		
CCvSCv		0.03 B ± 0.02	19		0.83 A ± 0.31		
CSWCv		0.07 A ± 0.04	27		0.35 A ± 0.50		
Cover crop phase	0	0.40 ± 0.56	15	95	1.56 ± 0.50		
Wheat phase	110	1.44 ± 0.70	22	72	1.44 ± 1.54		

[a]CC, continuous corn; CS, Corn-soybean; CCvSCv, corn-cover crop-soybean-cover crop or small grain; CSWCv, corn-soybean-wheat-cover crop.

suggest the majority of losses occur within the cropping system. The meta-analysis of Shang et al. (2020) found annual EFs for corn fields were only slightly (0.03%) higher than growing season values. Nevertheless, regions with snowfall and multiple freeze-thaw cycles would likely differ more (Wagner-Riddle et al., 2017) and this ties to our preliminary results showing moisture in winter was not well simulated (Figure 2), in which case the modeling of winter soil N_2O emissions and subsequently annual EF can be associated with large uncertainty. In particular, the relationship between soil N_2O emissions and water filled pore space, which is highly influenced by soil moisture, has been modeled to be a non-linear curve that increases to a degree due to maximum denitrification before dropping down caused by N_2O consumption (Van Der Weerden et al., 2012; Rabot et al., 2015). This, coupled with low nitrate availability in winter favoring N_2O consumption (Davidsson and Leonardson, 1997; van Groenigen et al., 2015) pose challenges to accurate estimation of non-growing season N_2O emissions. Relatively few data are available for evaluation of non-growing season N_2O emissions since many studies reported either annual or growing season cumulative N_2O emissions. Ideally model validation can be carried out at a monthly or finer temporal resolution with new data describing relationship between N_2O and soil moisture in winter-spring.

Reported average N input rates were about 20% lower for corn within ***CS*** (161 kg N ha^{-1}) than ***CC*** (199 kg N ha^{-1}) rotations (Table 3). While data-derived estimates suggest N_2O_{gs}-emissions during the corn phase were reduced by 24, 41, and 51% within ***CS***, ***CCvSCv***, or ***CSWCv*** rotations compared to ***CC*** (3.7 kg N_2O ha^{-1}), differences among rotations were not statistically significant due to high variability in field observations (Table 3). This variability resulted from edaphic factors and variability in both the quantity and quality of residues returned by cover crops and organic amendments applied before corn. Lower corn phase N_2O emissions observed following soybean likely reflect adjustment of N inputs based on rotation and N credits (Sawyer et al., 2006; Castellano et al., 2018; Morris et al., 2018) that can reduce N_2O flux. The $_p$CENTURY-based corn N_2O EF for the ***CS*** baseline scenario was 0.91 ± 0.19% when results from all counties considered were pooled and weighted based on corn planting area. This estimate was slightly lower than database-derived Tier-2 estimates (1.07%) and the IPCC (2006) Tier-1 estimate for agricultural soils (1%). The $_p$CENTURY-based estimates for N_2O_{gs}-emissions from the corn phase of ***CS***, ***CSWCv*** and, ***CCvSCv*** rotations were significantly greater than from the ***CC*** rotation (Table 3). Statistical separation is due to lower variability of simulated estimates and to the fact that N rates were not altered for different rotation scenarios. Discrepancies between the observed results and simulated results suggest simulations may exaggerate feedbacks that increase flux from diversified rotations associated with return of low C/N residues (Chen et al., 2013), increased organic matter

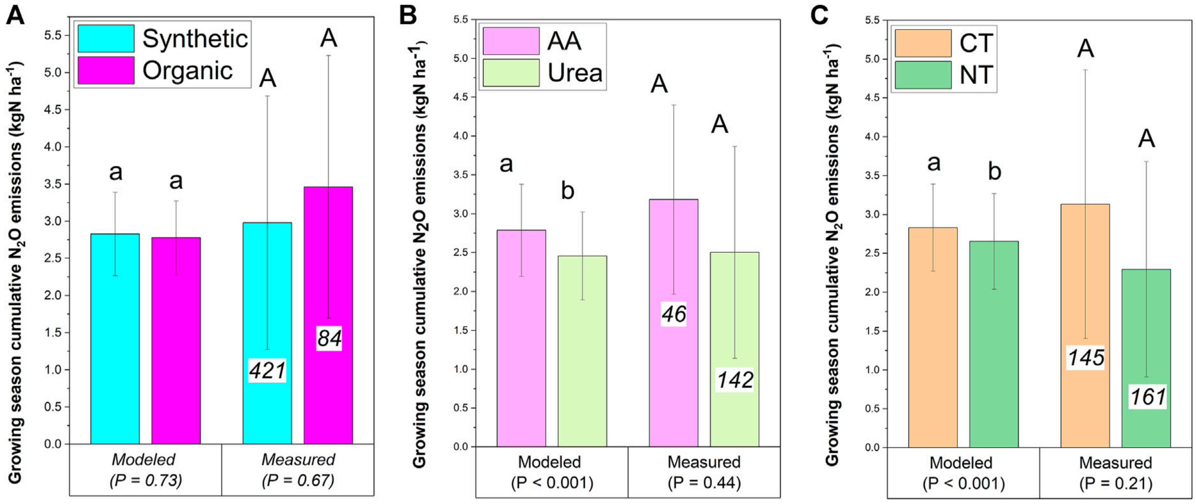

FIGURE 3
Comparison of means and standard deviations of growing season cumulative soil N_2O emissions from corn phase under different **(A)** N input types (synthetic versus organic), **(B)** N fertilizer types (anhydrous ammonia (AA) versus urea), and **(C)** tillage practices (conventional (CT) versus no-till (NT)). The results are reported for $_p$CENTURY-based model simulation and summarized from the meta-dataset of field observations. Number of observations within each category of the field dataset used for validation are shown within the columns. Paired and unpaired t-tests were used to compare treatment differences with *p* values shown with labels on the *X*-axis. Different letters represent significant difference at $p < 0.05$ identified with the *t* tests.

(Varvel, 2006; Mitchell et al., 2013) and plant available N (Kuo and Sainju, 1998; Peyrard et al., 2016).

Non-corn phase N_2O flux was generally tied to N input rates. The magnitude of modeled and estimated N_2O_{gs}-emissions was almost identical for the wheat phase, but the variance was again greater for database-derived estimates (Table 3). While the relatively low estimates of flux from the soybean phase (<0.1 kg N_2O ha^{-1}) resulted from simulations that add no N fertilizer to that crop phase, field observations reporting use of N fertilizers or manures in 28% of observations produced estimates that were least ten-fold higher. Both direct fertilizer additions and N applied to the previous crop might contribute to enhanced N_2O emissions following corn (Iqbal et al., 2015).

The $_p$CENTURY simulated N_2O_{gs}-emissions for the cover crop phase were much lower (74%) than estimates derived from field observations (Table 3). Similarly, Jiang et al. (2020) also showed that soil N_2O emissions during the cover crop phases were modeled with much lower accuracy than those from the corn years. Our assumption that cover crops were unfertilized likely reduced model estimates. Additionally, the model may have overestimated cover crop N uptake and diminished associated N_2O loss. Alternatively, our simulations may have overestimated soil moisture during winter (Figure 2) and so created redox conditions that promoted full reduction to N_2 (Chapuis-lardy et al., 2007; Wu et al., 2013). Foltz et al. (2021) also found that the DNDC model failed to capture field-observed decreases in N_2O_{gs}-emissions caused by winter cover crops. Improvements to soil moisture estimates and temporal interactions are needed to successfully capture 'hot' moments registered in the field. Improvement in $_p$CENTURY modeling for non-corn crop phases will require more detailed data inputs and model calibration. Ideally, such data can be acquired from long-term cover crop experiments that measured yield, SOC changes, and the associated GHG emissions.

3.2.2 Soil N_2O emissions influenced by N fertilizer type

The simulated N_2O_{gs}-emissions from corn plots amended with inorganic and or organic fertilizers did not differ ($p > 0.05$) and were slightly lower than field observations. Means derived from the field observations were 16% greater after organic amendments were used (Figure 3A), but the difference between organic and inorganic sources was non-significant ($p > 0.05$). Elevated N_2O_{gs}- emissions are rate sensitive and expected where manure additions deplete oxygen by stimulating heterotrophic activity (Petersen et al., 1996; Decock, 2014). While our simulations used the same rates for fertilizer and manure treatments to compare the effects of N forms, the average N input rates used for field trials were 58% greater for organic (261 kg N ha^{-1}) than inorganic N (165 kg N ha^{-1}) applications. More information about farming systems might be needed to justify assumptions about manure application rates to ensure that the database-derived EFs for organic (1.16%) and synthetic fertilizers (0.92%) (Table 4) are meaningful for making management recommendations. Only 16% of field observations were measured from soils treated with organic fertilizers so more

TABLE 4 Management and climate associated emission factors (EFs) of cumulative growing season soil N_2O emissions (N_2O_{gs}) calculated from $_P$CENTURY simulation and field measurements used for evaluation. The EF results are reported as model simulated county or field measured averages followed by standard deviations.

Scenario for comparison	Meta-dataset summary		$_P$CENTURY model simulation	
	N input rate	EF	N input rate	EF
	kg ha^{-1}	%	kg ha^{-1}	%
N input type				
Synthetic fertilizer	165	1.16 ± 0.66	187	0.94 ± 0.19
Organic fertilizer	261	0.92 ± 0.47		0.92 ± 0.16
N fertilizer type				
Anhydrous ammonia	166	1.28 ± 0.49	187	0.92 ± 0.20
Urea	162	0.89 ± 0.48		0.75 ± 0.17
Tillage practice				
Conventional tillage	167	1.24 ± 0.68	187	0.95 ± 0.19
No-tillage	173	0.71 ± 0.43		0.85 ± 0.20
Climate scenario				
Dry	NA		187	1.19 ± 0.32
Normal				0.95 ± 0.19
Wet				0.88 ± 0.19
Management region divided into Agroecological zones (AEZs)				
AEZ 7, 8, and 9	196	0.26 ± 0.15	183	0.89 ± 0.17
AEZ 10	158	1.06 ± 0.59	182	0.97 ± 0.19
AEZ 11	207	1.62 ± 0.86	194	0.97 ± 0.17

data must be collected from diversified cropping systems. For example, a meta-analysis by Skinner et al. (2014) found lower N rates were applied in certified organic farming systems than in their conventional counterparts and that could be translated into reduced N_2O emissions. Nevertheless, a different comparison result might be expected for concentrated feeding operations. N rate assumptions are also complicated by organic fertilizer availability that can significantly influence soil N_2O emissions over time (Pang and Letey, 2000; Eghball et al., 2002; Shakoor et al., 2021). Accurate manure activity data is needed to effectively model GHG emissions for specific sites (Walling and Vaneeckhaute, 2020). For broad-scale modeling and policy-making, we must be aware of the influence that rate assumptions may exert on outcomes.

Both $_P$CENTURY and database-derived estimates showed N_2O_{gs}-emissions were greater after use of AA than urea used at similar rates (Figure 3B), but differences were only statistically significant for modeled results. The meta-analyses of Bouwman (1996) and Eagle et al. (2017) concur. This indicates that fertilizer-based scalers used by models like CENTURY effectively represent the mechanistic influences inorganic N forms exert on N_2O production rates as suggested by Breitenbeck and Bremner (1986) that AA is more commonly applied through the injection method which induces highly alkaline soil zones that can accumulate a large amount of NH_4^+ as substrates for N_2O production. Another explanation is that the enhanced NO_2^- level under AA treatment could promote subsequent soil N loss (Venterea et al., 2010). Because N rates are similar between the AA and urea treatments according to the meta-database, both $_P$CENTURY and meta-analytical summary found higher EFs for AA (1.28 and 0.92%) than urea treatment (0.89 and 0.75%; Table 4). Since AA and urea are the two major sources of synthetic N inputs in the United States Corn Belt (Snyder et al., 2014), their different impacts on N_2O should be evaluated with other environmental consequences (e.g., CO_2 emissions, N leaching) in order to inform better management practices at the broad scale.

3.2.3 Soil N_2O emissions influenced by tillage

Model simulation suggested soil N_2O_{gs}-emissions are significantly greater from fields using conventional than no-tillage ($p < 0.001$, Figure 3C). This agreed with database-derived estimates showing average N_2O_{gs}-emissions were increased 37% by tillage. The metadata-derived EFs were also, on average, higher under conventional (1.24%) than no-tillage (0.71%) because N rates were shown to be similar between the treatments (Table 4). Again, differences in field-based comparisons were non-significant due to inter-field variability (Figure 3C). Increased N_2O flux has been shown to result from better aeration that permits more N_2O to escape the soil rather than being converted to N_2 (Chatskikh and Olesen, 2007). Use of no-till has variable effects on bulk density (Blanco-Canqui and

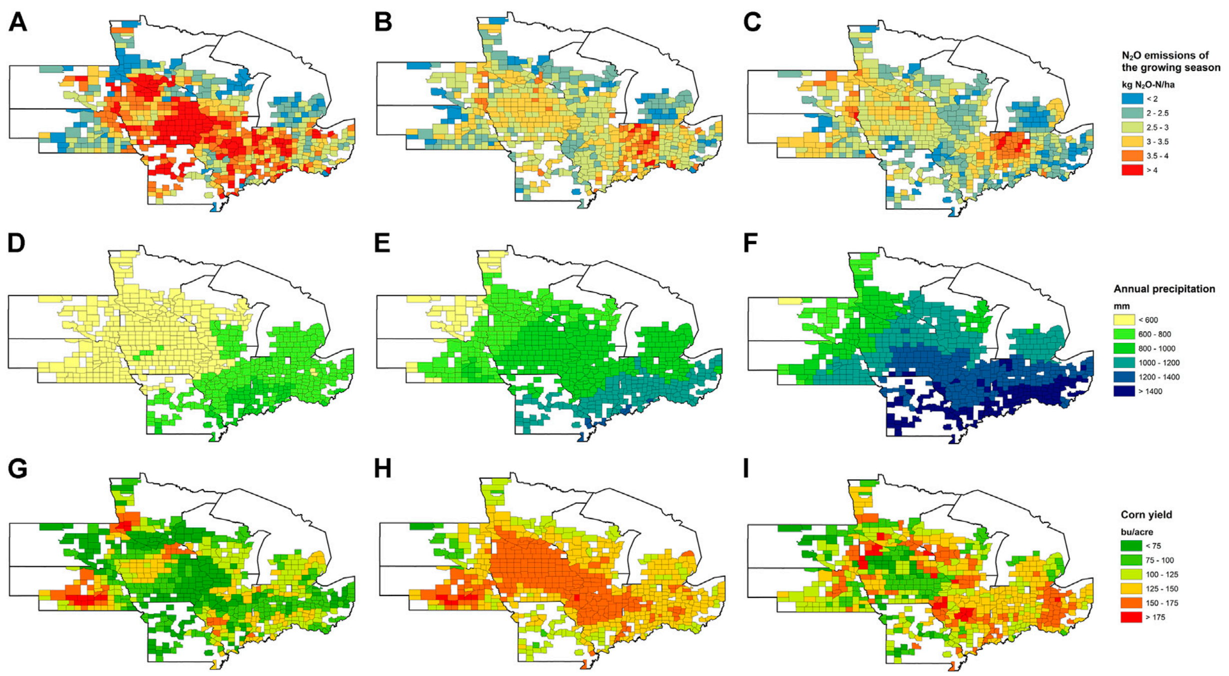

FIGURE 4
$_{\rm P}$CENTURY-based county-level estimates for: corn growing season N_2O emissions under **(A)** dry, **(B)** normal, and **(C)** wet weather scenarios; annual precipitation under **(D)** dry, **(E)** normal, and **(F)** wet weather scenarios; corn yield under **(G)** dry, **(H)** normal, and **(I)** wet weather scenarios. The model estimates are based on baseline scenario (corn-soybean rotation, conventional tillage) for a 6-year (2016–2021) simulation period for the major United States corn states.

Ruis, 2018) but can commonly increase N_2O_{gs}-emissions when used in poorly drained soils (Rochette et al., 2008). On the other hand, use of no-tillage or conservation tillage most often reduces N_2O emissions when practiced long-term where soil structure is improved to decrease anaerobic soil microsites conductive to N_2O production (Six et al., 2004; van Kessel et al., 2013). Because tillage can have mixed impacts on soil N_2O emissions depending upon how practices influence substrate availability, aeration, yield, and soil water status (Linn and Doran, 1984; Smith et al., 2001; Mei et al., 2018), development or use of a tillage-based N_2O scaler or coefficient could be unwise. Therefore, there is a need to highlight effective modeling of soil moisture and the soil redox environment to better predict tillage associated N_2O emissions.

3.3 Spatial N_2O emissions influenced by weather scenarios

Our regional assessment of N_2O_{gs}-emissions revealed variability within and across regions in the United States Corn Belt (Figure 4). While the $_{\rm P}$CENTURY simulations for the normal weather scenario (Figure 4B) are similar to state-level N_2O emissions patterns reported by McNunn et al. (2020), we identify potential for notable variability within states using county-level weather records. Spatial differences considered using normal weather data found the highest N_2O emissions occurred in Iowa and Indiana (Figure 4), which is driven by the relatively high N input rates reported in Xia et al. (2021). Weather scenarios exploring dry and wet conditions suggested cumulative N_2O_{gs}-emissions from the corn phase of the ***CS*** baseline would be greater under dry (3.3 kg N_2O ha^{-1}) and similar under wet (2.7 kg N_2O ha^{-1}) weather conditions when compared to results from normal (2.8 kg N_2O ha^{-1}) weather scenarios (SI: Supplementary Table D2). The ranking for EFs remains dry (1.19%) > normal (0.95%) > wet (0.88%) for model simulation because we assumed the same N input rates (Table 4). In reality, N input rates can vary because corn yield would change according to climate change scenarios, in which case yield-scaled EF that considers both N inputs and crop productivity (Aguilera et al., 2013; Iqbal et al., 2018) may better reflect the interaction between climate change and human activities.

Regression-based exploration of the spatial distribution of N_2O_{gs}-emissions suggested increased flux with soil moisture, fertility, and plant available N and decreased emissions with precipitation, water filled pore space, and corn yield (p < 0.05) (Table 5). Precipitation, plant available N, and corn yields were found lowest in the dry years, and plant available N and crop

TABLE 5 Linear regression model built on estimating $_p$CENTURY simulated growing season corn N_2O emissions using fertilizer N rate (FERT), growing season moisture (MOS) and water filled pore space (WFPS), corn-year average plant available N (PAN), annual precipitation (PPT), and corn yield (YLD). The N_2O emissions were estimated for normal, dry, and wet weather scenarios for corn-soybean baseline scenario during the simulation period of 2016–2021. The results are summarized by agroecological zone (AEZ).

AEZ	Linear regression model estimating growing season N_2O emissions	Model fit (adjusted R^2)
All AEZs	N_2O = 1.7*** + 0.01 FERT*** + 1.6 MOS*** - 0.07 WFPS - 0.03 YLD*** - 0.005 PPT*** + 0.03 PAN***	0.68
7	N_2O = -4.9 + 0.02 FERT + 49.4 MOS*** - 9.2 WFPS - 0.07 YLD* + 0.001 PPT + 0.08 PAN*	0.82
8	N_2O = 0.4 + 0.01 FERT*** + 14.6 MOS*** - 3.8 WFPS*** - 0.02 YLD*** + 0.0003 PPT + 0.02 PAN***	0.75
9	N_2O = 0.6* + 0.01 FERT*** + 7.9 MOS*** - 1.8 WFPS*** - 0.04 YLD*** - 0.0006 PPT*** + 0.04 PAN***	0.72
10	N_2O = 1.8*** + 0.01 FERT*** + 1.0 MOS* + 0.5 WFPS* - 0.03 YLD*** - 0.0008 PPT*** + 0.03 PAN***	0.71
11	N_2O = 2.2*** + 0.01 FERT*** + 1.4 MOS* - 0.9 WFPS*** - 0.03 YLD*** - 0.0007 PPT*** + 0.03 PAN***	0.80

*Significant at the 0.05 probability level. **Significant at the 0.01 probability level. ***Significant at the 0.001 probability level.

yields were greatest in the normal weather years (SI: Supplementary Table D2). Lower yields that resulted in reduced N uptake by crops created hotspots for N_2O emissions. Average crop yield was also reduced by 13% in wet years compared to the normal weather but did not cause increased N_2O_{gs}-emissions. Loss of N_2O occurring outside of the growing season, the conversion of N_2O to N_2 under prolonged wet conditions, or increased leaching losses could all account for reduced level of available N in wet weather scenarios (Hernandez-Ramirez et al., 2009). In addition, the reduction in N_2O_{gs} caused by wet conditions could also be attributed to $_p$CENTURY using a monthly time-step, which could not capture rapid changes in water filled pore space and N_2O emissions following rainfall events (Schmidt et al., 2000; Beheydt et al., 2007; Xia and Wander, 2022). Soil N_2O changes can occur at a sub-daily time step so studies have attempted to capture high temporal resolution N_2O dynamics (Laville et al., 2011; Lognoul et al., 2017; Su et al., 2021) using data collected with advanced techniques such as automated chamber and micrometeorological measurements (Hensen et al., 2013; Bréchet et al., 2021). However, such calibration data would be too expansive to collect at the broad scale for N_2O modeling. In the future, the evolving networks such as GRACEnet (Del Grosso et al., 2013) and COntinuous SOil REspiration network COSORE (Bond-Lamberty et al., 2020) could be used for more detailed calibration of model nitrification and denitrification parameters (e.g., a maximum fraction of N_2O to nitrified N at field capacity, adjustment coefficient on effect of moisture on denitrification, maximum fraction of ammonia nitrified during nitrification) at a finer temporal resolution if data collection and reporting can be further standardized.

The $_p$CENTURY derived N_2O EF for the ***CS*** scenario under normal weather conditions was approximately 60% lower than the revised IPCC (2019) Tier-1 estimate (1.6 ± 0.3%) proposed for wetter climate conditions. This may be partially explained by the fact that several counties within AEZs 7 and 8 do not fit within the wet climate category as their annual precipitation > potential evapotranspiration (Stocker et al., 2018). IPCC's 'dry' value (EF = 0.5%) (Hergoualc'h et al., 2019) is much closer to our average for those AEZs (Table 4). Even though the definition of "dry" and "wet" conditions is different in IPCC and that used for our model simulation in that the IPCC definition is based on spatial variability under current climate conditions, both results support the implications of Shang et al.'s meta-analysis (2020) that suggests regional N_2O EFs are needed.

The average EFs derived from our study (0.9% from model and 1.1% from meta-database) under normal weather conditions were lower than that (1.7% for well-drained soils and 3.9% for poorly drained soils) estimated by Lawrence et al. (2021) for the United States Corn Belt. This difference might be partially explained by the fact that Lawrence et al. (2021) investigated annual cumulative N_2O while ours focused on N_2O_{gs}-emissions. The difference in data coverage concerning both N_2O emissions and N input rates can also cause varied estimates of N_2O EFs. In addition, the method of estimating background emissions and organic N inputs based on rates and/or availability can result in uncertainty associated with reported EFs, which emphasizes the cautions needed to interpret direct soil N_2O EFs. Ideally comparison of EFs can be carried out at finer time-step.

3.4 Implications on future agricultural management and climate adaptations

The increased atmospheric N_2O concentration has been closely associated with food production system and fertilizer use (Kroeze et al., 1999; Mosier and Kroeze, 2000) and is projected to continue rising if no mitigation strategies are adopted to improve agricultural nitrogen use efficiency (Montzka et al., 2011; Kanter et al., 2016). Studies have shown significant differences in estimated atmospheric N_2O concentration based on IPCC's representative concentration pathways (RCPs) representing scenarios from little mitigation efforts to aggressive goals (Davidson, 2012). Accurate estimation

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of N_2O emissions from different management practices is therefore critical for selecting and promoting practices that can alleviate climate change risks for the future. Our study showed an example of comparing management associated N_2O emissions and EFs at the broad scale through both process-based modeling and meta-analytical summary. Future work is needed to compare more management scenarios that are not included in this study but are known to influence soil N_2O emissions including irrigation (Scheer et al., 2013; Maharjan et al., 2014), drainage (Datta et al., 2013; Fernández et al., 2016; Grossel et al., 2016), and the timing and method for fertilizer incorporation (Smith et al., 1997; Yan et al., 2001; Ma et al., 2010).

The study of Tesfaye et al. (2021) showed that soil N_2O mitigation potential can be mostly fulfilled with the reduction of excessive N inputs. This is in line with our finding that N_2O_{gs}-emissions were mostly observed and simulated to be higher under crop rotations incorporating a large amount of N inputs. According to Xia et al. (2021), excessive corn N inputs were calculated to be prevalent in the United States Corn Belt, meaning that there is great potential for management associated N_2O mitigation within the region. Although our model assumed zero or only a small amount of N inputs in non-corn phases and therefore generated lower estimates of N_2O_{gs}-emissions, our meta-dataset demonstrated studies with excessive N inputs during the cover crop phases which can lead to greater N losses through N_2O and N leaching. However, if cover crops were managed properly, meta-analysis found that soil N_2O emissions would be reduced or not affected compared to non-cover crop treatments considering the balance between increased SOC and reduced nitrate contents (Basche et al., 2014; Kaye and Quemada, 2017). The key to N_2O mitigation in a diversified cropping system is, therefore, to avoid the overapplication of fertilizers by better estimating N balance that takes into account N credits from cover crops, which can be achieved through the use of remote sensing (Xia et al., 2020) and N calculators (Gaskin et al., 2019).

We investigated the impacts of N input, fertilizer type, and tillage on N_2O_{gs}-emissions but none of the comparisons were identified to be significant according to the meta-database due to high variability. This cautions the interpretation of management associated N_2O mitigation potential by considering only a single management factor. Likely the interaction of management practices can lead to various N_2O responses among different sites. Our model simulation illustrated significant differences in N_2O_{gs}-emissions caused by N input and fertilizer types, but such results are heavily influenced by the model coefficients derived based on previous studies. Ideally, the coefficients should be updated to reflect findings from meta-databases and developed to reflect interactions with site-specific management (fertilizer incorporation method) and soil factors (e.g., texture and soil drainage class).

Our modeling of N_2O_{gs}-emissions under various climate scenarios showed a potential of increased N_2O emissions under future drought conditions. We did not investigate the impacts of raised temperature and CO_2 concentration on N_2O emissions, but studies have reported increased N_2O emissions under such scenarios because of enhanced microbial activity and denitrification (Butterbach-Bahl and Dannenmann, 2011; Li et al., 2020; Wang et al., 2021). Increased N_2O emissions under projected future climate conditions, especially those with higher levels of RCP (Riahi et al., 2011), can then contribute to a feedback loop that aggravates climate change. The regional differences in $_p$CENTURY-modeled soil N_2O emissions under dry and wet weather scenarios could be tied to soil pH and drainage class, which were identified as key factors explaining the spatial variability of observed annual N_2O emissions (Lawrence et al., 2021). Likewise, the modeling study of Zhang et al. (2020) also emphasized regional differences in SOC changing trend under future climate scenarios that is influenced by soil properties and management in the United States Corn Belt. These findings suggest that management adaptations to a changing climate should consider regional differences, in which case it would be critical to use modeling tools to simulate site-based management and climate interactions.

4 Conclusion

A parameterized CENTURY model ($_p$CENTURY) was used to estimate direct soil N_2O emissions under various management and climate scenarios from United States corn fields. The $_p$CENTURY model adequately predicted the magnitude of growing season N_2O (N_2O_{gs}) emissions from corn (N_2O_{gs} = 2.68 kg/ha) and wheat (N_2O_{gs} = 1.44 kg/ha) crop phases based on comparison with a Tier-2 meta-analytical summary. Model estimated N_2O_{gs} emissions and emission factors (EFs) differed by N fertilizer type (AA > urea) and tillage practice (conventional > no-tillage), which matched with the comparison of average values under these treatments from the meta-database. Differences between modeled and measured results for scenarios including soybean or cover crops were tied to model assumptions of N inputs and the greater variety of inputs and practices summarized within categories contained in the meta-database. Comparison with Tier-1 values for corn suggests that broad-scale process-based modeling can successfully generate regionalized EFs that are representative of generalized management scenarios. Discrepancies between Tier-2 and $_p$CENTURY-derived EFs on synthetic versus organic N inputs revealed not only the importance of N input data but also data describing the quantity and quality of organic inputs for estimating N_2O emissions from non-corn phases and complex rotations. Weather scenarios determined that decreases in corn yields in dry years reduced crop N uptake and created N_2O hotspots. Yield reductions occurring in wet years did not increase N_2O flux. Regional differences in weather and soil N_2O

flux justify need for model-based (Tier-3) EFs that consider interactions between management and climate; however, we find improvements in the model's ability to accurately simulate soil moisture during the winter and capture crop N uptake are needed to successfully estimate soil N_2O emissions and develop regional EFs that can better inform management decisions in a future climate.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

YX, MW, and HK contributed to conception and design of the study. SQ and SY provided soil moisture database and critical information behind the database. YX and MW performed statistical analysis. HK performed process-based modeling of N_2O emissions from soils. YX and MW prepared several drafts of manuscript and all authors contributed to the final manuscript revision.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.971261/full#supplementary-material

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