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Nitrous oxide emissions from soil: A review of cropping practices and their consideration in process-based models

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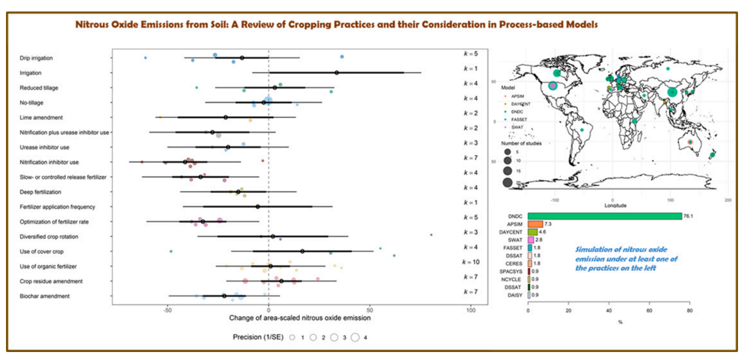
HIGHLIGHTS

- Agriculture soil management is the largest source of anthropogenic N_2O emissions.
- Biochar, inhibitors, controlled-release fertilizers, deep fertilizer placement and drip irrigation reduced N_2O emissions by 15–41%.
- Crop rotation, cover cropping, organic manures, crop residues and conservation tillage did not affect N_2O emissions.
- Crop models differ in management detail and often omit key processes such as fertilizer placement and inhibitor effects.
- Several models simulate pH effects, but they are rarely applied to assess liming as a mitigation measure.

GRAPHICAL ABSTRACT



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ABSTRACT

Nitrous oxide (N_2O) is a major anthropogenic greenhouse gas. Agriculture represents its largest source, but the estimation, projection and mitigation measures pose considerable challenges. We conducted a secondary meta-analysis to synthesize and quantify the impact of various agricultural practices on observed N_2O emissions. In addition, we synthesized how various process-based crop models considered these impacts and related processes when modeling N_2O emissions in order to identify research gaps. We examined 134 field experiments and 108 modeling articles on N_2O emissions. The application of biochar, nitrification and/or urease inhibitors, reduced fertilizer rates, controlled-release/coated fertilizers, deep fertilizer placement compared to surface application, and drip irrigation compared to broadcast surface irrigation consistently reduced observed N_2O emissions (7–29%). In contrast, crop residue addition compared to removal increased N_2O emissions. Many crop models

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already account for some of the practices, such as crop rotations, organic amendments, irrigation, fertilizer management in terms of rates, timing and sources, and, to a lesser degree, placement. Tillage practices are included in several models, but the considered approaches vary. Other important practices to increase fertilizer efficiency, such as the use of nitrification and urease inhibitors, are only included in a few models. While no modeling studies have explicitly assessed the liming effects on N_2O emissions, biochar effects were only represented indirectly through carbon dynamics rather than nitrogen transformations. Overall, model improvements are necessary to accurately quantify N_2O emissions associated with current agricultural practices, thereby contributing to the design of sustainable cropping systems that minimize the trade-off between climate change mitigation and crop productivity.

1. Introduction

Nitrous oxide (N_2O) is a potent greenhouse gas (GHG) with a global warming potential 265–298 times that of carbon dioxide (CO_2) over a 100-year time frame (IPCC, 2022). In addition to its impact on global warming, N_2O contributes to stratospheric ozone depletion, making it a critical environmental issue worldwide (Ravishankara et al., 2009). Since the preindustrial period, atmospheric N_2O levels have increased from approximately 270 nmol mol^{-1} to more than 330 nmol mol^{-1}, with the sharpest increase observed in recent years (Prokopiou et al., 2018). The extensive use of synthetic fertilizers and increased cultivation of legume crops have accelerated N_2O emissions due to intensified soil nitrogen (N) cycling (Tian et al., 2019). Consequently, croplands have become the leading source of human-driven N_2O emissions, underscoring the significant impact of agriculture on the global N cycle (Butterbach-Bahl et al., 2013; Reay et al., 2012).

Soil-based N_2O emissions are primarily driven by microbial nitrification and denitrification, both sensitive to environmental conditions and soil properties (Butterbach-Bahl et al., 2013; Deng et al., 2024). Nitrification, an aerobic process conducted mainly by ammonia-oxidizing bacteria (AOB) and archaea (AOA), produces N_2O as a by-product when ammonium (NH_4^+) is converted to nitrate (NO_3^-) through intermediates like hydroxylamine, nitric oxide (NO) and nitrite (NO_2^-) (Hink et al., 2018). Denitrification, on the other hand, occurs under anaerobic conditions, where NO_3^- and NO_2^- are reduced to N gases (NO, N_2O and N_2) by denitrifying bacteria (Chee-Sanford et al., 2020). N_2O emission rates from these processes are influenced by soil mineral N availability, oxygen status and soil organic carbon (SOC), as well as by key soil conditions including pH, temperature, and water-filled pore space (WFPS) (Butterbach-Bahl et al., 2013; Shaaban et al., 2018).

Temperature exponentially increases N_2O and N_2 production, primarily by stimulating microbial enzyme activity and enhancing denitrification through O_2 depletion caused by increased soil respiration (Butterbach-Bahl et al., 2013; Yu et al., 2023). The effect of N fertilizer on N_2O emissions also increases with mean annual temperature, although N_2O reduction may occur in some soils when temperatures exceed 15 °C, further highlighting the temperature sensitivity of these soil processes (Yu et al., 2023; Li et al., 2024). Soil pH can limit the enzyme activity required to reduce N_2O to N_2, particularly in acidic soils, thereby increasing N_2O emissions (Qu et al., 2014). Loamy soils generally exhibit higher N_2O emissions than sandy soils (Pelster et al., 2012; Maag and Vinther, 1996), as soil texture strongly regulates moisture availability, shaping the dominant N_2O production pathways.

Soil moisture plays a crucial role in regulating N_2O emissions, with its effect on denitrification depending on water-filled pore space (WFPS). Higher WFPS (>60%) favours denitrification, whereas lower WFPS supports nitrification, influencing the relative proportions of N_2O and N_2 produced (He et al., 2025; Ruser et al., 2006). In conjunction with texture and moisture, soil compaction is an important driver of N_2O emissions. Compaction typically increases N_2O emissions—often by up to twofold—by reducing soil porosity and gas diffusion, with particularly pronounced effects in croplands and pastures (Hernandez-Ramirez et al., 2021). Controlled traffic can mitigate these emissions, while heavy-textured soils are particularly prone to compaction-induced N_2O fluxes. In addition, dynamic moisture fluctuations, such as wetting-drying and freeze-thaw cycles, can trigger episodic microbial activity, leading to N_2O "hot moments" (Groffman et al., 2009). Both processes are likely to become more pronounced under climate change, further amplifying N_2O emissions. These complex interactions highlight the combined influence of biological, physico-chemical and management-related factors on N_2O flux variability.

As concerns about climate change grow, the need to reduce N_2O emissions from croplands remains urgent. Up to half of the N applied as fertilizer can be lost through leaching, volatilization, and microbial conversion to N_2O, resulting in both environmental risks and economic inefficiencies for farmers (Harris et al., 2022). With rising global food demand, N fertilizer use is expected to increase, especially in regions with limited regulatory oversight on N management (Tian et al., 2019). This trend emphasizes the need for N management approaches to improve crop yields while reducing GHG emissions. Accordingly, several management practices are being investigated to reduce N_2O emissions and/or optimize fertilizer use by improving N use efficiency (NUE). Strategies such as the use of slow-release/polymer-coated fertilizers, the addition of nitrification inhibitors and/or urease inhibitors to fertilizers have been shown to mitigate N losses (Dai et al., 2013; Thapa et al., 2016; Ma et al., 2023). Slow-release fertilizers, for instance, provide N gradually, better aligning with plant uptake and reducing the N available for N_2O-producing microbial processes (Thorman et al., 2020). Nitrification inhibitors (NI) slow down the conversion of ammonium from fertilizers to nitrate by bacteria in the soil, while urease inhibitors (UI) reduce the activity of the urease enzyme, thereby slowing the conversion of urea to ammonia, but do not completely block these processes (Matse et al., 2024). When combined, these inhibitors provide a multi-step safeguard against N loss. However, their effectiveness varies, and more research is needed to optimize their performance across different soil and climate conditions and production intensities (Du et al., 2024; Li et al., 2018; Nair et al., 2020; Thapa et al., 2016).

Broader soil management approaches, including organic amendments (such as crop residues, manure, and biochar), soil tillage, and diversified crop rotations, have been found to influence N_2O emissions. Organic amendments like biochar improve soil structure and enhance SOC, fostering conditions that support the reduction of N_2O to N_2 (Charles et al., 2017; Schmidt et al., 2021). Conservation tillage and deeper fertilizer placement reduce N exposure to surface microbes, thereby limiting denitrification (Bhuiyan et al., 2023). Crop rotations that incorporate cover crops improve soil health, reduce the need for synthetic fertilizers, and enhance nutrient cycling; however, their specific effects on N_2O emissions require further investigation (Shrestha et al., 2021). Additionally, irrigation management influences soil moisture levels, a key driver of N_2O emissions. While these practices show promise, their effectiveness varies across soil types and climatic conditions, and their detailed mechanisms remain incompletely understood (Chahal et al., 2021). Moreover, their representation in current crop growth simulation models is inconsistent, which limits their applicability for guiding mitigation strategies (Tian et al., 2019; Deng et al., 2024; Gabbrielli et al., 2024).

N_2O emissions at regional and larger scales often rely on the IPCC Tier 1 or Tier 2 emission factor approaches, which introduce substantial uncertainties. More accurate estimates (Tier 3), can be obtained through process-based models (Del Grosso et al., 2009), which explicitly simulate soil biogeochemical processes and account for management and environmental factors (Del Grosso et al., 2009). These crop-soil models integrate factors such as precipitation, air temperature, soil properties, and management practices (e.g., fertilizer application, organic amendments, tillage, and crop rotation) to predict N_2O fluxes (Seidel et al., 2024; Wang et al., 2021). They also enable upscaling of emissions estimates and in-silico testing of mitigation strategies (Del Grosso et al., 2009). However, current models incompletely capture the complex interactions between soil properties, environmental conditions, and management practices. Key factors such as soil pH, microbial activity, and SOC turnover are often underrepresented, leading to uncertainties in their predictive capacity (Dueri et al., 2023; Grosz et al., 2023; Gabbrielli et al., 2024; Zhang et al., 2022a).

While multiple meta-analyses have evaluated the impact of agricultural management practices on N_2O emissions, an updated synthesis of recent findings is needed to assess how these insights refine existing knowledge and inform process-based models. The most recent comprehensive meta-analysis, Grados et al. (2022), synthesized studies up to May 2021, but many relevant studies have since been published. Similarly, Wang et al. (2021) provided a review of how N_2O emissions are represented in models. Advances in model calibration, validation, and process representation, along with the need to improve model structure to reduce prediction error and inter-model variability (Wallach et al., 2024), necessitate further evaluation. Moreover, Wang et al. (2021) focused on only four management factors (fertilizer, irrigation, crop residues, and tillage), whereas our review examines 17 factors (see Fig. 1), providing a more comprehensive assessment of agricultural management practices that influence N_2O emissions. Additionally, whereas there are previous studies that have emphasized specific biogeochemical processes (e.g., nitrification) within models, our review shifts the focus to agronomic events (e.g., the use of urease inhibitors) and their observed relevance in terms of effect size. This approach enables us to bridge the gap between model representations and real-world agricultural practices and to identify key shortcomings in how N_2O emissions are currently modeled. By doing so, our review highlights critical areas for improvement in predictive modeling and guides future research toward more effective mitigation strategies. Specifically, this review (i) synthesizes findings from recent meta-analyses and studies published since May 2021 on how selected crop management practices influence N_2O emissions, (ii) evaluates how these effects are represented in process-based crop models, and (iii) identifies key gaps in model-based representation and model-data integration. We emphasize that this review does not aim to conduct a full comparative assessment of all crop models under diverse management practices and environmental conditions, which would require harmonized datasets and ensemble modeling. Instead, we focus on summarizing the extent to which key biophysical processes and management effects are incorporated in models and how this aligns with empirical evidence. By clarifying these gaps, our review provides guidance for improving the accuracy, scalability, and applicability of crop models in supporting N_2O mitigation strategies.

2. Materials and methods

2.1. Synthesis of meta-analytical studies

2.1.1. Literature search and study selection

We conducted a secondary meta-analysis by synthesizing existing

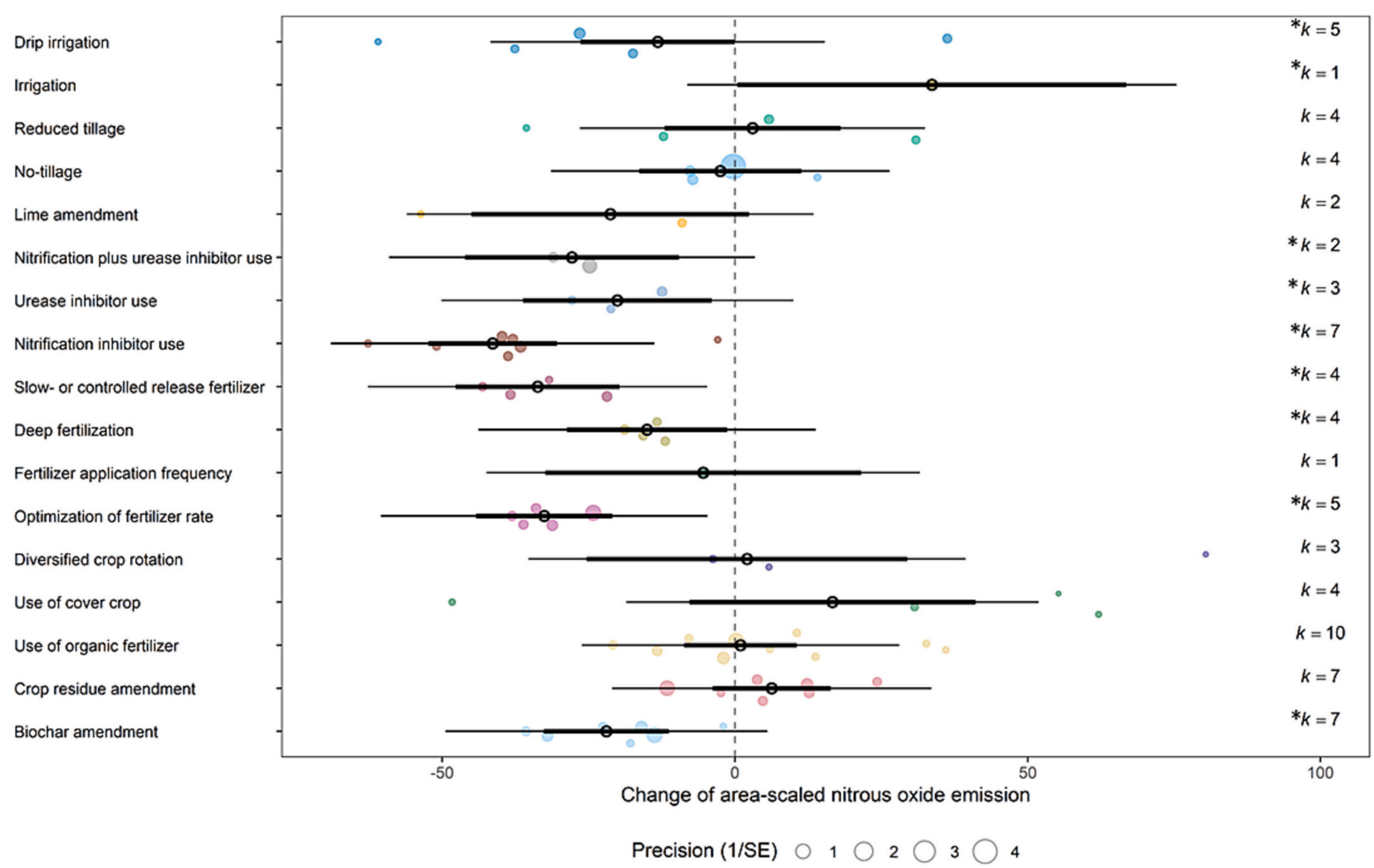

Fig. 1. Effect size (% change) of agricultural management practices on area-based N_2O emissions. * stands for significant effect at $p < 0.05$; k = number of meta-analysis studies; SE = standard error. Open points indicate mean effect size; colored points indicate effect size of individual meta-analysis; thick and light horizontal lines indicate 95% confidence and prediction intervals, respectively.

meta-analytic studies to assess the impact of management practices (Table 1) on N_2O emissions. To this end, we expanded the dataset from Grados et al. (2022) with recent meta-analysis studies published in the last four years, using a literature search conducted on the Web of Science platform. Terms for specific agricultural practices (e.g., crop rotation, cover crops) were combined with "nitrous oxide" OR "N_2O" AND "meta-analysis," OR "systematic review," OR "quantitative review". To ensure that relevant studies with paired comparisons were retrieved, we also included search terms for control practices (e.g., "mono-cropping," "continuous cropping," "single cropping"). The complete list of the search terms is provided in Supplementary Table S1.

Our selection criteria align closely with the methodology outlined by Grados et al. (2022). Initially, we focused on studies examining agricultural practices (such as diversified crop rotation, crop residue management, and tillage effects) similar to those analyzed by Grados et al. (2022). In addition to the practices compiled by Grados et al. (2022), we also included irrigation management practices in comparison to rainfed conditions. For studies unrelated to irrigation, literature searches were conducted between May 2021 and July 2024, with no specified start date for irrigation-related studies but a uniform cut-off in July 2024. Studies were selected if they examined at least one relationship between agricultural management practices and N_2O emissions from arable cropping and grasslands on upland or paddy soils. To be suitable, studies had to report cumulative N_2O emissions in area-scaled values (kg N_2O ha^{-1}) and be published as peer-reviewed articles or conference papers. Only meta-analyses based on field measurements, or predominantly field-based data to calculate effect sizes, were considered. Each included study was required to use meta-analytical methods to calculate effect sizes for treatments and controls under similar environmental and management conditions. The reported effect sizes must also report a precision measure, such as standard deviation (SD), standard error (SE), or confidence intervals (CI). This ensured that the reliability of the estimates could be assessed. The newly identified studies were added to those already selected by Grados et al. (2022) and subjected to an overlap estimation process (see Supplementary Fig. S1) to refine the final dataset for synthesis. This was because, when using the same primary studies across multiple meta-analyses that focus on the same N_2O mitigation practice, non-independence among meta-analyses can be introduced. Based on this assessment, we established an additional eligibility criterion: only meta-analyses with less than 30% overlap among primary studies were retained in the database (Tamburini et al., 2020). Table 1 provides an overview of the management practices included in the analysis and their corresponding control treatments while Supplementary Table S2 shows the list of candidate meta-analyses synthesized in this study.

Table 1
Agricultural practices and corresponding control treatments considered for the synthesis of management practices and their impacts on N_2O emissions.

Management practice	Treatment	Control
Organic amendments	Biochar amendment	No biochar
	Manure amendment	Inorganic/chemical fertilizer
	Crop residue amendment	No crop residue amendment
Liming	Lime amendment	No lime amendment
Crop rotation	Crop rotation	Monoculture/ continuous cropping
	Cover cropping	No cover crop
Irrigation	Irrigation	Rainfed (no irrigation)
	Drip irrigation	Surface irrigation/ sprinkler
Fertilizer efficiency enhancement	Controlled-release/coated fertilizer	Inorganic fertilizer
	Urease inhibitor, nitrification inhibitor, nitrification + urease inhibitor	Non-treated fertilizer
Fertilizer optimization	Deep N fertilizer placement	Surface N fertilizer placement
	Split fertilizer application	Single application
	Reduced fertilizer rate	Conventional/ recommended rate
Tillage	No/reduced tillage	Conventional tillage

2.1.2. *Data extraction, standardization, and synthesis*

Key details from each study, including geographic scope, management practices, reported effect sizes, standardization methods, statistical models, the total number of studies, and paired observations, were extracted. Information from text and tables was directly extracted, while data from figures were digitized using WebPlotDigitizer v5.2 (Rohatgi, 2024). Response ratios (relative changes due to management practices) and other estimates of relative change for each practice were collected. Variability measures (SD or SE) were converted into a unified standard error format to enable comparison and the calculation of weighted means. All effect sizes, including response ratios and percentage changes, were standardized to a common metric — the log response ratio (lnRR; Eq.1). The lnRR is converted to a percentage change scale using (Eq.2). Sampling error variance was calculated from reported 95% CIs, assuming a normal distribution (Castellanos and Verdú, 2012).

$$\ln(\mathrm{RR}) = \ln\left(\frac{X_T}{X_C}\right) = \ln(X_T) - \ln(X_C) \tag{1}$$

where: X_T and X_C are the mean values for cumulative N_2O emissions in target practice (treatment T) and corresponding control practice (treatment C), respectively.

$$\text{Percent change} = 100\%\text{x}\ [\exp(\ln\mathrm{RR}) - 1\,] \tag{2}$$

2.1.3. *Statistical analysis of observed emissions*

A meta-analysis of meta-analyses following Grados et al. (2022) was used to evaluate the impact of N_2O mitigation practices, employing a multi-level mixed-effects meta-regression model with a categorical moderator (mitigation practice). The model uses overall effect sizes and variances extracted from each meta-analysis rather than individual pairwise observations. The statistical model (Eq. 3) was:

$$\widehat{\theta}_{ik} = \theta + \beta D_g + w_i + u_{ik} + e_{ik} \tag{3}$$

where: $w_i \sim N(0, \sigma^2{}_B)$ accounts for between-meta-analysis variance,$u_{ik} \sim N(0, \sigma^2{}_W)$ for within-meta-analysis variance, and$e_{ik} \sim N(0, v_{ik})$ represents sampling error variance.

The model, fitted without an intercept, estimated parameters ($\widehat{\theta}_{ik}$) for each level of the categorical predictor. Nested random effects were assumed, weighted by the inverse of sampling variance. Estimates were obtained using restricted maximum likelihood (Viechtbauer, 2005) and transformed into percent change for interpretation. Results are presented with 95% confidence intervals (CIs) and prediction intervals (PIs). CIs indicate the range of the average true effect, while PIs represent the range where 95% of future effects are expected. Statistical significance was assumed when CIs did not include zero, and tests followed a z-distribution. The omnibus test of moderators (Q_M) and R^2 marginal were used to assess heterogeneity explained by the moderator. The analysis was conducted in R using metafor v4.8.0 (Viechtbauer, 2010), and results were visualized as orchard plots via orchaRd v2.0 (Nakagawa et al., 2021). Publication bias was evaluated using funnel plots and the Egger regression test (Sterne et al., 2005).

2.2. *Identification of process-based crop models*

A comprehensive literature search was conducted using the Web of Science platform to identify widely used process-based crop models for simulating N_2O emissions under the key management practices considered in this study (Table 1). The search terms included: “nitrous oxide,” “N_2O”, “process-based model”, “simulation” and “model”, combined with practice-specific keywords listed in Section 2.1 (Supplementary Table S1). Articles were selected based on two main criteria: (i) the simulation of N_2O emissions under at least one targeted agricultural practice, and (ii) the validation of simulated results with experimental field data. Models that met these criteria were identified from the selected articles. The features of the most frequently used models are detailed and discussed.

3. Results and discussion

3.1. Agricultural practices and controlling factors for N_2O emissions

Our analysis included 18 meta-analyses (2570 paired observations) from the 27 studies analyzed by Grados et al. (2022) and 21 new studies (5230 paired observations), resulting in a total of 39 meta-analyses. This represents an average increase of 44% (ranging from 0% to 400%) relative to Grados et al. (2022). The current meta-analysis represents 73 effect sizes and 7801 paired comparisons to assess the impact of selected agricultural practices on N_2O emissions. As shown in Fig. 1, crop rotation (2.1 ± 14.0%; range: −25.3 to 29.4) and cover cropping (16.7 ± 12.5%; range: −7.8 to 41.1) did not significantly affect emissions. For organic residue amendments, biochar application reduced N_2O emissions by 21.9 ± 5.5% (range: −32.6 to −11.3), likely due to its modulation of the denitrifying bacterial community, specifically suppressing nirK gene abundance (Li et al., 2016) and its possible role in promoting the reduction of N_2O to N_2 (Charles et al., 2017; Schmidt et al., 2021), while crop residue amendments (6.3 ± 5.1%, range: −3.8 to 16.4) and organic manure application (0.9 ± 4.93.3%; range: −8.7 to 10.6) was found to have no effect ($p > 0.05$). Although lime application showed a tendency to reduce emissions (−21.3 ± 12.1%; range: −45.0 to 2.4), its effect was not significant ($p > 0.05$).

Optimizing fertilizer management through reduced application rates and deep placement significantly lowered emissions by −32.6 ± 5.9% (range: −44.2 to −20.9) and −15.0 ± 7.0% (range: −28.7 to −1.3), respectively. In contrast, split fertilizer application, with a mean reduction of −5.4 ± 13.8%% (range: −32.4 to 21.5), was not statistically significant.

Fertilizer efficiency-enhancing strategies, including nitrification inhibitors (−41.4 ± 5.6%; range: −52.4 to −30.4), urease inhibitors (−20.1 ± 8.2%; range: −36.2 to −3.9), a combination of nitrification and urease inhibitors (−27.8 ± 9.3%; range: −46.1 to −9.6), and slow/controlled-release fertilizers (−33.7 ± 7.1%; range: −47.7 to −19.7), consistently demonstrated their effectiveness in reducing N_2O emissions. Irrigation and tillage practices showed varying impacts on N_2O emissions. Irrigation generally increased N_2O emissions (33.6 ± 16.9; range: 0.4 to 66.9). Specifically, adopting drip irrigation significantly reduced emissions by 13.2 ± 6.7% (range: −26.4 to 0.0). Conservation tillage practices had minimal effects on N_2O emissions, with zero tillage (−2.5 ± 7.1%; range: −16.4 to 11.4) and minimum tillage (3.0 ± 7.7%; range: −12.0 to 18.0) showing no significant effects. Overall, reducing N application rates, incorporating nitrification inhibitors, and applying biochar emerged as effective strategies to reduce N_2O emissions, highlighting their role as essential components of climate-smart agriculture and their value as targeted mitigation practices. Although the current meta-analysis included additional studies compared to Grados et al. (2022), the overall direction of the impact of the agricultural practices observed in our study remained generally consistent with previous findings (Grados et al., 2022; Young et al., 2021). Additionally, our study confirmed a reduction in emissions with drip irrigation (~13%) and found no significant effects of no-till or reduced tillage, consistent with Grados et al. (2022). However, Young et al. (2021) reported a 5% increase in N_2O emissions resulting from these tillage practices. One notable divergence from Grados et al. (2022) is the impact of cover cropping. While their study reported a ~ 40% increase in N_2O emissions, our analysis found a ~ 20% increase, which was not statistically different from zero. This difference may be attributed to variations in the number of studies and observations included (4 vs. 2 meta-analyses; 255 vs. 118 observations). However, our findings align with Rietra et al. (2022), who also reported no significant effect of cover cropping on emissions.

3.1.1. Crop rotation (crop rotation, cover cropping)

The current synthesis suggests that crop rotations, instead of continuous/mono-cropping and adopting cover cropping within crop rotations, can influence N_2O emissions in cropping systems. However, the results vary depending on management practices and environmental conditions. Crop rotation showed an overall neutral effect on N_2O emissions (about 2%; Fig. 1), with more than 50% of studies reporting no significant changes (Supplementary Fig. 1), while some reported increases of up to 38% and reductions of 13% (Shrestha et al., 2021; Raglin et al., 2022). Key factors affecting these emissions include crop sequence, tillage practices, residue management, and soil structure, which can alter N dynamics and microbial community distribution (Drury et al., 2004; Putz et al., 2018). Although there was no significant effect of cover cropping on N_2O emissions, it is important to note that three out of the four effect sizes in our analysis also showed an increasing trend. The impact of cover crops on N_2O emissions depends on factors such as cover crop species (e.g., legume vs. non-legume), termination date, and soil incorporation (Basche et al., 2014). As reported by Grados et al. (2022), cover cropping may increase N_2O emissions, influenced by the type of cover crop used, biomass production, and soil moisture conditions (Vangeli et al., 2022; Hung et al., 2021).

While beneficial for N fixation, leguminous cover crops tend to elevate N_2O emissions due to their N-rich residues, which enhance microbial activity, particularly N mineralization, nitrification and denitrification (Vangeli et al., 2022). For example, Li et al. (2024) found that legume species tended to increase N_2O emissions in their meta-analysis. Non-legumes had a mitigating effect, though these differences were not statistically significant. Legume cover crops may contribute to higher N_2O emissions due to their input of biologically fixed N, which can be substantial compared to the global inorganic fertilizer use (Li et al., 2024) and the rather low C:N ratios of their residual biomass. In contrast, non-legume cover crops may reduce soil N_2O emissions by scavenging excess N, limiting its availability for microbial processes that produce N_2O. However, soil type strongly influences the impact of cover cropping on N_2O emissions due to differences in nitrate leaching and nitrogen retention. Field trials across Germany revealed contrasting effects: On loess soils, cover cropping increased direct N_2O emissions without reducing indirect emissions from leaching. On sandy soils, direct emissions remained similar, but leaching, and thus indirect N_2O losses, was significantly reduced (Helfrich et al., 2024). Additionally, the subsequent main crop is crucial, as a large share of N_2O emissions occurs during residue mineralization—an aspect often overlooked in studies and meta-analyses (Kühling et al., 2025). The choice of species or mixture (frost-intolerant or hardy) and the timing of cover crop planting and termination are critical, as early planting can maximize N uptake and reduce emissions. However, in climates with pronounced freeze-thaw cycles, frost-killed cover crops (frost-intolerant cover crops) can increase N_2O emissions during freeze-thaw events due to the rapid release of labile C and N from their residues. Yet, if the biomass has low N content at the time of freezing, the overall emission potential may be limited by N availability (Sedghi et al., 2024; Chahal et al., 2021).

3.1.2. Organic soil amendments (incorporation of manure, biochar, crop residues)

The impact of organic soil amendments on N_2O emissions in cropping systems was distinct, with effects varying by amendment type. Biochar consistently reduced N_2O emissions by an average of 22% (Fig. 1), with its effectiveness primarily influenced by soil pH, application rate, and biochar composition. Alkaline biochars, for example, can raise the pH, favouring N_2 over N_2O production (Firestone et al., 1980; Cayuela et al., 2015). In this analysis, organic manure showed a neutral effect on N_2O emissions, although previous studies (Zhou et al., 2017) suggest that N_2O emissions from organic manure may be affected by factors like soil pH, soil texture, and N content. For instance, high rates of manure application on alkaline soils can increase emissions, particularly in grasslands or fallow lands with coarse-textured soils (Shakoor et al., 2021; Han et al., 2017). Overall, the primary factors that drive N_2O emission from organic amendments include the amendment's N content, soil pH, moisture, and the amendment-specific dynamics of nutrient release and decomposition (Wang et al., 2021).

Leaving crop residues on the field increased N_2O emissions marginally (6% on average), a trend consistent with previous studies (Abalos et al., 2022; Grados et al., 2022). Abalos et al. (2022) reported a 40–50% increase in soil N_2O emissions when residues were incorporated rather than removed. This increase occurs because retention of aboveground residue supplies both N and C compounds, fueling microbial processes that drive N_2O production. The impact of crop residues on soil N_2O emissions primarily depends on their biochemical composition, specifically the C:N ratio and the degree of crop maturity at the time of residue generation. Low-C:N residues (C:N $<$ 20−30) decompose rapidly, promoting net N mineralization and supplying more N for microbial nitrification and denitrification, thereby increasing N_2O emissions (Chahal et al., 2021). High soil moisture can further enhance denitrification rates (Chen et al., 2013). In contrast, residues with a C:N ratio above 30, such as cereal straw, promote net N immobilization, reducing available ammonium and nitrate, thereby limiting nitrification and denitrification and decreasing N_2O emissions (Redin et al., 2014).

3.1.3. Fertilizer management (placement, rate, frequency)

The fertilization optimization techniques for synthetic N sources considered in this study (deep placement and reduced application rates) positively impacted N_2O emission reduction in cropping systems. This is achieved by more closely matching N availability to plant demand and by reducing N exposure to microbial processes. Deep placement of N fertilizer modestly reduces N_2O emissions (15% on average; Fig. 1), with its efficacy influenced by factors like soil moisture, placement depth, and cropping system type (Bhuiyan et al., 2023; Sánchez-Martín et al., 2008; Hondebrink et al., 2017). Reducing N application rates results in the most substantial N_2O emission reductions (33% on average), primarily by decreasing N excess in soils, as N rates exceeding plant uptake capacity lead to exponential increases in N_2O emissions (Han et al., 2017; Bouwman et al., 2002; Shcherbak et al., 2014). Yangjin et al. (2021) found that while reducing excessive N fertilizer use can curb emissions and sustain yields, reductions exceeding 25% significantly reduce crop yields. The increased frequency of smaller applications (split) had no significant effect on N_2O emissions (5% reduction on average; Fig. 1), although the practice is expected to prevent N buildup and synchronize availability with crop uptake. It is, however, reported that its effectiveness may depend on total N rate, application timing, crop growth stages and fertilizer type (Chen et al., 2011; Zhang et al., 2012; An et al., 2020), as indicated by the different effect sizes (Supplementary Fig. 2).

3.1.4. Fertilizer efficiency enhancement (slow/controlled release fertilizer and inhibitors)

Our synthesis also shows that improving N fertilizer efficiency through nitrification inhibitors, urease inhibitors, or slow/controlled-release fertilizers generally reduces N_2O emissions. These products moderate N availability and reduce N losses at multiple stages of the N cycle. On average, nitrification inhibitors reduced N_2O emissions by 41%, urease inhibitors by 20%, combined nitrification and urease inhibitors by 28%, and slow/controlled-release fertilizers by 34%, but reductions ranged from 4% to 52% (Fig. 1). The effectiveness of these practices depends on several controlling factors, including soil properties, environmental conditions (temperature, precipitation), and the synchronization of N release with plant uptake. For instance, slow-release fertilizers are sensitive to climate, with higher temperatures and precipitation accelerating nutrient release, which can limit their effectiveness under suboptimal conditions (Azeem et al., 2014). Nitrification inhibitors like dicyandiamide (DCD) and 3,4-dimethylpyrazole phosphate (DMPP) are particularly effective in grasslands, reducing N_2O emissions by up to 50% (Gilsanz et al., 2016; Tufail et al., 2022). When DMPP (Du et al., 2024; Nyameasem et al., 2023) or DCD (Thorman et al., 2020; Hargreaves et al., 2021) is applied with manure or slurry on grasslands, its effectiveness can vary significantly, ranging from 0 to 90%. This variability is influenced by environmental factors like temperature and soil moisture (Guo et al., 2022), soil properties like texture (Barth et al., 2001), and characteristics and dosage of the nitrification inhibitors themselves and a wide range of application techniques including pre-application treatments like homogenization/stirring/pumping and acidification (Li et al., 2021; Nyameasem et al., 2023).

Our results are consistent with previous reports highlighting NI as the most effective due to its direct inhibition of nitrification and NO_3^- formation, key precursors to N_2O (Akiyama et al., 2010). The moderate effectiveness of UI aligns with its ability to enhance plant N uptake efficiency, especially under lower N input conditions (Singh et al., 2013; Abalos et al., 2012). Contrary to studies reporting a greater reduction in N_2O emissions under UINI than NI alone (Grados et al., 2022; Ding et al., 2011; Zaman et al., 2009), our findings indicate that UINI was less effective than NI alone. This aligns with previous research (Ni et al., 2023; Fan et al., 2022; Thapa and Chatterjee, 2017; Zhao et al., 2017; Engel et al., 2015) and may be attributed to the persistence of NH_4^+ in the soil after UI loses effectiveness (Engel et al., 2015; Schwarzer and Haselwandter, 1991). Additionally, potential biochemical interactions between NI and UI, as suggested by Sanz-Cobena et al. (2012), may have diminished the effectiveness of NI under UINI conditions. The discrepancy between our results and those of Grados et al. (2022) may be due to differences in the studies included, variations in soil conditions, or other methodological factors that influence the interaction between NI and UI.

3.2. Liming application

The liming effect on N_2O emission was estimated from two meta-analyses. The liming effect was not statistically significant, but we observed a mitigating tendency of approximately 21% (CI = −45% to 2%, Fig. 1), similar to the 21% reduction reported by Wang et al. (2021). The primary factors influencing this effect are soil pH and the balance between nitrification and denitrification pathways. By raising the pH, liming stimulates the conversion of NO_2^- to NO_3^-, reducing essential N_2O precursors (NH_2OH and NO_2^-), and activates N_2O reductase, which favours the conversion of N_2O to N_2 rather than further N_2O emissions (Barton et al., 2013; McMillan et al., 2016). However, the effectiveness of liming is moderated by environmental factors like climate, soil texture, and WFPS. For instance, high clay content and WFPS above 50% in warmer climates can limit the N_2O reduction potential of liming (Hassan et al., 2023). In addition, soil properties such as a low C/N ratio ($\leq$15) or a soil pH greater than 4.5 make liming less effective in reducing N_2O emissions. Increased plant productivity from liming also plays a role, as greater N uptake by plants further reduces soil N availability, thereby decreasing potential N_2O emissions (Abalos et al., 2020).

3.3. Tillage

We observed no substantial effect of conservation tillage practices on N_2O emissions compared to no tillage. Specifically, no tillage and minimum tillage led to only slight changes in N_2O emissions by −2.5% (CI = −16% to 11%) and 3% (CI = −12% to 18%) (Fig. 1; Supplementary Fig. 2), respectively, suggesting minimal impact overall. However, previous studies have reported mixed responses, with both increases and decreases in N_2O emissions under conservation tillage practices (Smith and Conen, 2004; Pelster et al., 2021). These mixed results are likely influenced by critical factors such as soil texture, precipitation, and soil structure, which control moisture retention and aeration as two primary regulators of N_2O emissions. Conservation tillage practices retain more soil moisture, potentially creating anaerobic microsites that favor denitrification, particularly in fine-textured soils (Pelster et al., 2024). However, under drier conditions or with coarse-textured soils, minimum and no tillage may reduce N_2O emissions compared to conventional tillage due to limited anaerobic activity (Rochette, 2008). The broad range of effect sizes observed in our analysis suggests that the impact of conservation tillage on N_2O emissions may be site-specific, modulated by local soil and climatic conditions, and also influenced by the duration of the implementation of conservation tillage, as N_2O reduction effects often emerge only in the long term (Six et al., 2004; Ma et al., 2013; Grandy et al., 2006).

3.4. Irrigation

Irrigation generally increases N_2O emissions in soils because increased moisture increases the WFPS, which affects oxygen availability and microbial activity. Our analysis indicated that irrigation increases N_2O emissions by an average of 37% (CI = 0 to 67%; Fig. 1) compared to rainfed systems. This enhancement is likely related to irrigation-induced changes in soil moisture, which can either sustain higher moisture levels conducive to N_2O production or create repeated dry–wet cycles that stimulate N_2O emissions through microbial reactivation and nitrification–denitrification pulses (Song et al., 2020). However, the irrigation method significantly influenced these emissions, with drip irrigation, a more precise application method, showing a 13% reduction in N_2O emissions compared to surface irrigation (CI = −26 to 0%; Fig. 1). This is likely due to its controlled moisture delivery, which reduces oxygen fluctuations and suppresses N_2O-producing microbial activity (Saad and Conrad, 1993; Yao et al., 2023). N_2O emissions from irrigated systems can be influenced by various factors, including the type and rate of fertilizer applied, which affects soil pH and the availability of N substrates. Furthermore, precipitation and temperature play critical roles in shaping the activity of nitrifying and denitrifying microbes (Zheng et al., 2023; Li et al., 2024). SOC, crop type, and soil texture further control N_2O production by influencing soil moisture and microbial dynamics (Saad and Conrad, 1993).

3.5. N_2O emission simulations in process-based crop models

Process-based crop models (or agroecosystem models) are widely used simulation tools for managing the timing and amount of fertilizer application, helping to reduce greenhouse gas emissions. Specific processes considered in these models include plant growth, plant N demand and uptake, soil water and N and SOC dynamics (Asseng et al., 2015). However, accurate simulation of N_2O emissions at the field scale remains a challenge (Ehrhardt et al., 2018). A number of reviews (Chen et al., 2008; Del Grosso et al., 2020; Gabbrielli et al., 2024; Wang et al., 2021) and model comparisons (Ehrhardt et al., 2018; Xing et al., 2023) have been conducted in terms of modeling approaches (implemented equations) of crop models to simulate N_2O emissions. In the following, we review the approaches used to simulate the most common agricultural practices identified in this study and assess the ability of each model to accurately simulate these practices and N_2O emissions.

3.5.1. Trends and gaps in modeling N_2O emissions

In total, we gathered 108 studies on modeling N_2O emissions. Most of the studies on modeling N_2O emissions focused either on cover crops (26 studies), crop rotations (22 studies), or (green) manure and organic fertilizer application (21 studies; see dataset 2). Crop residue amendment, irrigation, and mineral fertilizer management (rate & frequency) were considered in 6, 9 and 9 studies, respectively. Only 5 studies considered slow/controlled release fertilizer and 3 studies considered nitrification inhibitors and/or urease inhibitors. Fertilizer placement (broadcast vs. injected) was considered only once (Nasielski et al., 2020), the same is true for direct comparisons of no tillage vs. conventional tillage (He et al., 2018). No article was found on modeling N_2O emissions after liming amendment. In terms of main crop groups, about 90% of modeling articles were on croplands (including paddy rice and vegetables), and the rest of the articles were on grassland (including forage and grass-clover). In terms of regional differences, 26 papers simulated N_2O emissions in China, 24 in Europe, 22 in the USA and only 3 in Africa (Kenya and Ethiopia) (Fig. 2A). As for the spatial scale, 64% of the studies were conducted at the field/farm scale, while 36% were conducted at the landscape or regional scale; all met the model validation criterion (i.e., comparison with observed N_2O emissions).

3.6. Applied crop models and their implemented approaches

Our results indicate that DNDC (Li et al., 1992) is by far the most widely used model for simulating N_2O emissions, with 83 publications, followed by APSIM (8; Keating et al., 2003), DayCent (5; Parton et al., 2001), SWAT (3; Arnold et al., 1998), DSSAT (3; Jones et al., 2003), FASSET (2; Berntsen et al., 2003), CERES-EGC (2; Gabrielle et al., 1995), and SPACSYS (Wu and McGechan, 1999), NCYCLE (Scholefield et al., 1991), and Daisy (Hansen et al., 1991) (Fig. 2B). An overview of how the selected model approaches consider the impacts of soil N content, soil available carbon, soil moisture, soil temperature, and soil pH to simulate nitrification and denitrification and related N_2O emissions and the respective model documentations are presented in the literature (Dueri et al., 2023; Gabbrielli et al., 2024; Vogeler et al., 2013; Wang et al., 2021). Models STICS, MONICA, and SiriusQuality (Dueri et al., 2023) share the same N_2O emission module, as does SIMPLACE. We focused on the models with at least 2 studies as well as on the approach implemented in STICS, MONICA, SiriusQuality and SIMPLACE to account for a broad overview on implemented approaches. Table 2 provides an overview on which farming practices are considered in the selected models with available documentation.

3.7. N_2O emissions due to denitrification

The selected crop models simulate N_2O emissions from denitrification, and several of them also simulate emissions from nitrification. Five approaches were identified to simulate N_2O emissions from denitrification (Beaudoin et al., 2023; Del Grosso et al., 2020; Wang et al., 2021). In DNDC, fluxes of N gases (i.e., NH_3, NO, N_2O, and N_2) are predicted either as products or intermediates by simulating the relevant N transformation processes (Li et al., 1992; Li, 2000). N_2O emissions are a direct function of microbial biomass, organic carbon, soil water content, temperature, redox potential, soil pH and soil NO_3^- concentration. Additionally, gaseous N_2 is simulated explicitly. In APSIM, N_2O emissions are a function of soil organic carbon and NO_3^- concentration, as well as soil water content and temperature. The partitioning of denitrified NO_3^- between N_2O and N_2 depends on the NO_3^-: CO_2 ratio, soil water content and temperature (Keating et al., 2003; Li et al., 2025). In CERES-EGC, N_2O emissions are calculated as a function of soil organic carbon and NO_3^- concentrations, CO_2 (heterotrophic respiration), soil gas diffusivity, soil water content and temperature. The denitrified NO_3^- is partitioned between N_2O and N_2, and it is dependent on soil type. In DayCent, N_2O emissions are a function of soil organic carbon and NO_3^- concentrations, CO_2 (heterotrophic respiration), soil gas diffusivity, and soil water content (Del Grosso et al., 2020). Also here, denitrified NO_3^- is partitioned between N_2O and N_2, depending on the NO_3^-:CO_2 ratio, soil water content, and temperature. Finally, in STICS, MONICA, SiriusQuality, and SIMPLACE, N_2O emissions are either a constant fraction of denitrified N emitted as N_2O or a function of soil pH, water-filled pore space, and NO_3^- concentration, in decreasing order of importance. Acid

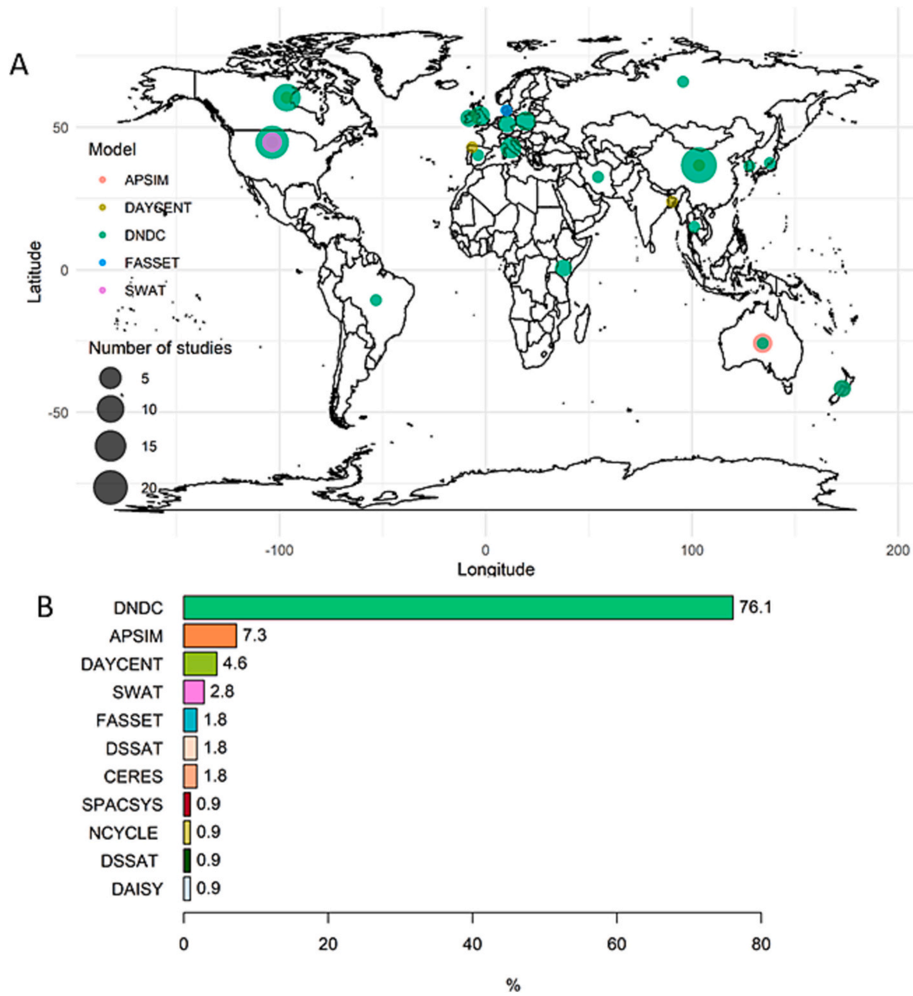

Fig. 2. Countries where process-based models were applied to simulate management practices affecting area-based N_2O emissions (A); Frequency distribution (%) of model usage for simulating management effects on N_2O emissions (B).

pH strongly inhibits the reduction of N_2O to N_2. High soil water content favours the reduction of N_2O to N_2. In DSSAT, N_2O simulations are simulated as gaseous N output that combines N_2, NO and N_2O (Lutz et al., 2019). In FASSET, N_2O simulations are mediated by soil temperature and moisture, soil NO_3^- content, and a N_2O diffusion factor that depends on clay content and soil depth (Doltra et al., 2015; Fang et al., 2015). SWAT has a similar approach to DayCent and APSIM, based on Del Grosso et al. (2000) and Parton et al. (2001), where N_2O emissions due to denitrification are calculated as a function of denitrification rate, the N_2:N_2O ratio, soil CO_2, WFPS, soil NO_3^- content, denitrified N, and soil density (Ghimire et al., 2020; Smith et al., 2019).

3.8. N_2O emissions due to nitrification

Different approaches to simulate N_2O emissions due to nitrification have been identified based on the work of Del Grosso et al. (2020), Wang et al. (2021), and Beaudoin et al. (2023). In the approach implemented in DNDC, temperature, soil moisture, pH, Eh and substrates (NH_4^+, dissolved organic carbon) affect nitrification. N_2O emissions are a direct function of microbial biomass, organic carbon, soil water content, temperature, redox potential, soil pH and NO. In the second approach, implemented by models such as STICS, MONICA, SiriusQuality, and SIMPLACE, the actual nitrification rate is a function of the potential nitrification rate (fixed or calculated as the product of a maximum nitrification rate and a function dependent on the ammonium concentration), soil pH, temperature, and water content. SIMPLACE so far does not account for soil pH effects. In these models, the N_2O emissions associated with nitrification are either calculated as a fraction of nitrified N with a default value of 0.16% (Khalil et al., 2004), or as a function of WFPS.

In DSSAT, gaseous nitrogen losses are modeled as functions of soil ammonium concentration, moisture, oxygen availability, and pH. However, N_2O emissions are not represented as a discrete flux; rather, they are encompassed within the model's aggregate simulation of total gaseous nitrogen losses (Lutz et al., 2019). In FASSET, N_2O emissions due to nitrification are a function of a fixed fraction of nitrification amount (0.047), NO_3^- concentration and further affected by soil water content, temperature, and a N_2O diffusion factor depending on clay content and soil depth. Soil microbial activity is not directly considered. Similar to denitrification, nitrification is influenced by a diffusion factor, which depends on clay content and depth (Doltra et al., 2015; Fang et al., 2015). For the SWAT model, N_2O emissions are calculated as a function of the maximum and the minimum nitrification rates, maximum fraction of ammonia nitrified during nitrification, soil water content (including wilting point and field capacity), temperature, depth, pH, and NH_4^+. In DayCent and CERES-EGC, N_2O emissions due to nitrification are a function of soil NH_4^+ content, WFPS and soil temperature, while SOC content is not considered (Gabrielle et al., 2006; Wang et al., 2021). In APSIM, N_2O emissions from nitrification are calculated using a multiplication factor based on the amount of nitrified nitrogen (Smith et al., 2019). The representation of microbial dynamics across various models is described in Del Grosso et al. (2020). In general, soil carbon

Table 2

Detailed comparison of the selected models in terms of their approaches to simulating N_2O emissions, their consideration of agronomic practices, and their applicability in process-based crop models.

Model	N_2O emission approach							Crop rotation	Residue incorporation	Fertilizer management	Nitrification/urease inhibitors	Liming effects	Tillage effects	Irrigation/heavy rainfall
Variables	SOC	SW	Temp	pH	NO_3^-	CO_2	NH_4^+							
DNDC	✔	✔	✔	✔	✔	✔	✔	✔	✔	Includes mineral and organic fertilizers with defined N and C contents; considers pH impacts.	Models nitrification and urease inhibitors dynamically based on soil pH, temperature, and inhibitor type.	✔	Considers tillage impacts on soil properties like mixing of residues and organic pools.	Simulates water effects on nitrification and denitrification processes.
APSIM	✔	✔	✔	X	✔	X	X	✔	✔	Includes impacts of fertilizers on soil mineral N pools; does not consider liming effects explicitly.	Does not include nitrification inhibitors.	X	Incorporates residue mixing indirectly; no explicit bulk density changes due to tillage.	Includes rainfall-related WFPS adjustments; not soil ponding.
DayCent	✔	✔	✔	X	✔	✔	✔	✔	✔	Includes mineral and organic fertilizers with defined N content.	Nitrification inhibitors modeled by reducing nitrification rates by 50% for 2 months after application.	X	Considers increased mineralization rates post-tillage.	Considers water effects on denitrification and nitrification processes.
CERES-EGC	✔	✔	✔	X	✔	✔	X	✔	✔	Considers fertilizer impacts on soil NH_4^+ and NO_3^-.	Does not include nitrification inhibitors.	X	Does not explicitly consider tillage impacts.	Includes WFPS adjustments.
SWAT	X	✔	✔	X	✔	X	✔	X	X	Includes impacts of fertilizer applications.	Does not include nitrification inhibitors.	X	Soil texture considered; does not simulate physical tillage impacts.	Simulates WFPS effects on N_2O emissions but lacks detailed irrigation impacts.
DSSAT	X	✔	X	✔	✔	X	✔	✔	✔	Includes mineral and organic fertilizer applications.	Limited information available on nitrification inhibitor use.	X	Considers tillage effects on soil bulk density and water redistribution.	Includes water content for nitrification; limited detail on rainfall effects.
FASSET	X	✔	✔	X	✔	X	✔	✔	✔	Fertilizer impacts considered.	Does not include nitrification inhibitors.	X	Does not explicitly consider tillage impacts.	Simulates soil moisture effects but lacks explicit irrigation scenarios.
STICS	X	✔	✔	✔	✔	X	✔	✔	✔	Includes fertilizer impacts on soil NH_4^+ and NO_3^-.	Does not include inhibitors.	✔	Simulates bulk density changes and effects on hydraulic properties due to tillage.	Simulates WFPS effects; allows hourly time steps for intensive rainfall scenarios.
MONICA	X	✔	✔	✔	✔	X	✔	✔	X	Includes fertilizer applications.	Does not include inhibitors.	X	Does not consider tillage impacts.	Simulates WFPS effects.
SiriusQuality	X	✔	✔	✔	✔	X	✔	✔	X	Includes fertilizer impacts on nitrification processes.	Does not include inhibitors.	✔	Does not consider tillage impacts.	Simulates WFPS effects.
SIMPLACE	X	✔	X	✔	✔	X	✔	✔	X	Includes fertilizer impacts on soil nitrogen processes.	Does not include inhibitors.	X	Includes preliminary tillage models not integrated with soil process models.	Simulates WFPS effects; lacks hourly rainfall routines.

Temp: soil temperature; SW: soil water/water filled pore space; ✔ = included, X = not included.

pools are characterized by their turnover rates and C/N ratios. The representation of soil C/N dynamics in various models is described in reviews such as Gabrielle et al. (2002) and in the respective model documentation.

3.8.1. Representation of the cropping practices and N_2O emission controls in crop models

Generally, the representation of identified management practices affecting N_2O emissions varies across models. Table 3 presents an overview of management practices for the selected models.

3.9. Simulation of N_2O emissions in single and diversified crop rotations

Process-based agroecosystem models are commonly driven by four primary ecological drivers, namely climate, soil, vegetation, and management practices. In theory, models that simulate single-season crops can capture the temporal dynamics of N_2O within a season. However, for continuous cropping seasons, where crop residues, cover crops, and soil C and N turnover are considered, it is essential to differentiate between a "true" handover of initial parameters between crops and merely conducting sequential single-crop simulations. Only models implementing the former approach can accurately investigate long-term N_2O emissions. Moreover, model capabilities for reproducing cropping-season dynamics, both above- and below-ground, vary depending on the model and the target variable (Kollas et al., 2015). Different models employ varying levels of complexity to capture crop-soil management interactions and simulate nitrification and denitrification processes under crop rotation. DNDC, APSIM, DayCent, CERES-EGC, DSSAT, FASSET, STICS and MONICA have the capacity to simulate crop rotations (Table 3). Since crop rotations influence soil biogeochemical processes and N_2O emissions, models must incorporate these interactions to improve predictions of N_2O emissions. Selecting an appropriate model depends on its ability to represent nitrogen-cycling dynamics and soil-crop interactions in diversified cropping systems. Some of the models, like DNDC, APSIM and DSSAT have extra ability to handle tillage and residue incorporation effects on N_2O emission.

Table 3
Overview of crop models for simulating N_2O emissions based on agronomic management practices.

Management approach	Models considering this approach	Details
Crop rotation	DNDC, APSIM, DayCent, CERES-EGC, DSSAT, FASSET, STICS, MONICA, SIMPLACE	Models include crop rotation as part of their management practices, impacting nutrient dynamics and N_2O emissions.
Residue incorporation	DNDC, APSIM, DayCent, DSSAT, FASSET, STICS, SiriusQuality,	Models include explicit representation of residue mixing into the soil, affecting organic matter decomposition and subsequent nitrogen cycling.
Fertilizer management	All Models (DNDC, APSIM, DayCent, CERES-EGC, SWAT, DSSAT, FASSET, STICS, MONICA, SiriusQuality, SIMPLACE)	Models incorporate the effects of fertilizers (organic and mineral) on soil N pools, though specific levels of detail vary.
Nitrification/ urease inhibitors	DNDC, DayCent	DNDC dynamically simulates inhibitor impacts based on environmental factors, while DayCent uses a simpler reduction in nitrification rates for a fixed duration.
Liming effects	DNDC, STICS, SiriusQuality	Models consider the impacts of liming on soil pH and associated N cycling processes, including nitrification and denitrification.
Tillage effects	DNDC, APSIM, DayCent, DSSAT, STICS	Models simulate how tillage impacts soil properties, such as residue mixing, bulk density, or organic pool redistribution, affecting N cycling and N_2O emissions.
Irrigation/heavy rainfall	DNDC, APSIM, DayCent, SWAT, DSSAT, STICS, MONICA, SiriusQuality, SIMPLACE	Models consider water management practices, with varying levels of detail. DNDC and STICS include hourly rainfall effects, while other models primarily incorporate water-filled pore space (WFPS) adjustments.

3.9.1. Simulation of N_2O emissions for the incorporation of residue amendments

Residue, soil organic matter and nutrient redistribution and incorporation after tillage are implemented in most models (Table 3) (Delve and Probert, 2004; Doltra et al., 2015; Maharjan et al., 2018). SiriusQuality, MONICA and SIMPLACE do not consider tillage practices (Dueri et al., 2023). A preliminary SimComponent has been developed in SIMPLACE, but currently not linked with the SimComponents related to soil processes. Some models, such as DayCent and DNDC, also include an increase in the mineralization rate for a period after a tillage event (Lutz et al., 2019). In STICS and APSIM, mineralization of organic matter releasing mineral N is affected indirectly by soil tillage: Each tillage event is assumed to mix the residues with humified C and N pools, the water and the mineral N contents uniformly in the ploughed soil layer. The decomposition and mineralization rates, and thus, the C and N cycles and N_2O emissions in the topsoil, can be affected in two ways: new organic residues may be mixed into the soil, and the environmental conditions (temperature, soil water content, aeration and mineral N availability) may be affected.

Different cover crop and residue types, particularly legumes and non-legumes, exert distinct influences on N_2O emissions due to differences in nitrogen inputs and residue quality. Process-based models, such as DNDC, can capture these contrasts by representing the dynamics of biological N fixation and residue decomposition (Deng et al., 2018b). Higher simulated N_2O losses are often observed from legume-based systems (Plant, 1999). Other models, including DayCent, APSIM, and PaSim, have also differentiated N_2O responses to residue type. In a four-year multi-model evaluation, Fuchs et al. (2020) found that DayCent best simulated annual N_2O fluxes, while APSIM captured short-term emission peaks, with the ensemble reducing flux estimation error by 41% relative to IPCC estimates. Thus, process-based models can represent management-driven variability in N_2O emissions from different residue types, though uncertainties remain due to soil–plant–microbe interactions and parameterization.

3.9.2. Simulation of N_2O emissions due to fertilizer management

Most crop models consider the application of mineral N fertilizers and organic fertilizers with defined N content, and, in the case of organic fertilizers, also defined C content and, sometimes, pH (Table 3). Fertilizer addition increases the N (and C) concentration in the respective soil mineral N (C) and/or soil organic N (C) pools of the topsoil layer. In all models, N_2O emissions from denitrification increase with soil NO_3^- concentration, as N_2O emissions also increase with increasing soil NO_3^- concentration. In DNDC, N_2O emissions from nitrification are affected by the substrate NH_4^+, which affects nitrification, and the related N_2O emissions are influenced by soil NO, among other factors. Models such as CERES-EGC, DSSAT, SWAT, APSIM, and FASSET generally consider only soil NH_4^+, while STICS, MONICA, SiriusQuality, and SIMPLACE compute nitrification rates as a function of soil NH_4^+ concentration; however, the associated N_2O emissions do not directly account for soil N availability.

Recent studies highlight the importance of N_2O priming effects in determining soil N_2O emissions following fertilizer application. The priming effect refers to the short-term increase or decrease in soil organic matter mineralization in response to additions of C and/or N, which can amplify, diminish, or maintain N_2O production from soil organic N (SOM-N) mineralization (Daly et al., 2024). This process can differentially augment N_2O-producing pathways, such as nitrification or denitrification, and may substantially influence net N_2O emissions, with reported contributions ranging from −39% to +76% following C and N amendments. N_2O priming is particularly relevant under changing environmental conditions, including climate warming, and in under-studied soils such as those affected by permafrost, alpine regions, and tropical regions. Incorporating these effects into mechanistic models remains a research gap, requiring expanded empirical datasets and model development to capture the complex interactions between soil organic N dynamics, fertilizer inputs, and environmental drivers.

3.9.3. Simulation of N_2O emissions after use of nitrification or urease inhibitors

Nitrification and urease inhibitors are widely used to mitigate N_2O emissions (Adu-Poku et al., 2022). However, their effects are only explicitly included in a few process-based models, such as DNDC and DayCent (Table 3). In DNDC, urease inhibitor activity is incorporated by modifying the urea hydrolysis routine from a fixed-efficiency approach to a dynamic approach that accounts for soil pH as follows: $y = -5.93 + 1.13x$; where y is the half-life of N-(n-butyl) thiophosphoric triamide (NBPT) in days, and x is the impact of soil pH on NBPT effectiveness (Engel et al., 2015; Jiang et al., 2023a). The effect of nitrification inhibitors is typically modeled as a reduction in nitrification rates, depending on the type and amount of nitrification inhibitor applied, soil temperature, WFPS, soil pH and the duration of inhibitor activity (Li et al., 2020). For example, DayCent reduces nitrification rates by 50% for two months following inhibitor application (Del Grosso et al., 2009). In DSSAT, nitrification rates can also be reduced by nitrification inhibitors, although detailed implementation is not well documented (Gabbrielli et al., 2024).

Recent work by Grant et al. (2020) provides a more mechanistic approach within the ecosys model, in which NI effects are simulated using a time-dependent algorithm that slows NH_4^+ oxidation. This approach reproduces measured seasonal and annual N_2O emission reductions following fall and spring- applied slurry, capturing variability in emissions due to environmental conditions. The model showed that NI reduced N_2O emissions more during wetter periods than during drier periods, and that annual-scale reductions were smaller than reductions during specific emission events. Additionally, the model accounted for indirect effects, including increases in NH_3 emissions and reductions in NO_3^- leaching, which can influence overall N_2O budgets. This study demonstrates that models can more accurately represent NI effects when the processes causing variability in emissions are explicitly simulated.

3.9.4. Simulation of N_2O emissions due to liming application

With regard to liming impacts on N_2O emissions, experimental data show that increasing soil pH reduces N_2O emissions (Barton et al., 2013; Zhang et al., 2022b), but the effects also depend on the type of liming materials (Shaaban et al., 2020). To our knowledge, no modeling study has explicitly considered liming effects (Wang et al., 2021). The simulated N_2O emissions due to denitrification are affected by soil pH in DNDC, but not in APSIM, CERES-EGC, SIMPLACE, DSSAT, DayCent and FASSET. In STICS, MONICA, and SiriusQuality, N_2O emissions are either a constant fraction of denitrified N emitted as N_2O, or a function of soil pH, among other factors. DNDC also accounts for soil pH to simulate N_2O emissions from denitrification. Regarding N_2O emission from nitrification, just DNDC, SIMPLACE, SWAT, and DSSAT consider pH. As for STICS, MONICA, and SiriusQuality, although the actual nitrification rate is a function of pH, the N_2O emissions associated with nitrification are not affected by soil pH.

3.9.5. Simulation of N_2O emissions after soil tillage

Commonly, models consider soil texture and soil structure as permanent characteristics. However, physical operations such as tillage may affect soil physical and chemical properties and, consequently, N_2O emissions. Modeling approaches for the effects of tillage on soil properties are described in detail by Maharjan et al. (2018), Lutz et al. (2019) and the respective model documentations. Several crop models, including DNDC, STICS and DSSAT consider tillage in their model routines by implementing functions or factors that include the impacts of tillage on bulk density, soil texture redistribution (deep tillage), soil hydraulic properties, and redistribution of soil organic matter, residues or/and nutrients in the top soil up to certain tillage depth (Maharjan et al., 2018). In terms of changes in bulk density, just DNDC, STICS and DSSAT consider this effect, as well as the soil settlement of the tilled soil due to subsequent rainfall (Beaudoin et al., 2023; Lutz et al., 2019). In STICS, if tillage occurs, soil bulk density decreases and soil infiltrability increases (Beaudoin et al., 2023); while in DSSAT, soil moisture is indirectly affected via a change in soil physical properties (Lutz et al., 2019). Soil texture distribution resulting from deep tillage is considered by SWAT. Changes in soil hydraulic properties are just considered in DSSAT and STICS (Beaudoin et al., 2023).

3.9.6. Simulation of N_2O emissions after irrigation or heavy rainfall events

As denitrification is an anaerobic process, higher soil water content or WFPS results in less aerated soils and therefore, more active denitrification. In most crop models, denitrification-driven N_2O emissions are strongly influenced by soil moisture, although the exact representation differs among models. For example, DNDC, APSIM, DSSAT, DayCent and FASSET simulate denitrification and N_2O as functions of soil moisture interacting with other factors such as soil redox potential, carbon availability, and nitrate content (Li, 2000; Parton et al., 2001; Keating et al., 2003; Berntsen et al., 2003; Del Grosso et al., 2009). Conversely, models such as SWAT, STICS, MONICA, SiriusQuality, and SIMPLACE typically use water-filled pore space (WFPS) as a key driver to regulate denitrification and N_2O fluxes in combination with substrate availability and temperature (Gabrielle et al., 2006; Nendel et al., 2011; Wu et al., 2007).

In DNDC, soil water content influences nitrification and associated N_2O emissions indirectly by affecting soil redox conditions and oxygen availability. In contrast, models such as SWAT, DSSAT, FASSET, STICS, MONICA, SiriusQuality, and SIMPLACE use more empirical approaches, where nitrification rates are directly controlled by soil water content or water-filled pore space (WFPS), and N_2O from nitrification is calculated either as a fixed fraction of nitrified nitrogen or as a function of WFPS. In STICS, soil water content and WFPS can be simulated at hourly time steps, assuming that soil layers become saturated following rainfall and then desaturate exponentially. Similarly, DNDC simulates hydrological processes and calculates soil water content at hourly time steps, using this hourly moisture data to simulate nitrification and denitrification processes, despite soil moisture being reported at the end of the day. This approach may improve emission prediction after intensive rainfall or irrigation events. APSIM does not consider soil water content or WFPS in N_2O emissions due to nitrification, whereas DayCent and CERES-EGC do. In various models, soil water content also modifies the mineralization rate and thus the availability of NH_4^+ and NO_3^-. Water ponding on soil surfaces following heavy rainfall or irrigation can increase N_2O emissions. Rainfall and irrigation also affect nitrate leaching, which changes the availability of substrates for N_2O production, and can influence the vertical movement of N_2O from deeper soil layers to the atmosphere. While earlier model comparisons suggested that many models only partially represent these processes, several models, such as DNDC, explicitly simulate nitrate leaching and its feedback on N_2O emissions, as well as runoff-induced N losses (Li et al., 2006; Deng et al., 2011). Other models, such as APSIM (particularly under flooded rice conditions), also include routines that link leaching with N_2O dynamics.

Process-based models simulate the impact of soil water on N_2O emissions by representing how rainfall and irrigation influence soil moisture, which in turn regulates nitrification and denitrification processes. Most models, such as APSIM, DAYCENT, DSSAT, and STICS, capture the effects of rainfall and irrigation events on soil moisture and subsequent N_2O fluxes but typically focus on the amount and timing of water rather than specific irrigation methods (Gabbrielli et al., 2024). The DNDC family of models, including LandscapeDNDC and DSSAT, is currently among the few capable of explicitly distinguishing irrigation types (e.g., surface and drip) and simulating their effects on soil water dynamics and N_2O emissions (Dar et al., 2017; Deng et al., 2018a; Mumford, 2021). Evidence for similarly detailed representations of irrigation method in other models remains limited in current literature reviews. Ultimately, model accuracy depends strongly on site-specific parameterization of soil–water–nitrogen interactions and the precision with which rainfall and irrigation events are simulated (Gabbrielli et al., 2024; Mumford, 2021).

3.10. *Strengths, limitations & gaps in model representations*

Many modeling studies have examined the effects of cover crops, crop rotations, and the application of mineral and organic fertilizers on N_2O emissions. Crop rotations and cover cropping have been shown to influence N_2O emissions, with reported impacts ranging from a 38% increase to a 13% reduction. This variability underscores the significant interactions between crop rotation practices, other management strategies, and site-specific factors. While many crop models can simulatecrop rotations, accurately representing cropping sequences remains a challenging task. This involves not merely running one crop after another but ensuring precise transfer of post-harvest parameters, such as soil conditions and residue effects, into the initial parameter set for the subsequent crop. The accuracy of such simulations depends heavily on the model's complexity and parameterization (Kollas et al., 2015). Uncertainty in these models increases over the long term due to cumulative effects on soil water, nutrient dynamics, and carbon storage, all of which influence N_2O emissions (Basso et al., 2020). The scarcity of continuous long-term data on N_2O emissions further limits the ability to validate and refine these models effectively.

For some practices, such as biochar and liming, experimental data have provided relatively clear results, but modeling studies remain scarce. In contrast, practices such as crop rotation require not only more experimental data but also more differentiated meta-analyses and modeling efforts, as their outcomes often depend on interrelated management factors and vary significantly across different contexts. Thus, additional field measurements and modeling studies are needed to better understand their context-dependent impacts across different soils, climates, and cropping systems. Alternatively, a comprehensive meta-analysis could serve as a critical first step to synthesizing existing data, identifying patterns, and highlighting research gaps. While fertilizer management (e.g., rate, timing, splitting, use of slow-release fertilizers) has been extensively studied due to its strong influence on N_2O fluxes, comparatively less attention has been given to other practices such as residue amendments. These practices warrant greater focus to improve mitigation strategies and enhance model predictions.

For climate mitigation, improving N-use efficiency, which is generally considered to be less than 50% under most farming conditions, remains a key strategy in agricultural production (Reay et al., 2012). Fertilizer management is a key mitigation strategy, with the rate and type of fertilizer application being the most commonly studied variables. However, interactions between fertilizer timing and placement are less well understood and underexplored in both experimental and modeling contexts (Maaz et al., 2021). While crop models often include fertilizer rates and timing, they rarely account for fertilizer placement, limiting their ability to fully represent the complexities of N_2O emissions. The use of urease and nitrification inhibitors has been shown to significantly reduce N_2O emissions by more than 20%, but these practices are rarely incorporated into models and tested against data, with exceptions such as DNDC, DayCent, and, to a lesser extent, DSSAT. Similarly, slow-release fertilizers, which also have significant mitigation potential, are considered in only a few models (e.g., DSSAT, DNDC).

In general, conservation tillage has a relatively small effect on N_2O emissions compared to conventional tillage, which alters soil properties such as bulk density and nutrient mixing. Despite its importance, tillage practices are only partially incorporated into some models, and a more comprehensive implementation is needed. Additionally, long-term data are crucial for improving model accuracy in simulating the impacts of tillage practices, as reduced tillage may increase N_2O emissions in the short term but can lead to reductions over time, particularly through carbon sequestration (Six et al., 2004). Liming, which can significantly reduce N_2O emissions, is another practice that remains poorly represented in current models. Although liming may increase N_2O emissions in well-drained soils due to increased nitrification (Nadeem et al., 2020), no modeling studies that explore its effects were identified.

Biochar amendments have demonstrated the potential to reduce N_2O emissions by 10–90%, depending on soil conditions, through mechanisms such as liming effects and buffering capacity (Cayuela et al., 2015). Recent advances in modeling have begun to represent these effects more explicitly. Mechanistic models, such as APSIM, incorporate the effects of biochar on soil pH, moisture, and microbial activity, thereby modifying nitrification and denitrification pathways (Archontoulis et al., 2016). Process-based models, such as RothC, MIMICS-BC, and DNDC, simulate biochar impacts primarily through carbon dynamics, capturing N_2O responses indirectly rather than through explicit nitrogen transformations (Pulcher et al., 2022; Han et al., 2024; Jiang et al., 2023b). While simplified decay models remain limited in this respect, emerging machine-learning approaches provide data-driven predictions of microbial and N_2O responses to biochar (Lei et al., 2023). A broader review of crop models indicates that critical processes driving N_2O emissions, such as nitrification and denitrification, are often oversimplified. While widely used practices like crop rotations, cover cropping, and fertilizer application are included in many models, newer and alternative practices are frequently overlooked. This omission risks over- or underestimation of N_2O emissions, especially over the long term.

3.11. *Future directions for model improvements*

To advance the modeling of N_2O emissions, future efforts should prioritize integrating underrepresented yet impactful agricultural practices such as the use of inhibitors, precise fertilizer placement, and biochar application. However, refining the representation of existing management strategies will not automatically enhance model accuracy, as increased model complexity does not necessarily translate into improved predictive performance. Achieving greater accuracy requires careful evaluation of which control factors, such as soil moisture, temperature, microbial activity, root structure, and N dynamics, should be included and at what spatial and temporal resolutions (Weinert et al., 2002; Nett et al., 2011). Expanding consideration of soil type, environmental conditions, and crop growth stages can further improve the reliability of estimates of N use efficiency and N_2O emission (McSwiney and Robertson, 2005; Van Groenigen et al., 2010; Xia et al., 2017). However, achieving meaningful improvements in model performance will depend on closer collaboration among modelers to identify the most relevant control factors and determine the appropriate spatial and temporal resolutions for their inclusion. Ultimately, model development should balance complexity and practicality, incorporating only the most influential processes are incorporated to maintain computational efficiency, usability, and relevance for mitigation-oriented applications.

Given the structural variability among existing process-based models, a universal enhancement strategy is impractical. Instead, future research should focus on tailoring improvements to each modeling framework, aligning with its specific structure, assumptions and data requirements (Lutz et al., 2019). It is also important to recognize that some mitigation practices, such as tillage or residue incorporation, are considerably more complex to represent than others, such as the use of nitrification inhibitors, due to their broader effects on soil physical, chemical, and biological processes. Collaborative model intercomparison and module exchange efforts are therefore essential to identify optimal model structures, spatial resolutions, and parameterizations for accurately simulating these diverse mitigation strategies. The integration of new experimental data and field measurements is equally critical for model validation and refinement. Continuous in-situ monitoring techniques, such as eddy-covariance systems, provide valuable real-time insights into the temporal and spatial dynamics of emissions (Aubinet et al., 2012). Expanding and harmonizing these datasets will strengthen model calibration and facilitate the development of sustainable, adaptive cropping systems that optimize productivity and N_2O mitigation across different agroecosystems.

Addressing geographic gaps in N_2O emission modeling is another crucial direction for future research. Regions such as South America and Africa remain underrepresented despite their significant contributions to global emissions (Lutz et al., 2019; Tian et al., 2019). Expanding studies in these areas will improve the comprehensiveness of global models. Furthermore, facilitating data accessibility through platforms like the "Global N_2O Database" (https://samples.ccafs.cgiar.org) will encourage broader utilization and collaboration among modelers. Ensuring that datasets are complete and standardized will be essential for maximizing their impact on future modeling advancements.

4. Conclusions

The current study underscores the need for research to optimize management practices to effectively mitigate N_2O emissions across varying local conditions. Future studies should prioritize understanding the interactions and tradeoffs between crop management practices and site-specific factors, as these significantly influence N_2O emissions and crop productivity. Investigating the long-term effects of techniques such as inhibitor use, deep fertilizer application, reduced tillage and organic amendments can further clarify their role in sustainable N management in crop production.

Current process-based models have been used to represent management practices such as crop rotations, cover crops and fertilizer application, providing valuable insights into their effects on N_2O emissions. However, their performance remains constrained by oversimplified representations of nitrification and denitrification processes and by limited inclusion of practices such as fertilizer placement, slow-release fertilizers, biochar amendments, and liming. These gaps, compounded by the scarcity of long-term N_2O emission data, hinder the models' ability to capture complex interactions and cumulative effects over time. Improving model performance will require not merely the addition of more variables or processes, but a deeper understanding of how the spatial resolution of soil variables and the structural representation of key processes influence the accuracy of simulated mitigation outcomes. Addressing these limitations through the incorporation of underrepresented practices, the generation and use of long-term datasets, and the application of well-calibrated process-based crop models can provide robust, site-specific insights into the effects of management practices within different farming systems. Such improvements will enhance the capacity to derive, regionalize, and translate model outputs into actionable guidance for agricultural management and evidence-based policy recommendations for N_2O mitigation in line with Tier 3 IPCC approaches.

CRediT authorship contribution statement

John Kormla Nyameasem: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Sabine J. Seidel:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Funding acquisition, Conceptualization. **Milena Ulrich:** Writing – review & editing, Writing – original draft. **Morten Möller:** Writing – review & editing, Writing – original draft, Conceptualization. **Insa Kühling:** Writing – review & editing, Writing – original draft, Conceptualization. **Alberto Andrino:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Timo Kautz:** Writing – review & editing, Writing – original draft, Supervision, Resources, Funding acquisition, Conceptualization. **Nicolas Brüggemann:** Writing – review & editing, Writing – original draft, Funding acquisition, Conceptualization. **Ixchel M. Hernandez-Ochoa:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2026.181506.

Data availability

The data supporting the findings of this study will be made available on request.

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