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Variability and Driving Mechanisms of Cropland N_2O Emission Factors: A Review

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ABSTRACT

Nitrous oxide (N_2O) is an important component of agricultural greenhouse gas emissions, and nitrogen inputs to croplands represent one of the major anthropogenic sources of N_2O. The emission factor (EF), which links nitrogen input to direct N_2O emissions, has long been used in national greenhouse gas inventories and agricultural mitigation assessments. The conventional fixed-EF approach is simple and suitable for large-scale accounting, but extensive field observations have shown that cropland EFs vary substantially across climate zones, soil backgrounds, cropping systems, and management practices. A single fixed coefficient cannot adequately capture the spatial heterogeneity, interannual variability, and event-driven pulse characteristics of cropland N_2O emissions. In recent years, with the development of global field observation databases, meta-analyses, machine learning, and interpretable modelling approaches, EF research has gradually shifted from estimating average coefficients to explaining the mechanisms underlying EF variability. Existing studies indicate that cropland N_2O emissions are jointly regulated by nitrification, denitrification, and N_2O reduction processes. Their variability is mainly controlled by nitrogen substrate availability, soil moisture and oxygen diffusion, soil pH, soil organic carbon, temperature, precipitation, and agricultural management practices. Acidic soils, high SOC, high nitrogen input, humid conditions, and heavy rainfall after fertilization are more likely to create high-emission risks. Meanwhile, drying–rewetting, freeze–thaw cycles, and extreme rainfall events can trigger short-term emission peaks, further challenging the fixed-EF approach. This review synthesizes current knowledge on the variability, driving mechanisms, multifactorial interactions, and methodological advances in cropland N_2O EF research. It further suggests that future EF systems should move from fixed empirical coefficients toward regionalized, dynamic, and mechanism-constrained parameter frameworks, thereby improving the scientific basis of cropland N_2O inventories and mitigation strategies.

KEYWORDS

Cropland; Nitrous Oxide; Emission Factor; Driving Mechanism; Climate Sensitivity; Extreme Events; Machine Learning.

1. INTRODUCTION

N_2O is an important long-lived greenhouse gas and one of the most difficult agricultural emission components to quantify accurately. After nitrogen is applied to cropland soils, part of it is taken up by crops, part is lost through leaching, runoff, or ammonia volatilization, and the remaining nitrogen enters soil nitrogen cycling processes[1]. It may then be transformed into N_2O through nitrification and denitrification and released to the atmosphere. Because N_2O has a high global warming potential and a long atmospheric lifetime, accurate estimation of cropland N_2O emissions is essential not only for greenhouse gas inventory development but also for nitrogen management and mitigation policy design[2].

The emission factor method is currently the most widely used approach for estimating cropland N_2O emissions. In this approach, nitrogen input is multiplied by an EF to estimate direct N_2O emissions induced by fertilization. The IPCC Tier 1 method uses a fixed EF, which requires limited data and is easy to implement, making it suitable for countries and regions where detailed field observations are lacking[3]. However, this approach implicitly assumes that the proportion of nitrogen input emitted as N_2O is relatively stable across cropland systems. As field observations have accumulated, the limitations of this assumption have become increasingly clear. Cropland EFs may differ by several-fold or even orders of magnitude across climate zones, soil types, cropping systems, and management practices[4]. EFs are often higher in humid climates than in dry climates, higher in acidic soils than in neutral or alkaline soils, and more likely to show emission peaks in high-nitrogen systems after heavy rainfall. Based on a reassessment of global field measurements, Hergoualc'h et al. [5] showed that EF_1 varies significantly with climate zone and nitrogen source, indicating that a uniform fixed coefficient is insufficient for complex cropland systems.

The limitation of fixed EFs does not mean that the emission factor method has lost its value. Rather, it indicates that the parameterization of EF needs to be further refined. EF is not an intrinsic and fixed property of nitrogen fertilizer itself; it is the integrated response of a cropland system to nitrogen input, soil conditions, and climatic disturbance. The same nitrogen input may induce high N_2O emissions in acidic and humid soils but relatively low emissions in water-limited drylands. Similarly, the same fertilizer type may lead to different outcomes under different temperature, moisture, and cropping conditions. Therefore, the central question in cropland N_2O EF research is no longer simply whether the default EF is appropriate, but why EF varies and which combinations of factors determine high-emission risks.

Over the past few decades, cropland N_2O research has undergone a clear shift in both methodology and understanding. Early studies were mainly based on single-site experiments or regional observations and focused on comparing the effects of nitrogen application rate, fertilizer type, and tillage on N_2O emissions. Later, meta-analyses and regional databases enabled researchers to identify EF drivers at broader spatial scales[6]. In recent years, machine learning and interpretable modelling approaches have further pushed research from single-factor comparisons toward multifactorial explanations[4]. These approaches have helped reveal nonlinear responses and threshold characteristics of EF in relation to soil pH, SOC, precipitation, temperature, nitrogen application rate, and extreme events[7]. This development suggests that cropland N_2O EF is evolving from an empirical inventory parameter into an integrated indicator for understanding soil nitrogen cycling, climate sensitivity, and agricultural management effects.

This review focuses on the variability and driving mechanisms of cropland N_2O EFs. It first summarizes the applicability limits of fixed EF methods and the heterogeneous characteristics of EF. It then discusses the main drivers from the perspectives of soil, climate, and management. The review further examines how multifactorial interactions, extreme events, and data-driven models extend conventional understanding. The overall aim is to provide a scientific basis for improving cropland N_2O inventories and optimizing agricultural mitigation strategies.

2. VARIABILITY OF CROPLAND N_2O EMISSION FACTORS

2.1. Applicability Limits of Fixed Emission Factors

The fixed-EF approach allows rapid estimation of cropland N_2O emissions under data-limited conditions, but its application relies on simplifying complex soil nitrogen transformations into a relatively stable proportional relationship. Cropland N_2O emissions are not a simple linear consequence of nitrogen input. Instead, they result from the combined effects of nitrification, denitrification, and N_2O reduction under specific hydrothermal, oxygen diffusion, and substrate conditions[8]. These processes are highly sensitive to soil moisture, temperature, pH, carbon and nitrogen substrates, and microbial activity. As a result, actual EF values can differ substantially among cropland systems[9].

Evidence from field studies shows that the applicability limits of fixed EFs are mainly reflected in three aspects. First, climatic background can significantly alter EF levels[10]. In humid regions, higher soil water content restricts oxygen diffusion and facilitates the formation of low-oxygen microsites, thereby enhancing denitrification and often resulting in higher EFs than in dry regions. The global reassessment by Hergoualc'h et al.[5]showed that EF_1 under humid climates was clearly higher than that under dry climates, and this finding has been incorporated into refined IPCC methods. Second, soil background affects both N_2O production and consumption. In acidic soils, the reduction of N_2O to N_2 is inhibited, increasing the proportion of N_2O in denitrification products; therefore, fixed EFs may underestimate emission risks in such soils[11]. Third, management practices alter nitrogen substrate availability and emission peaks. High-nitrogen-input systems are more likely to generate short-term high emissions after rainfall, irrigation, or rewetting events, and such event-driven characteristics are difficult to represent using annual average coefficients[12].

Examples from different regions clearly illustrate the limitations of fixed EFs. In Mediterranean-type cropping systems, Cayuela et al. [13]reported an average EF of 0.5%, substantially lower than the IPCC Tier 1 default value of 1%; rain-fed systems showed even lower EFs than irrigated systems, indicating that water availability and irrigation regime strongly regulate fertilizer-induced N_2O emissions. In contrast, in high-nitrogen vegetable fields, tea plantations, or paddy–upland rotation systems in humid climates, high soil moisture, abundant nitrogen substrates, and acidic soil conditions often act together, and EF may be substantially higher than the default value[14, 15]. Similarly, in cold regions, if residual inorganic nitrogen remains after autumn fertilization, spring thaw can trigger N_2O emission peaks, while such non-growing-season emissions are often insufficiently captured by fixed-coefficient accounting[16].

Therefore, fixed EFs remain useful as baseline accounting tools in data-scarce regions, but their results are better interpreted as coarse estimates rather than precise descriptions of specific cropland emission mechanisms. With increasing field observations and model development, EF research is moving from a single default value toward more context-dependent parameterization. Incorporating regional climate, soil background, crop type, and management practice into EF refinement has become an important direction in both research and inventory improvement. In the longer term, dynamic EFs that adjust with environmental conditions and event processes will be more useful for identifying high-emission risks and designing targeted mitigation measures.

2.2. Regional Differences in Emission Factors

Regional differences in EF represent a major challenge for fixed-coefficient methods. Across climate zones, croplands differ substantially in hydrothermal conditions, soil development, and management practices, leading to different limiting factors for N_2O production and reduction. Regional differences are therefore not merely differences in emission magnitude; more importantly, they reflect shifts in the dominant controlling mechanisms.

Humid subtropical and tropical monsoon regions are typically characterized by high temperatures, intense rainfall, and high nitrogen inputs. Frequent wetting of soils favors denitrification. In parts of East and Southeast Asia, multiple cropping systems, vegetable fields, tea plantations, and paddy–upland rotations are often associated with high nitrogen inputs, maintaining high levels of inorganic nitrogen substrates in soils[17]. When heavy rainfall or irrigation increases water-filled pore space (WFPS), oxygen diffusion is restricted, low-oxygen microsites form rapidly, and denitrification is enhanced[18]. If the soils are also acidic, the reduction of N_2O to N_2 is constrained, increasing the proportion of N_2O in denitrification products and further elevating EF risk. In paddy–upland rotations or rice systems with alternating wetting and drying, soils undergo repeated aerobic–anaerobic transitions. NO_3^- produced during upland or drained phases can be rapidly denitrified during subsequent flooding or rewetting, leading to distinct N_2O pulses[19]. Such combined conditions of high moisture, abundant nitrogen substrates, and acidic soil background represent an important regional type in which fixed EFs may underestimate emission risks.

Arid and semi-arid regions show a different mechanism. Under rain-fed conditions, insufficient water often limits microbial activity and denitrification, resulting in relatively low baseline EFs. Barton et al.[20]found that measured EFs in semi-arid Australian croplands were far below the IPCC default value, demonstrating that water limitation can strongly constrain fertilizer-induced N_2O emissions. However, irrigation can fundamentally alter this pattern. After dry soils are rewetted, microbial activity recovers, accumulated NO_3^- and soluble organic carbon are rapidly utilized, and distinct emission peaks may occur over short periods[21]. If flood irrigation or inefficient irrigation rapidly raises WFPS into the denitrification-sensitive range, N_2O production can increase markedly. Therefore, EFs in drylands are highly sensitive to rainfall events, irrigation methods, and fertilization timing. Under precision irrigation, EF may remain low, whereas high emission risks may occur when irrigation is poorly managed or when fertilization overlaps with rewetting.

In cool temperate and high-latitude croplands, low temperature and freeze–thaw processes become key controls. Low temperatures during the growing season may suppress microbial activity and keep emissions relatively low, but non-growing-season and spring-thaw periods may contribute substantially to annual emissions. If residual inorganic nitrogen remains after autumn fertilization, high soil moisture, low oxygen availability, and microbial recovery during spring thaw can jointly trigger N_2O emission pulses[22]. Heavy-textured soils retain more water and restrict gas diffusion during freeze–thaw periods, making prolonged low-oxygen microsites more likely. These emissions often show temporal displacement: fertilization occurs in the previous season, whereas emission risk is concentrated during thaw in the following year. Conventional annual-average EF methods may therefore underestimate this process.

2.3. Differences among Crops and Cropping Systems

The influence of crop type and cropping system on EF reflects the combined differences in crop physiology, nitrogen management, field water regime, and residue input. Different crops vary in nitrogen demand, root architecture, growing-season length, and management practices, thereby affecting nitrogen uptake efficiency, residual soil nitrogen, and soil microenvironment. High-nitrogen-input vegetables, tea plantations, and some cash crop systems usually have higher emission risks. Rice and paddy–upland rotation systems show complex N_2O emission patterns due to flooding, drainage, and drying–rewetting processes[2]. Perennial crops and grasslands may show different EF patterns because of differences in root uptake capacity and soil structure.

Crop type itself is not a purely biological variable but a comprehensive reflection of an agricultural management system. Maize, wheat, rice, and vegetables differ not only in root structure and nitrogen demand but also in fertilization intensity, irrigation method, residue treatment, and growing-season arrangement. Maize and vegetable systems often involve high nitrogen inputs; when crop uptake does not match nitrogen application, residual inorganic nitrogen accumulates in soil and emission risk increases[2]. In rice systems, long-term flooding may promote complete denitrification, but drainage, mid-season drying, or paddy–upland rotation reintroduces oxygen and alters the coupled nitrification–denitrification pathway, increasing N_2O emissions during specific stages[23]. Perennial grasslands and forage systems often have stronger root uptake and more stable soil structure, but dung and urine patches or localized high-nitrogen inputs can still create emission hotspots.

Therefore, differences in EF among crops should not be attributed simply to crop identity. Crop type should be understood as the combined outcome of crop physiology, field management, and regional cropping system. Future crop-specific EF development should consider crop nitrogen uptake, fertilization regime, water management, and residue return simultaneously, rather than grouping solely by crop name.

3. MAIN DRIVERS OF CROPLAND N_2O EMISSION FACTORS

3.1. Regulation by Soil Properties

Soil properties determine the baseline responsiveness of cropland systems to nitrogen input. Soil pH, SOC, texture, and moisture status are among the most consistently identified key factors[4]. These variables do not affect N_2O emissions in isolation; instead, they jointly shape EF by regulating nitrogen substrate availability, oxygen diffusion, microbial activity, and N_2O reduction capacity.

Soil pH is closely related to the product ratio of denitrification. During denitrification, NO_3^- is reduced stepwise to NO, N_2O, and N_2. Whether N_2O can be further reduced to N_2 is crucial for net emissions. Low pH suppresses N_2O reductase activity, making denitrification more likely to terminate at the N_2O stage. Qu et al. (2014) found a significant negative relationship between pH and the $N_2O/(N_2O + N_2)$ product ratio in an incubation experiment using soils from long-term fertilization trials. Wang et al.[9]based on a global meta-analysis, also showed that EF increased as pH decreased and that acidic soils were more sensitive to nitrogen input. Therefore, acidic soils are more likely to generate high N_2O emissions and may lead fixed-EF methods to underestimate actual emissions. Long-term excessive nitrogen application can also cause soil acidification, further amplifying fertilizer-induced emissions and forming a “nitrogen input–acidification–high EF” feedback chain[24].

SOC regulates denitrification by providing carbon substrates and shaping soil microenvironments. Denitrifying microorganisms require available carbon as an electron donor; therefore, under sufficient moisture and nitrogen substrates, soils with high SOC usually have stronger denitrification potential[25]. SOC also affects aggregate structure, pore distribution, and water retention, thereby influencing the formation of low-oxygen microsites[26]. However, SOC does not always increase emissions. When moisture is insufficient, nitrogen substrates are limited, or oxygen diffusion conditions are unsuitable, the stimulatory effect of SOC may be weak. In a meta-analysis of conservation tillage, Mei et al. [27]found that SOC was not always a stable predictor of changes in N_2O emissions. SOC is therefore better understood as a condition-dependent factor whose effect depends on moisture, nitrogen supply, and soil structure.

Soil texture regulates N_2O emissions by affecting water retention, aeration, and gas diffusion. Clay-rich soils are more likely to develop low-oxygen microsites, favoring denitrification. Sandy soils have better aeration, which may enhance nitrification, but sustained denitrification conditions are less likely[28]. Rochette et al. [7]proposed the use of soil texture for EF stratification, indicating that texture can serve as an important basis for regional EF refinement. Texture also modifies the effects of fertilizer and rainfall events. For example, the same heavy rainfall event is more likely to restrict oxygen diffusion in heavy-textured soils, whereas in sandy soils it may be more strongly associated with nitrogen leaching.

Soil moisture is the key variable linking soil physical conditions with microbial nitrogen transformations. At low WFPS, nitrification tends to dominate. At intermediate to moderately high WFPS, nitrification and denitrification may occur simultaneously, and N_2O emission risk is often highest. At very high WFPS, complete denitrification may be enhanced, allowing N_2O to be further reduced to N_2. Therefore, the effect of moisture on EF shows clear threshold characteristics rather than a simple linear relationship. The impacts of rainfall, irrigation, drying–rewetting, and freeze–thaw processes on EF are fundamentally related to rapid changes in soil moisture and oxygen diffusion status.

3.2. Effects of Climate Conditions

Climate conditions influence EF by regulating soil hydrothermal status and crop growth processes. Climate not only determines the regional mean hydrothermal background but also affects the timing of fertilization, crop growth, and extreme events, thereby altering N_2O emission risks.

Precipitation affects N_2O emissions by increasing soil moisture, restricting oxygen diffusion, and promoting denitrification. In arid and semi-arid regions, precipitation or irrigation often relieves water limitation and rapidly increases emissions. In humid regions, precipitation more often controls the timing and magnitude of emission peaks. Grace et al.[10] reported that in Australian rain-fed systems, the EF of synthetic nitrogen fertilizer increased with annual rainfall. Together, these studies indicate that precipitation is a key variable linking climatic background with soil denitrification processes.

Temperature regulates N_2O emissions mainly through microbial activity, nitrogen mineralization, and nitrification and denitrification rates. Under sufficient moisture and substrate conditions, warming generally promotes N_2O production. Under drought, however, high temperature may intensify water stress and limit microbial processes. Dobbie and Smith [29]observed an exponential relationship between daily N_2O fluxes and soil temperature, but temperature effects usually need to be interpreted together with moisture. High temperature, high moisture, and high nitrogen substrate availability are most likely to produce emission peaks.

Differences among climate zones further demonstrate the regional dependence of EF. In dry regions, water is often the limiting factor. In humid regions, the dominant controls often shift toward pH, SOC, texture, and management practices. Cold regions also require consideration of freeze–thaw processes and non-growing-season emissions. Climate is therefore not merely a background variable; it determines which soil and management factors become dominant. If fixed EFs ignore climate-zone differences, they may overestimate emissions in water-limited regions and underestimate emissions in humid, acidic, high-input systems.

3.3. Effects of Cropland Management Practices

Cropland management practices directly alter nitrogen input, carbon and nitrogen substrate supply, and soil microenvironment, making them important anthropogenic drivers of EF. Compared with soil and climate conditions, management practices are more directly adjustable by human intervention and are therefore central to agricultural N_2O mitigation.

Nitrogen application rate is the most direct driver, but its relationship with N_2O emissions is not simply linear. In a continuous maize system, McSwiney and Robertson [30] found that N_2O fluxes remained low when nitrogen application was below crop demand but increased markedly once nitrogen exceeded crop requirements. The meta-analysis by Kim et al. [31] also showed that N_2O emissions followed exponential or hyperbolic responses to nitrogen input in most multi-rate datasets. Thus, excessive nitrogen application, rather than nitrogen application itself, better explains high EF risk. Improving nitrogen use efficiency and reducing nitrogen surplus are fundamental strategies for lowering EF.

Fertilizer type affects nitrogen release rates and carbon–nitrogen substrate supply. Synthetic fertilizers rapidly increase inorganic nitrogen substrates, whereas organic fertilizers supply both nitrogen and available carbon and may stimulate denitrification. Zhou et al.[32] showed that manure application can stimulate soil N_2O emissions and may partly offset the carbon benefits associated with organic amendments. Consistently, Xia et al.[33] found that manure-induced N_2O responses varied strongly with climate, crop type, manure characteristics, and WFPS, with the net manure-induced EF being broadly comparable to those reported for synthetic N fertilizer and crop residues. Therefore, fertilizer-type effects must be evaluated in relation to soil moisture, pH, SOC, and climatic background. In humid, acidic, and high-SOC conditions, carbon inputs from organic fertilizers may significantly enhance denitrification potential. Under water-limited conditions or when nitrogen release is slow, their emission effect may be weaker.

Tillage affects N_2O emissions by changing soil structure, aeration, residue distribution, and SOC. Conservation tillage may increase SOC and water retention, but it may also promote the formation of low-oxygen microsites near the soil surface. Mei et al. [27] found that the effect of conservation tillage on N_2O emissions varied substantially among scenarios, indicating that its mitigation effect cannot be generalized. Crop type reflects nitrogen demand, root characteristics, residue input, and field management systems. High-nitrogen-input crops and vegetable systems usually have higher emission risks, whereas rice, upland grain crops, and perennial grasslands involve different emission mechanisms. Nitrification inhibitors and urease inhibitors can reduce N_2O emissions by delaying nitrogen transformation and reducing nitrogen losses, but their effectiveness depends on temperature, moisture, soil texture, and fertilization method[34]. Therefore, the mitigation effects of management practices should be evaluated within specific cropland contexts rather than treated as universally applicable measures.

4. MULTIFACTORIAL INTERACTIONS AND RESEARCH ADVANCES

4.1. Interactions and Nonlinear Responses

Cropland N_2O emissions are rarely controlled by a single factor. Interactions are common between pH and nitrogen application, moisture and temperature, SOC and precipitation, and fertilizer type and soil texture[4]. In acidic soils, added nitrogen is more likely to be converted into high N_2O emissions. High-SOC soils tend to develop strong denitrification only when moisture and nitrogen substrates are sufficient. High temperature promotes emissions under humid conditions but may be constrained by moisture limitation under drought. Fertilizer-type effects also depend on soil and climatic background; organic fertilizer may substantially enhance denitrification potential in humid acidic soils but have weaker effects under water-limited conditions[35].

These interactions indicate that EF variability is not a simple sum of individual factors but is jointly determined by soil, climate, and management[36]. High-emission risks often occur when several unfavorable conditions overlap, such as acidic soil, high SOC, high nitrogen input, and heavy rainfall. In such scenarios, acidic conditions increase the N_2O/N_2 product ratio, high SOC provides carbon for denitrification, high nitrogen input increases NO_3^- substrates, and heavy rainfall restricts oxygen diffusion. These factors jointly promote N_2O production and accumulation. Compared with managing a single factor, identifying these high-risk combinations is more useful for targeted mitigation.

Nonlinearity is another important consensus in EF research. Nitrogen application rate, pH, WFPS, SOC, and temperature may all show thresholds or sensitive ranges in their effects on N_2O emissions[37]. Emissions often increase rapidly once nitrogen application exceeds crop demand. When pH declines beyond a certain range, N_2O reduction becomes constrained and EF may rise markedly. At intermediate to moderately high WFPS, nitrification and denitrification can coexist, resulting in high N_2O emission risk. The effect of SOC may also strengthen rapidly once carbon is no longer limiting. Conventional linear models are poorly suited to describing such responses, whereas random forests, gradient boosting models, and other machine-learning methods can more effectively identify nonlinear structures. Interpretable methods such as SHAP and ALE further help evaluate variable importance and response curve shapes. Their significance lies not only in improving prediction accuracy but also in revealing which factors matter most within specific ranges, thereby moving EF research from average-effect comparison toward threshold identification and risk-scenario diagnosis.

4.2. Extreme Events and Emission Pulse Risks

Extreme events represent an important emission source that fixed-EF methods cannot adequately capture. Cropland N_2O emissions often show strong pulse characteristics, with a small number of key events contributing substantially to annual emissions. Drying–rewetting, freeze–thaw cycles, extreme rainfall, and heat events can rapidly alter soil moisture, oxygen diffusion, substrate release, and microbial activity, thereby triggering emission peaks[38].

Drying–rewetting is especially important in arid and semi-arid regions. During drought, NO_3^- and soluble organic carbon may accumulate in soil while microbial activity remains constrained. After rewetting, soil moisture increases rapidly, microbial activity recovers, oxygen diffusion becomes limited, and accumulated substrates are rapidly consumed, producing short-term N_2O emission peaks. This process is often regarded as an important "hot moment" for N_2O emissions in drylands. Barton et al. [20]found that a large proportion of annual emissions in semi-arid cropland occurred after rainfall events during fallow periods, indicating that the timing and intensity of rainfall events can explain some high-emission phenomena better than annual precipitation alone.

Freeze–thaw cycles are important pulse processes in cold regions. During thawing, meltwater increases soil moisture, oxygen diffusion becomes limited, disrupted aggregates and dead microbial biomass release available carbon and nitrogen substrates, and the recovery of microbial activity can trigger denitrification emissions[39]. If residual inorganic nitrogen remains after autumn fertilization, emission risk during spring thaw increases further. Therefore, EF in cold regions cannot be judged only from growing-season fertilization and mean temperature; cross-season nitrogen carryover and freeze–thaw dynamics must also be considered.

Extreme rainfall after fertilization can rapidly increase WFPS and create anaerobic microsites. When heavy rainfall coincides with high NO_3^- availability, high SOC, or acidic soil background, emission peaks may become more pronounced. Heat events can increase emission potential by stimulating microbial metabolism and nitrogen transformations, but their effect depends strongly on soil moisture. N_2O emissions are most likely to increase when high temperature coincides with high moisture. When heat occurs under severe drought, microbial processes may be constrained by water limitation, and emissions may not increase.

Therefore, annual mean temperature and annual precipitation alone cannot fully explain EF. Future EF systems need to incorporate event frequency, event intensity, and event timing, especially the temporal relationship between fertilization and rainfall, irrigation, freeze–thaw, or rewetting. The key significance of extreme-event research is not only to explain short-term emission peaks but also to indicate that inventory methods should move from mean-climate backgrounds toward dynamic frameworks that combine background conditions with event triggers.

4.3. Data-Driven Research and Model Development

With the accumulation of observational data, cropland N_2O EF research is entering a data-driven stage. Meta-analysis can integrate field trials across regions and identify major influencing factors, while machine learning can handle complex nonlinear relationships and multifactorial interactions. Random forests, gradient boosting models, and neural networks can be used to predict EF and generate spatially explicit EF maps[35]. Interpretable machine learning further improves the ecological interpretability of model results, allowing researchers to analyze variable contributions, response thresholds, and differences in regional dominant drivers.

The value of data-driven research lies in its ability to re-identify EF driving structures in larger samples and more complex variable systems. Traditional statistical methods often require predefined linear relationships or simple interaction terms, whereas machine learning can capture complex nonlinear relationships among pH, SOC, precipitation, temperature, and management practices. Methods such as SHAP and ALE further shift model interpretation from black-box prediction toward mechanism-informed understanding, providing a new technical pathway for identifying high-risk scenarios[40].

Nevertheless, data-driven models still face extrapolation limitations. Regions underrepresented in training datasets, such as tropical croplands, Africa, and South America, are associated with greater prediction uncertainty. In addition, low-frequency manual chamber measurements may miss emission peaks and underestimate annual emissions. More high-frequency automated flux observations, long-term field experiments, and cross-regional databases are needed to improve model reliability.

The integration of process-based models and machine learning is likely to be an important future direction. Process-based models can represent soil carbon and nitrogen cycling, hydrothermal dynamics, and microbial processes, whereas machine learning is effective at identifying complex patterns and key variables. Combining the two can help build dynamic EF systems with both predictive capacity and mechanistic constraints. Remote sensing information on soil moisture, vegetation indices, and crop growth may also provide continuous inputs for regionalized EF estimation. An ideal future EF framework should be able to use dynamic models in data-rich regions, apply regional correction parameters in data-limited regions, and update continuously as observations accumulate.

5. CONCLUSIONS AND PERSPECTIVES

The central question in cropland N_2O EF research has shifted from "what value should a unified emission factor take?" to "why do emission factors vary, and how can such variation be predicted under different scenarios?" Existing studies show that EF is not a fixed property of nitrogen fertilizer itself but a dynamic parameter shaped by soil background, climatic conditions, and agricultural management. Soil pH, SOC, texture, and moisture determine the basic environment for N_2O production and reduction. Precipitation and temperature shape regional differences and interannual variability. Nitrogen application rate, fertilizer type, tillage, and cropping system directly alter nitrogen substrate supply and soil microenvironment. Drying–rewetting, freeze–thaw cycles, and extreme rainfall further increase the pulse-like nature and uncertainty of EF.

Future research should advance in four directions. First, global cropland N_2O observation databases should be improved, with particular attention to data gaps in tropical and subtropical regions, Africa, South America, and dryland agricultural systems, in order to enhance the regional representativeness of EF models. Second, high-frequency observations and extreme-event experiments should be strengthened to capture emission peaks after fertilization, rainfall, drying–rewetting, freeze–thaw, and heat events. Third, nonlinear responses and multifactorial interactions should be given more attention, rather than continuing to rely on simple linear relationships to explain EF. Fourth, machine learning, remote sensing data, and process-based models should be integrated to develop regionalized, dynamic, and mechanism-constrained EF systems.

Overall, cropland N_2O EF research is moving from empirical accounting toward mechanistic explanation and dynamic prediction. Fixed EFs remain useful as baseline accounting tools, but they are no longer sufficient for precise inventories and targeted mitigation management. Only by integrating soil background, climatic conditions, management practices, and extreme events into a unified framework can high-emission risk scenarios be more accurately identified and more reliable scientific support be provided for agricultural nitrogen management and greenhouse gas mitigation.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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REFERENCE

[1] Ju, X.-t., & Zhang, C. (2017). Nitrogen cycling and environmental impacts in upland agricultural soils in North China: A review. *Journal of Integrative Agriculture*, *16*(12), 2848–2862. https://doi.org/10.1016/s2095-3119(17)61743-x

[2] Tian, H., et al. (2020). A comprehensive quantification of global nitrous oxide sources and sinks. *Nature*, *586*(7828), 248–256. https://doi.org/10.1038/s41586-020-2780-0

[3] IPCC. (2006). N_2O emissions from managed soils and CO_2 emissions from lime and urea application. In H. S. Eggleston, L. Buendia, K. Miwa, T. Ngara, & K. Tanabe (Eds.), *2006 IPCC guidelines for national greenhouse gas inventories: Vol. 4. Agriculture, forestry and other land use* (Chapter 11). Institute for Global Environmental Strategies.

[4] Yue, Q., et al. (2019). Deriving emission factors and estimating direct nitrous oxide emissions for crop cultivation in China. *Environmental Science & Technology*, *53*(17), 10246–10257. https://doi.org/10.1021/acs.est.9b01285

[5] Hergoualc'h, K., Mueller, N., Bernoux, M., Kasimir, A., van der Weerden, T. J., & Ogle, S. M. (2021). Improved accuracy and reduced uncertainty in greenhouse gas inventories by refining the IPCC emission factor for direct N_2O emissions from nitrogen inputs to managed soils. *Global Change Biology*, *27*(24), 6536–6550. https://doi.org/10.1111/gcb.15884

[6] Zhang, L., Zhang, X., Gao, Q., & Yan, L. (2023). Nitrogen application effect on maize yield, NH_3, and N_2O emissions in Northeast China by meta-analysis. *Agronomy*, *13*(6), 1479. https://doi.org/10.3390/agronomy13061479

[7] Rochette, P., et al. (2018). Soil nitrous oxide emissions from agricultural soils in Canada: Exploring relationships with soil, crop and climatic variables. *Agriculture, Ecosystems & Environment*, *254*, 69–81. https://doi.org/10.1016/j.agee.2017.10.021

[8] Qiu, L., et al. (2023). Nitrogen addition stimulates N_2O emissions via changes in denitrification community composition in a subtropical nitrogen-rich forest. *Journal of Environmental Management*, *348*, 119274. https://doi.org/10.1016/j.jenvman.2023.119274

[9] Wang, Y., Yao, Z., Zheng, X., Subramaniam, L., & Butterbach-Bahl, K. (2022). A synthesis of nitric oxide emissions across global fertilized croplands from crop-specific emission factors. *Global Change Biology*, *28*(14), 4395–4408. https://doi.org/10.1111/gcb.16193

[10] Grace, P., et al. (2023). Revised emission factors for estimating direct nitrous oxide emissions from nitrogen inputs in Australia's agricultural production systems: A meta-analysis. *Soil Research*, *62*(1). https://doi.org/10.1071/sr23070

[11] Amundson, R., et al. (2023). Simultaneous production and consumption of soil N_2O creates complex effects on its stable isotope composition. *Global Biogeochemical Cycles*, *37*(9). https://doi.org/10.1029/2022gb007536

[12] Duan, J., et al. (2024). Agricultural management practices in China enhance nitrogen sustainability and benefit human health. *Nature Food*, *5*(5), 378–389. https://doi.org/10.1038/s43016-024-00953-8

[13] Cayuela, M. L., et al. (2017). Direct nitrous oxide emissions in Mediterranean climate cropping systems: Emission factors based on a meta-analysis of available measurement data. *Agriculture, Ecosystems & Environment*, *238*, 25–35. https://doi.org/10.1016/j.agee.2016.10.006

[14] Cheng, Y., Wang, J., Zhang, J.-B., Müller, C., & Wang, S.-Q. (2014). Mechanistic insights into the effects of N fertilizer application on N_2O-emission pathways in acidic soil of a tea plantation. *Plant and Soil*, *389*(1–2), 45–57. https://doi.org/10.1007/s11104-014-2343-y

[15] Wang, Y., et al. (2020). Tea-planted soils as global hotspots for N_2O emissions from croplands. *Environmental Research Letters*, *15*(10). https://doi.org/10.1088/1748-9326/aba5b2

[16] Wagner-Riddle, C., Congreves, K. A., Brown, S. E., Helgason, W. D., & Farrell, R. E. (2024). Overwinter and spring thaw nitrous oxide fluxes in a northern prairie cropland are limited but a significant proportion of annual emissions. *Global Biogeochemical Cycles*, *38*(4). https://doi.org/10.1029/2023gb008051

[17] Liu, J., et al. (2023). Crop residue return achieves environmental mitigation and enhances grain yield: A global meta-analysis. *Agronomy for Sustainable Development*, *43*(6). https://doi.org/10.1007/s13593-023-00928-2

[18] Ottaiano, L., Di Mola, I., Di Tommasi, P., Mori, M., Magliulo, V., & Vitale, L. (2020). Effects of irrigation on N_2O emissions in a maize crop grown on different soil types in two contrasting seasons. *Agriculture*, *10*(12), 623. https://doi.org/10.3390/agriculture10120623

[19] Tang, H., Huang, Y., Yuan, J., Hassan, M. U., Liu, N., & Yang, B. (2023). Effects of typical cropping patterns of paddy-upland multiple cropping rotation on rice yield and greenhouse gas emissions. *Agronomy*, *13*(9), 2384. https://doi.org/10.3390/agronomy13092384

[20] Barton, L., et al. (2007). Nitrous oxide emissions from a cropped soil in a semi-arid climate. *Global Change Biology*, *14*(1), 177–192. https://doi.org/10.1111/j.1365-2486.2007.01474.x

[21] Li, X., Leizeaga, A., Rousk, J., Hugelius, G., & Manzoni, S. (2023). Drying intensity and acidity slow down microbial growth recovery after rewetting dry soils. *Soil Biology and Biochemistry*, *184*. https://doi.org/10.1016/j.soilbio.2023.109115

[22] Lei, S., et al. (2025). Long-term legacy impacts of nitrogen fertilization on crop yield, nitrate accumulation, and nitrogen recovery efficiency. *European Journal of Agronomy*, *164*. https://doi.org/10.1016/j.eja.2025.127513

[23] Tang, Y., Minasny, B., & McBratney, A. (2024). Partitioning denitrification pathways in N_2O emissions from re-flooded dry paddy soils. *Biogeochemistry*, *167*(10), 1315–1333. https://doi.org/10.1007/s10533-024-01164-w

[24] Zhang, Y., et al. (2022). Soil acidification caused by excessive application of nitrogen fertilizer aggravates soil-borne diseases: Evidence from literature review and field trials. *Agriculture, Ecosystems & Environment*, *340*. https://doi.org/10.1016/j.agee.2022.108176

[25] Chen, L., Liu, Q., Du, H., Cui, J., & Chen, Y. (2024). Organic materials return suppressed soil N_2O emissions by changing the composition instead of abundance of denitrifying microbial community. *Applied Soil Ecology*, *204*. https://doi.org/10.1016/j.apsoil.2024.105759

[26] Zhou, M., et al. (2020). Soil aggregates stability and storage of soil organic carbon respond to cropping systems on black soils of Northeast China. *Scientific Reports*, *10*(1), 265. https://doi.org/10.1038/s41598-019-57193-1

[27] Mei, K., et al. (2018). Stimulation of N_2O emission by conservation tillage management in agricultural lands: A meta-analysis. *Soil and Tillage Research*, *182*, 86–93. https://doi.org/10.1016/j.still.2018.05.006

[28] Wang, C., Amon, B., Schulz, K., & Mehdi, B. (2021). Factors that influence nitrous oxide emissions from agricultural soils as well as their representation in simulation models: A review. *Agronomy*, *11*(4), 770. https://doi.org/10.3390/agronomy11040770

[29] Dobbie, K. E., & Smith, K. A. (2002). The effects of temperature, water-filled pore space and land use on N_2O emissions from an imperfectly drained gleysol. *European Journal of Soil Science*, *52*(4), 667–673. https://doi.org/10.1046/j.1365-2389.2001.00395.x

[30] McSwiney, C. P., & Robertson, G. P. (2005). Nonlinear response of N_2O flux to incremental fertilizer addition in a continuous maize (*Zea mays* L.) cropping system. *Global Change Biology*, *11*(10), 1712–1719. https://doi.org/10.1111/j.1365-2486.2005.01040.x

[31] Kim, D.-G., Hernandez-Ramirez, G., & Giltrap, D. (2013). Linear and nonlinear dependency of direct nitrous oxide emissions on fertilizer nitrogen input: A meta-analysis. *Agriculture, Ecosystems & Environment*, *168*, 53–65. https://doi.org/10.1016/j.agee.2012.02.021

[32] Zhou, M., Zhu, B., Wang, S., Zhu, X., Vereecken, H., & Bruggemann, N. (2017). Stimulation of N_2O emission by manure application to agricultural soils may largely offset carbon benefits: A global meta-analysis. *Global Change Biology*, *23*(10), 4068–4083. https://doi.org/10.1111/gcb.13648

[33] Xia, F., Mei, K., Xu, Y., Zhang, C., Dahlgren, R. A., & Zhang, M. (2020). Response of N_2O emission to manure application in field trials of agricultural soils across the globe. *Science of the Total Environment*, *733*, 139390. https://doi.org/10.1016/j.scitotenv.2020.139390

[34] Fan, D., et al. (2022). Global evaluation of inhibitor impacts on ammonia and nitrous oxide emissions from agricultural soils: A meta-analysis. *Global Change Biology*, *28*(17), 5121–5141. https://doi.org/10.1111/gcb.16294

[35] Ge, X., Xie, D., Mulder, J., & Duan, L. (2024). Reevaluating the drivers of fertilizer-induced N_2O emission: Insights from interpretable machine learning. *Environmental Science & Technology*, *58*(35), 15672–15680. https://doi.org/10.1021/acs.est.4c04574

[36] Cui, X., et al. (2021). Global mapping of crop-specific emission factors highlights hotspots of nitrous oxide mitigation. *Nature Food*, *2*(11), 886–893. https://doi.org/10.1038/s43016-021-00384-9

[37] Shcherbak, I., Millar, N., & Robertson, G. P. (2014). Global meta-analysis of the nonlinear response of soil nitrous oxide (N_2O) emissions to fertilizer nitrogen. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(25), 9199–9204. https://doi.org/10.1073/pnas.1322434111

[38] An, Z., Bork, E. W., Olefeldt, D., Carlyle, C. N., & Chang, S. X. (2022). Simulated heat wave events increase CO_2 and N_2O emissions from cropland and forest soils in an incubation experiment. *Biology and Fertility of Soils*, *58*(7), 789–802. https://doi.org/10.1007/s00374-022-01661-w

[39] Risk, N., Snider, D., & Wagner-Riddle, C. (2013). Mechanisms leading to enhanced soil nitrous oxide fluxes induced by freeze–thaw cycles. *Canadian Journal of Soil Science*, *93*(4), 401–414. https://doi.org/10.4141/cjss2012-071

[40] Saha, D., Basso, B., & Robertson, G. P. (2021). Machine learning improves predictions of agricultural nitrous oxide (N_2O) emissions from intensively managed cropping systems. *Environmental Research Letters*, *16*(2). https://doi.org/10.1088/1748-9326/abd2f3