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RESEARCH ARTICLE

Enhanced nitrous oxide emission factors due to climate change increase the mitigation challenge in the agricultural sector

Linchao Li[1] | Chaoqun Lu[1] | Wilfried Winiwarter[2,3] | Hanqin Tian[4,5] | Josep G. Canadell[6] | Akihiko Ito[7,8] | Atul K. Jain[9] | Sian Kou-Giesbrecht[10] | Shufen Pan[4,11] | Naiqing Pan[4] | Hao Shi[12] | Qing Sun[13] | Nicolas Vuichard[14] | Shuchao Ye[1] | Sönke Zaehle[15] | Qing Zhu[16]

Correspondence
Chaoqun Lu, Department of Ecology, Evolution, and Organismal Biology, Iowa State University, Ames, Iowa, USA.
Email: clu@iastate.edu

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Abstract

Effective nitrogen fertilizer management is crucial for reducing nitrous oxide (N_2O) emissions while ensuring food security within planetary boundaries. However, climate change might also interact with management practices to alter N_2O emission and emission factors (EFs), adding further uncertainties to estimating mitigation potentials. Here, we developed a new hybrid modeling framework that integrates a machine learning model with an ensemble of eight process-based models to project EFs under different climate and nitrogen policy scenarios. Our findings reveal that EFs are dynamically modulated by environmental changes, including climate, soil properties, and nitrogen management practices. Under low-ambition nitrogen regulation policies, EF would increase from 1.18%–1.22% in 2010 to 1.27%–1.34% by 2050, representing a relative increase of 4.4%–11.4% and exceeding the IPCC tier-1 EF of 1%. This trend is particularly pronounced in tropical and subtropical regions with high nitrogen inputs, where EFs could increase by 0.14%–0.35% (relative increase of 11.9%–17%). In contrast, high-ambition policies have the potential to mitigate the increases in EF caused by climate change, possibly leading to slight decreases in EFs. Furthermore, our results demonstrate that global EFs are expected to continue rising due to warming and regional drying–wetting cycles, even in the absence of changes in nitrogen management practices. This asymmetrical influence of nitrogen fertilizers on EFs, driven by climate change, underscores the urgent need for immediate N_2O emission reductions and further assessments of mitigation potentials. This hybrid modeling framework offers a computationally efficient approach to projecting future N_2O emissions across various climate, soil, and nitrogen management scenarios, facilitating socio-economic assessments and policy-making efforts.

KEYWORDS
climate change, emission factors (EFs), global warming, nitrogen regulation pathways, nitrous oxide (N_2O), sustainable development goals

For affiliations refer to page 14.

1 | INTRODUCTION

Nitrous oxide (N_2O) is one of the powerful and long-lived greenhouse gases (GHG). Its atmospheric concentration has increased by approximately 24.8% from pre-industrial levels to 2023 (Lan et al., 2024). Among all known N_2O surface emission sources, agricultural soil accounts for around 50% of the anthropogenic N_2O emissions (Shcherbak et al., 2014; Tian et al., 2020). Emissions of N_2O from soil have been rising, particularly in recent decades, largely due to increased nitrogen (N) inputs from fertilizers (Lu et al., 2022; Thompson et al., 2019). Although sufficient N fertilizer application is essential for food supply (Ahvo et al., 2023), overfertilization gives rise to N pollution leading to annual global economic costs of around 200–2000 billion US$ (Kanter, Winiwarter, et al., 2020; Sutton et al., 2013), especially for the financial expenses associated with mitigating N_2O emissions (Feng & Li, 2023). Furthermore, a wide variety of studies argue that the effectiveness of GHG mitigation is likely to decrease due to global warming (Köberle et al., 2021; Shaaban, 2024; Xu et al., 2022; Yao et al., 2024), suggesting an urgency of early mitigation (Peng & Guan, 2021). Many studies seek to develop mitigation strategies that balance crop yields with reduced GHG emissions without compromising crop productivity in specific regions (Burney et al., 2010; Lamb et al., 2016; Lugato et al., 2018). Several mitigation pathways have been developed (Gu et al., 2023; Kanter, Chodos, et al., 2020; Sutton et al., 2021), which provide general insights into how current N policies impact future environmental scenarios and targeted interventions for N pollution reduction. However, the applicability of these regionally specific hypotheses has not been fully tested on global scales, which limits our understanding of hotspot areas for N_2O emission mitigation. More importantly, how effective different N regulating policies will be under the future climate has not been systematically investigated. This knowledge gap may lead to missing key timing for actions to effectively reduce N_2O emissions, that is relevant for simultaneously achieving both Goal 2 (Zero Hunger) and Goal 13 (Climate Action) of the United Nations Sustainable Development Goals (United Nation, 2015).

The N_2O emission factor (EF) is a widely used bottom-up approach for estimating anthropogenic soil N_2O emissions from N fertilizer input. The recent report by the Intergovernmental Panel on Climate Change (IPCC) suggests a default EF (tier-1) (Hergoualc'h et al., 2019; Klein, 2006) and more detailed country-specific EFs (tier-2) to guide the N_2O emission assessment. Despite being easy to use, this approach overlooks the large variance and long-term dynamics of EF due to different environmental conditions such as climate, soil, and management (Lesschen et al., 2011; Shcherbak et al., 2014; Wang, Zhou, et al., 2020). EF change is mainly attributed to factors like environmental conditions, N fertilizer input rate, soil properties, or carbon substrates (Hu et al., 2016; Nelson et al., 2016; Shcherbak et al., 2014; Venkiteswaran et al., 2014). However, these attribution analyses are often based on short-term field observations that may not fully represent the long-term impacts of climate change (Harris et al., 2022) and evolving nitrogen management practices on EF dynamics. Although evaluating the spatial patterns of EF based on statistical models and field observations could provide insights into mitigation potentials and N_2O emission projections (Cui et al., 2021; Harris et al., 2022), EF dynamics under climate change are not adequately addressed in the existing EF maps. This oversight may result in biases in EF-based estimates of N_2O emissions and lead to a failure in identifying the optimal timing for implementing effective mitigation strategies (Harris et al., 2022). Such a lapse not only impedes the accuracy of global N_2O estimations but also hampers policymakers from developing more effective mitigation strategies over both short- and long-term periods.

Process-based models represent another bottom-up approach to dynamically project N input-induced N_2O emissions by simulating biological and biogeochemical processes in croplands and pasture lands, where N fertilizer is a primary input source, under climate change and different management practices (Del Grosso et al., 2022; Tian et al., 2018, 2019). These models provide dynamic predictions of N_2O emissions driven by climate and environmental data. However, their application is limited by the requirement for input data preparation, extensive model calibration and validation (Ouatahar et al., 2021; Sandor et al., 2018), process representation, and substantial computational resources, particularly when various N management scenarios and future climate scenarios are assessed for N_2O emission projection (Perlman et al., 2014; Tian et al., 2018). In the era of big data, artificial intelligence has become increasingly influential in fields based on large datasets (Delavaux et al., 2023; Ham et al., 2019; Reichstein et al., 2019; Wang et al., 2023; Xu et al., 2024). However, these approaches (e.g., machine learning and deep learning) can mainly provide references for responses under current conditions (Franke et al., 2020), and projects integrating different potential future N management and climate scenarios are challenging. Furthermore, statistical models can be misleading due to the lack of detailed understanding of processes and causal relationships (Feng et al., 2019). Thus, it may be of interest to develop a hybrid approach that combines the advancement of process-based models and machine learning to emulate the process-based model behaviors (Xiao et al., 2024). Such statistical emulations could offer an efficient and timely approach to estimating the efficacy of mitigation strategies under different climate scenarios.

Here, we develop a modeling framework that employs machine learning to emulate the behavior of eight state-of-the-art process-based terrestrial biosphere model ensembles from the global Nitrogen/N_2O Model Inter-comparison Project phase 2 (NMIP2) (Tian et al., 2024). This approach can dynamically evaluate global EF for N fertilizer input-induced N_2O emission projections with improved accuracy, effectively combining the two bottom-up methods. We then perform an attribution analysis of EF change based on our dynamic EF (Dym-EF) model. Finally, we estimate the potential change of EF based on seven N management scenarios from 2010 to 2050, each N management scenario with a corresponding climate scenario based on 37 global climate models (GCMs) (Figure 1). The objectives of this study are to (1) explore the key factors influencing EFs and their potential changes over time; (2) reveal the nonlinear relationships between EFs and environmental factors; (3) dynamically project EF under various nitrogen mitigation strategies and climate scenarios; (4) identify the opportunities and hotspots with high EF

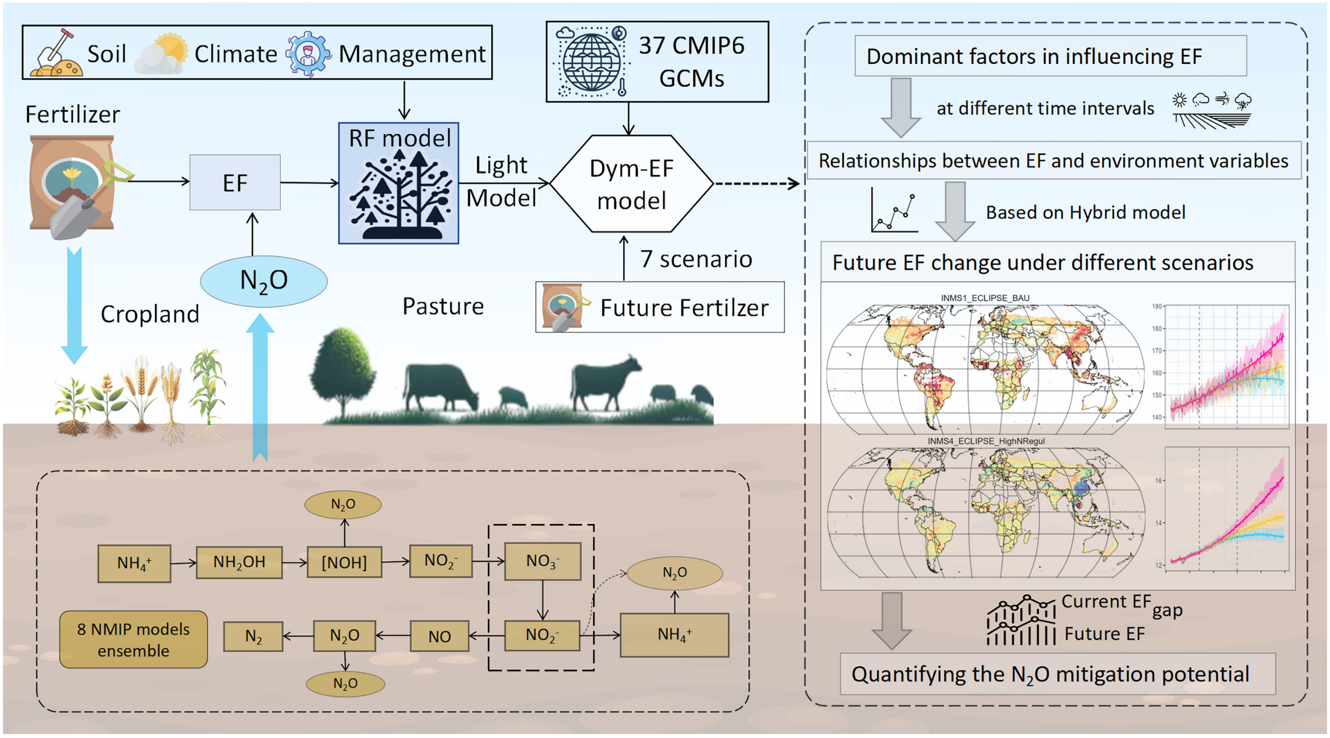

FIGURE 1 Modeling framework integrating machine learning and process-based model ensembles (NMIP2) for assessing global nitrogen fertilizer input-induced nitrous oxide (N_2O) emission factors (EFs) and projecting EF change under various climate and N management scenarios. The NMIP2 was performed under 0.5°×0.5° resolution. This modeling framework was used to emulate the NMIP2 ensemble behaviors rather than individual NMIP2 models. RF, Random Forest model; seven scenarios including INMS1, business-as-usual; INMS2, low N regulation (Low ambition); INMS3, medium N regulation (moderate ambition); INMS4, high N regulation (High ambition); INMS5, best case (High ambition); INMS6, best-case plus (High ambition); INMS7, Bioenergy (High ambition); NMIP, global N_2O model intercomparison project. Dym-EF, Dynamic EF.

reduction potentials from seven nitrogen regulation policies at three ambition levels that have been developed under the International Nitrogen Management System (INMS) project (Kanter, Winiwarter, et al., 2020). The INMS scenarios combine specific policies to reduce nitrogen pollution with the shared socioeconomic pathways (SSP: Riahi et al. (2017)) and the representative concentration pathways (RCP: Van Vuuren et al. (2011)) developed under the IPCC. This study can improve our understanding of balancing policies, N_2O emission, and food production under future climate scenarios, which is crucial for developing effective mitigation strategies. Moreover, this Dym-EF modeling framework offers flexibility and can easily extend to other different nitrogen management scenarios, providing a broader and timely evaluation of global GHG mitigation potentials.

2 | DATA AND METHODS

2.1 | Estimating the N_2O EF by learning the non-linear EF dynamics from the NMIP2 model ensemble

In this study, we estimate the N_2O EFs based on eight process-based Terrestrial Biosphere models that participate in N_2O Model Intercomparison Project phase 2 (NMIP2) (Tian et al., 2018, 2024), including CLASSIC, DLEM, ELM, ISAM, LPX-Bern, OCN, ORCHIDEE, and VISIT. These models integrate the impacts of atmospheric N deposition, biological N fixation, manure N application, and N fertilizer use on the nitrogen cycle processes related to N_2O emissions (Tian et al., 2019, 2020). Each of the models uses a "Demand and Supply-driven" approach for plant N uptake. Differences in how models represent nitrification and denitrification processes and their contributions to N_2O emissions with the modification of climate and agricultural management practices are a main source of uncertainty in our estimates. More information on the N_2O emission approaches in NMIP2 models is described in Tian et al. (2024). A set of factorial simulations was performed to disentangle the respective contribution of drivers to the N_2O emissions. Among these simulations, the SH1 aims to estimate the dynamics of N_2O emission in response to changes in Climate + CO_2 + Land cover + Irrigation + N deposition + N Fertilizer + Manure N; while the SH3 yields the estimates of N_2O emissions without considering N fertilizer input, that is estimations driven by changes in Climate + CO_2 + Land cover + Irrigation + N deposition + Manure N. To estimate the EF, we first obtain the N_2O emissions directly resulting from N fertilizer inputs that were calculated using SH1–SH3 (i.e., simulations with vs. without N fertilizer input). We estimate the annual EF from 1961 to 2020 allowing us to assess how changes in warming trends and nitrogen application rates have influenced the variation in EFs. The NMIP2 models were driven by consistent input datasets, including nitrogen inputs, atmospheric CO_2 concentrations, daily climate variables, irrigation, and land cover changes, ensuring a standardized basis for comparison and analysis of global N_2O estimation. Most models output monthly N_2O estimates (Tian et al., 2024). The complete list of abbreviations is shown in Table S1.

2.2 | N regulation scenarios

Optimizing management practices can improve N use efficiency (NUE) and reduce N_2O emissions (Winiwarter et al., 2018). These N policy data have been used to estimate the N pollution globally (Cui et al., 2024; Kanter, Chodos, et al., 2020). Thus, understanding the potential changes in N_2O emissions from food production under future land management scenarios (based on current and potential technological advancements) is essential for developing more comprehensive and cohesive nitrogen strategies, while additionally reducing the conflicts in food production and its environmental impacts (Gu et al., 2023; Kanter, Chodos, et al., 2020). They have been formalized by Kanter, Winiwarter, et al. (2020), who developed seven scenarios within the SSP/RCP framework that include three different levels of policy ambition to tackle nitrogen pollution in general (low, moderate, and high ambitions to remove nitrogen pollution, See Table 1), as part of the project Towards an International Nitrogen Management System (INMS: see https://www.inms.international). In this paper, we use projections of synthetic N fertilizer consumption as implemented in the GAINS model (Amann et al., 2011; Winiwarter et al., 2018) and in accordance with these seven scenarios.

2.2.1 | High ambition N regulation scenarios

The high-ambition scenarios align with the sustainable development goals, which extend to 2030. These ambition levels include four distinct approaches: high N regulation (INMS4, under RCP4.5 and SSP2), the “best case” (INMS5, under RCP4.5 and SSP1), the “best-case plus” (INMS6, under RCP4.5 and SSP1), and bioenergy (INMS7, under RCP2.6 and SSP1). The high ambition N regulation level represents technological advancements within the period of the sustainable development goals until 2030. The “best case” scenario envisages ambitious climate action combined with a strong commitment to sustainable agriculture and low-meat diets in line with the expectations under SSP1. The best-case “plus” scenario extends this ambition further, incorporating significant dietary changes and reducing food loss. As for the bioenergy scenario, improving bioenergy production is likely crucial for achieving the targets of a 1.5°C and 2°C world. From an N perspective, the RCP 4.5 scenario appears to be more favorable than RCP 2.6, unless substantial efforts are undertaken to improve NUE in bioenergy production in RCP 2.6. Generally, the high nitrogen policy ambition is expected to achieve the target NUE by 2030 and maintain it through to 2100 (Kanter, Winiwarter, et al., 2020).

2.2.2 | Moderate ambition N regulation scenario

The moderate ambition (Medium N regulation, INMS3, under RCP4.5 and SSP2) scenario aims to achieve the same goals but over a longer period, either by 2050 or 2070. It expects countries to continue their current high-input, low-efficiency N fertilizer for 30 years before making improvements.

2.2.3 | Low ambition N regulation scenarios

The low ambition scenarios indicate no significant improvement and a stagnant NUE. The INMS1 scenario assumes a continuation of past trends (RCP8.5 and SSP5) while INMS2 considers climate policy (RCP4.5 and SSP2) but little policy attention to N pollution.

To integrate the seven scenarios, we employed the relative change metrics, comparing the future period (2011–2050) against a baseline period (1990–2010). This approach was used to align with the NMIP2 nitrogen (N) input data, which include synthetic N fertilizer. Since the NMIP-derived EFs used to train our Dym-EF model were based on specific NMIP N fertilizer data, the nitrogen regulation pathways from INMS1–S7 could not be directly applied

TABLE 1 The seven future climate, land use, diet, and N management scenarios.

Name	Scenario	Climate	Land use regulation	Productivity	Diet	Ambition level
INMS1	Business-as-usual	RCP8.5	Medium	High	Meat & dairy-rich	Low
INMS2	Low nitrogen regulation	RCP4.5	Medium	Medium	Medium meat & dairy	Low
INMS3	Medium nitrogen regulation	RCP4.5	Medium	Medium	Medium meat & dairy	Moderate
INMS4	High nitrogen regulation	RCP4.5	Medium	Medium	Medium meat & dairy	High
INMS5	Best-case	RCP4.5	Strong	High	Low meat & dairy	High
INMS6	Best-case “Plus”	RCP4.5	Strong	High	Ambitious diet shift and food loss/waste reductions	High
INMS7	Bioenergy	RCP2.6	Strong	High	Low meat & dairy diet	High

Note: Modified from Kanter, Winiwarter, et al. (2020). The colors represent different scenarios.

as inputs to project future EFs. Consequently, we adapted the seven scenarios to align with the NMIP inputs as follows:

$$NFer_{S\_NMIP} = NFer_{H\_NMIP} + RN \times NFer_{H\_NMIP}, \tag{1}$$

$$RN = \frac{(S\_INMS - His\_INMS)}{His\_INMS}, \tag{2}$$

where the $NFer_{S\_NMIP}$ represents the synthetic fertilizer N input for the seven NMIP-compatible scenarios (2011–2050), $NFer_{H\_NMIP}$ is the historical NMIP synthetic fertilizer N input data (1990–2010), RN is the relative change, S_INMS represents the seven future scenarios (Table 1), and His_INMS is the historical N input data for these N regulation scenarios during 1990–2010. We developed the N management data at gridded scales with 0.5° by 0.5° grids. Through the above approach, we have developed a set of N input data tailored to these seven future scenarios for NMIP2. This ensures that the scenarios are appropriately linked to the current NMIP's N input data, thereby facilitate the creation of a series of detailed N input scenarios. Figure S1 shows the total N inputs under seven scenarios during 1961–2050.

2.3 | Climate data

We collect monthly temperature and precipitation data from 37 GCMs under SSP126 (SSP1, RCP2.6), SSP245 (SSP2, RCP4.5), and SSP585 (SSP5, RCP8.5) of CMIP6 (Table S2). The use of 37 global climate models (GCMs) allows for comprehensive coverage of the range of equilibrium climate sensitivity (ECS) and transient climate response (TCR) values (Meehl et al., 2020). This breadth is crucial for adequately representing the spectrum of potential climate change scenarios. To match the resolution of NMIP2 input, we resample these GCMs to 0.5° by 0.5° grids. Since the historical data from the GCMs exhibit discrepancies when compared with NMIP2 inputs, we employ the delta approach for bias correction at grid scales:

$$GCM_b = GCM_{raw} + Delta, \tag{3}$$

where the GCMb is the bias-corrected GCMs during 2011–2050, GCMraw is the raw GCMs climate variable (seasonal temperature and precipitation, and annual aridity index) during 2011–2050, and Delta is Observed Historical Data–Model Historical during 1980–2010. In a few small arid regions where bias correction resulted in negative precipitation values, we adjusted these to zero. NMS1 corresponds to SSP5 ("Fossil-fueled Development"), INMS2–S4 corresponds to SSP2 ("Middle of the Road"), and INMS5–S7 corresponds to SSP1 ("Sustainability"). However, since SSP1-4.5 is not available for all GCMs (O'Neill et al., 2016), we use climate projections from SSP2-4.5 to approximate it and assemble the scenarios of best-case and best-case+ (INMS5–S6) as the combination of moderate-mitigation climate, sustainable development (SSP1), and high ambition N regulation policies. More details can be found in Kanter, Winiwarter, et al. (2020). Figures S2 and S3 show the time series for precipitation and temperature, and their changes over areas of nitrogen application. Generally, there is a significant increase in temperature across various scenarios, especially under SSP585. Precipitation demonstrates a slight increase, with SSP126 marginally exceeding SSP245 and SSP585 during 2011–2050.

2.4 | Developing an explainable model to project EF change

The process-based models are capable of estimating nonlinear responses of N_2O emissions through various biophysical processes, such as nitrification and denitrification. These models consider factors that potentially impact N_2O emissions and EFs, such as soil properties (including soil pH, initial soil organic carbon content, bulk density, and clay content), as well as environmental conditions like precipitation and temperature, along with management practices. Several studies have compared N_2O models in agriculture under historical conditions (Ehrhardt et al., 2018; Fuchs et al., 2020). However, for future projections, these models require substantial computational resources (Franke et al., 2020) and are challenging to apply directly to a large number of GCMs for assessing the N_2O dynamics under climate change scenarios. Statistical models can capture the nonlinear relationship between N_2O emissions and environmental variables. However, these statistically based models do not incorporate biophysical processes, and their performance largely depends on the quality and quantity of the available data (Li et al., 2023). Thus, there is growing interest in developing a hybrid model (or statistical emulation) that combines the advantages of both approaches, providing a more efficient and flexible method for estimating N_2O emissions.

In this study, we use the Random Forest (RF) model to reproduce the multimodel median of NMIP2 EF based on the NMIP2 input data (Tian et al., 2024). The climate data include seasonal temperature and precipitation and yearly aridity index (AI). The soil data consisted of pH, initial soil organic carbon content (DOM_SOC), soil bulk density (BULK_DEN), percentage of sandy content (PCT_SAND), and clay content (PCT_CLAY). Management data included synthetic nitrogen fertilizer (NFer) and irrigation (Irr). We excluded grids where both cropland and pasture cover are less than 10%. In addition, we find the EF from the NMIP2 ensemble is highly sensitive to nitrogen inputs when the N input was less than 0.1 kg N/ha/year. To ensure the accuracy of the Dym-EF model, we exclude data grids with extremely high EF caused by a lower N input, as well as those grids where the N input was less than 0.1 kg N/ha/year, noting that atmospheric deposition alone often exceeds this level in many regions. Such extremely high EFs for low fertilizer inputs are likely artifacts from the NMIP2 models. Notably, to encompass a wider range of environmental conditions, our Random Forest (RF) model was trained on yearly data spanning 60 years (1961–2020) from NMIP2. This training allows us to dynamically generate annual EFs at a high spatial resolution of 0.5° × 0.5°.

We performed the RF model using the "ranger" package in R 4.1.1, optimizing the two hyperparameters (n_{tree} and m_{try}) with the "caret" package. The n_{tree} parameter is the number of decision trees in the RF model, and the m_{try} parameter determines the number of features to consider at each split. The extensive size of our dataset, which was comprised of over one million datasets made tuning hyperparameters with the entire dataset challenging. Therefore, we used data from the most recent 10 years (2011–2020) as a representative subset to calibrate the hyperparameters. We set the range for "m_{try}" from 1 to 9 in steps of 2, and for "n_{tree}" from 100 to 900 in steps of 200 (refer to Figure S4). We find that when m_{try} was set as 7 and n_{tree} at 700 or "m_{try}" at 5 and "n_{tree}" at 900, the model can achieve optimal performance with RMSE is 0.32 and the R^2 is .775. However, there is a trade-off between model performance and computational demand. Although such hyperparameters can provide better performance, they require significant computational resources. A setting of "n_{tree}" at 500 and "m_{try}" at 7 offered a similar performance (RMSE of 0.32% and R^2 of .774) but with a significantly reduced computational load. Consequently, we selected these values (m_{try} = 7 and n_{tree} = 500) as the final hyperparameters for our model. To evaluate our model's performance at each grid. Then, we aggregated the results from these periods to assess the overall performance through R^2 and RMSE across the 60 years (1961–2020). Our approach showed reliable model performance with an R^2 higher than .9 and an RMSE lower than 0.1 in most regions (Figures S5 and S6). Although N fertilizer is known to significantly influence EF (Akiyama et al., 2006; Wang et al., 2011), it casts doubt on the models' efficacy when solely using N fertilizer for EF estimation. Therefore, we compared the model performance of estimating EF using only N rates with using multiple environmental variables. The results showed that the predictions based solely on N fertilizer were not as reliable as those using multi-source environmental data (Figures S5 and S6). This indicates that EF is affected not only by N management but also significantly by different environmental conditions. Generally, our modeling framework demonstrates reliable performance both at the grid level and in the combined overall assessment.

2.5 | Attribution analysis

To identify the dominant factors influencing the EF, the Shapley additive explanations (SHAP) value was used to quantify the contribution of each predictor. We explain the overall impact of different predictors of estimating the EF using the mean absolute SHAP value. For a more granular and detailed explanation at the grid level, the SHAP values are more efficient to explain the dominant factors influencing the EF across different time intervals. The SHAP can isolate the impact of different variables on the EF. This approach, based on work in game theory (Lundberg & Lee, 2017), is used to determine how each individual factor affects a team's overall performance. It has been extensively applied in quantifying the marginal contributions of each predictor to the target variable (Chen et al., 2022; Chen, Cheng, et al., 2023; Li et al., 2022; Wang et al., 2023). The management and climate change significantly between different periods, especially for N input. Thus, in our study, to effectively capture how different environmental conditions influence the EF, we divide the study period into three time intervals: 1961–1990, 1991–2020, and 2021–2050. The period of 2021–2050 was analyzed using multi-GCM model ensembles under various future scenarios (INMS1–S7). Since INMS5 (best-case scenario) and INMS6 (best-case "plus") exhibit similar characteristics, we chose INMS6 to represent both in our analysis. We use the absolute value of SHAP values and select the highest values as the dominant factor.

2.6 | Partial dependence

We use the partial dependence plots (PDPs) to analyze the marginal effects of predictors, including soil, climate, and management variables, on the EF. The PDP plots can effectively capture the nonlinear relationship between different environmental variables and EF. In this study, we use the "pdp" package of R 4.1.1 to analyze their nonlinear impact on EF (Greenwell, 2017).

3 | RESULTS AND DISCUSSION

3.1 | Dominant drivers in influencing EF

We developed a Dym-EF model by learning the relationship between the median ensemble estimates of eight process-based models from NMIP2 and a time-series gridded database of key environmental factors such as climate, soil properties, and agricultural management at a spatial resolution of 0.5° during 1961–2020. The grid-based RF model is proven to have a great performance in reproducing NMIP2 EF estimates over space and time (see Section 2 and Figures S4 and S5). For temporal variation, we assessed the R^2 and RMSE for each grid with a great performance for most regions (Figure S6). We found that temperature in June, July, and August (T_JJA); nitrogen fertilizer (NFer); precipitation in June, July, and August (Pr_JJA); and precipitation in September, October, and November (Pr_SON), are the most important factors influencing EF (Figure S7). Summer temperature and summer/fall precipitations have a higher importance in determining EF dynamics than climate variables in other seasons, possibly because the NMIP2 model ensembles do not have information on fertilizer application timing in the input data and models assume one application without side-dressing or equal daily distribution of fertilizer input during crop-growing season. NFer directly influences soil nitrogen content, significantly impacting EF. However, the combined effects of various seasonal climate variables are higher than the influence of N fertilizer alone in determining EF. The climate conditions in the northern summer months (JJA) are crucial for the growth of summer crops like corn and soybean, which frequently undergo nitrogen management (Lu et al., 2022; Maier et al., 2022). In addition, the warmer temperature and high soil moisture in summer can also create a suitable environment condition for nitrification and denitrification processes in the soil and thus increase the EF. In autumn (SON), cumulative precipitation often leads to soil saturation throughout the year, creating anaerobic conditions, especially when

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combined with residual nitrogen from fertilizers applied during the growing season, thus, increasing the denitrification and N_2O emissions (Glenn et al., 2021; Perego et al., 2016; Vinzent et al., 2018). Our results showed that climate factors and N fertilizer are more important in altering EF than the initial soil properties. This is probably because soil conditions and processes are cumulatively impacted by long-term climate variables (e.g., temperature and precipitation) and management, which might overshadow the effects of initial soil properties. More importantly, changes in climate and management practices could further enhance their dominance in influencing the long-term trends of EFs (Baral et al., 2022).

In this study, we found the dominant factors influencing EF are not constant but change with different environmental conditions (e.g., climate and management) (Figure 2a), particularly in high EF and N input regions. For instance, in Southeast Asia, the dominant drivers have shifted from spring temperature (T_MAM) and N fertilizer to summer temperature possibly due to increased heatwaves. The increasing temperature combined with wet conditions enhances nitrification and denitrification rates, leads to an increase in both the abundance and activity of ammonia oxidizers and denitrifiers, and thereby amplifies N_2O emissions (Dai et al., 2020; Griffis et al., 2017). Similarly, Central Europe, the US Corn-Belt and Rice-Belt areas, Southeast Asia, and Southwest China exhibited a shift in dominant EF drivers from NFer to summer precipitation (T_JJA) and temperature. This change suggests that in areas with high nitrogen input levels, EF is likely more sensitive to environmental change due to the increased interaction of increased nitrogen input and climate change (Xu, Tian, et al., 2020). By contrast, in South America and Africa, where N input has been historically low, we found a significant shift from temperature being the dominant driver during 1961–1990 to the N fertilizer use rate during 1991–2020 This indicated that enhanced N input may be more important in explaining the EF dynamics. Moreover, increased nitrogen leads to faster soil organic matter decomposition (Li et al., 2017) and changes in agriculture management practices with different nitrogen uptake efficiencies (Sainju et al., 2020; Thapa et al., 2016). In several regions (e.g., BRA and SAS), climate variables tend to become the predominant factors influencing EF when nitrogen inputs are increased. We found that T_SON is the dominant factor influencing EFs across most regions during 1961–1990, while summer temperatures (T_JJA) emerged as the primary influence in most regions during the period 1991–2020 (Figure 2b). This transition is likely due to global warming's intensified effects during the summer months in recent decades (Butterbach-Bahl et al., 2013; Xu, Chen, et al., 2020), making summer conditions, along with heightened nitrogen inputs, more impactful on EFs compared to the relatively cooler autumn. Similarly, the summer precipitation also increased the dominance of EF in many regions (Figure 2b), likely because the recent increase in precipitation has raised soil moisture levels, thereby enhancing microbial activities such as nitrification and denitrification, which in turn, elevate N_2O emissions (Yue et al., 2024). This finding is crucial in understanding the combined effects of climate change and nitrogen management on EF, which is key to developing effective strategies for reducing N_2O emissions.

3.2 | Relationships between EF and multiple environmental factors

The nonlinear relationships reveal the effects of various environmental variables on EF (Figure 3), which may increase and decrease by up to 10% or even more due to a single variable. Although the EF has a positive relationship with temperature, they have different response curves in different seasons. In JJA and SON, EF largely increases when temperatures exceed 2–6°C, whereas in spring month (MAM), EF increases consistently with temperature (Figure 3). In early spring, soil freeze–thaw cycles, particularly in the Northern Hemisphere, significantly drive N_2O emissions through different mechanisms such as enhanced biological denitrification, changes in microbial composition and enzyme activity, and the release of trapped N_2O (Del Grosso et al., 2022; Wagner-Riddle et al., 2017). Therefore, EF can still increase with temperature even in a cold condition. However, it is important to note that these dynamics may not be fully captured by NMIP2 models, unlike those that have improved processes such as Del Grosso et al. (2022). EF's response to seasonal precipitation shows an increase up to a specific threshold, beyond which additional precipitation has little impact on EF. This threshold varies by season, likely influenced by the soil's water-holding capacity, different plant growth stages and their water uptake, and the seasonally varying rates of evaporation due to temperature changes (Bell et al., 2016; Cayuela et al., 2017). The EF also increases with NFer use level, albeit at a slower rate when annual fertilizer input is higher. Compared with different soil properties, soil pH is the most critical factor influencing EF (Figure S7). It is possibly because the soil PH mainly impacts EF the denitrifier community composition (Qiu et al., 2024). EF shows a negative relationship with pH, particularly when pH is above 5–5.3 (Figure 3), similar to previous studies (Russenes et al., 2016; Shang et al., 2024; Wang et al., 2018). In moderately acidic soils, alterations in soil microbial communities and chemical reactions favor N_2O-producing microorganisms, potentially increasing N_2O emissions (Qiu et al., 2024). Additionally, these conditions enhance processes such as denitrification, leading to higher N_2O emissions even at lower nitrate levels (Tierling & Kuhlmann, 2018; Zhang et al., 2021). The higher presence of ammonium (NH_4^+) coupled with conditions conducive to denitrification can lead to elevated emissions of nitrous oxide (N_2O). Consequently, soil acidification in the future may significantly increase the risk of N_2O emissions (Chen, Xiao, & Chen, 2023).

3.3 | Projecting EF under different scenarios

Our projections up to 2050, including for the SSP585, generally fall within the historical data range, indicating the reliability of our near-future projections based on our Dym-EF model. For historical

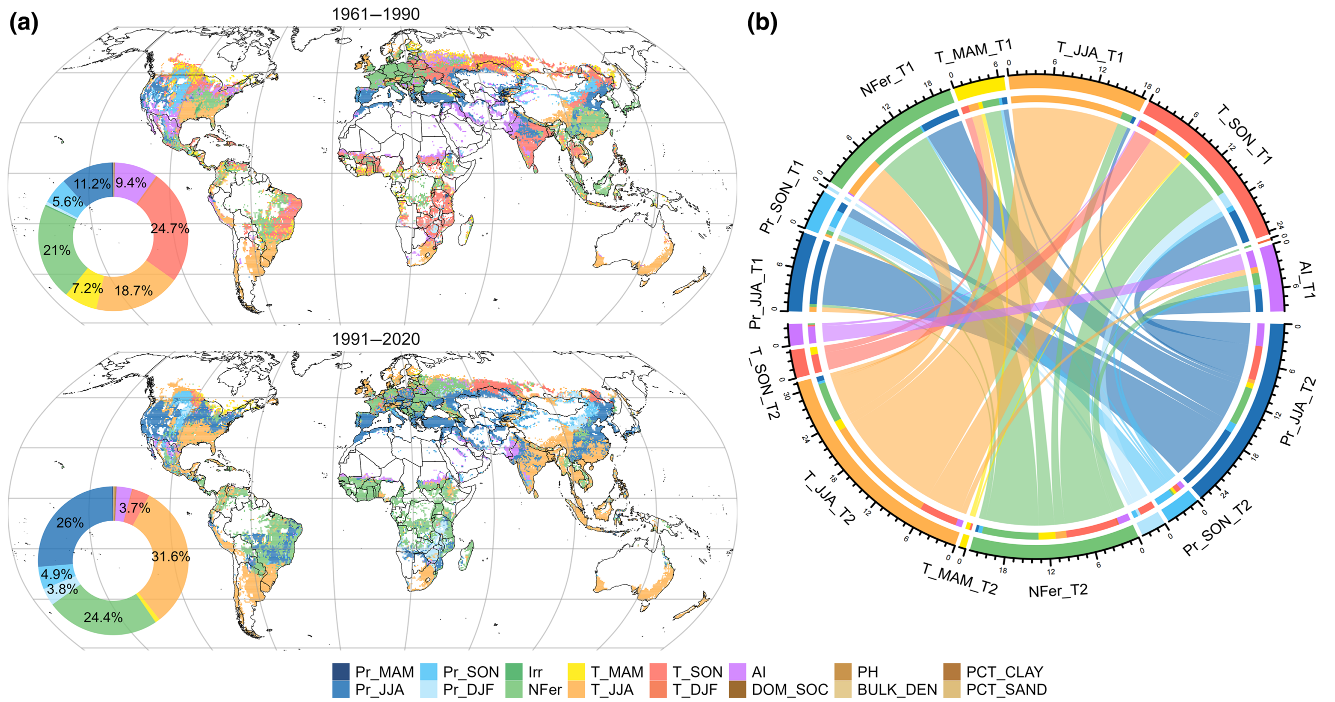

FIGURE 2 The dominant driver of N_2O emission factor (EF) at each pixel and the partial dependence of EF on different variables. (a) Spatial map showing the primary factors influencing EF, with pie charts depicting the percentage area of dominant factors across different time intervals and scenarios. (b), Chord diagram to demonstrate the shift of the dominant factor in influencing EF from T1 (1961–1990, upper half of circle) to T2 (1991–2020, lower half of circle). Numbers represent the percentage of the area influenced by each variable, with different colors indicating different variables. Linked variables (such as T_SON_T1 to NFer_T2) illustrate the shift in dominant factors from T1 to T2. Variables consist of Irr (irrigation rate), NFer (nitrogen fertilizer), Pr_MAM (total precipitation in March, April, and May), Pr_JJA (total precipitation in June, July, and August), Pr_SON (total precipitation in September, October, and November), Pr_DJF (total precipitation in December, January, and February), T_MAM (mean temperature in March, April, and May), T_JJA (mean temperature in June, July, and August), T_SON (mean temperature in September, October, and November), T_DJF (mean temperature in December, January, and February), and AI (aridity index); DOM_SOC, soil organic carbon; BULD_DEN, soil bulk density. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

periods, we found that the multimodel ensemble estimates of EFs in 2010 had exceeded the IPCC's default average value of 1% in most regions. Compared to the generalized IPCC Tier-1 EF of 1%, spatially detailed EFs enable the identification of regional hotspots with significant N_2O mitigation potential. Areas with higher EFs often correspond to higher nitrogen inputs, potentially leading to an underestimation of N_2O emissions when using the uniform IPCC Tier-1 EF. Furthermore, in humid areas, EFs are consistent with or exceed the IPCC suggested average of 1.6% (IPCC default at humid regions) (Hergoualc'h et al., 2019), and in tropical regions like southern Asia, eastern Asia, and Central America, EFs often surpass 2%–2.5% (Figure 4). The relatively higher EF in humid and warm areas is attributable to the climate acceleration of microbial processes like nitrification and denitrification (Griffis et al., 2017). Higher soil moisture and temperature create conditions conducive to denitrifying microbes. Moreover, in humid regions where anaerobic conditions are more prevalent, denitrification becomes a dominant process and subsequently elevates EFs (Griffis et al., 2017; Rowlings et al., 2015; Veldkamp et al., 1998).

The EFs under various scenarios over the future periods are projected to change significantly, compared with 2010. This is mainly attributed to the changes in alternative N regulation practices and future climatic scenarios (Figure 4; Figure S8). Detailed information about these different scenarios is provided in Table 1. Under the INMS scenarios 1–3 (i.e., business-as-usual, low, and mediate ambition N regulation), the global average EFs by 2030 are projected to increase to 1.22%–1.29% among different GCMs (relative increase of 0.5%–8.0% from 2010 levels of 1.18%–1.22%), 1.22%–1.28% (relative increase of 0.03%–6.3%), and 1.18%–1.24% (relative increase of 0.01%–2.5%), respectively, compared with 2010. By 2050, the EF is expected to increase to 1.27%–1.34% (4.4%–11.4%), 1.24%–1.31% (2.8%–9.9%), and around 1.18%–1.25% (0.01%–3.2%). Under the INMS4 (high ambition N regulation) scenario, EF is projected to decrease to 1.15–1.21 (0%–5%) by 2030, aligning with INMS3's projection by 2050 (Figure S9). The EF changes under INMS5–S7 (Best-case, Best-case "plus," and Bioenergy) would be similar to INMS4, yet slightly lower than INMS4 due to further reduction in N input. This raises the question here: why do high-ambition strategies with reduced N input only slightly decrease or sometimes even increase EFs? It is likely caused by the high sensitivity of EFs to climate (Griffis et al., 2017); as climate change intensifies (Figures S2 and S3), the increases in EFs might offset the benefits of high-ambition strategies.

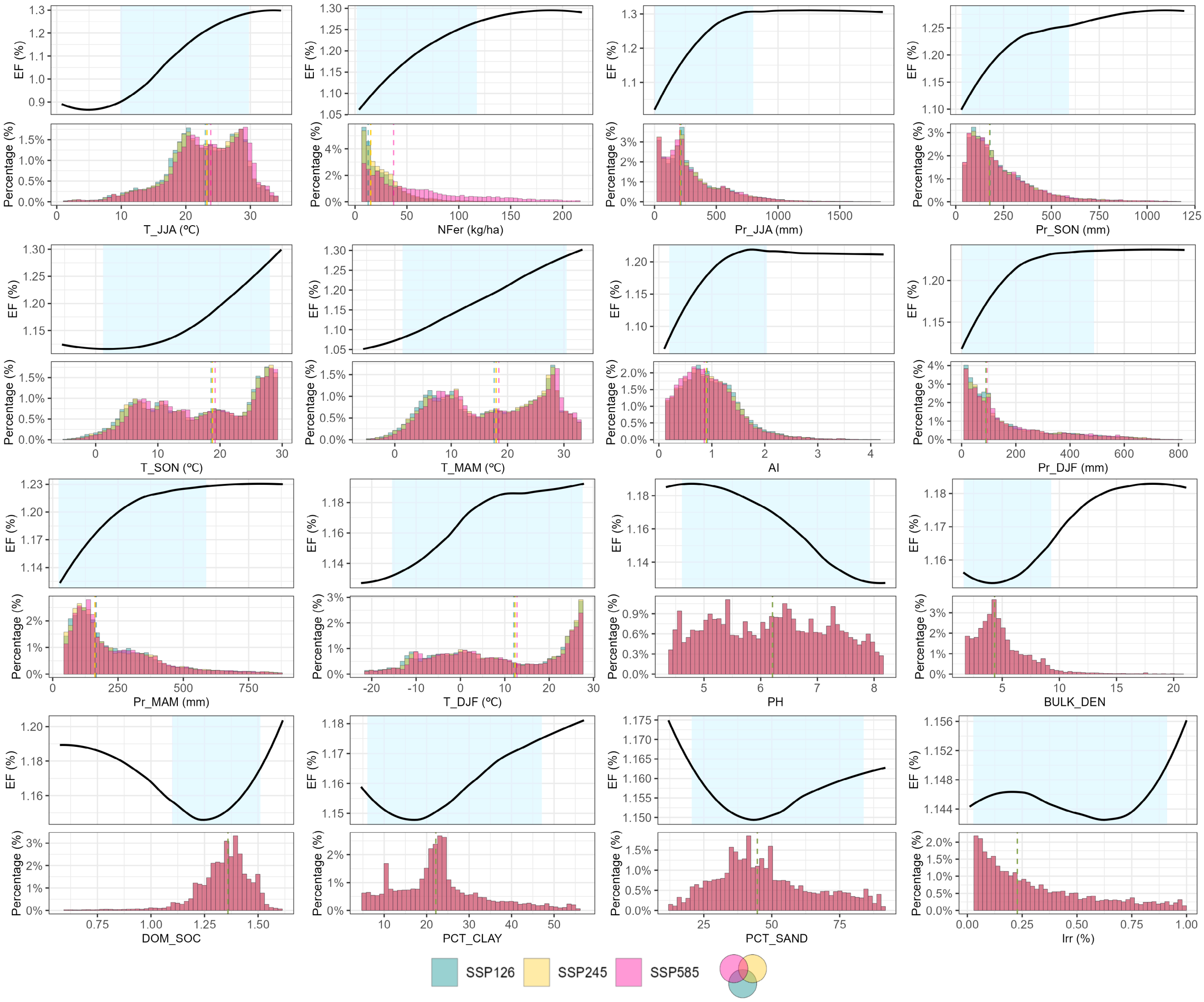

FIGURE 3 Partial dependence plots for annual emission factor change across different predictors (ranked by feature importance see Figure S7). The smooth black lines depict the average model's response, alongside fitted values for the calibration data. Histograms display the probability distributions for the indices of SSP126, SSP245, and SSP585 scenarios in 2050. The blue shaded area denotes calibration data ranging between the 5th and 95th percentiles.

The INMS1 and INMS2 scenarios are characterized by a lack of dedicated nitrogen management, which will not change nitrogen use efficiency (NUE) and, with increased production, greater nitrogen loss, thus increasing EFs (Baral et al., 2017). The EF under INMS1 is slightly higher than INMS2 perhaps because more N input and higher temperature under SSP585 will further amplify the EF due to increased soil N mineralization and denitrification rates (Kanter et al., 2016; Revell et al., 2015). The moderate and high-ambition scenarios, aimed at minimizing N loss and increasing NUE, are projected to keep crop N surpluses within planetary boundaries until 2050 (Kanter, Winiwarter, et al., 2020; Zhang et al., 2015), which potentially decreases EF. In addition, the high ambition scenarios (INMS4–S7) also consider dietary shifts, like reduced meat consumption and waste (Geyik et al., 2023; Revell et al., 2015). These changes could lower the demand for N-intensive animal feed crops, reducing N use and consequently reducing N_2O emissions and EFs (Figure 4; Figure S8).

Compared with the IPCC's default value (Hergoualc'h et al., 2019), our Dym-EF modeling characterizes EF variability over space and time by taking into account the effects of environmental factors, and various climate scenarios and ambition levels of N intervention over the coming decades. This improved methodology is crucial for making informed management decisions in mitigation strategies. Relying on a stationary EF fails to capture the various impacts of climate change, soil properties, and management practices. For example, if the EF increased from 1% to 1.1% due to climate warming, keeping EF unchanged could lead to a 10% underestimation of N_2O emissions. The underestimation would be more pronounced when nitrogen inputs are increased. Our results showed that densely populated areas in developing countries typically exhibit large differences

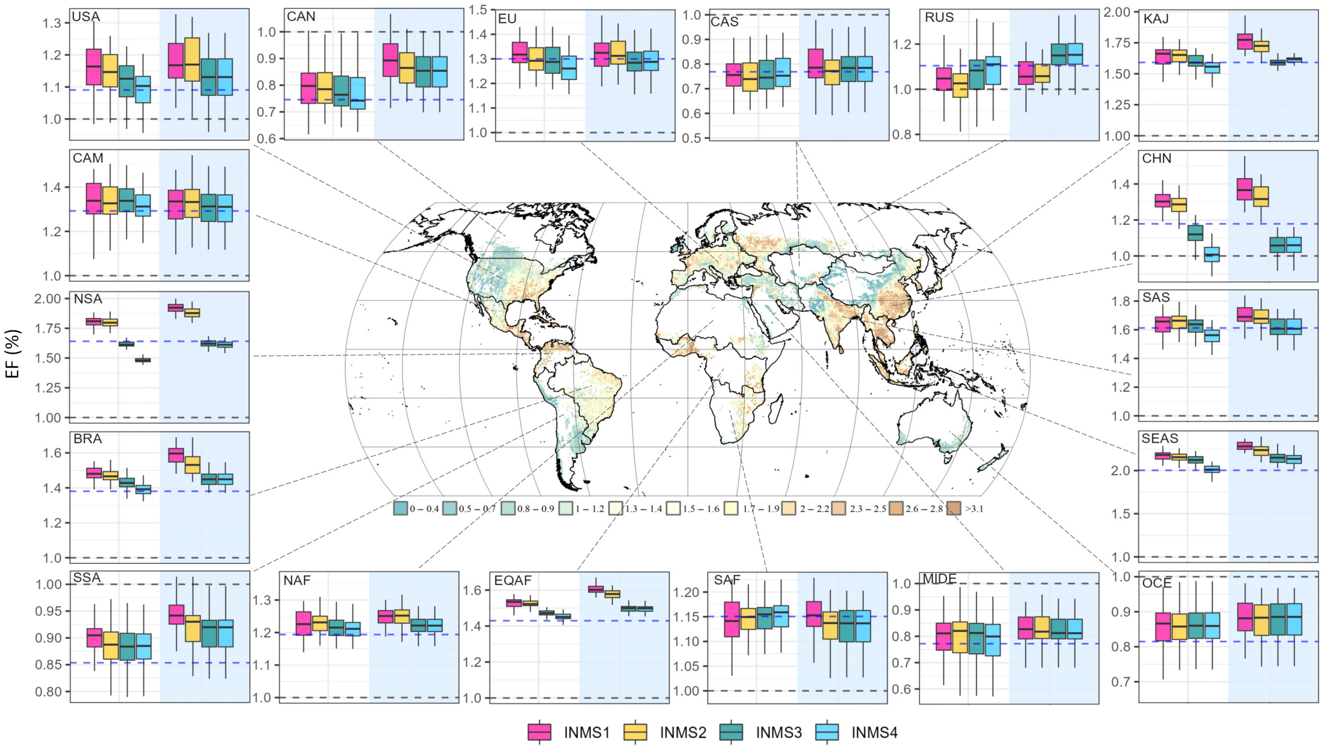

FIGURE 4 Projected N_2O emission factor (EF) across various subregions in 2030 (white area) and 2050 (blue-shaded area). The spatial map indicates the median EF estimated by NMIP ensembles in 2010. The black dashed line in each panel represents the Tier-1 EF (1%), and the blue dashed line indicates the 2010 EFs based on a multi-model median (extracted from the central map). INMS1–S4 represents four nitrogen management scenarios (Table 1). Box boundaries show the 25th and 75th percentiles of EF estimates, and whiskers below and above the box indicate the estimate range driven by climate data from 37 GCMs. The median is indicated by the black line within each box. BRA, Brazil; CAM, Central America; CAN, Canada; CAS, Central Asia; CHN, China; EQAF, Equatorial Africa; EU, Europe; KAJ, Korea and Japan; MIDE, Mideast; NAF, Northern Africa; NSA, Northern South America; OCE, Oceania; RUS, Russia; SAF, Southern Africa; SAS, South Asia; SEAS, Southeast Asia; SSA, Southwest South America; USA, The United States of America.

across the three ambition level scenarios, likely due to their high food demand leading to increased N inputs (Ramírez-Melgarejo et al., 2019; Springmann et al., 2018). For instance, in 2030, under the INMS1 and INMS4 scenarios, we find the EFs could be approximately 1.75%–1.86% and 1.45%–1.5% in Northern South America (NSA), 1.5%–1.56% and 1.42%–1.47% in Equatorial Africa (EQAF), 1.22%–1.36% and 0.93%–1.07% in China (CHN), and 2.11%–2.24% and 1.93%–2.07% in Southeast Asia (SEAS). The large EF difference between BAU and high ambition N regulation scenarios indicates a large potential in reducing N_2O emission. These areas, especially in tropical regions (e.g., NSA, EQAF, and SEAS), are expected to see EF increases of around 0.17%–0.28% under low ambition policies by 2050, which is equivalent to 12%–17% of EF in 2010. Therefore, to meet the Goal 13 (climate action) of United Nations' sustainable development goal (United Nation, 2015), intensified efforts are needed in such regions to reduce N_2O emissions by improving NUE and reducing N loss (van Vuuren et al., 2015; Zhang et al., 2015).

It is important to note that there is a trade-off between accessibility and accuracy in the EF estimation approaches such as the IPCC Tire-1 and our Dym-EF. The IPCC Tire-1 is designed to be generic and easily adopted without a need to provide any detailed local information, which is accessible for a wide range of applications. As for Dym-EF, although it provides more accurate EF projections and is easier to apply than process-based models, it still requires specific input data, limiting its scalability and accessibility. To enhance the accessibility of our model, we have used publicly available and commonly used datasets in global modeling, ensuring that input data are easily accessible to potential users. However, uncertainties remain due to potential variations in datasets. We suggest downscaling and bias-correcting the data to better match local information. Generally, balancing accuracy with ease of use is crucial to enhance broader applicability.

3.4 | Potential for N_2O mitigation

The spatial maps of EF changes provide quantitative insights for pinpointing hotspots requiring mitigation efforts (Figure 5). In low ambition scenarios (INMS1 to INMS2), we predict significant EF increases in regions such as Northeast and North China, the Midwest US, northern South America, northern Brazil, and parts of northern Africa, driven by the substantial increase in nitrogen (N) inputs from population growth and escalating food demands. Targeting reduction efforts in these high-emission hotspots is more effective than

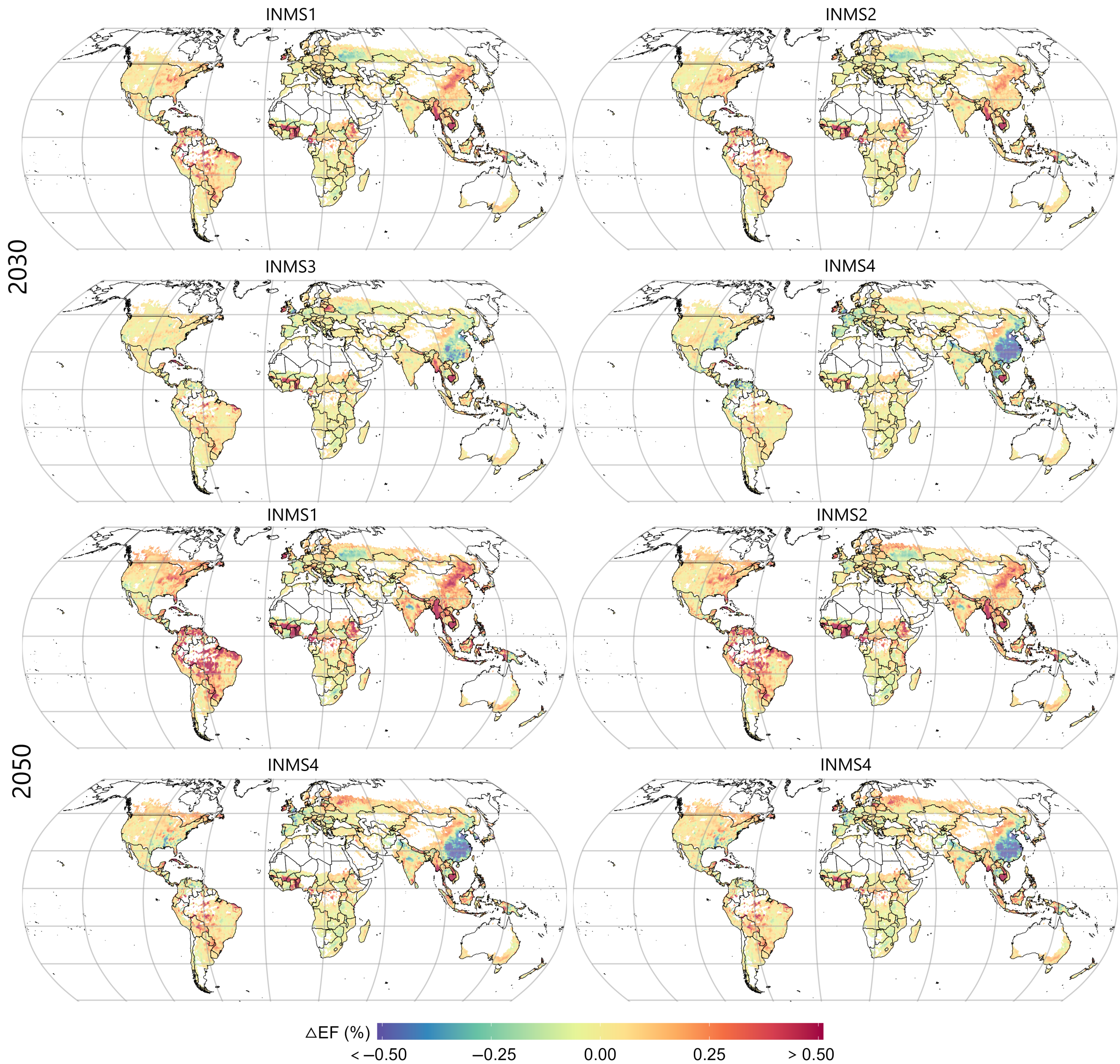

FIGURE 5 The projected emission factor (EF) changes at global and regional scales. The maps illustrate the changes in EF in 2030 and 2050, respectively, compared to 2010 under INMS1 to INMS4. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

solely focusing on the largest country emitters (West et al., 2014). The moderate ambition scenario (INMS3) demonstrates a slight decrease in EF in southeastern China, RUS, part of SEAS, and the EU by 2030, with notable reductions in these areas by 2050. These are hotspots characterized by high N input and high EF at the current stage (Figure 4), but they are projected to have huge potential in EF reduction under moderate and high ambition N regulation scenarios (INMS4 to INMS7). However, slight increases are noted in regions like Vietnam, EQAF, and SEAS, even under high-ambition scenarios, attributed to increased food demands. The "best-case" and "bioenergy" scenarios (INMS5 to INMS7) illustrate that further reductions in EF can be achieved through reduced N input by High N use efficiency, adoption of low meat diets, and food waste reduction efforts (Kanter, Winiwarter, et al., 2020). To meet the food gap and address N_2O mitigation needs, various studies have explored potential optimal management practices (Gerber et al., 2016; Shang et al., 2024), while climate change potentially impacts the effectiveness of mitigations (Carlson et al., 2016). Our study quantifies the potential of reducing global agricultural soil EF as one of nature-based climate solutions, underscoring the need to consider EF changes under future climate and N regulation scenarios. It is important to clarify that higher EF reduction does not necessarily yield higher N_2O reduction and that lower EFs do not necessarily lead to lower N_2O emissions, given that EF change direction may not consistently align with nitrogen input changes in some cases. The actual N_2O emissions are the product of EF and the amount of anthropogenic nitrogen inputs. For instance, regions identified as hotspots for high EF (e.g., RUS and EQAF) in our study (Figure 4) may often differ from the areas with the highest soil N_2O emissions in the global N_2O budget study (Tian et al., 2019, 2024).

The temporal and spatially varying EFs are important in determining the effectiveness of mitigation efforts. We found the EFs were expected to increase under future climate change even without increasing N fertilizer input (Figure 6a). This is because the EFs are positively correlated with temperature and precipitation (Figure S8), which are projected to increase (Figures S2 and S3), resulting in increased EFs. Although the temperature under SSP126 does not show a substantial rise, the increased precipitation under this scenario significantly amplifies the EFs. Consequently, the relationship between N input and EFs is asymmetric due to the impacts of climate change. This asymmetry leads to substantial EF increases when higher N input (INMS1–S2) is combined with climate change effects (Figure 6b). Conversely, reductions in N input alone may not fully buffer the EF increase caused by warmer climates and changed precipitation patterns, especially in some climate-sensitive regions. Among the four high-ambition policy scenarios, our findings indicate that, despite INMS7 containing a best-case climate scenario (SSP126), EFs are not always projected to be the lowest among the "best-case" climate scenarios by 2030 even with similar N input to current management? (Figure S1). This discrepancy may arise from varying temperature and precipitation patterns (Figure 3), which could elevate EFs by 2030 (Figures S2 and S3). However, by 2050, rising temperatures in INMS5–S6 could lead to higher EFs even in the "best-case" climate scenarios (Figure 6b).

Our study highlights the urgency to take relatively stringent N regulation practices as early as possible, as delays could exacerbate the challenges of mitigating N_2O emissions due to climate-induced increases in EFs. In addition, it is important to account for the impact of future climate changes on effective evaluations and to harness the potential for identifying easily achievable targets (e.g., prioritized mitigation goals, specific regions, and feasible practices) across the globe. More comprehensive strategies need to be considered, including cost-effective mitigation measures, which are essential to reduce greenhouse gas (GHG) emissions while ensuring the stability of food production (Gu et al., 2023; Peng & Guan, 2021; Ren et al., 2023). Furthermore, crop switching is proposed to be an effective strategy for sustainable agriculture (Rising & Devineni, 2020; Xie et al., 2023). This approach holds the potential for reducing N_2O emissions and enhancing crop productivity in the context of future climate change (Jägermeyr et al., 2021; Peng & Guan, 2021). However, the impact of crop switching on dietary diversity and nutritional intake remains a critical question (Carlson et al., 2016; West et al., 2014). Consequently, international food trade becomes crucial in striking a balance between maintaining food diversity and adapting to climate change (Janssens et al., 2020, 2022). Generally, collective action by different organizations is critical for us to achieve the climate mitigation goal in a race against time.

3.5 | Limitations and future framework

Our study comprehensively explores N_2O emission under different policy interventions and climate scenarios, identifying the direction toward achieving sustainable development goals.

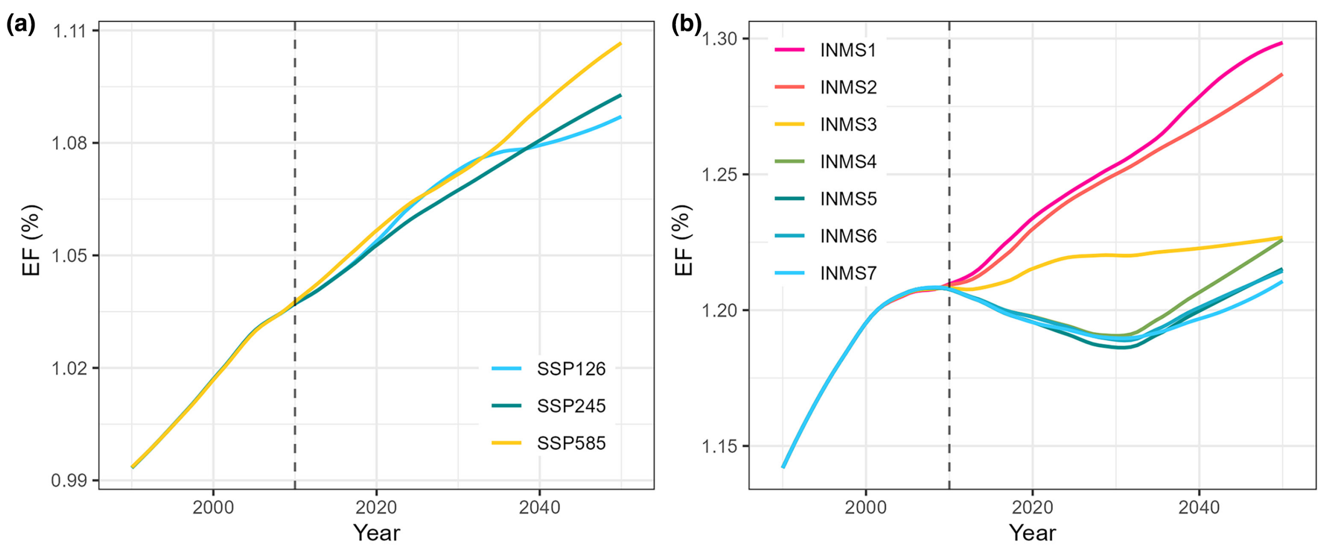

FIGURE 6 Global cropland and pasture emission factor (EF) changes under different scenarios. This figure displays smoothed lines reflecting changes in EF. (a) The change in EF compared to the average EF during 1990–2010, excluding nitrogen fertilizer impacts under scenarios SSP126, SSP245, and SSP585. (b) The change in EF compared to the average EF during 1990–2010 including nitrogen fertilizer effects under scenarios INMS1 to INMS7.

However, we understand that there are several uncertainties in this study. Different process-based models have different structures and algorithms to represent nonlinear N_2O responses to key environmental drivers. Although the cross-model divergence can be minimized by using the model ensemble median estimates of EF as the learned variable, the uncertainties in projections derived from model inputs and structure still persist (Tian et al., 2024). Extensive measurements of soil N_2O emissions could help improve the parameterization of individual NMIP2 models and better constrain their estimates of EF in various climate and soil conditions. The method of emergent constraint can be effective in reducing uncertainties in process-based models (Wang, Zhao, et al., 2020), as applied in studies on crop yield changes (Li et al., 2023), soil carbon (Varney et al., 2020), and land evapotranspiration based on field observed data (Lian et al., 2018). However, no such work is available for EF.

The machine learning-based approaches have a common challenge in extrapolating, especially beyond the training dataset. In this study, to cover the range of potential future conditions, we trained our model on a large dataset spanning a wide range of time periods (1961–2020), covering the period with rapid changes in climate and human activities, such as enhanced anthropogenic N input in particular. However, the learning effort is still limited by the availability of input data and how process-based modeling has handled them. For example, some detailed information on nitrogen management practices, such as the seasonal application of nitrogen, the use of organic amendments, or slow-release forms of nitrogen, are either missing at the global level or over-simplified in the N_2O modeling assessment. Incorporating a broader range of data and management practices will enhance the robustness of this hybrid model and make it more practical for future users who have more detailed information.

For N fertilizer input, the EFs associated with manure deposition and application were not considered despite their significant role in N_2O emissions (Charles et al., 2017; Walling & Vaneeckhaute, 2020). The changes in synthetic fertilizer and manure application rates vary substantially across different policy scenarios, influenced by dietary shifts, and changed NUE. Synthetic fertilizers are widely used in crop production, enhancing crop yield efficiently but increasing the risk of N pollution. Although changes in synthetic fertilizer composition (e.g., ammonium vs. nitrate) might affect outcomes, this aspect was not explored in our study. Manure, while beneficial for soil health and providing a more sustainable N source, adds challenges in managing N_2O emissions and N leaching. Selection between them should balance efficiency, environmental impact, and soil health considerations. Since data on N_2O emissions induced by manure were not available for all the eight participant models in NMIP2, we did not include manure-induced N_2O emissions and the potential change in EFs for manure. Incorporating manure EFs into future studies could further optimize nitrogen inputs by balancing the trade-offs between synthetic fertilizers and manure. In addition, we mainly focus on annual EFs, derived from NMIP2 model ensembles that handle annual fertilizer input in various ways and assumptions without knowing how fertilizer application timings vary across the globe and over time. This may not fully capture the interactive effects of seasonal climate variations and nitrogen application on EFs.

Considering crop-specific variations in using N and releasing N_2O from soils (e.g., wheat, maize, and rice) could provide more nuanced guidance (Cui et al., 2021; Shang et al., 2024), an aspect not covered in our current study. Future work ought to explore how different policy ambition levels influence N_2O emissions for different crops under future climate scenarios. This will offer targeted recommendations, helping to bridge these knowledge gaps and enhance our comprehension and management of N_2O mitigation strategies.

4 | CONCLUSIONS

In this study, we have developed a novel hybrid modeling framework that incorporates machine learning with process-based modeling to predict the nonlinear dynamics of EF under various climate, soil, and management conditions across global agricultural lands. This approach provides new insights into global EF changes that can improve our understanding of N_2O mitigation potential under different climate and policy scenarios. Our results provide a strong indication of a future increase in N_2O EF due to climate change, independent of N management. The increase of EFs when coupled with increased N input and climate change impacts is largely higher than the EF reductions through decreased N input. This asymmetry between nitrogen input and EFs poses additional challenges for N_2O mitigation in the future, highlighting the urgency of nitrogen reductions as delayed actions could increase mitigation costs. Such information might not be fully captured by studies using country-specific EFs, which are considered appropriate for "tier 2" approaches in national inventories. Furthermore, although the EFs are impacted by different environmental factors, optimizing N inputs to crop needs remains the most effective mitigation option. Our finding is a critical step toward achieving sustainable development goals, by improving the current static EF (IPCC tiers 1–2) approach with a more precise N_2O emissions estimation under global change scenarios. Future efforts in enhancing measurement and data analysis with a uniform protocol would be helpful to reduce the EF estimation uncertainty from process-based modeling, and to improve the database used for dynamic EF learning and mitigation potential assessment under various management options.

AUTHOR CONTRIBUTIONS

Linchao Li: Conceptualization; data curation; formal analysis; methodology; software; validation; visualization; writing – original draft; writing – review and editing. **Chaoqun Lu:** Conceptualization; data curation; funding acquisition; investigation; project administration; resources; supervision; validation; visualization; writing – original draft; writing – review and editing. **Wilfried Winiwarter:**

Conceptualization; data curation; formal analysis; methodology; software; supervision; validation; writing – original draft; writing – review and editing. **Hanqin Tian:** Conceptualization; data curation; formal analysis; methodology; project administration; resources; software; supervision; validation; writing – original draft; writing – review and editing. **Josep G. Canadell:** Conceptualization; data curation; methodology; resources; software; writing – original draft; writing – review and editing. **Akihiko Ito:** Data curation; formal analysis; resources; software; writing – original draft; writing – review and editing. **Atul K. Jain:** Conceptualization; data curation; formal analysis; methodology; software; writing – original draft; writing – review and editing. **Sian Kou-Giesbrecht:** Conceptualization; data curation; formal analysis; software; writing – original draft; writing – review and editing. **Shufen Pan:** Conceptualization; data curation; formal analysis; project administration; resources; writing – review and editing. **Naiqing Pan:** Conceptualization; data curation; formal analysis; methodology; resources; software; writing – review and editing. **Hao Shi:** Conceptualization; data curation; formal analysis; methodology; resources; software; validation; writing – original draft; writing – review and editing. **Qing Sun:** Conceptualization; data curation; formal analysis; funding acquisition; resources; software; writing – original draft; writing – review and editing. **Nicolas Vuichard:** Conceptualization; data curation; formal analysis; software; writing – original draft; writing – review and editing. **Shuchao Ye:** Data curation; formal analysis; methodology; software. **Sönke Zaehle:** Conceptualization; data curation; formal analysis; methodology; software; writing – original draft; writing – review and editing. **Qing Zhu:** Conceptualization; data curation; formal analysis; software; validation; writing – original draft; writing – review and editing.

AFFILIATIONS

[1]Department of Ecology, Evolution, and Organismal Biology, Iowa State University, Ames, Iowa, USA
[2]International Institute for Applied Systems Analysis, Laxenburg, Austria
[3]Institute of Environmental Engineering, University of Zielona Góra, Zielona Góra, Poland
[4]Center for Earth System Science and Global Sustainability, Schiller Institute for Integrated Science and Society, Boston College, Chestnut Hill, Massachusetts, USA
[5]Department of Earth and Environmental Sciences, Boston College, Chestnut Hill, Massachusetts, USA
[6]CSIRO Environment, Canberra, Australian Capital Territory, Australia
[7]Graduate School of Agricultural and Life Sciences, The University of Tokyo, Tokyo, 113-8657, Japan
[8]Earth System Division, National Institute for Environmental Studies, Tsukuba, Japan
[9]Department of Climate, Meteorology, and Atmospheric Sciences, University of Illinois, Urbana-Champaign, Urbana, USA
[10]Department of Earth and Environmental Sciences, Dalhousie University, Halifax, Nova Scotia, Canada
[11]Department of Engineering and Environmental Studies Program, Boston College, Chestnut Hill, Massachusetts, USA
[12]Research Center for Eco-Environmental Sciences, Chinese Academy of Sciences, Beijing, China
[13]Climate and Environmental Physics, Physics Institute and Oeschger Centre for Climate Change Research, University of Bern, Bern, Switzerland
[14]Laboratoire des Sciences du Climat et de l'Environnement, LSCE, CEA CNRS, UVSQ UPSACLAY, Gif sur Yvette, France
[15]Max Planck Institute for Biogeochemistry, Jena, Germany
[16]Climate and Ecosystem Sciences Division, Lawrence Berkeley National Laboratory, Berkeley, California, USA

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CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest regarding the publication of this article.

DATA AVAILABILITY STATEMENT

All data required to evaluate the conclusions in this paper are available within the paper itself or its Supplementary Materials. The data and code that support the findings of this study are available in Figshare at https://doi.org/10.6084/m9.figshare.26384401. The NMIP2 model outputs are accessible at https://doi.org/10.18160/RQ8P-2Z4R. Historical climate data are accessible at https://data.ceda.ac.uk/badc/cru/data/. CMIP6 data can be found at https://aims2.llnl.gov/search/cmip6/. Soil properties data are provided by the Harmonized World Soil Database v1.2, available at https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/. The cropland area dataset from the History Database of the Global Environment v3.2 (HYDE 3.2) is available at https://doi.org/10.17026/dans-25g-gez3.

ORCID

Linchao Li https://orcid.org/0000-0002-6615-1309
Chaoqun Lu https://orcid.org/0000-0002-1526-0513
Hanqin Tian https://orcid.org/0000-0002-1806-4091
Atul K. Jain https://orcid.org/0000-0002-4051-3228
Sian Kou-Giesbrecht https://orcid.org/0000-0002-4086-0561
Sönke Zaehle https://orcid.org/0000-0001-5602-7956
Qing Zhu https://orcid.org/0000-0003-2441-944X

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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