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Biochar

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Mineral nitrogen input modulates the methane mitigation potential of biochar in rice systems: based on meta-analysis and field experiment demonstration

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Abstract

The application of organic materials has a profound impact on CH_4 emissions from paddy fields. Biochar has been reported to mitigate CH_4 emissions, but this conclusion has recently been challenged and requires further investigation. This study aimed to determine the effect of biochar on paddy CH_4 emissions by integrating organic amendment emission data through network meta-analysis (NMA), and to identify the key moderators using multiple meta-regression (MR) approaches. Field experiments were conducted to verify the conclusions of MR. Based on 146 entries from 51 studies, a mixed-effects meta-analysis was conducted to evaluate the effects of organic material applications on soil CH_4 emissions. We focused on the biochar mitigation potential in rice systems and validated the conclusions through a field experiment. Biochar demonstrated the lowest methane emissions among all treatments. Carbon to nitrogen ratio of biochar (MC:N) and mineral nitrogen input (ICN) were identified as key moderators influencing the methane mitigation potential of biochar in rice cultivation. ICN was the most influential factor. When ICN exceeded 291.18 kg ha^{-1}, biochar tended to increase methane emissions, whereas at lower ICN levels, it contributed to emission reductions. Field experiments confirmed that at high mineral N levels (310 kg ha^{-1}), biochar significantly increased CH_4 flux and emission potential. Overall, this study highlights the potential of biochar to reduce methane emissions in rice systems and underscores the importance of regulating mineral nitrogen inputs to maximize its mitigation effectiveness.

Highlights

- Biochar has better CH_4 emission reduction potential compared to the application of other organic materials in rice cultivation based on meta-analysis (MA).
- High ICN can weaken the mitigation effects of biochar on CH_4 emissions, and when ICN > 291.18 kg ha^{-1}, biochar induces an increase in CH_4 emissions.
- Field experiments confirmed that at high mineral N levels, biochar increased both CH_4 fluxes and emission potential.

Keywords Mineral nitrogen addition, Biochar, CH_4 emissions, Network meta-analysis, Field experiment

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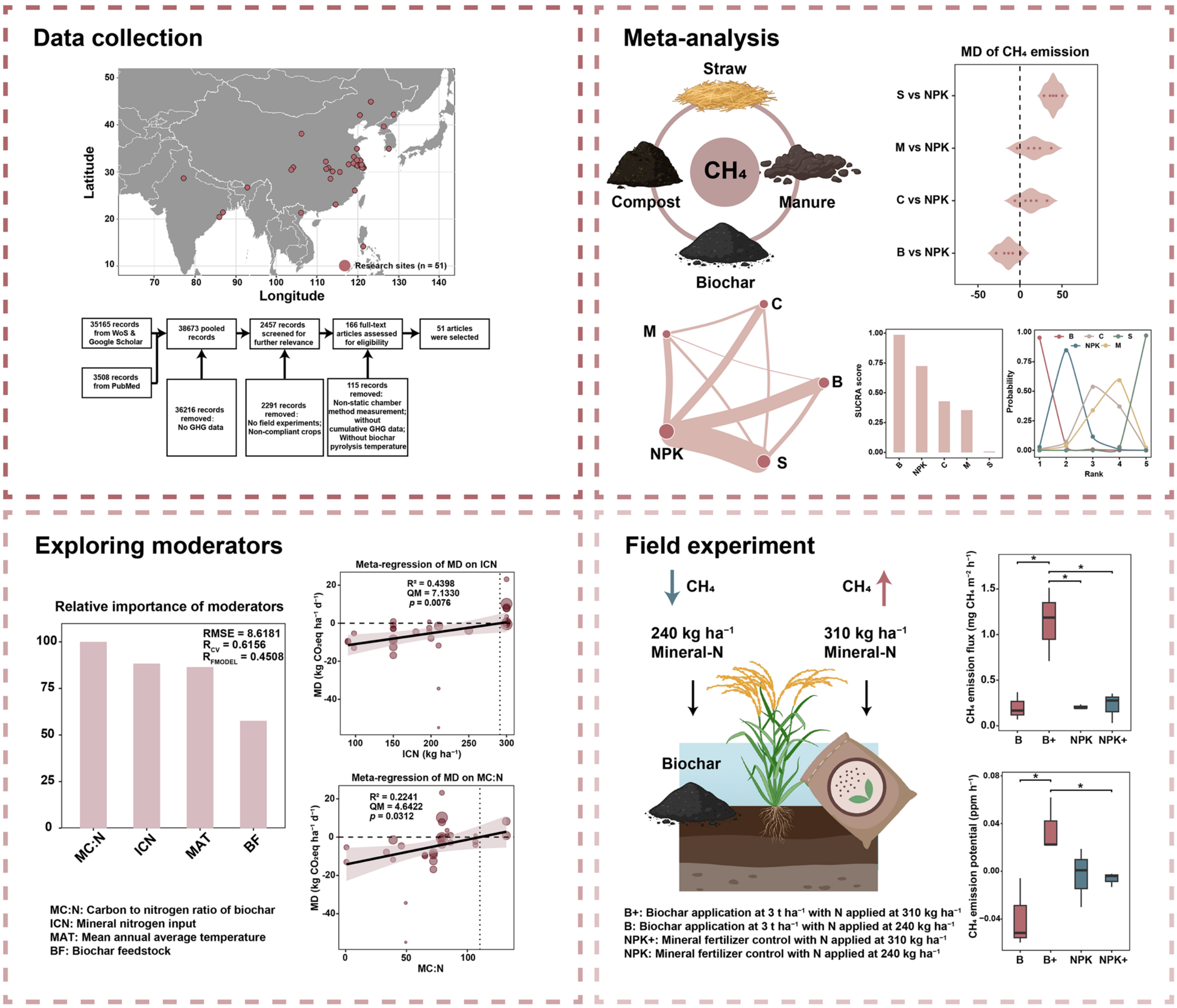
Graphical Abstract



1 Introduction

Agricultural systems are a major source of CH_4 emissions, contributing approximately 10–17% of global anthropogenic CH_4 emissions (Khosa et al. 2010; Sander et al. 2014; Tariq et al. 2017; Slingo and Slingo 2024). Within farmland systems, rice paddies alone account for about 30% of total CH_4 emissions (Crippa et al. 2020; Khatibi et al. 2025). As rice serves as the staple food for nearly half of the world's population, it plays a vital role in ensuring global food security (Xia et al. 2016; Liu et al. 2021). Consequently, reducing CH_4 emissions from paddy fields has become a global concern. Agricultural practices, particularly the application of organic materials in rice cultivation, are recognized as a key strategy for mitigating CH_4 emissions from these systems (Smith et al. 2010; Qian et al. 2023a).

Organic materials are commonly used in agriculture to enhance crop yields, improve soil physicochemical properties, and influence soil microbial communities (Pittelkow et al. 2015; Xia et al. 2017, 2018; Sun et al. 2020; Qian et al. 2023b). However, these practices also significantly impact soil CH_4 emissions. Current understanding suggests that the addition of organic materials to farmland does not typically result in a net climate benefit (Liu et al. 2014). In contrast, different organic materials have significantly different impacts on soil CH_4 emissions. For example, straw return can significantly increase methane emissions in rice paddies (Xia et al. 2014). The impact of manure application on soil CH_4 emissions is uncertain, with reports indicating both reductions (Maillard and Angers 2014) and increases in emissions (Chen et al. 2023). Biochar is commonly reported to have significant mitigation effects (Nan et al. 2021). From the perspective of reducing agricultural soil CH_4 emissions, it is crucial to clearly understand the emission differences associated with various organic materials, the underlying emission profiles caused by their application, and the influencing factors.

A quantification of the impact of the application of organic materials on CH_4 emissions from rice can be achieved through MA. However, the field of agricultural and ecological environment research faces many challenges in conducting meta-analyses, including the lack of rigorous evaluation criteria, methodological difficulties in handling multi-arm trials, and the need for more diverse and robust analytical approaches (Hungate et al. 2009; Nakagawa et al. 2017; Haddaway et al. 2020; Fohrafellner et al. 2023). NMA is widely applied in the medical field (Ng et al. 2022; Song et al. 2020; Hou et al. 2020), using indirect evidence to refine the results of direct evidence, enabling a more comprehensive analysis of differences. Multilevel meta-regression analysis (MMRA) is employed to address situations where multiple treatment arms are reported within the same study. Meta Forest (MF) has been used to analyze important environmental factors (Terrer et al. 2021), offering valuable approaches. The MF combines the random forest algorithm with MA, using multiple study data as input to build models for variable selection and prediction. Overall, the application of these techniques and methods can significantly enhance the conduct of meta-analyses in the agricultural sector.

In this study, we employed mixed-effects meta-analysis (MEMA), NMA, MMRA and MF approaches to assess the differences in CH_4 emissions resulting from the use of different organic materials in rice cultivation. Meanwhile, an in-depth analysis of biochar application on CH_4 emission was conducted, and a field experiment was conducted to validate the conclusions derived from the analysis. The aims of our study were to apply diverse meta-analytical approaches to assess the effects of organic material application on paddy soil CH_4 emissions, and to further elucidate the influence of different moderating factors on CH_4 emissions under biochar application.

2 Materials and methods

2.1 Case selection and data collection

Several databases (Web of Science, Google scholar, and PubMed) were searched for peer-reviewed articles published between 2000 and 2024. The following criteria were used to exclude studies that did not meet the study requirements: (a) Lack of GHG data, (b) data derived from non-field experiments, (c) crops not including rice, and (d) gas measurements not conducted using the static chamber method, and cumulative fluxes not calculated. The keyword search formula, and data selection process are illustrated in Additional file 1 and Fig. 1b, respectively. Based on the exclusion criteria, 146 entries from 51 independent studies (Fig. 1a) were included in the analysis.

To investigate the impact of different organic materials on CH_4, we selected several mainstream organic material treatments as research subjects: straw return with chemical fertilizer (S), compost with chemical fertilizer (C), manure with chemical fertilizer (M), and biochar with chemical fertilizer (B), along with chemical fertilizer application alone (NPK) in each study. NPK served as the control group. Comparisons were made between each pair of treatments, and mean cumulative emissions, sample size, and standard deviation were extracted for each season. For studies with data across multiple seasons and treatments with different amounts, an average was taken. Cumulative emission data were standardized to daily emissions based on the duration of the experiment. Mean and standard deviation values were extracted from reports with data displayed as figures using GetData Graph Digitizer v2.26 (Shakoor et al. 2021; Zhou et al. 2023) (https://getdata-graph-digitizer.software.informer.com).

In addition to cumulative CH_4 emissions, information on 20 moderators was collected to investigate their impacts and heterogeneity among treatments. The 20 moderators included: mean annual average temperature (MAT), mean annual average precipitation (MAP), soil total nitrogen (TN), soil organic carbon (SOC), soil pH (pH), soil carbon to nitrogen ratio (SC:N), initial bulk density (IBD), content of sand (Sand), content of clay (Clay), and content of silt (Silt). Number of planting seasons (Season), water management (WM), mineral nitrogen input (ICN), total nitrogen input (ITN), nitrogen of organic materials (ION), carbon of organic materials (IOC), carbon to nitrogen ratio of biochar (MC:N), application rate of biochar (I), pyrolysis temperature of biochar (BPT), and biochar feedstock (BF) (abbreviations list in Additional file 1). Missing values of MAT and MAP (21.56% for MAT and MAP) for 1970–2000 were extracted from WorldClimv2.1 (Fick and Hijmans 2017). Missing values of IBD, pH, SOC, Clay, Sand, and Silt (0–30 cm; 43.14% for IBD, 3.92% for pH and SOC, 49.02% for Clay, Sand, and Silt) were extracted from the 1 km Harmonized World Soil Database (HWSD v1.2; http://www.iiasa.ac.at/), based on site latitudes and

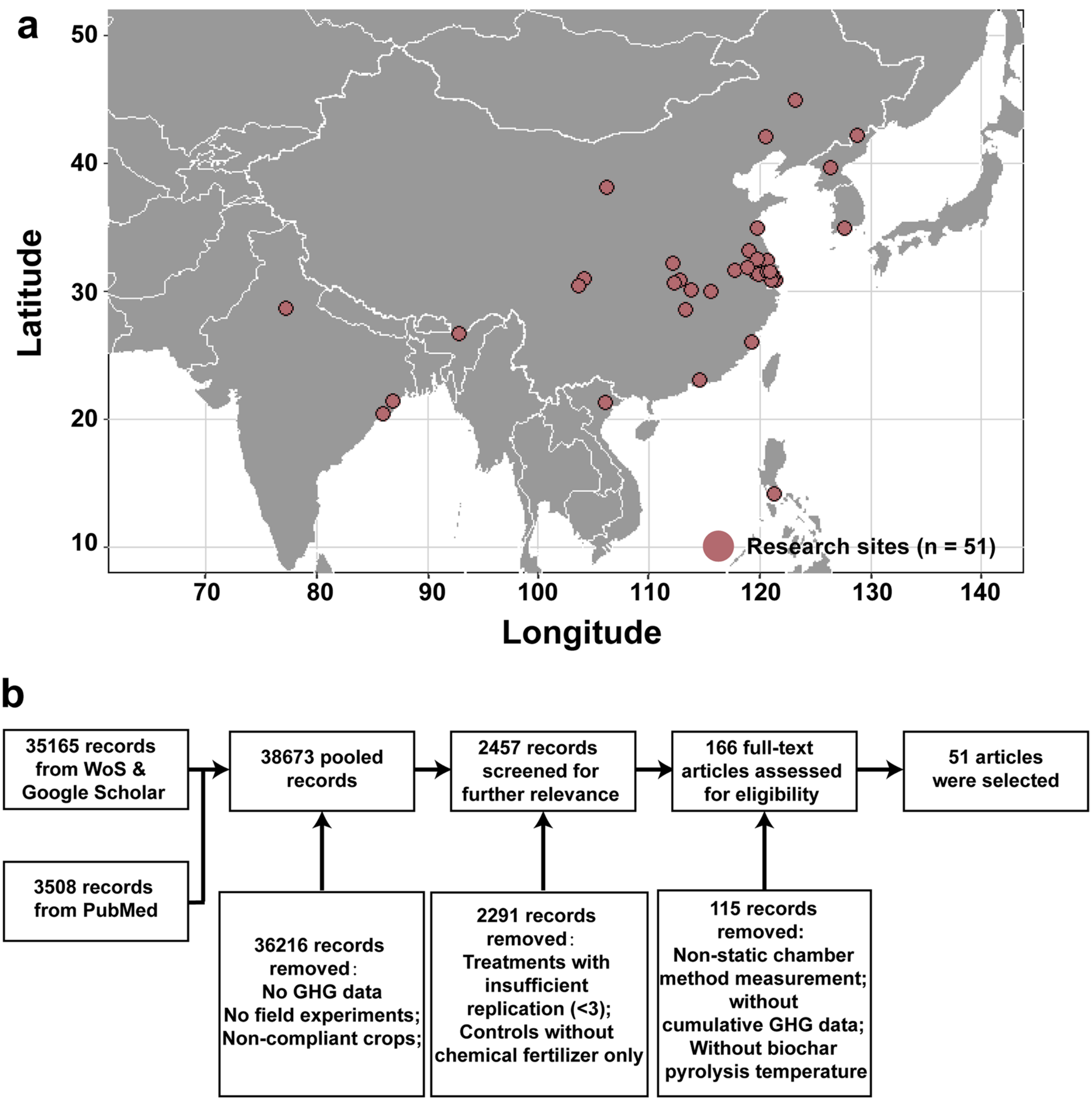


Fig. 1 Research site and flowchart of selection criteria. **a** Research site map; **b** flowchart of selection criteria. The circles in the map represent independent studies

longitudes (Shang et al. 2021). Missing values of TN and SC:N (7.84% for TN, 7.84% for SC:N) were supplemented from the Land–Atmosphere Interaction Research Group database (Shangguan et al. 2014; http://globalchange.bnu.edu.cn/research). Missing organic material parameters were supplemented using the mean values for the same materials. There were 6 studies lacking standard deviations, and they were consequently imputed based on studies with comparable mean values, using a resampling method in the *metagear* package in *R* (Rubin and Schenker 1991; Lajeunesse 2016).

2.2 Effect size calculation

The difference in equivalent carbon dioxide emissions between two treatments in each comparison pair was estimated using the mean difference (MD) of response sizes (Harrer et al. 2019). Effect sizes were calculated using the *pairwise ()* function in the *netmeta* package

(Balduzzi et al. 2023). Publication bias was assessed based on Egger's test, with $p > 0.05$ considered indicative of no publication bias (Egger et al. 1997); this analysis was also performed using the *netmeta* package. The daily emissions of methane from all the studies were homogenized based on the 100-year global warming potential, standardized to the unit kg CO_2-eq ha^{-1} d^{-1}. All calculation formulas are provided in Additional file 1.

2.3 Meta-analysis

The *rma.mv* function in the *metafor* package (Viechtbauer 2010) calculates the overall effect in mixed-effects models by weighting the effect size measures of individual studies in an MA using the inverse of their variance (Osenberg et al. 1999). Moreover, by incorporating 'studyid' as a random effect, *rma.mv* accounts for potential non-independence within the same study.

NMA employed both frequentist (FNMA) and Bayesian approaches (BNMA) to reduce sensitivity and enhance the reliability of conclusions. In FNMA, the CH_4 dataset was analyzed using NMA with the *netmeta* package. Forest plots were generated with the *forest()* function, and P-scores were calculated using the *netrank()* function to determine the contribution of different treatments to emissions. The P-score has been shown to be equivalent to the SUCRA score (Rücker and Schwarzer 2015). In BNMA, the dataset was analyzed using NMA based on the *gemtc* package (Van Valkenhoef et al. 2012; Van Valkenhoef and Kuiper 2023). The models separately calculated the consistency model (CM) and the inconsistency model (USE), using 'random' as the linear model. The MCMC analysis involved four chains, with a burn-in of 5000 iterations followed by 20,000 iterations and a thinning interval of 1. The parameter selection was based on the Cochrane Handbook (Higgins et al. 2024). The *gelman.plot()* function was used to check the model's potential scale reduction factor (PSRF) values, where studies with a PSRF value < 1.05 were included in subsequent analyses (Harrer et al. 2019). After 20,000 iterations, the PSRF values for all comparison pairs were below 1.05. Overall consistency is confirmed by comparing the Deviance Information Criterion (DIC) values between the consistency and inconsistency models, where a DIC difference of less than 5 indicates that the consistency model is acceptable (Spiegelhalter et al. 2002; Spiegelhalter et al. 2014). The node-splitting method (Van Valkenhoef et al. 2016), *mtc.nodesplit()*, was used to identify any inconsistencies within the network. Estimated values for comparisons were obtained using the *relative.effect()* function from the *gemtc* package. The ranking probabilities between treatments were determined using the *rank.probability()* function. Surface Under the Cumulative Ranking (SUCRA) values were calculated using the *dmetar* package (Salanti et al. 2011; Harrer et al. 2019). All results were visualized in *R* using the *ggplot2* package (Wickham 2016) and the evidence network was constructed using the *igraph* package (Csárdi and Nepusz 2006).

2.4 Moderator importance and meta-regression

For the biochar dataset that included multi-arm treatments, a split-control approach combined with MF was adopted to predict the importance of moderators (Higgins et al. 2024). The meta-forest method, with 10,000 iterations using the *metaforest* package (Van Lissa 2017), was applied to each comparison pair, combined with 100 replications of a recursive algorithm from the preselection function of the *metafor* package (Terrer et al. 2021). This was followed by the removal of moderators for which the lower bound of their importance was less than 0 at the 95% confidence level to reduce model overfitting. Subsequently, fivefold cross-validation was applied using the *caret* package (Kuhn 2008), selecting the top 4 moderators with the highest average importance as the most significant influencers for the comparison pair. To evaluate the predictive accuracy of MF and to further explore the relationships between moderating factors and effect sizes, we performed MMRA using a multilevel effect model by using the *rma.mv* function in the *metafor* package. This approach accounts for the covariance among different arms within the same study, thereby addressing the potential inaccuracies in meta-analysis arising from correlations among multi-arm treatments (Harrer et al. 2019; Higgins et al. 2024). Furthermore, based on the multilevel effect model, we conducted subgroup analyses for the top four most influential factors.

2.5 The field experiment

Field experiments were conducted in Nanjing, Jiangsu Province, China (31.99°N, 118.59°E), under a rice–wheat rotation system. The region is characterized by a typical subtropical climate, with an average temperature of 24.6 °C during the rice-growing season and relatively high seasonal precipitation averaging 1118 mm. The soil at a depth of 0–20 cm had the following properties: pH 7.42, total nitrogen 1.41 g kg^{-1}, and soil organic carbon 21.34 g kg^{-1}. A randomized block design was adopted, with each plot measuring 6.9 m × 6.2 m. In June 2024, four treatments were established, each with three replicates: (1) chemical fertilizer control with N applied at 240 kg ha^{-1} (NPK); (2) high-N chemical fertilizer control with N applied at 310 kg ha^{-1} (NPK+); (3) biochar application at 3 t ha^{-1} with N applied at 240 kg ha^{-1} (B); (4) biochar application at 3 t ha^{-1} with N applied at 310 kg ha^{-1} (B+). Fertilization was applied in two splits, basal and topdressing, with urea as the nitrogen source.

Phosphorus and potassium fertilizers were applied as basal inputs at rates of 40 kg P_2O_5 ha^{-1} and 60 kg K_2O ha^{-1}, respectively. The biochar was produced from wheat straw pyrolyzed at 450 °C by Nanjing Qinfeng Technology Co, Ltd, with a carbon content of 469 g C kg^{-1}, nitrogen content of 6.00 g N kg^{-1}, an initial pH of 9.10, cation exchange capacity of 24.10 cmol kg^{-1}, and ash content of 20.80%. Details of greenhouse gas sampling, emission flux calculations, and soil emission potential measurements are provided in Additional file 1.

3 Results

3.1 Effects of organic material application on CH_4 emissions based on MA

Prior to conducting the meta-analysis, we examined the dataset for publication bias. The results indicated that Egger's test yielded a *p*-value of 0.2403 ($p > 0.05$, Additional file 1: Fig. S1), suggesting no significant evidence of publication bias. For BNMA, the DIC of the consistency model was 232.180, while that of the inconsistency model was 230.118 (Fig. 1a). The difference was less than 5, indicating that the overall consistency of the evidence network was acceptable. Although one local inconsistency was detected (Additional file 1: Fig. S2), the direction and significance of the effect sizes were consistent. Meanwhile, after 20,000 iterations, the PSRF values of all parameters were below 1.05 (Additional file 1: Fig. S3), indicating good convergence of the model. Overall, the results demonstrate that the consistency model of BNMA was acceptable and could be applied for further analysis.

A comparison of the results from BNMA, FNMA, and MEMA showed that B consistently reduced CH_4 emissions across all three approaches. The effects were statistically significant in FNMA and MEMA, with reductions of 6.070–15.768 and 0.199–10.554 kg CO_2-eq ha^{-1} d^{-1}, respectively (Fig. 2b). M and compost C both exhibited consistent effect directions across the three methods, with both treatments increasing CH_4 emissions. These effects were also significant in FNMA and MEMA, with M increasing emissions by 6.288–19.785 and 2.106–12.196 kg CO_2-eq ha^{-1} d^{-1}, and C increasing emissions by 3.706–16.576 and 2.066–11.515 kg CO_2-eq ha^{-1} d^{-1}, respectively (Fig. 2b). S showed a significant enhancement of CH_4 emissions in all three approaches, with effect sizes of 28.632–50.356, 30.722–38.517, and 26.120–52.448 kg CO_2-eq ha^{-1} d^{-1}, respectively (Fig. 2b).

The NMA approach provides a more intuitive ranking of emission differences among treatments. The results showed that the SUCRA scores and probability rankings from BNMA were consistent with the P-scores from FNMA (Fig. 2c and d). In terms of CH_4 emissions from paddy fields, the treatments ranked from lowest to highest were B, C, M, and S, with B demonstrating a clear potential for CH_4 mitigation (Fig. 2c and d).

3.2 Exploration of important moderators

For the rice methane emission dataset comparing B and the control, key regulatory factors for specific comparisons were identified through five-fold cross-validation. Specifically, the four most important moderators were MC:N, ICN, MAT, and BF (Fig. 3a; $R^2_{CV} = 0.6156$, $R^2_{FM} = 0.4508$, RMSE = 8.6181). Multilevel meta-regression analyses (MMA) were performed for the four most important moderators. Among them, ICN ($R^2 = 0.4398$, $p = 0.0076$) (Fig. 3c) and MC:N ($R^2 = 0.2241$, $p = 0.0312$) were significantly positively correlated with MD (Fig. 3d). In contrast, mean annual temperature (MAT; $R^2 = -0.0720$, $p = 0.2714$) showed no significant relationship with MD (Additional file 1: Fig. S5). Similarly, BF was not significantly correlated with MD ($p = 0.1084$), explaining only 10.63% of the heterogeneity (Additional file 1: Fig. S6). Based on the combined results of MF and multilevel meta-regression, we identified ICN and MC:N as the most critical moderating factors and therefore conducted subgroup analyses. When ICN exceeded 291.28 kg ha^{-1}, biochar significantly increased CH_4 emissions from paddy fields by 3.188–3.386 kg CO_2-eq ha^{-1} d^{-1}. Conversely, under ICN $\leq$ 291.28 kg ha^{-1} conditions, B exhibited a significant mitigation potential, reducing CH_4 emissions by 4.280–11.900 kg CO_2-eq ha^{-1} d^{-1} (Fig. 3b). For MC:N, a significant CH_4 reduction effect of B (1.688–21.849 kg CO_2-eq ha^{-1} d^{-1}) was observed only when MC:N ranged from 0 to 50 (Fig. 3b).

(See figure on next page.)

Fig. 2 Predicted results based on the NMA and MEMA. **a** The evidence network of CH_4 emission and the DIC for each model. In the evidence network, lines represent the existence of direct observations, numbers indicate the number of observations, and the size of the points represents the number of treatments. In the DIC of the model. CM represents consistency model and USE represents the inconsistency model. **b** Forest plots of effect sizes for BNMA, FNMA, and MEMA from the revised model, where the range of the plot represents the distribution of estimates, and the endpoints denote the upper and lower bounds of the 95% CrI or CI. **c** The SUCRA values and probability rankings for these networks, with higher values indicating lower emissions and dots representing the probability of each treatment achieving this order. **d** The P-score for networks, with higher values indicating lower emissions and dots representing the probability of each treatment achieving this order

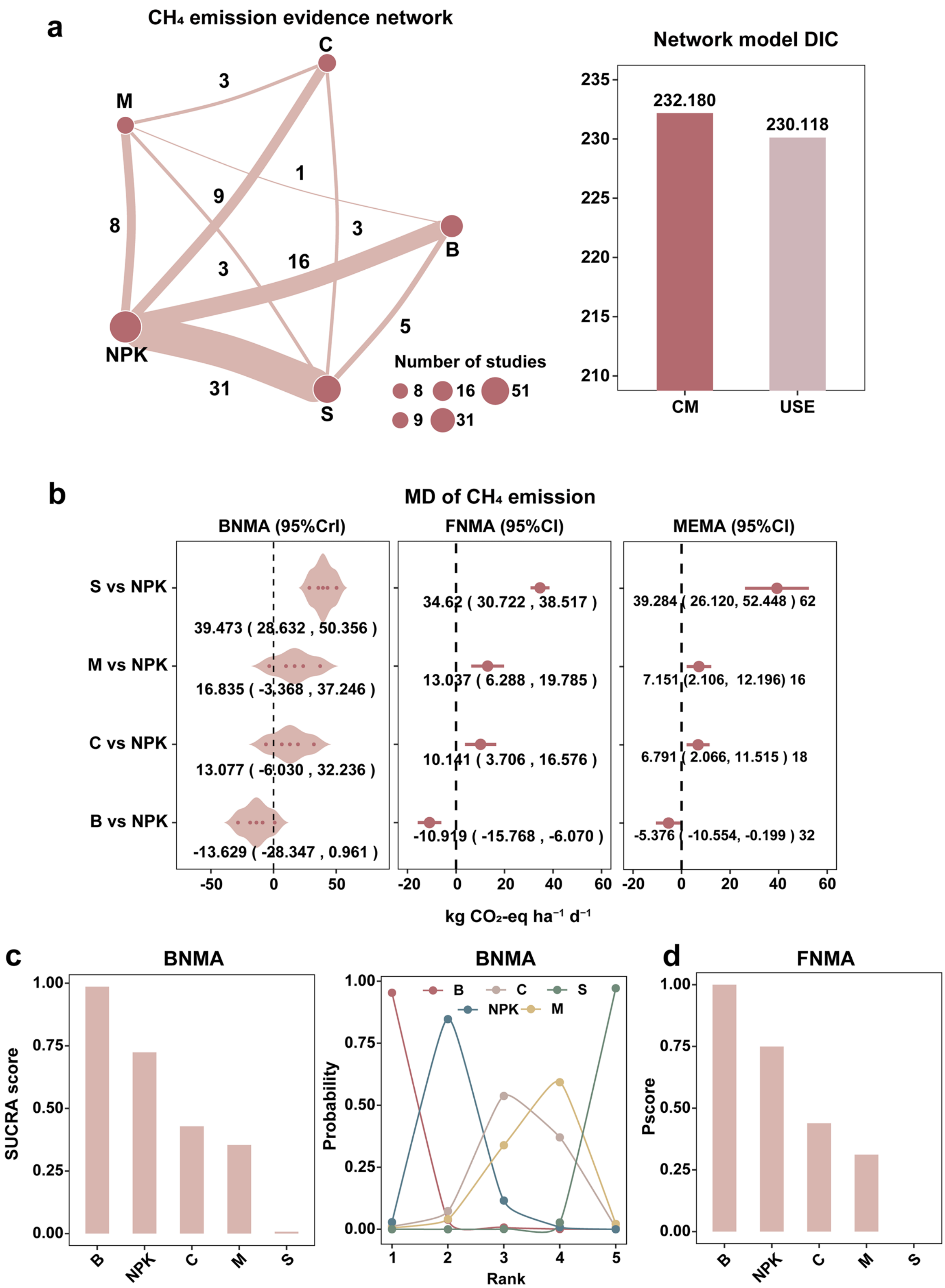


Fig. 2 (See legend on previous page.)

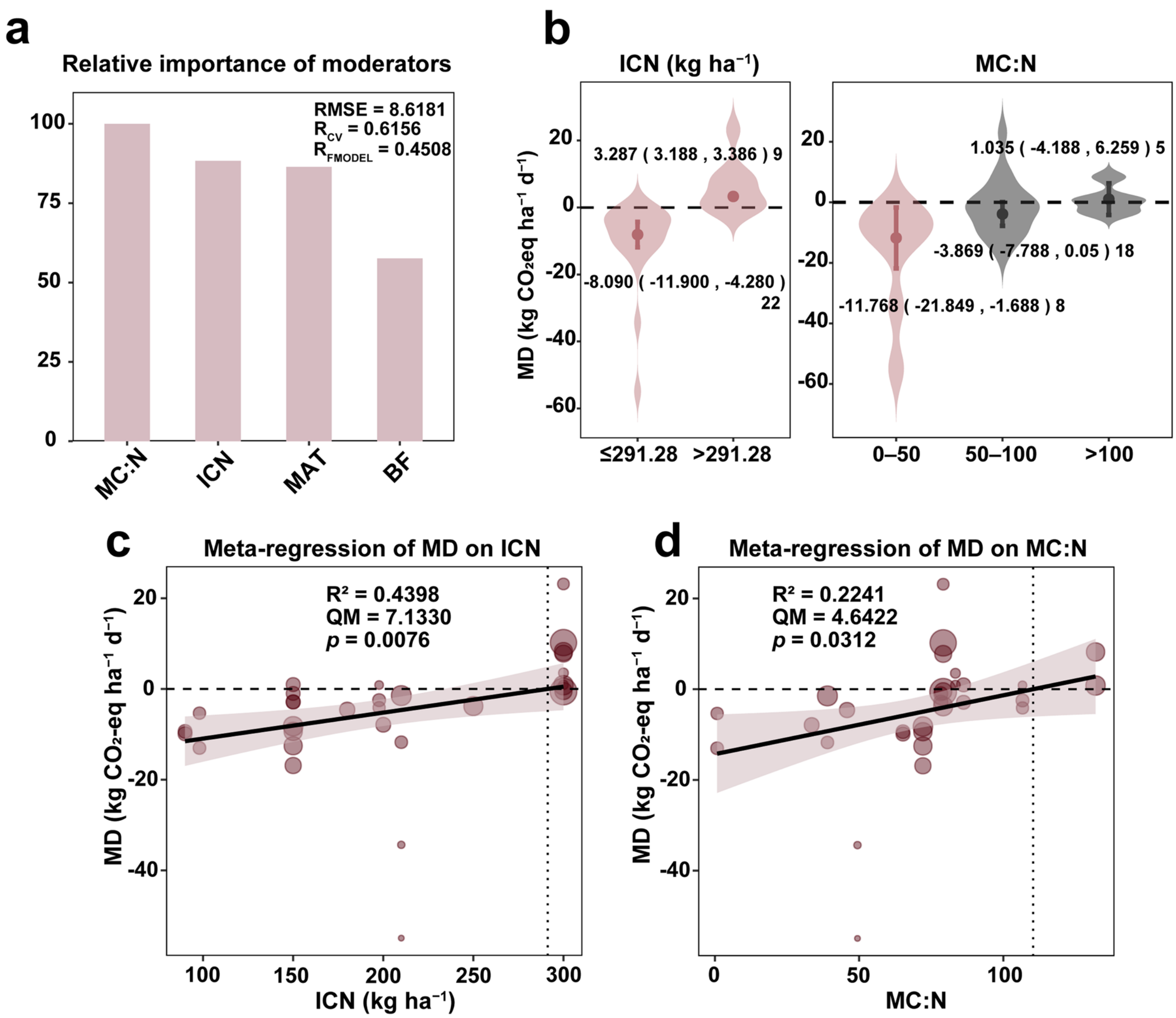


Fig. 3 Exploration of key moderators. **a** Importance ranking of the top four most important moderators based on the meta-forest method, with R^2_{CV} representing the model's R^2 from cross-validation and R^2_{FMODEL} representing the model's R^2 from the final model. **b** Subgroup analysis for the comparison between NPK and B based on ICN and MC:N. The points in the forest plot represent the estimated mean difference between the two comparisons, while the horizontal lines indicate the 95% confidence intervals. **c** Results of the multilevel meta-regression analysis for ICN, with point size representing the weight of each study. **d** Results of the multilevel meta-regression analysis for MC:N, with point size representing the weight of each study

3.3 Investigation in field experiments

In terms of CH_4 fluxes, the B+treatment produced significantly higher emissions of 1.159 mg CH_4 m^{-2} h^{-1} compared with B, NPK, and NPK+, while no significant difference was observed between NPK and NPK+(Fig. 4a). Measurements of soil CH_4 emission potential showed a similar pattern. After 24 h of incubation, B+exhibited a significantly greater soil CH_4 emission potential of 0.005 ppm h^{-1}, whereas no significant difference was detected between NPK and NPK+(Fig. 4b).

4 Discussion

4.1 Impact of the organic materials on CH_4 emissions

CH_4 is a major non-CO_2 greenhouse gas source emitted from rice cultivation (Qian et al. 2023a). Numerous studies have demonstrated that the incorporation of organic materials substantially influences CH_4 emissions from paddy fields, though the effects vary greatly (Yan et al. 2005; Lee et al. 2020; Song et al. 2021). Our results confirmed that organic material incorporation significantly affected CH_4 emissions, but the direction and magnitude of these effects depended on the material type.

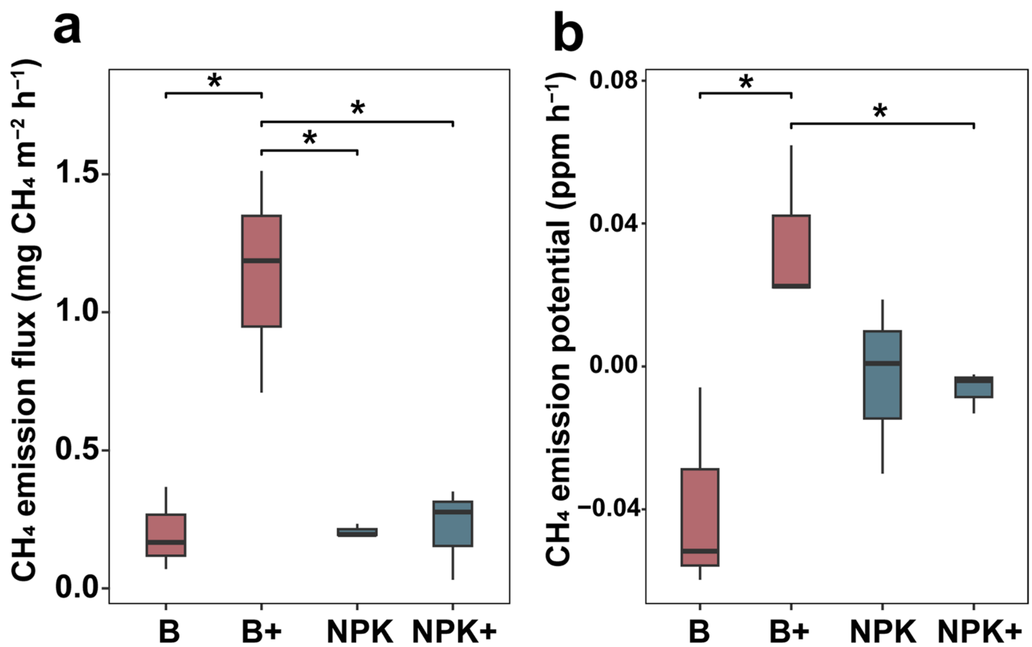


Fig. 4 Soil CH_4 emission flux and emission potential. **a** Boxplot of CH_4 emission fluxes. **b** Boxplot of CH_4 emission potential. Different letters indicate significant differences (* $p < 0.05$, Wilcoxon rank-sum test, ns indicates no significance) between different treatments of the same subculturing (n = 3)

Straw addition produced the largest increase in CH_4 emissions among all treatments, elevating fluxes by 26.120–52.448 kg CO_2-eq ha^{-1} d^{-1} (Fig. 2b). This response is consistent with previous field reports (Yan et al. 2005; Song et al. 2021), and can be attributed to the high content of labile carbon that stimulates methanogenesis and limits O_2 diffusion. This effect can be explained by the abundant labile carbon in straw, which serves as a direct substrate for methanogens, while straw decomposition further depletes the limited oxygen in anaerobic paddy soils, thereby suppressing methanotrophic activity (Weber et al. 2001; Wang et al. 2024). Manure application also markedly enhanced CH_4 emissions, ranking second after straw in our analysis. It contains easily decomposable organic matter that provides strong substrate supply for methanogens (Rajendran et al. 2024). In addition, manure often carries diverse anaerobic microbial consortia, including methanogens themselves, which can proliferate rapidly once incorporated into flooded soils (Kim et al. 2018).

In contrast, compost exhibited a more variable response. Although composting stabilizes organic matter and introduces aerobic microbes that could reduce CH_4 formation (Jeong et al. 2018; Qian et al. 2023a), our dataset revealed that many compost applications still increased emissions. This suggests that incomplete stabilization or high application rates can override the potential mitigation effect.

Biochar, on the other hand, generally reduced CH_4 emissions in our meta-analysis, consistent with its known ability to improve soil aeration and redox status (Nan et al. 2021). However, an increasing number of field observations have reported cases where biochar also enhanced CH_4 emissions (Ji et al. 2018; Qian et al. 2023a). Consistent with this emerging evidence, our study found that although the overall effect of biochar was mitigation, both MF and multilevel MA revealed heterogeneous responses. These results underscore the need for further research to clarify under which conditions biochar promotes or suppresses CH_4 emissions and to unravel the underlying mechanisms.

4.2 Key drivers of CH_4 mitigation by B in rice cultivation

Our study investigated the key factors influencing the CH_4 mitigation effects of biochar amendments, among which MC:N, ICN, MAT, and BF emerged as the most critical variables (Fig. 3a). Multilevel meta-regression analysis further identified MCN and ICN as the dominant moderators. These findings highlight two major aspects governing the impact of biochar on CH_4 emissions from paddy fields: (i) the intrinsic properties of biochar (C:N ratio), and (ii) an anthropogenic management moderator (the rate of mineral N application). With respect to the biochar C:N ratio, low-C:N biochar derived from crop residues (30–50) significantly reduced CH_4 emissions (Fig. 3b). This effect can be attributed to their relatively higher ash and metal oxide contents (Wang et al. 2013), which serve as alternative electron acceptors and compete with methanogenic pathways, thereby suppressing CH_4 production (Sriphirom et al. 2022; Middelanis et al. 2025).

Mineral N input explained the largest proportion of heterogeneity in the multilevel meta-regression analysis. Its impact on CH_4 emissions in biochar-amended paddy fields can be interpreted through several mechanisms. First, high mineral N input promotes vigorous growth of rice shoots and roots, which increases the supply of labile substrates available to methanogens, thereby enhancing CH_4 emissions (Schimel 2000). Second, CH_4 monooxygenase may preferentially bind to NH_4^+, reducing CH_4 oxidation (Gulledge and Schimel 1998). Third, biochar exerts a liming effect by increasing soil pH, which can facilitate the recovery of key methanotrophic populations (Nan et al. 2021; Ali et al. 2022; Kerner et al. 2023). However, excessive N fertilizer application may counteract these benefits by causing soil acidification, leading to the inactivation of methane-oxidizing microorganisms and increasing Al^{3+} toxicity, ultimately resulting in elevated CH_4 emissions (Weber and Quicker 2018; Tamai et al. 2007).

4.3 Interaction between biochar and mineral nitrogen in regulating CH_4 emissions

Based on the above analyses, we found that at high mineral N levels (input of mineral N > 291.18 kg ha^{-1}), biochar application increased CH_4 emissions from paddy fields, a finding further supported by our field experiments (Fig. 4). A more noteworthy observation was that high mineral N input alone did not significantly enhance soil CH_4 emissions; a significant increase was observed only when biochar was applied in combination with high mineral N. This indicates that the elevated CH_4 emissions originated from biochar rather than nitrogen addition itself. We propose several hypotheses to explain this phenomenon. Biochar, as a relatively stable carbon pool, is generally resistant to microbial decomposition, and its beneficial effects on soil aeration, redox potential, and pH are often associated with CH_4 mitigation (Nan et al. 2021). However, previous studies suggest that N input can stimulate microbial degradation of complex carbon sources (Li et al. 2018; Jing et al. 2021), thereby providing additional substrates for methanogens and further depleting oxygen in the soil environment. This highlights the importance of microbial interactions and their responses to mineral N inputs and biochar amendments, which deserve further investigation to unravel the underlying mechanisms.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1007/s42773-025-00563-y.

Additional file 1.

Additional file 2.

Additional file 3.

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Author contributions

Weijie Huang: Conceptualization, Methodology, Investigation, Formal analysis, Visualization, and Writing—original draft. Xingyan Liu: Investigation, Formal analysis, Visualization, and Writing—review and editing. Yu Deng: Investigation, Formal analysis, Visualization. Daoyuan Zhao: Methodology, Writing—review and editing. Jun Yuan: Conceptualization, Supervision, Writing—review and editing. Qirong Shen: Conceptualization, Supervision, Writing—review and editing. Chao Xue: Conceptualization, Supervision, Methodology, Writing—review and editing.

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Data availability

The datasets used or analyzed during the current study are available from the corresponding author upon reasonable request. All R codes have been provided in the supplementary materials.

Declarations

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

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