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Key words: biochar, meta-analysis, methane flux, soil properties, non-independence

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Croplands are a major source of greenhouse gases to the atmosphere contributing over 10% of methane emissions annually worldwide. Biochar treatment has been examined as a potential method to decrease methane emissions from agricultural soils; however, reported effects of biochar on soils have been highly variable across meta-analysis studies likely due to interaction of multiple factors. We present a multivariate meta-regression approach that allows for the examination of factor interactions to determine the master variables that control change in methane flux upon biochar addition, augmenting most traditional meta-analysis methods that only allow for modeling effects of individual factors at a time.

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Abstract

In an effort to optimize soil management practices that can help mitigate terrestrial carbon emissions, biochar has been applied to a wide range of soil environments to examine their effect on soil greenhouse gas emissions. Such studies have shown that soil methane (CH_4) flux response can vary widely leading to both increase and decrease in CH_4 flux upon biochar amendment. To address this discrepancy, multiple meta-analysis studies have been performed in recent years to determine the key factors that may control the direction of CH_4 flux upon biochar treatment. However, even comparing across conclusions from meta-analyses reveals disagreement upon which factors ultimately determine the change in direction and magnitude of CH_4 flux due to biochar additions. Furthermore, using multiple observations from a single study can lead to misinterpretation of the influence of a factor within a meta-analysis due to non-independence. In this study, we use a multivariate meta-regression approach that allows factor interactions to investigate which biochar, soil, and management practice factors in combination or individually best explain CH_4 flux response in past biochar amendment studies. Our results show that the interaction of multiple soil factors (i.e., water saturation, soil texture, soil organic carbon content) best explains soil CH_4 flux response to biochar additions (minimum deviance information criterion, DIC, value along with lowest heterogeneity) as compared to all models utilizing individual factors alone. These findings provide insight into the specific soil factors that should be taken into account simultaneously when optimizing CH_4 flux response to biochar amendments and building empirical models to quantitatively predict soil CH_4 flux.

Introduction

Methane is a potent greenhouse gas that contributes approximately 30% of the total net anthropogenic radiative forcing of 1.6 W m^{-2} [1], where about 30% of all CH_4 sources are associated with soil CH_4 flux [2]. Therefore, implementing effective soil treatment strategies to decrease CH_4 flux from soils can substantially decrease GHG climate impacts. Application of biochar to agricultural land has been proposed as an effective method to decreasing GHG emissions from farmlands while also providing benefits including improved water quality and soil fertility leading to increased crop yield [3,4]. Biochar is produced by heating biomass under low oxygen or anoxic conditions to produce a stable, carbon-rich product that is composed of various redox active minerals and organic phase [5–8]. Due to the electrochemical properties of biochar, it also has the capacity to alter soil redox conditions, E_h, soil pH, the diversity and/or abundance of microorganisms, and therefore, the rate of CH_4 emission/uptake from soils [9].

Although biochar has been presented in many reports as having an impact on soil CH_4 flux [10,11], these individual studies have provided findings ranging from substantial increase to decrease in CH_4 flux in soils amended with biochar, including some with such findings within a single report [12–14]. To determine the key factors controlling these response variations, existing experimental results have been used in multiple meta-analyses to compare the impact of soil, biochar, and management factors on soil CH_4 flux across different studies. Unfortunately, even a comparison of recent meta-analysis studies revealed disagreements in the factors identified as master controls that can be used to explain CH_4 emission direction (flux versus sink) and magnitude. For example, one meta-analysis reports that paddy (i.e., flooded) soils amended with biochar could cause up to 19% greater CH_4 emissions [15], while meta-analysis results presented by Jeffery *et al.* [16] showed biochar addition to flooded soils and acidic soils has high potential to decrease CH_4 emission strength from these soils. Similarly, a recent meta-analysis by He *et al.* [17] found that soil texture, biochar pyrolysis temperature and pH were key factors affecting CH_4 flux, where biochar amendment to coarse texture soils along with higher biochar pyrolysis temperatures and pH produced a significant negative response in CH_4 flux. However, the authors noted that although these factors were found to correlate significantly, their ability to thoroughly explain GHG flux response was low.

Due to the statistical design of previous meta-analyses, only the contribution of individual factors to CH_4 flux change during biochar amendment were evaluated, which effectively implies that a single factor can regulate the soil CH_4 flux response strength under biochar amendment. However, since soil CH_4 emission/uptake is controlled by a complex set of biogeochemical processes occurring including interactions between soil moisture [18], soil redox state [19], soil texture [20], soil pH [21,22], and the availability of organic compounds and inorganic constituents [23,24], the effect of combinations of factors should better explain CH_4 flux changes upon biochar addition. The disagreement within previous reports determining critical factors that control soil CH_4 flux response to biochar addition likely results from the interaction between soil, biochar properties, and management factors, where the effect of these interactions have not been examined in previous meta-analyses.

Another concern is that the Hedges' *d* metric used in some meta-analysis studies is influenced not only by the differences between two groups of studies, but also by the precision of the studies. For example, studies with small replication numbers can give rise to unusually small standard errors purely due to sampling error [25]. Furthermore, meta-analysis in previous studies assumed that all observations were independent even when multiple observations were derived from a single study. To our knowledge, no study has taken into consideration the non-independence influence of observations from the same study [26] when performing such analyses.

In the present study, we aim to further decrease uncertainties in our understanding of soil CH_4 flux response to biochar amendment and identify the combination of factors that best explain variability in methane flux upon biochar amendments. First, we assess whether study-level CH_4 flux differences exhibit similar response to distinct level of interaction soil, biochar and management properties. To do this, we first established the Bayesian mixed-effects meta-analysis (BMM) models to handle non-independence among observations from the same studies. We then assessed the magnitude and variability influence of a single factor and interaction factors for CH_4 flux response difference and whether these influences differ from study-level analysis by comparison of deviance information criterion values (DIC) and heterogeneity computed by BMM models.

Materials and methods

Data sources

A literature search was conducted using Scopus, Web of Science, and Google Scholar databases using the keywords “biochar” or “charcoal” or “black carbon” and “CH_4” or “methane” or “greenhouse gas” taking all publications published before July 2016. For each paper the title and abstract were evaluated to verify if they reported original quantitative data on CH_4 emissions and examined in detail for quality criteria. A minimum of three replicates per treatment was required for the study to be included in the meta-analysis. Only studies where gas sampling frequency was 3 times or more during the entire experiment were included. Data was collected on studies that compared CH_4 emissions/uptake between a control and a biochar treatment, where the control was defined as being identical to the treatment for all variables except biochar addition. A total of 158 treatments from 40 peer-reviewed articles published between 2009 and 2016 met the criteria and were used in this meta-analysis, inclusive of 35% pot studies, 30% incubation studies and 35% field-based studies.

From each study, data were extracted for (i) soil properties (water saturation, texture, pH, soil organic carbon content (SOC), and total nitrogen (TN), (ii) biochar properties (feedstock, production temperature, pH, and C/N ratio), and (iii) management practices and study design (field/pot/incubation study; biochar application rate; study duration; N, P_2O_5 and K_2O-fertilizer application rate). Plot Digitizer 2.6.6 was used to extract data points that were only provided in figures. When necessary, we contacted authors for information on parameters that were missing in the publications; if we were unable to attain the missing data, the study was excluded from the data analysis. If data from the same experiment and study period were reported in several papers (e.g., in chronosequence studies with different papers utilizing data from the same experiment) only data from the longest study was included.

Data standardization

Data were subjected to a standardization process to allow for comparisons across studies. To examine the effect of water saturation as a major control on CH_4 flux from biochar amended soils, compiled data were grouped as "paddy soil" or "upland" for the meta-analysis. The criteria for inclusion in these categories are as follows: (i) "paddy soil" is defined as soils for cultivating rice that are continuously flooded, while (ii) "upland soil" are soils that are not continuously flooded for extended periods of time, including forest, grassland, wildland, and farmland except rice paddies. After separating studies into the two major water saturation categories, data were compiled on soil and biochar properties and management practices within each study. Each variable was separated into interval or nominal categories, where intervals were determined based on data distributions. The data distribution of each variable is provided in Supporting Information (Fig. S1) and category definitions are as follows:

CH_4 flux rates were identically transformed to amount per kilogram per day (expressed as mg CH_4-C kg soil^{-1} week^{-1}) according to the soil layer (defined as 15 cm if not provided because most soil properties value in literatures were from the top 15 cm soil) and the bulk density or bulk density estimated from soil texture [27] reported in each study. In the cases that seasonal or annual mean soil CH_4 fluxes were not reported directly, we estimated the value by dividing total CH_4 emissions/uptake into average daily fluxes over the measurement period.

Soil texture was grouped into three categories: (i) coarse (sandy loam, sandy clay loam, loamy sand), (ii) medium (clay loam, loam, silty clay loam, silt, silt loam) or (iii) fine (clay, silt clay, sandy clay) (USDA, 1999). Soil pH values measured with $CaCl_2$ were transformed to be able to compare pH values acquired using distilled water using Equation *(1)* [28]:

$$pH[H_2O] = 1.65 + 0.86 \times pH[CaCl_2] \tag{1}$$

Soil pH, SOC, TN and C/N data were then separated into a number of categories defined by data distribution (Fig. S1).

A similar data processing procedure was performed on biochar properties where values were grouped into categories based on data distribution. Biochar pyrolysis temperatures were grouped into three temperature ranges (≤400, 401-500, >500°C). When temperature was reported as a range in the original study (e.g., 500-600°C), the average value was chosen (i.e. 550°C). Feedstocks were grouped into five categories: (i) biosolids (sewage sludge from water treatment plants), (ii) manures or manure-based materials (poultry, pig or cattle), (iii) wood (oak, pine, willow, sycamore and unidentified wood mixtures), (iv) herbaceous plant materials (green waste, bamboo, straws), and (v) lignocellulosic waste (rice husk, nuts shells, paper mill waste). Biochar pH ranged from 6.2 to 10.5 in soils, being predominantly alkaline, and were grouped into four categories (<7, 7.0-<8.0, 8.0-9.0, >9). Biochar TOC, TN and C/N were also grouped based on data distribution (Fig. S1).

Biochar application rates were transformed into percentage of dry weight ratio (w:w biochar:soil) where the weight of soil was calculated using the height of the soil layer in which biochar was added (or a height of 15 cm when no value is reported) and the bulk density (BD) of the soil. If BD was not provided, it was calculated from the soil texture according to Saxton et al. [27]. Biochar application rate was then grouped into five categories (<1, 1-<2, 2–<5, ≥5%, dry weight ratio (w:w) basis). Experimental method was grouped into three categories (field, pot and incubation). Experimental time was measured in days (<60, 60-150, >150).

Data analysis

CH_4 flux in the biochar treatment minus CH_4 flux in the control was used as a metric to describe the change in the net sink/source status in the soil defined as the raw mean difference. Equation *(2)* was used to calculate raw mean difference, d_{ij} [26]:

$$d_{ij} = X_{ij}^{E} - X_{ij}^{C} \quad (2)$$

where d_{ij} is calculated for the *j*th study in the *i*th treatment, and X_{ij}^{C} is the mean CH_4 flux of the control, X_{ij}^{E} is the mean CH_4 flux of the biochar treatment.

Thus,

$$s_{ij} = \sqrt{\frac{(S_{ij}^{E})^2}{N_{ij}^{E}} + \frac{(s_{ij}^{C})^2}{N_{ij}^{C}}} \quad (3)$$

where s_{ij} is the standard deviation of the raw mean difference, N_{ij}^{C} is the total number of observations in the control, N_{ij}^{E} is the total number of observations in the biochar treatment, s_{ij}^{C} is the standard deviation of observations in the control, and s_{ij}^{E} is the standard deviation of observations in the biochar treatment.

A negative *d* indicates an increase in soil CH_4 net sink or decrease in net source due to biochar addition and a positive *d* indicates a decrease in soil CH_4 net sink (or increase in net source). If *d* has a zero value, then there is no shift in CH_4 net sink/source in soil.

Statistical analysis

Non-independence between data points considered within a meta-analysis can arise due to the fact that one individual study can contribute several data points on the effect of biochar treatment on CH_4 flux (e.g., from testing multiple treatment factors for example). Many meta-analysis methods assume that all data points are independent, which would not be suitable for this scenario. Therefore, we used Bayesian mixed-effects meta-analysis (BMM) models to address the non-independence of observations within the a single study[29]:

$$d_i = \mu + u_{j[i]} + e_i + m_i \quad (4)$$

$$\mathbf{e} \sim \mathrm{N}(0, \sigma_e^2 I) \quad (5)$$

where d_i is the raw mean difference for the *i*th treatment, μ is the intercept, $u_{j[i]}$ is the study specific effect of the *j*th study, m_i is a sampling error effect for the *i*th treatment, e_i is the within-study effect for the *i*th effect size, and **e** is a 1 by N_{study} vector of e_j, which is normally distributed around 0 with the within-study variance $\sigma_e^2 I$ ($\sigma_e^2 I$ is a N_{study} by N_{study} matrix with its diagonal elements being σ_e^2).

We adopted R package MCMCglmm to carryout Bayesian mixed-effects meta-analysis (BMM) [30]. For all models, studies were treated as random factors. Water saturation, soil and biochar properties and management factors and their interactions were used as fixed effects. We assessed heterogeneity across studies by the proportion of the total variance in a model accounted by a particular random factor [29]. Combinations of the two, three and four factor interactions among the soil, biochar properties and management factors as the fixed effects were calculated by BMM, which generated a total of 271 models. In this report, we only show the results from the models with the lowest DIC (deviance information criterion) and heterogeneity (i.e., inconsistency across studies) and models using single soil and biochar properties and management factor as the fixed factors. DIC is a Bayesian equivalent of Akaike's information criterion (AIC) and the Bayesian information criterion (BIC). Because DIC is calculated from the posterior distributions of the models by Markov chain Monte Carlo (MCMC) simulation, it is easily gained compared with AIC and BIC. DIC can be used for model comparisons and where the lower the DIC values indicate better the model fits [31]. Model 1 only considered random effects (i.e., no fixed effects) in each study and model 2-19 considered the random and the fixed effects in each study [29]. All calculated DIC and heterogeneity values from mixed-effects models (Model 2 through 19) were then compared with Model 1; a test model with lower DIC value than Model 1 meant the test model can better fit the data than Model 1. Publication bias was assessed by using funnel plots and Egger's regression [29].

Results

There is no significant soil CH_4 emission/uptake response to biochar addition across studies ($d_{\text{intercept estimate}}$ = -0.02, 95% credible interval, CI: -0.15 - 0.13, Supporting Information Table S1), but heterogeneity (Model 1; 12%, Fig. 1) arising from studies existed. Incorporating the interaction moderator with water saturation, soil texture and SOC significantly decreased the heterogeneity among studies (Model 19; 8%, Fig. 1). Furthermore, BMM with interactions between water saturation, soil texture, and SOC concentration significantly decreased the DIC, indicating this model best explained data variation among the eighteen models tested (Model 19; DIC of -717, Fig. 1). There was a significant negative effect when taking into account interaction between upland, SOC concentration (10-20 g kg^{-1}), and coarse soil texture on soil CH_4 emission (or positive effect on CH_4 uptake) after biochar amendment ($d_{\text{fixed effect estimate}}$ = -0.26, 95% credible interval, CI: -0.44 to -0.07; Fig. 2 and supporting information, Table S19). Incorporating the interaction moderator with water saturation, soil texture, and soil pH did not decrease the heterogeneity among studies (i.e., heterogeneity of 18%, Fig. 1).

There was little evidence that application of water saturation, soil texture, and soil organic carbon moderators individually decreased the model DIC and heterogeneity among studies (Fig. 1). Without interaction, water saturation, soil texture, and soil organic carbon subgroups did not explain variation in soil CH_4 emission/uptake after biochar addition (Supporting Information, Table S2-S4). Also, there was little evidence that individual soil properties (soil pH and soil N concentration), biochar properties (feedstocks, pH, C/N and pyrolysis temperature), and management practice (experimental method, time, biochar application rate and fertilizer N, P_2O_5, K_2O) subgroups significantly affected soil CH_4 emission/uptake across studies, respectively (Supporting Information, Table S5-S17).

There were no signs of publication bias for model 1 and 19 as shown in Fig. 3 and the Egger's regression test supported the lack of publication bias in our dataset (-0.001, 95% CI: -0.005 – 0.003); the slope of the regression is not significantly different from zero, indicating little evidence for publication bias.

Discussion

Accounting for non-independence of within-study observations in meta-analyses avoids underestimation of variance

Several studies that have applied meta-analyses to determine the influence of biochar amendment on CH_4 flux strength utilized multiple results (effect sizes) from a single study (i.e., a total of 158 experimental treatments or individual observations from 40 articles), but did not take into account the non-independence of within-study observations. Without taking into account non-independence of such observations, the standard error of mean effect size could potentially be underestimated, leading to increased probability of committing a type I error [29]. To determine the impact of non-independence of within study observations on our meta-analysis results, the traditional random-effect meta-analysis model (i.e., ignores non-independence of within-study observations) and the Bayesian mixed-effects meta-analysis model (i.e., takes non-independence into account) were used to estimate the variance for the mean effect sizes and their results were compared (Table S20). We found that standard errors from the traditional random-effect meta-analysis model is about 17% of the standard errors from Model 1 which takes non-independence into account. This implies biochar addition would not cause a significant change in soil CH_4 flux in any coarse textured soil in Bayesian mixed-effects meta-analysis, but could be deemed significant by traditional random-effect meta-analysis. Consistent with our hypothesis, this comparison demonstrated that non-independence arising from multiple observations from the same study will underestimate the variance for the summary effect, and they may therefore bias the overall meta-analysis result.

Incorporation of factor interactions better explains soil CH_4 response to biochar addition than analyses based upon individual factors

Previous meta-analysis studies concluded that biochar application could significantly decrease CH_4 flux from coarse soils and from soils amended with low pH biochar [17], and that biochar application also decreased CH_4 flux strength from paddy fields and/or acidic soils [16]. In this way, these analysis attribute CH_4 flux changes upon biochar addition to individual moderators, which have contrasting effects when interacting with other soil parameters. For example, to explain the effect of texture on CH_4 flux, decreased CH_4 flux from biochar amended coarse soils is reportedly due to increased aeration upon amendment [32]; in contrast, biochar amendment to fine-textured soils can lead to minimal aeration effects and maintained methanogenesis because of clay particles filling biochar pore spaces [17]. However, addition of biochar to fine textured soils can also lead to decrease in CH_4 flux [14] due to interactions of soil texture with other soil parameters including land use and SOC content [33]. In the individual study from our studies library, no study specifically controlled for and tested the influence of interaction of water saturation and soil organic carbon, soil texture simultaneously on CH_4 emission/uptake. This demonstrates a need to utilize multiple parameters simultaneously in meta-analyses to more accurately represent ecosystem-to-pore scale soil processes controlling of CH_4 flux controls upon biochar addition.

Our Bayesian mixed-effects meta-analysis shows that individual soil, biochar, and management practice parameters cannot explain overall soil CH_4 flux change when biochar was applied (Fig. 1, Models 2 through 17), whereas taking into account the interaction between multiple factors significantly increased explanation of CH_4 flux response based on highest magnitude negative DIC values and lowest heterogeneity percentages (Fig.1, Models 18 and 19). Specifically, the interaction between three factors, soil texture, water saturation, and soil organic carbon content, provided the optimal values in DIC (-717) and heterogeneity (8%). Therefore, our results show that factor interactions can better explain variations in CH_4 flux response to biochar addition than use of individual factors. Specifically, the interactions between soil properties exert greatest influence when compared to interactions that included biochar and management practice parameters.

These results collectively suggest that to accurately assess the effect of biochar addition on soil CH_4 flux, these specific soil properties, water saturation, SOC content, and texture should be considered jointly. This is in agreement with past reports [35,36] that soil type and soil organic carbon content are major determinants of CH_4 production potential [37]. When building empirical models for CH_4 flux change prediction in biochar added soil, these results emphasize the need to integrate soil properties interaction, with weaker emphasis on biochar properties and management input parameters. For example, by excluding management practice parameters, the model goodness-of-fit will likely increase while also decreasing computational time [38]. Ultimately, implementation of the empirical model can be valuable for determining best practices that can minimize methane emissions or maximizing methane sink.

Interactions between soil texture, water saturation*, and soil organic carbon determine soil response to biochar amendment*

Net soil CH_4 emission is determined by a complex set of biogeochemical processes occurring simultaneously, where the competition between methanogenic and methanotrophic processes has been ascribed as a major determinant of net CH_4 flux [39–41]. Methanogenesis can be stimulated or inhibited by a number of soil factors including changes in soil moisture, SOC content, and soil texture. Soil moisture affects soil redox state, SOC content can influence the availability of carbon sources to fuel microbial growth and metabolism, and soil texture controls the transport of substrates and products including carbon and oxygen [23]. Water saturation, in this study, is defined by irrigation type or water input which are grouped into two general categories that either impose long-term inundation (paddy) or mostly aerated (upland) conditions, which can therefore be used as a proxy for soil moisture and redox conditions on the landscape scale. The resultant change in CH_4 flux in a range of soil textures will differ drastically based upon available carbon content and water saturation. For example, high SOC availability in combination with inundation (e.g., paddy soils) and fine textured soils will either maintain or return to low redox conditions even after additional of biochar and therefore show minimal change or even increase in CH_4 flux [10]. In contrast, addition of biochar to fine textured soils in upland soils of moderate SOC will lead to more effective aeration due to the introduction of oxygen and additional pore spaces to previously anaerobic sites during biochar addition, leading to suppression of CH_4 flux or increased CH_4 sink [42]. Generally, biochar incorporation to upland clayey soils should lead to increased aeration during amendment while also increasing soil porosity resulting in decreased methane flux [12,42]. In contrast, the impact of biochar addition to upland soils more dependent upon soil texture which controls rate of oxygen diffusion into soil aggregates [44].

Interestingly, only biochar addition to soils with moderate SOC content (10-20 g kg^{-1}) in coarse textured, upland soils lead to a significant change (decrease in CH_4 flux/increased CH_4 sink) in soil CH_4 flux when factor interactions were taken into account (Fig. 2b). An upland soil with coarse texture will have the highest potential to aerate most effectively in the event of biochar amendment [45], where fine particles are unavailable to fill pores and oxygen diffusion into the soil profile is not inhibited by inundation. In addition, biochar particles have been shown to provide additional habitats for soil microbes [33]; our results show that biochar amendment to coarse soils likely provide habitats that favor methanotroph growth to outcompete methanogens [39]. Furthermore, the presence of biochar may augment methanotrophic activity through enhanced priming effect in a coarse soil, where biochar can adsorb labile organic carbon species [46,47] for microbial metabolism which would otherwise be transported out of the soil profile more readily than in the absence of biochar. Nevertheless, the presence of inter-study variation (heterogeneity of 8%) causes a portion of the studies to not be explained by this three-component factor interaction.

Our results are based on the mean CH_4 flux, but not the cumulative CH_4 uptake/emission in the experimental time for the flux changes comparison among studies. That means the effect of some environmental factors (soil temperature and moisture etc.) are usually less consistent in field experiments compared to lab incubations and may therefore result in more substantial CH_4 flux variation. Unfortunately, very few field studies have tested the effect of soil temperature and moisture trends on amended plots over large time scales; such studies are necessary to further our understanding of the response patterns and regulators of soil CH_4 flux identified as key factors in this study. This warrants further exploration by designing targeted studies that can directly interrogate the mechanistic relationship between the three soil properties and their combined influence on soil CH_4 flux in the presence of biochar.

Conclusion

In summary, the patterns emerging from existing studies as revealed by our meta-analysis show there is substantial variation in soil CH_4 flux response to biochar amendment. Interaction of soil properties tends to regulate soil CH_4 emission/uptake response to biochar addition. Soil CH_4 emission/uptake can be best explained as a function of soil organic carbon concentration, soil texture, and water saturation, specifically where biochar amendment to upland soils with coarse texture and soils with 10-20 g kg^{-1} C concentration tend to have decreased soil CH_4 emission/increase CH_4 uptake. Variations in individual soil properties, biochar properties, and management practices showed no consistent increase or decrease in soil CH_4 flux across studies, which likely demonstrates that regulation of these properties are highly non-independent.

Author contributions. WC performed data collection and data anlaysis, SCY performed data interpretation. The manuscript was written by WC and SCY with comments from JM.

Competing interests. *The authors declare that they have no conflicts of interest.*

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Figures

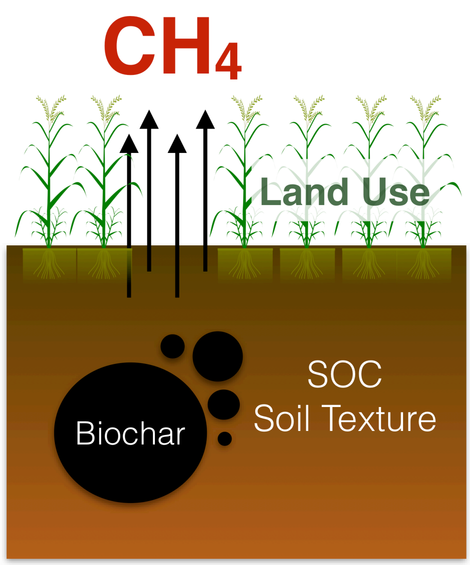

Table of Contents Entry/Graphical Abstract

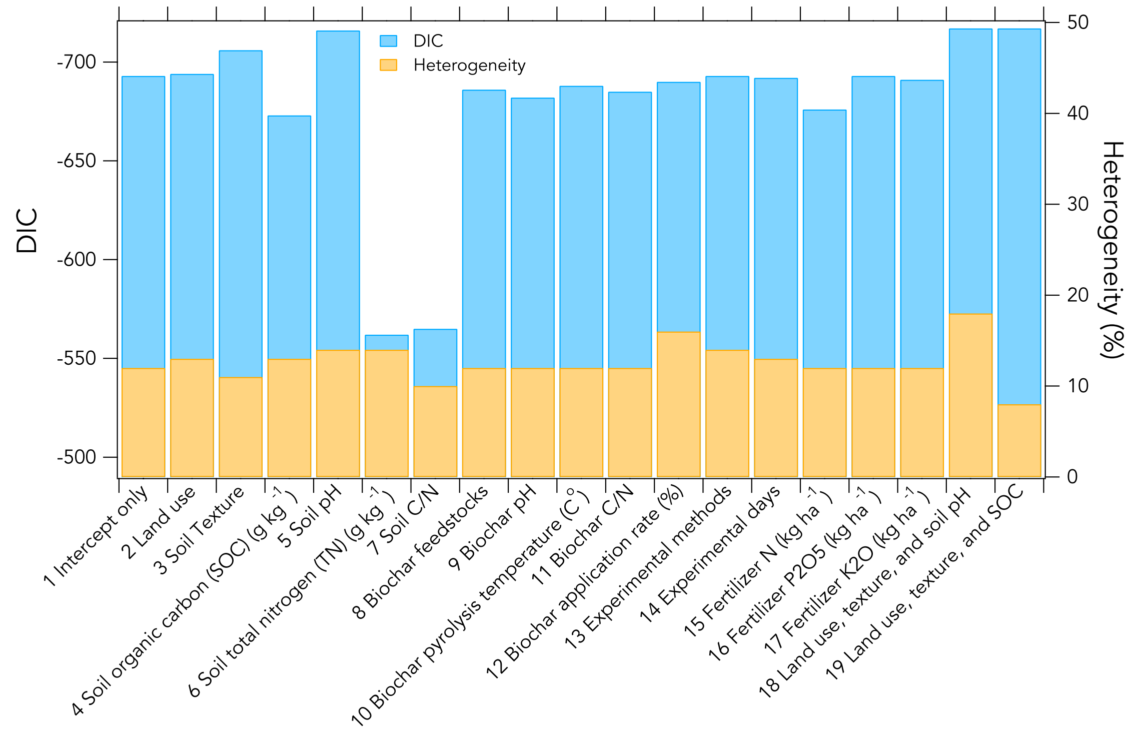

Figure 1. Meta-analysis models run in this study with moderators defined for each. Column labels along axis show model number followed by moderators for each model, where models 18 and 19 represent factor interactions models. Deviance information criteria (DIC, blue bars) and heterogeneity (%, yellow bars) resulting from fixed effects (the proportion of variance for a particular fixed factor in relation to the sum of all variance components) are provided for each model; values for DIC and heterogeneity are the posterior modes (for detailed results, see Supporting Information, Tables S1–S19). DIC Factors with lower (more negative) DIC values are better predictors than a more positive DIC value.

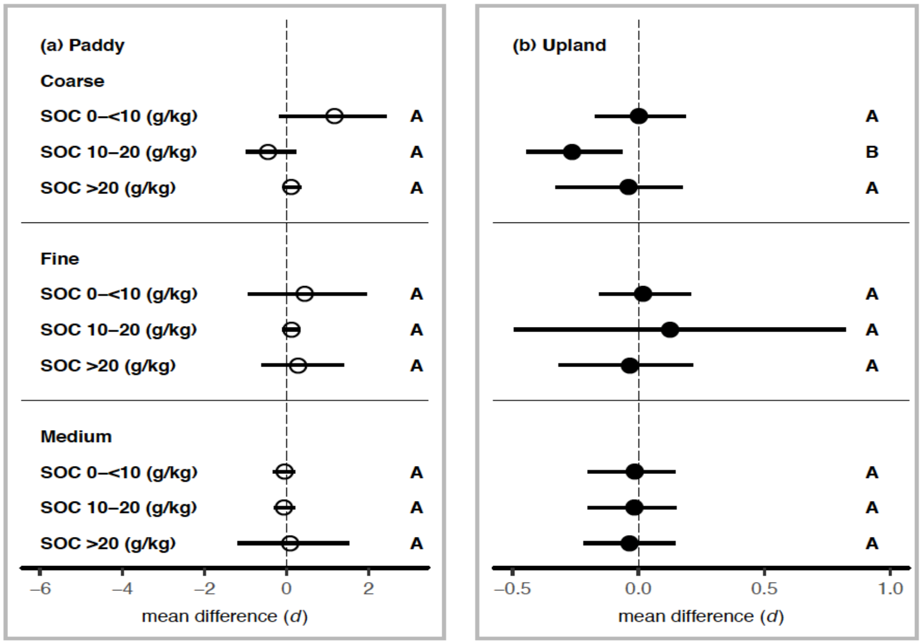

Figure 2. A forest plot of meta-analysis results of Model 19 (interaction of land use type, soil texture, and soil organic carbon content in g kg^{-1}) which yielded the most negative DIC value (-717) and lowest heterogeneity (8%) for (a) paddy (open circles) and (b) upland (solid circles) land use types.

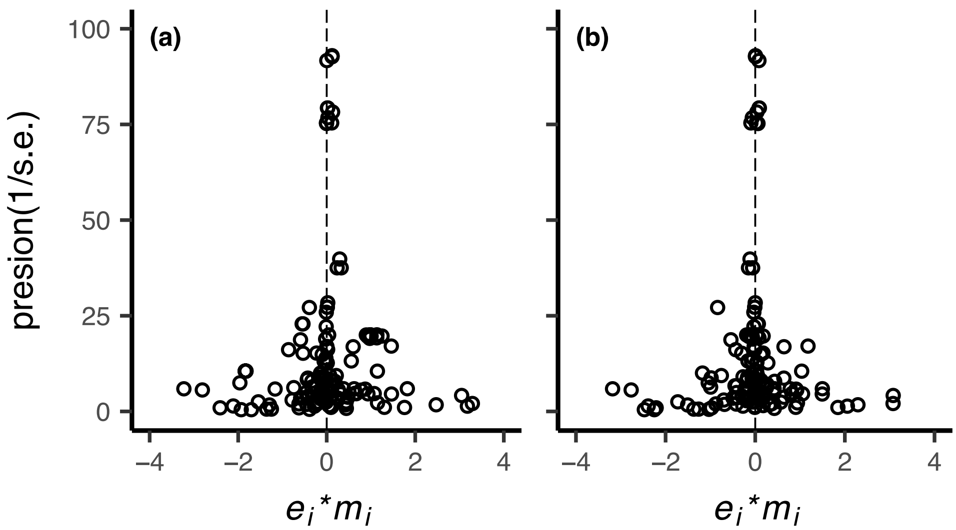

Figure 3. A funnel plot of (a) Model 1 and (b) Model 19 with precision representing within-study effects, e_i plus sampling-error effects, and m_i (meta-analytic residuals) from Model 1 and 19, separately (see Fig. 1) plotted against the inverse of standard errors (s.e.).