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A Meta Regression Analysis of Soil Organic Carbon Sequestration in Corn Belt States: Implication for Cellulosic Biofuel Production

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Abstract

This study investigated the extent to which statistical heterogeneity among results of multiple studies on soil organic carbon (SOC) sequestration rate in response to conventional tillage (CT) and no-till (NT) can be related to one or more characteristics of the studies. The analysis employed a random effect meta-regression technique using the data obtained from recently published experimental trials under continuous corn (CC) and corn soybean (CS) rotation system from selected Corn Belt states.

Regarding the difference in the rate of SOC sequestration between NT and CT, our results shows that the percentage of heterogeneity in the true treatment effect that is attributable to between-study variability is 49%, whereas 51 % is attributable to within-study sampling variability.

We find that 26% of the between-study variance is explained by the explanatory variables considered, and the remaining between-study variance appears almost zero. The regression results support the argument that the difference between NT and CT decreases as measurement depth increases. The results also show that the higher the initial SOC the higher the NT SOC sequestration rate relative to the CT sequestration rate. A test for publication biases in the analysis indicated no evidence for the presence of small-study effects.

Key words: SOC sequestration rate, no-till, conventional tillage, Meta regression

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1. Introduction

Results from many individual experimental studies across Midwest states and globally showed considerable heterogeneity on the results of rate of SOC sequestration in response to NT and CT practices. Given the range and variability of estimated sequestration rate, this study combines the results of independent studies and doing regional assessments in order to uncover the source of this heterogeneity.

Large areas of cropland in U.S. Corn Belt are being gradually converted from CT to conservation tillage particularly to NT systems, and this change is partly driven by the fact that widespread adoption of conservation tillage, specifically NT, would sequester a substantial amount of SOC than CT (Christopher et.al 2009; Gal et.al 2007; Baker et.al 2007; Al-Kaisi and Yin 2005; Lal et.al 1998; West and Post 2002; Blanco-Canqui & Lal, 2007). However, it is an unsettled argument whether such practices actually sequester SOC. Higher SOC sequestration in NT systems is reported in many studies when soil was sampled up to 30cm depth. However in a few studies where sampling extended deeper than 30cm (Ga'l et.al 2007; Ogle et.al 2008) and in experimental trials based on gas exchange measure (Verma et.al 2005; Baker et al. 2007), NT showed a higher or lower SOC sequestration.

Approximately 49% of agricultural SOC sequestration can be achieved by adopting conservation tillage and residue management (Lal et al. 1998). However SOC loss consistently increases with percentage residue harvest (Blanco-Canqui & Lal 2007). The partial or complete removal of corn stover to produce biofuel reduces the amount of residue returned to the soil and may increase the risk of soil degradation and eventually leads to depletion of the SOC pool and greenhouse gases (GHG) emission of (Lal 2002 2004; Johnson et.al 2004 2007). SOC

sequestration is a key component in the life cycle of biofuel production (Ney & Schnoor 2002; Adler et al., 2007) and crucial in determining the GHG reduction potential of biofuels relative to fossil fuels (Anderson-Teixeira et.al 2009). Various studies have quantified changes in SOC under potential biofuel crops. Results are variable and have yet extensive effort is needed to develop coherent pictures (Johnson et.al 2007; Wilhelm et.al 2007).

In the time of recent trend toward development of cellulosic biofuel production from crop residues, it is crucial to put forward research findings related to SOC sequestration to understand the relative advantage of conservation tillage over the CT. There is disparity among reported experimental results on the relative advantage of NT over CT in SOC sequestration rate and yet this is the information we should discern in such kind of study. Hence a regional assessment, examining data from distinct cultivation systems could justify a broad understanding of NT and CT effects on SOC in Corn Belt states. Therefore analyzing the results of different studies with heterogeneous results across Corn Belt states using Meta regression analysis is essential to elucidate the source of heterogeneity, particularly now when large areas of cropland are being converted to long-term NT systems based on the premise that NT soils sequester SOC.

There have been several meta-analyses and scientific literature reviews on the effects of NT and CT on SOC globally (West and Post 2002; Alvarez 2005; Angers and Eriksen-Hamel 2007; Angers et al. 1997; Six et al 2002; Anderson-Teixeira et.al 2009) and also regionally in North America (Christopher et.al 2007; Blanco-Canqui et.al 2007; Ogle et.al 2003).

The purpose of this study is therefore to conduct a Meta-regression analysis to investigate the extent to which statistical heterogeneity among results of multiple studies on SOC sequestration can be related to one or more characteristics of the studies. The analysis would help us to explore study-to-study variation of SOC sequestration rate by determining the extent to which methods,

design and data affect reported results. The analysis is based on recently peer reviewed published studies on SOC sequestration from long-term paired experiments exclusively under continuous corn (CC) and corn soybean (CS) rotation system . The data collected were from multiyear paired experiments that ran at least for five years. To give fresh perspective and augment the rapid development in approach of SOC measurements, only published studies since year 2000 are included in our sample. In the study we also investigate publication and related biases since most meta-analysis are susceptible to such problems.

The remainder of the paper is organized into four sections. Section 2 exposits the theoretical model. This theoretical and analytical model is based on Meta regression and its estimation procedure is using random effect model. Section 3 describes the data and approached followed to construct some of the data used in this study. The empirical results of our application and implication of this study is presented in section 4, and in the last section summary and concluding remarks are then provided. The appendixes section contains results and figures from the regression analysis, and a tabular summary of the data used in our meta-analyses.

2. Analytical Model

2.1. Meta-Regression Model

The classical meta-regression model here is based on random effects with a generic form shown in equation 1. For the subject i in the study j , we can write the basic underling model for outcome Y_{ij}

$$Y_{ij} = \beta_0 + \beta_i X_{ij} + \upsilon_j + \varepsilon_{ij} \quad (1)$$

We assume that each study j provides a total of n studies to estimate the effect of interest, i, which here is a difference in rate of SOC sequestration from NT to CT. Each study also reports a standard error for this estimate, σ_i, which we assume is known. Inference is based on the assumption that the studies are a random sample of some hypothetical population of studies. β_0 is an intercept of the regression model.

β is a k × 1 vector of regression coefficients to estimate, and X_i is a 1 × k vector containing the observed trial-level explanatory variables for study j. Explanatory variables used here are initial SOC, depth of the soil sampled, yield of corn and soybean, mean annual temperature and dummy for crop rotation (continuous corn verses corn-soybean rotation).

Our model allows for residual heterogeneity, assuming that the true effects follow a normal distribution around the linear predictor:

$$Y_i \mid \theta_i \sim N(\theta_i, \sigma_i^2), \text{ where } \theta_i \sim N(X_i\beta, \tau^2) \quad (2)$$

$$\varepsilon_{ij} \sim N(0, {\sigma_e}^2) \text{ and } \upsilon_j \sim N(0, \tau^2) \quad (3)$$

θ_i is a true effect and has a normal distribution around the linear predictor, $X_i\beta$. Here ε_{ij} is within study error term whereas υ_j is between study error. τ^2 is between study variance and should be estimated from the data[1].

As shown on equation 4, β_i , is determined by the true effect θ_i plus the within-study error ε_i. In turn, θ_i, is determined by the mean of all true effects, μ and the between-study error υ_i. More generally, for any observed effect β_i,

[1] In the random effects model, there is between-study as well as within-study components of the variance term (Borenstein et.al 2007).

$$\beta_i = \theta_i + \varepsilon_i = \mu + \upsilon_i + \varepsilon_{ij} = \beta X_i + \upsilon_i + \varepsilon_{ij} \quad (4)$$

There are two levels of sampling and two sources of error when we are dealing with random effect model. At first, the true effect sizes θ_i are distributed about μ with a variance τ^2 that reflects the actual distribution of the true effects about their mean. Second, the observed effect β_i for any given θ_i will be distributed about that θ_i with a variance σ^2 that depends primarily on the sample size for that study. Therefore, in assigning weights to estimate μ, we need to deal with both sources of sampling error – within studies (ε_{ij}), and between studies (υ_j). An excellent treatment of this approach with regard to meta-regression can be found from (Borenstein et.al 2007; Harbord and Higgins 2008)

As Harbord and Higgins (2008) presented in their analysis, all algorithms for random-effects meta-regression first estimate the between-study variance, τ^2, and then estimate the coefficients, β, by weighted least squares by weighting using $1/(\sigma_i^2 + \tau^2)^2$. The default algorithm in our regression is residual (restricted) maximum likelihood (REML) is used The fact that in meta-analysis we are strongly interested in the size of the between-study variance component, Restricted Maximum Likelihood (RML) estimation is the best approach. and directly maximizes the residual (restricted) log likelihood.

The method used to decompose the variance is to calculate the total variance and then to isolate the within-studies variance. The variance between-studies (τ^2) is obtained as the difference between these two values. The proportion of between-study variance explained by

independent variables can be calculated by comparing the estimated between-study variance, $\hat{\tau}^2$, with its value when no covariates are fit, $\hat{\tau}_o^2$. Adjusted R^2 is the relative reduction in the between-study variance as shown in equation 5.

$$R_{adj}{}^2 = (\hat{\tau}_o^2 - \hat{\tau}^2) / \hat{\tau}_o^2 \quad (5)$$

2.2. Mechanism to Investigate Publication Biases

In this section we provide the mechanism to investigate publication and small sample bias using funnel plots and Egger test (Egger et al. 1997; Harbord and Harris 2009). If publication bias exists, any meta-analysis based on it will be similarly biased (Sterne et.al 2000; Palmer and Peters 2008). Funnel plot is a visual method used to test for the likely presence of publication and related biases in meta-analysis (Sterne et.al 2005; Palmer and Peters 2008; Sterne and Egger 2001; Harbord and Harris 2009). Funnel plot is a simple scatter plots of the treatment effects (difference in rate of SOC sequestration in our case) estimated from individual studies against a measure of study size here in our case a standard error of the effect size Publication bias may lead to asymmetrical funnel plots, however this bias is only one of a number of possible causes of funnel-plot asymmetry (Sterne and Harbord 2004)[3].Judgment based on such visual interpretation for asymmetry is inherently subjective (Harbord and Harris 2009).

[3] Egger et al. (1997) pointed out potential sources of asymmetry in funnel plots: Selection biases (e.g. Publication bias), true heterogeneity (e.g. Size of effect differs according to study size), Data irregularities (e.g. Poor methodological design of small studies, Inadequate analysis), Heterogeneity due to poor choice of effect measure.

Rather we used an Egger test based on a linear regression approach to measure funnel plot asymmetry (Egger et al. 1997) shown in equation 6 below.

$$effect_i = \delta_1 + \alpha_1 S.E_i + \varepsilon_i \quad (6)$$

$effect_i$ in our case is the difference in ΔSOC sequestration rate of each study i, $S.E_i$ is the standard error of study j. We can test for H0: α_1=0, this simple meta-regression model is to investigate whether a research literature is affected by publication selection (Egger et al. 1997; Harbord and Harris 2009; Stanley and Doucouliagos 2011).

3. The Data

We found 13 peer-reviewed published studies that reported rate of SOC sequestration in nine states (Illinois, Indiana, Iowa, Minnesota, Nebraska, South Dakota, Ohio, Pennsylvania and South Dakota). The total number observations are 78, (table 8). Studies were included in the data set if the following criteria were met: (1) paired studies that compared NT with CT exclusively under continuous corn and corn-soybean rotation system. The tillage could be a multisystem with fertilizer treatment but with no residue treatment trials. (3) Studies published on year 2000 and onward. To be part of the analysis, each study must also report at least the rate of SOC sequestration and initial or final SOC value. We dropped studies, if the specific paired tillage experimental studies included crops other than corn and soybean in the CC and CS crop rotation. (4) SOC was sampled to depths ≥15cm.[4] (5) experiments that ran at least for five years,

[4] The necessity of deeper depth sampling is for improved accuracy in the assessment of C or N sequestration with no-till versus conventional tillage systems is vital (Ga'l et.al 2007).

since a multiyear experimental study is necessary as there is difficulty to adequately detect a small change in SOC stock over a time period of less than 5yr (Post et.al. 2001; Ellert et.al 2002; Baker et.al 2007; personal communication with Varvel 2011).

Key data gatherer were soil depth, duration of tillage study, yield of corn and soybean, types of rotations, mean annual precipitation and temperature at experimental sites. In addition, the standard error of the rate of SOC sequestration for each study was gathered. If these standard errors were not reported, we estimated taking the mean of SOC sequestration rate and divide by the number of replication of experimental plots. Furthermore, if specific details such as yield, temperature and precipitation of the study were not reported, we estimated them based on the county level information where the experiment was conducted. The yield for corn and soybean are the average yield during the experimental period. For example in studies that didn't report yield, we used the average yield of the county where the experimental trails ran during the experimental period.

Almost all of the studies reviewed were from dry land agriculture trails except four irrigated trials from Nebraska. Except 3 eddy covariance studies , the majority of samples are based on the standard method for assessment of SOC sequestration using soil sampling of long-term tillage research trial plots.

4. Empirical Results and Discussion

Table 1 and 2 portray the summary statistics of the data used in this study. The results of the regression analysis are summarized from Tables 3 through 6. The summary statistics indicate that the duration of the studies varied from 4 to 51 year, with an average of 16 years. The average depth of the soil sampled under both tillage practices across all studies was 30 cm. The dependent variable which is the difference in the rate of SOC from NT to CT has a mean value of 0.09 Mg C $ha^{-1}yr^{-1}$.

The percentage of between-study heterogeneity that is attributable to variability in the true treatment effect is 49%, whereas 51 % is attributable to within-study sampling variability. Our regression results also show that 26% of the between-study variance is explained by the explanatory variables considered, and the remaining between-study variance appears almost zero, 0.003, depicted on table 3. We examined whether specific variables in the regression analysis explain any of the heterogeneity of treatment effects between studies. The joint test for all five independent variables gives a p-value of 0.009, indicating there is evidence for an association of at least one or more of the explanatory variables with the size of the treatment effect.

The positive coefficient on the initial SOC on table 3 indicates that the predicted rate of SOC sequestration under NT relative CT increases. We can infer based on this result that on average a plot under NT sequester 0.086 Mg C $ha-^{1}yr^{-1}$ more SOC than CT. The plotted figure with fitted meta-regression line of the rate of ΔSOC against the initial SOC on Figure 2 shows that at the low level of initial SOC the difference between these two tillage systems was smaller

and close to zero, but as the initial SOC level is higher the NT system gains more rate sequestration of SOC than the corresponding CT system.

Negative regression coefficients on the depth of soil measurement support the contention that the relative no-till advantage over conventional tillage declined with deeper measurement depth. Figure 4 also shows the clear relationship between depth and SOC sequestration rate across all studied experimental samples. This result conforms to the argument that SOC gain from NT that is based on shallow sample depth disappears when deeper samples are included (Angers et al.1997; Dolan et al. 2006; Baker et.al 2007; Six et al. 2002; Gal et.al 2005; Vandenbygaart et al. 2002, 2003).

Our regression result on Table 3 and 5 also showed that for every bushel of corn yield increase, keeping other factor constant , the rate of ΔSOC sequestration under NT system increases 0.001 Mg C ha-^{1}yr^{-1} higher SOC than CT. However for every bushel increase in a soybean yield provides a 0.004 to 0.013 Mg C ha-^{1}yr^{-1} fewer SOC sequestration rate to NT than CT. Agronomically it is believed that the actual effect of the different tillage practices on soil C storage is highly dependent on the types of crops produced in the field (Ga´l et.al 2007; Huggins et.al 2007; Varvel 2006). In this regard corn has a greater biomass production than soybean and combination of this quantity of biomass with NT practices may give an additional advantage for corn to sequester more SOC than the CT.

The dummy variable rotation for coefficient measures the average difference in SOC sequestration rate between CC and CS rotation given the same level of initial SOC, depth, corn and soybean yield and temperature variables. After controlling the above explanatory variables, NT system sequesters 0.05 Mg C ha-^{1}yr^{-1} less SOC than CT when the rotation system is under continuous corn than corn-soybean, shown on table 3. The above result seems odd from the

agronomic stand point under ideal condition. Various studies in Midwest showed that SOC sequestration under continuous corn has been normally higher than under corn–soybean rotation (Lal et al. 1997; Paustian et al. 1997; Gal et.al 2007; Jagadamma et.al 2007; Jarecki and Lal 2003). It is also believed that differences in SOC sequestration between crop rotations is largely influenced by the quantity of crop residues returned to the soil. However the differential in SOC sequestration in our analysis may be due to rotation or other factors other than rotation that we have not controlled for in the regression. Studies indicated that tillage effects on SOC storage have been characterized either as a single factor or in combination with crop residue management, N fertilization, or both (Huggins et.al. 2007 Havlin et al. 1990; Franzluebbers et al. 1994; Paustian et al. 1997).

It is informative to compare the intercept (our base variable in the dummy, CC) on the equation to be estimated when all other explanatory variables are dropped from the equation. The intercept on the result of this simple regression is the average difference that we can get for a rate of ΔSOC when the rotation is under continuous corn system. From table 4 result therefore, plots under CC would provide 0.0161 Mg C ha-^{1}yr^{-1} fewer rate of ΔSOC to NT than CT. The coefficient on this dummy is the difference in the average a rate of ΔSOC of CC relative to CS. The above results offer comparison of-means-test between CC and CS rotation system. The estimated difference between CC to CS is 0.037 Mg C ha-^{1}yr^{-1}. However this difference is not statistically significant (table 4).

Among other factors, the differential effects of rotation on SOC sequestration rate in both tillage systems may vary by the depth of the soil. Clap et.al (2000) argued that very little crop residue was mechanically buried below 15 cm in the NT treatment unless moved by earthworm activity. Fourteen years of experiment on tillage and rotation interaction, (Huggins et.al 2005),

indicated that significant contributions to greater SOC under CC for Chisel Plough and NT, as compared with Mold board Plough, occurred from C storage below tillage operating depths (30- to 45-cm). To put the above arguments in perspective, we added an interaction variable of the dummy rotation with depth-this actually would allow us to have different slope and give more exposition on the relationship among tillage practices, crop rotation and depth. Using our new interaction variable, we then tested whether the effect of continuous corn and corn-soybean rotation over rate of ΔSOC is the same at all depth of the soil.

We are now testing the hypothesis that the average difference in rate of SOC sequestration between NT and CT are identical for CC and CS rotation that have similar depth of soil measurement. Under the null hypothesis the coefficient over the dummy and interaction term must both be zero. Our F test value gave us $F(2, 70) = 3.14$ and $Prob > F = 0.0495$. Therefore we rejected the above hypothesis, implying that there would be variation in SOC sequestration between CC and CS at the same depth of soil. Another important hypothesis we test is that the difference in rate of SOC sequestration (from NT to CT) is the same for CC and CS rotation system across all depth of soil. Our test $F(1, 70) = 3.19$, $Prob > F = 0.0470$. We then accepted the hypothesis that the difference in ΔSOC sequestration rate is similar across all depth.

Another important factor that can influence the relative impacts of tillage practices on SOC sequestration rate is the temperature. The regression results, (Table 3 and 5 and Figure 5) shows the effects of average regional temperature variation on SOC sequestration over the difference between NT to CT had a significant correlation between temperature variable and differential SOC sequestration rates. The regression results reveal that a one degree Celsius increase in temperature would reduce the sequestration of NT to CT by -0.0612 (table 3).

Publication Bias

The diagonal lines on figure 5 are representing the 95% confidence limits around the summary treatment effect. As shown on the figure 5, the 95% of the studies lied within the funnel defined by these straight lines and the plot resembled a symmetrical, inverted funnel. This may suggest the absence of publication bias. To avoid subjective judgment we performed a test of small-study effects based on equation 6. The estimated bias coefficient shown on Table 6 is -0.202 with a standard error of 0.295, giving a p-value of 0.496. The test thus provides no evidence for the presence of small-study effects. It is also seen on Figure 6 that absence of this bias.

5. Conclusion and Implications

In this study we used meta-regression model to explore the sources of study-to-study variation on the reported results of SOC sequestration rate due to NT and CT in selected Corn Belt states. Our analysis underscores that nearly half of the variation on the results of reported rate of SOC sequestration between published studies is due to variability in the true treatment effect while the remaining half is as a result of within study sampling variation. Our regression result also showed a quarter of between-study variance is explained by the explanatory variables considered, and the remaining within-study variance appears very small.

Although most of the coefficient of explanatory variables in the regression results exhibited expected sign from agronomic stand point, some of the coefficients were not significant. An important point we can infer based on our analysis is that the rate of SOC sequestration differences between NT and CT disappears as measurement depth increases. On

average No-Till system sequesters more SOC than conventional tillage for every bushel of corn yield increases however the opposite was true for the case of soybean yield. The observed gain in SOC sequestration rate of CT over NT when the crop rotation system was under continuous corn contrast with previous results and agronomic practices in Corn Belt states, this may be attributed to several factors other than variables which we cannot fully observed and controlled in our study.

In the analysis we only showed the absence of publication bias or small study effect via funnel plot and a test for funnel plot asymmetry. One should note that these tests do not offer a solution to the bias problems if any exist rather alert us the potential presence of the problem. Therefore correcting for publication bias will make an important practical ways to provide better understanding on Meta-analysis results.

Overall the combined results clearly showed that there is considerable variation in the rate of SOC sequestration in response to NT and CT across the study states. In addition to the tillage management, the presence of having heterogeneous biophysical characteristics such as yield, initial SOC, temperature and other explanatory variables we listed, difference trial design and quality as well as publication selection bias are responsible for heterogeneity in reported differences in SOC sequestration rate.

Our analysis is subject to several limitations such as the assumption we made on standard error, and other explanatory variables, as a result estimated coefficients and results should be interpreted with caution.

I. Tables of Result

Table 1 Summary statistics for the variables under this study

Variable	Mean	Std. Dev.	Min	Max
[5]Rate of ΔSOC, Mg C ha^{-1} yr^{-1}	0.088	0.47	-1.13	2.4
Initial SOC, Mg C ha^{-1}	54	29	21	159
Duration, year	16	15	4	51
Depth, cm	30	18	15	75
Corn yield, bu ha^{-1} yr^{-1}	132	47	66	245
Soybean yield, bu ha^{-1} yr^{-1}	40	15	24	92
Temperature, ^{O}C	9.4	1.7	6.2	11.1
Rain fall, mm/annum	837	126	580	1112

Note: total observations=78

Table 2 Rate of ΔSOC sequestration by depth of soil measured

Depth, cm	Rate of Δsoc, Mg C ha^{-1} yr^{-1}	Depth frequency (%)
15	-0.03	47.4
20	-0.08	2.6
30	0.16	23.1
45	0.51	5.1
46	0.05	5.1
60	0.28	14.1
75	-0.04	2.6

Note: 63% of the observation is under Corn-soybean rotation while the remaining 37% is under Continuous corn

[5] The dependent variable is the difference in SOC sequestration rate from NT to CT.

Table 3 Joint Meta-regression results: the dependent variable is rate of ΔSOC, Mg C/ha/yr

REML estimate of between-study variance	tau2=0.003
% residual variation due to heterogeneity	I^2-res 49.43%
Proportion of between-study variance explained	Adj R^2= 25.83%
Joint test for all covariates	Model F(6,71)= 3.14
With Knapp-Hartung modification	Prob > F= 0.0087

Explanatory variables	Coeff.	At mean
Initial SOC	0.0016*	0.086
	(2.12)	
Depth	-0.0014	-0.042
	(-0.98)	
Corn yield	0.0008	0.106
	(1.64)	
Soybean yield	-0.013*	-0.520
	(-2.13)	
temperature	-0.057*	0.536
	(-2.34)	
Continuous corn rotation	-0.0495	
	(-1.05)	
_cons	0.860**	
	(2.81)	

t statistics in parentheses;* p<0.05, ** p<0.01, *** p<0.001; The F-table distribution at 95% is F(6,71)=2.23

Note the mean is calculated based on the mean observed values for each variable shown on table 3.1.

Table 4 Independent regression results for continuous corn and corn-soybean rotation

	Coef.	Std. Err.	t	P>t
continuous corn rotation	0.0367	0.0311	1.18	0.241
_cons	-0.0161	0.0251	-0.64	0.523

Adj R-squared =2.07%; I^2 residual = 80.27%

Table 5 Joint regression results: the dependent variable is rate of ΔSOC, Mg C/ha/yr

REML estimate of between-study variance	tau2= 002
% residual variation due to heterogeneity	I^2-res= 52.74%
Proportion of between-study variance explained	Adj-R^2= 45.9%
Joint test for all covariates	Model F(7,70)= 3.80
With Knapp-Hartung modification	Prob > F= 0.0015

Explanatory variables	Coeff.	At mean
Initial SOC	0.0042**	0.227
	(3.23)	
Depth	-0.0013	-0.039
	(-0.98)	
Corn yield	0.0008	0.106
	(1.71)	
Soybean yield	-0.0042	-0.168
	(-1.73)	
temperature	-0.0612*	-0.575
	(-2.53)	
continuous corn rotation	0.115	
	(1.32)	
depth*cont	-0.0064*	
	(-2.22)	
_cons	0.675*	
	(2.15)	

t-statistics in parentheses;* p<0.05, ** p<0.01, *** p<0.001. The F-table distribution F(7,70)=2.14

Note the mean is calculated based on the mean observed values for each variable shown on table1.

Table 6 Egger's test for small-study effects: Regress standard normal deviate of intervention effect estimate against its standard error

Std_Eff	Coef.	Std. Err	t	P>t
Slope	-0.054	0.012	4.43	0.000
Bias	-0.202	0.295	-0.68	0.496

Test of H0: no small-study effects, P = 0.496

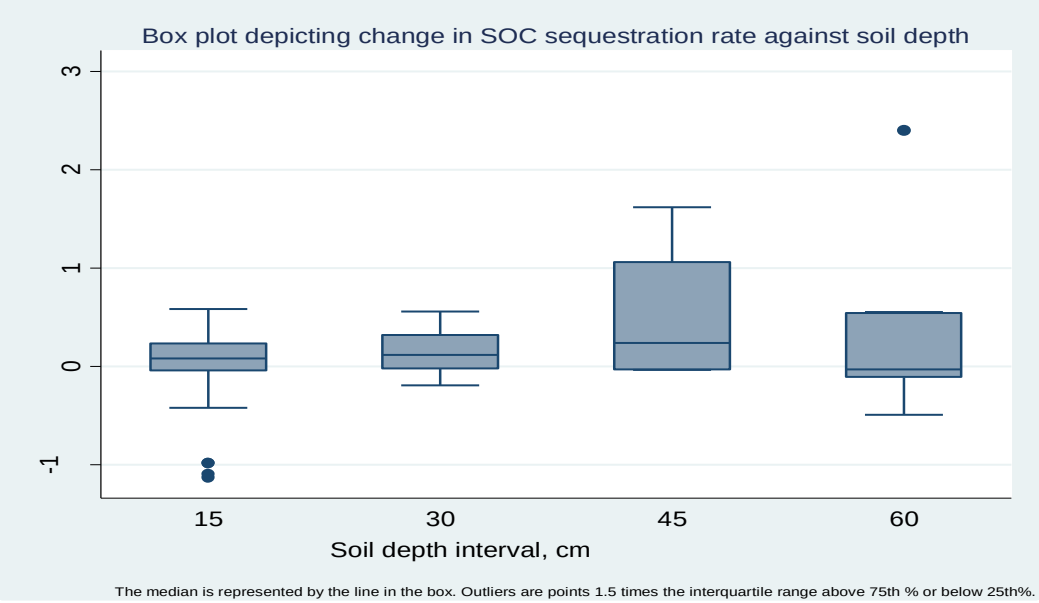

Figure 1 Boxplot depicting change in SOC against the depth of soil (cm) with 15cm interval

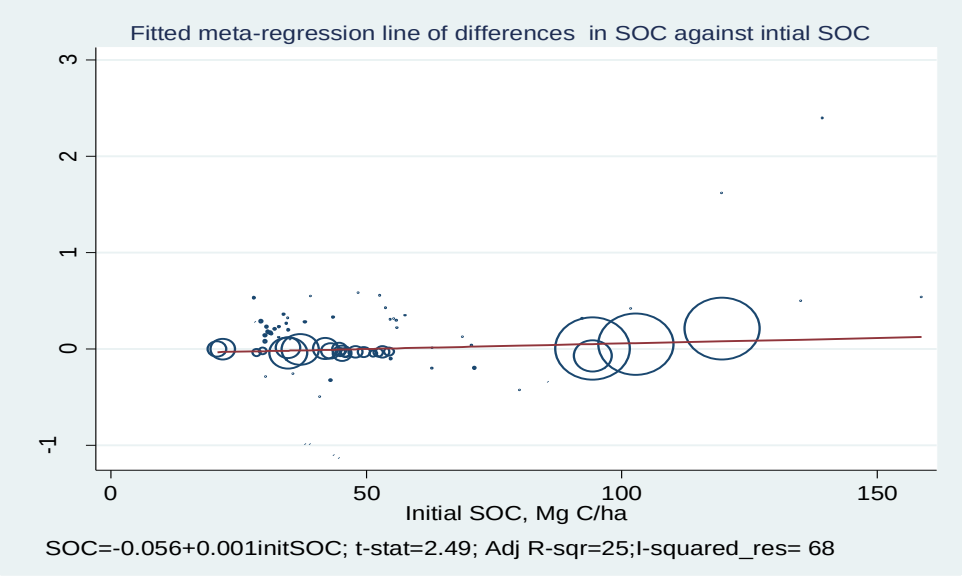

Figure 2 “Bubble” plots of Meta regression line of the ΔSOC (NT-CT) against the initial SOC level

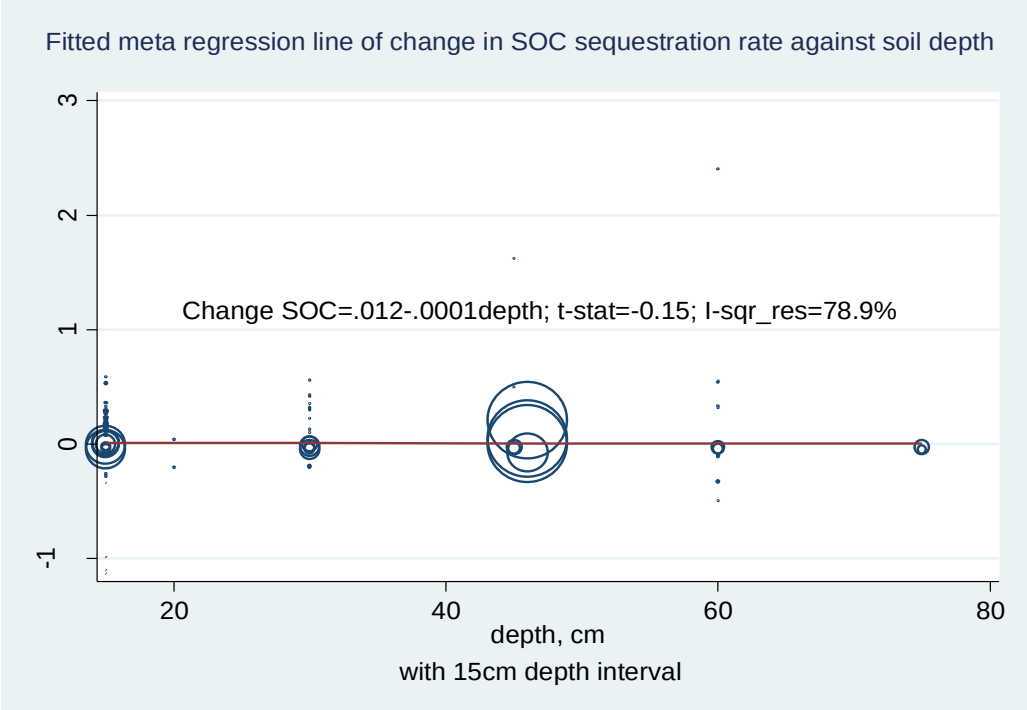

Figure 3 “Bubble” plots of Meta regression line of the ΔSOC (NT-CT) against the depth of SOC measured

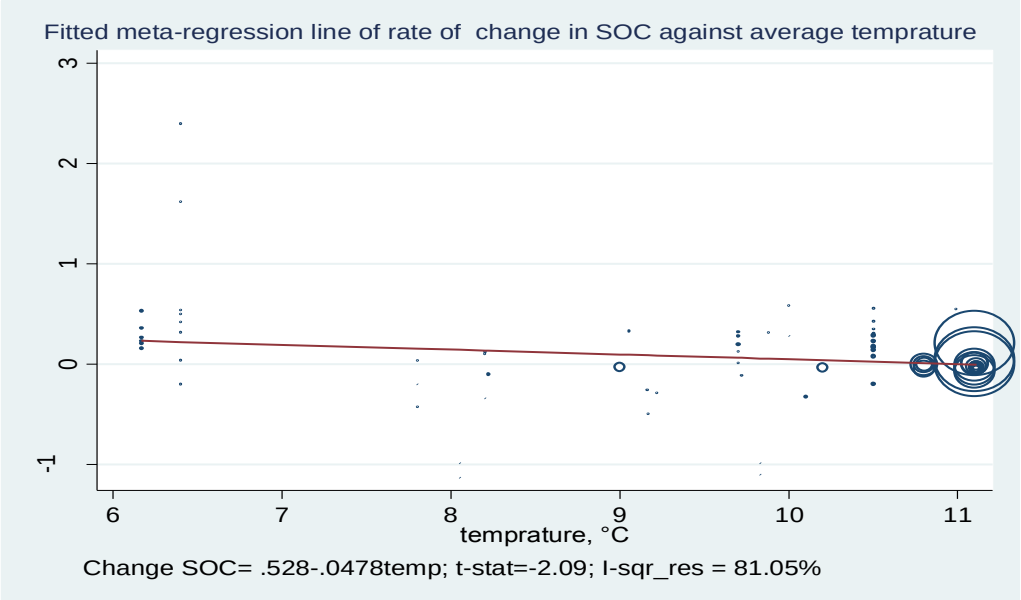

Figure 4 “Bubble plot” with fitted meta-regression line ΔSOC against average temperature of the experimental sites.

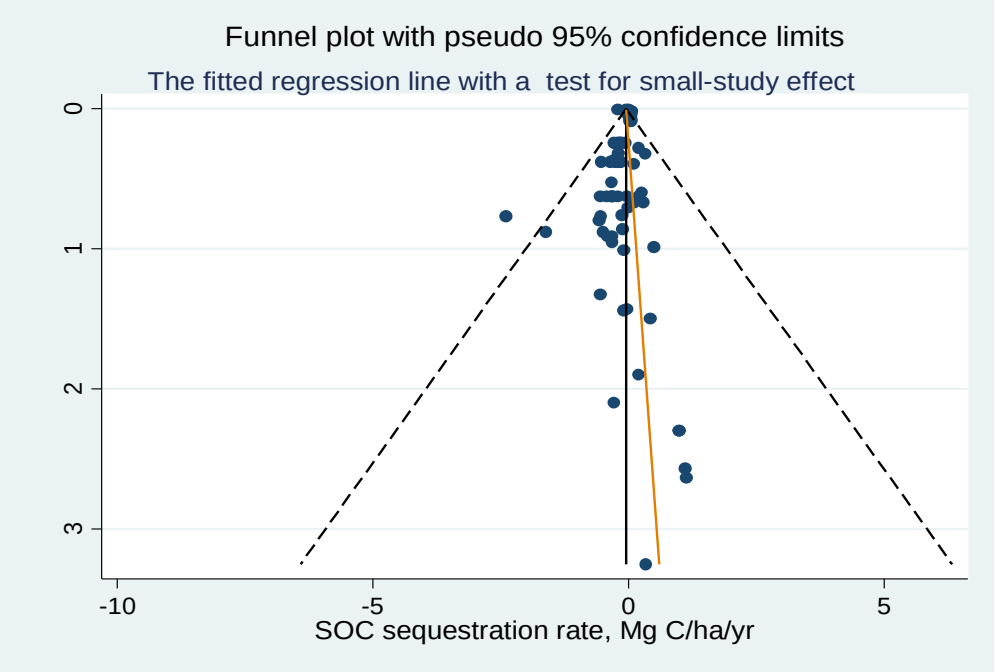

Figure 5 Funnel plot, using SOC sequestration rate against their standard error[6]

[6] The diagonal lines representing the 95% confidence limits around the summary treatment effect, i.e., [summary effect estimate ± (1.96 × standard error)] for each standard error on the vertical axis. This shows the expected distribution of studies in the absence of selection biasesy, 95% of the studies should lie within the funnel defined by these straight lines. Because these lines are not strict 95% limits, they are referred to as "pseudo 95% confidence limits" (Sterne and Harbord, 2004).Results from small studies will therefore scatter widely at the bottom of the graph, with the spread narrowing among larger studies. In the absence of bias, the plot will resemble a symmetrical, inverted funnel.

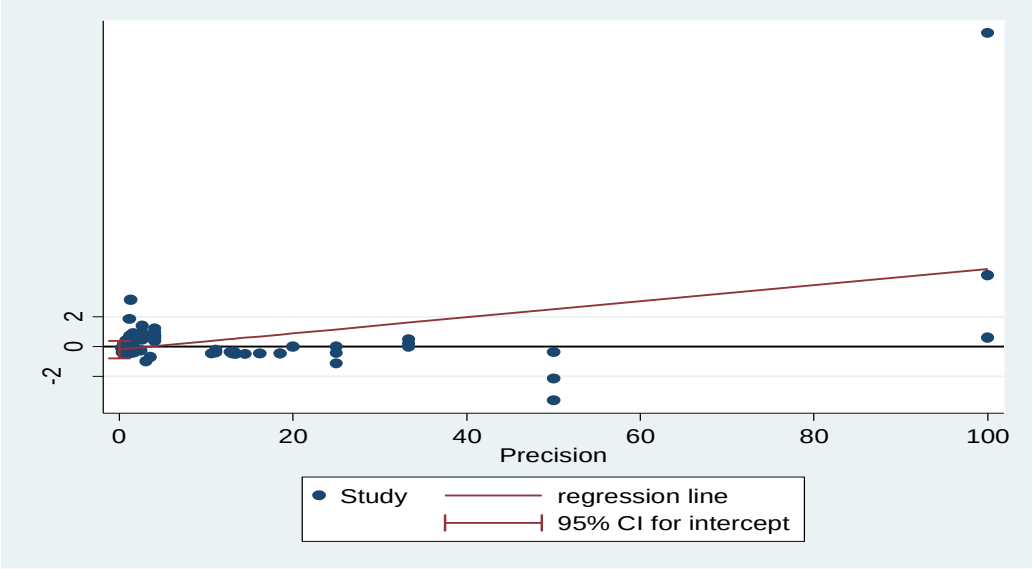

Figure 6 Publication biases estimated based on Egger test

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Appendix

Table 8 Summary of the data from published studies used in a meta-regression analysis of SOC sequestration under no-till (NT) and conventional tillage (CT)

Author	Rate of Δsoc, Mg C ha^{-1} yr^{-1}	Initial SOC, Mg C ha^{-1}	Duration, Year	Soil depth, cm	State
Venterea et.al (2006)	-0.20	70.6	5	20	MN
Venterea et.al (2006)	1.00	62.8	5	20	MN
Venterea et.al (2006)	-2.10	101.8	5	30	MN
Venterea et.al (2006)	-1.60	92.2	5	30	MN
Venterea et.al (2006)	-2.50	135.0	5	45	MN
Venterea et.al (2006)	-8.10	119.5	5	45	MN
Venterea et.al (2006)	-2.70	158.6	5	60	MN
Venterea et.al (2006)	-12.0	139.2	5	60	MN
Olson et.al (2005)	0.24	29.8	12	15	IL
Olson et.al (2005)	0.45	28.6	12	15	IL
Olson et.al (2005)	0.22	43.0	12	30	IL
Olson et.al (2005)	0.45	46.0	12	30	IL
Olson et.al (2005)	0.32	47.8	12	45	IL
Olson et.al (2005)	0.42	46.0	12	45	IL
Olson et.al (2005)	0.37	49.5	12	60	IL
Olson et.al (2005)	0.46	52.3	12	60	IL
Olson et.al (2005)	0.32	53.3	12	75	IL
Olson et.al (2005)	0.56	51.4	12	75	IL
Jareckia et.al (2004)	0.39	44.9	13	30	OH
Jareckia et.al (2004)	0.38	54.4	14	30	OH
Ussiri & Lal (2008)	0.00	44.8	43	30	OH
Ussiri & Lal (2008)	2.00	45.3	43	30	OH
Ussiri & Lal (2008)	0.0001	20.8	43	15	OH
Ussiri & Lal (2008)	-0.002	21.9	43	15	OH
Khan et.al (2007)	-0.70	34.7	51	15	IL
Khan et.al (2007)	2.20	34.7	51	15	IL
Khan et.al (2007)	-0.30	42.0	51	15	IL
Khan et.al (2007)	0.40	37.1	51	15	IL
Khan et.al (2007)	3.70	94.3	51	46	IL
Khan et.al (2007)	-0.30	94.3	51	46	IL
Khan et.al (2007)	-10.70	119.6	51	46	IL
Khan et.al (2007)	-2.43	102.7	51	46	IL
Verma et.al (2005)	-1.13	37.9	4	15	NE
Verma et.al (2005)	-0.51	68.8	4	30	NE
Verma et.al (2005)	-0.80	34.8	4	15	NE
Verma et.al (2005)	-0.04	62.9	4	30	NE

Table 8 Continues…

Author	Rate of Δsoc, Mg C ha^{-1} yr^{-1}	Initial SOC, Mg C ha^{-1}	Duration, Year	Soil depth, cm	State
Verma et.al (2005)	-0.40	64.0	4	30	NE
Moorman et.al (2004)	-3.40	28.1	12	15	IA
Moorman et.al (2004)	-7.00	48.4	12	15	IA
Al-Kaisi et.al (2005)	7.90	44.6	7	15	IA
Al-Kaisi et.al (2005)	1.80	35.7	7	15	IA
Al-Kaisi et.al (2005)	6.90	38.0	7	15	IA
Al-Kaisi et.al (2005)	2.00	30.3	7	15	IA
Al-Kaisi et.al (2005)	6.90	38.9	7	15	IA
Al-Kaisi et.al (2005)	7.70	43.5	7	15	IA
Blanco-Canqui & Lal (2007)	-4.76	55.3	15	60	OH
Blanco-Canqui & Lal (2007)	-6.63	39.1	12	60	OH
Blanco-Canqui & Lal (2007)	3.34	34.4	30	60	OH
Blanco-Canqui & Lal (2007)	4.94	40.9	10	60	PA
Blanco-Canqui & Lal (2007)	-2.65	43.5	8	60	PA
Blanco-Canqui & Lal (2007)	1.98	54.7	20	60	PA
Blanco-Canqui & Lal (2007)	1.62	43.0	5	60	PA
Varvel (2006)	-5.60	52.7	10	30	NE
Varvel (2006)	-4.30	53.8	10	30	NE
Varvel (2006)	-3.10	54.7	10	30	NE
Varvel (2006)	-3.50	57.5	10	30	NE
Varvel (2006)	-3.00	55.8	10	30	NE
Varvel (2006)	-2.20	56.0	10	30	NE
Varvel (2006)	-2.90	29.4	10	15	NE
Varvel (2006)	-2.30	30.5	10	15	NE
Varvel (2006)	-1.70	31.2	10	15	NE
Varvel (2006)	-1.80	30.7	10	15	NE
Varvel (2006)	-1.40	30.2	10	15	NE
Varvel (2006)	-0.80	30.2	10	15	NE
Russell et.al (2005)	-1.47	32.8	12	15	IA
Russell et.al (2005)	-1.23	35.1	12	15	IA
Russell et.al (2005)	-0.47	38.4	12	15	IA
Russell et.al (2005)	2.40	96.7	12	15	IA
Russell et.al (2005)	4.05	85.5	12	15	IA
Russell et.al (2005)	5.10	79.9	12	15	IA
Pikul et.al (2008)	-2.30	32.0	11	15	ND
Pikul et.al (2008)	-1.77	31.4	11	15	ND
Pikul et.al (2008)	-5.86	28.0	11	15	ND
Pikul et.al (2008)	-2.54	32.9	11	15	ND
Pikul et.al (2008)	-2.92	34.3	11	15	ND

Pikul et.al (2008)	-3.94	33.8	11	15	ND
Jagadamma et.al (2007)	4.48	71.2	23	30	IL