Corn or soybean? From the aspect of soil carbon in the Corn Belt

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Soil is receiving increasing attention as a natural sink for carbon which can reduce atmospheric CO2. Crop species choices, however, are usually overlooked as a way to increase soil organic carbon. This paper tries to answer whether we can increase soil organic carbon stocks under the predominant corn-soybean cropping systems by changing crop rotation sequences. We find corn-soybean rotation significantly increases SOC stocks as deep as 100 cm compared to always fallow, with corn having a stronger impact on increasing SOC stocks compared to soybean. Specifically, monocropping of corn in the past three years increases SOC stocks in 100 cm by 15.03% compared to monocropping of soybean, and by 12.41% compared to corn for one year followed by soybean for two years. Evidence also shows that having corn for two years in the past three years results in higher SOC stocks than if not. Taking the soil health and crop yield into consideration, having corn for two years and soybean for one year is suggested to be the best cropping sequence. Applying this result to Corn Belt states - Ohio, Indiana, Iowa, and Illinois, we estimate that the total potential increase of SOC stocks by transferring current soils covered by continuous soybean, soybean for two years and corn for one year, or always fallow into corn for two years and soybean for one year in every three years is 22 million Mg in Ohio, 45 million Mg in Indiana, 92 million Mg in Iowa, and 44 million Mg in Illinois.

Introduction

Global climate change is happening faster and more drastic than expected. According to Intergovernmental Panel on Climate Change (IPCC, 2022), global warming of 1.5 ℃ and 2 ℃ will be exceeded during this century unless deep reductions in CO_2 and other greenhouse gas emissions occur in the coming decades. Soil is receiving increasing attention as a natural sink for carbon which can reduce atmospheric CO_2. It is also a potentially large and uncertain source of CO_2 emissions as croplands under intensive cultivation have less soil carbon compared to pre-cultivation land uses like forests or grasslands (Lal, 2002; Don, Schumacher and Freibauer, 2011). Changes in soil organic carbon stocks are a result of the imbalance between carbon inputs, mainly in the form of dead plant material or manure and outputs, mainly caused by decomposition, leaching and erosion (Poeplau and Don, 2015). Historically, between 32.5 and 35.7 million km^2 of natural vegetation, encompassing forests, woodlands, savannas, grasslands, and steppes have been converted to croplands (DeFries et al., 1999). It is thus crucial to find effective methods to increase SOC stocks while simultaneously enhancing and maintaining high agricultural productivity.

Many efforts have been devoted to examining the effects of cropland management practices on soil carbon storage, including cover cropping, intensified rotations, minimum tillage, advance nutrient management, and integrated crop-livestock systems (Dick et al., 1998), (Paustian et al., 2016). Crop species choices, however, are usually overlooked as a way to increase soil organic carbon. Current findings include comparing long-term or short-term effects of perennial, semi-perennial, and annual crops (Ferchaud, Vitte and Mary, 2016), carbon benefits of converting traditional crops into biomass energy crops (Chen et al., 2021) or to permanent herbaceous cover (Swan et al., 2020). However, under the pressure of food security, there is a need to identify the various effects of soil carbon within the traditional cropping system that increases soil organic matter and is supportive of enhanced food production and other ecosystem services.

With this goal in mind, we estimate the impact of the sequences of the most predominant crops - corn and soybean on soil organic carbon (SOC) stocks. We find corn-soybean rotation significantly increases SOC stocks as deep as 100 cm compared to always fallow, with corn having a stronger impact on increasing SOC stocks compared to soybean. Specifically, monocropping of corn in the past three years increases SOC stocks in 100 cm by 15.03% compared to monocropping of soybean, and by 12.41% compared to corn for one year followed by soybean for two years. Evidence also shows that having corn for two years in the past three years results in higher SOC stocks than if not. Taking the soil health and crop yield into consideration, having corn for two years and soybean for one year is suggested to be the best cropping sequence. Applying this result to Corn Belt states - Ohio, Indiana, Iowa, and Illinois, we estimate that the total potential increase of SOC stocks by transferring current soils covered by continuous soybean, soybean for two years and corn for one year, or always fallow into corn for two years and soybean for one year in every three years is about 22 million Mg in Ohio, 45 million Mg in Indiana, 92 million Mg in Iowa, and 44 million Mg in Illinois.

Soil carbon effects of different corn-soybean sequences

We estimate the impact of crop types on SOC stocks by linking Rapid Carbon Assessment (RaCA) with Crop Data Layer (CDL). We obtain the measurements of SOC stocks and soil characteristics at depths of 5cm, 30 cm, and 100 cm at 2,105 cropland sites from RaCA data, which was conducted by USDA-NRCS between 2010 to 2011 in order to provide contemporaneous measurements of SOC across the US. A multi-level stratified random sampling scheme was created using major land resource area (MLRA) and then a combination of soil groups and land use/land cover classes. Next, using the latitude and longitude of RaCA sites, we extract crop types from CDL the year when collected by RaCA, one year before, and two years before. The CDL from USDA-NASS is an annual raster, geo-referenced, crop-specific land cover data layer (2008-) with a ground resolution of 30 or 56 meters depending on the state and year. We also extract quarterly mean temperature and mean precipitation at each site from PRISM Climate Data. Due to the different inputs and management across different crops, which are hard to control, here we consider the in aggregate effects of crop species on soil carbon and assume that management is homogeneous within each crop type. Figure 1 shows the distribution of crop types over the last two years. We can find corn-soybean rotation is the predominant cropping system in the U.S.

Then we focus on the 9 cropping sequences - continuous corn, continuous soybean, always fallow, and corn-soybean rotation including corn-corn-soybean, corn-soybean-corn, corn-soybean-soybean, soybean-corn-corn, soybean-corn-soybean, and soybean-soybean-corn (the order indicates crop type two years before-one year before -this year). We constrain the sites to be covered by either corn or soybean or fallow in the past three years. We model the SOC stocks in depths of 1 to 100 cm at each site as a function of cropping sequences in the past 3 years. Control variables include environmental characteristics including quarterly mean temperature, quarterly mean precipitation, latitude, as well as soil texture. We also include region, year and month fixed effects. In order to control for pretreatment imbalances, we use Propensity Score Matching (PSM), where the propensity score is the probability of a site being cropped with different treatments separately as a function of the environmental/soil characteristics.

$$log\left(SOC_{it}\right) = \beta_0 + \beta_1 Envr_{it} + \beta_2 Soil_i + \beta_4 Rotation_{it} + \beta_5 X_{it} + \varepsilon_{it} \tag{1}$$

where i indexes site and t indexes the observed time. SOC_{it} denotes the amount of soil carbon stock (Mg/ha) for site i in year t. Envr_{it} are environmental variables at site i in year t including mean temperature, mean precipitation, and latitude. Soil_i denotes soil characteristics variables at site i (soil texture). $\mathrm{Rotation}_{it}$ indicates the cropping sequence at site i in year t, 1 year before year t, and 2 years before year t. X_{it} are region fixed effect and time fixed effect (year and month). ε_{it} is error term.

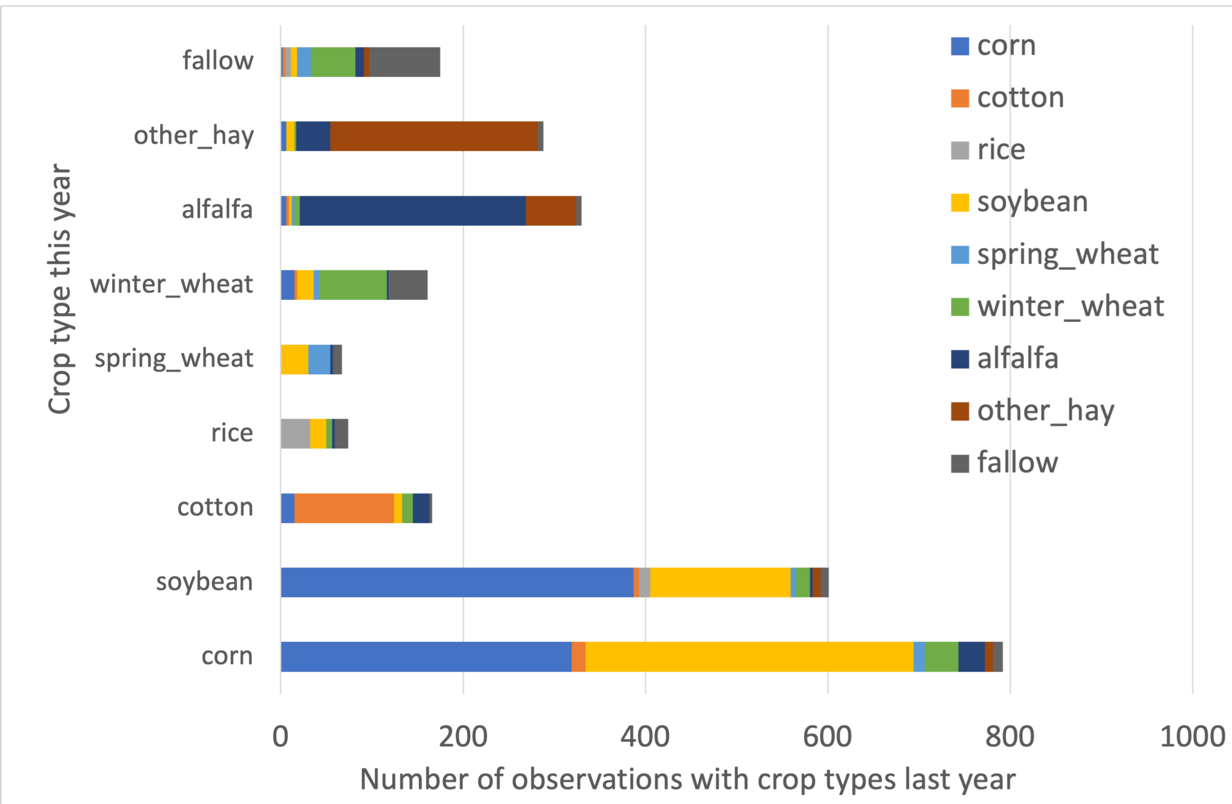


Figure 1: Distribution of crop types last year across crop types this year

Table 1: The effects of different sequences of corn-soybean rotation on log(SOC(0-100cm)) stocks

	Dependent variable:								
	log(SOCstock100)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
relevel(treat, control)ccs	-0.054		-0.096^{*}	0.029	0.074	-0.054	-0.036	-0.0003	0.068
	(0.051)		(0.049)	(0.069)	(0.072)	(0.053)	(0.051)	(0.076)	(0.070)
relevel(treat, control)ccc		0.036	-0.040	0.117^{*}	0.215^{***}	0.020	0.019	0.064	0.140^{**}
		(0.055)	(0.036)	(0.069)	(0.072)	(0.049)	(0.037)	(0.076)	(0.064)
relevel(treat, control)csc	-0.008	0.034		0.131^{*}	0.130^{*}	0.028	0.009	-0.010	0.151^{**}
	(0.037)	(0.055)		(0.069)	(0.072)	(0.049)	(0.034)	(0.076)	(0.064)
relevel(treat, control)css	-0.094^{*}	-0.040	-0.136^{***}		0.034	-0.094^{*}	-0.076	-0.036	0.028
	(0.054)	(0.057)	(0.051)		(0.075)	(0.056)	(0.054)	(0.076)	(0.073)
relevel(treat, control)fff	-0.127^{**}	-0.074	-0.169^{***}	-0.031		-0.128^{**}	-0.110^{**}	-0.044	-0.006
	(0.051)	(0.055)	(0.049)	(0.069)		(0.053)	(0.051)	(0.076)	(0.070)
relevel(treat, control)scc	0.001	0.060	-0.041	0.141^{**}	0.147^{**}		0.018	0.032	0.122^{*}
	(0.046)	(0.055)	(0.044)	(0.069)	(0.072)		(0.046)	(0.076)	(0.066)
relevel(treat, control)scs	-0.033	-0.027	-0.079^{**}	0.032	0.053	-0.031		-0.026	0.065
	(0.037)	(0.055)	(0.033)	(0.069)	(0.072)	(0.049)		(0.076)	(0.064)
relevel(treat, control)ssc	-0.053	0.001	-0.095	0.041	0.075	-0.053	-0.035		0.069
	(0.060)	(0.063)	(0.058)	(0.075)	(0.082)	(0.062)	(0.060)		(0.078)
relevel(treat, control)sss	-0.107^{**}	-0.077	-0.148^{***}	-0.027	0.028	-0.082^{*}	-0.089^{**}	0.018	
	(0.043)	(0.055)	(0.041)	(0.069)	(0.072)	(0.049)	(0.043)	(0.076)	
Constant	1.548^{***}	1.494^{***}	1.590^{***}	1.454^{***}	1.420^{***}	1.548^{***}	1.530^{***}	1.495^{***}	1.426^{***}
	(0.030)	(0.039)	(0.029)	(0.049)	(0.051)	(0.035)	(0.031)	(0.053)	(0.055)
Observations	205	110	244	96	110	135	244	72	140
Log Likelihood	107.023	63.914	136.429	42.140	34.272	71.333	125.438	37.629	64.689
Akaike Inf. Crit.	-196.047	-109.828	-254.859	-66.280	-50.543	-124.667	-232.876	-57.259	-111.377

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

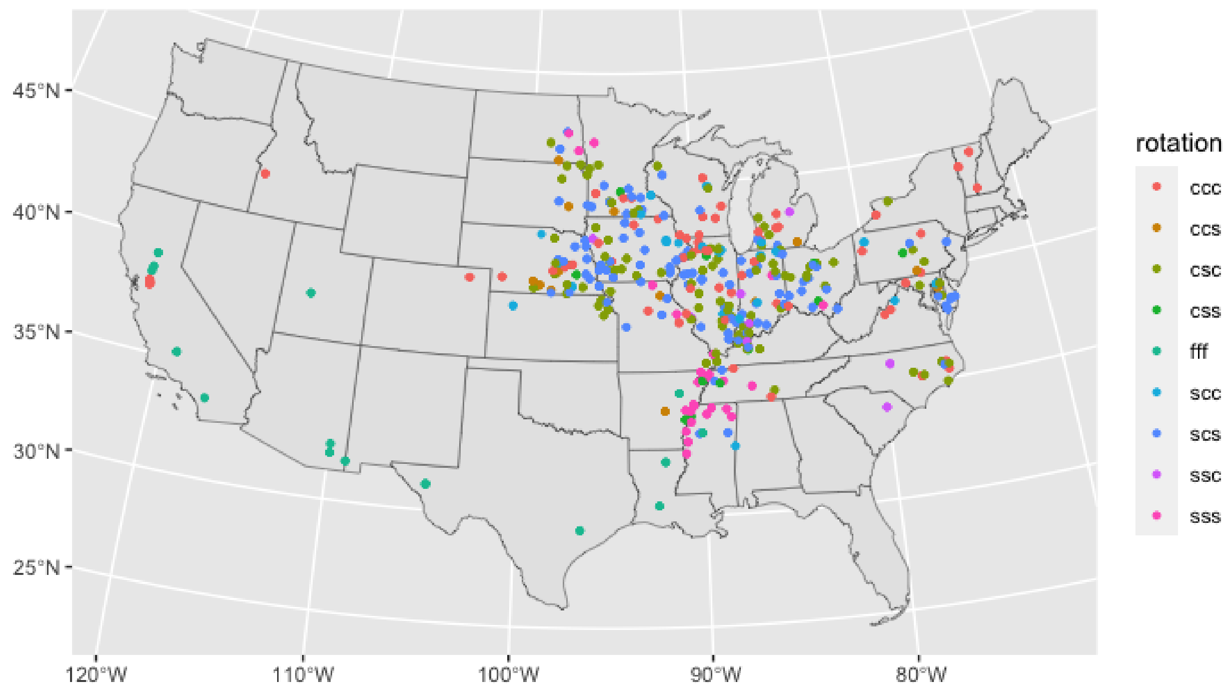
Results in Table 1 indicate crops have different impacts on SOC stocks at different depths with a lag effect. We find corn-soybean rotation significantly increases SOC stocks as deep as 100 cm compared to always fallow, with corn having a stronger impact on increasing SOC stocks compared to soybean. Specifically, monocropping of corn in the past three years increases SOC stocks in 100 cm by 15.03% compared to monocropping of soybean, by 12.41% compared to corn-soybean-soybean, and by 23.99% compared to always fallow. Evidence also shows that having corn for two years in the past three years results in higher SOC stocks than if not. Corn-soybean-corn increases SOC stocks in 100 cm by 16.30% compared to monocropping of soybean, by 14.00% compared to corn-soybean-soybean, and by 13.88% compared to always fallow. Soybean-corn-corn increases SOC stocks in 100 cm by 12.98% compared to monocropping of soybean, by 15.14% compared to corn-soybean-soybean, and by 15.84% compared to always fallow. Corn plays an important role in the cropping system in improving SOC stocks, which might be explained by high residues after harvest.

Based on the result, we propose nine hypothetical policies - converting fallow-fallow-fallow, soybean-soybean-soybean, and corn-soybean-soybean to corn-corn-corn separately, converting fallow-fallow-fallow, soybean-soybean-soybean, and corn-soybean-soybean to corn-soybean-corn separately, converting fallow-fallow-fallow, soybean-soybean-soybean, and corn-soybean-soybean to soybean-corn-corn separately. Due to the unequal population variances, we choose to do one-tailed Welch two-sample t-test. Table 2 shows that the policies could increase the SOC stocks at 10% significance level.

Table 2: Welch Two Sample t-test

>0	estimate	t-value	p-value	95% conf.low	95% conf.high
ccc-fff	249	3.84	0.000157	141	Inf
ccc-sss	209	2.99	0.00193	92.2	Inf
ccc-css	223	3.35	0.000691	112	Inf
———	———-	———	———-	————–	————–
csc-fff	104	3.72	0.000161	57.5	Inf
csc-sss	63.1	1.67	0.0498	0.0826	Inf
csc-css	77.4	2.47	0.0079	25.2	Inf
———	———-	———	———-	————–	————–
scc-fff	-184	-1.74	0.0483	1.94	Inf
scc-sss	144	1.32	0.0999	-43	Inf
scc-css	-158	-1.48	0.0769	-25.7	Inf

Corn-soybean cropping systems in the Corn Belt



As Figure 2 shows, most of the corn-soybean rotation observations center in the Corn Belt. We randomly sampled 40,000 points within CDL in Ohio, Indiana, Iowa, and Illinois, separately from 2008 to 2021 to track the crop types on the same points across time. As Figure 3 shows, planting each of corn and soybean equally for 7 years in the past 14 years is a large majority. The percentage decreases with the deviation from the center. Among the four states, farmers in Ohio and Indiana tend to prefer planting soybean more often, while farmers in Iowa and Illinois tend to prefer planting corn more often.

Applying the result of SOC stocks discussed above, we estimate the potential increase of SOC stocks with nine hypothetical policies as Table 3 shows. We estimate that the total potential increase of SOC by converting fallow-fallow-fallow, soybean-soybean-soybean, and corn-soybean-soybean to corn-corn-corn is 20 million Mg, 43 million Mg, 71 million Mg, and 62 million Mg for Ohio, Indiana, Iowa, and Illinois separately. The total potential increase of SOC by converting fallow-fallow-fallow, soybean-soybean-soybean, and corn-soybean-soybean to corn-soybean-corn is estimated to be 22 million Mg, 45 million Mg, 92 million Mg, and 44 million Mg for Ohio, Indiana, Iowa, and Illinois separately. The total potential increase of SOC by converting fallow-fallow-fallow, soybean-soybean-soybean, and corn-soybean-soybean to soybean-corn-corn is estimated to be 23 million Mg, 47 million Mg, 99 million Mg, and 47 million Mg for Ohio, Indiana, Iowa, and Illinois separately. The second and the third policy (converting fallow-fallow-fallow,

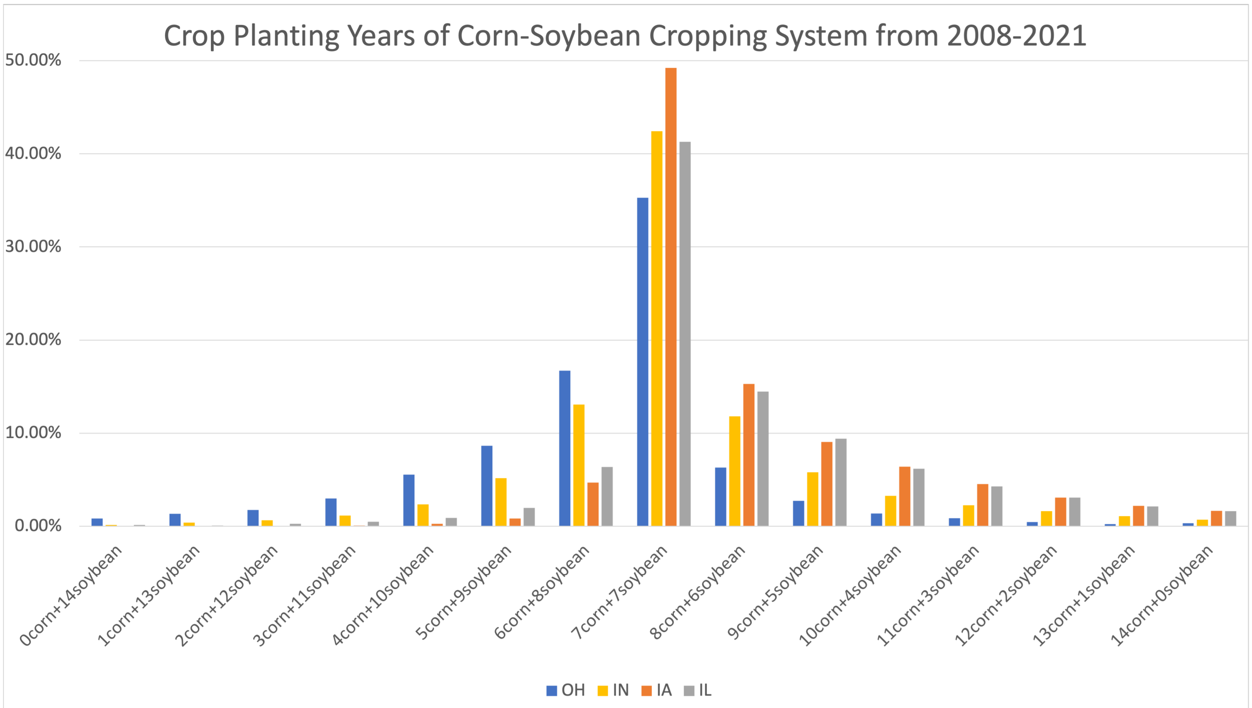


Figure 2: Crop planting years of corn-soybean cropping system from 2008-2021

soybean-soybean-soybean, and corn-soybean-soybean to corn-soybean-corn or soybean-corn-corn) are estimated to have higher gain in SOC stocks on the whole compared to the first one (converting fallow-fallow-fallow, soybean-soybean-soybean, and corn-soybean-soybean to corn-corn-corn). Taking the soil health and crop yield into consideration, having corn for two years and soybean for one year is suggested to be the best cropping sequence.

Table 3: Potential increase of SOC stocks (Mg) across polices and states

policy	OH	IA	IL	IN	Corn Belt
fff to ccc	30,075.21	0.00	19,608.11	0.00	49,683.32
sss to ccc	4,385,512.96	1,319,692.44	2,911,428.11	4,453,460.47	8,616,633.51
css to ccc	15,356,574.46	69,244,881.13	59,176,222.83	38,758,940.90	143,777,678.43
total	19,772,162.63	70,564,573.57	62,107,259.06	43,212,401.38	152,443,995.26
————	—————	—————	—————	—————	—————-
fff to csc	17,407.07	0.00	11,348.87	0.00	28,755.94
sss to csc	4,756,810.31	1,431,423.57	3,157,922.78	4,830,510.57	9,346,156.66
css to csc	17,317,398.75	90,182,317.00	40,779,343.87	39,941,649.89	148,279,059.62
total	22,091,616.13	91,613,740.57	43,948,615.52	44,772,160.46	157,653,972.22
————	—————	—————	—————	—————	—————-
fff to scc	19,855.30	0.00	12,945.04	0.00	32,800.34
sss to scc	3,786,676.71	1,139,490.11	2,513,876.29	3,845,346.08	7,440,043.11
css to scc	18,734,890.16	97,564,064.23	44,117,279.93	43,211,017.69	160,416,234.33
total	22,541,422.17	98,703,554.34	46,644,101.26	47,056,363.77	167,889,077.78

Appendix

Table 4: Descriptive statistics summary

Variable		Mean	Sd	Min	Max	N
Soil Organic Carbon (Mg/ha)	0-5 cm	16.82	22.04	0.46	262.26	367
	5-30 cm	66.92	108.87	2.78	1005.52	364
	30-100 cm	94.63	221.47	4.17	2076.73	334
—————————————	————	———	———	———	———	——
Crop sequences	ccc					181
	ccs					41
	csc					287
	css					35
	fff					46
	scc					69
	scs					304
	ssc					26
	sss					76
—————————————	————	———	———	———	———	——
Soil texture	Clay					47
	Loam					902
	Sand					50
—————————————	————	———	———	———	———	——
Year	2010					493
	2011					572
—————————————	————	———	———	———	———	——
Latitude (degree)		40.07	3.14	29.4	47.34	1065
—————————————	————	———	———	———	———	——
Mean temperature (degree celsius)	Spring	11.56	3.3	2.02	22.34	1065
	Summer	24.06	2.23	17.87	30.39	1065
	Autumn	12.77	2.76	6.21	22.34	1065
	Winter	-2.65	5.22	-13.51	11.73	1065
—————————————	————	———	———	———	———	——
Mean precipitaiton (inch)	Spring	112.11	55.65	0	271.94	1065
	Summer	118.46	46.01	1.89	243.19	1065
	Autumn	80.21	41.73	4.05	221.42	1065
	Winter	56.25	35.17	3.82	169.71	1065

Table 5: The effects of crop type on log(SOC(0-100 cm)) stocks

	Dependent variable:		
		log(SOC)	
	0-5 cm	5-30 cm	30-100 cm
	(1)	(2)	(3)
relevel(as.factor(CDL_0), ref = "fallow")corn	0.116	0.489	1.030**
	(0.275)	(0.320)	(0.439)
relevel(as.factor(CDL_0), ref = "fallow")soybean	0.025	0.342	0.963**
	(0.268)	(0.311)	(0.427)
relevel(as.factor(CDL_1), ref = "fallow")corn	0.032	0.160**	0.147
	(0.068)	(0.080)	(0.113)
relevel(as.factor(CDL_1), ref = "fallow")soybean			
relevel(as.factor(CDL_2), ref = "fallow")corn	0.035	0.142	0.086
	(0.077)	(0.090)	(0.126)
relevel(as.factor(CDL_2), ref = "fallow")soybean			
Constant	0.330	5.422*	11.858**
	(2.678)	(3.132)	(5.105)
Observations	345	342	312
R^2	0.456	0.438	0.336
Adjusted R^2	0.384	0.364	0.238
Residual Std. Error	0.476 (df = 304)	0.553 (df = 301)	0.744 (df = 271)
F Statistic	6.365*** (df = 40; 304)	5.876*** (df = 40; 301)	3.434*** (df = 40; 271)
Note:			*p<0.1; **p<0.05; ***p<0.01

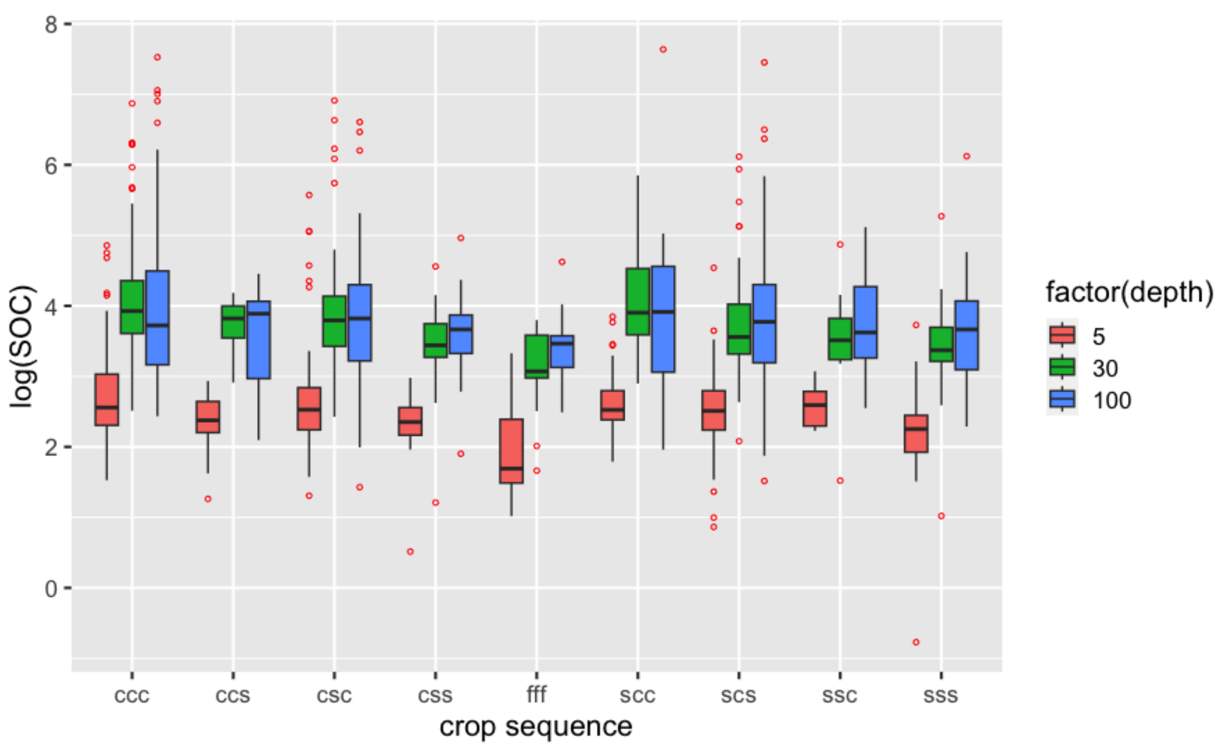


Figure 3: log (SOC stocks (Mg/ha)) for different crop sequences at 0-5cm, 5-30 cm, 30-100cm depth

Table 6: The effects of different sequences of corn-soybean rotation on log(SOC(0-100 cm)) stocks

	Dependent variable:	
	log(SOCstock100)	log(SOCstock100)
	OLS	*matching*
	(1)	(2)
relevel(as.factor(rotation), ref = "fff")ccc	0.787^{**}	1.130^{***}
	(0.331)	(0.344)
relevel(as.factor(rotation), ref = "fff")ccs	0.538	0.318
	(0.366)	(0.344)
relevel(as.factor(rotation), ref = "fff")csc	0.678^{**}	0.652^{*}
	(0.332)	(0.344)
relevel(as.factor(rotation), ref = "fff")css	0.552	0.191
	(0.361)	(0.359)
relevel(as.factor(rotation), ref = "fff")scc	0.742^{**}	0.656^{*}
	(0.355)	(0.344)
relevel(as.factor(rotation), ref = "fff")scs	0.573^{*}	0.295
	(0.329)	(0.344)
relevel(as.factor(rotation), ref = "fff")ssc	−0.015	0.351
	(0.410)	(0.394)
relevel(as.factor(rotation), ref = "fff")sss	0.576^{*}	0.152
	(0.337)	(0.344)
Constant	6.833^{*}	4.164^{***}
	(3.924)	(0.243)
Observations	312	110
R^2	0.420	
Adjusted R^2	0.324	
Log Likelihood		−137.985
Akaike Inf. Crit.		293.969
Residual Std. Error	0.567 (df = 267)	
F Statistic	4.392^{***} (df = 44; 267)	
Note:		*p<0.1; **p<0.05; ***p<0.01

References

Chen, Luoye, Elena Blanc-Betes, Tara W. Hudiburg, Daniel Hellerstein, Steven Wallander, Evan H. DeLucia and Madhu Khanna. 2021. "Assessing the Returns to Land and Greenhouse Gas Savings from Producing Energy Crops on Conservation Reserve Program Land." *Environmental Science & Technology* 55(2):1301–1309. Publisher: American Chemical Society.
URL: *https://doi.org/10.1021/acs.est.0c06133*

DeFries, R.S., C.B. Field, I. Fung, G.J. Collatz and L. Bounoua. 1999. "Combining satellite data and biogeochemical models to estimate global effects of human-induced land cover change on carbon emissions and primary productivity." *Global Biogeochemical Cycles* 13(3):803–815. 267 citations (Crossref) [2023-04-24].

Dick, W. A, R. L Blevins, W. W Frye, S. E Peters, D. R Christenson, F. J Pierce and M. L Vitosh. 1998. "Impacts of agricultural management practices on C sequestration in forest-derived soils of the eastern Corn Belt." *Soil and Tillage Research* 47(3):235–244. 97 citations (Crossref) [2023-04-10].
URL: *https://www.sciencedirect.com/science/article/pii/S0167198798001123*

Don, Axel, Jens Schumacher and Annette Freibauer. 2011. "Impact of tropical land-use change on soil organic carbon stocks – a meta-analysis." *Global Change Biology* 17(4):1658–1670. 867 citations (Crossref) [2023-04-11] _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-2486.2010.02336.x.
URL: *https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2486.2010.02336.x*

Ferchaud, Fabien, Guillaume Vitte and Bruno Mary. 2016. "Changes in soil carbon stocks under perennial and annual bioenergy crops." *GCB Bioenergy* 8(2):290–306. 59 citations (Crossref) [2023-04-11] _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/gcbb.12249.
URL: *https://onlinelibrary.wiley.com/doi/abs/10.1111/gcbb.12249*

Lal, R. 2002. "Soil carbon dynamics in cropland and rangeland." *Environmental Pollution* 116(3):353–362. 360 citations (Crossref) [2023-04-11].
URL: *https://www.sciencedirect.com/science/article/pii/S0269749101002111*

Paustian, Keith, Johannes Lehmann, Stephen Ogle, David Reay, G. Philip Robertson and Pete Smith. 2016. "Climate-smart soils." *Nature* 532(7597):49–57. 1045 citations (Crossref) [2023-04-10] Number: 7597 Publisher: Nature Publishing Group.
URL: *https://www.nature.com/articles/nature17174*

Poeplau, Christopher and Axel Don. 2015. "Carbon sequestration in agricultural soils via cultivation of cover crops – A meta-analysis." *Agriculture, Ecosystems & Environment* 200:33–41. 689 citations (Crossref) [2023-04-11].
URL: *https://www.sciencedirect.com/science/article/pii/S0167880914004873*

Swan, Amy, Keith Paustian, Ejeong Baik and Eric D Larson. 2020. "Princeton's Net-Zero America study Annex Q: Potential for Negative Emissions from Carbon Sequestration on US Agricultural Land.".