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RESEARCH LETTER

Cover crops and weed suppression in the U.S. Midwest: A meta-analysis and modeling study

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Abstract

In addition to soil health and conservation benefits, cover crops (CCs) may offer weed control in the midwestern United States, but individual studies report varying effects. We conducted a meta-analysis of studies measuring weed biomass (WBIO) or density (WDEN) in paired CC and no-cover treatments in corn (*Zea mays* L.)–soybean [*Glycine max* (L.) Merr] rotations in the U.S. Midwest. Fifteen studies provided 123 paired comparisons of WBIO and 119 of WDEN. Only grass CCs significantly reduced WBIO, while no CC reduced WDEN. We found no evidence CC management factors (e.g., termination method) directly affected outcomes. Our dataset showed that a 75% reduction in WBIO requires at least 5 Mg ha^{-1} of CC. Simulations from a process-based model (SALUS) indicated achieving 5 Mg ha^{-1} requires substantially earlier fall planting and later spring termination in most years, conflicting with typical cash-crop planting and harvesting. We conclude CCs significantly reduce WBIO, but current CC management constraints render these reductions variable and uncertain.

1 | INTRODUCTION

Winter annual cover crops (CCs) have been heavily promoted in the midwestern Corn Belt region of the United States due to an increasing need for practices that enhance

Abbreviation: CC, cover crop; CCBIO, cover crop biomass; CI, confidence interval; SALUS, System Approach to Land Use Sustainability; WBIO, weed biomass; WDEN, weed density.

soil health and water quality. Despite clear environmental benefits (Daryanto, Fu, Wang, Jacinthe, & Zhao, 2018; Kaspar & Singer, 2011), less than 10% of midwestern cropland is currently managed with CCs (Seifert, Azzari, & Lobell, 2018). The lack of short-term economic returns from growing CCs overwhelms long-term environmental benefits, creating a major barrier to wide adoption (Plastina, Liu, Miguez, & Carlson, 2018; Roesch-Mcnally et al., 2018). If CCs can reduce weed management costs, this could provide immediate monetary incentives for adoption. Previous literature syntheses have found CCs reduce weed pressure across various cropping systems, but the direction and magnitude of effects are context-specific (Osipitan, Dille, Assefa, & Knezevic, 2018). Given its ubiquity and significance in the U.S. Midwest, the corn (*Zea mays* L.)–soybean [*Glycine max* (L.) Merr] production system merits explicit examination. Unfavorable fall–winter climatic conditions in the Midwest are known to limit CC establishment and growth (Baker & Griffis, 2009; Strock, Porter, & Russelle, 2004), which in turn may affect factors governing CC performance relative to weed management. Region-specific analyses can also provide more precise CC biomass (CCBIO) production targets for weed suppression (Baraibar et al., 2018; Mirsky et al., 2013) and explore how planting or termination timing affects the feasibility of achieving those targets.

To address these gaps, we synthesized data from published field studies measuring weed responses to CCs in corn–soybean systems in the Midwest. Our objectives were (a) to quantify how environmental conditions and management practices affect weed responses to CCs, (b) to identify Midwest-specific CCBIO targets for providing significant weed suppression, and (c) to evaluate the feasibility of achieving these targets under different CC planting and termination scenarios.

Core Ideas

- Cover crops reduce weed biomass but not weed density.
- Grass monoculture cover crops offer the most consistent weed suppression.
- At least 5 Mg ha^{-1} of cover crop is required to reduce weed biomass 75%.
- Producing 5 Mg ha^{-1} of cover crop requires early planting and late spring termination.
- Managing cover crops for weed suppression will require changes in policy and agronomy.

2 | METHODS

2.1 | Meta-analysis of weed-responses to cover crops

We conducted a systematic search of the literature using Web of Science Core Collection (Clarivate Analytics) and CAB Direct (CAB International) databases. Search details, including a PRISMA diagram and list of included publications, are in the supplementary material (Supplemental Material S1). In our database, we included weed biomass (WBIO), weed density (WDEN), and cash-crop yield as response variables. We recorded values in a paired format, requiring each pair of response variables to be measured in the same crop at the same time with all aspects of management held constant except for a treatment of a fall-planted CC. Ancillary data included geographical location, climate, and soil characteristics of the study site; cash-crop and CC management including species, tillage system, planting and termination methods and dates; and experimental information such as timing of weed measurements and type of weed (Supplemental Material S1). The complete database is published and available on Iowa State University's DataShare platform (Nichols, Basche, & Weisberger, 2020).

All data manipulation and statistical modelling were done in R version 3.6.1 (R Core Team, 2019) using the *tidyverse* meta-package (Wickham, Averick, Bryan, Chang, & McGowan, 2019) and others (Firke, 2019; Grolemund & Wickham, 2011). A detailed account of statistical methods is presented in Supplemental Material S2, and all R code is available on github (https://github.com/vanichols/ccweedmeta-analysis). In brief, all statistical models used the log-transformed response ratio (measurement in the CC treatment over measurement in the no-cover treatment) as the response variable (Gurevitch, Koricheva, Nakagawa, & Stewart, 2018). Mixed-effect models were used with the modifier of interest as a fixed effect and a random intercept for each study using nonparametric weighting based on the number of replicates (Adams, Gurevitch, & Rosenberg, 1997). All linear models were fit using the *lme4* package (Bates, Mächler, Bolker, & Walker, 2015), and results were analyzed using *lmerTest* (Kuznetsova, Brockhoff, & Christensen, 2017) and *emmeans* (Lenth, Singmann, & Love, 2018). Means and 95% confidence intervals were back-transformed for reporting purposes. To identify suites of practices predictive of achieving both a reduction in weeds and an increase in cash-crop yield with CCs, we fit random forest models (Kuhn & Johnson, 2013) using several R packages (Hothorn, Hornik, & Zeileis, 2006). All statistical results are in Supplemental Material S3.

2.2 | Simulation of cover crop biomass

To investigate the feasibility of growing CCs for effective weed control in the Midwest, we used the System Approach to Land Use Sustainability (SALUS) model (Basso & Ritchie, 2015) to simulate winter rye (*Secale cereal* L.) biomass across a range of soils and weather conditions of the Midwest. Rye is the most prevalent CC species used in the Midwest (Singer, 2008) and represents the best choice for maximizing CCBIO production in this region (Appelgate, Lenssen, Wiedenhoeft, & Kaspar, 2017; Ruis et al., 2019). Specific simulation details are provided in Supplemental Material S4. Three CC planting dates were explored: 15 September (optimistic), 7 October (realistic), and 1 November (late).

3 | RESULTS

3.1 | Meta-analysis results

Fifteen articles fit our criteria, producing 123 response ratios for WBIO and 119 response ratios for WDEN (Nichols et al., 2020). The studies include a range of site characteristics and management representative of midwestern corn–soybean production systems (Supplemental Material S1). Overall, CCs significantly reduced WBIO ($p = .02$), which was robust against publication bias (>3,000 unpublished null studies needed; Rosenthal, 1979) and the removal of individual studies (p values ranged from .01 to .04). There was no evidence CCs reduced WDEN ($p = .98$). Neither WBIO nor WDEN responses were affected by the subsequent cash crop (corn or soybean), meaning the response of weeds to CCs was not confounded by differences in cash-crop competition with weeds.

The following categorical modifiers had levels with significantly different effects on WBIO (Figure 1): CC type (after controlling for CCBIO production; grass, nongrass), measurement in reference to cash-crop planting (before, after), and weed growth habit (winter annual, summer annual, perennial). WDEN had no significant modifiers. For WBIO, grass monoculture CCs reduced WBIO by 68% (confidence interval [CI] :41–82%) compared with a nonsignificant reduction of 33% for mixtures and other types of CCs ($p < .01$; Figure 1). Measurements taken before cash-crop planting showed a 74% (CI: 51–85%) reduction in WBIO, compared with only 44% (CI: 12–64%) in measurements taken after planting ($p < .01$). Winter annual weeds showed the largest reductions (65%; CI: 27–83%), followed by summer annuals (47%; CI: 10–68%), with perennial weeds being unaffected by CCs.

Weed suppression was significantly affected by CCBIO for both WBIO ($p = .03$) and WDEN ($p < .01$). We found an estimated 5 Mg ha^{-1} of CCBIO at termination reduced WBIO by 75% for grass CCs but only 40% for other CCs (Figure 1).

The response of WBIO or WDEN to CC did not depend on any other modifiers tested. A full list of nonsignificant modifiers can be found in Supplemental Material S3 and included production system tillage regime; CC planting and termination method; termination–planting gap; and study-site latitude, aridity, and soil type.

In our database only 23% of the comparisons exhibited a “win-win” situation, with a concomitant increase in cash-crop yield and decrease in weed pressure (Figure 1). Using a random forest model, we found no scenarios that were strong predictors of whether an observation would fall in the win-win category, suggesting maximizing cash-crop yields and weed suppression may not have overlapping CC management strategies.

3.2 | Simulation model results

For the “realistic” planting date (7 Oct.), 2% of counties achieved 5 Mg ha^{-1} by 1 May in ≥80% of the weather-years, increasing to only 30% under an “optimistic” CC-planting scenario (15 Sept.; Figure 2). With “late” planting (1 Nov.), none of the counties reached the threshold by 1 May, and only half did so by 1 July. Aggregated on a state level, Illinois, Missouri, and Kansas were the only states that could consistently achieve 5 Mg ha^{-1} of biomass before typical cash-crop planting dates of early May with optimistic CC planting dates (Figure 2).

4 | DISCUSSION

Cover crops affect weeds through interference mechanisms of resource competition and allelopathy (Teasdale & Mohler, 1993), delaying weed germination and development that manifests as lower WBIO. Management that disrupts rather than interferes with weed trajectories, such as crop rotation, may be more effective at reducing WDEN (Weisberger, Nichols, & Liebman, 2019). However, given that reductions in WBIO can increase susceptibility to herbicides (Wallace, Curran, & Mortensen, 2019) and weed size is directly related to seed output (Thompson, Weiner, & Warwick, 1991), reductions in WDEN may be possible with long-term CC use. More long term (>5 yr) work is needed to answer this question.

Monocultures of grass CCs significantly reduced WBIO (by 68%), while other CCs did not (Figure 1), consistent with recent studies (MacLaren, Swanepoel, Bennett, Wright, & Dehnen-Schmutz, 2019; Smith, Warren, & Cordeau, 2020). Cover crops interfere with weeds via

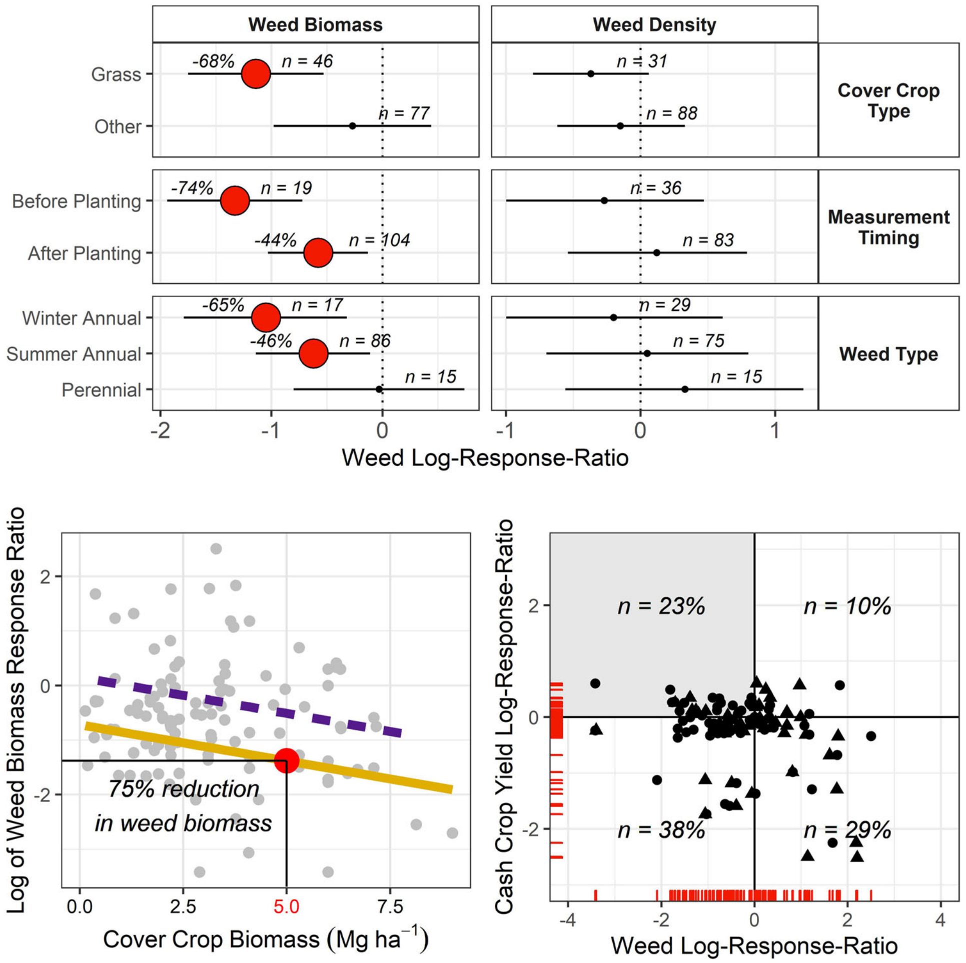

FIGURE 1 (Top) Factors with significantly different effects by level; values <0 (dotted vertical line) indicate cover crop reduced weeds, large red points indicate significant effects ($p < .05$) with estimates transformed to percentage change, and n values indicate number of observations for the estimate, error bars are 95% confidence intervals. (Bottom left) Linear regressions of weed biomass response to grass (yellow solid line) and other (dotted purple) cover crop biomass production. (Bottom right) Comparisons where cover crops increased cash-crop yields and reduced weed biomass (circles) or density (triangles) made up 23% of the points (gray quadrant)

physical and chemical means, and grasses such as rye may be more effective than legumes and brassicas at both (Creamer, Bennett, Stinner, Cardina, & Regnier, 1996; Smith et al., 2020). Furthermore, higher carbon-to-nitrogen ratios of grass CCs (Martinez-Feria, Nichols, Basso, & Archontoulis, 2019; Quemada & Cabrera, 1995) potentially increase residence time of residue and thus suppress weeds longer after CC termination (Ruffo & Bollero, 2003; Teasdale & Mohler, 1993).

While CCs had a stronger effect on weeds before cash-crop planting (Figure 1), weeds measured after planting are likely of more interest to producers, as they directly represent resource competition with the cash crop. The stronger reduction in winter annual weeds is not surprising, given the winter growth period of the CC.

The environmental context of the studies had no significant effect on the weed responses or on CCBIO. This could simply reflect the lack of plot-specific information (Eagle et al., 2017; Gerstner et al., 2017), but it does suggest environmental context has only an indirect effect on CC-mediated weed suppression.

To prevent an increase in weed seedbanks, reductions in WDEN of 90% (comparable to herbicide effectiveness) are needed (Liebman & Nichols, 2020); our study shows that even with 5 Mg ha^{-1} of CCBIO, producers are unlikely to achieve this level of weed control, consistent with studies from other areas (Baraibar et al., 2018; Mirsky et al., 2013). Moreover, our SALUS simulations indicate achieving 5 Mg ha^{-1} of rye CCBIO regularly under typical Midwest production scenarios and climates would be challenging (Figure 2). Even with optimistic CC planting dates (15 Sept.), achieving 5 Mg ha^{-1} of CCBIO would require a mid-May or later termination date most years (≥80%)

	Planting Date		
	15-Sep (optimistic)	7-Oct (realistic)	1-Nov (late)
ND	25-Jun	16-Jul	29-Jul
MN	16-Jun	9-Jul	20-Jul
WI	16-Jun	6-Jul	21-Jul
SD	4-Jun	1-Jul	15-Jul
MI	31-May	24-Jun	12-Jul
IA	23-May	17-Jun	1-Jul
NE	6-May	3-Jun	20-Jun
OH	5-May	2-Jun	21-Jun
IN	5-May	31-May	17-Jun
IL	28-Apr	27-May	18-Jun
MO	22-Apr	17-May	5-Jun
KS	14-Apr	13-May	3-Jun

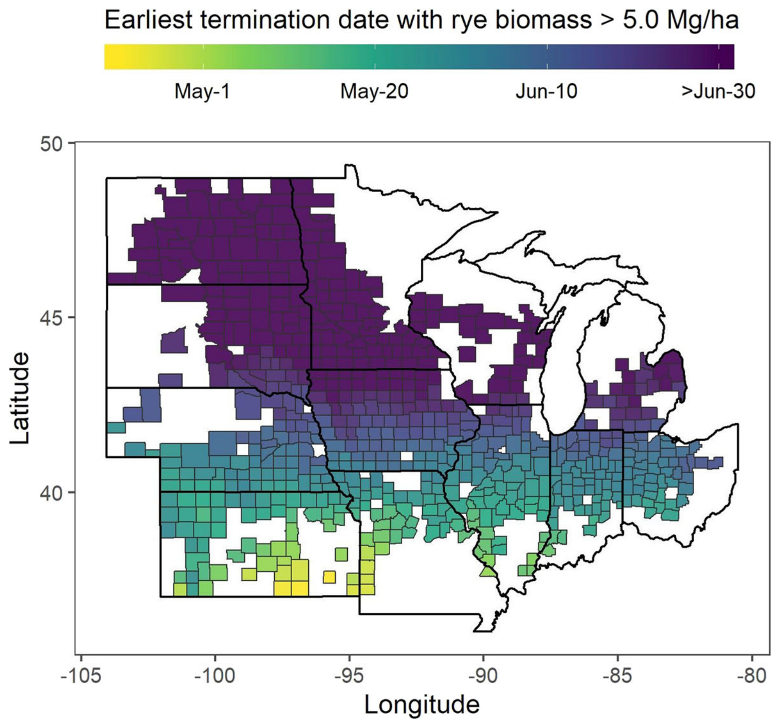

FIGURE 2 Earliest termination date with rye biomass in excess of 5 Mg ha^{-1} as predicted by the SALUS crop model using 30 yr of historical weather for three rye planting date scenarios (15 Sept., 7 Oct., 1 Nov.). (Left) Results summarized by state at 80% probability levels. In Iowa, for example, rye biomass was >5 Mg ha^{-1} in 80% of the years if planted on 7 Oct. and terminated on or after 17 June (highlighted in red). (Right) Results corresponding to the 7 Oct. planting scenario, summarized by county at the 80% probability level

in the majority of counties, well after typical cash-crop planting dates. It should be noted our simulations assumed direct CC seeding with uniform germination (Supplemental Material S4) and are therefore not to be extrapolated to other planting methods. While aerial- or interseeding can be used to establish CCs into standing crops, these methods are often unreliable (Wilson, Allan, & Baker, 2014), and standing crops prevent full sunlight penetration for CC growth well into October. Delayed corn and soybean planting consistently reduces yields (Baum, Archontoulis, & Licht, 2019; De Bruin & Pedersen, 2008), and delayed CC termination could be hindered by concerns over crop insurance eligibility (USDA-NRCS, 2019). High CCBIO production could increase other ecosystem services (Blanco-Canqui et al., 2015; Thapa, Mirsky, & Tully, 2018) but may also introduce issues with nitrogen immobilization and CC termination (Whalen et al., 2020). Other studies examined the effects of CCs on subsequent cash-crop yields (Marcillo & Miguez, 2017), showing no yield benefit from grass CCs. Choosing a CC species to maximize cash-crop yields may be at odds with choosing one for maximizing weed suppression, and while no-till may amplify yield responses (Marcillo & Miguez, 2017), it may not enhance weed control from CCs. The existence of these trade-offs is supported by the low percentage of observations with a "win-win" scenario (Figure 1) in our database.

5 | CONCLUSIONS

Our study, which synthesized work from the Corn Belt region of the U.S. Midwest, shows that grass CCs effectively reduce WBIO. We estimated 5 Mg ha^{-1} of grass CCBIO decreases WBIO by 75%, a threshold at which reduction of herbicide use is possible, but not always advisable. Furthermore, consistently achieving that level of CCBIO in the Midwest may not be feasible within the traditional corn–soybean fallow season. In our dataset, concomitant increases in yields and decreases in weeds with the use of CCs were minimal, highlighting the need to evaluate CC practices using multiple metrics. Therefore, we conclude that although CCs significantly reduce WBIO, which may render other weed management strategies more effective and reduce WDEN in the long-term, current CC management does not consistently suppress weeds. Optimizing CCs for weed suppression will entail both agronomic (e.g., use of different cash-crop maturity groups) and policy (change in insurance structure around CC termination requirements) changes at a broad scale.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY

All data associated with this analysis have been published (Nichols et al., 2020) and are publicly available at https://iastate.figshare.com/. Additionally, the data are available as an R package on github (https://github.com/vanichols/ccweedmetapkg), and all R code used to analyze the data is available in a github repository (https://github.com/vanichols/ccweedmeta-analysis).

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SUPPORTING INFORMATION

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

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S1. Literature search methodology and results

The methodology for this research sought to follow best-practices for agronomic meta-analyses (Philibert et al., 2012).

Literature search

A search was conducted in October 2018 using the following Boolean string: (weed* AND ("cover crop*" OR "green manure" OR "catch crop*") AND ("corn" OR "maize" OR "soybean*")) using the Web of Science (WoS) and CAB abstract databases. This resulted in a total of 676 studies that were screened for eligibility based on the following three criteria:
(1) Studies must have been conducted in a US 'Corn Belt' state, defined as a state in the contiguous Midwestern region with the largest acreages of maize acres harvested in the most recent five years of available data (US Department of Agriculture National Agricultural Statistics Service) including: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin
(2) Studies must have measured weed biomass and/or weed density
(3) Studies must have included a treatment that tested the effects of a fall-planted cover-crop (CC) followed by either maize or soybean against a treatment that included no CC holding all other factors constant. From this search, we screened the full text of 220 articles for inclusion in the database, with an additional screening of literature cited by selected articles. From this, 15 articles met our three criteria (**Fig. S1.1**).

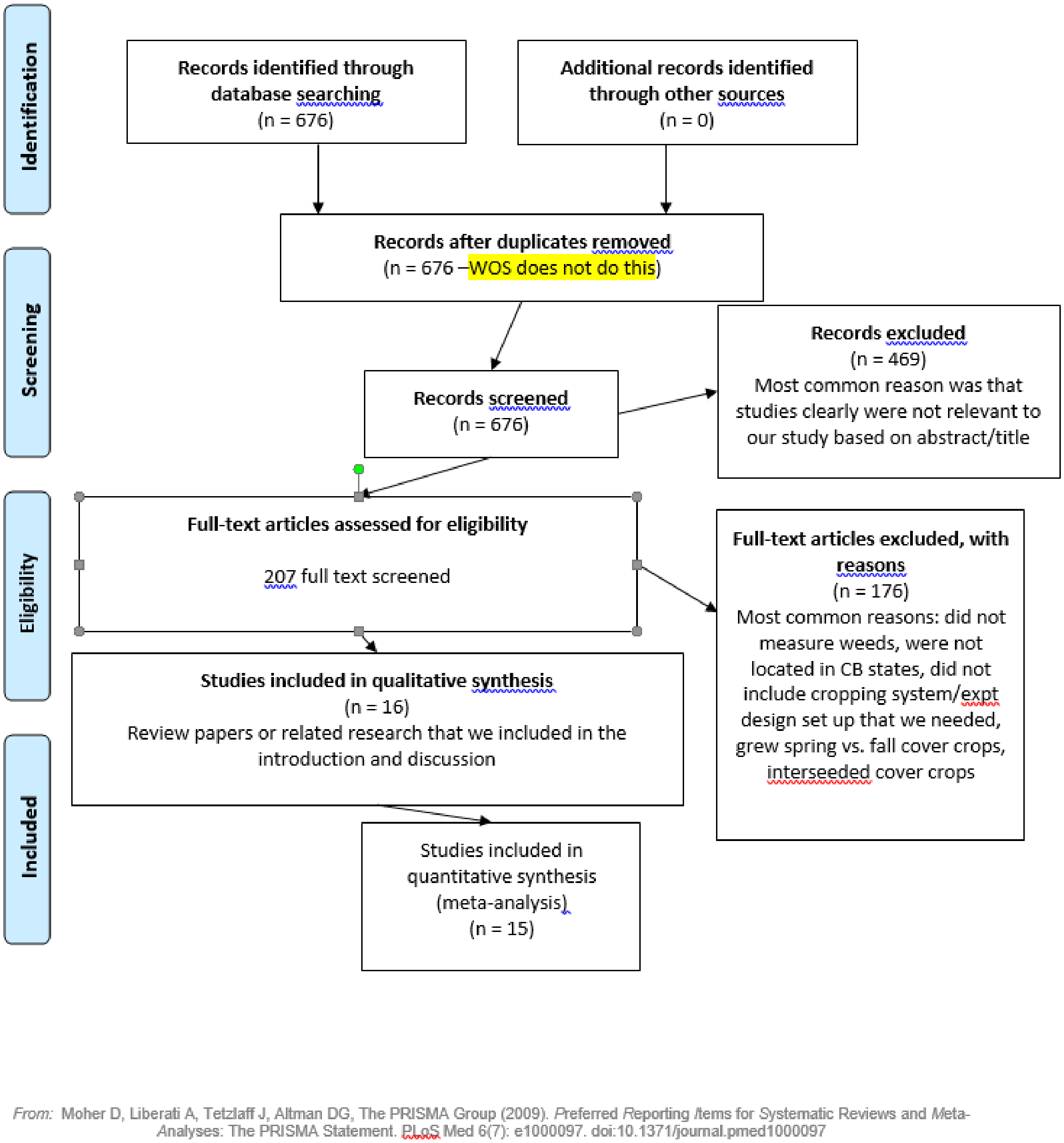

Figure S1.1. *PRISMA diagram* (Moher et al., 2009) for the literature search

The 15 publications included in the database are listed below in alphabetical order:

1. Bernstein ER, Posner JL, Stoltenberg DE, Hedtcke JL (2011) Organically managed no-tillage rye-soybean systems: Agronomic, economic, and environmental assessment. Agron J 103:1169–1179. doi: 10.2134/agronj2010.0498
2. Cornelius CD, Bradley KW (2017) Influence of Various Cover Crop Species on Winter and Summer Annual Weed Emergence in Soybean. Weed Technol 31:503–513. doi: 10.1017/wet.2017.23
3. Crawford LE, Williams MM, Wortman SE (2018) An early-killed rye (Secale cereale) cover crop has potential for weed management in edamame (Glycine max). Weed Sci 66:502–507. doi: 10.1017/wsc.2018.5
4. Currie RS, Klocke NL (2005) Impact of a terminated wheat cover crop in irrigated corn on atrazine rates and water use efficiency. Weed Sci 53:709–716. doi: 10.1614/ws04-170r1.1
5. Davis AS (2010) Cover-Crop Roller–Crimper Contributes to Weed Management in No-Till Soybean. Weed Sci 58:300–309. doi: 10.1614/ws-d-09-00040.1
6. De Bruin JL, Porter PM, Jordan NR (2005) Use of a rye cover crop following corn in rotation with soybean in the upper Midwest. Agron J 97:587–598. doi: 10.2134/agronj2005.0587
7. Delate K, Cwach D, Chase C (2012) Organic no-tillage system effects on soybean, corn and irrigated tomato production and economic performance in Iowa, USA. Renew Agric Food Syst 27:49–59. doi: 10.1017/S1742170511000524
8. Fisk JW, Hesterman OB, Shrestha A, et al (2001) Weed suppression by annual legume cover crops in no-tillage corn. Agron J 93:319–325. doi: 10.2134/agronj2001.932319x
9. Forcella F (2014) Short- and full-season soybean in stale seedbeds versus rolled-crimped winter rye mulch. Renew Agric Food Syst 29:92–99. doi: 10.1017/S1742170512000373
10. Gallagher RS, Cardina J, Loux M (2003) Integration of cover crops with postemergence herbicides in no-till corn and soybean. Weed Sci 51:995–1001. doi: 10.1614/p2002-062
11. Gieske MF, Wyse DL, Durgan BR (2016) Spring- and Fall-Seeded Radish Cover-Crop Effects on Weed Management in Corn. Weed Technol 30:559–572. doi: 10.1614/wt-d-15-00023.1
12. Hoffman ML, Regnier EE, Cardina J (1993) Weed and corn (Zea mays) responses to a hairy vetch (Vicia villosa) cover crop. Weed Technol 7: 594-599. Doi:10.1017/S0890037X00037398
13. Mock VA, Creech JE, Ferris VR, et al (2012) Influence of Winter Annual Weed Management and Crop Rotation on Soybean Cyst Nematode (Heterodera glycines) and Winter Annual Weeds: Years Four and Five . Weed Sci 60:634–640. doi: 10.1614/ws-d-11-00192.1
14. Werle R, Burr C, Blanco-Canqui H (2017) Cereal rye cover crop suppresses winter annual weeds. Can J Plant Sci 98:498–500. doi: 10.1139/CJPS-2017-0267
15. Williams MM, Mortensen DA, Doran JW (1998) Assessment of weed and crop fitness in cover crop residues for integrated weed management. Weed Sci 46:595–603. doi: 10.1017/s0043174500091153

Data were recorded as reported (each site-year separately or averaged). No zero values were reported. When available, we sought to extract ancillary information (**Table S1.1**) from each study to accompany each paired observation.

Table S1.1 *Summary of factors recorded in database accompanying weed responses to cover cropping.*

Category	Variable
Management	System tillage; time between cover-crop termination and cash crop planting; cover crop species, planting date, planting method, planting density, termination date, termination method, biomass at termination, subsequent crop; cash crop planting date, yield
Environment	State, latitude, longitude, soil type, organic matter content, aridity index*
Experiment	Publication year, number of replicates, type of weed(s) measured, duration of experiment, timing of weed measurement with respect to crop planting, season of weed measurement**

*an integrated measure of temperature, precipitation and potential evapotranspiration were derived from location coordinates using the CGIAR-CSI Global-Aridity and Global-PET databases (Zomer et al., 2008)

** Spring: January-June; Summer: June-September; Fall : September – December

Over 95% of comparisons were done in treatments imposed the same or previous calendar year; we were therefore unable to include the duration of the experiment as an explanatory variable. The subsequent cash-crop's planting density can affect a CC's weed suppression effectiveness (Ryan et al., 2011), but that was also not included due to paucity of such data reporting. One comparison resulted in an extremely low LRR due to a CC treatment weed biomass of 1 g m^{-2} (SE = 1 g m^{-2}) corresponding to a 99.9% reduction in weed biomass (Forcella 2013). This comparison was found to disproportionately influence results of the statistical models, and was therefore adjusted to equal the next highest reduction (97%) in weed biomass observed in the database.

Database description

These 15 published studies done in one of the 12 Midwest states measured weed biomass or weed density in a winter cover-cropped and no-cover treatment of maize or soybean (**Fig. S1.2**)

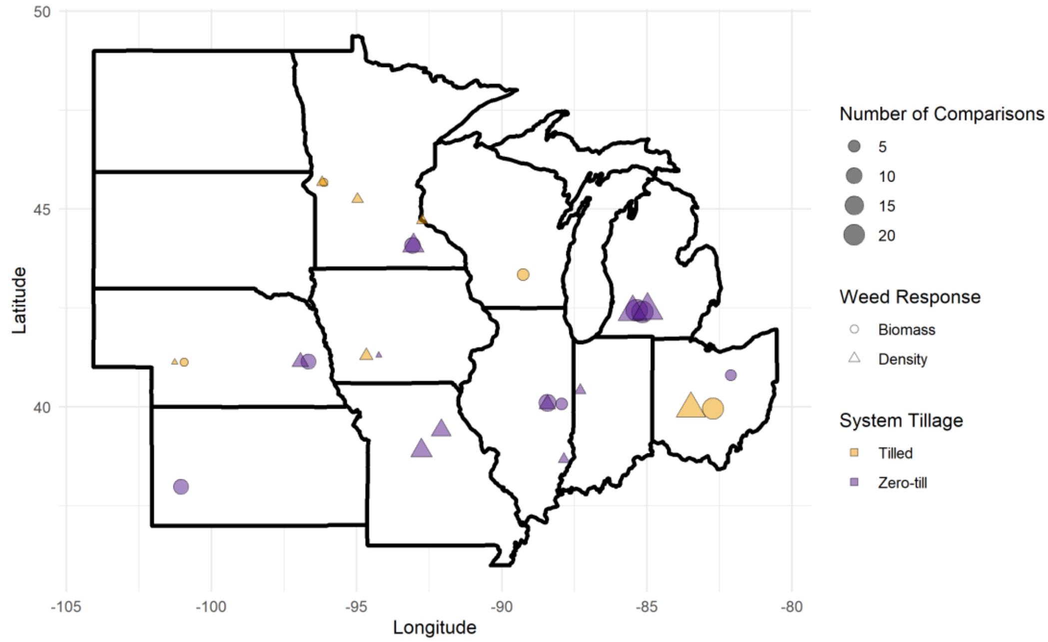

Figure S1.2 *The 12 contiguous US states with the highest maize production with published studies concerning cover-cropping effects on weed biomass and density; point shape indicates the weed response reported, point size the number of comparisons extracted from the study location, and point color the tillage classification of the study. No studies from North and South Dakota met our selection criteria.*

The studies represented a range of management, environmental, and experimental contexts representative of the region (**Table S1.2**).

Table S1.2 *Management, environment, and experimental characteristics were extracted from each publication; weed biomass and weed density responses were separated into two datasets.*

Category	Factor	Biomass (n = 123)	Density (n = 119)
Management			
System	Tillage	Tilled (n=30) Zero-till (n=93)	Tilled (n=31) Zero-till (n=88)
	Time between cover crop termination and cash crop planting	-31 – 29 days	-31 – 13 days
Cover Crop	Type	Grass (n=46) Non-grass (n=77) *Non-grass category includes brassicas (3), legumes (74)*	Grass (n=31) Non-grass (n=88) *Non-grass category includes brassicas (9), legumes (73), mixtures (6)*
	Planting date	Aug 15 – Oct 18	Aug 15 – Oct 31
	Planting density	13.4 – 180 kg seed ha^{-1}	9 – 135 kg seed ha^{-1}
	Termination date	April 18 – June 18	April 18 – June 18
	Termination method	Several methods (n = 3) herbicides (n = 54) mechanical (roller crimper, mowing; n = 29) winterkill (n = 37)	Several methods (n = 3) herbicides (n = 53) mechanical (roller crimper, mowing; n = 22) winterkill (n = 37) none (n = 4)
	Cover crop biomass at termination	130 – 9003 kg ha^{-1}	0 – 9003 kg ha^{-1}
Cash crop	Subsequent crop	Maize (n=78) Soybean (n=45)	Maize (n=73) Soybean (n=42) Averaged over maize and soybean phases† (n=4)
	Cash crop planting date	April 20 – June 30	April 27 – June 18
	Corn yield	40-13500 kg ha^{-1}	40-11200 kg ha^{-1}
	Soybean yield	300-3618	300-3310 kg ha^{-1}
Environment			
	State	Illinois (17) Kansas (9) Michigan (44) Minnesota (12) Nebraska (11) Ohio (25) Wisconsin (5)	Iowa (4) Illinois (5) Indiana (4) Michigan (45) Minnesota (16) Missouri (18) Nebraska (6)

			Ohio (21)
	Latitude	38.0 - 45.7N	38.7 - 45.7N
	Longitude	81.9 – 101W	83.0 – 101W
	Soil type	Loam (n = 46) Sandy loam (n = 1) Silt Loam (n = 67) Silty Clay Loam (n = 9)	Loam (n = 59) Silt Loam (n = 61) Silty Clay Loam (n = 9)
	Organic matter content	1.5 - 4.15%	1 – 3.4%
	Aridity index*	0.37 – 0.94	0.44 – 0.96
	Publication year	1993 - 2018	1993 - 2018
Experiment			
Design	Number of replicates	3 - 5	3 – 6
	Type of weed(s) measured	Summer annual (86) Winter annual (17) Perennial (15) Unknown (5)	Summer annual (75) Winter annual (29) Perennial (15)
	Duration of experiment	1-3 years (n=123) 4-5 years (n=0)	1-3 years (n=115) 4-5 years (n=4)
Timing	Timing of weed measurement with respect to cash crop planting	Before (38) After (119)	Before (38) After (119)
	Season of weed measurement**	Spring (January-June; n = 19) Summer (June-September; n = 104) Fall‡ (October – December; n = 4)	Spring (n = 36) Summer (n = 79)

†The study (Mock et al. 2012) reported weed densities averaged over both phases, but did not report crop yields

‡This category was removed from analyses testing the significance of this modifier due to the small number of points representing the category

*an integrated measure of temperature, precipitation and potential evapotranspiration were derived from location coordinates using the CGIAR-CSI Global-Aridity and Global-PET databases (Zomer et al. 2008).

** Spring: January-June; Summer: June-September; Fall : September – December

S2. Fitting statistical models

Note that all R code for statistical analyses is available in the github repository ***https://github.com/vanichols/Nichols_et_al_2020***. The response (y) variable in all statistical analyses was the response ratio, defined as the value of the response in the CC treatment divided by the value in the no-cover treatment (Gurevitch et al., 2018). The ratios exhibited a log-normal distribution and were therefore log-transformed (log-response-ratio, LRR) for all statistical analyses. Values were back-transformed and presented as a percent change for interpretation purposes and reported as geometric means. To estimate over-all effect sizes, we fit a linear mixed-model using the *lmer4* package (Bates et al. 2015) using the LRR as the response variable and a random intercept for each study with non-parametric weighting based on sample sizes (Adams et al., 1997) because only three of the 15 studies reported variances on weed measurements. Results were analyzed using the *lmerTest* (Kuznetsova et al., 2017) and *emmeans* (Lenth et al., 2018) packages.

For all linear mixed models subsequently described, a random intercept for each study and non-parametric weighting was used. Cover crop biomass is known to have a strong effect on weed suppression (Mirsky et al., 2013; Wallace et al., 2018; Baraibar et al., 2018). To assess an individual modifiers' effect on weed responses, we first assessed whether the CC biomass produced at each modifier level was significantly different by fitting a mixed linear model with CC biomass as the response and an individual modifier as a predictor. Because these analyses showed CC type (grass and non-grass) significantly affected CC biomass production (p=0.01), we included CC biomass as a covariate when testing for the effect of CC type on weed suppression to control for these differences. This was done by including CC type (grass and non-grass), CC biomass at termination, and their interaction as fixed effects (plus the random intercept for study as previously described). The interaction was not significant based on nested model comparison, so the interaction was not included in the final model. For all other modifiers, they were assessed individually using a linear mixed model as described above with only one fixed effect modifier included at a time.

Significance was assigned at a p-value <0.05, but intermediate p-values (0.05-0.10) and effect sizes were investigated (Ho et al., 2019). The robustness of our results was assessed by removing one study at a time from the dataset and fitting the statistical model for each dataset individually (Philibert et al., 2012). Additionally, select individual points were assessed for disproportionately influencing results in the same manner. For significant results, robustness against possibly un-published non-significant results was assessed using a fail-safe number (Rosenthal, 1979).

In the weed biomass (WBIO) database, the CC type significantly affected the amount of CC biomass (CCBIO) produced (p = 0.01), with grass CCs producing an estimated 3.95 Mg ha^{-1} of biomass, compared to 2.56 Mg ha^{-1} in non-grass. Therefore, CCBIO was used as a covariate in the statistical model testing for differences in CC type.

To estimate the amount of grass CCBIO needed at termination to achieve a 75% reduction in weed biomass, we fit a linear mixed model with CC type and CCBIO at termination as predictors (with study as a random intercept). The unconditioned fitted parameters were used to back-calculate the grass CC biomass at a CC-induced 75% reduction in weed biomass. The uncertainty around this value was estimated using the delta method (Ver Hoef, 2012). Each point was categorized based on cash-crop yield and weed pressure responses; if the comparison exhibited both an increase in cash-crop yield and a decrease in weed pressure it was assigned 'win-win', otherwise it was assigned a value of 'other'. To explore possible predictor combinations for win-win scenarios, we fit random forest models (Kuhn and Johnson, 2013) using several R packages (Hothorn et al., 2006).

S3. Results from statistical model-fitting

Effect sizes for individual study model fits

Individual study effect sizes are presented in **Figure S3.1.**

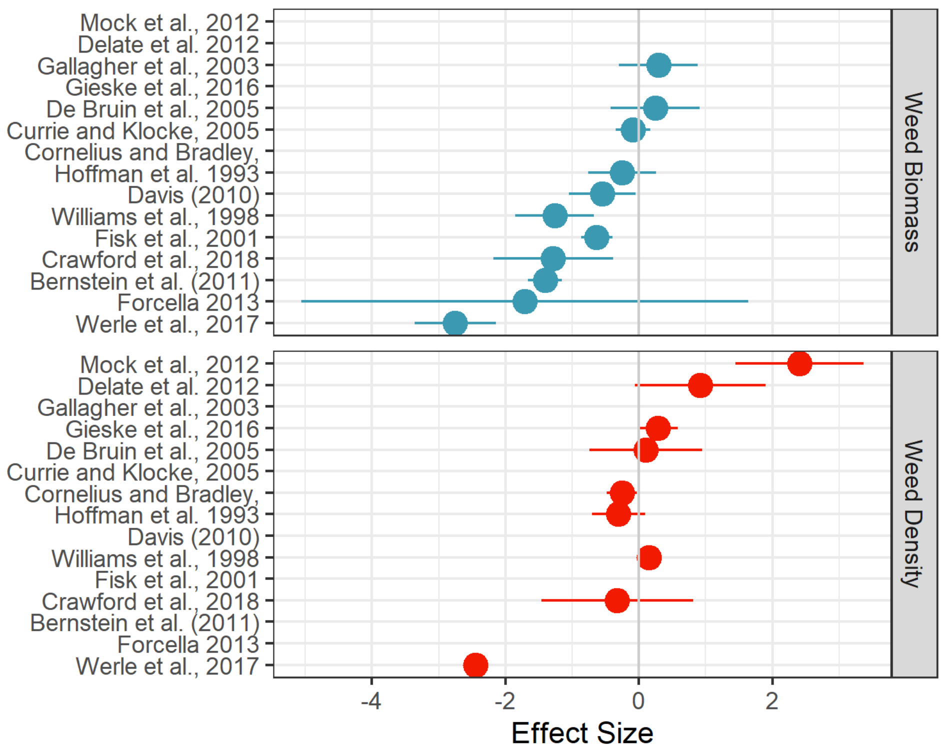

Figure S3.1 *Effect sizes ($ln(Rcc_{treatment}/R_{cotnrol})$) for the 15 individual studies for the two response variables (weed biomass, weed density) represented by points; line-ranges represent 95% confidence intervals.*

Overall model fits

There was no evidence CCs reduced weed density (p=0.98; **Table S3.1**), but the sensitivity analysis identified one study (Gieske et al. 2016) using a radish (*Raphanus sativus*) CC whose removal drastically lowered the non-significance of the p-value (lowered from 0.98 to 0.26).

Table S3.1 *Overall model results with leave-one-study-out sensitivities*

Weed Response	p-value	Estimate	Lower 95% CI Bound	Upper 95% CI Bound	Study Left Out
Density	0.98	0.01	-0.72	0.74	NA
	0.95	-0.02	-0.86	0.82	3
	0.83	0.08	-0.73	0.88	4
	0.76	0.1	-0.66	0.87	5
	0.81	-0.09	-0.88	0.71	6
	0.94	-0.03	-0.85	0.8	8
	0.93	0.03	-0.8	0.86	9
	0.26	-0.19	-0.68	0.3	10
	0.64	0.14	-0.54	0.83	11
	0.93	0.03	-0.79	0.85	12
	0.91	0.04	-0.78	0.86	13
	0.97	-0.01	-0.84	0.81	15
Biomass	0.02	-0.72	-1.27	-0.17	NA
	0.03	-0.76	-1.39	-0.12	1
	0.04	-0.65	-1.25	-0.04	2
	0.01	-0.82	-1.39	-0.25	3
	0.03	-0.73	-1.36	-0.1	4
	0.03	-0.66	-1.23	-0.08	5
	0.01	-0.8	-1.37	-0.23	7
	0.02	-0.81	-1.44	-0.18	9
	0.02	-0.59	-1.06	-0.11	11
	0.04	-0.67	-1.28	-0.06	12
	0.02	-0.79	-1.4	-0.19	14
	0.04	-0.66	-1.28	-0.05	15

Table S3.2 *Overall model results for models assessing differences in cash crop yields under cover-cropping versus no-cover treatments*

Database	p-value	Estimate	Lower 95% CI Bound	Upper 95% CI Bound
Weed Biomass	0.147	-0.461	-1.329	0.406
Weed Density	0.117	-0.262	-0.607	0.084

Table S3.2 *Weed biomass categorical modifier level contrasts*

Modifier	Level 1	Level 2	Estimate	Standard Error	Degrees of Freedom	Statistic	p-value
msmt_season	spring	summer	-0.75	0.26	395.41	-2.82	0.01
msmt_planting	after	before	0.75	0.26	395.41	2.82	0.01
weed_group	perennial	winter annual	1.03	0.33	432.46	3.14	0.01
cc_type2	grass	non-grass	0.44	0.17	80.66	2.50	0.01
cropsys_tillage	N	Y	0.82	0.51	13.52	1.61	0.13
weed_group	perennial	summer annual	0.60	0.33	379.78	1.81	0.17
ccterm_meth	H	M	0.52	0.31	194.51	1.67	0.34
weed_group	summer annual	winter annual	0.43	0.32	324.47	1.35	0.37
crop_follow	corn	soybean	0.38	0.47	16.53	0.82	0.42
cc_type2	grass	non-grass	0.11	0.14	24.96	0.81	0.43
ccterm_meth	M	W	-0.64	0.45	160.63	-1.42	0.49
ccterm_meth	D	W	-0.88	0.70	393.73	-1.25	0.59
ccterm_meth	D	H	-0.76	0.62	443.61	-1.23	0.61
ccterm_meth	H	W	-0.12	0.33	273.22	-0.35	0.99
ccterm_meth	D	M	-0.24	0.69	369.01	-0.35	0.99

Table S3.3 *Weed density categorical modifier level contrasts*

Modifier	Level 1	Level 2	Estimate	Standard Error	Degrees of Freedom	Statistic	p-value
msmt_planting	after	before	0.39	0.26	336.64	1.49	0.14
weed_group	perennial	winter annual	0.52	0.29	435.50	1.77	0.18
msmt_season	spring	summer	-0.40	0.22	79.59	-1.77	0.19
weed_group	summer annual	winter annual	0.25	0.24	420.34	1.02	0.56
weed_group	perennial	summer annual	0.28	0.29	439.41	0.94	0.61
crop_follow	corn	soybean	0.08	0.36	10.28	0.24	0.97
ccterm_meth	D	H	-0.31	0.60	435.98	-0.52	0.99
ccterm_meth	D	none	-0.60	1.35	18.43	-0.45	0.99
ccterm_meth	D	M	-0.31	0.72	358.66	-0.43	0.99
ccterm_meth	H	W	0.11	0.31	399.01	0.34	1.00
ccterm_meth	none	W	0.40	1.25	13.53	0.32	1.00
ccterm_meth	D	W	-0.21	0.67	428.18	-0.31	1.00
ccterm_meth	H	none	-0.29	1.22	12.51	-0.24	1.00
ccterm_meth	M	none	-0.30	1.25	13.59	-0.24	1.00
ccterm_meth	M	W	0.10	0.51	213.45	0.20	1.00
ccterm_meth	H	M	0.00	0.41	185.11	0.01	1.00

Table S3.4 *Continuous modifier regression results*

resp	mod	n	sumsq	meansq	NumDF	DenDF	statistic	p.value
den	aridity_index	110	3.736053	3.736053	1	28.01681	2.424336	0.130689
den	om_pct	32	6.839874	6.839874	1	28.23631	9.650271	0.004285
den	cc_bm_Mgha	102	28.71745	28.71745	1	64.75331	23.2525	8.97E-06
bio	aridity_index	123	1.587642	1.587642	1	7.586298	0.957572	0.357968
bio	om_pct	44	3.344446	3.344446	1	3.332166	3.221653	0.161314
bio	cc_bm_Mgha	113	11.46623	11.46623	1	104.6375	6.852609	0.010163

S4. SALUS model calibration

Systems Approach to Land-Use Sustainability (SALUS) model overview

SALUS (Basso and Ritchie, 2015) is a cropping systems simulation platform that allows estimating the impact of diverse agricultural management strategies on various processes within the soil–plant–atmosphere continuum. The platform contains a suite of interconnected processed-based models derived from the well-validated CERES (Crop Estimation through Resource and Environment Synthesis) model, providing simulation of crop growth and development, and carbon, water, nitrogen, and phosphorus cycling dynamics on a daily time step. The model uses as input daily values of incoming solar radiation (MJ m^{-2}), maximum and minimum air temperature (°C), and rainfall (mm), as well as information on soil characteristics and management. SALUS has been tested extensively for its ability to simulate various soil-crop processes including: soil carbon dynamics (Senthilkumar et al., 2009; Basso et al., 2018), crop yield (Basso et al., 2007), plant N uptake and phenology (Basso et al., 2010, 2011; Albarenque et al., 2016), nitrate leaching (Giola et al., 2012; Syswerda et al., 2012; Basso et al., 2016), water use efficiency (Ritchie and Basso, 2008) and transpiration efficiency (Basso and Ritchie, 2012). A general description on SALUS is provided by Basso and Ritchie (2015).

In SALUS, crop growth can be simulated following a complex or a simple modeling approach. In this study, we used the simple modeling approach. The simple crop model (SALUS-Simple henceforth) represents a ‘generic’ crop model with 20-25 predefined crop parameters, which can be easily adapted to characterize growth of many annual crops. SALUS-Simple follows the same approach used by ALMANAC (Agricultural Land Management Alternatives with Numerical Assessment Criteria, Kiniry et al., 1992). Briefly, the model uses crop parameters to calculate potential leaf area index (LAI) and radiation use efficiency (RUE) curves as function of thermal time, which in turn are used to estimate daily crop resource acquisition and potential crop growth. When run with water and nutrient limitations, the model calculates water and nutrient stress factors based on a daily supply-demand balance, which then are applied to reduce the rate of potential biomass growth. For a detailed description of the SALUS-Simple crop model, we refer the reader to Dzotsi et al. (2013).

Data sources and model set up

We assembled a dataset of published literature studies conducted within the Corn Belt to set up and calibrate the SALUS-simple model. All of these studies reported measurements of winter rye cover crop biomass at termination, as well as cover crop planting and termination dates. This dataset contains observations from 12 studies, 6 of which also were included in our original meta-analysis dataset and the rest were available from a literature search from a previous study (Martinez-Feria et al., 2016). In total, the dataset included observations from 15 sites, amounting to 52 site-year combinations (**Figure S4.1**). We used 60% of the data for model training and 40% for model testing. The assembled dataset is shown in **Table S4.1**.

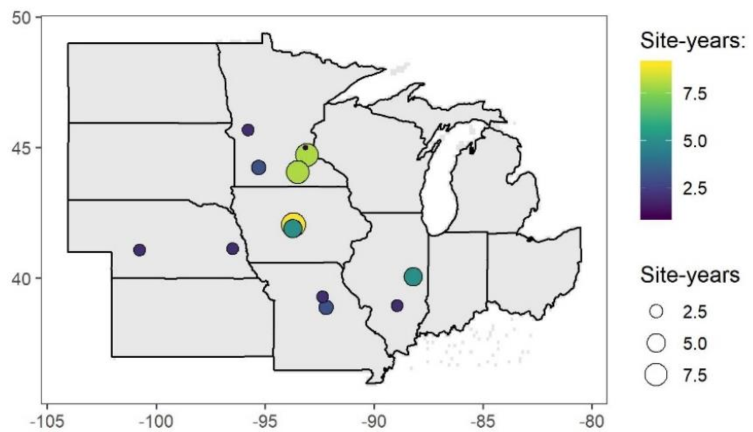

Figure S4.1. *Geographical location of the experiments used for model calibration.*

For each of the 15 sites, we retrieved daily weather data from the North American Land Data Assimilation System project phase 2 (NLDAS-2) dataset (Xia et al., 2012) using the single-pixel (0.125° resolution) extraction tool and formatter for SALUS (https://salusmodel.ees.msu.edu/NLDAS/). Soil information for each site was retrieved from the Soil SURvey GeOgraphic database (SSURGO; Soil Survey Staff), from which we selected data for the predominant soil series (map unit key) at each location.

Simulation for each experiment were run independently, from 1-Jan to 30-June of the following year, meaning that each simulation comprised a period of 18 months. We assumed both water- and N-limited rye cover crop growth. To provide for realistic initial conditions for soil water at cover crop planting, we simulated a maize crop, prior to cover crop planting. In the model, maize was planted in early May, fertilized with 150 kg N ha^{-1} at planting and harvested 10 days before the prescribed cover crop planting date. Planting density for rye cover crop was assumed at 300 plants m^{-2}, 1.0 cm depth and 20 cm row spacing. No fertilizer was applied to rye in the model.

Table S4.1. *Dataset of published estimates of rye cover crop biomass at terminations which was used for model training and testing*

Obs. ID	Used for	Source	Location	Planting	Termination	Biomass (Mg ha^{-1})
1	Training	Cornelius and Bradley, 2017	Columbia, MO	2012-9-11	2013-4-25	2.89
2				2013-9-12	2014-5-2	2.19
3				2014-9-10	2015-4-23	1.15
4			Moberly, MO	2013-9-12	2014-5-2	1.39
5				2014-9-10	2015-4-23	3.93
6		Davis, 2010	Urbana, IL	2004-10-1	2005-5-13	7.10
7				2005-10-1	2006-5-12	6.00
8				2006-10-1	2007-5-11	6.00
9		Bruin et al., 2005	Rosemont, MN	2001-10-25	2002-5-1	0.49
10				2001-10-25	2002-5-8	0.73
11				2001-10-25	2002-5-15	1.03
12				2001-10-25	2002-5-22	1.80
13				2002-11-1	2003-5-13	0.15
14				2002-11-1	2003-5-23	0.41
15				2002-11-1	2003-6-2	1.42
16				2002-11-1	2003-6-17	2.93
17			Waseca, MN	2001-10-18	2002-5-1	0.38
18				2001-10-18	2002-5-8	0.85
19				2001-10-18	2002-5-20	2.19
20				2001-10-18	2002-5-28	3.77
21				2002-10-11	2003-5-1	0.15
22				2002-10-11	2003-5-7	0.22
23				2002-10-11	2003-5-14	0.52
24				2002-10-11	2003-5-20	0.99
25		Feyereisen et al., 2006	St. Paul, MN	2000-9-18	2001-5-25	5.90
26		Forcella, 2014	Stevens county, MN	2009-9-2	2010-6-9	6.00
27				2010-9-20	2011-6-14	6.00
28		Kaspar et al., 2007	Ames, IA	2001-9-20	2002-4-17	2.43
29				2002-9-10	2003-5-6	2.50
30				2003-10-2	2004-4-16	1.48
31				2004-10-6	2005-4-25	2.74
32	Testing	Kaspar et al., 2012	Ames, IA	2005-9-30	2006-4-21	2.44
33				2006-10-24	2007-5-10	0.61

34				2007-9-28	2008-4-29	1.26
35				2008-10-29	2009-5-21	0.50
36				2009-9-28	2010-4-19	1.73
37		Martinez-Feria et al., 2016	Kelley, IA	2008-10-21	2009-5-6	0.37
38				2009-11-6	2010-5-5	1.18
39				2010-10-4	2011-5-10	1.53
40				2011-10-10	2012-4-18	2.50
41				2012-10-15	2013-5-11	0.50
42		Ruffo and Bollero, 2003	Brownstown, IL	1998-10-3	1999-4-28	4.73
43				1999-10-2	2000-4-29	2.92
44			Urbana, IL	1998-10-1	1999-5-2	4.02
45				1999-10-5	2000-5-4	3.16
46		Strock et al., 2004	Lamberton, MN	1998-10-1	1999-4-30	2.70
47				1999-9-29	2000-4-11	1.00
48				2000-10-4	2001-5-16	0.50
49		Werle et al., 2018	North Platte, NE	2016-9-20	2017-4-18	4.08
50				2016-10-17	2017-4-18	3.77
51		Williams et al., 1998	Ithaca, NE	1994-9-20	1995-6-6	6.31
52				1995-9-20	1996-5-23	2.89

Model calibration and performance

To calibrate the SALUS-simple model for simulating rye cover crop biomass, we first compared simulated values to data from the testing dataset (Table S4.1). To quantify model fit to the observed data we computed the Nash-Sutcliffe model efficiency (NSE) and root-mean-squared error (RMSE). The RMSE is a measure of model error (the closer to zero, the better), while NSE is a measure of model precision compared to an arithmetic mean (a value of 1 indicates perfect fit). The equation for these two measures can be seen in Archontoulis and Miguez (2013). Model fit was also evaluated visually by means of plotting the observed vs. simulated values, with the regression line as measure of model bias.

We used as a starting point the rye crop species parameters available in the ALMANAC model (Kiniry and Spanel, 2009; Table S2.2). Using this parameterization, however, the model tended to overestimate fall growth, which resulted in premature senescence in the spring. Therefore, we evaluated increasing the length of the growth cycle (TTtoMatr from 1200 to 1800 °C-day) and adjusting phenology (relTT_P1, relTT_Sn) and LAI curve parameters (relLAI_P2). Additionally, because the model tended to overpredict biomass growth in the spring, we decreased maximum potential radiation use efficiency (RUEmax) from 3.0 to 2.0 g MJ (PAR)-1. A list of parameter values derived from the model training step are included in Table S4.2, and a model fit to the training data set is shown in Figures S4.2 and S4.3.

Table S4.2. *Calibrated SALUS-simple parameters used to simulate winter rye cover crop growth.*

Parameter	Description	Units	Value	
			ALMANAC (original)	Calibrated*
relTT_P1	Relative development thermal time at point 1	°C-day °C-day^{-1}	0.3	0.25 (0.05-0.45)
relLAI_P1	Relative LAI at point 1	m^{2} m^{-2}	0.01	-
relTT_P2	Relative development thermal time at point 2	°C-day °C-day^{-1}	0.5	-
relLAI_P2	Relative LAI at point 2	m^{2} m^{-2}	0.95	0.9 (0.9-0.99)
LAImax	Maximum leaf area index	m^{2} m^{-2}	3	-
RUEmax	Maximum potential radiation use efficiency	g MJ (PAR)$^{-1}$	3	2 (1-3.5)
relTT_Sn	Relative development thermal time at senescence	°C-day °C-day^{-1}	0.8	0.5 (0.5-0.85)
SnParLAI	Parameter for RUE decline after senescence	unitless	1	-
SnParRUE	Parameter for RUE decline after senescence	unitless	1	-
TbaseDev	Base temperature for development	°C	0	-
ToptDev	Optimal temperature for development	°C	15	-
TTtoGerm	Development thermal time to germinate	°C-day	20	-
TTtoMatr	Development thermal time to mature	°C-day	1200	1800 (1200-2500)
EmgInter	Intercept of emergence time calculation	leaf eq.	15	-
EmgSlope	Slope of emergence time calculation	leaf eq. cm^{-1}	6	-
HrvIndex	Harvest index	Mg Mg^{-1}	0.42	-

PlntN_Em	Optimal N in plant at emergence	g g^{-1}	0.0226	-
PlntN_Hf	Optimal N in plant halfway to maturity	g g^{-1}	0.018	-
PlntN_Mt	Optimal N in plant at maturity	g g^{-1}	0.014	-
GrnN_Mt	Optimal N in grain at maturity	g g^{-1}	0.023	-
CHeight	Approximate height of crop	m	1.0	-
*Values within parenthesis show the range explored in the calibration				

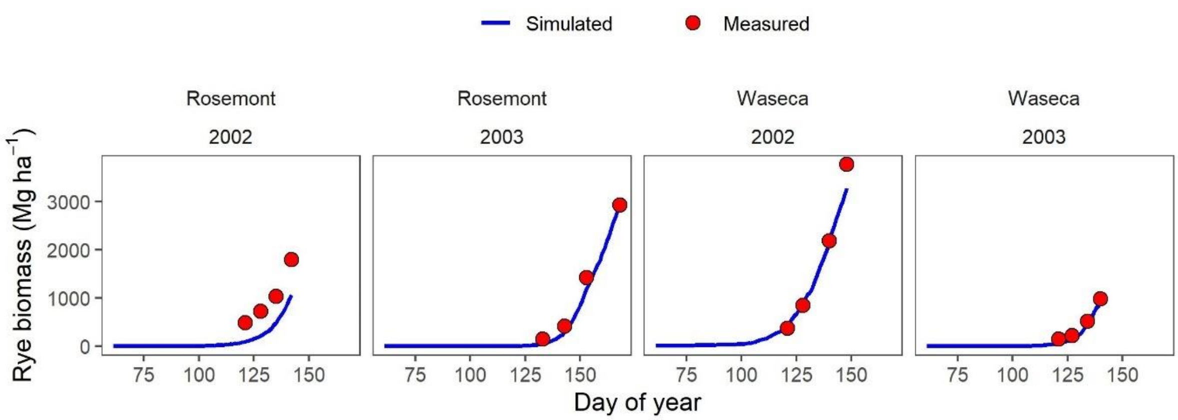

Figure S4.2. *Example of rye cover crop spring growth as simulated by the SALUS-simple crop model. The data for the experiments shown here were obtained from Bruin et al. (2005).*

Having calibrated the SALUS-Simple crop model to simulate rye growth, the next step was to compare the simulated values to the independent measurement in the testing dataset. Considering that set-up and model training was largely based on limited (i.e. publicly available) data and literature values, the SALUS-simple model was able to satisfactorily reproduce the measured cover crop biomass at termination in the testing dataset. Biomass across all sites in the testing dataset were simulated with a RMSE of 1.2 Mg ha^{-1}. This was about the same compared to the training dataset (1.1 Mg ha^{-1}), which suggest no overfitting of the training data. The model did tend to overpredict the rye biomass in the testing dataset compared to the training, especially in the high yielding environments. This translated to lower NSE compared to the training data (0.74 vs. 0.39), although it was still within acceptable ranges. Based on these results we deemed this model calibration appropriate for estimating rye biomass growth as a function of weather, soils and management across the US Corn Belt.

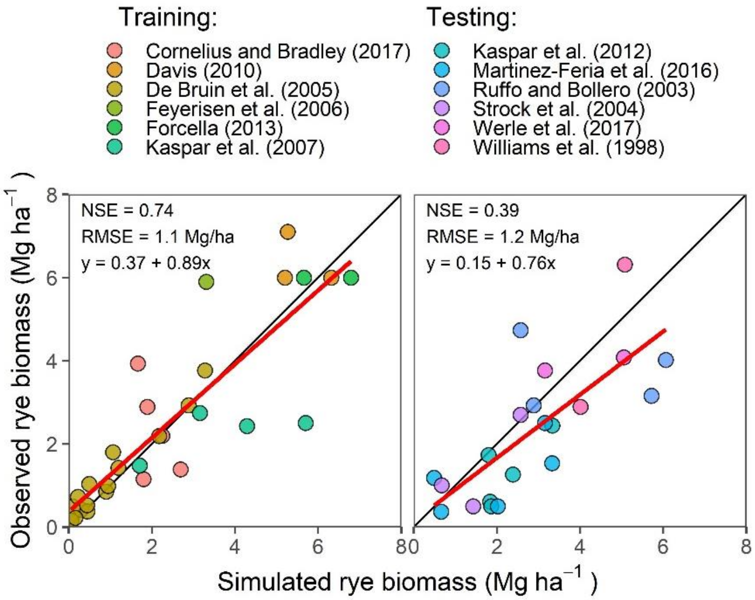

Figure S4.3. *SALUS simple model fit to the training and testing datasets. NSE = Nash-Sutcliffe model efficiency; RMSE = root mean squared error.*

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