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Effects of Fall and Winter Cover Crops on Weed Suppression in the United States: A Meta-Analysis

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Abstract: Cover cropping recently emerged as a promising alternative to conventional tillage and herbicide use for weed suppression in agricultural systems. We investigated their effectiveness in weed control and the varying effects of different management strategies using a meta-analysis. Our analysis studied two categories: weed biomass control and weed density control. We employed a random-effect model to analyze weed biomass to address between-study heterogeneity and found that cover crop treatments led to a significant 62.6% reduction in weed biomass. These results are robust to outliers and publication bias. Furthermore, subgroup analysis found that planting a mixture of cover crop types was more effective than planting a single type. Additionally, planting a mixture of cover crop species, which are subcategories of cover crop types, was found to be more effective than planting a single species. Our analysis also unveiled a persistent, albeit diminishing, reduction in weed biomass even after the termination of cover crops. For weed density analysis, we used a fixed-effect model due to the absence of between-study heterogeneity and found a statistically significant reduction (45.4%) in weed density. Subgroup analysis revealed no significant difference in weed density control between legume and grass cover crop types.

Keywords: cover crop; meta-analysis; weed suppression; weed biomass; weed density

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1. Introduction

Traditional weed control methods rely heavily on tillage and herbicide application, resulting in detrimental environmental impact. For example, intensive tillage causes soil erosion, nutrient runoff, and greenhouse gas emissions [1], contributing to issues such as the formation of dead zones in water bodies (e.g., the Gulf of Mexico dead zone [2]) and significant water and wind erosion in U.S. cropland [3]. In addition, the overuse of herbicides leads to herbicide resistance. According to the latest data from the International Herbicide-Resistant Weed Database [4], there exist 530 distinct cases (species × site of action) of herbicide-resistant weeds globally, involving 272 species, with resistance observed in 21 out of 31 known herbicide sites of action and 168 different herbicides. Herbicide-resistant weeds have been reported in 100 crops across 72 countries [4]. Furthermore, herbicides can enter surface water indirectly through runoff or leachate, resulting in contamination and biological impairments in water bodies and ecosystems [5] and posing risks to human health through dermal contact, inhalation, and consumption of food and water. Chronic exposure to pesticides through water ingestion can mimic the body's hormones, compromising immune function, disrupting hormone balance, triggering reproductive issues, and potentially leading to carcinogenic effects. This impact is particularly pronounced among children in their developmental stages, potentially resulting in reduced intelligence [6,7]. Recent studies have detected trace herbicides in drinking wells across multiple countries, including numerous European countries [8–10], China [11,12], the United States [13,14], New Zealand [15], Argentina [16], and Brazil [17]. In the United States, at least one pesticide compound was identified in 491 out of 1204 wells [18].

Improving weed control strategies that reduce reliance on tillage and herbicides can address these concerns from environmentalists, consumers, and governments. Integrated weed management strategies which include a diverse range of weed control methods such as biological and cultural approaches [19] offer promising alternatives. As a cultural weed control method, cover cropping involves the use of crops, such as grasses, legumes, and forbs [20], in suppressing weeds while providing additional benefits including the reduction in soil erosion and nutrient leaching, improvement in soil quality and fertility, enhanced soil moisture and water infiltration, and decreased insect populations (e.g., [21–29]).

However, the effectiveness of cover crops for weed suppression can vary depending on agronomic management strategies. Factors such as cover crop species, planting and termination dates, termination methods, tillage systems, and the mixture of cover crop species can all influence the outcome [30–32]. Variations in these factors may explain the varied effects of cover crops on weed control, as shown in the national cover crop survey [33]. According to the survey, 44% of farmers strongly agreed and 44% somewhat agreed that there was an improvement in weed control, while 10% neither agreed nor disagreed, and the remaining respondents somewhat disagreed or strongly disagreed. The variations in the effectiveness of weed control achieved by cover crops have made farmers hesitant to adopt cover cropping as a component of integrated weed management strategies, which is compounded by factors such as rising costs and increased management efforts [34].

Therefore, to encourage a wider adoption of cover cropping among farmers, it is crucial to gain a comprehensive understanding of its efficacy in weed control and the varying effects of different management strategies. This will enable the provision of valuable recommendations to farmers. Our study conducts a meta-analysis to investigate the effects of cover crops on weed control. A meta-analysis can not only document the statistical significance, magnitude, and direction of cover crop effects and provide a synthesis of results from individual studies but also identify variables that account for the variance in the effects. While several meta-analyses have examined the weed-suppressive effects of cover crops (e.g., [32,35–37]), our study uniquely concentrates on fall and winter cover crops sown in rotation with the main crop in the United States. This focus is justified by the diverse production practices and weather conditions across countries as well as the seasonal effects in cover crops growth throughout the year, which could potentially dilute the analysis and lead to misleading conclusions.

Our study aims to address the following questions: (1) Does cover cropping effectively reduce weed biomass and weed density? (2) How does the species of cover crop affect its ability to suppress weed? (3) Is the use of a mixture of multiple cover crops more effective in weed suppression compared to planting a single cover crop? (4) Does the weed suppression persist after the termination of the cover crop?

2. Cover Crop Types and Their Adoption in the United States

Legumes and grasses are currently the two most popular cover crop types [38]. In addition to weed suppression, the characteristics of cover crops play an important role in farmers' adoption decision. Legumes distinguish themselves from others by their ability to fix nitrogen from the atmosphere and add it to the soil. Based on growing season, legumes can be grouped into summer annual legumes and winter annual legumes. Among winter legumes, some winterkill, while some can tolerate frost.

Hairy vetch emerges as the most widely used winter annual legume in northern regions because of its winter hardiness, high N content, and high productivity [39]. Crimson clover is favored as a top choice for cover crops in southern regions due to its fast maturation and large N addition to the following crops [38]. In addition, field peas and subterranean clover are also preferred options for their efficient N production.

Grass cover crops encompass a variety of species, including annual cereals such as rye, wheat, barley, and oats, as well as annual or perennial forage grasses like ryegrass, and warm-season grasses such as sorghum–sudan grass [38]. Because of their capacity to generate substantial amounts of residue and extensive roots, grass cover crop can effectively suppress weed germination and growth [38]. In general, grass cover crops can help reduce more NO_3 leaching compared to legumes. Some grass cover crops like rye and barley grow rapidly and consequently are commonly used for erosion protection. Others, like winter rye and oats, can help reduce soil-borne diseases [38,40]. Oats winterkill, which makes them a mulch the following spring, helping reserve moisture and suppress weeds [38]. While oats have no need for killing in spring, they produce less biomass compared to winter hardy crops.

In addition to legumes and grasses, buckwheat and Brassica (such as mustard, rapeseed, and forage radish) can also be used as cover crops [41]. Buckwheat is summer annual and is not winter hardy. It grows fast even in low-fertility soil and can effectively suppress weeds. Brassica has fast growth in late summer and fall. It can improve rainfall infiltration and the storage of soil.

Cover crops can suppress weeds through various mechanisms: they can impede weed germination, emergence and establishment by forming a mulch layer with cover crop residues on the soil surface [42–44]. In addition, the living and decomposed biomass of cover crops release allelochemicals that inhibit weeds [45]. Furthermore, cover crops compete for limited resources such as space, nutrients, water, and light [46,47], creating an ecological disadvantage for weeds.

The practice of employing cover crops in agricultural strategies in the United States dates back to the 18th century and experienced significant expansion throughout the 19th century. At that time, they primarily served as green manures [34,48]. The post-World War II era witnessed the widespread replacement of cover crops with synthetic fertilizers, which is driven by the latter's ease of use and cost-effectiveness. However, in recent years, there is a renewed interest in cover crops among both governments and farmers who recognize the various benefits of cover crops. For example, out of all the conservation practices eligible for USDA Environmental Quality Incentives Program (EQIP) funding between 2018 and 2022, cover crops received the highest amount of funding, totaling $448.9 million [49]. In addition, USDA/NRCS has recently introduced a new collaboration with Farmers for Soil Health, an initiative of the United Soybean Board, National Corn Growers Association, and National Pork Board. With a substantial investment of $38 million from NRCS, the initiative aims to achieve a major milestone by doubling the utilization of cover crops on corn and soybeans acres, reaching 30 million acres by the year 2030 [50]. In addition to EQIP and the Conservation Stewardship Program (CSP) at the national level, there are at least 22 state-level financial incentives for cover crops [51].

With government financial support and increased knowledge of the benefits of cover cropping, the adoption of crop crops by farmers has surged over the past decade in the United States. For example, from 2011 to 2021, cover crops adoption in the Midwest quadrupled, although the adoption rate remains relatively low at 7.2% in the region [52]. Nationally, cover crop acreage increased from 10.3 million acres in 2012 to about 20 million acres in 2020, nearly doubling in less than a decade [53]. While improving soil health and adding soil organic matter/sequestering carbon are still the primary reasons for the adoption of cover crops, as reported by over 90% of surveyed farmers in a recent national cover crop survey [33], nearly 80% of farmers adopt cover crops to improve weed management. This stands in sharp contrast to the 2012–2013 survey, where only 40% of surveyed farmers had a weed management goal when adopting cover crops.

3. Methodology and Data Analysis

Many studies have investigated the effect of cover crops on weed suppression. However, individual findings exhibit considerable variation in terms of statistical significance, magnitude, and direction. The diverse characteristics of experimental sites and crop management practices (such as cover crop species, number of cover crops, and planting and termination time, etc.) have been associated with disparities in the results of these studies. Therefore, our meta-analysis aims to not only quantitatively assess the effects of cover crops on weed suppression but also evaluate how much management practices contribute to the variations in study results.

Meta-analysis, originally defined by Glass [54], is a statistical method for synthesizing a large collection of individual study analyses to produce integrated findings. Essentially, meta-analysis allows for the consolidation of results from independent studies to calculate an overall effect through statistical techniques.

3.1. Effect Size

In meta-analysis, the key variable under investigation is the effect size, which measures the magnitude of observed responses or effects. Specifically, in this study, we focus on weed biomass and weed density. Various measures of effect size have been proposed, including Pearson's correlation coefficient, Cohen's d [55,56], and the odds ratio [57]. Here, we adopt the method suggested by Hedges, Gurevitch, and Curtis [58] for assessing effect size: the logarithm of the response ratio. The logarithm of the response ratio is computed as shown below:

$$L = ln(RR) = ln(\frac{\overline{X}_{tr}}{\overline{X}_c}) \tag{1}$$

where $\overline{X}_{tr}$ and $\overline{X}_c$ are the mean responses in treatment and control groups, respectively. The logarithm transformation helps normalize the distribution of effect size [58], while the ratio transformation ensures that the effect size is unitless, thereby facilitating comparisons across studies with different units of measurement.

To assess the overall effects within the population by synthesizing effect sizes from various individual studies, it is crucial to assign weights for calculating a weighted mean of the effect size. As discussed by Field and Gillett [59], studies with higher sampling accuracy should be given more weight, whereas those with less precise estimates should be given less weight. In this study, the overall mean effect is computed as the weighted mean of individual effect sizes with the reciprocal of the total variance of the effect size serving as the weights. The weighted mean of the effect size is calculated using the following formula:

$$\overline{L} = \frac{\sum_{i=1}^{k} w_i L_i}{\sum_{i=1}^{k} w_i} \tag{2}$$

where

$$w_i = \frac{1}{\gamma^2 + \tau^2} \tag{3}$$

Here, L_i indicates the individual effect size calculated by using Equation (1), w_i indicates the weight of the ith study, τ^2 denotes the between-study variance, and γ^2 indicates the within-sample variance.

3.2. Variance of Effect Size

Meta-analysis can be conducted using two main approaches: fixed-effect and random-effect models [60], which are each based on different assumptions. The fixed-effect model assumes that studies are sampled from a population with a constant average effect size, thus presuming homogeneity in sample effect sizes [61]. Consequently, the average effect size of the population can be predicted from a few predictors [61]. The fixed-effect size measure can be expressed as shown below:

$$\hat{\mu_f} = \mu + e \tag{4}$$

where $\hat{\mu_f}$ is the estimated common effect, μ is the true common effect, and $e \sim N(0, \gamma^2)$ is the sampling error with γ^2 as the within-sample variance.

In contrast, the random-effect model assumes that studies are drawn from populations with varying average effect sizes, leading to heterogeneous effect sizes. The random effect size can be represented as shown below:

$$\hat{\mu_r} = \mu + \vartheta_\tau + e \tag{5}$$

where $\vartheta_\tau \sim N\left(0,\ \tau^2\right)$ is the random error with τ^2 as the between-study variance. In contrast to the fixed-effect model, the random-effect model incorporates two sources of error: sampling error and additional error arising from variability across studies, which is referred to as between-study variance [62]. When the between-study variance is zero, the fixed-effect model becomes a special case of the random-effects model. The choice between the random- and fixed-effect models depends on the characteristics of the data. We will assess heterogeneity to determine the appropriate model for our analysis.

3.3. Heterogeneity Measurement

There are three commonly used methods to measure the degree of heterogeneity (variability) between groups [63]: τ^2, Cochran's Q, and Higgin's and Thompson's I^2. τ^2 is simply the between-study variance in the meta-analysis. Cochran's Q -statistic is calculated as a weighted sum of squared difference between the observed values of effect size and the estimate from the fixed-effect model.

$$\text{Cochran's } Q = \sum_{i=1}^{k} w_i \left(L_{0i} - \frac{\sum_{j=1}^{k} w_j L_j}{\sum_{l=1}^{k} w_l} \right)^2 \tag{6}$$

It follows a chi-squared distribution with $k - 1$ degrees of freedom, testing the null hypothesis that all studies evaluate the same effect. Higgin's and Thompson's I^2 is calculated as the percentage of variation in effect size due to heterogeneity rather than chance [64,65]. It is derived from Cochran's Q value.

$$I^2 = \max\{0, \frac{Q - (k-1)}{Q}\} \tag{7}$$

Higgins et al. [65] offer a "rule of thumb" for interpreting I^2: low heterogeneity if I^2 = 25%, moderate heterogeneity if I^2 = 50%, and substantial heterogeneity if I^2 = 75%.

As many studies often report only the sample mean and sample size without providing variances or standard errors, there is a challenge in calculating weights and mean effect sizes. To tackle this obstacle, we employ a technique introduced by Sangnawakij et al. [66], which constructs the variance of the mean effect size in the random effects model using the maximum likelihood approach and an iterative procedure.

3.4. Influence Analysis and Subgroup Analysis

If heterogeneity is detected, it becomes appealing to investigate whether the variability between groups is driven by outliers, which have a much higher effect size. Following the methods proposed by Viechtbauer and Cheung [67], several influence diagnostics such as the externally standardized residual, Cook's distance, and leave-one-out method are conducted to identify outliers. If the results of the analysis remain largely unaffected by the exclusion of outliers, then the previous findings are deemed robust. However, if the analysis is substantially influenced by the exclusion of outliers, it suggests that the outliers have a substantial impact on the results.

Given that the effect size may vary across different subgroupings, we will perform subgroup analysis on cover crop species, the number of cover crop species, and the duration between weed measurement and cover crop termination. This final subgroup will provide insights into the enduring impact of cover crops on weed suppression.

3.5. Publication Bias

Publication bias can arise when a study's chances of being published are significantly influenced by the statistical significance of its findings [68–72]. If smaller sample-size studies are only able to be published when they report larger effect sizes, publication bias may result in an overestimation of the true effect size. To examine publication bias, we utilize Egger's regression test [73]. Specifically, the test examines whether the intercept equal to 0 in a linear regression of a standardized effect size estimates against their standard errors. In the absence of publication bias, the regression intercept is expected to be zero.

3.6. Selection of Studies

The application of meta-analysis requires a collection of studies that include a comparison between a control and experimental treatments. In our meta-analysis investigating the weed suppression effects of cover crops, we compile existing studies based on the following criteria: (1) the presence of both a control under bare fallow and a randomized treatment involving cover crops; (2) identification of the cover crop species utilized; (3) reporting of the number of replications; (4) conducting experiments with winter cover crops planted in late summer or fall; (5) cover crops being terminated in the spring or being winter-killed; (6) reporting of the termination (if not winter-killed) and sampling dates; (7) planting cover crops in rotation with main crops; (8) conducting studies in the United States; and (9) publication in English during or after 1990. In cases where multiple cover crops are compared within a single study, the effect of each cover crop treatment is assessed independently. Similarly, if various management practices (such as tillage and pesticide application) are involved and compared with a corresponding control group with the same management practices, each practice is treated as an independent case.

As cover crops are generally cultivated during periods when cash crops are not actively growing [74], we specifically select studies where cover crops are planted and terminated before the active growth of cash crops, thereby excluding inter-seeding. If a study collects experimental data from multiple sites over several years, each dataset from an experimental site–year is considered as an observation.

We conducted a search for relevant studies using the Web of Science and Google Scholar databases. Keywords such as "cover crops", "cover cropping", individual cover crop names (such as "ryegrass", "hairy vetch", "clover", "oats", and "radish", etc.), "weed depression", "weed management" or "weed control" were employed to identify relevant studies. In addition, studies were collected through cross-referencing with other relevant literature. Detailed information including authors, geographic locations, experimental years and duration, replications, main crop types, weed density and/or weed biomass, cover crop varieties, and planting and termination dates was compiled into spreadsheets for analysis. Some studies present their findings in graphical format. Data extraction was performed through scale calibration and conversion techniques. The summary of the included studies is presented in Table 1.

Table 1. List of the included studies for cover crop's weed control analysis.

Authors	Publication Year	Region	Cover Crop Species	Cover Crop Type
Baraibar et al. [31]	2018	PA	red clover, Austrian winter pea, canola, forage radish, cereal rye, oats	legume, brassica, grass, and mixed types
Hayden et al. [30]	2012	MI	hairy vetch, cereal rye	legume, grass, mixed types
Mischler et al. [75]	2010	PA	rye	grass
Crawford et al. [76]	2018	IL	radish, canola, rye	brassica, grass
Fisk et al. [77]	2001	MI	Santiago burr medic (Medicago polymorpha), Mogul barrel medic (Medicago truncatula), red clover, berseem clover	legume
Gallagher et al. [78]	2003	OH	wheat, hairy vetch	grass, legume

Table 1. *Cont.*

Authors	Publication Year	Region	Cover Crop Species	Cover Crop Type
Hoffman et al. [79]	1993	OH	hairy vetch	legume
Mock et al. [80]	2012	IN	rye, wheat	grass
Werle et al. [81]	2017	NE	rye	grass
Curran et al. [82]	1994	PA	hairy vetch	legume
Reddy and Koger [83]	2004	MS	hairy vetch	legume
Reddy et al. [84]	2003	MS	crimson clover, rye	legume, grass
Reddy [85]	2001	MS	Italian ryegrass, oat, rye, wheat, hairy vetch, crimson clover, subterranean clover	grass, legume
Cornellius and Bradley [86]	2017	MO	Australian winter pea, hairy vetch, crimson clover, oilseed radish, winter oats, annual ryegrass, cereal rye, winter wheat	legume, brassica, grass, and mixed types
Echtenkamp [87]	1989	NE	rye, oats, vetch, chewings fescue, ladino	legume, mixed grasses, and mixed types
Smith [88]	2020	NH	barley, cereal rye, hairy vetch, triticale, wheat, canola, forage radish, oats, sunn hemp	grass, legume, mixed types
Grint et al. [89]	2022	WI	rye	grass
Koger and Reddy [90]	2005	MS	hairy vetch	legume
Koger, Reddy, and Shaw [91]	2002	MS	rye	grass
Reddy [92]	2003	MS	rye	grass
Yenish et al. [93]	1996	NC	rye, crimson clover, subterranean clover, hairy vetch	grass, legume
DeSimini et al. [94]	2020	IN	rye, canola	grass, brassica
Burgos et al. [95]	1996	AK	hairy vetch, rye, wheat	legume, grass, mixed types
Lassiter et al. [96]	2011	NC	cereal rye, Italian ryegrass, oats, triticale, wheat	grass
Lawley et al. [97]	2011	MD	forage radish, rye	brassica, grass
Ngouajio and Mennan [98]	2005	MI	rye, hairy vetch	grass, legume
Teasdale et al. [43]	1991	MD	rye, hairy vetch	grass, legume
Mischler et al. [99]	2010	PA	hairy vetch	legume
Creech et al. [100]	2008	IN	ryegrass, wheat	grass

4. Estimation Results

The effect size was estimated using the generic inverse variance method. The confidence interval around the pooled effect size was calculated using the Knapp–Hartung adjustment [101]. For the estimation of between-study variance τ^2, the Sidik–Jonkman estimator [102] was utilized, with its confidence interval determined using the method proposed by Jackson (2013) [103]. Estimation was carried out using R version 4.3.2 [104]. While some studies report both weed biomass and weed density, others provide data for only one of these metrics. Separate analyses were conducted for weed biomass and weed density.

4.1. Weed Biomass Analysis Results

Our meta-analysis included a total of 250 site–year–management cases for weed biomass control analysis. The Higgin's and Thompson's I^2 was calculated to be 80.7% with a 95% confidence interval of [78.4%, 82.8%]. This indicates that approximately 81% of the variation is attributed to between-study heterogeneity, which is categorized as substantial according to Higgins and Thompson's "rule of thumb". Furthermore, the heterogeneity test is significant with Q equal to 1291.77 and a p-value < 0.0001. The rejection of the null hypothesis suggests heterogeneity between studies. Moreover, the variance in the true effect was estimated to be τ^2 = 1.9660 with a 95% confidence interval of [1.6244; 2.7339]. Since the confidence interval does not contain zero, it indicates the significance of the variance, thereby suggesting the presence of between-study heterogeneity in the data as well. Given the indication of the heterogeneity by all above three measurements, a random-effect model is utilized to estimate the weed biomass control effect of cover crops. The pooled-effect size is estimated to be −0.9831 with a 95% confidence interval at [−1.1885; −0.7777]. The statistically significant effect size (measured by log-response ratio) of −0.9831 implies a 62.6% reduction in weed biomass with cover crop treatment, which is close to the 68% reduction found by Nichols et al. [37]. The estimation results are reported in Table 2.

Table 2. Results of random-effect model estimation and influence analysis for weed biomass control.

	Effect Size	I^2	τ^2	Q
Main analysis	−0.9831 * [−1.1885; −0.7777]	80.7% * [78.4%; 82.8%]	1.9660	1291.77 * p-value < 0.0001
Influential cases removed	−0.8381 * [−0.9804; −0.6958]	10.0% * [0.0%; 25.1%]	0.6006	232.33 p-value = 0.1285

Note: 95% confidence interval is reported below the estimation; * indicates statistical significance at 95% significance level; p-value for heterogeneity test Q is provided.

As previously mentioned, between-study heterogeneity may be influenced by one or more studies with extreme effect sizes. To ensure the accuracy of the pooled effect estimate, it is essential to remove such outliers from the analysis and examine the pooled effect size. Using the methods proposed by Viechtbauer and Cheung (2010) [67], we identified 40 outliers. Upon removing these outliers, influence analysis was conducted, with the results reported in Table 2. The results show that after removing the 40 studies from the analysis, the value of τ^2 decreases from 1.9660 to 0.6006, and the I^2 reduces to nearly 10.0%. The pooled effect size is −0.8381, which is slightly smaller in magnitude than the initial estimate of −0.9831 but still within the same orders of magnitude. This suggests that our analysis results are robust to outliers.

4.1.1. Subgroup Analysis

Several subgroup analyses were conducted to provide deeper insights. The subgroup analysis based on the number of cover crops reveals a statistically significant between-group difference with $Q = 43.7$ and p-value < 0.0001. The estimated effect sizes are presented in Figure 1. The findings suggest that employing multiple cover crops is more effective in controlling weed biomass compared to using a single cover crop. Specifically, using one cover crop led to a statistically significant effect size of 75.4%, implying a 52.9% reduction in weed biomass. In contrast, the simultaneous use of two cover crops resulted in a statistically significant effect size of 167.7% (implying an 81.3% reduction in weed biomass), while the utilization of more than two species of cover crops led to an effect size of 252–257% (implying a roughly 92% reduction in weed biomass).

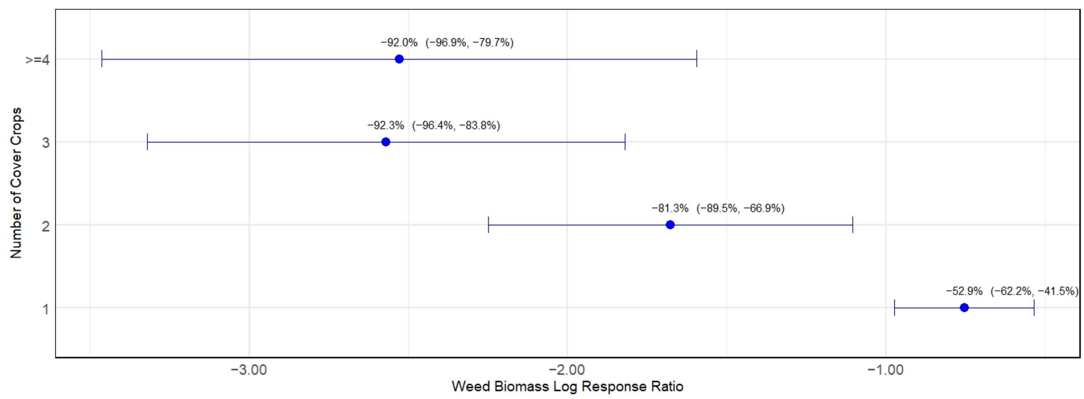

Figure 1. Weed biomass log-response ratio by number of cover crops utilized.

The results of the subgroup analysis based on cover crop types are depicted in Figure 2. Studies included in the analysis experimented with five types/combinations of cover crops: Brassica, grass, legume, a mixture of different grasses (like rye and oats), and a mixture of cover crops across different types (such as grass combined with legume, Brassica with grass, and Brassica with legume). As there are only three cases that experimented with a mixture of different grasses, we exclude it from the subgroup analysis due to the concern about statistical power [105]. The findings indicate that a mixture of different types of cover crops was most effective in weed biomass control, resulting in an effect size of 232% (or a 90.1% reduction in weed biomass). In comparison, the use of a single species of cover crops led to a smaller reduction in weed biomass, with grass being the most effective type (69.5% reduction), followed by Brassica (46.9%) and legume (38.3%). The differences between groups are statistically significant with the p-value of the Q-test less than 0.0001. Nichols et al. (2020) [37] and Osipitan et al. (2019) [32] also found that grass is more effective in suppressing weed biomass than other types.

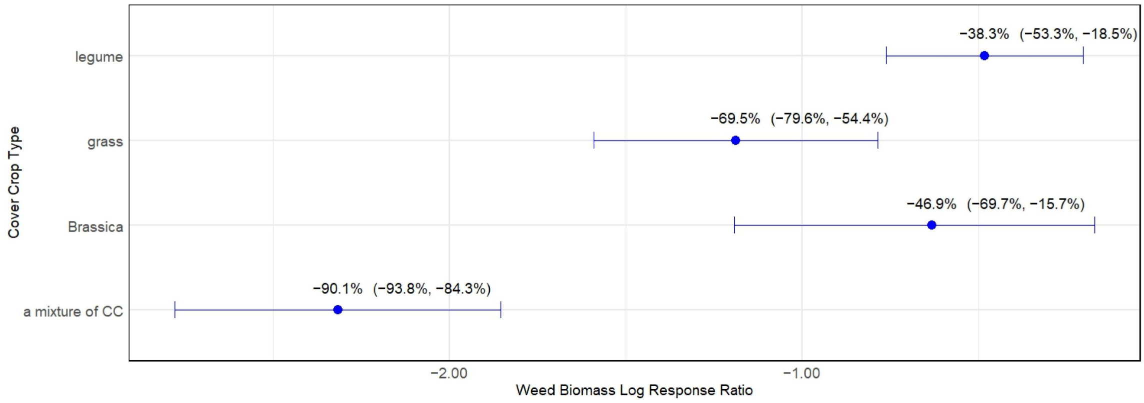

Figure 2. Weed biomass log-response ratio by types of cover crops.

The subgroup analysis based on the number of days between weed measuring and cover crop termination revealed that cover cropping has a statistically significant effect size of 187.23%, 74.32%, and 46.51% (implying an 84.6%, 52.4%, and 37.2% reduction in weed biomass), respectively, at termination, within 50 days, and over 50 days. Although the weed biomass reduction effect diminishes after cover crops are terminated, their residue still suppresses weed emergence compared to no cover crops. The results are presented in Figure 3.

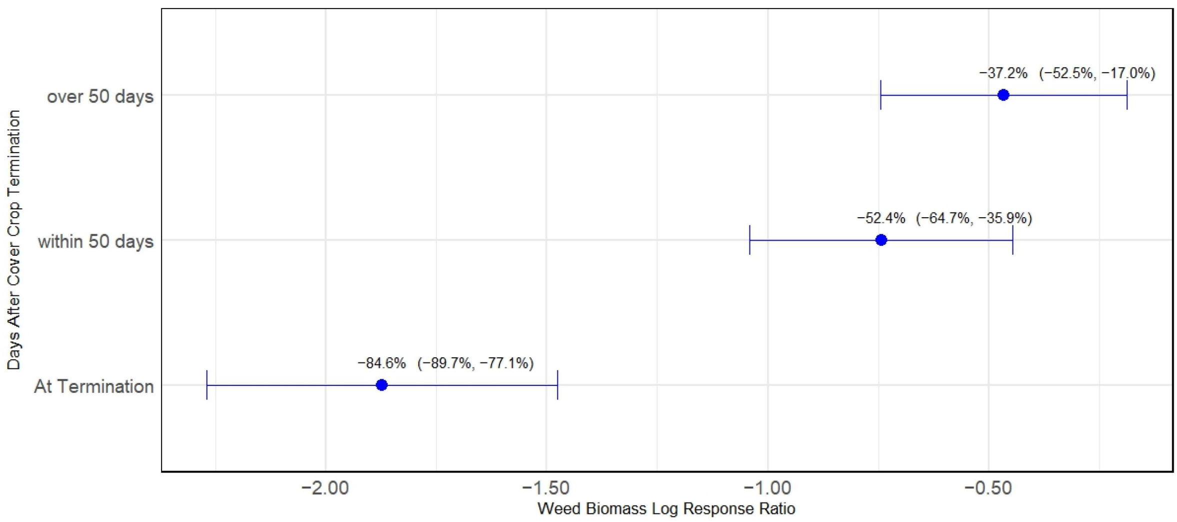

Figure 3. Weed biomass log-response ratio by days after cover crop termination.

4.1.2. Publication Bias

To statistically test for publication bias, we conducted the Egger regression test. The p-value for the estimated value of the intercept is less than 0.0001, indicating the presence of publication bias in weed biomass meta-analysis. Therefore, we utilize the trim and fill approach proposed by Duval and Tweedie (2000) [106] to adjust for publication bias. Considering between-study heterogeneity, outliers were removed in the trim and fill estimation. The estimated effect size is −0.7486 with a 95% confidence interval of [−0.9003; −0.5969] and a p-value < 0.0001. Although the adjusted weed biomass reduction effect becomes smaller than previously estimated, suggesting likely overestimation due to publication bias, the difference is only about 10%. Therefore, the effect of publication bias effect appears to be minimal.

4.2. Weed Density Analysis Results

The same analysis applied to the analysis of weed biomass was also applied to the analysis of weed density. In total, 102 site–year–management cases are included in our meta-analysis for weed density control. The Higgin's and Thompson's I^2 is 0, and the heterogeneity test Q is not significant. Therefore, we concluded that there was no heterogeneity between studies, and thus, a fixed-effect model was estimated. The pooled effect size estimated from the fixed-effect model is −0.6060 with a p-value < 0.0001, indicating a negative treatment effect of cover crops on weed density. This is on average equal to a 45.4% reduction in weed density. The results are reported in Table 3. Three cases were identified as outliers. Upon the removal of these three studies from the analysis, the pooled effect is −0.5253 with τ^2 decreasing from 0.3655 to 0.1886. The slight change in magnitude of the effect size indicates that the analysis results for weed density are robust to the outliers.

Table 3. Results of fixed-effect model estimation and influence analysis for weed density control.

	SMD	I^2	τ^2	Q
Main analysis	−0.6060 * [−0.7839; −0.4280]	0.0% * [0.0%; 24.2%]	0.3655	81.53 p-value = 0.9224
Influential cases removed	−0.5253 * [−0.7059; −0.3447]	0.0% * [0.0%; 24.5%]	0.1886	52.06 p-value = 1.0000

Note: SMD stands for standardized mean difference. 95% confidence interval is reported below the estimation; * indicates statistical significance at 95% significance level; p-value for heterogeneity test Q is provided.

Among the 102 cases included for weed density analysis, 99 cases experimented with only one species of cover crops. Therefore, subgroup analysis on the number of cover crops is not conducted for weed density. Additionally, as only two cases experimented with Brassica and a mixture of different species/types of cover crops, subgroup analysis on cover crop types excluded those types and was only conducted on grass and legume. As shown in Figure 4, while the legume is slightly more effective in controlling weed density comparing to grass, the difference is not substantial, with the legume effect size being −0.6968 (implying a 50.18% reduction) and grass −0.5849 (implying a 44.28% reduction). Moreover, the between-group difference is not statistically significant based on a Q-test with a p-value equal to 0.5468.

The subgroup analysis on days between cover crop's termination and weed measurement, as presented in Figure 5, indicates that weed density control effectiveness decreases after 50 days. However, the between-group difference is not statistically significant with a p-value of 0.4007 for a Q test. Eggers' regression test did not detect publication bias in the weed density analysis. The intercept is 0.465 with a p-value equal to 0.1315, indicating that it is not statistically significantly different from 0.

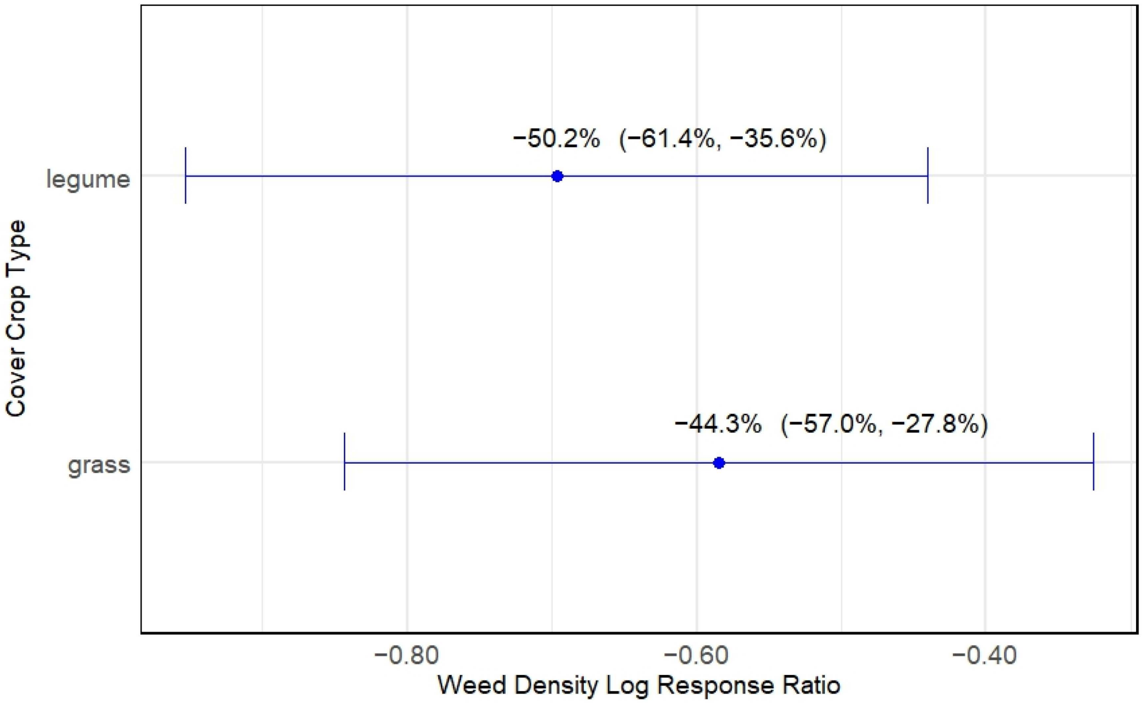

Figure 4. Weed density log-response ratio by types of cover crops.

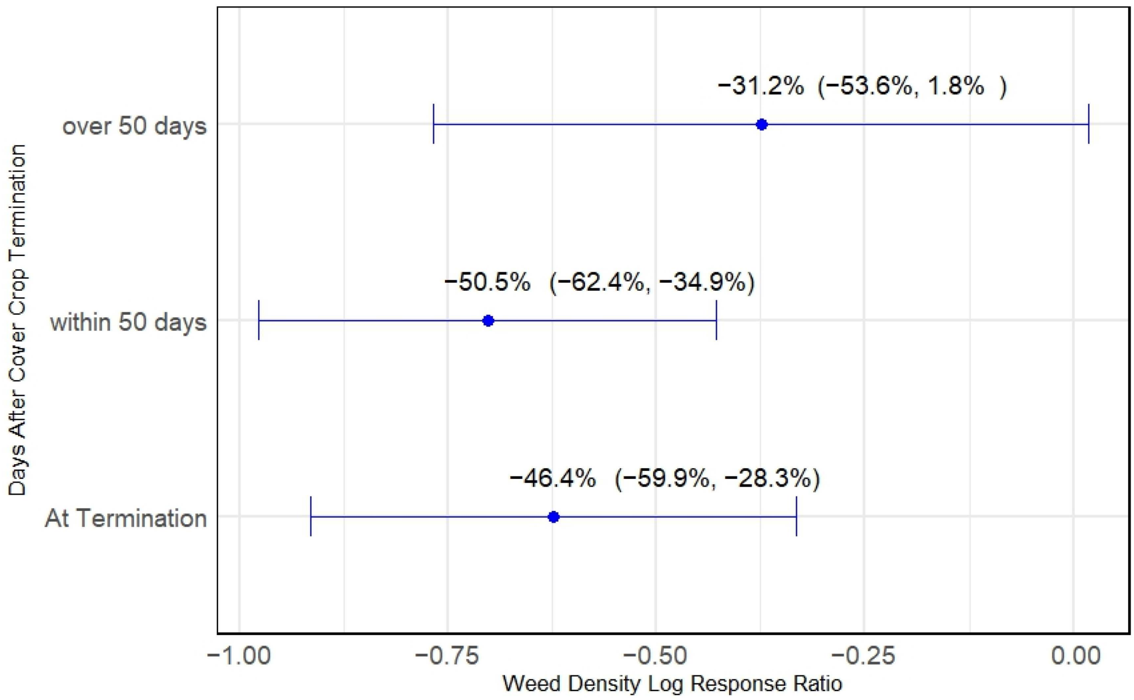

Figure 5. Weed density log-response ratio by days between cover crop termination and weed measurement.

5. Conclusions

Our study finds that cover crops effectively suppress weeds. We use a random-effect model to address substantial between-study heterogeneity among the 250 site–year–management cases included in our analysis of weed biomass control. On average, cover crop treatments led to a 62.6% reduction in weed biomass. Despite some outliers, our influence analysis demonstrated the robustness of our results. Subgroup analysis highlighted the superior efficacy of employing multiple cover crop types to control weed biomass compared to using a single cover crop type, with grass being the most effective among the single types. In addition, a mixture of different cover crop species was found to be more effective in weed biomass control compared to a single cover crop species. Moreover, our analysis revealed a persistent, albeit diminishing, weed biomass reduction effect even after termination of cover crops. Adjusting the effects for publication bias did not change the original estimate noticeably, suggesting the robustness of our results.

We used a fixed-effect model due to the absence of between-study heterogeneity in the weed density analysis and found a statistically significant reduction in weed density. Since very few studies in weed density control utilize Brassica or a mixture of cover crops, the subgroup analysis focused on comparing legume and grass and found no statistically significant difference in weed density control between the two.

Overall, our study highlights the effectiveness of cover cropping in controlling both weed biomass and weed density. It offers promise as a component in integrated weed management systems and provides a sustainable alternative to tillage and pesticide use, with the latter two posing environmental risks and compromising agricultural sustainability. In addition, our analysis shows the effects of various management strategies on weed control, including cover crop species, mixtures, and termination timing. By describing these characteristics and the additional benefits of different cover crops discussed earlier in the paper, our findings can help farmers make more informed decisions on cover crop management strategies.

One limitation of our analysis is that most of the included studies do not assess economic costs incurred by cover cropping, including expenses for seed, labor, and management. In addition, they do not measure the economic benefits of cover crops, such as increased yield of the main crop and improved soil quality, which could reduce fertilizer costs. Future studies should address this gap to provide a more comprehensive understanding of the costs and benefits of cover cropping. This will both assist farmers in decision making and allow policymakers to make more informed decisions regarding policies and programs, such as insurance structures and financial support to incentivize farmers to adopt cover cropping as a weed suppression practice.

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