Review of Corn Yield Response under Winter Cover Cropping Systems Using Meta-Analytic Methods

Fernando E. Miguez and Germán A. Bollero*

ABSTRACT

Extensive research on the use of winter cover crops (WCC) under different agricultural practices in the USA and Canada has shown both negative and positive effects on subsequent corn (Zea mays L.) yield. These contrasting results determine the need for a comprehensive quantitative review. The objective of this study was to use meta-analytic methods to summarize and quantitatively describe the effects of WCC on corn yield based on peer-reviewed published research. Thirty-six studies were included in the analysis representing different regions of the USA and Canada under different agricultural practices (i.e., species, fertilization, tillage, etc.). The effect-size used to compare studies was the response ratio, calculated as yield of corn following WCC over yield of corn following no cover. Biculture WCC increased corn yield by 21%, but there is greater variation due to the small number of studies in this group. Overall, grass WCC neither increased nor decreased corn yields and this response was not dependent on the use of N fertilizer. Legume WCC increased corn yield by 37% when no nitrogen (N) fertilizer was applied and this benefit decreased with application of N fertilizer.

Natural resource conservation and profitable farming are essential goals in agriculture. Among conservation practices, the introduction of WCC to cropping systems has been recognized as a management option for maintaining and enhancing soil and water quality (Reeves, 1994). In terms of soil quality, WCC are effective in protecting the soil against erosion (Langdale et al., 1991), improving soil structure (Dapaah and Vyn, 1998), and enhancing soil fertility (Latif et al., 1994). Furthermore, the effects are highly variable when differences among studies, which represent different agricultural practices, locations and years (i.e., different soil types and climates) are considered. Thus, different environments and managements are a major source of variability and have important implications for crop response to WCC (Power and Biederbeck, 1991).

The contrasting results and the large volume of evidence of the effects of WCC on corn yield determine the need for a comprehensive quantitative review (Frye et al., 1985; Huntington et al., 1985; Kuo and Jellum, 2000; Larson et al., 1998; Wagger, 1989). To our knowledge, there are few reviews that combine independent studies using quantitative methods to relate the impact of management practices and environmental effects on crop yield. Ainsworth et al. (2002) evaluated the effects of high CO₂ treatments on soybean [Glycine max (L.) Merr.] physiology, growth, and yield. Looking at different cropping systems, Marra and Kaval (2000) compared the relative profitability of organic and no-till with that of conventional systems. These studies used meta-analytic methods that have been widely applied in other disciplines, such as the medical, physical, and behavioral sciences (Cooper and Hedges, 1994), and recently in the ecological sciences (Curtis and Wang, 1998; Gurevitch and Hedges, 1999; Osenberg et al., 1999).
Meta-analysis is a quantitative method for research synthesis in which independent studies are combined to estimate treatment effects and their variability (Hedges and Olkin, 1985). This method can be advantageous because it relies on quantitative information and allows for testing of hypotheses that cannot be answered by a single study (Cooper and Hedges, 1994). Additionally, in agricultural research there is the potential for a substantial increase in statistical power because in single studies there is a prevalence of small true differences, small Type I errors (falsely rejecting a true null hypothesis) and few replications, which generate experiments with low statistical power (large Type II Errors, failure of rejecting a false null hypothesis) (Arnqvist and Wooster, 1995). A disadvantage of meta-analysis, as well as of narrative reviews, is that some details of individual studies are necessarily disregarded in exchange for reaching general conclusions (Gurevitch and Hedges, 2001).

In meta-analysis, the two main sources of variation are within- and between-studies (Gurevitch and Hedges, 1999). Within-studies variability is often represented by the factors year and location, which are sometimes combined into the single factor, environment (Carmer et al., 1989). Traditionally, the factor year has been considered as fixed mainly because of the inability to solve statistical models that included random factors before modern statistical software (Piepho et al., 2003). Considering year as fixed restricts the inference space to the levels chosen in a particular study, which is of limited practical interest. On the other hand, when year is considered as random and only information from two or three years is available, the variance component estimate for year and the interactions with other factors are unreliable (Littell et al., 1996). Therefore, when little information is available, there are limitations to considering year as either random or fixed. Using meta-analytic methods has the advantage of including the random variability due to year in the error but with a relatively larger number of observations.

Between-studies variability is attributed to the different characteristics (i.e., soil type, weather, methodologies) among studies and is also included as part of the meta-analysis (Raudenbush, 1994). Accounting for this source of variability in the model allows for inferences beyond the studies included in the analysis because these studies are considered to be a random selection from a larger population of potential studies (Raudenbush, 1994). Improving our understanding of the effects of WCC on corn yield requires consideration of the species used, the agricultural practices employed and the regions where the experiments were conducted. Meta-analytic methods allow for these considerations, and thus can be useful in summarizing the effects of WCC on corn yield.

The objectives of this review were: (i) to use meta-analytic methods to summarize and quantitatively describe the effects of WCC on corn yield, (ii) to examine the effect of variables (e.g., tillage system, killing date, N fertilization) that were included in the meta-analysis to explain the variability of the response of corn yield following WCC, and (iii) to estimate the magnitude and significance of the response of corn yield following WCC in different regions and under different agricultural practices.

MATERIALS AND METHODS

Database Compilation

A literature search of primary research was conducted with Silver-Platter (Ovid Technologies, New York) and Web of Science (ISI, Philadelphia, PA) electronic databases, and through location of studies included in the references of selected papers. We intended for a comprehensive review of all relevant studies on the topic. The conditions for including a paper were (i) reported corn yield data following WCC and a control (i.e., no cover) in more than one environment (i.e., years and/or locations), (ii) the study was conducted in the USA or Canada, and (iii) enough information was provided to estimate the variance (error). On the basis of these criteria, 37 peer reviewed manuscripts were selected (Appendix A).

Estimating the Error of Each Individual Study

All of the papers included used standard methods for designing and conducting the experiments. The experimental designs were randomized complete blocks (55%), split-plot arrangements (30%), and others (15%) with replications ranging from three to six. Therefore, we assumed that the designs and methods were homogeneous across studies and that they produced similar sampling errors as suggested by Gurevitch and Hedges (1999). The studies differed in the number of years and locations in which the experiments were conducted. This approach considered year or location as the true replication within each study and then obtained the standard deviation for the control (no cover) and the treatment group (WCC) to use in the estimation of the within-studies variance (see Eq. [3] below).

Statistical Analysis

The categorical variables identified as possible moderators of the response variable were: WCC [no cover (NC), legume, grass or biculture], N fertilizer rate (NFR: range 0–300 kg N ha⁻¹), kill date (days before corn planting: 0–6, 7–13, > 13 d), tillage system [no-till (NT) and conventional tillage (CT)], region [Southeast, Northeast, eastern Canada, North Central, Great Plains, Southwest, Northwest, according to Power and Biederbeck (1991)], and yield variable (grain or biomass). The species included in the legume group were (in order of decreasing abundance): hairy vetch (Vicia villosa Roth), crimson clover (Trifolium incarnatum L.), white clover (Trifolium repens L.), red clover (Trifolium pratense L.), and others. The species included in the grass group were (in order of decreasing abundance): cereal rye (Secale cereale L.), wheat (Triticum aestivum L.), oats (Avena sativa L.), and ryegrass (Lolium multiflorum Lam), and others. The biculture group included various combinations of the legume and grass species mentioned above. Hairy vetch and cereal rye were present in almost 50% of the studies. Nitrogen fertilizer rate was considered as a categorical variable and was coded in three levels (0–99, 100–199, > 200 kg N ha⁻¹). The selection of these categories was arbitrary and allowed similar studies to be compared as suggested by Ainsworth et al. (2002).

The dependent variable was the ratio between corn yield (grain or biomass) receiving a legume, grass, or biculture WCC
treatment to corn yield from plots with NC and this was used to evaluate the effect of WCC on corn yield (Hedges et al., 1999).

\[
RR = \frac{Yield_{WCC}}{Yield_{NC}} = \frac{\bar{Y}_{WCC}}{\bar{Y}_{NC}}
\]  

[1]

This response ratio (RR) was also used by Frye et al. (1985) and Kuo and Jellum (2000) to compare yields of corn with and without hairy vetch and by Olson et al. (1986) to compare interseeding vs. no interseeding of rye in continuous irrigated corn.

The response ratio for each ith study was transformed as suggested by Hedges et al. (1999) for normality.

\[
L_i = \ln (RR)
\]  

[2]

where \(ln\) is the natural logarithm.

The variance \(v_i\) for each ith study was calculated as in Hedges et al. (1999)

\[
v_i = \frac{SD_{WCC}^2}{n_{WCC} + \bar{Y}_{WCC}^2} + \frac{SD_{NC}^2}{n_{NC} + \bar{Y}_{NC}^2}
\]

[3]

where \(SD_{WCC}, n_{WCC}, ar{Y}_{WCC}\) and \(SD_{NC}, n_{NC}, ar{Y}_{NC}\) are the squared standard deviation, the sample size, and the squared mean for WCC and NC, respectively.

A mixed model was used in the statistical analysis as suggested by Ainsworth et al. (2002), Curtis and Wang (1998), and Gurevitch and Hedges (2001). The total variance was calculated as the sum of the between-studies (\(\sigma_i^2\)) and the within-studies variance (\(v_i = \sigma_i^2 + v_i\)). The within-studies variance was calculated by Eq. [3] and the between-studies variance was calculated as suggested by Hedges et al. (1999)

\[
\sigma_i^2 = \frac{Q_i - (k - 1)}{\sum_{i=1}^{k} w_i}
\]

[4]

\[
\sum_{i=1}^{k} w_i = \sum_{i=1}^{k} w_i^2
\]

where \(k\) is the number of studies, \(w_i\) is the inverse of the within-studies variance \(w_i = 1/v_i\) and \(Q_i\) is the weighted total sums of squares for \(L_i\) calculated as

\[
Q_i = \sum_{i=1}^{k} w_i (L_i)^2 - \left(\frac{\sum_{i=1}^{k} w_i L_i}{\sum_{i=1}^{k} w_i}\right)^2
\]

[5]

The analysis proceeded in three steps following methods analogous to ANOVA (Hedges and Olkin, 1985). In the first step, the \(Q_i\) statistic was calculated for the entire data set by Eq. [5]. The \(Q_i\) statistic follows a chi-square distribution with \(k - 1\) degrees of freedom. This first step is analogous to the ANOVA test in ANOVA and is interpreted as an indication of the homogeneity of the \(L_i\)s in the entire data set. If this test is significant at \(\alpha = 0.05\), there is enough evidence to conclude that the \(L_i\)s are not homogeneous and therefore categorical variables can be introduced to explain this significant variability. The second step involved the calculation of the between-studies variance using Eq. [4] and the between-group homogeneity analysis, partitioning the total weighted sums of squares in each categorical variable. The categorical variables investigated in this study were WCC, NFR, kill date, tillage system, region, and yield variable. In this second step, the weighting factor was the inverse of the total variance \(w_i^* = 1/v_i^*\) (Gurevitch and Hedges, 2001). In this way, the total weighted sums of squares \(Q_i\) were partitioned in between-group \((Q_b)\) and within-group \((Q_e)\), such that \(Q_i = Q_b + Q_e\) (Hedges and Olkin, 1985).

\[
Q_b = \sum_{i=1}^{k} w_i^* (L_i)^2 - \left(\frac{\sum_{i=1}^{k} w_i L_i}{\sum_{i=1}^{k} w_i}\right)^2
\]

[6]

where WCC has \(p\) levels (i.e., \(j = \) biculture, grass, legume).

The degrees of freedom for \(Q_b\) are equal to the levels of each categorical variable - 1. The third step involved the subdivision of the data set into the levels of those categorical variables that were significant at \(\alpha = 0.05\) in the second step. Thus, the first step of the analysis was repeated within the levels of significant categorical variables. For the subgroup analysis \(\alpha = 0.01\) was used to protect against Type I errors (Gates, 2002). Weighted means were calculated following Hedges et al. (1999)

\[
L^\beta = \sum_{i=1}^{k} w_i^* L_i
\]

[7]

and 95% confidence limits as

\[
L^\beta - z_{0.025} SE(L^\beta) \leq \mu \leq L^\beta + z_{0.025} SE(L^\beta)
\]

[8]

where \(\alpha = 0.05\) and \(z_{0.025}\) is the value corresponding to the standard normal distribution (1.96) and the standard error, \(SE(L^\beta)\), was calculated as

\[
SE(L^\beta) = \sqrt{\frac{1}{\sum_{i=1}^{k} w_i^*}}
\]

[9]

The mean response ratio and the confidence limits were obtained by computing the antilog in Eq. [8]. The data were analyzed visually for outliers by a funnel plot (Fig. 1) as suggested by Gates (2002). In Torbert et al. (1996), yields for the no N fertilizer treatment in study year 1990 were nearly zero; therefore, these values were excluded from the analysis. A summary of the methods for meta-analysis is included in Appendix B.

Categorical variables that were deemed significant in the between group homogeneity analysis (Eq. [6]) were included in an analysis analogous to regression methods following St-Pierre (2001). The dependent variable \(L_i\) was regressed over NFR as the continuous explanatory variable. The variables WCC and NFR were included because they explained significant variation in the between-group homogeneity analysis for categorical variables. Studies were considered to have a random intercept, slope, and covariance (St-Pierre, 2001). Winter cover crop treatment was used as the categorical variable. The main effects of WCC, NFR and the WCC × NFR interaction were investigated (Appendix B). The weighting factor was the total variance \((w_i^* = 1/v_i^*)\).

The statistical model was:

\[
L_{ijk} = \beta_0 + s_i + WCC_j + \beta_1 NFR_k + \beta_2 WCC \times NFR_{ijk} + b_i NFR_k + e_{ijk}
\]

where \(L_{ijk}\) = natural logarithm of the response ratio in the \(i\)th STUDY, receiving \(j\)th level of factor WINTER COVER CROP (WCC) and \(k\)th level of factor NITROGEN FERTILIZER RATE (NFR), \(\beta_0\) = overall intercept across all studies (fixed effect), \(s_i\) = random effect due to the \(i\)th level of STUDY. Assumed identically and independently distributed...
Fig. 1. Variance (\(v_i\)) associated with each of the observations included in the meta-analysis against the natural logarithm of the response ratio [\(\ln(\text{yield of corn following winter cover crops/yield of corn following no cover})\)] (Li).

### RESULTS AND DISCUSSION

In the first step of the analysis, the test of homogeneity for the entire data set was significant (\(Q_t = 428.7, \text{df} = 161, p < 0.0001\)). Thus, there is sufficient variability in the entire data set to warrant further analysis by the introduction of categorical variables. In the second step, the between-studies variance was calculated (\(\sigma^2 = 0.0087\)) and the between-group homogeneity analysis was conducted (Table 1). The results of the second step showed that the main effects of WCC, NFR, and region were significant. Since WCC accounted for a significant proportion of the variability, the third step of the analysis was conducted by subdividing the analysis into the three levels of WCC: biculture, grass, and legume (Fig. 2).

#### Winter Cover Crops

The test of homogeneity within biculture WCC was not significant so no further analyses were conducted within this group (\(Q_t = 8.06, \text{df} = 9, p = 0.528\)). For biculture WCC, the mean response ratio was 1.215, with a 95% confidence interval that did not encompass one (Fig. 3). Thus, it can be inferred that corn following biculture WCC yielded 21.5% more than following NC on average. The wide confidence interval was the result of the limited number of studies (10) that included biculture WCC (Ranells and Wagger, 1997). Biculture WCC can produce larger amounts of dry biomass than grass or legume WCC alone (Clark et al., 1994; Kuo and Jellum, 2002; Sullivan et al., 1991), providing benefits associated with reduced soil erosion and improved weed management. Kuo and Jellum (2002) suggested that the larger dry biomass production of biculture WCC in their study was mainly due to the higher combined seeding rate than grass or legume WCC alone. The amount of dry biomass reported by Clark et al. (1997) was also higher for biculture WCC and strongly depended on kill date, ranging from 433 kg ha\(^{-1}\) in January to 6326 kg ha\(^{-1}\) in July.

### Table 1. Between-group homogeneity analysis for all the categorical variables included in the review.

<table>
<thead>
<tr>
<th>Categorical Variable</th>
<th>Df</th>
<th>(Q_b)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>WCC</td>
<td>2</td>
<td>67.38</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Tillage System</td>
<td>1</td>
<td>1.88</td>
<td>0.170</td>
</tr>
<tr>
<td>Kill date</td>
<td>2</td>
<td>2.44</td>
<td>0.294</td>
</tr>
<tr>
<td>NFR</td>
<td>2</td>
<td>9.02</td>
<td>0.011</td>
</tr>
<tr>
<td>Yield Variable</td>
<td>1</td>
<td>0.05</td>
<td>0.816</td>
</tr>
<tr>
<td>Region</td>
<td>4</td>
<td>21.87</td>
<td>0.0002</td>
</tr>
</tbody>
</table>

WCC = winter cover crops, NFR = nitrogen fertilizer rate.
kg ha\(^{-1}\) in early May. Therefore, proper management of biculture WCC involves optimum selection of seeding rate and kill date, which will affect the chemical composition of the residue (Ruffo and Bollero, 2003) and ultimately control the rate of decomposition and the subsequent release of N to the corn crop. On the basis of our quantitative review, the effect of biculture WCC on corn yield is positive. However, the large size of the confidence interval of the response ratio (Fig. 3) suggests that adequate management practices (e.g., seeding rate, planting and killing date, tillage) to enhance positive effects and minimize negative effects on corn yield have not yet been established mainly because of the limited number of studies. Biculture WCC have the advantages of effectively sequestering soil N, which decreases the potential for N loss and supplying N to the following crop, thus providing benefits associated with both grass and legume WCC (Thorup-Kristensen et al., 2003). However, this cannot be conclusively derived from our review.

The test of homogeneity within grass WCC was not significant so no further analyses were conducted within this group \((Q = 62.19, df = 70, p = 0.735)\). For grass WCC, the mean response ratio was 0.99 with a 95% confidence interval that encompassed one; thus, corn following grass WCC yielded the same as following NC (Fig. 3). This resulted from 71 observations in 26 independent studies (Fig. 2). Although the use of grass WCC did not increase corn yield, the inclusion of grass WCC in the rotation could still be beneficial where the priority
is improving soil properties and/or reducing nitrate (NO$_3$–N) losses. For example, cereal rye has proven effective in increasing soil organic N after 9 yr of continuous use (Kuo and Jellum, 2000) and has also been effective in conserving N fertilizer within the cropping system, preventing losses that could cause NO$_3$–N contamination of groundwater (Shipley et al., 1992; Thorup-Kristensen et al., 2003). Grass WCC provide environmental services but fail to increase corn yield; therefore, they are suitable in cropping systems after harvesting corn and before planting a crop that would not rely on N fertilizer (e.g., soybean). As suggested by Ruffo et al. (2004), grass WCC can effectively retain soil NO$_3$–N in the system without the risk of N immobilization for the following crop.

For legume WCC the test of homogeneity was significant ($Q = 293.5$, df = 81, $p < 0.0001$) and the between-studies variance ($\hat{\sigma}_1^2$) was estimated to be 0.017. The mean response ratio was 1.24 with a 95% confidence interval that did not encompass one (Fig. 3). Corn following legume WCC yielded 24% more than following NC. This resulted from 80 observations in 30 independent studies (Fig. 2). Since the test of homogeneity was significant, subgroup analysis was conducted to evaluate categorical variables within legume WCC (Table 2). The between-group homogeneity analysis within legume WCC showed that the main effect of kill date and region accounted for some of the variation but they were not considered significant at $\alpha = 0.01$. The main effect of NFR significantly affected the response of corn to legume WCC (Table 2).

The between-group homogeneity analysis for NFR within legume showed that the response ratio decreased as NFR increased (Fig. 4). When the N fertilizer rate used was 0 to 99 kg ha$^{-1}$, the increase in corn yield was estimated to be 34% greater than following NC. This yield increase was only 17% when the N fertilizer rate was increased to 100 to 199 kg ha$^{-1}$, and there was no significant difference when the N fertilizer rate was 200 kg N ha$^{-1}$ or higher. The lesser response to higher NFR suggests that the most important contribution of legume WCC is the N mineralized from the residue decomposition (Smith et al., 1987). This analysis also suggests that the amount of N supplied by legume WCC is considerable, since the yield increase was 17% and did not encompass zero even at NFR in the range 100 to 199 kg ha$^{-1}$. However, the fact that application of N fertilizer decreased the response ratio of legume WCC does not necessarily imply that the sole contribution of legume WCC was N supply (Bruce et al., 1991). There are examples where legume WCC have improved the yield potential of corn without decreasing N requirements for achieving optimum corn yield (Clark et al., 1995; Ebelhar et al., 1984; Frye et al., 1988). This may indicate that legume WCC can provide additional non-N related beneficial effects even at considerably high fertilizer N rates (Fig. 5). Legume WCC may provide benefits such as supply of nutrients other than N, improved soil properties, soil moisture conservation, and reduction of pests, pathogens, and weeds (Thorup-Kristensen et al., 2003). When these non-N beneficial effects exist it is difficult to establish a clear distinction among them because they are likely to interact. For example, legume WCC residue

![Fig. 3. Mean response ratio (yield of corn following winter cover crops/yield of corn following no cover (RR)) and 95% confidence interval (horizontal bars) for the three levels of winter cover crop (WCC).](image)

<table>
<thead>
<tr>
<th>Categorical variable</th>
<th>df</th>
<th>$Q_b$</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tillage</td>
<td>1</td>
<td>2.59</td>
<td>0.107</td>
</tr>
<tr>
<td>Kill date</td>
<td>2</td>
<td>6.40</td>
<td>0.040</td>
</tr>
<tr>
<td>NFR</td>
<td>2</td>
<td>10.93</td>
<td>0.004</td>
</tr>
<tr>
<td>Yield Variable</td>
<td>1</td>
<td>0.002</td>
<td>0.964</td>
</tr>
<tr>
<td>Region</td>
<td>4</td>
<td>9.55</td>
<td>0.048</td>
</tr>
</tbody>
</table>

$\alpha = 0.01$ was used for protection against Type I errors.

NFR = nitrogen fertilizer rate.
may improve water use efficiency resulting in higher soil N uptake even at comparable levels of inorganic soil N availability (Frye et al., 1988).

**Region**

In the region analysis, 83 observations were from experiments in the Southeast, 39 in the Northeast, 24 in eastern Canada, 11 in the North Central, five in the Northwest, and one in the Great Plains. This latter region was excluded from the analysis because only one observation was available. Furthermore, the frequencies of legume and grass observations are almost equal in each region. The test for between group homogeneity for region was significant (Table 1). More importantly when compared with a response ratio of 1 (i.e., corn yield after no WCC equals corn yield after WCC), the Northeast and Southeast confidence intervals did not encompass one; thus, they were significantly different from the control. Conversely, eastern Canada, the North Central, and the Northwest did encompass one. The region analysis has implications for the suitability of WCC for different environments (Fig. 6). In the Southeast and Northeast the response was similar (15% increase). This reflects the potential of WCC in these
regions for increasing corn yields and providing environmental benefits (Power and Biederbeck, 1991). Corn grown in eastern Canada and the North Central USA had marginal benefits from the use of WCC. In these regions, growing seasons are shorter and WCC are planted late in the fall. Late fall WCC growth is limited and spring growth is generally interrupted by corn planting (Tollenaar et al., 1992). This narrow window for plant growth restricts WCC biomass production and the associated benefits of WCC. In the Northwest, benefits of WCC are more uncertain, but there may likely be a great potential for increase in corn yield (Kuo and Jellum, 2000).

Regression

In the regression analysis, variables that explained significant variation in the between-group analysis (Table 1) were selected. The main effect of WCC and the WCC × NFR interaction were significant (Table 3). The intercept for grass WCC did not differ statistically from one (Table 3). When no N fertilizer was applied (NFR = 0), corn following biculture WCC yielded 17% more than following NC, and corn following legume WCC yielded 37% more than following NC. The slope for legume WCC statistically differed from zero (95% confidence limits: −0.0023; −0.0011). For biculture and grass WCC, the response ratio tended to increase with increasing NFR, whereas for legume WCC the response ratio decreased (Fig. 5). In this analysis, corn yields following grass WCC were comparable to NC with a very slight (not statistically significant) decrease at low NFR (Fig. 5). The fact that NFR did not explain much of the variability found within grass WCC does not mean that corn following grass WCC did not respond to N. Rather, it indicates that it responded in a similar fashion as corn following NC.

The yield response of corn in this study is similar to a hypothetical model presented in Smith et al. (1987). This model predicts that corn following legume WCC yields more than following NC at low N rates, that this difference diminishes as NFR increases, and finally that yields are comparable at high NFR. Strikingly, this analysis showed that yields are comparable only at very high NFR (Fig. 5). Even though NC can achieve yields similar to legume WCC at very high NFR, beneficial effects beyond N supply should not be disregarded. One con-

### Table 3. Analysis of variance and estimates for the regression parameters illustrating the relationship between the response ratio (RR) and two explanatory variables [winter cover crops (WCC) and nitrogen fertilizer rate (NFR)].

<table>
<thead>
<tr>
<th>Source</th>
<th>F</th>
<th>p Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>WCC</td>
<td>68.26</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>NFR</td>
<td>0.07</td>
<td>0.7901</td>
</tr>
<tr>
<td>WCC × NFR</td>
<td>53.90</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter estimates</th>
<th>WCC</th>
<th>Lower CL †</th>
<th>Upper CL</th>
<th>Slope</th>
<th>Lower CL</th>
<th>Upper CL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biculture</td>
<td>1.168</td>
<td>1.003</td>
<td>1.360</td>
<td>0.000934</td>
<td>−0.00092</td>
<td>0.00279</td>
</tr>
<tr>
<td>Grass</td>
<td>0.962</td>
<td>0.896</td>
<td>1.032</td>
<td>0.000428</td>
<td>−0.00015</td>
<td>0.001003</td>
</tr>
<tr>
<td>Legume</td>
<td>1.367</td>
<td>1.278</td>
<td>1.462</td>
<td>−0.00169</td>
<td>−0.00226</td>
<td>−0.001112</td>
</tr>
</tbody>
</table>

† CL = 95% confidence limits.
Concern about the use of WCC has been the possible increase in production risk by increasing variability in corn yields when compared with NC (Larson et al., 1998). Although there is variability in the response of corn (Fig. 5), legume WCC consistently increase corn yields compared with NC, especially at low NFR.

**CONCLUSIONS**

This quantitative review used meta-analytic methods to show that WCC have a great potential to increase or maintain corn yields. However, increasing corn yields may not be the only incentive for adoption of WCC by farmers. Winter cover crops can also provide environmental benefits that make WCC suitable for enhancing N and water use efficiency in a corn cropping system.

The evidence in this review showed that biculture WCC had positive effect on corn yield. However, additional studies should be conducted to fine tune suitable management practices associated with biculture WCC. Grass WCC had an overall neutral effect on corn yield. In addition, the other categorical variables showed no significant effect when analyzed within the grass WCC group. Legume WCC had an overall positive effect on corn yield even at high NFR and consistently increased corn yield at lower NFR. This result is important if environmental concerns about the use of N fertilizer or soil erosion are considered priorities.

**APPENDIX A**

Table A1. Reference, year, location of the study, and winter cover crop (WCC) used for each study included in the meta-analysis database.

<table>
<thead>
<tr>
<th>Publication</th>
<th>Year</th>
<th>Location</th>
<th>WCC†</th>
</tr>
</thead>
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<tr>
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† G: grass winter cover crop, L: legume winter cover crop, B: biculture winter cover crops.

**APPENDIX B**

This is a summary of the steps for conducting the meta-analysis of the effects of winter cover crops on corn yield. Additionally, SAS editors are included.

1. Select all the papers that fit a priori criteria from an extensive literature search.
2. Create a database with these papers.
3. Select an appropriate effect-size (Eq. [1]).
4. Calculate \( L_i \) (natural logarithm of the response ratio, Eq. [2]) and \( v_i \) (within studies variance, Eq. [3]).
5. Calculate weighted sums of squares (Eq. [5]).

```sas
/**** HOMOGENEITY ANALYSIS ****/
title 'WEIGHTED TOTAL SUMS OF SQUARES':
ods listing close:
proc mixed data = Meta method = type3:
weight W:
model L = :;
ods output type3 = SumsS;
data test:
set SumsS;
Qprob = 1-probchi(SS, DF);
ods listing;
```
MIGUEZ & BOLLERO: CORN YIELD META-ANALYSIS UNDER WINTER COVER CROPS

6. Calculate between-studies variance (Eq. [4]).

7. Complete the file: SAS EDITOR.

8. Identify significant sources of variation.

9. Break down the analysis in the levels of the significant sources of variation and repeat steps 5, 6, and 7.

10. Estimate weighted means and confidence intervals for levels of significant sources of variation (Eq. [7, 8] and [9]).

REFERENCES


