Corn response to nitrogen is influenced by soil texture and weather

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Abstract

Soil properties and weather conditions are known to affect soil nitrogen (N) availability and plant N uptake. However, studies examining N response as affected by soil and weather sometimes give conflicting results. Meta-analysis is a statistical method for estimating treatment effects in a series of experiments to explain the sources of heterogeneity. In this study, the technique was used to examine the influence of soil and weather parameters on N responses of corn (*Zea mays* L.) across 51 studies involving the same N rate treatments which were carried out in a diversity of North American locations between 2006 and 2009. Results showed that corn response to added N was significantly greater in fine-textured soils than in medium-textured soils. Abundant and well-distributed rainfall and, to a lesser extent, accumulated corn heat units enhanced N response. Corn yields increased by a factor of 1.6 (over the unfertilized control) in medium-textured soils and 2.7 in fine-textured soils at high N rates. Subgroup analyses were performed on the fine-textured soil class based on weather parameters. Rainfall patterns had an important effect on N response in this soil texture class, with yields being increased 4.5-fold by in-season N fertilization under conditions of "abundant and well-distributed rainfall." These findings could be useful for developing N fertilization algorithms that would allow for N application at optimal rates taking into account rainfall pattern and soil texture, which would lead to improved crop profitability and reduced environmental impacts.

Abbreviations: AWDR, Abundant and Well-Distributed Rainfall; CHU, corn heat units; I^2, ratio of between-studies variance to total variance; ISNR, in-season N rates; n_a, number of days after sidedressing; n_b, number of days before sidedressing; N-rich, rich N rate; NUE, nitrogen use efficiency; PPT, cumulative precipitation; RR, response Ratio; SD, sidedressing; SDI, Shannon diversity index.

Because natural soil nitrogen (N) availability and crop N uptake may vary considerably with soil properties, weather conditions and interactions between these factors, optimal N rates vary from year to year and field to field (Tremblay, 2004; Olfs et al., 2005; van Es et al., 2005; Melkonian et al., 2007; Zhu et al., 2009). Owing to this uncertainty, producers tend to apply additional N for insurance to protect against yield losses (Schröder et al., 2000; Shanahan et al., 2008). The excess levels of N that are associated with low N use efficiency (NUE) result in environmental contamination from denitrification, volatilization and nitrate N leaching to surface and ground waters (Tremblay and Bélec, 2006).

Applying N at optimal rates has the potential to improve NUE, crop yield, and profitability as well as to reduce environmental impacts (Kyveryga et al., 2009; Wang et al., 2003). However, guidelines on adjusting optimal N rates based on soil and weather conditions are lacking (Tremblay, 2004). Many current N management decisions disregard the effect of interannual temperature and rainfall variations on soil N mineralization (Raun et al., 2005; Melkonian et al., 2007; Shanahan et al., 2008). Weather is a major determinant of soil biological activity, including the decomposition of soil organic matter, and climatic conditions can vary significantly in space and time across North American regions (Bolinder et al., 2007; van Es et al., 2007; Lokupitiya et al., 2010).

Crop growth models can be used to assess optimal N rates. However, the predictions are fairly imprecise and vary substantially among these models (Kyveryga et al., 2007; Naud et al., 2008). Under site-specific N fertilization strategies, some authors recommend applying more N to historically high yielding areas and less to low yielding areas, whereas others advocate the opposite approach (James and Godwin, 2003). Producers typically apply rates of N fertilizer they consider sufficient to support near maximum yields.

The influence of soil texture on N response is well documented but contradictory results exist as well. In wet climates, yield is generally higher (and N response lower) in coarse-textured soils than in fine-textured soils (Tremblay et al., 2011). In arid climates, higher crop yields are often obtained in clayey soils (higher water-holding capacity) than in sandy soils (Armstrong et al., 2009). Approaches based solely on yield maps do not provide robust information for the determination of management zones (Kitchen et al., 2008). Topography, remote sensing, and soil apparent electrical conductivity have also been used with varying degrees of success to delineate zones of differential response to N rates (Cambouris et al., 2008; Shanahan et al., 2008; Tremblay et al., 2011). However, these methodologies also disregard the effects of weather in determining crop N fertilizer requirements.

Soil properties (including texture, water-holding capacity, and fertility) strongly affect soil N availability and crop yield (Zhu et al., 2009; Armstrong et al., 2009). Some studies have reported that corn N response is only marginally affected by soil texture and that yearly variation has a more pronounced effect than soil spatial variability (van Es et al., 2005; Tremblay and Bélec, 2006; Kyveryga et al., 2009). Precipitation and thermal units have been found to significantly affect soil mineral N and thus corn response to N (Tremblay, 2004; Tremblay and Bélec, 2006; Shanahan et al., 2008; Kyveryga et al., 2007). Shahandeh et al. (2011) showed that corn grain yield was either negatively or positively related to clay content depending on precipitation. Anwar et al. (2009) reported that crop growth is highly sensitive to factors that vary in both space (soil properties) and time (rainfall and temperature). Interactions between these factors control water and nutrient availability as well as N mineralization during the growing season (Schröder et al., 2000; Kay et al., 2006). It follows that proper N management should consider soil texture as well as seasonal conditions of temperature and precipitation (Derby et al., 2005; Shanahan et al., 2008; Sogbedji et al., 2001). Based on models for corn crop growth and N uptake, soil N transformations and water and N transport, Melkonian et al. (2007) have developed the Precision Nitrogen Management (PNM) model to improve N use efficiency and reduce N losses. This model uses soil textural class, SOM, weather data and other information about management practices such as tillage, plant density and rotations to determine in-season N recommendations in northeast USA.

Before the 1990s, data from multiple studies were combined in a narrative review in which a researcher would summarize the response curves of individual studies in order to reach a conclusion. This approach assigns the same weight to each study and captures the solution as the number of studies increases (Borenstein et al., 2009). Meta-analysis is a statistical method that synthesizes the results of a set of studies. It is used in many fields of research such as medicine, social science and ecology. Meta-analysis is commonly used to assess the consistency of treatment effect (also called “effect size”) across a series of studies or experiments. If the treatment effect varies from one study to the next (which is often the case for N fertilization studies), meta-analysis can be applied to assess the levels of effects for subgroups and thus identifies factors associated with the magnitude of the effect sizes (Borenstein et al., 2009). Meta-analysis is a systematic method for combining the results from a series of studies and addressing apparently conflicting findings by identifying potential explanatory variables (Olkin and Shaw, 1995). Meta-analysis is suitable for agronomic research in which several investigators have examined similar problems and generated substantial information sometimes characterized by heterogeneity and contradictions. Valkama et al. (2009) studied the response to phosphorus fertilizer application rates in 400 experiments conducted over an 80-year period in Finland, and used plant groups, soil properties, and cultivation zones to explain the differences. Tonitto et al. (2006) conducted a meta-analysis on experiments reported in the literature in order to compare crop yield response to N fertilization and soil N status as affected by climate, soil texture and management practices. Chivenge et al. (2011) conducted a meta-analysis of 57 studies concerning smallholder farms in sub-Saharan Africa and found that corn response to added N is higher in clay soils comparatively to loam and sand and also higher for higher annual precipitations. Xia and Wan (2008) studied the response of 456 plant species to N additions in their meta-analysis of a log-ratio of plant biomass and tissue from 304 published studies. The authors used a mixed (random) model and a subgroup heterogeneity analysis and found that N response increased with temperature and annual precipitation.

There is a need to learn more about the effect of soil properties and weather conditions on soil N dynamics and crop response to N in order to develop algorithms that can be used to recommend appropriate in-season N application rates (Khosla et al., 2002; Chang et al., 2003; Franzen, 2004). With a better understanding of the spatial and temporal variability of N levels in soil and plant N uptake, N management practices could be adjusted to ensure that both economic and environmental objectives are met (Jemison and Fox, 1994; Shahandeh et al., 2011; Shanahan et al., 2008). The high spatial and temporal variability in yield response to N fertilizer that is observed in individual yield response trials leads to a high degree of uncertainty when estimating economic optimum rates of N for a group of trials and when extrapolating these rates from one location to another (Kyveryga et al., 2009). So far, no studies have quantified the effect on N responses of combined soil and weather conditions over a number of years in a large geographic area devoted to corn production in North America. Furthermore, it is difficult to have a uniform dataset that considers identical treatments for a given region.

The aim of this study was to quantify the effects of soil characteristics and weather properties and the interactions between these factors on corn response to N applications. A meta-analysis was conducted using mirror studies undertaken in several North American locations between 2006 and 2009 with the same N treatments, in order to address the following questions: (1) To what extent do soil and weather properties affect corn response to N fertilization? (2) How significant are the relationships between corn response and N fertilization in homogeneous classes of soil and weather properties?

MATERIALS AND METHODS

Site locations and soil properties

Experiments were conducted between 2006 and 2009 on experimental farms in the United States, Mexico and Canada (Fig. 1) to cover a wide range of soil and climatic conditions. Each site is described in Table 1.

Soil textures were first grouped into three categories in keeping with the approach used by Tonitto et al. (2006): fine textures (clay + silty clay + silty clay loam + clay loam), medium textures (loam + silt loam), and coarse textures (sandy loam/sandy clay loam + loamy fine sand + fine sandy loam). However, since medium and coarse textures showed a similar N response behavior (data not shown) only two classes were retained: (1) fine-textured soils, including clay, silty clay, silty clay loam, and clay loam textures; and (2) medium/coarse textures (hereafter called “medium” for greater simplicity), including loam, silt loam, sandy loam/sandy clay loam, loamy fine sand, and fine sandy loam textures. Fifteen of the 51 studies involved fine-textured soils and 36 involved medium-textured soils (Table 1). In this classification, the soil was considered fine textured above a clay content threshold of 30%.

Nitrogen treatments and replications

An important characteristic of this research was that the same N rates were applied in all 51 mirror studies. Nine N rate treatments were randomized within three or four blocks in each field. The control treatment received 0 kg N ha^{-1}. Seven other treatments consisted of the same amount of N as a starter (36 kg ha^{-1}) at sowing and increasing N rates at sidedressing (in-season N rates, ISNR): 0, 27, 54, 80, 107, 134, and 161 kg ha^{-1} applied according to local timing practices at growing stages ranging from V4 to V10 (median: V7) with incidentally 10 pairs of studies with growth stages V4 and V8 at sidedressing in Ohio at the same years and sites (Table 1). The last N treatment consisted of 178 kg ha^{-1} applied at sowing with no N fertilizer at sidedressing; it is referred to as a rich N rate (N-rich). This treatment provided the opportunity to examine the effect of weather on a high N rate applied early in the season.

Weather data and weather parameters

Daily rainfall (*Rain*) data and daily minimum and maximum temperatures (T_{min} and T_{max}) were collected at each site-year. For practical reasons, these simple and easily available data were selected to calculate corn heat units (*CHU*; Bootsma et al., 2005), cumulative precipitation (*PPT*), and the Shannon diversity index (*SDI*; Bronikowski and Webb, 1996). The *SDI* was used to assess the distribution of rainfall during a given period. These weather parameters were calculated using the equations presented in Table 2. Cumulative *CHU* values were computed using daily maximum and minimum temperatures; *PPT* and *SDI* were calculated from the daily rainfall data (Table 2).

We also proposed a parameter representing optimal water availability (abundant rainfall, well distributed in time). We define “Abundant and Well-Distributed Rainfall” (*AWDR*) as:

$$AWDR = PPT \cdot SDI \qquad [1]$$

Four examples of weather data and derived parameters are given in Fig. 2. Water provided as irrigation (NO_3-N content not assessed) was considered equivalent to natural rainfall. This assumption was validated by conducting a meta-analysis on the responses to N rate of irrigated and non-irrigated sites under the same soil and rainfall conditions which revealed no significant difference between the presence and the absence of irrigation (data not shown).

The time period covered by weather parameters overlapped the date of N sidedressing (SD). In order to determine the period during which a weather parameter is most closely related to the N response (or Response Ratio, $RR = Yield_{Nrate}/Yield_{Control}$), the weather parameters were tested for periods from n_b days before SD to n_a days after SD (with n_b and n_a varying between 1 and 35). The optimal period for any weather parameter was the one that maximized difference in N response across N rates. Thus, for *CHU*, *PPT*, *SDI*, and *AWDR*, we had to find (n_b, n_a) that maximized the contrast between the two classes of global effect size ($\overline{Y}$) across studies and N rates. The global effect size is defined as follows:

$$\overline{Y} = \frac{1}{K} \sum_{all\ studies} \sum_{all\ Nrate} \log(RR) \qquad [2]$$

where K is the number of studies, and $\overline{Y}$ is calculated for the high and low classes of each weather parameter (*CHU*, *PPT*, *SDI*, and *AWDR*) and each (n_b, n_a) pair. These low and high classes were determined by histogram-based thresholding using the Otsu method (Otsu, 1979) which consists in maximizing the between class variance (and minimizing the within class variance) to get the optimum threshold separating both classes.

In contrast with low *CHU*, high *CHU* before the SD period led to a higher $\overline{Y}$ (Fig. 3a). The period ranging from 30 days before SD (n_b = 30) to 15 days after SD (n_a = 15) was therefore selected. Rainfall properties (*PPT*, *SDI*, and their product, *AWDR*) were more crucial for long periods after SD, while the period before SD was less important (Fig. 3b, 3c, and 3d). For rainfall properties, a critical period from n_b = 15 to n_a = 30 was selected. The testing of alternative periods such as SD-30 to SD, SD to SD+30, SD-30 to SD+30, SD-20 to SD, SD to SD+20, SD-20 to SD+20, SD-10 to SD, SD to SD+10 and SD-10 to SD+10 resulted in either not significant or less significant differences between low and high classes (for CHU, PPT, SDI and AWDR) than the ones obtained with the periods selected (n_b = 30 to n_a = 15 for *CHU* and n_b = 15 to n_a = 30 for *PPT*, *SDI* and *AWDR*).

CHU, *PPT*, *SDI*, and *AWDR* were separated into low and high classes for the periods of maximum effect on N response for each weather parameter using the Otsu histogram thresholding method. The thresholds between low and high classes are as follows: 1160 for *CHU* (n_b = 30, n_a = 15); 180 mm for *PPT* (n_b = 15, n_a = 30); 0.55 for *SDI* (n_b = 15, n_a = 30); and 99 for *AWDR* (n_b = 15, n_a = 30). Low *AWDR* could be considered as sub-optimal rainfall (rare and sparse) and high *AWDR* as optimal rainfall (abundant and well distributed).

The distribution of studies in the (*CHU*, *AWDR*) space (Fig. 4) shows that several studies with both fine- and medium-textured soils can be found for all combinations of *CHU–AWDR* classes, except the "high *AWDR*–high *CHU*" subgroup, for which only one study was conducted on a fine-textured soil.

Meta-analysis

The meta-analysis carried out in this research is based on the principles described in detail by Borenstein et al. (2009) and summarized below.

The effect size, Y, is a value that reflects the magnitude of the treatment effect. The outcome (in our case, corn grain yield at 14.5% moisture in t ha^{-1}) is measured on a physical scale, and the effect size is expressed as a *RR*, which is the ratio of the yield obtained for various N rates ($Yield_{Nrate}$) to the yield measured for the N rate = 0 plots ($Yield_{control}$). Thus, for each study, i, and each N rate, r:

$$Y_{i,r} = \log\left(\frac{\overline{Yield}_{Nrate}}{\overline{Yield}_{control}}\right) \qquad [3]$$

The overlines in equation 3 indicate the yields are averaged over the replicates. The log scale is used to maintain symmetry (Tonitto et al., 2006) and allow for the addition of effect sizes.

The replicates are also used to assign a weight to the trials in each study and to each N rate. This weight is assumed to be inversely proportional to the variance $Vy_{i,r}$ (within-study variance) of the yields measured in replicates of any study, i, at any N rate, r. Since two treatments are involved in the definition of the effect size (treatment N rate and control), the variance of the effect size is the pooled (combined) variance of these two groups (equations 4a and 4b).

$$Vy_{i,r} = S^2_{pooled}\left(\frac{1}{n_{N\,rate}\overline{Yield}^2_{N\,rate}} + \frac{1}{n_{control}\overline{Yield}^2_{control}}\right) \qquad [4a]$$

where:

$$S^2_{pooled} = \frac{(n_{Nrate}-1)Var(Yield_{Nrate}) + (n_{control}-1)Var(Yield_{control})}{n_{Nrate}+n_{control}-2} \qquad [4b]$$

And n_{Nrate} and $n_{control}$ are the number of replicates (sample size) of the two groups.

The weight, $W_{i,r}$, assigned to each study, i, for each N rate, r, is inversely proportional to variance as follows:

$$W_{i,r} = \frac{1}{Vy_{i,r}} \qquad [5]$$

This summary effect across studies is the weighted mean of effects as follows:

$$\mu_r = (\sum_{i=1}^{K} W_{i,r} Y_{i,r}) / (\sum_{i=1}^{K} W_{i,r}) \qquad [6]$$

where i is the study ID number and K, the number of studies. The weighted mean, μ_r, is calculated for each N rate, r.

The analysis of the effect size requires a mathematical model. While the N treatment effect Y can vary from one study to another depending (among other things) on N rate, soil properties and weather conditions, a variable-effect (also called "random-effect") model is used to consider both within-study variance and between-studies variance. We consider the observed effect size, $Y_{i,r}$, for a given study, i, at a given N rate, r, which varies from the overall mean, μ_r, by a deviation, $\xi_{i,r}$, that reflects the variability of the effect size across the studies and a sampling error $\varepsilon_{i,r}$:

$$Y_{i,r} = \mu_r + \xi_{i,r} + \varepsilon_{i,r} \qquad [7]$$

Thus, for each N rate, r, the observed effect size $Y_{i,r}$ varies from its true value $\theta_{i,r} = \mu_r + \xi_{i,r}$ with an error $\varepsilon_{i,r}$. The analysis of the heterogeneity of the studies (the magnitude of $\xi_{i,r}$) allows us to identify subgroups characterized by the same treatment effects. This analysis is performed by estimating the two components of the observed variance (Q): the between-studies variance (T^2 = Var(θ)) and the within-study variance (Var(ε)). For each N rate, r, the observed variance is calculated by assigning a weight, $W_{i,r}$, to each study, i:

$$Q_r = \sum_{i=1}^{K} W_{i,r}(Y_{i,r} - \mu_r)^2 \qquad [8]$$

Since $W_{i,r}$ is the inverse of the variance of $Y_{i,r}$, Q_r is a standardized measure not affected by the metric of $Y_{i,r}$. To partition the observed variance, Q_r, we assume that, at a given N rate, r, if studies share the same effect size ($\xi_{i,r} = 0$) and all variation is due to sampling errors, $\varepsilon_{i,r}$, within studies, the expected value of Q_r is equal to the degree of freedom, $df = K - 1$ (i.e., Var(ε) = df), where K is the number of studies (central limit principle). The excess variation, Q_r-df, reflects the differences in the true effects from study to study. Borenstein et al. (2009) proposed two different statistics that can be used to perform a heterogeneity test that is independent of the number of studies (df): T^2, the estimated variance of the true effect size given by:

$$T_r^2 = (Q_r - df)/C_r \qquad [9]$$

$$\text{where } C_r = \sum_{i=1}^{k} W_{i,r} - (\sum_{i=1}^{k} W_{i,r}^2)/(\sum_{i=1}^{k} W_{i,r})$$

and I_r^2, the proportion of the between-studies variance relative to the total variance given by:

$$I_r^2 = 100 \times \frac{Q_r - df}{Q_r} \qquad [10]$$

The T statistic is expressed in the same metric as the effect size Y, while I^2 is a ratio independent of the metric and the number of studies.

With the variable-effect (random-effect) model, the between-studies variance should be considered in calculating the weights, $W_{i,r}$, assuming that the total variance of a study is the sum of the within-study variance, $Vy_{i,r}$, and the between-studies variance, T_r^2:

$$W_{i,r}^* = \frac{1}{Vy_{i,r}^*} = \frac{1}{Vy_{i,r} + T_r^2} \qquad [11]$$

$W_{i,r}$ is replaced by $W_{i,r}^*$ (equations 6, 8 and 9). The use of the weight $W_{i,r}^*$ avoids allocating an excessive weight to any study, *i*, if its variance, $Vy_{i,r}$, is too small, since T_r^2 is considered in the definition of $W_{i,r}^*$.

Meta-analysis is useful for quantifying the extent of the heterogeneity and understanding the underlying causes. The method used to determine if the studies are heterogeneous is based on I^2 (proportion of between-studies variance) levels. For each N rate, *r*, if I_r^2 is close to zero (or negative), the groups are considered homogenous: the observed variance is random and due to sampling error. On the other hand, if I_r^2 is high, the causes of the variations should be investigated by performing analyses on subgroups using potential explanatory factors. The values 0.25, 0.50, and 0.75 correspond to low, medium, and high I^2 levels, respectively (Parent 2012, personal communication). From this point in the paper, the index '*r*' will be omitted and the I^2 symbol will be used for all N rates.

The above-described heterogeneity analysis on all the studies was used to assess:

- Subgroups of soil textures established from N response behavior across studies.
- Subgroups of weather conditions established from N response behavior across studies.
- Subgroups of combined soil textures and weather conditions.

The variance explained by the classification into subgroups is defined as the ratio of explained variance and total variance (Borenstein et al., 2009). Since explained variance = total variance - unexplained variance (within subgroups), the proportion of the variance explained is given by:

$$R^2 = 1 - \frac{T^2_{within\ subgroups}}{T^2_{all\ studies}} \quad [12]$$

$$\text{where } T^2_{within\ subgroups} = \sum_{all\ subgroups}(Q - df) \quad / \sum_{all\ subgroups} C$$

RESULTS

Raw yield data

Figure 5 shows corn grain yields (mean of replicates) in each study by N rate and the corresponding information on soil texture and *AWDR–CHU* classes. In fine-textured soils, yields never exceeded 12.5 t ha^{-1}. Very low yields were found in both medium- and fine-textured soils at low N rates (e.g., studies 3 and 39) and at high N rates (e.g., studies 14 - 15 and 48 - 49). The N-rich (178 kg ha^{-1} all at sowing) produced a significantly lower yield (according to a *t* test) than an equivalent split application (starter 36 + ISNR 134) in 15% of the cases when *AWDR* was low (for both fine- and medium-textured soils); 33% of the cases for "medium texture–high *AWDR*" class; and 63% of the cases for "fine texture–high *AWDR*" class. The N-rich gave significantly higher yields than “starter 36 + ISNR 134” in only two studies (5 and 33) corresponding to the "medium texture–low *AWDR*" condition. The control rate (0N) produced low yield particularly under high *AWDR*, especially in fine-textured soils. Indeed, $Yield_{control}$ was lower than 5 t ha^{-1} in 9% of the cases for "medium texture–low *AWDR*" class; 27% of the cases for "medium texture–high *AWDR*" class; 14% of the cases for "fine texture–low *AWDR*" class; and 100% of the cases for "fine texture–high *AWDR*" class. In the latter case, the low $Yield_{control}$ was likely due to N losses, mainly by denitrification, caused by abundant precipitations in poorly drained soils (van Es et al., 2007; Sogbedji et al., 2001).

Figure 5 also shows that both yields and yield response to N are highly variable among studies, but it does not reveal clear relationships between yields, soil texture, and weather. It illustrated the need for a meta-analysis in order to provide greater weights to more reliable studies with a goal of building homogeneous subgroups with meaningful summary effect sizes.

Meta-analysis of subgroups

Meta-analysis provided a summary effect size for each subgroup by N rate (N rate = starter + ISNR, or N-rich). The I^2 values indicated some heterogeneity when all studies were grouped together (across N rates, except N rate at ISNR = 0) and justified subgroup analysis (Table 3). Subgroups were formed for soil texture classes, weather parameter classes and texture–weather class combinations. The I^2 values were calculated for each subgroup and each N rate. Negative values of I^2 were not set to zero in order to give a better idea of the relative degree of homogeneity of the subgroups.

The tree diagram of the meta-analysis is shown in Figs. 6a and 6b. The subgroups were either combinations of soil texture and *CHU* (Fig. 6a) or combinations of soil texture and *AWDR* (Fig. 6b). *AWDR* was considered to be more representative of rainfall conditions than *PPT* or *SDI* taken alone (see section "Weather class"). The effect sizes, Y_i, are indicated by circular points with a size (surface) proportional to the weight W_i^*. The error bars indicate the standard deviation ($\pm SE_Y$), which is equal to the root square of Vy^*.

The Y_i values are characterized by higher dispersion across studies for higher ISNR as well as for N-rich rate (Figs. 6a and 6b). The I^2 for N rate = 36 + 0 indicated high homogeneity in almost all subgroups (Table 3). This was expected since a higher N rate leads to more variability of the N response depending on the growing conditions in each study (Haberle et al., 2008). However, this dispersion does not fully explain heterogeneity because it also depends on the variance Vy_i (experimental error, indicated by the error bars in figures). The heterogeneity of the effect sizes described by the between-studies variance, I^2, reflected the dispersion of the Y_i values

(Table 3). The weighted averages of Y_i indicated by dotted lines show the different levels of the effect size in each subgroup (Figs. 6a and 6b). The subgroup "fine texture–high *AWDR*" shows a higher effect size than the other subgroups across N rates. A more detailed subgroup analysis is presented in the next section.

Soil texture classes

Soil texture class (fine or medium) determined N response to a large extent (Fig. 7). The average (weighted mean) *RR* was higher in fine texture classes than in medium texture classes, and this difference increased with the N rate. The *RR* also showed greater heterogeneity across studies at higher N rates (Figs. 6a and 6b) as evidenced by higher I^2 values (Table 3) and larger error bars (Fig. 7). The heterogeneity test (Table 3) showed that the effect size, *Y*, was homogeneous in medium-textured soils ($I^2 \leq 0.1$) but heterogeneous in fine-textured soils (medium to high I^2), except with N rate = 0.

Soils in the medium-textured class tended to show similar responses to added N, with yield gains varying between 40% ($RR \approx 1.4$) and 65% ($RR \approx 1.65$) and marginal improvements above 134 kg N ha^{-1} (Fig. 7). The fine-textured class was characterized by a much higher *RR*, reaching 2.7 at the highest N rate. However, there was too much heterogeneity (Table 3) to determine a reliable summary effect size. The variance explained, R^2, by soil texture subgrouping did not exceed 10%, mainly because of a large component affecting the fine-textured class. Subgroup analyses should also consider weather parameters.

Weather classes

Corn heat units (*CHU*), cumulative precipitation (*PPT*), Shannon diversity index (*SDI*) and the proposed parameter, Abundant and Well-Distributed Rainfall ($AWDR = PPT \cdot SDI$), can influence N uptake, mineralization, leaching, and denitrification. This study considered the following periods: 30 days before SD to 15 days after SD for *CHU*; and 15 days before SD to 30 days after SD for *PPT*, *SDI*, and *AWDR*. This period was chosen because it showed the strongest relationship with effect of in-season added N.

Twenty-eight of the 51 studies had low *CHU* values and 23 had high *CHU* values (Table 3). Responses (*RR*) were slightly higher at high *CHU* levels than at low *CHU* levels (Fig. 8a). The difference was small and error bars overlapped, indicating that *CHU* alone could not explain effect size variation. Low *CHU* subgroups were heterogeneous across most N rates (except ISNR = 0). Hence, *CHU* alone could not capture the response ratios.

The threshold used for cumulative precipitation yielded 28 studies in the low *PPT* class and 23 in the high *PPT* class. The high *PPT* group was characterized by higher response to added N than the low *PPT* across N rates (Fig. 8b). The difference was proportional to added N. Overall, the difference between high and low *PPT* classes was larger than in the case of the *CHU* classes (Fig. 8a). Low *PPT* conditions were characterized by higher heterogeneity, except in the case of ISNR = 0 (Table 3). The high *PPT* group was homogenous across most N rates.

The *SDI* was low in 30 trials and high in 21 trials (Table 3). Low *SDI* trials were heterogeneous across N rates, except at ISNR = 0. The high *SDI* group was homogeneous for most N rates, except ISNR = 107 kg ha^{-1} and N-rich. Response ratios were higher in the high *SDI* class than in the low *SDI* class (Fig. 8c). The difference was greater for higher N rates and was comparable to that for *PPT* classes. The correlation between *SDI* and *PPT* was very low (0.24). This is indicative of the fact that the spread of precipitation over time has an influence of its own on response to N.

Since high *PPT* and *SDI* classes enhanced *RR* compared to low classes, their product ($AWDR = PPT \cdot SDI$) tended to further increase the difference (Fig. 8d). The increase in *RR* associated with abundant and well-distributed rainfall (i.e., high *AWDR*) as compared to low *AWDR* was very large and likewise proportional to the N rate. At the two highest N rates, *RR* increased from 1.6 at low *AWDR* to 2.6 at high *AWDR*. Moreover, the *AWDR* classes showed lower heterogeneity compared with *PPT* or *SDI* (Table 3). Infrequent rain situations (low *SDI*) are leading to dry soil conditions in which precipitation events, when they occur, are less likely to impact N losses by leaching or denitrification. Frequent rain situations (high *SDI*) tend to preserve soil moisture, increase the likeliness of leaching and/or denitrification and therefore crop response to N fertilization.

In summary, rainfall-based parameters and *CHU* (to a lesser extent) influenced *RR*. However, the heterogeneity remaining in the effect sizes of the subgroups indicates that neither factor can fully explain the variability in N response. The variance explained, R^2, by *CHU*, *PPT*, *SDI* or *AWDR* alone did not exceed 12%, 8%, 4% and 14%, respectively. It is therefore warranted to combine soil texture and weather classes in order to obtain more homogeneous subgroups.

Combined soil texture and weather classes

Soil texture and weather classes were combined factorially into "texture–weather" subgroups.

For *CHU* classes:

- fine texture–low *CHU*
- fine texture–high *CHU*
- medium texture–low *CHU*
- medium texture–high *CHU*

For rainfall classes:

- fine texture–low AWDR
- fine texture–high AWDR
- medium texture–low AWDR

• medium texture–high AWDR

Medium-textured soils formed a homogeneous subgroup across N rates (Table 3). Separating the medium-textured class into two *CHU* classes [medium texture–high *CHU*″ (20 studies) and ″medium texture–low *CHU*″ (16 studies)] did not increase the homogeneity. The trials classified into the "medium texture–high *CHU*" subgroup generally showed higher effect size than those in the "medium texture–low *CHU*" subgroup (Fig. 9a). However, this difference was of little significance because at higher N rates, *RR* increased from 1.6 in the low *CHU* subgroup to 1.9 in the high *CHU* subgroup.

Separating the medium soil texture group into high and low *AWDR* subgroups improved homogeneity slightly at most N rates (Table 3). The subgroup "medium texture–high *AWDR*" showed higher *RR* than the "medium texture–low *AWDR*" subgroup (Fig. 9b). The difference was greater at higher N rates, where *RR* increased from 1.6 at low *AWDR* to more than 2 at high *AWDR*.

The effect size of studies involving fine-textured soils showed a high level of heterogeneity that was reduced by subgroup analysis (Table 3). The ″fine texture–high *CHU*″ subgroup (3 studies) was generally homogeneous but the ″fine texture–low *CHU*″ subgroup (12 studies) was not. Fig. 9c shows that *RR* weighted mean of ″fine texture–high *CHU*″ studies was lower than that of ″fine texture–low *CHU*″ studies for ISNR > 134 $kg \cdot ha^{-1}$. This difference was not consistent since the subgroups were not homogeneous.

AWDR reduced the heterogeneity of effect size in the fine-textured soil class, especially for the "fine texture–high *AWDR*″ subgroup (7 studies) which had a considerably higher *RR* (reaching 4.5 at high N rates) than the "fine texture–low *AWDR*" subgroup (Fig. 9d) and the other texture–weather subgroups (Fig. 9a, 9b, and 9c). The difference increased with N rates. Hence, rainfall patterns had an appreciable effect on N response in the fine-textured soil class.

The variance explained, R^2, was in the interval 10 to 18% for texture–*CHU* subgrouping and in the interval 25 to 35% for texture–*AWDR* subgrouping. No relationship between R^2 and N rates was observed.

Since heterogeneity was not observed among all weather subgroups for the fine soil texture group, the subgroup analysis was refined by using combined *CHU* and *AWDR* classes as follows:

- fine texture–low AWDR–low CHU (5 studies)
- fine texture–low AWDR–high CHU (2 studies)
- fine texture–high AWDR–low CHU (7 studies)
- fine texture–high AWDR–high CHU (1 study)

The subgroups were not consistently homogeneous, particularly at high N rates (Table 3). Therefore, greater precision could be attained with this subgrouping of fine soil texture studies. *CHU* classes produced different *RR* levels in both the high and the low *AWDR* subgroups (Fig. 10). The subgroup "fine texture–low *AWDR*–high *CHU*" gave a higher *RR* than "fine texture–low *AWDR*–low *CHU*." However, for "fine texture–high *AWDR*", high *CHU* gave a lower *RR* than low *CHU* for N rates > 80 $kg \cdot ha^{-1}$. This is likely due to the very high *RR* of studies #38 and #39 (Table 1; Figs. 6a and 6b) in the subgroup "fine texture–high *AWDR*–low *CHU*" compared to study #37, which alone made up the subgroup "fine texture–high *AWDR*–high *CHU*." With so few studies in these subgroups, it appeared reasonable to rely on previous findings, which simply indicated that *RR* increased with high *CHU*. In general, in fine-textured soils, it is important to combine *CHU* and rainfall conditions to better characterize the potential impact of in-season N rates.

The variance explained, R^2, by subgroupings involving texture, *AWDR* and *CHU* was in the range 42 – 60%. This level can be considered as very high in comparison with those reported by Kyveryga et al. (2009) who found that the variance of corn yield response to N explained by year did not exceed 25% and the one explained by soil properties did not exceed 16%.

Summary of corn response (*RR*) in homogeneous subgroups

In the medium-textured soil group, both weather parameters (*CHU* and *AWDR*) are helpful for forming subgroups of N response. In the case of the fine-texture soil class, it was more effective to use low *AWDR* and high *AWDR* classes (Fig. 10a).

The medium texture *RR* was < 2.2 and *AWDR* improved the *RR* as the N rate increased (Fig. 10b). Splitting the medium texture group into low and high *CHU* improved the response ratio to a level close to that observed for the *AWDR* classes.

In the fine soil texture group, low *RR* values were obtained when *AWDR* was low. The *RR* in fine texture–low *AWDR* subgroup showed similar levels to those for the medium texture group. In such circumstances, the N response behavior of fine soil textures is similar to that of medium textures, at same *CHU* class.

The fine texture group showed high *RR* (from 3 to 4.5) when *AWDR* was high and N rate ≥ 116 kg N ha^{-1} (starter 36 + ISNR 80) (Fig. 10a). Our data suggest that *CHU* classes have an inverse effect (high *CHU* gives lower *RR* than low *CHU*) for the subgroup "fine texture–high *AWDR*" which contained only 1 study with high *CHU*. The fine texture–high *AWDR* subgroup was homogeneous across the *CHU* classes, even though I^2 reached 30% at some N rates (Table 3).

DISCUSSION

Soil textures (fine or medium) determined N response to a large extent. Responses to added N were more pronounced for fine texture groups (clay + silty clay + silty clay loam + clay loam) than for medium texture groups (loam + silt loam + sandy loam/sandy clay loam + loamy fine sand). It has been reported that corn is more responsive to N fertilization in clayey soils. For instance, Ping et al. (2008) found that corn needed less N fertilizer in sandy soils than in clayey soils. Shahandeh et al. (2011) showed that a higher soil N supply was associated with lower clay content, and lower N supply with higher clay content, likely because of lower N mineralization in clayey soils (Ros et al., 2011; Zhu et al., 2009). We found that corn yields increased by a factor of 1.6 at high N rates in medium-textured soils, but by a factor of 2.7 in fine-textured soils.

The *CHU* parameter had an especially pronounced influence on N rate effects in the period from 30 days before SD to 15 days after SD. The higher relative importance of *CHU* accumulation before sidedressing than after sidedressing justifies its inclusion in a decision-making system. Rainfall patterns (*PPT*, *SDI*, and their product *AWDR*) had a particularly pronounced influence on size effects in the period from 15 days before SD to 30 days after SD. According to van Es et al. (2007), if high rainfall occurs before SD when the corn plants are still small, it tends to result in N losses, and therefore higher N response. If high rainfall occurs after SD, it mostly allows for higher yields (no drought stress) and therefore greater N response as well (Fox and Piekeliek, 1998). The greater influence of rainfall patterns following fertilizer N application shows the interest for reliable precipitation forecasts in the prediction of crop N demand. Anwar et al. (2009) expressed the same concern in relation to barley (*Hordeum vulgare* L.), in order to predict seasons where the application of N fertilizer would be beneficial. This is less of a problem under irrigated conditions, given that, according to our observations, water provided through irrigation has the same effect on N responses as water received as rainfall.

High *CHU* tended to enhance corn responses to added N. Higher heat accumulation may lead to more N mineralization from the soil but also to more volatilization, growth and therefore N uptake from the crop. Current recommendations in Ontario (OMAFRA Staff, 2012) suggest a heat unit adjustment, since corn in the long season areas of the province require more nitrogen than the short season areas. This may be due to greater moisture stress on the crop in areas with higher average temperatures, which would decrease N use efficiency, or it could be related to differences in soil organic matter content. The adjustment is approximately 1.8 kg N per 100 CHU above or below the base value of 2650. More importantly, higher N rates were more beneficial as *PPT* increased and was evenly distributed over the season. *AWDR* was a powerful integrated descriptor of precipitation amount and spread over time. High N rates increased yield by a factor of 2.6 under high *AWDR* compared to only 1.6 under low *AWDR*. Ros et al. (2011) explained that mineralizable N is closely related to temperature and moisture content. Xia and Wan (2008) showed in their meta-analysis of 304 published studies that plant responses to N increased with temperature and annual precipitation. According to Tremblay (2004), dry years are characterized by poor response to N fertilization, and a greater response is observed in wet years. Kyveryga et al. (2009) and Zhu et al. (2009) also found a greater response in years of higher rainfall. Shahandeh et al. (2011) reported that in a wet year, corn response to 180 kg N ha^{-1} almost doubled in medium-textured soils and tripled in fine-textured soils compared to drier years. This difference was attributed to the decrease in residual soil NO_3–N over time under abundant rainfall regimes and to the increase in water available for growth.

In our study, the interactions between soil texture and weather conditions had the greatest influence on response ratio. At the lower end of the spectrum were medium-textured soils and the

CHU parameter; at the higher end, fine-textured soils under low or high *AWDR* conditions. N applications may increase corn yield in fine-textured soil by a factor of 1.5 under low *AWDR* and a factor of 4.5 under high *AWDR* conditions. In this particular case (fine texture–high *AWDR*), lower (and not higher) *CHU* favored the higher response to N rate. Kravchenko et al. (2005) found that spatial variability of corn yield response to added N can increase in high rainfall years. In a meta-analysis of 57 experimental studies in sub-Saharan regions, Chivenge et al. (2011) showed that N response was higher in clay soils than in loam or sand, and also higher at higher annual precipitation levels. According to van Es et al. (2005) N response was greater in finer textured soils in years with wet springs. Dharmakeerthi et al. (2006) reported that corn N uptake differed at a landscape scale; the magnitude of the difference was greater in seasons with abundant rainfall. The interaction between soil texture and rainfall is likely related to the drainage capacity of soils (sand has a higher capacity, clay a lower capacity) (Taylor et al., 2003; Shahandeh et al., 2011). Clay retains water for a longer time after precipitation compared to sand (van Es et al., 2005). According to Armstrong et al. (2009), soil water and rainfall affect the relationship between soil texture and the spatial variations in yield through two mechanisms: the first is a complex relationship between subsoil physical-chemical constraints and soil water availability affecting crop growth; the second relates to osmotic effects in the root zone, which increase as soil water content decreases.

It is noteworthy that the application of N all-at-sowing tended to be less effective than split applications under high *AWDR* both in fine-textured soils (Fig. 9d) and in medium-textured soils (Fig. 9b). Thus, as mentioned by van Es et al. (2007), a highest precision in N management may be achieved through in-season N applications that are based on information on late-spring precipitation pattern. This allows to take into account the N losses (leaching or denitrification) occurring due to possible excessive rainfall (Kay et al., 2006). It is worth mentioning that there was generally no influence of growth stages (V4 and V8) on the effectiveness of the application of N fertilizer [Ohio studies ID : 14–15 , 16–17, 18–19, 20–21, 22–23, 24–25, 26–27, 28–29, 41–42 and 43–44 (Table 1; Figures 6a, 6b)].

Meta-analysis allowed us to build homogeneous groups based on soil texture, rainfall (*AWDR*), and *CHU* classes. Summary effect sizes were computed for each subgroup at each N fertilization rate. The variance explained by this subgrouping reached 42 to 60% (across N rates), which is high considering the large geographic and climatic zones covered by the database. Residual variability within these subgroups is probably not attributable solely to experimental error. Other parameters such as topography, soil organic matter content, previous crop, diseases, insects, nitrate content of the irrigation water and drainage problems may be involved (Tremblay, 2004; Dharmakeerthi et al., 2006; van Es, et al., 2005). The rules derived from this study are based on yield improvement and do not take environmental risks into account. However, it is generally recognized that N rates resulting in significant yield increases do not lead to unreasonable N losses, particularly when in-season applications are made (Olfs et al., 2005).

In summary, responses to applied N were found to be higher in sites with soils containing more than 30% clay. In conditions of high temperatures during the period from 30 days before to 10 days after sidedress time, the differences should be greater, particularly for fine-textured soil when seasonal rainfall is abundant and well distributed over time (high *AWDR*). The results may be used for variable N rate management within and between fields and seasons. This study provides guidelines for deriving optimal N rates adapted to local soil texture data and weather conditions (both actual and forecast) both at the regional level and field level. The quantitative information can be easily summarized in an Aided Decision System using a set of fuzzy inference system rules from which optimal rates can be calculated, as shown by Tremblay et al. (2010) and Bouroubi et al. (2011).

CONCLUSIONS

Several authors have reported that differential N responses are due to spatial and temporal variations in crop demand and soil N supply and losses; however, N responses have not been quantified according to different soil and weather conditions. This meta-analysis study using a uniform pan-American database provides an approach for deriving in-season N rates that are adapted to soil and weather information. This approach appears particularly well suited to answering questions that cannot easily be addressed using limited experimental data encompassing different soil textures and/or weather conditions. Soil and weather properties were found to have a fairly pronounced effect on corn response to N fertilization. Under certain soil-weather conditions (*AWDR–CHU* subgroups for fine-textured soils), accurate summary effect sizes could not be obtained owing to the limited number of studies. Further studies are necessary to establish reliable patterns for these soil-weather conditions. The measured effects of N rates in relation to soil textures and temperature and precipitation data can be used to derive algorithms permitting in-season N fertilization at levels that are both economical and environmentally benign. If long-term weather forecasts become more reliable, it will be possible to make adjustments not only for past weather conditions but also for those expected up to 30 days after N sidedressing. In the meantime, decisions may be based mainly on historical weather information.

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Figures

Figure 1

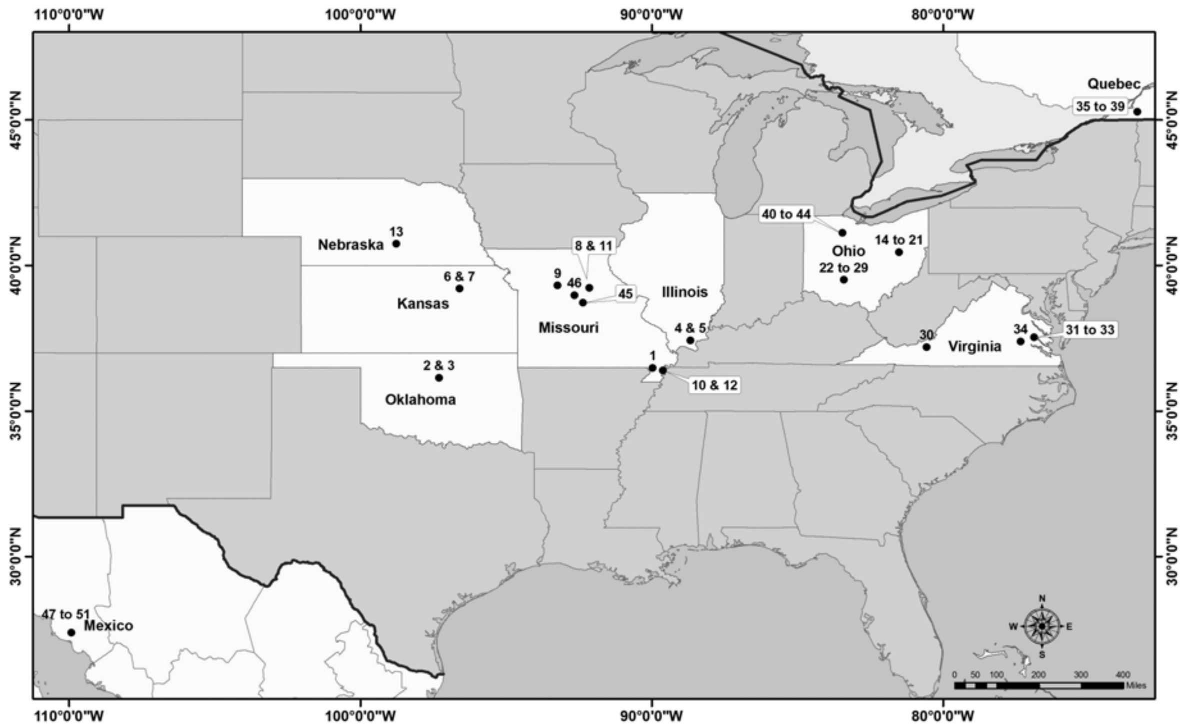

Figure 1. Geographic locations of the sites examined in this study.

Figure 2

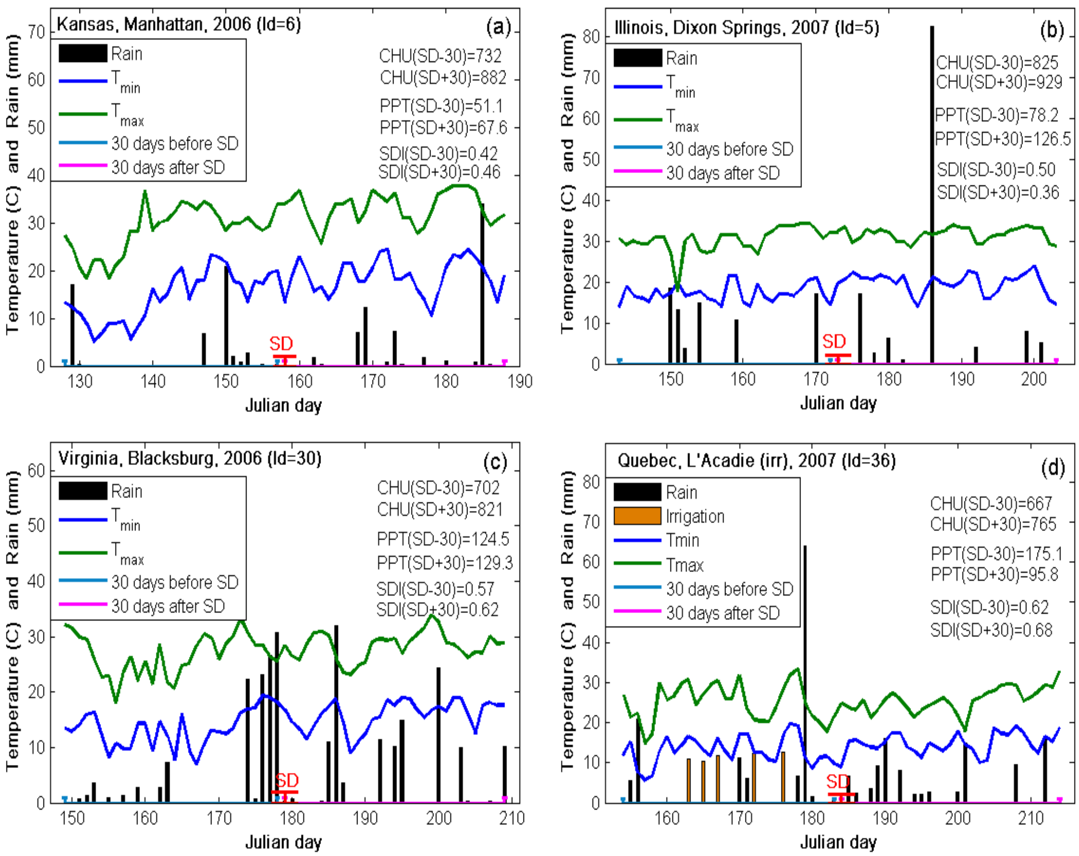

Figure 2. Examples of contrasting weather conditions among sites 30 days before and after sidedressing (SD). (a): low *PPT*–low *SDI* before SD and low *PPT*–low *SDI* after SD; (b): low *PPT*–high *SDI* before SD and high *PPT*–low *SDI* after SD; (c): high *PPT*–high *SDI* before SD and high *PPT*–high *SDI* after SD; (d): high *PPT*–high *SDI* before SD and low *PPT*–high *SDI* after SD.

Figure 3

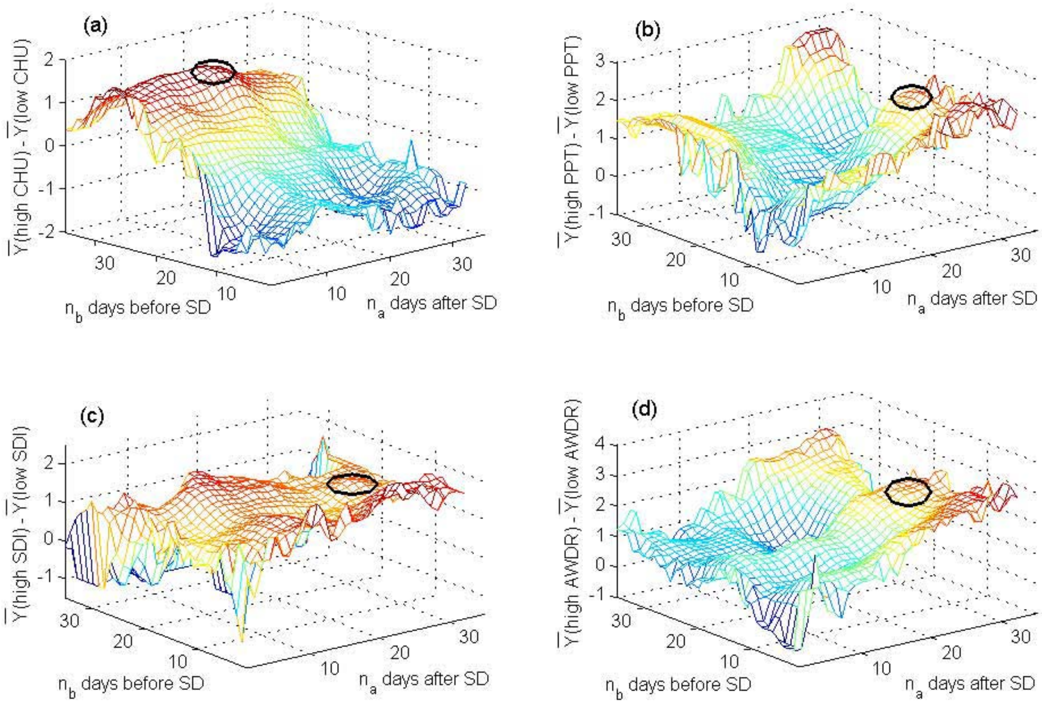

Figure 3. Effects of weather parameters before and after sidedressing (SD). Selected values of n_b and n_a leading to a higher contrast between the two classes (high and low) are indicated by black circles.

Figure 4

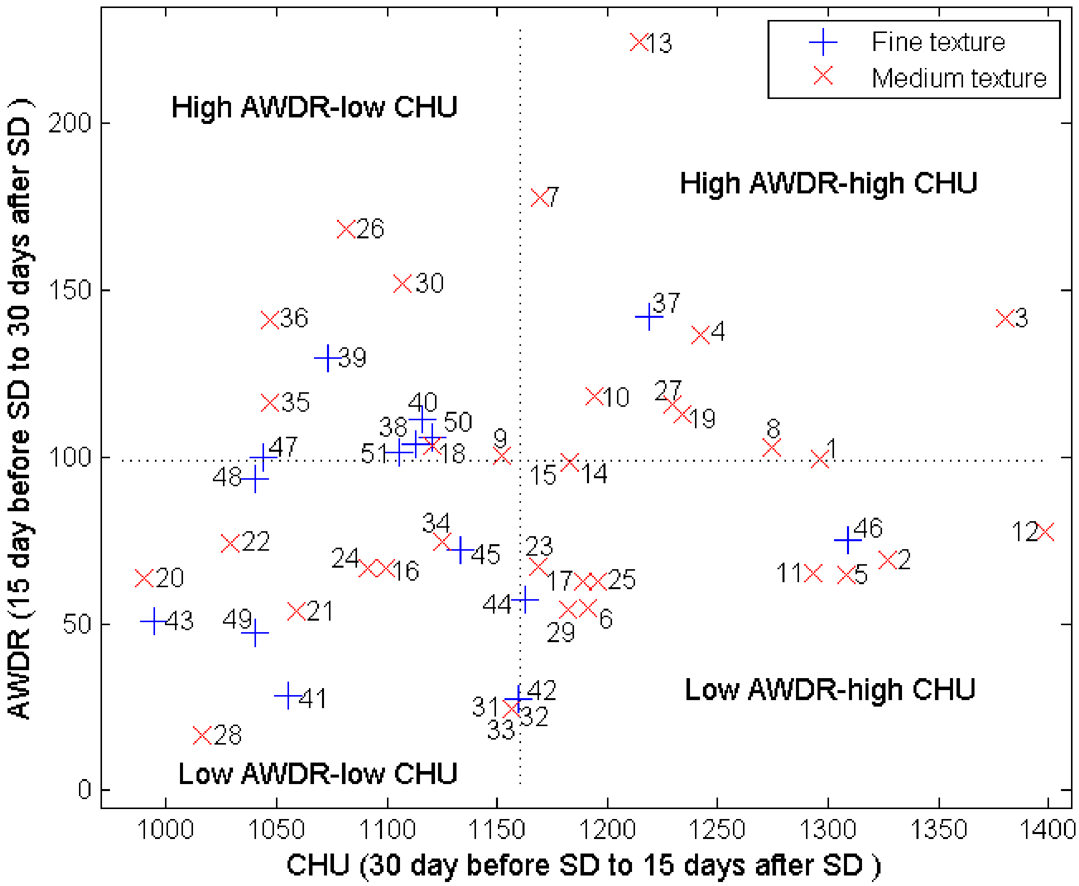

Figure 4. Distribution of studies in the space (*CHU*, *AWDR*). Labels indicate the ID number of each study as given in Table 1.

Figure 5

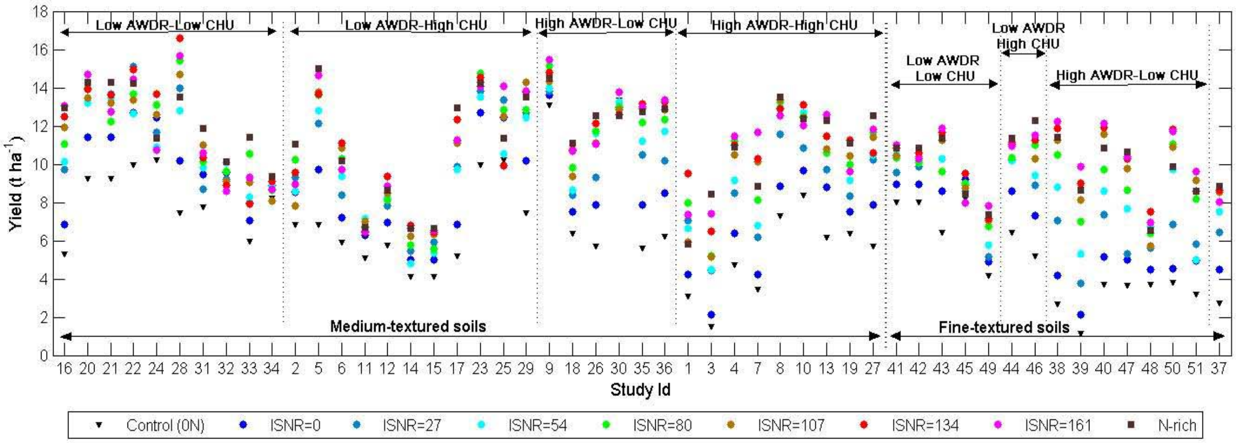

Figure 5. Yields (mean of replicates) for each study by N rate. Studies are grouped by soil texture (fine or medium) and weather parameters (low or high *AWDR* [abundant and well-distributed rainfall] and *CHU* [corn heat units]).

Figure 6a

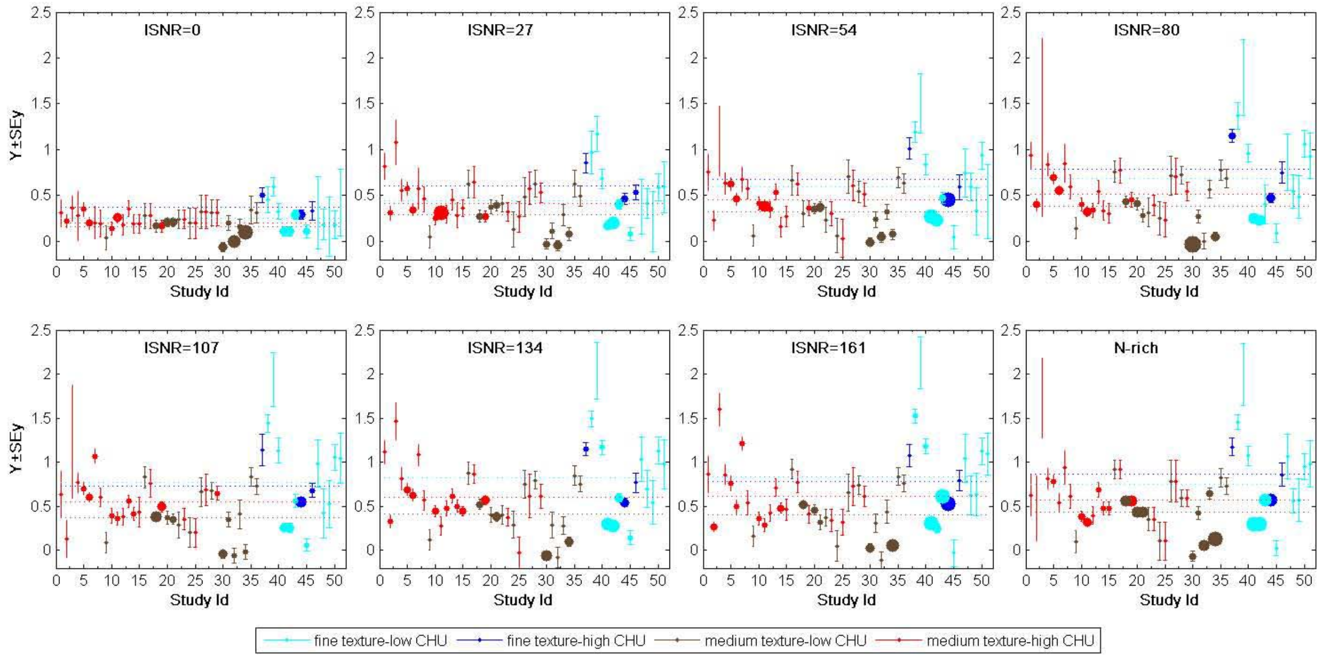

Figure 6a. Tree diagram with the effect size ($Y \pm SE_Y$) for all studies grouped in fine- and medium-textured soil classes combined with low and high *CHU* classes. The standard deviation SE_Y is the square root of Vy. Dashed lines indicate weighted mean of Y_i for each "texture–*CHU*" subgroup.

Figure 6b

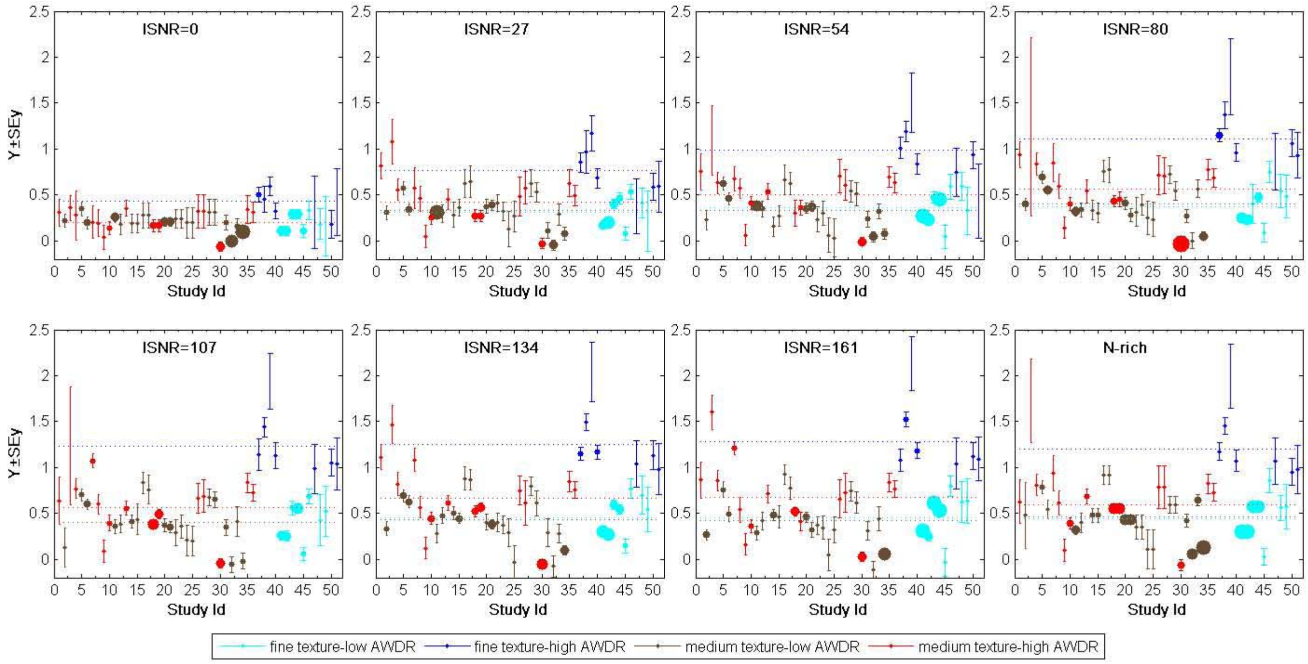

Figure 6b. Tree diagram with the effect size ($Y \pm SE_Y$) for all studies grouped in fine- and medium-textured soil classes combined with low and high *AWDR* classes. The standard deviation SE_Y is the root square of Vy. Dashed lines indicate weighted mean of Y_i for each "texture-*AWDR*" subgroup.

Figure 7

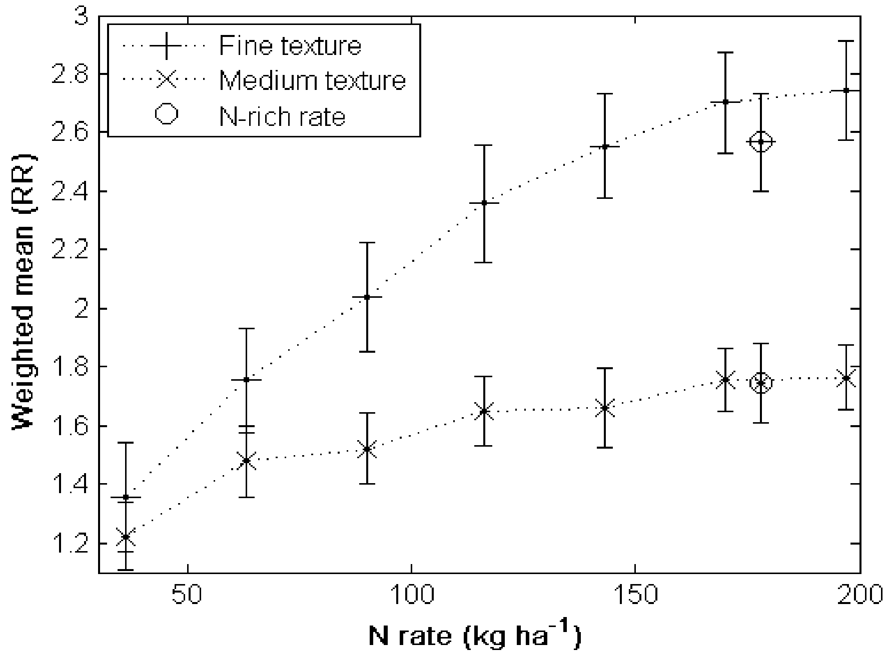

Figure 7. Weighted means of *RR* for subgroups of fine- and medium-textured soil classes. Error bars represent standard deviations of *RR* in each subgroup by N rate (N rate = starter + ISNR, or N-rich).

Figure 8

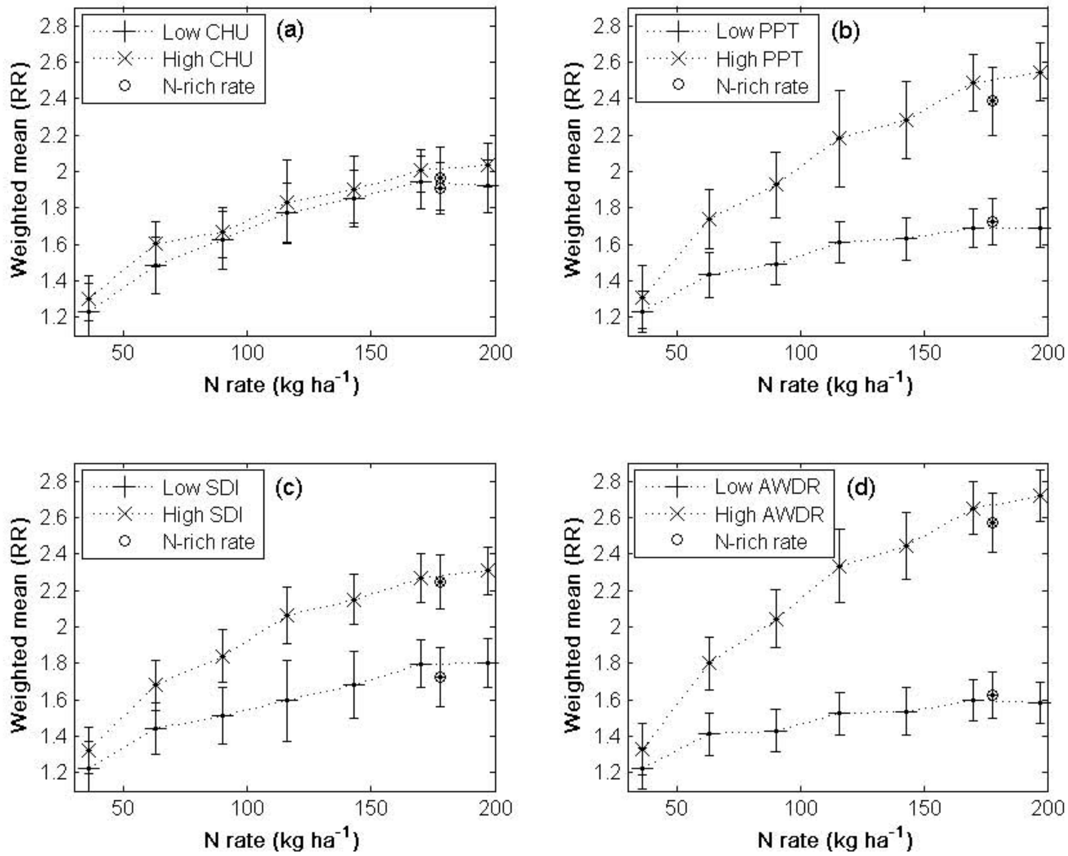

Figure 8. Weighted means of *RR* for subgroups of high and low *CHU*, *PPT*, *SDI* and *AWDR*. Error bars represent standard deviations of *RR* in each subgroup at each N rate (N rate = starter + ISNR, or N-rich).

Figure 9

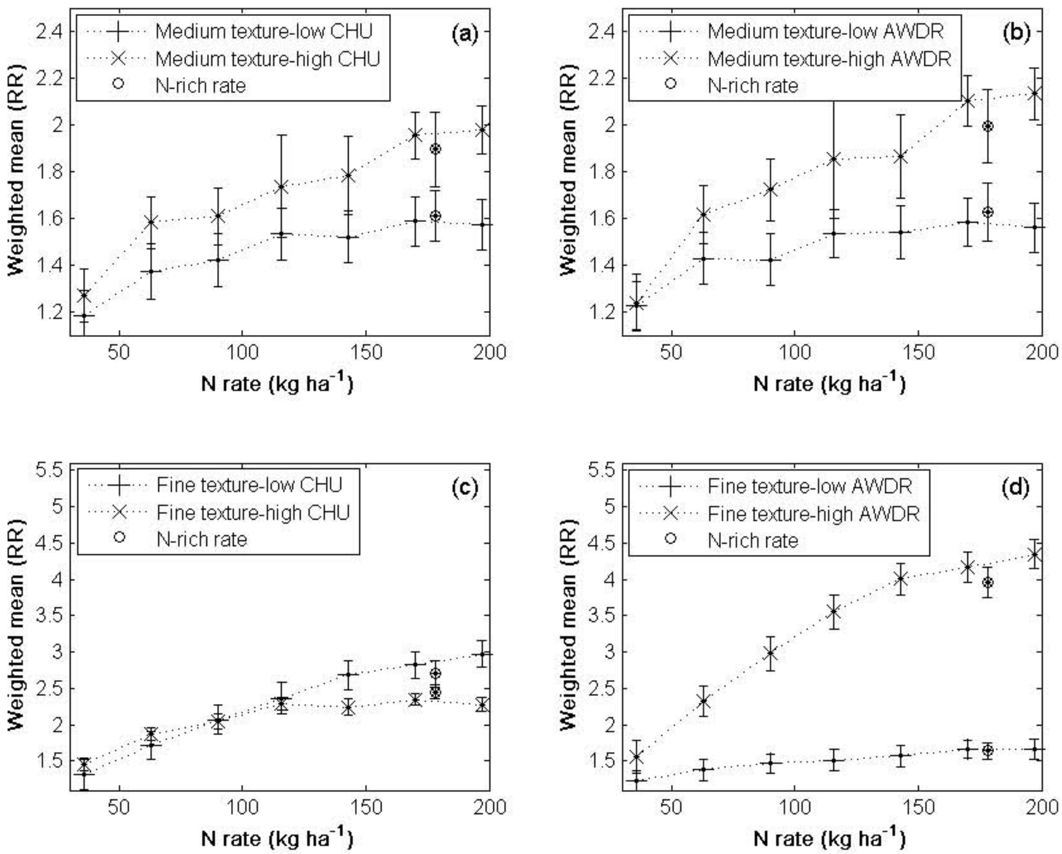

Figure 9. Weighted means of *RR* for subgroups combining fine or medium soil texture classes with low or high *AWDR*. Error bars represent standard deviations of *RR* in each subgroup at each N rate (N rate = starter + ISNR, or N-rich).

Figure 10

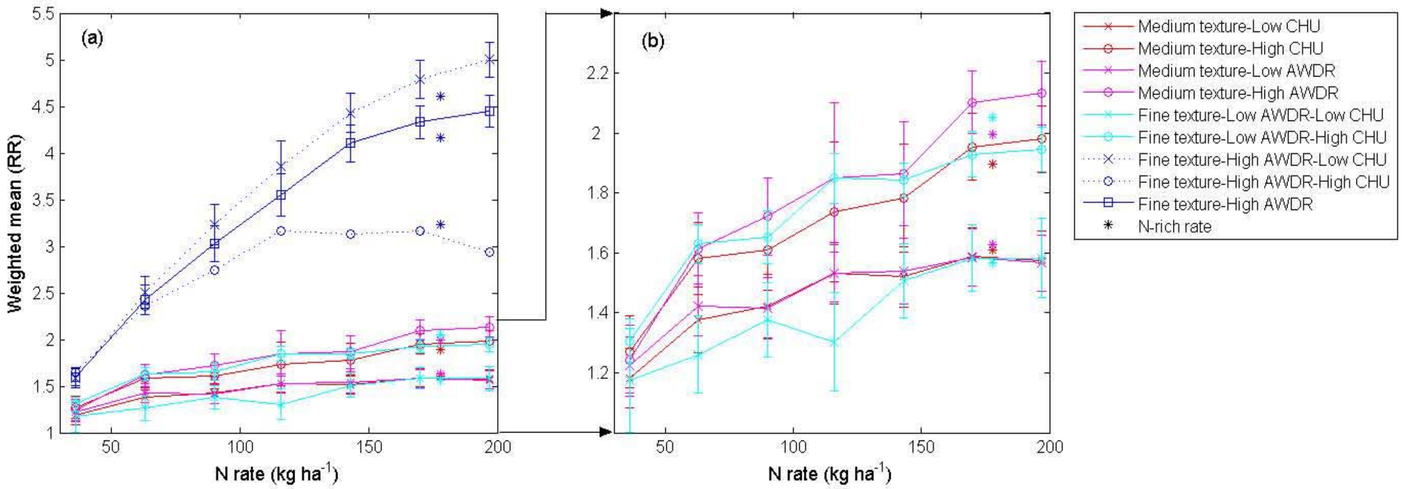

Figure 10. Weighted averages of *RR* for retained subgroups. Subplot (b) shows details of subplot (a) in the zone showing lower *RR* subgroups. Error bars represent standard errors in each subgroup and N rate (N rate = starter + ISNR, or N-rich).

Table 1. Studies ranked according to location and soil type with growth stage at sidedressing. Medium soils are numbered from 1 to 36 and fine soils from 37 to 51. The abbreviation “irr.” indicates irrigated sites; the abbreviation “SL/SCL” indicates sandy loam/sandy clay loam.

ID	Study	Surface soil texture	Growth stage at sidedressing
1	Missouri, Clarkton, 2006 (irr.)	Loamy Fine Sand	V6
2	Oklahoma, Stillwater, 2006	Fine sandy loam	V8
3	Oklahoma, Stillwater, 2008	Fine sandy loam	V8
4	Illinois, Dixon Springs 2006	Silt loam	V5
5	Illinois, Dixon Springs, 2007	Silt loam	V8
6	Kansas, Manhattan, 2006	Silt loam	V9
7	Kansas, Manhattan, 2008	Silt loam	V9
8	Missouri, Centralia, 2006 (irr.)	Silt loam	V10
9	Missouri, Miami, 2006	Silt loam	V9
10	Missouri, Portageville, 2006 (irr.)	Silt loam	V6
11	Missouri, Centralia, 2007	Silt loam	V9
12	Missouri, Portageville, 2008 (irr.)	Silt loam	V8
13	Nebraska, Shelton, 2006 (irr.)	Silt loam	V8
14	Ohio, Wooster1, 2006	Silt loam	V4
15	Ohio, Wooster2, 2006	Silt loam	V8
16	Ohio, Wooster1, 2007	Silt loam	V4
17	Ohio, Wooster2, 2007	Silt loam	V8
18	Ohio, Wooster1, 2008	Silt loam	V4
19	Ohio, Wooster2, 2008	Silt loam	V8
20	Ohio, Wooster1, 2009	Silt loam	V4
21	Ohio, Wooster2, 2009	Silt loam	V8
22	Ohio, Western1, 2006	SL/SCL	V4
23	Ohio, Western2, 2006	SL/SCL	V8
24	Ohio, Western1, 2007	SL/SCL	V4
25	Ohio, Western2, 2007	SL/SCL	V8
26	Ohio, Western1, 2008	SL/SCL	V4
27	Ohio, Western2, 2008	SL/SCL	V8
28	Ohio, Western1, 2009	SL/SCL	V4
29	Ohio, Western2, 2009	SL/SCL	V8
30	Virginia, Blacksburg, 2006	Loam	V6
31	Virginia, ATD, 2007	Loam	V6
32	Virginia, BHD, 2007	Loam	V6
33	Virginia, MCD, 2007	Loam	V6
34	Virginia, Varina, 2007	Loam	V4
35	Quebec, L’Acadie, 2007	Loam	V8
36	Quebec, L’Acadie 2007 (irr.)	Loam	V8
37	Quebec, L’Acadie, 2006	Clay loam	V6
38	Quebec, L’Acadie, 2008	Clay loam	V7
39	Quebec, L’Acadie, 2009	Clay loam	V6
40	Ohio, Northwest1, 2006	Silty clay loam	V8
41	Ohio, Northwest1, 2007	Silty clay loam	V4
42	Ohio, Northwest2, 2007	Silty clay loam	V8

43	Ohio, Northwest1, 2009	Silty clay loam	V4
44	Ohio, Northwest2, 2009	Silty clay loam	V8
45	Missouri, Wilton, 2006	Silty clay	V10
46	Missouri, Rocheport, 2007	Silty clay	V9
47	Mexico, Cd Obregón, 2007	Clay	V7
48	Mexico, MC, 2007	Clay	V7
49	Mexico, MP, 2007	Clay	V7
50	Mexico, MC, 2008	Clay	V7
51	Mexico, MP, 2008	Clay	V7

Table 2. Weather parameters used in the meta-analysis. The sum $\sum$ is taken over daily data during a given time period.

Weather parameters	Definitions
Corn heat units (CHU)	$CHU = \sum(Y_{max} + Y_{min})/2$ Y_{max} and Y_{min} are the contributions to CHU from daily maximum (T_{max}, up to 30°C) and minimum (T_{min}) air temperatures, respectively: $Y_{max} = 3.33\ (T_{max} - 10.0) - 0.084\ (T_{max} - 10.0)^2$; (if $T_{max} < 10.0$, $Y_{max} = 0.0$) $Y_{min} = 1.8\ (T_{min} - 4.44)$; (if $T_{min} < 4.44$, $Y_{min} = 0.0$)
Cumulative precipitation (PPT)	$PPT = \sum Rain$, $Rain$ is the daily rainfall (mm).
Precipitation evenness: Shannon Diversity Index (SDI)	$SDI = \left(-\sum pi \ln(pi)\right)/\ln(n)$ Where $pi = Rain/PPT$ is the fraction of daily rainfall relative to the total rainfall in a given time period and n is the number of days in that period. An SDI equal to 1 implies complete evenness (i.e., equal amounts of rainfall in each day of the period). An SDI equal to 0 implies complete unevenness (i.e., all rain in 1 day).

Table 3: Ratio of between-studies variance to total variance (I^2). Nb is the number of studies in each subgroup.

Subgroups of soil texture and weather conditions	Nb	N rate (kg ha^{-1} at sowing + ISNR)							N-rich
		36+0	36+27	36+54	36+80	36+107	36+134	36+161	(178)
All studies together									
All textures, all weather	51	-0.26	0.20	0.28	0.21	0.26	0.27	0.31	0.34
Subgroups for texture properties									
Fine texture	15	-0.02	0.29	0.46	0.26	0.38	0.33	0.54	0.49
Medium texture	36	-0.43	0.07	0.01	-0.32	-0.07	0.11	0.03	0.08
Subgroups for weather properties									
Low *CHU*	28	-0.02	0.31	0.40	0.33	0.39	0.37	0.42	0.49
High *CHU*	23	0.01	0.18	0.32	-0.02	0.22	0.36	0.21	0.26
Low *PPT*	28	-0.37	0.15	0.31	0.30	0.27	0.30	0.28	0.31
High *PPT*	23	-0.62	-0.12	-0.11	-0.61	0.02	0.09	0.07	0.23
Low *SDI*	30	-0.50	0.15	0.24	0.26	0.13	0.43	0.38	0.24
High *SDI*	21	-0.33	0.03	0.03	-0.26	0.25	0.03	0.13	0.26
Low *AWDR*	29	-0.50	0.01	0.13	0.07	0.11	0.25	0.15	0.16
High *AWDR*	22	-0.59	-0.09	-0.27	-0.68	0.09	-0.09	-0.03	0.17
Subgroups for combined texture and weather properties									
Fine texture–low *CHU*	12	0.07	0.43	0.42	0.40	0.29	0.44	0.51	0.56
Fine texture–high *CHU*	3	-0.12	0.16	-0.11	-0.46	0.44	-0.34	-0.16	-0.40
Medium texture–low *CHU*	16	-0.13	-0.01	0.09	-0.13	0.06	-0.06	0.04	0.13
Medium texture–high *CHU*	20	0.39	0.18	0.19	0.14	0.04	0.40	0.07	0.17
Fine texture–low *AWDR*	8	-0.16	0.08	0.26	0.28	0.10	0.25	0.43	0.47
Fine texture–high *AWDR*	7	-0.07	0.09	0.09	0.10	0.11	0.26	0.25	0.16
Medium texture–low *AWDR*	21	-0.66	-0.07	-0.04	-0.10	-0.01	0.14	-0.06	-0.10
Medium texture–high *AWDR*	15	-0.45	0.03	-0.37	-0.91	-0.27	-0.13	-0.09	0.17
Subgroups for rainfall and *CHU* for fine soil textures combined									
Low *AWDR*–low *CHU*	5	-0.22	-0.06	0.26	0.03	0.19	0.11	0.17	0.28
Low *AWDR*–high *CHU*	2	-0.02	-0.11	0.00	-0.01	0.07	-0.01	0.01	-0.02
High *AWDR*–low *CHU*	7	-0.15	0.09	0.07	0.14	0.25	0.27	0.30	0.06
High *AWDR*–high *CHU*	1	-	-	-	-	-	-	-	-