Published September 24, 2012

Soil Fertility & Crop Nutrition

Corn Response to Nitrogen is Influenced by Soil Texture and Weather

Nicolas Tremblay,* Yacine M. Bouroubi, Carl Bélec, Robert William Mullen, Newell R. Kitchen, Wade E. Thomason, Steve Ebelhar, David B. Mengel, William R. Raun, Dennis D. Francis, Earl D. Vories, and Ivan Ortiz-Monasterio

ABSTRACT

Soil properties and weather conditions are known to affect soil 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 response of corn (*Zea mays* L.) across 51 studies involving the same N rate treatments that were performed 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 prescribe N application at optimal rates taking into account rainfall pattern and soil texture, which would lead to improved crop profitability and reduced environmental impacts.

Because natural soil 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 result in environmental contamination from denitrification, volatilization, and NO_3–N leaching to surface and groundwater (Tremblay and Bélec, 2006).

Applying N at optimal rates has the potential to improve N use efficiency, 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 researchers have recommended 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 that 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) on coarse-textured soils than on 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,

N. Tremblay, Y. Bouroubi, and C. Bélec, Agriculture and Agri-Food Canada, Horticultural R&D Center, St-Jean-sur-Richelieu J3B 3E6, Canada; R.W. Mullen, Potash Corporation of Saskatchewan, Wooster, OH 44691; N.R. Kitchen, USDA-ARS, Univ. of Missouri, Columbia, MO 65211; W.E. Thomason, Crop & Soil Environmental Sciences, Virginia Tech, Blacksburg, VA 24061; S. Ebelhar, Univ. of Illinois, Dixon Springs Agricultural Center, Simpson, IL 62985; D.B. Mengel, Kansas State Univ., Manhattan, KS 66506; W.R. Raun, Plant and Soil Sciences, Oklahoma State Univ., Stillwater, OK 74078; D.D. Francis, USDA-ARS, Univ. of Nebraska, Lincoln, NE 68583; E.D. Vories, USDA-ARS Delta Center, Portageville, MO 63873; and I. Ortiz-Monasterio, CIMMYT, Mexico D.F., Mexico. Received 23 May 2012. *Corresponding author (Nicolas.Tremblay@agr.gc.ca).

Published in Agron. J. 104:1658–1671 (2012)
Posted online 12 Sept. 2012
doi:10.2134/agronj2012.0184
Available freely online through the author-supported open access option.

Abbreviations: AWDR, abundant and well-distributed rainfall; CHU, corn heat units; I^2, ratio of between-studies variance to total variance; ISNR, in-season nitrogen rates; PPT, cumulative precipitation; RR, response ratio; SD, sidedressing; SDI, Shannon diversity index.

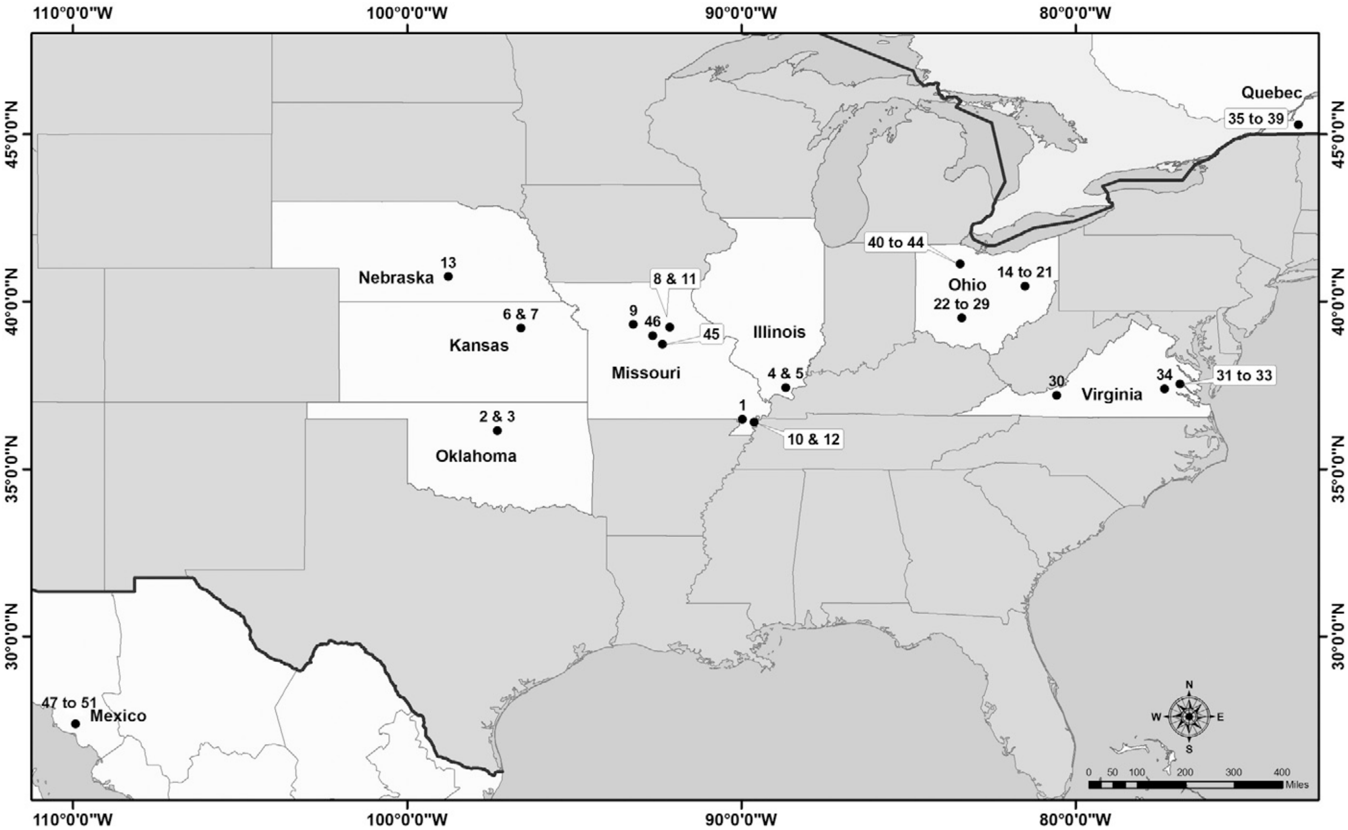

Fig. 1. Geographic locations of the sites examined in this study.

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 among 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 model to improve N use efficiency and reduce N losses. This model uses soil textural class, soil organic matter, weather data, and other information about management practices such as tillage, plant density, and rotations to determine in-season N recommendations for the northeastern United States.

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 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 effect for subgroups and thus identify 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 P fertilizer application rates in 400 experiments conducted during an 80-yr period in Finland and used plant groups, soil properties, and cultivation zones to explain the differences. Tonitto et al. (2006) conducted a meta-analysis of experiments reported in the literature 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)

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.

Study no.	Study	Surface soil texture	Growth stage at sidedressing
1	Missouri, Clarkton, 2006 (irrigated)	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 (irrigated)	silt loam	V10
9	Missouri, Miami, 2006	silt loam	V9
10	Missouri, Portageville, 2006 (irrigated)	silt loam	V6
11	Missouri, Centralia, 2007	silt loam	V9
12	Missouri, Portageville, 2008 (irrigated)	silt loam	V8
13	Nebraska, Shelton, 2006 (irrigated)	silt loam	V8
14	Ohio, Wooster 1, 2006	silt loam	V4
15	Ohio, Wooster 2, 2006	silt loam	V8
16	Ohio, Wooster 1, 2007	silt loam	V4
17	Ohio, Wooster 2, 2007	silt loam	V8
18	Ohio, Wooster 1, 2008	silt loam	V4
19	Ohio, Wooster 2, 2008	silt loam	V8
20	Ohio, Wooster 1, 2009	silt loam	V4
21	Ohio, Wooster 2, 2009	silt loam	V8
22	Ohio, Western 1, 2006	sandy loam/sandy clay loam	V4
23	Ohio, Western 2, 2006	sandy loam/sandy clay loam	V8
24	Ohio, Western 1, 2007	sandy loam/sandy clay loam	V4
25	Ohio, Western 2, 2007	sandy loam/sandy clay loam	V8
26	Ohio, Western 1, 2008	sandy loam/sandy clay loam	V4
27	Ohio, Western 2, 2008	sandy loam/sandy clay loam	V8
28	Ohio, Western 1, 2009	sandy loam/sandy clay loam	V4
29	Ohio, Western 2, 2009	sandy loam/sandy clay loam	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 (irrigated)	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, Northwest 1, 2006	silty clay loam	V8
41	Ohio, Northwest 1, 2007	silty clay loam	V4
42	Ohio, Northwest 2, 2007	silty clay loam	V8
43	Ohio, Northwest 1, 2009	silty clay loam	V4
44	Ohio, Northwest 2, 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

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 than loam and sand and also higher for higher annual precipitation. 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. They 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 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 economically 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 response of combined soil and weather conditions across a number of years in a large geographic area devoted to corn production in North America. Furthermore, it is difficult to have a uniform data set 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 among 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 to address the following questions: (i) to what extent do soil and weather properties affect the corn response to N fertilization; and (ii) 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, and clay loam), medium textures (loam and silt loam), and coarse textures (sandy loam, sandy clay loam, loamy fine sand, and fine sandy loam). Because medium and coarse textures showed a similar N response behavior (data not shown), however, only two classes were retained: (i) fine-textured soils, including clay, silty clay, silty clay loam, and clay loam textures; and (ii) medium to 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 in the same years at the same 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 the N-rich rate. 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 for each site-year. For practical reasons, these simple and easily available data were

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

Weather parameter	Definition
Corn heat units (CHU)	CHU = $\Sigma(Y_{max} + Y_{min})/2$, where 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 = Σ(Rain), where Rain is the daily rainfall (mm)
Precipitation evenness: Shannon diversity index (SDI)	SDI = $[-\Sigma pi \ln(pi)]/\ln(n)$, 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. SDI = 1 implies complete evenness (i.e., equal amounts of rainfall in each day of the period); SDI = 0 implies complete unevenness (i.e., all rain in 1 d)

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).

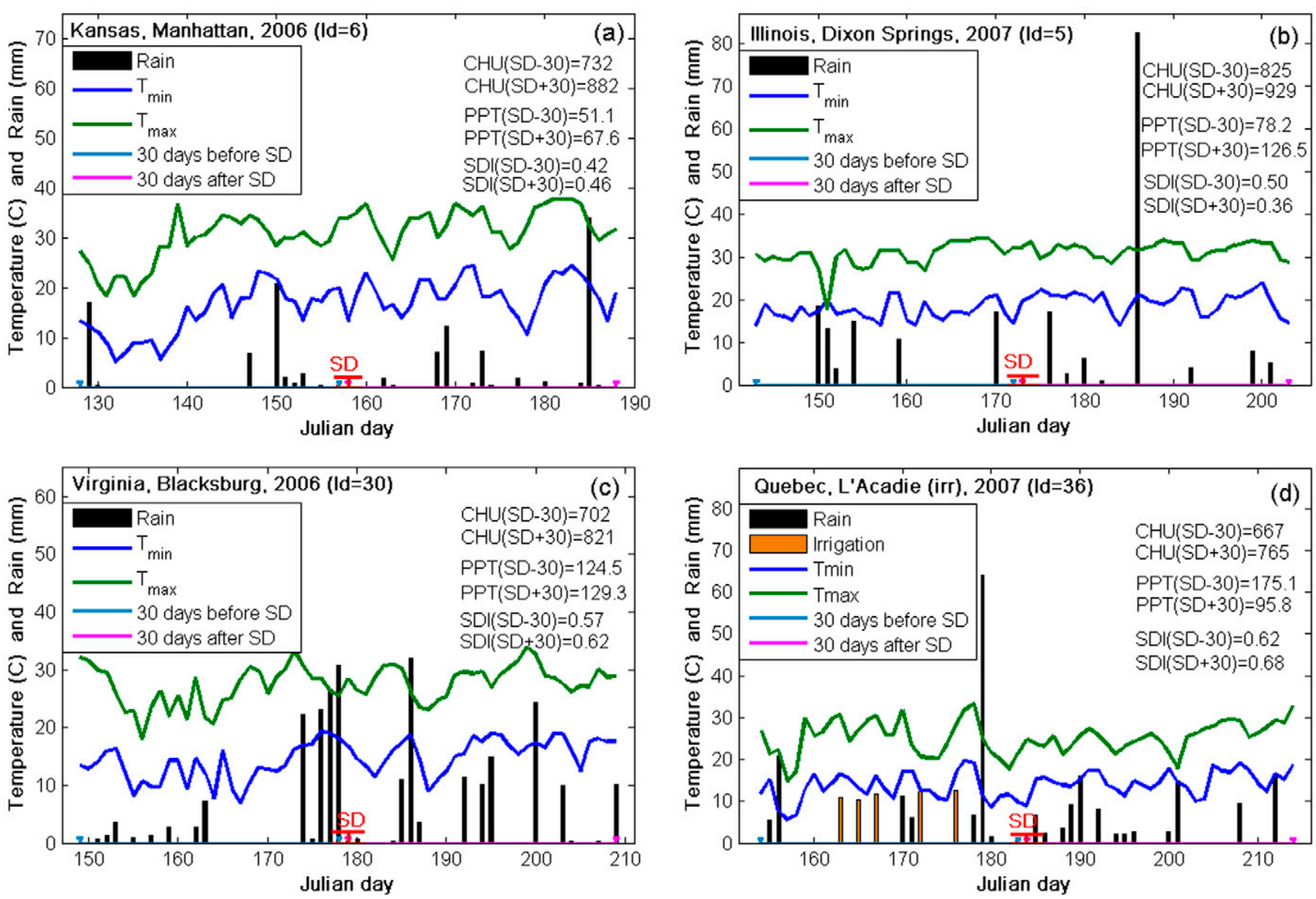

Fig. 2. Examples of contrasting weather conditions among sites 30 d before and after sidedressing (SD): (a) low cumulative precipitation (PPT)–low precipitation evenness (Shannon's diversity index, SDI) before SD and low PPT–low SDI after SD; (b) low PPT–high SDI before SD and high PPT–low SDI after 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; CHU is corn heat units, T_{max} and T_{min} are maximum and minimum temperatures, respectively.

We also proposed a parameter representing optimal water availability (abundant rainfall, well distributed in time). We defined abundant and well-distributed rainfall (AWDR) as

$$\mathrm{AWDR} = \mathrm{PPT} \times \mathrm{SDI} \qquad [1]$$

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 unirrigated sites under the same soil and rainfall conditions, which revealed no significant difference between the presence and absence of irrigation (data not shown).

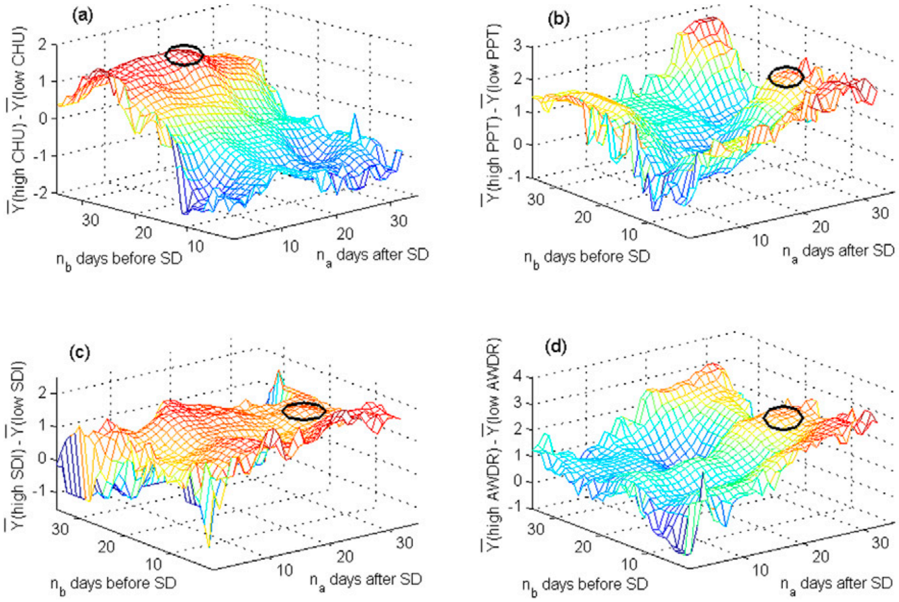

Fig. 3. Effects of weather parameters before and after sidedressing (SD): (a) corn heat units (CHU), (b) cumulative precipitation (PPT), (c) precipitation evenness determined as Shannon's diversity index (SDI), and (d) abundant and well-distributed rainfall (AWDR = PPT × SDI). Selected values for n_b and n_a leading to a higher contrast between the two classes (high and low) are indicated by black circles.

The time period covered by weather parameters overlapped the date of N sidedressing (SD). To determine the period during which a weather parameter is most closely related to the N response (or response ratio, RR = $\mathrm{Yield}_{\mathrm{Nrate}}/\mathrm{Yield}_{\mathrm{control}}$), 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 d). The optimal period for any weather parameter was the one that maximized the difference in N response across N rates. Thus, for CHU, PPT, SDI, and AWDR, we had to find [n_b, n_a] pairs 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

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

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 the two 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 d before SD (n_b = 30) to 15 d 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 d to n_a = 30 d 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 d to n_a = 15 d for CHU and n_b = 15 d to n_a = 30 d for PPT, SDI, and AWDR).

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

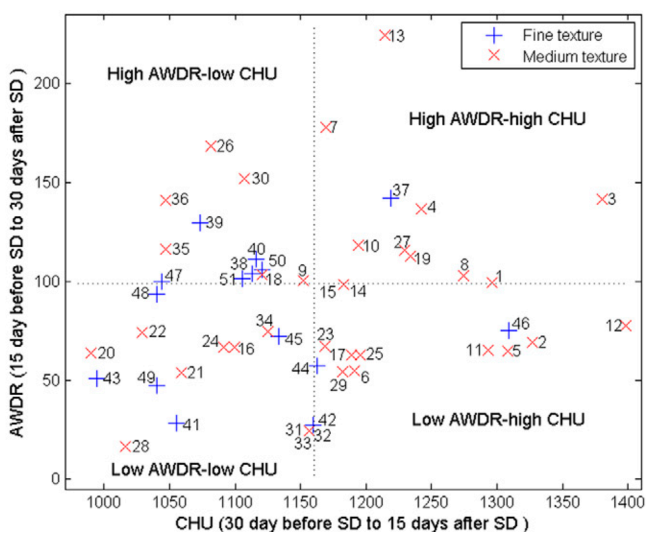

Fig. 4. Distribution of studies in the space according to corn heat units (CHU) and abundant and well-distributed rainfall (AWDR). Labels indicate the identification number of each study as given in Table 1.

except the high AWDR–high CHU subgroup, for which only one study was conducted on a fine-textured soil.

Meta-analysis

The meta-analysis performed in this research was 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 Mg 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 ($\text{Yield}_{\text{Nrate}}$) to the yield measured for the N rate = 0 plots ($\text{Yield}_{\text{control}}$). Thus, for each study i and each N rate r:

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

The overbars in Eq. [3] indicate that the yields are averaged across the replicates. The logarithmic scale is used to maintain symmetry (Tonitto et al., 2006) and allow the addition of effect sizes.

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

$$\text{Vy}_{i,r} = S^2_{\text{pooled}}\left(\frac{1}{n_{\text{Nrate}}\overline{\text{Yield}}^2_{\text{Nrate}}} + \frac{1}{n_{\text{control}}\overline{\text{Yield}}^2_{\text{control}}}\right) \quad [4a]$$

where

$$S^2_{\text{pooled}} = \frac{(n_{\text{Nrate}}-1)\text{var}(\text{Yield}_{\text{Nrate}})}{n_{\text{Nrate}}+n_{\text{control}}-2} + \frac{(n_{\text{control}}-1)\text{var}(\text{Yield}_{\text{control}})}{n_{\text{Nrate}}+n_{\text{control}}-2} \quad [4b]$$

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 the variance:

$$W_{i,r} = \frac{1}{\text{Vy}_{i,r}} \quad [5]$$

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

$$\mu_r = \frac{\sum_{i=1}^{K} W_{i,r}Y_{i,r}}{\sum_{i=1}^{K} W_{i,r}} \quad [6]$$

where K is 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 considered 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 $\xi_{i,r}$, which reflects the variability of the effect size across the studies, and a sampling error $\varepsilon_{i,r}$:

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

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:

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

Because $W_{i,r}$ 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 Q_r, we assumed 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 $\varepsilon_{i,r}$, then within studies, the expected value of Q_r is equal to the degrees 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, is given by

$$T_r^2 = \frac{Q_r - \text{df}}{C_r} \quad [9]$$

where

$$C_r = \sum_{i=1}^{k} W_{i,r} - \frac{\sum_{i=1}^{k} W_{i,r}^2}{\sum_{i=1}^{k} W_{i,r}}$$

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

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

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

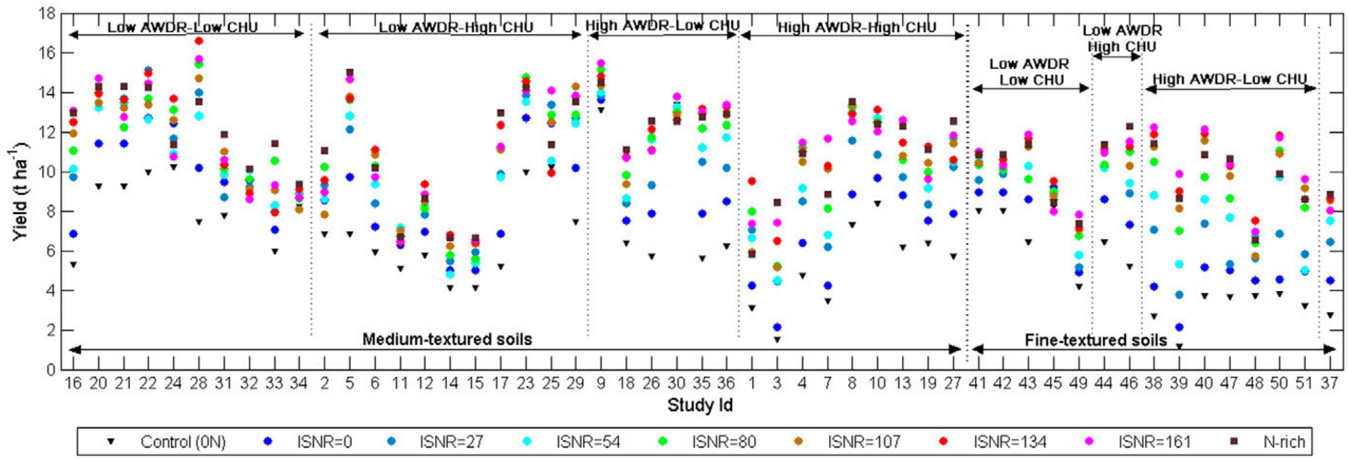

Fig. 5. Yields (mean of replicates) for each study by in-season N rate (ISNR) or 178 kg ha^{-1} applied at sowing with no N fertilizer at sidedressing (N-rich rate). Studies are grouped by soil texture (fine or medium) and weather parameters (low or high abundant and well-distributed rainfall [AWDR] and corn heat units [CHU]).

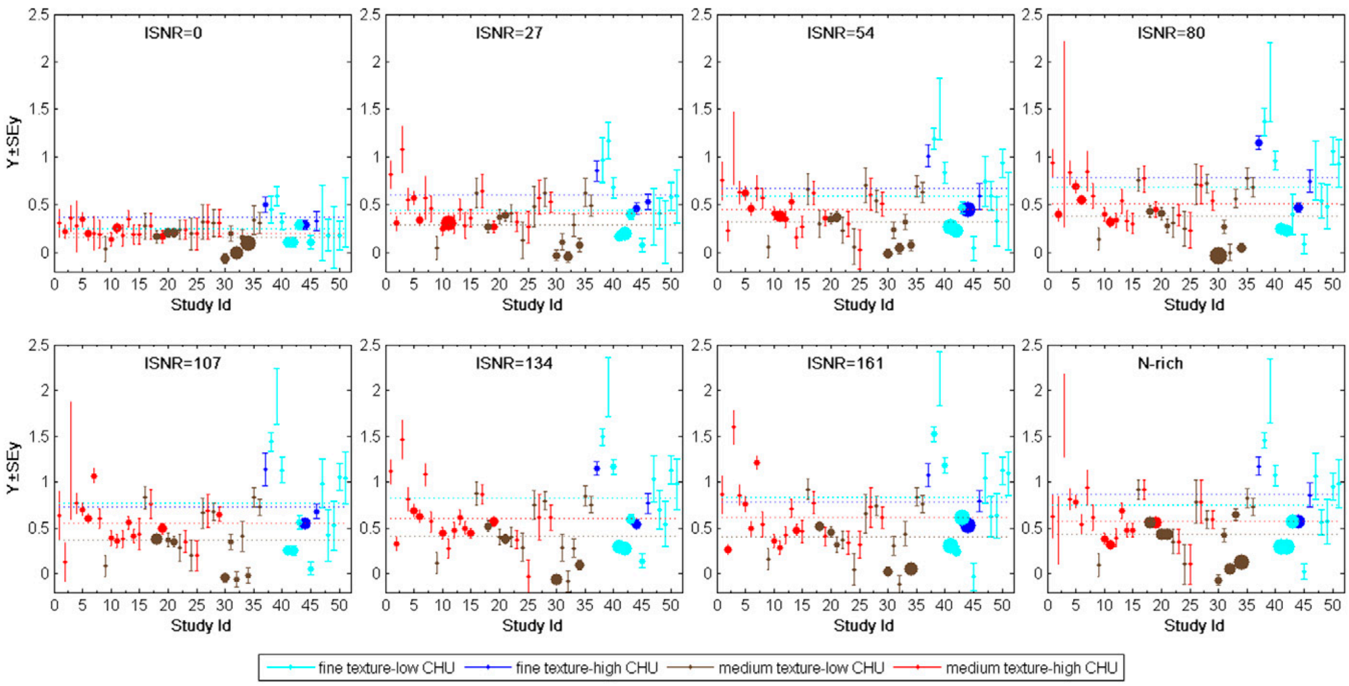

Fig. 6a. Tree diagrams for each in-season N rate (ISNR) or 178 kg ha^{-1} applied at sowing with no N fertilizer at sidedressing (N-rich rate) with the effect size ($Y \pm SE_Y$) for all studies grouped in fine- and medium-textured soil classes combined with low and high corn heat unit (CHU) classes. The standard error SE_Y is the square root of the variance Vy. Dashed lines indicate the weighted mean of Y_i for a given study i for each texture–CHU subgroup.

the sum of the within-study variance, $Vy_{i,r}$, and the between-studies variance, T_r^2:

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

The variable $W_{i,r}$ is replaced by $W_{i,r}{}^{*}$ (Eq. [6], [8], and [9]). The use of the weighted $W_{i,r}{}^{*}$ avoids allocating an excessive weight to any study i if its variance $Vy_{i,r}$, is too small because 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, personal communication, 2012). From this point, the index r will be omitted and I^2 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.

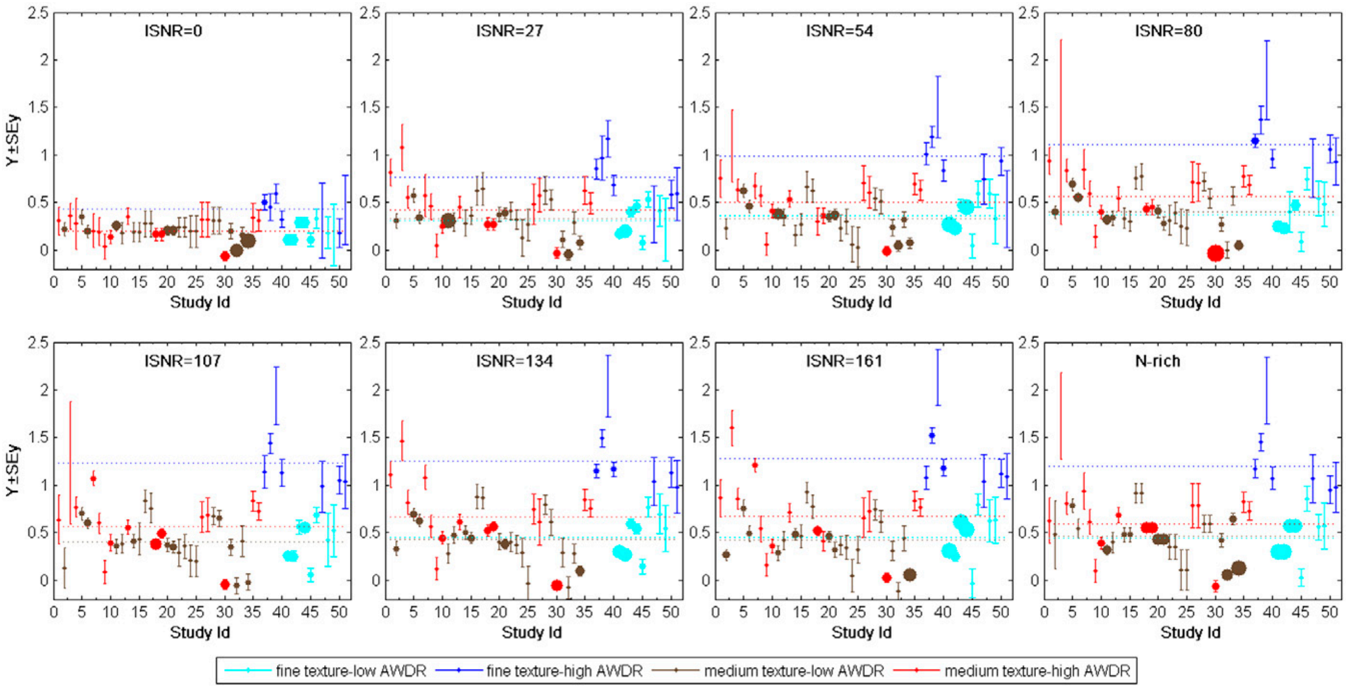

Fig. 6b. Tree diagrams for each in-season N rate (ISNR) or 178 kg ha^{-1} applied at sowing with no N fertilizer at sidedressing (N-rich rate) with the effect size ($Y \pm SE_Y$) for all studies grouped in fine- and medium-textured soil classes combined with low and high abundant and well-distributed rainfall (AWDR) classes. The standard error SE_Y is the root square of the variance Vy. Dashed lines indicate the weighted mean of Y_i for a given study *i* for each texture–AWDR subgroup.

Table 3. Ratio of between-studies variance to total variance (I^2) for N rates used in the studies (N rate = starter + in-season N rate [kg ha^{-1}] or the N-rich rate, which was 178 kg ha^{-1} applied at sowing with no N fertilizer at sidedressing).

Subgroup†	Nb‡	I^2							
		36 + 0	36 + 27	36 + 54	36 + 80	36 + 107	36 + 134	36 + 161	N rich
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	–	–	–	–	–	–	–	–

† CHU, corn heat units; PPT, cumulative precipitation; SDI, Shannon's diversity index, a measure of precipitation evenness; AWDR, abundant and well-distributed rainfall, representing optimal water availability and determined as PPT × SDI.

‡ Nb, number of studies in each subgroup.

The variance explained by the classification into subgroups is defined as the ratio of explained variance and total variance (Borenstein et al., 2009). Because the explained variance equals total variance minus unexplained variance (within subgroups), the proportion of the variance explained is given by

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

where

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

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 Mg 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 rate (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 kg ha^{-1}) in 15% of the cases when AWDR was low (for both fine- and medium-textured soils), 33% of the cases for the medium texture–high AWDR class, and 63% of the cases for the fine texture–high AWDR class. The N-rich rate gave significantly higher yields than starter 36 + ISNR 134 kg ha^{-1} in only two studies (5 and 33) corresponding to the medium texture–low AWDR condition. The control rate (0 N) produced low yield, particularly under high AWDR and especially in fine-textured soils. Indeed, $\text{Yield}_{\text{control}}$ was lower than 5 Mg ha^{-1} in 9% of the cases for the medium texture–low AWDR class, 27% of the cases for the medium texture–high AWDR class, 14% of the cases for the fine texture–low AWDR class, and 100% of the cases for the fine texture–high AWDR class. In the latter case, the low $\text{Yield}_{\text{control}}$ was probably due to N losses, mainly by denitrification, caused by abundant precipitation in poorly drained soils (van Es et al., 2007; Sogbedji et al., 2001).

Figure 5 also shows that both yield and yield response to N were highly variable among studies, but it does not reveal clear relationships between yield, soil texture, and weather. It illustrates the need for a meta-analysis 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 rate). 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 to give a better idea of the relative degree of homogeneity of the subgroups.

The tree diagram of the meta-analysis is shown in Fig. 6a and 6b. The subgroups were either combinations of soil texture and CHU (Fig. 6a) or combinations of soil texture and AWDR (Fig. 6b). The AWDR was considered to be more representative of rainfall conditions than PPT or SDI taken alone (see discussion of weather classes below). 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 error ($\pm SE_Y$), 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 the N-rich rate (Fig. 6a and 6b). The I^2 for N rate = 36 + 0 kg ha^{-1} indicated high homogeneity in almost all subgroups (Table 3). This was expected because a higher N rate leads to more variability of the N response depending on the growing conditions in each study (Haberle et al., 2008). This dispersion does not fully explain heterogeneity, however, because it also depends on the variance Vy_i (experimental error, indicated by the error bars in the 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 (Fig. 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 next.

Soil Texture Classes

Soil texture class (fine or medium) determined the 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 increasing N rate. The RR also showed greater heterogeneity across studies at higher N rates (Fig. 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 kg ha^{-1}.

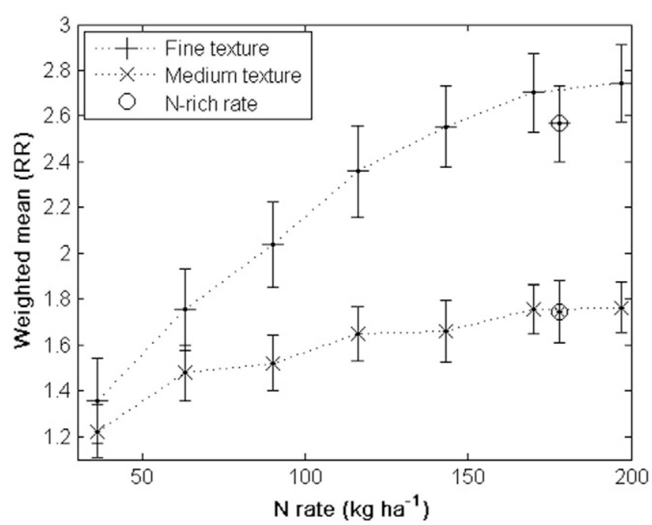

Fig. 7. Weighted means of the response ratio (RR) for subgroups of fine- and medium-textured soil classes. Error bars represent standard errors of RR in each subgroup by N rate (N rate = starter + in-season N rate or 178 kg ha^{-1} applied at sowing with no N fertilizer at sidedressing [N-rich rate]).

Soils in the medium-texture class tended to show similar responses to added N, with yield gains varying between 40% (RR ~ 1.4) and 65% (RR ~ 1.65) and marginal improvements above 134 kg N ha^{-1} (Fig. 7). The fine-texture class was characterized by a much higher RR, reaching 2.7 at the highest N rate. There was too much heterogeneity (Table 3), however, 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-texture class. Subgroup analyses should also consider weather parameters.

Weather Classes

Corn heat units, PPT, SDI, and the proposed parameter AWDR (= PPT × SDI) can influence N uptake, mineralization, leaching, and denitrification. This study considered the following periods: 30 d before SD to 15 d after SD for CHU; and 15 d before SD to 30 d after SD for PPT, SDI, and AWDR. These periods were chosen because they 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 the 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 the N-rich rate. 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 with time has an influence of its own on the response to N.

Because high PPT and SDI classes enhanced the RR more than low classes, their product (AWDR) tended to further increase the difference (Fig. 8d). The increase in the RR associated with high AWDR compared with low AWDR was very large and likewise proportional to the N rate. At the two highest N rates, the RR increased from 1.6 at low AWDR to 2.6 at high AWDR. Moreover, the AWDR classes showed lower heterogeneity than PPT or SDI (Table 3). Infrequent rain situations (low SDI) lead 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 or denitrification, and therefore increase the crop response to N fertilization.

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

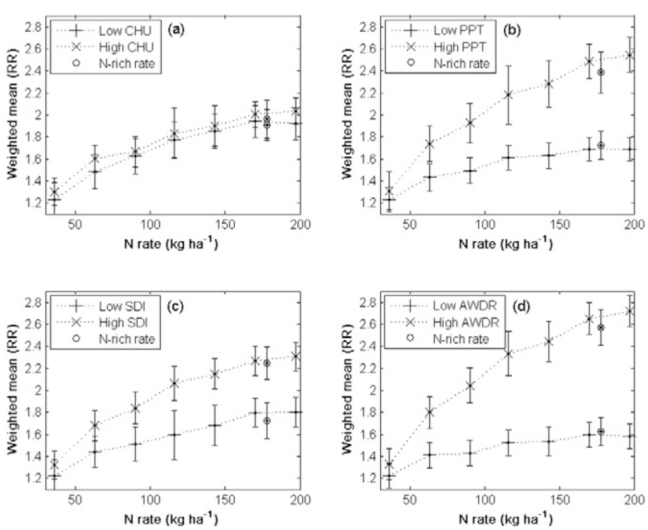

Fig. 8. Weighted means of the response ratio (RR) for subgroups of high and low (a) corn heat units (CHU), (b) cumulative precipitation (PPT), (c) precipitation evenness as Shannon's diversity index (SDI), and (d) abundant and well-distributed rainfall (AWDR = PPT × SDI). Error bars represent standard errors of RR in each subgroup at each N rate (N rate = starter + in-season N rate or 178 kg ha^{-1} applied at sowing with no N fertilizer at sidedressing [N-rich rate]).

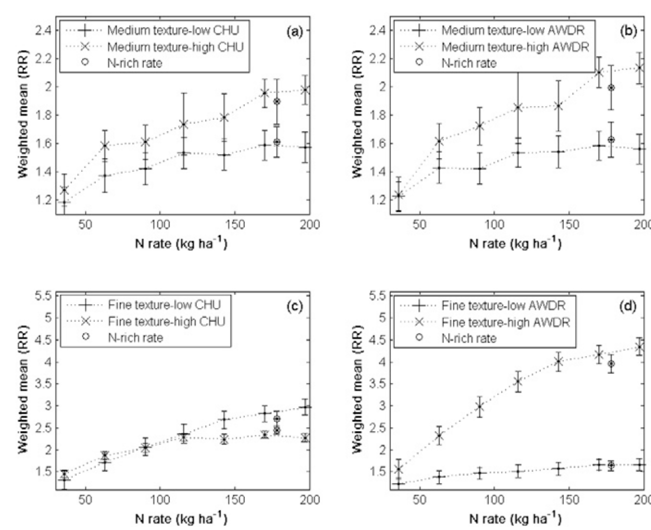

Fig. 9. Weighted means of the response ratio (RR) for subgroups combining (a,b) medium or (c,d) fine soil texture classes with low or high (a,c) corn heat units and (b,d) abundant and well-distributed rainfall (AWDR). Error bars represent standard errors of RR in each subgroup at each N rate (N rate = starter + in-season N rate or 178 kg ha^{-1} applied at sowing with no N fertilizer at sidedressing [N-rich rate]).

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 a higher effect size than those in the medium texture–low CHU subgroup (Fig. 9a). This difference was of little significance, however, because at higher N rates, the 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 a higher RR than the medium texture–low AWDR subgroup (Fig. 9b). The difference was greater at higher N rates, where the RR increased from 1.6 at low AWDR to >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 (three studies) was generally homogeneous but the fine texture–low CHU subgroup (12 studies) was not. Figure 9c shows that the RR weighted mean of the fine texture–high CHU studies was lower than that of fine texture–low CHU studies for ISNR > 134 kg ha^{-1}. This difference was not consistent because the subgroups were not homogeneous.

The AWDR reduced the heterogeneity of effect size in the fine-textured soil class, especially for the fine texture–high AWDR subgroup (seven 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 increasing N rates. Hence, rainfall patterns had an appreciable effect on the 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.

Because 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 (five studies)
- fine texture–low AWDR–high CHU (two studies)
- fine texture–high AWDR–low CHU (seven studies)
- fine texture–high AWDR–high CHU (one 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. The 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. For fine texture–high AWDR, however, high CHU gave a lower RR than low CHU for N rates >80 kg ha^{-1}. This was probably due to the very high RR of Studies 38 and 39 (Table 1; Fig. 6a and 6b) in the subgroup fine texture–high AWDR–low CHU compared with 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 the 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 to 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 that explained by soil properties did not exceed 16%.

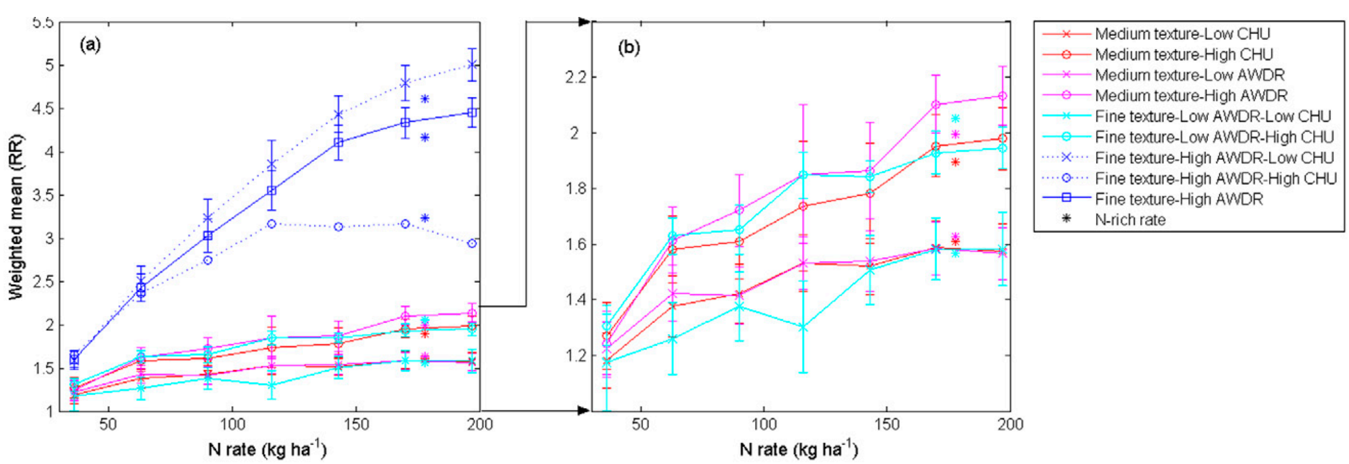

Fig. 10. Weighted averages of the response ratio (RR) for retained subgroups: (a) all retained subgroups, and (b) details in the zone showing lower RR subgroups. Error bars represent standard errors in each subgroup and N rate (N rate = starter + in-season N rate or 178 kg ha^{-1} applied at sowing with no N fertilizer at sidedressing [N-rich rate]).

Summary of Corn Response in Homogeneous Subgroups

In the medium-textured soil group, both weather parameters (CHU and AWDR) were helpful for forming subgroups of N response. In the case of the fine-texture soil class, it was more effective to use low 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 RR 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 the fine texture–low AWDR subgroup showed similar levels to those for the medium texture group. In such circumstances, the N response behavior of the fine soil textures was similar to that of medium textures in the same CHU class.

The fine texture group showed a high RR (3–4.5) when AWDR was high and the N rate $\geq$116 kg N ha^{-1} (starter 36 + ISNR 80 kg ha^{-1}) (Fig. 10a). Our data suggest that CHU classes have an inverse effect (high CHU gives a lower RR than low CHU) for the subgroup fine texture–high AWDR, which contained only one 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 the N response to a large extent. Responses to added N were more pronounced for fine texture groups (clay, silty clay, silty clay loam, and clay loam) than for medium texture groups (loam, silt loam, sandy loam, sandy clay loam, and 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, probably 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 d before SD to 15 d 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 d before SD to 30 d 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 a higher N response. If high rainfall occurs after SD, it mostly results in higher yields (no drought stress) and therefore greater N response as well (Fox and Piekielek, 1998). The greater influence of rainfall patterns following fertilizer N application shows the interest in reliable precipitation forecasts for the prediction of crop N demand. Anwar et al. (2009) expressed the same concern in relation to barley (*Hordeum vulgare* L.) to predict seasons when 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 the N response as water received as rainfall.

High CHU tended to enhance the corn response 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 (Ontario Ministry of Agriculture, Food, and Rural Affairs, 2012) suggest a heat unit adjustment because corn in the long-season areas of the province requires more N than in 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 throughout the season. The AWDR was a powerful integrated descriptor of precipitation amount and spread with time. High N rates increased yield by a factor of 2.6 under high AWDR compared with 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 a 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 with drier years. This difference was attributed to the decrease in residual soil NO_3–N with 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 the RR. 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. Nitrogen applications may increase corn yield in a 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 the spatial variability of the 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), the N response was greater in finer textured soils in years with wet springs. Dharmakeerthi et al. (2006) reported that corn N uptake differed at the landscape scale; the magnitude of the difference was greater in seasons with abundant rainfall. The interaction between soil texture and rainfall is probably related to the drainage capacity of the 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 with 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 the soil water content decreases.

It is noteworthy that the application of all N 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), the highest precision in N management may be achieved through in-season N applications that are based on information on late-spring precipitation patterns. This allows the N losses (leaching or denitrification) occurring due to possible excessive rainfall (Kay et al., 2006) to be taken into account. It is worth mentioning that there was generally no influence of growth stage (V4 or V8) on the effectiveness of the application of N fertilizer (Ohio Studies 14 vs. 15, 16 vs. 17, 18 vs. 19, 20 vs. 21, 22 vs. 23, 24 vs. 25, 26 vs. 27, 28 vs. 29, 41 vs. 42, and 43 vs. 44 [Table 1; Fig. 6a and 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. The 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, NO_3 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 were based on yield improvement and do not take environmental risks into account. It is generally recognized, however, 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 at sites with soils containing >30% clay. Under conditions of high temperatures during the period from 30 d before to 10 d after sidedressing time, the differences should be greater, particularly for fine-textured soils when seasonal rainfall is abundant and well distributed with 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 and field levels. The quantitative information can be easily summarized in an aided decision support 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 researchers 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 weather conditions. Soil and weather properties were found to have a fairly pronounced effect on the corn response to N fertilization. Under certain soil and 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 d after N sidedressing. In the meantime, decisions may be based mainly on historical weather information.

ACKNOWLEDGMENTS

We would like to thank Professor Léon-Étienne Parent of Laval University, Quebec, Canada, for his guidance in the use of meta-analysis and for his critical review of this manuscript. We are also grateful to Dr. Martin Bolinder for reviewing the manuscript and to P. Vigneault for his help.

REFERENCES

Anwar, M.R., G.J. O'Leary, M.A. Rab, P.D. Fisher, and R.D. Armstrong. 2009. Advances in precision agriculture in south-eastern Australia: V. Effect of seasonal conditions on wheat and barley yield response to applied nitrogen across management zones. Crop Pasture Sci. 60:901–911. doi:10.1071/CP08351

Armstrong, R.D., J. Fitzpatrick, M.A. Rab, M. Abuzar, P.D. Fisher, and G.J. O'Leary. 2009. Advances in precision agriculture in south-eastern Australia: III. Interactions between soil properties and water use help explain spatial variability of crop production in the Victorian Mallee. Crop Pasture Sci. 60:870–884. doi:10.1071/CP08349

Bolinder, M.A., O. Andrén, T. Kätterer, R. de Jong, A.J. VandenBygaart, D.A. Angers, et al. 2007. Soil carbon dynamics in Canadian agricultural ecoregions: Quantifying climatic influence on soil biological activity. Agric. Ecosyst. Environ. 122:461–470. doi:10.1016/j.agee.2007.03.001

Borenstein, M., L.V. Hedges, J.P.T. Higgins, and H.R. Rothstein. 2009. Introduction to meta-analysis. John Wiley & Sons, New York.

Bootsma, A., S. Gameda, and D.W. McKenney. 2005. Potential impacts of climate change on corn, soybeans and barley yields in Atlantic Canada. Can. J. Soil Sci. 85:345–357. doi:10.4141/S04-025

Bouroubi, M.Y., N. Tremblay, P. Vigneault, C. Bélec, B. Panneton, and S. Guillaume. 2011. Fuzzy logic approach for spatially variable nitrogen fertilization of corn based on soil, crop and precipitation information. Lect. Notes Comput. Sci. 6782/2011:356–368.

Bronikowski, A., and C. Webb. 1996. A critical examination of rainfall variability measures used in behavioral ecology studies. Behav. Ecol. Sociobiol. 39:27–30. doi:10.1007/s002650050263

Cambouris, A.N., B.J. Zebarth, M.C. Nolin, and M.R. Laverdière. 2008. Apparent fertilizer nitrogen recovery and residual soil nitrate under continuous potato cropping: Effect of N fertilization rate and timing. Can. J. Soil Sci. 88:813–825. doi:10.4141/CJSS07107

Chang, J., D.E. Clay, C.G. Carlson, S.A. Clay, D.D. Malo, R. Berg, et al. 2003. Different techniques to identify management zones impact nitrogen and phosphorus sampling variability. Agron. J. 95:1550–1559. doi:10.2134/agronj2003.1550

Chivenge, P., B. Vanlauwe, and J. Six. 2011. Does the combined application of organic and mineral nutrient sources influence maize productivity? Plant Soil 342:1–30. doi:10.1007/s11104-010-0626-5

Derby, N.E., D.D. Steele, J. Terpstra, R.E. Knighton, and F.X.M. Casey. 2005. Interactions of nitrogen, weather, soil and irrigation on corn yield. Agron. J. 97:1342–1351. doi:10.2134/agronj2005.0051

Dharmakeerthi, R.S., B.D. Kay, and E.G. Beauchamp. 2006. Spatial variability of in-season nitrogen uptake by corn across a variable landscape as affected by management. Agron. J. 98:255–264. doi:10.2134/agronj2005.0028

Fox, R.H., and W.P. Piekielek. 1998. Long-term nitrogen fertilization of continuous manured and non-manured corn and corn in a 3-year alfalfa, 3-year corn rotation. Agron. Ser. 141. Agron. Dep., Penn. State Univ., University Park, PA.

Franzen, D.W. 2004. Delineating nitrogen management zones in a sugarbeet rotation using remote sensing: A review. J. Sugar Beet Res. 41:47–60. doi:10.5274/jsbr.41.1.47

Haberle, J., P. Svoboda, and I. Raimanova. 2008. The effect of postanthesis water supply on grain nitrogen concentration and grain nitrogen yield of winter wheat. Plant Soil Environ. 54:304–312.

James, I.T., and R.J. Godwin. 2003. Soil, water and yield relationships in developing strategies for the precision application of nitrogen fertilizer to winter barley. Biosyst. Eng. 84:467–480. doi:10.1016/S1537-5110(02)00284-2

Jemison, J.M., and R.H. Fox. 1994. Nitrate leaching from nitrogen-fertilized and manured corn measured with zero-tension pan lysimeters. J. Environ. Qual. 23:337–343. doi:10.2134/jeq1994.00472425002300020018x

Kay, B.D., A.A. Mahboubi, E.G. Beauchamps, and R.S. Dharmakeerthi. 2006. Integrating soil and weather data to describe variability in plant available nitrogen. Soil Sci. Soc. Am. J. 70:1210–1221. doi:10.2136/sssaj2005.0039

Khosla, R., K. Fleming, J.A. Delgado, T.M. Shaver, and D.G. Westfall. 2002. Use of site-specific management zones to improve nitrogen management for precision agriculture. J. Soil Water Conserv. 57:513–518.

Kitchen, N.R., K.W.T. Goulding, and J.F. Shanahan. 2008. Proven practices and innovative technologies for on-farm crop nitrogen management. In: J.L. Hatfield and R.F. Follett, editors, Nitrogen in the environment. Elsevier Science Publ., Amsterdam. p. 483–517.

Kravchenko, A.N., G.P. Robertson, K.D. Thelen, and R.R. Harwood. 2005. Management, topographical, and weather effects on spatial variability of crop grain yields. Agron. J. 97:514–523. doi:10.2134/agronj2005.0514

Kyveryga, P.M., A.M. Blackmer, and F. Morris. 2007. Alternative benchmarks for economically optimum rates of nitrogen fertilization for corn. Agron. J. 99:1057–1065. doi:10.2134/agronj2006.0340

Kyveryga, P.M., A.M. Blackmer, and J. Zhang. 2009. Characterizing and classifying variability in corn yield response to nitrogen fertilization on subfield and field scales. Agron. J. 101:269–277. doi:10.2134/agronj2008.0168

Lokupitiya, E., K. Paustian, M. Easter, S. Williams, O. Andrén, and T. Kätterer. 2010. Carbon balances in US croplands during the last two decades of the twentieth century. Biogeochemistry 107:207–225. doi:10.1007/s10533-010-9546-y

Melkonian, J., H.M. van Es, A.T. DeGaetano, J.M. Sogbedji, and L. Joseph. 2007. Application of dynamic simulation modeling for nitrogen management in maize. In: T.W. Bruulsema, editor, Managing Crop Nitrogen for Weather: Proceedings of the Symposium "Integrating Weather Variability into Nitrogen Recommendations," Indianapolis, IN. 15 Nov. 2006. Int. Plant Nutr. Inst., Norcross, GA. p. 14–22.

Naud, C., D. Makowski, and M.H. Jeuffroy. 2008. Is it useful to combine measurements taken during the growing season with a dynamic model to predict the nitrogen status of winter wheat? Eur. J. Agron. 28:291–300. doi:10.1016/j.eja.2007.08.005

Olfs, H.W., K. Blankenau, F. Brentrup, J. Jasper, A. Link, and J. Lammel. 2005. Soil- and plant-based nitrogen-fertilizer recommendations in arable farming. J. Plant Nutr. Soil Sci. 168:414–431. doi:10.1002/jpln.200520526

Olkin, I., and D.V. Shaw. 1995. Meta-analysis and its applications in horticultural science. HortScience 30:1343–1348.

Ontario Ministry of Agriculture, Food, and Rural Affairs. 2012. New OMAFRA general recommended nitrogen rates for corn: The Ontario corn N worksheet. Explanation of worksheet factors. OMAFRA, Guelph, ON, Canada. http://www.omafra.gov.on.ca/english/crops/facts/nitrorates-corn.htm (accessed 16 Aug. 2012).

Otsu, N. 1979. A threshold selection method from gray-level histograms. IEEE Trans. Syst. Man Cybern. 9:62–66. doi:10.1109/TSMC.1979.4310076

Ping, J.L., R.B. Ferguson, and A. Dobermann. 2008. Site-specific nitrogen and plant density management in irrigated maize. Agron. J. 100:1193–1204. doi:10.2134/agronj2007.0174

Raun, W.R., J.B. Solie, M.L. Stone, K.L. Martin, K.W. Freeman, R.W. Mullen, et al. 2005. Optical sensor-based algorithm for crop nitrogen fertilization. Commun. Soil Sci. Plant Anal. 36:2759–2781. doi:10.1080/00103620500303988

Ros, G.H., M.C. Hanegraaf, E. Hoffland, and W.H. van Riemsdijk. 2011. Predicting soil N mineralization: Relevance of organic matter fractions and soil properties. Soil Biol. Biochem. 43:1714–1722. doi:10.1016/j.soilbio.2011.04.017

Schröder, J.J., J.J. Neeteson, O. Oenema, and P.C. Stuik. 2000. Does the crop or soil indicate how to save nitrogen in maize production? Reviewing the state of the art. Field Crops Res. 66:151–164. doi:10.1016/S0378-4290(00)00072-1

Shahandeh, H., A.L. Wright, and F.M. Hons. 2011. Use of soil nitrogen parameters and texture for spatially-variable nitrogen fertilization. Precis. Agric. 12:146–163. doi:10.1007/s11119-010-9163-8

Shanahan, J.F., N.R. Kitchen, W.R. Raun, and J.S. Schepers. 2008. Responsive in-season nitrogen management for cereals. Comput. Electron. Agric. 61:51–62. doi:10.1016/j.compag.2007.06.006

Sogbedji, J.M., H.M. van Es, S.D. Klausner, D.R. Bouldin, and W.J. Cox. 2001. Spatial and temporal processes affecting nitrogen availability at the landscape scale. Soil Tillage Res. 58:233–244. doi:10.1016/S0167-1987(00)00171-9

Taylor, J.C., G.A. Wood, R. Earl, and R.J. Godwin. 2003. Soil factors and their influence on within-field crop variability: II. Spatial analysis and determination of management zones. Biosyst. Eng. 84:441–453. doi:10.1016/S1537-5110(03)00005-9

Tonitto, C., M.B. David, and L.E. Drinkwater. 2006. Replacing bare fallows with cover crops in fertilizer-intensive cropping systems: A meta-analysis of crop yield and N dynamics. Agric. Ecosyst. Environ. 112:58–72. doi:10.1016/j.agee.2005.07.003

Tremblay, N. 2004. Determining nitrogen requirements from crops characteristics: Benefits and challenges. Recent Res. Dev. Agron. Hortic. 1:157–182.

Tremblay, N., and C. Bélec. 2006. Adapting nitrogen fertilization to unpredictable seasonal conditions with the least impact on the environment. HortTechnology 16:408–412.

Tremblay, N., M.Y. Bouroubi, B. Panneton, S. Guillaume, and P. Vigneault. 2010. Development and validation of a fuzzy logic estimation of optimum N rate for corn based on soil and crop features. Precis. Agric. 11:621–635. doi:10.1007/s11119-010-9188-z

Tremblay, N., M.Y. Bouroubi, P. Vigneault, and C. Bélec. 2011. Guidelines for in-season nitrogen application for maize (*Zea mays* L.) based on soil and terrain properties. Field Crops Res. 122:273–283. doi:10.1016/j.fcr.2011.04.008

Valkama, E., R. Uusitalo, K. Ylivainio, P. Virkajarvi, and E. Turtola. 2009. Phosphorus fertilization: A meta-analysis of 80 years of research in Finland. Agric. Ecosyst. Environ. 130:75–85. doi:10.1016/j.agee.2008.12.004

van Es, H.M., B.D. Kay, J.J. Melkonian, and J.M. Sogbedji. 2007. Nitrogen management for maize in humid regions: Case for a dynamic modeling approach. In: T.W. Bruulsema, editor, Managing Crop Nitrogen for Weather: Proceedings of the Symposium "Integrating Weather Variability into Nitrogen Recommendations," Indianapolis, IN. 15 Nov. 2006. Int. Plant Nutr. Inst., Norcross, GA. p. 6–13.

van Es, H.M., C.L. Yang, and L.D. Geohring. 2005. Maize nitrogen response as affected by soil type and drainage variability. Precis. Agric. 6:281–295. doi:10.1007/s11119-005-1387-7

Wang, D., T. Prato, Z. Qiu, N.R. Kitchen, and A. Sudduth. 2003. Economic and environmental evaluation of variable rate nitrogen and lime application for claypan soil fields. Precis. Agric. 4:35–52. doi:10.1023/A:1021858921307

Xia, J., and S. Wan. 2008. Global response pattern of terrestrial plant species to nitrogen addition. New Phytol. 179:428–439. doi:10.1111/j.1469-8137.2008.02488.x

Zhu, Q., J.P. Schmidt, H.S. Lin, and R.P. Sripada. 2009. Hydropedological processes and their implications for nitrogen availability to corn. Geoderma 154:111–122. doi:10.1016/j.geoderma.2009.10.004