

Predicting Risk from Reducing Nitrogen Fertilization Using Hierarchical Models and On-Farm Data

P. M. Kyveryga,* P. C. Caragea, M. S. Kaiser, and T. M. Blackmer

ABSTRACT

Current systems for developing N recommendations for corn (*Zea mays* L.) lack methods to quantify the effects of factors influencing yield responses to N and quantify the uncertainty in N recommendations. We utilized hierarchical modeling and Bayesian analysis to quantify the risk from reducing N to corn using on-farm observations. Across Iowa, farmers conducted 34 trials in 2006 and 22 trials in 2007. Each trial had a farmer's normal N rate alternating with a reduced rate (by about 30% less) in three or more replications. Yield losses (YLS) from reduced N were calculated at 35-m intervals. Posterior distributions were used to identify across-field and within-field factors affecting YL and to quantify the risk of economic YL ($>0.31 \text{ Mg ha}^{-1}$) from reducing N in unobserved fields. In 2006 (dry May and June), the economic YL for corn after soybean (C-S) was predicted to be 20% larger than that for corn after corn. Also in 2006, C-S fields with above-normal June rainfall had economic YLS 35% larger than those with below-normal June rainfall, and sidedress applications were about 20% riskier than spring applications. In 2007 for C-S, N reductions with above-normal spring rainfall were riskier than with below-normal spring rainfall. Areas with higher soil organic matter (SOM) had economic YLS about 20% smaller than those with lower SOM. Many on-farm trials can be conducted across the state and the use of the proposed statistical methodology can improve decisions on where to reduce N applications across and within fields.

NITROGEN MANAGEMENT OF corn under rainfed conditions in the U.S. Midwest has been studied extensively during the last 50 yr but has become a subject of intensive scientific and public debate only during the last two decades. The recent focus on N management is attributed to environmental concerns about pollution of water bodies by NO_3 escaping from corn fields, emission of greenhouse gases (i.e., N_2O) to the atmosphere, and the large amount of petroleum-based energy required to produce, transport, and apply N.

Historically, N fertilizer recommendations for corn have been based on a simplified empirical formula called the *yield goal* (Hoeft et al., 2000; Stanford, 1973). The major premise of yield goal recommendations is that corn N requirements or optimal N rates are proportional to corn yields, with a constant multiplier of $21.4 \text{ kg N Mg}^{-1}$ corn grain. These calculations were based on the assumption of a constant supply of N from the soil under a wide range of soil and weather conditions. While the yield goal recommendations were based on a mass balance approach (N rates should approximate N removed by grain plus adjustments for N losses and N supplied by the soil),

several studies have shown a low correlation of corn yields and optimal N rates (Scharf et al., 2006; Vanotti and Bundy, 1994). The low correlation is often attributed to large variability in the N supply from the soil and variable N losses by different mechanisms such as leaching, volatilization, or denitrification.

Another method for estimating N fertilizer needs for corn was developed in the late 1950s based on conducting the so-called yield response trials. This method considered applying a wide range of N rates in small-size plots, measuring the yield at each applied N rate, and fitting a model (i.e., fitting regression curves) to the yield values to calculate the rates at which the marginal increase in grain value would equal the marginal N fertilizer cost (Heady et al., 1955, p. 292–332; Voss, 1975). This calculation produced economically optimum N rates (EONR) that would maximize, after the fact, the return to N per unit of area. Unlike the yield goal approach, the economic optimization method indirectly considered the variability in N supplied from the soil and fluctuations in the prices of N fertilizer and corn with time. Except when calibrating soil and plant tissue tests in soil fertility studies, the EONR method has seldom been used as the basis for N fertilizer recommendations in production agriculture.

Recently, combined efforts involving several land grant universities led to the creation of a multistate database of yield response trials to estimate the EONR for corn (Sawyer et al., 2006). These data enable researchers to partially address large spatial and temporal variability in the EONR as well as fluctuations in the prices of N fertilizer and corn grain. At least two issues remain to be resolved, however. Nitrogen yield

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Published in *Agron. J.* 105:85–94 (2013)
doi:10.2134/agronj2012.0218

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Abbreviations: C-C, corn after corn; C-S, corn after soybean; GPS, global positioning system; SOM, soil organic matter; YL, yield loss.

response studies on farmers' fields require close supervision by researchers to control all potential sources of variation. The decision support system for making N recommendations from the EONR is often based on a single value or a range of values that fit a wide range of weather and management conditions.

The inefficacy of the choices when using the EONR stems from using inappropriate models (response curves) fitted to corn yield data and from the fact that these response curves are usually relatively flat in the near-optimum range of fertilization (Cerrato and Blackmer, 1990). The uncertainty in estimated model parameters can be partially addressed by calculating confidence intervals for the EONR for individual trials (Bachmaier and Gandorfer, 2009; Hernandez and Mulla, 2008; Jaynes, 2011) or by estimating additional benchmarks for the EONR when pooling data from many trials (Kyveryga et al., 2007; Sawyer et al., 2006). The challenge, however, consists in determining how to use a given EONR value (or range of values) to make reliable predictions of corn N needs for another field, another farm, or the next growing season. The need for developing a reliable decision-making process when using EONRs under uncertainty has been discussed (Barreto and Bell, 1995; Bullock and Bullock, 2000) but such systems have not been developed and implemented as N fertilizer recommendations.

There are several challenges for developing reliable N fertilizer recommendations. One of them is the scale at which individual observations are measured and individual EONR values are calculated. Often, agronomists are not sure whether to use average yields across many fields and several years to calculate the EONR, or whether to use data measured only for individual trials, or whether to include or exclude information from nonresponsive trials in the analysis (Bullock and Bullock, 1994; Kim et al., 2008). While agronomists believe that EONRs are affected by the amount of rainfall during a growing season, mineralization of soil organic matter, and the timing and method of N fertilizer application, quantifying these effects and incorporating them into N fertilizer recommendations have been difficult.

The wide array of problems faced by agronomists when developing N recommendations for field ecosystems is not unique. The same problems are commonly found when studying other complex biological systems (e.g., water bodies or forests), which are also characterized by extremely large variability and uncertainty observed at different spatial and temporal scales and at different levels of management decision-making. One recently proposed solution for dealing with large uncertainty is to use hierarchical modeling (Cressie et al., 2009; Gelman et al., 2004; Gelman and Hill, 2007). Hierarchical analysis can be used to address multiple sources of variability present at different scales or levels. In hierarchical modeling, the observed data are modeled conditionally on model parameters that are themselves represented by a probability model. Although not unique to hierarchical modeling, the analysis is also suited to make probabilistic predictions for unobserved locations or future events (Gelman and Hill, 2007; Nyberg et al., 2006). In Bayesian analysis, prior distributions are assigned to parameters to represent knowledge or belief about the parameters before collecting observations. The observed data are then used to update

that knowledge in the form of a posterior distribution for the parameters. Inferences in hierarchical modeling consist of probability statements about the posterior and can be expanded for future unobserved situations. This can be useful to improve the current N fertilizer recommendation systems, which do not quantify uncertainties in both the observed data and future predictions or recommendations. Although much development must still be done, hierarchical modeling and Bayesian methodology for developing decision support systems for making optimal fertilizer decisions have received some attention in the literature (Theobald and Talbot, 2002; Wallach, 1995)

With the surge in adoption of precision agriculture technologies (global positioning systems [GPS], yield monitoring, and remote sensing), farmers can conduct yield response trials on their own fields and collect site-specific data that may help develop decision support systems to improve their N management at a relatively low cost (Blackmer and Kyveryga, 2010). The wider use of results from on-farm trials, however, is hindered by the lack of suitable methods for data analysis. For example, on-farm trials are often conducted without following commonly used controlled experimental designs such as randomized block design or split-plot design (Piepho et al., 2011), and farmers are solely responsible for all steps in executing the trials and collecting the data. In addition, farmers prefer to study research questions that are more relevant to their site-specific soil, weather, and management conditions. One common question is when and where normal N fertilizer rates for corn can be reduced without the risk of reduced yields and returns to N.

The objective of this study was to quantify the risk of economic YL from reducing farmers' normal N fertilizer rates applied to corn by about one-third. The data were collected using two-treatment, on-farm evaluation trials conducted across Iowa. The analyses used hierarchical modeling and Bayesian analysis to identify among- and within-field level factors that affected the probability of economic YL from reduced N fertilizer.

MATERIALS AND METHODS

Field Methodology and Data Processing

Data were collected from 34 on-farm evaluation trials conducted in production corn fields across Iowa in 2006 and 22 trials in 2007 (Fig. 1). Each trial alternated a normal N fertilizer rate (used by an individual farmer) and a reduced N rate, which was 56 kg N ha⁻¹ or one-third less than the normal N rate (Fig. 2A). The treatments were applied in strips that went the full length of each field. The summary statistics for normal N fertilizer rates for two categories based on the previous crop are shown in Table 1. The treatments were replicated three to eight times within each field, covering from 5 to 15 ha within 25- to 35-ha corn fields. The farmers used their own fertilizer application equipment to apply the strips and GPS to record the strip locations in more than half of the trials. In the rest of the trials, the strips were identified using the farmers' personal records or flags left during the fertilizer applications. The farmers harvested the strips with grain combines equipped with GPS and yield monitors that recorded yield observations every 1 s. The N fertilizer form (anhydrous

NH₃ or urea-NH₄NO₃ solution) and timing of N application (fall, spring, or sidedress) were consistent within each trial but varied from one trial to another, depending on the specific management practice used by each farmer.

The two N fertilizer treatments were not randomized within each pair of N rates (Fig. 2A). The data collection mechanism used was designed to simplify treatment applications by farmers to ensure that the position of the strips could be easily identified after the N applications and to calculate yield differences between the two rates in the same way for each trial. In general, a combination of randomization and blocking is used in agricultural field experiments to help mitigate spatial effects due to soil fertility or trends arising from soil tillage, application of chemicals, or other field operations. Accounting for such effects can be important, particularly for experiments conducted on small plots in one or only a few fields. In this study, farmers across the state used different management practices with different traffic patterns and different normal N fertilizer rates. Our objective was to evaluate the practical risk of yield loss that might be expected by a reduction of the N rates that farmers would typically use under varying environmental and management conditions across an entire state. Many factors cannot be controlled in such a production setting. A basic assumption in our analysis was that a sufficiently large and diverse collection of fields was obtained to reflect the variability in such factors in a manner representative of what exists across the region of interest. The best justification for this assumption would be if the fields used in our study were obtained as a random sample from all fields in the state. This was not possible, so the assumption that the fields used in our analysis are representative of fields in the state remains a primitive assumption.

After the harvest, corn yield data were processed using Ag Leader SMS 7.0 to 8.5 software (Ag Leader Technologies) or JD Office software (John Deere). Yield observations located <50 m from the beginning and the end of each strip were removed because of potential soil compaction problems and non-constant grain flow through a combine yield monitor when harvesting the fertilized strips. Additional observations (flooded areas, areas with fertilizer skips, and other application errors) were also removed based on the late-season digital aerial

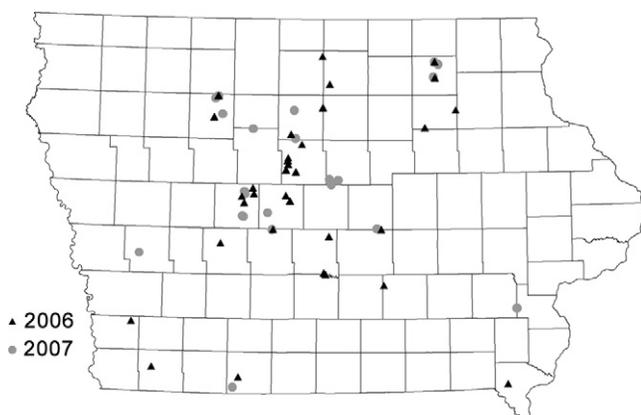


Fig. 1. Locations of 34 on-farm evaluation trials across Iowa in 2006 and 22 trials in 2007 comparing normal and reduced (by about one-third from normal) N fertilizer rates applied to corn by participating farmers.

Table 1. Summary statistics for normal N fertilizer rates applied by farmers to corn after corn (C-C) and corn after soybean (C-S) in on-farm evaluation trials comparing normal and reduced N applications in 2006 and 2007. Seven trials were planted to C-C in 2006 and eight trials in 2007; 27 trials were planted to C-S in 2006 and 14 trials in 2007. Nitrogen rates included all total N applied during the growing season. According to Iowa State University Extension, the average statewide N rate for maximizing return to N for C-C is about 210 kg N ha⁻¹ and 150 kg N ha⁻¹ for C-S.

Statistics	2006		2007	
	C-C	C-S	C-C	C-S
Mean	192	162	190	160
SD	13	18	22	17
Min.	168	140	168	134
Max.	207	202	224	202

imagery of the corn canopy and observed variation in grain moisture and combine speed. Individual yield observations were aggregated in 35-m quadrants (Fig. 2B), and YLs from reduced N fertilizer were calculated as differences between yields at the normal and reduced N rates in each quadrant. Each trial had from 30 to 200 YL observations. Yield loss values that were two standard deviations above and below the mean YL for each trial were considered as outliers (about 3% of the total number of observations) and were also not used in the analysis.

Digital soil maps for the trials were downloaded from the Iowa Cooperative Soil Survey (<http://icss.agron.iastate.edu/>). Soil characteristics such as soil drainage class, SOM level, and slope were also aggregated in 35-m quadrants similar to the yield observations. Monthly 4-km-grid rainfall data were obtained from the Iowa Environmental Mesonet (<http://mesonet.agron.iastate.edu/rainfall/>). Each trial was assigned

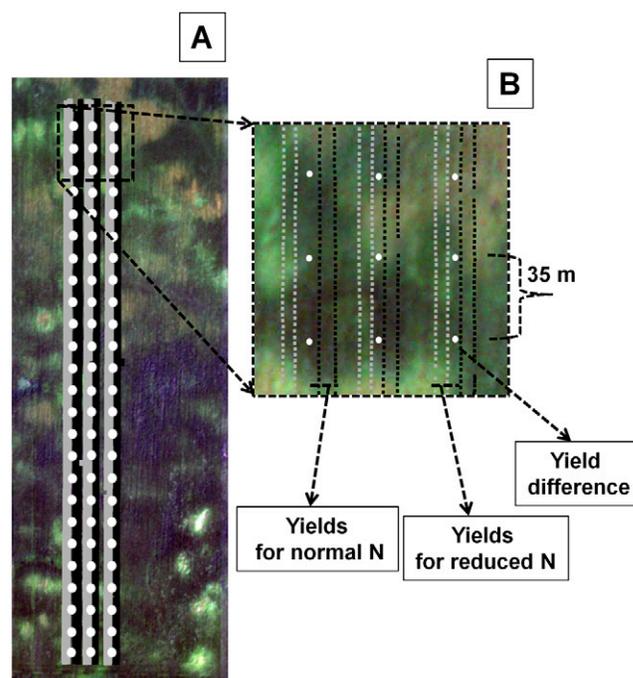


Fig. 2. (A) Schematic on digital color aerial imagery of a 30-ha corn field with yield strips harvested for normal and reduced N fertilizer rates and (B) locations of yield loss observations due to reduced N calculated as differences between yields at the normal and reduced N rates at 35-m intervals along the strips.

a rainfall value from the nearest grid using the spatial join function of a geographic information system software.

A YL of 0.31 Mg ha⁻¹, which covers the cost of 56 kg N at a N price of US\$1.10 kg⁻¹ and a grain price of US\$200 Mg⁻¹, was used as an economic threshold; YL values >0.31 Mg ha⁻¹ were considered an economic YL due to reduced N applications.

Hierarchical Models and Bayesian Statistical Analysis

A specific interest in this study was estimation of the potential effects of different covariates (factors) on the magnitude of any YL and the risk of an economic YL from reduced N applications. Because YL observations and some of the other covariates were observed at different scales (across-field or within-field levels), we used hierarchical statistical analysis. Hierarchical statistical models incorporate multiple sources of variability and different scales (Cressie et al., 2009; Gelman et al., 2004; Gelman and Hill, 2007; McMahan and Diez, 2007).

A schematic illustration of a hierarchical model for estimating the effect of site-specific variables on corn YL due to reduced N applications is shown in Fig. 3. The model is comprised of three levels: data, field-level, and regional-level process models. The data model takes the distribution of YL values (YL_{*nj*}) within a trial (where *n* = 1, ..., *N*) for an individual grid cell (where *j* = 1, ..., *M*) to be normally distributed with a mean μ_{*n*} and a precision λ_{*n*} unique for that trial. The precision parameter is defined as the reciprocal of the variance: the higher the precision, the lower the variation. Mathematically, it is easier to work with the precision parameter, but interpretation is often easier using the variance parameter. We, therefore, used the precision for modeling but interpreted the results based on its inverse, i.e., the variance. We assume that the distribution of YL_{*nj*}, given μ_{*n*} and λ_{*n*}, is

$$[YL_{nj} | \mu_n, \lambda_n] \sim N(\mu_n, \lambda_n^{-1}) \quad [1]$$

and we refer to this as the data model.

The trial means, μ_{*n*}, are assumed to follow a normal distribution with the regional mean μ₀ and regional precision λ₀. The distribution of μ_{*n*}, given μ₀ and λ₀, is assumed to follow

$$[\mu_n | \mu_0, \lambda_0] \sim N(\mu_0, \lambda_0^{-1}) \quad [2]$$

and the μ_{*n*} are assumed to be independent across trials.

The trial precision parameters λ_{*n*} are assumed to follow a γ distribution with parameters α and β. The distribution of λ_{*n*}, given α and β, is

$$[\lambda_n | \alpha, \beta] \sim \gamma(\alpha, \beta) \quad [3]$$

We refer to Eq. [2] and [3] as the field-level model, where the λ_{*n*} are assumed to be independent across trials. Note that the independence among YL values within fields is conditional on values of the field mean and precision, while these variables are in turn assumed to be marginally independent across fields. The result is that in the joint marginal distribution of all YL

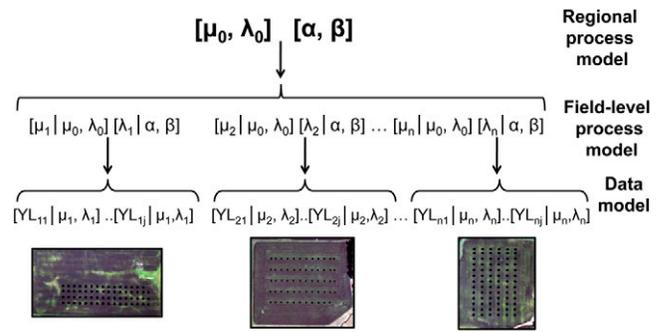


Fig. 3. Schematic of a hierarchical model for estimating the effect of field and within-field level factors on yield loss of corn from reduced N fertilizer applications. The model comprises three levels: data, field-level processes, and regional processes; YL_{*nj*} is yield loss in field *n* and grid *j*, mean μ_{*n*} and precision λ_{*n*} are field-level parameters, and μ₀, λ₀, and parameters α and β control the regional process.

values, or likelihood values, within fields are correlated while values from different fields are not correlated.

The parameters μ_{*n*} and λ_{*n*} govern the distribution of YL within a trial. The “regional” parameters μ₀ and λ₀ govern the probabilities with which various mean differences in YL are realized among fields, with μ₀ representing the mean YL across fields and a ratio of α/β representing the average within-field precision.

In a Bayesian analysis, prior distributions are assigned to parameters to represent belief or knowledge of the possible values of those parameters before observations are available. Observed data are then used to update this knowledge in the form of a posterior distribution for the parameters. Inferences consist of probability statements about the parameter values made on the basis of the posterior.

We used a normal prior for the regional mean μ₀, and γ priors for each of λ₀, α, and β. These priors are mathematically convenient and accurately reflect the necessary parameter space. All prior distributions were taken to be “diffuse,” meaning that these priors were given large variances so that they had little influence on the analysis relative to the observed data.

Posterior distributions were obtained using Markov-chain Monte Carlo simulation (Gelman et al., 2004), in particular a Gibbs sampling algorithm with 10,000 random draws from each posterior after a suitable burn-in period of about 100 iterations. The Gibbs sampling algorithm produces values simulated from joint posterior distributions. To determine the burn-in period for the Gibbs algorithm, multiple chains were run with different starting values for μ₀, λ₀, and α/β. Visual examination of trace plots as well as the scale reduction factor of Gelman and Rubin (1992) indicated that the chains mixed well after about 25 to 50 iterations. Autocorrelation plots showed that the effects of starting values wore off rapidly, by about 10 to 15 iterations. Model adequacy was checked by comparing the distribution of simulated field means (simulated from the posterior predictive distribution) to the empirical distribution of the average YL in fields. From posterior simulations, we obtained posterior distributions for the regional mean YL, μ₀, regional precision, λ₀, and regional within-field precision, α/β. The uncertainty in posterior expectations (means) for the parameters was quantified using

Table 2. Summary values for posterior distributions of fixed regional distribution parameters for different categories showing the effect of a year and previous crop on yield loss (YL) from reduced N applications in 2006 and 2007: μ_0 , regional mean YL; λ_0 , regional precision; α/β within-field average precision. Reciprocals of precision parameters, λ_0^{-1} and $(\alpha/\beta)^{-1}$, indicate variances.

Category†	2006			2007		
	μ_0	λ_0^{-1}	$(\alpha/\beta)^{-1}$	μ_0	λ_0^{-1}	$(\alpha/\beta)^{-1}$
	Mg ha ⁻¹	Mg ² ha ⁻²		Mg ha ⁻¹	Mg ² ha ⁻²	
All trials	0.36 (0.24, 0.48)‡	0.17 (0.12, 0.28)	0.12 (0.09, 0.15)	0.77 (0.57, 0.98)	0.30 (0.19, 0.56)	0.23 (0.18, 0.30)
C-C	0.26 (0.13, 0.39)	0.03 (0.01, 0.11)	0.07 (0.04, 0.14)	0.64 (0.41, 0.88)	0.12 (0.06, 0.40)	0.31 (0.21, 0.48)
C-S	0.39 (0.23, 0.53)	0.21 (0.14, 0.36)	0.12 (0.10, 0.17)	0.85 (0.55, 1.16)	0.36 (0.23, 0.91)	0.19 (0.13, 0.28)

† In 2006, seven trials were corn after corn (C-C) and 27 trials were corn after soybean (C-S). In 2007, eight trials were C-C and 14 trials were C-S.

‡ 90% credible intervals are provided in parentheses.

90% credible intervals. The lower bound for these credible intervals was chosen as the 5% quantile of the posterior, and the upper bound as the 95% quantile.

Of particular interest was the estimation of the posterior predictive distributions, the distributions of field-level means μ_n for fields not actually observed but assumed to follow the same model as the observed fields. Posterior predictive distributions were produced using the Gibbs sampling algorithm. Plotting posterior predictive distributions as cumulative densities facilitated the estimation of the probability of economic YL for the average corn and N fertilizer prices reported by farmers during the 2 yr of the study.

A specific objective was to estimate the effects of field-level as well as within-field covariates on YL. For field-level covariates, we used total N rates applied to normal N treatments, average monthly rainfall, cumulative spring rainfall, and the timing and form of N application. For within-field covariates, we used soil information such as SOM level, slope, and drainage category from the digital soil survey map for each county. For simplicity, continuous covariates were classified into two categories: one representing the low and the other high values. The effect of within-field covariates was estimated by including the covariates marginally, by changing the definition of a field to a combination of the physical field and the level of the covariate.

All calculations and simulations were done using the statistical software R (R Development Core Team, 2009).

RESULTS AND DISCUSSION

Comparison of Yield Loss Due to Reduced Nitrogen Fertilizer in 2006 and 2007

Posterior distributions represent the updated knowledge about possible values of parameters after observing the data.

Posterior expected values for the regional mean (μ_0), reciprocals of the regional precision (λ_0^{-1}), within-field average regional precision $(\alpha/\beta)^{-1}$, and their corresponding 90% credible intervals are shown in Table 2. Using data from all trials, the posterior expected regional mean YL (μ_0) from reduced N fertilization was slightly above the economic threshold (0.31 Mg ha⁻¹) in 2006, but it was about twice as much as the same economic threshold in 2007. Assuming that the trials shown in Fig. 1 represent Iowa, the posterior regional means reflect the average expected YL across the state. With 90% belief, the regional posterior mean ranged from 0.24 to 0.48 Mg ha⁻¹ in 2006 and from 0.57 to 0.98 Mg ha⁻¹ in 2007. Because the two credible intervals for the posterior regional means did not overlap (Table 2), the average YL in 2007, a year

with slightly above-normal rainfall, was significantly larger than that in 2006, a year with below-normal rainfall (Fig. 4).

The reciprocal of the posterior regional precision (λ_0^{-1}) characterizes the variability in YL among the field-level means across the state. The reciprocals of the within-field average regional precision $(\alpha/\beta)^{-1}$ characterizes the average within-field variability. Both λ_0^{-1} and $(\alpha/\beta)^{-1}$ for the 2006 data were about half as large as those for the 2007 data, indicating larger across- and within-field variability in 2007 than in 2006 (Table 2). Although the two 90% credible intervals for the reciprocals of regional precisions (λ_0^{-1}) for the 2006 and 2007 data overlapped, it appeared that a larger amount of rainfall increased not only the average YL but also across- and within-field variability in 2007.

Both posterior regional and within-field average precision parameters indicated large variation in YL (Table 2). For example, the within-field posterior standard deviation for estimation using data from all trials [estimated as $(\alpha/\beta)^{-0.5}$], was 0.34 Mg ha⁻¹ in 2006 and 0.48 Mg ha⁻¹ in 2007. Therefore, the within-field standard deviation in 2006 was almost the same as the posterior regional mean of 0.36 Mg ha⁻¹ and the regional field standard deviation was about 15% higher than the posterior regional mean YL. Posterior standard deviations for among- and within-field variability in 2007 were about 35% smaller than the posterior regional mean of 0.77 Mg ha⁻¹. The relatively large observed within-field variability in both years is partially attributed to potential errors in yield monitor observations, errors in calculating yield differences, errors in fertilizer application, or differences in soil properties (e.g., soil drainage, SOM, or soil compaction) or other factors between two neighborhood grid cells. Additional

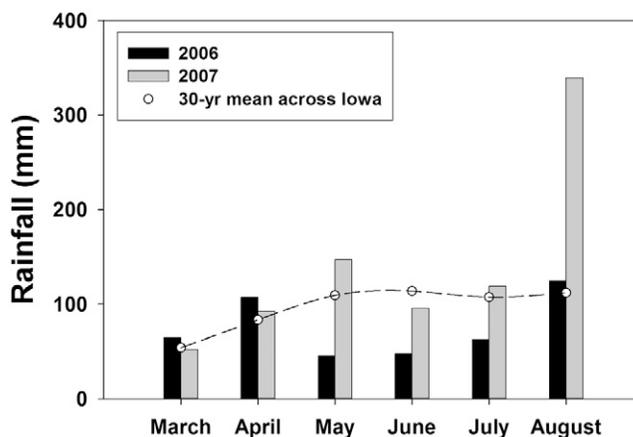


Fig. 4. Monthly average rainfall for 34 trial locations studied in 2006 and 22 trial locations studied in 2007.

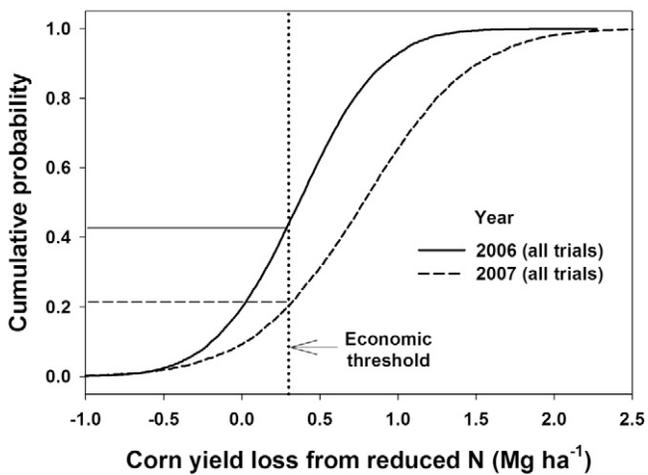


Fig. 5. Posterior predictive probabilities of yield loss from reduced N applications for unobserved field-level means for all trials conducted under conditions similar to 2006 and 2007. A yield loss of 0.31 Mg ha⁻¹ was considered as the economic threshold.

analyses showed that increasing the quadrant cell size (>35 m) slightly decreased within-field variability in YL (data not shown); however, this cell size also decreased the number of observations in each trial by about 10 to 15%, which would limit the ability to detect potential effects of within-field level factors on YL.

Posterior predictive distributions reflect our belief about parameter values in an unobserved situation that follows the same model. The distribution curves show the probability at which the predicted YL is equal to or less than a given value (Fig. 5). For example, for the 2006 data, the probability of having a YL of 0 Mg ha⁻¹ or less was about 20%. The predicted probability of an economic YL can be estimated as the distance (on the y axis) between 1 and the intersection of the economic threshold in YL (the dotted vertical line on the graph) with the probability curve. For example for the average corn and N fertilizer prices used in this study, the probability of an economic YL from reduced N applications across the state for all trials was about 0.55 for the 2006 data and about 0.80 for the 2007 data. We note that the posterior in 2007 is shifted to the right of the 2006 posterior curve, and the two probability curves do not intersect in the range of interest. This indicates the stochastic dominance of the 2006 curve over the 2007 curve and the higher risk from reducing N applications in 2007, which was a relatively wet year.

Effect of the Previous Crop on Yield Loss due to Reduced Nitrogen Fertilizer

Posterior regional mean (μ_0), regional variances (λ_0^{-1}), and within-trial average precision $(\alpha/\beta)^{-1}$ for corn after corn (C-C) and corn after soybean (C-S) categories in 2006 and 2007 are shown in Table 2. In 2006, the posterior regional mean YL for C-C was below the economic threshold (i.e., >0.31 Mg ha⁻¹) and slightly above the economic threshold for C-S. In 2007, the posterior mean YL for C-C and C-S was an economic YL, >0.31 Mg ha⁻¹. The 90% credible intervals for posterior means for C-C and C-S substantially overlapped in both years, indicating the uncertainty in estimated regional mean YL for the two categories; however, the 90% credible intervals for the

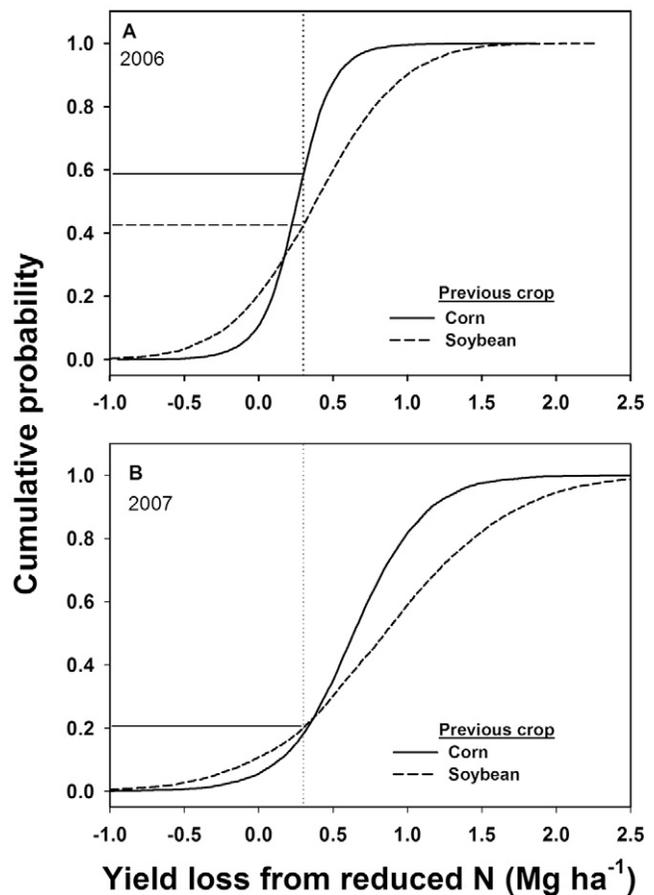


Fig. 6. Posterior predictive probabilities of yield loss from reduced N applications for unobserved field-level means for two categories based on the previous crop under conditions similar to those observed in (A) 2006 and (B) 2007. A yield loss of 0.31 Mg ha⁻¹ was considered as the economic threshold.

posterior mean YL for C-C in 2006 and 2007 and for C-S in 2006 and 2007 did not overlap. This suggests a significant temporal effect, mostly due to rainfall.

Predictions for unobserved field-level means for C-C and C-S under similar conditions observed in each year are shown by posterior predictive distributions in Fig. 6. For the 2006 data, the probability of an economic YL from reduced N for C-S was predicted about 20% higher than that for C-C (Fig. 6A). For the 2007 data, the probability of an economic YL in unobserved trials for C-C and C-S was almost the same, about 80%, strongly indicating widespread economic losses from reduced N applications in a year with above-normal rainfall. The distribution curves for both years indicate that if the cost of N fertilizer is increased by two- or threefold, the gap between the two curves will widen, making it less risky to reduce the N rate for C-C compared with C-S. The scenario with more expensive N is probably unlikely because in recent years N fertilizer prices have followed corn grain prices.

Because information about the previous crop is known before N fertilizer is applied, effects of other across- and within-field level factors on YL could also be important. These effects, however, cannot be identified for C-C for these data because only a relatively small number of trials was evaluated each year.

Table 3. Summary values for posterior distributions of fixed regional distribution parameters of different categories showing the effect of June rainfall and timing of fertilizer application on yield loss (YL) from reduced N applications for corn after soybean (C-S) in 2006: μ_0 , regional mean YL; λ_0 , regional precision; α/β within-field average precision. Reciprocals of precision parameters, λ_0^{-1} and $(\alpha/\beta)^{-1}$, indicate variances.

Parameter	μ_0	λ_0^{-1}	$(\alpha/\beta)^{-1}$
	Mg ha ⁻¹	Mg ² ha ⁻²	
June rainfall, mm†			
<76	0.27 (0.13, 0.41)‡	0.14 (0.09, 0.25)	0.15 (0.11, 0.20)
>76	0.76 (0.31, 1.22)	0.31 (0.14, 1.14)	0.08 (0.04, 0.17)
Timing§			
Spring	0.26 (0.09, 0.43)	0.11 (0.06, 0.25)	0.14 (0.09, 0.20)
Sidedress	0.55 (0.26, 0.83)	0.30 (0.17, 0.71)	0.12 (0.08, 0.20)

† Twenty-one trials were in the lower category of June rainfall and seven trials were in the higher category.

‡ 90% credible intervals are provided in parentheses.

§ Sidedress application was used in 12 trials and spring application was used in 13 trials.

Effect of Early Season Rainfall on Yield Loss due to Reduced Nitrogen Fertilizer for Corn after Soybean

In 2006, C-S fields receiving >76 mm of rainfall in June had a posterior regional mean YL about 0.5 Mg ha⁻¹ higher than those that received <76 mm (Table 3), suggesting potential differences in YL between these two categories, although the 90% credible intervals overlapped slightly. Based on posterior regional and within-field precisions, across-trial variability with higher rainfall in June was about two times larger than that with less rainfall. Within-trial variability, however, was about two times higher in trials with less rainfall than in those with more rainfall in June.

Classifying C-S trials into two categories based on June rainfall in 2006 decreased the expected variability among trials for the lower June rainfall category and within-trial variability for the high June rainfall category (Table 3) compared with those for all trials for the C-S category in Table 2. Based on posterior predictive distributions for unobserved trial-level means, C-S trials that received >76 mm of rainfall in June were predicted to have an economic YL about 30% higher than those that received <76 mm of rainfall in June (Fig. 7A). The two distribution curves intersected only in the lower range (<0.1) of cumulative probabilities, strongly suggesting a higher risk of economic YL due to reduced N when there is more rainfall in June.

In 2007, C-S trials receiving above-normal (>300-mm) spring rainfall had a posterior regional mean YL about 0.4 Mg ha⁻¹ higher than those receiving <300 mm of spring rainfall (Table 4), but both posterior regional means indicated an economic YL (i.e., >0.31 Mg ha⁻¹). The 90% credible intervals for the posterior means of the two categories overlapped, indicating large variability in YL.

Higher spring rainfall in 2007 increased the within-field variability in YL (Table 4). This might be explained by larger N losses within corn fields that received above-normal spring rainfall. For example, a separate study showed that the percentage of N-deficient area within corn fields estimated using late-season digital aerial imagery and the corn stalk NO₃

Table 4. Summary values for posterior distributions of fixed regional distribution parameters showing the effect of spring rainfall and soil organic matter (SOM) on yield loss (YL) from reduced N applications for corn after soybean (C-S) in 2007: μ_0 , regional mean YL; λ_0 , regional precision; α/β within-field average precision. Reciprocals of precision parameters, λ_0^{-1} and $(\alpha/\beta)^{-1}$, indicate variances.

Parameter	μ_0	λ_0^{-1}	$(\alpha/\beta)^{-1}$
	Mg ha ⁻¹	Mg ² ha ⁻²	
Spring rainfall, mm†			
<300	0.62 (0.23, 1.02)‡	0.23 (0.10, 1.01)	0.15 (0.06, 0.22)
>300	1.03 (0.56, 1.45)	0.49 (0.24, 1.56)	0.42 (0.21, 0.41)
SOM, %§			
>6	0.47 (0.18, 0.75)	0.17 (0.08, 0.60)	0.14 (0.08, 0.26)
3–6	0.97 (0.61, 1.32)	0.43 (0.24, 1.08)	0.22 (0.14, 0.35)

† Six trials were in the lower category of spring rainfall and eight trials were in the higher category.

‡ 90% credible intervals are provided in parentheses.

§ Eight modeling trials were in the lower category of SOM and 12 trials were in the higher category.

test increased with an increase in spring or early-season rainfall in 2007 (Kyveryga et al., 2011).

Posterior predictive distributions showed that trials receiving above-normal spring rainfall had an economic YL only about 10% higher than those receiving below-normal rainfall in the spring (Fig. 7C). The distribution curves intersected in the very low range of probability values, suggesting that the category of higher spring rainfall was much riskier than the category of lower spring rainfall.

Effect of Application Timing on Yield Loss due to Reduced Nitrogen Fertilizer for Corn after Soybean

In 2006, C-S trials with sidedress N applications had a regional posterior mean YL about 0.3 Mg ha⁻¹ higher than that for trials with spring N applications (Table 3). The expected variability among trial means for sidedress application was about three times higher than for spring application. For spring applications in 2006, across-trial variability was about half that of the reference category of all C-S trials in 2006 (Table 2).

The observed differences in expected YL and within- and among-field variability between sidedress and spring N application were not related to differences in total N rates applied to these two categories. Trials with sidedress N received, on average, 154 kg N ha⁻¹, while trials with spring N application received 160 kg N ha⁻¹. The observed differences in YL were probably the result of the below-normal rainfall observed in May, June, and July in 2006 (Fig. 4). As a result, N applied in early summer was partially unavailable to corn plants. A statewide survey of about 700 corn fields across Iowa also showed relatively large N-deficient areas (up to 40%) within some corn fields that received sidedress urea-NH₄NO₃ applications in 2006 (Kyveryga et al., 2011). The posterior predictive probability of economic YL for sidedress application was about 20% higher than for spring N application (Fig. 7B), with sidedress application showing also the larger risk.

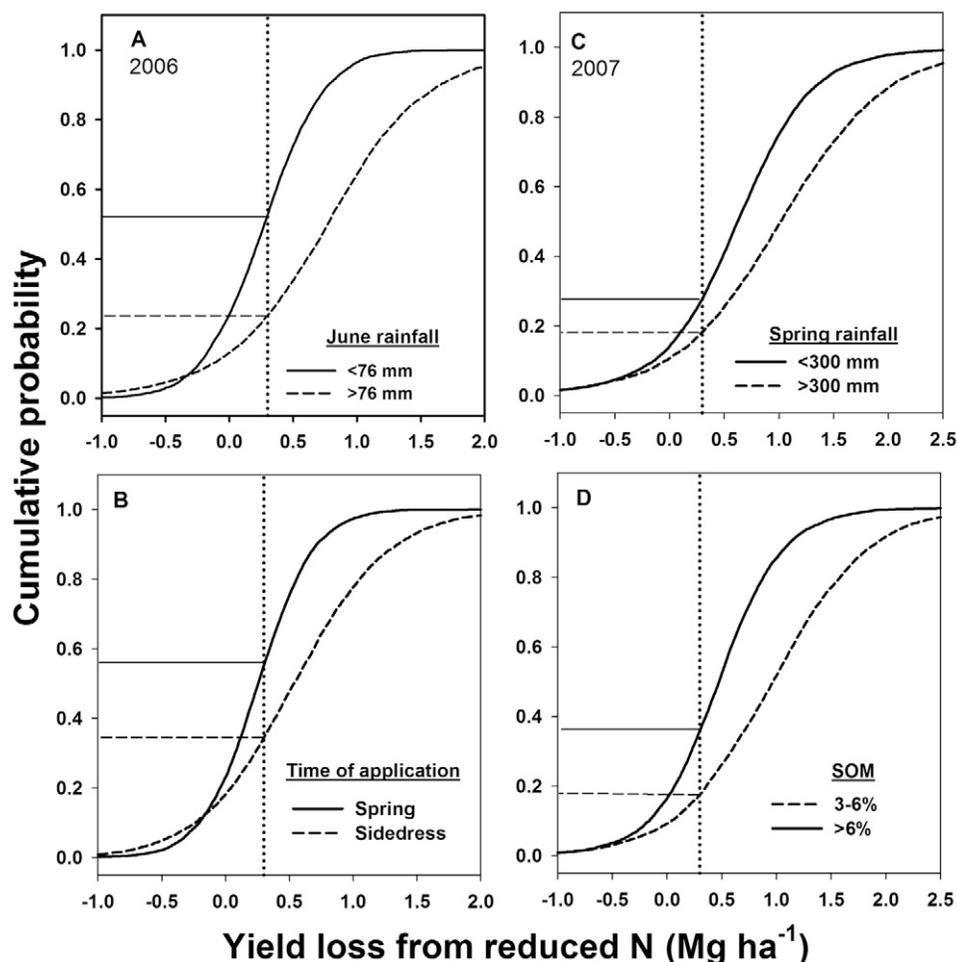


Fig. 7. Posterior predictive probabilities of yield loss from reduced N applications for unobserved field-level means for corn after soybean (C-S) for two categories based on (A) June rainfall and (B) timing of N application under conditions similar to those observed in 2006, and for two categories based on (C) spring rainfall and (D) soil organic matter (SOM) under conditions similar to those observed in 2007. A yield loss of 0.31 Mg ha^{-1} was considered as the economic threshold.

Effect of Soil Organic Matter on Yield Loss due to Reduced Nitrogen Fertilizer for Corn after Soybean

In 2007 for C-S trials, areas with SOM $>6\%$ had a posterior regional mean YL of about 0.5 Mg ha^{-1} smaller than for areas with SOM in a range of 3 to 6% (Table 4), suggesting potential differences in YL between these two categories, although the 90% credible intervals overlapped slightly. Within-field variability for the higher SOM category decreased by about 1.5 times, while within-field variability for the lower SOM increased only slightly compared with that for the C-S category of all trials (Table 2). The probability of an economic YL for an unobserved field-level mean was about 20% smaller in areas within higher SOM than in those with lower SOM (Fig. 7D), probably due to a larger supply of soil-derived N that compensated for N losses within fields.

The SOM data were derived from county digital soil maps (Iowa Cooperative Soil Survey, <http://icss.agron.iastate.edu/>); these data represent average values for common soil map units in 22 counties studied (Fig. 1). Using more accurate SOM data or using proxy data derived from digital elevation models or field topography might help estimate more accurately the effects of SOM level on the magnitude of YL and the risk of reducing N fertilizer applications.

Identifying Risk due to Reduced Nitrogen Fertilizer Applications

Using posterior predictive probabilities from Fig. 5, 6, and 7, we can construct a decision tree to quantify the risk from reduced N applications and help farmers decide when and where to reduce normal N rates for corn. An example of such a decision tree is shown in Fig. 8. The tree has two branches, showing possible different management decisions during a year with below-average rainfall in May and June and during a year with above-average rainfall in the spring. For example, the marginal posterior predictive probability of an economic YL from reduced N for all trials (without considering the previous crop) during a dry May and June is 55%, and it is 25% less than in a year with above-normal spring rainfall. For each lower branch of the decision tree, posterior predictive probabilities of an economic YL are shown for two alternative categories or two decisions. During a dry spring and dry June, the probability of an economic YL from spring N applications was 44 vs. 65% from sidedress N applications to C-S. In general, probabilities $<50\%$ would indicate a relatively low economic risk from reducing N, while probabilities $>50\%$ would indicate a relatively high economic risk.

There is a great need to use rainfall data to explain the results of N response trials and integrate rainfall data into N

Probabilities of economic YL from reduced N

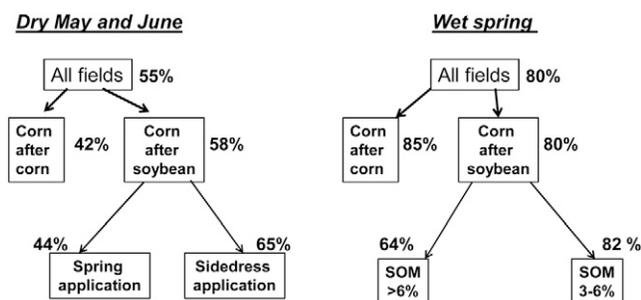


Fig. 8. Example of a decision tree based on posterior predictive probabilities of economic yield loss (YL) from reduced N applications for different categories identified in years with different rainfall patterns observed in spring and June. For example, the probability of economic YL from reduced N for all fields (without considering the previous crop) was 55% when May and June rainfall were below long-term averages. Dry is defined as below and wet as above the long-term average rainfall; SOM is soil organic matter.

fertilizer recommendations. Currently, rainfall data are not considered in N fertilizer recommendations for corn, although rainfall profoundly influences the magnitude of yield response to N fertilizer and the percentage of N loss from the soil and fertilizer. Also, the probabilities shown in Fig. 8 could be used to improve the use of the crop and soil model along with real-time, high-resolution spatial rainfall data to predict the N rate needed to sidedress the corn crop (Melkonian et al., 2008). Similarly, the N form and the timing of application also profoundly influence the N fertilizer management, but both of these factors are difficult to incorporate into N fertilizer recommendations.

CONCLUSIONS

Relatively simple two-treatment evaluation trials conducted by farmers can be analyzed using hierarchical modeling and Bayesian statistical analysis for predicting the risk from reducing N fertilization and identifying factors that affect this risk. Although all trials had only two N rates (normal and reduced), potentially important factors other than the N rate could be identified at both field and within-field levels.

Posterior predictive distributions for unobserved field-level means were used to quantify the risk of an economic YL from reduced N. We found relatively large among- and within-field variability in YL in both years. The predicted probability of an economic YL from reduced N under conditions similar to those observed in 2007 (a relatively wet spring) was about 25% larger (55 vs. 80%) than under conditions observed in 2006 (relatively dry May and June). The risk of an economic YL for unobserved C-S fields in 2006 was about 20% higher than that for C-C fields. Also in 2006, C-S fields with below-normal June rainfall were predicted to have an economic YL about 35% higher than those with above-normal June rainfall. Sidedress N applications were also predicted to lead to an economic YL about 20% higher than spring N applications when corn plants were under moisture stress in June of 2006. Under conditions similar to 2007, N fertilizer reductions in C-S fields with above-normal spring rainfall were about 10% riskier than in those with below-normal spring rainfall. For

C-S fields in 2007, within-field areas with a higher percentage of SOM were predicted to have an economic YL about 20% smaller than those areas with a lower percentage of SOM. In general, these risk estimates can be used to develop a decision support system by utilizing farmers' management information, site-specific rainfall data, soil properties, and yield response observations measured by yield monitoring and GPS technologies.

Due to the ease and relatively low cost of implementation, many on-farm evaluation trials can be conducted across the state to improve decisions on where to increase or reduce common N fertilizer applications at field and within-field levels. We presented the analysis of several factors that influenced YL by using only simple two-category classifications. Additional studies should be focused on using more complex, cross-classifications with more than two categories of the same factor or more than two factors affecting YL at field and within-field levels. In addition, large within-field variability suggests that the potential exists for determining fine-scale covariates that influence yield differences. The models introduced here should be extended to include more sophisticated modeling of within-field spatial structure that may be important in uncovering and understanding the effects of such covariates.

ACKNOWLEDGMENTS

The study was partially funded by the Iowa Soybean Association with soybean check-off dollars and by the Integrated Farm Livestock Management Project from the Soil Conservation Division of the Iowa Department of Agriculture and Land Stewardship. We are very thankful to all farmers, agronomists, and technical providers who participated in the study. This study would not have been possible without the On-Farm Network staff, who contributed numerous hours to this project.

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