Meta-analysis of Enhanced Efficiency Fertilizers in Corn Systems in the Midwest

Rachel Cook[1], Amy Nail[2], April Vigardt[1], Andrew Trlica[3], Brooke Hagarty[1], Travis Williams[1], Jeff Wolt[4]

[1]Southern Illinois University-Carbondale, [2]Honestat, LLC, [3]Boston University, [4]Iowa State University

Executive Summary

Enhanced efficiency fertilizers such as nitrification inhibitors, urease inhibitors, and polymer coated fertilizers may provide environmental and agronomic benefits in nitrogen fertilization of corn production systems. Their effectiveness, however, can be influenced by agricultural management practices and can vary by location due to climate and soil characteristics. In this study we performed a systematic review of published data from the Midwest to address the effectiveness of enhanced efficiency fertilizers on corn yield, nitrous oxide emissions, and nitrate leaching. We identified 46 studies comprising 1248 observations which were amenable to meta-analyses describing corn yield response for the years 1994-2014. We modeled corn yield data by primary fertilizer sources (anhydrous ammonia (AA), urea ammonium nitrate (UAN), and urea). In the model for anhydrous ammonia, the effect of nitrapyrin was non-significant (p = 0.16). The model for UAN also showed a non-significant effect of enhanced efficiency fertilizers (NBPT, NBPT+DCD, Nitrapyrin, Calcium thiosulfate, or Nutrisphere; p = 0.84). The factor of enhanced efficiency fertilizer in the model for urea was moderately significant (p = 0.05) where the order of yield was urea+NBPT+DCD, polymer-coated urea, urea+NBPT, urea+nitrapyrin, and finally urea, though means could not be separated statistically. The difference in yield between urea versus urea+NBPT+DCD was 8 bushels per acre. Other factors such as nitrogen rate, application time, seasonal precipitation and temperature, and soil characteristics influenced corn yield to a greater extent than enhanced efficiency fertilizers. Our understanding of the effects of enhanced efficiency fertilizers on corn yield under a variety of growing conditions in the Midwest would be much improved by 1) a greater number of published studies with more consistent reporting of means with variation, 2) finer scale in-season meteorological data, 3) more complete geographic coverage, 4) simultaneous measurement of environmental effects on water-quality and N_2O emissions with standardization of reporting in area or yield-based results. Direct modeling of NO_3 and N_2O was restricted due to a lack of sufficient coverage. Overall, this meta-analysis indicates a variable and condition-specific impact of enhanced efficiency fertilizers on corn yields in the Midwest. The database created will be publicly available to help inform future research efforts in nitrogen management in corn production systems.

Table of Contents

Executive Summary **1**

Table of Contents **2**

1 Background and Motivation **3**

1.1 Environmental Impacts **3**

1.1.1 Subsurface Nitrate losses 3

1.1.2 Nitrous oxide emissions 4

1.1.3 Crop Yield 5

1.2 Study Objectives **6**

2 Methods **6**

2.1 Database Development **6**

2.2 Meta-analysis vs. Systematic Review **8**

2.3 Meta-Analysis of crop yield through direct modeling **8**

2.3.1 Explanatory variables and random effects 9

2.3.2 Model construction 10

2.3.3 Weighting 10

2.3.4 Publication bias 11

3 Results and Discussion **11**

3.1 Crop yield **11**

3.1.1 Anhydrous Ammonia 11

3.1.2 UAN 12

3.1.3 Urea 12

3.1.4 NUE 13

3.2 Discussion **14**

3.3 Systematic Review of Environmental Impacts **16**

3.3.1 N_2O Emissions 16

3.3.2 Nitrate leaching 18

4 Conclusion **20**

4.1 Recommendations for future work **20**

References **20**

Appendix: Statistical Analysis **25**

1 Background and Motivation

Nitrogen management has remained at the forefront of agronomic and environmental issues surrounding corn production in the Midwest due to increasing pressure to meet crop yield demands while minimizing environmental impacts. Over 47 of the 87 million acres of corn harvested in the US in 2013 (USDA NASS, 2013) were harvested in the Midwest (Illinois, Iowa, Indiana, Ohio, Missouri, Michigan, Minnesota, and Wisconsin). This magnitude of corn production and its high nitrogen requirement can lead to nitrate (NO_3^-) contamination in groundwater and in surface waters as well as nitrous oxide (N_2O) emissions to the atmosphere. Therefore, corn production in the Midwest is arguably the most important agricultural system for studying ways to more efficiently manage nitrogen fertilizers.

Nutrient stewardship in production agriculture through the 4Rs (right source, right rate, right time, and right place) provides a framework for contextualizing best management practices. Enhanced efficiency fertilizers (EEFs) including polymer coated fertilizers (PCFs) and amendments such as nitrification inhibitors and urease inhibitors represent nitrogen management tools that may reduce environmental impact and increase crop yields. The exceedingly large number of possible combinations of nitrogen source, rate, time, and placement, even within one cropping system, can make it difficult to compare results from studies located in different regions, with variable climate, soils, and accepted management practices. To prevent needless duplication and suggest future study directions, the soil fertility and fertilizer community needs to periodically systematically compile what is known in order to move forward in the most efficient manner possible. Systematic review and meta-analysis provide a framework to compile and understand the effects of enhanced efficiency fertilizers across the Midwestern region on environmental impacts and crop yield.

1.1 Environmental Impacts

Protecting nitrogen from transformation and subsequent losses is highly environmentally dependent. Agricultural management practices with the appropriate EEFs may be one means by which to reduce environmental impacts such as nitrate leaching and soil nitrous oxide emissions.

1.1.1 Subsurface Nitrate losses

Nitrate contributes to N-leaching losses due to its negative charge and greater likelihood for off-site movement (Jacinthe et al., 1999). Leaching of nitrogen into groundwater, subsurface drainage, and surface runoff can result in eutrophication and is a well-documented environmental consequence of production agriculture (Carpenter et al., 1998; McIsaac et al., 2001; Gardner and Drinkwater, 2009).

Nitrification inhibitors slow the conversion of ammonium to nitrate, thereby potentially reducing losses to leaching (Wolt, 2004). Most corn hybrids take up about 40% of N applied at preplant during the grain-filling stage (Ciampiti and Vyn, 2011) and so maintaining more N in the soil profile as ammonium during this period of crop growth may improve efficient N use, in addition to restriction of N losses from the soil profile.

The most commonly used nitrification inhibitors include nitrapyrin and dicyandiamide (DCD). Nitrapyrin (sold as N-Serve® and Instinct®, Dow Agrosciences, LLC) has traditionally been added during fall anhydrous ammonia application to prevent subsurface losses (Randall et al., 2003), while the more recently available micro-encapsulated liquid version of nitrapyrin (Instinct) allows for increased use of nitrification inhibitors with liquid UAN applications. Nitrification inhibitors have been found to decrease nitrate leaching by 16% and increase yields by 7% in studies located primarily in the Midwest (Wolt, 2004). DCD is a water-soluble nitrification inhibitor with its effectiveness depending on temperature (declines from 10°C to 30°C) and soil texture (McCarty and Bremmer 1989). It can be applied alone or together with the urease inhibitor n-butyl thiophosphoric triamide (NBPT) and sold as AgrotainPlus® and SuperU® (Koch Agronomic Services, LLC). When used alone with ammonium sulfate, DCD was found to decrease nitrate leaching by 30% in corn grown in a Mediterranean climate (Diez et al., 2010).

Polymer-coated urea (PCU), commonly sold as "environmentally smart nitrogen" or ESN® (Agrium, Inc.) is designed to help increase crop uptake and reduce nitrate leaching losses by allowing a more gradual release of urea to match crop demand compared to conventional urea (Nelson et al., 2009). In potato crops, ESN significantly reduced nitrate leaching when compared to a split application of soluble N (Wilson et al., 2010), but was found to be less effective in reducing nitrate leaching under corn compared to urea impregnated with NBPT+DCD (SuperU) and to split-urea applications (Maharjan et al., 2014).

The potential for urease inhibitors to reduce nitrate leaching is not well studied. Because the urease inhibitor NBPT is often formulated with the nitrification inhibitor DCD, few studies have investigated the effect of NBPT alone on nitrate leaching. Urease inhibitors would not be expected to have a great effect on nitrate leaching, but there is little empirical data to support this assumption.

1.1.2 Nitrous oxide emissions

Nitrous oxide is about 310 times more potent than CO_2 in global warming potential. While the Agriculture sector is only responsible for 8.1% of total U.S. greenhouse gas emissions, agricultural activities are estimated to contribute 69% (247.2 Tg CO_2 eq.) of the total 356.9 Tg CO_2 eq. anthropogenic N_2O emissions in the U.S. Of this, 26% can be attributed to synthetic fertilizer inputs (USEPA, 2013). Soil emissions of N_2O have been shown to increase exponentially with increasing nitrogen application rates, especially when N rates exceed plant uptake capacity (Bouwman et al., 2002; Kim et al., 2012; Millar et al., 2010; Van Groenigen et al, 2010). In addition to direct N_2O emissions, attempts are being made to measure and better estimate the contributions that volatilized ammonia and leached nitrate found in estuaries, rivers, and lakes may have in off-site N_2O formation. In 2011, it was estimated that indirect N_2O emissions were 40.3 Tg CO_2 eq. for cropland, with 14 Tg CO_2 eq. attributed to ammonia volatilization and 26.4 Tg CO_2 eq. attributed to nitrate leaching (USEPA, 2013).

The potential of EEFs to directly or indirectly mitigate N_2O emissions is based on how well microbial processes, in interaction with environmental factors and management practices, can be influenced to release nitrogen in conjunction with plant uptake. An understanding of which environmental and management factors have the most effect on N_2O emissions and how these factors affect the mitigation potential of an EEF is necessary to make site specific and effective choices. Previous meta-analyses and evaluations have looked at the effect of EEFs on N_2O emissions (Akiyama et al., 2009; Decock, 2014; Wolt, 2004), but a meta-analysis of the effects of EEFs on environmental effects with a focus on the Midwest has yet to be accomplished. Nitrification inhibitors have been shown to consistently and significantly reduce N_2O emissions by 38% (Akiyama et al., 2009) and 51% (Wolt, 2004), while data for PCFs were more variable and subject to environmental and management differences. Akiyama et al. (2009) found a significant reduction of 35% in N_2O emissions with PCFs but this reduction varied greatly by region and soil type, while Decock (2014) found no N_2O reduction with use of PCF compared to urea. Decock (2014) further analyzed the effect that environmental and management practices would have on N_2O emissions in the Midwestern region and found significant effects for precipitation, aridity, soil carbon, soil order, and irrigation, but no significant effects for N placement, timing, tillage, or rotation. However, Decock also found that 40% of the heterogeneity of the data could be explained by differences among agroecological regions which encompassed the Atlantic Maritime states, Lake states, Midwest, Great Plains and Atlantic Gulf regions. These larger-scale effects may have masked effects within regions. For this reason, it may be more useful to narrow the scope to within-region review and analysis to more accurately inform best management practices and inform the agricultural community.

1.1.3 Crop Yield

Appropriate fertilizer N rate, timing, placement, and source can influence optimal nitrogen use by crops. Of these factors, attaining optimal fertilizer rate is the most important factor for limiting N losses (Power and Schepers, 1989), and may contribute to the variable yield responses measured with EEFs. Variable response in crop yield to the use of nitrification inhibitors, urease inhibitors, and polymer-coated fertilizers is often attributed to the timing, quantity, and frequency of rainfall after fertilizer application, as well as soil texture (Nelson et al., 2008).

Ammonia (NH_3) volatilization can lead to significant losses of N from urea-based fertilizers, leading to yield decline. Soil pH, CEC, soil moisture, temperature, and surface residue have been shown to be important factors influencing NH_3 emissions following N application (Nelson, 1982, Sommer et al., 2004). Urease inhibitors discourage NH_3 losses to volatilization by reducing the amount of NH_3 released as a result of urea hydrolysis by inhibiting the urease enzyme. The most commonly used urease inhibitor, NBPT, has also been shown to increase yields when used with urea and UAN, especially in surface applications (Hendrickson, 1992). The combined effect of nitrification and urease inhibitors may also have an additive effect in reducing NH_3 volatilization compared to use of urease inhibitors alone (Zaman and Blennerhassett, 2010), but these results have not been replicated on a wide enough range of conditions to make generalizations of efficacy (Kim et al., 2012). Conversely, under controlled experimental conditions a urease inhibitor (NBPT) and a nitrification inhibitor (DCD) combined with urea caused an increase in NH_3 volatilization by maintaining higher soil pH and soil ammonium (NH_4^+) for greater duration, thereby offsetting the benefits of the urease inhibitor in a lab setting (Soares et al., 2012). Further study of the indirect formation of N_2O from NH_3 volatilization is needed to better assess the mitigation potential of these inhibitors.

1.2 Study Objectives

For this project, our purpose was to determine whether there are environmental or agronomic benefits to using enhanced efficiency fertilizers for N management in Midwestern corn production systems using a systematic review of recent literature and meta-analysis of reported results when enough information was available. Comparisons were made between traditional nitrogen fertilizers and their respective EEFs (nitrification inhibitors, urease inhibitors, and/or polymer-coated fertilizers) for effect on 1) agronomic yield, 2) N_2O emissions, and 3) nitrate leaching.

2 Methods

2.1 Database Development

The ability to perform a meta-analysis is dependent on the quantity and quality of data in the literature**.** Studies were identified using online searches for combinations of terms such as:

corn, maize, Midwest, enhanced efficiency fertilizers (both brand names and chemical names), and state names. The full list can be found in the search terms tab of the database spreadsheet. Searches were performed using Web of Science and Google Scholar, and additional sources were collected from literature references and personal communications. Peer-reviewed studies, scientific reports, and theses and dissertations were considered acceptable if the study reported sufficient information. For inclusion in the dataset, studies needed to (i) address nitrogen EEFs in Midwest corn cropping systems, (ii) be conducted under field conditions, (iii) be published after 1994, and (iv) have reported replication and means. Data needed to be reported with enough information to convert reported results to common forms that allowed for inter-study comparisons (i.e. percent moisture of grain yield).

The search criteria for the systematic review and meta-analysis also included that studies take place in the Midwestern region of the U.S., which was considered to be comprised of Illinois, Iowa, Indiana, Minnesota, Missouri, Michigan, Ohio, and Wisconsin. In addition, Colorado, North Dakota, Kansas, and Nebraska were included in our search and dataset to provide additional data and to reflect a widening of the Corn Belt into the north and western regions where corn production has increased over the years.

We recorded the following variables describing physical and chemical properties of the soil: Soil series, soil taxonomic classification, soil order, texture class, texture group, soil organic matter (SOM), soil organic carbon (SOC), pH, pH measurement method, bulk density, water-filled pore space (WFPS), percent sand, and percent clay. If a soil variable was not reported in a particular study, we obtained the value of that variable from the National Resource Conservation Service (NRCS) Web Soil Survey (Soil Survey Staff, 2014).

The climate variables mean annual precipitation (MAP, mm) and mean annual temperature (MAT, °C) were generated from Worldclim data that provides yearly averages of climatic variables from the years 1950–2000 (Hijmans et al., 2005). We recorded maximum and minimum annual temperatures by state for each study year from the beginning of the most active planting date range to the end of the most active harvesting date range (USDA NASS, 1997). These temperatures were calculated from daily weather data collected from Daymet (Oak Ridge National Laboratory Distributed Active Archive Center, Thornton et al., 2014). Growing season precipitation (mm) was recorded as reported by the research paper when available. When not reported, estimated cumulative growing season precipitation (mm) was entered from the sum of Daymet precipitation data from the beginning of the most active planting dates to the end of the most active harvesting dates (USDA NASS, 1997). Research site coordinates (decimal degrees) were entered as obtained from the studies when reported or from a search based on the name of the research site.

Environmental impact variables included a seasonal cumulative N_2O-N emissions which were area-based (kg N ha^{-1}) and yield-scaled (g N Mg^{-1} grain), and flow-weighted NO_3^-N leaching (mg L^{-1}). Corn yield (Mg ha^{-1}) was standardized to 15.5% moisture. For potential future analyses, indices of treatment effectiveness were calculated from yield and cumulative N_2O-N data when available, such as: nitrogen use efficiency (NUE) and yield-scaled N_2O emissions (g N_2O-N Mg^{-1} oven dry grain):

$$NUE = \frac{yield\ of\ fertilized - yield\ of\ nonfertilized}{N\ rate}$$

$$Yield\ scaled\ emissions\ = \frac{N2O\ emissions}{oven\ dry\ yield}$$

where N_2O emissions are expressed as g N_2O-N g ha^{-1} and oven dry yield is expressed as Mg ha^{-1}.

When information was extracted from graphical data using GraphClick (Arizona Software, 2012) or study authors were contacted for missing information, the source of this information was indicated in the database “source” column.

2.2 Meta-analysis vs. Systematic Review

After compiling the study data, we considered three response variables for a model-based meta-analysis: yield, N_2O emissions, and nitrate leaching. There were sufficient studies and observations to warrant a meta-analysis of yield. However, N_2O and nitrate were less well represented in the literature. For this reason, we performed a quantitative meta-analysis on corn yield and a systematic review of N_2O emissions and nitrate leaching. Available studies are included in the database so that as future studies are published, meta-analysis of EEF effects on N_2O emissions and nitrate leaching may be performed. For yield, our goal was to answer the question: Do any EEFs produce significantly greater corn yield when other factors, such as placement, application time, N rate, climate/weather, and soil characteristics are taken into account?

2.3 Meta-Analysis of crop yield through direct modeling

We performed a meta-analysis via direct modeling of treatment means for yield. We used multiple linear regression mixed models, specifically, analysis of covariance (ANCOVA) models, of yield as a function of explanatory variables and random effects, under the assumption of normality. We developed one model for each of three major nitrogen sources: Anhydrous ammonia (AA), urea ammonium nitrate (UAN), and urea since each fertilizer source is characterized by different common management methods.

In each of the models, the categorical variable, or factor, *fertilizer* has multiple values (levels), one of which is the non-enhanced source. The values for each model of the same N source were: AA+nitrapyrin or AA; UAN+Agrotain, UAN+AgrotainPlus, UAN+calcium thiosulfate, UAN+Nutrisphere, UAN+Nfusion, or UAN; and urea+Agrotain, SuperU, ESN, urea+Nutrisphere, urea+nitrapyrin, or urea. Calcium thiosulfate (cats), Nutrisphere, and Nfusion were labeled as "slow-release" (S.R.) in the database. If the variable *fertilizer* was statistically significant, then Tukey-Kramer pairwise comparisons was used to separate the least-squares mean yield estimates (LSmeans). The data available determined what models could be developed.

2.3.1 Explanatory variables and random effects

In addition to using *fertilizer* as an explanatory variable, we selected a subset of the variables detailed in Section 2.1 for use in the statistical models that we hypothesized would have the greatest likelihood of an effect on yield. These effects included application timing (*apptime*) which was divided into fall, pre-planting (N-applied in the winter or spring > 5 days prior to planting), at planting (N-applied 5 days before to 20 days after planting), sidedress (N-applied > 20 days after planting), pre-planting/sidedress, and at planting/sidedress. Placement (*place*) was sorted into broadcast, broadcast incorporated, surface banded, and subsurface banded. Crop rotation (*rotate*) had various combinations, but for modeling purposes was divided into rotated or continuous corn cultivation. Tillage (*till*) was primarily either tilled or no-till, though some instances of strip-till were included. Total N rate (*ratetot*) was included and transformed to a centered-normalized form and in the form of categorical binned values (See Appendix A 2.3).

For the meteorological variables, we included the maximum and minimum daily temperatures in the growing season and *totalwater* (the sum of precipitation and irrigation applied). We used the cumulative growing season precipitation reported by the authors when available or, if none was reported, cumulative growing season precipitation estimated using Daymet. We included maximum and minimum temperatures to provide information about the effect an extreme weather effects, but unfortunately, these do not provide information concerning distribution of temperature throughout the growing season or the cumulative growing degree days, which would have been ideal.

We included the soil variables percent sand and clay, pH, and SOM. Other variables that described soil—soil series, soil class, soil order, and soil texture—were often were overlapping with values of *county*. Thus the *county* random effect was used to account for between-site differences in *yield* due to soil variables as well as meteorological differences.

Functional forms were considered for continuous variables. The relationship of yield to the continuous variables was examined as linear, quadratic, and exponential. Interactions among the continuous variables were also considered (see Appendix A 2.4).

Random effects consisted of *year* nested within *county* to take into account variability across locations and over years. Rotation and tillage were considered random effects in models where there were not enough observations to test them as fixed effects due to a lack of sufficient combinations. To implement the linear models with random effects, we used Proc Glimmix® in SAS 9.3 (SAS Institute Inc., Cary, NC, USA).

2.3.2 Model construction

Variable selection was conducted according to a process of iterative model construction, examining for issues of collinearity and estimability (see Section A 2.5). Residuals analysis was performed to check model assumptions (see Section A 2.6). For each final model, we used Q-Q plots, histograms, and boxplots of residuals to assess the assumption of normality, scatterplots of residuals vs. predicted yield to assess heterogeneity and overall goodness-of-fit, and scatterplots of residuals vs. each continuous variable to assess functional form decisions and influence of individual observations on model fit.

We used the alpha = 0.01 level for the backward elimination steps. Constructing a model for observational data entailed performing more hypothesis tests than one would perform when analyzing the results of a designed experiment and therefore requires a more conservative alpha level. Reducing the statistical significance level to 0.01 was implemented to reduce the number of tests that would incorrectly support rejecting the null hypothesis of zero effect.

2.3.3 Weighting

Weighting can be an important component of a meta-analysis if individual studies differ greatly in their levels of accuracy (Philibert et al., 2012). Each study selected for analysis will have a different level of variability in yield for a given treatment and may also have had different sample sizes. Weights can be assigned to observations in the model to adjust for these attributes. For the UAN and urea models, we performed an analysis to examine to what extent conclusions about the effect of *fertilizer* on *yield* were sensitive to the use of weights. We considered the weights $1/SE^2$ (the reciprocal of the squared standard error of the mean) and r, the number of replicates that supported each treatment mean. See Section A4.3 for a discussion of weighting schemes and sensitivity analysis. When we used a significance level of alpha = 0.01, we did not find that using weights changed our conclusions about the significance of the effect of *fertilizer*.

2.3.4 Publication bias

There is a well-known publication bias towards significant results which could distort the results of meta-analysis towards finding greater significance than actually occurs (Philibert et al., 2012). We used funnel plots to examine the likelihood of bias across all EEFs and did not find evidence of significant publication bias (data not shown). However, through personal communications, we are aware of many field trials involving EEFs in the Midwest that are currently unpublished. This is often due to a reluctance of journals to publish non-significant results, often biasing the literature towards significance.

3 Results and Discussion

3.1 Crop yield

3.1.1 Anhydrous Ammonia

The data available for anhydrous ammonia included 148 observations from 24 studies by six different author groups in four states and six counties. The data supported a complete factorial ANCOVA model in which the factors (and their levels) were *fertilizer* (AA, AA+N-serve), *till* (no-till, tilled), and *apptime* (at planting, pre-plant, fall;

Table A 3.6). Each combination of *fertilizer*, *till*, and *apptime* had at least two observations. All observations were under a corn/soybean rotation with subsurface banded placement. There were sufficient data to test the effect of *fertilizer, apptime,* and *till*, but there were not enough continuous corn experiments to test *rotate.* There were enough values of continuous variables such as total N rate (*ratetot*) at each categorical variable level to test for interactions between continuous and categorical variables. Full details regarding dataset selection and model building can be found in Section A3.

The fixed effects in the final model included: *apptime*, *ratetot*, *pH*, and the interaction of *ratetot* with *pH* (Table A 3.10). The effect of *fertilizer* was not significant ($p = 0.16$), meaning that the 1.5% difference (0.16 Mg ha^{-1} or 2.6 bu ac^{-1}) between AA+nitrapyrin and AA was not significant after controlling for other factors in the model. There were no values of *apptime*, *till*, or any of the continuous variables that had a significant interaction with *fertilizer*. While a broader literature search would be required to directly address the effect of application timing, for the studies included in this analysis, in comparison, there was a significant 1.1 Mg ha^{-1} (17 bu ac^{-1}) increase in yield when nitrogen was applied at planting, which was significantly greater than preplant or fall application, which were statistically similar (Table A 3.11).

3.1.2 UAN

The final model for UAN-based fertilizers contained 262 observations from 17 studies by six author groups in five states and 12 counties. This dataset for UAN supported an ANCOVA model in which the factors (and their levels) were *fertilizer* (UAN, UAN+Agrotain, UAN+AgrotainPlus, UAN+Calcium thiosulfate, UAN+Nutrisphere, UAN+Nfusion), *apptime* (at planting, at planting/sidedress, preplant, and sidedress), and *place* (broadcast incorporated, broadcast, subsurface band, and surface band). Of the 384 combinations of values of the three factors, there were 50 that were represented by at least three observations in the dataset. Since not every level of each factor was observed in combination with each level of each other factor, we examined main effects of categorical variables but were not able to examine interactions among them. Due to this lack of coverage, we chose to use *rotate* and *till* as random effects. Additionally, there were insufficient values of the continuous variables at each level of each categorical variable to support inferences regarding interactions between categorical and continuous variables. Total N rate was modeled with an exponential functional form (*erate*) in this model. Full details regarding dataset selection and model building can be found in Section A4.

The fixed effects in the final model included *apptime*, *erate*, *tempmax*, *tempmin*, *pH*, *SOM*, and the interactions between *tempmax* and *erate*, *tempmin* and *erate*, *pH* and *erate*, and *SOM* and *erate* (Table A 4.9). *Fertilizer* was added back to the model to demonstrate its effect, but was not significant ($p = 0.837$). None of the enhanced versions of UAN produced a significantly higher yield than UAN alone even after controlling for other factors that affected yield, and none of the EEFs were significantly different from any other EEF. It was not possible to examine the interaction of *fertilizer* with the categorical or continuous variables. This lack of sufficient information to form interactions is a significant gap in the literature. In comparison, application time for the studies included in this analysis, showed that splitting nitrogen application between at planting and sidedress increased yields between 0.9 to 16 Mg ha^{-1} (14 to 32 bu ac^{-1}) over other application times (Table A 4.10).

3.1.3 Urea

Crop yield with urea-based fertilizer sources had the greatest number of observations. The final model was based on 479 observations from 38 studies by 16 different author groups from eight states and 19 counties. The dataset for urea supported an ANCOVA model in which the factors were *fertilizer* (urea, urea+Agrotain, SuperU, ESN, urea+Nutrisphere, urea+nitrapyrin), *apptime* (at planting, at planting/sidedress, preplant, preplant/sidedress, sidedress, and fall), and *place* (broadcast incorporated, broadcast, subsurface band, surface band). Of the 720 combinations of values of the three factors, there were 74 that were represented by at least three observations each. Since not every level of each factor was observed in combination with each level of each other factor, we examined main effects of categorical variables but not interactions among them. The lack of interactions in the model means that it was not possible to examine the effect of to *apptime*, *place*, *rotate* or *till* on *fertilizer,* but they could still be included in the model as fixed effects. There were also insufficient values to support inferences regarding interactions between continuous and categorical variables. Full details regarding dataset selection and model building can be found in Section A4.4.

The fixed effects that remained in the final model included *apptime*, *tempmax*, *tempmin*, *pH*, *SOM*, *totalwater*, and *erate*. The fixed effect of fertilizer was added back to the model to examine its level of significance ($p = 0.0525$), which was not statistically significant at the 0.01 level, and therefore means for fertilizer types could not be separated statistically. The numerical differences in LSmeans of EEFs compared to urea were at most 5%. There was a non-significant difference of 0.5 Mg ha^{-1} (8 bu ac^{-1}) for SuperU, and a 0.4 Mg ha^{-1} (6.4 bu ac^{-1}) for PCU and urea+Agrotain (Table A 4.24). None of the enhanced versions of urea produce a significantly higher yield than urea alone, after controlling for other factors that affected yield, and none of the EEFs was significantly different from each other. It was not possible to test the effect of fertilizer on yield as an interaction with any of the categorical or continuous variables. Application timing, in comparison, like in AA and UAN, had a much greater effect on yields than *fertilizer*. Sidedress yielded 2.9 Mg ha^{-1} (46 bu ac^{-1}) higher than preplant and 2.5 Mg ha^{-1} (40 bu ac^{-1}) higher than fall in these studies. At planting yielded 1.0 Mg ha^{-1} (16 bu ac^{-1}) higher than preplant (Table A 4.25).

3.1.4 NUE

Nitrogen use efficiency was calculated for studies that included a control (no nitrogen fertilizer added) and is included in the database. There was a negative relationship between N rate and NUE, showing that as increasing amounts of fertilizer are applied NUE decreased (Figure 1). Improved NUE in corn with the use of EEFs could result in N-rate reductions without compromising yield (Shoji, 2001). When N rates were reduced in one study in Colorado, ESN was found to improve nitrogen-use efficiency compared to urea by 4–14% at N rates from 168–280 kg N ha^{-1}, while no benefit to NUE was found with SuperU compared to urea (Halvorson et al., 2014).

Additional modeling will be required to assess possible differences in effect of enhanced efficiency fertilizers on NUE, but preliminary analysis suggests there may be differences among fertilizer sources (data not shown). Synchronizing crop uptake with fertilizer nitrogen availability by using EEFs may improve nitrogen use efficiency and reduce N losses, but more information will be required to assess this hypothesis.

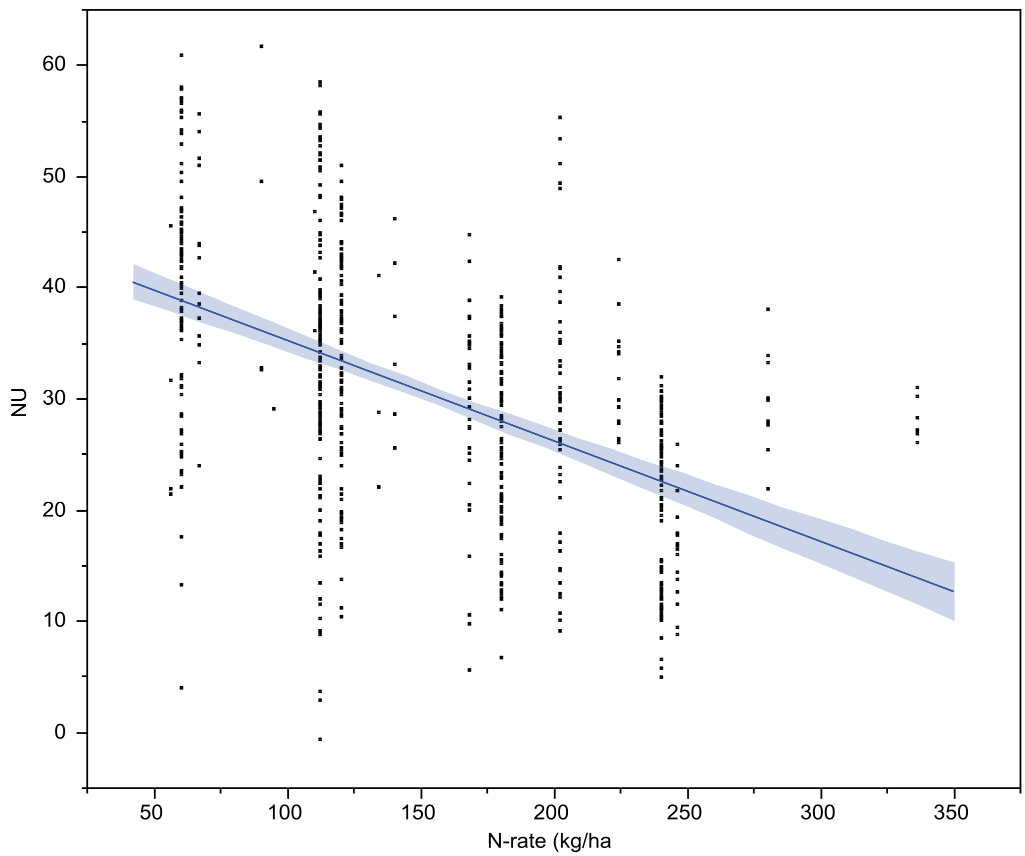

Figure 1 Nitrogen use efficiency has a significant negative relationship with N-rate applied NUE = 44.3 - 0.09*Nrate.

3.2 Discussion

This direct modeling meta-analysis showed that, based on the reported literature, there are no statistically significant differences between conventional fertilizer sources and their enhanced efficiency counterparts when management, soil, and meteorological factors were taken into account. Other meta-analyses have also found no effect of nitrification inhibitors on yield, or a negative effect of controlled release fertilizers on yield (Quemada et al., 2013). In rice systems however, both nitrification inhibitors and urease inhibitors were found to have a positive effect on yield, though the effect was a modest 5.6%, while DCD was found to not be effective when the added nitrogen was taken into account (Linquist et al., 2013). Wolt (2004) also found a slight increase in yield (7%) with the use of nitrapyrin in a pairwise comparison, though no meta-analytical procedure were used.

The conditions under which a yield benefit with the use of EEFs may be realized are highly variable and depend on the mechanisms for N loss. Interactions of enhanced efficiency fertilizers with timing, application, and N rate are variable and may be heavily influenced by the environment, thereby changing year-to-year. For example, we typically would expect to see a reduction in N loss from a urease inhibitor if urea were broadcast applied in no-till, high residue conditions to moist soil and followed by a dry period (Schlegal et al., 1986; Sommer et al., 2004). For nitrification inhibitors, we might expect to see a reduction in N loss by delaying nitrification when warm soil temperatures were combined with saturated fine-textured soils (denitrification) or high rainfall in coarse-textured soils (leaching) (Ferguson et al., 2003).

It is possible that available data cannot appropriately describe the conditions in which N losses lead to yield decline without the use of enhanced efficiency fertilizers. With more specific meteorological information, it may be possible to better understand under which conditions across the Midwest, we would be most likely to see a response to enhanced efficiency fertilizers. Additionally, the lack of full factorial datasets for categorical variables and insufficient coverage of continuous variables for each categorical variable for urea and UAN models may have limited our ability to discover interactions. This gap in the literature could be filled by new research informed by the current database compiled for this study.

It is commonly assumed that nitrogen rate is an overriding factor in the likelihood of seeing a response to EEFs. Above optimum N rates would compensate for any savings in nitrogen due to EEFs preventing N losses. We found no significant interactions of fertilizer and N rates, nor did Linquist et al. (2013) in rice systems.

Our modeling results did suggest that application timing was of much greater importance in these studies than EEFs. Though this database was not constructed to analyze application timing across the Midwest, the relative magnitude of significance of application timing would suggest that a meta-analysis of application timing may be a worthwhile endeavor.

We can conclude from the meta-analysis that EEFs have a rather small and mostly non-significant effect on corn yield in the Midwest when other management and environmental variables are taken into account. While there are certain situations in which enhanced efficiency fertilizers can have a positive effect, when compiled across the published literature in the Midwest, we can consider EEFs more of an insurance policy than a means to consistently and significantly increase yield. There may be more potential benefits on the environmental impacts, which will require even greater amounts of study.

3.3 Systematic Review of Environmental Impacts

3.3.1 N_2O Emissions

There were 11 studies and 146 total observations for N_2O that fit the search criteria for this dataset. There were seven studies with area-scaled emissions, six of which included *SE*. There were nine studies where yield-scaled emissions were either given or able to be calculated, but only one included a report of variance. A further complication with modeling N_2O emissions included the fact that measurements were collected over different intervals ranging from 89–184 days, so that cumulative emissions were not directly comparable. There were greater fertilizer induced emission from AA over other sources (Figure 2), but more data coverage as studies are published and in depth modeling and analysis will be required to better examine this effect.

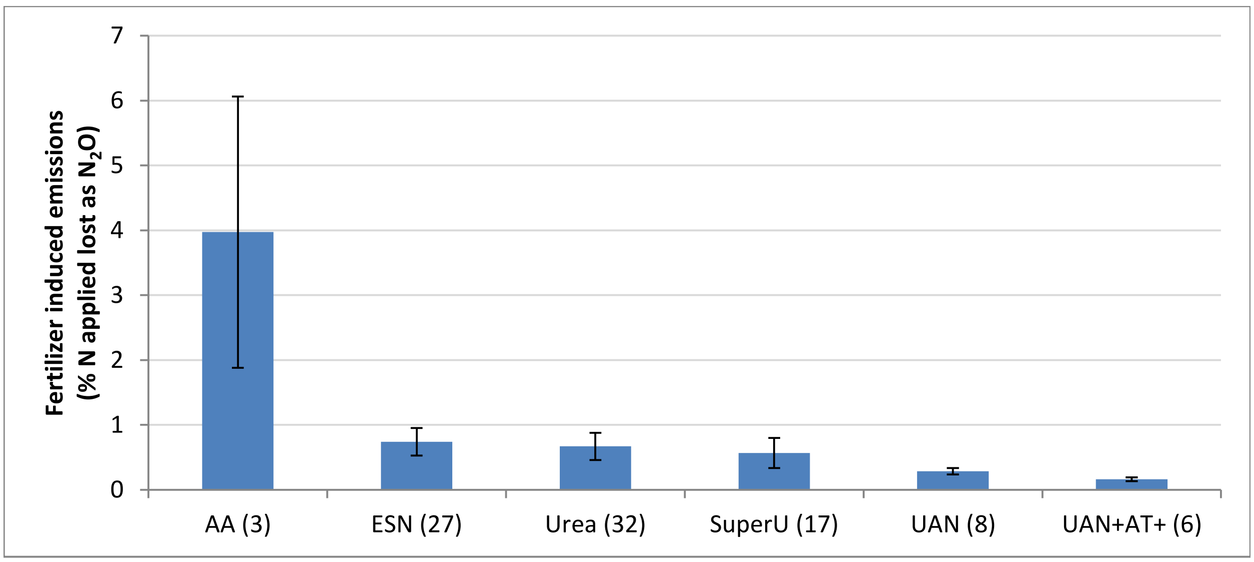

Figure 2 Fertilizer induced N_2O emissions (calculated at the percent of N applied that is lost as N_2O-N) shows that AA has significantly greater emissions than any other N fertilizer treatment. Error bars represent standard error of the mean; number of observations in parentheses.

Decock et al. (2014) found that variation in Fertilizer-Induced Emissions (FIE) was most affected by N-source (44%) and the use of nitrification inhibitors (16%) and less by N timing, placement, tillage and rotation. In comparing between fertilizer source and tillage systems, Venterea et al. (2005) found that N_2O emissions with AA were significantly higher than UAN or broadcast urea regardless of tillage, and two out of three summary reports found the range of N_2O emissions to be higher in AA than urea and UAN (Snyder, 2009).

Nitrification inhibitors have been shown to reduce N_2O emissions by 30–80% across a broad spectrum of agricultural soils (Wolt, 2004; Akiyama et al., 2009; Decock, 2014). However, nitrapyrin added to AA in Iowa was not found to significantly reduce N_2O emissions during the growing season, although a significant reduction was seen between fall application and planting (Parkin and Hatfield, 2010). In Indiana, when nitrapyrin (Instinct) was added to UAN, N_2O was reduced 19–27% over three years and significantly reduced (67%) in one year (Omonode, 2013).

The nitrification inhibitor DCD is applied with the urease inhibitor NBPT when added to urea (SuperU) and UAN (AgrotainPlus). In trials in Colorado, compared to urea, UAN+AgrotainPlus and SuperU both significantly reduced N_2O emissions between 46-62% (Halvorson et al. 2010, 2011, 2012). Compared to UAN, SuperU and UAN+AgrotainPlus significantly reduced N_2O by 29 and 35%, respectively, in no-till and strip tilled systems (Halvorson et al., 2010).

Polymer coated fertilizers (PCFs) slow down nitrogen release but have only shown to be effective in reducing N_2O emissions in some cases (Akiyama et al., 2010; Halvorson and Del Grosso, 2012). Compared to urea, ESN significantly reduced N_2O emissions by 34–57%, which was higher than the reductions seen by UAN without inhibitors, although ESN and UAN were not significantly different from each other (Halvorson et al., 2010, 2012). In comparison to UAN and UAN+AgrotainPlus, ESN had significantly higher N_2O emissions in Iowa (Parkin and Hatfield 2013). Venterea (2011) found no difference between ESN, SuperU, and urea regardless of tillage.

In regards to fertilizer placement, several studies have found that fertilizer banding (Argoti, 2013; Bouwman, et. al. 2002; Gagnon, 2011; Halvorson et al., 2011; Halvorson and Delgrosso, 2013) and split applications (Burzaco et al., 2013; Ma et al., 2010) increased N_2O emissions, although more data are needed to explore the differences among N placements in various climates with different EEFs.

Increasing temperature, precipitation, and water-filled pore space (WFPS) have been shown to increase N_2O production. Higher soil temperature may increase N_2O through increased respiration with reduction in the amount of available soil oxygen and creation of anaerobic microsites. With increasing % WFPS the ratio of NO-N/N_2O-N changes, from about 3–5 in the 50–60% range to <1 at or above 80% due to consumption of NO by denitrifiers (Smith, 2003). Pulses of N_2O emissions have been observed following fertilization, soil disturbance such as tillage, rainfall events and freeze/thaw cycles. In Illinois, Fernandez et al. (2014) found that the largest N_2O peaks were seen after heavy rainfall (>20mm) regardless of N source. Flessa (1995) and Kaiser (1998) stated that half of all annual N_2O from arable land can be generated by freeze/thaw cycles. Halvorson (2012) found that N_2O emissions were detected in plots during the March thaw with an estimated 18, 12, 17, and 42% of the yearly N_2O emissions for ESN, SuperU, UAN+AgrotainPlus, and a no fertilizer treatment, respectively. Soil structure, carbon content, and drainage have also been found to have significant effects on N_2O formation

(Decock, 2013; Motavalli, 2008; Maharjan, 2014; Stehfast and Bouwman, 2006). In a data summary, N_2O fluxes had been found to be higher for fine textured (2.9 kg N_2O-N ha^{-1}) than medium textured soils (1.9 kg N_2O-N ha^{-1}) and as soil organic matter increased above 6%, N_2O emissions increased from 1.9 kg N_2O-N ha^{-1} to 4.2 kg N_2O-N ha^{-1} (Bouwman et al., 2002).

To better understand the complex process of N_2O formation and mitigation more studies are needed to better address the complex interactions witnessed between environmental and management factors. Due to the high variability of the results so far obtained as to the efficacy of EEFs, more studies comparing these products in the Midwestern region are needed, particularly in locations that have been identified as having a high potential for N_2O emissions (i.e., high intensity and frequent rainfall events shortly after fertilization, fine-textured clayey soils prone to poor drainage, soils with high organic matter, high N inputs, and land in transition to no-till). Furthermore, accounting of indirect N_2O emissions is needed, especially due to potential nitrate leaching.

3.3.2 Nitrate leaching

Out of six studies and 135 total location-year observations for nitrate leaching there were only two studies that included any measure of variability. One study reported three mean treatment observations (Randall et al., 2011) and another reported four (Maharjan et al., 2014), both in area-scaled results. Maharjan et al. (2014) gave 16 yield-scaled observations, but these unfortunately could not be compared across studies. Due to the low number of studies, we were not able to perform a meta-analysis on the effect of EEFs on nitrate leaching, but could complete a systematic review.

In this Midwest dataset, five of the six studies that examined nitrate leaching used nitrapyrin as a nitrification inhibitor. Some results reported flow-normalized data (kg ha^{-1} cm^{-1}), which are NO_3^--N losses normalized for annual flow volume and expressed on a per-centimeter basis. Over a six-cycle corn-soybean rotation average, the addition of nitrapyrin to fall-applied AA has been found to decrease average flow-normalized NO_3^--N losses by 18% and 10% compared to fall-applied AA alone (Randall et al., 2003; Randall and Vetsch, 2005). Spring-applied AA with nitrapyrin did not reduce flow-normalized NO_3^--N losses when compared to spring-applied AA alone. However, when comparing against fall-applied AA without nitrapyrin, spring-applied AA without nitrapyrin reduced flow-normalized NO_3^--N losses by 14% while spring-applied AA with nitrapyrin reduced flow-normalized NO_3^--N losses by 6% (Randall and Vetsch, 2005). In contrast, annual reports by Randall and Vetsch (2002 & 2003) indicate flow-weighted NO_3^--N concentrations (mg N L^{-1}) in drainage water under corn from fall-applied AA were not affected by nitrapyrin. An annual report from Vetsch and Randall (2011) indicated that adding nitrapyrin to spring-applied UAN did not affect average flow-weighted NO_3^--N concentrations when compared to UAN alone. Lawlor et al. (2004) found that the addition of nitrapyrin to aqua-ammonia applications did not reduce average flow-weighted NO_3^- concentrations in fall or spring in a corn-soybean rotation at a 168 kg ha^{-1} rate, and there were no significant differences three of four years among the treatments. The results for each application from highest NO_3^--N concentrations in subsurface drainage to the lowest rank as follows: spring with inhibitor > fall with inhibitor > spring alone > fall alone, though results were not statistically significantly different. A study by Maharjan et al. (2014) used SuperU and ESN as treatments, resulting with the amount of NO_3^- leached (kg NO_3^--N ha^{-1}) under corn among treatments as follows: ESN > SuperU > split-urea > control (no urea). The study also reported NO_3^- leaching in yield-scaled units (kg N Mg^{-1} grain) which changed the arrangement of nitrate leached among treatments to the following order: Control > ESN > SuperU > split-U. Reporting N losses as yield-scaled units provides a useful way of comparing crop production versus nitrate losses.

Subsurface losses of nitrate from continuous corn have tended to be higher than other types of crop rotations (Weed and Kanwar, 1996). Management practices, such as diversified crop rotations, can reduce the loss of nitrate, but there is little information regarding the interactions of enhanced efficiency fertilizers with crop rotation. Reduced losses have occurred in corn-soybean rotations when compared to continuous corn, though the reduction is often dependent on climatic conditions (Randall et al., 1997). Rotations including nitrogen fixers, such as soybeans, do not require N inputs in the legume phase of the rotation. Soybean has been thought to contribute less to subsurface leaching of NO_3^--N than corn, but residual soil nitrate from the corn phase and N that has mineralized in the soil can leach into subsurface drainage during the soybean phase. Close agreement was found for the relative amounts of NO_3^--N losses in corn-soybean rotations by Randall et al. (2003) with 45% leached in soybean and 55% in corn, and by Randall and Vetsch (2005) with 46% leached in soybean and 54% in corn. Insights may be gained studying the interaction of rotation with NO_3^--N losses, particularly when using slow-release fertilizers, with nitrate losses in corn/soybean systems compared to continuous corn.

Timing of N application is known to affect nitrate leaching. Depending on climatic factors and water availability, nitrogen applied in the fall may have more opportunities for loss before crops can utilize the nutrient than nitrogen applied in the spring. With fall application, Randall and Mulla (2001) reported 36% more NO_3^--N losses in tile drainage than when compared to spring application. Significantly higher NO_3^--N concentrations from fall manure applications were found when compared to spring manure applications by Van Es et al. (2006), suggesting increased denitrification and leaching potential from fall application. However, outside of Minnesota there are very few studies that compare fall and spring applications of AA and their effects on nitrate leaching with the use of inhibitors. To inform potential future regulations or guidelines, this information would be highly desirable.

4 Conclusion

Overall, there were non-significant differences among AA, UAN, and urea and their enhanced efficiency fertilizer counterparts when taking into account management and environmental factors. Application timing and N rate had much greater effects on yield than EEFs. The data available for this direct modeling may not encompass the important information to discerning conditions where EEFs may be most effective (i.e. rainfall and soil conditions within a few weeks after application). A greater coverage of studies across more locations would provide a more robust dataset for meta-analysis of the effect of local and temporal conditions on relative yield. In regards to environmental impacts, preliminary analysis shows that fertilizer induced N_2O emissions may be greatly affected by fertilizer source, with anhydrous ammonia resulting in greater emissions. Additional modeling will be required to evaluate this highly variable phenomenon, published using a variety of methods of reporting conventions. Nitrate leaching, unfortunately, shows the greatest lack of published literature despite the heavy environmental consequences. Nitrate leaching and water-quality information reported with measures of variability are the biggest information gap at this time for both tile-drained and non-tile-drained systems.

4.1 Recommendations for future work

1. Standard deviations or standard errors should be estimated and reported so that results can beincluded in the meta-analysis.
2. Additional studies of corn yield in response to EEFs with urea, UAN, or AA sources as they interact with the 4Rs should be done to provide additional data points to add to the analytical procedure developed here.
3. More data should be gathered to better represent meteorological conditions (growing degree days, rainfall, humidity, soil temperature/moisture) and used in place of the surrogates used in the present analysis.

References

Akiyama, H., Yan, X., and Yagi, K. (2009). Evaluation of effectiveness of enhanced-efficiency fertilizers as mitigation options for N_2O and NO emissions from agricultural soils: meta-analysis. *Global Change Biology* **16**, 1837-1846.

Argoti, M. A. A. (2013). Nitrous oxide emissions: Measurements in corn and simulations at field and regional scale, Kansas State University. Dissertation.

Arizona-Software. GraphClick (Version 3.0) [Computer software]. 20.02.12

Awale, R., Chatterjee, A., Kandel, H., Ransom, J. (2013) Denitrification loss of fertilizer nitrogen during drought year under soil with high clay content. *Crops and Soils.* July-August, 24-32.

Basche, A.D., Miquez, F.E., Kaspar, T.C., and Castellano, M.J. (2014). Do cover crops increase or decrease nitrous oxide emissions? A meta-analysis. *Journal of Soil and Water Conservation* **69**, 471-782.

Borenstein, M., Hedges, L.V., Higgins, J.P.T., Rothstein, H.R. (2009) *Introduction to Meta-Analysis*. John Wiley & Sons, Ltd. ISBN: 978-0-470-05724-7.

Bundy, L. G., and Andraski, T. W. (2007). Polymer-coated urea (ESN) for corn. *In* "Proc. 2007 Wisconsin Fertilizer, Aglime, and Pest Management Conf", Vol. 46, pp. 54-59. Citeseer.

Burzaco, J. P., Smith, D. R., and Vyn, T. J. (2013). Nitrous oxide emissions in Midwest US maize production vary widely with band-injected N fertilizer rates, timing and nitrapyrin presence. *Environmental Research Letters* **8**, 035031.

Carpenter, S. R., Caraco, N. F., Correll, D. L., Howarth, R. W., Sharpley, A. N., and Smith, V. H. (1998). Nonpoint pollution of surface waters with phosphorus and nitrogen. *Ecological applications* **8**, 559-568.

Ciampitti, I. A., and Vyn, T. J. (2011). A comprehensive study of plant density consequences on nitrogen uptake dynamics of maize plants from vegetative to reproductive stages. *Field Crops Research* **121**, 2-18.

Decock, C. (2014). Mitigating nitrous oxide emissions from corn cropping systems in the Midwestern U.S.: potential and data gaps. *Environ Sci Technol* **48**, 4247-56.

Diez, J., Arauzo, M., Hernáiz, P. J., Sanz, A., and Vallejo, A. (2010). Comparison of nitrification inhibitors to restrict nitrate leaching in a maize crop irrigated under mediterranean conditions. *Spanish Journal of Agricultural Research* **8**, 481-492.

Ebelhar, S., Hart, C., and Hernandez, J. (2005). Nitrogen source and rate effects on corn in southern Illinois.

Ebelhar, S. A., C. D. Hart, J. D. Hernandez, L. E. Paul, and J. J. Warren. 2007. Evaluation of new nitrogen fertilizer technologies for corn. In E. D. Nafziger (Ed.) 2007 Illinois Fertilizer Conf. Proc., pp 64-71.

Fernández, F. G., Terry, R. E., and Coronel, E. G. (2014). Nitrous Oxide Emissions from Anhydrous Ammonia, Urea, and Polymer-Coated Urea in Illinois Cornfields. *Journal of Environment Quality*, **44**, 415-422.

Flessa, H., Dörsch, P., and Beese, F. (1995). Seasonal variation of N_2O and CH_4 fluxes in differently managed arable soils in southern Germany. *Journal of Geophysical Research: Atmospheres (1984–2012)* **100**, 23115-23124.

Foster, T. (2014). The use of nitrogen timing and nitrification inhibitors as tools in corn and wheat production in Kansas. Kansas State University. Thesis.

Ferguson, R., Lark, R., Slater, G., (2003). Approaches to management zone definition for use of nitrification inhibitors. *Soil Sci. Soc. Am. J.* **67**, 937-947.

Gagnon, B., Ziadi, N., Rochette, P., Chantigny, M. H., and Angers, D. A. (2011). Fertilizer Source Influenced Nitrous Oxide Emissions from a Clay Soil under Corn. *Soil Science Society of America Journal* **75**, 595.

Gardner, J. B., and Drinkwater, L. E. (2009). The fate of nitrogen in grain cropping systems: a meta-analysis of 15N field experiments. *Ecological Applications* **19**, 2167-2184.

Gordon, W.B. (2014). Management of Urea-Containing Fertilizers for No-Tillage Corn using Nitrogen Stabilizers and Coated-Granule Technology. *J. Plant Nutrition* **37**, 87-94.

Halvorson, A. D., and Bartolo, M. E. (2014). Nitrogen Source and Rate Effects on Irrigated Corn Yields and Nitrogen-Use Efficiency. *Agronomy Journal* **106**, 681.

Halvorson, A. D., and Del Grosso, S. J. (2012). Nitrogen source and placement effects on soil nitrous oxide emissions from no-till corn. *J Environ Qual* **41**, 1349-60.

Halvorson, A. D., and Del Grosso, S. J. (2013). Nitrogen placement and source effects on nitrous oxide emissions and yields of irrigated corn. *J Environ Qual* **42**, 312-22.

Halvorson, A. D., Del Grosso, S. J., and Alluvione, F. (2010a). Nitrogen Source Effects on Nitrous Oxide Emissions from Irrigated No-Till Corn. *Journal of Environment Quality* **39**, 1554.

Halvorson, A. D., Del Grosso, S. J., and Alluvione, F. (2010b). Tillage and Inorganic Nitrogen Source Effects on Nitrous Oxide Emissions from Irrigated Cropping Systems. *Soil Science Society of America Journal* **74**, 436.

Halvorson, A. D., Del Grosso, S. J., and Jantalia, C. P. (2011). Nitrogen source effects on soil nitrous oxide emissions from strip-till corn. *Journal of environmental quality* **40**, 1775-1786.

Halvorson, A. D., Snyder, C. S., Blaylock, A. D., and Del Grosso, S. J. (2014). Enhanced-Efficiency Nitrogen Fertilizers: Potential Role in Nitrous Oxide Emission Mitigation. *Agronomy Journal* **106**, 715.

Hatfield, J. L., and Parkin, T. B. (2014a). Enhanced Efficiency Fertilizers: Effect on Agronomic Performance of Corn in Iowa. *Agronomy Journal* **106**, 771.

Hatfield, J. L., and Venterea, R. T. (2014b). Enhanced Efficiency Fertilizers: A Multi-Site Comparison of the Effects on Nitrous Oxide Emissions and Agronomic Performance. *Agronomy Journal* **106**, 679.

Hendrickson, L. (1992). Corn yield response to the urease inhibitor NBPT: five-year summary. *Journal of production agriculture* **5**, 131-137.

Hijmans, R.J., S.E. Cameron, J.L. Parra, P.G. Jones and A. Jarvis (2005) Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* **25**, 1965-1978.

Jacinthe, P.-A., Dick, W., and Brown, L. (1999). Bioremediation of nitrate-contaminated shallow soils using water table management techniques: Nitrate removal efficiency. *Transactions of the ASAE* **42**, 1251-1259.

Kaiser, E.-A., Kohrs, K., Kücke, M., Schnug, E., Heinemeyer, O., and Munch, J. (1998). Nitrous oxide release from arable soil: importance of N-fertilization, crops and temporal variation. *Soil Biology and Biochemistry* **30**, 1553-1563.

Kim, D.-G., Hernandez-Ramirez, G., and Giltrap, D. (2013). Linear and nonlinear dependency of direct nitrous oxide emissions on fertilizer nitrogen input: A meta-analysis. *Agriculture, Ecosystems & Environment* **168**, 53-65.

Lawlor, P.A, Baker, J.L., Stewart, M.W., Helmers, M.J. (2004). Nitrification Inhibitor and Nitrogen Application Timing Effects on Yields and Nitrate-Nitrogen Concentrations in Subsurface Drainage from a Corn-Soybean Rotation. *2004 ASAE/CSAE Annual International Meeting.* Paper number 042273.

Linquist, B. A., Liu, L., van Kessel, C., van Groenigen, K.J. (2013). Enhanced efficiency nitrogen fertilizers for rice systems: Meta-analysis of yield and nitrogen uptake. *Field Crops Research* **154**, 246-254.

Ma, B. L., Wu, T. Y., Tremblay, N., Deen, W., Morrison, M. J., McLaughlin, N. B., Gregorich, E. G., and Stewart, G. (2010). Nitrous oxide fluxes from corn fields: on-farm assessment of the amount and timing of nitrogen fertilizer. *Global Change Biology* **16**, 156-170.

Maharjan, B., Venterea, R. T., and Rosen, C. (2014). Fertilizer and Irrigation Management Effects on Nitrous Oxide Emissions and Nitrate Leaching. *Agronomy Journal* **106**, 703.

McCarty, G., and Bremner, J. (1989). Laboratory evaluation of dicyandiamide as a soil nitrification inhibitor 1. *Communications in Soil Science & Plant Analysis* **20**, 2049-2065.

McIsaac, G. F., David, M. B., Gertner, G. Z., and Goolsby, D. A. (2001). Eutrophication: nitrate flux in the Mississippi River. *Nature* **414**, 166-167.

Motavalli, P. P., Goyne, K. W., and Udawatta, R. P. (2008). Environmental impacts of enhanced-efficiency nitrogen fertilizers. *Crop Management* **7**, 0-0.

Motavalli, P. P., Nelson, K. A., and Bardhan, S. (2012). Development of a Variable-Source N Fertilizer Management Strategy Using Enhanced-Efficiency N Fertilizers. *Soil Science* **178**, 693-703.

Nash, P.R., Nelson, K.A., Motavalli, P.P. (2013). Corn Yield Response to Polymer and Non-Coated Urea Placement and Timings. Inter. J. of Plant Production. **7**, 373-391.

Nelson, D. W. (1982). Gaseous losses of nitrogen other than through denitrification. *In* "Nitrogen in agricultural soils", Vol. 22, pp. 327-363. American Society of Agronomy Madison, Wisconsin,, USA.

Nelson, K. A., Motavalli, P. P., and Dudenhoeffer, C. J. (2014). Cropping System Affects Polymer-Coated Urea Release and Corn Yield Response in Claypan Soils. *Journal of Agronomy and Crop Science* **200**, 54-65.

Nelson, K. A., Paniagua, S. M., and Motavalli, P. P. (2009). Effect of Polymer Coated Urea, Irrigation, and Drainage on Nitrogen Utilization and Yield of Corn in a Claypan Soil. *Agronomy Journal* **101**, 681.

Nelson, K. A., Scharf, P. C., Bundy, L. G., and Tracy, P. (2008). Agricultural Management of Enhanced-Efficiency Fertilizers in the North-Central United States. *cm* **7**, 0.

Nelson, K. A., Scharf, P. C., Stevens, W. E., and Burdick, B. A. (2011). Rescue Nitrogen Applications for Corn. *Soil Science Society of America Journal* **75**, 143.

Noellsch, A. J., Motavalli, P. P., Nelson, K. A., and Kitchen, N. R. (2009). Corn Response to Conventional and Slow-Release Nitrogen Fertilizers across a Claypan Landscape. *Agronomy Journal* **101**, 607.

Norton, J.M., 2008. Nitrification in agricultural soils. In: Schepers, J.S., Raun, W.R.(Eds.), Nitrogen in Agricultural Systems. Agronomy monograph 49. American Society of Agronomy, Madison, WI, USA, pp. 173–199.

Omonode, R. A., and Vyn, T. J. (2013). Nitrification Kinetics and Nitrous Oxide Emissions when Nitrapyrin is Coapplied with Urea–Ammonium Nitrate. *Agronomy Journal* **105**, 1475.

Parkin, T. B., and Hatfield, J. L. (2010). Influence of nitrapyrin on N_2O losses from soil receiving fall-applied anhydrous ammonia. *Agriculture, Ecosystems & Environment* **136**, 81-86.

Parkin, T. B., and Hatfield, J. L. (2014). Enhanced Efficiency Fertilizers: Effect on Nitrous Oxide Emissions in Iowa. *Agronomy Journal* **106**, 694.

Philibert, A., Loyce, C., and Makowski, D. (2012). Assessment of the Quality of Meta-Analysis in Agronomy. *Agriculture, Ecosystems, and Environment* **148**, 72-82.

Pittelkow, C.M., Liang, X., Linquist, B., van Groenigen, K.J., Lee, J., Lundy, M.E., van Gestel, N. Six, J., Venterea, R.T., van Kessel, C. (2015). Productivity limits and potentials of the principles of conservation agriculture. *Nature* **517**, 365-368.

Power, J., and Schepers, J. (1989). Nitrate contamination of groundwater in North America. *Agriculture, ecosystems & environment* **26**, 165-187.

Quemada, M., Baranski, M., Nobel-de Lange, M., Vallejo, A., Cooper, J., (2013). Meta-analysis of strategies to control nitrate leaching in irrigated agricultural systems and their effects on crop yield. *Agric. , Ecosyst. Environ*.**174**, 1-10.

Randall, G., Huggins, D., Russelle, M., Fuchs, D., Nelson, W., and Anderson, J. (1997). Nitrate losses through subsurface tile drainage in conservation reserve program, alfalfa, and row crop systems. *Journal of Environmental Quality* **26**, 1240-1247.

Randall, G., and Vetsch, J. (2005). Nitrate losses in subsurface drainage from a corn–soybean rotation as affected by fall and spring application of nitrogen and nitrapyrin. *Journal of environmental quality* **34**, 590-597.

Randall, G., Vetsch, J., and Huffman, J. (2003). Nitrate losses in subsurface drainage from a corn–soybean rotation as affected by time of nitrogen application and use of nitrapyrin. *Journal of Environmental Quality* **32**, 1764-1772.

Randall, G. W., and Mulla, D. J. (2001). Nitrate nitrogen in surface waters as influenced by climatic conditions and agricultural practices. *Journal of Environmental Quality* **30**, 337-344.

Robertson, G. P., Field, C., and Raupach, M. (2004). Abatement of nitrous oxide, methane, and the other non-CO2 greenhouse gases: the need for a systems approach. *The global carbon cycle: integrating humans, climate and the natural world*, 493-506.

Rochette, P., Angers, D. A., Chantigny, M. H., and Bertrand, N. (2008). Nitrous Oxide Emissions Respond Differently to No-Till in a Loam and a Heavy Clay Soil. *Soil Science Society of America Journal* **72**, 1363.

Schlegel, A., Nelson, D., Sommers, L., (1986). Field evaluation of urease inhibitors for corn production. *Agron. J.* **78**, 1007-1012.

Schröder, J., Ten Holte, L., Van Keulen, H., and Steenvoorden, J. (1993). Effects of nitrification inhibitors and time and rate of slurry and fertilizer N application on silage maize yield and losses to the environment. *Fertilizer research* **34**, 267-277.

Six, J., Ogle, S. M., Conant, R. T., Mosier, A. R., and Paustian, K. (2004). The potential to mitigate global warming with no-tillage management is only realized when practised in the long term. *Global change biology* **10**, 155-160.

Smith, K., Ball, T., Conen, F., Dobbie, K., Massheder, J., and Rey, A. (2003). Exchange of greenhouse gases between soil and atmosphere: interactions of soil physical factors and biological processes. *European Journal of Soil Science* **54**, 779-791.

Smith, P., Martino, Z., and Cai, D. (2007). 'Agriculture', in Climate change 2007: mitigation.

Snyder, C. S., Bruulsema, T. W., Jensen, T. L., and Fixen, P. E. (2009). Review of greenhouse gas emissions from crop production systems and fertilizer management effects. *Agriculture, Ecosystems & Environment* **133**, 247-266.

Soares, J. R., Cantarella, H., and de Campos Menegale, M. L. (2012). Ammonia volatilization losses from surface-applied urea with urease and nitrification inhibitors. *Soil biology and biochemistry* **52**, 82-89.

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. Web Soil Survey. Available online at http://websoilsurvey.nrcs.usda.gov/. Accessed [8/15/2014].

Sommer, S.G., Schjoerring, J.K., Denmead, O., (2004). Ammonia emission from mineral fertilizers and fertilized crops. *Adv. Agron.* **82**, 557-622.

Stehfest, E., and Bouwman, L. (2006). N_2O and NO emission from agricultural fields and soils under natural vegetation: summarizing available measurement data and modeling of global annual emissions. *Nutrient Cycling in Agroecosystems* **74**, 207-228.

Stehouwer, R., and Johnson, J. (1990). Urea and anhydrous ammonia management for conventional tillage corn production. *Journal of Production Agriculture* **3**, 507-513.

Thornton, P.E., M.M. Thornton, B.W. Mayer, N. Wilhelmi, Y. Wei, R. Devarakonda, and R.B. Cook. 2014. Daymet: Daily Surface Weather Data on a 1-km Grid for North America, Version 2. Data set. Available on-line [http://daac.ornl.gov] from Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, Tennessee, USA. Data accessed between 2014/07/15 and 2014/11/24. Temporal range: 1987/04/26-2013/11/08. Spatial range: N=45.38, S=33.60, E=-81.33, W=-104.98. http://dx.doi.org/10.3334/ORNLDAAC/1219

USDA-NASS (1997). *Usual Planting and Harvesting Dates for U.S. Field Crops* (Agricultural Handbook Number 628). http://www.nass.usda.gov/Publications/Usual_Planting_and_Harvesting_Dates/uph97.pdf

USEPA (2013). Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2011. *EPA 430-R-13-001*, http://www.epa.gov/climatechange/emissions/usinventoryreport.html.

Van Es, H. M., Sogbedji, J. M., and Schindelbeck, R. R. (2006). Effect of manure application timing, crop, and soil type on nitrate leaching. *Journal of environmental quality* **35**, 670-679.

Van Groenigen, J. W., Velthof, G. L., Oenema, O., Van Groenigen, K. J., and Van Kessel, C. (2010). Towards an agronomic assessment of N_2O emissions: a case study for arable crops. *European Journal of Soil Science* **61**, 903-913.

van Kessel, C., Venterea, R., Six, J., Adviento-Borbe, M. A., Linquist, B., and van Groenigen, K. J. (2013). Climate, duration, and N placement determine N_2O emissions in reduced tillage systems: a meta-analysis. *Glob Chang Biol* **19**, 33-44.

Venterea, R. T., Bijesh, M., and Dolan, M. S. (2011). Fertilizer source and tillage effects on yield-scaled nitrous oxide emissions in a corn cropping system. *J Environ Qual* **40**, 1521-31.

Venterea, R. T., Burger, M., and Spokas, K. A. (2005). Nitrogen oxide and methane emissions under varying tillage and fertilizer management. *J Environ Qual* **34**, 1467-77.

Venterea, R. T., Halvorson, A. D., Kitchen, N., Liebig, M. A., Cavigelli, M. A., Grosso, S. J. D., Motavalli, P. P., Nelson, K. A., Spokas, K. A., Singh, B. P., Stewart, C. E., Ranaivoson, A., Strock, J., and Collins, H. (2012). Challenges and opportunities for mitigating nitrous oxide emissions from fertilized cropping systems. *Frontiers in Ecology and the Environment* **10**, 562-570.

Venterea, R. T., and Stanenas, A. J. (2008). Profile analysis and modeling of reduced tillage effects on soil nitrous oxide flux. *Journal of environmental quality* **37**, 1360-1367.

Vetsch, J. A., and Randall, G. W. (2004). Corn production as affected by nitrogen application timing and tillage. *Agronomy Journal* **96**, 502-509.

Weber, H.S. (2008). Use of Nitrogen Management Products and Practices to Enhance Yield and Nitrogen Uptake in No-Till Corn and Grain Sorghum. Kansas State University. North Central Extension-Industry Soil Fertility Conference **25.**

Weed, D., and Kanwar, R. (1996). Nitrate and water present in and flowing from root-zone soil. *Journal of Environmental Quality* **25**, 709-719.

Wilson, M. L., Rosen, C. J., and Moncrief, J. F. (2010). Effects of polymer-coated urea on nitrate leaching and nitrogen uptake by potato. *Journal of environmental quality* **39**, 492-499.

Wolt, J. D. (2004). A meta-evaluation of nitrapyrin agronomic and environmental effectiveness with emphasis on corn production in the Midwestern USA. *Nutrient Cyclcling in Agroecosystem* **69**, 23-41.

Yahdjian, L., and Sala, O. E. (2010). Size of precipitation pulses controls nitrogen transformation and losses in an arid Patagonian ecosystem. *Ecosystems* **13**, 575-585.

Zaman, M., and Blennerhassett, J. D. (2010). Effects of the different rates of urease and nitrification inhibitors on gaseous emissions of ammonia and nitrous oxide, nitrate leaching and pasture production from urine patches in an intensive grazed pasture system. *Agriculture, Ecosystems & Environment* **136**, 236-246.

Appendix: Statistical Analysis

A1 Introduction

The specific objective of this quantitative meta-analysis is to determine whether using an enhanced efficiency fertilizer (EEF) will produce greater corn yield than will using the non-enhanced version of the same N source, to compare the yields produced by different EEFs, and to determine whether and to what extent the ability of EEFs to increase yield is affected by placement, application time, application rate, or other management, meteorological, or soil variables. To this end, we developed three models of the response variable *yield*—one for each of the primary N sources anhydrous ammonia (AA), urea ammonium nitrate (UAN), and urea—

as a function of the explanatory variables fertilizer, application timing, rate, placement, cropping system, tillage, climate and meteorological variables, and soil characteristics.

A1.1 Notation and language use

The factors were italicized to specifically refer to the mathematical variable. In some cases, particularly for the variables fertilizer and yield, the use of the word as a mathematical variable is almost the same as is its normal usage, and in this case either italics or non-italics may be used. Italics are also used for emphasis, as they are in non-mathematical documents.

Variable names refer to column headings in the spreadsheet unless the variable was created from those columns, in which case it was be defined in the text.

A factor is a categorical variable being considered as an independent variable in a model.

The following words are synonyms: independent variable, explanatory variable, predictor variable, and covariate.

A2 Methods

A2.1 Selecting data for models

The availability of data determined which models could be developed and what questions could be answered with them. We started with the 1281-observation dataset found in the "yield" tab of the database (*Midwest_Corn_EEF_Meta-analysis Database.xlsx*). An observation—or row—in this dataset represents a *yield* treatment mean from a study with associated explanatory variables. We excluded 11 observations from 3 studies that were missing the *yield* treatment mean due to technical problems the authors encountered, but we kept the other observations from these studies. We omitted 22 additional observations from three studies in which treatment means were reported as averages over factors of interest (Nelson 13, Nelson 11, and Burzaco 14 in the dataset). These studies were averaged over application timing, over three cropping systems, and with results representing complicated averages over sites and years (Nelson et al., 2011; Nelson et al., 2014; Burzaco et al., 2014).

Those edits produced the 1248-observation dataset with *source-inhibitor-fertilizer* combinations shown in Table A 2.1, which gives the number of observations in each combination and the number of observations for which the standard error (*SE*) associated with the treatment mean was available. *SE* could have been reported in the paper, provided by the author in personal communications, or derived from the standard deviation (SD) that was reported or provided by the author ($SE = SD/\sqrt{r}$), where r is the number of replicates supporting the treatment mean). The total number of observations with *SE* is 917.

There was considerable range of number of observations for the different fertilizer source and enhancement types (Table A 2.1). Based on the observation totals, and the fact that some management practices are inherently different for different N sources (e.g., AA is only applied subsurface), we estimated a separate model to assess the effects of enhancements for AA, UAN, and urea. The other fertilizer sources were represented by too few observations to attempt to model these effects.

Table A 2.1 *Source-inhibitor-fertilizer* combinations with number of observations (treatment means) and number of observations that include *SE*.

Combination	*Source*	*Inhibitor*	*Fertilizer*	*n*	*n_with_se*
1	AA	nitrapyrin	AA+nitrapyrin	72	23
2	AA	none	AA	92	30
3	Aq. A	nitrapyrin	Aq. A+Nitrapyrin	8	0
4	Aq. A	none	Aq. A	16	0
5	Nitamin	S.R.	Nitamin	6	6
6	Nurea	S.R.	Nurea	1	1
7	UAN	NBPT	UAN+Agrotain	56	56
8	UAN	NBPT+DCD	UAN+AgrotainPlus	58	46
9	UAN	S.R.	UAN+Nfusion	2	2
10	UAN	S.R.	UAN+Nutrisphere	9	0
11	UAN	nitrapyrin	UAN+Instinct	13	13
12	UAN	none	UAN	117	105
13	UAN	thiosulfate	UAN cats	40	40
14	ammonium sulfate	DCD	ammonium sulfate+DCD	2	0
15	ammonium sulfate	none	ammonium sulfate	4	0
16	control	control	control	194	145
17	urea	NBPT	urea+Agrotain	51	40
18	urea	NBPT+DCD	SuperU	78	74
19	urea	PCF	Duration III	2	2
20	urea	PCF	ESN	160	118
21	urea	PCF	PCU	8	8
22	urea	PCF	urea/ESN	4	0

Combination	Source	Inhibitor	Fertilizer	n	n_with_se
23	urea	S.R.	urea+Nutrisphere	17	14
24	urea	nitrapyrin	urea+Instinct	28	28
25	urea	nitrapyrin	urea+N-Serve	4	0
26	urea	nitrapyrin	urea+nitrapyrin	1	1
27	urea	none	urea	205	165
				1248	917

A2.2 Meta-analysis via direct modeling

We performed a meta-analysis via direct modeling of treatment means for *yield*. We used multiple linear regression models of *yield* as a function of explanatory variables and random effects, under the assumption of normality.

In each of the models, the categorical variable, or factor, *fertilizer* has multiple values (levels), one of which is the non-enhanced N source: AA, UAN, or Urea. The other values are enhanced versions of the same N source: AA+nitrapyrin for AA; UAN+Agrotain, UAN+AgrotainPlus, UAN+calcium thiosulphate, UAN+Nutrisphere, UAN+Nfusion for UAN; and urea+Agrotain, SuperU, ESN, urea+Nutrisphere, urea+nitrapyrin for urea. If the variable *fertilizer* was statistically significant, then the mean *yield* for at least one of the fertilizer/enhancement combinations for that N source was significantly different from the means of all the others. To interpret a statistically significant effect of *fertilizer*, we looked at the pairwise comparisons of model-based least-squares mean estimates (LS means) for each fertilizer to determine which means were significantly different.

To determine the effect of *fertilizer* using a meta-analysis, it was necessary to control for factors that might have contributed to variability in *yield* but may have differed between studies covering a wide variety of sites and years. Within an individual study, researchers control for or include variables such as rate, application time, placement, cropping system, and tillage; meteorology, soil characteristics, drainage systems, and topology are controlled by using a single site, by replicating treatments over multiple sites, or by blocking over individual plots on the same site that have different characteristics.

Meta-analysis data, however, is observational rather than produced via experimental design. For this analysis, factors other than *fertilizer* that might have affected *yield* were controlled by including each in the model as either a fixed effect or a random effect. We use a fixed effect when we were interested in drawing conclusions about the factor itself and its interaction with *fertilizer*, and if the data are sufficient to support such inferences. We use a random effect if we were not interested in quantifying the effect of the factor itself, but must account for its effect to avoid drawing erroneous conclusions about the effect of *fertilizer*, or if the data were insufficient for quantification as a fixed effect. It was necessary to include all factors that might affect *yield* simultaneously in a single model, so that the degree to which each factor and/or each interaction among factors describing variability in *yield* could be appropriately discerned and allocated. Constructing multiple models of yield using only one explanatory factor at a time, which has been done in other meta-analyses (Basche, et al. 2014, Decock 2014), can lead to inflated estimates of effect of these factors on *yield* and their level of significance because each factor is the only one being allowed to explain variability in the model, without competing with other factors.

A2.3 Explanatory variables and random effects

To control for the simultaneous effect of the several factors examined in this study, we selected a subset of the variables detailed in Section 2.1 for use in the statistical models. Of the 4R's, the N source is accounted for by using a different model for AA, UAN, and Urea. Application timing, or *apptime,* was divided into fall, pre-planting (N-applied in the winter or spring > 5 days prior to planting), at planting (N-applied 5 days before to 20 days after planting), side dress (N-applied > 20 days after planting), pre-planting/sidedress, and at planting/sidedress. Placement or *place* was sorted into broadcast, broadcast incorporated, surface banded, and subsurface banded. Other management variables included crop rotation, which was represented by the variable *rotate*, which takes the value "no" for continuous corn, and "yes" otherwise. The variable *till* takes values "tilled" or "no-till."

Total N rate (*ratetot*) was a continuous variable. Since the positive effect of N rate on *yield* is known to diminish with greater yield, we also considered use of a transformation of *ratetot* that would produce such a curve: *erate* = exp(-(*ratetot* – mean)/standard deviation). The mean and standard deviation of *ratetot* were calculated separately for each model. For the UAN and urea models, we also considered *ratetot* as a categorical variable describing discrete bins of N rate during the exploratory model-building process. For the AA model, we found a linear function of *ratetot* to be sufficient. This finding is consistent with the fact that any exponential function can be approximated by a line over a small range of values, and the range of values of *ratetot* for the AA model was much smaller (90-194 kg ha^{-1}) than that of UAN (67-268 kg ha^{-1}) and Urea (56-336 kg ha^{-1}).

We included the meteorological variables *tempmax* and *tempmin*, the maximum and minimum daily temperatures in the growing season, and *totalwater* (mm), the sum of precipitation (*precip*) and irrigation applied (*irrigapp*). For *precip* we used the cumulative growing season precipitation reported by the authors (*preciprep*) or, if none was reported, cumulative growing season precipitation estimated using Daymet (*precipest*). Maximum and minimum temperatures provide information about the effect of short-term extreme temperatures might have on *yield*, but do not give information about the distribution of temperature throughout the growing season or the cumulative growing degree days. Cumulative precipitation, while important, does not show the distribution of precipitation over the growing season. To account for meteorological differences between sites, and between years at one site, that might affect *yield* but are not quantified by variables in our data, we include a random effect of *year* nested within *county*.

We included the site- and/or plot-specific variables *sand*, the percent of the soil that is sand; *clay*, the percent of the soil that is clay; *pH*; and soil organic matter (*SOM*). We excluded other variables that described soil (soil series, soil class, soil order, and soil texture) due to the fact that their values often were confounded with values of *county*. Thus the *county* random effect accounts for between-site differences in *yield* due to soil variables not modeled explicitly and other site-specific variables, in addition to the meteorological differences.

A2.4 Functional forms

To determine the functional form (linear, quadratic, or exponential) through which each of the continuous variables (*ratetot*, *tempmax*, *tempmin*, *totalwater*, *sand*, *clay*, *pH*, and *SOM*) should enter the model, we examined scatterplots of *yield* vs. each variable, existing knowledge of the nature of the relationship between *yield* and these variables, and plots of residuals vs. each variable after fitting a model with a linear functional form for the variable.

We considered interactions among the continuous variables. It might have been the case, for example, that the effect of *tempmax* was be different for a site/year with lower *totalwater* than for one with higher *totalwater*.

Creating higher-order polynomial terms and interactions can result in a design matrix with multicollinearity, which can lead to inflated standard error estimates for regression parameters, inflated p-values, and erroneously declaring terms to be non-significant. To minimize multicollinearity, we centered and scaled each continuous variable—by subtracting its mean and dividing by its standard deviation—prior to creating interaction terms, quadratic terms, or exponential terms. Centering minimizes the degree to which creation of interactions and higher order terms produces multicollinearity, while scaling mitigates other issues in the numerical algorithms that can occur when very large numbers occur in the same matrix as very small numbers. Because all models were run on centered-and-scaled variables, the regression parameter estimates must be interpreted with care, but interpreting regression parameter estimates is not the objective of this study.

A2.5 Variable selection

Variable-selection decisions occurred at many steps along the way. The first stage was in the compilation of the database. The second was in selecting that subset of each type of variable—management practice, climate, meteorology, or soil—that best supported a regression model, as listed in Section A2.2. It is also necessary to eliminate from consideration some variables due to collinearity and estimability issues.

A2.5.1 Collinearity

At a given research site, continuous variables such as *sand, clay, SOM*, and sometimes *pH* are constant over all treatment combinations and years. The values of *tempmax, tempmin*, and *totalwater* vary year-to-year at a given site, but are the same for all treatment means at the same site in the same year. When continuous variables are measured at a small number of values, sometimes putting many of them together in a single model with interactions and higher order terms results in a great deal of multicollinearity, even after using prophylactic measures such as centering and scaling.

To assess and eliminate remaining collinearity issues, we used an eigenvalue/eigenvector analysis of the design matrix for which the columns consist of all (centered-and-scaled) continuous variables and their pairwise interactions. Such an analysis captures overall collinearity among all columns in the design matrix, as opposed to comparing correlation coefficients of two variables at a time. This analysis gives the eigenvalues of X'X, where X is the design matrix, along with the condition index for each eigenvector. The largest condition index is called the condition number. Any condition index over 30 indicates the presence of a moderate collinearity. If it is over 100, it is a severe collinearity. The analysis also gives the percent of variability in each column explained by the eigenvector associated with each condition index. This allows identification of the columns involved in the collinearity. We identified interaction terms that contributed to collinearities and eliminated them until the condition number was around 30. We did not eliminate main effects in the collinearity analysis. Note that if an interaction term was eliminated based on collinearity, the variability in *yield* that might be attributable to that interaction will be accounted for by other variables that remain, by the definition of collinearity. Thus eliminating variables in this collinearity exercise does not prevent us from using variables other than *fertilizer* as controls.

A2.5.2 Estimability

Limitations in what variables can be considered also occur when not every combination of two categorical variables is represented in the data. Section A3 shows that the AA data support a full-factorial model since every combination of the categorical variables (apptime, till, and fertilizer) is represented in the data. For UAN and Urea, however, (Sections A4.1.4 and A4.5.4) the categorical variables must be considered as either main effects only or each 3- or 4-way interaction must be treated as the value of a new categorical variable we could call *treatment*. In other words, for UAN and urea, we could consider main effects of the categorical variables or interactions, but not both, in the same model because of lack of balance in the data.

For the UAN and urea models, we also were unable to consider 2-way interactions between continuous and categorical variables due to not having enough different values of a continuous variable for each value of the categorical variables. A concrete example of this phenomenon is given in Section A4.2.3.

A2.6 Residual analyses

For each final model, we used Q-Q plots, histograms, and boxplots of residuals to assess the assumption of normality, scatterplots of residuals vs. predicted yield to assess heterogeneity and overall goodness-of-fit, and scatterplots of residuals vs. each continuous variable to assess functional form decisions and influence of individual observations on model fit.

A3 Anhydrous ammonia (AA)

A3.1 Selecting data

A3.1.1 Original AA data

Since there was only one enhanced efficiency fertilizer in the AA data (Table A 3.1), the variable *fertilizer* took only two values: AA+nitrapyrin and AA. The number of observations for each fertilizer and the overall number of observations was sufficient to support modeling over a variety of other conditions. If we had omitted observations for which *SE* was missing, more than two-thirds of the data would have been unusable.

Table A 3.1 *Source-inhibitor-fertilizer* combinations in original AA data, number of observations, and number of observations with *SE*.

Combination	*Source*	*Inhibitor*	*Fertilizer*	*n*	*n_with_se*
1	AA	nitrapyrin	AA+nitrapyrin	72	23
2	AA	none	AA	92	30
			Total	164	53

A3.1.2 Edits

The numbers of studies, author sets, states, counties, and years covered by the original AA data for all observations and for only observations including *SE* are shown in

Table A 3.2. To draw conclusions based on observations covering as wide a variety of conditions as possible, for the AA model we included all data, not omitting those observations lacking *SE*.

Table A 3.2 Numbers of studies, author sets, states, counties, and years covered by the original AA data, for all observations and for observations that included *SE*.

	Studies	Author sets	States	Counties	Years
All observations	26	6	5	7	27
Observations with *SE*	20	3	3	2	10

To be included in the dataset for the model, values of explanatory variables such as rate, placement, application timing, tillage, and rotation needed to be adequately represented and distributed among observations for AA vs. AA+nitrapyrin.

At planting/sidedress and pre-planting/sidedress applications are only found with AA, not with AA+nitrapyrin, in the original AA data (Table A 3.3). To avoid potential bias in conclusions about the effect of *fertilizer* vs the effect of *apptime*, we omitted these seven observations from the data.

Table A 3.3 *Apptime-fertilizer* combinations in the original AA data, number of observations, and number of observations with *SE*.

Combination	*apptime*	*Fertilizer*	*n*	*n_with_se*
1	AtPl	AA	15	6
2	AtPl	AA+nitrapyrin	11	4
3	AtPl/SD	AA	2	0
4	PrePl	AA	38	16
5	PrePl	AA+nitrapyrin	20	9
6	PrePl/SD	AA	5	0
7	fall	AA	32	8
8	fall	AA+nitrapyrin	41	10
			164	53

Only nine observations in the AA data were continuous corn, which was not enough to allow us to discern effects of rotation (

Table A 3.4). We omitted these observations from the data, which ensured that the cropping system is controlled in the data.

Table A 3.4 *Rotate-fertilizer* combinations in the original AA data, number of observations, and number of observations with *SE*. *Rotate* = no represents continuous corn, and *rotate* = yes includes corn/soy, corn /double-crop soy, and corn/red clover.

Combination	*rotate*	*Fertilizer*	*n*	*n_with_se*
1	no	AA	7	5
2	no	AA+nitrapyrin	2	0
3	yes	AA	85	25
4	yes	AA+nitrapyrin	70	23
			164	53

Strip-tilled plots were represented for AA but not for AA+nitrapyrin (Table A 3.5). To avoid confounding of the effect of *fertilizer* with the effect of *till*, we omitted those two observations.

Table A 3.5 *Till-fertilizer* combinations in the original AA data, number of observations, and number of observations with *SE*.

Combination	*till*	*Fertilizer*	*n*	*n_with_se*
1	no-till	AA	34	0
2	no-till	AA+nitrapyrin	20	0
3	strip	AA	2	2
4	tilled	AA	56	28
5	tilled	AA+nitrapyrin	52	23
			164	53

Final AA data

Table A 3.6 shows the combinations of values of *apptime* (AtPl = at planting, PrePl = pre-plant, fall), *till* (no-till, tilled), and *fertilizer* (AA, AA+nitrapyrin) that remained after the above edits. The observations omitted in each step above were not mutually exclusive, thus a total of 16 observations were omitted, resulting in a 148-observation dataset that allowed a complete factorial model to be fit. All combinations of each level of each factor were represented, with at least two observations for each combination. The dataset included only corn/soybean rotations and subsurface banded placements.

Table A 3.6 *Apptime-till-fertilizer* combinations in the final AA data, number of observations, and number of observations with *SE*.

Combination	*apptime*	*till*	*Fertilizer*	*n*	*n_with_se*
1	AtPl	no-till	AA	4	0
2	AtPl	no-till	AA+nitrapyrin	2	0
3	AtPl	tilled	AA	11	6
4	AtPl	tilled	AA+nitrapyrin	9	4
5	PrePl	no-till	AA	9	0
6	PrePl	no-till	AA+nitrapyrin	4	0
7	PrePl	tilled	AA	23	11
8	PrePl	tilled	AA+nitrapyrin	15	9
9	fall	no-till	AA	12	0
10	fall	no-till	AA+nitrapyrin	12	0
11	fall	tilled	AA	19	8
12	fall	tilled	AA+nitrapyrin	28	10
			Total	148	48

Fertilizer rate was balanced reasonably over the values of *fertilizer* (Figure A 3.1). The histograms below show that most values of *ratetot* (total N rate) for AA and AA+nitrapyrin were in the 114-150 kg ha^{-1} bins. AA had six, and AA+nitrapyrin five, observations in the 174 kg ha^{-1} bin or higher. AA+nitrapyrin had four observations in the 90 kg ha^{-1} bin. If AA+nitrapyrin truly produced higher *yield* than AA, the small number of observations for AA with higher values of *ratetot* than those for AA+nitrapyrin was unlikely to skew results toward declaring AA to produce higher *yield*. The same was true for the four observations for AA+nitrapyrin that fell in the 90 kg ha^{-1} bin, which was lower than that for any AA observation. After the final model was fit, we examined influence statistics to see if any observations exerted much more influence than others on conclusions about effects of different explanatory variables on *yield*. None of the highest and lowest values of *ratetot* had unusual influence on conclusions about the effect of *ratetot* on *yield*.

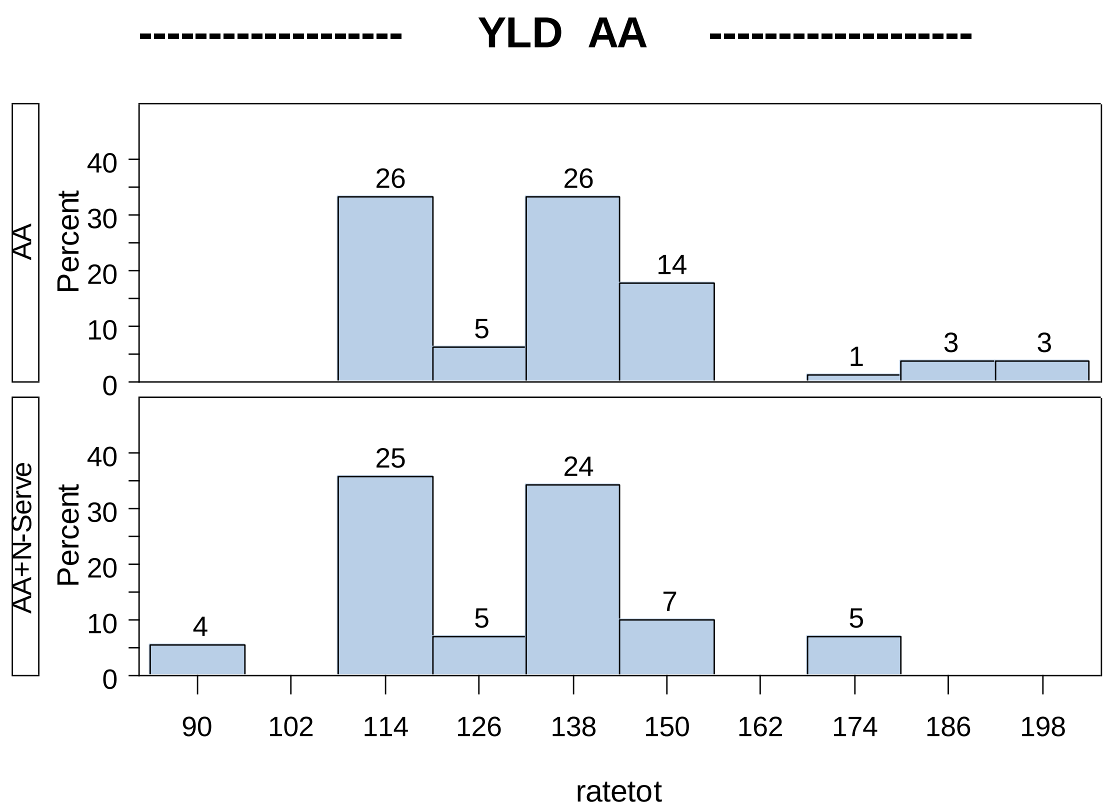

Figure A 3.1 Histograms of *ratetot* where *fertilizer* = AA and AA+N-Serve.

We also examined balance of the other continuous variables between the two levels of *fertilizer*, and all of those variables had better balance than did *ratetot*. We further examined balance of all continuous variables over levels of *apptime* and *till*, and again saw good balance.

A3.2 Model runs

A3.2.1 Categorical variable model

To see if the conclusions about the effect of *fertilizer* on *yield* were sensitive to the inclusion of the continuous variables, we began by fitting a categorical-variable-only AA model, with factors *fertilizer*, *apptime*, and *till*. The model included a random effect of *year* nested within *county*. *Ratetot* will be included as a continuous variable in model runs described below.

Because all combinations of all levels of each of the three factors are represented, it was possible to examine main effects of each factor, along with two- and three-way interactions. Table A 3.7 gives the tests of significance for the full model. None of the terms containing *fertilizer*--the main effect or the two- or-three-way interaction terms— were statistically significant.

Table A 3.7 Type III tests of fixed effects for the anhydrous ammonia categorical variable only model. The values of the variable *fertilizer* are AA and AA+nitrapyrin.

Effect	*Num DF*	*Den DF*	*F Value*	*Pr > F*
Fertilizer	1	103.3	2.34	0.1292
apptime	2	105	9.09	0.0002
till	1	33.92	5.15	0.0297
*apptime*Fertilizer*	2	103.3	0.77	0.4655
*till*Fertilizer*	1	103.3	0.38	0.5391
*apptime*till*	2	105	1.31	0.2746
*apptime*till*Fertili*	2	103.3	0.32	0.7251

Terms were backward eliminated until all terms were significant at the alpha = 0.05 level, which resulted in a model that included only the main effects of *apptime* (p-value <0.0001) and *till* (p-value 0.035). Further elimination to the alpha = 0.01 and 0.001 levels resulted in a model that included only the main effect of *apptime*. Table A 3.8 and Table A 3.9 give the LSMeans for *till* and *apptime* in the alpha = 0.05 model. Mean *yield* for tilled plots, 11 Mg ha^{-1} is significantly higher than for no-till plots, 9.8 Mg ha^{-1}. Mean *yield* for at planting applications was significantly higher than for pre-planting and fall applications, which were not significantly different from each other.

Table A 3.8 Tukey-Kramer grouping for *till* least squares means (Alpha=0.05). LSmeans with the same letter are not significantly different.

till	*Estimated mean yield (Mg ha^{-1})*	
tilled	11.5	A
no-till	9.8	B

Table A 3.9 Tukey-Kramer grouping for *apptime* least squares means (Alpha=0.05). LSmeans with the same letter are not significantly different.

apptime	*Estimated mean yield (Mg ha^{-1})*	
AtPl	11.3	A
PrePl	10.3	B
fall	10.3	B

A3.2.2 Categorical and continuous variable models

We next put the factors *fertilizer*, *apptime*, and *till* into a model along with all of the continuous variables, two-way interactions between each of the continuous variables and each of the three categorical factors, and those two-way interactions between pairs of continuous variables that remained after the collinearity analysis. For this model, *fertilizer* occurred as a main effect, in two-way interactions with each of *apptime* and *till*, in a three-way interaction with *apptime* and *till*, and in interactions with each of the continuous variables, *ratetot*, *tempmax*, *tempmin*, *sand*, *clay*, *pH*, *SOM*, and *totalwater*. None of the p-values for any of the terms containing *fertilizer* was lower than 0.26 (not statistically significant).

A3.2.3 Final model

We back-eliminated from this model all terms that were not significant at the alpha = 0.01 level. Main effects remained in the model if there was a significant interaction of that effect with another variable. The final remaining variables included *apptime*, *ratetot*, *pH*, and *ratetot***pH*. To this model we added *fertilizer*, and it had a non-significant p-value of 0.16 (Table A 3.10). Thus the effect of *fertilizer* on *yield* was not significant, and this conclusion was not sensitive to variable-selection decisions or sequence.

Table A 3.10 Type III tests of fixed effects for the AA final model.

Effect	*Num DF*	*Den DF*	*F Value*	*Pr > F*
Fertilizer	1	107.6	2.00	0.1604
apptime	2	109.6	17.18	<.0001
ratetot	1	106.5	0.88	0.3496
pH	1	140.1	0.21	0.6463
ratetot_ph	1	113.4	8.65	0.0040

Mean *yield* for at-planting applications was significantly higher than those for pre-planting and fall applications, which were not significantly different from each other (Table A 3.11).

Table A 3.11 Tukey-Kramer grouping for *apptime* least squares means (alpha=0.05). LSmeans with the same letter are not significantly different.

apptime	*Estimated mean yield (Mg ha^{-1})*	
AtPl	11.7	A
PrePl	10.7	B
fall	10.6	B

A4 Urea ammonium nitrate (UAN)

A4.1 Selecting data

A4.1.1 Original UAN data

UAN had 6 enhanced efficiency fertilizers to examine. We omitted UAN + Nfusion from the analysis due to having too few observations.

Table A 4.1 *Source-inhibitor-fertilizer* combinations in the original UAN data, number of observations, and number of observations with *SE*.

Combination	*Source*	*Inhibitor*	*Fertilizer*	*n*	*n_with_se*
1	UAN	NBPT	UAN+Agrotain	56	56
2	UAN	NBPT+DCD	UAN+AgrotainPlus	58	46
3	UAN	S.R	UAN + Nfusion	*2*	*2*
4	UAN	S.R	UAN+Nutrisphere	9	0
5	UAN	nitrapyrin	UAN+Instinct	13	13
6	UAN	none	UAN	117	105
7	UAN	thiosulfate	UAN+cats	40	40
			Total	295	262

A4.1.2 Edited UAN data

Table A 4.2 gives the remaining number of observations for each fertilizer. The factor *fertilizer* had 6 levels: UAN+Agrotain, UAN+AgrotainPlus, UAN+Nutrisphere, UAN+Instinct, UAN, and UAN+cats. If we included observations that are missing *SE*, we gained ten observations for UAN+AgrotainPlus, nine for UAN+Nutrisphere, and 12 for UAN.

Table A 4.2 Values of the variable *fertilizer* in the edited UAN data, number of observations, and number of observations with *SE*.

Fertilizer	*n*	*n_with_se*
UAN+Agrotain	56	56
UAN+AgrotainPlus	58	46
UAN+Nutrisphere	9	0
UAN+Instinct	13	13

Fertilizer	*n*	*n_with_se*
UAN	117	105
UAN+cats	40	40
Total	293	260

The factor *apptime* had 4 levels: at planting (AtPl), at planting/ sidedress (AtPl/SD), pre-planting (PrePl), and sidedress (SD) (Table A 4.3). Including observations with missing *SE* added 21 and 12 additional observations for at planting and sidedress, respectively.

Table A 4.3 Values of the variable *apptime* in the edited UAN data, number of observations, and number of observations with *SE*.

apptime	*n*	*n_with_se*
AtPl	211	190
AtPl/SD	16	16
PrePl	27	27
SD	39	27

The factor *place* had 4 levels in the UAN data: broadcast, broadcast incorporated (bcast inc), subsurface banded (sub band), and surface banded (surf band) (Table A 4.4). Including observations with missing *SE* improved coverage of broadcast, subsurface banded, and of surface banded.

Table A 4.4 Values of the variable *place* in the edited UAN data, number of observations, and number of observations with *SE*.

place	*n*	*n_with_se*
bcast inc	112	112
broadcast	134	114
sub band	23	21
surf band	24	13

The continuous variable *ratetot* ranged in value from 67 to 268 kg ha^{-1}. To allow a comparison of coverage similar to that for the other 4R factors, we created a categorical variable *rate* to divide *ratetot* into four evenly spaced bins from 67-117, 118-167, 168-217, and 218-268 kg ha^{-1} (

Table A 4.5). Including observations with missing *SE* was especially helpful for rates between 67 and 117 kg ha^{-1}, creating an increase from 65 to 92 observations.

Table A 4.5 Values of the variable *rate* in the edited UAN data, number of observations, and number of observations with *SE*.

Rate	*n*	*n_with_se*
Bin 1: 067-117	92	65
Bin 2: 118-167	76	73
Bin 3: 168-217	71	71
Bin 4: 218-268	54	51

A4.1.3 All combinations

The total number of combinations of values of the four factors *fertilizer*, *apptime*, *place*, and *rate* was 6*4*4*4 = 384. Of these, the 70 listed in Table A 4.6 were represented in the data. Of the 70, we included the subset of 50 treatment combinations for which there were at least 3 observations.

Table A 4.6 *Fertilizer-apptime-place-rate* combinations in the edited UAN data, number of observations, and number of observations with *SE*.

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
1	UAN+Nutrisphere	AtPl	broadcast	Bin 1: 067-117	3	0
2	UAN+Nutrisphere	AtPl	broadcast	Bin 2: 118-167	1	0
3	UAN+Nutrisphere	AtPl	broadcast	Bin 4: 218-268	1	0
4	UAN+Nutrisphere	AtPl	surf band	Bin 1: 067-117	2	0
5	UAN+Nutrisphere	SD	broadcast	Bin 1: 067-117	1	0
6	UAN+Nutrisphere	SD	surf band	Bin 1: 067-117	1	0
7	UAN	AtPl	bcast inc	Bin 1: 067-117	9	9
8	UAN	AtPl	bcast inc	Bin 2: 118-167	11	11
9	UAN	AtPl	bcast inc	Bin 3: 168-217	5	5
10	UAN	AtPl	bcast inc	Bin 4: 218-268	5	5
11	UAN	AtPl	broadcast	Bin 1: 067-117	14	11
12	UAN	AtPl	broadcast	Bin 2: 118-167	6	5
13	UAN	AtPl	broadcast	Bin 3: 168-217	5	5
14	UAN	AtPl	broadcast	Bin 4: 218-268	6	5
15	UAN	AtPl	surf band	Bin 1: 067-117	2	0
16	UAN	AtPl	surf band	Bin 3: 168-217	3	3
17	UAN	AtPl	surf band	Bin 4: 218-268	1	1

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
18	UAN	AtPl/SD	broadcast	Bin 3: 168-217	4	4
19	UAN	AtPl/SD	broadcast	Bin 4: 218-268	2	2
20	UAN	PrePl	bcast inc	Bin 1: 067-117	2	2
21	UAN	PrePl	bcast inc	Bin 2: 118-167	6	6
22	UAN	PrePl	broadcast	Bin 1: 067-117	3	3
23	UAN	PrePl	broadcast	Bin 3: 168-217	3	3
24	UAN	SD	bcast inc	Bin 3: 168-217	1	1
25	UAN	SD	broadcast	Bin 1: 067-117	2	0
26	UAN	SD	sub band	Bin 1: 067-117	7	6
27	UAN	SD	sub band	Bin 2: 118-167	5	5
28	UAN	SD	sub band	Bin 3: 168-217	5	5
29	UAN	SD	sub band	Bin 4: 218-268	5	5
30	UAN	SD	surf band	Bin 1: 067-117	2	0
31	UAN	SD	surf band	Bin 3: 168-217	3	3
32	UAN+cats	AtPl	bcast inc	Bin 1: 067-117	5	5
33	UAN+cats	AtPl	bcast inc	Bin 2: 118-167	5	5
34	UAN+cats	AtPl	bcast inc	Bin 3: 168-217	5	5
35	UAN+cats	AtPl	bcast inc	Bin 4: 218-268	5	5
36	UAN+cats	AtPl	broadcast	Bin 1: 067-117	5	5
37	UAN+cats	AtPl	broadcast	Bin 2: 118-167	5	5
38	UAN+cats	AtPl	broadcast	Bin 3: 168-217	5	5
39	UAN+cats	AtPl	broadcast	Bin 4: 218-268	5	5
40	UAN+Agrotain	AtPl	bcast inc	Bin 1: 067-117	5	5
41	UAN+Agrotain	AtPl	bcast inc	Bin 2: 118-167	5	5
42	UAN+Agrotain	AtPl	bcast inc	Bin 3: 168-217	5	5
43	UAN+Agrotain	AtPl	bcast inc	Bin 4: 218-268	5	5
44	UAN+Agrotain	AtPl	broadcast	Bin 1: 067-117	5	5
45	UAN+Agrotain	AtPl	broadcast	Bin 2: 118-167	5	5
46	UAN+Agrotain	AtPl	broadcast	Bin 3: 168-217	5	5
47	UAN+Agrotain	AtPl	broadcast	Bin 4: 218-268	5	5
48	UAN+Agrotain	AtPl/SD	broadcast	Bin 2: 118-167	4	4
49	UAN+Agrotain	AtPl/SD	broadcast	Bin 3: 168-217	4	4

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
50	UAN+Agrotain	AtPl/SD	broadcast	Bin 4: 218-268	2	2
51	UAN+Agrotain	PrePl	broadcast	Bin 1: 067-117	3	3
52	UAN+Agrotain	PrePl	broadcast	Bin 3: 168-217	3	3
53	UAN+AgrotainPlus	AtPl	bcast inc	Bin 1: 067-117	5	5
54	UAN+AgrotainPlus	AtPl	bcast inc	Bin 2: 118-167	5	5
55	UAN+AgrotainPlus	AtPl	bcast inc	Bin 3: 168-217	5	5
56	UAN+AgrotainPlus	AtPl	bcast inc	Bin 4: 218-268	5	5
57	UAN+AgrotainPlus	AtPl	broadcast	Bin 1: 067-117	8	5
58	UAN+AgrotainPlus	AtPl	broadcast	Bin 2: 118-167	6	5
59	UAN+AgrotainPlus	AtPl	broadcast	Bin 3: 168-217	5	5
60	UAN+AgrotainPlus	AtPl	broadcast	Bin 4: 218-268	6	5
61	UAN+AgrotainPlus	AtPl	surf band	Bin 1: 067-117	2	0
62	UAN+AgrotainPlus	AtPl	surf band	Bin 3: 168-217	3	3
63	UAN+AgrotainPlus	AtPl	surf band	Bin 4: 218-268	1	1
64	UAN+AgrotainPlus	SD	broadcast	Bin 1: 067-117	2	0
65	UAN+AgrotainPlus	SD	sub band	Bin 1: 067-117	1	0
66	UAN+AgrotainPlus	SD	surf band	Bin 1: 067-117	2	0
67	UAN+AgrotainPlus	SD	surf band	Bin 3: 168-217	2	2
68	UAN+Instinct	AtPl	bcast inc	Bin 2: 118-167	6	6
69	UAN+Instinct	PrePl	bcast inc	Bin 1: 067-117	1	1
70	UAN+Instinct	PrePl	bcast inc	Bin 2: 118-167	6	6

A4.1.4 UAN FARP3 data

Table A 4.7 lists the 50 treatment combinations in the 262-observation dataset we refer to as UAN FARP3 (*fertilizer*, *apptime*, *rate*, and *place* with at least 3 observations). Rather than further break down treatments according to rotation and tillage, we treated those variables as random effects, due to a lack of sufficient observations for every possible combination. The values of each of the variables in the UAN FARP 3 dataset were the same as the values in the edited UAN dataset. All of the levels listed in

Table A 4.2, Table A 4.3, Table A 4.6, and

Table A 4.5 for each factor were still represented in the data.

Table A 4.7 *Fertilizer-apptime-place-rate* combinations in the UAN FARP3 data, number of observations, and number of observations with *SE*.

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
1	UAN+Nutrisphere	AtPl	broadcast	Bin 1: 067-117	3	0
2	UAN	AtPl	bcast inc	Bin 1: 067-117	9	9
3	UAN	AtPl	bcast inc	Bin 2: 118-167	11	11
4	UAN	AtPl	bcast inc	Bin 3: 168-217	5	5
5	UAN	AtPl	bcast inc	Bin 4: 218-268	5	5
6	UAN	AtPl	broadcast	Bin 1: 067-117	14	11
7	UAN	AtPl	broadcast	Bin 2: 118-167	6	5
8	UAN	AtPl	broadcast	Bin 3: 168-217	5	5
9	UAN	AtPl	broadcast	Bin 4: 218-268	6	5
10	UAN	AtPl	surf band	Bin 3: 168-217	3	3
11	UAN	AtPl/SD	broadcast	Bin 3: 168-217	4	4
12	UAN	PrePl	bcast inc	Bin 2: 118-167	6	6
13	UAN	PrePl	broadcast	Bin 1: 067-117	3	3
14	UAN	PrePl	broadcast	Bin 3: 168-217	3	3
15	UAN	SD	sub band	Bin 1: 067-117	7	6
16	UAN	SD	sub band	Bin 2: 118-167	5	5
17	UAN	SD	sub band	Bin 3: 168-217	5	5
18	UAN	SD	sub band	Bin 4: 218-268	5	5
19	UAN	SD	surf band	Bin 3: 168-217	3	3
20	UAN+cats	AtPl	bcast inc	Bin 1: 067-117	5	5
21	UAN+cats	AtPl	bcast inc	Bin 2: 118-167	5	5
22	UAN+cats	AtPl	bcast inc	Bin 3: 168-217	5	5
23	UAN+cats	AtPl	bcast inc	Bin 4: 218-268	5	5
24	UAN+cats	AtPl	broadcast	Bin 1: 067-117	5	5
25	UAN+cats	AtPl	broadcast	Bin 2: 118-167	5	5
26	UAN+cats	AtPl	broadcast	Bin 3: 168-217	5	5
27	UAN+cats	AtPl	broadcast	Bin 4: 218-268	5	5
28	UAN+Agrotain	AtPl	bcast inc	Bin 1: 067-117	5	5
29	UAN+Agrotain	AtPl	bcast inc	Bin 2: 118-167	5	5

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
30	UAN+Agrotain	AtPl	bcast inc	Bin 3: 168-217	5	5
31	UAN+Agrotain	AtPl	bcast inc	Bin 4: 218-268	5	5
32	UAN+Agrotain	AtPl	broadcast	Bin 1: 067-117	5	5
33	UAN+Agrotain	AtPl	broadcast	Bin 2: 118-167	5	5
34	UAN+Agrotain	AtPl	broadcast	Bin 3: 168-217	5	5
35	UAN+Agrotain	AtPl	broadcast	Bin 4: 218-268	5	5
36	UAN+Agrotain	AtPl/SD	broadcast	Bin 2: 118-167	4	4
37	UAN+Agrotain	AtPl/SD	broadcast	Bin 3: 168-217	4	4
38	UAN+Agrotain	PrePl	broadcast	Bin 1: 067-117	3	3
39	UAN+Agrotain	PrePl	broadcast	Bin 3: 168-217	3	3
40	UAN+AgrotainPlus	AtPl	bcast inc	Bin 1: 067-117	5	5
41	UAN+AgrotainPlus	AtPl	bcast inc	Bin 2: 118-167	5	5
42	UAN+AgrotainPlus	AtPl	bcast inc	Bin 3: 168-217	5	5
43	UAN+AgrotainPlus	AtPl	bcast inc	Bin 4: 218-268	5	5
44	UAN+AgrotainPlus	AtPl	broadcast	Bin 1: 067-117	8	5
45	UAN+AgrotainPlus	AtPl	broadcast	Bin 2: 118-167	6	5
46	UAN+AgrotainPlus	AtPl	broadcast	Bin 3: 168-217	5	5
47	UAN+AgrotainPlus	AtPl	broadcast	Bin 4: 218-268	6	5
48	UAN+AgrotainPlus	AtPl	surf band	Bin 3: 168-217	3	3
49	UAN+Instinct	AtPl	bcast inc	Bin 2: 118-167	6	6
50	UAN+Instinct	PrePl	bcast inc	Bin 2: 118-167	6	6
				Total	262	248

A4.2 Model runs

Building a model designed to answer a question such as whether the effect of *fertilizer* on *yield* was statistically significant requires making decisions and judgement calls regarding what to put in the model and how to put it in. To examine the sensitivity of conclusions about the effect of *fertilizer* to these decisions, we ran several different models.

A4.2.1 Estimability

With an observational dataset that had categorical variables with many levels, estimability of treatment means must be considered. For example, for the 262-observation UAN dataset described above, there were 6 levels of the factor *fertilizer*, and 4 levels of the factor *apptime*, but only 12 of the 24 combinations of values of *fertilizer* and *apptime* were in the observational data. If all 24 combinations were available, it would be possible to consider in a model the main effects of *fertilizer* and *apptime* and the interaction effect *fertilizer*apptime*. When the factorial is not complete, however, it is possible to look at either the main effect of *fertilizer* and *apptime* or the interaction effect, but not both. A model that contains the interaction essentially treats each of the 12 combinations as a treatment.

A4.2.2 Categorical variable only model

To see if the conclusions about the effect of *fertilizer* on *yield* were sensitive to the inclusion of the continuous variables, we began by fitting a categorical-variable-only UAN model, with factors *fertilizer*, *apptime*, *place*, and *rate*—the categorical version of *ratetot* described above. The model included a random effect of *year* nested within *county* and random effects of each of *rotate* and *till*. Since the random effects of *rotate* and *till* were not significantly different from zero, we tried a random effect of the interaction *rotate*till*. It was not significant either, so it was eliminated from the model. The random effect of *year* within *county* was highly significant. The p-values for *fertilizer*, *apptime*, *place*, and *rate* were, respectively, 0.99, 0.21, 0.07, and <0.0001. Though at this point the effect of *fertilizer* was non-significant, we back-eliminated other insignificant terms one at a time to obtain a model with *place* and *rate* with p-values 0.02 and <0.0001, respectively. Even though *place* was significant at the alpha = 0.05 level, the LSMeans for each level of *place* were not significantly different from one another based on a Tukey means comparison. There were significant differences in the LSMeans for some levels of *rate* (Table A 4.8). These results were consistent with the expectation that *yield* increases and then levels off as a function of N rate.

Table A 4.8 Tukey-Kramer grouping for *rate* least squares means (alpha=0.05). LSmeans with the same letter are not significantly different.

rate	*Estimated mean yield (Mg ha^{-1})*	
Bin 4: 218-268	11.7	A
Bin 3: 168-217	11.5	A
Bin 2: 118-167	10.8	B
Bin 1: 067-117	9.4	C

A4.2.3 Categorical and continuous variable models

We next put the factors *fertilizer*, *apptime*, and *place* into a model along with all of the continuous variables, but with no interactions. Now N rate was being quantified as the continuous variable *erate*. In this model, the p-values for *fertilizer*, *apptime*, *place*, and *erate* were 0.97, 0.005, 0.005, and <0.0001. The addition of main effects of the continuous variables did not change the conclusion about the effect of *fertilizer*. Since there are times when a variable has an effect on a response only by interacting with another variable, we added to the above model interactions between each of the continuous variables and *fertilizer*. None of the interaction terms had a p-value lower than 0.25. Including these interactions did not change the conclusion that the effect of *fertilizer* is not significant.

We next fit a model with *fertilizer*, *apptime*, *place*, all of the continuous variables, and all 2-way interactions between pairs of continuous variables that remained after the collinearity analysis. The p-values for *fertilizer*, *apptime*, *place*, and *erate* in this model, which included both categorical and continuous variables were 0.97, 0.0004, 0.0010, and <0.0001, respectively. We did not include interactions between continuous and categorical variables—with the exception of the exercise described in the previous paragraph—because there were not enough values of each continuous variable within each level of each factor to allow reasonable estimation of individual slopes. Figure A 4.1 illustrates this point. For at-planting, there was a wide range of values of *tempmax*, but for AtPl/SD there were only two values of *tempmax*. To estimate the slope of a line, it is best to have quite a few more than two values of the independent variable represented to determine true underlying trends as opposed to over-fitting the data.

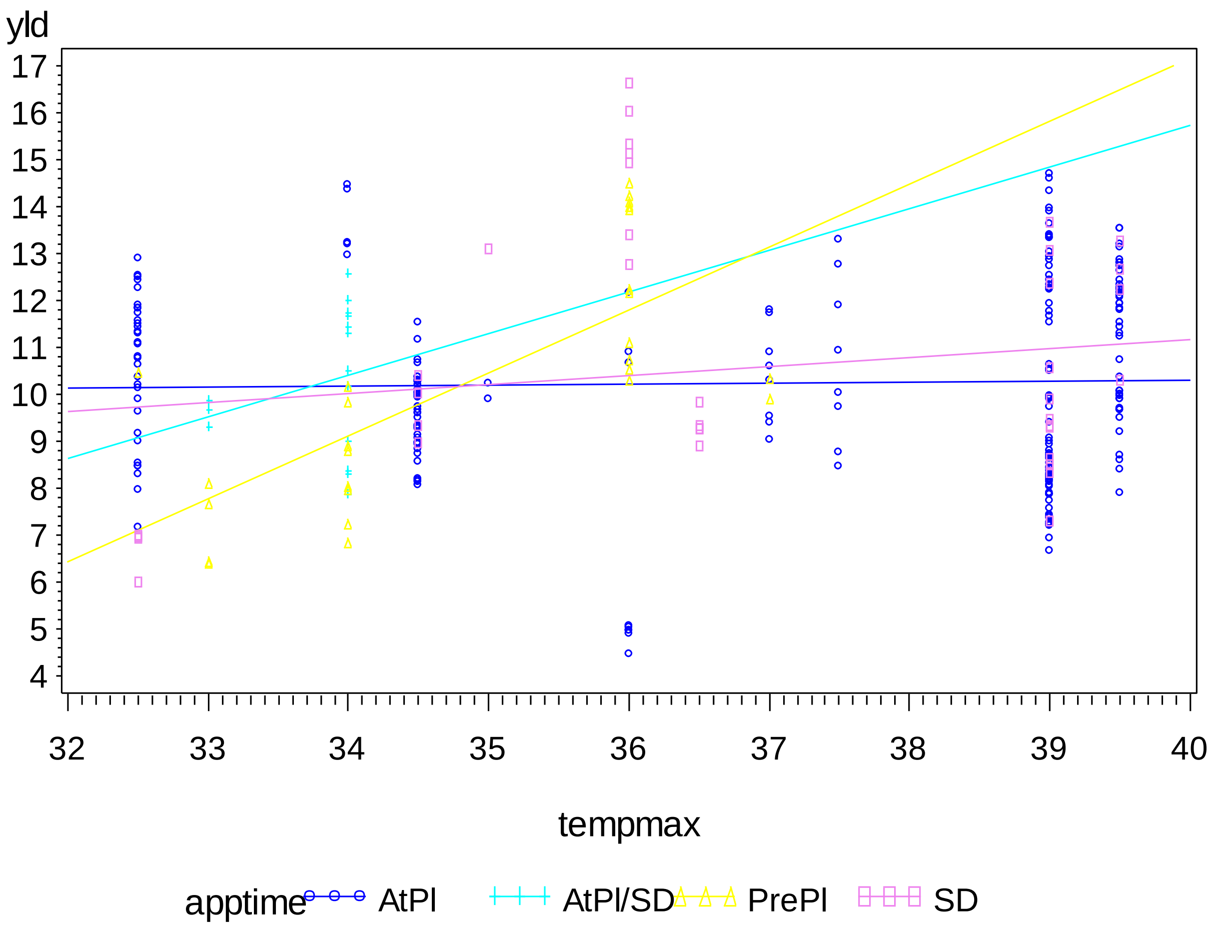

Figure A 4.1 Scatterplot of *yield* vs. *tempmax*, with different colors/symbols for each value of *apptime*, and a different regression line for each value of *apptime*: at planting (AtPl; dark blue circles), at planting/sidedress (AtPl/SD; cyan crosses), preplant (PrePl; yellow triangles), and sidedress (SD; pink squares).

A4.2.4 Final model

From the categorical and continuous model with interactions, we back-eliminated all terms that were not significant at the alpha = 0.01 level. We did not back-eliminate a main effect if there was a significant interaction between it and another variable (Table A 4.9).

Table A 4.9 Type III tests of fixed effects for final UAN model.

Effect	*Num DF*	*Den DF*	*F Value*	*Pr > F*
Fertilizer	5	227.1	0.42	0.8376
apptime	3	234.2	4.95	0.0024
erate	1	236.6	134.84	<.0001
tempmax	1	24.18	12.38	0.0017
tempmin	1	35.22	6.73	0.0138
pH	1	177.7	17.02	<.0001
SOM	1	227.1	28.08	<.0001
tempmax_erate	1	239.4	7.69	0.0060
tempmin_erate	1	234.7	31.82	<.0001
ph_erate	1	232.2	22.42	<.0001
SOM_erate	1	236.2	10.04	0.0017

The LSMeans yield estimates and comparisons for the values of *apptime* (Table A 4.10) showed that the mean yield for at-planting/sidedress was significantly higher than those for pre-planting, at-planting, and sidedress, none of which were significantly different from the others.

Table A 4.10 Tukey-Kramer grouping for *apptime* least squares means (alpha=0.05). LSmeans with the same letter are not significantly different.

apptime	*Estimated mean yield (Mg ha^{-1})*	
AtPl/SD	11.1	A
PrePl	10.2	B
AtPl	9.4	B
SD	9.1	B

A4.3 Sensitivity to using weights

In meta-analyses in which the response variable is effect size (as opposed to treatment mean, which we use), authors use weights such as $1/V$, where V is the variance of the effect size (Basche et al., 2014; Decock, 2014); r, the number of replicates supporting each treatment (Linquist et al., 2013); $1/n_{study}$, where n_{study} is the number of observations from the same study; or some function of these (Decock, 2014; Pittelkow et al., 2015). How V is calculated depends on the choice of effect size, which depends on the nature of the data and the objectives of the researchers (Borenstein et al., 2009). Using $1/V$ gives more weight to effect sizes based on more precise treatment mean estimates. In our study, the response variable is not effect size, but the treatment means of yield, and the variance of the treatment means is the square of the standard error. Using $1/SE^2$ as a weighting factor is the analog to using $1/V$. Using r as a weighting factor gives more credit to treatment means based on more replicates, but it does take into account relative precision for two different treatment means based on the same number of replicates. The rationale for using $1/n_{study}$ is to prevent any single study from having an overwhelming influence on conclusions. That might be a good idea if every study covered a single site and a single year, but different studies had different numbers of treatments, but that is not the way studies are published. While one study might cover a single year at a single site with several treatments, a second study might have the same treatments for a single year at multiple sites, thus covering multiple sets of geographical, climatological, and soil conditions. A third study might have the same treatments for multiple years at one site, covering multiple sets of meteorological conditions, but with geographical, climatological, and soil conditions fixed, and a fourth study might have the same treatments at multiple sites for multiple years, covering multiple sets of geographical, climatological, meteorological, and soil conditions. Using $1/n_{study}$ would give far too much weight to the observations from the first of the four hypothetical studies, and far too little weight to the fourth. Of these choices of weights, using $1/V$ for effect sizes or $1/SE^2$ for treatment means are the only ones with a basis in probability theory.

We examined to what extent conclusions about the effect of *fertilizer* on *yield* were sensitive to the use of weights. From the UAN FARP3 data, we created a new 248-observation dataset consisting of those treatment means for which *SE* was available (

Table A 4.7). We call this the UAN FARP3W data, where the W signifies that we are using this dataset for a weighting exercise. We considered the weights w_1 as $1/SE^2$ and w_2 as r (Table A 4.11) because they have frequently been used in meta-analysis literature. We do not, however, advocate use of r as a weight, since its use has no basis in probability theory. Table A 4.11 shows the quantiles for each weight in the UAN FARP3W data. The smallest value of $1/SE^2$ is 1, while the largest is 400. Since the "weights" are applied in the fitting algorithm after the squaring in least-squares occurs, and also after the squaring when maximum-likelihood or pseudo-likelihood methods are used, the actual weight applied to the observation is $\sqrt{w_1} = 1/SE$. Thus, using $1/SE^2$ results in weighting at least one observation 20 times more than at least one other observation. The weight r does not produce vast differences in weights among the observations since most field studies have similar numbers of replicates.

Table A 4.11 Distribution of values of weights $1/SE^2$ and r in the UAN FARP3W dataset.

Variable	Minimum	1st Pctl	10th Pctl	Lower Quartile	Median	Upper Quartile	90th Pctl	99th Pctl	Maximum
$1/SE^2$	1	1	2	3	5	12	23	83	400
r	3	3	3	4	4	4	4	5	5

Table A 4.12 gives the p-values of *fertilizer* for 5 different models. The first p-value is the same as the one given in Section A4.2.4 for the model fit to the 262-observation UAN FARP3 data with explanatory variables *fertilizer*, *apptime*, *place*, all of the continuous variables, all 2-way interactions between pairs of continuous variables that made the cut after the collinearity analysis, but no interactions between continuous and categorical variables. The reason for using these terms was to go back to the last step prior to eliminating terms based on p-values, because those p-values were calculated without weights.

The second p-value is for a model with all the same explanatory variables, but fit to the 248-observation UAN FARP3W data, again with no weights. Comparing these two p-values shows the difference in conclusions about the statistical significance of *fertilizer* that would result from dropping the 14 observations. It is not surprising that there is very little difference, given that the number of observations dropped is less than six percent of the total number of observations.

The next two rows give the p-values resulting from fitting the same model using each of the two weights. Comparing the p-value for the model fit to the UAN FARP3W data with no weights, 0.9401, to that for the same data using w_1, 0.9401, shows the difference in conclusions about the statistical significance of fertilizer that results from weighting the observations with w_1. The statistical significance of *fertilizer* in the UAN model is not sensitive to the use of weights.

Table A 4.12 P-values of *fertilizer* for UAN models that include the same explanatory variables, but different numbers of observations, or the same number of observations, but different weights.

Dataset	n	Weight	*Fertilizer* p-value
UAN FARP3	262	none	0.9418
UAN FARP3W	248	none	0.9468
UAN FARP3W	248	w_1 $1/SE^2$	0.9401
UAN FARP3W	248	w_2 r	0.9603

We were able to perform this sensitivity analysis for the UAN and urea models because the number of observations for which *SE* is available is close to the number when it is not (

Table A 4.7), and thus the coverage of treatment mean combinations is similar, and the continuous predictor variable coverage is similar. We did not do such an analysis for AA because the number of observations with *SE* is less than one third the total number of observations in the AA data (

Table A 3.6). Thus we would have to build a completely different model to do a weight-sensitivity exercise because the coverage of explanatory variables by the reduced dataset would not support the model in Section A3.2.3. If we built an entirely new *un-weighted* model based on the reduced dataset, we might see a difference in the statistical significance of fertilizer due to eliminating 2/3 of the data. We could then apply weights and see if that significance changed. We did not think it advisable to draw conclusions based on 1/3 of the data when the weighting analysis suggested that it would not greatly change our conclusions. We assume that if the statistical significance of the effect of fertilizer is not sensitive to weighting for the UAN and urea models, it is unlikely that it would be for the AA model.

A4.4 Urea

A4.5 Selecting data

The third model focuses on urea as the nitrogen fertilizer source and includes several enhanced efficiency fertilizers (Table A 4.13). Based on the availability of data, we classified Duration III, ESN, and generic polymer coated fertilizer (PCF), and called the group “PCU.” We omitted the 4 observations where *fertilizer* = “urea/ESN,” since it was a mixture of ESN and urea, and there were not enough observations to treat it as a separate fertilizer treatment. We omitted the observation with fertilizer urea+nitrapyrin because the author did not specify which commercial formulation of nitrapyrin was used, and we lumped the observations for urea+Instinct and urea+N-Serve into one group which we called “urea+nitrapyrin.”

A4.5.1 Original Urea data

Table A 4.13 *Source-inhibitor-fertilizer* combinations in original Urea data, number of observations, and number of observations with *SE*.

Combination	*Source*	*Inhibitor*	*Fertilizer*	*n*	*n_with_se*
1	urea	NBPT	urea+Agrotain	51	40
2	urea	NBPT+DCD	SuperU	78	74

Combination	*Source*	*Inhibitor*	*Fertilizer*	*n*	*n_with_se*
3	urea	PCF	Duration III	2	2
4	urea	PCF	ESN	160	118
5	urea	PCF	PCU	8	8
6	urea	PCF	urea/ESN	4	0
7	urea	S.R	Nutrisphere	17	14
8	urea	nitrapyrin	urea+Instinct	28	28
9	urea	nitrapyrin	urea+N-Serve	4	0
10	urea	nitrapyrin	urea+nitrapyrin	1	1
11	urea	none	urea	205	165
			Total	558	450

A4.5.2 Edited Urea data

Table A 4.14 gives the results after the above-mentioned edits. In this 553-observation dataset, the factor *fertilizer* had 6 levels, urea+Agrotain, SuperU, ESN, urea+Nutrisphere, urea+nitrapyrin, and urea.

Table A 4.14 Values of the variable *fertilizer* in the edited Urea data, number of observations, and number of observations with *SE*.

Fertilizer	*n*	*n_with_se*
urea+Agrotain	51	40
SuperU	78	74
PCU	170	128
urea+Nutrisphere	17	14
urea+nitrapyrin	32	28
urea	205	165
Total	553	

The factor *apptime* had 6 levels, at planting (AtPl), at planting/side dress (AtPl/SD), pre-planting (PrePl), pre-planting/side dress (PrePl/SD), side dress (SD), and fall (Table A 4.15).

Table A 4.15 Values of the variable *apptime* in the edited urea data, number of observations, and number of observations with *SE*.

apptime	*n*	*n_with_se*
AtPl	319	257

apptime	*n*	*n_with_se*
AtPl/SD	8	4
PrePl	103	81
PrePl/SD	3	3
SD	44	32
fall	76	72

The factor *place* had 4 levels: broadcast, broadcast incorporated (bcast inc), subsurface banded (sub band), and surface banded (surf band) (Table A 4.16).

Table A 4.16 Values of the variable *place* in the edited urea data, number of observations, and number of observations with *SE*.

place	*n*	*n_with_se*
bcast inc	112	112
broadcast	134	114
sub band	23	21
surf band	24	13

The continuous variable *ratetot* had values from 56 to 276 kg ha^{-1}. To allow a comparison of coverage similar to that for the other 4R factors, we created the categorical variable *rate* to divide *ratetot* into five evenly spaced bins from 56-96, 97-156, 157-216, 217-276, and 277-336 kg ha^{-1}(Table A 4.17).

Table A 4.17 Values of the variable *rate* in the edited urea data, number of observations, and number of observations with *SE*.

rate	*n*	*n_with_se*
Bin 1: 56- 96	87	65
Bin 2: 97-156	208	182
Bin 3: 157-216	153	116
Bin 4: 217-276	79	70
Bin 5: 277-336	26	16
Total	553	

A4.5.3 All combinations

The total number of combinations of the six levels of *fertilizer*, six levels of *apptime*, four levels of *place*, and five levels of *rate* was 720. Of these combinations, the 127 that were represented are listed in Table A 4.18.

Table A 4.18 *Fertilizer-apptime-place-rate* combinations in the edited Urea data, number of observations, and number of observations with *SE*.

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
1	PCU	AtPl	bcast inc	Bin 1: 56- 96	8	8
2	PCU	AtPl	bcast inc	Bin 2: 97-156	15	11
3	PCU	AtPl	bcast inc	Bin 3: 157-216	11	7
4	PCU	AtPl	bcast inc	Bin 4: 217-276	5	5
5	PCU	AtPl	bcast inc	Bin 5: 277-336	4	0
6	PCU	AtPl	broadcast	Bin 1: 56- 96	11	8
7	PCU	AtPl	broadcast	Bin 2: 97-156	11	9
8	PCU	AtPl	broadcast	Bin 3: 157-216	10	8
9	PCU	AtPl	broadcast	Bin 4: 217-276	7	5
10	PCU	AtPl	broadcast	Bin 5: 277-336	1	0
11	PCU	AtPl	sub band	Bin 2: 97-156	1	0
12	PCU	AtPl	sub band	Bin 3: 157-216	1	1
13	PCU	AtPl	surf band	Bin 3: 157-216	5	5
14	PCU	AtPl	surf band	Bin 4: 217-276	6	6
15	PCU	AtPl/SD	broadcast	Bin 2: 97-156	1	0
16	PCU	AtPl/SD	broadcast	Bin 3: 157-216	1	0
17	PCU	AtPl/SD	broadcast	Bin 4: 217-276	1	0
18	PCU	AtPl/SD	broadcast	Bin 5: 277-336	1	0
19	PCU	PrePl	bcast inc	Bin 1: 56- 96	1	1
20	PCU	PrePl	bcast inc	Bin 2: 97-156	5	5
21	PCU	PrePl	bcast inc	Bin 3: 157-216	9	3
22	PCU	PrePl	bcast inc	Bin 4: 217-276	3	3
23	PCU	PrePl	bcast inc	Bin 5: 277-336	5	5
24	PCU	PrePl	broadcast	Bin 1: 56- 96	3	0
25	PCU	PrePl	broadcast	Bin 2: 97-156	4	3
26	PCU	PrePl	broadcast	Bin 3: 157-216	3	3
27	PCU	PrePl	sub band	Bin 2: 97-156	1	0
28	PCU	SD	bcast inc	Bin 3: 157-216	3	3
29	PCU	SD	broadcast	Bin 1: 56- 96	1	0
30	PCU	SD	broadcast	Bin 2: 97-156	3	2

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
31	PCU	SD	sub band	Bin 3: 157-216	1	1
32	PCU	SD	surf band	Bin 3: 157-216	6	6
33	PCU	fall	bcast inc	Bin 2: 97-156	4	4
34	PCU	fall	broadcast	Bin 2: 97-156	6	5
35	PCU	fall	sub band	Bin 1: 56- 96	2	2
36	PCU	fall	sub band	Bin 2: 97-156	7	6
37	PCU	fall	surf band	Bin 1: 56- 96	1	1
38	PCU	fall	surf band	Bin 2: 97-156	2	2
39	SuperU	AtPl	bcast inc	Bin 1: 56- 96	5	5
40	SuperU	AtPl	bcast inc	Bin 2: 97-156	5	5
41	SuperU	AtPl	bcast inc	Bin 3: 157-216	5	5
42	SuperU	AtPl	bcast inc	Bin 4: 217-276	5	5
43	SuperU	AtPl	broadcast	Bin 1: 56- 96	7	5
44	SuperU	AtPl	broadcast	Bin 2: 97-156	5	5
45	SuperU	AtPl	broadcast	Bin 3: 157-216	5	5
46	SuperU	AtPl	broadcast	Bin 4: 217-276	5	5
47	SuperU	AtPl	surf band	Bin 3: 157-216	3	3
48	SuperU	AtPl	surf band	Bin 4: 217-276	3	3
49	SuperU	AtPl/SD	broadcast	Bin 3: 157-216	1	1
50	SuperU	PrePl	bcast inc	Bin 1: 56- 96	1	1
51	SuperU	PrePl	bcast inc	Bin 2: 97-156	2	2
52	SuperU	PrePl	bcast inc	Bin 3: 157-216	2	2
53	SuperU	PrePl	bcast inc	Bin 4: 217-276	2	2
54	SuperU	PrePl	bcast inc	Bin 5: 277-336	3	3
55	SuperU	PrePl	broadcast	Bin 2: 97-156	2	2
56	SuperU	PrePl	broadcast	Bin 3: 157-216	2	2
57	SuperU	PrePl/SD	broadcast	Bin 2: 97-156	2	2
58	SuperU	PrePl/SD	broadcast	Bin 3: 157-216	1	1
59	SuperU	SD	bcast inc	Bin 3: 157-216	3	3
60	SuperU	SD	broadcast	Bin 1: 56- 96	1	0
61	SuperU	SD	broadcast	Bin 2: 97-156	3	2
62	SuperU	SD	surf band	Bin 3: 157-216	5	5

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
63	urea	AtPl	bcast inc	Bin 1: 56- 96	8	8
64	urea	AtPl	bcast inc	Bin 2: 97-156	25	21
65	urea	AtPl	bcast inc	Bin 3: 157-216	11	7
66	urea	AtPl	bcast inc	Bin 4: 217-276	4	4
67	urea	AtPl	bcast inc	Bin 5: 277-336	4	0
68	urea	AtPl	broadcast	Bin 1: 56- 96	9	6
69	urea	AtPl	broadcast	Bin 2: 97-156	9	8
70	urea	AtPl	broadcast	Bin 3: 157-216	10	8
71	urea	AtPl	broadcast	Bin 4: 217-276	9	7
72	urea	AtPl	sub band	Bin 2: 97-156	1	0
73	urea	AtPl	sub band	Bin 3: 157-216	1	1
74	urea	AtPl	surf band	Bin 3: 157-216	7	7
75	urea	AtPl	surf band	Bin 4: 217-276	7	7
76	urea	AtPl/SD	broadcast	Bin 3: 157-216	1	1
77	urea	AtPl/SD	surf band	Bin 3: 157-216	2	2
78	urea	PrePl	bcast inc	Bin 1: 56- 96	3	3
79	urea	PrePl	bcast inc	Bin 2: 97-156	15	15
80	urea	PrePl	bcast inc	Bin 3: 157-216	11	5
81	urea	PrePl	bcast inc	Bin 4: 217-276	5	5
82	urea	PrePl	bcast inc	Bin 5: 277-336	8	8
83	urea	PrePl	broadcast	Bin 1: 56- 96	3	0
84	urea	PrePl	broadcast	Bin 2: 97-156	1	0
85	urea	PrePl	sub band	Bin 2: 97-156	1	0
86	urea	SD	bcast inc	Bin 3: 157-216	3	3
87	urea	SD	broadcast	Bin 1: 56- 96	1	0
88	urea	SD	broadcast	Bin 2: 97-156	3	2
89	urea	SD	sub band	Bin 3: 157-216	2	0
90	urea	SD	sub band	Bin 4: 217-276	2	0
91	urea	SD	surf band	Bin 3: 157-216	5	5
92	urea	fall	bcast inc	Bin 2: 97-156	11	11
93	urea	fall	broadcast	Bin 1: 56- 96	1	1
94	urea	fall	broadcast	Bin 2: 97-156	8	7

Combination	Fertilizer	apptime	place	rate	n	n_with_se
95	urea	fall	broadcast	Bin 3: 157-216	1	1
96	urea	fall	broadcast	Bin 4: 217-276	1	1
97	urea	fall	sub band	Bin 1: 56- 96	2	2
98	urea	fall	sub band	Bin 2: 97-156	7	6
99	urea	fall	surf band	Bin 1: 56- 96	1	1
100	urea	fall	surf band	Bin 2: 97-156	2	2
101	urea+Agrotain	AtPl	bcast inc	Bin 1: 56- 96	5	5
102	urea+Agrotain	AtPl	bcast inc	Bin 2: 97-156	5	5
103	urea+Agrotain	AtPl	bcast inc	Bin 3: 157-216	9	5
104	urea+Agrotain	AtPl	bcast inc	Bin 4: 217-276	5	5
105	urea+Agrotain	AtPl	broadcast	Bin 1: 56- 96	8	5
106	urea+Agrotain	AtPl	broadcast	Bin 2: 97-156	5	5
107	urea+Agrotain	AtPl	broadcast	Bin 3: 157-216	6	5
108	urea+Agrotain	AtPl	broadcast	Bin 4: 217-276	6	5
109	urea+Agrotain	SD	broadcast	Bin 1: 56- 96	1	0
110	urea+Agrotain	SD	broadcast	Bin 2: 97-156	1	0
111	urea+Nutrisphere	AtPl	bcast inc	Bin 2: 97-156	2	2
112	urea+Nutrisphere	AtPl	broadcast	Bin 1: 56- 96	2	1
113	urea+Nutrisphere	AtPl	broadcast	Bin 2: 97-156	2	2
114	urea+Nutrisphere	AtPl	broadcast	Bin 3: 157-216	2	1
115	urea+Nutrisphere	AtPl	broadcast	Bin 4: 217-276	2	1
116	urea+Nutrisphere	fall	bcast inc	Bin 2: 97-156	2	2
117	urea+Nutrisphere	fall	broadcast	Bin 1: 56- 96	1	1
118	urea+Nutrisphere	fall	broadcast	Bin 2: 97-156	2	2
119	urea+Nutrisphere	fall	broadcast	Bin 3: 157-216	1	1
120	urea+Nutrisphere	fall	broadcast	Bin 4: 217-276	1	1
121	urea+nitrapyrin	AtPl	bcast inc	Bin 2: 97-156	5	5
122	urea+nitrapyrin	AtPl	bcast inc	Bin 3: 157-216	4	0
123	urea+nitrapyrin	AtPl	broadcast	Bin 2: 97-156	2	2
124	urea+nitrapyrin	PrePl	bcast inc	Bin 1: 56- 96	1	1
125	urea+nitrapyrin	PrePl	bcast inc	Bin 2: 97-156	7	7

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
126	urea+nitrapyrin	fall	bcast inc	Bin 2: 97-156	7	7
127	urea+nitrapyrin	fall	broadcast	Bin 2: 97-156	6	6

A4.5.4 Urea FARP3 data

Of those 127 combinations, we chose the 74 for which there were at least 3 observations. We call this the Urea FARP3 dataset. There are a total of 479 observations in these combinations (Table A 4.19).

Table A 4.19 *Fertilizer-apptime-place-rate* combinations in the edited urea FARP3 data, number of observations, and number of observations with *SE*.

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
1	PCU	AtPl	bcast inc	Bin 1: 56- 96	8	8
2	PCU	AtPl	bcast inc	Bin 2: 97-156	15	11
3	PCU	AtPl	bcast inc	Bin 3: 157-216	11	7
4	PCU	AtPl	bcast inc	Bin 4: 217-276	5	5
5	PCU	AtPl	bcast inc	Bin 5: 277-336	4	0
6	PCU	AtPl	broadcast	Bin 1: 56- 96	11	8
7	PCU	AtPl	broadcast	Bin 2: 97-156	11	9
8	PCU	AtPl	broadcast	Bin 3: 157-216	10	8
9	PCU	AtPl	broadcast	Bin 4: 217-276	7	5
10	PCU	AtPl	surf band	Bin 3: 157-216	5	5
11	PCU	AtPl	surf band	Bin 4: 217-276	6	6
12	PCU	PrePl	bcast inc	Bin 2: 97-156	5	5
13	PCU	PrePl	bcast inc	Bin 3: 157-216	9	3
14	PCU	PrePl	bcast inc	Bin 4: 217-276	3	3
15	PCU	PrePl	bcast inc	Bin 5: 277-336	5	5
16	PCU	PrePl	broadcast	Bin 1: 56- 96	3	0
17	PCU	PrePl	broadcast	Bin 2: 97-156	4	3
18	PCU	PrePl	broadcast	Bin 3: 157-216	3	3
19	PCU	SD	bcast inc	Bin 3: 157-216	3	3
20	PCU	SD	broadcast	Bin 2: 97-156	3	2
21	PCU	SD	surf band	Bin 3: 157-216	6	6
22	PCU	fall	bcast inc	Bin 2: 97-156	4	4

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
23	PCU	fall	broadcast	Bin 2: 97-156	6	5
24	PCU	fall	sub band	Bin 2: 97-156	7	6
25	SuperU	AtPl	bcast inc	Bin 1: 56- 96	5	5
26	SuperU	AtPl	bcast inc	Bin 2: 97-156	5	5
27	SuperU	AtPl	bcast inc	Bin 3: 157-216	5	5
28	SuperU	AtPl	bcast inc	Bin 4: 217-276	5	5
29	SuperU	AtPl	broadcast	Bin 1: 56- 96	7	5
30	SuperU	AtPl	broadcast	Bin 2: 97-156	5	5
31	SuperU	AtPl	broadcast	Bin 3: 157-216	5	5
32	SuperU	AtPl	broadcast	Bin 4: 217-276	5	5
33	SuperU	AtPl	surf band	Bin 3: 157-216	3	3
34	SuperU	AtPl	surf band	Bin 4: 217-276	3	3
35	SuperU	PrePl	bcast inc	Bin 5: 277-336	3	3
36	SuperU	SD	bcast inc	Bin 3: 157-216	3	3
37	SuperU	SD	broadcast	Bin 2: 97-156	3	2
38	SuperU	SD	surf band	Bin 3: 157-216	5	5
39	urea	AtPl	bcast inc	Bin 1: 56- 96	8	8
40	urea	AtPl	bcast inc	Bin 2: 97-156	25	21
41	urea	AtPl	bcast inc	Bin 3: 157-216	11	7
42	urea	AtPl	bcast inc	Bin 4: 217-276	4	4
43	urea	AtPl	bcast inc	Bin 5: 277-336	4	0
44	urea	AtPl	broadcast	Bin 1: 56- 96	9	6
45	urea	AtPl	broadcast	Bin 2: 97-156	9	8
46	urea	AtPl	broadcast	Bin 3: 157-216	10	8
47	urea	AtPl	broadcast	Bin 4: 217-276	9	7
48	urea	AtPl	surf band	Bin 3: 157-216	7	7
49	urea	AtPl	surf band	Bin 4: 217-276	7	7
50	urea	PrePl	bcast inc	Bin 1: 56- 96	3	3
51	urea	PrePl	bcast inc	Bin 2: 97-156	15	15
52	urea	PrePl	bcast inc	Bin 3: 157-216	11	5
53	urea	PrePl	bcast inc	Bin 4: 217-276	5	5
54	urea	PrePl	bcast inc	Bin 5: 277-336	8	8

Combination	*Fertilizer*	*apptime*	*place*	*rate*	*n*	*n_with_se*
55	urea	PrePl	broadcast	Bin 1: 56- 96	3	0
56	urea	SD	bcast inc	Bin 3: 157-216	3	3
57	urea	SD	broadcast	Bin 2: 97-156	3	2
58	urea	SD	surf band	Bin 3: 157-216	5	5
59	urea	fall	bcast inc	Bin 2: 97-156	11	11
60	urea	fall	broadcast	Bin 2: 97-156	8	7
61	urea	fall	sub band	Bin 2: 97-156	7	6
62	urea+Agrotain	AtPl	bcast inc	Bin 1: 56- 96	5	5
63	urea+Agrotain	AtPl	bcast inc	Bin 2: 97-156	5	5
64	urea+Agrotain	AtPl	bcast inc	Bin 3: 157-216	9	5
65	urea+Agrotain	AtPl	bcast inc	Bin 4: 217-276	5	5
66	urea+Agrotain	AtPl	broadcast	Bin 1: 56- 96	8	5
67	urea+Agrotain	AtPl	broadcast	Bin 2: 97-156	5	5
68	urea+Agrotain	AtPl	broadcast	Bin 3: 157-216	6	5
69	urea+Agrotain	AtPl	broadcast	Bin 4: 217-276	6	5
70	urea+nitrapyrin	AtPl	bcast inc	Bin 2: 97-156	5	5
71	urea+nitrapyrin	AtPl	bcast inc	Bin 3: 157-216	4	0
72	urea+nitrapyrin	PrePl	bcast inc	Bin 2: 97-156	7	7
73	urea+nitrapyrin	fall	bcast inc	Bin 2: 97-156	7	7
74	urea+nitrapyrin	fall	broadcast	Bin 2: 97-156	6	6
				Total	479	397

A4.6 Model runs

A4.6.1 Categorical variable only model

As with the UAN model, to see if the conclusions about the effect of *fertilizer* on yield were sensitive to the inclusion of the continuous variables, we began by fitting a categorical-variable-only urea model, with factors *fertilizer*, *apptime*, *place*, and *rate*—the categorical version of *ratetot* described above. The model included a random effect of *year* nested within *county* and random effects of each of *rotate* and *till*. Since the random effects of *rotate* and *till* were not significantly different from zero, we tried a random effect of the interaction *rotate***till*. It was not significant and eliminated from the model. The random effect of *year* within *county* was highly significant. The p-values for *fertilizer*, *apptime*, *place*, and rate are shown in Table A 4.20.

Table A 4.20 Type III tests of fixed effects for categorical variable only urea model.

Effect	*Num DF*	*Den DF*	*F Value*	*Pr > F*
Fertilizer	4	424.3	1.59	0.1747
apptime	3	447.5	4.09	0.0069
place	3	445.7	2.17	0.0908
rate	4	438.1	28.61	<.0001

The LSMeans tables for *apptime* and rate from this model show that mean yield for sidedress application was significantly higher than that for pre-plant and fall applications, but was not significantly different from at planting applications (Table A 4.21). There were no significant differences in mean yield among at planting, pre-planting, or fall applications.

Table A 4.21 Tukey-Kramer grouping for apptime least squares means (Alpha=0.05). LS-means with the same letter are not significantly different.

apptime	*Estimated mean yield (Mg ha^{-1})*		
SD	12.8		A
AtPl	11.0	B	A
PrePl	10.6	B	
fall	10.5	B	

Mean yield for Bin 5, representing the highest N rates, was significantly higher than those for Bins 1-4. Mean yield for Bin 4 was significantly higher than for Bins 2 and 1, but was not significantly different from Bin 3. Mean yields for Bins 2 and 3 were significantly higher than for Bin 1, but were not significantly different from one another.

Table A 4.22 Tukey-Kramer grouping for rate least squares means (Alpha=0.05). LS-means with the same letter are not significantly different.

rate	*Estimated mean yield (Mg ha^{-1})*		
Bin 5: 277-336	13.1		A
Bin 4: 217-276	11.6		B
Bin 3: 157-216	11.3	C	B
Bin 2: 97-156	10.7	C	
Bin 1: 56- 96	9.4		D

A4.6.2 Categorical and continuous

We next put the factors *fertilizer*, *apptime*, and *place* into a model along with all of the continuous variables, but with no interactions. In this model, we used N rate as the continuous variable *erate* (where rate was modified to an exponential functional form). In this model, the p-values for *fertilizer*, *apptime*, *place*, and *erate* were 0.058, <0.0001, 0.042, and <0.0001.

At this stage for UAN, we considered a model with *fertilizer*, *apptime*, *place*, *erate*, all other continuous variables, and interactions of *fertilizer* with all of the continuous variables. This was not possible for urea, however, because the only way to include interactions between *fertilizer* and the continuous variables would have been to omit the main effects of the continuous variables from the model. There were not enough unique values of each continuous variable for each level of the variable *fertilizer*, which, as was the case for UAN, was also the reason interactions between the other categorical variables and the continuous variables were not included.

We next fit a model with *fertilizer*, *apptime*, *place*, all of the continuous variables, and all 2-way interactions between pairs of continuous variables that remained after the collinearity analysis. As noted above, this model did not include interactions between categorical and continuous variables. The p-values for *fertilizer*, *apptime*, *place*, and *erate* in the model were 0.029, <0.0001, 0.0093, and <0.0001, respectively.

A4.6.3 Final model

Finally, we back-eliminated from this model all terms that were not significant at the alpha = 0.01 level. We performed this elimination in blocks, eliminating a few variables at a time. A main effect would not be eliminated, however, if an interaction of that effect with another variable remained in the model. After performing the back-eliminations, we examined residual plots to assess model fit and to determine whether any observations exerted undue influence on results. We found a distinct downward-trend-pattern in the plot of residuals vs. predicted values that indicated a problem with the fit. Our investigation showed that outlying values of *sand* and *clay* caused variables formed as interactions between *sand* and *clay* and other continuous variables to appear to have statistical significance, but inclusion of these terms in the model created the pattern mentioned. We added and subtracted terms from the model and examined residual plots and statistical significance of the remaining terms. We also reconsidered the random effect *rotate*till*, which is significant based on the 95% confidence bounds. We arrived at a final model that included main effects of all of the continuous variables, all of which were significant at the alpha = 0.01 level, except for *tempmax*, which was very close to being significant at this level (Table A 4.23). The final model includes no interactions, but does include *apptime*, which was highly significant, the random effect of *year* nested within *county*, and the random effect *rotate*till*. As with the other sources, we left *fertilizer* in the final model. Fertilizer was not significant at the alpha = 0.05 level, and, as the *fertilizer* LSMeans table demonstrates (Table A 4.24), there were no significant differences in the mean yield for the different urea-based fertilizers.

Table A 4.23 Type III tests of fixed effects for final urea model.

Effect	*Num DF*	*Den DF*	*F Value*	*Pr > F*
Fertilizer	4	385.8	2.36	0.0525
apptime	3	430.8	6.15	0.0004
tempmax	1	34.38	7.39	0.0102
tempmin	1	43	7.69	0.0082
pH	1	291.6	7.84	0.0055
SOM	1	425.6	16.46	<.0001
totalwater	1	167.8	47.60	<.0001
erate	1	388.2	148.04	<.0001

Table A 4.24 Tukey-Kramer grouping for Fertilizer least squares means (alpha=0.05). LSmeans with the same letter are not significantly different.

Fertilizer	*Estimated mean yield (Mg ha^{-1})*	
SuperU	10.3	A
PCU	10.2	A
urea+Agrotain	10.2	A
urea+nitrapyrin	9.8	A
urea	9.8	A

In the urea model, mean yield for sidedress applications was significantly higher than for pre-plant and fall applications, but was not significantly different from that for at planting applications (Table A 4.25). Mean yield for at planting applications was significantly higher than that for pre planting applications, but was not significantly different from fall applications. Mean yield for fall and pre planting applications were not significantly different. Interpretation of these results should be with care as the dataset was developed to model enhanced efficiency fertilizers, not to quantify effects of application timing on yield.

Table A 4.25 Tukey-Kramer grouping for apptime least squares means (alpha=0.05). LSmeans with the same letter are not significantly different.

apptime	*Estimated mean yield (Mg ha^{-1})*		
SD	11.9		A
AtPI	10.0	B	A
fall	9.4	B	C
PrePI	9.0		C

A4.7 Sensitivity to weights

Just as we did for the UAN model, we performed an analysis to test the sensitivity of the effect of *fertilizer* on *yield* based to the use of weights. From the 479-observation Urea FARP3 data set, we created a new 397-observation dataset consisting of those treatment means for which *SE* was available. We call this the urea FARP3W data, where the W signifies that we are using this dataset for a weighting exercise.

We again considered the weights: $1/SE^2$ and *r*. Quantiles for each weight in the Urea FARP3W data show that the distribution of values of w_1 are more disparate for the urea data than for the UAN data (Table A 4.26). The maximum value is still 400, but the minimum value is 0.2, so that the observation given weight 400 will be given $\sqrt{2000} \approx 45$ times the weight of the observation given weight 0.2. The reason that *r*, the number of replicates, takes a maximum value of 12 is that there are some treatment means that were reported by the authors as averages over years. Thus those means are based on the sum of the replicates over those years.

Table A 4.26 Distribution of values of weights $1/SE^2$ and *r* in the urea FARP3W dataset.

Variable	*Minimum*	*1st Pctl*	*10th Pctl*	*Lower Quartile*	*Median*	*Upper Quartile*	*90th Pctl*	*99th Pctl*	*Maximum*
$1/SE^2$	*0.2*	*0.3*	*1.5*	*2.8*	*5.2*	*12.8*	*27.7*	*277.8*	*400.0*
r	*3.0*	*3.0*	*3.0*	*4.0*	*4.0*	*4.0*	*4.0*	*12.0*	*12.0*

The p-values of *fertilizer* for five different models are shown in Table A 4.27. The first p-value, 0.0572 is for a model including *fertilizer*, *apptime*, *place*, and main effects of all continuous variables. It differs from the urea final model only in that we added *place* back to this model, since *place* had been eliminated based on non-weighted p-values. The second p-value, 0.0738, is for a model with all the same explanatory variables, but fit to the 397-observation urea FARP3W data, again with no weights. Comparing the first two p-values shows the difference in conclusions that would result from dropping the 82 observations: the effect of *fertilizer* was not significant at the alpha=0.05 level before or after removing the observations.

The next two rows give the p-values resulting from fitting the same model using the two weights. We can see that for a model fit to the urea FARP3W data, going from using no weight to using $1/SE^2$ changed the p-value from 0.0738 to 0.0465. The latter p-value would indicate statistical significance at the alpha = 0.05 level. Fertilizer would probably be eliminated if we took this model and back-eliminated until all terms were significant at the alpha = 0.01 level, as we did with the urea final model. The reason we used the alpha = 0.01 level was that we are performing many tests in all of these models for the sensitivity analyses and backward elimination steps – far more hypothesis tests than one would perform when analyzing the results of a designed experiment. Reducing the statistical significance level reduces the number of tests that would be incorrect. Using the alpha = 0.01 level, the significance of fertilizer was not sensitive to the use of weights.

Table A 4.27 P-values of *fertilizer* for UAN models that include the same explanatory variables, but different numbers of observations, or the same number of observations, but different weights.

Dataset	Weight	*Fertilizer* p-value
UREA FARP3	none	0.0572
UREA FARP3W	none	0.0738
UREA FARP3W	$1/SE^2$	0.0465
UREA FARP3W	r	0.0841