ABSTRACT

HONG, NAN. Spatial Analysis of In-Season Site-Specific Nitrogen Management Effects on Groundwater Nitrate and Agronomic Performance. (Under the direction of D. Keith Cassel and Jeffrey G. White)

In-season, site-specific (SS) N management based on remote sensing (RS) has been suggested as a way of reducing groundwater NO₃-N contamination. In-season N management seeks to match the temporal variability of crop N needs by applying appropriate amounts of N at critical crop growth stages. Site-specific N management attempts to match the spatial variability of crop N requirements by applying appropriate, spatially variable N rates within fields. We evaluated the environmental and agronomic benefits of two in-season, RS-informed N management strategies applied on a uniform field-average (FA) or SS basis. We compared these to current uniform N recommendations based on "Realistic Yield Expectations" (RYE) in a typical coastal plain cropping system. We also sought to understand the spatial and temporal dynamics of shallow groundwater NO₃-N. An additional objective was to develop a statistical procedure for the analysis of spatially dense, georeferenced subsample data in randomized complete block designs, a common characteristic of precision agriculture research. The experiment was established in a 12-ha North Carolina field with a 2-yr winter wheat double-crop soybean-corn rotation. The three N management treatments were applied to 0.37 ha plots in a randomized complete block design with 10 replications. Groundwater NO₃-N and water table depth were measured every two weeks at 60 well nests (two per plot) sampling 0.9- to 1.8-, 1.8- to 2.7-, and 2.7- to 3.7-m depths from 2001 to 2003. We developed a statistical procedure for selecting an appropriate covariance model in randomized complete block analyses in the presence of spatial
correlation. When warranted, incorporating spatial covariance in the statistical analysis provides greater efficiency in estimating treatment effects. Elevations, soil organic matter (SOM), and water table elevations (WTE) were spatial covariates used for explaining NO$_3$-N spatial correlation. Compared to RYE, SS achieved: (i) less groundwater NO$_3$-N by reducing fertilizer N and increasing the harvest N ratio (the ratio of N harvested in grain or forage to the total fertilizer N applied) for wheat in 2001; (ii) increased yield associated with higher N applied and decreased harvest N ratio for corn in 2002; and (iii) increased yield associated with similar fertilizer N and increased harvest N ratio for wheat in 2003. Overall, FA performed similarly to SS for wheat, but differed greatly for corn due to an overapplication of N at tasselling. These results indicate that RS-informed SS and FA might improve groundwater quality with no sacrifice in yield, or increase grain yield with similar fertilizer N compared to RYE-based N recommendations in the Coastal Plain. Mean NO$_3$-N concentrations averaged over sampling depth at each well nest showed clear temporal fluctuations and were positively correlated with WTE. Groundwater NO$_3$-N was frequently spatially correlated and spatial covariance structure changed periodically. The spatial correlation range varied over time from 46 to 551 m, and appeared to follow the trend of the mean water table depth. Blocking alone or together with elevation, SOM, and WTE frequently explained NO$_3$-N spatial correlation. Our data suggest that to assess the environmental efficacy of N management, frequent and periodic monitoring of groundwater NO$_3$-N, especially after significant rainfall, is essential to capture in-season treatment effects. Simultaneous measurement of precipitation and water table depth facilitate understanding of these effects. The traditional sampling of NO$_3$-N only at or after harvest is likely to be insufficient to capture the entirety of treatment effects throughout the growing season. This is
especially true in coastal plain and other coarse-textured soils where in-season NO$_3$-N leaching may be pronounced. Our data also suggest that residual effects of differential N management may appear long after N application, even on these coarse-textured soils, indicating a need for longitudinal sampling.
SPATIAL ANALYSIS OF IN-SEASON SITE-SPECIFIC NITROGEN MANAGEMENT EFFECTS ON GROUNDWATER NITRATE AND AGRONOMIC PERFORMANCE

by

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A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the requirements for
the Degree of Doctor of Philosophy

SOIL SCIENCE

Raleigh
2004

APPROVED BY:

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BIOGRAPHY

I was born in Heilongjiang province, in the northeast of China. I received my Advanced Diploma in Grassland Management from Heilongjiang Province Animal Husbandry and Veterinary Science School (1992), and my B.S. degree from Northeast Agricultural University, China, in Agronomy (1995). I taught at Heilongjiang Province Animal Husbandry and Veterinary Science School from 1995 to 1999. I continued my graduate studies at Wageningen University, the Netherlands from 1999 to 2001, where I earned my M.S. degree in Ecological Agriculture. In August 2001, I began my Ph.D. study in Soil Science in North Carolina State University, and will receive the Ph.D. degree in December 2004.
ACKNOWLEDGEMENTS

It is a great pleasure for me to thank my graduate committee Drs. D. Keith Cassel, Jeffrey G. White, Marcia L. Gumpertz, and Hugh Devine for the excellent supervision on my study and research. In particular I would like to acknowledge Dr. White’s freely-knock-the-door-and-problem-solved working style, and Dr. Gumpertz’s invaluable guidance and assistance with spatial-statistical analyses.

I am greatly appreciative of Dr. Randy Weisz, who has given me constructive comments and excellent suggestions on writing Chapters 2 and 3. I am grateful to Drs. C. Brownie and L. Nelson for valuable comments; two consulting graduate students from Statistics Department, Jung-Wook Park and Kristi Gael O’Grady, for insights on the statistical analyses in Chapter 2; and Dr. W.J. Gilliam for providing information and suggestions on the nitrate analysis in Chapter 4.

I also wish to acknowledge Brian Roberts for excellent technical assistance in groundwater sampling, Guillermo Ramirez for lab analysis of groundwater data, and Dr. R. Heiniger and R. P. Sripada for sampling and processing the corn yield data. I extend my appreciation to the faculty, students, and staff in the Department of Soil Science who helped me during the study.

Last but not least, I greatly acknowledge the support, encouragement and patience of my wonderful and caring wife and lovely son.

This study was funded in part by the USDA Initiative for Future Agricultural and Food Systems (IAFS) grant # 00-52103-9644.
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LIST OF ABBREVIATIONS

AIC = Akaike Information Criterion
BIC = Schwarz’ Bayesian Information Criterion
CE = Correlated errors analysis
CIR = Color infrared photography
FA = Field-average
GS = Growth stage
LIDAR = Light detection and air ranging
LRT = Likelihood ratio $\chi^2$ test
LRT_{01} = Likelihood ratio $\chi^2$ test whose statistics has a mixture of half $\chi^0_\alpha$ (which is a constant) and half $\chi^1_\alpha$ distributions
NUE = N-use efficiency
RCB = Randomized complete block
RCBCE = Randomized complete block with correlated errors
RCBiid = Randomized complete block with iid errors
RS = Remote sensing
RYE = Realistic Yield Expectation
SCS = Spatial covariance structure
SOM = Soil organic matter
SS = site-specific
WTE = Water table elevation
INTRODUCTION

Nitrate-related health problems have received considerable attention during the past several decades. In 1945, Comly (1945) first stated that 10 mg L\(^{-1}\) nitrate-nitrogen (NO\(_3\)-N) in drinking water could cause “blue baby” syndrome, a potentially fatal illness in infants less than one year old. In 1950, Metzler and Stoltenber (1950) reported that 20 mg NO\(_3\)-N L\(^{-1}\) in drinking water may cause cyanosis in infants. Also, elevated NO\(_3\) concentrations in rural ground water are linked to the occurrence of non-Hodgkin's lymphoma (Weisenburger, 1990). Because of the potential hazard of NO\(_3\)-N to the health of infants, in 1962, the U.S. Public Health Service established a public drinking water standard of 10 mg NO\(_3\)-N L\(^{-1}\) referred to as the maximum contaminant level (MCL). In 1994, the U.S. Environmental Protection Agency (USEPA) adopted this standard to protect the public drinking water supplies.

Nitrate pollution of ground and surface waters is also an environmental concern. Nitrogen is the limiting nutrient in many aquatic ecosystems (Socolow, 1999), thus nitrate loading to surface waters can affect aquatic life by eutrophication. This can stimulate algae growth, the death and decay of which decrease dissolved oxygen content available to other aquatic organisms.

The extensive application of N fertilizer in production agriculture has been reported as the major contributor to NO\(_3\) contamination in surface and groundwater in the United States (USEPA, 1992). This has become an important environmental issue and is receiving considerable attention. Nitrate groundwater contamination in the southeastern Coastal Plain and elsewhere has become a regulatory and social issue threatening regional crop production.
The application of N fertilizer in agricultural areas has been directly linked to high NO$_3^-$ concentration in shallow groundwater (Spruill et al., 1996). This is typically true in the Neuse River basin, one of 17 major river basins in North Carolina (NC). The NO$_3^-$ concentrations detected in groundwater under agricultural fields in this area have been at levels from 10 to 20 mg NO$_3$-N L$^{-1}$ (Osmond et al., 2002). This differs from typical values of other common land uses in the region. For example, it is greater than beneath an unfertilized, North Carolina coastal plain forest where groundwater NO$_3^-$ is typically quite low (less than 0.1 mg NO$_3$-N L$^{-1}$; Karr et al., 2001). In contrast, shallow groundwater NO$_3^-$ concentrations beneath swine effluent sprayfields in the North Carolina Coastal Plain typically range from 5 to 30 mg NO$_3$-N L$^{-1}$ (Karr et al., 2001) and have been detected at concentrations greater than 100 mg NO$_3$-N L$^{-1}$ (Sloan et al., 1999). In 1998, the “Neuse River Rules” (North Carolina Administrative Code, 1998) became effective as permanent rules to protect water sources in the Neuse River basin. The rule requires “… reducing the average annual load of nitrogen delivered to the Neuse River Estuary from point and non-point sources by a minimum of 30 percent of the average annual load…”.

Under current North Carolina regulations for the Neuse and Tar-Pamlico river basins, N fertilizer rates are determined independent of growing season by multiplying whole-field Realistic Yield Expectations by a slope and erosion adjustment factor and by a nitrogen factor (Hardy et al., 2002). The nitrogen factor is defined for each crop grown on a predominant soil type in a field based on “the efficiency of a specific crop in converting N into yield” (Hardy et al., 2002) and on expectations of N contributions and dynamics of the soil type as indicated by its inclusion within a soil management group. Practically, selection of a nitrogen factor relies on soil productivity and crop management. The RYE N fertilizer is
applied uniformly across the field. This strategy may produce a large gap between crop N needs and fertilizer N applied. The resulting excess fertilizer N may eventually reach shallow groundwater, especially on coarse-textured coastal plain soils, causing groundwater NO$_3^-$ contamination. Precision, in-season, site-specific management of fertilizer N is thus receiving considerable attention.

In-season site-specific (SS) N management is intended to minimize differences between in-season crop N requirement and fertilizer inputs while maintaining or increasing yield and N-use efficiency (NUE). By applying appropriate spatially variable rates of N fertilizer at critical crop growth stages, in-season SS N management is hypothesized to increase NUE and reduce surplus N, thus improving groundwater quality compared to current, uniform RYE-based N recommendations. Flowers et al. (2004) evaluated SS N management and demonstrated that associated improvements in crop yield and NUE were primarily the result of using pre- or in-season estimates of a specific field and crop’s N requirement. Remote sensing (RS) methods to make such estimates that are applicable to SS have been reported (Filella et al., 1995; Flowers et al., 2001; Flowers et al., 2003a; Flowers et al., 2003b: Lukina et al., 2001: and Raun et al., 2002). Recent research (Dinnes et al., 2002 and Ferguson et al., 2002) has suggested that in-season SS N management based on RS might also be a way of reducing surface- and groundwater NO$_3^-$-N contamination, but this hypothesis has yet to be tested.

The main objective of this study was to evaluate the effects of RS-informed, in-season, SS N management on groundwater NO$_3^-$ concentrations. We assessed the environmental benefits and agronomic performance of RS-informed, in-season N management applied either on a uniform field-average or a site-specific basis. We compared
these treatments to current uniform RYE-based recommendations in a typical coastal plain cropping system. Additional objectives were to: (i) understand the spatial and temporal dynamics of shallow groundwater NO$_3^-$, and (ii) develop a step-by-step statistical procedure for guiding covariance model selection in spatial analysis of precision agricultural treatments in randomized complete blocks.

LITERATURE REVIEW

Nitrate Dynamics in Soils

Nitrate is very dynamic in soils, undergoing a series of transformations (Fig. 1) which may occur simultaneously in soils as part of the overall N cycle. Nitrate can be (i) added to the soil as fertilizers; (ii) formed in situ via N mineralization and nitrification; (iii) taken up by the soil microbial community together with ammonium and stored in soils as soil organic matter; (iv) taken up by crops, or (v) transformed to gaseous N including N$_2$, NO, N$_2$O via microbial denitrification under anaerobic conditions. This denitrification is not expected to be significant in deep soils due to negligible activity of denitrifying organisms (e.g., Richards and Webster, 1999) and low dissolved organic carbon concentrations (Kalbitz et al., 2000) even though the soil may be waterlogged. Hence, NO$_3^-$ below the root zone is usually not readily degraded and remains relatively stable.

Another important fate and transport of nitrate is leaching to the groundwater, which is the predominant pathway of N loss from freely draining agricultural soils (Dinnes et al., 2002). Nitrate is very soluble. Most soils have net negative charge, thus NO$_3^-$ adsorption by most soils is minimal (Keeney, 1983; Bailey and Swank 1983). Any excess nitrate in the root zone can readily leach to groundwater, which may cause groundwater nitrate contamination. Nitrate leaching occurs predominantly in sandy, well-drained soils with shallow water tables,
such as those in the Coastal Plain. Nitrate leaching occurs when significant excess rainfall is evident and groundwater is recharged. The greater the excess rainfall, especially soon after N application, the greater the possibility of nitrate leaching (Hatfield et al., 1998).

**Nitrate Leaching as Affected by Water Table**

In coastal plain agricultural soils, NO$_3^-$ leaching is associated with the amount of percolating water moving to shallow groundwater (Terry and McCants, 1970). Understanding shallow groundwater table dynamics facilitates better understanding of the NO$_3^-$ leaching process.

Water table fluctuations reflect weather changes and indicate field water conditions. Excess rainfall flows through the soil profile and eventually reaches the water table and contributes to its recharge. During this process, if the soil contains excess N not taken up by the crop or retained in the soil, it may leach to shallow groundwater. Water tables, especially perched water tables, exhibit seasonal and yearly patterns in response to varying weather conditions especially in relation to rainfall events. Monitoring water table fluctuations can provide useful information to understand soil hydrology, providing indications of potential NO$_3^-$ leaching events.

When the water table reaches the rooting zone in agricultural soils, significant denitrification is likely if soil NO$_3^-$ and organic carbon are present and temperatures are favorable. This is because anoxic conditions and the presence of easily assimilable organic substrates favor denitrifiers’ growth. This process reduces soil NO$_3^-$ concentrations and NO$_3^-$ leaching potential, thus NO$_3^-$ concentrations tend to be lower where water table is higher. However, if this process happens in the cropping season, it can reduce soil N
available to crops thus affecting yield, although groundwater NO$_3^-$ concentration is reduced (Sarwar and Kanwar, 1996). Jiang et al. (1997) also reported that shallow water table with long residence time can reduce NO$_3^-$ leaching. The authors also stated that the variation of NO$_3^-$ breakthrough patterns in their 0.3- by 1.2-m soil columns was associated with water table depth.

**Strategies to Reduce Nitrate Leaching**

Many efforts to reduce NO$_3^-$ leaching have focused on optimizing N fertilizer rate and timing (e.g., Ferguson et al., 2002); monitoring soil N mineralization to match crop N requirement (e.g., Magdoff et al., 1990); using nitrification inhibitors (e.g., Stehouwer and Johnson, 1990); using cover crops to take up residual N (e.g., Staver and Brinsfield, 1998); tillage management (e.g., Randall and Iragavarapu, 1995); or water table management (e.g., Gilliam and Skaggs, 1986; Madramootoo et al, 1993). For this research, we focused on optimizing N rate and timing, which can play dominant roles in reducing potential surface- and groundwater NO$_3^-$ contamination.

Precision N management is intended to optimize N rate on a crop growth stage (GS)- and/or site-specific basis. The rationale of GS-specific N management is that crop N need varies over the life of the crop, e.g., winter wheat (Fig. 2a) and corn (Fig. 2b). Growth stage-specific N management is intended to optimize crop yield and NUE and minimize N loss to the environment by applying N at appropriate rates at critical growth stages. For most cereal crops, this means splitting the total crop fertilizer N need into multiple applications. The GS-specific N rate may be determined in-season on a whole-field- or site-specific basis. Split fertilizer N applications have yielded inconsistent results. For example, Banfiled et al. (1981) and Grant et al. (1985) reported that there was no agronomic return using split N application
on wheat, but an agronomic advantage was reported by, e.g., Davies et al. (1979), Mulla et al. (1992), Bhatti et al. (1998), Raun et al. (2002), and Flowers et al. (2004).

Site-specific N management is intended to minimize differences between crop N requirements and N fertilizer inputs at a manageable spatial scale, e.g., submeter by submeter (Stone et al., 1996), 1 by 1 m (Raun et al., 1998), 18.3 by 564-655 m (Mulla et al., 1992), or a management zone (e.g., Fleming et al., 2000). Much research was conducted on site-specific N-fertilizer management in the 1990s (e.g., Robert et al., 1995; Braga et al., 1999). The site-specific N rate was generally determined prior to the growing season in various ways, e.g., based on: soil series (Carr et al., 1991); a combination of grid soil sampling and yield maps (Redulla et al., 1996); a combination of yield maps, soil organic matter (SOM) content, and soil N status (Mulla and Bhatti, 1997); or grid soil sampling (Ferguson et al., 2002). Site specific N management has been reported to achieve agronomic success of improving grain yield and NUE (e.g., Flower et al., 2004), environmental benefit of reducing NO$_3^-$ pollution in the watershed (e.g., Rejesus and Hornbaker 1999), or varied success with soil type and weather year (Braga et al., 1999).

In situations with substantial spatial and temporal variability in crop N need, neither growth-stage specific nor site-specific N management alone will likely provide optimum N management; the former ignores spatial differences in N need and the latter ignores yearly and in-season temporal differences in N demand. Consequently, the integration of GS-specific and site-specific N management (hereafter referred to as in-season SS N management) should be optimal. To achieve this goal, we need a solution which allows us to determine N needs on a GS and site-specific basis. Plant tissue tests have been reported as a way of successfully determining in-season N status of several grain crops (e.g., Baethgen and
Alley, 1989; Smeal and Zhang, 1994), but can be expensive, difficult, and time-consuming. Several studies reported that chlorophyll meter readings were related to whole-plant N concentration or grain yield (e.g., Blackmer and Schepers, 1994; Fox et al., 1994). Chlorophyll meters are expensive, but their use to estimate in-season N status is quicker and less expensive than tissue sampling and testing. However, for optimal application this approach requires within-field calibration based on a number of high-N reference areas. This can require intensive chlorophyll meter readings, making this method labor consuming.

Crop canopy reflectance of visible and near-infrared light has been related to crop N status and fertilizer requirement, so another alternative is remote sensing of in-season crop N status using on-the-go sensors or aerial photography. Remote sensing to make such estimates using methods applicable to SS have been reported (Filella et al., 1995, Flowers et al., 2001, Flowers et al., 2003a, Flowers et al., 2003b, Lukina et al., 2001, and Raun et al., 2002).

By applying appropriate spatially variable rates of N fertilizer at critical growth stages, in-season SS N management is hypothesized to reduce surplus N while maintaining or increasing yield and NUE, thus improving groundwater quality compared to uniform N recommendations. Recent research (Dinnes et al., 2002 and Ferguson et al., 2002) has suggested that in-season SS N management based on remote sensing might be a way of reducing groundwater NO₃⁻ contamination, but this hypothesis has yet to be tested.

**Study Site**

Research was conducted in two adjacent fields totaling 12 ha at the Lower Coastal Plain Tobacco Research Station located in Lenoir County in the Neuse River Basin, NC (Fig. 3). This station is near the center of the North Carolina Coastal Plain, thus the climate is strongly influenced by the ocean. The average length of freeze-free growing season is
approximately 225 days (from late March to early November). The 30-yr mean monthly temperature ranges from 44°F to 80°F (Fig. 4). Small amounts of snow and sleet often occur in December through March and generally melt in a few hours. The precipitation is variable throughout the year (Fig. 4). In summer, thunderstorms are the main sources of rainfall, thus causing temporal and spatial variation of rainfall across years, months, and space. The highest evapotranspiration is mainly from May to August (State Climate Office of North Carolina, http://www.nc-climate.ncsu.edu/).

The lower Coastal Plain is a wide and flat plain extending from the Atlantic Ocean west to the Goldsboro area. Its geology consists mostly of marine sedimentary rocks. Sand and clay are the primary sediment types. The soils developed from sandy to clayey unconsolidated marine and fluvial deposits (Osmond et al., 2002). A typical soil profile description of these fields is given in Table 1. The research fields are on the Wicomico geomorphic surface formed in Pleistocene time (North Carolina Agricultural Experiment Station, 1977). The upper Pleistocene Wicomico morphostratigraphic unit (msu) and the Cretaceous Pee Dee formation are the major sedimentary units. The Wicomico msu is noncalcareous and fairly uniform in composition across the profile dominated by sands and clays. The major horizontal water flow occurs at the zone of the basal sand bed in the Wicomico msu (Fig. 5). The Pee Dee formation is a relatively dense, locally calcareous, black (5Y 2/1) to dark greenish gray (5G 4/1) loam. It acts as a major barrier to downward water movement. Consequently, nitrate that reaches the groundwater can become part of the surface water contamination problem (Osmond et al., 2002).

An order one soil survey (North Carolina Agricultural Experiment Station, 1977) delineated three soil map units in these fields (Fig. 3): Norfolk (No) loamy sand with 0-2%
slope (fine-loamy, siliceous, thermic, Typic Paleudults), Goldsboro (Go) loamy sand (fine-loamy, siliceous, thermic, Aquic Paleudults), and Lynchburg (Ly) sandy loam (fine-loamy, siliceous, thermic, Aeric Paleaquults). These soils represent millions of acres of land in the lower and middle North Carolina Coastal Plain and in southeastern United States.

**Statistical Analysis of Data from Randomized Complete Block Designs**

The randomized complete block (RCB) design is commonly used in agricultural trials. Under a RCB design, the field is divided into a number of blocks ideally based on a gradient of field heterogeneity. Within a block, the treatments are randomly assigned to plots. Within a plot, one or more observations are taken. The RCB design typically includes three critical elements: randomization, blocking, and replication. Randomization provides unbiased estimates of treatment effects, valid estimates of residual variation, and valid test of hypotheses. Effective blocking increases precision by accounting for the local field gradient and helps ensure treatments are compared under similar conditions. Replication increases the number of observations to allow estimation of experimental error and provide a basis for determination of statistical significance of treatment differences.

**Issues**

Precision technologies, e.g., global positioning systems (GPS), geographic information systems (GIS), and variable rate technologies (VRT), have evolved rapidly and been incorporated into production agriculture, making precision farming an operational reality. For example, crops are commonly harvested using a combine equipped with a yield monitor linked with GPS. The resultant yield data consist of numerous georeferenced sample points across the field and dense sub-sampling within experimental plots. This is not at all common to traditional small-plot research. Precision agricultural research may benefit from
analyses encompassing multiple spatially georeferenced sampling points within plots (e.g., Ferguson et al., 2002; Eghball et al., 2003, Weisz et al., 2003).

Spatial correlation in the observations and in the residuals of the statistical model used to analyze the data is also common in precision agriculture research. This is due to several factors. It has been well documented that soil physical properties (e.g., Davidoff and Selim, 1988), moisture relations (e.g., Achouri and Gifford, 1984), and soil nutrient status (e.g., Webster and Nortcliff, 1984) vary spatially across fields. Thus, it is always possible that observations such as crop yield will also be spatially correlated and have heterogeneous variances (Scharf and Alley, 1993). Precision agriculture research is often carried out on a large spatial scale resulting in more spatial variability within and among blocks (and plots) than is typical of traditional small-plot research. In traditional small-plot research, treatments are applied and harvest is conducted on a plot-by-plot basis. This is a central element in the usual statistical definition of a “plot”. In precision agriculture research, plots are large compared to harvest and application equipment, and treatment application and crop harvest are not applied on a plot-by-plot basis. Instead applicators and harvesters move across the field in a serpentine fashion changing application rates as they pass from plot to plot, or assigning yield data to individual plots depending on their location at any given time. Consequently, the equipment may make many passes through a plot before completing harvest or application. All of these factors can lead to increased spatial variability and correlation that may not be accounted for with traditional blocking.

Classical analysis

The RCB model is a mixed model that contains both fixed and random effects. The classical RCB analysis focuses on analysis of variance (ANOVA) to determine the treatment
and/or factor effects with the assumption that the errors within blocks are independent and identically distributed (iid) with the same variance.

These assumptions are often violated, especially in agricultural research, in part because the media of agricultural trials, e.g., soils, are rarely homogeneous. When field heterogeneity is evident, ideally blocking coupled with appropriate spatial covariates can account for spatial correlation. However, in practice this is often not possible due to imperfect block size, shape, location, and/or unknown or unmeasured covariates. This is especially problematic in on-farm and precision agriculture research which frequently involves very large plots and correspondingly large blocks compared to traditional small-plot studies.

Under conditions where blocking is not efficient, the estimates of treatment mean differences will vary among blocks. The greater the variation within blocks, the greater the variation of treatment effect estimation across blocks, thus the lesser the precision of the experiment. Any variation present within blocks does not invalidate the classical RCB analysis; validity is provided by the randomization of the treatment assignment to plots within a block. However, within-block variability does reduce the efficiency in estimating treatment comparisons and treatment means (Stroup et. al., 1994). One solution for this concern is to reduce block size, although this is often impractical especially in precision agriculture. An alternate approach is to apply spatial analysis that accounts for spatial correlation. Precision agriculture research typically yields many georeferenced observations or samples within an experimental plot. This facilitates the characterization of spatial variability and accounting for it in statistical analyses.
**Spatial analysis**

The basic principal of spatial analysis is to integrate spatial correlation in the mixed model. Spatial correlation is modeled using an appropriate covariance model, which is then used to perform spatial adjustment to estimate treatment significance and means. Development and selection of an appropriate covariance model are critical elements of this process.

Spatial analysis can be grouped into trend analysis (e.g., Brownie et al., 1993), Papadakis analysis (e.g., Zimmerman and Harville, 1991), and correlated error (CE) analysis (e.g., Zimmerman and Harville, 1991) depending on the method used to account for spatial variation. In trend analysis, the spatial correlation of responses is modeled by a polynomial response surface with the assumptions that the responses follow a smooth trend and the model-fit errors are not correlated. The key step of trend analysis is to select a “best” polynomial function. It has been suggested that a stepwise regression procedure be used to determine polynomial terms significant at $P < 0.01$ as a (e.g., Tamura et al., 1988). Trend analysis may increase analytical efficiency if the responses do include a trend that varies in a manner that can be described by the selected polynomial function. However, trend analysis has two major potential shortcomings: under- and over-fitting or using an inappropriate model. The chosen model may have too few terms to adequately model the trend, or may include too many terms, which decreases the degrees of freedom and power available for treatment comparisons.

In Papadakis analyses, often referred to as nearest neighbor analyses, spatial correlation of the responses is indirectly modeled using residuals from neighboring plots. The residual of each plot is derived by subtracting the overall mean from the plot mean. The
model of Papadakis analysis contains one covariate whose value for each plot is the average of the residuals of the neighboring plots. A crucial element of the Papadakis analysis is the need to select the best covariate(s).

In the CE analysis, spatial correlation is directly accounted for by correlated errors. The key step of this analysis is to select an appropriate spatial covariance function for a given dataset. The general formulation and discussions of this analysis were given in detail by Zimmerman and Harville (1991).

A number of articles have compared these three methods in terms of efficiency or precision of the estimates of treatment comparisons compared to the classical RCB analysis (e.g., Zimmerman and Harville, 1991; Brownie et al., 1993; Brownie and Gumpertz, 1997). All of these studies reached the conclusion that spatial analysis can achieve more efficient estimation of treatment contrasts compared to the classical RCB analysis. Within spatial analytical methods, the CE analysis has proven similarly as or more powerful than the other two. Moreover, the covariance parameters estimated by the CE analysis usually have meaningful interpretation (Zimmerman and Harville, 1991), while those derived from the other two methods may or may not. Hence, the CE analysis was chosen for this research. The CE analysis is a likelihood-based approach. A brief overview of likelihood theory is given below.

**Likelihood theory**

The basic concept of likelihood theory is that the best estimate of an unknown parameter is its most likely numerical value derived by maximizing the likelihood function. Suppose we have samples \( X_1, \ldots, X_n \) from a normal distribution with mean \( \mu \) and variance \( \sigma^2 \). Let \( f(x | \mu, \sigma^2) \) denote the joint probability distribution function (pdf) of the
sample. Then given that $X = x$ (x is the observation), the likelihood function estimating the parameters $\mu, \sigma^2$ is:

$$L(\mu, \sigma^2 | x) = f(x | \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \quad [2]$$

where $-\infty < x < +\infty$, $-\infty < \mu < +\infty$ and $\sigma > 0$ (e.g., Casella and Berger, 2002). This likelihood $L(\mu, \sigma^2 | x)$ can be read as “the likelihood of a particular numerical value of the unknown parameters $\mu, \sigma^2$, given the observation x. Clearly, the likelihood is a function of only the unknown parameters ($\mu, \sigma^2$ in this example). In many applications, the natural logarithm of the likelihood function is often used. If the likelihood function has two or more unknown parameters, iterative numerical methods are often applied to determine the solution. At the maximum point of the likelihood function, the resultant values of the unknown parameters ($\mu, \sigma^2$ in this example) are called the maximum likelihood estimate (MLE).

The maximum likelihood (ML) and restricted maximum likelihood (REML) estimation methods are frequently used in commercial statistical software (e.g., SAS, S-PLUS, and R) to determine the MLE for a given dataset. The more general introduction of the REML approach was first given by Thompson (1962). A basic idea of REML is to exclude the fixed-effect part of the likelihood by fitting the data using ordinary least squares and maximize the “residual” part of the likelihood. The REML approach is preferred to ML, especially for unbalanced data, because, e.g., when estimating variance components, the ML approach does not consider the degrees of freedom that are involved in estimating fixed effects while REML does.

Likelihood theory is related to least-squares (LS) theory. For example, the LS estimates of model parameters (except variance components) are the same as the MLEs for
linear and non-linear models when the residuals are assumed to be iid. Because likelihood theory is more general, it has been widely applied in modern statistics.

**Spatial covariance model selection**

“All models are wrong but some are useful” – Box (1976)

**Justification of Model Selection in CE Analysis**

The data (samples) contain the information representing the “truth” or reality. Modeling is a process to capture and transfer the information by model specification and selection, and express this information by the estimates of model parameters. However, in practice, we cannot really achieve this goal. The selected “best” model is an approximation of reality. Consequently, a “best” model only provides us with the inferences the data support, but not necessarily what the reality is. However, a “good” model can lead us to make valid statistical inferences from the data to reality.

As stated earlier, the key step of the CE analysis is to find this “good” model. In the CE analysis, spatial correlation is generally modeled using one of several possible spatial functions. For example, as implemented in SAS PROC MIXED Release 8 (SAS Institute, 1999a), just considering isotropic spatial covariance models, the researcher may choose among linear, spherical, exponential, Gaussian, and power functions, all with or without the inclusion of a nugget effect. Consequently, there are ten possible models to choose from. Making matters more complex, some of these candidate models may result in different treatment P-values, and different estimates of treatment means.

Between the traditional RCBiid method and the CE analysis lies a rich land of hybrid models, many of which are available in SAS PROC MIXED. These models are considered randomized complete block with correlated errors (RCBCE) because they consist of both
random block and/or block by treatment effects in addition to using a spatial function to model correlated errors. The option to include up to three random effects in a model (i.e. block, or block by treatment, or both) and a choice of ten spatial functions results in 30 candidate RCBCE models, each of which could result in different conclusions concerning treatment effects and separation of treatment means.

Clearly, when considering the CE approach to data analysis, two critical questions emerge. The first one is simply “is this necessary, or would the traditional RCBiid method be sufficient”? The second and most daunting question is, “given the abundance of potential CE and RCBCE models, which model or models adequately explain the covariance structure and should be used for data analysis?” It is not uncommon for agronomists to simply assume a given model is adequate. For example, Bruckler et al. (1997) and Weisz et al. (2003) simply assumed that the spherical covariance model they used to analyze precision agriculture data was adequate. Marx and Stroup (1993) suggested that no-nugget spatial functions could generally be assumed to be adequate for correlated error analysis of agricultural data. Littell et al. (1996) suggested a general approach to covariance model selection using information criteria and variography. However, it remains a somewhat daunting task to choose among candidate models and determine which analysis may be best for a given data set.

The advent of precision agriculture research brings into high relief the question of how to make the best use of spatially correlated subsamples. In this light, it is necessary to develop a systematic, step-by-step approach (procedure) that agronomists can use to select a covariance model for a RCB analysis when spatial correlation is present.
Model Selection Tools

Information criteria and the likelihood ratio $\chi^2$ test (LRT) together with variography are key tools of spatial covariance model selection. Variography, e.g., the semivariogram, is often useful for visualizing the nature of spatial correlation, defining the spatial model forms, and providing guidance in choosing starting parameters as implemented in SAS PROC MIXED (SAS Institute, 1999a).

Information criteria often used for model selection are Akaike’s Information Criterion (AIC; Akaike, 1974) and Schwarz’ Bayesian Information Criterion (BIC; Schwarz, 1978). In the last two decades, AIC has been used most often in time-series analysis; recently, it has been applied to spatial analysis. The AIC value can be used to evaluate the relative goodness-of-fit of candidate models and rank them. Note that it is the relative values (not the absolute values of AIC) among competing models that must be considered, i.e., the differences between AIC values of competing models are important for model selection. Burnham and Anderson (2002) commented that “AIC provides a simple, effective, and objective means for the selection of an estimated ‘best approximating model’ for data analysis and inference.” However, we caution that even if all the candidates are poorly defined, AIC still selects a “best” model among them. Thus, pre-defining appropriate candidate models is critical in model selection.

The LRT test is more complicated compared to information criteria. Ideally, we would like to evaluate the relative goodness of fit of potential models using the LRT. This test, however, is only applicable when comparing two nested covariance models. When models are nested, hypothesis testing may be possible with the LRT statistic ($\lambda$) which approaches a $\chi^2$ distribution, and which is defined as:
where $l_1$ and $l_2$ denote the residual log likelihoods of the reduced model and the full model, respectively, and $j$ is the difference in the number of random effect parameters in the reduced and full models (Littell et al., 1996).

In practice, there is another condition that must be met for the LRT to apply. The hypothesized value of the parameter being tested must not be on the boundary of the parameter space. For example, by definition a variance component must be nonnegative, therefore the value zero is on the boundary of the parameter space. In this case, the asymptotic distribution of $\lambda$ does not follow a $\chi^2$ distribution. When the models being compared differ by such parameters, e.g., variance components or spatial ranges, the distribution of the test statistic $\lambda$ consists of mixtures of $\chi^2$ distributions (Verbeke and Molenberghs, 2000). If the models being compared differ by only one such parameter, the distribution of $\lambda$ has a mixture of half $\chi^0_0$ (which is a constant) and half $\chi^2_1$ distributions. In this case, the appropriate P-value for the LRT is one half the reported P-value from the $\chi^2$ distribution with one degree of freedom (consistent with dropping one parameter from the full model), hereafter referred to as LRT$_{01}$ (Littell et al., 1996). If the models being compared differ by more than one such parameter, then the actual distribution of $\lambda$ is unknown and we use AIC values (as described above) to determine which model has the better goodness of fit.

Information criteria and the LRT test are both likelihood based. There is a close relationship between AIC and LRT. Suppose we have one model with a number $i$ of parameters and another with $i + j$ parameters. Thus the LRT statistics (Burnham and Anderson, 2002) can be written as:

$$\lambda = 2(l_2 - l_1) \sim \chi^2_j$$
\[ \text{LRT} = \text{AIC}_i - \text{AIC}_{i+j} + 2j. \]  

However, the LRT test is more conservative than the AIC. For example, if \( j = 1 \), i.e., the two nested models differ by one parameter, the AIC uses a “critical value” of 2, but the LRT test uses 3.84 (the 95th percentile of \( \chi^2_1 \)) or 2.71 (the 95th percentiles of \( \text{LRT}_{01} \), defined below) (Morgan and Gumpertz, 1996), depending on whether the parameter being tested is not or is on the boundary of the parameter space. Here \( \text{LRT}_{01} \) is a special case of the LRT, whose statistics follow a mixture of half \( \chi^2_0 \) (which is a constant) and half \( \chi^2_1 \) distributions. If \( j = 2 \), i.e., the two models differ by two parameters, AIC uses the “critical value” of 4 but the LRT test uses 5.99 if the parameter being tested is not on the boundary of the parameter space. In this case, if the parameter is on the boundary of the parameter space, the LRT will not apply.

**Further Remarks**

Spatial covariance model selection is a critical step of spatial analysis leading to valid and efficient inference. Critical conceptualization of the real problem and a priori definition of model forms is advocated. The approach of simply trying all possible models should be avoided (Burnham and Anderson, 2002). Model selection in most literature typically assumes that the “true” model is contained among the candidate models. This may not be true, and we never know what the “true” model actually is. It is always recommended (e.g., Burnham and Anderson, 2002) to define candidate models as well as possible based on our prior understanding of the underlying processes and exploratory data analysis.

The model selected is often questioned as to whether it has been over- or under-fitted. The under-fitted model has more bias but less variance (uncertainty), and thus tends to underestimate treatment significance. The over-fitted model has less bias but larger estimated sampling variances thus readily leading to questionable treatment effects. Box and Jenkins
(1970) stated that the selected model should have “the smallest possible number of parameters for adequate representation of the data”. However, in reality, it is difficult to determine if a “best” model has been selected.

In the following chapter, a step-by-step statistical procedure guiding the covariance model selection in the spatial analysis of precision agriculture treatments in randomized complete blocks is demonstrated. In Chapter 3, this procedure is applied to evaluate in-season RS-informed SS N management effects on shallow groundwater NO$_3^-$ concentrations and agronomic. Chapter 4 describes the field-scale complexity of groundwater NO$_3^-$ in space and time.
Table 1. A typical stratigraphic description of the study field (adapted from North Carolina Agricultural Experiment Station, 1977).

<table>
<thead>
<tr>
<th>Depth (ft)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 – 3.5</td>
<td>Dominantly brownish yellow (10 YR 6/6) sandy clay loam with few soft red mottles in lower part; grades to</td>
</tr>
<tr>
<td>3.5 - 8.5</td>
<td>Red (2.5 YR 5/8) firm sandy clay loam to sandy clay with few yellow and white streaks; gradual to</td>
</tr>
<tr>
<td>8.5 - 9.5</td>
<td>Yellow (10 YR 7/8) tough, firm clay; clear to</td>
</tr>
<tr>
<td>9.5 – 12.0</td>
<td>Yellow (10YR 8/6) medium coarse sand gradual to</td>
</tr>
<tr>
<td>12.0 – 17.0</td>
<td>Yellowish red (5 YR 5/8) to reddish yellow (5YR 6/8) medium, coarse sand; few well rounded gravels 4 mm long; abrupt lower boundary; base of Wicomico msu</td>
</tr>
<tr>
<td>17 +</td>
<td>Red (2.5YR 5/6) compact loam grading at 18.5 feet to black (5Y 2/1) loam; Pee Dee formation</td>
</tr>
</tbody>
</table>
Figure 1. Schematic representation of nitrate-related nitrogen transformations in soils.
Figure 2. (a) Winter wheat N uptake (lb acre\(^{-1}\)) during the growing season (adapted from Alley et al., 1999). GS 25, 30 and 58 denote growth stages (Zadoks, 1974); (b) Corn nutrient uptake in different plant parts during the growing season (adapted from Hanaway, 1962).
Figure 3. Research site including two adjacent fields at the Lower Coastal Plain Tobacco Research Station located in Lenoir County in the Neuse River Basin, NC.
Figure 4. Thirty-year-average (1974 – 2003) monthly temperature and precipitation at the study site.
Figure 5. Cross section of the research site showing the distribution of beds in the Wicomico morphostratigraphic unit (adapted from North Carolina Agricultural Experiment Station, 1977).
CHAPTER 2: SPATIAL ANALYSIS OF PRECISION AGRICULTURE
TREATMENTS IN RANDOMIZED COMPLETE BLOCKS: GUIDELINES FOR
COVARIANCE MODEL SELECTION

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For Submission to: Agronomy Journal – Statistics Section
ABSTRACT

Failure to account for spatially correlated errors when present in the classical randomized complete block (RCB) analysis may cause inefficient estimation of treatment significance. Covariance model selection is a necessary component for spatial adjustment to estimate treatment significance. We discuss methods for selecting a covariance model in RCB analyses in the presence of spatial correlation and demonstrate one procedure in detail. The procedure uses three models: the randomized complete block with independent and identically distributed errors (RCBiid), RCB with correlated errors, and models with correlated errors but no block effects. The semivariogram of the residuals from fitting a model with just fixed effects, the likelihood ratio test, and Akaike Information Criterion are used for model selection. To illustrate the procedure, we analyzed winter wheat (Triticum aestivum L.) forage and corn (Zea mays L.) grain yield in the presence of spatial heterogeneity within blocks from a site-specific N management study. We compared the selected covariance models to the RCBiid models and to other spatial models with respect to the estimation of treatment significance. The procedure can be extended to any experiment with fixed effects, or with both fixed and random effects, and which may potentially have spatially correlated errors. The procedure is systematic and readily implemented, however it remains difficult to evaluate whether an adequate covariance model has been selected.
INTRODUCTION

Precision technologies, e.g., global positioning systems (GPS), geographic information systems (GIS), and variable rate technologies (VRT), have evolved rapidly and been incorporated into production agriculture, making precision farming an operational reality. For example, crops are commonly harvested using a combine equipped with a yield monitor linked with GPS. The resultant yield data consist of numerous georeferenced sample points across the field and dense sub-sampling within experimental plots. This is not at all common to traditional small-plot research, and precision agricultural research may benefit from analyses encompassing multiple spatially georeferenced observations within plots (e.g., Ferguson et al., 2002; Eghball et al., 2003, Weisz et al., 2003).

Spatial correlation in the observations and in the residuals of the statistical model used to analyze the data is also common in precision agriculture research. This is due to several factors. It has been well documented that soil physical properties (e.g., Davidoff and Selim, 1988), moisture relations (e.g., Achouri and Gifford, 1984), and soil nutrient status (e.g., Webster and Nortcliff, 1984) vary spatially across fields. Thus, it is always possible that observations such as crop yield will also be spatially correlated and have heterogeneous variances (Scharf and Alley, 1993). Precision agriculture research is often carried out on a large spatial scale resulting in more spatial variability within and among blocks and plots than is typical of traditional small-plot research. In traditional small-plot research, treatments are applied and harvest is conducted on a plot-by-plot basis. This is a central element in the usual statistical definition of a “plot”. In precision agriculture research, plots are large compared to harvest and application equipment, and treatment application and crop harvest are not applied on a plot-by-plot basis. Instead applicators and harvesters move across the
field in a serpentine fashion changing application rates as they pass from plot to plot, or assigning yield data to individual points depending on their location at any given time. Consequently, the equipment may make many passes through a plot before completing harvest or application. All of these factors can lead to increased spatial variability and correlation that may not be accounted for with traditional blocking.

The classical randomized complete block (RCB) design which focuses on analysis of variance (ANOVA) is commonly used in agricultural and precision agricultural research. The RCB analysis is based on the assumption that the model errors within blocks are independent and identically distributed (iid) with the same variance. When spatial variability is present at a scale that blocking is not able to fully account for, the RCB model errors may be spatially correlated, which violates this assumption. In addition, in the classical RCB design and its traditional analysis, only one, or possibly a few, observations are taken per plot, whereas the distinctive feature of precision agriculture experiments is that the field is densely subsampled within each plot. While an RCB analysis with subsampling can still be justified based solely on the randomization of treatments within blocks (Brownie et al., 1993), the efficiency of the classical ANOVA in making treatment comparisons and in estimating treatment means is reduced (Stroup et. al., 1994). In precision agriculture research where many factors can lead to spatial correlation and a large number of observations are taken within each plot, the RCBiid analysis to test treatment effects may be made more powerful by incorporating spatial correlation.

Zimmerman and Harville (1991) proposed a random field approach that can account for spatially correlated errors (CE) among spatially georeferenced observations, and thus may provide a more efficient estimation of treatment comparisons. Brownie and Gumpertz (1997)
investigated the validity and robustness of CE analysis and concluded that the method could achieve substantial increases in precision compared to classical RCBiid analysis when errors are spatially correlated. In CE analysis, instead of blocking being used to account for spatial variability, spatial correlation is modeled using one of several possible functions. For example, as implemented in SAS PROC MIXED Release 8 (SAS Institute, 1999a), just considering isotropic spatial covariance models, the researcher may choose among linear, spherical, exponential, Gaussian, and power functions, all with or without the inclusion of a nugget effect. Consequently, there are ten possible models from which to choose. Making matters more complex, some of these candidate models may result in different treatment P-values and different estimates of treatment means.

A further safari into what for many agronomists is the wilderness of SAS PROC MIXED documentation reveals that between the traditional RCBiid method and the CE analysis lies a rich land of hybrid models. These models are considered randomized complete block with correlated errors (RCBCE) because they consist of both random block and/or block by treatment effects in addition to using a spatial function to model correlated errors. The option to include up to three random effects in a model (i.e. block, or block by treatment, or both) and a choice of ten spatial functions results in 30 candidate RCBCE models, each of which could result in different conclusions concerning treatment effects and separation of treatment means.

As described above, models with correlated errors may include block effects and plot effects, or not, and quite often the block and plot effects are omitted. The idea of omitting block and plot effects from a model for an RCB design needs some explanation, because it contradicts traditional practice that dictates that the model for RCB designs with subsampling
include terms for random block and plot effects. There are two approaches that lead to the traditional analysis of variance: (1) a randomization approach, and (2) a model-based approach. The randomization approach does not require that the data be normally distributed or uncorrelated. It simply assumes that the treatments have been randomly assigned to the plots. The basic unit of data, the experimental unit, in this analysis is the plot mean, because plots have been randomly assigned to treatments; within plots there is no randomization. The distributions of the test statistics in the analysis of variance are based solely upon this randomization, and the statistical analysis must include block and plot effects to be valid.

In the second approach to developing the analysis of variance, the assumptions are that the block effects, plot effects, and within-block errors are drawn from separate normal distributions that are independent of each other, and that the within-plot errors are independent. These assumptions imply a certain covariance structure, namely that all plots within a block are equally correlated, all observations within a plot are equally correlated, and that observations in different blocks are uncorrelated. The validity of the analysis depends on the correctness of these assumptions, not on the randomization, hence the analysis depends upon finding an appropriate covariance structure. The unit that is being modeled is the individual subsample rather than the plot mean, and it often happens that the covariance pattern that best fits the data does not include random block effects and/or random plot effects. The hazard to using a model-based approach is that the assumptions are much stronger than in the randomization approach, and if the model is not at least approximately adequate, the analysis can give wildly invalid results.

Clearly, when considering a correlated errors approach to data analysis, two critical questions emerge. The first one is simply “is this necessary, or would the traditional RCBiid
method be sufficient”? The second and most daunting question is, “given the abundance of potential CE and RCBCE models, which model or models adequately explain the covariance structure and should be used for data analysis?” It is not uncommon for agronomists to simply assume a given model is adequate. For example, Bruckler et al. (1997) and Weisz et al. (2003) simply assumed that the spherical covariance model they used to analyze precision agriculture data was adequate. Marx and Stroup (1993) suggested that no-nugget spatial functions could generally be assumed to be adequate for correlated error analysis of agricultural data. Littell et al. (1996) suggested a general approach to covariance model selection using information criteria and variography. However, it remains a somewhat daunting task to choose among candidate models and determine which analysis may be best for a given data set.

The advent of precision agriculture research brings into high relief the question of how to make the best use of spatially correlated subsamples. In this light, our primary objective is to present a systematic, step-by-step approach that agronomists can use to select a covariance model for RCB analysis when spatial correlation is present. Our secondary objective is to demonstrate using real examples how the tests of treatment effects may be affected by the inclusion or exclusion of block effects, nugget effects, and spatial autocorrelation in the model. Toward these objectives, we present analyses of two separate datasets with different within-plot subsampling intensities from two trials in a site-specific N management experiment: wheat forage in 2001, corn for grain in 2002.

**COVARIANCE MODEL SELECTION PROCEDURE**

**Three Methods For RCB Analyses**

The foundation of our analysis is the linear mixed model, which takes the form:
where $y$ is an $n \times 1$ vector of responses, $X$ is an $n \times p$ design matrix for fixed treatment effects, $\beta$ is a $p \times 1$ vector of fixed treatment effect parameters, $Z$ is a $n \times q$ design matrix for the random block and block×treatment effects, $u$ is a $q \times 1$ vector of random effects, $\varepsilon$ is an $n \times 1$ vector of errors, where $n$, $p$, and $q$ are the number of responses, fixed effect parameters and random effects, respectively. Key assumptions for this model are that $u$ and $\varepsilon$ are uncorrelated and their expectations are zero. If we set the variance of random effects $\text{var}(u) = \Sigma_u$, and $V_1 = \text{var}(Zu) = ZZ_u \Sigma_u Z'$ and the variance of errors $V_2 = \text{var}(\varepsilon)$, the variance of $y$ is $\text{var}(y) = V_1 + V_2$. Thus, any correlation of observations can be specified in $V_2$ and/or $V_1$.

Building on this foundation, we chose to focus on three potential methods for analyzing RCB designs in the presence of spatial correlation. Each of these methods is described in detail below.

**Randomized complete block with iid errors** (RCBiid method): This is the classical RCB analysis. It assumes iid within-block errors ($\varepsilon$) for which $V_1 = ZZ_u \Sigma_u Z'$ and $V_2 = \sigma^2 I_n$, where $I_n$ denotes the $n \times n$ identity matrix. Consequently, any spatial correlation of observations is reflected only in $V_1$.

**Randomized complete block with correlated errors** (RCBCE method): This is a nonclassical RCB analysis with spatially correlated errors in which $V_1 = ZZ_u \Sigma_u Z'$. When a no-nugget model is used to describe the spatial covariance, $V_2 = \sigma^2 W$, where $W$ is the $n \times n$ spatial covariance matrix whose $ij^{th}$ element is defined as a function of the distance ($h_{ij}$) between site $i$ and $j$. If a nugget model is used to describe the spatial covariance, $V_2 = I_n \sigma^2_g + \sigma^2 W$. The nugget, $I_n \sigma^2_g$, is generally due to significant variation among observations within
extremely short or zero separation distance and/or measurement errors (Isaaks and Srivastava, 1989). We consider three isotropic spatial covariance functions: the spherical, Gaussian, and exponential. We chose these because of their applicability in describing spatial covariance commonly encountered in agriculture, because of the form of our exploratory semivariograms, and because they are available in SAS PROC MIXED Release 8. In this approach, any spatial correlation of observations is reflected in both $V_1$ and $V_2$. Clearly the RCBiid model is a reduced form of the RCBCE model, because if no spatial correlation is present, $W$ will reduce to $I_n$.

For an example of an RCBCE model, consider an RCB design with three plots in a block and two observations in a plot for which a no-nugget exponential covariance function is chosen to model the spatial covariance. (NB: This analysis can be extended to include any number of observations per plot.) Then, $\text{Cov} (\varepsilon_i, \varepsilon_j) = \sigma^2 e^{-\beta h_{ij}/\theta}$ (Isaaks and Srivastava, 1989), and

$$V_1 = \begin{bmatrix}
\Sigma_u \\
\Sigma_u \\
\vdots \\
\Sigma_u \\
\end{bmatrix} = \begin{bmatrix}
\sigma_p^2 + \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 \\
\sigma_b^2 & \sigma_p^2 + \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 \\
\sigma_b^2 & \sigma_b^2 & \sigma_p^2 + \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 \\
\sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_p^2 + \sigma_b^2 & \sigma_b^2 & \sigma_b^2 \\
\sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_p^2 + \sigma_b^2 & \sigma_b^2 \\
\sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_p^2 + \sigma_b^2
\end{bmatrix}$$

where $V_1$ is a positive $n \times n$ block diagonal matrix with $k$ ($6 \times 6$) covariance matrices along the diagonal and the off-diagonal elements are 0s. Here $k$ is the number of blocks and 6 is the total number of observations within a block. Each matrix has $2 \times 2$ diagonal blocks with elements $(\sigma_p^2 + \sigma_b^2)$ which denote the covariance of two observations within the same plot. The variance components $\sigma_p^2$ and $\sigma_b^2$ denote the variance components within blocks, i.e.,
among plots, and among blocks, respectively. Matrix $V_2$ is an $n \times n$ symmetric matrix in which the sill $\sigma^2$ is the variance of the random errors. The sill is also the limit of the semivariance as distance increases; it appears at inter-observation distances large enough that observations are no longer correlated. The parameter $\theta$ is the practical range defined as the value of $h$ at which the semivariogram without nugget reaches 95% of the sill, since the correlation of two observations fit to exponential or Gaussian functions approaches zero only when $h$ goes to infinity. If a spherical function is fit, $\theta$ is the actual range (Isaaks and Srivastava, 1989).

In our example where a no-nugget exponential function is used to model the spatial covariance, SAS PROC MIXED reports the value of the sill in the covariance parameter estimates table, and labels this parameter as the “Residual”. If a function with a nugget had been specified, SAS PROC MIXED would have labeled the nugget (i.e., microscale variation) value as the “Residual”, and added a new parameter to the parameter estimates table labeled “Variance”. In this case, the sill consists of the sum of the “Residual” (i.e., nugget) and the component labeled “Variance”.

Also in our example, we caution that SAS PROC MIXED defines $\text{Cov} (\varepsilon_i, \varepsilon_j) = \sigma^2 e^{-\frac{h_{ij}}{a}}$ and labels the parameter $a$ as “SP (EXP)”. Here the parameter $a$ does not equal the practical range $\theta$ as stated previously but is one third of $\theta$. Thus, the practical range $\theta$ is computed by multiplying the parameter $a$ by 3 (SAS Institute, 1999b). If a Gaussian function is specified, Isaaks and Srivastava (1989) define $\text{Cov} (\varepsilon_i, \varepsilon_j) = \sigma^2 e^{-\frac{3h_{ij}}{\theta}}$ with the parameter $\theta$ as the practical range. However, PROC MIXED defines $\text{Cov} (\varepsilon_i, \varepsilon_j) = \sigma^2 e^{-\frac{h_{ij}}{a}}$ and labels the parameter $a$ as “SP (GAU)”, thus the practical range $\theta$ is computed by multiplying the
parameter $a$ by $\sqrt{3}$ (SAS Institute, 1999b). If a spherical function is specified, SAS PROC MIXED labels the parameter $a$ as “SP (SPH)”, where this parameter is the actual range. For a more complete discussion of these functions see SAS Institute Inc. (1999b). There are many spatial covariance functions that can be specified in the RCBCE method.

**Correlated errors analysis** (CE method): The CE method assumes that $V_1 = 0$, which means the random block and block×treatment effects are not considered and are removed from the model in Eq. [1]. Any spatial correlation present is defined only in $V_2$. Clearly the CE model is a reduced form of the RCBCE model. If the random effects of the RCBCE models are determined ineffective, i.e. the elements of the matrix $\Sigma_u$ are all zeros, RCBCE models become CE models. Additionally, all the considerations discussed above for the RCBCE method about specifying a function to model the spatial covariance also apply to CE implementation.

**Overview of Model Selection**

We believe that a useful guideline for choosing between candidate covariance models is that the selected model should adequately describe the covariance structure but with the fewest covariance parameters. Toward this end, step-by-step procedures describing model selection for a given data set are outlined in Figure 1. The first step is to determine candidate RCBCE and CE models. This is done by finding the functions which best model the spatial correlation in the RCBCE and CE methods. Once this is complete, the field of all possible candidate covariance models has been narrowed down to only three; the RCBiid model, one candidate RCBCE, and one candidate CE model. In keeping with our guideline, we propose that analysis should begin with the simplest model (i.e. the RCBiid method) and a test of the hypothesis that the errors are not spatially correlated. This is done by comparing the RCBiid
and candidate RCBCE model. If this hypothesis is not rejected, the RCBiid method is selected and the process is complete. Conversely, if the hypothesis is rejected, then RCBCE or CE analysis is warranted and the third step is to compare the candidate CE and RCBCE models. Also in keeping with our guideline, if blocking in the RCBCE method is not significant, then the CE approach with fewer covariance parameters is selected. If blocking is significant, then the candidate RCBCE model is chosen for data analysis.

**Statistical Tools for Model Selection**

We suggest the use of three types of statistical tools in the procedure outlined in Fig. 1. The first is the semivariogram of the residuals from a model containing just fixed effects (“fixed-effect model-fit residuals”). These residuals contain variation from all sources except the fixed treatment effects. This tool is used to visualize the nature of spatial correlation and to provide guidance in choosing starting parameters (i.e., nugget, range, and sill) for the RCBCE and CE methods.

The second type of tool consists of the information criteria that are used to compare the relative goodness-of-fit among non-nested candidate models. These criteria are the Akaike Information Criterion (AIC; Akaike, 1974) and Schwarz’ Bayesian Information Criterion (BIC) (Schwarz, 1978). The AIC and BIC values are computed in SAS PROC MIXED Release 8 as:

\[
AIC = -2l + 2q \quad [2]
\]

\[
BIC = -2l + q \log N \quad [3]
\]

where \( l \) is the residual log likelihood if restricted maximum likelihood (REML) is implemented, \( q \) is the number of random effect parameters being estimated using REML, and \( N \) is determined as described below. In SAS PROC MIXED Release 8, \( N \) is specified as the
number of levels of the first random effect defined in the RANDOM statement. If no
RANDOM statement is specified, \( N \) is the number of the observations used. Thus, BIC
values are only valid for model comparisons within the RCBiid, the RCBCE, or the CE
methods, and cannot be used to compare across methods. In SAS Release 8, smaller AIC and
BIC values indicate better fit. In SAS Release 6, more positive AIC values (defined as the
negative half of Eq. [2]) indicate better fit, and BIC is determined incorrectly (Littell et al.,
2002) and should not be used.

Guerin and Stroup (2000) compared the performance of AIC and BIC on covariance
model selection for repeated measures and stated that AIC tended to result in a more complex
model but with better Type I error rate control than BIC. Thus, if treatment effects are of
interest, AIC will be a better criterion. Consistent with their findings, and because BIC
cannot be used to compare across methods, and because of the computational error in SAS
release 6, we do not use BIC in the procedure outlined here.

The third statistical tool is the likelihood ratio \( \chi^2 \) test (LRT). Ideally, we would like
to test all hypotheses concerning the relative goodness of fit of potential models with the
LRT using REML. This test, however, is only applicable when comparing two nested
covariance models with the same \( X \) matrix (fixed effects). Consequently, when testing a
hypothesis that involves comparison of non-nested covariance models (still with the same \( X \)
matrix), AIC is used (as described above). When models are nested, hypothesis testing may
be possible with the LRT statistic (\( \lambda \)) which approaches a \( \chi^2 \) distribution, and which is
defined as:

\[
\lambda = 2 (l_2 - l_1) \sim \chi^2
\]  

[4]
where \( l_1 \) and \( l_2 \) denote the residual log likelihoods of the reduced model and the full model, respectively, and \( j \) is the difference in the number of random effect parameters in the reduced and full models (Littell et al., 1996). In SAS PROC MIXED Release 8, “–2\( l \)” instead of “2\( l \)” is reported and labeled “–2 Res Log Likelihood” in the fit statistics table.

In practice, there is another condition that must be met for the LRT to apply. The hypothesized value of the parameter being tested must not be on the boundary of the parameter space. For example, by definition a variance component must be nonnegative, therefore the value zero is on the boundary of the parameter space. In this case, the asymptotic distribution of \( \lambda \) does not follow a \( \chi^2 \) distribution. When the models being compared differ by such parameters, e.g., variance components or spatial ranges, the distribution of the test statistic \( \lambda \) consists of mixtures of \( \chi^2 \) distributions (Verbeke and Molenberghs, 2000). If the models being compared differ by only one such parameter, the distribution of \( \lambda \) has a mixture of half \( \chi^0 \) (which is a constant) and half \( \chi^1 \) distributions. In this case, the appropriate P-value for the LRT is one half the reported P-value from the \( \chi^2 \) distribution with one degree of freedom (consistent with dropping one parameter from the full model), hereafter referred to as LRT\(_{01}\) (Littell et al., 1996). If the models being compared differ by more than one such parameter, then the actual distribution of \( \lambda \) is unknown and we use AIC values (as described above) to determine which model has the better goodness of fit.

The use of AIC to determine which model has a better fit is the same as an LRT but uses a critical value of twice the difference in the number of random effect parameters between the two models under consideration (see Eq. [2]). Hence if the two models have the same number of parameters, the AIC just selects the model with higher likelihood, which
may not be a very reliable criterion. If the two models differ by one random effect parameter, the AIC uses a “critical value” of 2, which is less conservative than an LRT, which has a “critical value” of 3.84 (the 95th percentile of $\chi^2_1$), or $\text{LRT}_01$, which has a “critical value” of 2.71 (the 95th percentiles of $\text{LRT}_01$) (Morgan and Gumpertz, 1996).

Consequently, while the use of LRT or $\text{LRT}_01$ can be seen as adding complexity to model selection compared to simply using AIC values, it also adds a degree of robustness and confidence in the selection process that are absent when using AIC values alone.

**Spatial Function Selection for the RCBCE and CE Methods**

The first step in Fig. 1 is to use a semivariogram of the fixed-effect model-fit residuals to choose candidate nugget and/or no-nugget spatial functions to use with the RCBCE and CE methods. In practice, the estimated sill, nugget, and range from the semivariogram will be good starting parameter values for the mixed model procedure which will then iteratively search for its own best-fit values. Providing starting parameter values for each spatial function is important for two reasons. The first is that the mixed models analysis is very sensitive to starting parameters values and good starting values increase the likelihood that the algorithm will converge. The second reason is that SAS PROC MIXED can require a large amount of computer time with the large data sets typical of precision agriculture and yield monitoring ($n > 2000$). Good starting parameter values can reduce this run time considerably.

Once candidate spatial functions and their associated starting parameter values are chosen (based on the semivariogram of the fixed-effect model-fit residuals), the resultant RCBCE models are run. If a tested model initially results in nonconvergence, infinite likelihood, or a nonpositive definite Hessian matrix (a multiple of the inverse of the
estimated covariance matrix of the covariance parameter estimates), we recommend a “trial-
and-error” approach for changing the starting parameter values. If subsequent attempts also
result in one of these failures, the model is excluded (SAS Institute, 1999b).

Spatial functions may or may not include a nugget. Consequently, the second step in
our demonstration is to compare all candidate RCBCE models based on no-nugget functions.
Because the various spatial covariance functions are not nested, we select the best no-nugget
model using AIC values as described above (Fig.1). Since the three spatial covariance
functions under consideration have the same number of random effect parameters, this
amounts to simply picking the covariance function with the highest likelihood value. This is
then repeated for RCBCE models based on spatial functions that include a nugget. Best CE
models based on no-nugget and nugget spatial functions are then determined in the same
manner (Fig.1).

**Hypothesis Testing**

Three hypotheses are tested to select a covariance model (Fig.1). These hypotheses
and the statistical tools used to test them are described below.

**Hypothesis 1**: The nugget effect $\sigma^2_g = 0$, which means the no-nugget spatial
covariance function is more appropriate than one with a nugget for the RCBCE or CE
method. After selecting the best RCBCE nugget and no-nugget models (Fig.1), the two are
compared to determine which results in the better fit. If the two models are based on different
spatial functions, they are not nested and AIC values are used to determine the one with the
better fit. If they are based on the same spatial function, then they are nested. However,
because the hypothesis involves testing whether a variance component (the nugget) equals
zero, the LRT$_{01}$ is used and the P-value of the test is half of the reported P-value from
the $\chi^2$ distribution with one degree of freedom. The same procedure is used to determine whether the selected no-nugget or nugget CE model has the better fit.

**Hypothesis 2:** The errors are not spatially correlated; i.e., the RCBiid method is more appropriate than the RCBCE method. When the best RCBCE model does not contain a nugget, the difference between the two models is only one parameter, the range. The $LRT_{01}$ statistic can be used to test Hypothesis 2 using half of the reported P-value from the $\chi^2$ distribution with one degree of freedom.

When the best RCBCE model contains a nugget, the RCBiid model is still nested within it, but the models differ by two parameters: the range and the nugget. In this case the distribution of $\lambda$ is unknown, so determination of the model with the better fit is based on AIC values.

**Hypothesis 3:** The RCBCE block and plot effects are $\sigma_b^2 = \sigma_p^2 = 0$; i.e., $V_1 = 0$ and $V_2 = \sigma^2 W$, which means that blocking is not significant and the CE method is more appropriate than the RCBCE method. There is one case where Hypothesis 3 can be tested with the $LRT_{01}$. If the best RCBCE and CE models are both based on the same spatial function they are nested and the first requirement for using the $LRT_{01}$ is met. If the RCBCE model has dropped either the block or plot effect, (i.e., the estimate for either of these parameters is zero), and this model only differs from the best CE model by the one remaining block or plot effect (a variance component), then the $LRT_{01}$ can be implemented using half of the reported P-value from the $\chi^2$ distribution with one degree of freedom. In all other cases, we use AIC values to determine which model has the better fit.
**Estimation of Treatment Significance and Mean**

Once the covariance model is selected, it is used to estimate treatment means and conduct treatment comparisons using estimated generalized least squares (EGLS). The covariance parameters of the model are estimated using REML (Zimmerman and Harville, 1991).

**APPLYING THE PROCEDURE: A TWO YEAR SITE-SPECIFIC N MANAGEMENT STUDY**

**Field Description and Layout**

Two trials were conducted in a 12 ha field at the Lower Coastal Plain Tobacco Research Station, Kinston, NC (Fig. 2a). There are three major soil map units in the field: Norfolk (No) loamy sand (fine-loamy, siliceous, thermic, Typic Paleudults), Goldsboro (Go) loamy sand (fine-loamy, siliceous, thermic, Aquic Paleudults), and Lynchburg (Ly) sandy loam (fine-loamy, siliceous, thermic, Aeric Paleaquults).

The experiment began in November 2000 with the establishment of a two-year winter wheat-double crop soybean[Glycine max (L.) Merr.] (year 1) – corn (year 2) rotation typical of the Coastal Plain. The experiment was established in an RCB design with three N management treatments replicated ten times in plots 60.8 by 60.8 m (0.37 ha). Note that the blocks were not all the same shape (Fig. 2a). The three N treatments were:

(i) “RYE”: Whole-field Realistic Yield Expectation (RYE) N management based on the estimated yield expectation and the N-use factor for the predominant soil type (Go) in the field derived from the North Carolina RYE database (North Carolina Nutrient Management Workgroup, 2003). Fertilizer N was applied uniformly to treatment plots at planting and at
wheat growth stage GS-30 (Zadoks et al., 1974) or corn growth stage V2 (Ritchie et. al. 1993);

(ii) “FA”: Whole-field N management based on field-averaged in-season estimates of optimal N fertilizer rates determined by color infrared aerial photography (CIR) (Flowers et al., 2003; Carter et al., 2003; Sripada et al., 2002). Fertilizer N was applied uniformly to treatment plots at planting, and at GS-25 and GS-30 for wheat, and at V2 and VT for corn;

(iii) “SSNM”: Site-specific N management based on site-specific in-season estimates of optimal N fertilizer rates determined by CIR. For SSNM, each 0.37 ha plot was divided into 78 4.6-by-9.1-m “miniplots” for applying variable rates of N fertilizer. The optimal N rate for each miniplot was determined via CIR and applied uniformly to each miniplot at the same growth stages as FA.

All fertilizer N was applied in a serpentine fashion by an applicator tacking back and forth across the field in adjacent swaths, switching the amount of fertilizer applied whenever a plot or miniplot boundary was crossed. Thus, the treatments were not applied to a plot all at one time, but partially and sequentially to adjacent plots.

Nitrogen rates and timing for the RYE, FA, and SSNM treatments for wheat forage in 2001, and for corn for grain in 2002 are summarized in Table 1. For wheat forage, the total RYE N fertilizer rate was 44 and 34% greater than for FA and SSNM respectively. For corn, the total FA N fertilizer rate was 95 and 51% greater than for RYE and SSNM respectively. Nitrogen fertilizer was not applied to the 2001 soybean crop.

For this presentation of covariance model selection, we analyzed the 2001 wheat forage data, and the 2002 corn grain yield data. Wheat forage was harvested from 18 1.2-by-18 m sample harvest areas within each 0.37 ha treatment plot using a forage harvester with a
1.2-m header and Metler weigh system. Sample harvest area forage yield was assigned to the center point of each sample area georeferenced using a differential global positioning system (DGPS). Ten samples were lost during drying, resulting in a total of 530 sampling points (Fig. 2b). Corn was harvested using a grain combine equipped with a yield monitor and DGPS. After the corn yield data were cleaned and edited following the general guidelines suggested by Doerge (1999) and Blackmore and Moore (1999), there were a total of 2542 sampling points, with a range of 69 to 102 sub-samples per plot (Fig. 2c).

**Model Selection Steps Common to Both Crops**

To investigate spatial correlation within the 2001 wheat forage and the 2002 corn grain yields, the observations were fit to two models: (i) with only fixed treatment effects (i.e., N management) to compute the fixed-effect model-fit residuals, and (ii) with both fixed treatment effects and random block and block \( \times \) treatment effects to compute the RCBiid model-fit residuals. The normality of the observations and these residuals was assessed by diagnostic plots (e.g., histograms) coupled with the Shapiro-Wilk test in SAS PROC CAPABILITY (SAS Institute, 1999a). There was no strong evidence of nonnormality for the original observations nor for the residuals for either crop, so the data were analyzed in the original scale. An isotropic and stationary spatial process was assumed, and all tests were conducted in SAS Release 8 and determined at the 0.05 significance level.

To visualize any spatial correlation present, the empirical semivariogram of the fixed-effect model-fit residuals \( \gamma_e(h) \), which takes the form:

\[
\hat{\gamma}_e(h) = \frac{1}{2N(h)} \sum_{a=1}^{N(h)} [r(u_a) - r(u_a + h)]^2
\]  

[5]
where $h$ is the distance between two sampling sites $u_a$ and $u_a + h$, $r(u_a)$ is a residual value observed at the $a$th location $u_a$, and $N(h)$ is the number of pairs of sampling sites a lag distance $h$ meters apart (Goovaerts, 1997), was computed in SAS PROC VARIOGRAM (SAS Institute, 1999a). The semivariograms of the observations $\hat{\gamma}(h)$, and the RCBiid model-fit residuals $\hat{\gamma}_e(h)_{RCB}$, were also computed and compared to determine qualitatively whether blocking accounted for spatial correlation among observations. Scaled plots of $\hat{\gamma}(h)$, $\hat{\gamma}_e(h)$, and $\hat{\gamma}_e(h)_{RCB}$ for the 2001 wheat forage crop, and for the 2002 corn yield are illustrated in (Fig. 3).

For the wheat 2001 data, plots of $\hat{\gamma}_e(h)$ were used to estimate starting parameters for candidate RCBCE and CE models. It was assumed (based on Fig. 3) that the spatial covariance of the errors would be best modeled with either a Gaussian, exponential, or spherical function either with or without a nugget effect. Consequently, in addition to the RCBiid model, six candidate RCBCE and six CE models were evaluated in SAS PROC MIXED. The denominator degrees of freedom of F-tests for treatment effects were computed using the KENWARDROGER method for all models. All candidate models and their related statistics and covariance parameter estimates for wheat forage are summarized in Table 2. This process was then repeated for the corn 2002 data set.

**Wheat 2001 Model Selection**

The positive spatial correlation apparent for both the original observations and the fixed-effect model-fit residuals for 2001 wheat forage (Fig. 3) indicated that observations closer together tended to be more similar than ones farther apart and that functions with
nugget effects might be important in modeling this spatial correlation. The plot of $\hat{\gamma}_e(h)_{RCB}$ was nearly a pure nugget effect. This suggested that blocking was effective in accounting for the spatial correlation among the observations, and that blocking was likely to be an important component of the selected covariance model.

Following the flow chart (Fig. 1), the covariance model for wheat forage was selected as follows:

(i) No-nugget RCBCE Gaussian and spherical models both resulted in a nonpositive definite final Hessian matrix, and consequently were excluded.

(ii) Among RCBCE nugget candidate models, the nugget exponential model did not converge.

(iii) In testing Hypothesis 1, the two RCBCE models were not nested so AIC was used and the nugget Gaussian model was selected as the best RCBCE model (Table 2).

(iv) In testing Hypothesis 2, the RCBCE nugget Gaussian model was compared to the RCBiid model using AIC because the nugget and a second parameter, the range, were involved. The RCBCE nugget Gaussian model with smaller AIC value was chosen over the RCBiid method.

(v) Among the CE no-nugget candidate models, the no-nugget exponential model was selected because it had the smallest AIC value compared to the CE no-nugget Gaussian and spherical models.

(vi) Among the CE nugget candidate models, the nugget Gaussian model was selected because it had the smallest AIC value compared to the nugget spherical and exponential models.
(vii) Between the CE no-nugget exponential and nugget Gaussian models (Hypothesis 1), the CE nugget Gaussian model with smaller AIC value was chosen.

(viii) To compare the best RCBCE- and CE-nugget-Gaussian models (Hypothesis 3), the LRT$_{01}$ was used. Because (i) these models were based on the same spatial function they were nested, and (ii) the block effect had been dropped from the RCBCE model (Table 2), thus the models differed by only one parameter (the plot effect). The value of $\lambda$ for the comparison of these models was computed as $8479 - 8468 = 11$. Here $\lambda$ has a mixture of half $\chi^2_0$ and half $\chi^2_1$ distributions with one degree of freedom. The P-value of the $\chi^2_1$ with a value of 11 is 0.0009, thus the P-value of LRT$_{01}$ test is $0.0009/2 \approx 0.0005$. Thus, the LRT$_{01}$ was significant and the RCBCE nugget Gaussian model was selected as the covariance model to be used for wheat forage yield.

**Corn 2002 Model Selection**

As found in the previous year’s wheat forage data, spatial correlation with an apparent nugget effect was evident in the plots of $\hat{\gamma}(h)$ and $\hat{\gamma}_e(h)$ (Fig. 3). Furthermore, these plots were nearly identical, which was consistent with the fact that the RCBiid model indicated that treatment effects were not significant. Unlike the scaled semivariograms for 2001 wheat forage, the plot of 2002 corn $\hat{\gamma}_e(h)_{RCB}$ continued to show spatial correlation. This suggested that blocking may not have been adequate to account for the spatial variability in these data. Additionally, all three plots indicated that functions with nugget effects might be necessary to model the spatial correlation.
Following Fig. 1, the covariance model for 2002 corn yield was performed as follows:

(i) Among RCBCE no-nugget candidate models, the no-nugget exponential model was selected because it had the smallest AIC value compared to the no-nugget Gaussian and exponential models (Table 2).

(ii) Among RCBCE nugget candidate models, the nugget spherical model was selected because it had the smallest AIC value compared to the nugget Gaussian and exponential models.

(iii) To compare the RCBCE no-nugget exponential model and nugget spherical model (Hypothesis 1), AIC was used instead of the LRT because these models were not nested. The RCBCE nugget spherical model with smaller AIC value was selected as the best RCBCE model.

(iv) To compare the RCBiid method versus the RCBCE nugget spherical model (Hypothesis 2), AIC was again used because the models differed by two parameters: the range and the nugget, thus the distribution of $\lambda$ is unknown. The RCBCE nugget spherical model with a smaller AIC value was chosen over the RCBiid method.

(v) Among the CE no-nugget candidate models, the CE no-nugget exponential model was excluded due to a nonpositive definite final Hessian matrix. The CE no-nugget spherical model was also excluded because it did not converge to a finite range or sill. Consequently, only the CE no-nugget Gaussian model remained.
Among the CE nugget candidate models, the CE nugget spherical model was selected because it had the smallest AIC value compared to the nugget Gaussian and exponential models.

To compare the best CE nugget and no-nugget models (Hypothesis 1), AIC was used because they were based on different spatial functions. The spherical nugget model with a smaller AIC value was selected as the best CE model.

To compare the best RCBCE- and CE-nugget-spherical models (Hypothesis 3), the LRT01 was used because (i) these models were based on the same spatial function thus they were nested, and (ii) the best RCBCE model had no plot effect (Table 2), thus the models differed by only one parameter (the block effect). The value of $\lambda$ for the comparison of these models was 0. Clearly, the LRT01 was not significant and the CE nugget spherical model was selected for 2002 corn yield.

**INTERPRETATION AND DISCUSSION**

The RCBCE nugget Gaussian model and CE nugget spherical model were selected for the 2001 wheat forage and 2002 corn grain yield analyses, respectively. This indicated that in both trials, the RCBiid model-fit residuals were significantly spatially correlated, providing evidence of field heterogeneity within blocks that could make the RCBiid method less powerful than a method that incorporated the spatial correlation.

**Semivariograms, Spatial Ranges, and Selected Covariance Models**

The selection of covariance models for wheat and corn was supported by the semivariograms of the observations, the fixed-effect model-fit residuals, and the RCBiid model-fit residuals (Fig.3). For wheat, the fixed-effect-model-fit residual semivariances were slightly lower than those of the observations, indicating that there was a small degree of
variation accounted for by the fixed effects and that the data were spatially correlated. Additionally, the RCBiid model-fit residual semivariogram appeared to be essentially a pure nugget effect, indicating that blocking accounted for much of the spatial correlation (at distances greater than the minimum lag). Each of these facts is consistent with the selection of the RCBCE nugget Gaussian model (Table 2) which resulted in a significant treatment effect, used a nugget effect to model the spatial correlation, and incorporated blocking effects. The shape of the wheat semivariograms at the shortest lag distances (Fig. 3) was also consistent with the selection of a Gaussian spatial function.

If the wheat semivariograms had been the only criteria used to select the covariance model for the wheat analysis, one might have selected the RCBiid model based on the nearly pure nugget effect of the RCBiid model-fit residuals. The fact that the model selection procedure (Fig. 1) found the RCBCE nugget Gaussian model to be better is instructive. The covariance structure of the errors is not identical to that visualized by the semivariogram analysis of the residuals (Brownie and Gumpertz, 1997). This is the primary reason we emphasize using the semivariograms for estimating starting parameters, and not for selecting a final covariance model.

For wheat forage, the estimated range of spatial dependence of the errors from the selected model (RCBCE nugget Gaussian, Table 2) was 99 m, which was less than the maximum distance within a block (~172 m) but greater than the plot dimensions (~61 m). This indicated that spatially correlated errors were present within and among blocks, probably due to the omission of one or more unknown covariates from the model. In this case, the random block effect would not be expected to be fully effective in explaining the spatial structure. However, the random block \times treatment effect was significant.
Consequently, for wheat forage, both blocking and spatial covariance modeling of the errors were important.

For the corn data set, the fixed-effect-model-fit residual semivariogram was nearly identical to that of the observations, indicating that the treatment effects accounted for very little of the spatial variability. In contrast to wheat, the corn RCBiid model-fit-residual semivariogram indicated substantial spatial correlation despite the block effect being in the model. This semivariogram had about half the sill-to-nugget semivariance and half the range of the fixed-effect-model-fit residual semivariogram. This indicated that while blocking accounted for a substantial proportion of variability at longer lag distances, it was ineffective at accounting for spatial correlation within the scale of a plot. Additionally, all three corn semivariograms suggested the need for a spatial function which included a nugget effect. These facts are consistent with the model selection procedure’s choice of the CE nugget spherical model for the corn analysis (Table 2), and indicated that the spatial correlation was better accounted for by ignoring the blocking and including an estimation of the spatial covariance structure of the errors in the model.

The estimated range of spatial dependence of the errors from the selected corn model was 52 m, slightly less than the plot size, indicating that spatially correlated errors were present within the scale of adjacent plots. In such a case, neither a block nor block×treatment effect could be expected to be effective in accounting for spatial heterogeneity. In this case, a spatial covariance function alone was better in accounting for the spatial correlation.

These two examples show that variography is an important tool in selecting covariance models. The semivariograms are useful in determining starting parameters. They give an indication of when spatial functions may require inclusion of nugget effects, and they
hint at the appropriate form the spatial function may take (i.e. spherical, exponential, etc). However, consistent with the findings of Brownie and Gumpertz (1997), the exact model that will be selected cannot be fully predicted from the semivariograms alone.

**Model Impact on P-values**

In both the wheat forage and corn-for-grain trials the errors were spatially correlated, the estimated range was less than the block size, and the RCBiid method tended to give higher estimates of the variance of treatment comparisons than the other models (Table 2). Consequently, for both data sets, the RCBiid and the selected covariance model resulted in different conclusions regarding treatment significance. The selected covariance model for wheat resulted in a smaller significance level for treatment comparison, $P = 0.03$ compared to $P = 0.07$ for the RCBiid model. This would have affected conclusions about treatment effects at the 0.05 level of significance. The selected covariance model for corn indicated significant treatment effects ($P = 0.05$), which were completely obscured by the RCBiid model ($P = 0.43$). This is because the RCBiid method assumes the spatial correlation persists for a longer distance (the width of a block, ~172 m) than the selected CE model with an estimated range of 52 m (Table 2). Clearly, when the model errors are spatially correlated, as they were in both of these data sets, the use of the selection procedure may result in a more powerful statistical test than the classical RCBiid method.

The data in Table 2 indicates that the treatment P-value associated with any given candidate covariance model is very sensitive to the form of that model. For the wheat data, all of the models that included block effects gave P-values for the treatment effect in the range of 0.03 to 0.07. If block effects were omitted from the wheat models, the P-values dropped to < 0.0001. Clearly, arbitrary selection of a covariance model can result in
dramatically different treatment conclusions. In the wheat example presented here, both the selection procedure based on AIC and LRT comparisons (Fig. 1) and the initial variography (Fig. 3) support the selection of the RCBCE nugget Gaussian model for data analysis. The LRT decisively selects the RCBCE nugget Gaussian model over the CE nugget Gaussian model (p-value = 0.0009 against dropping the block effects).

In the corn data, the inclusion of block effects in the models also affected the P-values of the F-test for treatment effects, but the most dramatic impact was associated with the inclusion or omission of a nugget effect in the spatial functions used in the RCBCE and CE methods (Table 2). The P-values for models with block effects and no nugget ranged from 0.27 to 0.43. If a nugget was included in the RCBCE candidate models, the P-values ranged from 0.06 to 0.15. If no nugget and no block effects were included, the P-value dropped dramatically to 0.0003 for the CE no-nugget Gaussian model, which was the only one of this type that converged. The CE models that included a nugget effect had P-values that ranged from 0.04 to 0.13. Consistent with the wheat trial, the corn data demonstrate that it is possible for results of tests of treatment effects to differ greatly under different spatial covariance models and that covariance models should not be selected arbitrarily. In this case, the AIC values made it obvious that models without nugget effects were not adequate, and variography supported this conclusion. The nugget spherical model provided the best fit, either with or without block effects (AIC=41341 and AIC=41339, respectively). The LRT for block effects showed that the block effects were not significant. Including non-significant blocks in the model should not have much effect one way or the other; and it did not: the p-values for testing treatment effects were similar whether blocks were included or not (p= 0.06 with block effects and 0.05 without, Table 2).
The dominator degrees of freedom (DDF) of F-tests for treatment effects were computed using the Kenward-Roger method provided in SAS PROC MIXED (Kenward and Roger, 1997). This method computes degrees of freedom based on the estimated covariance structure rather than on the randomization plan of the experiment. When block and plot effects are present and have an impact on the covariance structure, the denominator degrees of freedom for the test of treatment effects will be based on the number of plots. If the block and plot effects are small or nonexistent, the denominator degrees of freedom will be much larger. In the two trials presented here, the degrees of freedom varied considerably between candidate models (Table 2). For example, the DDF ranged from 27 to 347 and from 18 to 1033 for the wheat and corn candidate models, respectively. On first consideration, it might seem that this alone should result in the decrease in treatment P-values associated with some of the CE candidate models. However, in our experience, this is not the case even in these types of experiments that involve dense sub-sampling within plots. For example, Table 4 shows the impact of changing the DDF in the wheat RCBCE nugget Gaussian and in the corn CE nugget spherical models, i.e., the selected models for these two data sets. The DDF were computer using the “Residual” and “Kenward-Roger” methods, and by forcing them to equal the DDF used by the RCBiid method. For the wheat data, when DDF ranged from 19 to 527 the associated change in P-values was only from 0.03 to 0.01. For the corn data, when DDF ranged from 18 to 2539, the change in P-values was also small, ranging only from 0.07 to 0.05. Clearly, the treatment P-values of the selected covariance models were relatively insensitive to changes in DDF over the range exhibited by the candidate models. Differences in P-values among candidate models cannot be accounted for simply by the changes in DDF among the RCBiid, RCBCE, and CE methods.
Model Impact on Treatment Means and Standard Errors

For both the wheat and corn trials, the estimated deviations of treatment means from the overall mean were very similar between the selected covariance model and the RCBiid method (Table 3). For wheat, the standard errors of the treatment means were very similar between the two models (Table 3), but for corn, the selected CE model had standard errors of the means strikingly lower than the RCBiid method.

The treatment means estimated for wheat forage and corn grain yield by the selected models were lower than those computed by the RCBiid method (Table 3). Our experience has shown that while this happened in these examples, it is not always the case. The differences in treatment estimates between the selected models and the RCBiid method differed across treatments. This was probably due, at least in part, to the spatial arrangement of the treatments (Fig. 2a). For example, there were eight pairs of adjoining plots that both received the RYE treatment, whereas there were only six and five pairs of adjoining plots that both received the FA and SSNM treatments, respectively. Each plot’s contribution to the treatment mean depended on how close it was to other plots of the same treatment. Thus, for the RCBCE and CE methods, within a specific distance the covariance of any two sampling sites of each treatment was different.

Other Strategies for Model Selection

In our two examples, if only AIC had been used for model selection, the same models would have been selected as we found using the LRT\textsubscript{01} together with AIC. However, our experience with other data has shown that this is not always the case. Overall, we prefer using the LRT in all hypothesis tests if the distribution of a LRT is known. For cases where the distribution of a LRT is unknown, AIC gives a method of comparing models. As with the
LRT, there are uncertainties about the behavior of the AIC statistic when parameters are on
the boundary of the parameter space.

Other model selection sequences for choosing the best-fit RCBCE or CE model are
possible. Within the RCBCE or CE method, we can first compare a nugget versus no-nugget
model based on the same spatial function using LRT$_{01}$, and then compare the selected models
across different spatial functions using AIC. Additionally, we can also first compare the
best-fit RCBCE and CE models to determine the blocking significance, and then compare the
selected model to the RCBiid model to determine if spatial correlation is significant. We
examined these procedures for our two examples, and they resulted in the selection of the
same best-fit models as our original model selection sequence.

**CONCLUSIONS**

We began this research with a concern about RCB analysis in precision agriculture
experiments. The spatial scale of these experiments, the dense sub-sampling within plots
associated with yield monitor sampling, and the unusual way in which treatments may be
applied to these plots (compared to traditional small plot experiments) lead to issues that the
traditional RCB analysis was not designed to address. Our primary objective was to present
a step-by-step, systematic approach that agronomists could use to select a covariance model
for RCB analysis when spatial correlation is present. That approach was outlined in Fig. 1,
and tested with data from two trials within a large-scale site-specific N management study.
This procedure is somewhat complex, but systematic and conceptually straightforward. It is
readily implemented in SAS, though it may require substantial computing time for large data
sets. Additionally, the procedure is not restricted to RCB analyses but is appropriate to any
mixed-model analysis with potentially spatially correlated errors. Inferences based on the
fitted covariance structure are expected to be more precise than other candidate models rejected in the selection process. Our second objective was to evaluate the impact that different covariance models have on treatment effect P-values. Both the 2001 wheat and the 2002 corn data sets demonstrate that the resultant treatment P-values may be highly sensitive to the choice of covariance model, particularly to which of the component parts are included: spatial correlation, nugget effects, plot effects, and block effects. Clearly, arbitrary selection of a covariance model can result in misleading conclusions about treatment effects.

**FURTHER CONSIDERATIONS**

Covariance model selection based on one dataset is difficult, and no single tool will necessarily select an appropriate model. For example, the candidate CE nugget exponential wheat model had AIC values that were nearly identical to the other wheat candidate CE nugget models (Table 2), but the estimated range and sill were nearly an order of magnitude larger. These estimates were not only inconsistent with the estimates from the other candidate models, but clearly did not fit the wheat data presented in Fig. 3. Our procedure rejected this candidate model, but it is still of concern that the AIC for this model gave little indication that its parameter estimates were apparently incorrect.

A further concern raised by the results presented here is the extreme sensitivity of the treatment P-values to covariance model selection. Clearly, care must be taken in selecting a model for data analysis, and untested assumptions about the adequacy of a given spatial function, the presence or absence of nugget effects, or the need to include or omit block effects can lead to erroneous conclusions. We believe that a selection procedure like the one outlined in Fig.1 combined with variography are important if adequate models are to be used for data analysis. However, given the concerns about using AIC and LRT comparisons, all
conclusions about covariance model selection and the resultant treatment effect P-values need to be carefully evaluated. For example researchers need to ask if the estimated parameters are realistic, and if the conclusions regarding treatment effects are agronomically meaningful. Simulation studies would be useful in evaluating the probability of selecting an adequate covariance structure and the effect of the covariance structure on the estimation of treatment significance with or without the inclusion of block and block by treatment (plot) effects.
Table 1. Rate and timing of N fertilizer applications for the three N management treatments for wheat and corn.

<table>
<thead>
<tr>
<th>Time of Application</th>
<th>N management treatments</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>RYE‡</td>
</tr>
<tr>
<td>Wheat (2 Nov 2000 to 25 May 2001) †</td>
<td>…………………..</td>
</tr>
<tr>
<td>Starter (22 Oct 2000)</td>
<td>34</td>
</tr>
<tr>
<td>GS§-25 (14 Feb 2001)</td>
<td>0</td>
</tr>
<tr>
<td>GS-30 (12 Mar 2001)</td>
<td>119</td>
</tr>
<tr>
<td>Total</td>
<td>153</td>
</tr>
<tr>
<td>Corn (3 Apr 2002 to 22 Aug 2002)</td>
<td></td>
</tr>
<tr>
<td>Starter (5 Apr 2002)</td>
<td>8</td>
</tr>
<tr>
<td>V₂§ (24 Apr 2002)</td>
<td>104</td>
</tr>
<tr>
<td>V₇ (17 June 2002)</td>
<td>0</td>
</tr>
<tr>
<td>Total</td>
<td>112</td>
</tr>
</tbody>
</table>

† Planting to harvest.

‡ RYE = Realistic Yield Expectation N management; FA = field-average N management; SSNM = site-specific N management.

§ GS denotes Zadok’s Growth Stage (Zadoks et. al. 1974); V₂ denotes two-leaf growth stage, and V₇ tasselling growth stage (Ritchie et. al. 1993).

¶ The weighted average of the variable rates of N fertilizer applied.

# The variable rates of N fertilizer applied.
Table 2. Wheat and corn candidate covariance models and their related statistics and covariance parameters including randomized complete block with iid errors (RCBiid), randomized complete block with correlated errors (RCBCE), and correlated errors analysis (CE) models.

<table>
<thead>
<tr>
<th>Models</th>
<th>Covariance parameter estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Range</td>
</tr>
<tr>
<td></td>
<td>Models</td>
</tr>
<tr>
<td>wheat</td>
<td></td>
</tr>
<tr>
<td>RCBiid model</td>
<td>8479</td>
</tr>
<tr>
<td>RCBCE no-nugget exponential model</td>
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</tr>
<tr>
<td>RCBCE nugget Gaussian model</td>
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</tr>
<tr>
<td>RCBCE nugget spherical model</td>
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</tr>
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<td>CE no-nugget spherical model</td>
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<tr>
<td>CE nugget Gaussian model</td>
<td>8479</td>
</tr>
<tr>
<td>CE nugget exponential model</td>
<td>8486</td>
</tr>
<tr>
<td>CE nugget spherical model</td>
<td>8487</td>
</tr>
<tr>
<td>corn</td>
<td></td>
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63
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<th>Model Type</th>
<th>Code1</th>
<th>Code2</th>
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<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
<th>g</th>
<th>h</th>
<th>i</th>
<th>j</th>
<th>k</th>
<th>l</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCBiid model</td>
<td>42549</td>
<td>42555</td>
<td>18</td>
<td>0.43</td>
<td>254</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>125</td>
<td>343</td>
<td>311</td>
<td>140</td>
<td>320</td>
<td></td>
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<td>RCBCE no-nugget Gaussian model</td>
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<td>41959</td>
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<td>0.43</td>
<td>254</td>
<td>8</td>
<td>994</td>
<td>637</td>
<td>NA</td>
<td>118</td>
<td>429</td>
<td>298</td>
<td>142</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td>RCBCE no-nugget exponential model</td>
<td>41528</td>
<td>41537</td>
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<td>0.27</td>
<td>220</td>
<td>24</td>
<td>1170</td>
<td>924</td>
<td>NA</td>
<td>85</td>
<td>293</td>
<td>145</td>
<td>621</td>
<td>NA</td>
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<td>RCBCE no-nugget spherical model</td>
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<td>41902</td>
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<td>0.41</td>
<td>254</td>
<td>10</td>
<td>1001</td>
<td>899</td>
<td>NA</td>
<td>117</td>
<td>605</td>
<td>295</td>
<td>967</td>
<td>NA</td>
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<td>41356</td>
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<td>186</td>
<td>35</td>
<td>1327</td>
<td>641</td>
<td>515</td>
<td>730</td>
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<td>931</td>
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<td>41347</td>
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<td>172</td>
<td>123</td>
<td>1815</td>
<td>490</td>
<td>374</td>
<td>892</td>
<td>13</td>
<td>009</td>
<td>NI</td>
<td>NA</td>
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<tr>
<td>RCBCE nugget spherical model</td>
<td>41333</td>
<td>41341</td>
<td>589</td>
<td>0.06</td>
<td>158</td>
<td>52</td>
<td>1445</td>
<td>310</td>
<td>394</td>
<td>345</td>
<td>26</td>
<td>670</td>
<td>NI</td>
<td>NA</td>
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<tr>
<td>CE no-nugget Gaussian model</td>
<td>42245</td>
<td>42249</td>
<td>1033</td>
<td>0.003</td>
<td>87</td>
<td>9</td>
<td>1255</td>
<td>995</td>
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<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td></td>
</tr>
<tr>
<td>CE nugget Gaussian model</td>
<td>41349</td>
<td>41355</td>
<td>561</td>
<td>0.04</td>
<td>160</td>
<td>36</td>
<td>1407</td>
<td>535</td>
<td>519</td>
<td>684</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
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</tr>
<tr>
<td>CE nugget exponential model</td>
<td>41339</td>
<td>41345</td>
<td>560</td>
<td>0.13</td>
<td>168</td>
<td>126</td>
<td>1840</td>
<td>215</td>
<td>374</td>
<td>629</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
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<tr>
<td><strong>CE nugget spherical model</strong></td>
<td>41333</td>
<td>41339</td>
<td>640</td>
<td>0.05</td>
<td>156</td>
<td>52</td>
<td>1458</td>
<td>190</td>
<td>392</td>
<td>719</td>
<td>NA</td>
<td>NA</td>
<td>NA</td>
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</tr>
</tbody>
</table>

† $-2 \ell = -2 \times$ residual log likelihood.

‡ Akaike Information Criterion

§ The denominator degrees of freedom of F-tests for treatment effects computed using the Kenwardroger method for the RCBiid, RCBCE and CE models in SAS PROC MIXED.

¶ P-value of F-tests for treatment effects.

# The average of standard errors of treatment comparisons.
†† The actual range for models defined by a spherical function or practical range for models defined by a Gaussian or exponential function.

‡‡ Total sill

§§ Block × Treatment random effect.

¶¶ NA = not applicable.

## NI = parameter estimated to be zero, thus not included in the reduced model.

Bold type indicates the selected model.
Table 3. Comparisons of generalized-least-squares treatment means and deviations of treatments means from overall means for wheat and corn between the randomized complete block with iid errors (RCBiid) model versus the best-fit spatial covariance model. The standard error of the mean is in parenthesis.

<table>
<thead>
<tr>
<th>Model name</th>
<th>Overall mean</th>
<th>Treatment means (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>RYE†</td>
</tr>
<tr>
<td>Wheat</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCBiid model</td>
<td>6479</td>
<td>6818 (169)</td>
</tr>
<tr>
<td>Treatment mean – overall mean</td>
<td>339 (138)</td>
<td>- 175 (138)</td>
</tr>
<tr>
<td>RCBCE nugget Gaussian model‡</td>
<td>6423</td>
<td>6778 (173)</td>
</tr>
<tr>
<td>Treatment mean – overall mean</td>
<td>335 (119)</td>
<td>- 180 (120)</td>
</tr>
<tr>
<td>Corn</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RCBiid model</td>
<td>6122</td>
<td>5952 (212)</td>
</tr>
<tr>
<td>Treatment mean – overall mean</td>
<td>- 170 (147)</td>
<td>4 (147)</td>
</tr>
<tr>
<td>CE nugget spherical model‡</td>
<td>5994</td>
<td>5804 (150)</td>
</tr>
<tr>
<td>Treatment mean – overall mean</td>
<td>- 190 (86)</td>
<td>15 (95)</td>
</tr>
</tbody>
</table>

† RYE = Realistic Yield Expectation N management; FA = field-average N management; SSNM = site-specific N management.

‡ The best-fit model.
Table 4. Impact of the dominator degrees of freedom (DDF) on the treatment P-value of the selected covariance model.

<table>
<thead>
<tr>
<th>DDF Method</th>
<th>DDF</th>
<th>F-value</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat 2001 RCBCE Nugget Gaussian Model</td>
<td></td>
<td></td>
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<tr>
<td>Residual</td>
<td>527</td>
<td>4.29</td>
<td>0.01</td>
</tr>
<tr>
<td>DDFM = 27</td>
<td>27</td>
<td>4.29</td>
<td>0.02</td>
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<tr>
<td>Kenward-Roger</td>
<td>19</td>
<td>4.29</td>
<td>0.03</td>
</tr>
<tr>
<td>Corn 2002 CE Nugget Spherical Model</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residual</td>
<td>2539</td>
<td>3.09</td>
<td>0.05</td>
</tr>
<tr>
<td>Kenward-Roger</td>
<td>640</td>
<td>3.09</td>
<td>0.05</td>
</tr>
<tr>
<td>DDFM = 18</td>
<td>18</td>
<td>3.09</td>
<td>0.07</td>
</tr>
</tbody>
</table>
The RCBiid model has the best-fit

The RCBCE model has the best-fit

The CE model has the best-fit
Figure 1. Schematic representation of the best-fit covariance model selection procedure for RCB analyses in the presence of spatial correlation. The LRT denotes likelihood ratio $\chi^2$ test. AIC denotes Akaike Information Criterion.
Go-Goldsboro loamy sand
Ly-Lynchburg sandy loam
No-Norfolk sandy loam
1-RYE; 2-FA; 3-SSNM

Wheat Yield (kg/ha)
- 3268 - 5700
- 5701 - 6546
- 6547 - 7400
- 7401 - 9265

Corn Yield (kg/ha)
- 1613 - 4367
- 4368 - 5711
- 5712 - 6921
- 6922 - 11154
Figure 2. (a) Field layout of the randomized complete block design at the Lower Coastal Plain Tobacco Research Station, Kinston, NC. The shading pattern indicates which plots are the same block (three plots per block). The treatment number is in the upper left corner of each plot; (b) yield maps of wheat forage and (c) corn grain yield. RYE = Realistic Yield Expectation N management; FA = field-average N management; SSNM = site-specific N management.
Figure 3. Spatial correlation of wheat forage and corn grain yield illustrated by the isotropic semivariograms of the original observations $\hat{\gamma}(h)$, the residuals from fitting a model with just fixed effects $\hat{\gamma}_e(h)$, and the RCBiid model-fit residuals $\hat{\gamma}_e(h)_{RCB}$. The semivariances were divided by 100 000 before plotting.
APPENDIX

Following are examples of SAS PROC MIXED code used to perform the covariance model selection for both the 2001 wheat and 2002 corn data sets.

TITLE “RCBIID ANALYSIS”;  
PROC MIXED METHOD = REML;  
CLASS TREATMENT BLOCK;  
MODEL YIELD = TREATMENT/DDFM=KR;  
RANDOM BLOCK BLOCK*TREATMENT;  

TITLE “RCBCE ANALYSIS”;  
/* An example of an RCBCE nugget Gaussian model */  
PROC MIXED METHOD = REML;  
CLASS TREATMENT BLOCK;  
MODEL YIELD = TREATMENT/DDFM=KR;  
RANDOM BLOCK BLOCK*TREATMENT;  
REPEATED / SUBJECT = INTERCEPT LOCAL TYPE= SP(GAU) (X Y);  
/* Insert actual starting parameter values for: */  
PARMS (BLOCK) (BLOCK*TREATMENT) (SILL) (RANGE)(NUGGET);  
/* An example of an RCBCE no-nugget Gaussian model */  
PROC MIXED METHOD = REML;  
CLASS TREATMENT BLOCK;
MODEL YIELD = TREATMENT/DDFM=KR;

RANDOM BLOCK BLOCK*TREATMENT;

REPEATED / SUBJECT = INTERCEPT  TYPE= SP(GAU) (X Y);

/* Insert actual starting parameter values for: */

PARMS (BLOCK) (BLOCK*TREATMENT) (RANGE) (SILL);

TITLE “CE ANALYSIS”;

/* An example of a CE nugget Gaussian model */

PROC MIXED METHOD = REML;

CLASS TREATMENT BLOCK;

MODEL YIELD = TREATMENT/DDFM=KR;

REPEATED / SUBJECT = INTERCEPT LOCAL TYPE= SP(GAU) (X Y);

/* Insert actual starting parameter values for: */

PARMS  (SILL) (RANGE)(NUGGET);

/* An example of a CE no-nugget Gaussian model */

PROC MIXED METHOD = REML;

CLASS TREATMENT BLOCK;

MODEL YIELD = TREATMENT/DDFM=KR;

REPEATED / SUBJECT = INTERCEPT  TYPE= SP(GAU) (X Y);

/* Insert actual starting parameter values for: */
PARMS (RANGE) (SILL);
CHAPTER 3: REMOTE SENSING INFORMED IN-SEASON SITE-SPECIFIC NITROGEN MANAGEMENT: EFFECTS ON GROUNDWATER NITRATE CONCENTRATION AND AGRONOMIC PERFORMANCE

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For Submission to: Journal of Environmental Quality
ABSTRACT

In-season site-specific (SS) N management based on remote sensing (RS) has been suggested as a way of reducing groundwater NO$_3$-N contamination. We evaluated the environmental and agronomic benefits of two in-season, RS-informed N management strategies applied either on a uniform field-average (FA) or SS basis, compared to current uniform N recommendations based on "Realistic Yield Expectations" (RYE) in a typical Coastal Plain cropping system. The experiment was located in a 12-ha North Carolina field with a two-year winter wheat (*Triticum aestivum* L.)-double-crop soybean [Glycine max (L.) Merr.]-corn (*Zea mays* L.) rotation. Groundwater NO$_3$-N and water table depth were measured every two weeks at 60 well nests sampling 0.9- to 1.8-, 1.8- to 2.7-, and 2.7- to 3.7-m depths. Compared to RYE, SS achieved (i) less groundwater NO$_3$-N by reducing fertilizer N and harvest N ratio (the ratio of harvest N in grain or forage yield to the total fertilizer N applied) for wheat in 2001, (ii) increased yield associated with higher N applied and decreased harvest N ratio for corn in 2002, and (iii) increased yield associated with similar fertilizer N and increased harvest N ratio for wheat in 2003. Overall, FA performed similar to SS for wheat, but differed greatly for corn due to an over-application of N that resulted from an error in estimating N requirements at tasselling. Even small differences in N fertilizer rates resulted in statistically significant treatment effects on groundwater nitrate concentration that carried over into the subsequent growing seasons. Our data suggest that to assess the environmental efficacy of N management in coastal plain and other coarse-textured soils where in-season NO$_3$-N leaching may be pronounced, frequent and periodic monitoring of groundwater NO$_3$-N, especially after significant rainfall, and for weeks or even
months beyond the current cropping season, are essential to capture fertilizer treatment
effects.
INTRODUCTION

Nitrate-N groundwater contamination in the southeastern Coastal Plain has become a regulatory and social issue threatening regional crop production. The application of N fertilizer in agricultural areas has been cited as the cause of high NO$_3$-N concentrations in shallow groundwater (Spruill et al., 1996). This is true in the Neuse River basin, one of 17 major river basins in North Carolina (NC). Groundwater NO$_3$-N concentration in this area has been detected at levels up to 20 mg NO$_3$-N L$^{-1}$ (Osmond et al., 2002). In 1998, the “Neuse River Rule” (North Carolina Administrative Code, 1998) became effective to protect this endangered watershed. The rule requires “… reducing the average annual load of nitrogen delivered to the Neuse River Estuary from point and nonpoint sources by a minimum of 30 percent of the average annual load…” Similar rules have been established to protect another nutrient-sensitive North Carolina watershed, the Tar-Pamlico.

As a result of these rules, N fertilizer rates in the Neuse and Tar-Pamlico River basins are determined independent of growing season using whole-field Realistic Yield Expectations (RYE; North Carolina Nutrient Management Workgroup, 2003), and are applied uniformly across a field (Crozier et al., 2004). However, soil physical properties (e.g., Davidoff and Selim, 1988), moisture relations (e.g., Achouri and Gifford, 1984), and soil nutrient availability (e.g., Webster and Nortcliff, 1984) can vary spatially within fields, resulting in within-field variability of crop growth, N uptake, and N-fertilizer requirements (Ferguson et al., 1995). Additionally, even for a given field, crop N uptake and consequently optimal N rates can vary greatly among and within seasons (e.g., Baethgen and Alley, 1989 (winter wheat); Hanaway, 1962 (corn)). Therefore, season-independent, uniform, whole-field N application, as mandated by the Neuse Rule and practiced widely in traditional
agriculture, may result in large under- or over-application. Excess fertilizer N has been linked directly to NO₃-N leaching (Andraski et al., 2000). Leachate may reach shallow groundwater, especially on coarse-textured coastal plain soils, causing groundwater NO₃-N contamination, thus defeating the very intention of the Neuse Rule.

In-season N management is intended to match the temporal variability of crop N needs by applying appropriate amounts of N fertilizer at critical crop growth stages. Historically, this was first attempted simply by splitting total crop fertilizer N needs into multiple applications of appropriate amounts timed to meet temporal differences in crop requirements. Subsequent refinements have included estimating appropriate N rates and timings based on soil, tissue, and petiole sap tests, or remote sensing-based estimation of crop N and moisture status, yield potential, or optimal N rate. Split fertilizer N applications have yielded inconsistent results. Banfield et al. (1981) and Grant et al. (1985) reported that there was no agronomic return using split N application on wheat, but an agronomic advantage was reported by, e.g., Davies et al. (1979), Mulla et al. (1992), Bhatti et al. (1998), Raun et al. (2002). Scharf and Alley (1993a,b), and Flowers et al. (2004) demonstrated that in-season optimization of N applications to winter wheat resulted in increased crop N use efficiency, reduced N applied, and higher economic return.

In-season N rates might be determined on a whole-field- or site-specific basis. Site-specific N management is intended to match the spatial variability of crop N needs by applying appropriate spatially variable rates of N fertilizer. Site-specific N rates have been determined prior to planting in various ways, e.g., based on: soil series (Carr et al., 1991); a combination of grid soil sampling and yield maps (Redulla et al., 1996); a combination of yield maps, soil organic matter (SOM) content, and soil N status (Mulla and Bhatti, 1997);
grid soil sampling (Ferguson et al., 2002); and stand density and tissue testing (Flowers et al., 2004). Site specific N management has been reported to achieve agronomic success by improving grain yield and NUE (e.g., Flower et al., 2004), environmental benefit by reducing NO$_3$-N pollution in the watershed (e.g., Rejesus and Hornbaker 1999). Braga et al., (1999) reported greater crop yield associated with SS management of N in some soil types and years.

In fields with substantial spatial and temporal variability in crop N requirement, neither in-season nor site-specific N management alone will likely provide optimum N management; the former ignores spatial differences in N need and the latter ignores yearly and in-season temporal differences in N demand. Consequently, the integration of in-season and site-specific N management, i.e., in-season SS N management should be the most effective way to optimize crop yield and N applications and reduce the risk of NO$_3$ pollution. To achieve this goal, methods for determining N requirements on an in-season and site-specific basis are needed. Plant tissue tests have been used to determine the in-season N status of several grain crops (e.g., Baethgen and Alley, 1989a; Smeal and Zhang, 1994), but can be expensive and labor intensive when conducted on a SS scale. Several studies reported that chlorophyll meter readings were related to whole-plant N concentration or grain yield (e.g., Blackmer and Schepers, 1994; Fox et al., 1994). Chlorophyll meters are expensive, but their use to estimate in-season N status is quicker and less expensive than tissue sampling and testing. However, for optimal application, this approach requires within-field calibration based on a number of high N reference areas. In addition, site-specific application of chlorophyll meters would require that multiple measurements be made across a field, making this method labor and time consuming. Crop canopy reflectance of visible and near-infrared
light has been related to crop N status and fertilizer requirement. Consequently, remote sensing in the form of on-the-go sensors and aerial photography has been applied to in-season SS N management (Filella et al., 1995, Flowers et al., 2001, Flowers et al., 2003a, Flowers et al., 2003b, Lukina et al., 2001, and Raun et al., 2002). Remote sensing has the potential to make in-season SS N management a practical reality that might reduce groundwater NO$_3$-N contamination (Dinnes et al., 2002 and Ferguson et al., 2002).

By applying appropriate spatially variable rates of N fertilizer at critical growth stages, in-season SS N management is hypothesized to reduce N loss to the environment (hereafter referred to as surplus N) while maintaining or increasing yield and NUE, thus improving groundwater quality compared to current, uniform, RYE-based N recommendations. Recent research (Dinnes et al., 2002 and Ferguson et al., 2002) has suggested that in-season SS N management based on RS might be a way of reducing groundwater NO$_3$-N contamination, but this hypothesis has yet to be tested.

Our objectives were to evaluate the environmental benefits of in-season, RS-informed N management, applied either on a uniform field-average (FA) or SS basis, compared to current uniform RYE-based recommendations in a typical Coastal Plain cropping system. Environmental benefits were evaluated based on NO$_3$-N concentrations in shallow groundwater. Additionally, the ratio of N harvested in grain or forage to the total fertilizer N applied, hereafter referred to as the harvest N ratio, and surplus N were estimated for each N treatment. We sought to test the hypothesis that RS-informed FA and SS have higher harvest N ratio, and result in less surplus N and lower groundwater NO$_3$-N concentrations compared to RYE-based N management.
MATERIALS AND METHODS

Site Description

The experiment was conducted in two adjacent fields totaling 12 ha at the Lower Coastal Plain Tobacco Research Station, Kinston, NC (Fig. 1). An order one soil survey (North Carolina Agricultural Experiment Station, 1977) delineated three soil map units in these fields: Norfolk (No) loamy sand with 0-2% slope (fine-loamy, siliceous, thermic, Typic Paleudults), Goldsboro (Go) loamy sand (fine-loamy, siliceous, thermic, Aquic Paleudults), and Lynchburg (Ly) sandy loam (fine-loamy, siliceous, thermic, Aeric Paleaquults). These soils represent millions of acres of land in the lower and middle North Carolina Coastal Plain and in the southeastern United States. A typical stratigraphic description of these fields is given in Table 1. The clay bed at 2.6- to 2.9-m depth has low permeability. During periods of high rainfall, water will perch above the clay forming a zone of saturation up to 1.8 m or less. The major horizontal water flow occurs at the zone of the basal sand bed at 2.9- to 3.7-m depth (North Carolina Agricultural Experiment Station, 1977). The fields have a tile drainage system with two outlet control structures managed to optimize drainage and reduce drought stress.

Experimental Setup

The experiment began in November 2000 with the establishment of a two-year winter wheat-double crop soybean (year 1) – corn (year 2) rotation typical of the Coastal Plain. The experiment was established in a randomized complete block (RCB) design with three N management treatments for wheat and corn replicated ten times in plots 60.8 by 60.8 m (0.37 ha). In early March 2001, two well nests were installed in each plot (Fig. 1) to monitor shallow groundwater NO₃-N concentrations. One nest was placed at the plot center to
minimize the influence of neighboring plots. The other nest was placed randomly within the constraints of being an adequate distance from the plot center, outside a plot border-harvest buffer area, and inline from plot to plot parallel to crop rows to facilitate field operations. We designed the field layout this way to minimize the influence of potential groundwater lateral flow across treatments. Each well nest consisted of three PVC pipe groundwater-sampling wells screened to sample over depths of 0.9 to 1.8, 1.8 to 2.7, and 2.7 to 3.7 m. We sampled to 3.7-m depth to ensure water samples were available throughout the season.

The three N management treatments were:

**Uniform Realistic Yield Expectation N management (RYE):** This is the current regulated N management system for the NC Neuse and Tar-Pamlico River basins. The RYE N rate was determined based on the published RYE and N-use factor for the predominant soil type (Go) in the field derived from the NC RYE database (North Carolina Nutrient Management Workgroup, 2003). Fertilizer N was applied uniformly to these plots at planting and at the appropriate growth stages (GS): for wheat, GS-30 (Zadoks et al., 1974), for corn, V2 (Ritchie et al., 1993).

**Uniform field average in-season RS-informed N management (FA):** The FA top-dress (wheat) or side-dress (corn) N rates were determined based on field-averaged in-season estimates of optimal N demand at critical growth stages using color infrared photography (CIR). Methods used to determine in-season N rates are detailed below. Fertilizer N was applied uniformly to plots at planting, and for wheat at GS-25 (Zadoks et al., 1974) and GS-30, and for corn at V2 and VT (Ritchie et al., 1993). Thus FA considered in-season, growth stage-specific N demand, but ignored site-specific variability.
Site-specific in-season RS-informed N management (SS): The SS rates were determined based on site-specific estimates of N demand at critical growth stages using CIR. As in RYE and FA, starter fertilizer N was applied uniformly to plots at planting. Subsequently, each SS plot was divided into 78 4.6- by 9.1-m “miniplots” (about 1% of the whole-plot size) for spatially variable rate N application. The SS N was determined by averaging N demand within each miniplot and fertilizing each miniplot accordingly at the same growth stages as FA. Thus SS considered both growth stage- and site-specific N demand during the growing season.

Treatment N Rate Determination

Nitrogen rates and timings for the RYE, FA, and SS treatments for 2001 wheat, 2002 corn, and 2003 wheat are summarized in Table 2. There was no fertilizer N applied to soybean. Nitrogen as aqueous urea-ammonium nitrate \([\text{CO(NH}_2\text{)}_2\text{-NH}_4\text{NO}_3; 30\% \text{ N}]\) was applied to wheat using a variable rate sprayer; for corn at V2 and VT, it was dribbled to row middles using high-clearance, variable-rate equipment with drop nozzles. In 2002 in cases where the row spacing of corn prevented mechanized operations adjacent to the well nests, seeding and fertilization were done manually.

Wheat 2001 and 2003

For wheat FA and SS, N rates at GS-25 and GS-30 were based on RS-estimated tiller density and RS-estimated whole-plant tissue N content respectively. The relationships between GS-25 tiller density, GS-30 tissue N content, and optimum N rates have been previously reported (Flowers et al., 2004; Weisz and Heiniger, 2000). In the experiments reported here, the N-rate optimization schemes published by Flowers et al., (2004) were modified so that they could be based on RS.
GS-25 N rates

Aerial CIR photography, ground based calibration, and the specific algorithms used to convert near infrared digital counts (NIR) into optimum N rates for the 2001 GS-25 wheat crop were as described in Flowers et al., 2003b. In brief, a linear relationship was developed using NIR to estimate wheat tiller density at any point in the field based on ground truth tiller densities determined at small calibration areas. The best estimations were obtained by developing one algorithm for the Ly soil and a second for the rest of the field. Nitrogen application was based on a tiller density threshold of 500 tillers m\(^{-2}\), with only areas below this threshold receiving N (Flowers et al., 2004; Weisz and Heiniger, 2000). Tiller densities in the FA plots were above the N application critical threshold, thus fertilizer N was not applied to these areas. However, about 24% of the SS miniplots had tiller densities below the threshold and consequently received GS-25 N.

In 2003, the same aerial CIR photography methods were used, however the GS-25 tiller densities were lower than those examined by Flowers et al., (2001, 2003b) and their NIR-based algorithm did not adequately fit the data. At these low tiller densities with a high percentage of bare soil showing in the photographs, the best relationship with tiller density was found using a normalized near infrared spectral index (Jain, 1989) defined as:

\[
\text{NormNIR} = \frac{\text{NIR}}{(\text{NIR} + \text{RED} + \text{GREEN})}
\]  

[1]

where RED and GREEN are the digital counts associated with the red and green CIR film bands (Flowers et al., 2003b). A quadratic relationship provided a good estimate of tiller density from NormNIR across all soil types (\(R^2 = 0.69\)). All FA plots and all of the SS miniplots had tiller densities below the critical threshold, and GS-25 N was applied to all of these areas in 2003.
GS-30 N rates

Nitrogen fertilizer rates at this growth stage were based on RS estimates of whole-plant N content. The relationship between whole-plant N content and optimum N rates, and the RS methods used to estimate whole-plant N-content-based N rates were described by Flowers et al., 2004 and 2003a, respectively. In brief, calibrations strips were established at GS-25 by applying various rates of N fertilizer to wheat growing just outside the experimental area (Fig. 1). At GS-30, approximately four weeks after GS-25, a new CIR was taken and used together with wheat tissue N content determined at small sample areas in the fertilizer calibration strips to estimate whole-plant-N-content based optimum-N rates everywhere in the field.

In 2001, tissue N-content-based optimum N rates were best estimated using the green normalized vegetative index (GNDVI; Gitelson et al., 1996) defined as:

\[ \text{GNDVI} = \frac{\text{NIR} - \text{GREEN}}{\text{NIR} + \text{GREEN}} \]

A linear relationship between GNDVI and optimum-N rate was developed for the Ly soils \((R^2 = 0.69)\), and an exponential relationship was used for all other soils \((R^2 = 0.67)\). In 2003, optimum-N rates were best estimated across all soil types using a quadratic relationship and GREEN \((R^2 = 0.62)\). In the FA plots, the average RS-estimated optimum-N rate was applied. In the SS plots, N rates were grouped into seven discrete ranges, the maximum possible with our variable rate applicator (Table 2).

Corn 2002

At planting, high-N reference strips were established by applying 120 kg N ha\(^{-1}\) to corn growing at plot boundaries within the experimental area (Fig. 1). At V2, the RYE plots received the remainder of total RYE N, while 53 kg N ha\(^{-1}\) was applied uniformly to FA and
SS plots to maintain yield potential. High-N reference strips received an additional 160 kg N ha\(^{-1}\).

At VT, FA and SS N rates were determined from CIR using an algorithm relating the relative green difference vegetation index (RGDVI) to economic optimum VT N rate (Sripada et al., 2002). The RGDVI was defined as the Green Difference Vegetation Index (GDVI; Tucker, 1979) relative to the high N strips. The GDVI was the difference between GREEN and NIR, which was determined for each pixel in the FA and SS plots.

Once the GDVI was determined at all sites, the FA N rate was determined by (i) averaging GDVI across FA plots, (ii) averaging GDVI of high N-strips, (iii) computing RGDVI, and inserting it to the algorithm to derive the optimum N rate. Because RGDVI averaged in this way reached the plateau of the algorithm, the maximum N rate was determined and uniformly applied to FA plots. Calculating the FA N rate in this way resulted in a higher FA N rate compared to first calculating N rates at the pixel or plot level and then averaging those. We believe that the manner in which we calculated the FA N rate for corn resulted in an erroneously high N recommendation.

The SS N rates were determined at the miniplot level based on the average RGDVI for each miniplot. To account for potential soil effects on the SS rate determination, soil types were attributed to miniplots and high-N reference strips by GIS overlay with a soil type coverage derived from an order one soil survey (North Carolina Agriculture Experiment Station, 1977). The RGDVI in a miniplot was computed as the GDVI relative to the nearest high N-strips within the corresponding soil type. The SS N rates at VT were grouped into four discrete application rates (Table 2).
Yield and Groundwater Sampling

A late freeze aborted wheat flowers in 2001 and prevented complete grain development. Consequently, crop yield, N uptake, and harvest N ratio were determined based on total aboveground biomass. To determine aboveground biomass, wheat forage was harvested after the crop had senesced. A forage harvester with a 1.2-m header and Metler weigh system was used to harvest 18 1.2- by18-m strips within each treatment plot. The center point of each strip was georeferenced using a differential global positioning system (DGPS). After weighing, a forage sample was collected and analyzed for total N; the remaining forage was then redistributed across the harvested strip.

Corn and 2003 wheat grain were harvested using a combine equipped with a yield monitor and DGPS. Yield monitor data were cleaned and edited following the general guidelines suggested by Doerge (1999) and Blackmore and Moore (1999). To determine treatment harvest N ratio and surplus N, multiple georeferenced grab samples of grain were collected at the top of the combine auger and analyzed for total N.

Groundwater samples (about 25 ml each) were collected from March 2001 until July 2003, and the depth to the groundwater table was measured from July 2001, both approximately every two weeks or after significant rainfall. Depth to the water table at each well nest was adjusted to water table elevation based on the well elevations derived from NC Floodplain Mapping Program LIDAR (Light Detection and Air Ranging) data (http://www.ncfloodmaps.com). Groundwater NO\textsubscript{3}-N concentrations were determined using an automated ion analyzer (QuicChem 8000, Lachat, Loveland, CO) employing a Cd reduction method (Greenberg et al., 1992). Daily precipitation data (Fig. 2) were collected at the experiment station using a rain gauge. Thirty-year (1974 - 2003) average monthly
precipitation data were obtained from the State Climate Office of North Carolina (http://www.nc-climate.ncsu.edu/).

**Spatial-Statistical Analysis**

Statistical procedures used to analyze these data have been reported previously in detail by Hong et al. (in review). In brief, due to the large spatial scale of this study, the classical analysis of variance assumptions of independent and identically distributed model errors was violated on many sampling dates, resulting in spatially correlated model errors. To account for spatially correlated errors, up to 13 different covariance models were evaluated to determine which model had the best fit for each individual data set. The criteria and statistical tools used to determine the best-fit model included variography, the Akaike Information Criterion, and a modified likelihood ratio $\chi^2$ test. The best-fit model was used to evaluate treatment effects and to estimate treatment means. Variables including yield, harvest N ratio, surplus N, and groundwater NO3-N for individual dates and depths were examined in this manner using SAS PROC MIXED (SAS Institute, 1999).

The harvest N ratio was calculated as:

$$\text{Harvest N ratio (%) = } \left( \frac{\text{yield} \times \text{N content}}{\text{N applied}} \right) \times 100\%$$ [3]

where yield was forage or grain dry matter yield (kg ha$^{-1}$); N content was the forage or grain N concentration (g kg$^{-1}$) on a dry matter basis; and N applied was the total fertilizer N (kg ha$^{-1}$). We caution that the calculation of the harvest N ratio in Eq. [3] ignored crop uptake of native soil N and consequently is not identical to N-use efficiency (NUE). However, in these sandy soils, harvest N ratio should approximate NUE

Surplus N was defined as the difference between the total N applied and N uptake in forage or in grain yield and was calculated as:
Surplus N (kg ha\(^{-1}\)) = N applied – (yield \times N content) \[4\].

Treatment harvest N ratio and surplus N were estimated at each sample location where we measured N content in the grain or forage.

The treatments and, consequently, the well nests, were not evenly distributed among soil types (Table 3). To account for potential soil effects on the estimation of treatment significance, groundwater NO\(_3\)-N concentrations for individual dates and depths were evaluated with treatment \(\times\) soil type as a fixed effect in the model. In the cases where this effect was significant, we refitted the model using only data from wells located in Go and Ly soils. If the treatment \(\times\) soil type effect was still significant, only data from wells in the Go soil (40 out of 60 total wells) were used (Table 3). Thus, any treatment \(\times\) soil type effects were removed from the data analysis.

**RESULTS**

**Yield and Harvest Nitrogen Ratio**

The comparisons of N applied, grain yield or aboveground biomass, harvest N ratio, and surplus N by treatment and crop are shown in Fig. 3. For 2001 wheat, FA and SS used about 40 kg ha\(^{-1}\) less N fertilizer, had 14% higher harvest N ratios, resulted in about 25 kg ha\(^{-1}\) less surplus N, and about 7% less aboveground biomass than RYE. For 2002 corn, SS applied 32 kg ha\(^{-1}\) more N, had 370 kg ha\(^{-1}\) (about 6%) greater yield, similar harvest N ratio, and 37 kg ha\(^{-1}\) more surplus N than RYE. The FA treatment resulted in substantially greater N applied due to the error in estimation, similar yield, substantially lower harvest N ratio, and considerably higher surplus N than SS and RYE. For 2003 wheat, FA and SS resulted in about 14 kg ha\(^{-1}\) more N applied, but about 670 kg ha\(^{-1}\) higher yield, about 10% higher harvest N ratio, and 9 kg ha\(^{-1}\) less surplus N (only for SS) than RYE.
Groundwater Nitrate-Nitrogen Concentrations

Groundwater samples were not always attainable at the 0.9- to 1.8- and 1.8- to 2.7- m depths (Fig. 4) when the water table was low (Fig. 5). In turn, the water table depth was closely related to precipitation events (Fig. 2a and 2b) and evapotranspiration. High evapotranspiration periods in North Carolina are mainly from May to August (State Climate Office of North Carolina, http://www.nc-climate.ncsu.edu/). Precipitation from January to April 2001 and from September 2001 to September 2002, except January 2002, was below the 30-yr average, making groundwater samples frequently unavailable at the shallower depths during these periods.

In the No soil there were two, one, and three well nests in the RYE, FA, and SS plots, respectively (Table 3). Not only were there fewer well nests in the No soil, but on sampling dates when the water table was low, No well nests were often dry at some or all depths, further reducing the number of NO₃-N samples associated with this soil type. Furthermore, NO₃-N concentrations of the few No samples were often much greater or less than those from the Go and Ly soils. Consequently, to reduce bias in the estimation of treatment effects, the well nests in the No soil were excluded from subsequent analyses. Results from analyzing NO₃-N concentrations from wells in Go and Ly soils showed that the treatment × soil type interaction was significant on 1 of 23 dates at the 0.9- to 1.8-m depth, 3 of 35 dates at the 1.8- to 2.7-m depth, and 4 of 54 dates at the 2.7- to 3.7-m depth. Hence, NO₃-N concentrations from wells in the Go soil were analyzed for those dates. For the other dates, NO₃-N concentrations from wells in Go and Ly soils were analyzed.
Temporal variation

Groundwater NO$_3$-N concentrations exhibited apparent temporal trends independent of treatment. Nitrate-N concentrations frequently exceeded the USEPA maximum drinking water contaminant level of 10 mg L$^{-1}$ NO$_3$-N (Fig. 4); this occurred mainly in spring. At each depth, mean groundwater NO$_3$-N concentrations averaged over treatments for individual dates were positively correlated with the mean water table depth averaged over all well nests for individual dates (Fig. 5). The Pearson correlation coefficients for the 0.9- to 1.8-, 1.8- to 2.7-, and 2.7- to 3.7-m depths were $r = 0.73$ [$P = 0.0002$, $N = 23$], $r = 0.55$ [$P = 0.001$, $N = 35$], and $r = 0.76$ [$P < 0.0001$, $N = 54$], respectively, where $N$ represents the sample size. This correlation may have been caused by several factors. When rainfall was sufficient to raise the water table, it also likely moved NO$_3$-N to shallow groundwater, especially when it occurred soon after N application. During dry periods (e.g., Fall 2002), the water table fell, thus NO$_3$-N loading to the groundwater was not expected; and NO$_3$-N might have been diluted by lateral inflow of surrounding water with lower NO$_3$-N concentrations.

Response to treatment

Groundwater NO$_3$-N concentrations occasionally differed by treatment (Fig. 4). Response of groundwater NO$_3$-N concentration to treatment was interpreted based on treatment N rate and timing, significant excess rainfall occurring soon after differential N applications, and varying water table depth. For ease of discussion, we divided the sampling period into five phases, as follows.

March 2001 to early April 2002: At the 1.8- to 2.7-m depth (Fig. 4b), RYE NO$_3$-N tended to be greater than FA and SS from early July 2001 to early April 2002, significantly so compared to SS in mid-July, mid-August, and mid-September 2001 and from late January
through early April 2002, and compared to FA in early February 2002. This trend in treatment differences also appeared at the 2.7- to 3.7-m depth from late February to early April 2002, and RYE NO₃-N was also significantly greater than SS in early March 2002. This may have been a consequence of the GS-30 N application to wheat in March 2001, when RYE received substantially more N than the other treatments, and produced the lowest harvest N ratio and the highest surplus N (Fig. 3). This is especially noteworthy since the RYE treatment was based on the currently regulated N rate developed specifically to reduce groundwater contamination.

**Early April to late May 2002:** At the 1.8- to 2.7-m depth, RYE NO₃-N was greater than FA from mid to late May. This was probably due to the combination of residual surplus N from 2001 RYE wheat plus N leaching from the corn V2 application on 24 April 2002. At that time, two times more N was applied to RYE than FA and SS (Table 2). This is because the current RYE N-fertilizer approach applies sidedress N at an early vegetative stage to avoid late sidedress, while ignoring the risk of N loss due to weather-related events prior to the period of peak N demand.

**Late May 2002 to mid-March 2003:** At the 2.7- to 3.7-m depth (Fig. 4c), and similar to the previous period at the 1.8- to 2.7-m depth, RYE NO₃-N tended to be greater than FA and SS from late November 2002 to mid-March 2003, significantly so compared to SS in early and mid-January and mid-February in 2003, and compared to FA in mid-February 2003. These treatment effects were probably due to the combination of residual surplus N from 2001 RYE wheat plus N leaching from the corn V2 application on 24 April 2002. This trend in treatment differences did not appear again until late November 2002, probably because from early June until late November 2002, the water table decreased greatly and then
remained below the 2.7-m depth, hence NO₃-N leaching into the groundwater would have been unlikely during that period. When the water table rose in late November 2002, NO₃-N levels increased, probably due to NO₃-N leaching and/or groundwater rising into a zone of elevated soil NO₃, allowing treatment effects to be expressed during this period.

**From Mid-March to mid-June 2003:** At the 0.9- to 1.8-, and 1.8- to 2.7-m depths, FA and SS NO₃-N tended to be greater than RYE. This tendency was significant for FA in early April and from late April to mid-June at the 0.9- to 1.8-m depth, and from late March to early April and in late April, late May, and mid-June at the 1.8- to 2.7-m depth. This effect was also significant for SS in mid-June at the 0.9- to 1.8-m depth, and in mid-March, from late April to late May, in mid-June in 2003 at the 1.8- to 2.7-m depth. Treatment effects during this period were attributed mainly to the excessive N erroneously applied to FA corn in 2002, as well as the lack of N applied to RYE wheat at GS-25 in 2003. An accumulated 23.2 cm of rain fell from 10 February to 8 April 2003 causing the water table to rise dramatically during this period, with a concurrent increase in groundwater NO₃-N and an expression of treatment differences.

**From Mid-June to Mid-July:** No treatment effects were detected in this period.

**DISCUSSION**

**Wheat**

For 2001 wheat, RS-informed FA and SS resulted in less N applied, greater harvest N ratio, less surplus N, and thus less groundwater NO₃-N than RYE at the 1.8- to 2.7-m depth. This indicated that RS-informed N management in 2001 wheat resulted in more efficient N use compared to the current N RYE regulations, and demonstrated the potential of RS-informed N management in reducing groundwater NO₃-N contamination.
For 2003 wheat, FA and SS resulted in similar N fertilizer rates, but higher yield, and higher harvest N ratio compared to RYE. The SS treatment also resulted in less surplus N compared to RYE, with FA being intermediate. These data indicated that even when FA or SS treatments called for higher N rates, they still resulted in reduced N loss to the environment compared to RYE. This was not, however, reflected in the groundwater sampled through July 2003, the last sampling reported in this study. This was likely due to a variety of factors. Depending upon soil moisture conditions, there can be substantial lags between the time when differential N rates are applied and the time any excess N appears in groundwater. Thus, NO$_3$-N in the latter sampling dates of this study may reflect the continued influence of the surplus N from the prior corn crop. Secondly, heavy rainfall occurred immediately after the GS-25 wheat N application, when N was applied only to FA and SS to promote tiller development to increase yield potential. The broadcast N application rates necessary to achieve this (Weisz et al., 2001) almost inevitably exceed actual plant N needs during this period (Baethgen and Alley, 1989). Given that significant excess rainfall occurred right after GS-25 N application, substantial N leaching may have occurred from the FA and SS treatments receiving GS-25 N. Additional research is necessary to investigate, and ameliorate if necessary, the apparent conflict between agronomic and water quality goals in recommending a GS-25 N application to promote tillering.

Our results with both wheat crops are consistent with those previously reported by Flowers et al., (2004) who showed that SS and FA wheat N management (not RS-informed) generally resulted in reduced N inputs compared to typical growers’ practices. The fact that SS performed similarly to FA was probably because crop growth heterogeneity was minimal.
within FA and SS plots. Thus no additional advantage may have been associated with SS N fertilizer management.

**Corn**

For corn, FA and SS resulted in much greater or greater N applied, much lower or similar harvest N ratio, and much greater or greater surplus N than RYE, respectively. Thus, greater groundwater NO$_3$-N with SS and FA compared to RYE was expected, and was observed nine months after N application at VT. This suggests that the methods used to determine SS and FA N rates overestimated N demand, especially for FA. This may be explained by several factors. As stated previously, we overestimated the FA VT N rate due to the manner in which we calculated a field-average N rate from our recommendation algorithm. In addition, potential soil effects were not considered when computing the RGDVI of FA plots as they were in calculating SS rates. Finally, the N rate algorithm used by SS and FA at VT assumed that soil moisture would be sufficient through maturity. However, the 2002 corn experienced a very dry growing season (Fig. 2a and 2b), and corn yields were about 2 Mg ha$^{-1}$ lower than the realistic yield expectations for these coastal plain soils (North Carolina Nutrient Management Workgroup. 2003). Consequently, SS and especially FA resulted in considerable excess N.

**Groundwater Nitrate-Nitrogen Concentrations**

It is noteworthy that differences in groundwater NO$_3$-N concentrations associated with even small increases in N application were detected in these experiments. In 2001, the difference between the RYE and SS N application rates was only 39 kg ha$^{-1}$ and yet these treatments resulted in significantly different NO$_3$-N concentrations (about 2 mg N L$^{-1}$) that were still detectable almost one year after application. Similarly, in the 2002 corn crop, the
total SS N application was only 32 kg ha\(^{-1}\) higher than the total RYE rate, but it also resulted in significantly higher groundwater NO\(_3\)-N concentrations that persisted through the following wheat season. Clearly, groundwater NO\(_3\)-N concentrations in these coastal plain soils are very sensitive to even small modifications in agronomic practices.

Groundwater NO\(_3\)-N concentrations were strongly associated with water table elevation (WTE), indicating that WTE could be a good covariate for temporal analyses of NO\(_3\)-N behavior. Further research will be valuable to better understand the interaction of groundwater NO\(_3\)-N with shallow water tables, which might provide guidance in soil management to improve groundwater quality.

**SUMMARY**

We evaluated environmental benefits of two in-season, RS-informed N management options: uniform FA and site-specific SS compared to current, uniform, RYE-based N recommendations in a common Coastal Plain cropping system. In contrast to RYE, SS achieved (i) a maximum of 2.3 mg L\(^{-1}\) less groundwater NO\(_3\)-N in the 2001-wheat crop due to about 40 kg ha\(^{-1}\) reduced fertilizer N inputs and a 14% increase in harvest N ratio, (ii) 370 kg ha\(^{-1}\) greater 2002-corn grain yield associated with 32 kg ha\(^{-1}\) greater N applied and similar harvest N ratio, and (iii) 670 kg ha\(^{-1}\) greater 2003-wheat grain yield associated with 14 kg ha\(^{-1}\) greater fertilizer N and 10% greater harvest N ratio.

Effects of N management on groundwater NO\(_3\)-N concentrations were complex and difficult to interpret mainly due to the long-term carryover of treatment effects from one crop into subsequent growing seasons, and differences in rainfall from season to season. The largest variations in groundwater NO\(_3\)^- concentrations were associated with rainfall and water table fluctuations rather than with fertilizer management. Nevertheless, on specific dates,
significant N management treatment effects occurred that appeared to be the result of N fertilizer applications made several weeks or even months prior to the sampling date. In some cases, yield and harvest N ratio advantages observed with RS-informed management were associated with reduced groundwater NO$_3^-$ concentration. This was especially true following the 2001 wheat crop, and following the early sidedress application of N to corn in 2002. Conversely, where higher N fertilizer rates were applied (e.g. corn 2002 FA treatment), statistically significant increases in groundwater NO$_3^-$ concentrations were observed in the subsequent months. Clearly, even small changes in N management can impact groundwater NO$_3^-$ concentrations in these sandy coastal plain soils.

Our data suggest that to assess the environmental efficacy of N management, frequent and periodic monitoring of groundwater NO$_3$-N, especially after significant rainfall, and for weeks or even months after application, is essential to capture in-season treatment effects. Simultaneous measurement of precipitation and water table depth facilitate understanding of these effects. The traditional sampling of NO$_3$-N only at or after harvest is likely to be insufficient to capture the entirety of treatment effects. This is especially true in coastal plain and other coarse-textured soils where in-season NO$_3$-N leaching may be pronounced.
Table 1. A typical stratigraphic description of the study fields (adapted from North Carolina Agricultural Experiment Station, 1977).

<table>
<thead>
<tr>
<th>Depth (m)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 – 1.1</td>
<td>Dominantly brownish yellow (10 YR 6/6) sandy clay loam with few soft red mottles in lower part; grades to</td>
</tr>
<tr>
<td>1.1 – 2.6</td>
<td>Red (2.5 YR 5/8) firm sandy clay loam to sandy clay with few yellow and white streaks; gradual to</td>
</tr>
<tr>
<td>2.6 – 2.9</td>
<td>Yellow (10 YR 7/8) tough, form clay; clear to</td>
</tr>
<tr>
<td>2.9 – 3.7</td>
<td>Yellow (10YR 8/6) medium coarse sand gradual to Yellowish red (5 YR 5/8)</td>
</tr>
</tbody>
</table>
Table 2. Mean N rates and timing for the three N treatments in the two-year winter wheat-double crop soybean (year 1) – corn (year 2) rotation.

<table>
<thead>
<tr>
<th>Time of Application</th>
<th>N management treatments$^\dagger$</th>
<th>RYE</th>
<th>FA</th>
<th>SS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat (2 Nov 2000 to 25 May 2001)†</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Starter (22 Oct 2000)</td>
<td>34</td>
<td>34</td>
<td></td>
<td>34</td>
</tr>
<tr>
<td>GS§-25 (14 Feb 2001)</td>
<td>0</td>
<td>0</td>
<td>9</td>
<td>(0 or 67)</td>
</tr>
<tr>
<td>GS-30 (12 Mar 2001)</td>
<td>119</td>
<td>72</td>
<td>74</td>
<td>(0, 34, 58, 79, 101, 123, 135)</td>
</tr>
<tr>
<td>Total</td>
<td>153</td>
<td>106</td>
<td>114</td>
<td>(34 to 202)</td>
</tr>
<tr>
<td>Corn (3 Apr 2002 to 22 Aug 2002)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Starter (5 Apr 2002)</td>
<td>8</td>
<td>8</td>
<td></td>
<td>8</td>
</tr>
<tr>
<td>V2§ (24 Apr 2002)</td>
<td>104</td>
<td>53</td>
<td></td>
<td>53</td>
</tr>
<tr>
<td>VT (17 June 2002)</td>
<td>0</td>
<td>157</td>
<td>83</td>
<td>(0, 53, 104, 157)</td>
</tr>
<tr>
<td>Total</td>
<td>112</td>
<td>218</td>
<td>144</td>
<td>(61 to 218)</td>
</tr>
<tr>
<td>Wheat (4 Nov 2002 to 25 May 2003)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Starter (4 Nov 2002)</td>
<td>34</td>
<td>34</td>
<td></td>
<td>34</td>
</tr>
<tr>
<td>GS-25 (25 Feb 2003)</td>
<td>0</td>
<td>67</td>
<td></td>
<td>67</td>
</tr>
<tr>
<td>GS-30 (1 Apr 2003)</td>
<td>119</td>
<td>67</td>
<td>65</td>
<td>(45, 59, 67)</td>
</tr>
<tr>
<td>Total</td>
<td>153</td>
<td>168</td>
<td>166</td>
<td>(146 to 168)</td>
</tr>
</tbody>
</table>

$^\dagger$ Planting to harvest.

$^\ddagger$ RYE = uniform Realistic Yield Expectation N management; FA = remote sensing-informed uniform field-average N management; SS = remote sensing-informed site-specific N management.

$§$ GS denotes Zadok’s Growth Stage (Zadoks et. al. 1974); V2 denotes two-leaf growth stage, and VT tasselling growth stage (Ritchie et. al. 1993).

$¶$ The weighted average of the variable N rates.
Table 3. Number of well nests in each treatment by soil type combination.

<table>
<thead>
<tr>
<th>Soil types†</th>
<th>Go</th>
<th>Ly</th>
<th>No</th>
<th>Subtotal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment‡</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RYE</td>
<td>12</td>
<td>6</td>
<td>2</td>
<td>20</td>
</tr>
<tr>
<td>FA</td>
<td>18</td>
<td>1</td>
<td>1</td>
<td>20</td>
</tr>
<tr>
<td>SS</td>
<td>10</td>
<td>7</td>
<td>3</td>
<td>20</td>
</tr>
<tr>
<td>Subtotal</td>
<td>40</td>
<td>14</td>
<td>6</td>
<td>60</td>
</tr>
</tbody>
</table>

† Go = Goldsboro loamy sand; Ly = Lynchburg sandy loam; No = Norfolk loamy sand.
‡ RYE = uniform Realistic Yield Expectation N management; FA = remote sensing-informed uniform field-average N management; SS = remote sensing-informed site-specific N management.
Figure 1. Field layout of the randomized complete block design at the Lower Coastal Plain Tobacco Research Station, Kinston, NC. The same shading pattern indicates a block with three plots. The treatment number is in the upper left corner of each plot. RYE = uniform Realistic Yield Expectation N management; FA = remote sensing-informed, uniform field-average N management; SS = remote sensing-informed site-specific N management.
Figure 2. (a) Daily precipitation from June 2001 to August 2003 and (b) actual- (January 2001 to July 2003; bars) and 30-yr-average (1974 – 2003; line) monthly precipitation at the study site.
Figure 3. Comparisons of N applied, yield (or aboveground biomass in the case of wheat in 2001), harvest N ration and surplus N for three N management treatments in a wheat-soybean-corn rotation from 2001 to 2003. Mean values are shown above the columns. Bars indicate +1 standard error. Different letters above the bar indicates significant differences among estimated treatment means at the 0.05 significance level. RYE = uniform Realistic Yield Expectation N management; FA = remote sensing-informed uniform field-average N management; SS = remote sensing-informed site-specific N management.
Figure 4. Nitrogen management treatment effects on groundwater NO$_3$-N concentrations sampled biweekly from March 2001 to July 2003 at (a) 0.9- to 1.8-m, (b) 1.8- to 2.7-m and (c) 2.7- to 3.7-m depths. Bars indicate +1 standard error. Different letters above bars indicate significant differences among the estimated treatment means at the 0.05 significance level. In some cases, the significance of a comparison is reported by the P-value. The reference line is at 10 mg L$^{-1}$. 
Figure 5. Field-average shallow water table depth measured from July 2001 to July 2003.

Bars indicate +1 standard error.
CHAPTER 4: FIELD-SCALE SPATIAL AND TEMPORAL DYNAMICS OF
SHALLOW GROUNDWATER NITRATE IN COASTAL PLAIN SOILS

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For Submission to: Soil Science Society of American Journal
ABSTRACT

Understanding spatial and temporal dynamics of shallow groundwater NO$_3$-N is essential when using it as an indicator of environmental impact. The interaction of groundwater NO$_3$-N with water tables provides challenges for soil management. In a study to compare the effectiveness of N management treatments on reducing groundwater NO$_3$-N, we sought to quantify NO$_3$-N spatial correlation over time and its temporal association with water tables and explain the spatial correlation. The experiment began with the establishment of a two-year winter wheat (*Triticum aestivum* L.)-double-crop soybean [Glycine max (L.) Merr.]-corn (*Zea mays* L.) rotation in a 12-ha North Carolina (NC) Coastal Plain field. A randomized complete block design was used with one variable and two uniform N-rate treatments. Water table elevation (WTE) and NO$_3$-N were measured every two weeks at 60 well nests sampling three equal depth increments from 0.9 to 3.7 m. We used spatial statistics incorporating spatial covariance modeling to quantify and explain NO$_3$-N spatial correlation. Elevations derived from NC floodplain mapping LIDAR data, soil organic matter (SOM) determined from grid sampling, and WTE were spatial covariates. Mean NO$_3$-N concentrations showed clear temporal fluctuations and were positively correlated with water table depth. Groundwater NO$_3$-N was frequently spatially correlated and spatial covariance structures changed periodically. The ranges of spatial correlation varied over time from 46 to 551 m, and appeared related to fluctuations of the water table. Blocking alone or together with elevations, SOM, and WTE frequently explained NO$_3$-N spatial correlation.
INTRODUCTION

Nitrate-N (NO₃-N) groundwater contamination in the southeastern Coastal Plain has become a regulatory and social issue threatening regional crop production. Nitrate-N concentration is an indicator of groundwater quality and is often used in precision agriculture research to assess effectiveness of N management strategies on reducing groundwater NO₃-N contamination (e.g., Casey et al., 2002; Hong et al., 2003). Nitrate-N is often sampled spatially and georeferenced at harvest or continuously throughout the season. Understanding NO₃-N spatial and temporal dynamics facilitates development of best management practices to reduce groundwater NO₃-N contamination and defining the appropriate methods of analysis when using it to evaluate management effects.

Spatial correlation refers to the tendency of observations closer together to be more similar than ones farther apart. In agricultural fields, soil physical properties (e.g., Davidoff and Selim, 1988), moisture relations (e.g., Achouri and Gifford, 1984), and soil nutrient availability (e.g., Webster and Nortcliff, 1984) are rarely spatially and temporally homogeneous. Thus, it is always possible that observations such as soil and groundwater NO₃-N are spatially correlated and have heterogeneous variances. It has been reported that soil NO₃-N in a crop field was spatially correlated at 0.3- to 1.2-m depth with spatial ranges varying from 40 to 275 m (Hergert et al., 1995). Recent research demonstrated that NO₃-N exhibited clear spatial patterns in soil and groundwater (Cain et al., 1999; Laverman et al., 2000; Kemp and Dodds, 2001; Eghball et al., 2003), and spatial correlation of soil NO₃-N varied over time in an irrigated salad crop field (Bruckler et al., 1997). To date, NO₃-N spatial correlation and temporal changes and patterns in shallow groundwater have not been well characterized.
In a four-year study to compare the effectiveness of N management treatments in reducing shallow groundwater NO$_3$-N concentrations conducted in a randomized complete block (RCB) design in a North Carolina Coastal Plain field, we sought to understand groundwater NO$_3$-N spatial and temporal dynamics. We investigated the temporal pattern of groundwater NO$_3$-N and its temporal association with water tables. We quantified groundwater NO$_3$-N spatial correlation over time and explained spatial correlation using blocking, spatial covariates, and correlated errors.

**MATERIALS AND METHODS**

**Experimental Setup**

The experiment began in November 2000 with the establishment of a 2-yr winter wheat-double crop soybean–corn rotation in two adjacent fields totaling 12 ha at the Lower Coastal Plain Tobacco Research Station, Kinston, NC. For the statistical analysis, we considered these to be one field. An order one soil survey of the experimental station delineated three soil map units in the fields: Norfolk (No) loamy sand with 0-2% slope (fine-loamy, siliceous, thermic, Typic Paleudults), Goldsboro (Go) loamy sand (fine-loamy, siliceous, thermic, Aquic Paleudults), and Lynchburg (Ly) sandy loam (fine-loamy, siliceous, thermic, Aeric Paleaquults) (Fig. 1). The experiment was established in an RCB design with three N management treatments for wheat and corn replicated ten times in square 0.35 ha plots. The three treatments tested were uniform Realistic Yield Expectation (RYE) N management, uniform field-average (FA) N management, and site-specific N management (SS), the latter two based on aerial color-infrared remote sensing of crop N status. The treatment N rates and dates of fertilization of wheat and corn are listed in Table 1, and additional descriptive information for each treatment is presented in Hong et al. (2004).
Groundwater Sampling

In early 2001, two well nests were installed in each plot. One nest was placed at the plot center to minimize influence of neighboring plots. The other was placed randomly within constraints of being an adequate distance from the plot center, outside a plot boundary buffer area, and aligned from plot to plot to facilitate field operations. Each well nest consisted of three PVC pipe groundwater-sampling wells screened to sample 0.9- to 1.8-, 1.8- to 2.7-, and 2.7- to 3.7-m depths. We sampled to 3.7-m depth to ensure that water samples were available throughout the season. Groundwater samples (~25 ml) were collected approximately every two weeks or after significant rainfall from March 2001 and will continue to be collected until September 2005. Depth to water table was measured from July 2001 and was adjusted to water table elevation based on well head elevations derived from a state LIDAR (Light Detection and Air Ranging)-derived database (http://www.ncfloodmaps.com). Groundwater NO$_3$-N concentrations were determined using an automated ion analyzer (QuicChem 8000, Lachat, Loveland, CO) employing a Cd reduction method (Greenberg et al. 1992). Daily precipitation data (Fig. 2) were collected at the experiment station rain gauge. Soil organic matter content determined by loss on ignition (360 °C) at well nests was derived by kriging data from grid soil sampling conducted in November 2000 before wheat planting (Li et al., 2002).

During the reporting period from early July 2001 to mid-July 2003, groundwater sample availability increased with sampling depth. Samples were frequently unavailable at the 0.9- to 1.8- and 1.8- to 2.7-m depths, corresponding primarily to periods of low rainfall and high evapotranspiration, which were mainly from May to August (State Climate Office of North Carolina). Thus, there were one, two, or three samples at a well nest at individual
dates. For this analysis, we averaged groundwater NO$_3$-N concentrations in these samples for each well nest for individual dates. Thus the resultant mean represents NO$_3$-N concentrations at each well nest and were used for further statistical analyses.

**Spatial-Statistical Analysis**

**Quantifying spatial correlation**

We used spatial-statistical analysis based on Zimmerman and Harville’s random field approach (Zimmerman and Harville, 1991) to quantify groundwater NO$_3$-N spatial correlation on individual sampling dates. The foundation of this analysis takes the form:

$$ y = \mu + \varepsilon \quad [1] $$

where $y$ is an $n \times 1$ vector of responses, $\mu$ is an overall mean, $\varepsilon$ is an $n \times 1$ vector of random errors, where $n$ is the number of responses. Any correlation of observations if present can be accounted for by the errors ($\varepsilon$).

We first fit groundwater NO$_3$-N concentrations on each sampling date to six isotropic spatial covariance functions: the spherical, Gaussian, and exponential with or without a nugget effect. We chose these because of their applicability in describing spatial covariance commonly encountered in agriculture, and because of the form of our exploratory semivariograms. We selected a best-fit spatial model based on the procedure described by Hong et al. (in review). The significance of the spatial correlation estimated by the best-fit spatial model was determined by testing if the spatial range of this model was significantly greater than zero.

**Explaining spatial correlation**

When groundwater NO$_3$-N spatial correlation was evident, we used a linear mixed model to identify significant spatial covariates. Spatial covariates examined included
elevations, SOM and water table elevations. Together with treatment, soil map unit and its 2-way interactions with each spatial covariate and treatment were considered as fixed effects. Block and block×treatment were considered as random effects. The statistical procedure used to analyze these data was analogous to that described above (Hong et al. (In Review).

RESULTS AND DISCUSSION

Temporal Dynamics of Groundwater Nitrate-N

Mean groundwater NO₃-N concentrations varied from 6 to 15 mg L⁻¹ and exhibited apparent temporal fluctuations. Groundwater NO₃-N seasonally exceeded the USEPA maximum drinking water contaminant level of 10 mg L⁻¹ NO₃-N (Fig. 3b), with this occurring mainly in spring. The mean NO₃-N concentrations were positively correlated with the mean water table elevations averaged over all well nests at individual dates (Fig. 3a; Pearson correlation coefficient r = 0.84; P < 0.001; N = 54). Water table depth varied from 0.4 to 3.1 m below the soil surface and were related to precipitation events (Fig. 2) and periods of high evapotranspiration, which are mainly from May to August in North Carolina (State Climate Office of North Carolina, http://www.nc-climate.ncsu.edu/). During the dry fall 2001 and very dry summer and fall 2002 periods when water tables dropped below 2 m, NO₃-N tended to decrease to less than 10 mg L⁻¹. When water tables were below 3 m in fall 2002, NO₃-N reached its lowest level during the study period. This may have been because there was no apparent NO₃ leaching during this period. Other factors potentially contributing to this outcome might be dilution by groundwater of lower NO₃ concentration arriving via lateral flow or N loss via denitrification, although the latter is not expected to be of importance 3 m below the soil surface (Gambrell et al., 1975). During summer 2001, spring 2002, and spring and summer 2003, when the water table was less than 2 m deep, NO₃-N
concentrations exceeded 10 mg L$^{-1}$. When the water table was less than 1 m deep in spring and summer 2003, NO$_3$-N reached its highest levels. This probably resulted due to leaching of the residual N from the 2002 corn crop and N applied to the 2003 wheat at GS-25 (Table 1) simultaneously with groundwater recharge.

The temporal association between NO$_3$-N and water table depth suggests that water table depth could be a covariate for temporal analyses of NO$_3$-N behavior. Further research will be valuable to better understand the interaction of groundwater NO$_3$-N with water tables, which might provide guidance in soil management to reduce groundwater NO$_3$-N contamination.

**Spatial Dynamics of Groundwater Nitrate-N**

**Visualization of spatial correlation**

Examples of spatial correlation of groundwater NO$_3$-N concentrations sampled from February 22 to April 9 2002 are illustrated by plots of the semivariograms $\gamma(h)$ of observations (Fig. 4). The semivariance of groundwater NO$_3$-N concentrations sampled on February 22 and March 7 and 19 increased with increasing lag distances and then leveled off at larger distances, indicating that observations were spatially correlated. In contrast, the semivariance of NO$_3$-N sampled on April 9 was essentially flat (pure nugget effect), suggesting no spatial correlation. Moreover, the strength of spatial correlation at small distances tended to decrease over this sampling period.

**Spatial covariance structure**

Over the 54 sampling dates examined, spatial models were selected predominantly (38 dates) over non-spatial (NS) models (Fig. 3c). Thus, groundwater NO$_3$-N tended to be spatially correlated throughout the season, although spatial correlation sometimes
disappeared, i.e., observations became independent. With one exception, when spatial
correlation was present, the no nugget exponential and nugget Gaussian models were
selected depending on the absence or presence of a nugget effect; a spherical nugget model
was selected in early July 2001. Spatial covariance structure (SCS) changed periodically
following an apparent pattern (Fig. 3c). Often, SCS shifted between one without a nugget to
one with a nugget (e.g., from mid-July 2001 to mid-March 2002). This suggests that spatial
and sampling variability at distances shorter than that separating adjacent well nests
temporally changed from negligible when a nugget was absent to considerable when a nugget
was present. Sometimes, the shift of SCS followed a trend of SCS with no nugget to NS and
then back to SCS with no nugget again (e.g., from Mid-January to mid-July in 2003).

**Spatial range**

When spatial correlation was evident, spatial correlation ranges of groundwater NO₃-
N varied dramatically over time from 46 to 551 m (Fig. 3c). Even within a common spatial
covariance structure, spatial ranges changed substantially over time (e.g., from late July 2001
to late January 2002). Thus, groundwater NO₃-N exhibited short, medium- and long-range
variability corresponding to dimensions within soil map units, among soil map units, and
across the entire field.

Overall, the fluctuation of groundwater NO₃-N spatial ranges appeared to follow the
trend of the mean water table depth (Fig. 3a and Fig. 5), although no statistically significant
linear relationships were detected. For ease of discussion, we divided the sampling period
into five phases (Fig. 3). In general, when water tables were rising or falling (e.g., in Phases
I, IV, and V), NO₃-N was spatially correlated and spatial ranges differed by date. This may
be attributed to the presence of spatial correlation (in the X-Y dimension) of vertical water
movement in the vadose zone during these fluctuating periods. When water table depth stabilized over a period of time, whether high or low, NO₃-N spatial correlation range decreased and in some cases, NO₃-N became independent (no spatial correlation). For example, in Phase II and Phase III, when water tables first increased or decreased, respectively, and then became stable, NO₃-N shifted from correlated to uncorrelated. This may be because in the absence of substantial vertical water movement, profile characteristics fostering spatial correlation were no longer expressed.

**Nature of spatial correlation**

As stated earlier, groundwater NO₃-N was spatially correlated on 38 of 54 sampling dates during a two-year period. When present, spatial correlation was accounted for by blocking alone (10 dates) or together with spatial covariates (18 dates) (Fig. 6). On the remaining 10 dates, blocking and spatial covariates did not capture the spatial correlation.

The nature of correlation between groundwater NO₃-N and spatial covariates also varied over time, either positive or negative. Compared to SOM and WTE, elevations often were more significant (13 out of 54 dates) and tended to be negatively associated with NO₃-N concentrations, indicating that the elevated NO₃-N occurred at low elevations. This may be because the sites at lower elevations were likely to be zones of water accumulation during significant rainfall events resulting in higher leaching potential.

Groundwater NO₃-N was spatially correlated with SOM on four out of 54 dates, and the nature of this correlation varied over time. During mid-March 2002 when soil conditions began to promote N mineralization, soil NO₃-N available to be leached might be expected to be greater where SOM was greater. During this period, several rainfall events occurred (Fig.2), providing the opportunity for mineralized N to leach and increase groundwater NO₃-
N. It is unclear why the same correlation exhibited in early July 2001 and mid-June 2002 when NO$_3$-N leaching was not likely as suggested by the decreasing water tables. During late June 2002, however, higher NO$_3$-N concentrations existed where SOM was lower. This may have been due in part to no apparent NO$_3$-N leaching after early June 2002, as indicated by the lower water table depth (Fig. 3a). Thus where SOM was higher, soil water holding capacity may have been higher, thus more N was kept in root zone resulting in less NO$_3$-N leaching.

Groundwater NO$_3$-N was spatially correlated with water table elevation (WTE) on 9 out of 54 dates. On three dates in 2001, WTE was negatively correlated with NO$_3$-N. This was possibly because during early July and mid-August, water tables were high (less than 1.5 m; Fig. 3a), which may have favored denitrification. It is unclear why there was also a negative WTE-NO$_3$ correlation in mid-December 2001, when water tables dropped below 2.5 m where denitrification would likely be minimal. On four dates during early December 2002 and January 2003 when water tables were deeper than 2 m, NO$_3$-N was positively correlated with WTE.

Soil map unit and its interaction with spatial covariates were sometime significant, as were the N treatments and their interaction with soil (Fig. 6). Treatment effects were significant on 5 out of 54 dates, but treatment mean differences were relatively small (not shown) compared to the temporal variation of groundwater NO$_3$-N concentrations.

Spatial correlation of groundwater NO$_3$-N was hypothetically attributed to spatial heterogeneity over depth, the expression of which was driven predominately by rainfall. But, the degree of this expression depended upon the soil water conditions.
The spatial and temporal dynamics of groundwater NO₃-N in this study suggest that the often-used “snapshot” measurement of groundwater NO₃-N at or just after harvest cannot represent NO₃ behavior throughout the season. Such measurements are also likely to be inadequate to assess the effectiveness of N management strategies, especially in Coastal Plain and other coarse-textured soils where in-season NO₃-N leaching may be pronounced. Our data suggest that frequent, periodic monitoring of groundwater NO₃-N concentrations, especially after significant rainfall, together with precipitation and water table depth measurements, facilitate better understanding of NO₃-N behavior and its use as an indicator of groundwater quality. The temporal variability in NO₃-N spatial correlation suggests that the determination of N treatment effects on NO₃-N concentrations should be done on individual dates. For spatiotemporal modeling of NO₃-N, it is necessary to divide the study period into different phases during which NO₃-N has a common spatial structure with similar spatial ranges.

**CONCLUSIONS**

Mean groundwater NO₃-N concentrations at 0.9- to 3.7-m depth during a two-year period in a North Carolina Coastal Plain field exhibited measurable temporal fluctuations and were positively correlated with water table elevation, indicating that increased NO₃-N concentrations were associated with groundwater recharge. Groundwater NO₃-N was frequently spatially correlated with spatial correlation ranges from 46 to 551 m corresponding to distances within soil map units, among soil map units, or across the whole field (~12 ha). The fluctuation of NO₃-N spatial correlation range appeared to coincide with that of the water table. The spatial covariance structure of NO₃-N changed periodically following a certain pattern: shift between no-nugget exponential to nugget Gaussian...
structures or no-nugget exponential and non-spatial structures. When present, the spatial
correlation of NO$_3$-N was accounted for on more than three quarter of the sampling dates by
blocking alone or together with the spatial covariates elevation, SOM, and WTE. The
correlations between NO$_3$-N and these covariates were not consistently positive or negative
over time.
Table 1. Mean N rates and timing for the three N treatments in a two-year winter wheat-double crop soybean (year 1) – corn (year 2) rotation in a coastal plain field.

<table>
<thead>
<tr>
<th>Time of Application</th>
<th>N management treatments‡</th>
<th>Kg N ha⁻¹</th>
<th>‡ RYE</th>
<th>FA</th>
<th>SS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wheat (2 Nov 2000 to 25 May 2001) †</td>
<td>†</td>
<td>34</td>
<td>34</td>
<td>34</td>
<td></td>
</tr>
<tr>
<td>Starter (22 Oct 2000)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GS§-25 (14 Feb 2001)</td>
<td>0</td>
<td>0</td>
<td>9 § (0 or 67)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GS-30 (12 Mar 2001)</td>
<td>119</td>
<td>72</td>
<td>74 § (0, 34, 58, 79, 101, 123, 135)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>153</td>
<td>106</td>
<td>114 § (34 to 202)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corn (3 Apr 2002 to 22 Aug 2002)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Starter (5 Apr 2002)</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>V₃§ (24 Apr 2002)</td>
<td>104</td>
<td>53</td>
<td>53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>V₅ (17 June 2002)</td>
<td>0</td>
<td>157</td>
<td>83 § (0, 53, 104, 157)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>112</td>
<td>218</td>
<td>144 § (61 to 218)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wheat (4 Nov 2002 to 25 May 2003)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Starter (4 Nov 2002)</td>
<td>34</td>
<td>34</td>
<td>34</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GS-25 (25 Feb 2003)</td>
<td>0</td>
<td>67</td>
<td>67</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GS-30 (1 Apr 2003)</td>
<td>119</td>
<td>67</td>
<td>65 § (45, 59, 67)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>153</td>
<td>168</td>
<td>166 § (146 to 168)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

† Planting to harvest.

‡ RYE = uniform Realistic Yield Expectation N management; FA = remote sensing-informed, uniform field-average N management; SS = remote sensing-informed, site-specific N management.
§ GS denotes Zadok’s Growth Stage (Zadoks et. al. 1974); V2 denotes two-leaf growth stage, and VT tasselling growth stage (Ritchie et. al. 1993).

¶ The weighted average of the variable N rates.
Figure 1. Field layout of the randomized complete block design at the Lower Coastal Plain Tobacco Research Station, Kinston, NC. The shading pattern indicates plots within the same block. The treatment number is in the upper left corner of each plot. Dots represent well nests. RYE, FA and SSNM are the N treatments.
Figure 2. Daily precipitation at the study site from June 2001 to August 2003.
Figure 3. (a) Field average water table depth; (b) the mean groundwater NO\textsubscript{3}-N concentrations sampled at 0.9- to 3.7-m depths from July 2001 to July 2003; (c) the spatial correlation range of NO\textsubscript{3}-N concentrations. Bars indicate ±1 standard error; NuSph = nugget spherical model; NonuExp = no nugget exponential model; NuGau = nugget Gaussian model; NS = non-spatial model.
Figure 4. Examples of spatial correlation of groundwater NO$_3$-N concentrations sampled at 0.9- to 3.7-m depths from February 22 to April 9 in 2002 illustrated by the isotropic semivariograms $\hat{\gamma}(h)$ of the observations.
Figure 5. Scatterplot of water table elevations vs. spatial correlation range of groundwater NO$_3$-N concentrations sampled at 0.9- to 3.7-m depths from July 2001 to July 2003.
Figure 6. Spatial covariates and factor effects explaining spatial correlation of groundwater NO$_3$-N concentrations sampled at 0.9- to 3.7-m depths from July 2001 to July 2003. Dates with arrows indicate that blocking and spatial covariates were insufficient to account for spatial correlation. On dates without significant spatial covariates, spatial correlation was explained by blocking alone. The symbols §, *, **, *** denote significance at the $P = 0.1, 0.05, 0.01$, and 0.001 probability levels,
respectively. The signs “-” and “+” indicate that the correlation between groundwater NO$_3$-N and spatial covariates was negative or positive, respectively. Elev = Elevations; SOM = soil organic matter; WTE = water table elevations; Soil = soil map unit; Soil by TRT = the interactions of soil map unit and treatment.
REFERENCES


Remote sensing for precision N management in a corn-wheat-soybean rotation. Proc. 7th International Conference on Precision Agriculture and Other Precision Resources Management (CD format). ASA Misc. Publ., ASA, CSSA, and SSSA, Madison, WI.


Int. Conf. on Precision Agric., 6th, Bloomington, MN, 14-17 July 2002. ASA-CSSA-SSSA, Madison, WI.


