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ANALYSIS OF EFFECTS OF SOIL PROPERTIES,
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PRACTICES ON SPATIAL-TEMPORAL VARIABILITY OF
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ANALYSIS OF EFFECTS OF SOIL PROPERTIES, TOPOGRAPHICAL VARIABLES AND MANAGEMENT PRACTICES ON SPATIAL-TEMPORAL VARIABILITY OF CROP YIELDS

By

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ABSTRACT

ANALYSIS OF EFFECTS OF SOIL PROPERTIES, TOPOGRAPHICAL VARIABLES AND MANAGEMENT PRACTICES ON SPATIAL-TEMPORAL VARIABILITY OF CROP YIELDS

By

Xuewen Huang

Crop yields are highly variable across fields and years as a result of the complex interactions among topography, weather conditions, and management practices. Understanding the relationship between yield and these factors is a critical component of site-specific management systems.

The first study was to demonstrate the feasibility of mapping soil carbon using newly developed on-the-go near infrared spectroscopy (NIRS) measurements and Landsat Enhanced Thematic Mapper (ETM) image reflectance in a 50-ha field. Regression coefficients between measured and predicted carbon values were equal to 0.70 and 0.46 using NIRS data and ETM imagery, respectively. When topographical attributes, such as elevation, wetness index (WI), and slope were included into the regression model along with NIRS and ETM data, the regression coefficients improved to 0.81 and 0.62. The results indicated that combination of the NIRS and ETM measurements with topography is a valuable tool for accurate total carbon mapping in glacial till soils.

The second study was to identify spatial clusters from historical yield data, and relate the clusters to the underlying soil electrical conductivity (EC), and topographical attributes, and to validate whether cluster groups can be used to accurately predict yield

patterns. Both EC and topographical attributes were found to be helpful in explaining yield variability. Consistently low and high yield clusters were identified. Four to five yield clusters can explain about 40 % of the yield variation. Areas with lower EC and slope tended to form high yield clusters in the studied fields. The information from historical yield classification could be helpful in delineating management zones within a field.

The third study was to analyze the effects of management practices on the relationship between crop yield and topography, yield and precipitation with 10-yr corn-soybean-wheat rotation in Long Term Ecological Research site, located at Kellogg Biological Station. A nonparametric spline regression was used to characterize boundary yields, that are maximum yields, versus WI. The algorithm was also used to compare the yield difference across the range of the WI between two treatments. Management practices significantly interact with WI and influence crop yields. The interaction can also be affected by summer precipitation. The yield difference between no-till and conventional tillage was strongly influenced by WI in dry or normal year but not in wet year. The relationship between boundary yield and WI in most of the crops for most of the studied years had a convex shape. No-till and low input systems tended to produce higher maximum and average yields than conventional system at the lower WI areas. The results suggested that it is possible to maximize yield and profit by farming site-specifically based on landscape position.

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CHAPTER I

INTRODUCTION

Crop yields are highly variable across fields as a result of the complex interactions between many factors, including topographical attributes, soil properties, precipitation, and management practices. Understanding the relationship between yield and these factors is a critical component of site-specific management systems. With the adoption of electrical sensors and global positioning system (GPS) in crop production in the last decade, tremendous data, such as yield map, densely-measured electrical conductivity (EC) and elevation were collected. How to efficiently extract the valuable information from those data is a challenge. In addition, characterizing spatial variation of field conditions and exploring the relationship between yields and the underlying factors will provide essential information for decision-making in precision farming.

Field topography has a major impact on water and also on nutrient availability for crop production. It is the major source of not only soil but also yield variability. However, yield/topography relationships vary substantially from year to year. These variations are often associated with the prevailing weather conditions during the growing season of each particular year. Weather conditions may substantially influence the apparent gains or losses due to management and other factors on a regional as well as field scale. Management practices, including tillage and chemical inputs, can interact with topographical attributes to influence yield variability.

With long-term data collection of crop yield and other variables and advances in topographical modeling and statistical methods in the recent years, exploring the relationship between yield and topographical attributes under various management practices and weather conditions will significantly improve our understanding of crop production. The overall goal of my research was to analyze the effects of soil properties, topographical variables and management practices on spatial-temporal variability of crop yields.

The first objective was to determine the feasibility of mapping soil organic carbon using newly developed on-the-go near infrared spectroscopy (NIRS) and Landsat ETM imagery reflectance data for predicting soil carbon in glacial till soils with and without additional topographical information in an undulated field. Accurate field maps of soil total carbon are important not only for defining site-specific management zones in precision agriculture, but also for reliable assessment of soil carbon sequestration potential on field and watershed scales. Highly variable soil and topographical attributes of glacial till soils can affect the quality of carbon map with a limited number of soil samples, because soil carbon is often highly spatially variable as influenced by natural soil variability and topography. Therefore, quick, reliable and cost-effective techniques are needed for measuring soil carbon changes in response to changes in land management on an agricultural field. A field study of carbon mapping was conducted in April 2004 in Kalamazoo County, Michigan. NIRS spectra were collected in a 50-ha field. Eighty-five soil samples were collected on the NIRS transects from 0 -10 cm depth. Landsat ETM imagery during the period of soil sampling was obtained. Principal component regression was used to relate NIRS and ETM reflectance data to measured soil carbon.

The second objective was to characterize relationship between yield and soil EC, yield and topographical attributes and to identify spatial clusters from historical yield data, and relate the clusters to the underlying soil EC, and topographical attributes.

Inexpensive and densely measured soil EC and topographical attributes were widely used to explain yield variability. Available historical yield data could also provide useful information about yield spatial variability and potential management zones, which will assist crop production site-specifically. Data used for this study were from 50-ha Carr Farm in Kalamazoo County, Michigan. Eight year corn-soybean yield data collected using GPS and yield monitor were available to study the spatial-temporal variability. Detailed elevation and soil EC were also available for analyzing yield variation. Cluster analysis on EC and topographical variables and historical yield data was used to identify management zones within the field.

The third objective was to analyze the effects of management practices on the relationship between crop yield and topography, yield and weather from long-term experiment. The management effects can be altered by field topography and weather conditions. To make a better farming decision site-specifically needs thorough analysis and understanding of production variability and its relationship with underlying environmental factors in multi-crop with long term data. Information on yield/topography/weather relationships will contribute to the effort in expanding the conservation management practices and likely increase the grower's profit from site-specific farming while shifting from conventional to conservation practice. Data used for this study were from the Long Term Ecological Research site at W.K. Kellogg Biological Station. Ten-year corn-soybean-wheat yield data collected using GPS and yield monitor were available to study the effects of management on yield variability. Detailed elevation and derived topographical variables in each plot were available to study effect of management practices on relationship between topography and yield.

A nonparametric spline regression was used to characterize relationship between maximum yields and wetness index (WI). The algorithm was also used to compare the yield difference across the range of the WI between two treatments. Average yields difference between treatments in this one-factor randomized complete block design experiment was first studied by analysis of variance (ANOVA). However, those varied field conditions can cause imprecision and incorrect interpretation of the experimental results using traditional ANOVA model. Incorporating spatially intense measurements of topographical variables into ANOVA models, called analysis of covariance (ANCOVA), one can correct for these confounding variables and obtain more precise estimates of yield performance of the treatment. The 2 models were compared in order to find better model and make the yield comparisons between treatments more precise.

CHAPTER II

TOTAL CARBON MAPPING IN GLACIAL TILL SOILS USING NEAR INFRARED SPECTROSCOPY, LANDSAT IMAGERY AND TOPOGRAPHICAL INFORMATION

ABSTRACT

Accurate mapping of total soil carbon is important for reliable assessment of carbon sequestration potential from small fields to regional scales. Highly variable soil and topographical attributes, such as elevation and slope, of glacial till soils cause difficulties in mapping soil carbon based on a limited number of soil samples. The objectives of this study were to determine the feasibility of mapping soil organic carbon using newly developed on-the-go near infrared spectroscopy (NIRS) measurements and Landsat ETM image reflectance in glacial till soils with and without additional topographical information. The studied field was about 50 ha in size and located in Kalamazoo County, Michigan. The predominant soil is Kalamazoo loam (fine-loamy, mixed, mesic Typic Hapludalfs). NIRS spectra were collected along 22 north-south transects separated by a distance of 25 m and the distance between the measurements within a transect was 5 m. The field was bare of vegetation and relatively dry during soil sampling. Landsat ETM imagery during the period of soil sampling was obtained. Eighty-five soil samples were collected on the NIRS transects from 0 -10 cm depth. Principal component regression was used to relate NIRS spectra and ETM data to measured soil carbon. Regression coefficients between measured and predicted carbon values were equal to 0.70 and 0.46 using NIRS data and ETM imagery, respectively.

When topographical attributes, such as elevation, wetness index, and terrain slope were included into the regression model along with NIRS and ETM data, the regression coefficients improved to 0.81 and 0.62, respectively. The results indicated that the combination of the NIRS and ETM measurements with topography is a valuable tool for accurate total carbon mapping in glacial till soils. Field soil moisture and texture can help explain carbon variation and improved its prediction for ETM imagery data, but were found to not be a very useful addition to NIRS measurements.

INTRODUCTION

Soil carbon plays an important role as a major source of plant nutrients and water holding capacity as an active agent in soil structure development. Accurate field maps of soil total carbon are important not only for defining site-specific management zones in precision agriculture (Chen, et al., 2000; Mueller and Pierce, 2003; Martin et al., 2002; Walter et al., 2003; Chen et al., 2005) and evaluating soil quality (Brejda et al., 2001; Homann et al., 1998), but also for reliable assessment of soil carbon sequestration potential on field and watershed scales (Young, 2003; Lal et al., 2004; Leifeld and Kogel, 2005).

Precision farming requires detailed spatial information on soil properties to manage crop production with increased farm profits and reduced environmental impacts. Detailed soil carbon maps provide essential information for site-specific decision-making in choosing sound management practices. For example, organic carbon concentrations in the surface soil are needed to determine site-specific application rates of some crop-production inputs, including nitrogen fertilizers and herbicides (Blackmer and White, 1998).

More recently, global climate change studies have shown that increasing carbon storage by soils is a practical method to mitigate greenhouse gas emissions (Robertson et al., 2000; Lal, 2004). Conservation management practices that enhance soil carbon storage, e.g. no-till and cover cropping, can stimulate carbon sequestration (Young, 2003; Lal et al., 2004). Growers may be able to benefit when switching their management practices to those that store more soil carbon by getting paid for stored carbon by private markets or government programs (Young, 2003). However, quick, reliable and cost-effective techniques are needed for measuring soil carbon changes in response to changes in land management on an agricultural field or a regional level.

Laser-induced breakdown spectroscopy was found to be a promising method for estimating total soil carbon (Cremers et al., 2001; Ebinger et al., 2003). A number of laboratory studies used near-infrared spectroscopy (NIRS) for rapid analysis of soil carbon (Dalal and Henry, 1986; Palacios-Orueta and Ustin, 1998; Chang et al., 2001; Martin et al., 2002; McCarty et al., 2002; Russell et al.,2003; Dematte et al., 2004; Chang et al., 2005), nitrogen (Dalal and Henry, 1986; Russell et al., 2003), clay content (Dematte et al., 2004; Sørensen and Dalsgaard, 2005), and soil moisture (Dalal and Henry, 1986; Chang et al., 2005). The NIRS is an analytical technique that allows estimating several soil properties with acceptable accuracy in a short time (Chang et al., 2001). But the spectral measurements obtained in laboratory conditions using a limited number of soil samples can not capture the field spatial variability of total carbon and are less representative of soil spatial heterogeneity present on a field or farm scale.

Recently, on-the-go NIRS was developed for in-field analysis of soil properties (Christy et al., 2003). Near-infrared spectra are dominated by weak overtones and combinations of fundamental vibrational bands for H-C, H-N, and H-O bonds from the near- and mid-infrared region (Chang et al., 2001; Christy et al., 2003; Sorensen and Dalsgard, 2005). Because organic matter in the soil mainly consists of C, H, O and N elements soil NIRS measurements are generally most affected by soil organic matter (Sorensen and Dalsgard, 2005). NIRS spectra were related to soil carbon in agricultural fields of central Iowa and Kansas (Christy et al., 2003).

Remote sensing is another cost-effective and nondestructive analytical technique to estimate soil carbon with acceptable accuracy (Frazier and Cheng, 1989; Chang et al., 2001; Qiang et al., 2002; Konen et al., 2003). The reflectance from remotely sensed imagery is well related to surface soil carbon when the surface is bare, dry and flat. Landsat Thematic Mapper band ratios were used to classify various levels of organic matter and iron oxides (Frazier and Cheng, 1989). The intensity of aerial photography showed a high correlation with soil organic carbon (Chen et al., 2000). The soil line Euclidean distance technique is based on relating a pixel's Euclidean distance of the red and near-infrared intensity values for the bottommost point on the soil line, which is a linear relationship between the near-infrared and visible reflectance of bare soil images. This technique was used to estimate soil surface organic matter and other properties from aerial images acquired by a digital camera system (Fox and Sabbagh, 2002). The regression coefficient between measured and predicted organic matter values obtained in their study was around 0.7.

Soil carbon is often highly spatially variable as influenced by natural soil variability and topography mainly due to soil erosion and deposition. In Michigan, the physiography is characteristic of a mature glacial outwash plain and moraine complex. Soils formed in materials deposited by the glacial till and outwash processes across the landscape resulting in formation of various landforms, such as undulating hills, valleys and plains even within small areas. Highly variable soil and topographical attributes of glacial till soils can affect the quality of carbon map with NIRS or imagery data only (Mueller and Pierce, 2003). However, the quality of soil carbon maps can be improved and spatial sampling intensities can be reduced by incorporating topographical attributes as a source of secondary information in soil carbon mapping (Bell et al., 2000; Mueller and Pierce, 2003; Chaplot et al., 2001; Terra et al., 2004).

Currently information on soil carbon is derived through standard procedures of soil sampling and laboratory analyses. The methods are expensive, time-consuming, and less accurate at the on-farm field scale level. We selected a corn-soybean rotated farm located at southwestern Michigan. The clay plus silt content of the field varied from 20 to 80 %. The range of field elevation was 13 m. The field was well-represented as glacial till soils in U.S. northern cornbelt. The objectives of this research were to demonstrate the feasibility of mapping soil organic carbon using newly developed on-the-go near infrared spectroscopy and Landsat ETM imagery reflectance data for predicting soil total carbon in glacial till soils with and without additional topographical information in an undulated field.

MATERIALS AND METHODS

Field Description and Data Collection

The studied field was about 50 ha in size and located in Kalamazoo County, MI (42°22′ N, 86°36′ W). The predominant soil mapping unit is Kalamazoo loam (fine-loamy, mixed, mesic Typic Hapludalfs) ((Austin, 1979, Kalamazoo County Soil Survey, Michigan). A small area of Oshtemo sandy loam (coarse-loamy, mixed, mesic Typic Hapludalfs) was scattered in the southwest portion of the field. In the top 10 cm, sand content ranged from 19 to 77 % and clay content ranged from 2 to 22 %. The field was in a corn/soybean rotation with nonirrigated minimum till management (Jiang and Thelen, 2004). The elevation of the field ranged from 290 m to 303 m with near level (0 – 2%), gentle (2 – 6%), and moderate (6 – 14%) slopes (Fig. 2.1).

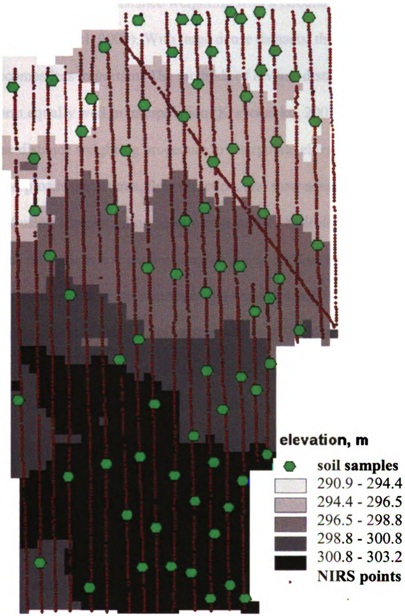

Fig. 2.1. Elevation and layout of soil samples and NIRS test sites in Carr Farm

Elevation was measured using a real-time kinetic global positioning system (RTK GPS) with a tractor-mounted receiver on a cart. The measurements were taken every 5 m within and 10 m between the transect (the cart passes). Topographical attributes were derived from the elevation data. First, irregular point elevation measurements were interpolated into a regular 15 x 15 m digital elevation model (DEM) using function

POINTINTERP with inverse distance weighting with a circular neighborhood of 20 m under ArcInfo Grid (ESRI, 2000). With large dense datasets, the spatial structure of soil properties becomes less important. The methods of inverse distance weighting and kriging perform equally well in interpolation (Kravchenko, 2003). Therefore, we applied simple inverse distance weighting procedure to interpolate elevation data.

Slope, plan and profile curvatures, flow direction, and flow accumulation were derived from the DEM using corresponding functions in surface hydrologic analysis of ArcInfo GRID. Detailed definitions and explanations of slope, curvature, flow direction, and flow accumulation functions are given elsewhere (Kravchenko and Bullock, 2000; McKenzie et al., 2000; and ArcInfo 8.1 help). Soil wetness index (WI) also called compound topographic index (McBratney et al., 2003) was calculated as proposed by Moore et al. (1993):

$$WI = \ln(A_s / \tan\beta) \qquad [1]$$

where $\mathbf{A_s}$ is the upslope area derived from flow accumulation and tan $\boldsymbol{\beta}$ is a tangent function of slope at percent-rise.

Near-infrared spectroscopy measurements were taken by Veris Technologies on April 19, 2004. The field surface condition was dry, bare, and relatively smooth. The NIRS spectra were collected along 22 north-south transects separated by a distance of approximately 25 m. The distance between measurements within each transect was equal to 5 m (Fig. 2.1). A total of approximately 3,700 NIRS measurements were collected in this field. The NIRS instrument was mounted on a tractor driven cart equipped with a steel shank get to a 10 cm depth. A quartz tungsten bulb was mounted within the shank to illuminate the soil while optical fibers were used to transmit reflected light to a spectrometer mounted above the shank. The measurement depth was held at approximately 7.5 cm. A spectroradiometer measured light density (reflectance) from wavelength 0.9 to 1.7 μm on every 6 μm interval. Approximately 20 spectra per second on one GPS location were acquired and then stored on a laptop computer. The reflectance values were converted to absorbance as a logarithm of the inverted reflectance spectra for further analyses. The detailed description of the NIRS measurement system was reported by Christy et al. (2003).

Remote sensing data, Landsat 7 ETM+ imagery from path 21 and row 31, were acquired on April 14, 2004 (Fig. 2.3), 5 days before NIRS and soil samples were taken. ETM imagery contains band 1 (0.45 – 0.52 μm spectral range), 2 (0.52 – 0.60 μm), 3 (0.63 – 0.69 μm), 4 (0.76 – 0.90 μm), 5 (1.55 – 1.75 μm), 7 (2.09 to 2.35 μm), and panchromatic band 8 (0.52 – 0.90 μm). Bands 1 to 5 and 7 have 30 m resolution and band 8 has 15 m resolution. The radiometric values on the image were converted to reflectance using image processing software (ERDAS Imagine, 2001). The bands 1 to 5 and band 7 were merged with band 8 to obtain a 15 m resolution using the principal component method of resolution merge under spatial enhancement of ERDAS imaging.

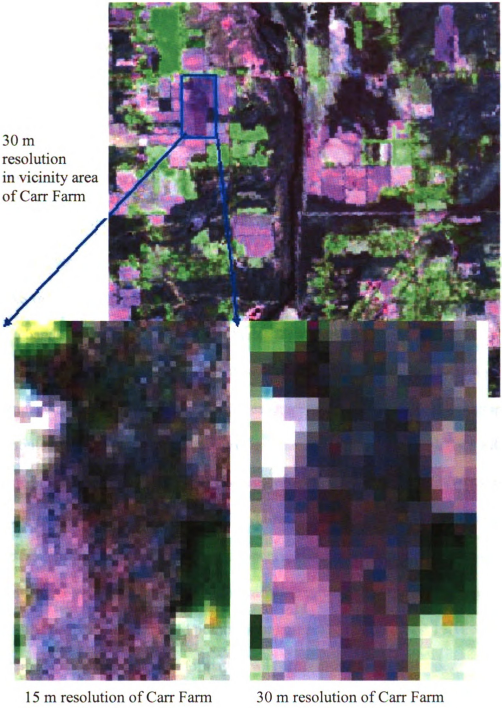

Fig. 2.2. ETM image taken on April 14, 2004 of Carr Farm and vicinity area

Eighty-five geo-referenced soil samples were randomly collected at the 0 - 10 cm depth immediately after the NIRS pass. Soil water content was measured using a gravimetric method and soil texture (clay, silt, and sand contents) was measured using a hydrometer method. Samples for total carbon analysis were air-dried at room temperature, cleaned from visible plant residues and ground to pass a 100-mesh sieve. Total carbon was analyzed by a dry combustion method using a Carlo-Erba, Series-2 Carbon-Nitrogen analyzer.

Statistical Data Analyses

Principal component analysis (PCA) was performed on the NIRS absorbance measurements on 128 wavelengths to reduce data dimension by SAS PROC PRINCOMP (SAS Inst., 2000). Similarly, PCA was performed on the ETM reflectance measurements on 6 bands for 30 m resolution and 7 bands for 15 m resolution.

Multiple linear regression analyses between total carbon content and principal components (PCs) of NIRS and ETM measurements with and without topographical attributes and soil moisture and texture variables were performed with SAS PROC REG. Principal component regression (PCR) described by Ehsani et al. (1999) was used to relate the spectral data of NIRS and ETM to soil total carbon content. Stepwise regression was employed for PCs and topographical variable selection. The 0.05 level of significance was used for retaining the variables in the final regression model.

For five of the sampled points in the east portion of the field, elevation was not obtained and topographical information was not available, so those points were excluded from the regression analysis. Further, two potential outliers (extremely high carbon content) were identified based on Cook's distances and excluded from the dataset. Finally, a total of 78 samples were used for the regression analysis. The regression models were compared based on R^2, adjusted R^2, RMSE, and PRESS statistics. The

PRESS statistics is a leave-one-out cross-validation in regression. The model that gives the smallest values of the PRESS is chosen as the best one.

Regression performance was tested by the jack-knifing method using ten independent test data sets. Each test data set consisted of 10 samples randomly selected from the main data set. The remaining data were used to perform multiple regression analyses and the regression predictions were compared with the measured values of the test data. Root mean square errors were calculated for each regression analysis of each test data set.

To obtain the map of soil carbon predictions for the studied field, PCs from NIRS and ETM and topographical attributes found to be significant in the step-wise regression procedures were interpolated to create 15- by 15-m cell maps in ArcView Spatial Analyst. Then the regression predictions of total carbon for each cell were calculated from the regression models using the PCs of NIRS and ETM and topographical attributes. The residuals from the regression models were found to be spatially correlated. Thus, the map of the residuals was obtained using ordinary kriging and added to the regression prediction map to obtain the final map of total carbon predictions for the studied field.

RESULTS AND DISCUSSION

Soil total carbon content in the studied field ranged from 5.5 g kg^{-1} to 28.9 g kg^{-1} with an average of 15.4 g kg^{-1}. The relatively wide range of total carbon values provided a good data set to test the performance of NIRS and remotely sensed imagery in predicting soil carbon.

Total carbon was significantly positively correlated with field soil water content, clay content, and wetness index with correlation coefficients, *r*, equal to 0.57, 0.37, and 0.36, respectively, and negatively correlated with sand content, elevation, and slope with *r* equal to -0.75, -0.56, and -0.28, respectively ($p = 0.05$). The observed correlations support the concern that relatively large variability of texture and elevation within the field might affect the accuracy of the carbon mapping using traditional methods when sample size is not sufficiently large.

Carbon Predictions Based on NIRS

The first 13 principal components of NIRS explained 99% of the variation in spectral data. Thus, the 13 PCs were used as initial explanatory variables in step-wise regression. Step-wise selected regression equations for soil total carbon versus NIRS with and without topography, soil moisture, and texture were presented in Table 2.1. A comparison of the regression results from NIRS PCs only, NIRS PCs plus topography, NIRS PCs plus topography and soil moisture, NIRS PCs plus topography and texture, and NIRS PCs plus topography and soil moisture and texture shows expected differences between R^2, adjusted R^2, RMSE, and PRESS values. The lowest R^2 values and the largest RMSE and PRESS of 0.70, 0.189, and 2.75, respectively, were observed in the regression with only NIRS PCs. The highest R^2 values and the lowest RMSE and PRESS of 0.88, 0.127, and 1.47, respectively, were observed in regression with NIRS PCs, topography, soil moisture and texture.

Table 2.1. Stepwise linear regression parameters ($p < 0.05$) used to estimate soil total carbon (TC) via NIRS and remotely sensed ETM reflectance data with and without, soil moisture, texture and topographical variables.

Variables	Regression Equation	R^2	Adj.R^2	RMSE	PRESS
NIRS					
PCs	TC = 1.455 + 0.022PC1 -1.133PC2 + 7.916PC4 + 7.77PC6 + 45.51PC8	0.70	0.68	0.189	2.75
PCs and elevation (Ele)	TC = 11.89 + 15.53PC4 – 20.22PC5 + 45.04PC6 – 975.2PC9 + 1886.3PC10 – 935.3PC12 – 16468PC13 -0.035Ele	0.81	0.78	0.156	2.68
PCs, moisture (Moist), and elevation	TC = 8.654 + 0.199PC2 - 0.11PC3 + 0.461PC4 - 5.494PC13 + 0.033Moist - 0.026Ele	0.83	0.81	0.144	1.78
PCs, texture, wetness index and slope	TC = 0.317 + 0.182PC2 - 0.162PC3 + 0.478PC4 - 3.777PC11 +4.165PC12 + 0.0167clay +0.41WI+ 0.01Slope	0.85	0.83	0.137	1.70
PCs, moisture, texture, slope, and wetness index (WI)	TC = 0.104 + 0.17C2 - 0.138PC3 + 0.331PC4 + 1.023PC7 -3.66PC11 + 4.25PC12 + 0.022Moist + 0.009Silt + 0.019Clay + 0.0417WI + 0.108Slope	0.88	0.86	0.127	1.47
ETM imagery					
PCs from 30 m image	TC =1.508 – 0.057PC1 + 0. 209PC2	0.33	0.31	0.269	6.23
PCs from 15 m image	TC =1.519 – 0.071PC1 – 0.114PC2 + 0.197PC3 – 0.211PC4	0.46	0.43	0.249	5.25
PCs from 15 m image and elevation, and WI	TC = 14.01 – 0.07PC1 – 0.0436Ele + 0.0617WI	0.62	0.60	0.208	3.56
PCs from 15 m image, moisture, elevation and wetness index	TC = 10.62 - 0.047PC1 + 0.093PC3 + 0.04Moist - 0.034Ele + 0.042WI	0.75	0.73	0.173	3.05
PCs from 15 m image, texture, slope, and wetness index	TC = -0.167 - 0.05PC1 + 0.23PC3 + 0.016Silt + 0.167Clay + 0.074WI + 0.137Slope	0.75	0.73	0.174	2.47
PCs from 15 m image, moisture, texture, slope, and wetness index, elevation	TC = 5.872 - 0.046PC1 + 0.113PC3 - 0.659PC7 + 0.029Moist - 0.009Sand - 0.017Ele + 0.066WI + 0.13Slope	0.81	0.78	0.156	2.48

For NIRS, elevation was the only topographical variable significant at the 0.05 probability level. By incorporating elevation the total carbon prediction was greatly improved. The regression explained 70% of the variations in total carbon using NIRS PCs only, whereas 81% of the variations in total carbon were explained using PCs plus elevation. Elevation negatively contributed to carbon content. The reason is possible attributed that soil carbon is usually transported by runoff from high elevation area to low elevation area. Our observations are consistent with other studies that found that terrain attributes can be used to improve the quality of spatial estimates of soil carbon or allow similar levels of map quality to be achieved with a reduced soil sampling density (Mueller and Pierce, 2003; Terra et al., 2004).

The improvement in carbon prediction when soil moisture was added to the regression model with NIRS PCs plus elevation was relatively small even though statistically significant. By adding soil moisture, the R^2 increased from 0.81 to only 0.83. Possible reason for low improvement due to adding soil moisture is that field soil moisture itself was significantly related to elevation (r = -0.26). Also soil moisture was found to be positively correlated with wetness index (r = 0.20) and negatively correlated with terrain slope, r of -0.37 (p = 0.05). Therefore the variability in soil moisture was already substantially explained by topography, thus not providing substantial improvement when added to multiple regression along with these variables. Chang et al. (2005) found that increase in moisture compared with dry soil caused a considerable increase of the absorbance baseline of the spectra when comparing the influence of soil moisture on laboratory NIRS measurements of soil carbon. The accuracy of the carbon prediction was better for the air-dried soil than for moist soil. However, consistent with our observations, the improvements in carbon prediction accuracy when including soil moisture in the regression were minimal. Based on these results it could be recommended that in soils similar to those of this study collecting soil moisture data might not be practical field carbon mapping using NIR if dense topographical information is available.

Adding soil texture information, clay content, to the regression model with NIR PCs and topography increased the R^2 from 0.81 to 0.85. Clay content significantly contributed to carbon content. The reason is that fine particles have greater capacity to hold organic matter through physical and chemical stabilization (Hassink, 1997; Krull, 2003). The regression model with NIR PCs, topography, soil moisture, and soil texture had an R^2 of 0.88.

These results are consistent with observations of Christy et al. (2003) who applied on-the-go NIRS in Iowa and Kansas fields and obtained an R^2 value of 0.87 using PCR. Lab based spectral measurements with PCR could explain 78% of the variation in organic carbon on a Canadian prairie soil (Martin et al., 2002). They also found that NIRS predictions underestimated the lower and higher carbon values while overestimated the mid-range values thus suggesting a possibly non-linear relation between soil carbon and NIRS PCs. Fig. 2.3a and 3b show observed carbon values and predictions from regression with and without topography. Similar to observations of McCarty et al. (2002) and Martin et al. (2002) the results obtained using NIRS PCs only indicate that there was a tendency to overestimate low total carbon content values and underestimate the higher soil carbon contents. The non-linearity was somewhat reduced in regressions with NIRS PCs and topography (Fig. 2.3b).

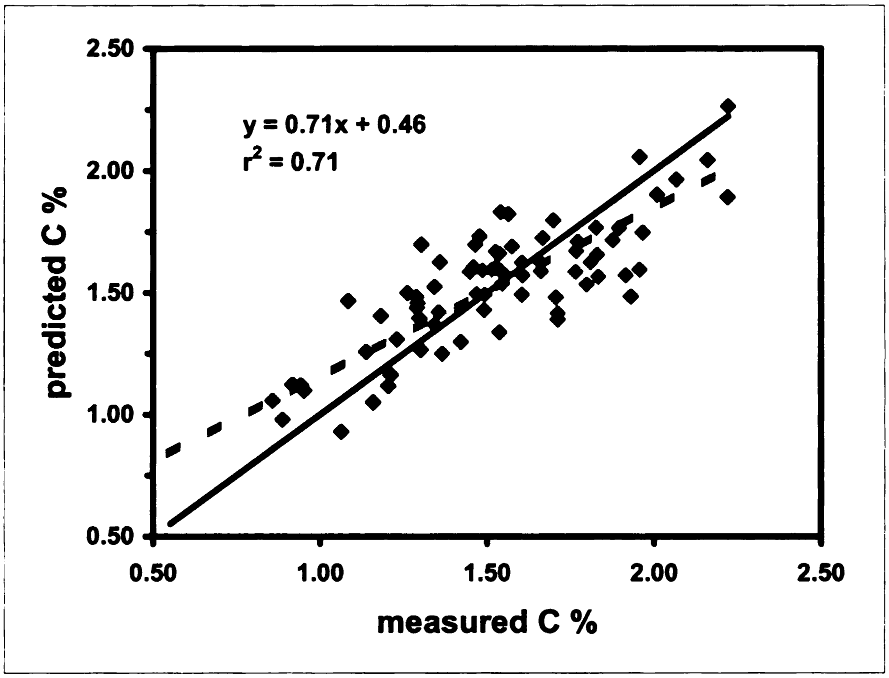

Fig. 2.3a. Plot of the observed total carbon values vs. predictions obtained from multiple regression equation with NIRS PCs, solid line represents a 1:1 relationship, dash line is regression line of predicted vs. measured.

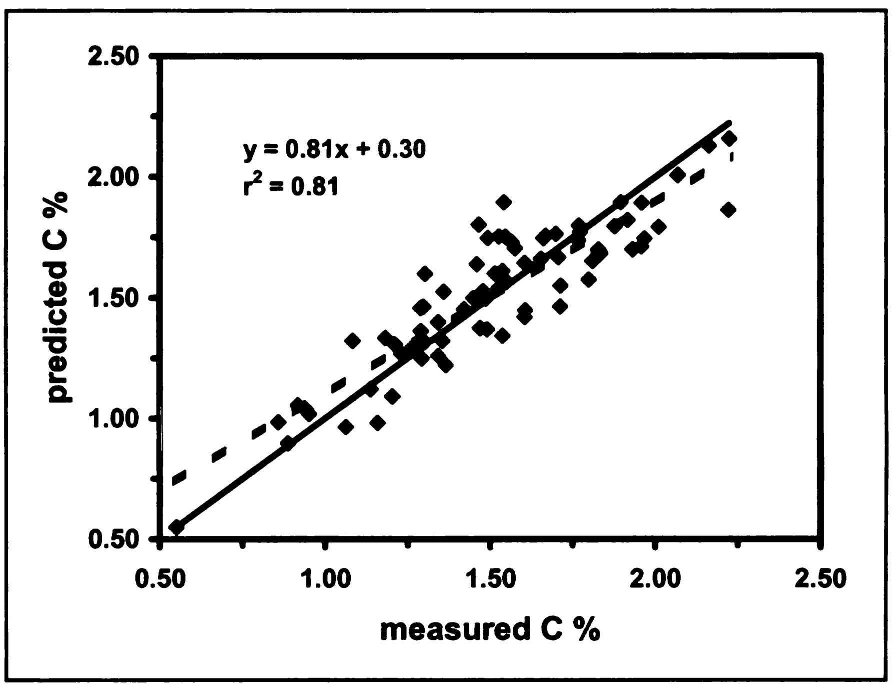

Fig. 2.3b. Multiple regression validation: TC vs. PCs from NIRS plus topography, solid line is 1:1 line of measured C, dash line is regression line of predicted vs. measured.

Carbon Predictions Based on Landsat ETM

The regression results obtained from the Landsat ETM data were inferior to those obtained from NIRS (Table 2.1). ETM PCs regression based on a 30 m resolution imagery explained only 33% of the variation in total carbon producing the highest observed RMSE and PRESS value of 0.269 and 6.23. Thus, Landsat ETM 30 m resolution imagery is not recommended for carbon prediction in the studied soils. The ETM PCs regression equation from 15 m resolution imagery performed much better explaining 46% of the variations in total carbon. When combined with topographical data, the 15 m resolution imagery explained as much as 62% of the variations in total carbon substantially reducing RMSE and PRESS. Elevation and wetness index were the topographical variables that were selected based on a step-wise selection procedure as those that significantly improved carbon prediction accuracy when added to the ETM 15 m resolution imagery data (p = 0.05).

Figures 3c and 3d show Plots of observed and predicted carbon values obtained from multiple regression models from 15 m resolution imagery ETM PCs only and ETM PCs plus topography. The discrepancy between measured and predicted values for ETM PCs only was substantial (Fig. 2.3c). It was obvious that the regression equation overestimated low and underestimated high carbon values. This is contrary to Sullivan et al. (2005) who reported a strong tendency to underestimate at low soil carbon content and over estimate at higher soil content from regression residual analysis using IKONOS imagery. The ETM PCs plus topography regression performed remarkably better than that of ETM PCs only (Fig. 2.3d). The results encourage a combined application of less costly satellite imagery and topographical data to map soil carbon in the studied soils.

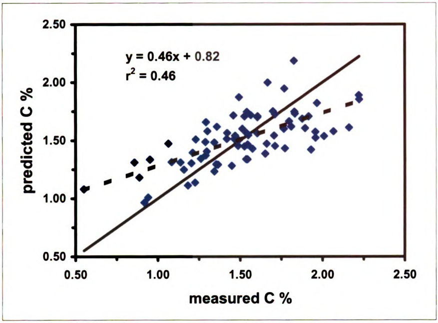

Fig. 2.3c. Multiple regression validation: TC vs. PCs from ETM, solid line is 1:1 line of measured C, dash line is regression line of predicted vs. measured.

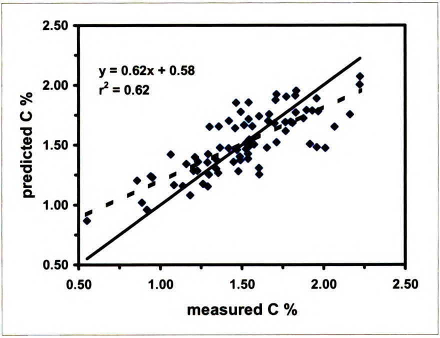

Fig. 2.3d. Multiple regression validation: TC vs. PCs rom ETM plus topography, solid line is 1:1 line of measured C, dash line is regression line of predicted vs. measured.

Carbon prediction was further improved by including soil moisture with regression explaining 75% of the variation in total carbon. The RMSE decreased from 0.208 to 0.173. Regression with texture produced results very similar to those of regression with soil moisture, where silt and clay was significant in the equation (Table 2.1). By adding moisture and texture data together, the R^2 value further increased to 0.81. Unlike the regression with texture only, silt and clay were found to be not significant when included in the regression model along with soil moisture. However, sand content was included in the model with significant negative contribution to carbon content. Soil moisture and/or texture addition to the regression improved carbon prediction more substantially when added to the regression model with ETM PCs as compared to the regression model with NIR. This is because remote sensed imagery is very sensitive to the soil surface condition, such as wetness and roughness. However, water molecules have a direct impact on near infrared absorbance via the O-H bond. The NIRS measurements indicated that water caused differences in NIRS absorbance (Christy et al., 2003).)

The positive regression coefficient for soil moisture and wetness index in the model suggested that high soil moisture is coincident with high soil carbon content. Moorman et al. (2004) also found that wetness index was positively correlated with soil carbon content. They suggested that wetness index was a strong predictor of soil organic C in glacially-derived Mollisolls of Iowa. Thus collection of soil moisture data can be used to achieve improving carbon prediction using ETM imagery even when dense topographical information is available. Apart from direct soil sampling, soil moisture data can be obtained from microwave and radar images. We hypothesize that combining ETM with Radar or Microwave images will produce low-cost accurate large-area soil carbon maps in soils similar to those of this study. Further research is needed to test this hypothesis.

Other studies support our findings in demonstrating that aerial photos and satellite images are less costly and practical in predicting soil carbon with reasonable accuracy. Fox and Metal (2005) employed 4-band aerial imaging to relate soil carbon with PCs of image intensity in two Iowa fields obtaining R^2 values of 0.68. In Georgia investigations of Coast Plain soils. Chen et al. (2000 and 2005) predicted soil organic carbon from fine resolution 3-band aerial imaging and multi-band ATLAS sensor image using non-linear regression with R^2 values ranging from 0.87 to 0.97. Sullivan et al. (2005) related IKONOS imagery reflectance to soil carbon with R^2 values equal to 0.38. They speculated that in the studied soils sandy epipedon and rough surface are the primary factors limiting the ability to obtain accurate soil carbon estimations.

Regression Validation and Total Soil Carbon Prediction

Figure 4 shows average RMSE values obtained based on 10 test data sets for four of the studied regressions, i.e., regression with NIRS PCs only, NIRS PCs plus topography, ETM PCs only and ETM PCs plus topography. The ETM PCs regression equation predictions produced the highest average RMSE, equal to 0.24. The NIRS PCs only regression equation and NIRS PCs with elevation equation had very similar RMSE values equal to 0.18 and 0.17, respectively. The RMSE for ETM PCs regression plys elevation and wetness index regression was only marginally higher than those of NIRS based methods and was equal to 0.19.

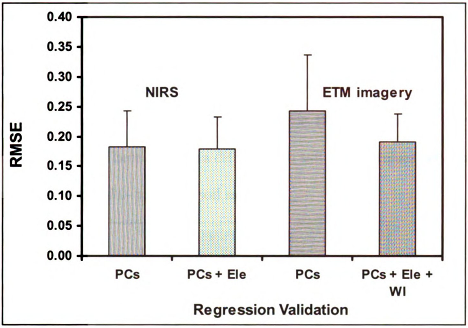

Fig. 2.4. Regression equation cross-calibration

The two regression equations of NIRS PCs plus topography and ETM PCs plus topography were used to generate a field-scale soil carbon map. The predicted soil carbon for Carr field was based on a 15 m x 15 m cell size map. The map was corrected by adding kriged residuals to the map obtained using linear regression predictions. Fig. 2.5a shows the total carbon map predicted by the regression equation using NIRS PCs plus elevation. The range of predicted soil total carbon was from 3.37 g kg^{-1} to 24.28 g kg^{-1} with an average of 14.4 g kg^{-1}. Fig. 2.5b shows a total soil carbon map predicted by ETM PCs plus elevation and wetness index. The range of predicted total soil carbon was from 4.5 to 22.86 g kg^{-1} with average of 14.6 g kg^{-1}. The averages of predicted carbon from the above two equations are very similar. However, the range of carbon values from NIRS was wider than that from the ETM imagery. The reason is that each map cell contained three NIRS measurements, whereas there was only one measurement in ETM imagery per map cell. Thus, more of the local carbon variation was detected by NIRS. Finer resolution imagery might improve accuracy of soil carbon prediction. In addition to the coarse resolution of the ETM imagery, another reason for lower R^2 ETM predictions was that the ETM imagery measured surface reflectance. However, soil samples were taken from 0- to 10-cm. There could be a difference in soil carbon values between the surface soil and the mixed 0- to 10-cm soil sample.

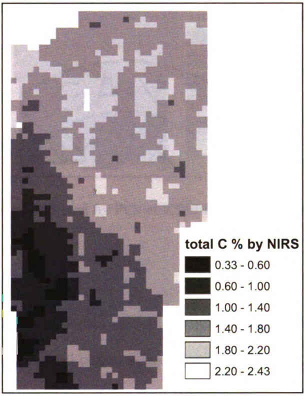

Fig. 2.5a. Carbon map predicted by PCs of NIRS and topography

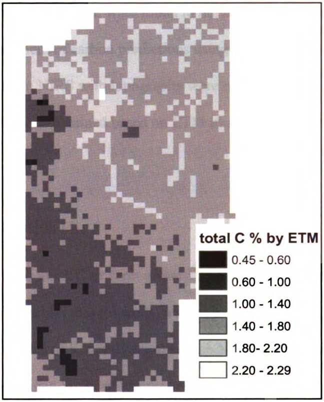

Fig. 2.5b. Carbon map predicted by PCs of ETM image and topography

SUMMARY

Highly variable soil properties and topographical attributes of glacial till soils cause difficulties in mapping soil carbon when the number of soil samples is limited. The results of this study indicate that on-the-go field NIRS is capable of quantifying the distribution of carbon in glacial till soil on a field-scale level rapidly and efficiently. Including topographical data can further improve carbon mapping accuracy and thus such data are strongly recommended in addition to NIRS measurements for effective and accurate carbon predictions in glacial till and other soils. ETM imagery is useful for assessing soil carbon in a bare field especially when combined with topographical data. Field soil moisture and texture helped explain carbon variation and improved its prediction for ETM image data, but were found to not be very useful additions to NIRS measurements. Assessment of carbon predictions using independent test data sets showed that predictions based on NIRS with topography were only marginally better in terms of RMSE than the predictions obtained based on ETM imagery with topography.

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REFERENCES

Austin, F.R. 1979. Soil Survey of Kalamazoo County, Michigan. United States Department of Agriculture, Soil Conservation Service, in cooperation with Michigan Agricultural Experiment Station. The Soil Conservation Service: Washington, DC.

Bell, J.C., Grigal, D.F., Bates, P.C. 2000. A soil terrain model for estimating spatial patterns of soil organic carbon. In: Wilson, J.P., Gallant, J.C. (Eds.), Terrain Analysis —Principles and Applications. Wiley, New York, pp. 295– 310.

Blackmer, A.M., White, S.E. 1998. Using precision farming technology to improve management of soil and fertilizer nitrogen. Australian Journal of Agriculture Research 49:555-564.

Brejda, J.J., Mausbach, M.J., Goebel, J.J. 2001. Estimating surface soil organic carbon content at a regional scale using the National Resource Inventory. Soil Sci Soc Am J. 65:842-849.

Chang, C.W., Laird, D.A., Hurburgh, C.R. 2005. Influence of soil moisture on near-infrared reflectance spectroscopic measurement of soil properties. Soil Science. 170:244-255.

Chang, C.W., Laird, D.A., Mausbach, M.J., Hurburgh, C.R. 2001. Near-infrared reflectance spectroscopy – principal components regression analyses of soil properties. Soil Sci Soc Am J. 65:480-490.

Chen, F., Kissel, D.E., West, L.T., Rickman, D., J.C. Luvall, J.C., Adkins, W. 2005. Mapping surface soil organic carbon for crop fields with remote sensing. J. Soil and Water Cons. 60:51-57.

Chen, F., Kissel, D.E., West, L.T., Adkins, W. 2000. Field-scale mapping of surface soil organic carbon using remotely sensed imagery. Soil Sci Soc Am J. 64:746-753.

Chaplot, V., Bernoux, M., Walter, C. 2001. Soil carbon storage prediction in temperate hydromorphic soils using a morphologic index and digital elevation model. Soil Science 166:46-60.

Christy, C.D., Drummond, P., Laird, D.A. 2003. An on-the-go spectral reflectance sensor for soil. 2003. American Society of Agricultural Engineers Meeting. page number: 031044.

Christy, C.D., Lund, E., Laird, D.A. 2003. Mapping soil carbon with on-the-go near infrared spectroscopy. http://www.oznet.ksu.edu/ctec/Fall%20Forum%20pdf%20files/ Papers_Abstracts/ Christy_Veris.pdf

Cremers, D.A., Ebinger, M.H., Breshears, D.D., Unkefer, P.J., Kammerdiener, S.A., Ferris, M.J., Catlett, K.M., Brown, J.R. 2001. Measuring total soil carbon with laser-induced breakdown spectroscopy (LIBS). J. Envir. Quality. 30:2202-2206.

Dalal, R.C., Henry, R.J. 1986. Simultaneous determination of moisture, organic carbon, and total nitrogen by near infrared reflectance spectrophotometry. Soil Sci Soc Am J. 50:120-123.

Dematte, J.A., Campos, R.C. Alves, M.C., Fiorio, P.R., Nanni, M.R. 2004. Visible-NIR reflectance: a new approach on soil evaluation. Geoderma 121:95-112.

ERDAS Imagine. 2001. ERDAS imaging help, version 8.5. ERDAS, Inc. Atlanta, Georgia.

ESRI, 2004. ArcView and ArcInfo. version 9.0. Redlands, California.

Ehsani, M.R., Upadhyaya, S.K., Slaughter, D., Shafii, S., Pelletier, M. 1999. A NIR technique for rapid determination of soil mineral nitrogen. Precision Agriculture. 1:217-234.

Ebinger, M.H., Norfleet, M.L., Breshears, D.D. 2003. Extending the applicability of laser-induced breakdown spectroscopy for total soil carbon measurement. Soil Sci Soc Am J. 67: 616-1619.

Fox, G.A., Sabbagh, G.J. 2002. Estimation of soil organic matter from red and near-infrared remotely sensed data using a soil line Euclidean distance technique. Soil Sci Soc Am J. 66:1922-1929.

Fox, G.A., Sabbagh, G.J., Searcy, S.W., Yang, C. 2004. An automated soil line identification routine for remotely sensed images Soil Sci Soc Am J. 68:1326-1331.

Frazier, B.F., Cheng, Y. 1989. Remote sensing of soils in the Eastern Palouse region with landsat thematic mapper. Remote Sensing of Environment 28:317-325.

Hassink, J. 1997. The capacity of soils to preserve organic C and N by their association with clay and silt particles. Plant and Soil. 191:77-87.

Homann, P.S., Sollins, P., Fiorella, M. 1998. Regional soil organic carbon storage estimates for western Oregon by multiple approaches. Soil Sci Soc Am J. 62:789-796.

Jenkinson, D.S., Coleman, K. 1994. Calculating the annual input of organic matter to soil from measurements of total organic carbon and radiocarbon. European Journal of Soil Science. 45:167-74.

Jiang, P., Thelen, K.D. 2004. Effect of Soil and Topographic Properties on Crop Yield in a North-Central Corn–Soybean Cropping System. Agron. J. 96: 252-258.

Konen, M.E., Burras, C.L., Sandor, J.A. 2003. Organic carbon, texture, and quantitative color measurement relationships for cultivated soils in North Central Iowa. Soil Sci Soc Am J. 67:1823-1830.

Kravchenko, A.N. 2003. Influence of spatial structure on accuracy of interpolation methods. Soil Sci Soc Am J. 67:1564–1571.

Krull, E.S., Baldock, J.A., Skjemstad, J.O. 2003. Importance of mechanism and processes of the stabilization of soil organic matter for modeling carbon turnover. Functional Plant Biology. 30:207-222.

Lal, R., Griffin, M., Apt, J., Lave, L., Morgan, M.G. 2004. Managing soil carbon. Science. 304:393.

Lal, R. 2004. Soil carbon sequestration impacts on global climate change and food security. Science. 304:1623-1627.

Leifeld, J., Kogel, K.I. 2005. Soil organic matter fractions as early indicators for carbon stock changes under different land-use? Geoderma. 124:143-155.

Martin, P.D., Malley, D.F., Manning, G. 2002. Determination of soil organic carbon and nitrogen at the field level using near-infrared spectroscopy. Canadian Journal of Soil Science. 82:413-422.

McCarty, G.W., Reeves, J.B., Reeves, V.B., Follett, R.F., Kimble, J.M. 2002. Mid-infrared and near-infrared diffuse reflectance spectroscopy for soil carbon measurement. Soil Sci Soc Am J. 66:640-646.

McBratney, A.B., M.L. Mendonca, and B. Minasny. 2003. On digital soil mapping. Geoderma. 117:3-52.

Moorman,T.B., Cambardella, C.A., James, D.E., Karlen, D.L., Kramer, L.A. 2004. Quantification of tillage and landscape effects on soil carbon in small Iowa watersheds. Soil and Tillage Research. 78:225-236.

Morra, M.J., Hall, M.H., Freeborn, L.L. 1991. Carbon and nitrogen analysis of soil fractions using near-infrared reflectance spectroscopy. Soil Sci Soc Am J. 55:288-291.

Mueller, T.G., Pierce, F.J. 2003. Soil carbon maps: enhancing spatial estimates with simple terrain attributes at multiple scales. Soil Sci Soc Am J. 67:258-267.

Qiang, X., Zhou, C., He, C. 2002. Using remote sensing to estimate the change of carbon storage: a case study in the estuary of Yellow River delta. International Journal of Remote Sensing. 23:1565-1580.

Palacios-Orueta, A., Ustin, S.L. 1998. Remote sensing of soil properties in the Santa Monica Mountains I. Spectral analysis. Remote Sensing of the Environment. 65:170-183.

Rickman, R.W., Douglas Jr., C.L., Albrecht, S.L. 2001. CQESTR: a model to estimate carbon sequestration in agricultural soils. J. Soil Water Cons. 56:237-42.

Robertson, G.P., Paul, E.A., Harwood, R.R. 2000. Greenhouse gases in intensive agriculture: contributions of individual gases to the radiative forcing of the atmosphere. Science. 289:1922-1925.

Russell, C.A. 2003. Sample preparation and prediction of soil organic matter properties by near infra-red reflectance spectroscopy. Communication of Soil Science and Plant Analysis. 34:1557-1572.

SAS Institute. 2001. SAS user's guide, Statistics, Version 8.2. SAS Institute Inc., Cary, North Carolina.

Sørensen, L.K., Dalsgaard, S. 2005. Determination of clay and other soil properties by near infrared spectroscopy. Soil Sci Soc Am J. 69:159-167.

Sullivan, D.G., Shaw, J.N., Rickman, D. 2005. IKONOS imagery to estimate surface soil property variability in two Alabama Physiographies. Soil Sci Soc Am J. 67:1789-1798.

Terra, J.A., Shaw, J.N., Reeves, D.W., Raper, R.L., van Santen, E., Mask, P.L. 2004. Soil carbon relationships with terrain attributes, electrical conductivity, and a soil survey in a coastal plain landscape. Soil Science. 169:819-831.

Walter, C., Viscarra Rossel, R.A., McBratney, A.B. 2003. Spatio-temporal simulation of the field-scale evolution of organic carbon over the Landscape. Soil Sci Soc Am J. 67:1477-1486

Wang, S.Q., Xu, J., Zhou, C.H., He, C.F. 2002. Using remote sensing to estimate the change of carbon storage: a case study in the estuary of Yellow River delta. International Journal of Remote Sensing. 23:1565-1580.

Young, L.M. 2003. Carbon sequestration in agriculture: the US policy context. American Journal of Agricultural Economics 85:1164-1170.

CHAPTER III

YILED VARIABILITY IN UNDULATING FIELDS: RELATIONSHIP TO SOIL ELECTRICAL CONDUCTIVITY AND TOPOGRAPHY, YIELD CLASSIFICATION AND PREDICTION

ABSTRACT

Crop yields are highly variable across fields as a result of complex interactions among yield-affecting factors including soil properties, topographical features, and precipitation. Understanding the relationship between yield and these factors is a critical component of site-specific management systems. The objectives of this study were (i) to characterize relationships of yield with soil electrical conductivity (EC) used as a proxy for soil properties, and with topographical features; (ii) to evaluate temporal yield variability under different precipitations during a multi-year period; and (iii) to identify spatial clusters from historical yield data, and relate the clusters to the underlying soil EC, and topographical factors, and to validate whether cluster groups can be used to accurately predict yield patterns. Corn (*Zea mays* L.) and soybean [*Glycine max* (L.) Merr.] yield data in two corn–soybean fields in southwestern Michigan were obtained from 1996 through 2003 using a combine yield monitor. Measurements of soil EC and topographic attributes, such as elevation, slope, curvature, and wetness index, were collected in the studied fields. Correlation analyses were used to investigate the relationship between these variables and yield. Cluster analysis using multi-year yield data was used to detect the spatial yield classes. Both EC and topographical attributes were found to be helpful in explaining yield variability. Yields were negatively correlated

with EC and terrain slope, while positively correlated with wetness index in most years. The relationship between standardized yield and early season (March and April) precipitation was curvilinear, while yield increased linearly with the increase of July precipitation. Roughly 60% of the yield variation was explained by either March and April or July precipitation. Consistently low and high yield clusters were identified. Four to five yield clusters can explain about 40 % of the yield variation. Areas with lower EC and slope tended to form high yield clusters in the studied fields. The results indicated that information from historical yield classification may be helpful in delineating management zones within a field and predict yield patterns on a large scale.

INTRODUCTION

Generally, crop yields are highly variable across fields as a result of complex interactions among yield-affecting factors including topographical features, soil properties and management practices (Timlin et al., 1998; Kravchenko and Bullock, 2000; Kravchenko et al., 2005). The quantitative characterization of spatio-temporal variability in crop grain yields is an important component of successful precision agriculture applications (Bakhsh et al., 2000; Machado et al., 2002). Farmers will be better able to implement site-specific management practices when they understand the causes of spatial and temporal variability of yield in their fields (Fleming et al., 1999; Kaspar, et al., 2004).

A number of studies have found that topography is the major source of yield variability (Simmons et al., 1989; Timlin et al., 1998; Kravchenko and Bullock, 2000; Kaspar et al., 2003; Si and Farrell, 2004; Jiang and Thelen, 2004). Field topography plays an important role in the hydrological response of rainfall catchment and has a major impact on water availability for crop production (Kitchen et al., 2003). In addition, topographical attributes and soil properties are often highly correlated with each other because of the processes of soil development, erosion, and sedimentation (Kaspar et al., 2004). Lark and Stafford (1997) found yield differences between areas with different topographic conditions because certain areas were associated with different soil types, soil texture, or seedbed quality, drainage, and compaction. However, Taylor et al. (2003) reported that up to 50% of the yield variation within the field was related to crop management practices rather than underlying soil factors.

The effect of topographical attributes on crop yield is indirect, acting by influencing soil physical and chemical properties. Within a field, areas with relatively low elevation often have higher soil moisture, finer texture and better nutrient status compared with high elevation areas. High crop yields are often observed in lower elevation areas. However, if the soil water availability is a major yield limiting factor in a landscape the elevation-yield relationships may vary depending on whether a specific year is wet or dry. Particularly, these variations are often associated with the prevailing weather conditions during the growing season of a given year, such as spring and summer precipitation (Halvorson and Doll, 1991; Jaynes and Colvin, 1997). The greatest effect of topography was often observed during extreme weather conditions and at locations with extreme topography, such as low depressions or high hilltops (Kravchenko and Bullock, 2000). Kaspar et al. (2003) found that in four years with less that normal growing season precipitation, corn yield was negatively correlated with relative elevation, slope, and curvature. In two years with greater than normal precipitation, yield was positively correlated with elevation and slope.

Negative relationships between terrain slope and crop yield were found by a number of studies (Ciha, 1984; Kravchenko and Bullock, 2000; Jiang and Thelen, 2004). In general, steep slope positions tend to have more severe runoff and soil erosion, as a result of lower soil productivity.

Surface curvature measures the rate of change of a slope. It can be positive or negative, with zero curvature indicating that surface is either flat or the convexity in one direction is balanced by the concavity in another direction (Wilson and Gallant, 2000). A positive curvature indicates that the surface is upwardly convex. A negative curvature indicates that the surface is upwardly concave. It can be used to describe the water flow as run-in or runoff processes. Negative correlations between curvature and yield were found during years with low precipitation because areas with concave shape (negative curvature) could provide more plant-available water than the areas with convex shape (positive curvature) during periods of drought (Kravchenko and Bullock, 2000).

Since yearly variations in soil wetness and moisture availability often appear to be the reason for the yield-topography relationships to vary from year to year, a cumulative topographical characteristic that effectively reflects soil moisture redistribution within a landscape would be useful. Such characteristic, called soil wetness index (WI), has been developed by Moore et al. (1988) who presented the relationship between topographic attributes and the distribution of surface soil water content in a small catchment, and later, developed a method to calculate the WI. Late, Moore et al. (1993) have used WI to characterize surface saturation and soil water content in landscape. Schmidt and Persson

(2003) calculated WI from digital elevation model (DEM) data. They found that WI is highly correlated with soil water content and is helpful for site-specific management.

Soil EC is not a direct measure of any specific yield-limiting factor. However, it reflects a number of soil characteristics related to plant growth and yield, such as soil type (Taylor et al., 2003); topsoil thickness in claypan soils (Kitchen et al., 2003); clay, soil water, and organic carbon content (Jaynes et al., 2003). Soil EC can be considered as a cost-effectively measure of spatially variable soil characteristics that affect crop growth. However, similar to topography, the relationships between yield and soil EC could fluctuate due to varied precipitation. Kravchenko et al. (2003) found that variations in the strength and direction of the relationship between yield and soil EC were related to the amounts of precipitation observed early in the growing season. Also, the relationship between EC and yield can be positive or negative depending on the type of clay in a given site or the growing conditions of a given year. For example, the relationships between a soil EC map and yield were not consistent and varied from field to field due to varied subsoil or soil drainage (Kitchen et al., 2003).

Inexpensive and densely measured soil EC and topographical attributes were widely used to explain yield variability (Kravchenko and Bullock, 2000; Kitchen et al., 2003; Jaynes et al., 2003) and identify management zones (Chang et al., 2003; Taylor et al., 2003; Godwin et al., 2003; Larson, 2001). Available historical yield data could also provide useful information about yield spatial variability and potential management zones (Lark and Stafford, 1997; Dobermann et al., 2003; Jaynes et al., 2003; Perez-Quezada et al., 2003). Additionally, yield maps can be used in conjunction with soil and landscape information to help growers account for yield variability and provide insight into improving production.

Characterizing spatial variation of field conditions, including EC and topography, and exploring the relationships between yields and the underlying factors will provide essential information for decision-making on site-specific management. Emerging applications of advanced statistical procedures such as cluster analysis could be used to identify management zones within fields and predict temporal yield patterns.

Cluster analysis was widely used to reveal patterns of soil homogeneity and for identifying relationships among soil properties and landforms (Young and Hammer, 2000). In recent years, cluster analysis of historical yields has been used to develop nutrient management zones (Fleming et al., 1999; Taylor et al., 2003) and economic profit management zones (Blackmore et al., 2003). Combining yield maps, aerial imagery, topography, and past management experience, enabled growers to develop effective variable rate fertilizer application maps (Fleming et al., 1999). Perez-Quezada et al. (2003) reported that yield of one crop was a poor predictor of yield of crops grown in different years, but after standardizing and averaging the yields, areas with the same average performance tended to be clustered together spatially.

I used 8-year yield data and detailed topographical and EC information from a 50 ha area, to understand the yield-topography and yield-EC relationships and their effect on yield variability. With this understanding it might be possible to predict early in the season the extent and strength of spatial continuity in crop yield distribution and provide recommendations for producers' decisions regarding size and location of potential management zones. The objectives of this study were, (i) to characterize relationship between yield and soil electrical conductivity (EC), and topographical features; (ii) to evaluate temporal yield variability under different precipitations during a multi-year period; and (iii) to identify spatial clusters from historical yield data, and relate the clusters to the underlying soil EC, and topographical factors, and to validate whether cluster groups can be used to accurately predict yield patterns.

MATERIALS AND METHODS

Field and Data Description

The study was conducted in two adjacent fields on Carr farm in Kalamazoo County, Michigan (42.22 N, 86.36 W). Field 1 was about 30 ha, and Field 2 was about 20 ha in size. The predominant soil type is Kalamazoo loam (fine-loamy, mixed, mesic Typic Hapludalf), with 0 to 6% slopes (Austin, 1979, Kalamazoo County Soil Survey, Michigan). The site was non-irrigated and a minimum tillage system was employed (Jiang and Thelen, 2004). Crop rotation sequences in these fields are shown in Table 3.1.

Table 3.1. Crop rotation sequences in the study sites (NA: data not available)

Year	1996	1997	1998	1999	2000	2001	2002	2003
Field 1	corn	soybean	corn	soybean	corn	corn	soybean	corn
Field 2	NA	corn	NA	corn	NA	corn	soybean	corn

Corn and soybean yield data were recorded using a commercial yield monitor mounted on a combine. Latitude and longitude for yield data points were recorded simultaneously by a GPS receiver. Each point measurement covered an area of about 2- by 5-m. In Field 2, because of malfunction monitor, yield data in 1996, 1998, and 2000 were not available. The yield data that were more than 3 standard deviations away from the means were considered to be outliers and excluded from further analyses. The yield point measurements were interpolated to regular 10- by 10-m grid with inverse distance weighting method using ArcView Spatial Analyst (ESRI, 2000). For better yield comparison among different crops, the original corn and soybean yield data were standardized according to Blackmore (2000) and Perez-Quezada et al. (2003).

$$Y_{si} = R_{si} / Y_s. \qquad [1]$$

where Y_{si} is the standardized yield of the i^{th} cell in the s^{th} year, R_{si} is the actual yield for the i^{th} cell in the s^{th} year, Y_s is average field yield in that year. The $Y_{si} = 1$ means the yield in the cell is equal to the average yield in the field in the s^{th} year.

Georeferenced EC measurements were taken in each field using Veris 3100 sensor that operates on a principle of electromagnetic induction (Lund et al., 2001). The measurements were taken every 3- to 5-m, along transects 10 m apart. Two sets of EC measurements were collected, corresponding to depths of approximately 0- to 30-cm (shallow EC, ECvsh) and 0- to 90-cm (deep EC, ECvdp). The irregular point measurements of EC were interpolated to regular 10- by 10-m grid with inverse distance weighting method using ArcView Spatial Analyst.

Elevation was measured with a real-time kinetic GPS system mounted on a cart. The measurements were taken approximately every 5- by 10-m. Irregular point measurements of elevation was interpolated to regular 10- by 10-m digital elevation model (DEM) with inverse distance weighting method using ArcInfo Grid (ESRI, 2000). The primary topographical features, slope, curvature, flow direction, and flow accumulation, were derived from the DEM using corresponding functions in surface hydrologic analysis of ArcInfo GRID. Soil wetness index (WI) was calculated according to Moore et al. (1993):

$$WI = \ln(A_s / \tan \beta) \qquad [2]$$

where A_S is the upslope area derived from flow accumulation and tan β is a tangent function of the slope when measured as percent-rise. Daily precipitation data from 1996 to 2003 were obtained from an automated weather station located about 10 miles from the study site (KBS LTER Site Weather Station, 42° 24' 33" N, 85° 22' 18" W). The monthly (March to August) precipitation values from 1996 to 2003 (Fig. 3.1) were used to relate yield variation to precipitation across years. I created 10- by 10-m grid for the 2 fields using Spatial Analyst of ArcView. Each grid cell contained yield, soil EC, and topographical variables. The data sets then were exported from ArcView for statistical analysis.

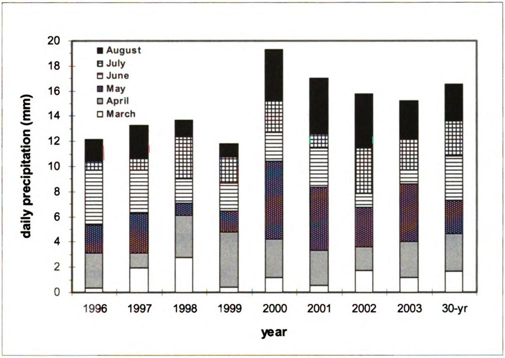


Fig. 3.1. Daily average precipitation from March to August in the study years

Data Analysis

Correlation and Regression Analysis

Descriptive statistics for raw yield, EC, and topographical variables were calculated by SAS PROC MEANS (SAS Inst., 2000). Spearman rank correlation coefficients were employed to measure the association between yield data among years. Spearman correlation (r_s) is a nonparametric measure of association based on the ranks of the data values. The r_s is calculated as:

$$r_s = 1 - \frac{6\sum_{i=1}^{n}(Ri,j - Ri,j')^2}{n(n^2 - 1)} \qquad [3]$$

where $R_{i,j}$ is the rank of the variable $S_{i,j}$ observed at location i on year j, and $R_{i,j'}$ the rank of the same variable, at the same location, but on date j', n is the number of the observations. The r_s can take values from -1 to 1.

Unlike Pearson correlation analysis, the r_s does not require any assumptions about the distribution of the values and independence of data sets. Yield data collected as time series in this studies were not totally independent. Spearman correlation analysis was superior compared with Pearson correlation analysis and has been widely used for temporal stability analysis (Vachaud et al., 1985; Cassel et al., 2000; Van Pelt and Wierenga, 2001). Pearson correlation coefficients were calculated between yields and soil EC or topographic variables. The SAS PROC CORR was used to compute Spearman rank and Pearson correlation coefficients.

Relationships between yields and precipitations were analyzed using regression techniques. Standardized yields combined from two fields were used as a dependent variable. Monthly or seasonal precipitations were used as independent variables. Totally, 13 paired standardized yield and precipitation data were used for the simple linear and quadratic regression analyses. The SAS PROC REG was used to fit the regression model and compute regression coefficients.

Cluster Analysis

Cluster analysis is used to classify individuals into two or more uniquely defined subgroups called clusters. Within a cluster, the individuals have similar characteristics with respect to the measured variables. However, the characteristics of individuals are not similar to those in the other clusters (Johnson, 2000). In this study, each cluster represents a certain area of the land with certain patterns of crop yield performance over the studied years. When the information from cluster analysis is obtained, the underlying factors for each cluster can be analyzed and recommendation for managing the field site-specifically to obtain highest profit can be made.

The principle of cluster analysis is to minimize within-group variability while maximizing among-group variability in order to produce relatively homogeneous groups that are distinct from one another. The analysis is based on similarity between two observations. The similarity measures Euclidean distance d(x, y) between two p-dimensional observations of x and y observations. The p is the number of measured variables on each individual.

$$d(x,y)=\sqrt{(x-y)'(x-y)} \qquad [4]$$

There are number of methods to group individuals into clusters. But all are based on the distance.

In this study, 8-year yield data from 2775 cells in Field1, and 5-year yield data from 2133 cells in Field 2 were used in a disjoint nonhierarchical cluster analysis using SAS PROC FASTCLUS procedure (SAS Inst., 2000). The clustering algorithm attempts to group the yield cells into clusters with high internal homogeneity and high between-group heterogeneity. The clustering algorithm groups each yield cell such that it belongs to one and only one cluster. A k-means method was used where the cluster centers are based on a least sum-of-squares estimation (SAS help, SAS Inst., 2000).

Cluster analysis was run multiple times with different numbers of clusters in order to determine the optimum number of clusters for the studied fields. Specifically, I considered analyses with two, three, four, five, six, seven, and eight clusters. The criteria that I used to estimate the best number of clusters were cubic clustering criterion (CCC) and approximate expected over-all R^2 (Khattree and Dayanand, 2000). The CCC has been developed by the SAS Institute and measures the deviation of the clusters from the distribution of points that would be expected if the points were actually from a uniform distribution (Sarle 1983). The CCC is used to estimate the number of clusters based on minimizing the within cluster sum of squares. It is obtained by comparing the observed R^2 to the approximate expected R^2 using an approximate variance stabilizing transformation.

$$CCC = \ln[\frac{1-E(R^2)}{1-R^2}] * K \qquad [5]$$

where $E(R^2)$ is expected R^2, and K is the variance stabilizing transformation. The higher CCC values indicate better clustering. The R^2 is the goodness-of-fit measure resulting from regressing a variable against the cluster means, calculated as a ratio of sum square of regression to sum square of total (Sarle 1983). This statistics increases with increasing number of clusters. It represents the proportion of variance explained by the clusters.

RESULTS AND DISCUSSION

Descriptive Statistics and Data distribution

Corn-soybean grain yields at the two studied Fields varied substantially from year to year within the studied period (from 1996 to 2003) (Table 3.2). In Field 1, the highest corn yield of 10.94 Mg ha^{-1} occurred in 2003, and lowest yield of 6.64 Mg ha^{-1} in 1996. The greatest variation of corn yield within the field was observed in 2003, followed by 1996. The lowest yield variation was in 1998. The order of soybean yield from high to low was 2002, 1997, and 1999. The standard deviations of soybean yield followed the same order. In Field 2, the average corn yield ranged from 10.56 to 7.58 Mg ha^{-1}. The highest yield was in 2003, followed by 1997, 1999, and 2001. Only 1 year soybean yield data were available in this field (Table 3.2).

The average standardized yields appear to be similar in both Fields (Table 3.2, Fig. 3.2). However, Field 2 had higher standard deviation of yield than Field 1 (Table 3.2, Fig. 3.3), which could be explained by higher variability of topographic features (Table 3.3, Figs. 10a, 10c, 11a, and 11c). Within-field variation in EC and topographic features for the two Fields is compared in Table 3.3. The average EC was higher in Field 1 than in Field 2. The average and range of elevation for the two Fields were similar. In addition, Field 2 appeared to have steeper slopes with the slopes in Field 2 ranging from 0.02 to 9.58° while in Field 1 from 0.03 to 7.08°.. In general, steep slopes and varied elevations tend to result in more runoff and greater variability in soil water distribution within a field (Moore et al., 1988; Lark and Stafford, 1997; Jiang and Thelen, 2004). In dry year, more water may be available at low elevations and flat areas, benefiting crop growth there. However, in wet year, low elevation areas could retain excessive water, potentially negatively affecting crop growth. This could be the reason why yields in Field 2 were more variable than in Field 1.

Table 3.2. Statistical summary of raw and standardized yields from 1996 to 2003 in two Fields

			Yield Mg ha^{-1}		Standardized yield	
	Crop	**Year**	**Avg.**	**Std. Dev.**	**Avg.**	**Std. Dev.**
Field 1	**Corn**	1996	6.64	0.91	0.73	0.14
	Soybean	1997	2.6	0.33	0.90	0.13
	Corn	1998	10.18	0.71	1.13	0.07
	Soybean	1999	2.29	0.28	0.79	0.12
	Corn	2000	9.59	0.81	1.06	0.08
	Corn	2001	7.79	0.75	0.86	0.10
	Soybean	2002	3.29	0.49	1.14	0.15
	Corn	2003	10.94	1.39	1.21	0.13
Field 2						
	Corn	1997	9.2	1.73	1.02	0.19
	Corn	1999	8.83	2.1	0.98	0.24
	Corn	2001	7.58	1.28	0.84	0.17
	Soybean	2002	3.39	0.56	1.17	0.17
	Corn	2003	10.56	2.03	1.17	0.19

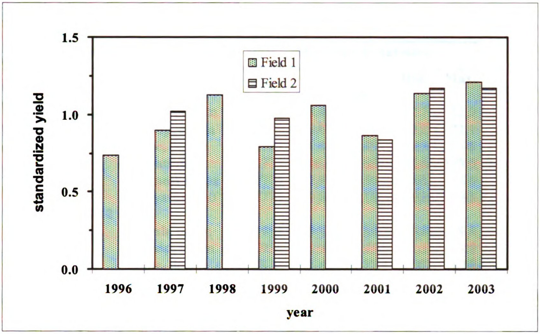


Fig. 3.2. Standardized yields in 2 Fields from 1996 to 2003

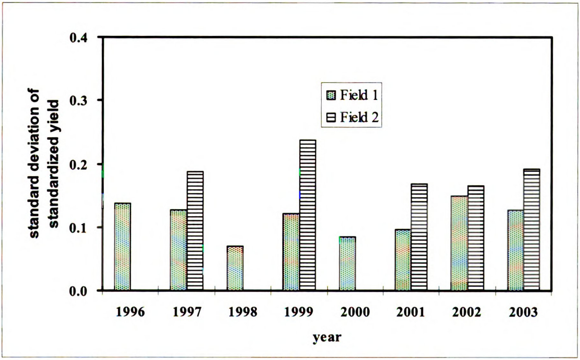


Fig. 3.3. The standard deviation of standardized yields in 2 Fields from 1996 to 2003

Table 3.3. Statistical summary of EC and topographical variables in two Fields.

Fields	Variables	N	Avg.	Std. Dev.	Min.	Max.
Field 1	**ECvsh**[¶], mS/m	2637	8.45	1.78	2.7	22.9
	ECvdp, mS/m	2637	6.67	1.96	3.2	22.1
	Slope, degree	2775	1.48	0.89	0.03	7.08
	Elevation, m	2775	298.0	2.88	292.6	303.0
	Wetness Index	2775	7.99	1.50	5.05	14.6
	Curvature, 10^{-2} m	2775	0.00	0.18	-1.88	5.65
Field 2						
	ECvsh, mS/m	1951	5.10	2.89	0.8	18.8
	ECvdp, mS/m	1951	5.98	2.75	1.1	18.9
	Slope, degree	2133	1.43	1.12	0.02	9.58
	Elevation, m	2133	298.6	2.93	291.4	302.6
	Wetness Index	2133	7.46	1.42	4.30	14.3
	Curvature, 10^{-2} m	2133	0.00	0.29	-5.62	3.13

[¶] ECvsh: shallow electrical conductivity; ECvdp: deep electrical conductivity.

Yield/precipitation relationship

Analyses of the growing season monthly precipitation and average yield data across years showed that high corn yields were often associated with normal or higher July precipitation (Fig. 3.1 and Fig. 3.4). Lower corn yields, such as in 1996 and 2001 in Field 1 were coincident with drier July (Table 3.2 and Fig. 3.1). Similarly, lower soybean yields in 1997 and 1999 coincided with drier July and August. Because corn and soybean are in reproductive period in July, crop growth and yields are very sensitive to soil water stress. Drought can cause remarkable yield loss in these nonirrigated fields.

Figure 5 shows the relationship between 8-yr standardized yields (2 crops and 2 Fields combined) and total precipitation of March and April. The relationship was best fit with a quadratic curve with R^2 of 0.68 (p-value $\leq$0.01). The data point of 1998 located in the far right side was considered to be an outlier and was excluded from the regression analysis. Year 1998 had very high spring precipitation and unusually high air temperature, which produced higher yield than what could be expected based on typical temperatures. The curve demonstrates that crop yield increased with the increase of early spring rainfall before reaching the peak at 119.9 mm precipitation. Then, as precipitation increased further yield gradually decreased. High yield required appropriate spring rainfall. Based on this regression equation, total rainfall in March and April should be between 105 and 135 mm in order to reach optimal yield. The estimation is within the range of water requirements of corn and soybean production in Midwest (Hoeft et al., 2000). The results suggested that either low or excessive spring precipitation tends to decrease yield by delaying planting and seed emergence (Lark and Stafford, 1997). Less rain can cause drought stress for seed emergence and growth. On other hand, excessive rain can saturate soil leading to undesired crop growth condition, such as lower soil temperature, and increased erosion that will severely affects early crop growth. The standardized yields had very little increase with the increase of growing season (May to August) rainfall (Fig. 3.6).

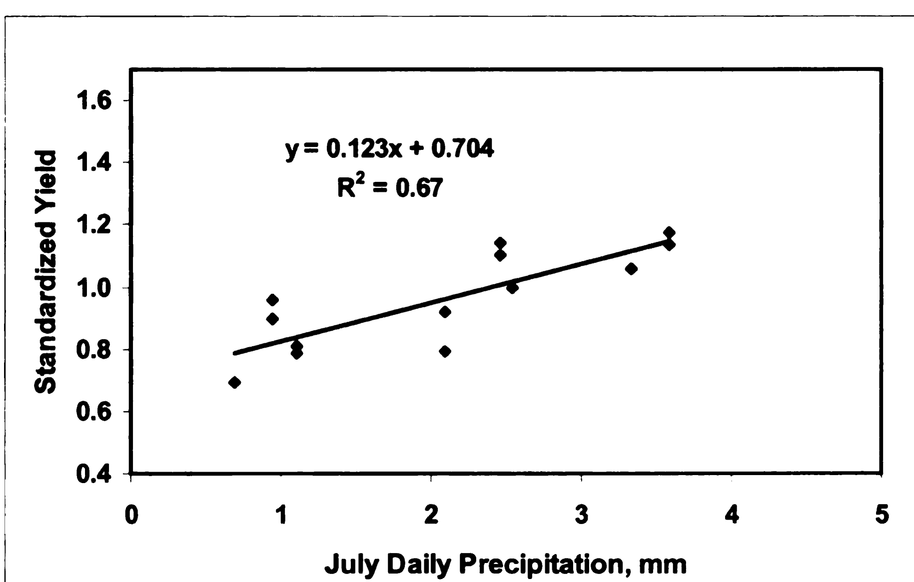


Fig. 3.4. Standardized yields vs. July daily precipitation over 8 years (2 crops and 2 Fields combined)

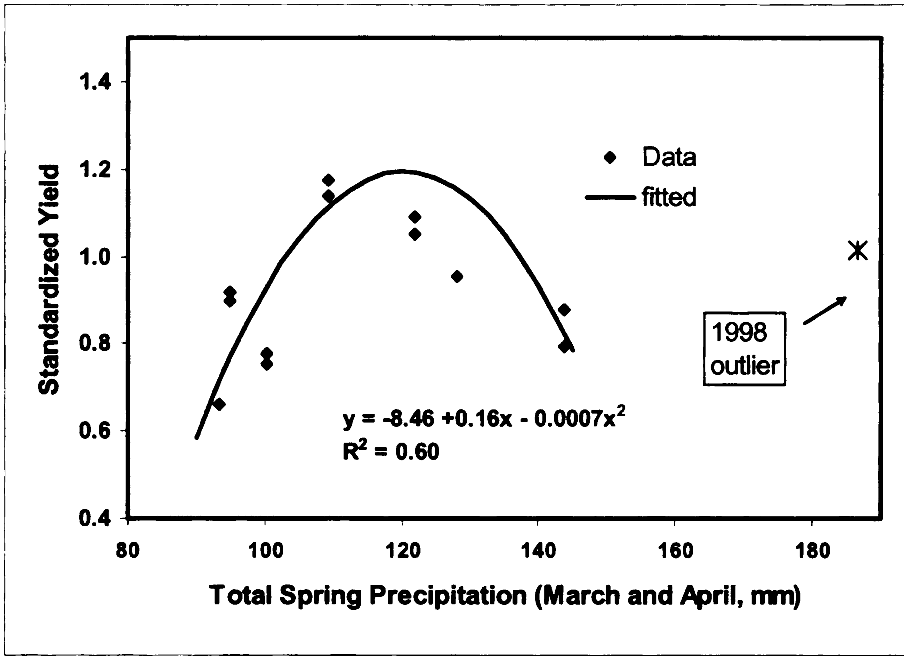


Fig. 3.5. Standardized yield vs. total precipitation of March and April (2 crops and 2 Fields combined)

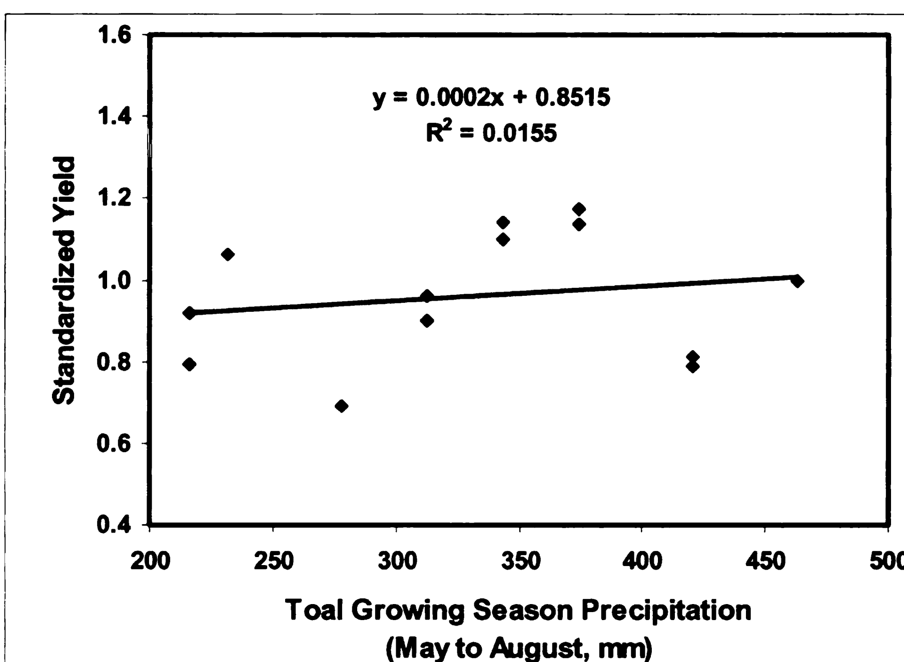


Fig. 3.6. Standardized yields vs. total growing season (May to August) precipitation over 8 years (2 crops and 2 Fields combined)

Spearman Correlation Coefficients among Yields

All Spearman correlation coefficients (r_s) between crop yields in two fields from 1996 to 2003 were positive and statistically significant at probability p $\leq$0.01 level (Table 3.4). The r_s between corn yields ranged from 0.1 to 0.58. The highest r_s occurred between 1996 and 2001 corn yields which both were dry in July. Extremely dry weather during the key growth period probably was the dominant yield limiting factor, while in normal or wet year, the weather factor could be minimal in affecting yield. Thus, yields from years with optimal weather conditions are likely to be only weakly related. The r_s between soybean yields varied from 0.20 to 0.35. The range of r_s between the soybean and the corn yields were from 0.12 to 0.40. There was no evidence that r_s between the same crops are lower than that between different crops. Significant r_s suggested that yield of corn or soybean grown at the same location in one year could serve as indicators of yield performance for one another in other years. However, correlation with quite low value of the correlation coefficient was statistically significant due to the very large number of data points in the studied data sets, even though it explained only a small portion of yield variability. Similar observation was also made by Kitchen et al. (2003). Perez-Quezada et al. (2003) reported that yield of one crop was a poor predictor of yield of crops grown in different years while they studied wheat–tomato–bean–sunflower rotation.

Table 3.4. Spearman Correlation Coefficients between Yields from 1996 to 2003 in two Fields.

Year	Crop	1997	1998	1999	2000	2001	2002	2003
Field 1		**Soybean**	**Corn**	**Soybean**	**Corn**	**Corn**	**Soybean**	**Corn**
1996	**Corn**	0.25§	0.41	0.53	0.45	0.58	0.34	0.23
1997	**Soybean**	1.00	0.15	0.35	0.12	0.15	0.20	0.22
1998	**Corn**		1.00	0.26	0.34	0.41	0.21	0.21
1999	**Soybean**			1.00	0.39	0.34	0.29	0.20
2000	**Corn**				1.00	0.28	0.27	0.18
2001	**Corn**					1.00	0.40	0.25
2002	**Soybean**						1.00	0.32
Field 2		**Corn**		**Corn**		**Corn**	**Soybean**	**Corn**
1997	**Corn**	1.00		0.41		0.40	0.40	0.22
1999	**Corn**			1.00		0.56	0.29	0.23
2001	**Corn**					1.00	0.34	0.22
2002	**Soybean**						1.00	0.36

§correlation coefficients are significant at *p*-value < 0.01 level.

Still, in this study, Spearman correlation coefficients had the same signs in all year yields indicating that the yields in corn-soybean rotation were somewhat spatially stable across years with varied weather. The stable variability of crop yield over time suggested that management zones within the field are practically possible for site-specific farming. This information will provide opportunity for further investigation of yield limiting factors. However, single-factor correlation analysis provides very little direct evidence for the cause of yield variation, thus it needs to be combined with other analyses to provide better understanding about the yield stability across years.

Pearson Correlation Coefficients among Yield, EC and Topography

Pearson correlation coefficients between soil EC, topography and yields across years in Field 1 and 2 are shown in Table 3.5. In most of the years, EC at shallow depth was negatively correlated with yield. Conversely, EC at large depth was positively correlated with yield in 5 out of 8 years. In these fields, higher portion of gravel and sand contents were observed in top 24 cm depth (Jiang, 2002). The deeper soil contains higher portion of clay contents. The difference in relationships between yield and shallow and deep EC could be attributed to varied soil texture and other physical or chemical properties from shallow to deep horizon. Clearly, shallow EC mainly represents soil texture. However, the direction of correlation coefficients between yield and shallow or yield and deep EC were consistent (Sudduth et al., 1996; Kitchen et al., 2003). Their fields had relatively uniform texture in the soil profile compared with glacial tilled soil of this study.

Table 3.5. Pearson Correlation Coefficients between EC, topographical variables and yield from 1996 to 2003 in two Fields.

Year	Crop	Ecvsh[¶]	Ecvdp	Ele	Slope	Curv	WI
Field 1							
1996	**Corn**	-0.16[§]	0.06	0.16	-0.07	-0.22	0.22
1997	**soybean**	-0.12	NS	0.15	NS	0.06	-0.05
1998	**Corn**	NS	0.14	-0.17	-0.17	-0.07	0.15
1999	**soybean**	-0.18	0.05	0.16	NS	-0.10	0.09
2000	**Corn**	NS	0.13	NS	NS	NS	NS
2001	**Corn**	-0.11	0.05	0.06	-0.10	-0.13	0.14
2002	**soybean**	-0.14	-0.09	0.15	-0.13	NS	NS
2003	**Corn**	-0.10	NS	0.17	-0.08	NS	0.09
Field 2							
1997	**Corn**	-0.26	NS	0.21	-0.30	-0.16	0.17
1999	**Corn**	-0.11	NS	NS	-0.24	-0.27	0.35
2001	**Corn**	NS	0.20	-0.12	-0.35	-0.17	0.34
2002	**Soybean**	-0.10	0.08	NS	-0.26	NS	0.05
2003	**Corn**	-0.19	NS	0.14	-0.25	-0.06	0.14

¶ ECvsh: shallow electrical conductivity; ECvsh: deep electrical conductivity; ele: elevation; curv: curvature; WI: wetness index. §correlation coefficients are significant at p-value < 0.01 level. NS indicates statistically non-significant.

Kitchen et al., (2003) noted that crop type and climate can produce very different correlation coefficients between yield and EC from year to year. They speculated that higher EC is associated with factors such as poor drainage and high-clay-content subsoils that restricts root growth. Kravchenko et al. (2003) found that variations in the strength and direction of the relationship between yield and soil EC were related to the amounts of precipitation observed early in the growing season. I did not find this kind of relationship in this study.

In Field 1, in 6 out of 8 years elevation was positively correlated with yield (Table 3.5). The Field is about 2000 m from Kalamazoo River. The condition of available soil water in this field is good because of relative low ground water table. As a result the areas with high elevation had other favorable conditions such as high soil temperature for crop growth. The relationship was negative in 1998 and not significant in 2000. Those negative or zero correlation coefficients could be related to rainfall amounts. Less than normal in August in 1998 could be responsible for negative relationship between yield and elevation (Fig. 3.1 and Table 3.5). Low elevation areas had higher soil water storage in dry weather. This resulted in high yield in low elevation compared with high elevation. In 2000, the precipitations from June to August were close to 30-year average, the correlation coefficients between yield and elevation was not significant. The elevation effect on yield in normal precipitation year, such as 2000, was minimal.

In Field 2, the relationship between yield and elevation were positive in 1997 and 2003, negative in 2001, and not significant in 1999 and 2002 (Table 3.5). Kaspar et al. (2001) found that in years with less than normal growing season precipitation, corn yield was negatively correlated with relative elevation, slope, and curvature. Conversely, in years with greater than normal precipitation, yield was positively correlated with relative elevation and slope. In this field, higher elevation areas are relative flat located at southern part of the field. But low elevation areas in northern field are with high slopes. The relationship between elevation and yield were more variable and could be affected by slope. There were more interactions between elevation and precipitation due to greater topographical variations in Field 2.

Slope had a significant negative correlation with yields in 5 out of 8 years and no relationship in rest of 3 years in Field 1 (Table 3.5). The similar result was also found in several previous studies (Ciha, 1984; Kravchenko and Bullock, 2000; and Jiang and Thelin, 2004). Steep slope positions tend to have more severe water erosion. As a result of thinner surface horizon and lower soil productivity in steep slope areas, the yields there are often low. Consistently negative correlation coefficients between slope and yields were observed across years in Field 2 (Table 3.5). Slope range in Field 2 was 2.5 degree larger than Field 1. As a result, slope played more important role in crop yield in Field 2.

Correlation coefficients between curvature and yields were negative in most years. The areas with negative curvature (concave shape) could provide more plant-available water than the areas with positive curvature (convex shape). The relationships between curvature and yields were similar to those between slope and yields. Kravchenko and Bullock (2000) found that the relationship between curvature and yields could change the direction depending on drought and wet weather. But the strength of the relationship between curvature and yields was generally weaker in this study. The differences in yield-curvature relationships in dry or wet years were not obvious in this study as compared with their finding.

Yields were positively correlated with soil wetness index in most years in both fields. Previous studies have found soil wetness index to be positively associated with soil water content (Schmidt, and Persson, 2003). High values of the wetness index are often present in converging and flat terrain, while low values were typical for steep and diverging areas (Schmidt, and Persson, 2003). This is understandably because wetness index is an inverse function of the slope. Steep slope positions generally have low infiltration rate and less fine particle content and less available water stored in soil (Moore et al., 1988; Wright et al., 1990; Moore et al., 1993). As a result, yield was low in areas with low wetness index not only caused by less available water, but also unfavorable topographical features. The relationship between wetness index and soybean yield on the whole was weaker than that between wetness index and corn. This could be reflecting the greater water consumption by corn than by soybean (Hoeft et al., 2000), which makes corn to be more sensitive to field soil moisture than soybean.

Yield Classification by Cluster Groups

Figure 7 shows plots of CCC and R^2 versus the number of clusters in Field 1. These plots were used to make a decision on optimum cluster number. The highest CCC value corresponding 2 clusters was equal to 47 with R^2 value equal to 0.19. This R^2 was considered to be too small to explain variation of clustering if 2 clusters were chosen. The second highest CCC values in Field 1 and Field 2 were obtained when the numbers of clusters were 5 and 4, respectively (the plots of CCC and R^2 versus the number of clusters in Field 2 was not shown). The corresponding R^2 were 0.37 and 0.43. Therefore, 5 clusters were considered to be the optimum number of clusters in Field 1 and 4 to be the optimum number of clusters in Field 2. Then, each of the total 2775 yield cells in Field 1 was assigned to one of the five clusters and each of the 2133 yield cells in Field 2 was assigned to one of the four clusters. The yields in the cells within each cluster were more similar to one another than to the cells from the other clusters. Dobermann et al.

(2003) also studied the classification of yield variability in irrigated fields using cluster analysis. They suggested that the classification is improper if less than 50% of the yield variability is accounted for and the number of clusters is less than five. However, for an undulating and rainfed field, such as the fields of this study, this suggestion may not be applicable. Varied topography greatly influenced the soil water distributions within a small field area during the studied years. The available soil water could be highly associated with elevation and curvature. The relationship can change the direction and strength depending on dry or wet weather conditions. As a result, it was not possible to get higher proportional variation explained by the classification.

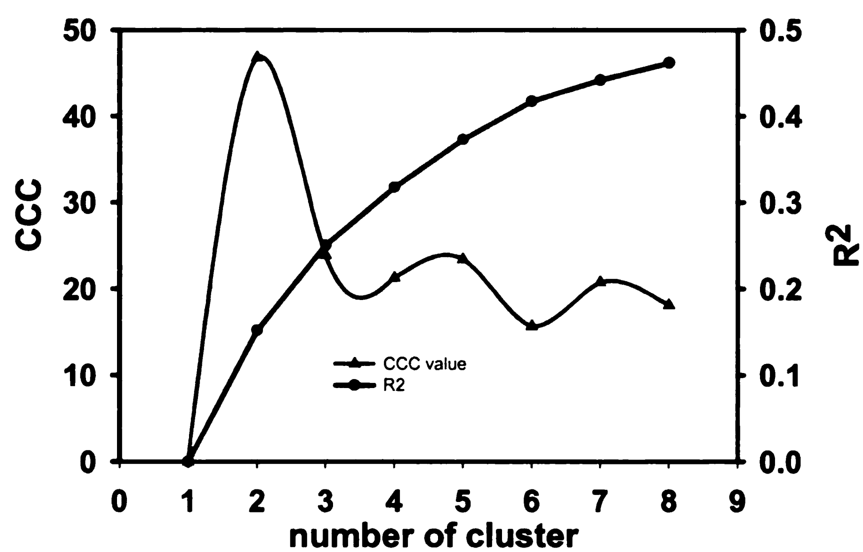


Fig. 3.7. The cubic clustering criterion (CCC) and over-all R^2 vs. number of cluster in Field 1

Figures 8 and 9 showed average standardized yields and their standard deviations by year for each cluster in the two fields. As expected, there were clusters with consistently high and low yields over years for each field. In Field 1, yields in clusters III and V were above the average yield in most of the years (Table 3.6). Clusters III and V occupied about 34 and 15 % of the field. The yields in clusters I and IV were below the average. They occupied about 10 and 11 % of the field. The yields in cluster II fluctuated around the average and accounted for 30 % of the total area. In Field 2, yields were consistently high in cluster IV, and low in cluster II (Table 3.6). They accounted for 46 % and 10 % of the total field area, respectively. The yields in clusters I and III were near average. The above clustering showed that yield patterns were stable over time. The occurrence of spatially homogenous yield areas over time encourages the application of site-specific management techniques.

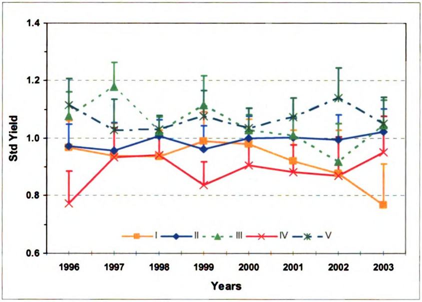


Fig. 3.8. Average standardized yields from 1996 to 2003 in Field 1. The length of vertical bars is equal to the cluster standard deviation. To avoid clutter in the figure, the bars are shown only on one side (top) of each average.

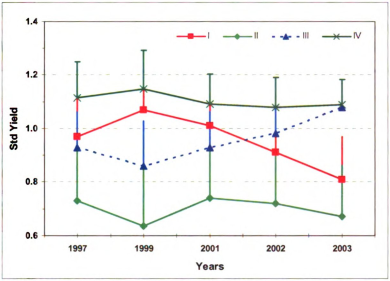


Fig. 3.9. Average standardized yields and their standard deviations represented by vertical bars for each cluster from 1997 to 2003 in Field 2.

Factors Underlying Yield Clusters

The homogeneity of yield clusters could be related to some underlying field factors. Finding the factors related to the yield patterns is helpful for practical applications in site-specific farming. I examined characteristics of topographical and EC variables in different yield clusters. Clearly, high shallow EC values corresponded to low yield clusters in both fields (Tables 6 and 7). Conversely, low EC values corresponded to high yielding clusters. The results agreed with the analysis of correlation coefficients between shallow EC and yield (Table 3.5). Other studies demonstrated that in not saline field soil EC was mainly affected by texture (Lund et al., 1999). In this field, shallow EC was believed to be positively associated with sand content. High EC area represents coarser-textured soils. Correspondingly, yield in those areas were low. Deep EC did not show a consistent trend among clusters (result not shown).

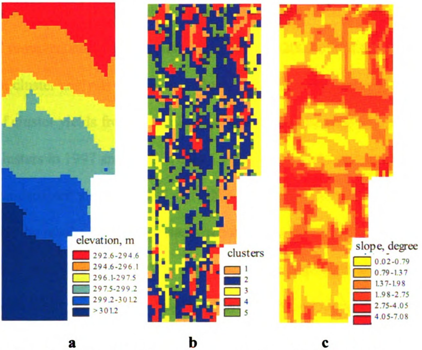
Table 3.6. Means of topographical variables and EC by cluster in Field 1 and 2
(Cluster III and V are high, II is average, and I and IV are low yield in Field 1; Cluster IV is high, I and III are average, and II is low yield in Field 2)

Field 1						**Field 2**			
Cluster	**I**	**II**	**III**	**IV**	**V**	**I**	**II**	**III**	**IV**
Cells	**281****	**818**	**953**	**308**	**415**	**332**	**211**	**577**	**953**
% Variables*	**10**	**30**	**34**	**11**	**15**	**16**	**10**	**28**	**46**
ele	298.0	297.8	298.5	297.3	298.5	298.2	297.2	299.1	298.7
slope	1.81	1.43	1.60	1.52	1.36	1.60	2.43	1.55	1.10
curv	0.00	0.01	-0.02	0.05	-0.03	-0.04	0.07	0.07	-0.05
wi	7.66	8.02	8.01	7.55	8.28	7.40	6.78	6.98	7.87
ECvsh	7.00	6.91	6.41	6.98	6.26	5.38	7.13	4.92	4.67

*ele: elevation (m); curv: curvature (10^{-2} m); wi: wetness index; ECvsh: shallow EC (mS/m); ** numbers of field map cells occupied by each cluster.

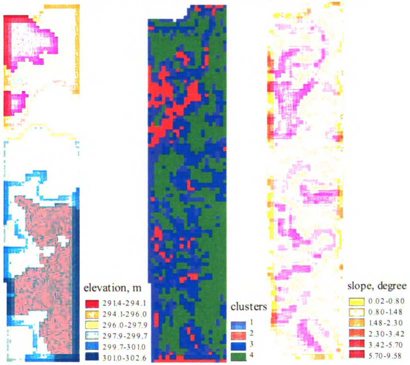
Generally, the most important effect of topography on yield consisted of governing soil water distribution within a field. The yield:topography relationship is complex, particular in large fields and under varying climate conditions. Average values of elevation for 5 clusters in Field 1 and 4 clusters in Field 2 were similar (Tables 6). Overall, the elevation itself did not play an important role on yield spatial distribution in the studied fields. Figures 10 and 11 showed a pattern of elevation decreasing from south to north in both fields. Yield clusters did not follow a similar pattern. High as well as low yield clusters were scattered around the fields.

The yield clusters appeared to be associated more with slope (Figures 10 and 11). Slope, curvature, and wetness index explained more variation of yield patterns (Table 3.6). Greater slope and positive curvature values coincided with lower yield cell clusters. Smaller slopes and negative curvature values occurred at high yield clusters. A steeper slope results in increasing water flow and a greater potential for erosion. Negative curvature indicates a concave surface which leads to decreasing flow and particle deposition. Higher wetness index coincided with high yield cell clusters. Abundant but not excessive soil water benefits plant growth and increases yield.



a b c

Fig. 3.10. Elevation (a), yield clusters (b), and slope (c) in Field 1.



a b c

Fig. 3.11. Elevation (a), yield clusters (b), and slope (c) in Field 2.

Yield Prediction from Cluster Groups

To further check accuracy of cluster analysis in predicting yield patterns, a separate independent testing of cluster prediction performance was conducted. For that purpose, I removed standardized yields for 1997 and 2002 out of the data sets for the two fields. The cluster analysis was then conducted using the remaining yield data. The average of cluster yields from the rest of the years could be used as a prediction for yield of these clusters in 1997 and 2002. Table 3.7 shows the yield cell means by cluster and the real standardized yields in 1997 and 2002. The real yield patterns in the two fields agreed with the results from the cluster analysis. This indicates that the high yielding cells of 1997 and 2002 indeed fell in the clusters with high yield as defined by the yield data from the other years and low yield fell in the clusters with the lower yield.

To facilitate comparison between actual and cluster-analysis predicted yields we grouped the clusters into three yield classes: high, medium, and low yielding. In Field 1, cluster II was labeled as a high yield class. Cluster IV was labeled as a low yield class. Clusters I, III, and V were labeled as a medium yield cell class. The areas of high, low and medium yield cells predicted from the cluster analysis for the 3 classes accounted for 30, 11, and 59 % of the total area of the field. In 1997 the actual high, low and medium yield cells accounted for 30, 17, and 53 % of the total area, respectively. In 2002, the proportions of the actual high, low and medium yield areas were 34, 16, and 50 %, respectively. Similarly good correspondences between overall sizes of areas with high, medium, and low yields in cluster analysis predictions and actual 1997 and 2002 yields were found in Field 2. High, medium and low yield patterns from cluster analysis were consistent with actual yield patterns. Figure 12 showed spatial distribution of the 3 yield cell clusters and actual standardized yields in 1997 and 2002 in Field 1. A number of misclassifications existed. However, large scale predictions obtained from the cluster analysis are considered to be reliable.

Table 3.7. Yield cell means by cluster in Field 1 and in Field 1 vs. the actual standardized yields in 1997 and 2002

			Cluster Means				Predicted Mean	Actual Means	
Field 1	**1996**	**1998**	**1999**	**2000**	**2001**	**2003**		**1997**	**2002**
Cluster									
I, N = 281	0.97	0.97	0.95	0.97	0.97	0.76	0.93	0.96	0.94
II, N = 818	1.14	1.04	1.07	1.04	1.08	1.06	1.07	1.04	1.08
III, N = 953	0.97	1.01	0.94	0.99	1	1.04	0.99	0.98	0.99
IV, N = 308	0.76	0.94	0.83	0.9	0.87	0.94	0.87	0.94	0.90
V, N = 415	1.01	0.98	1.14	1.03	0.96	0.99	1.02	1.04	0.99
Field 2									
Cluster									
I, N = 852			0.94		0.95	1.07	0.99	1.00	1.01
II, N = 823			1.19		1.12	1.05	1.12	1.07	1.12
III, N = 261			0.86		0.79	0.66	0.77	0.84	0.85
IV, N = 109			0.35		0.94	0.85	0.71	0.83	0.82

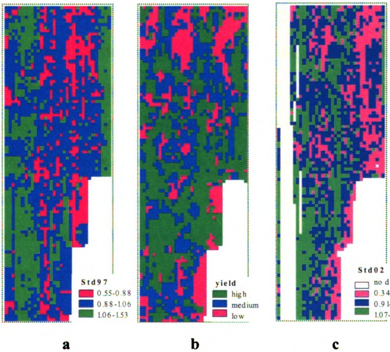


Fig. 3.12. Spatial distribution of standardized yields in 1997 (a) and 2002 (c) and 6-year yield clusters (b) in Field 1. Data in cells with light yellow in 2002 were missing.

SUMMARY

All Spearman correlation coefficient were positive and significant. The highly significant coefficient suggested that yield of one crop spatially could be a predictor of yield of crops grown in different years. In addition, stable yield variability over time can be helpful to delineate sub-areas within a field for site-specific management. The relationship between standardized yield and March and April precipitation exhibited a quadratic curve. The yield increased linearly with the increase of July precipitation. Roughly 60% of the yield variation can be explained by either March and April or July precipitation. In general, shallow EC and slope were negatively correlated with yield. The relationship between yield and deep EC was inconsistent. Wetness index was positively correlated with yield. The role of elevation on yield was inconsistent among years. These could be explained by varied precipitation among years. Consistently low, medium, and high yield cells were clearly identified using cluster analysis. The 4 to 5 yield clusters explained about 40% of the yield variation. Shallow EC values corresponded to high yield clusters in the studied fields. Elevation did not play an important role on spatial yield distribution. However, slope, curvature and wetness index values were closely associated with yield patterns. Greater slope and positive curvature values resulted in increased runoff. As a result, areas with higher slope and positive curvature values experienced lower water and nutrient availability which led to the observed decrease in crop yield. Historical yield data can be used to predict yield patterns. Corn and soybean grain yield predictions using cluster analysis on a large scale were found to be reliable.

REFERENCES

Austin, F.R. 1979. Soil Survey of Kalamazoo County, Michigan. United States Department of Agriculture, Soil Conservation Service, in cooperation with Michigan Agricultural Experiment Station. The Soil Conservation Service: Washington, DC.

Bakhsh, A., T.S. Colvin, D.B. Jaynes, R.S. Kanwar, U.S. Tim. 2000. Using soil attributes and GIS for interpretation of spatial variability in yield. Transactions of the ASAE. 43: 819-828.

Blackmore, S., R.J. Godwin, and S. Fountas. 2003. The Analysis of spatial and temporal trends in yield map data over six years. Biosystems Engineering. 84:455-466.

Cassel, D.K., O. Wendroth, and D.R. Nielsen. 2000. Assessing spatial variability in an agricultural experiment station field: opportunities arising from spatial dependence. Agron. J. 92:706-714.

Chang,J., D.E. Clay, C.G. Carlson, S.A. Clay, D.D. Malo, R. Berg, J. Kleinjan, W. Wiebold. 2003. Different techniques to identify management zones impact nitrogen and phosphorus sampling variability. Agron. J. 95: 6, 1550-1559.

Ciha,A.J. 1984. Slope position and grain yield of soft white winter wheat. Agron. J. 76:193-196.

Dobermann, A., J.L. Ping, V.I. Adamchuk, G.C. Simbahan, and R.B. Ferguson. 2003. Classification of Crop Yield Variability in Irrigated Production Fields. Agron. J. 95:1105-1120.

ESRI. 2000. ArcView 3.2 and ArcInfo. 8.1. ESRI, Redlands, CA.

Fleming, K.L., D.G. Westfall, D.F., Heermann, and J.V. Stafford. 1999. Farmer developed management zone maps for variable rate fertilizer application. In Rust-RH (ed.); the 2nd European Conference on Precision Agriculture, Odense, Denmark, pp 917-926.

Godwin, R.J., G.A. Wood, J.C. Taylor, S.M. Knight, and J.P. Welsh. 2003. Precision farming of cereal crops: a review of a six year experiment to develop management guidelines. Biosystems Engineering. 84:375-391.

Halvorson, G.A., and E.C. Doll. 1991. Topographic effects on spring wheat yields and water use. Soil Sci. Soc. Am. J. 55:1680–1685.

Heiniger, R.W., R.G. McBride and D.E. Clay. 2003. Using soil electrical conductivity to improve nutrient management. Agro. J. 95:508-519.

Hoeft, R. G., E.D. Nafziger, R.R. Johnson, and S.R. Aldrich. 2000. Modern corn and soybean production. MCSP Publications. Savoy, IL.

Jaynes, D.B., and T.S. Colvin. 1997. Spatiotemporal variability of corn and soybean yield. Agron. J. 89:30–37

Jaynes, D.B., T.C. Kaspar, T.S. Colvin, and D.E. James. 2003. Cluster analysis of spatiotemporal corn yield patterns in an Iowa field. Agron J. 95:574-586.

Jiang, P. 2002. Effects of properties and landscape features on a Michigan corn and soybean cropping system. M.S. Thesis. Michigan State University. East Lansing.

Jiang, P., and K.D. Thelen. 2004. Effect of soil and topographic properties on crop yield in a North-Central corn–soybean cropping system. Agron J. 96:252-258.

Johnson, D.E. 1998 Applied Multivariate Methods for Data Analysts. Duxbury Press.

Kaspar, T.C., T.S. Colvin, D.B. Jaynes, D.L. Karlen, D.E. James, D.W. Meek, D. Pulido, and H. Butler. 2003. Relationship between six years of corn yields and terrain attributes. Precision Agriculture 4:179-192.

Kaspar,T.C., D. J. Pulido, T. E. Fenton, T. S. Colvin, D. L. Karlen, D. B. Jaynes and D. W. Meek. 2004. Relationship of corn and soybean yield to soil and terrain properties. Agron. J. 96:700-709.

Khattree, R., and N.N. Dayanand. 2000. Multivariate Data Reduction and Discrimination with SAS Software. BBU Press and John Wiley Sons Inc.

Kitchen,N.R., S.T. Drummond, E.D. Lund, K.A. Sudduth, and G.W. Buchleiter. 2003. Soil electrical conductivity and topography related to yield for three contrasting soil–crop systems. Agron J. 95:483-495.

Kravchenko, A.N., and D.G. Bullock. 2000. Correlation of corn and soybean grain yield with topography and soil properties. Agron J. 92:75-83.

Kravchenko, A.N., K. D. Thelen, D. G. Bullock, and N. R. Miller. 2003. Relationship among crop grain yield, topography, and soil electrical conductivity studied with cross-correlograms. Agron J. 95:1132-1139.

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

Lark, R.M., and J.V. Stafford. 1997. Classification as a first step in the interpretation of temporal and spatial variation of crop yield. Ann. Appl. Biol. 130:111-121.

Larson, W.E. 2001. Variability of soil and landscape attributes within sub-field management zones. In Fridgen, J.J., N.P. Kitchen, K.A. Sudduth, P.C. Robert (ed.); Proceedings of the 5th International Conference on Precision Agriculture, Bloomington, Minnesota, USA. pp 1-16.

Lund, E.D., P.E. Colin, D. Christy, P.E. Drummond. 1999. Applying soil electrical conductivity technology to precision agriculture. Proc. the 4th International Conference on Precision Agriculture. ASA-CSS-SSSA,Madison,WI.

Machado, S. E. D. Bynum, Jr., T. L. Archer, R. J. Lascano, L. T. Wilson, J. Bordovsky, E. Segarra, K. Bronson, D. M. Nesmith, and W. Xu. 2002. Spatial and Temporal Variability of Corn Growth and Grain Yield Implications for Site-Specific Farming. Crop Science 42:1564-1576.

Moore, I.D., G.J. Burch, and D.H. Mackenzie. 1988. Topographic effects on the distribution of surface soil water and the location of ephemeral gullies. Transactions of the ASAE. 31:1098-1107.

Moore, I.D., P.E. Gessler, G.A. Nielsen, and G.A. Peterson. 1993. Soil attribute prediction using terrain analysis. Soil Sci Soc Am J. 57:443-452.Schmidt, F., A. Persson.2003. Comparison of DEM data capture and topographic wetness indices. Precision Agriculture. 4:179-192.

Perez-Quezada, J. F., G. S. Pettygrove, and R.E. Plant. 2003. Spatial–temporal analysis of yield and soil factors in two four-crop–rotation fields in the Sacramento Valley, California. Agron. J. 95:676-687.

Sarle, W.S. 1983. SAS Technical Report A-108: The Cubic Clustering Criterion. SAS Institute.

SAS Institute Inc. 1999. SAS/STAT User's Guide, Version 8. Cary, NC.

Schepers, A.R., J.F. Shanahan, M.A. Liebig, J.S. Schepers, S.H. Johnson and A. Luchiari, Jr. 2004. Appropriateness of management zones for characterizing spatial variability of soil properties and irrigated corn yields across years. Agron. J. 96:195-203.

Si, B.C., and R.E. Farrell. 2004. Scale-dependent relationship between wheat yield and topographic indices: a wavelet approach. Soil Sci. Soc. Am. J. 68:577-587.

Simmons, F.W., D.K. Cassel, and R.B. Daniels. 1989. Landscape and soil property effects on corn grain yield response to tillage. Soil Sci. Soc. Am. J. 53:534–539.

Stein, A., J. Brouwer, and J. Bouma. 1997. Methods for comparing spatial variability patterns of millet yield and soil data. Soil Sci Soc Am J. 61:861-870.

Sudduth, K.A., S.T. Drummond, S.J. Birrell, and N.R. Kitchen. 1996. Analysis of spatial factors influencing crop yield. p. 129–140. *In* P.C. Robert et al. (ed.) Precision agriculture. Proc. Int. Conf., 3rd, Minneapolis, MN. 23–26 June 1996. ASA, CSSA, and SSSA, Madison, WI.

Timlin, D.J., Ya Pachepsky, V.A. Snyder, and R.B. Bryant. 1998. Spatial and temporal variability of corn grain yield on a hillslope. Soil Sci. Soc. Am. J. 62:764-773.

Taylor, J.C., G.A. Wood, R. Earl, and R.J. Godwin. 2003. Soil factors and their influence on within-field crop variability, Part II: Spatial analysis and determination of management zones. Biosystems Engineering. 84:441-453.

Vachaud, G.A., A. Passerat de Silans, P. Balabanis, and M. Vauclin. 1985. Temporal stability of spatially measured soil water probability density function. Soil Sci Soc Am J. 49:822-828.

Van Pelt, R.S., and P. Wierenga. 2001. Temporal stability of spatial measured soil matric potential probability density function. Soil Sci Soc Am J. 65:668-677.

Wilson, J.P. and J.C. Gallant. 2000. Terrain analysis. John Wiley and Sons.

Wright, R.J., D.G. Boyer, W.M. Winant, and H.D. Perry. 1990. The influence of soil factors on yield differences among landscape positions in Appalachian cornfield. Soil Sci. 149:375-382.

Young, F.J., and R.D. Hammer. 2000. Defining geographic soil bodies by landscape position, soil taxonomy, and cluster analysis. Soil Sci. Soc. Am. J. 64:989-998.

CHAPTER IV

EFFECTS OF MANAGEMENT PRACTICES ON RELATIONSHIPS OF CORN, SOYBEAN, AND WHEAT GRAIN YIELDS WITH FIELD TOPOGRAPHY AND WEATHER

ABSTRACT

Crop yields are highly variable across fields and years as a result of complex interactions among topography, weather conditions, and management practices. The objective of this study was to analyze the effects of management practices on the relationship between crop yield and topography, yield and weather using 10-yr of yield data from a long-term corn (*Zea mays* L.)–soybean [*Glycine max* (L.) Merr.]–wheat (*Triticum aestivum* L.) rotation experiment in southwest Michigan. The 4 agronomic treatments used in this study are chisel plowed with conventional chemical inputs (T1), no-till with conventional chemical inputs (T2), chisel plowed with low chemical input and a winter leguminous cover crop (T3), and organic-based chisel plowed with a winter leguminous cover crop (T4). A nonparametric (spline) regression was used to characterize boundary line of yields, that are maximum yields, versus wetness index (WI). The algorithm was also used to compare the yield difference across the range of the WI between two treatments.

The results indicated that the yield differences between the management practices varied from year to year as a function of the prevailing precipitation and depending on the topographical position. Management practices significantly interacted with topographical attributes as represented by WI and influenced crop yields. The interaction

can be affected by summer precipitation. The yield difference between no-till and conventional tillage was strongly influenced by WI in dry or normal year but not in wet year. The relationship between boundary line yield data and WI in most of the crops for most of the studied years had a convex shape. Higher boundary line yields consistently occurred at intermediate WI levels. No-till and low input systems tended to produce higher maximum and average yields than conventional system at the lower WI areas. The results suggested that it is possible to maximize yield and profit by farming site-specifically based on landscape position. The nonparametric spline regression algorithm utilized in the study was robust and efficient in comparing the yield differences between treatments across a range of WI values.

INTRODUCTION

Conventional management practices relying on intensive tillage and high chemical input were questioned with limited economic return and environmental problems (Robertson et al., 2004; Pimentel et al., 2005). The management effects can be altered by field and weather conditions. To make a better farming decision landscape- or site-specifically needs thorough analysis and understanding of production variability and its relationship with underlying environmental factors in multi-crop with long term data. Generally, crop yields are highly variable across fields and years as a result of complex interactions among different factors, such as topography, soil properties, and management practices (Lamb et al., 1997; Doerge, 1999; Jaynes et al., 2003; Kravchenko et al., 2005). Therefore, better understanding of yield variation can lead not only to increase in profitability of farming but also to improve environmental quality.

A large number of studies assessed the interactive effects of topography and precipitation on yield variability for major Midwest crops, such as corn, soybean, and wheat (e.g., Simmons et al., 1989; Timlin et al., 1998; Kravchenko and Bullock, 2000; Kaspar et al., 2003; Jiang and Thelen, 2004; Si and Farrell, 2004). Topography has been often found explaining a substantial portion of yield variability, however, yield/topography relationships vary substantially from year to year. These variations are often associated with the prevailing weather conditions during the growing season of each particular year. Spring and summer precipitation often found to be of most importance (Halvorson and Doll, 1991; Jaynes and Colvin, 1997; Kravchenko and Bullock, 2000; Kaspar et al., 2003; Jaynes et al., 2003).

Weather conditions may substantially influence the apparent gains or losses due to management and other factors on a regional as well as field scale. Lobell and Asner (2003) investigated the relationship between weather variations and crop production by synthesizing data on temperature, precipitation, solar radiation, and county corn and soybean yields throughout the United States for the period 1982-98. The key characteristics were a large area centered in the Midwest where yields were favored by cooler, wetter years and a smaller region including the Northern Great Plains favored by hotter, drier years. Weather had a major influence on crop production in the Upper Great Lakes States of Michigan, Minnesota, and Wisconsin during the past century. Low precipitation and moisture stress were chief limitations to optimal corn and soybean yields (Andresen et al., 2001). Overall weather effects on corn yield in Missouri were found to operate through the within-season variations in rainfall and temperature (Hu and Buyanovsky, 2003). The growing-season distributions of rainfall and temperature for high-yield years were characterized by less rainfall and warmer temperature in the planting period and a rapid increase in rainfall further during the growing season, particularly with more rainfall and warmer temperatures during germination and emergence. More rainfall and cooler-than-average temperatures are the key features in the anthesis and kernel-filling periods from June through August, followed by less rainfall and warmer temperatures during the September and early October ripening time. Opposite variations in rainfall and temperature in the growing season correspond to low yield (Hu and Buyanovsky, 2003).

It is generally expected that the relationships between yield and topography and its dependence on the weather patterns may vary under different management practices. However, there is only limited quantitative information on how management affects yield/topography/weather relationships. For example, Simmons et al. (1989) found that yield reductions at drought-prone landscape positions such as shoulder and backslope were most common under discing tillage. Kravchenko et al. (2005) observed greater variability in crop yields under organic management as compared to conventional management practices with weather related stresses amplifying the differences in spatial variability patterns.

Of particular interest is assessment of these relationships in most commonly used agricultural management practices, such as conventional tillage with conventional chemical inputs, and comparisons with conservation management practices, including no-till, low input and organic practices. Information on yield/topography/weather relationships will contribute to the effort in expanding the conservation management practices and likely increase the grower's profit from site-specific farming while shifting from conventional to conservation practice.

One of the commonly faced difficulties in analyses of yield relationships with weather and topography is that the traditional correlation and regression data analyses tools fail to provide useful information because of complex interactions between topographical effects with a multitude of other yield-affecting factors. Boundary line analysis (BLA) introduced by Webb (1972) provides insights on individual effect of topographical factors in limiting the yield potential. BLA subdivides the response data into groups corresponding to the quantitative categories of the limiting factor of interest and then isolates a subset of the highest values from the response data within each group. This upper boundary dataset in a scatter plot then represents the maximum possible response to that limiting factor. The data points below the boundary line represent conditions where the other factors have limited the yield. The method assumes that there is a significant biological response between the potential limiting factor and a response variable, and implies a cause-and-effect relationship (Webb, 1972; Lark, 1997; Kitchen et al., 2003). BLA was used by a number of researchers to identify yield response to a single factor out of the many that affected the yield (Lark, 1997; Kitchen et al., 2003; Shatar and McBratney, 2004).

The relationships between crop yields and yield affecting factors often follow complex patterns that, if described by parametric models, may require prohibitively complex models with a very large number of parameters. Nonparametric regression provides a useful alternative (Härdle, 1990). For example, nonparametric spline regression can describe a complexly shaped relationship between a response and an independent variable and can provide predictions for response variable averages (Fan, and Gijbels, 1996; de Boor, 2001). Moreover, the algorithm developed by Wang and Yang (2006) for the spline regression allows efficient constructing of a 100(1-α) % spline confidence band around predicted response values. This algorithm can be expanded in comparisons between two-model predictions of crop yields across the range of the studied yield affecting factors. The advantages of this method not only test the overall difference between two treatments or models, but also visually show where the difference is significantly positive or negative across the range of the covariate by plotting the data. The information gained from this method is valuable for better understanding the relationship between yield and yield-affecting factors and for managing the factors.

The physiography of Michigan presents very advantageous settings for studying yield/topography/management interactions. It is characteristic of a nature glacial outwash plain and moraine complex. Soil materials were formed and altered by glacial till and outwash processes across the landscape resulting in formation of various landforms, such as undulating hills, valleys and plains, even within relatively small areas (Mokma and Doolittle, 1993; Crum and Collins, 1995). However, those varied field conditions can cause imprecision and incorrect interpretation of the experimental results using traditional analysis of variance (ANOVA) model. Incorporating spatially intense measurements of topographical variables into ANOVA models, called analysis of covariance (ANCOVA), one can correct for these confounding variables and obtain more precise estimates of yield performance of the treatment (Milliken and Johnson, 2002). The ANCOVA combines regression methodology with ANOVA. As a result, it removes the influence of the covariate and makes the treatment comparisons more precise.

The objective of this study was to analyze the effects of management practices on the relationship between crop yield and topography, yield and weather using 10-yr of yield monitor data from a long-term corn-soybean-wheat rotation experiment in southwest Michigan.

MATERIALS AND METHODS

Site Description and Data Collection

The data were obtained from the Long Term Ecological Research (LTER) site, located at Kellogg Biological Station (KBS) in southwest Michigan (85°24' W, 42°24' N). Soils are well-drained Typic Hapludalfs of the Kalamazoo (fine-loamy, mixed, mesic) and Oshtemo (coarse-loamy, mixed, mesic) series developed on glacial outwash (Crum and Collins, 1995). The maximum difference in elevation within the site is 8.8 m. There is clear decreasing gradient of elevation from north to south in the site (Fig. 4.1). There is also considerable elevation variation within many individual plots.

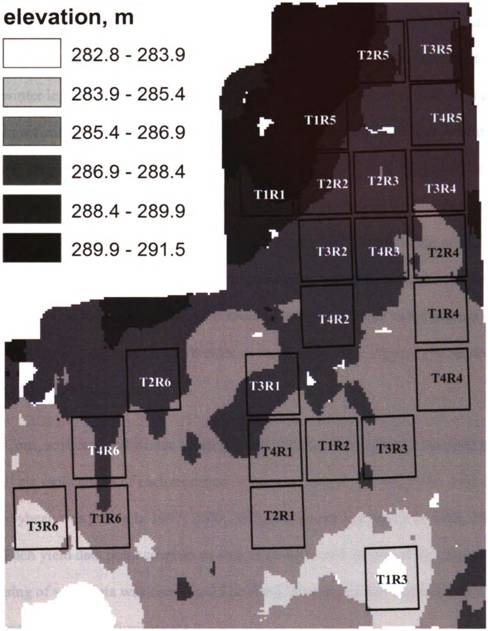


Fig. 4.1. Layout of the 24 plots in the experimental site (4 treatments and 6 replications for each treatment), and the 4 x 4 m interpolated elevation map of the LTER site at KBS. The plots are labeled with treatment codes and replication numbers, e.g., T2R1 is replication 1 that received treatment T2. Each plot is 1 hectare in size.

A one-factor randomized complete block design (RCBD) experiment with 6 replications was established at the site in 1988. Each experimental plot is about 110- by

90-m in size. The experiment consists of a total of 7 treatments. The 4 agronomic treatments used in this study are chisel plowed with conventional chemical inputs (T1), no-till with conventional chemical inputs (T2), chisel plowed with low chemical input and a winter leguminous cover crop (T3), and organic-based chisel plowed with a winter leguminous cover crop (T4). All treatments are managed as corn–soybean–wheat rotations. Detailed agronomic protocols can be found on the KBS LTER website (http://lter.kbs.msu.edu/protocols/104). The conventional chemical treatments T1 and T2 receive 123 kg nitrogen ha^{-1} for corn and 56 kg nitrogen ha^{-1} for wheat but not for soybean according to Michigan State University recommendations and insecticides and herbicides as necessary. The low input system (T3) receives only N fertilizer in the amount equal to 3/5 of that applied to T1 and no herbicides or insecticides. The organic system does not receive any chemical inputs.

Corn, soybean, and winter wheat grain yield data were collected via yield monitors from all six replications of each treatment. Corn was grown in 1996, 1999, 2002 and 2005, soybean was grown in 1997, 2000, 2003, and wheat was grown in 1998, 2001, and 2004. Each yield data point covered an area of about 2 x 2.5 m (Fig. 4.2). Cleaning and processing of yield data was conducted following Drummond and Sudduth's (2003) recommendations. To eliminate the border effects, only the yield data from the central 80 x 60 m portion of each plot were used in the analysis (Fig. 4.2). The measured yield data were interpolated into a cell-based yield map on a 4 x 4 m grid using ArcView Spatial Analyst (ESRI, 2000). For analyses that involved comparisons among the crops, the original yields were standardized (Blackmore, 2000; Perez-Quezada et al. 2003) as

$$Y_{si} = R_{si} / Y_{..} \quad [1]$$

where $\boldsymbol{Y_{si}}$ is the standardized yield (StdY) of the $\boldsymbol{i^{th}}$ plot in the $\boldsymbol{s^{th}}$ year, $\boldsymbol{R_{si}}$ is the actual yield for the $\boldsymbol{i^{th}}$ plot in the $\boldsymbol{s^{th}}$ year, $\boldsymbol{Y_{..}}$ is average field yield across years. For corn $\boldsymbol{Y_{..}}$ is 4-yr average. For soybean $\boldsymbol{Y_{..}}$ is 3-yr average. $\boldsymbol{Y_{si}} = 1$ means the yield in the $\boldsymbol{i^{th}}$ plot is equal to the average yield in the field in the $\boldsymbol{s^{th}}$ year. Because corn and soybean have similar growing seasons that differ from wheat, only combined standardized yield for 4-yr corn and 3-yr soybean were used to relate weather variables across years to study the crop yield temporal variation among treatments.

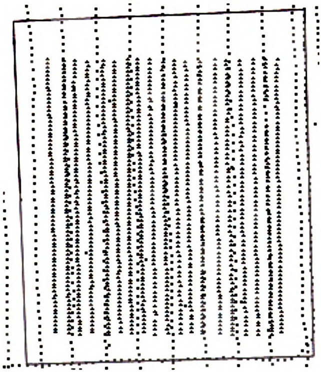


Fig. 4.2. Example of the layout of locations of the elevation (dots) and yield measurements (triangles) obtained in each plot of the LTER site at KBS.

Elevation was measured with a real-time kinetic GPS system mounted on a cart. The measurements within the agronomic plots were taken approximately every 2.5 m along each transect (Fig. 4.2). The distance between transects was 5 m. The elevation measurements were converted into a cell-based terrain map on a 4 x 4 m grid using ArcView Spatial Analyst and topographic variables including slope, curvature, flow direction and accumulation, and wetness index (WI) were derived from the elevation data using surface hydrologic analysis of ArcInfo GRID. WI has been proposed as an integrative characteristic describing distribution of soil moisture within a landscape (Moore et al., 1988 and 1993) and was found to be highly correlated with soil water contents (Schmidt and Persson, 2003). Based on preliminary analyses of topographical variables (data not shown) and based on the observations of yield/topography relationships made at a nearby site (Huang et al., 2005), I decided to use WI as the only topographical variable in this study. The definition and equation of wetness index were described in previous chapters. In the studied site the WI data in all treatments were approximately normally distributed with the mean of 7 and the standard deviation of ~1.4. The distributions of the WI data, as well as their mean, minimum and maximum values, of the four studied treatments were very similar (Table 4.1).

Table 4.1. Descriptive statistics of topographical variables from 4 treatments.

	elevation, m				slope, degree				wetness index			
	T1	T2	T3	T4	T1	T2	T3	T4	T1	T2	T3	T4
Mean*	287.4	287.6	286.9	285.8	1.19	1.27	1.14	0.85	6.99	6.94	6.92	7.03
Std dev	2.27	1.27	1.03	0.65	0.73	1.11	0.99	0.56	1.46	1.54	1.53	1.03
Min	283.7	285.6	284.0	287.0	0.01	0.01	0.01	0.01	4.23	3.64	3.13	4.39
Max	291.1	291.4	289.4	288.6	4.85	6.47	10.0	3.24	14.4	13.1	13.8	13.3

*sample size for T1, T2, T3, and T4 were 2672, 2931, 2816, and 3210, respectively.

Daily precipitation values were obtained from an automated KBS weather station located at the LTER site. The average daily precipitation values from March through August were used to relate yield variation to weather. The spring (March, April and May) and summer (June, July, and August) monthly daily precipitation averages for the studied period and 30-year average are shown in Fig. 4.3.

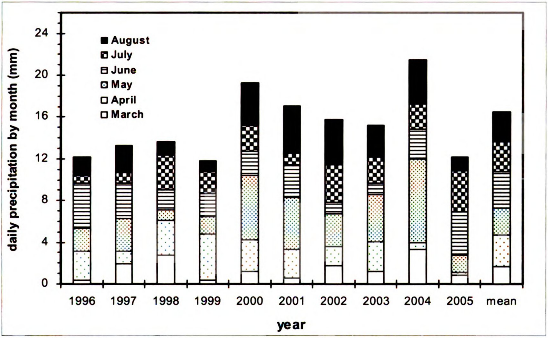


Fig. 4.3. March, April, May, June, July, and August daily average precipitations from 1996 to 2005 and 30-year average.

Statistical Analyses

Correlation and Regression Analysis

Descriptive statistics for yield and topographical variables for each treatment were calculated by SAS PROC MEANS procedure (SAS Inst., 2000). Relationship between StdY and precipitations were analyzed using regression techniques. StdY was the dependent variable. Spring and summer daily precipitations were the independent variables. Simple linear regression was applied to analyze the 7-yr spring and summer daily precipitations on StdY. Multiple regressions were employed to analyze the combined spring and summer daily precipitations on the StdY. The SAS PROC REG was used to fit the regression model and to compute regression coefficients. Partial correlation coefficients between StdY and spring precipitations where the effect of summer precipitations on the correlation was removed were calculated using SAS PROC CORR. Similarly, partial correlation coefficients between StdY and summer precipitations were calculated.

Boundary Line Analysis

The relationship between WI and yield was studied using BLA. The analysis starts with subdividing the range of values of the independent variable into classes. Then the maximum yields are identified within each class. Within literature, identification of the maximum yield within a class has been approached in different ways. For example, Webb (1972) and Schnug et al. (1996) selected a single highest-yielding data point for each class of the yield-affecting predictor variable. However, Kitchen et al. (2003) selected the upper edge of the yield by using the data points exceeding the 95th percentile of each class yield data. This selection method may produce only few data points in some classes while numerous data points in other ones. In this study, I divided the WI into approximately 50 classes in 0.2 increments and in each class I selected the top four yield data points. This method of selecting the upper edge data appeared as a way to use the best features of the methods reported in literature. It represented the upper edge yield in a more reliable manner than a single maximum data point and resulted in an equal number of data points representing each class. Example of the yield-WI data for one of the treatments in one of the studied years is shown on Fig. 4.4.

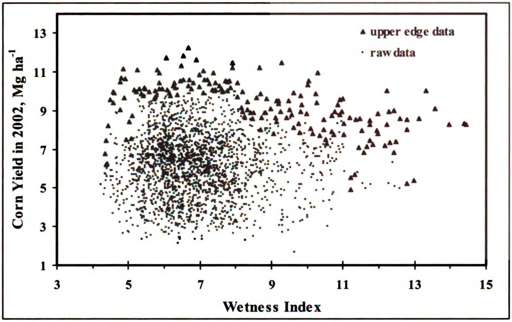


Fig. 4.4. Scatter plot and boundary line of corn yield vs. wetness index (WI) for T1 in 2002. Dots represent raw data. Triangles represent top 4 yield data for each increment of WI.

Parametric and nonparametric regression methods were used to fit the boundary line yields and WI. For parametric regression, after examining scatter plot, 2-line regression model, also called segmented linear regression, was used to quantify the relationship between maximum yield and WI. The segmented linear regression model is defined as:

$$\begin{aligned} Y &= \beta_{01} + \beta_{11}X, X \le A \\ Y &= \beta_{02} + \beta_{12}X, X \ge A \end{aligned} \qquad [2]$$

where $\boldsymbol{Y}$ is the response variable yield and $\boldsymbol{X}$ is independent variable WI; $\boldsymbol{\beta_{01}}$ and $\boldsymbol{\beta_{02}}$ are the intercepts of the segments of the line, $\boldsymbol{\beta_{11}}$ and $\boldsymbol{\beta_{12}}$ are the slopes, respectively; and $\boldsymbol{A}$ is the joint points. The procedure of SAS PROC NLIN with Marquardt method was used to perform the segmented regression as described by Shuai et al. (2003). By comparing the slopes and joint points of fitted models, the influence of WI on maximum yield can be revealed.

Visual assessment of the boundary yield lines showed that their relationships with WI can not be adequately described by a single regression line. It also appeared not possible to use a single non-linear equation for describing various shapes of the relationships observed in different treatments and years. Thus, I decided to apply nonparametric (spline) regression following the methodology developed by Wang and Yang (2006). The statistical model of spline regression can be expressed as:

$$Y_i = \mathrm{m}(X_i) + \sigma(X_i)e_i, i = 1, \ldots, n \qquad [3]$$

where $(\boldsymbol{X_i}, \boldsymbol{Y_i})$ are paired predictor and response variables; $\boldsymbol{m}$ is unknown regression function; $\boldsymbol{\sigma}$ and $\boldsymbol{e}$ are the standard deviation of the predictor variable and the observation errors, respectively. It is believed that the nonparametric regression is an effective tool to extract information from complex and less structured data (Härdle, 1990; Fan, and Gijbels, 1996; de Boor, 2001; Wang and Yang, 2006). In addition to capturing better trend of the complicated data, by constructing confidence bands for differences between 2 spline models from the two treatments, one can compare mean functions $\boldsymbol{m_1(x)}$ and $\boldsymbol{m_2(x)}$ of the treatments 1 and treatment 2 and test the hypotheses:

$$H_0 : m_1 = m_2 \quad \text{against} \quad H_1 : m_1 \neq m_2 \qquad [4]$$

where m_1 and m_2 are unknown regression functions for two models. In fact, the acceptance or rejection of H_0 is according to whether prediction difference $\Delta Y = 0$ line lies completely inside the confidence band. By plotting the difference between the two predicted functions with 95% confidence bands provides valuable information about where the yields between two treatments differ across covariate WI. The detailed theorem and algorithms to fit spline regression and construct the confidence bands were described by Wang and Yang (2006). The codes for implementing the analysis have been written in R by Wang.

ANOVA and ANCOVA

The effect of treatments on yield was first analyzed using ANOVA model. The statistical model with 10-yr and 3 crops is specified as:

$$Y_{ijkl} = \mu + T_i + B_j + C_k + X(C_k)_l + TC_{ik} + TX_{il} + TB_{ij} + TBC_{ijk} + \varepsilon_{ijkl} \quad [5]$$

where $\boldsymbol{Y}$ is measured yield; $\boldsymbol{T}$, $\boldsymbol{C}$, and $\boldsymbol{X}$ are fixed treatment, crop and year nested with crop effects, respectively; $\boldsymbol{TC}$ and $\boldsymbol{TX}$ are interactions between treatment and crop, treatment and year; $\boldsymbol{B}$ is random block effect; $\boldsymbol{TB}$ and $\boldsymbol{TBC}$ are random interaction effects; ε is random error. As the interaction between treatment and crop, treatment and year was significant, one-way ANOVA and ANCOVA model were used to determine the treatment effect for a specific crop on a year. One-way ANOVA model with subsampling is defined as:

$$Y_{ijk} = \mu + T_i + B_j + \varepsilon_{ij} + d_{ijk} \qquad [6]$$

$$\begin{cases} \varepsilon_{ij} \sim i.i.d. \sim N(0, {\sigma_e}^2) \\ d_{ijk} \sim i.i.d. \sim N(0, {\sigma_d}^2) \end{cases}$$

where ***Y*** is measured yield based on subsample within a plot; $\boldsymbol{\mu}$ is the overall mean; ***T*** is the fixed treatment effect; ***B*** is the random effect of the replications, **ε** and **d** are the random error and subsampling random error. One-way ANCOVA model with subsampling is defined as:

$$Y_{ijk} = \mu + T_i + \beta_i Z_{ijk} + B_j + \varepsilon_{ij} + d_{ijk} \qquad [7]$$

where ***Y*** is measured yield based on subsample within a plot; **μ** is the overall mean; ***T*** is the treatment effect; ***βZ*** is the topographical covariate and its interaction with treatments; ***B*** is the random effect of the blocks; **ε** and **d** are the random error and subsampling random error. The analyses of variance and covariance were performed using SAS PROC MIXED procedure.

RESULTS AND DISCUSSION

Descriptive Statistics of Topographical Variables and Crop Yields

The descriptive statistics of topographic variables in each treatment are shown in Table 4.1. The elevation ranged from 283.7 to 291.4 m, that is, it was approximately 8 m difference between highest and lowest area where 4 treatments were located. In addition, the relative range of elevation differed largely among 4 treatments, for example, the range for T1 was 7.4 m, whereas the range for T4 was only 2.8 m. The areas with high elevation were mainly at the northwestern corner of the field, and the areas with low elevation were at the southern part of the field (Fig. 4.1). The entire field gradually descended from north to south. Moreover, there was up to 2 m elevation difference within 1 hectare plot. The histograms of elevation for 4 treatments differed remarkably (Appendix 4.2). The distributions of elevation were flat in the T1 and T4, and skewed in the T2 and T3. In addition, the range of slope varied largely from one treatment to another. However, WI ranged from 4 to 13 for each treatment (Table 4.1). The average values and their ranges of WI were similar among treatments. The histogram of WI showed that the data were approximately normally distributed in each treatment (Fig. 4.5). My previous results demonstrated that WI was the topographical variable most strongly related to crop yields (Huang et al., 2005; Chapter III). Thus, the WI was selected as covariate to represent topography for yield variability characteristics.

The yield variations in corn, soybean, and winter wheat within a treatment across years are presented in Table 4.2. Average yield for each crop varied remarkably from year to year. Particularly for corn, for example, the yield in the T1 was 8.25 Mg ha^{-1} in 2005 that was more than twice of the yield in 1996 (3.66 Mg ha^{-1}) and in 1999 (3.06 Mg ha^{-1}). The primary reason was due to varied inter-annual weather conditions. The year-to-year variations observed in corn yields were higher than in wheat and soybean yields. All yield data were close to normal distribution (data not shown). As an example, histogram of corn yields in 2002 is shown in Appendix 4.3. Detailed yield comparison and the effect of covariate WI on yields between treatments will be reported in later section.

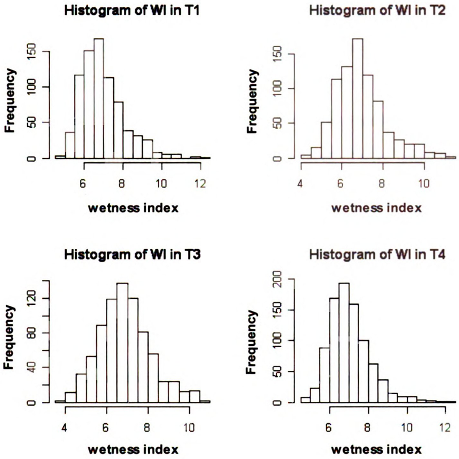


Fig. 4.5. Histograms of wetness index (WI) for 4 treatments.

Table 4.2. Average yield and standard deviation for corn, soybean and winter wheat from the four studied treatments.

Crop	year	Yield (Mg ha^{-1}) in treatment:			
		T1	T2	T3	T4
Corn	1996	3.66 ± 2.08	4.35 ± 1.69	4.34 ± 1.52	2.87 ± 1.24
	1999	3.06 ± 1.44	3.36 ± 1.28	3.95 ± 0.96	4.08 ± 1.09
	2002	6.35 ± 1.79	7.08 ± 1.38	7.24 ± 1.85	6.10 ± 2.10
	2005	8.25 ± 2.53	9.56 ± 1.75	8.80 ± 1.94	5.80 ± 1.84
Soybean					
	1997	1.37 ± 0.67	1.48 ± 0.41	1.68 ± 0.53	1.20 ± 0.43
	2000	1.67 ± 0.24	1.64 ± 0.36	1.84 ± 0.30	1.95 ± 0.26
	2003	1.50 ± 0.43	1.92 ± 0.72	1.36 ± 0.28	1.22 ± 0.27
Wheat					
	1998	3.03 ± 1.13	1.99 ± 0.49	1.51 ± 0.37	0.73 ± 0.28
	2001	3.62 ± 0.58	3.18 ± 0.67	3.08 ± 0.42	2.27 ± 0.36
	2004	4.53 ± 0.92	4.59 ± 0.93	4.21 ± 0.83	2.44 ± 0.61

Yield/ Precipitation Relationship among Management Practices

Since corn and soybean have similar growing seasons, StdY from 4 years of corn and 3 years of soybean yields were combined for analyses of yield relationships with precipitation. The three years of wheat yields were excluded from this analysis. In the studied site precipitation in May and precipitation of all three spring months combined was found to be not significantly related to the StdY ($p<0.05$) (data not shown). Thus, only the results for early spring (March through April) precipitation are discussed further. The StdY for the T1, T2, and T3 were significantly negatively correlated with early spring (March and April) daily average precipitation ($p < 0.01$, Fig. 4.6A, 6B, and 6C). Roughly 30 to 60% of the StdY variation can be explained by the spring precipitation. The negative correlation of the StdY with spring precipitation indicates that with the increase of the precipitation StdY decreased accordingly. It is likely due to unfavorable wet spring from excessive rainfall tends to reduce the yield by lowering soil temperature, delaying planting, and slowing seed emergence (Lark and Stafford, 1997; Hoeft et al., 2000). Noticeably, the relationship was possibly driven by corn data from 2005, where high yields were in company with low precipitation in spring and normal precipitation in summer (Fig. 4.3 and 6). But it did not appear that there was much correlation between the yield and spring precipitation in the other years. The StdY in organic system did not show significant correlation with the spring precipitation (Fig. 4.6D and Table 4.3). Contrary to conventional and reduced input systems, the yields in organic system did not show a remarkable high in 2005.

Table 4.3. Parameters of regression model for the relationship between standardized (Std) yield and spring and growing season daily rainfall from 4 treatments.

	T1	T2	T3	T4
Std Yield vs. March and April Rainfall				
N	40	36	41	37
β_1	-0.37*b	-0.48c	-0.34b	-0.04a
r^2	0.31	0.59	0.39	0.01
RMSE (Mg ha^{-1})	0.31	0.24	0.24	0.26
Std Yield vs. June, July, and August Rainfall				
N	40	36	41	37
β_1	0.54b	0.59c	0.55bc	0.39a
r^2	0.50	0.62	0.75	0.56
RMSE (Mg ha^{-1})	0.26	0.23	0.15	0.17

*regression slopes within a row followed by the same letter are not significantly different at the 0.01 level by the 2-side t-test.

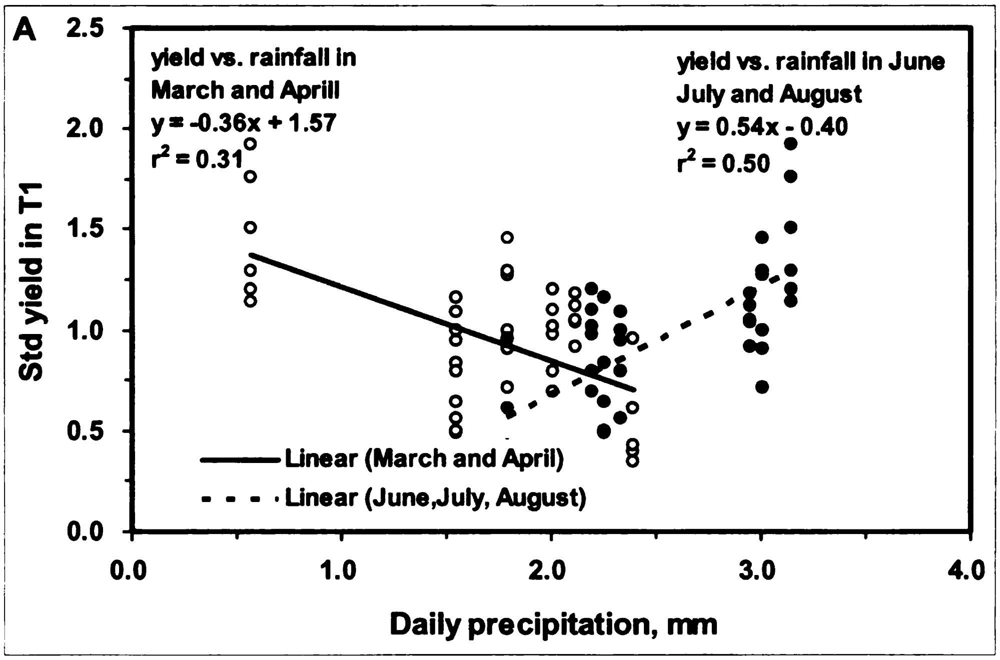


Fig. 4.6A. Standardized (Std) yield vs. Spring (march and April) and Summer (June, July and August) Daily Precipitation for treatment T1.

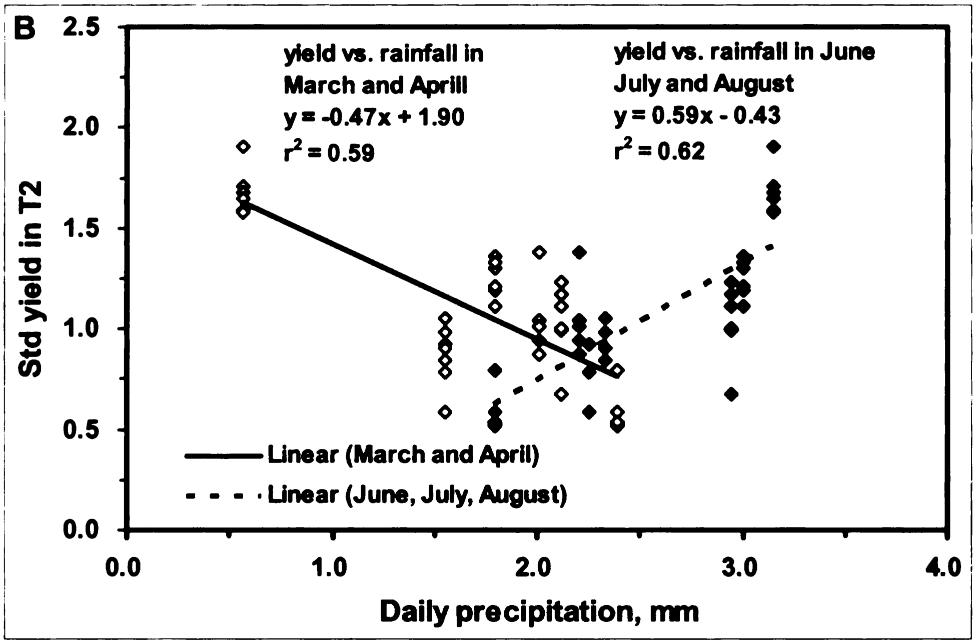


Fig. 4.6B. Standardized (Std) yield vs. Spring (march and April) and Summer (June, July and August) Daily Precipitation for treatment T2.

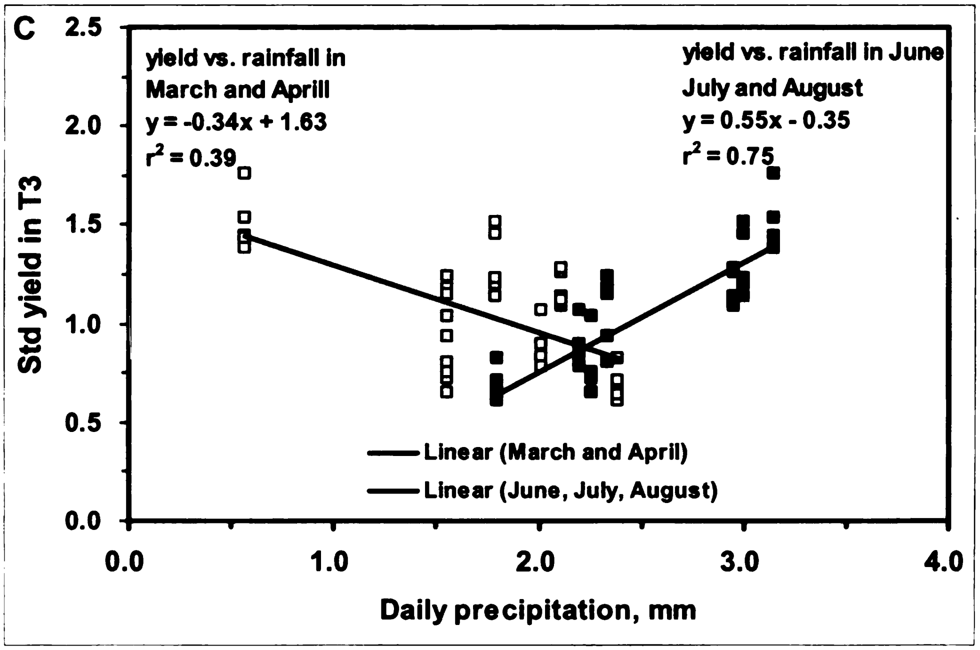


Fig. 4.6C. Standardized (Std) yield vs. Spring (march and April) and Summer (June, July and August) Daily Precipitation for treatment T3.

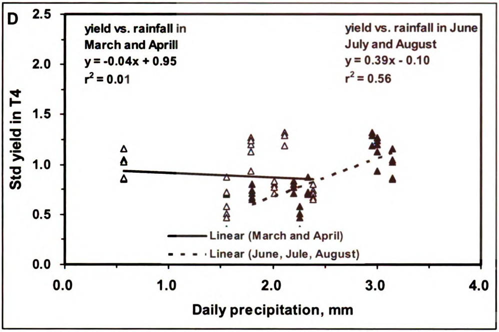


Fig. 4.6D. Standardized (Std) yield vs. Spring (march and April) and Summer (June, July and August) Daily Precipitation for treatment T4.

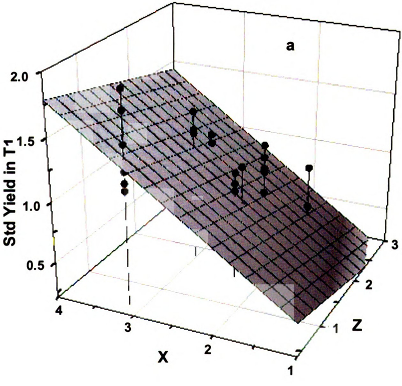


Fig. 4.7a. Standardized (Std) yield vs. summer (X) and spring season (Z) daily precipitation (mm) for treatment T1.

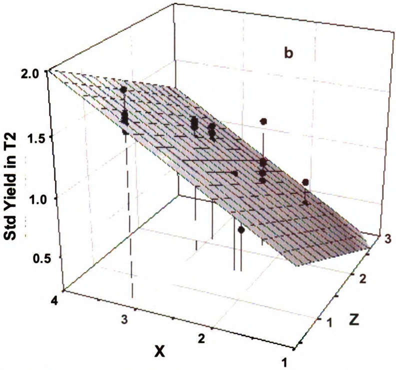


Fig. 4.7b. Standardized (Std) yield vs. summer (X) and spring season (Z) daily precipitation (mm) for treatment T2.

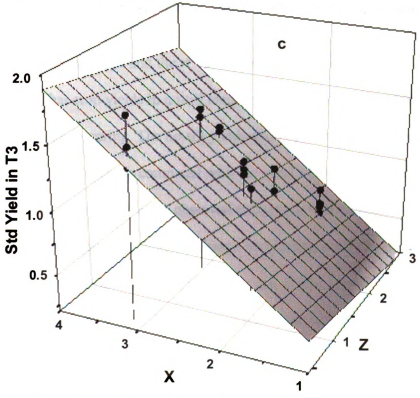


Fig. 4.7c. Standardized (Std) yield vs. summer (X) and spring season (Z) daily precipitation (mm) for treatment T3.

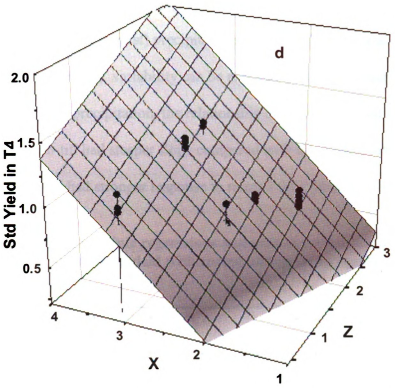


Fig. 4.7d. Standardized (Std) yield vs. summer (X) and spring season (Z) daily precipitation (mm) for treatment T4.

The regression slope and the r^2 value were the highest in no-till (T2) (Fig. 4.6B). This indicates that crop yields in no-till tended to vary more with the amount of precipitation in early spring. The no-till yields decreased at a greater rate with an increase of the spring precipitation as compared with the tilled treatments (Table 4.3). During wet and cold springs, tillage was often observed to improve soil aeration and soil temperature thus creating more favorable field conditions for planting and seed emergence as compared with no-till (Cox et al., 1990; Fortin and Pierce, 1991; Wilhelm and Wortmann, 2004; Kravchenko and Thelen, 2007). But in a drier year, no-till can reduce soil water losses from evaporation (Tomer et al., 2006) thus reducing the drought stress and benefiting crop growth as compared with tilled soil.

The StdY of all treatments were significantly positively correlated with the summer (June, July, and August) precipitations ($p < 0.01$, Fig. 4.6 and Table 4.3). Roughly 60 % of the StdY variability can be explained by the summer precipitation. Similar to the spring precipitation, the relationship between StdY and summer precipitation in no-till had steeper slope compared with tilled treatments, demonstrating that yields in no-till had stronger response to rainfall than those in tilled treatments.

Table 4.4. Results of multiple regressions and partial correlation coefficients between standardized (Std) yield with spring and growing season rainfall from 4 treatments.

Treatment	Spring + Growing season rainfall		Partial *r* of Std yield vs.	
	R^2	RMSE (Mg ha^{-1})	Spring rainfall	Growing rainfall
T1	0.53	0.26	-0.24^{NS}	0.56**
T2	0.77	0.18	-0.62***	0.65***
T3	0.78	0.15	-0.31*	0.80***
T4	0.78	0.12	0.72***	0.89***

^{NS} indicates no significant correlation; *, **, and *** represent significant Pearson partial correlation coefficients at $p < 0.05$, 0.01, and 0.001 levels.

The combined effects of spring and growing season precipitation on StdY were analyzed using multiple linear regression (Table 4.4). Three dimensional plots of the multiple regression results for 4 treatments are shown in Fig. 4.7. Combining early spring and summer precipitations effects on StdY in a multiple regression further supported the above discussed results and allowed for further insight into spring and summer precipitation effects on yields of the studied treatments (Table 4.4). In general, the R^2 values for T2, T3, and T4 were similar (about 0.78), while the R^2 value for T1 was much lower (0.53), indicating that the yields in high chemical input with conventional tillage system were less influenced by precipitation as compared with no-till, low chemical input or organic systems. The stronger relationship between precipitation and yields in low chemical input and organic treatments likely reflects a higher response of low input systems to additional stresses, e.g. water stress, that further enhance the stress due to lower availability of plant nutrients that the plants might be already experiencing. Similar results were found by Kravchenko et al. (2005).

To further assess independent contributions of the early spring and summer precipitations to the StdY, I calculated partial correlation coefficients (r_p) between the StdY and early spring precipitation, by partialing out the influence of summer precipitation and the r_p values for the summer precipitation by partialing out the early spring precipitation (Table 4.4). The r_p values for the early spring were negative in the T2 and T3, not significantly different from 0 in T1, and positive in T4. This further supported the previous observations of the negative effect that wet springs might have on T2 and an extra positive effect that better water supply may have in the organic system, while not being crucial in conventional tilled system. Independent of the early spring precipitation, the adequate water supply in summer had positive effect on yield in all treatments, still being more pronounced in the systems with lower chemical inputs (T3 and T4). The r_p in the T4 was the strongest (0.89), followed by in the T3 and T2 (p-value < 0.001). The r_p in the T1 was the lowest (0.56, p-value < 0.01).

It is interesting to note that in 1999, the extremely dry year, the organic system had higher corn yield than the conventional system (Table 4.2). Higher yields in organic systems as compared to conventional were observed by other studies as well, but not for corn. Pimentel et al. (2005) found that during the extreme drought of 1999 in Pennsylvania, organic legume system of Rodale farming trial had significantly lower corn yields and higher soybean yields than the conventional system. Average soil water content in the organic legume system was found to be 15% higher than that in the conventional system thus explaining the higher soybean yields in the organic system (Pimentel et al., 2005). In this study, the organic treatment was found to not have higher soil water content but have substantially higher soil organic matter content than in the conventional chemical treatment (Hao and Kravchenko, 2007). The management systems with cover crops are also known for having better soil structure with stronger aggregate stability and higher numbers of large aggregates (Kabir and Koide, 2000; Sainju et al., 2003; Liu et al., 2005). Increased soil organic matter and better aggregation improve soil hydraulic properties, which may have helped the plants in the T4 to better survive the drought conditions.

Relationship between Boundary Crop Yields and Wetness Index

Data Examination of Boundary Yields and Wetness Index

An examination of scatter plot from large data sets can be very helpful in understanding the association between variables. BLA focuses on the upper edge of the scatter-plot data. Those data marked as triangles represents the maximum yield response to corresponding WI as an independent variable (Fig. 4.4). The yields below the edge represent the conditions where other factors have limited the yield. Because of limited space, I arbitrarily presented here only the data for corn yields in the T1 in 2002. The rest of plots had similar pattern. The relationship between boundary yields and WI in most of the crops for most of the studied years had a convex shape. Higher boundary yields consistently occurred at intermediate WI levels. Corn yield increased over a range of WI from 4 to 6, and then reached to a plateau. Yields were then depressed as WI values rose further (Fig. 4.4).

Parametric versus Nonparametric Regression

First, the boundary yields and WI were modeled using two-segmented linear regression. The analysis assumed that the paired yield-WI relationship is characterized by 2-linear-line with different slopes. Through comparing the slopes and joint points between the treatments, one can gain insight on how WI affects the maximum yield. The two lines were connected by a joint point. The regression parameters for corn yields across 4-yr among 4 treatments were compared in Appendix 4.1. The model r^2 ranged from 0.14 to 0.61. The joint points were the highest for the T4 in 3 of 4 years, followed by the T1, T2 and T3. This means that the highest yields in T1 and T4 tended to be closer to the areas with lower level or footslope than in T2 and T3. In addition, the T1 yields had steeper slope in both the first and second lines compared with the T2 and T3. This indicated that yields in conventional system were highly variable to WI in term of field soil water moisture compared with no-till and reduced system.

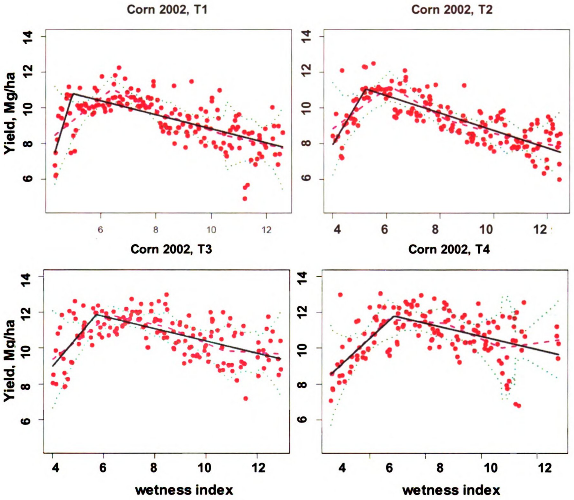


Fig. 4.8. Comparisons of 2-linear-line and spline regression for corn yield in 2002 vs. WI. Dots are top 4 yield data. Dotted lines indicate 95% confidence band. Dash line is spline line.

To test whether the segmented regression fit the boundary data better than nonparametric spline regression, a 95% confidence band for the data was constructed (Fig. 4.8). If the confidence band does not cover the fitted line, the parametric regression fit should be given up. Although the fitted line is covered by the band, the parametric regression is not guarantied a better fit compared with nonparametric regression for a complicated data (Wang, 2006, personal communication). The 95% confidence band showed that there were considerable deviations across WI values. The bands tended to be wider at the initial and the end of WI values where relatively few data points were available and yields were more variable. The segmented regression lines were not entirely covered by the 95% confidence band except for the T4 (Fig. 4.8). In addition, the regression coefficients in spline regression were higher than in segmented regression in 3 of 4 treatments (Table 4.5). The means square errors were smaller using spline regression than using segmented regression (Table 4.5). The results indicated that spline regression had superiority over segmented regression. Moreover, spline regression not only can be used to predict average response, but also can be used to compare difference by constructing confidence interval for the difference of 2 treatments. Therefore, it is more appropriate to characterize the maximum yield response to WI using nonparametric spline regression. I applied spline regression to fit all data and compare the yield difference between 2 treatments.

The relationship between boundary yields and WI varied across years among treatments. Figure 9 shows the splines for boundary yields of corn and WI in 4-yr among 4 treatments. The general trends of the lines were similar to 2-segmented lines. The spline curve, however, captured the local variation across the entire range of WI. Although maximum corn yields were the highest in the T1 and lowest in the T4 in 1996 and 2005, no consistent higher or lower yield for a specific treatment was observed in 4-yr period. Corn yields in the T2 and T3 were less variable from year-to-year compared with the T1 and T4. Moreover, the yields in the T1 were more variable to lower WI values compared with the T2 and T3, that is, the yields of T1 were very low in the lowest WI values, but with the increase of WI corn yields had greater increase rate except in 2002 (Fig. 4.9).

The splines for boundary soybean and wheat yields and WI are shown in Appendix 4.4 and 4.5. The shapes and patterns of the spline were similar to that for corn yields.

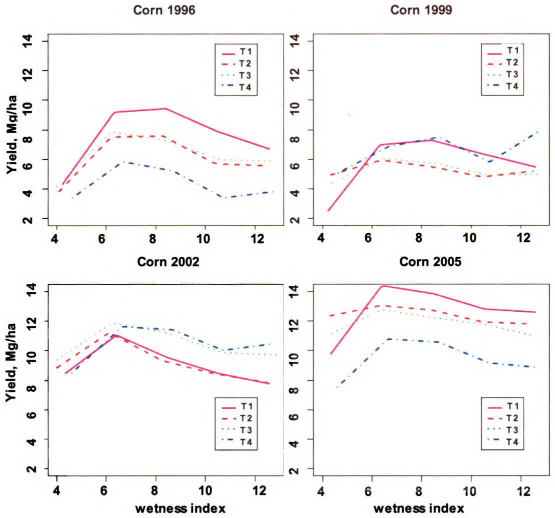


Fig. 4.9. Boundary line of corn yield vs. WI fitted by spline regression.

Table 4.5. The r^2 and mean square error (MSE) between nonparametric (spline) and parametric regression (segment) from 4 treatments in corn yield of 2002.

Treatment	MSE(Mg ha^{-1})		r^2	
	Spline	Segment	Spline	Segment
T1	0.90	1.00	0.49	0.43
T2	0.71	0.65	0.58	0.61
T3	0.91	0.91	0.38	0.37
T4	1.17	1.21	0.35	0.33

Maximum Yield Difference Influenced by Wetness Index

From all the possible comparisons that could be conducted among the studied treatments I have selected the three that appeared to be of most practical importance. The comparison between the T1 and T2 addresses the weather and topography considerations involved in choosing no-till as a conservation alternative to convention tillage. The comparison between the T1 and T3 evaluates the weather and topography related concerns involved in deciding on reducing the chemical inputs and using cover crops; and the comparison between the T3 and T4 evaluates the effect of complete elimination of chemical inputs. For each comparison the differences between the spline regression predictions of the boundary yields for each treatment were calculated for each class of WI values and examined along with 95% confidence band.

The differences and their confidence bands plotted versus WI for the 4-yr corn yield boundary line data are shown on Fig. 4.10. The difference was statistically significant at 0.05 probability level as can be interpreted from the 95% confidence interval band that did not include zero. The T1 yields were significantly higher than T2 across most of the WI values in 3 of 4 years. In 2002, the yields between 2 treatments did not differ statistically because the confidence intervals included zero. Noticeably, at the lower WI values (< 5, at the summit/steep-sloped areas), the T2 yields were significantly higher than T1 in 1999 and 2005, whereas the T2 yields equaled to T1 at WI > 10 (depression areas). The results suggested that the T2 tended to produce higher yields at the lowest WI, and lower yields at intermediate WI levels than T1. Speculatively, T2 probably performed better than T1 at lower WI due to reduction of erosion and evaporation, increase in soil carbon and improved soil structure that were often observed as a result of long-term implementation of the no-till (Reicosky et al., 1995; VandenBygaart et al., 1999; Rhoton, 2000).

For soybean the T2 yields were lower than T1 at higher WI values in 1997. On contrary, the T2 yields were significantly higher than T1 across the whole range of WI values in 2000 and 2003 (Appendix 4.6). On the other hand, the T2 yields of wheat were lower than T1 across the whole range of WI values in 1998 and 2001 (Appendix 4.7). But, no difference between the two treatments was found in 2004. Noticeably, either soybean or wheat yield difference between the T1 and T2 become smaller from year 1 to 3. The results suggested that no-till had considerable yield advantage over conventional tillage in a long-term run. The benefits from no-till were primarily due to improved soil properties as discussed earlier.

Corn yields in the T1 were significantly higher than in T3 in 1996, 1999, and 2005 across most of the WI values (Fig. 4.11). However, the yields in the T1 were lower than in the T3 in 2002. At lowest WI values, the T3 had clear yield advantages over T1 in

3 years. As in the case of T1 and T2 comparisons, this might be attributed to the improvement in soil organic matter and soil structure due to long-term implementation of leguminous cover crops of the T3 system, which might be particularly beneficial at the eroded areas with lower WI. Soybean yields in the T1 were significantly higher than in T3 in 1997 and 2003 (Appendix 4.8). But in 2000, the T3 had higher yields than T1. Wheat yields in the T1 were consistently higher than in T3 in 3 years (Appendix 4.9). It was noted that the wheat yield difference between the T1 and T3 became smaller from year 1 to year 3. Pimentel et al. (2004) observed the similar results in the Rodale experiments in Pennsylvania. They found that nitrogen levels in the organic systems have improved and have not been limiting the crop yields after the first 3 years. In the short term in organic systems, there may be nitrogen shortages that may reduce crop yields temporarily. But this disadvantage can be eliminated by raising the soil nitrogen level through the use of leguminous cropping systems.

Corn yields in the T3 were significantly higher than T4 in 1996 and 2005, lower than T3 in 1999, respectively (Fig. 4.12). In 2002, no yield difference was found between the 2 treatments. Soybean yields in the T3 were significantly higher than in T4 in 2 of 3 years (Appendix 4.10). Wheat yields in the T3 were consistently higher than in T4 in 3 years (Appendix 4.11). Overall, the low input system tended to produce higher corn and wheat yields compared with organic systems. This might be attributed to the fact that the T3 receives nitrogen fertilizer while T4 does not. The yield difference lines for most comparison paralleled to the horizontal line. This result means that covariate WI did not have profound effect on comparison of yield difference between the T3 and T4.

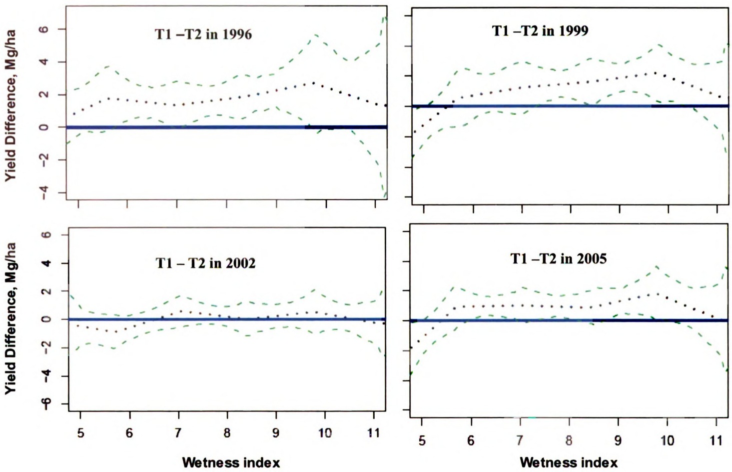


Fig. 4.10. Plot of 95% confidence band of the difference of corn maximum yield between T1 and T2 as a function of WI.

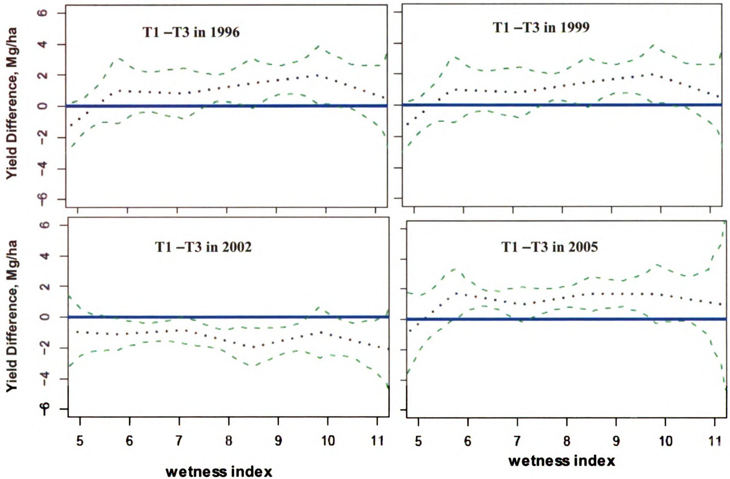


Fig. 4.11. Plot of 95% confidence band of the difference of corn maximum yield between T1 and T3 as a function of WI

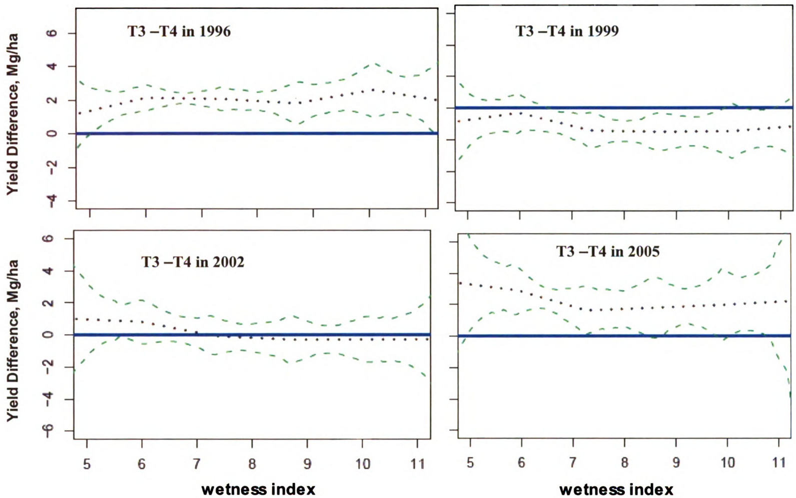


Fig. 4.12. Plot of 95% confidence band of the difference of corn maximum yield between T3 and T4 as a function of WI.

BLA is a useful diagnostic tool to identify yield potential and estimate the magnitude of yield loss due to variation in field WI. This analysis involved a single factor. It ignored the interaction effects between variables. Therefore, caution must be taken when insufficient data space coverage exists, and when interactions between one or more variables exist (Chambers et al., 1985). That problem can lead to oversimplify the reality of yield and overestimate the plant response to an environmental factor. Shatar and McBrataney (2004) used multivariate boundary line analysis to investigate the relationship between yield and soil properties. They found that major yield limiting factor within a field can vary from a location to another.

Relationship between Average Crop Yields and Wetness Index

Comparison of ANOVA with ANCOVA for RCBD

From F-test of ANOVA table, the average yield for a crop among management practices and years and their interactions were significantly different (data not shown). Crop yields often varied across years primarily due to inter-annual variation of weather conditions. In addition, field topography can interact with precipitation resulting in different treatment performance from year to year. Because this was 10-yr with 3 crops rotated in a RCBD experiment, detailed treatment comparisons for a specific crop on a year is more meaningful to explain the effect of topography and weather on yield.

The ANOVA and ANCOVA models were compared to select better one for treatment comparisons (Table 4.6). The model fit statistics Akaike Information Criterion (AIC) for ANCOVA were always smaller than for ANOVA. The smaller AIC indicates a better model fit (Littell et al., 2006). The *p*-values from ANOVA for corn yield in 3 of 4 years were greater than 0.05. Similarly, the *p*-values for soybean yield in 2 of 3 years were greater than 0.05. The higher p-value indicates that the effects of treatments on yield were not likely to be different. However, ANCOVA showed that the interaction between treatment and covariate WI was statistically significant ($p < 0.001$) for all crop and years. This indicates that there was a significant difference between the slopes of yield versus WI among treatments. Areas within a plot with different WI values responded differently to the applied treatments. The variance of residuals for ANCOVA was consistently smaller than for ANOVA. The variances of block and block by treatment in most of years were smaller in ANCOVA than in ANOVA. The smaller variance in ANCOVA can undoubtedly improve the predictive accuracy of a model.

Table 4.7 presents the average yield comparison between ANOVA and ANCOVA with WI at 7 (average) among 4 treatments. Corn yields in 3 of 4 years did not differ among treatments by ANOVA. However, the results from ANCOVA showed significant yield difference among treatments. Similar results were found for soybean. For wheat, however, the test results between ANOVA and ANCOVA were the same. This could be explained as when the difference between treatments was large enough the covariate was less useful in comparing the treatment effect. Table 4.7 also shows that ANCOVA reduced standard errors for treatment means and thereby improved the accuracy of estimates of yields for treatment means. Similar results were found by Kravchenko et al. (2005) when they using soil electrical conductivity as a covariate to determine the soil P among different treatments. Kaspar et al. (2006) found that terrain covariates can help to remove most of the spatial variability of soil carbon and to detect much smaller differences between treatment means. Therefore, I applied ANCOVA model to estimate least-squared means of crop yield and compared the treatment and WI effects on yield.

Table 4.6. Model fit statistics and variance components.

	model	AIC	p value‡	Residual	blk	blk*trt
Corn						
1996	**ANOVA**	24458	0.108	1.81	0.25	1.02
	ANCOVA	23944	<.0001	1.68	0.27	0.93
1999	**ANOVA**	25291	0.149	1.01	0.00	0.59
	ANCOVA	24064	<.0001	0.89	0.49	0.88
2002	**ANOVA**	39545	0.202	2.21	0.20	1.15
	ANCOVA	38877	<.0001	2.07	0.20	1.15
2005	**ANOVA**	44530	<.0001	3.09	0.31	0.99
	ANCOVA	43640	<.0001	2.85	0.35	0.89
Soybean						
1997	**ANOVA**	9648	0.08	0.23	0.00	0.06
	ANCOVA	8964	<.0001	0.21	0.00	0.04
2000	**ANOVA**	-755	0.075	0.05	0.00	0.04
	ANCOVA	-872	<.0001	0.05	0.00	0.04
2003	**ANOVA**	5298	0.019	0.09	0.02	0.12
	ANCOVA	5239	<.0001	0.09	0.02	0.12
Wheat						
1998	**ANOVA**	14376	<.0001	0.27	0.00	0.25
	ANCOVA	13668	<.0001	0.25	0.00	0.22
2001	**ANOVA**	7997	<.0001	0.16	0.05	0.08
	ANCOVA	7584	<.0001	0.15	0.05	0.07
2004	**ANOVA**	27515	<.0001	0.65	0.02	0.03
	ANCOVA	27456	<.0001	0.65	0.02	0.03

AIC: Akaike Information Criterion.
blk: block.
blk*trt: interaction of block x treatment.
‡: p value of F-test for treatment effects in analysis of variance (ANOVA), and for interaction between treatment and covariate in analysis of covariance (ANCOVA).

Table 4.7. Mean yield estimates (Mg ha^{-1}) among 4 treatments with and without wetness index (WI) as a covariate.

	Model	Treatment (standard error of the treatment mean) T1	T2	T3	T4
Corn					
1996	**ANOVA**^{NS}	3.74(0.46)	4.53(0.64)	4.34(0.46)	2.86(0.50)
	ANCOVA§	3.72(0.45)ab†	4.52(0.62)b	4.34(0.45)b	2.86(0.49)a
1999	**ANOVA**^{NS}	3.16(0.31)	3.36(0.34)	3.97(0.31)	4.07(0.31)
	ANCOVA	3.14(0.29)a	3.36(0.31)ab	3.99(0.29)b	4.06(0.29)b
2002	**ANOVA**^{NS}	6.28(0.48)	7.10(0.48)	7.24(0.48)	6.08(0.48)
	ANCOVA^{NS}	6.28(0.47)	7.09(0.47)	7.27(0.47)	6.07(0.47)
2005	**ANOVA**	8.34(0.47)b	9.56(0.47)c	8.81(0.47)bc	5.79(0.47)a
	ANCOVA	8.32(0.46)b	9.57(0.46)c	8.84(0.46)bc	5.78(0.46)a
Soybean					
1997	**ANOVA**^{NS}	1.39(0.11)	1.49(0.13)	1.68(0.11)	1.19(0.13)
	ANCOVA	1.37(0.10)a	1.49(0.11)ab	1.68(0.10)b	1.19(0.11)a
2000	**ANOVA**^{NS}	1.68(0.09)	1.63(0.08)	1.85(0.08)	1.95(0.09)
	ANCOVA	1.68(0.09)a	1.63(0.08)a	1.85(0.08)ab	1.95(0.09)b
2003	**ANOVA**	1.52(0.15)ab	1.91(0.15)b	1.36(0.15)a	1.22(0.15)a
	ANCOVA	1.52(0.15)ab	1.91(0.15)b	1.36(0.15)a	1.22(0.15)a
Wheat					
1998	**ANOVA**	3.08(0.21)c	1.98(0.22)b	1.51(0.22)b	0.73(0.21)a
	ANCOVA	3.08(0.19)c	1.99(0.21)b	1.51(0.21)b	0.73(0.19)a
2001	**ANOVA**	3.63(0.15)c	3.18(0.15)b	3.08(0.15)b	2.27(0.15)a
	ANCOVA	3.63(0.14)c	3.18(0.14)b	3.08(0.14)b	2.26(0.14)a
2004	**ANOVA**	4.55(0.09)c	4.59(0.09)c	4.22(0.09)b	2.44(0.09)a
	ANCOVA	4.55(0.09)c	4.59(0.09)c	4.22(0.09)b	2.44(0.09)a

^{NS} indicates no significant difference between treatments at $p < 0.05$ level.
† means within the same row followed by the same letter are not significant different ($p < 0.05$).
§ represents treatment mean adjusted at average value of WI (7.0).

Regression Slopes of Average Yield versus WI

Because of significant interaction between treatment and WI, unequal slope regression lines were plotted for corn yields versus WI among treatments in 4 years (Fig. 4.13). Generally, yields were positively associated with WI. But the regression slope for each treatment varied from year to year as a function of precipitation. In 1996 and 1999, summer precipitation values were less than normal (Fig. 4.3). The regression slope of yield versus WI for the T1 was significantly steeper than for T2. In 2005, the summer precipitation was close to normal. The T1 had steeper slope than T2 as well. In 2002, however, summer precipitation was more than normal. The regression slopes for the T1 and T2 were not significant different from zero. The results suggested that yields in wet year less depend on WI. But in dry and normal rainfall years, for example in 1996, 1999 and 2005, corn yields in conventional tillage had greater response to WI values compared with no-till.

Unlike the T1 and T2, the regression slopes for the T3 and T4 were significantly positive in wetter year of 2000. The results indicated that the yields in low input and organic systems increased with increase with WI values regardless of dry or wet weather. Although corn yields for high input system did not response on WI in wet year, it was positively related with WI for low and zero input system. This was probably due to that when the soil water is not a limiting factor in wet year, but nutrient may become major limiting factor on yield in low and zero input systems. The areas with higher WI values were located at depression areas coincident with flat slope and had relative abundant nutrient. Because of high chemical input in the T1 and T2, the influence of nutrient status due to topography was minimal compared with low or zero input in wet year.

Similar results were observed in soybean (Appendix 4.12). In 1997, the precipitation in summer was less than normal. The regression slope for the T1 was steeper than T2. But 2000 and 2003, which both were close to normal, the regression slopes for the T1 was still higher than T2, but the magnitude of the difference between T1 and T2 became minimal. The regression slope for the wheat yield in the T1 showed significant steeper slope than for the T2 in 1998 (Appendix 4.13). They were similar in

2001 and 2004, which were attributed as wetter years. It was noted that the relationship between yield and WI for T4 were more variable across years than expected.

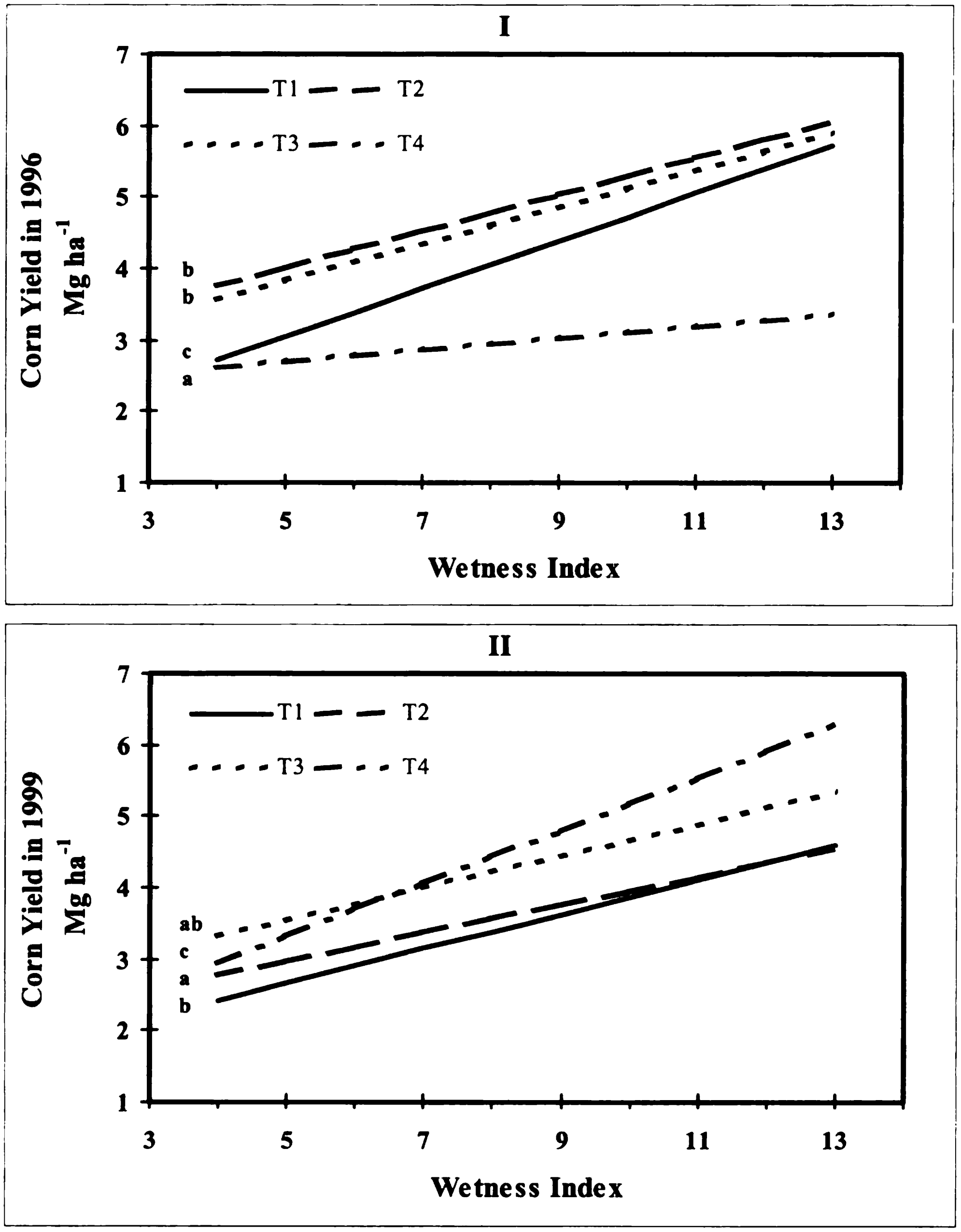
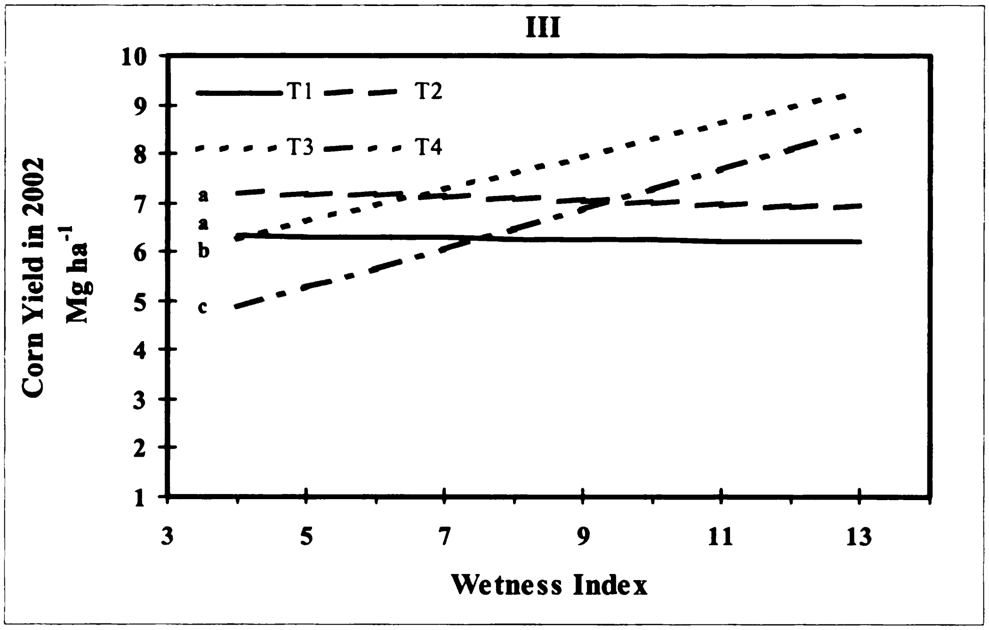


Fig. 4.13. Plot of estimated corn yield regression models for the 4 treatments at different WI values. I is for 1996, II is for 1999. Alphabetic letters at left of a line represent the value of regression slope from low to high. The same letters indicate no significant slope difference between treatments (p < 0.05).



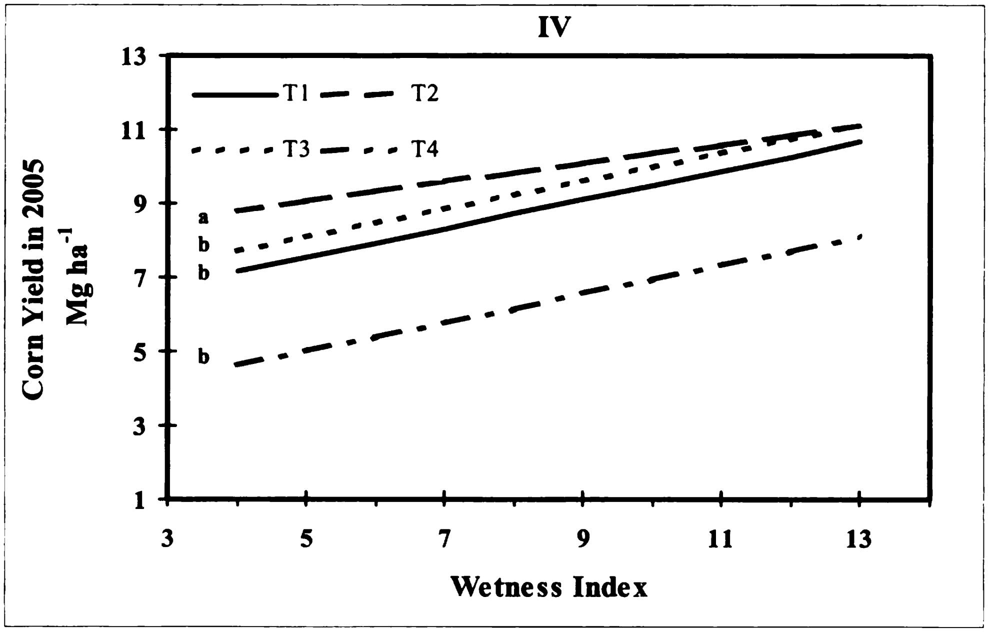


Fig. 4.13 cont'd. Plot of estimated corn yield regression models for the 4 treatments at different WI values. III is for 2002, IV is for 2005. Alphabetic letters at left of a line represent the value of regression slope from low to high. The same letters indicate no significant slope difference between treatments ($p < 0.05$).

Average Yield Difference Influenced by Wetness Index

Similar to the comparison of the maximum yield in previous section, I compared average yields between the T1 and T2, T1 and T3, T3 and T4 using ANCOVA model. The yield difference between treatments was shown by constructing 95% confidence band across the increment of WI level. A horizontal line was inserted to where the model difference is zero. Unlike nonparametric regression, where the fitted line is a curve, ANCOVA is combination of linear regression and ANOVA. The average yield and confidence band of the difference corresponding to WI were linear lines.

Except in 2005 year, the corn yields between the T1 and T2 did not significantly differ, although the T2 yields tended to be higher (Fig. 4.14). The 4-yr estimated yields across entire WI values were 5.72 Mg ha^{-1} and 6.39Mg ha^{-1} for the conventional tillage and no-till systems, respectively. In 2005, the T2 yields were significantly higher than T at WI < 7.5. The regression slope for the yield difference versus WI was positive with varied values across years. Noticeable, the slope was flat across whole WI values in 2002, which was wetter year. WI is hydrologically based index used to characterize the likely soil moisture regime (Moore et al., 1988). Higher summer rainfall could lead to higher soil water content. As a result, WI did not affect corn yields in a wet year but in a dry or normal year.

A number of yield comparisons between conventional tillage and no-till were reported (Kapusta et al., 1996; Wilhelm and Wortmann. 2004; Hoeft, et al., 2005; Grandy et al., 2006). But little information about the effects of topographic on the yield between the tillage methods was mentioned. I found that no-till corn tended to produce higher yields than conventional tillage, particular in lower WI values. The areas with lower WI were often characterized by summit, backslope and shoulder slope elements (Moorman et al., 2004). No-till offered higher potential for reduced erosion and evaporation and improved soil properties than conventional tillage in those areas as discussed earlier. Therefore, it is possible to maximize yield and profit by farming site-specifically based on landscape position. Through arranging no-till practice in the areas, such as hill, shoulder, back slope, whereas arranging tillage operation on foot slope and depression areas, growers might get higher yield and greater return.

No significant difference of soybean yields between the T1 and T2 was observed in 2000 (Appendix 4.14). However, the T2 yields at lower WI values were significantly higher than T1 in 1997 and 2003. Similar to corn, no-till system produced higher soybean yields at lower WI values compared with conventional tillage. Wheat yield in the T1 were significantly higher than T2 in 1998 and 2001 and equaled those in the T2 in 2004 (Appendix 4.15). Clearly, the magnitude of soybean and wheat yield difference became smaller from earlier to later years. The results indicated that no-till tended to produce higher or similar yields to conventional tillage in a long-term run.

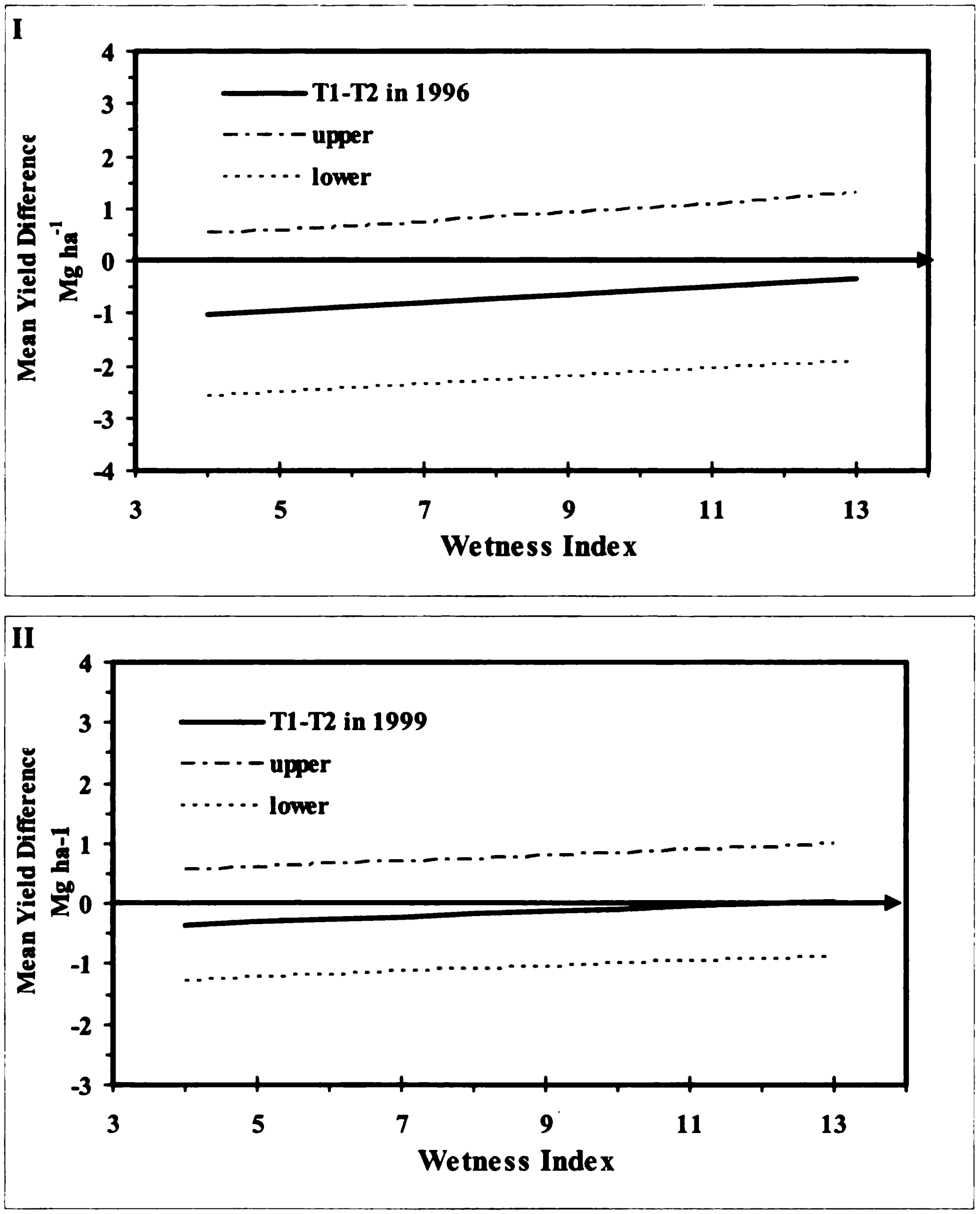
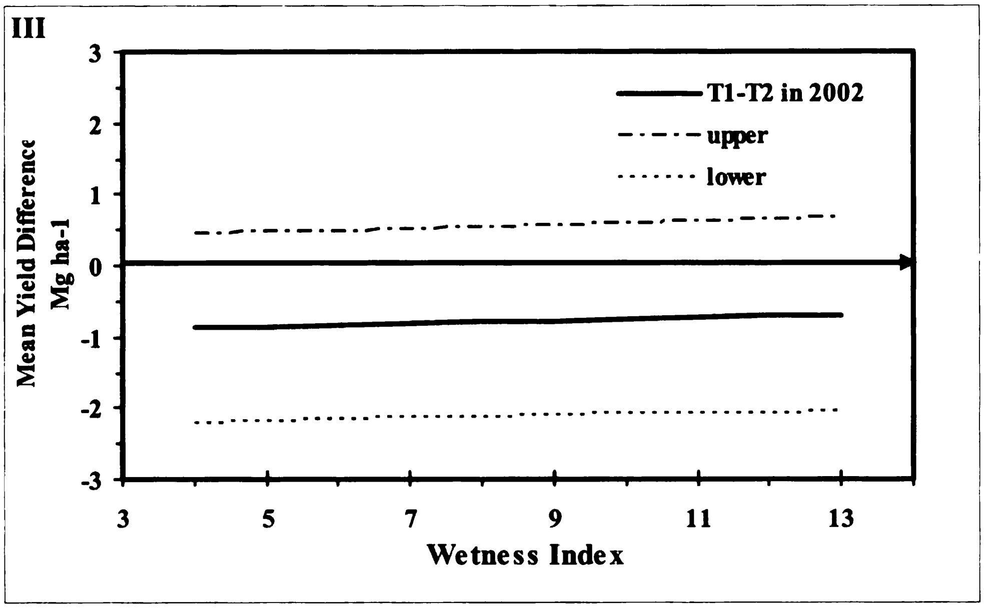


Fig. 4.14. Plot of 95% confidence band of corn yield difference between T1 and T2, where WI as covariate. I, II are for years 1996, 1999, respectively. Arrow-head line indicates zero yield difference.



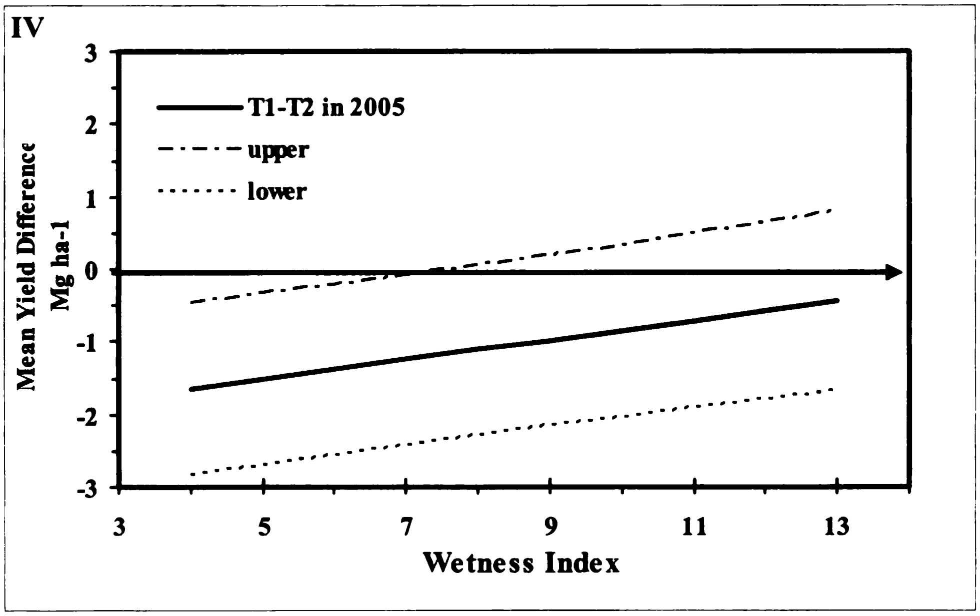


Fig. 4.14 cont'd. Plot of 95% confidence band of corn yield difference between T1 and T2, where WI as covariate. III, IV are for years 2002, 2005, respectively. Arrow-head line indicates zero yield difference.

No significant corn yields differences between the T1 and the T3 were found in 1996, 2005, although the yields in the T3 were slightly higher than in the T1 (Fig. 4.15). The T3 yields were significantly higher than the T1 in 1999 at lower WI values. But they were opposite in 2002. In 2002, summer rainfall was more than normal. Possibly, the areas with higher WI values in low input system had better nutrient supply which lead to considerable higher yields compared with conventional system in wet year. No significant difference of soybean yields between the T1 and T3 was observed in 2000 and 2003 (Appendix IV-15). The 3-yr average yields for the T1 were fairly similar to those in the T3. However, low input system produced higher soybean yields at lower WI values compared with conventional input system. Wheat yields in the T1 were consistently higher than in T3 across 3 years (Appendix 4.17). The yield difference between the T1 and T3 became smaller from 1998, 2001 to 2004. As previously discussed, there may be nitrogen shortages that may reduce crop yields temporarily, but these can be eliminated by raising the soil nitrogen level and improving soil productivity through the use of legume cropping systems (Kuo et al., 1997; Mader, et al., 2002; Pimentel et al., 2005; Villamil et al., 2006).

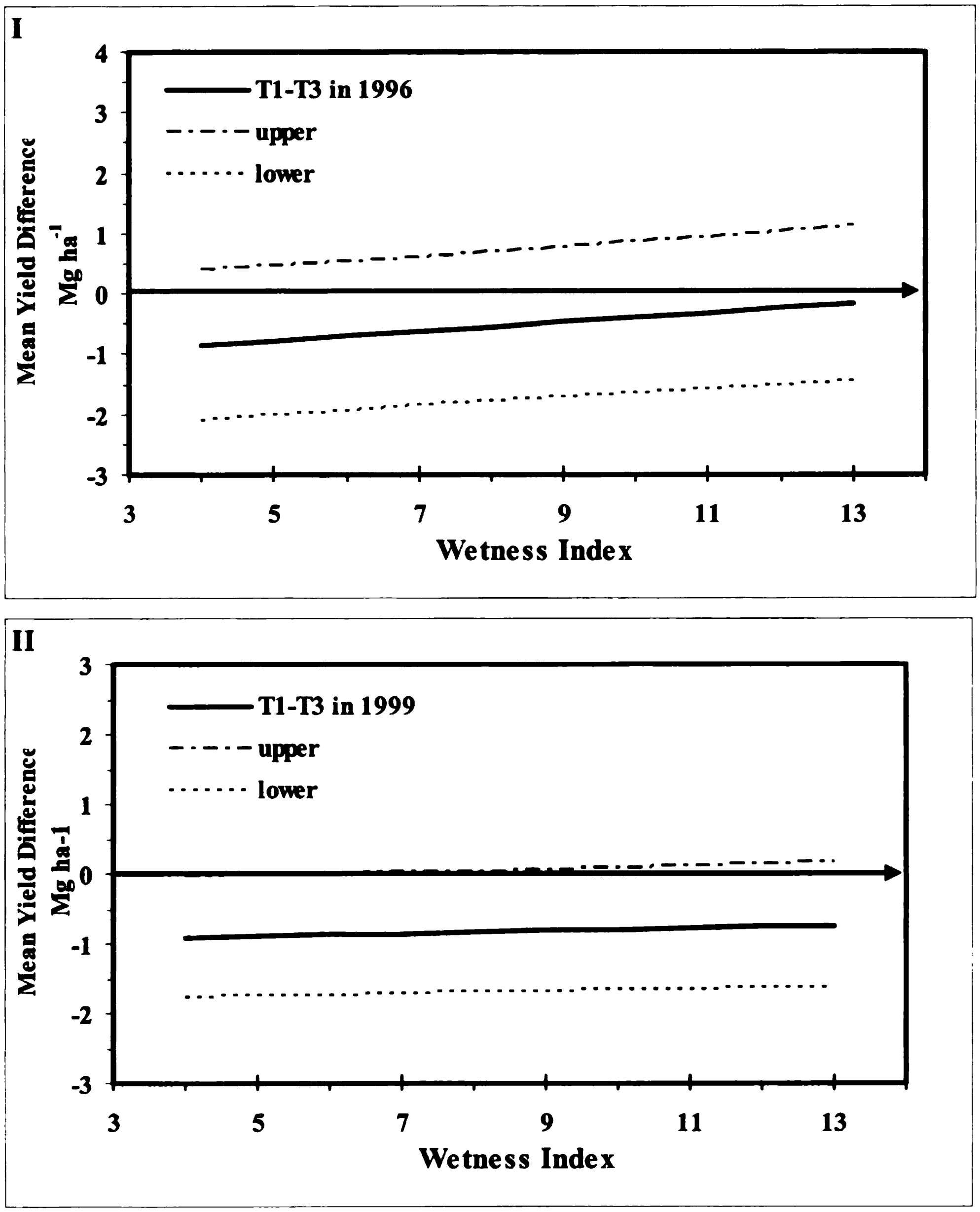
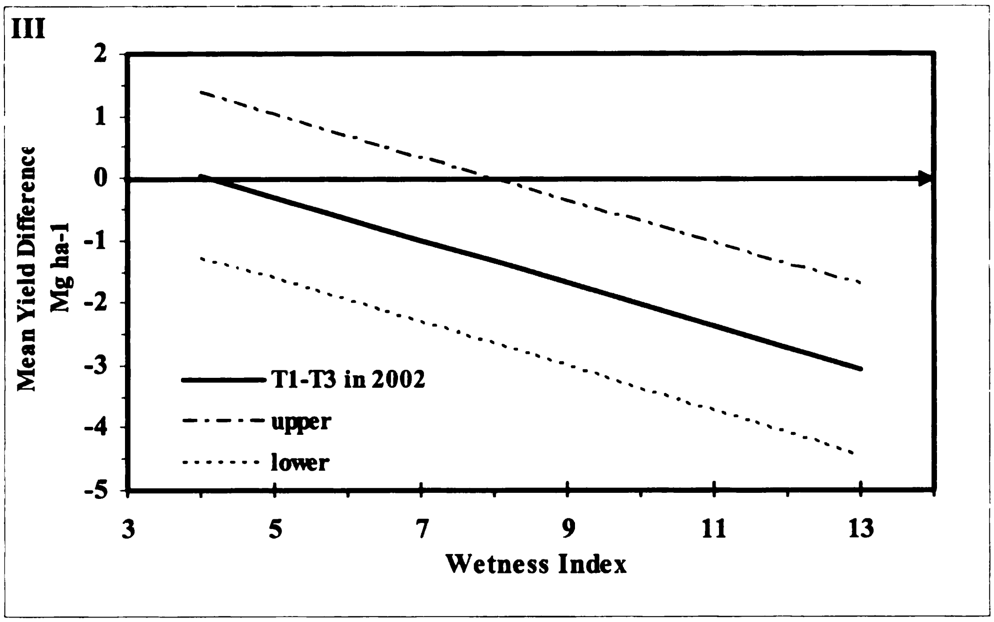


Fig. 4.15. Plot of 95% confidence band of corn yield difference between T1 and T3, where WI as covariate. I and II are for years 1996, 1999, respectively. Arrow-head line indicates zero yield difference.



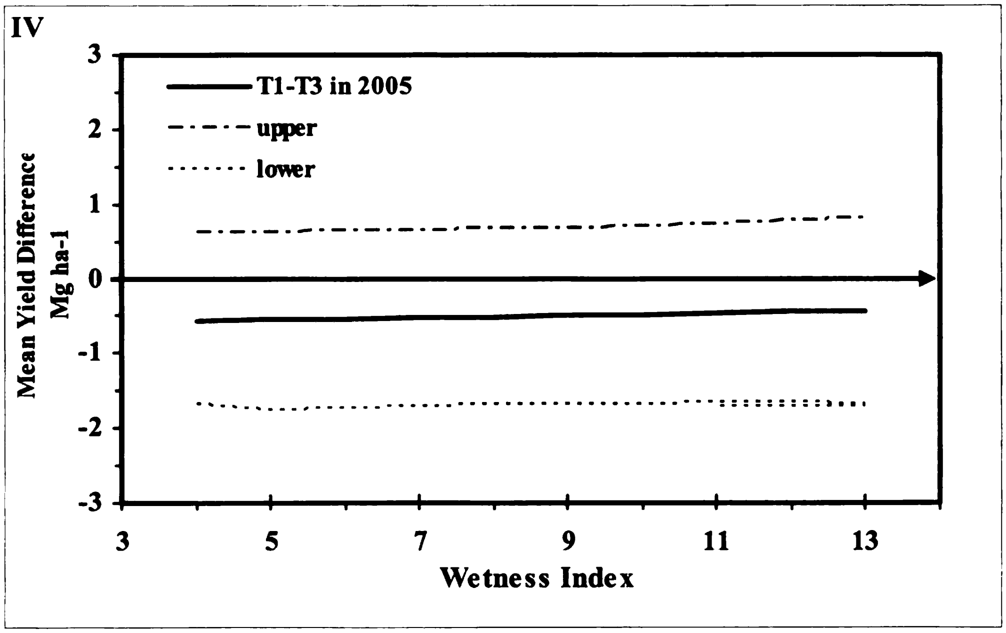


Fig. 4.15 cont'd. Plot of 95% confidence band of corn yield difference between T1 and T3, where WI as covariate. III and IV are for years 2002, 2005, respectively. Arrow-head line indicates zero yield difference.

The T3 yields of corn were significantly higher than T4 except for 1999 (Fig. 4.16). The regression slopes of yield difference were positive in 1996, negative in 1999 and 2002, close to zero in 2005, respectively. No consistent effect of WI on corn yields difference between T3 and T4 was found. Soybean yields in the T3 were significant higher than in T4 in 1997 only (Appendix 4.18). Wheat yields in the T3 were consistently higher than in T4 in 3-yr period (Appendix 4.19). Organic system showed yield disadvantage over low input system in corn and wheat, but not for soybean. European field data demonstrated that organic wheat and other cereal grain yields average from 30% to 50% lower than conventional cereal grain production (Mader, et al., 2002). The lower yields for the organic system compared with the conventional systems appear to be caused by lower nitrogen-nutrient inputs in the organic systems.

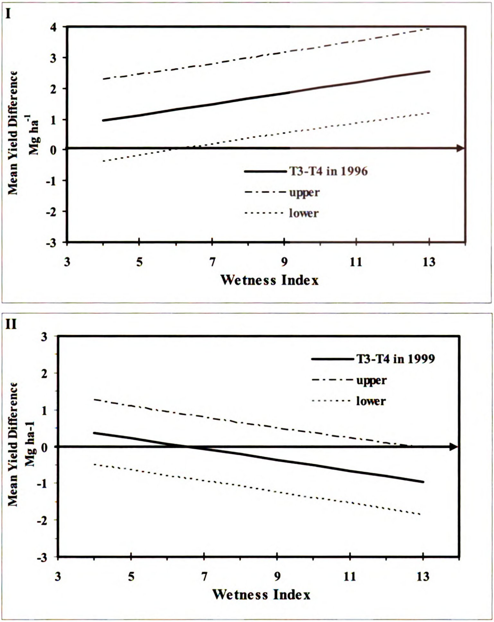
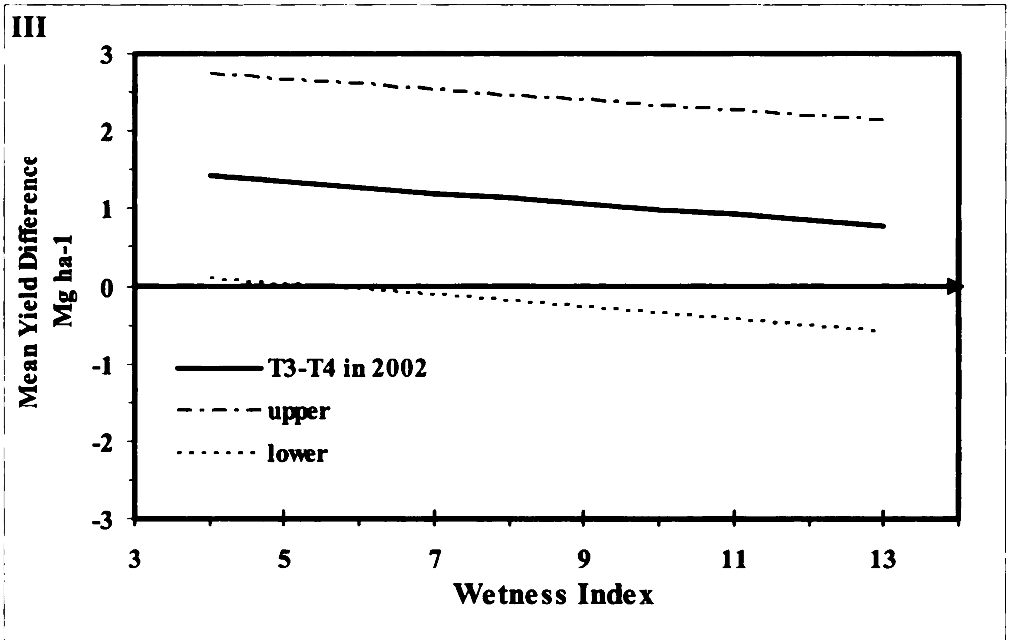


Fig. 4.16. Plot of 95% confidence band of corn yield difference between T3 and T4, where WI as covariate. I and II are for years 1996, 1999, respectively. Arrow-head line indicates zero yield difference.



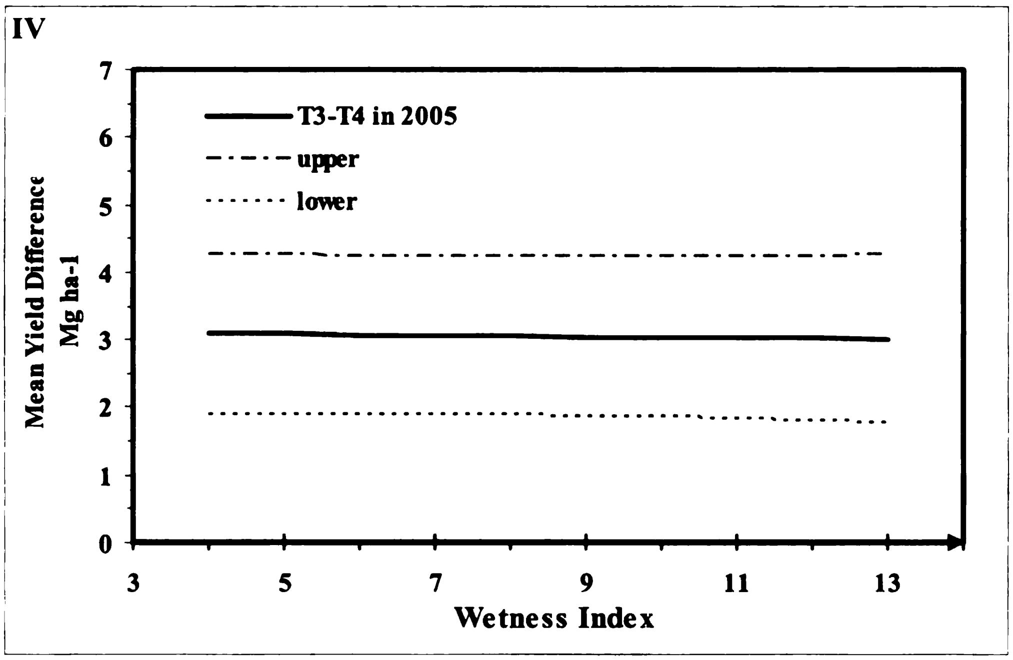


Fig. 4.16 cont'd. Plot of 95% confidence band of corn yield difference between T3 and T4, where WI as covariate. III and IV are for years 2002, 2005, respectively. Arrow-head line indicates zero yield difference.

CONCLUSION

Boundary line analysis is a useful diagnostic tool to identify yield potential and estimated the effects of topography on the maximum yield. The nonparametric spline regression algorithm utilized in the study was robust and efficient in describing the complexly shaped boundary line and comparing the yield differences between treatments across a range of WI values. The comparison of 2 treatments can be easily understood through visually plotted confidence bands for the difference.

The yield differences between the management practices varied from year to year as a function of the prevailing precipitation and depending on the topographical position. Management practices significantly interacted with topographical features as represented by WI and influenced crop yields. Further the interaction can be affected by summer precipitation. The yield difference between no-till and conventional tillage was strongly influenced by WI in dry or normal year but not in wet year.

The relationship between boundary line yield data and WI in most of the crops for most of the studied years had a convex shape. Higher boundary line yields, that are maximum yields, consistently occurred at intermediate WI levels. No-till and low input systems tended to produce higher maximum and average yields than conventional system at the lowest WI where were characterized as eroded summit and shoulder areas. It is possible to maximize yield and profit by farming landscape- or site-specifically based on landscape position. Through arranging no-till or low input practice in the areas, such as hill, shoulder, back slope, whereas arranging tillage operation on foot slope and depression areas, growers might obtain higher yield and return. The magnitude of crop yield difference between conventional and low input system became smaller from earlier to later year. Nitrogen shortages may reduce crop yields temporarily, but low input system tended to produce similar or higher yields to conventional tillage in a long-term run.

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REFREENCES

Andresen, J.A., G. Alagarswamy, C.A. Rotz, J.T. Ritchie, and A.W. LeBaron. 2001. Weather Impacts on Maize, Soybean, and Alfalfa Production in the Great Lakes Region, 1895-1996. Agron. J. 93:1059-1070.

Blackmore, S. 2000. The interpretation of trends from multiple yield maps. Computer and Electrics Agri. 26:37-51.

de Boor, C. 2001. A Practical Guide to Splines. Springer-Verlag, New York.

Chambers, J.L., T.M. Hinckley, G. Cox, C.L. Metcalf, R.G. Aslin. 1985. Boundary-Line Analysis and Models of Leaf Conductance for Four Oak-Hickory Forest Species. Forest Sci. 31(2):437-450.

Cox, W.J., R.W. Zobel, H.M. van Es, and D.J. Otis. 1990. Tillage effects on some soil physical and corn physiological characteristics. Agron. J. 82:806-812.

Crum, J.R., and H.P. Collins. 1995. KBS soils. Available at www.lter.kbs.msu.edu/soil/characterization. W.K.Kellogg Biol. Stn. Long-Term Ecol. Res. Project, Michigan State Univ., Hickory Corners, MI.

Doerge, T. 1999. Yield map interpretation. J. Prod. Agric. 12:54-61.

Drummond, S., and K. Sudduth. 2003. From sensors to information: Cleaning yield monitor data. Proc. InfoAg 2003 Conf., Indianapolis, IN. 29 July–1 Aug. 2003. Potash and Phosphate Inst., Norcross, GA.

ESRI. 2000. ArcView Spatial Analyst, Redlands, CA.

Fan, J. and I. Gijbels. 1996. Local Polynomial Modelling and Its Applications. Chapman and Hall, London.

Fortin, M.C., and F.J. Pierce. 1991. Timing and nature of mulch retardation of corn vegetative development. Agron. J. 83:258-263.

Grandy, A.S., T.D. Loecke, S. Parr, and G.P. Robertson. 2006. Long-Term Trends in Nitrous Oxide Emissions, Soil Nitrogen, and Crop Yields of Till and No-Till Cropping Systems. J. Environ. Qual. 35:1487–1495.

Halvorson, G.A., and E.C. Doll. 1991. Topographic effects on spring wheat yields and water use. Soil Sci. Soc. Am. J. 55:1680-1685.

Hao, X. and A.N. Kravchenko. 2007. Management practice effects on surface total carbon: Differences along a textural gradient. Agron. J. 99:18-26.

Härdle, W. 1990. Applied Nonparametric Regression. Cambridge University Press, Cambridge.

Hoeft, R. G., E.D. Nafziger, R.R. Johnson, and S.R. Aldrich. 2000. Modern corn and soybean production. MCSP Publications. Savoy, IL.

Hu, Q., and G. Buyanovsky. 2003. Climate Effects on Corn Yield in Missouri. J. Appl. Meteor. 42:1626-1635.

Huang, X., A. Kravchenko, K. Thelen, N. Martin, and G. Bollero. 2005. Yield variability in an undulating field: classification and prediction. Proceedings of the 7th International Conference on Precision Agriculture and Other Precision Resources Management. July 25-28, 2004. Minneapolis, MN. pp 419-431.

Jaynes, D.B., and T.S. Colvin. 1997. Spatiotemporal variability of corn and soybean yield. Agron. J. 89:30-37.

Jaynes, D.B., T.C. Kaspar, T.S. Colvin, and D.E. James. 2003. Cluster analysis of spatiotemporal corn yield patterns in an Iowa field. Agron. J. 95:574-586.

Jiang, P., and K.D. Thelen. 2004. Effect of soil and topographic properties on crop yield in a North-Central corn–soybean cropping system. Agron. J. 96:252-258.

Kabir, Z. and R.T. Koide. 2000. The effect of dandelion or a cover crop on mycorrhiza inoculum potential, soil aggregation, and yield of maize. Agric. Ecosyst. Environ. 78:167-174.

Kapusta, G., R.F. Krausz, and J.L. Matthews. 1996. Corn yield is equal in conventional, reduced, and no tillage after 20 years. Agron. J. 88: 812-817.

Kaspar, T.C., T.S. Colvin, D.B. Jaynes, D.L. Karlen, D.E. James, D.W. Meek, D. Pulido, and H. Butler. 2003. Relationship between six years of corn yields and terrain attributes. Precision Agriculture 4:179-192.

Kaspar, T.C., T.B. Parkin, D.B. Jaynes, C.A. Cambardella, D.W. Meek, and Y.S. Jung. 2006. Examining Changes in Soil Organic Carbon with Oat and Rye Cover Crops: Using Terrain Covariates. Soil Sci. Soc. Am. J. 70:1168–1177.

Kitchen, N.R., S.T. Drummond, E.D. Lund, K.A. Sudduth, and G.W. Buchleiter. 2003. Soil electrical conductivity and topography related to yield for three contrasting soil-crop systems. Agron. J. 95:483-495.

Kravchenko, A.N., and D.G. Bullock. 2000. Correlation of Corn and Soybean Grain Yield with Topography and Soil Properties. Agron. J. 92:75-83.

Kravchenko, A.N., G.P. Robertson, X.Hao, and D.G. Bullock. 2006. Management practice effects on surface total carbon: Differences in spatial variability patterns. Agron. J. 98: 1559-1568.

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

Kravchenko, A.G., and K.D. Thelen. 2007. Effect of winter wheat crop residue on no-till corn growth and development. Agron. J. 99:549-555.

Kravchenko, A.N., T.M. Harrigan, and B.B. Bailey. 2005. Soil Electrical Conductivity as a covariate to improve the efficiency of field experiments. Transactions of the ASAE. 48(4):1353-1357.

Kuo, S, U.M. Sainju, and E.J. Jellum. 1997. Winter cover crop effects on soil organic carbon and carbohydrate in soil. Soil Sci. Soc. Am. J. 61: 145-152.

Lamb, J.A., R.H. Dowby, J.L. Anderson, and G.W. Rehm. 1997. Spatial and temporal stability of corn grain yields. J. Prod. Agric. 10:410-414.

Lark, R.M. 1997. An empirical method for describing the joint effects of environmental and other variables on crop yield. Annals of Applied Biology 131:141-159.

Lark, R.M., and J.V. Stafford. 1997. Classification as a first step in the interpretation of temporal and spatial variation of crop yield. Ann. Appl. Biol. 130:111-121.

Liu, A., B.L. Ma, and A.A. Bomke. 2005. Effects of cover crops on soil aggregate stability, total organic carbon, and polysaccharides. Soil Sci. Soc. Am. J. 69:2041-2048.

Littell, R.C., G.A. Milliken, W.W. Stroup, R.D. Wolfinger, and O. Schabenberger. 2006. SAS for Mixed Models, 2nd Edition. SAS Institute Inc., Cary, NC.

Lobell, D.B. and G.P. Asner. 2003. Climate and management contributions to recent trends in U.S. agricultural yields. Science 299:1032.

Mäder, P., A. Fliebbach, D. Dubois, L. Gunst, P. Fried, and U. Niggli. 2002. Soil Fertility and Biodiversity in Organic Farming. Science 296:1694-1697.

Milliken, G.A., and D.E. Johnson. 2002. Analysis of Messy Data, Vol. 3: Analysis of Covariance. Chapman & Hall/CRC, New York.

Mokma, D.L., and J.A. Doolittle. 1993. Mapping soils and soil properties in southwest Michigan using ground-penetrating radar. Soil Survey Horizons 34:13-22.

Moorman, T.B., C.A. Cambardella, D.E. James, D.L. Karlen, and L.A. Kramer. 2004. Quantification of tillage and landscape effects on soil carbon in small Iowa watersheds. Soil & Tillage Research 78:225–236.

Moore, I.D., P.E. Gessler, G.A. Nielsen, and G.A. Peterson. 1993. Soil attributes prediction using terrain Analysis. Soil Sci. Soc. Am. J. 57:443-452.

Perez-Quezada, J.F., G.S. Pettygrove, and R.E. Plant. 2003. Spatial–temporal analysis of yield and soil factors in two four-crop–rotation fields in the Sacramento Valley, California. Agron. J. 95:676-687.

Pimentel, D. P. Hepperly, J. Hanson, D. Douds, and R. Seidel. 2005. Environmental, Energetic, and Economic Comparisons of Organic and Conventional Farming Systems. BioScience 55:573-582.

Reicosky D.C., W.D. Kemper, G.W. Langdale, C.L. Douglas, and P.E. Rasmussen. 1995. Soil organic-matter changes resulting from tillage and biomass production. J. Soil Water Cons. 50: 253-261.

Rhoton, F.E. 2000. Influence of time on soil response to no-till practices. Soil Sci. Soc. Am. J. 64: 700-709.

Robertson, G. P., J.C. Broome, E.A. Chornesky, J.R. Frankenberger, P. Johnson, M. Lipson, J.A. Miranowski, E.D. Owens, D. Pimentel, and L.A. Thrupp. 2004. Rethinking the Vision for Environmental Research in US Agriculture. BioScience 54:61-65.

Sainju, U.M., W.F. Whitehead, and B.P. Singh. 2003. Cover crops and nitrogen fertilization effects on soil aggregation and carbon and nitrogen pools. Can. J. Soil Sci. 83:155-165.

SAS Institute Inc. 1999. SAS/STAT User's Guide, Version 8. Cary, NC.

Schmidt, F., and A. Persson. 2003. Comparison of DEM data capture and topographic wetness indices. Precision Agriculture 4:179-192.

Schnug, E., J. Heym, and F. Achwan. 1996. Establishing critical values for soil and plant analysis by means of the Boundary Line Development System (Bolides). Communications in Soil Science and Plant Analysis 27:2739-2748.

Shatar, T.M., and A.B. McBratney. 2004. Boundary-line analysis of field-scale yield response to soil properties. J. Agricultural Science 142:553-560.

Shuai X., Z. Zhou, and R.S. Yost. 2003. Using Segmented Regression Models to Fit Soil Nutrient and Soybean Grain Yield Changes due to Liming. J Agricultural, Biological, and Environmental Statistics, 8(2):240–252.

Si, B.C., and R.E. Farrell. 2004. Scale-dependent relationship between wheat yield and topographic indices: A wavelet approach. Soil Sci. Soc. Am. J. 68:577-587.

Simmons, F.W., D.K. Cassel, and R.B. Daniels. 1989. Landscape and soil property effects on corn grain yield response to tillage. Soil Sci. Soc. Am. J. 53:534-539.

Timlin, D.J., Y. Pachepsky, V.A. Snyder, and R.B. Bryant. 1998. Spatial and temporal variability of corn grain yield on a hillslope. Soil Sci. Soc. Am. J. 62:764-773.

Tomer, M.D., C.A. Cambardella, D.E. James, and T.B. Moorman. 2006. Surface-Soil Properties and Water Contents across Two Watersheds with Contrasting Tillage Histories. Soil Sci. Soc. Am. J. 70:620–630.

VandenBygaart, A.J., R. Protz, A.D.Tomlin, and J.J. Miller. 1999. Tillage system effects on near-surface soil morphology: observations from the landscape to micro-scale in silt loam soils of southwestern Ontario. Soil Till. Res. 51:137-147.

Villamil, M.B., G.A. Bollero, R.G. Darmody, F.W. Simmons, and D.G. Bullock. 2006. No-Till Corn/Soybean Systems Including Winter Cover Crops: Effects on Soil Properties. Soil Sci. Soc. Am. J. 70:1936–1944.

Wang, L. and J. Yang. 2006. Simultaneous spline confidence bands for time series prediction function. Submitted.

Webb, R.A. 1972. Use of the Boundary Line in the analysis of biological data. J. Horticultural Science 47:309-319.

Wilhelm, W.W., and C.S. Wortman. 2004. Tillage and rotation interactions for corn and soybean grain yield as affected by precipitation and air temperature. Agron. J. 96:425-432.

CHAPTER V

CONCLUSION

Highly variable soil and topographical attributes in glacial till soils cause difficulties in mapping soil carbon based only on a limited number of soil samples. However, remote sense technology and statistical methods combined with inexpensive elevation data can estimate soil carbon with less cost and reasonable accuracy. Field on-the-go NIRS and Landsat ETM imagery determined that it is feasible to map soil carbon of agricultural fields on glacial till soils rapidly and cost-effectively. Regression coefficients between measured and predicted carbon values were equal to 0.70 and 0.46 using NIRS data and ETM imagery. When topographical attributes were included into regression model along with NIRS and ETM spectra reflectance values, the regression coefficients improved to 0.81 and 0.62. ETM imagery is useful in a large scale, particularly for assessing soil carbon in a bare field and combined with topographical attributes.

Both electrical conductivity and topographical attributes were found to be helpful in explaining yield variability. Areas with lower electrical conductivity and slope tended to form high yield clusters in the studied fields. Historical yield classification may be used to delineate management zones within a field and predict the yield patterns.

Crop yields were correlated negatively with spring and positively with summer daily precipitation. Roughly 60 % of the variability of the yield could be explained by the growing season precipitation. The yields for the high chemical input system were largely influenced by precipitation in drier years and less influenced in normal or wetter years as compared with low or zero input systems.

The yield differences between the management practices varied from year to year as a function of the prevailing precipitation and depending on the topographical position. Management practices significantly interacted with topographical attributes as represented by WI. The yield difference between no-till and conventional tillage was strongly influenced by WI in drier or normal years but not in wetter years.

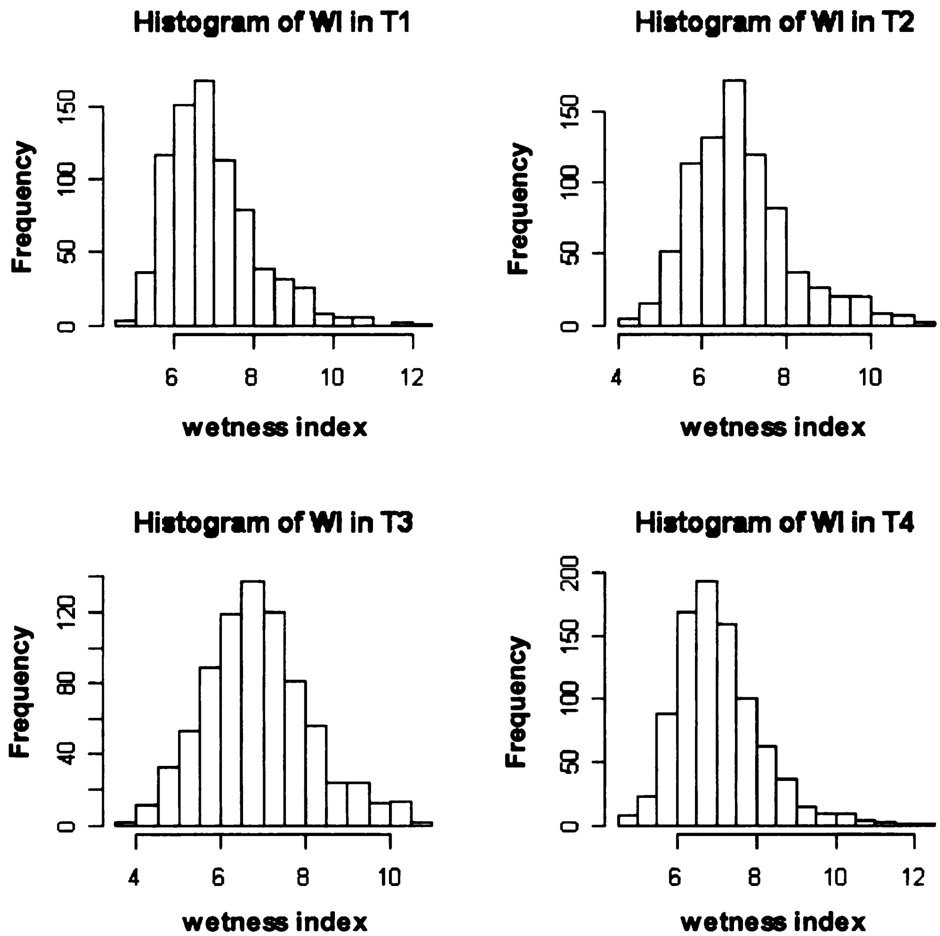
The relationship between boundary line yield data and WI in most of the crops for most of the studied years had a convex shape. Higher boundary line yields, that are maximum yields, consistently occurred at intermediate WI levels. No-till and low input systems tended to produce higher maximum and average yields than conventional system at the lowest WI. It is possible to maximize yield and profit by farming site-specifically based on landscape position.

APPENDICES

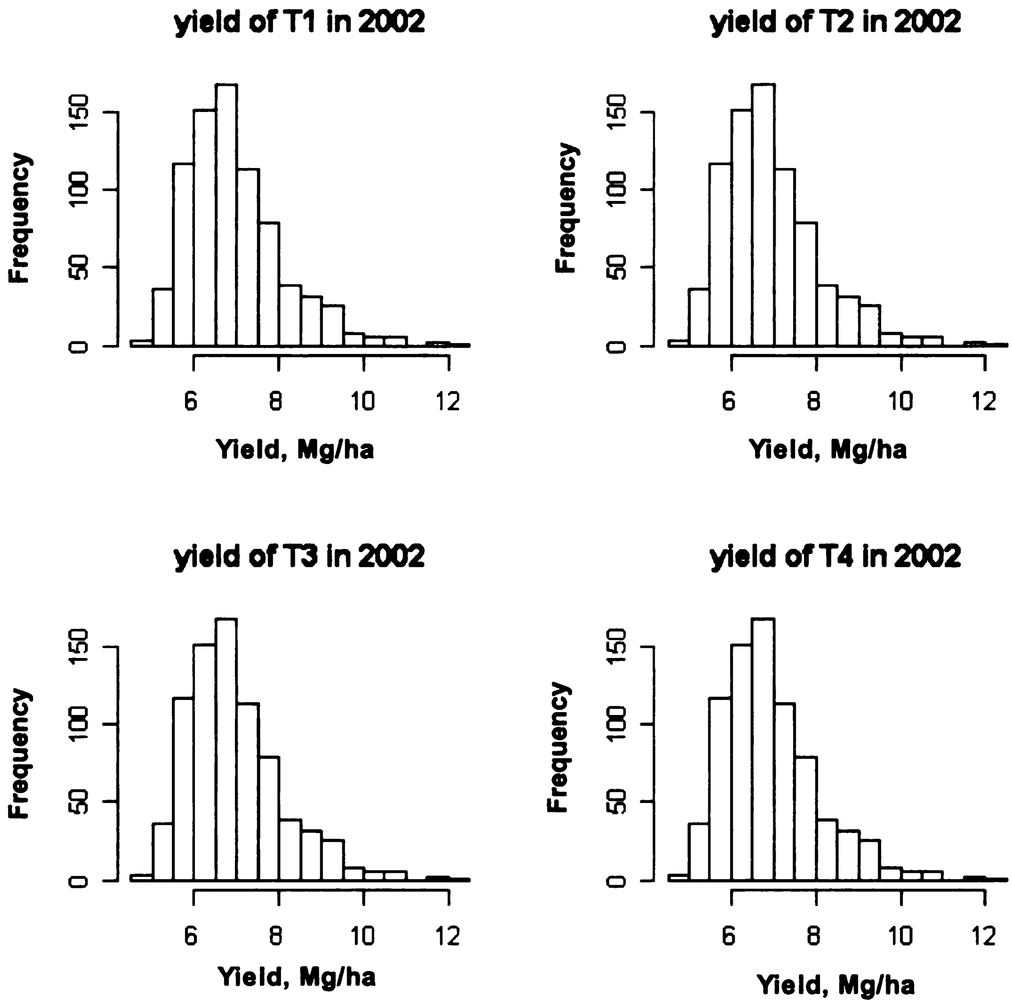
Appendix 4.1. Boundary lines fitted as 2-linear-line regression results for the corn yields in 4 year from 4 treatments.

	Corn in 1996				Corn in 1999			
	T1	T2	T3	T4	T1	T2	T3	T4
Yield in joint point, Mg ha^{-1}	9.97	7.90	7.91	5.94	7.63	5.86	6.03	7.35
N	163	164	161	140	163	164	156	142
Joint point	7.22c[§]	6.54b	6.25a	6.26a	7.15c	5.80a	6.26b	7.50d
Slope 1	1.71bc	1.63a	1.66ab	1.78c	1.59c	0.73a	0.94b	0.77a
Slope 2	-0.62a	-0.44b	-0.38c	-0.45b	-0.39a	-0.16c	-0.20c	-0.26b
R^2	0.35	0.37	0.55	0.42	0.36	0.17	0.39	0.20
	Corn in 2002				**Corn in 2005**			
	T1	**T2**	**T3**	**T4**	**T1**	**T2**	**T3**	**T4**
Yield in joint point Mg ha^{-1}	10.78	11.05	11.87	11.80	14.19	13.17	12.66	11.14
N	163	171	167	143	163	166	154	143
Joint point	4.99a	5.23b	5.72c	6.87d	5.65c	5.08b	4.98a	7.29d
Slope 1	5.10d	2.53c	1.70b	1.44a	4.04c	1.87b	4.79d	1.26a
Slope 2	-0.39ab	-0.49a	-0.34b	-0.36b	-0.24b	-0.20b	-0.17b	-0.52a
R^2	0.43	0.61	0.37	0.33	0.46	0.24	0.14	0.23

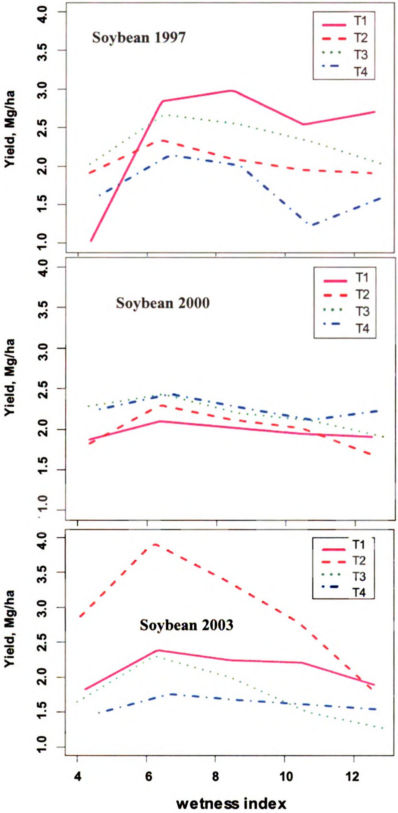
N: sample size; [§] estimated parameters within a row followed by the same letter are not significantly different between treatments at the 0.01 level by the 2-side t-test.



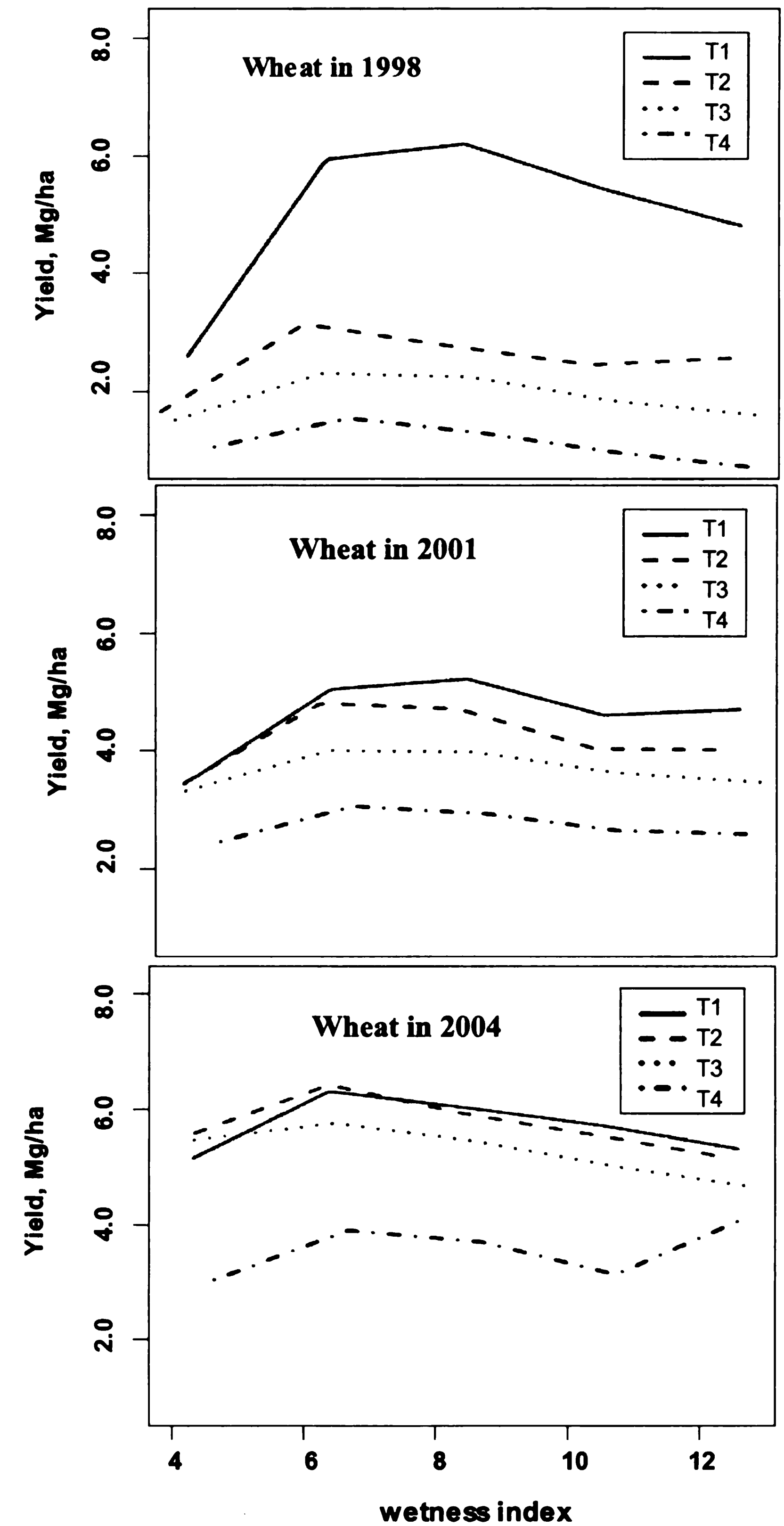
Appendix 4.2. Histograms of elevation in 4 treatments



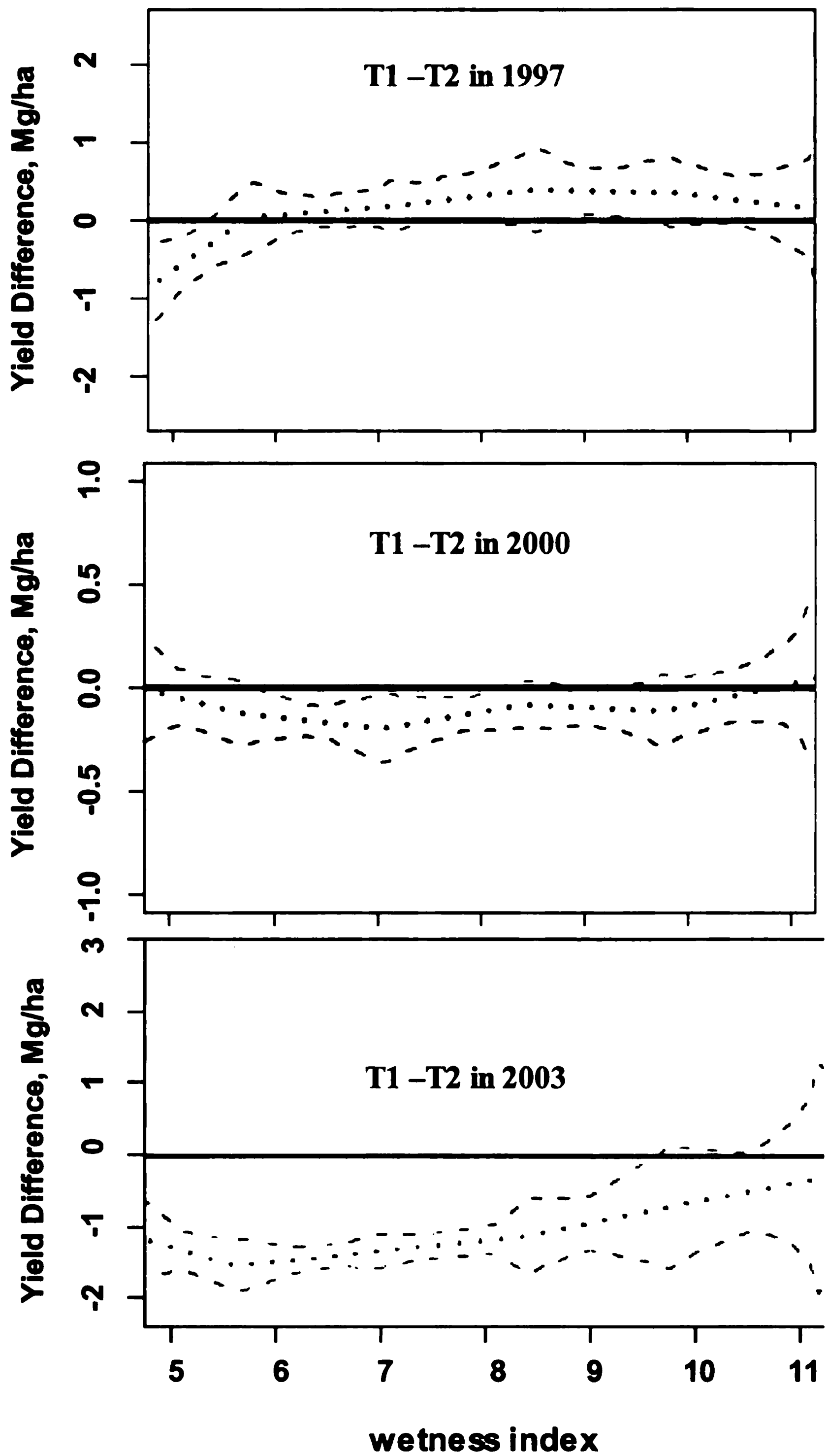
Appendix 4.3. Histograms of corn yield in 4 treatments in 2002



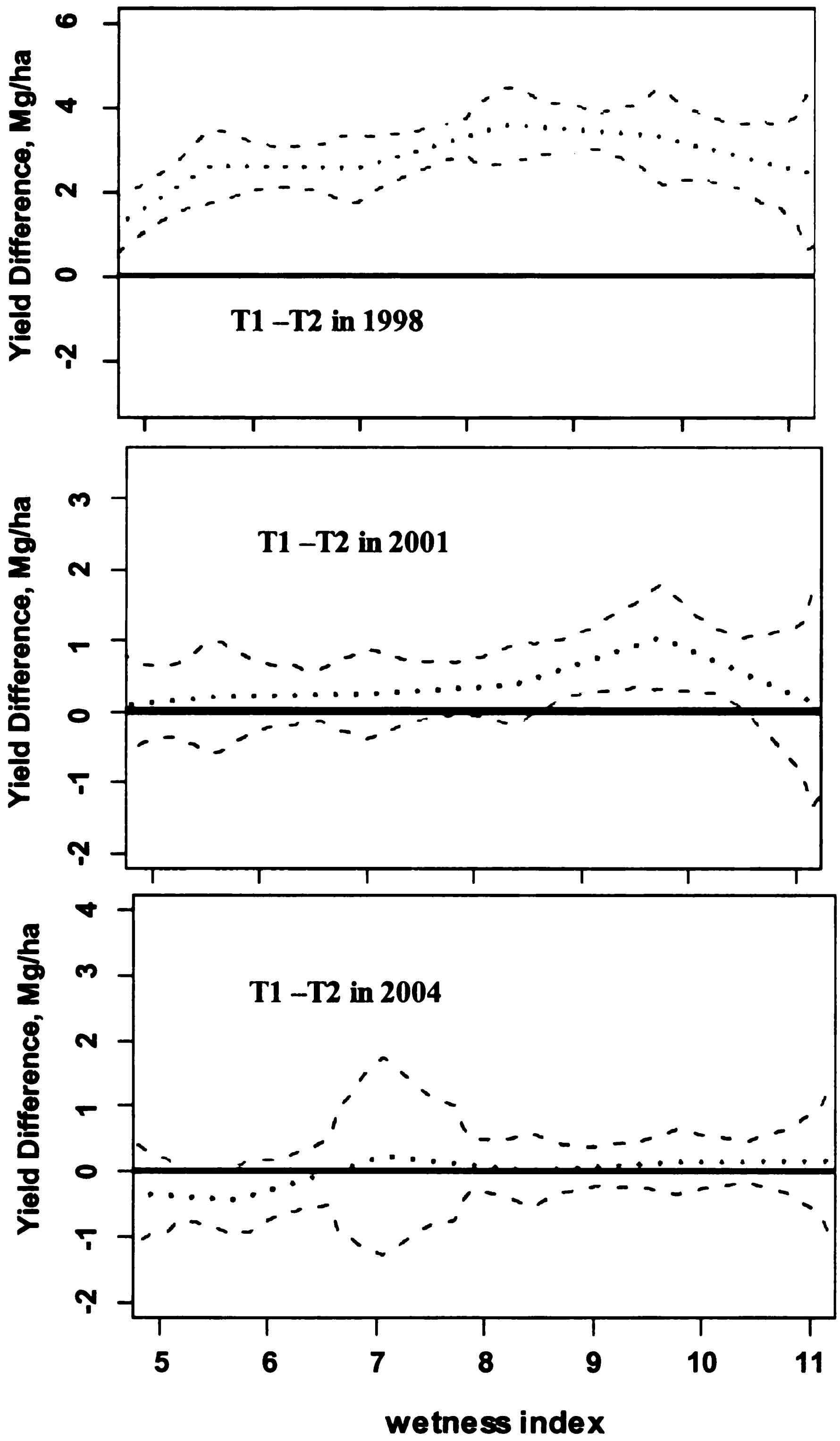
Appendix 4.4. Boundary line of soybean yield vs. WI fitted by spline regression.



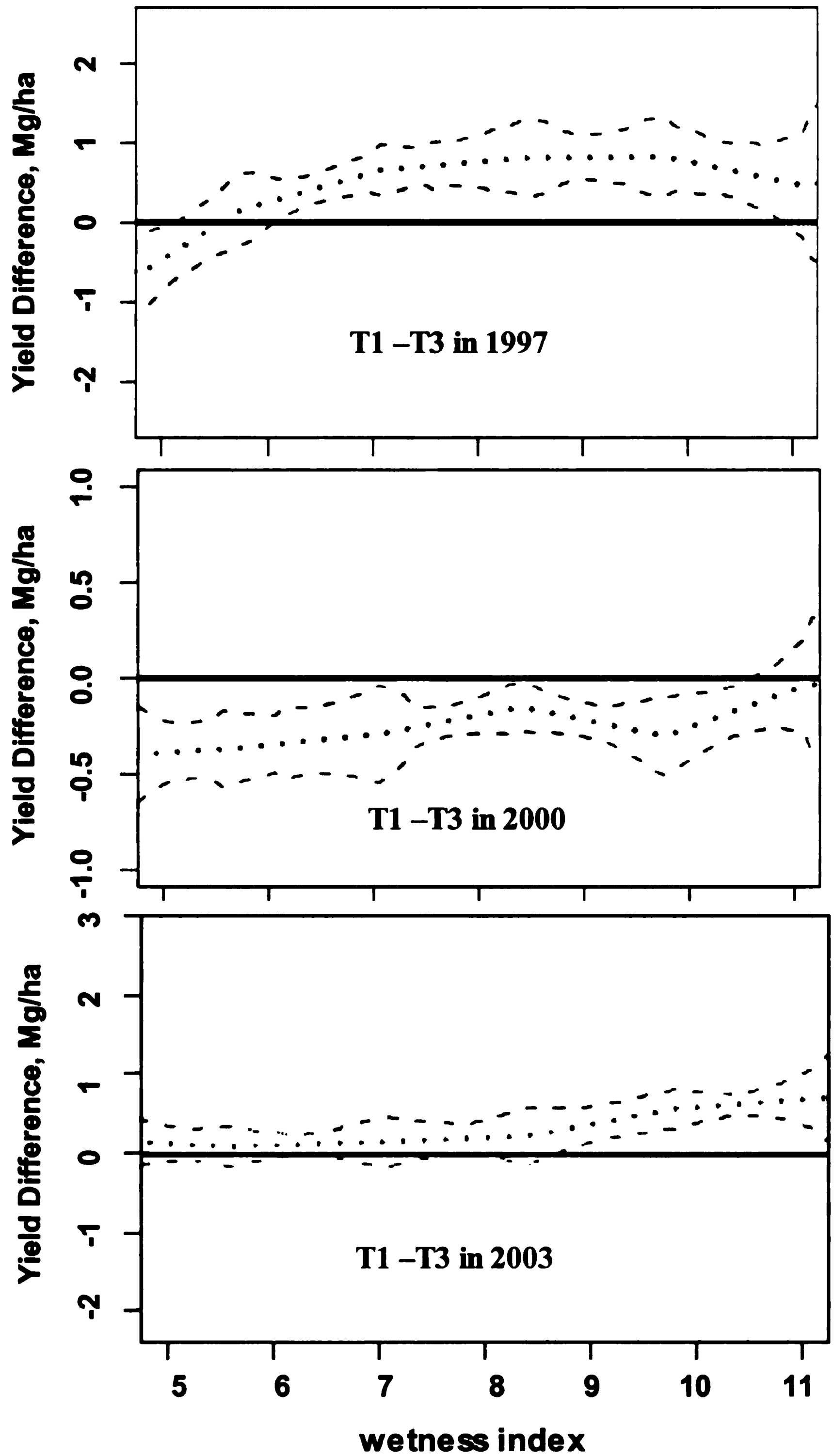
Appendix 4.5. Boundary line of wheat yield vs. WI fitted by spline regression.



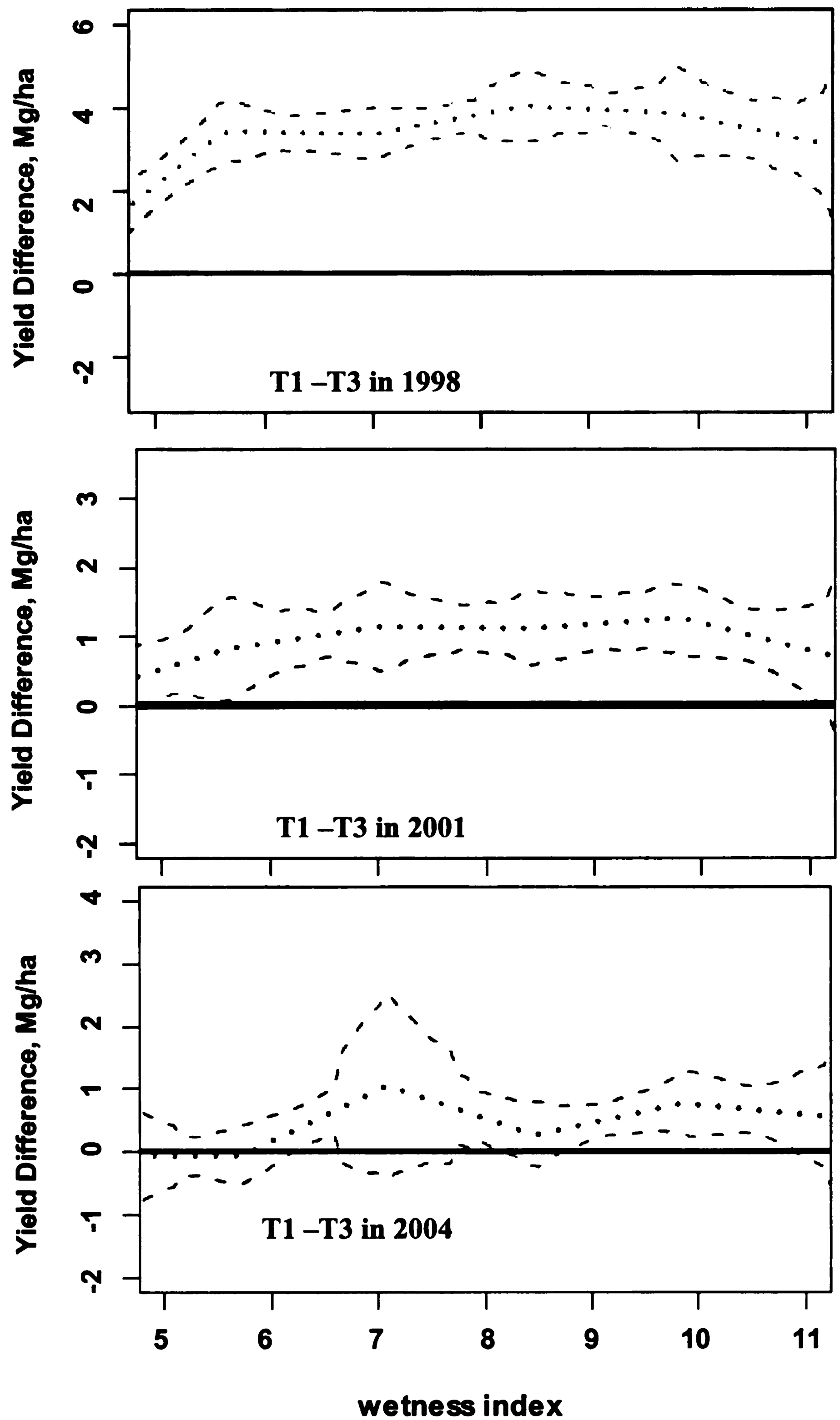
Appendix 4.6. Plot of 95% confidence band of the difference of soybean maximum yield between T1 and T2 as a function of WI.



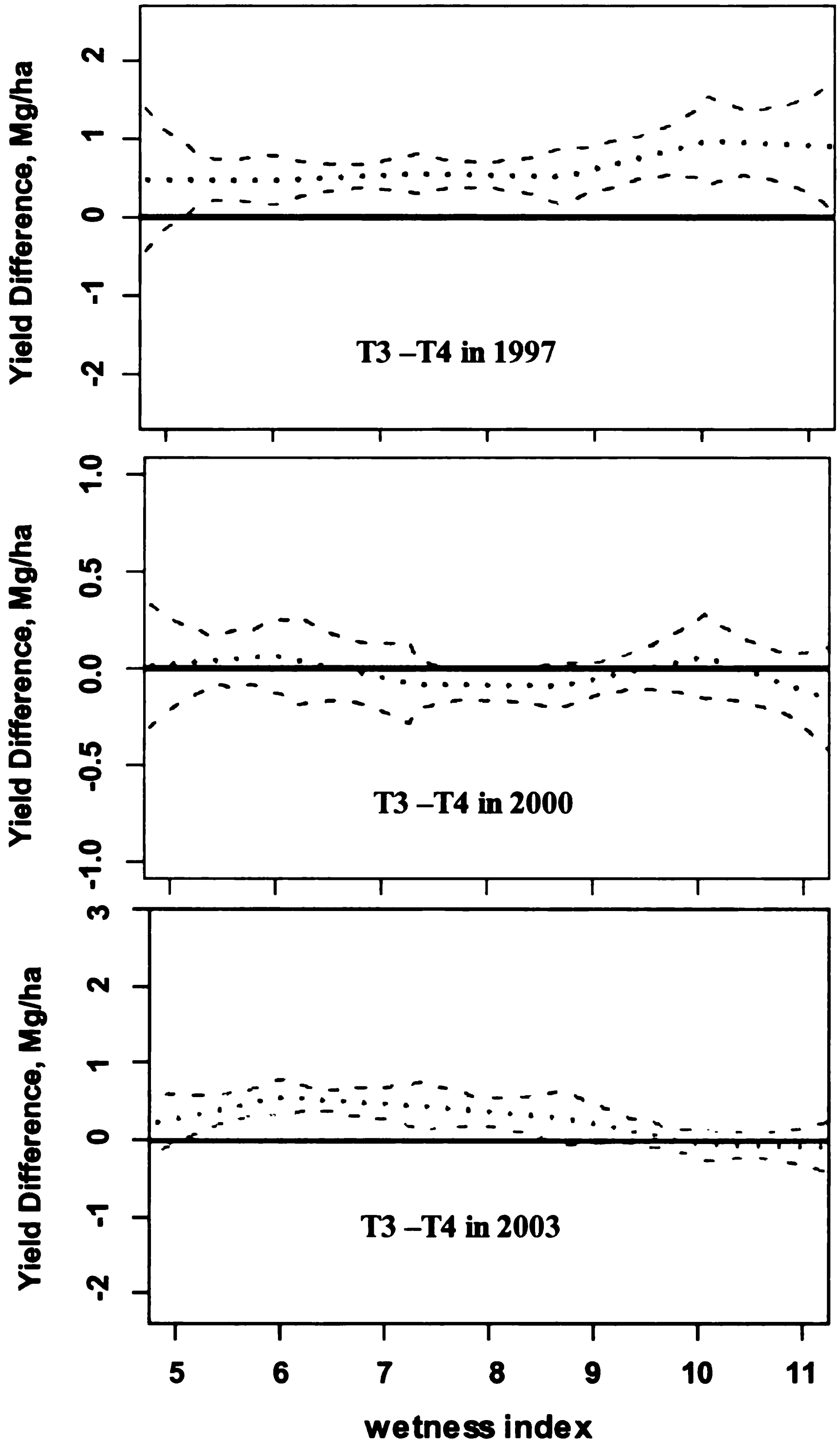
Appendix 4.76. Plot of 95% confidence band of the difference of wheat maximum yield between T1 and T2 as a function of WI.



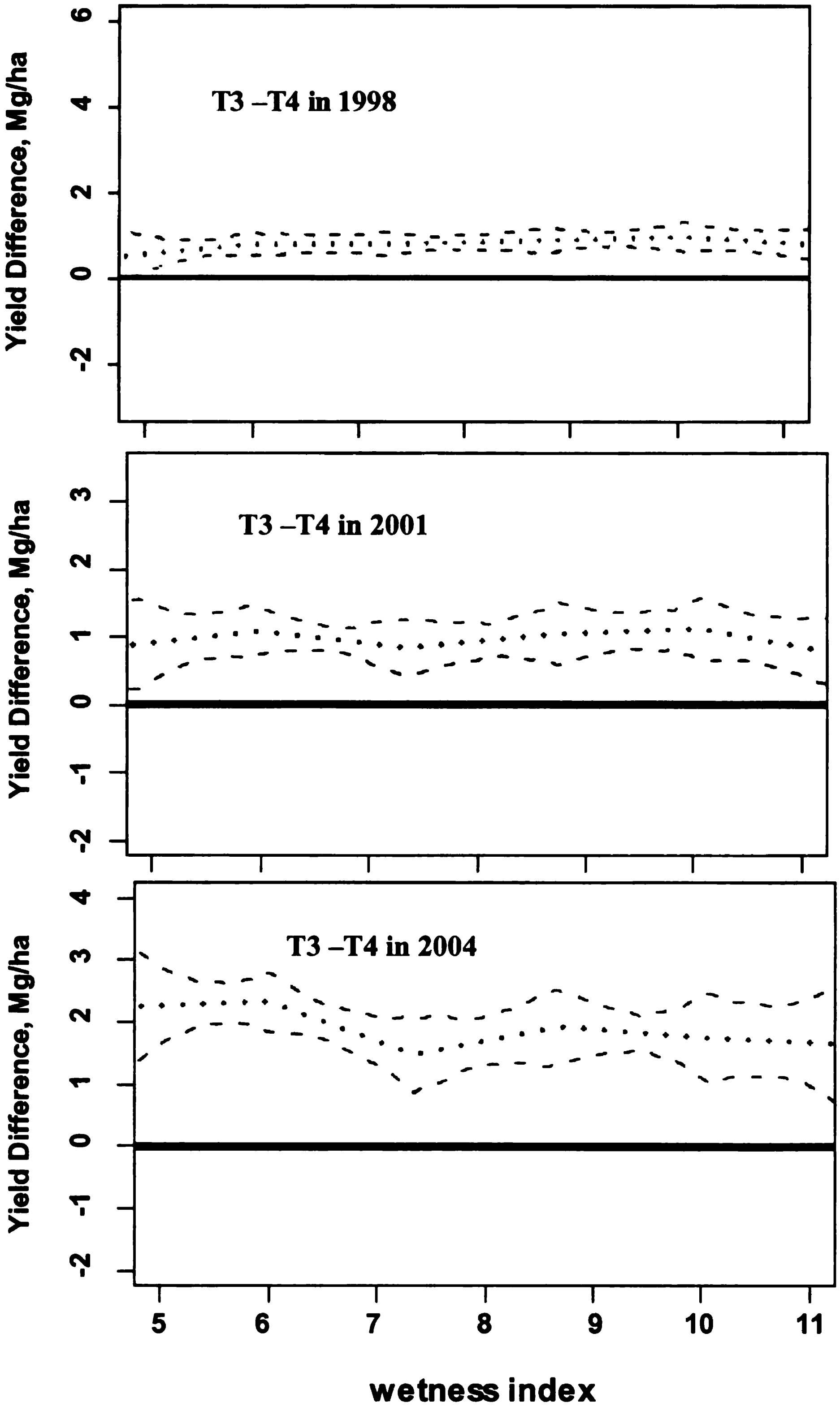
Appendix 4.8. Plot of 95% confidence band of the difference of soybean maximum yield between T1 and T3 as a function of WI.



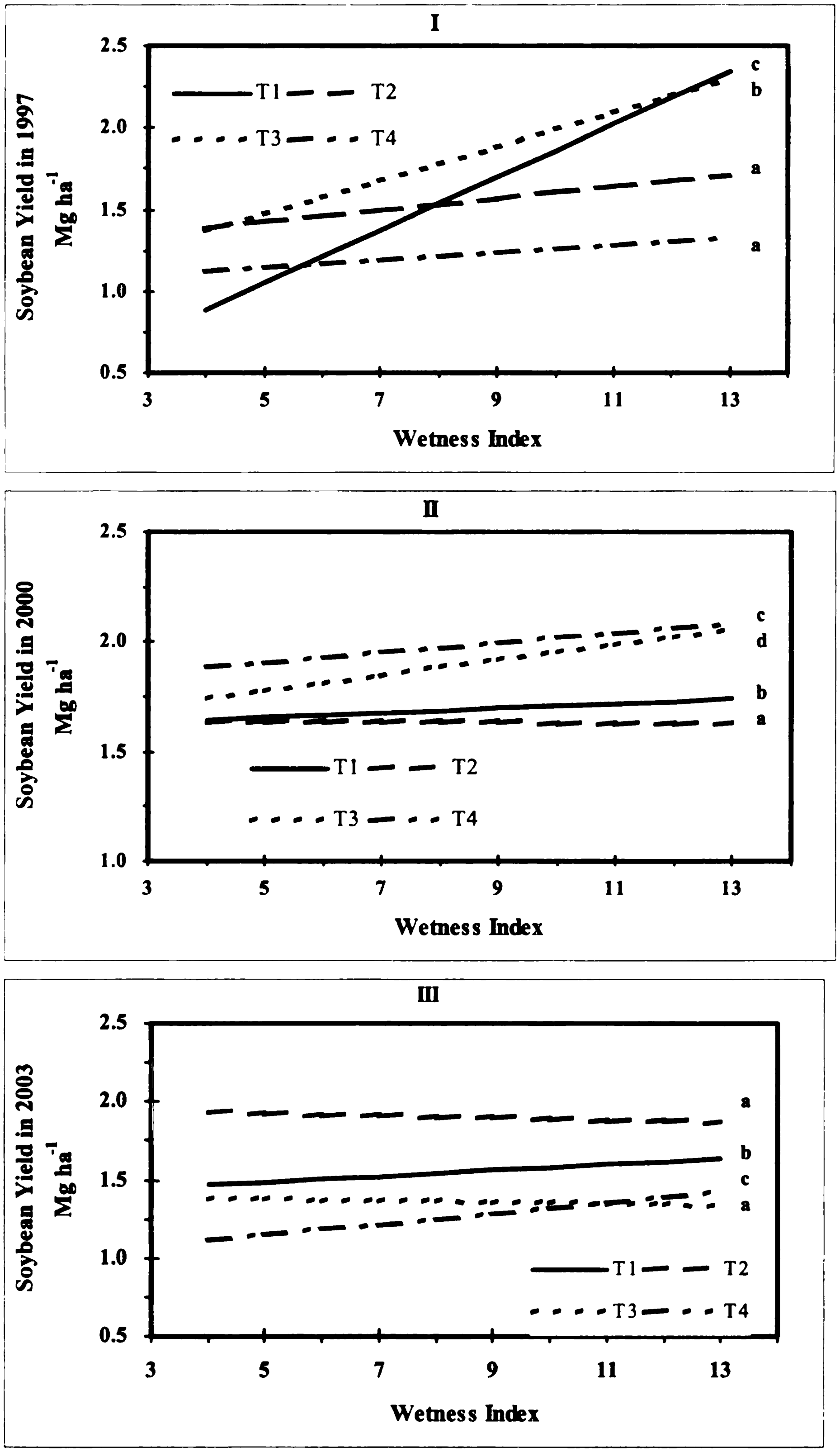
Appendix 4.9. Plot of 95% confidence band of the difference of wheat maximum yield between T1 and T3 as a function of WI.



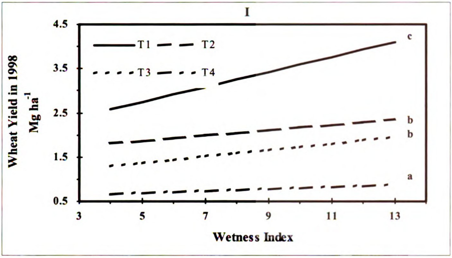
Appendix 4.10. Plot of 95% confidence band of the difference of soybean maximum yield between T3 and T4 as a function of WI.

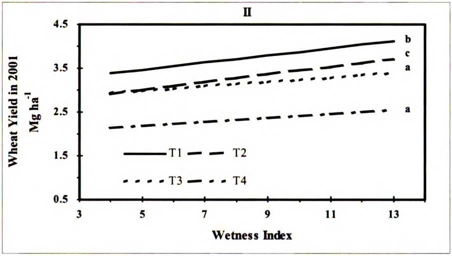


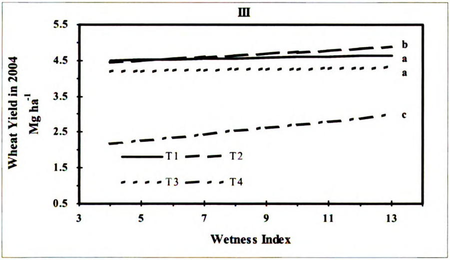
Appendix 4.11. Plot of 95% confidence band of the difference of wheat maximum yield between T3 and T4 as a function of WI.



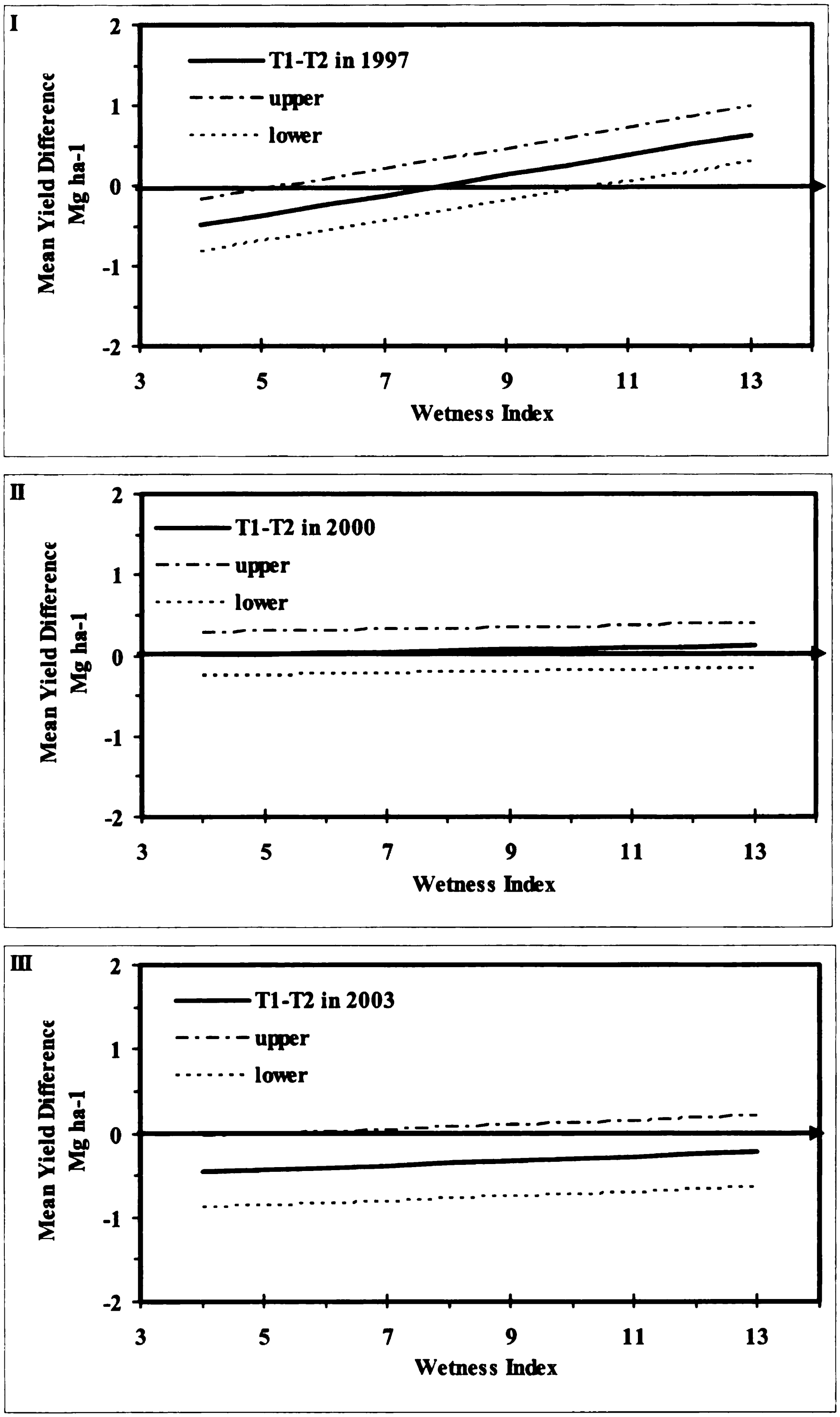
Appendix 4.12. Plot of estimated soybean yield regression models for the 4 treatments at different WI. Alphabetic letters at right of a line represent the value of regression slope from low to high. The same letters indicate no significant slope difference between treatments ($p < 0.05$).



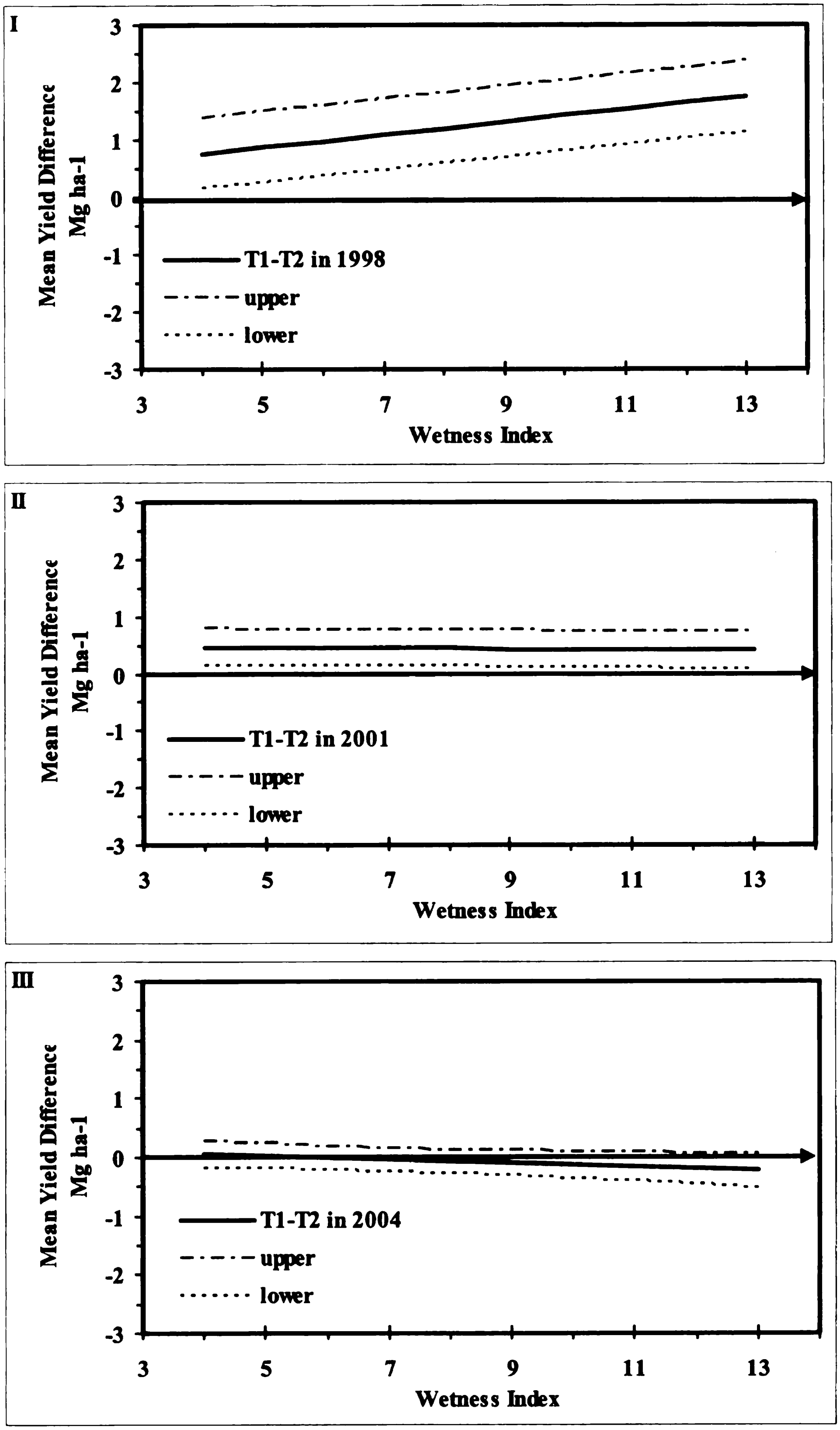




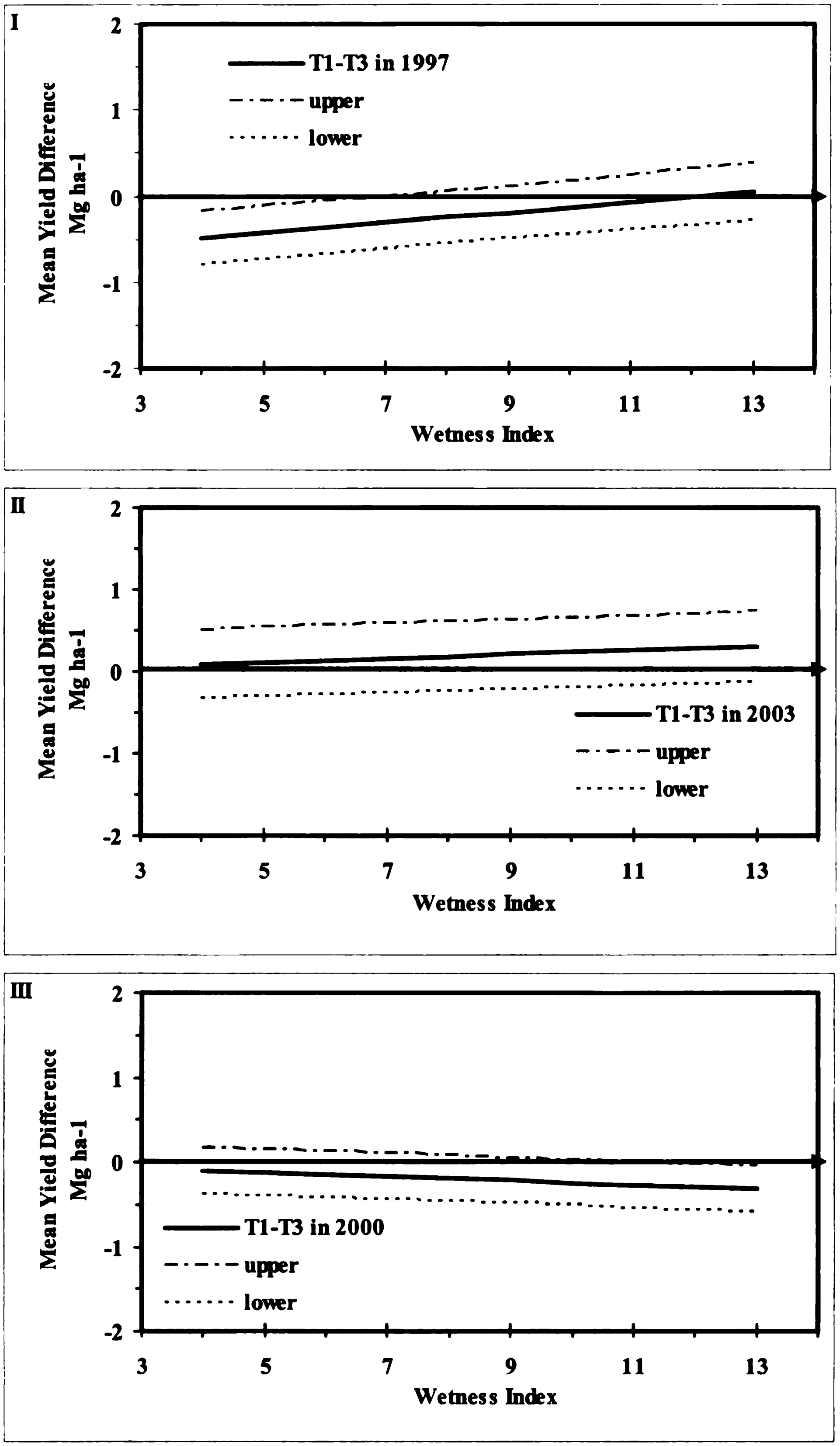
Appendix 4.13. Plot of estimated wheat yield regression models for the 4 treatments at different WI. Alphabetic letters at right of a line represent the value of regression slope from low to high. The same letters indicate no significant slope difference between treatments ($p < 0.05$).



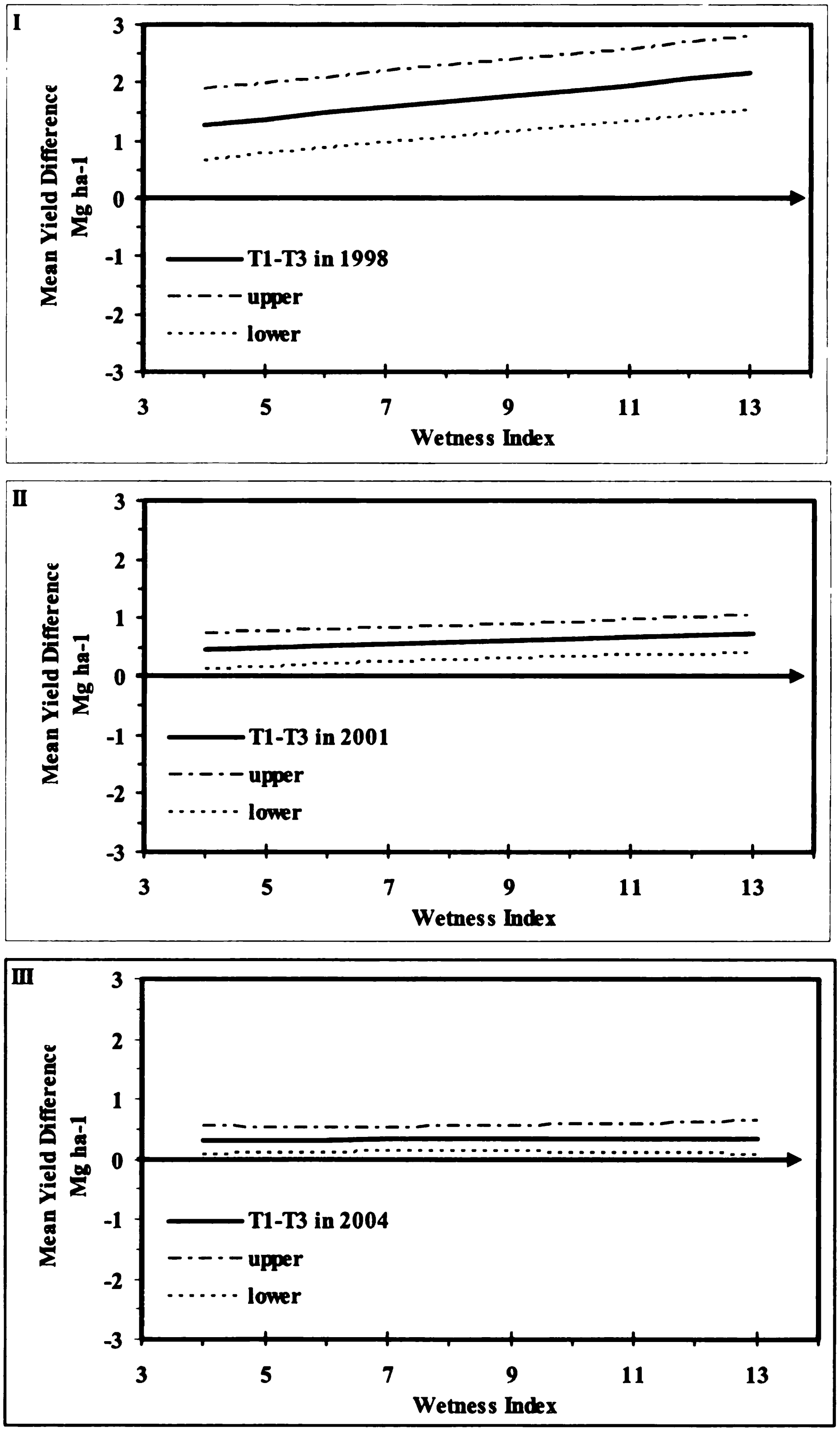
Appendix 4.14. Plot of 95% confidence band of soybean yield difference between T1 and T2, where WI as covariate. Arrow-head line indicates zero yield difference.



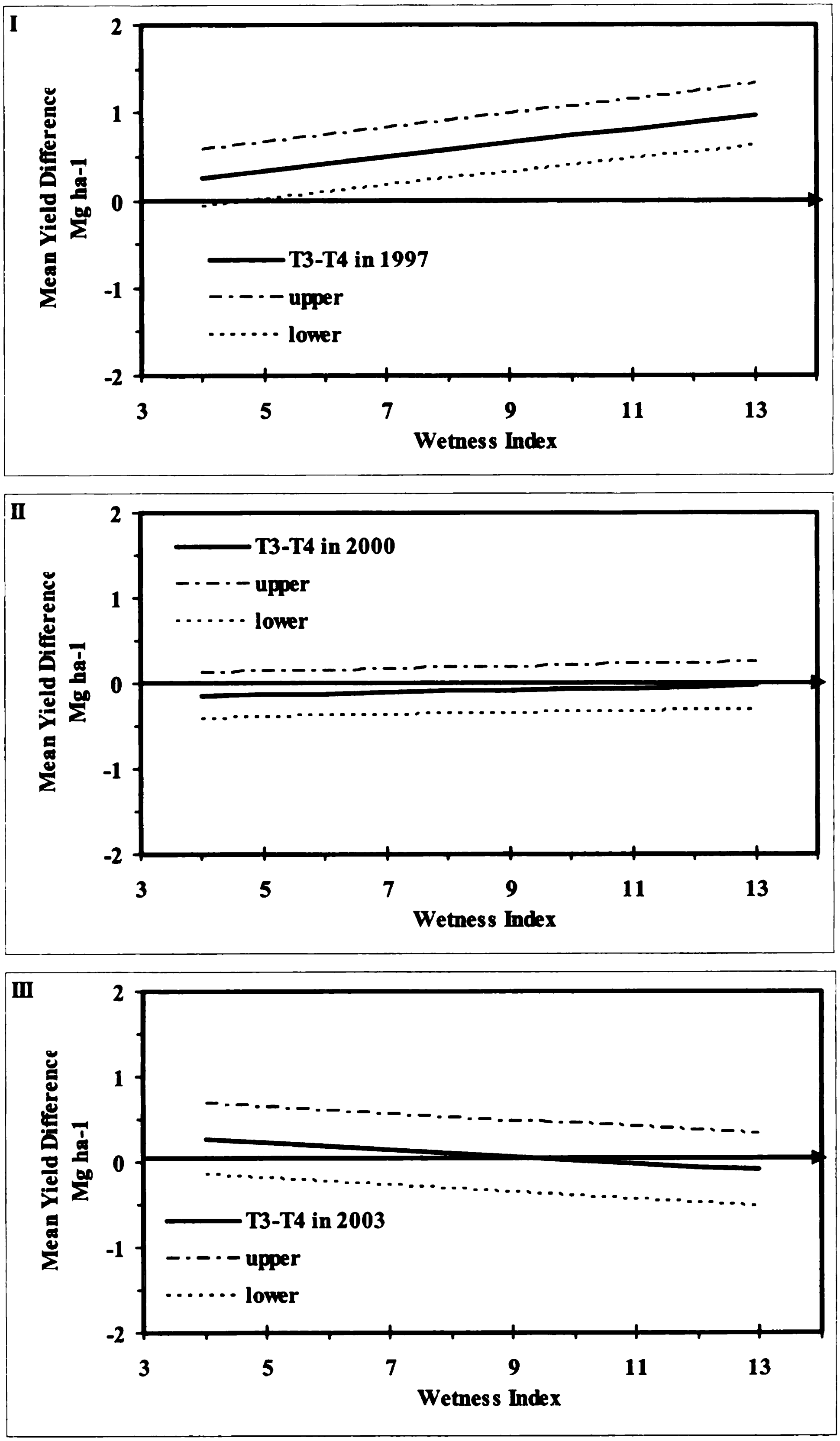
Appendix 4.15. Plot of 95% confidence band of wheat yield difference between T1 and T2, where WI as covariate. Arrow-head line indicates zero yield difference.



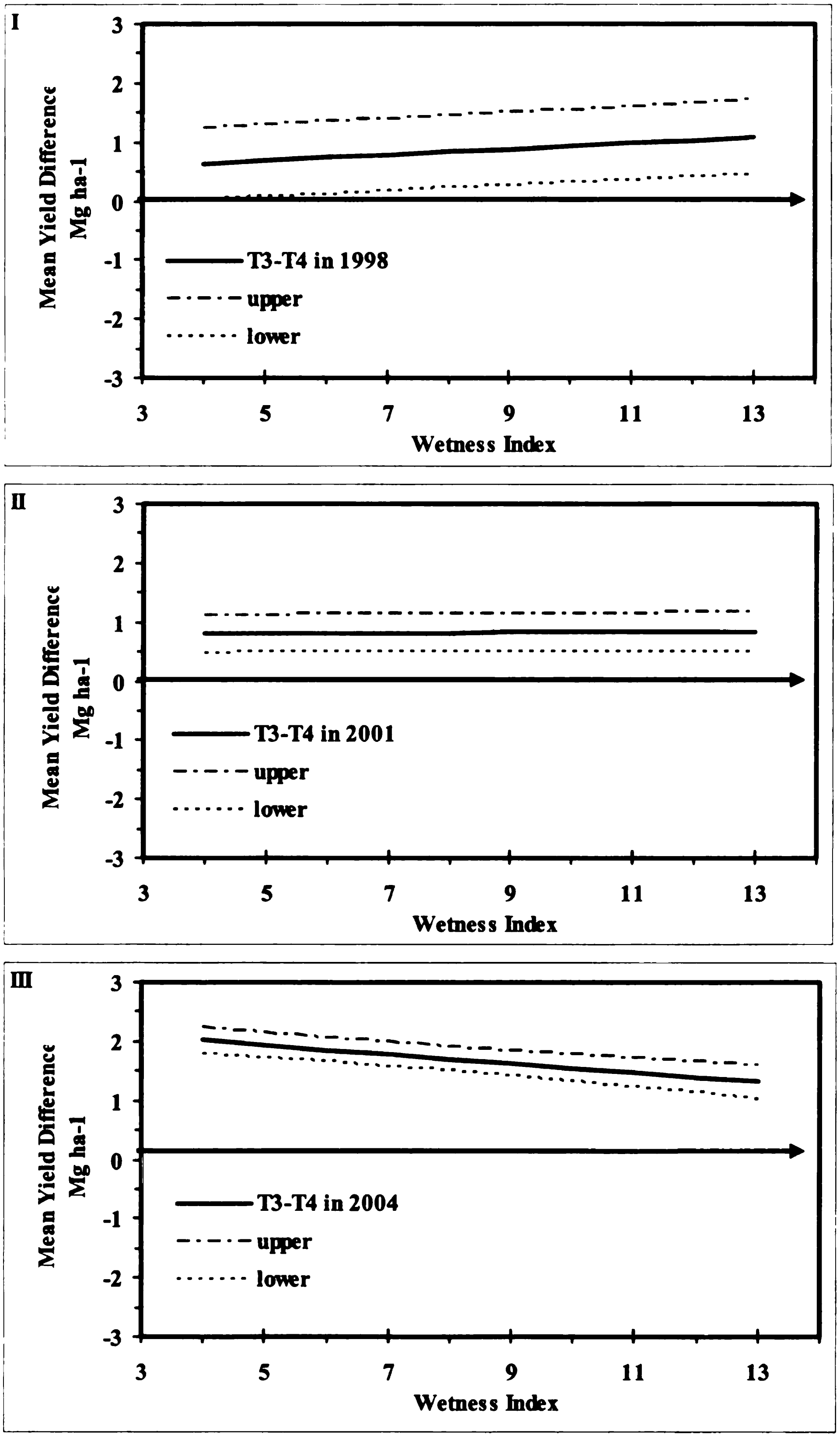
Appendix 4.16. Plot of 95% confidence band of soybean yield difference between T1 and T3, where WI as covariate. Arrow-head line indicates zero yield difference.



Appendix 4.17. Plot of 95% confidence band of wheat yield difference between T1 and T3, where WI as covariate. Arrow-head line indicates zero yield difference.



Appendix 4.18. Plot of 95% confidence band of soybean yield difference between T3 and T4, where WI as covariate. Arrow-head line indicates zero yield difference.



Appendix 4.19. Plot of 95% confidence band of wheat yield difference between T3 and T4, where WI as covariate. Arrow-head line indicates zero yield difference.