

Management Effects on Relationships of Crop Yields with Topography Represented by Wetness Index and Precipitation

Xuewen Huang, Li Wang, Lijian Yang, and Alexandra N. Kravchenko*

ABSTRACT

Crop yields are highly variable spatially and temporally 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 yields and precipitation and crop yields and topography 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 four agronomic treatments studied were chisel plowed with conventional chemical inputs (CT), no-till with conventional chemical inputs (NT), chisel plowed with low chemical input and a winter leguminous cover crop (CTL), and organic-based chisel plowed with a winter leguminous cover crop (CTO). A nonparametric (spline) regression was used to characterize the relationship between the maximal yields, as characteristics of yield potential, and a wetness index (WI), as an integrative characteristic of topographical features related to water flow, and to compare the yield differences between the treatments across a range of the WI values. Variability of yields in NT and CTO systems was better explained by precipitation in early spring and during pollination and grain fill than that in CT and CTL. No-till and CTL tended to produce higher maximal yields than CT at the summit/ steep-sloped areas (lower WI), while at intermediate and high WI levels the differences between them were inconsistent. The CTL often produced higher maximal yields than CTO at low and intermediate WI values, while the difference between them was mostly not significant at high WI levels (depression areas). The nonparametric spline regression algorithm used in the study was robust and efficient in comparing the yield differences between treatments across a range of WI values.

ROP 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). Better understanding of yield variations may lead to greater profitability of precision farming.

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 to explain a substantial portion of yield variability. However, yield/topography relationships are known to vary substantially from year to year. These variations are often associated with the prevailing weather conditions during the growing season of each particular year (Halvorson and Doll, 1991; Jaynes and Colvin, 1997; Kravchenko and Bullock, 2000; Jaynes et al.,

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2003; Kaspar et al., 2003). 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 to 1998. Low precipitation and moisture stress tend to be the chief limitations to optimal corn and soybean yields (Andresen et al., 2001). Hu and Buyanovsky (2003) observed that the growing-season distributions of rainfall and temperature for high-yielding years are 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 lower yields (Hu and Buyanovsky, 2003).

It is generally expected that the relationships between yield and topography and their 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 disking tillage. Kravchenko et

Abbreviations: LTER, Long Term Ecological Research site; KBS, Kellogg Biological Station; CT, chisel plowed with conventional chemical inputs; NT, no-till with conventional chemical inputs; CTL, chisel plowed with low chemical input and a winter leguminous cover crop; CTO, organic-based chisel plowed with a winter leguminous cover crop; WI, wetness index.

al. (2005) found that variability in crop yields was higher under organic management as compared to conventional management practices and that weather-related stresses amplified the differences in spatial variability patterns. Wetness index is the composite topographical characteristic that reflects general patterns of water flow across the landscape and thus can potentially be more useful in predicting yields and quantifying yield/topography/weather relationships than other topographical features.

Of particular practical importance is assessment of yield/topography/weather relationships in most commonly used agricultural management practices, such as conservation tillage with conventional chemical inputs, as well as in conservational management practices, including no-till and organic management. Information on yield/topography/weather relationships will contribute to the effort of expanding the conservation management practices and will likely increase the grower's profits from site-specific farming while using conservational managements.

One of the commonly faced difficulties in analyzing yield/ topography/weather relationships is that complex interactions between topography and a multitude of other yield-affecting factors often make the traditional correlation and regression data analyses tools fail to provide useful information. Boundary line analysis introduced by Webb (1972) might generate additional insights into roles of individual topographical characteristics in limiting crop yields. Boundary-line analysis subdivides the response data into groups corresponding to the quantitative categories of the potential limiting factor of interest and then isolates a subset of the highest values from the response data within each group. This upper boundary then represents, for the conditions of the data set, the maximum possible response to that limiting factor, and the yield data points below the boundary line represent conditions where the other factors have limited the yield. The method implies presence of a cause-and-effect relationship between the limiting factor and the response and assumes that there is no interaction between the primary yield affecting factors (Webb, 1972; Lark, 1997; Kitchen et al., 2003). Boundary line analysis was used by several 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 traditional parametric approach to analyze a regression relationship assumes that the functional form is fully described by a finite set of parameters. A typical example of a parametric model is a polynomial regression equation where the parameters are the coefficients of the independent variables. However, the relationships between crop yields and yield affecting factors often follow patterns that may require prohibitively complex models with a very large number of parameters. Thus it is very difficult to obtain any prior model information about the regression curve, and substantial estimation bias can result if a preselected parametric model is too restricted or too low-dimensional to fit unexpected features.

As an alternative one could try to estimate the unknown regression relationships nonparametrically without reference to a specific form. Compared to the parametric regression, nonparametric regression provides a useful tool for studying the dependence of crop yields on yield affecting factors, without constraining the dependence to a fixed form with few parameters, thus the term "nonparametric". The flexibility of

nonparametric regression is extremely helpful in exploratory data analysis as well as in obtaining robust predictions (Härdle, 1990; Fan and Gijbels, 1996). For example, nonparametric spline regression can describe a complex-shaped relationship between a response and an independent variable and provide predictions for response variable averages (Wahba, 1990; de Boor, 2001). Moreover, the algorithm developed by Wang (2007) for the spline regression allows efficient construction of a $100(1-\alpha)$ % simultaneous confidence band around the predicted response curve. This algorithm can be used in comparisons between the model predictions of crop yields across the range of the studied yield affecting factors.

The physiography of Michigan presents very advantageous settings for studying yield/topography/management interactions. It is characteristic of a mature 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). The objectives of this study were to analyze the effects of management practices on the relationship between crop yield and topography using a nonparametric regression model and examine the relationships between crop yield and precipitation 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, semiactive, mesic) and Oshtemo (coarse-loamy, mixed, active, mesic) series developed on glacial outwash (Crum and Collins, 1995). The maximum difference in elevation within the site is 8.8 m. The elevation map of the studied site and the plot locations were reported by Kravchenko et al. (2005).

A one-factor RCBD experiment with six replications was established at the site in 1988. Each experimental plot is about 110 by 90 m in size. The experiment consisted of a total of seven treatments. The four agronomic treatments used in this study were CT, NT, CTL, and CTO. All treatments were managed as corn-soybean-wheat rotations. The conventional chemical treatments CT and NT received 123 kg N ha⁻¹ for corn and 56 kg N ha⁻¹ for wheat but not for soybean according to Michigan State University recommendations and insecticides and herbicides as necessary. The low input system (CTL) received only N fertilizer in the amount equal to 3/5 of that applied to CT and no herbicides or insecticides. The organic system did not receive any chemical inputs. Detailed agronomic protocols can be found on the KBS LTER website ((http://lter.kbs.msu.edu/protocols/104) KBS, 2008).

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 by 2.5 m. Cleaning and processing of yield data was

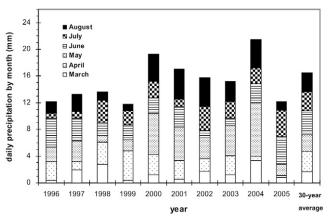


Fig. 1. March through August daily average precipitations from 1996 to 2005 along with the 30-yr averages.

conducted following Drummond's and Sudduth's (2003) recommendations. To eliminate the border effects, only the yield data from the central 60 by 80 m portion of each plot were used in the analysis. For analyses that involved comparisons among the crops, the original yields were standardized (Blackmore, 2000; Perez-Quezada et al., 2003) as

$$Y_{si} = R_{si}/Y_s \tag{1}$$

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, and Y_s is the average field yield in that year. $Y_{si} = 1$ means the yield in the *i*th cell is equal to the average yield in the field in the *s*th year.

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. The distance between transects was 5 m. The elevation measurements were converted into a cell-based terrain map on a 4- by 4-m grid with ArcView Spatial Analyst (Environmental Systems Research Institute, 2000) and topographic characteristics including terrain slope, curvature, flow accumulation, and WI were derived from the elevation data using surface hydrologic analysis of ArcInfo GRID.

The WI was calculated as defined by Moore et al. (1993):

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

where A_s is the upslope area derived from flow accumulation and $\tan \beta$ is a tangent function of slope as percent-rise. Wetness index has been proposed as an integrative characteristic describing distribution of soil moisture within a landscape (Moore et al., 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 near-by site (Huang et al., 2005) we decided to use WI as the only topographical variable in this study. 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 1).

Daily precipitation values were obtained from an automated weather station located at the LTER site. The average daily precipitation values from April through August were used in the study and are shown on Fig. 1 along with the 30-yr averages.

Statistical Analyses

Descriptive statistics and correlation and regression analyses were conducted in SAS using PROC CORR and PROC REG procedures (SAS Institute, 1999). Unless stated otherwise, in the Results and Discussion section we report the effects and differences as statistically significant for P < 0.05.

The relationship between WI and yield was studied using boundary line analysis. The analysis begins with subdividing the range of values of the independent variable, that is, WI, into classes. Then the characteristic values describing the maximum yields are identified within each class. In the 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. Kitchen et al. (2003) represented 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 others. In this study, we divided the WI into approximately 50 classes in 0.2 increments and in each class we selected the top four yield data points. This method of selecting the upper edge data appeared to us as a way to use the best features of the two 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. An example of the yield-WI data for one of the treatments in one of the studied years is shown on Fig. 2.

Generally, the boundary yield variable Y consists of a predictable mean function m(x) of the predictor x, that is, WI, and an unpredictable error. Visual assessment of the boundary

Table I. Averages and standard deviations for corn, soybean, and winter wheat yield data from the four studied treatments along with summary statistics of the wetness index values for the studied treatments. Comparisons between the treatments for the grain yield data (based on test weight data collection) in 1996 to 2001 have been reported previously by Kravchenko et al. (2005).

		Yield in treatment					
Crop	Year	СТ	NT	CTL	СТО		
		————Mg ha ⁻¹ ————					
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		
Wetness index							
Mean		7.0	7.0	6.9	7.0		
Standard deviation		1.5	1.5	1.5	1.0		
Minimum		4.2	3.6	3.1	4.4		
Maximum		14.4	13.1	13.8	13.3		

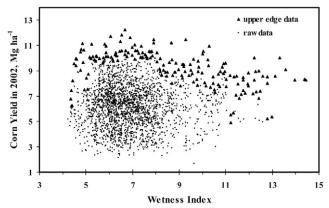


Fig. 2. Corn yield of conventional chisel plowed treatment in 2002 plotted vs. wetness index (WI). The triangles represent the top four yield data points for each increment class of WI used in boundary line analysis.

yield lines showed that function m(x) could not be adequately described by a straight line. It also appeared impossible to use a single nonlinear parametric equation for describing various shapes of the curves observed in different treatments and years. Effective tools for extracting information from such complex regression data have to be nonparametric in nature; that is, no particular formulae are imposed on the regression structures. Thus, we applied nonparametric (spline) regression following the methodology developed by Wang (2007), where linear spline estimator and $100(1-\alpha)\%$ simultaneous confidence bands were proposed for the mean regression function of m(x). As compared with other nonparametric methods this approach is characterized by straightforward implementation and fast computations.

By constructing confidence bands for the difference between two spline regression models from the two treatments, one can compare the mean functions $m_1(x)$ and $m_2(x)$ of Treatment 1 and Treatment 2 and test the hypotheses:

$$H_0: m_1(x) = m_2(x) \text{ against } H_1: m_1(x) \neq m_2(x)$$
 [3]

The following $100(1 - \alpha)\%$ simultaneous confidence bands for the difference between the regression functions, $m_1(x)$ and

 $m_2(x)$, are defined as

$$[\hat{m}_1(x) - \hat{m}_2(x)] \pm 2s_n(x)[\log(N+1)]^{1/2}d_n(\alpha/2),$$
 [4]

where $\hat{m}_1(\mathbf{x})$ and $\hat{m}_2(\mathbf{x})$ are the linear spline estimates of the unknown regression function m_k for the two treatments being compared (that is, k=1 and k=2) at particular level of the predictor variable x; n_k is the total number of data points in the treatment k; N is the pre-selected number of equally-spaced knots, set to be the smaller of $[n_1^{1/5}] + 3$ or $[n_2^{1/5}] + 3$, according to Wang (2007). According to this rule, for example, the number of knots in Fig. 5 is 5 for (a), (b), and (c). The inflation

factor $d_n(\alpha/2)$ is defined as

$$d_n(\alpha/2) = 1 - \{2\log(N+1)\} - 1[\log(\alpha/2) + 0.5 \{\log\log(N+1) + \log 4\pi \quad [5]$$

and, according to probability theory, $\{\log(N+1)\}^{1/2} d_n(\alpha/2)$ is the approximate $1-\alpha/2$ quantile of the maximum of N+1 independent standard normal random variables. Thus mimicking $z_{1-\alpha/2}$, the critical value for 1 standard normal random variable is used in conventional z test, and the standard error function

$$\begin{split} s_n(x) &= \{3\hat{\sigma}_1^2(x)/\left[2\hat{f}(x)n_1b\right] + 3\hat{\sigma}_2^2(x)/\left[2\hat{f}_2(x)n_2b\right]\}^{1/2} \\ &\times [\Delta^T(x)\Xi_{i(x)}\Delta(x)]^{1/2} \end{split} \tag{6}$$

mimics the pooled standard error in the two sample t test. The functions $\hat{\sigma}_k$, \hat{f}_k are the estimated standard deviation functions of boundary yield Y and the probability density functions of the predictor variable x in the two compared treatments, while Δ , Ξ are some matrices related to the design of knots; for complete details, see Wang (2007).

The confidence band in Eq. [4] has an approximate likelihood of $1-\alpha$ of containing the true function m_1-m_2 regardless of what the true functions m_1 and m_2 are. Under the null hypothesis H_0 , one would have $m_1-m_2=0$, and thus the zero line $\Delta Y=0$ would have to lie completely inside the confidence band. Thus one could reject H_0 , with $1-\alpha$ confidence if the zero line $\Delta Y=0$ were to fall outside the confidence band at any point. The confidence band can be compared with the zero line along the whole range of predictor values x.

To assess performance of spline regression we compared mean squared error values and \mathbb{R}^2 values obtained using spline regression with those obtained using other types of regression analysis, including simple linear regression and segmented regression. For vast majority of crops and treatments spline regression performed the best. Thus only results from spline regression are discussed further.

RESULTS AND DISCUSSION

Crop Yields and their General Relationships with Precipitation

The largest yearly variations in grain yields during the studied period were observed in corn (Table 1). For example, the yield in the CT was 8.25 Mg ha⁻¹ in 2005, more than twice of the yield in 1996 (3.66 Mg ha⁻¹) and in 1999 (3.06 Mg ha⁻¹). Coefficients of variation for average corn yields observed during the studied years were equal to 45, 46, 38, and 32% for CT, NT, CTL, and CTO treatments, respectively. The year-to-year variations observed in wheat yields were somewhat lower than those in corn and even lower in soybean yields. Coefficients of variation for the average soybean yields in all but organic treatments were substantially lower than those observed for corn, equal to 10, 13, 15, and 29% for CT, NT, CTL, and CTO.

Even though the relationships between yields, weather, and topography for corn and soybean were somewhat different, however in our experience and based on information presented in literature such differences were relatively minor in size and thus were difficult to detect in statistical analyses. Based on this result and the fact that, unlike wheat, corn and soybean have similar growing seasons, we felt it was appropriate to combine standardized corn and soybean yield data in order to get a bigger data set for assessing the general topography/weather/crop relationships. The standardized yields (StdY) from 4 yr of corn and 3 yr of soybean yields were combined for analyses

of yield relationships with precipitation (Fig. 3). In the studied site, precipitation in May and precipitation of all three spring months combined was found to be not significantly related to the standardized yields (P < 0.05) (data not shown). Thus, only the results for early spring (March through April) precipitation were discussed further. The StdY in the CT, NT, and CTL, but not CTO, were negatively correlated with early spring daily average precipitation (P < 0.01, Fig. 3). The relationship was somewhat driven by the corn data from 2005, a dry spring year, and by the soybean data from 2000, a year with relatively wet spring. But in the 5 yr with moderate spring rainfall the yields appeared to be less affected by the early spring precipitation. Lower yields in years with wet springs are likely due to delayed planting, lower soil temperatures, and slower seed emergence (Lark and Stafford, 1997; Hoeft et al., 2000). The regression slopes and the r^2 values in linear regression between StdY and early spring precipitation were the highest in NT (Fig. 3). This indicates that crop yields in NT tended to vary more with the amount of precipitation in early spring. During wet cold springs tillage is 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, notill 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 standardized yields of all four treatments were significantly positively correlated with the summer (June, July, August) precipitations (P < 0.01, Fig. 3). Similar to the spring precipitation, the relationship between StdY and summer precipitation in no-till had steeper slope compared with other treatments (P < 0.01, Fig. 3).

Combining early spring and summer precipitations in a multiple regression allowed for further insight into spring and summer precipitation effects on yields of the studied treatments (Table 2). In general, the R^2 values for NT, CTL, and CTO were similar (about 0.78), while the R^2 value for CT was much lower (0.53), indicating that the variations in yields

Table 2. R² values and root mean square errors (RMSE) for multiple regressions along with partial correlation coefficients between standardized corn and soybean yields and early spring and summer daily precipitation for the studied treatments.

	Multiple regression with early spring and summer precipitation		Partial correlation coefficients for precipitation in	
Treatment	R^2	RMSE	Early spring	Summer
		Mg ha ^{-l}		
CT	0.53	0.26	-0.24 NS†	0.56**
NT	0.77	0.18	-0.62***	0.65***
CTL	0.78	0.15	-0.31*	0.80***
СТО	0.78	0.12	0.72***	0.89***

^{*} Indicates that partial correlation coefficients were different from zero at P < 0.05 level.

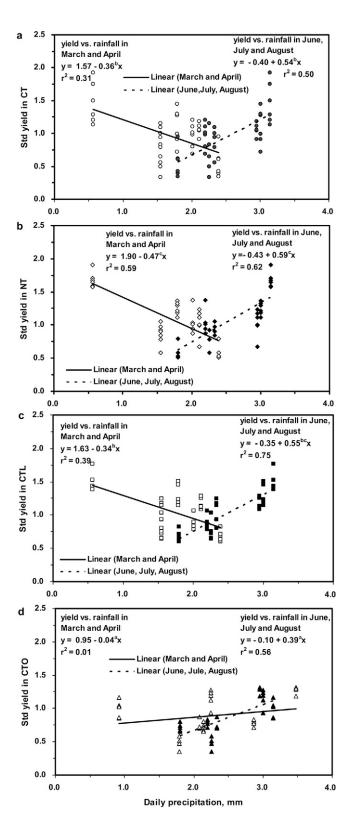


Fig. 3. Standardized (Std) corn and soybean yields vs. early spring (March and April) and summer (June, July, and August) average daily precipitation for (a) chisel plowed with conventional chemical inputs (CT), (b) no-till with conventional chemical inputs (NT), (c) chisel plowed with low chemical input and a winter leguminous cover crop (CTL), and (d) organic-based chisel plowed with a winter leguminous cover crop (CTO) treatments. Each data point represents a replicated plot. The regression slopes followed by the same letter are not significantly different from each other (P < 0.05) (within season group).

^{**} Indicates that partial correlation coefficients were different from zero at P < 0.01 level.

^{***} Indicates that partial correlation coefficients were different from zero at P < 0.001 level.

 $[\]uparrow$ NS indicates that partial correlation coefficient was not significantly different from zero (P < 0.05).

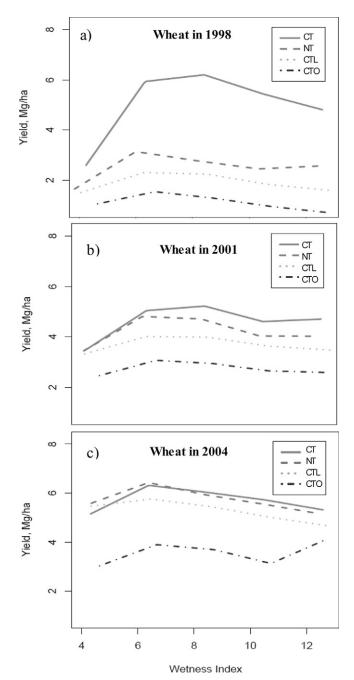


Fig. 4. Relationships between the boundary line yield data and wetness index (WI) fitted by spline regression for wheat in (a) 1998, (b) 2001, and (c) 2004.

in high chemical input conventional tillage system were not as well explained by precipitation as those of the conventional tillage systems with low chemical inputs or zero inputs. 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, for example, water stress, that further enhanced the stress due to lower availability of plant nutrients that the plants might be already experiencing.

To further assess independent contributions of the early spring and summer precipitations to the StdY, we calculated partial correlation coefficients $(r_{\rm p})$ between the StdY and early spring precipitation by partialing out the influence of summer precipitation; and the $r_{\rm p}$ values for the summer precipitation

by partialing out the early spring precipitation (Table 2). The $r_{\rm p}$ values for the early spring were negative in the NT and CTL, not significantly different from 0 in CT, and positive in CTO. This further supported the previous observations of the negative effect that wet springs might have on NT and an extra positive effect that better water supply may have in the organic 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 and zero input.

It is also possible that in some cases organic systems might provide advantages to plants in dry years as compared to the conventional systems. 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 have substantially higher soil organic matter content than that in the conventional chemical treatment (Hao and Kravchenko, 2007). 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 help the plants in organic system to better survive drought conditions.

Relationship between Boundary Crop Yields and Wetness Index

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. As an example we present the spline regression lines fitted to the boundary line data of the three studied years of wheat yields (Fig. 4). Similar patterns were observed in corn and soybean yields (data not shown).

From all the possible comparisons that could be conducted among the studied treatments we have selected the three that appeared to be of most practical importance. The comparison between CT and NT addresses the weather and topography considerations involved in choosing NT as a conservational alternative to conventional tillage. The comparison between CT and CTL evaluates the weather-related concerns involved in the decision on reducing the chemical inputs and using cover crops; and the comparison between CTL and CTO evaluates the effect of complete elimination of chemical inputs. For each comparison the differences between the spline regression predictions of the boundary line yields for each treatment were calculated for each class of WI values and examined along with 95% confidence band for the difference. An example of the differences and their confidence intervals plotted vs. WI for the soybean yield boundary line data in 1997 is shown in Fig. 5. The differences and the confidence intervals were interpreted as follows. In 1997 the boundary yields in CT were less than those in NT or CTL at WI around 5. The difference was statistically significant at 0.05 as can be interpreted from the 95%

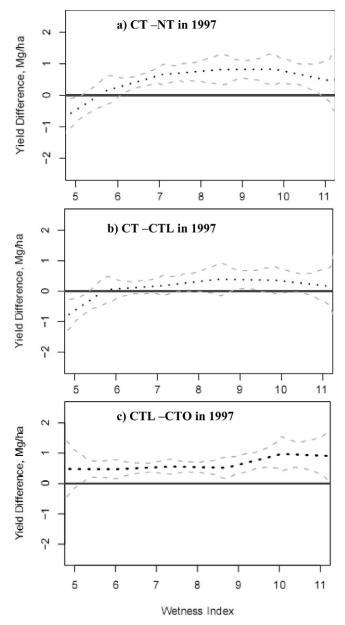
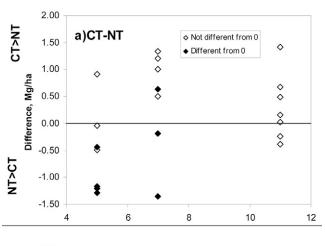
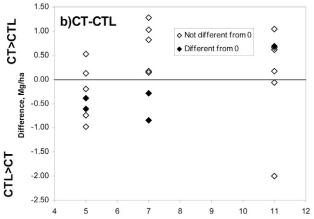


Fig. 5. Differences between spline regressions (dotted line) plotted vs. wetness index along with 95% confidence bands (dash lines) for the soybean boundary line yield data in 1997 for comparisons between (a) chisel plowed with conventional chemical inputs (CT) and no-till with conventional chemical inputs (NT), (b) CT and chisel plowed with low chemical input and a winter leguminous cover crop (CTL), and (c) CTL and organic-based chisel plowed with a winter leguminous cover crop (CTO).

confidence interval band that did not include zero. The CT yields were significantly higher than NT across most of the WI values, while barely greater than those of CTL. At the highest WI values the difference between CT and NT and CT and CTL was not statistically significant – the confidence intervals included zero. The boundary line yields of CTL were significantly higher than those of CTO for most of the WI values. The data from other years were examined and interpreted in a similar manner.

To summarize boundary line comparisons results, we selected three WI levels as low (WI = 5), intermediate (WI = 7), and high (WI = 11). The three levels can be regarded as





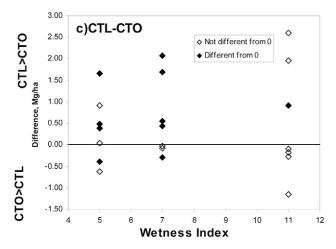


Fig. 6. The differences between the spline regression predictions of the maximum observed corn and soybean yields between (a) chisel plowed with conventional chemical inputs (CT) and no-till with conventional chemical inputs (NT); (b) CT and chisel plowed with low chemical input and a winter leguminous cover crop (CTL); and (c) CTL and organic-based chisel plowed with a winter leguminous cover crop (CTO). Black diamonds indicate the differences that were significantly different from zero based on the 95% confidence intervals.

representing, respectively, summits and convex steep slope areas with low contribution of water flow from the surrounding terrain, areas with intermediate slopes and intermediate surrounding terrain contributions, and low located depressions. Comparisons between CT and NT at the three WI levels for corn and soybean data are shown on Fig. 6a. The NT tended

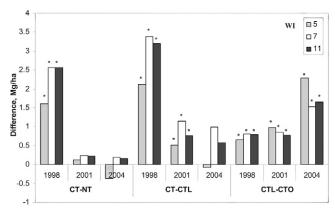


Fig. 7. The differences between the spline regression predictions of the maximum observed wheat yields between chisel plowed with conventional chemical inputs (CT) and no-till with conventional chemical inputs (NT); CT and chisel plowed with low chemical input and a winter leguminous cover crop (CTL); and CTL and organic-based chisel plowed with a winter leguminous cover crop (CTO) at wetness index (WI) equal to 5, 7, and II. Stars indicate the differences that were significantly different from zero based on the 95% confidence intervals.

to produce higher maximum yields than CT at the lowest WI. Speculatively, NT probably performed better than CT at lower WI due to reduction of erosion, increase in soil C and improved soil structure that are often observed as a result of long-term implementation of the no-till (Reicosky et al., 1995; Vanden Bygaart et al., 1999; Rhoton, 2000). At intermediate WI levels there appeared to be no consistent difference between the treatments with CT having higher boundary yields in some while NT in other years. We hypothesized that because of delayed soil warming in depression areas under no-till, the NT yields might be lower there than those of CT. However, contrary to our expectations there was no noticeable difference in CT and NT boundary yields at the highest WI values. For wheat yields, CT was better than NT across the whole range of WI values in 1998, while there was no difference between the two treatments in the other two wheat years (Fig. 7).

The CTL tended to perform better than CT at low and intermediate WI sites (Fig. 7b) as in the case of CT and NT comparisons. This might be attributed to the improvement in soil organic matter and soil structure due to long-term implementation of legume cover crops of the CTL system, which might be particularly beneficial at the eroded sites with low WI. There were no pronounced trends in the differences between CT and CTL at high WI values, indicating that over the long-run the management with reduced fertilizer inputs and cover crops performs similarly to the conventional chemical input management in terms of corn and soybean yields. Boundary line wheat yields under CT were higher than those of CTL in two of the studied years (1998 and 2001), while there was no difference between CT and CTL in 2004 across all WI levels (Fig. 7).

The boundary line yields in CTL tended to be higher than those of CTO across all WI levels (Fig. 6c). The exception was 1999 where CTO had higher yield than CTL at low and medium WI. CTL was noticeably better than CTO at summit and flat/sloped sites, while not significantly better than CTO in most cases at WI of 11. This might be attributed to the fact that CTL receives N fertilizer while CTO does not. The higher

areas are the ones that are expected to suffer from lack of N the most. At depressions which are known to get extra flux of NO₃ from the surrounding terrain, the difference between CTL and CTO becomes lower.

CONCLUSIONS

Boundary line analysis combined with nonparametric spline regression was found to be a useful diagnostic tool for identifying yield potential and for describing complexly-shaped relationships between yields and topography. However, this analysis ignores potential interactions among yield affecting factors, and thus needs to be treated with caution as it may lead to overestimation of the plant responses to a particular environmental factor (Chambers et al., 1985). The nonparametric spline regression algorithm used in the study was robust and efficient in assessing yield differences between treatments across the range of topographical variables.

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. Variability of corn and soybean yields in NT and CTO systems was better explained by precipitation in early spring and during pollination and grain fill than that in conventionally tilled soils with chemical inputs. The relationship between boundary line yield data and WI in corn and soybean for most of the studied years had a convex shape, with higher boundary line yields consistently occurring at intermediate WI levels. No-till tended to produce higher boundary line, that is, maximal, yields than conventional system at the lowest WI, that is, at summit/steep slope areas. At intermediate and high WI levels there appeared to be no consistent differences between the chiselplowed and no-till systems. The conventionally tilled system with reduced chemical inputs (N fertilization only) and leguminous cover crops performed better than the conventionally tilled system with conventional chemical inputs at summit and shoulder areas (low WI) as well as in areas with intermediate WI values. The reduced chemical input system produced higher yields than the organic system at low and intermediate WI, while there was no consistent difference between the two systems at high WI, that is, topographically low depression areas. Boundary line wheat yields in organic system were lower than those in the system with reduced chemical inputs, while those of conventional input system tended to be higher than in the reduced input system. The differences between the treatments for wheat yields were not sensitive to WI.

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REFERENCES

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 Electrics Agric. 26:37–51.

Chambers, J.L., T.M. Hinckley, G. Cox, C.L. Metcalf, and R.G. Aslin. 1985. Boundary-Line analysis and models of leaf conductance for four oakhickory 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 http://www.lter. kbs.msu.edu/about/site_description/soils.php (verified 19 July 2008). W.K. Kellogg Biol. Stn. Long-Term Ecol. Res. Project, Michigan State Univ., Hickory Corners, MI.
- de Boor, C. 2001. A practical guide to splines. Springer-Verlag, New York.
- 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.
- Environmental Systems Research Institute. 2000. ArcView Spatial Analyst, Redlands, CA.
- Fan, J., and I. Gijbels. 1996. Local polynomial modeling 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.
- 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 Univ. Press, Cambridge.
- Hoeft, R.G., E.D. Nafziger, R.R. Johnson, and S.R. Aldrich. 2000. Modern corn and soybean production. MCSP Publ., Savoy, IL.
- Hu, Q., and G. Buyanovsky. 2003. Climate effects on corn yield in Missouri. J. Appl. Meteorol. 42:1626–1635.
- Huang, X., A. Kravchenko, K. Thelen, N. Martin, and G. Bollero. 2005. Yield variability in an undulating field: Classification and prediction. p. 419–431. *In* D.J. Mulla (ed.) Proc. of the 7th Int. Conf. on Precision Agric.
- Jaynes, D.B., and T.S. Colvin. 1997. Spatiotemporal variability of corn and soybean yield. Agron. J. 89:30–37.

2004. Precision Agric. Ctr., Univ. of Minnesota, St. Paul.

and Other Precision Resources Manage., Minneapolis, MN. 25-28 July

- 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.
- 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. Precis. Agric. 4:179–192.
- 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, 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.
- 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. Ann. Appl. Biol. 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.
- Lobell, D.B., and G.P. Asner. 2003. Climate and management contributions to recent trends in U.S. agricultural yields. Science (Washington, DC) 299:1032.
- Mokma, D.L., and J.A. Doolittle. 1993. Mapping soils and soil properties in southwest Michigan using ground-penetrating radar. Soil Surv. Horiz. 34:13–22.
- 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 55:572–582.
- 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 Conserv. 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.
- 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. 1999. SAS/STAT user's guide. Version 8. SAS Inst., Cary, NC.
- Schmidt, F., and A. Persson. 2003. Comparison of DEM data capture and topographic wetness indices. Precis. Agric. 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). Commun. Soil Sci. Plant Anal. 27:2739–2748.
- Shatar, T.M., and A.B. McBratney. 2004. Boundary-line analysis of field-scale yield response to soil properties. J. Agric. Sci. 142:553–560.
- 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 Tillage Res. 51:137–147.
- Wahba, G. 1990. Spline models for observational data. Soc. for Industrial and Applied Mathematics, Philadelphia, PA.
- Wang, L. 2007. Polynomial spline smoothing for nonlinear time series. Ph.D. Diss., Dep. of Statistics and Probability, Michigan State Univ. (Diss. Abstr. AAT 3264251).
- Webb, R.A. 1972. Use of the Boundary Line in the analysis of biological data. J. Hortic. Sci. 47:309–319.
- Wilhelm, W.W., and C.S. Wortmann. 2004. Tillage and rotation interactions for corn and soybean grain yield as affected by precipitation and air temperature. Agron. J. 96:425–432.