Potential Application of Electrical Conductivity (EC) Map for Variable Rate Seeding

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ABSTRACT

A two-year field experiment was conducted to investigate the potential application of soil electrical conductivity for variable rate seeding. Map calculations and geo-statistical techniques were used to establish a relationship among EC, elevation, seeding rate, and yield. Yield data taken from the first year, which was a dry year, showed inconsistent relationships and the overall yield variation within the farm was very low at 700 kg ha^{-1}. However, yield data from the second year, being a wet year, exhibited relationships where an increase in EC indicated an increased yield potential, while increased seeding rates exhibited fluctuating trends in yield potentials. There is clear evidence that the existing relationship between the site properties as quantified by the EC, the seeding rate, and the crop yield, can favorably be used for Variable Rate Planting (VRP) in this particular production system. Regarding the development of prediction models for use in these situations, linear and non-linear parametric models were tried on the 2003 data, but with little success. A generalized additive model, a non-parametric approach, was used next and the yield model developed was found to regress the relationship adequately. To further improve the prediction accuracy, a Neural Network (NN) technique was used on the data. The diagnostics indicated that the yield estimation was precise (R^2 = 0.89). The NN approach was identified as a very promising technique for using EC data in the successful application of variable rate technology towards maximizing yield potential of sites. However, the results indicate that the modeled relationship is specific to only that particular crop production system.

Keywords: Yield prediction, Variable rate planting, Electrical conductivity, GAM, Neural Networks.

1. INTRODUCTION

The gap between average farm yields and yield potential is narrowing. The average farm yields have been predicted to reach 70-80% of the yield potential ceiling within 30 years, especially in major cereal cropping systems (Cassman, 1999). Achieving sustainable crop production at these high levels requires precise management of all production factors relevant to a given cropping system. Precision farming can allow regulation of several inputs for crop production, including type and quantity of fertilizers and pesticides, crop variety and plant population, cultivation practices, and irrigation and drainage decisions among many others. Each of these inputs is regulated based on response functions, which must reflect site-specific conditions. Tools and methods need to be developed to estimate and predict the response function on a site-specific basis to improve input management.

Researchers and producers alike have recently shown interest in characterizing soil and topographic variability in relation to crop growth and yield. Several authors (Kravchenko and Bullock, 2000; Nolin et al., 2001; Ward and Cox, 2001) have reported that there is usually little or no significant relationship between crop yield variation and individual soil characteristics such as organic matter, cation exchange capacity and texture. However, apparent Electrical Conductivity (ECa), which is affected by a number of soil properties such as the clay content, soil water content, temperature, salinity, organic compounds and metals (Kachanoski et al., 1990; Morgan et al., 2001) has been highly correlated with claypan topsoil thickness (Doolittle et al., 1994; Sudduth et al., 2001) causing variations in water storage characteristics and consequently to yield variations in average precipitation crop years (Kitchen et al., 1999).

Corwin et al. (2003) observed that, although the crop yield inconsistently correlates with apparent soil electrical conductivity (ECa), there is specific instances where yield correlates with ECa. They developed a model relating ECa and yield, and reported that it will serve as an implicit indicator of those factors that can be adjusted to improve yield. Kravchenko et al., (2003) used an experimental cross-correlogram to quantify the relationships between corn and soybean yield and soil apparent electrical conductivity (ECa) and elevation in their spatial context. Crop yield was strongly and negatively related to ECa in years with high March precipitation and positively or weakly negatively related to ECa in years with low or moderate March precipitation. Johnson et al., (2003), in a 250 ha dry land experiment, mapped EC against wheat and corn yields and found the corn yield to have positive correlations with EC. They expressed the possibility of using EC to make decisions on prescription maps for input metering and yield determination. Humphreys et al., (2004) took measurements of soil EC, normalized difference vegetative index (NDVI), and grain yield in five long-term soil fertility experiments across Oklahoma during 2001 and 2002. Results indicated that soil EC was not better than mid-season NDVI readings at predicting grain yield at any location or year. Amidst all these contradicting results, ECa is one sensor-based measurement parameter that has shown promise for precision agriculture. It is also clear that EC’s relationship to crop yield is so complex that it has to be modeled for the specific crop production system.

Another factor that has been observed to influence the yield potential is the ground topography (Yang et al., 1998; Bakhsh et al., 2000; Kravchenko and Bullock, 2000; and Fraisse et al., 2001). It plays an important role in the hydrological response and water availability for crop production, especially under rain-fed agriculture. Jiang and Thalan (2004) investigated the relationship between soil and topographic properties with crop yield and used Principal Component Analysis to identify that slope is the limiting factor for yield rather than elevation. Zeleke and Si (2004) used multi-fractal and joint multi-fractal approaches to characterize four topographic indices namely the relative elevation, wetness index, upslope length and curvature on wheat yield in an experiment on semi-arid land. Upslope length was deemed the best index among the four factors influencing grain yield.

Apart from the soil and topographic characteristics influencing the crop yield, evidence exists that a specific plant population suits a given location, leading to better yield at that spot. Variable rate planting (VRP) could be the answer to such situations. Planting lower plant populations in less yielding sites and increasing the plant populations in the more productive areas is believed to maximize grain yields. Bullock et al., (1998) reported that not all portions of fields have the same economically optimal corn plant density and hence precision farming principles could be applied. Shanahan et al., (2004) experimented with corn yield responses of two types of hybrids planted at four plant densities for three consecutive seasons from 1997. Hybrids responded similarly to field variation, while plant densities responded differentially, with the economically optimum plant densities changing by 5000 plants ha^{-1} between high and low-yielding field areas. The results suggested site-specific management of plant densities may be feasible. Nevertheless, there is considerable skepticism concerning the economical use of VRP. Doerge (1999) recorded that an optimal plant stand of 44,000 plants ha^{-1} is usually sufficient in fields where historical yields are below 14,000 kg ha^{-1}. Seasonal variations in optimum plant population were reported to be as high as 30,000 plants ha^{-1} in the same location in the same field and assigning specific seeding rates for zones within the field was claimed not realistic. DeBoer (2002) reported that VRP has profit potential only for farmers with some low yield potential land and surprisingly, only when the proportion of these low yielding lands is small.

Once again, decisions on varying plant population according to soil properties are fraught with uncertainty about the yield outcome to a particular level of plant population. Uncontrolled variation in the soil condition may prove to be disastrous if seeding rate decisions are made purely on yield history alone. Hence, profitable implementation of VRP will require detailed information regarding site characteristics, production inputs, and stochastic factors. The modeling of the relationship between yield, plant population, ECa and field topography is one way of exploring the possibilities for maximizing the production of the given system (Kitchen et al., 2003; Kravchenko et al., 2003).

Numerous techniques have been applied for modeling the relationship between crop yields and measured soil and site parameters. However, uncertainty over their appropriateness and predictive ability remains. Linear parametric models have mostly failed to predict the yield variability (Sudduth et al., 1996; Kravchenko and Bullock, 2000). If successful, these models would prove to be simple and directly applicable. Non-linear models can also be applied, but with a prerequisite of assuming the relationship between the dependent and independent variables, which in most cases may be unknown. Kitchen et al., (1999) investigated the relationship of apparent profile soil electrical conductivity (ECa) of claypan soils (Udollic Ochraqualfs) and grain yield of five site-years of corn, seven site-years of soybean, and one site-year of grain sorghum. They used a boundary log-normal function fit to the upper edge of the scatter plots between yield and EC to quantify the widely varying yield response. A significant relationship between grain yield and EC was reported. They mentioned that more information on climate, crop type, and specific field parameters were needed to explain the shape of the possible yield by EC interaction.

Sudduth et al., (1996) reported highly accurate predictions of crop yield from site and soil properties using a nonlinear, nonparametric method known as projection pursuit regression. The feed-forward back-propagation Neural Network (NN) is another highly accurate, nonlinear, nonparametric method that has received attention as a general prediction model. Drummond et al., (1998) experimented with several NN algorithms that were successful in predicting crop yield using soil and topographic properties, with minimum risk of over-fitting. Liu et al., (2001) designed a feed-forward, completely connected, back-propagation NN to approximate the nonlinear yield function relating corn yield to factors influencing yield. The RMS error for 60 verification patterns was about approximately 20%. Drummond et al., (2003) investigated the Stepwise Multiple Linear Regression (SMLR), Projection Pursuit Regression (PPR), and several types of supervised feed-forward neural networks in an attempt to identify methods able to relate soil properties and grain yields on a point-by-point basis within 10 individual site-years. To avoid over-fitting, evaluations were based on predictive ability using a 5-fold cross-validation technique. The neural techniques consistently outperformed both SMLR and PPR and provided minimal prediction errors in every site-year. Kitchen et al., (2003) studied the relationship of profile apparent soil electrical conductivity (ECa) and topographic measures to grain yield for three contrasting soil-crop systems and found that NN was able to provide the most accurate empirical models of the data, compared to methods such as multiple regression and boundary line methods. ECa alone explained yield variability (R^2 = 0.21, averaged over sites and years) better than topographic variables (R^2 = 0.17, averaged over sites and years). Combining ECa and topography measures together usually improved model R^2 values (R^2 = 0.32, averaged over sites and years). Regardless of the analytical procedure used, ECa and topographic properties showed to be important parameters influencing the yield variability.

An insight into the relationship between soil properties, plant stand and yield potential will pave the way for maximizing the production through an appropriate decision-making strategy. The main goal of this study was to determine the relationship between soil electrical conductivity, topography, and plant population to the yield response of a specific crop production system and to determine whether or not electrical conductivity and topography can be used as a criteria to change the plant population rate towards maximizing the yield.

2. MATERIALS AND METHODS

A two-year field experiment was conducted near Wooster, Ohio, USA The experiment was conducted during 2002 and 2003 crop years. The corn hybrid used had a relative maturity date of 105 days. The recommended seeding rate for this hybrid was approximately 65,000 seeds ha^{-1}. The variable seeding map and planting was created and controlled using the AGCO Fieldstar System. The planter was an AGCO White 6-row variable rate planter with a 750 mm spacing.

The corn was planted on May 22, 2002, and April 29, 2003. Each seeding rate was replicated three times by way of randomly allotted blocks (fig. 1). The variable rate planter used a prescription map with the specified seeding rates and locations. The seeding rates were varied at levels of 64,925, 69,825, 75,950, 80,850 and 85,750 seeds ha^{-1}. Each treatment strip was planted in a 5 m width so the harvester can be operated in the respective treatment strips to assess the yield data.

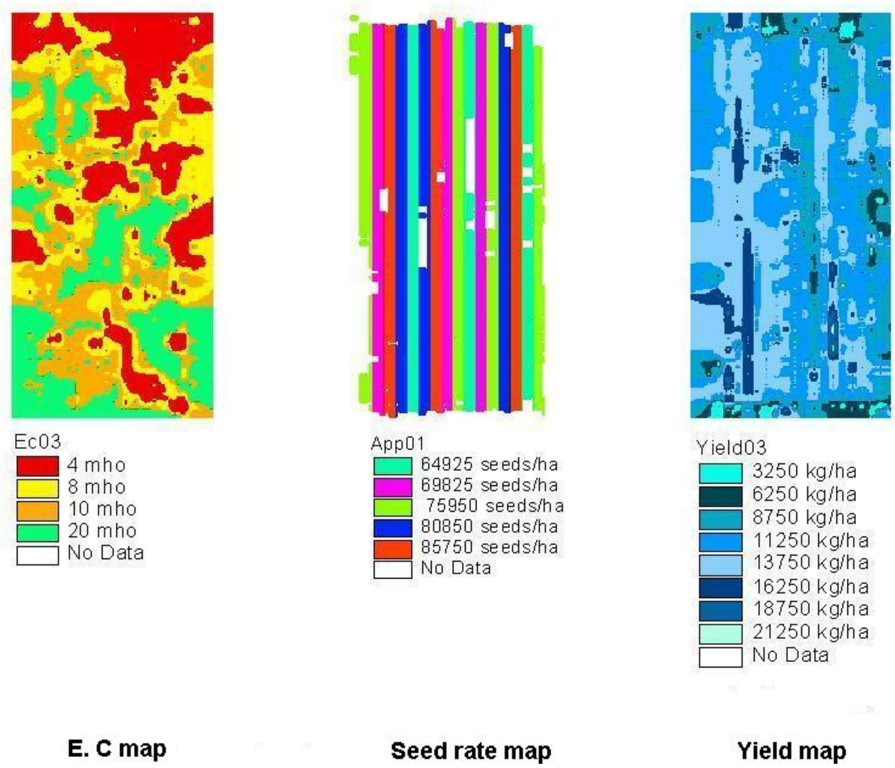


Figure 1. EC seeding rate and yield maps of the experimental plot during 2003

The electrical conductivity was measured using a Veris 3100 (Kansas City, Kansas). The distance between each EC swath was approximately 13.3 m. GPS location coordinates were collected for each EC measurement every second. The elevation data was collected simultaneously with the EC data, using a Trimble 4700/4800 Real-Time Kinematic (RTK) GPS receiver. Yield data was obtained while harvesting with combines fitted with GPS receivers.

GRASS, a GNU licensed GIS software (ITC-IRST, Trento, Italy. www.grass.itc.it) was used for creating all maps and data analysis. The georeferenced data files of each measurement were directly imported into the GIS software for map analysis. GNU licensed geo-statistic software "GSTAT" (Edzer J. Pebesma -www.gstat.org) was used on these grid files to analyze the spatial variability of the EC and yield map. The variograms of each of the factors and their co-variogram were plotted, and suitable variogram models were fitted concerning both N-S (latitudinal) and E-W (longitudinal) directions. GSTAT was also used for kriging the 'site' GPS tagged data to prepare the yield and EC maps.

3. RESULTS AND DISCUSSION

3.1 EC Profile of the Field

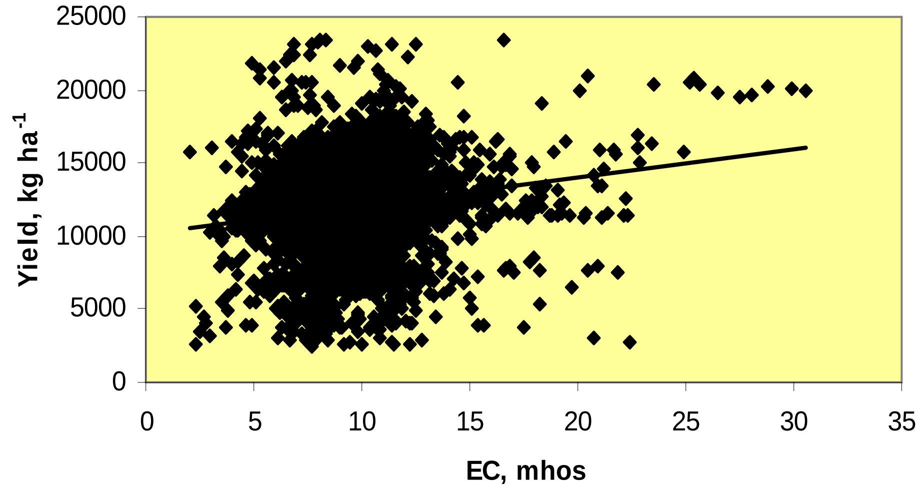
Figure 1 shows the map of applied seeding rates and the EC and yield maps obtained from the 2003 crop. The scatter plots of EC and seeding rate were plotted against the yield pertaining to 2003 data (fig. 2) showed a wide-spread scatter, expressing the very large variance of yield at each factor level. Table 1 shows the descriptive statistics of the EC values. The 2002 crop year was a dry year indicating much lower EC values than in 2003. This observation is due to the reason that EC increases as the water-filled pore space increases (Auerswald, 2001; Zhang and Wienhold, 2002). Generally the EC values of well drained soils are low and those in poorly drained soil are high (Clay et al., 2001).

The EC variograms of 2003 showed the longitudinal direction had more error components as shown by the higher intercept. Anisotropy in the spatial variability of EC was practically non-existent and both directions showed the correlation distance was within 0.0 004 degrees corresponding to approximately 40 m in both directions.

As for the yield variograms in 2003, anisotropy was present showing that the variability pattern pertaining to N-S direction had more random errors, even though the variability stabilized for both directions was within 40 m. The variograms showed an uptrend after a distance of 0.0 010 degrees (100 m), which is clear evidence of an embedded trend, particularly in the N-S direction. The co-variogram showed a flat sill indicating the predominance of random errors in the spatial relation between the yield and the EC.

Table 1. Descriptive statistics of electrical conductivity (EC) values for the experimental field

Crop year	2002	2003
Mean	7.465666	9.662306
Standard Error	0.071143	0.044422
Standard Deviation	3.154459	2.759869
Median	6.800000	9.514577
Skewness	1.126287	1.469003
Minimum	1.800000	1.994978
Maximum	21.900000	30.559930



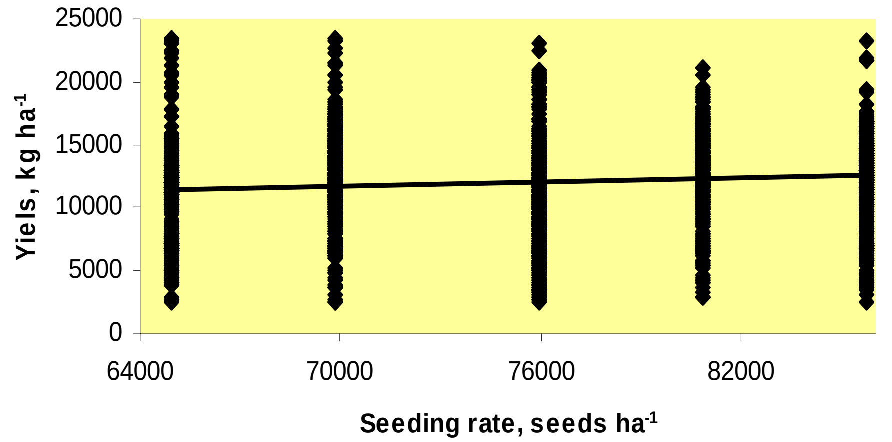


Figure 2. Actual yield variations in 2003

3.2 Statistical Modeling of the Experiment

A statistical test was attempted to assess the influence of EC, ground elevation and seeding rate on the yield potential of the given field sites. The variability of the EC, relative to the field locations, did not allow the treatments to be contiguously blocked into definite units of a particular treatment. Also, it did not allow the choice of equal-spaced EC levels for a balanced statistical design, since each such EC level did not have an equal number of sample locations in the field. It was decided to use the complete range of EC values in the field, to compute the 25, 50 and 75 percentile values and to acquire a set of four EC levels based on these percentile values.

This implied each of these EC levels will have equal number of experimental locations in the field, making the experimental plan balanced. The choice of four EC levels as opposed to five seeding rate levels allowed for statistical testing of their influence on the yield attained at a given location.

GRASS GIS was used to segregate the required data for statistical analysis. The EC and ground elevation data were kriged and converted to raster files. The EC map was reclassified into category ranges commensurate with the selected ranges of EC values. These maps were then queried for their category values at the locations corresponding to the yield data map. The resulting data provided a yield response table to the four levels of EC and the five levels of seeding rate.

Before proceeding with the analysis, paired correlations between the selected factors, were tested to eliminate interdependence of factors. The EC and elevation data, taken from the same locations were found to have a strong positive correlation (fig. 3). A clear linear trend was visible between the two for both years; therefore, ground elevation was eliminated as a factor for studying its influence on the yield potential.

The area-wise distribution of different yield levels against a given seeding rate and EC level for 2003 data was approximately normal, but had a large variance and skew. Neither the maximum nor the mean yield from that distribution was an appropriate quantitative index pertaining to that EC and seeding rate. Hence, cumulative distributions of yield categories were plotted (fig. 4) for each EC and seeding rate from which the median yield representative of the distribution was drawn pertaining to the given factors. These median values could be regarded as the 'Number Median Yields' (NMY) of the given EC and seeding rate in question.

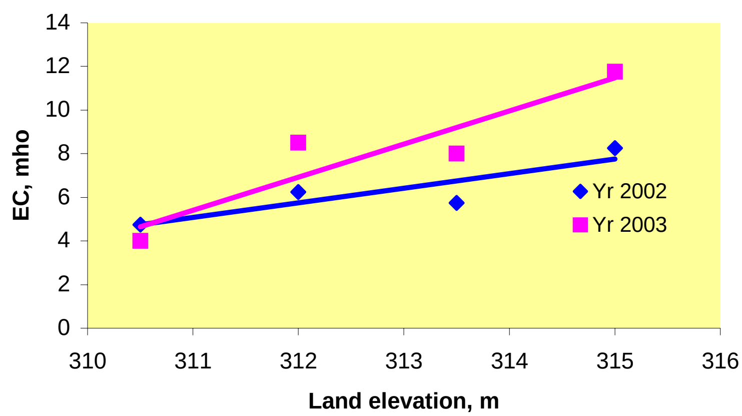


Figure 3. Relationship between EC and land elevation

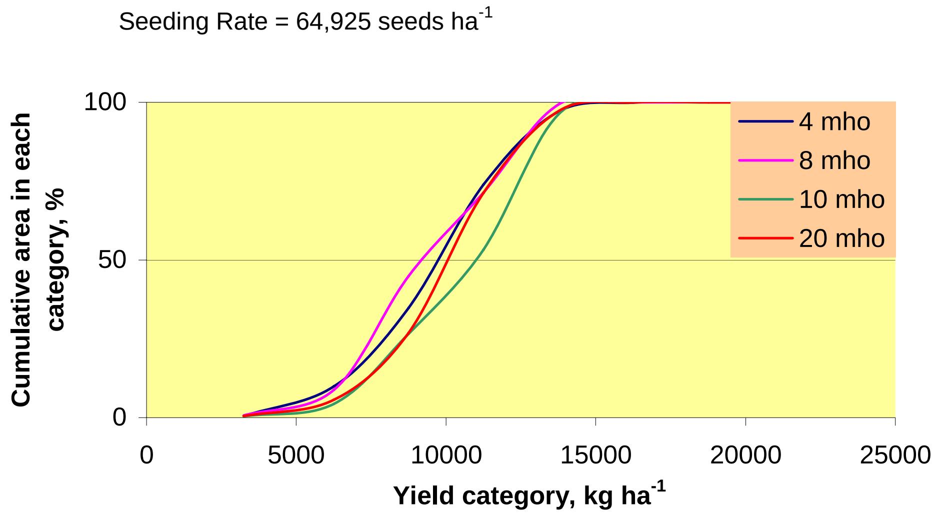


Figure 4. Cumulative distribution of yield categories for one seeding rate

Figure 5 shows the relationship between EC, seeding rate and the 'NMY' yield obtained in the two crop years. In 2003, it is evident that an EC in the 10-12 mho range has maximized the corn yield under all seeding rates. Thereafter, the yield response decreased marginally at slightly higher EC values.

The yield response to seeding rate was peculiar since it exhibited a periodic pattern; first a high peak at 69,825 seeds ha^{-1} and then a marginally small peak at 80,850 seeds ha^{-1}. Current corn hybrids grown across a wide range of environmental conditions have been reported to produce maximum grain yields at plant populations between 67,000-73,000 plants ha^{-1} (Bullock et al., 1998; Doerge, 1999). In this study, yield has increased to a maximum of 12,500 kg ha^{-1} at a seeding rate of 80,850 seeds ha^{-1}, which could have easily corresponded to the final crop stand of the recommended 67,000-73,000 plants ha^{-1}. Within the range of seeding rates between 64,925 to 75,950 seeds ha^{-1}, a particular seeding rate of 69,825 seeds ha^{-1} has brought about a maximum yield of 11,500 kg ha^{-1}. An increase in seeding rate exceeding 80,850 seeds ha^{-1} level decreased the yield marginally. Our results corroborate with Bullock et al., (1998) in regards that for all EC levels more than 10 mho, a maximum yield was obtained at an optimal rate of 80,850 seeds ha^{-1}. However, field sites possessing EC values lesser than 10 mho, provided equal or higher crop yields.

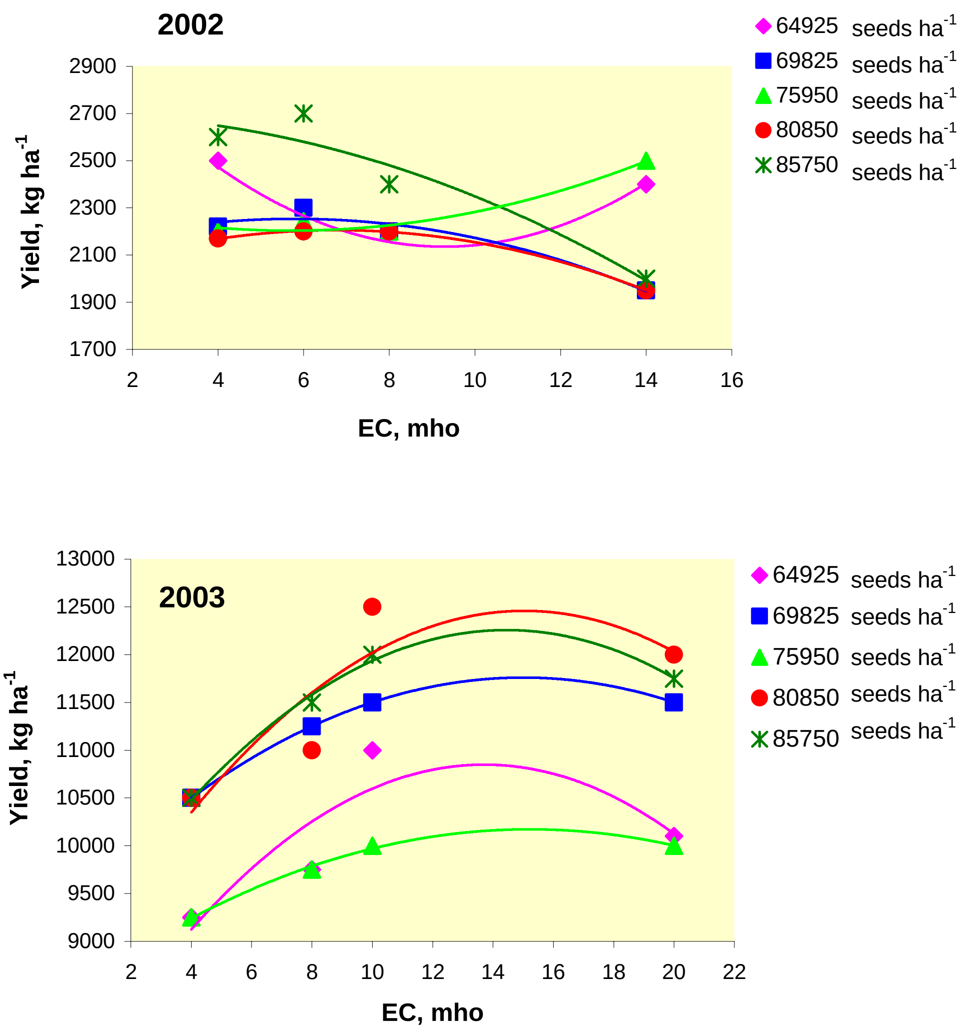


Figure 5. Influence of EC and seeding rate on corn yield

It may be noted that a seeding rate of 69,825 seeds ha^{-1} at sites possessing 4 mho, yielded the same 10,500 kg ha^{-1} of corn yield provided by a much higher rate of 85,750 seeds ha^{-1}. At sites with an EC of 8 mho, the seeding rate of 80,850 seeds ha^{-1} could only give a smaller yield than that provided by a rate of 69,825 seeds ha^{-1}. This clearly indicates this production system would do very well with variable rate planting (VRP) and can use a prescription model for varying the plant densities according to the EC of the given site. It may be noted that the above analysis is based on the median values of the yield.

The average yield in 2002 was very low (about 2,700 kg ha^{-1}) because of a dry year. No clear relationship existed between the EC, seeding rate and the yield. Within whatever small variation in yield potential, its relationship with EC and the seeding rate was thoroughly contrary to the 2003 data. The influence of the seeding rate is attributed to the fact that at yield levels below 5,700 kg ha^{-1}, little response has been reported to changes in plant population (Bullock et al., 1998; Doerge, 1999). For most plant populations, the increase in EC decreased yield potential substantially. Kitchen et al., (2003) reported similar results stating that the correlation between yield and EC was positive one year and negative the next and have associated these trends to the variation of water holding capacity as exhibited by EC. Nevertheless, it may be noted from the yield response to the field sites having an EC more than 10 mho, that a reduction of seeding rate to 75,950 seeds ha^{-1} had increased the yield. This situation is hence, a candidate for variable rate of planting (VRP), but the increase in yield one would expect for this instance was a meager 400 kg ha^{-1}.

To arrive at prediction models on the 2003 data for use in the VRP situations, further statistical analysis through parametric and non-parametric approaches were attempted on both the NMYs and the means of the categorized map data. The GNU ‘R’ statistical package (The R foundation – www.r-project.org) was used as interfaced with GRASS GIS to analyze the complete map data relevant to each factor map and yield map. General Linear Models (GLMs), both linear and non-linear, were attempted on the data, but produced very bad fits with R^2 values of 0.02 to 0.04.

Hence, a non-parametric approach was contemplated. In all the GLMs, an assumption is made about the parametric form of the function to be fitted to the data. Whereas Generalized Additive Models (GAM) extends the range of application of Generalized Linear Models by allowing non-parametric smoothers combined with a range of link functions. GAM works by replacing the coefficients found in parametric models by these smoothers. The model is fit by iteratively smoothing partial residuals in a process known as backfitting.

The General Regression and Statistical Prediction (GRASP-R) (Centre Suisse de Cartographie de la Faune, Neuchâtel, Switzerland - www.cscf.ch/grasp) software developed as a package for ‘R’ is a powerful non-parametric GAM modeling tool, which was used on the 2003 data. The step-wise GAM procedure produced a final model using a bi-directional fitting algorithm, which gave an exactly similar picture of the relationship observed earlier between the factors and the yield potential. The final GAM model and its summary are shown in Table 2.

The proposed GAM model uses a Gaussian distribution and an identity link function just like a GLM. The yield is modeled by a linear combination of non-parametric smoothers on both EC and seeding rate. The smoothers have used a smoothening degree of k= 5, which is the number of neighboring points used for the smoothening process. Both factors, namely the EC and the seeding rate were significant in the fit. The GRASP-R routines were able to effectively choose the best possible fit for the given data. Since the R^2 value was 0.128 with only 12.9 percent of the total deviance being fully explained by the fit, a separate deviance analysis on the final GAM model was attempted using the ‘gam’ package of the ‘R’ ware. The given model proved to be a better fit than those without smoothing terms for the selected factors.

Table 2. GAM model on corn yield

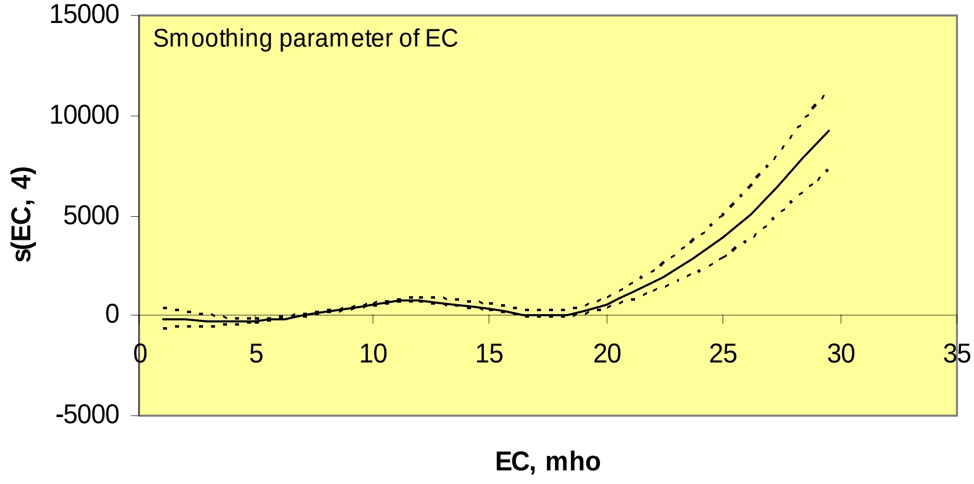
Response distribution:		Gaussian		
Link function:		Identity		
GAM formula:		Yield ~ s(EC, k = 5) + s(Seeding rate, k = 5)		
	Estimate	Std. Err.	t ratio	Pr(>|t|)
Constant	12003	48.37	248.2	< 2.22e-16
	Estimated d.f.	Chi.sq.		p-value
S(EC)	4	144.31		< 2.22e-16
S(SeedRate)	4	403.29		< 2.22e-16
R-sq.(adj) = 0.128 Deviance explained = 12.9%				
GCV score = 9.0511e+06 Scale est. = 9.03e+06 n = 3860				

The smoothing curves of EC (fig. 6) showed an increasing trend in the 10 to 12 mho range, which flattens slightly over those values. This is the same response as proposed by the earlier analysis using NMYs. The GAM model also showed an increasing trend with further increases in EC. The smoothing coefficient of seeding rate fluctuates periodically (fig. 6) and confirms the earlier result that the seeding rate has to be optimal at each EC level to draw the maximum yield. Though a simpler and less tedious procedure of comparing the Number Mean Yield (NMY) levels may explain the yield response adequately, the prescriptions for site specific planting would demand a rugged model, which the GAM has provided adequately through an empirical fit.

3.3 Neural Network (NN) Solution for Yield Prediction

Liu et al., (2001) used a standard backprop network for estimating corn yield from plot data on soil, weather and management factors and observed that the predictive errors were within 20 percent. Drummond et al., (2003) evaluated the predictive ability of linear, non-linear and neural network (NN) techniques on data sets of yield and soil characteristics and reported that NN techniques consistently outperformed simple multiple linear regressions and projection pursuit regressions and provided minimal prediction errors.

Hence, NN was tested next on our data set to evaluate its efficacy in predicting the exact yield potentials. The uncategorized EC values of the 2003 data set ranged between 1.99 to 30.55 mho and may not be a candidate for direct input into the neural network. Hence, the EC data was categorized into 9 levels. The NMY yields of these EC levels as categorized by each seeding rate were then computed and used for training and validating the neural network. The ‘nnet’ package of ‘R’ was used for implementing the neural solution. All factor and response levels were converted into normalized values with respect to the maximum value of each. A simulation was attempted using variable number of hidden nodes and a constant number of epochs on the full data set, based on which, the number of hidden nodes was optimized to be six.



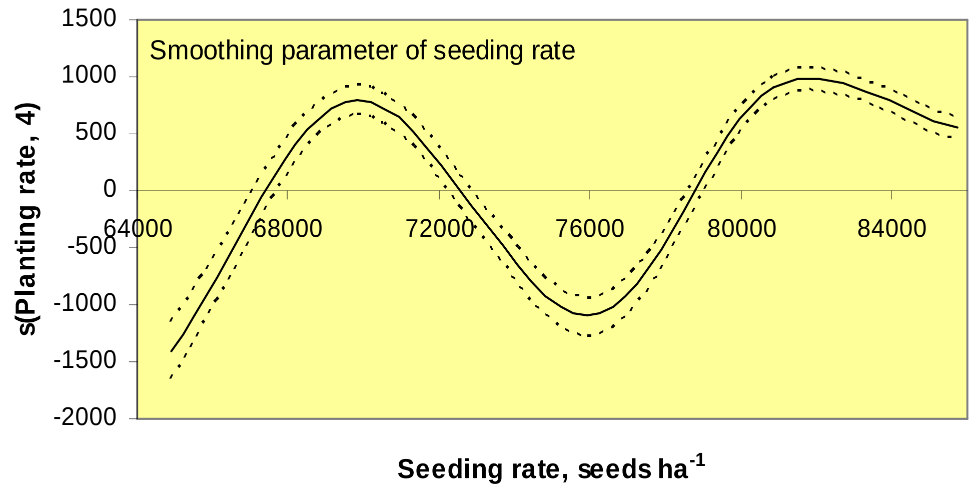


Figure 6. Smoothing parameters of the GAM model of yield

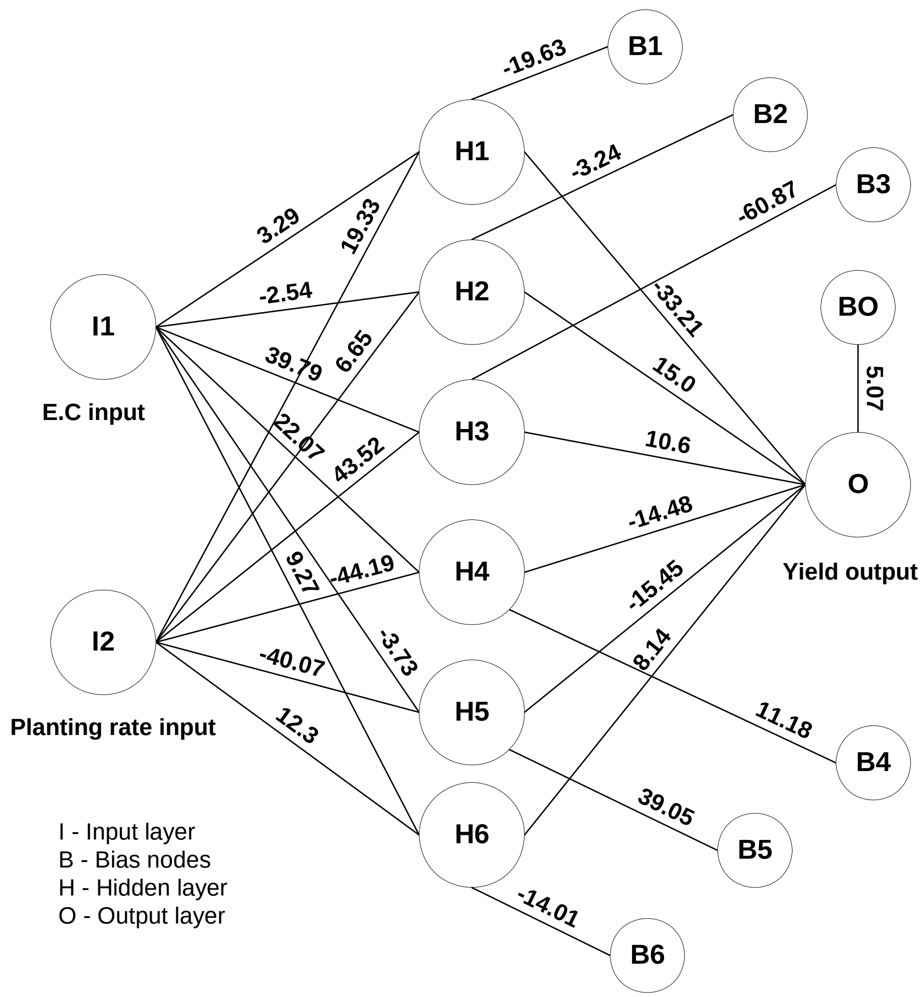


Figure 7. Neural network model for predicting yield from EC and seeding rate.

One serious problem with NN is that the prediction model may become “over-fit”. This means that it may do an excellent job of fitting the data points with an error tending to zero, but would not predict well if new data is applied. The simplest and most widely used means of avoiding this is to divide the whole data set into two sets, one for training and one for validating the model. The first set of data is used for training the network and following every finite number of iterations, the training sequence is stopped and the ‘predict’ function of the NN package is used for validating the network using the independent validation set as input. The iterations are stopped when the error of prediction on validation is minimum. This method was adopted on our data set and the final model (fig. 7), consisting of six hidden nodes in a single hidden layer was developed providing an exact prediction. A comparison was made between the actual and predicted yields (fig. 8). The deviation from a perfect fit was within about 11 percent.

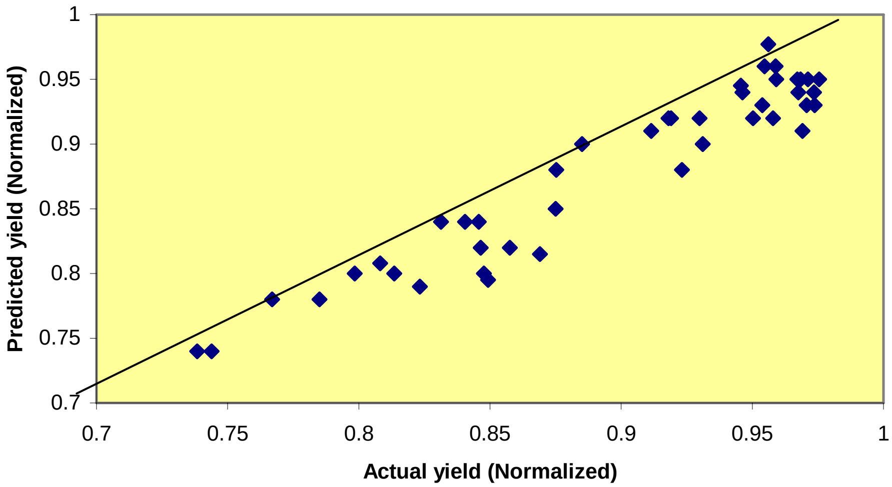


Figure 8. Comparison of actual and predicted yields.

4. CONCLUSIONS

This study explored the possibility of using the EC data of a specific crop production system to model the crop yield as influenced by the seeding rate. Visual examination of the yield response curves demonstrates that the relationship between yield, seeding rate and EC can be nonlinear with potential interactions between the variables. Different approaches including GAM and GLM, were attempted to statistically model these relationships. The GAM model was adequate in relating EC values to the yield for each seeding rate and could provide a prescription model for variable rate planting towards maximizing corn yield. Since there was further scope for improving the predictions, artificial neural network techniques were used on the data. A neural network technique was used to create a prescription seeding rate based on EC; however, the results confirm finding in earlier works that show the use of variable rate planting (VRP) can not be generalized for all crop production systems for maximizing the yield. Further, data from areas with low yield potential obtained from dry crop years indicate this approach may not be adequate for prediction and prescription work. In a rain-fed system, precipitation amount could significantly affect the outcome of the model. Future work warrants including weather data in the model.

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