1317 Integrated Effects of Root-Knot Nematode, Fertility, and Landscape Features on Cotton Yield Response

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ABBREVATONS: RKN (Southern root-knot nematode); SSM (Site-specific management); EC_a (Apparent soil electrical conductivity), EC_d (Soil electrical conductivity – Deep); VWC (Volumetric water content)

Site-specific management (SSM) of cotton (*Gossypium hirsutum* L.*)* fields may reduce yield losses and pest management costs. Effectively implementing SSM requires identification of the factors contributing to yield variability. Several factors may limit potential yield and can interact to exacerbate yield losses; therefore, it is necessary to determine the combined influence of yield limiting and reducing factors on crop growth and yield. The objectives of this study were to: i) use multiple regression analysis to evaluate the relationship between cotton yield, soil physical and chemical properties, and southern root-knot nematode [*Meloidogine incognita (Kofoid & White*) Chitwood] pressure (population density); ii) integrate the significant variables from the cotton yield regression model into a logistic regression model to predict the probability of cotton yield losses; and iii) utilize the cotton yield loss response model to develop maps depicting different probability levels of yield loss which could be transformed into management zone (MZ) maps. The effects of soil physical properties (apparent soil electrical conductivity - EC_a, slope, soil texture, and elevation), soil chemical properties (P, K, Ca, Mg, and soil pH), and disease [southern root-knot nematode (RKN)] on cotton yield were evaluated in two cotton fields in southern Georgia, USA, in 2006. Multiple linear regression and logistic regression were used to develop a site-specific response model of cotton yield and a probabilistic model depicting the factors associated with the risk for cotton yield losses. The models indicated that the percentage of sand in the soil, measured indirectly by EC_d, was the most yield limiting factor. However, the presence of aggregated high population densities of RKN in coarse textured areas exacerbated yield losses due to the conjunction of low uptake of water and K by nematode infected plants and the low availability of these resources in sandy areas. The results indicated that the need for RKN management not only depends on nematode population density, but also on soil texture and the interaction between soil texture and the nematode. Maps of probability of risk for yield losses based on EC_d identify low and high risk areas for yield losses, thereby providing the producers with a basis for utilizing SSM as a means to better allocate on-farm resources and maximize profitability.

KEYWORDS: *Gossypium hirsutum* L, logistic regression, multiple linear regression, *Meloidogine incognita*,precision agriculture, apparent soil electrical conductivity, southern root-knot nematode, site specific management, yield spatial variability

INTRODUCTION

In the last two decades, cotton (*Gossypium hirsutum L.)* production in the Southern Coastal Plain of Georgia, USA, has grown from 50,000 harvested hectares in 1983 to 580,000 harvested hectares in 2006. Cotton growth is continuously impacted by several biotic and abiotic factors. The soil physical properties, texture and structure, determine permeability and greatly influence rates of infiltration and plant-available water and nutrient uptake. Consequently, soil texture and structure are seminal factors affecting crop yield. Management of weeds and insects has been facilitated in recent years by utilization of transgenic cotton varieties. However, homopteran and hemipteran insects, seedling diseases, and nematodes still challenge cotton producers and impact yield and quality.

The continuing development of site-specific management (SSM) has facilitated the evaluation of cotton yield variability and permitted the spatial correlation of yield with soil factors and terrain. Several studies have shown the interaction of soil and landscape properties with cotton yield. Iqbal et al. (2005) showed that elevation, flow direction, sediment transport, sand content, and volumetric water content explained a high percentage of cotton lint variability. Terra et al. (2003) explained up to 60% of yield variability using apparent soil electrical conductivity (EC_a), slope, soil texture, and elevation. Corwin et al. (2003) developed a site-specific response model of cotton yield where salinity (indirectly measured by EC_a), plant-available water, leaching fraction, and pH were the most significant properties impacting cotton yield. Other studies have shown that both physical factors (relative elevations and sand content) and plant nutrient status of soils are highly correlated with cotton yields (Cox et al., 2005, Ping et al., 2005). Apparent soil electrical conductivity (EC_a) has been included in many studies as an explanatory variable for cotton yield because of its power as surrogate data for assessing differences in soil texture.

Cotton yield is also impacted by biotic factors. Southern root-knot (*Meloidogyne incognita*) has caused the highest yield losses of any pathogen in the US Cotton Belt during the last two decades (Koenning et al., 2004). Recent studies in Georgia have indicated that areas at risk for presence of the Southern root-knot (RKN) can be identified by using EC_a and soil spectral reflectance data, both indicators of soil textural changes (Ortiz et al., 2006, Ortiz et al., 2007). Monfort et al. (2007) explained 65 - 86% of cotton yield variability measured in plots of similar geographic locations using initial population of RKN and sand content.

The objectives of this study were to: i) evaluate the relationship between cotton yield, soil physical and chemical properties, and root-knot nematode populations; i) use multiple regression analysis to evaluate the relationship between cotton yield, soil physical and chemical properties, and southern root-knot nematode [*Meloidogine incognita (Kofoid & White*) Chitwood] pressure (population density); ii) integrate the significant variables from the cotton yield regression model into a logistic regression model to predict the probability of cotton yield losses; and iii) utilize the cotton yield loss response model to develop maps depicting different probability levels of yield loss which could be transformed into management zone (MZ) maps. The basic hypothesis was that cotton growth and development varies spatially due to the variability in soil physical and chemical properties, as well as nematode population density. A better understanding of factors contributing to yield losses could lead to improved cotton management strategies.

MATERIALS AND METHODS

Study field description and data collection. Two fields located in the Little River Watershed, in the Southern Coastal Plain of south central Georgia, USA, were selected for this study in 2006. The CC field was 20 ha and the CMP field was 25 ha. The fields were planted with 'Delta & Pineland (DPL) 555 Boll-Guard®, Round-Up-Ready®' cotton.

Discrete data were collected on a square grid (0.20 ha). Sample locations were georeferenced using a Trimble AgGPS 114 DGPS receiver. Around the center of each grid cell (1.5 m radius), five soil samples were collected and combined for phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), and soil pH determination. Soil samples were collected 30 days after planting. Volumetric water content (VWC) was collected using Time Domain Reflectometry (TDR) equipment twice during the growing season (first square and flowering).

Soil samples for RKN second stage juveniles were collected three times during the growing season: July-August (RKN S1), September (RKN S2), and November (RKN S3). At each sample location, eight individual subsamples were collected from the root zone within a 1.5 m radius and combined. Root galling was evaluated on a 0 to 10 scale after harvest by digging and rating five plants within each grid cell. In the scale of rating used, the value of 0 corresponded with no galls and 10 indicated 100% of the root system galled (Davis and May, 2005).

Continuous apparent soil electrical conductivity (EC_a) [shallow (0-30 cm)- EC_s, deep (0-90 cm)- EC_d] data were collected prior to planting using the VERIS® 3100 implement. An AgGPS 214 real-time kinematic (RTK) Trimble GPS receiver mounted on the tractor pulling the VERIS® 3100 implement was used to collect topographic (elevation) data. The data set comprised approximately 7000 points of EC_a and elevation per field. The spatial variability of lint mass, cotton yield in subsequent references, on each field was recorded using an Ag Leader cotton yield monitor system (Ag Leader Technology, Ames, IA) installed on a 9965 four-row John Deere picker. The system used an AgGPS 132 DGPS receiver with differential correction to calculate the position of the harvester at any time in the field.

Data processing. To match elevation and EC_a at the RKN and soil sampling locations, continuous surface maps of 1 m^2 grid size for elevation and EC_a were created by ordinary punctual kriging using the Geostatistical Analyst extension on ArcVIEW 9.2. Although this procedure tends to smooth the data set, the density of data points used suggests that the impact of estimation at unsampled locations was minimal. Slope maps were derived from the elevation maps. Next, buffer areas of 4 m radius were created around each RKN sampling location. Pixel values from the surface maps (EC_a, elevation, slope) within the buffer were averaged. An inverse distance weighted (IDW) average of raw cotton yield data within the buffer area was calculated instead of using interpolated data which sometimes are smoothed by the interpolation method.

Statistical analysis. When RKN data departed from normality, data were log-transformed. Descriptive statistics of soil physical and chemical properties, RKN, VCW, and cotton yield at CC field (n = 99) and CMP field (n = 98) were calculated. Pearson's correlation coefficients (*r*) were calculated between measured RKN, soil physical and chemical properties and cotton yield. Soil chemical properties included P, K, Ca, Mg, and soil pH. Soil physical properties included elevation, slope, VCW, and EC_a. Because VWC and RKN data were collected several times during the growing season, the sampling event best correlated with cotton yield was selected for regression analyses. Covariates in the data set were identified using the variance inflation factor (VIF) in the PROC REG model procedure in SAS (SAS Institute, 200). All variables with VIF > 7 were sequentially removed from the data set prior to the regression analysis.

A cotton yield response model was developed using ordinary least squares (OLS) regression to explain the influence of abiotic and biotic factors on yield variability. The soil physical and chemical properties, as well as RKN represented independent variables, and the estimated average lint yield represented the dependent variable. A forward variable selection procedure in SAS was used to eliminate variables that did not significantly contribute to yield response (*alpha = 0.10*) and to alleviate the inherent multicollinearity between some of the predictor variables. Semivariograms of the residuals from the OLS model were constructed to study the spatial correlation of the errors. When errors exhibited spatial dependency, a restricted maximum-likelihood approach was employed to evaluate the significance of the estimated, spatial-error parameters. This procedure simultaneously estimates the model parameters and spatial error parameters.

Next, a stepwise logistical regression analysis was used to determine which biotic (RKN) and abiotic (soil properties) factors contributed to the highest probability (*P*) of having cotton yield less than the mean cotton yield for a particular field and to establish *P* as a function of the significant factors. The model used for the logistic regression was $P = e^{[(\alpha+\beta*X)+\text{kriged residuals}]} / (1 + e^{[(\alpha+\beta*X)+\text{kriged residuals}]})$ (*alpha = 0.15*). The significance of each regression model was evaluated using a likelihood ratio (–2LogL) with an approximated chi-square distribution. In this case, the lower the –2LogL of a model the better the model. Models with one, two, three, and four variables (resulting from the model selection procedure) were compared to evaluate the impact of each variable or combination of variables on the explanation of the probability of yield loss. The process of comparison was based on the evaluation of the Akaike information criterion (AIC), -2LogL, and probability level (*alpha=0.15*). The lower the –2LogL and AIC of a model, the better it explain the data. A McFadden coefficient (R^2_{MF}) was calculated as a measure of fitness (R^2) for the logistic regression (Menard, 2000).

The degree of spatial correlation of the residuals was also used as an additional criterion of model selection. The spatial dependence of the residuals of the logistic model was inspected using semivariograms. When the null hypothesis for errors, i.e. that the errors were not spatially correlated was rejected, the kriged residual predictions were added to the model.

For each variable used in the logistic regression model a surface map (raster map) was generated in ArcVIEW 9.2. The prediction formula of the final logistic model was then used with the ArcVIEW map calculator routine to produce the probability of yield losses map

RESULTS AND DISCUSSION

Cotton yield response model. The variables that were most highly correlated with cotton yield at the CC field included elevation, Ca, EC_d, VWC measured in September, and Log_{10}RKNS2 (-0.67, 0.61, 0.59, 0.57, and -0.52 respectively). Although elevation was the variable with the highest negative correlation with yield, the small changes in the field, coefficient of variation (CV) of 2.1%, and the negative correlation with EC_a which contradicts previous findings (Ortiz et al., 2007) lead to the non-inclusion of elevation into the cotton yield response selection model. The negative correlation of elevation with yield could be due to a rapid movement of water from areas with high to low elevations in the field leaving higher elevations drier. Although Ca was not below recommended levels (< 335 kg/ha, low level for the Coastal plain soils) 30 days after planting, the low cation exchange capacity (CEC) in the area with the lowest EC_d might indicate that Ca was not retained by the soil in this part of the field. This result could explain the positive relation between Ca and yield. However, because there is a significant correlation between Ca and EC_d (r = 0.68), EC_d may be used instead of Ca in the yield model to minimize multicollinearity. The positive correlation between yield and EC_d implies that yield decreased in areas with low EC_d which are mainly of coarse texture. The negative correlation between RKN and EC_d found by Ortiz et al. (2007) could also suggest an additional impact of RKN on yield in areas with low EC_d. The positive correlation between VWC and either EC_s or EC_d, 0.83 and 0.84, respectively, indicated that EC_s and EC_d could be used to explain variability in VWC with respect to soil textural changes. The significant correlation between Log_{10} RKNS2 and galling ($r = 0.53$, $P < 0.05$) and between galling and cotton yield ($r = -0.39$, $P < 0.05$) evidenced the impact of RKN on yield.

Multiple linear regression analyses indicated that EC_d explained the highest percentage of variability in yield (partial $r^2 = 0.35$). The multiple linear regression for the CC field resulted in the equation: cotton yield = 759.25 – 66.17*(Log_{10} RKNS2) + 90.93*(EC_d) + 63.19*(Slope) + 2.35*(K) + ε, $R^2 = 0.54$. The positive relationship between cotton yield and EC_d indicates that yield increases with increasing EC_d. Because EC_d is highly, negatively correlated with sand content ($r = -0.95$, data not shown), this data re-emphasized that soil texture is the primary yield limiting factor. A secondary contributor to yield reduction was Log_{10} RKNS2, explaining 12% of the variability in yield. This result indicates that Log_{10} RKNS2, with the highest mean of RKN population density during the growing season, was more useful for the explaination of yield variability than the RKN S1 and RKN S3. The negative relationship between RKN and cotton yield indicated that increasing RKN densities can lead to a reduction in yield. The preference of RKN for sandy areas with low EC_a reported by Monfort et al. (2007) and Ortiz et al. (2007) explains the high significance of these two variables on the cotton yield model

The remaining variables in the model, slope and K, explained 2 and 5% of the variability in yield, respectively. The positive relation between cotton yield and slope observed in this field contradicts previous studies were this relation was negative (Kravchenko et al., 2000). This could be due to its low spatial variability throughout the field. Although the CV of 48% indicates a moderate variation, high values of slope were localized. Potassium was deficient in 39% of the total area of CC field with values less than 78 kg/ha. The marginal availability of K supports the positive correlation ($r = 0.37$, $P < 0.05$) of K with cotton yield in the response model. The variables EC_s, Ca, and Mg were not included in the regression model due to the high covariance with other variables within the data set.

At the CMP field, the most highly correlated variables with cotton yield were EC_d, VWC measured in September and K (0.59, 0.56, 0.48, respectively). As observed for the CC field, the good correlation between VWC with either EC_s or EC_d, 0.48 and 0.63, respectively, supported the relationship between VWC and observed variability in soil texture. The low correlation between Log_{10} RKNS2 and galling ($r = 0.14$), and between galling and cotton yield ($r = -0.11$), suggested that RKN did not significantly reduce cotton yields in this field this year because RKN populations were reduced by rotation with the non-RKN host crop, peanut (*Arachis hypogaea* L.) in the field the previous year.

Multiple linear regression analyses for the CMP field resulted in the equation: cotton yield = −1702.77 + 9414*(EC_d) +24.83*(Elevation) + 2.22*(K) + 19.09*(VWC) + ε, $R^2 = 0.43$. The coefficients from this model were adjusted using a restricted maximum likelihood approach due to a spatially correlated error term. As observed for the CC site, the factor explaining the highest percentage of variability in yield was EC_d (partial $r^2 = 0.35$). The positive relationship between cotton yield and EC_d indicated that high yield areas can be associated with areas of high EC_d and likely relatively higher clay content. In this field as well as in the CC field, sandy soils with low EC_d, have correspondingly lower soil water holding capacities compared to heavier textured soils, thus low EC_d, indicates lower plant-available water in these areas. The remaining variables in the model (VWC, elevation and K) were positively related with yield, explaining from 2–5% of the variability in yield. Volumetric water content was a secondary factor affecting yield at this site. Keeping this in mind, VWC was highly correlated with EC_d ($r = 0.63$, $P < 0.0001$) suggesting that the interactive effects of water management and soil texture may significantly affect yield.

Probabilistic model for cotton yield losses. While multiple linear regression models identified the factors influencing within a field observed cotton yield, logistic regression of these factors allowed estimation of the probability of yield losses. The logistic model also identified the relative weight of each factor on the probability of yield losses, and facilitated the generation of predictive maps depicting different levels of probability (risk) for yield losses which could then be used for a SSM. The Akaike information criterion (AIC), and the likelihood ratio (–2LogL) of the logistic models for the CC and CMP fields are presented in the tables 1 and 2 respectively.

CC Field. The results from the logistic regression for the CC field indicated that EC_d was the single variable with the lowest AIC value (74.3) and lowest likelihood ratio (–2LogL = 70.3). Soil electrical conductivity deep (EC_d) alone, explained 48% of the variability in yield losses based on the following logistic regression equation:

$$P_{(\text{cotton yield} < \text{mean yield of the field})} = e^{[(5.953-6.943*EC_d)+\text{kriged residuals}]} / (1 + e^{[5.953-6.943*EC_d)+ \text{kriged residuals}]}). \quad [\ 1\ ]$$

The second best indicator of yield loss was VWC, having an AIC = 90.4. The Log_{10} RKNS2 was also significant, but exhibited a much higher AIC and likelihood ratio than EC_d and VWC (AIC = 117.4, –2LogL = 113). The remaining variables exhibited AIC values > 117.4.

Two variable models improved the explanation of yield loss only slightly, compared to the single variable model using EC_d. Significant improvements to model estimates of yield loss were observed when EC_d and VWC were added to the single variable model of Log_{10} RKNS2 (AIC = 73.1, –2LogL = 67.1 and AIC = 84.3, –2LogL = 78.3 respectively) (Table 1). Although the likelihood ratio was reduced with additions of individual variables to the model of EC_d, only the models including Log_{10} RKNS2 or VWC were significantly different from the EC_d model (AIC = 73.1, –2LogL = 67.1 and AIC = 73.0, –2LogL = 67.0 respectively, $P <$ 0.15). The additions of Log_{10} RKNS2 or EC_d to the model of VWC were also significant (–2LogL = 78.3 and –2LogL = 67.0 respectively). The presence of RKN in the two variable models demonstrates that the probability of yield losses increases when nematodes are present in sandy areas, locations which are also short in supply of water and nutrients. Soil electrical conductivity deep (EC_d) and RKN, combined in a two variable model, explained 51% of the variability in yield losses based on the following logistical regression equation:

$$P_{(\text{cotton yield} < \text{mean yield of the field})} = e^{[(4.266+ 0.854*\text{LogRKN} -6.747*EC_d)+\text{kriged residuals}]} / (1 + e^{[4.266+ 0.854*\text{LogRKN} -6.747*EC_d)+ \text{kriged residuals}]}) \ ; [\ 2\ ]$$

From the three variable models, two models explained significantly more of the variability in yield losses compared to the single variable model using EC_d. These two models included: 1) Log_{10} RKNS2+ EC_d + VWC (AIC = 71.4, –2LogL = 63.4, $R^2_{MF} = 0.54$) and 2) VWC + P+ EC_d were significant (AIC = 72, –2LogL = 64.0, $R^2_{MF} = 0.53$). Based on the previous analysis, yield losses may be expected in soils with low soil water retention (i.e. coarse textures, low EC_d). Model 1 [3] suggests that yield losses associated with sandy soil and low VWC may be exacerbated by an increment in the population density of RKN. The significance of phosphorous in the second model, VWC + P+ EC_d reinforces the importance of fertility management and its contribution to yield loss. The logistic regression model with three variables that exhibited the highest percentage of prediction of cotton yield losses was Log_{10} RKNS2+ EC_d + VWC:

$$P_{(\text{cotton yield} < \text{mean yield of the field})} = e^{[(8.428+ 0.919* \text{LogRKN}-5.491*EC_d- 0.626*\text{VWC})]} / (1 + e^{(8.428+ 0.919* \text{LogRKN}-5.491*EC_d- 0.626*\text{VWC})}) \ ; [\ 3\ ]$$

A single four variable model integrating Log_{10} RKNS2, EC_d , VWC , and P ((AIC = 70.4, –2LogL = 60.4, $R^2_{MF} = 0.56$) improved estimates of yield losses only slightly (Table 1):

$$P_{(\text{cotton yield} < \text{mean yield of the field})} = e^{[(5.33-0.512*VWC+0.03*P+0.939*LogRKN-6.074*EC_d)} / (1 + e^{(5.33-0.512*VWC+0.03*P+0.939*LogRKN-6.074*EC_d)}) \ ; \ [4]$$

No other models significantly improved estimates of yield loss compared to the single variable EC_d model.

Even though the probability of yield losses was not sufficiently explained by EC_d, the single model of yield losses based on EC_d is the most informative of the models . The prediction of areas at risk for yield losses based on EC_d may also be used as an indication of areas at risk for high nematode population and lack of nutrients which leads an increase on the probability of yield losses. However, the inclusion of RKN population density, soil fertility and water content factors into the logistic regression model increases the prediction of the probability of yield losses.

The results of these logistic regression analyses provide evidence that the factors influencing yield loss comprise two categories: 1) manageable factors (i.e.water, fertility and disease control) and 2) edaphic features (i.e. soil texture). While edaphic features are not easily managed or changed, water management by changing the frequency of irrigation, fertility and disease control can be managed to alleviate some potential yield losses.

Maps of the CC field showing the spatial distribution of yield losses based on a single variable, EC_d (Figure 1b); and the combination of the best three significant variables (Figure 1c) indicated that the zone with the highest probability of yield losses corresponded with the zone of lowest cotton yield (Figure 1a). When the maps of the spatial distribution of cotton yield, probability of yield losses (Figure 1b-1c), and EC_d (Figure 1d) were compared, a series of similarities were found. In the map of cotton yield, the zone with less yield than the mean (< 1126 kg/ha) agrees with the zone of the lowest EC_d values (Figure 1d). This may explain why EC_d was the variable with the highest contribution on the cotton yield response model. Previous studies have shown that low EC_d has been associated with coarse texture soils at the Southern Coastal plain of Georgia (Perry et al., 2007); therefore, the low soil water retention characteristic of this type of soil texture could be considered one of the major factors contributing to yield loses at the CC field.

When the map of Log_{10} RKNS2 (Figure 1e) was compared to the cotton yield map, the RKN map exhibited more spatial variability than the cotton yield map, contrasting with the significance of Log_{10} RKNS2 in the cotton yield and logistic regression models. The zone of highest yield loss did not overlay exactly with the areas of high population density of RKN; therefore, other factors appear to be influencing yield losses caused by RKN. However, the fact that yield losses in cotton could increase by the presence of RKN in coarse textured soils, with low EC_a values, shows the importance of a probabilistic map of yield losses based on EC_d as the major contributing factor.

Similarities between the maps of cotton yield, probability of yield losses and K content were also found (Figure 1f). The zone with the highest yield losses corresponded to a zone with K levels less than 78 kg/ha. This value is considered low for the Coastal Plain soils thereby contributing to plant stress and exacerbating problems with high or low micronarie. However, this zone also corresponded with an area of coarse textured soils which may contribute to K deficiency due to leaching. Potassium stress in cotton fields decreases yield and lint weight per boll, and may adversely affect micronaire, reducing fiber length and strength (Makhdum et al., 2004; Read et al., 2006). In contrast, cotton growing in areas with more sufficient K levels, produced higher yields than areas with less soil K.

The combined effects of sandy soil textures, high RKN population density and low levels of K contributed to the less than average yields observed. These yield limiting and reducing factors can be grouped as edaphic factors (coarse texture) and management factors (RKN, water, and K) which may imply a need for different strategies depending of soil texture for avoiding yield losses.

Maps of probability of yield losses based on EC_d can be used as a basis for management zone (MZ) delineation. The MZ maps depicting different levels of risk for yield losses can be used for implementation of different strategies of water and fertilization management and guidance for nematode sampling to target specific areas for nematicide application.

CMP Field. The results from the logistic regression for the CMP field indicated that EC_d was the single variable with the lowest AIC value (97.2) and lowest likelihood ratio (−2LogL = 93.2). As also observed for the CC field, electrical conductivity - deep (EC_d) alone, explained 31 % of the variability of yield losses based on the following logistic regression equation:

$P_{(\text{cotton yield} < \text{mean yield of the field})} = e^{[(4.663-3.092*EC_d)+\text{kriged residuals}]} / (1 + e^{[(4.663-3.092*EC_d)+\text{kriged residuals}]})$; [5]

The second best indicator of yield loss was VWC, having an AIC = 118.5 and −2LogL = 114.5. Potassium was also significant ($R^2_{MF} = 0.15$), but exhibited a much higher AIC and likelihood ratio than EC_d and VWC (AIC = 119.0, −2LogL = 115.0) (Table 2). The Log_{10} RKNS2 exhibited the highest AIC and likelihood ratio (AIC = 132.0, −2LogL = 128.0) indicating its low contribution to observed yield losses. Data suggest that the RKN population density at the CMP field did not build up fast enough early in the growing season to cause a significant impact on yield.

The two variable models only improved the explanation of yield losses slightly, compared to the single variable model using $EC_{d.}$ Slight improvements to the model estimate of yield loss were only observed when Log_{10} RKNS2 was added to the single variable model of EC_d (AIC = 96.4, −2LogL = 90.4). However, when the map of yield was compared with the map of RKN, there was not much agreement between the two maps. The logistic regression model of EC_d and Log_{10} RKNS2 explained 33% of the variability in yield, less than the mean yield based on the following logistic regression equation:

$P_{(\text{cotton yield} < \text{mean yield of the field})} = e^{(6.414-2.933*EC_d-0.8525*LogRKN)} / (1 + e^{(6.414-2.933*EC_d-0.8525*LogRKN)}$; [6]

The K + EC_d model was the second best significant model between the group of two variable models compared to the single variable EC_d model. The models with three and four variables did not significantly improve estimates of yield loss compared to the single variable EC_d model. The logistic regression model using all the contributing variables explained 34% of the cotton yield losses:

$P_{(\text{cotton yield} < \text{mean yield of the field})} = e^{(7.018-0.785*\ LogRKN\ -0.154*VWC-0.0089*K-2.466*EC_d)} / (1 + e^{(7.018-0.785*\ LogRKN\ -0.154*VWC-0.0089*K-2.466*EC_d)})$ [7]

As well as in the CC field, the results from the logistic regression analyses at the CMP field indicated that edaphic factors (soil texture) considerably influenced yield losses. However, manageable factors (water, fertility, and diseases control) also contributed. The low percentage of yield losses explained through the suggested models indicated that other variables different from those used in these analyses may be driving the changes on yield loss. For example, nitrogen (N), having a high impact on plant growth and development, could be a limiting factor and should be included in future studies.

When maps of predicted probability of yield losses (Figure 2b), cotton yield (Figure 2a), EC_d (Figure 2d), and K (Figure 2f) were compared, a high level of agreement was observed between the areas with cotton yield less than the mean yield and the areas with low EC_d and K values. The contribution of these variables to yield losses could indicate that low yield may have occurred due to a low soil water retention characteristic of coarse textured soils, low $EC_{d\ ,}$ and deficiencies in K which also coincided with areas of low $EC_{d,}$ suggesting leaching of K in these areas.

In conclusion, the most yield limiting factor at the two studied fields was soil texture. The presence of aggregated high population densities of RKN in coarse textured areas exacerbated yield losses. Therefore, the spatial distribution of soil texture, indirectly assessed by soil EC_a through mobile soil sensors, will give insights on coarse textured areas where differential management of nematodes is needed. Although significant, the inclusion of potassium (K) in the models of cotton yield response and probability of yield losses only improved the predictions by a small percentage. The importance of having a probabilistic map of yield losses based on EC_d as the major contributing factor is beneficial for identifying areas at risk not only for lack of water, but also for high nematode population density. Maps of EC_d and probability of yield losses based on EC_d can be used as a basis for management zone (MZ) delineation. The MZ maps depicting different levels of risk for yield losses can be used for implementation of different strategies of water and fertilization management and guidance for nematode sampling to target specific areas requiring nematicide application.

The identification of the factors related to the spatial variability of cotton yield and the probability of yield losses facilitate their use as surrogate data for MZ delineation. The MZ will allow the farmer to use different management according to the potential yield of each zone thereby minimizing risk and optimizing on-farm resources and profitability.

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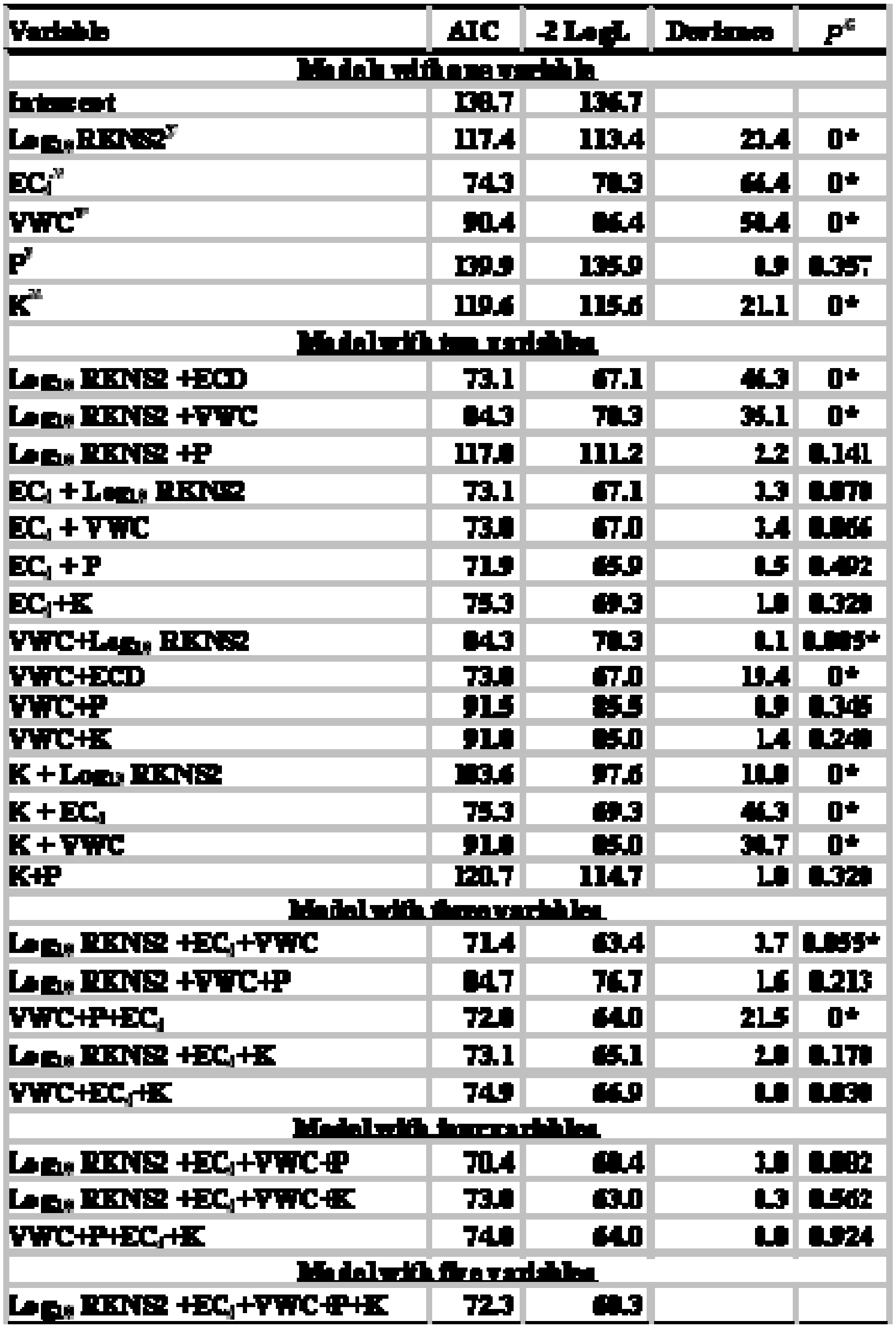
Table 1. Akaike information criterion (AIC) and likelihood ratio (-2LogL) of the logistic models with one, two, three, four, and five variables and increases in the explained deviances by the addition of a new variable . CC field



Variable	AIC	-2 LogL	Deviance	P^z
Models with one variable				
Intercept	138.7	136.7		
Log_{10} RKNS2^y	117.4	113.4	23.4	0*
EC_i^{x}	74.3	70.3	66.4	0*
VWC^w	90.4	86.4	50.4	0*
P^v	139.9	135.9	0.8	0.357
K^u	119.6	115.6	21.1	0*
Model with two variables				
Log_{10} RKNS2 +ECD	73.1	67.1	46.3	0*
Log_{10} RKNS2 +VWC	84.3	78.3	35.1	0*
Log_{10} RKNS2 +P	117.2	111.2	2.2	0.141
EC_i + Log_{10} RKNS2	73.1	67.1	3.3	0.070
EC_i + VWC	73.0	67.0	3.4	0.066
EC_i + P	71.9	65.9	0.5	0.492
EC_i+K	75.3	69.3	1.0	0.320
VWC+Log_{10} RKNS2	84.3	78.3	8.1	0.005*
VWC+ECD	73.0	67.0	19.4	0*
VWC+P	91.5	85.5	0.9	0.345
VWC+K	91.0	85.0	1.4	0.240
K + Log_{10} RKNS2	103.6	97.6	18.0	0*
K + EC_i	75.3	69.3	46.3	0*
K + VWC	91.0	85.0	30.7	0*
K+P	120.7	114.7	1.0	0.320
Model with three variables				
Log_{10} RKNS2 +EC_i+VWC	71.4	63.4	3.7	0.055*
Log_{10} RKNS2 +VWC+P	84.7	76.7	1.6	0.213
VWC+P+EC_i	72.0	64.0	21.5	0*
Log_{10} RKNS2 +EC_i+K	73.1	65.1	2.0	0.170
VWC+EC_i+K	74.9	66.9	0.0	0.830
Model with four variables				
Log_{10} RKNS2 +EC_i+VWC+P	70.4	60.4	3.0	0.082
Log_{10} RKNS2 +EC_i+VWC+K	73.0	63.0	0.3	0.562
VWC+P+EC_i+K	74.0	64.0	0.0	0.924
Model with five variables				
Log_{10} RKNS2 +EC_i+VWC+P+K	72.3	60.3		

[z] Probability level, significant (*)at $P < 0.15$

[y] Logarithm of the root knot nematode population sampled in September

[x] Soil electrical conductivity deep

[w] Phophorus (Kg/ha)

[u] Potassium (Kg/ha)

Table 2. Akaike information criterion (AIC) and likelihood ratio (-2LogL) of the logistic models with one, two, three, and four variables and increases in the explained deviances by the addition of a new variable . CMP field

Variable	AIC	-2 LogL	Deviance	P^z
Models with one variable				
Intercept	137.5	135.5		
Log_{10} RKNR[y]	132.0	128.0	7.5	0*
EC_d[x]	97.2	93.2	42.3	0*
K[w]	119.0	115.0	20.5	0*
VWC[u]	118.5	114.5	21.0	0*
Model with two variables				
EC_d+Log_{10} RKNR	96.4	90.4	2.8	0.097
EC_d+K	98.2	92.2	1.0	0.313
EC_d+VWC	98.1	92.1	1.1	0.299
K+EC_d	98.2	92.2	22.8	0.000
K+VWC	113.3	107.3	7.7	0.000
VWC+EC_d	98.1	92.1	22.3	0.000
Model with three variables				
EC_d+Log_{10} RKNR+K	98.0	90.0	0.5	0.482
EC_d+K+VWC	99.5	91.5	0.6	0.788
Model with four variables				
EC_d+Log_{10} RKNR+K+VWC	99.2	89.2		

[z] Probability level, significant (*)at $P < 0.15$

[y] Logarithm of the root knot nematode population sampled in September

[x] Soil electrical conductivity deep

[w] Potassium (Kg/ha)

[u] Volumetric water content

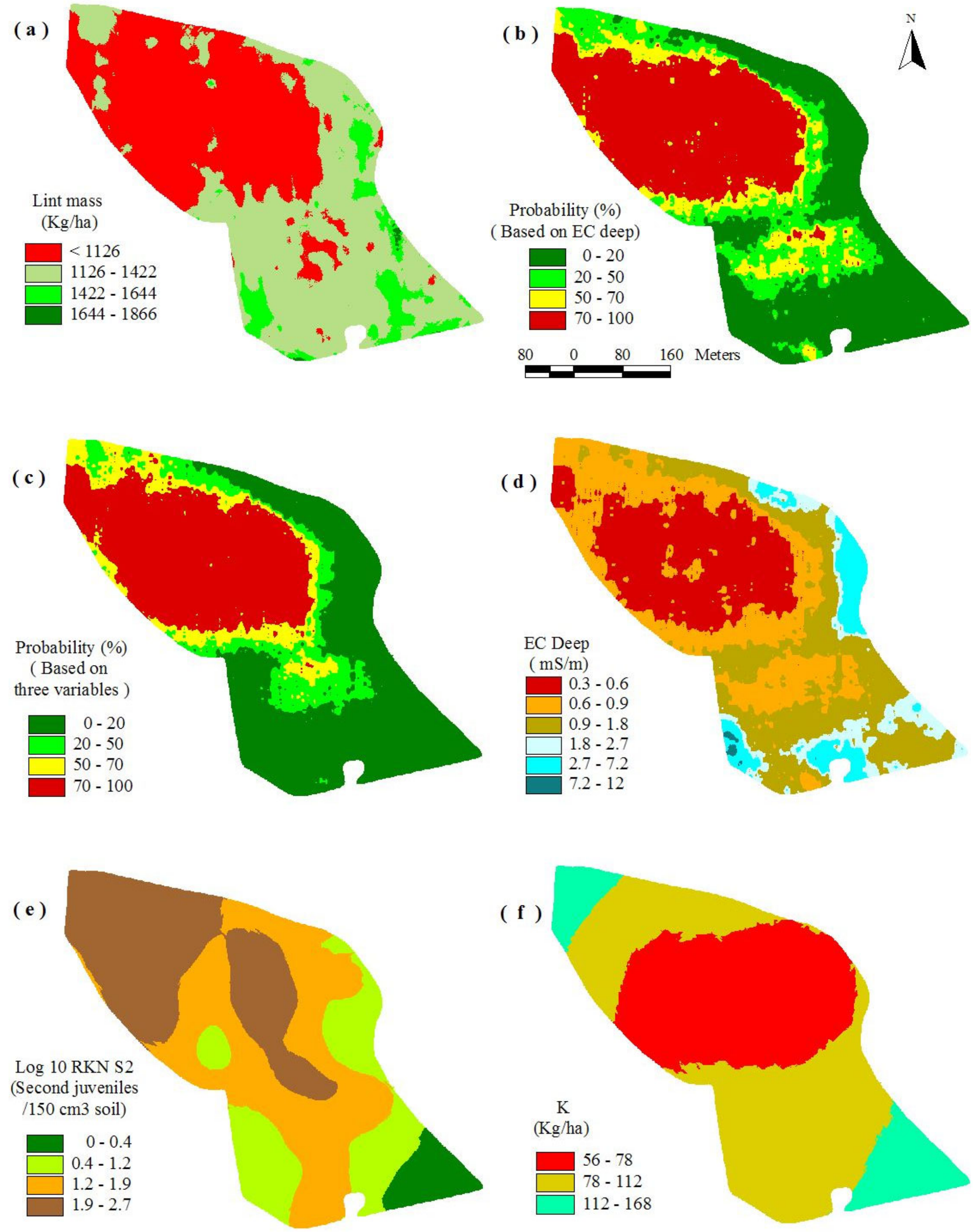


Figure 1. Maps of the CC field including the spatial distribution of yield (a), probability of yield losses based on EC_d (b), probability of yield losses based on the model: Log_{10} RKNS2+ EC_d + VWC (c), EC_d (d), Log_{10} RKN S2 (e), K (f).

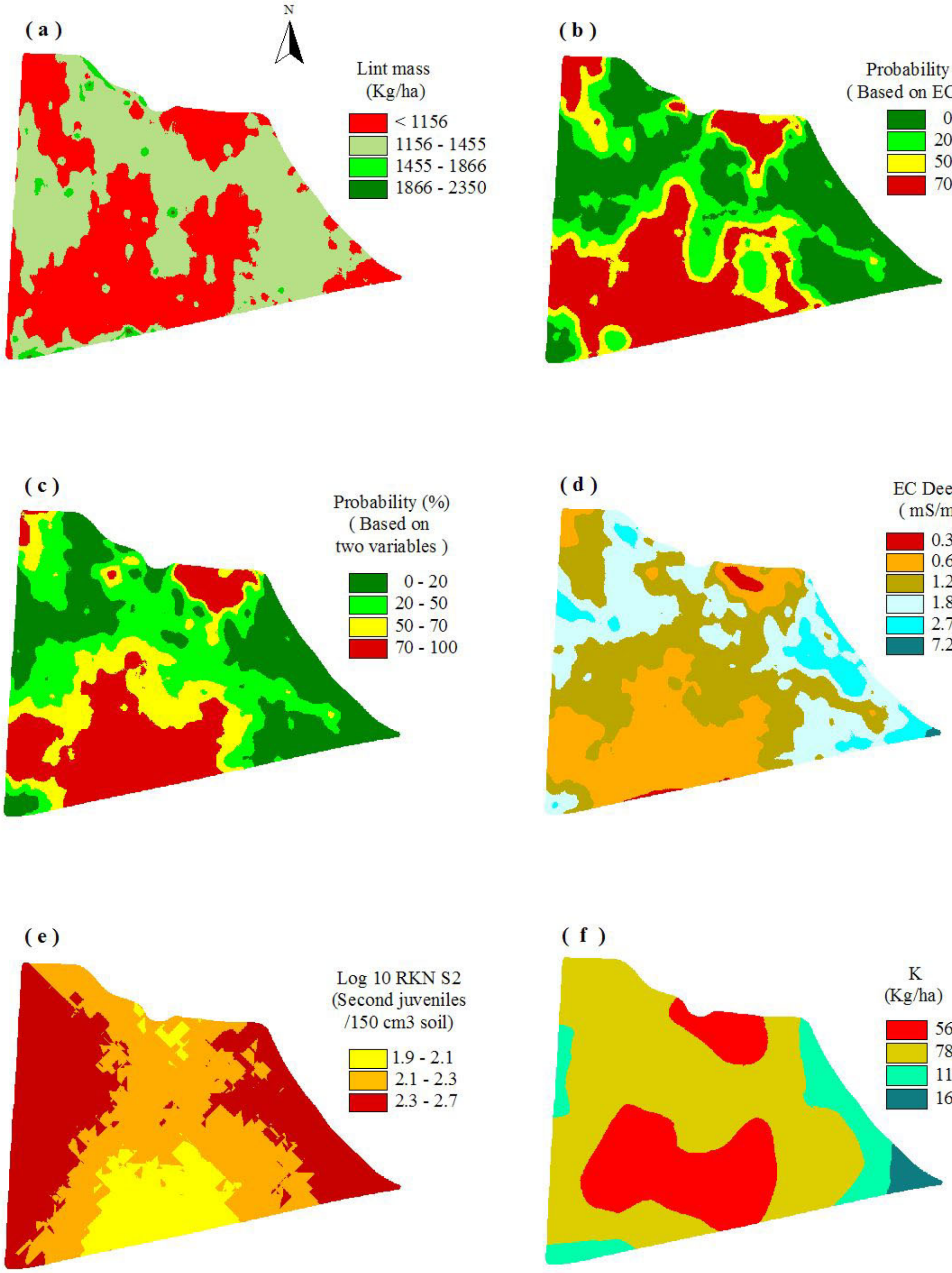


Figure 2. Maps of the CMP field including the spatial distribution of yield (a), probability of yield losses based on EC$_d$ (b), probability of yield losses based on the model: EC$_d$ + K (c), EC$_d$ (d), Log$_{10}$ RKN S2 (e), K (f).