# RESPONSE SURFACE MODELS OF SUBSOIL K CONCENTRATION FOR LOESS OVER TILL SOILS IN MISSOURI

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## Abstract

Crop uptake of potassium (K) has demonstrated sensitivity to subsoil variation in K content. This fact has not been sufficiently considered in K management strategies in part due to logistical difficulties in sampling spatially variable subsoil K. We propose a simplified soil factorial model, a response surface, to enable site-specific accounting of whole root zone K supply for loess over till soils. We compared the performance of two peak functions and a non-parametric local regression procedure to model soil-landscape K variation. These models were trained and tested on soil profile K sampled from within Missouri's Major Land Resource Area 113, the Central Claypan Areas. The local regression procedure was found to be most appropriate for mapping subsoil K because it is simple, quick, and readily provides prediction intervals. These results highlight the potential we have to account for and manage whole root zone K site-specifically.

Abbreviations: CEC, cation exchange capacity; $DTC_{max}$, depth to clay maximum; ECa, bulk apparent soil electrical conductivity; K, potassium; LOESS, locally weighted regression procedure; LPP, logistic power peak function; MLRA, major land resource area; PIV, Pearson IV peak function; RMSE, root mean squared error; $R^2$, coefficient of determination

## Introduction

Soil fertility management is crucial for optimizing crop production. Application of fertility amendments is physically limited to the depth of incorporation in tilled cropping systems and to the surface or near surface in no-till and perennial cropping systems. Likewise, due to physical limitations and traditional practice, soil sampling procedures measure the surface (15 to 20 cm) layer often referred to as the 'plow layer'. But plant nutrients in the entire root zone are important, and if accounted for, could help to better understand plant response (or lack of response) to surface soil amendments.

Previously it was demonstrated that depth profiles of clay in MLRA 113 exhibit a peak shape (Myers et al., 2007). Subsequently, we used asymmetric peak functions to model continuous 1D depth profiles of clay, silt, and pH at multiple landscape positions (Myers et al., 2011). Parameters of peak functions such as Depth to Clay Maximum ($DTC_{max}$) and others controlling the abruptness, magnitude, and width of the peak were correlated to landscape geomorphology. Because subsoil K in MLRA 113 is so governed by the mineralogy of the argillic peak (Bray, 1935), it also expresses a peaked profile distribution.

Variable depth distribution of subsoil K may have implications for K management. Subsoil can provide a large portion of the K required by grain and forage species. Kuhlmann et al. (1985) found that loess derived subsoils supplied spring wheat an average of 34% of the K taken up by the plant. Haak (1981) demonstrated that 25 to 50% of K uptake in barley and oats comes from subsoil, and found a 100% greater K uptake in grain from a clayey subsoil compared to a loamy sand subsoil. Soybeans and corn showed reduced or no K leaf concentration response to surface applied K (Woodruff and Parks, 1980) on Southeastern USA coastal plains soils which have clay horizons within 50 cm depth. These studies suggest clay-bound K in subsoil argillic horizons is an important source for plant K uptake.

Soil fertility management guidelines do not usually consider the contribution of subsoil K in their recommendations. Some notable exceptions in the U.S. are South Carolina (Mylavarapu and Moore, 1998), Wisconsin (Kelling et al., 1999), and Iowa (Sawyer et al., 2003). Each of these states belongs to regions with soil morphology that can impact root zone K supply and crop response to plow layer K levels.

The glacially derived landscapes of Wisconsin and Iowa have regions with differing capacities to supply plant-available K from the subsoil. University of Wisconsin fertilizer recommendations consider the variable subsoil nutrient supply, providing different critical values and interpretation classes for plow layer soil test K within 5 distinct subsoil fertility groups. The groupings are of relatively large extent and defined by texture and mineralogy (Laboski et al., 2006). Iowa classifies the major corn and soybean producing soils within 12 general soil associations as either high or low subsoil K. Iowa State University Extension recommendations provide different plow layer soil test K critical values and interpretive classes based on the subsoil K classification (Sawyer et al., 2003). Each of these examples provides regional or soil map-unit level modifications in K nutrient management guidelines, but the potential exists to account for subsoil K supply at sub-field scales with better subsoil K information. For instance, Winzeler et al. (2008) documented the use of a 3D covariance model to explain field-scale soil wetness and topographic effects on subsoil K availability in loess over till soils of Indiana.

The findings in Wisconsin, Iowa, and Indiana are applicable to the landscapes of the Missouri and Illinois Central Claypan Areas, Major Landscape Resource Area 113 (MLRA 113) (USDA-NRCS, 2006). The soils in this domain have a common morphology and pedogenic history and like those of Iowa, Indiana, and Wisconsin, are also of glacial origin. Upland soil profiles in MLRA 113 have a loess over till morphology with variable depth to more or less ubiquitous argillic (Bt) soil horizons having large clay concentration (450 -650 g kg-1 soil) and a large CEC (10.6 – 44.7 cmol [+] 100-1 g soil). These subsoil argillic horizons have a large influence on soil function. They are dominated by 2:1 layered aluminosilicate minerals that both adsorb and supply large quantities of K+ (Spautz, 1998) and other cations (Bray, 1935). Further, we know that roots of soybean and corn in these landscapes preferentially explore the subsoil argillic horizons (Yang et al., 2003; Fraisse et al. 2001; Wang et al., 2003; Myers et al. 2007).

Field scale maps of the spatial variation in subsoil K could prove useful to improve plow layer soil test K interpretive classes and to refine fertilizer application recommendations. However, direct measurement of subsoil K, especially in fields with variable depth to Bt horizons, would be prohibited by the labor and laboratory costs required. Depth to claypan (upper boundary of the first argillic horizon) has been successfully mapped with ECa in the study domain (Doolittle et al., 1994; Sudduth et al., 2010), and similar techniques were adopted to map $DTC_{max}$ (Myers, 2008).

The plow layer soil test levels of K are greatly modified from natural levels on production agriculture fields. Conversely, pedogenic factors determine the spatial distribution of subsoil nutrient levels and fertility properties more than past management. This is because the soil morphology and clay mineralogy have a dominant influence on nearly all physical and chemical fertility properties. Spatial variation in these pedogenic processes is tightly coupled to spatial variation in both $DTC_{max}$ and subsoil K content. Therefore, to account for and to map subsoil K levels we propose that it is more effective to use a quantitative soil-landscape model to estimate spatially variable subsoil K rather grid sampling of soil profiles.

## Objective

The objective of the study was to develop and test quantitative soil-landscape models (LPP, PIV, and LOESS) estimating subsoil (15 to 100 cm) K distribution for MLRA 113 upland soils.

## Materials and Methods

### Soil Profile and Sensor Measurements

A model training dataset of subsoil K measurements was collected from several sources. Table 1 provides a description and includes references for more detailed methods used to develop each dataset. The samples of dataset 3 were collected by soil scientists of the National Cooperative Soil Survey in accordance with standard methods (Soil Survey Staff, 1993). The samples in datasets 1-4 were used as a training dataset for modeling procedures (n=1722), while an independent set of samples measured from the target field and a nearby field (dataset 5) were held out as a model testing dataset (n=111). Potassium was measured by emission spectroscopy from $NH_4OAc$ extractions following the standard North Central Region methodology (Brown, 1998). Analyses were conducted either by the University of Missouri Soil and Plant Diagnostic Laboratory (datasets 2 and 4) or by the University of Missouri Soil Characterization Laboratory (datasets 1, 3, and 5).

Table 1. Data sources and sampling/modeling support.

| Dataset | Train/Test | Sites | n | Sample Support | Reference |
|---|---|---|---|---|---|
| 1 | Train | 76 | 440 | 0.15 - 1.2 m x horizon | (Miles and Hammer, |
| 2 | Train | 108 | 552 | 0.15 - 1.2 m x 15 cm layers | (Spautz, 1998) |
| 3 | Train | 110 | 645 | 0.15 - 2 m x horizon | (unpublished) |
| 4 | Train | 85 | 85 | 0.15 - 1.2 m x 15 cm layers | (Jung et al., 2005) |
| | Training Total | 379 | 1722 | | |
| 5 | Test | 26 | 111 | 0.15 - 1.2 m x horizon | (Kitchen et al., 1999) |

Depth to clay maximum for the soil profiles were collected by observation or calculated by anisotropic projection (Myers, 2008). An EM-38 (Geonics Ltd., Mississagua Ontario) ground conductivity sensor was used to map the test field site on 10-m transects using an ATV and cart (Sudduth et al., 2003). The DTCmax calibration model from (Myers et al., 2008) was applied to the interpolated ECa map of the target field to produce a field extent map of $DTC_{max}$ (RMSE = 11.6 cm).

**Pedogenic Response Surface Functions: LOESS, LPP, and PIV**

The argillic peak shape can be complex and variable as $DTC_{max}$ changes across the landscape. As such, models were selected that allow flexibility in fitting peaked forms, and have been chosen to represent landscape driven argillic peak variation. These were two parametric functions, the logistic power peak (LPP) (Romanenko, 2005) and the Pearson IV (PIV) (Pearson, 1895) functions and the non-parametric locally weighted regression (LOESS) procedure (Cleveland and Devlin, 1988).

**Locally Weighted Regression**

Locally weighted regression models were fitted to the training dataset to develop a nonparametric response surface for estimating K. The LOESS procedure fits a set of robust regression models within a moving window across the multivariate predictor space. In our case the predictor space was a 3D response surface defined by profile depth (d) and the pedogenic gradient, $DTC_{max}$. Pointwise estimates of fit standard error are readily available from the LOESS algorithm and were used to approximate a 95% prediction envelope for the fitted LOESS PRS model of K.

**Peak Functions**

The LPP and PIV peak functions were previously described in Myers et al. (2010). Reviewed succinctly, these two functions have 5 or 6 parameters that determine their peak shape. A model of subsoil K can be constructed from these peak functions by selecting constants or sub-functions of the parameters which match observed pedogenic variation in the landscape. In the following candidate LPP response surface, the constant 0.1 cmol/100 g is chosen for the intercept (α), a quadratic function describes variation in the amplitude of the clay peak (β), and linear functions determine the depth (μ), thickness (δ), and asymmetry (ε) of the PRS (eq. 4).

$$\widehat{\mathbf{K}} = PEAK\left(\mathbf{d}, \boldsymbol{\lambda}\begin{cases}\alpha = 0.1 \\ \beta = \beta_0 + \mathbf{DTC}_{\boldsymbol{max}}\beta_1 + \mathbf{DTC}_{\boldsymbol{max}}{}^{\mathbf{2}}\beta_2 \\ \mu = \mu_0 + \mathbf{DTC}_{\boldsymbol{max}}\mu_1 \\ \delta = \delta_0 + \mathbf{DTC}_{\boldsymbol{max}}\delta_1 \\ \varepsilon = \varepsilon_0 + \mathbf{DTC}_{\boldsymbol{max}}\varepsilon_1\end{cases}\right) \quad [1]$$

$$\mathbf{DTC_{max}} \in [\mathbf{10}, \mathbf{100}] \quad [2]$$

$$\mathbf{d} \in [\mathbf{15}, \mathbf{100}] \quad [3]$$

For equations 1, 2, and 3, $\widehat{\mathbf{K}}$ is a pedogenic response surface matrix of subsoil K concentration, PEAK is a peak function , d is the vector of depths at which $\widehat{\mathbf{K}}$ is to be estimated, and λ are the parameters of the peak function (α, β, μ, δ, ε). Equation 1 and the analog for the PIV were rearranged as objective functions of the unknown parameters. Nonlinear optimization procedures were implemented to solve the objective equations. Model performance was gauged by calculating root mean squared error (RMSE) and coefficient of determination ($R^2$) from regression of the model estimates on both the training and independent test datasets ($RMSE_{train}$, $RMSE_{test}$, $R^2_{train}$, and $R^2_{test}$).

## Results

The LOESS, LPP, and PIV models resulted in an $R^2_{train}$ of 0.67, 0.64, and 0.63 and an $RMSE_{train}$ of 0.07, 0.08, and 0.08 cmol $K^+$ 100 g $soil^{-1}$respectively. For an example, the fitted PIV model is displayed in figure 1with the training data (greyscale spheres) and the testing data (white spheres). The test measurements were under-estimated by all approaches demonstrating a bias of about 0.1 cmol $K^+$ 100 g $soil^{-1}$ (figure 1).

### Comparison of PRS Models

Each of the three techniques used to build subsoil K models has strengths and weaknesses. First, it is useful to discuss the major tradeoffs between the nonparametric LOESS model versus the parametric LPP and PIV models. Foremost, the LOESS PRS model is capable of fitting any form of surface. A major disadvantage of the LPP and PIV models is the fairly specific form of depth function that a parametric PRS model could fit.

There is a major difference in the complexity of implementation between the LOESS and the two parametric models. Fitting the PIV and LPP PRS models requires i) choosing a functional form - including that of the sub-functions, ii) pre-selecting starting values for as many as a dozen parameters, iii) setting bounds on the solutions of the parameters, iv) successful implementation of a nonlinear optimization algorithm. By contrast, the LOESS algorithm is straightforward to implement, fast, no parameters need be pre-specified, and it directly approximates the prediction envelope of the model.

It is critically important that numerical soil mapping techniques are able to provide an estimate of the accuracy of the map. This is a key advantage of data driven soil mapping over traditional methods. The LOESS procedure implemented here provides point-wise standard error estimates for the training data, giving a reasonable approximation of not just the range in characteristics of a soil property at any given place in the domain, but also the confidence level of the target property estimate. The LOESS PRS method offers the capability to better propagate errors through the modeling procedure and improves the utility of the estimated map for management decisions.

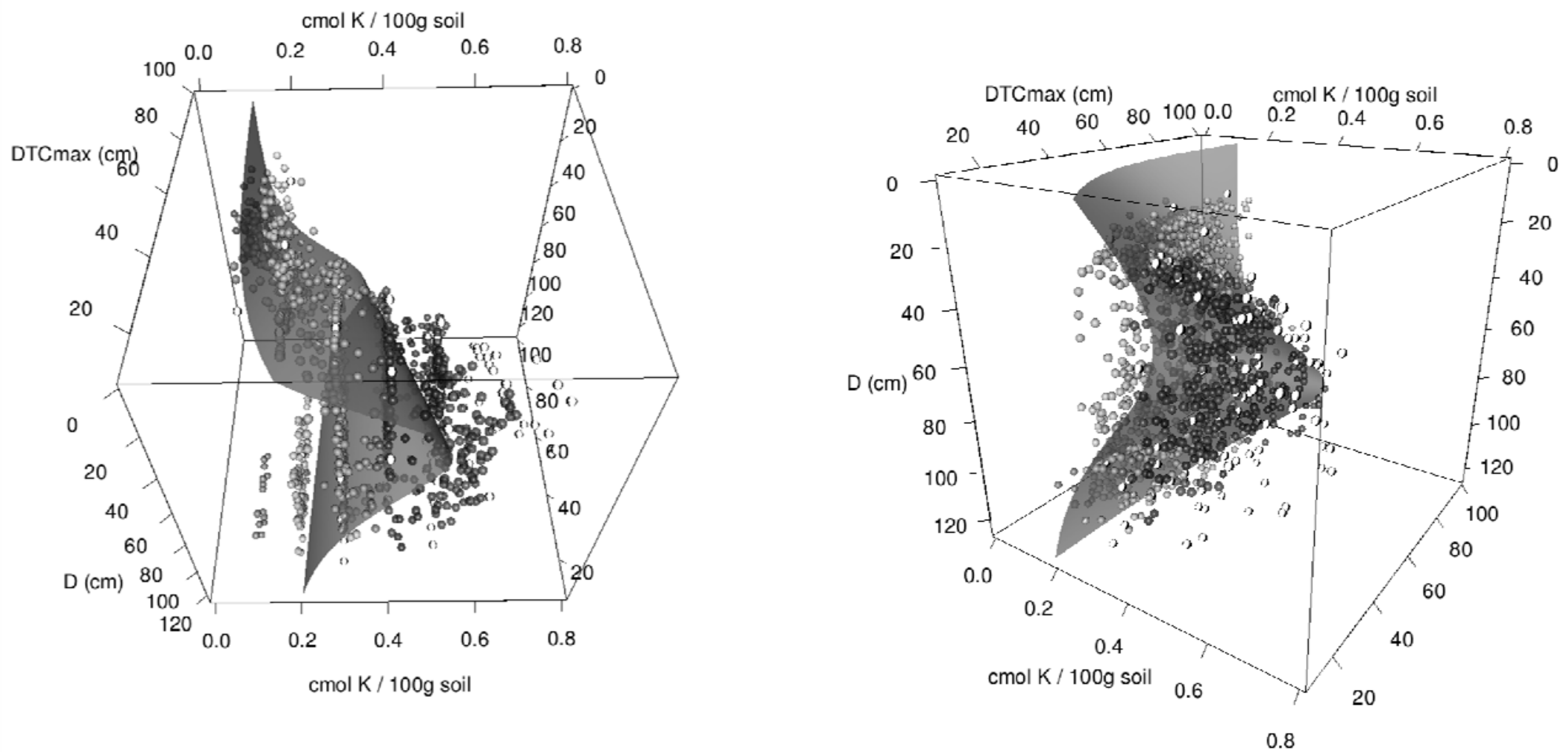


Figure 1. The fitted Pearson IV (PIV) response function is shown with the training (greyscale) and testing (white) data points.

**Mapping the Subsoil K Model**

Given the results above, especially the added benefit of readily obtainable prediction envelope estimates, the LOESS model was selected to demonstrate mapping subsoil K (15 to 100 cm) in one of the testing fields. A volumetric cutaway view of the continuous depth function estimate (fig. 2) gives an indication of how the spatially variable argillic peak results in spatially variable subsoil K. Some key features in this field are distinct areas of high and low subsoil K concentration.

The response surface models estimate subsoil K at depths of 15 to 100 cm with a range of $DTC_{max}$ from 10 to 100 cm. The models are applicable anywhere an argillic horizon exists in loess or upper till in the study area; therefore, the model excludes areas of inceptisols and entisols in floodplains. The subsoil models are fitted without respect to spatial location and instead the spatial mapping of the continuous depth function may be achieved by mapping the response surface model to the soil-landscape through $DTC_{max}$. (fig. 2).

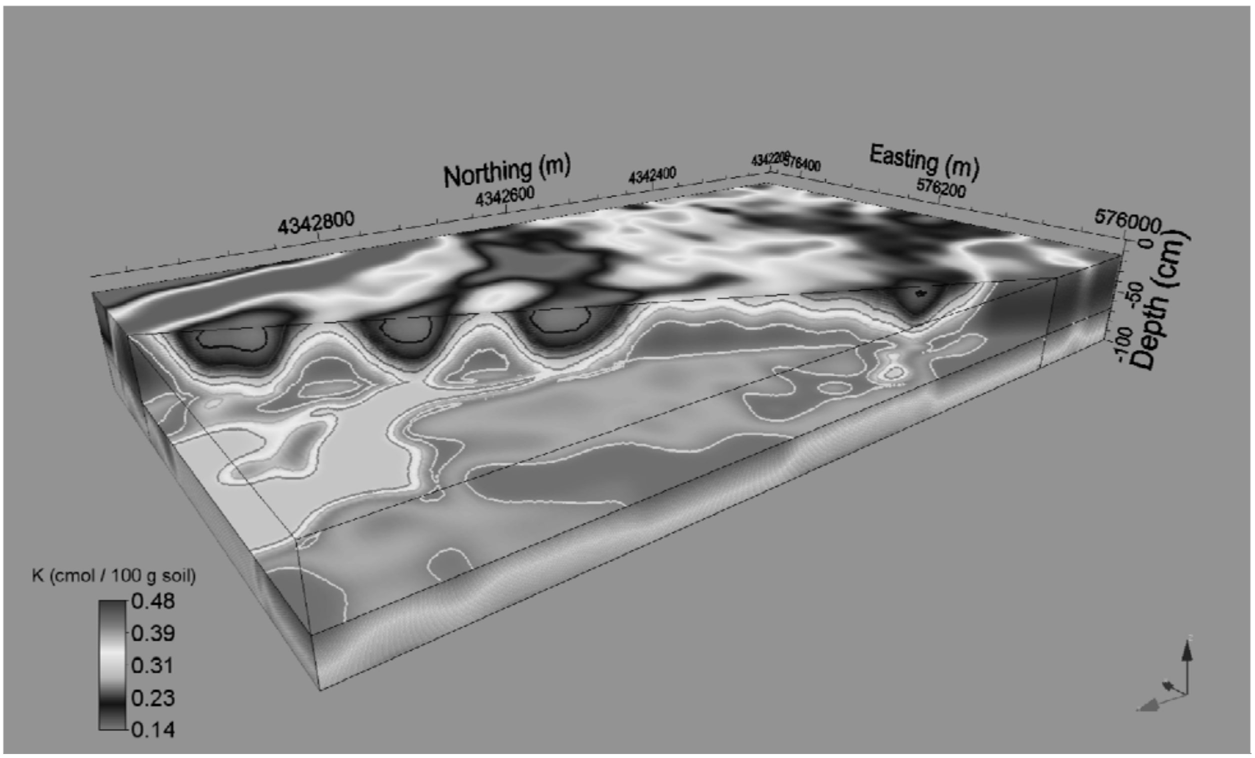


Figure 2. Cutaway view of the continuous depth function estimate of K for a 30 ha field in MLRA 113.

## Discussion

**Using Subsoil Fertility Information in Crop Management**

Soil nutrient management might be improved by using high resolution subsoil fertility maps such as those developed in this study. Foremost, K application recommendation equations could be modified to consider spatially variable subsoil supply within fields like the example field. Amounts of applied K fertilizer may potentially be reduced on soils with a large subsoil K reservoir, such as a site with small $DTC_{max}$, or increased on a site with deep silty sediments and low subsoil K. This is more important in areas where subsoil K can vary substantially at the field, farm, or regional extent, such as it does in MLRAs 113.

Fertilizer applications must be made on the basis of good information about the nutrient needs of the crop species grown, the nutrient levels available to the plant, and the response of the crop to changes in soil test values. However, Missouri's existing K fertilizer recommendation equations are calibrated statewide to *surface* soil test K levels. Subsoil K maps can provide better information about plant available K, but this information is not sufficient by itself to apply the correct level of fertilizer. Linking these two management tools there needs to be a body of 'calibration' research that relates the soil test level and/or ameliorating additions to crop yield response. However, at this point, there is little in the way of calibration research to estimate the portion of crop yield response due to subsoil K, and then to modify the surface applied fertilizer recommendation.

## Conclusion

Crop uptake of K has demonstrated sensitivity to subsoil variation in K content and may not be sufficiently considered in K management research and recommendations. The techniques employed here could allow within-field estimation of spatially-variable subsoil K supply in the Central Claypan Regions and similar landscapes. Combined with standard surface sampling techniques, subsoil K maps could be used to develop spatially variable estimates of whole root zone plant available K. However, very little soil test calibration or crop physiology research is available to account for this nutrient reservoir in fertilizer recommendations. This is a knowledge gap that warrants future research to optimize productivity and economic sustainability of cropping systems.

Among the modeling methods used here to map subsoil K, the non-parametric LOESS procedure was the simpler to implement, readily generated confidence statistics, and produced similar results to the two peak functions. Finally the technique is useful to map other soil properties in the study domain when correlated to clay mineralogy. The method is directly extendable to map CEC and other cations such as those of Ca, Mg, Na, Al, and H, as well as base saturation. A more complete assessment of the impact of subsoil nutrient supply on plant response and uptake could improve both the profitability and sustainability of crop production.

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## References


Bray, R.H. 1935. The origin of horizons in claypan soils. Amer. Soil Survey Assoc. Bui. 16: 70–75.

Brown, J.R. (Ed). 1998. Recommended chemical soil test procedures for the North Central Region. Missouri Agricultural Experiment Station, University of Missouri–Columbia.

Cleveland, W.S., and S.J. Devlin. 1988. Locally weighted regression: an approach to regression analysis by local fitting. J. Amer. Stat. Assoc. 83(403): 596–610.

Doolittle, J.A., K.A. Sudduth, N.R. Kitchen, and S.J. Indorante. 1994. Estimating depths to claypans using electromagnetic induction methods. J. Soil Water Conserv. 49(6): 572–575.

Fraisse, C.W., K.A. Sudduth, and N.R. Kitchen. 2001. Calibration of the CERES-Maize model for simulating site-specific crop development and yield on claypan soils. Appl. Eng. Agric. 17(4): 547–556.

Haak, E. 1981. Nutrient uptake from subsoil by cereals. p. 87–94. In Agricultural Yield Potentials in Continental Climates. International Potash Institute, Warsaw, Poland.

Jung, W.K., N.R. Kitchen, K.A. Sudduth, R.J. Kremer, and P.P. Motavalli. 2005. Relationship of apparent soil electrical conductivity to claypan soil properties. Soil Sci. Soc. Am. J. 69(3): 883–892.

Kelling, K.A., L.G. Bundy, S.M. Combs, and J.B. Peters. 1999. Optimum soil test levels for Wisconsin. Extension publication, A3030. University of Wisconsin-Extension, Madison, WI.

Kitchen, N.R., K.A. Sudduth, and S.T. Drummond. 1999. Soil electrical conductivity as a crop productivity measure for claypan soils. J. Prod. Ag. 12(4): 607–617.

Kuhlmann, H., N. Claassen, and J. Wehrmann. 1985. A method for determining the K-uptake from subsoil by plants. Plant Soil 83(3): 449–452.

Laboski, C.A.M., J.B. Peters, and L.G. Bundy. 2006. Nutrient application guidelines for field, vegetable, and fruit crops in Wisconsin. Division of Cooperative Extension of the University of Wisconsin-Extension.

Martens, D.C., L.W. Zelazny, and D.L. Sparks. 1980. Plant uptake and leaching of applied and indigenous potassium in Dothan soils. Agron. J. 72(3): 551–555.

Miles, R.J., and R.D. Hammer. 1989. One hundred years of Sanborn Field: Soil base line data. p. 100–108. In Preceedings of the Sanborn Field Centennial. University of Missouri-Columbia, Columbia, MO.

Myers, D.B. 2008. Methods for High Resolution Soil-landscape Modeling in Midwest Upland Landscapes. Ph.D. Dissertation. University of Missouri.

Myers, D.B., N.R. Kitchen, K.A. Sudduth, R.J. Miles, E.J. Sadler, and S. Grunwald. 2011. Peak functions for modeling high resolution soil profile data. Geoderma 166(1): 74–83.

Myers, D.B., N.R. Kitchen, K.A. Sudduth, R.E. Sharp, and R.J. Miles. 2007. Soybean root distribution related to claypan soil properties and apparent soil electrical conductivity. Crop Sci. 47(4): 1498–1509.

Mylavarapu, R., and K. Moore. 1998. Nutrient recommendations for coastal plain soils based on subsoil sample analysis. IL68. Clemson University Cooperative Extension Service, Clemson, SC.

Pearson, K. 1895. Contributions to the mathematical theory of evolution. II. skew variation in homogeneous material. Phil. Tran. R. Soc. London A. 186: 343–414.

Romanenko, S.V., A.G. Stromberg, and T.N. Pushkareva. 2006. Modeling of analytical peaks: peaks properties and basic peak functions. Anal. Chim. Acta. 580(1): 99–106.

Sawyer, J.E., A.P. Mallarino, R. Killorn, and S.K. Barnhart. 2003. A general guide for crop nutrient and limestone recommendations in Iowa. Iowa State University Extension publication PM 1688. Iowa State University, Ames, IA.

Soil Survey Division Staff. 1993. Soil Survey Manual. U.S. Department of Agriculture Handbook 18. U.S. Government Printing Office, Washington, DC.

Spautz, R.E. 1998. Topsoil thickness influence on phosphorus and postassium availability and crop response. M.S. Thesis. University of Missouri.

Sudduth, K.A., N.R. Kitchen, G.A. Bollero, D.G. Bullock, and W.J. Wiebold. 2003. Comparison of Electromagnetic Induction and Direct Sensing of Soil Electrical Conductivity. Agron. J. 95(3): 472–482.

Sudduth, K.A., N.R. Kitchen, D.B. Myers, and S.T. Drummond. 2010. Mapping depth to argillic soil horizons using apparent electrical conductivity. J. Environ. Eng. Geophys. 15(3): 135–146.

Systat. 2002. TableCurve 2D. SYSTAT Software Inc., Evanston, IL.

USDA-NRCS. 2006. Land resource regions and major land resource areas of the United States, the Caribbean, and the Pacific Basin. U.S. Department of Agriculture Handbook 296. U.S. Government Printing Office. Washington, DC.

Wang, F., C.W. Fraisse, N.R. Kitchen, and K.A. Sudduth. 2003. Site-specific evaluation of the CROPGRO-soybean model on Missouri claypan soils. Agric. Sys. 76(3): 985–1005.

Winzeler, H.E., P.R. Owens, B.C. Joern, J.J. Camberato, B.D. Lee, D.E. Anderson, and D.R. Smith. 2008. Potassium fertility and terrain attributes in a Fragiudalf drainage catena. Soil Sci. Soc. Am. J. 72(5): 1311-1320.

Woodruff, J.R., and C.L. Parks. 1980. Topsoil and subsoil potassium calibration with leaf potassium for fertility rating. Agron. J. 72(2): 392–396.

Yang, J., R.D. Hammer, and R.W. Blanchar. 2003. Minirhizotron quantification of soybean root growth as affected by reduced A horizon in soil. J. Plant Nut. Soil Sci. 166(6): 708–711.

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