PREDICTING CROP YIELD LOSSES DUE TO SOIL-WATER SALINITY: A COMPARISON OF TRADITIONAL AND ALTERNATIVE APPROACHES

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ABSTRACT

It is estimated that 2,000 ha of cropland are taken out of production daily worldwide due to salinization and sodification. Salinity is estimated to result in economic losses of $27.3 billion U.S. dollars annually. Our project aims to jointly develop techniques for quantifying the severity of soil-water salinity and impacts on crop production on surface-irrigated fields in Pakistan's Indus River Valley and the Lower Arkansas River Valley (LARV) in Colorado. The Fairmont Drainage District study site in the LARV is a furrow-irrigated, tile-drained area of about 200 ha that suffers from salt-affected (primarily gypsum) soils due to shallow water tables resulting from inefficient irrigation practices and inadequate drainage. The objective of this study was to model crop relative (Y_r) and absolute yield using two traditional and two alternative approaches with electromagnetic induction derived bulk apparent soil electrical conductivity (EC_a; 0 – 1.5m depth), and saturated paste extract electrical conductivity (EC_e) used as inputs, and compare results. The first method is a traditional piecewise linear approach where EC_e predicts Y_r using a salinity tolerance threshold, and a sensitivity to accrued salinity. The second involved a "modified discount function" that utilized a single empirical parameter to fit a sigmoidal function relating Y_r to EC_e. The third and fourth methods were purely empirical linear and sigmoidal four parameter logistic (4PL) models that used EC_a or EC_e to predict Y_r. Results showed that the empirical sigmoidal 4PL model yielded the greatest accuracy for 190 field data points using EC_a and EC_e as the predictor, with a root mean squared error of ±16.71 % and ±14.37 %, respectively. This suggests that EC_a is an effective predictor of Y_r for this dataset, indicating that it might not be necessary to collect and analyze soil samples for EC_e when trying to map salinity impacts on maize yield when it is known that salinity is the primary yield reducing factor; this would save time, labor, and resources. The fitted Y_r -EC_e regression relationships, however, indicate that the threshold EC_e value at which significant maize yield loss commences for these gypsum soils is markedly higher than the value reported for halite soils by Maas and Hoffman (1977).

INTRODUCTION

Salt-affected and waterlogged soils exist as a growing global problem for agricultural production. These are defined as soils in which salts are in enough quantity to interfere with normal plant growth. The Harmonized World Soil Database (Nachtergaele et al., 2009) estimates the global extent of salt-affected land to be 1128 Mha, 60% of which is saline, 26% is sodic, and the remaining 14% is saline sodic. It is estimated that 2000 ha worldwide are taken out of production every day due to salinization and sodification (Nellemann, 2009; Qadir et al., 2014). This salinity impact was estimated to have an economic impact of $27.3 billion U.S. dollars annually (Qadir et al., 2014). These economic and environmental issues will only be magnified as the area of salt-affected soils expands each year as intensive irrigation practices continue globally.

Salt tolerance of a crop is traditionally described through plotting a crop's relative yield as a continuous function of soil salinity. Relative yield (Y_r) is used to circumvent differences in absolute yield (Y) due to differences in crop species, cultivar, ambient environment, soil fertility, pest damage, and factors other than salinity. The conventional method to convert Y into Y_r involves scaling each observation of Y by the maximum yield observed (Y_m) (Grieve et al., 2013). Various models have been attempted to accurately describe this phenomenon (Steppuhn et al., 2005). Each model, although different in form, require the average root zone salinity (C), where C can be expressed as solute concentration (C_s), osmotic potential (Ψ_o), saturated paste electrical conductivity (EC_e), or the electrical conductivity of irrigation water (EC_w).

One of the most popular methods used for the accurate quantification of soil salinity on field and regional scales is through electromagnetic induction (EMI) techniques that calibrate apparent soil electrical conductivity (EC_a) to other edaphic physical and chemical properties. In cases where EC_a correlates with a soil property of interest, an EC_a – directed sampling strategy has been found successful in quantifying the spatial distribution and variability of that soil property, all while minimizing the number of sample locations, keeping the lab and labor costs to a minimum (Corwin et al., 2003a; Shaner et al., 2008). Furthermore, it has been shown that if EC_a correlates with crop yield, these directed sampling approaches can be used to identify soil properties that are causing yield variability, and thus direct management decisions for remediation (Corwin et al., 2003b).

Correlating yield with EC_a directly has been met with uncertainty, as resulting relationships are often inconsistent due to the plethora of factors influencing the measurement of EC_a, confounding their interpretation (Corwin and Lesch, 2003; Jaynes et al., 1995). This uncertainty is not well understood, however, as previous studies trying to quantify this relationship have had limitations because of crop types (i.e. the crop was too tolerant of the soil properties affecting growth to make a strong correlation), or a mismatch between the dominant factors affecting yield and the dominant factors affecting EC_a readings. The objective of this study was to model crop relative and absolute yield using traditional and alternative approaches, comparing EC_a and EC_e as predictors, observing the potential of each method used as a practical yield prediction tool. To this end, we pursued an observational experiment in Swink, Colorado (United States) where maize yield, and soil salinity data were used with salinity tolerance models to estimate yield over the study region.

MATERIALS AND METHODS

Study Site Description

Soil salinity as an issue in the Lower Arkansas River Valley (LARV) in southeastern Colorado originated in the 1970s due to the increase in river diversions for the use of irrigation water, a lack of efficient irrigation systems (which leads to a severe over application of water), and a decrease in the use of groundwater as a source for irrigation. These practices have led to an increase in the height of the water table within the LARV, pushing salts up into the root zones of many crops (Gates et al., 2002). Salts have negative impacts on crop yields throughout the valley; research and intervention are needed to develop more sustainable water use practices.

A sub-region of the LARV, called the Fairmont Drainage District (FDD), (37°58'56.2" N; 103°38'38.5" W; **Error! Reference source not found.**), was identified as a suitable area of study for observing and quantifying the magnitude of salinity effects in gypsiferous soils. The FDD itself refers to an area of 200 hectares having a drainage tile network installed in the early 20th century as a result of the Colorado Drainage District Act (CO Rev Stat § 37-28-101). The intent of installing drainage tiles in the FDD was to reduce waterlogging caused by a shallow water table. Despite this, salt presence continues to negatively affect the agronomic systems in the region.

The FDD contains approximately 20 different fields averaging 10 ha each. In this context, field is defined as a homogenously managed piece of land devoted to the growth of a singular crop for commercial value. The dominant crops in the region consist of alfalfa (*Medicago sativa* L.) with 65% coverage, maize (*Zea Mays* L.) with 20% coverage, and winter wheat (*Triticum aestivum* L.) with 10% coverage. The remaining 5% of land is fallow or rangeland (not harvested for economic value). Irrigation methods consist of siphon tube irrigation down furrows and center pivot sprinkler irrigation, with application rates varying based on specific field management. Soil textures range from Silty Clay Loam to Clay Loam.

Electromagnetic Induction Surveys for Field Characterization of Salinity and Yield

In 2019, EMI surveys were carried out using mobile equipment (i.e. EM38-MK2, Trimble™ GPS system, and Juniper Allegro CX for datalogging) on 5 corn fields within the FDD prior to corn planting (approx. early May) in order to quantify salinity presence in the region. The EM38-MK2 provided a continuous stream of EC_a measurements (one reading every 4 seconds) at 0-0.75 m (EM_h) and 0-1.5 m (EM_v) depths simultaneously. This averaged to approximately 500 locations of EC_a measurement in each field. Model-based sampling design via the Electromagnetic Sampling Analysis and Prediction model (ESAP, ver. 2.35) was used in each field. ESAP uses a response surface sampling design (RSSD) strategy which, in essence, creates a 3-D surface of the EC_a measurements and, based on the range and variation, selects locations that characterize the EC_a variation while maximizing the distances between adjacent sampling locations (Lesch et al., 2002).

ESAP-RSSD was used to select 6 soil sample locations per field. At each location, soil samples were collected using an 8 cm diameter soil auger at 0.3, 0.6, 0.9, and 1.2 m depths. Gravimetric water content and a saturation extract of each soil sample were prepared to derive EC_e using the method presented by Rhoades (1996). Deionized water was added to approximately 400-500 g of air-dried soil such that a saturated condition was reached. A 50-75 g sub sample of the paste was taken to be oven dried to determine saturation percentage (SP% or $\theta_{g,e}$). Analysis of Covariance (ANOCOVA) linear regression was used to develop a calibration model, converting EC_a into predicted EC_e (Corwin and Lesch, 2017; Corwin and Lesch, 2014).

ESAP-RSSD was used once again in conjunction with EC_a survey data to determine ideal sampling locations for maize yield. 38 locations were identified in each field, resulting in a total of 190 samples. At each location, a one meter by 0.76 m plot was sectioned off for cob selection. This amounted to seven cobs per plot for yield analysis. Samples were oven dried at 70°C for 14 days before being shucked and weighed to determine marketable yield. After yields were determined, Y_r was calculated by averaging the top three yields (to identify a reasonable yield unaffected by salinity), dividing each point by this average, and multiplying by 100.

Model Selection and Goodness of Fit Evaluation

Y_r was predicted using two traditional models: the modified discount function (Steppuhn et al., 2005) and the threshold-slope function (Maas and Hoffman, 1977), as well as two alternative statistical models: a sigmoidal four parameter logistic (4PL) model, and single variate linear regression (Table 1). Furthermore, each model was tested using EC_e and EC_a as the input variable.

Table 1. Summary of salinity tolerance models used to predict relative yield losses in the Fairmont Drainage District using saturated paste extract and soil bulk apparent electrical conductivities (EC_e and EC_a, respectively).

Model	Model Form	Input
Sigmoidal Four Parameter Logistic (4pl) Model	$\hat{Y}_r = d + \frac{a-d}{1+\left(\frac{x}{c}\right)^{\mathrm{b}}}$	EC_e, EC_a
Modified Discount Function	$\hat{Y}_r = \frac{1}{1+\left(\frac{C}{C_{50}}\right)^{\exp(sC_{50})}}$	EC_e, EC_a
Threshold-Slope Function	$\hat{Y}_r = 1; 0 < C < C_t$ $\hat{Y}_r = 1 - m(C - C_t); C_t < C < C_0$ $\hat{Y}_r = 0; C > C_0$	EC_e
Linear Regression	$\hat{Y}_{r,i} = \beta_0 + \beta_1 \mathrm{C}_i + \varepsilon_i$	EC_e, EC_a

Where $\hat{Y}_r$ is model predicted relative yield (%), $a,\ b,\ c,\ d,\ s,\ \beta_0$, and β_1 are empirically fit shaping parameters, C is average root zone salinity (can be expressed as EC, osmotic potential, or solution concentration), C_{50} is C at $Y_r = 0.5$, C_t is the maximum value of C without yield reduction, $C_0$is the lowest value of C where $Y_r = 0\%$, m is the absolute value of the declining slope in Y_r, i is the sample site within a field.

RESULTS AND DISCUSSION

The goodness of fit (GOF) for each model was evaluated in R studio using the HydroGOF package using root mean squared error (RMSE), root mean squared prediction error (RMSPE), and index of agreement (IOA). RMSE and RMSPE were chosen to understand error in terms of yield units, but RMSPE is a measurement of the model's prediction error using a leave-one-point out approach for cross-validation. IOA was chosen to understand model agreement with observations. A value of 0 indicates no fit, while 1 indicates a perfect fit.

GOF evaluation results for each model are summarized in Table 2. EC_a and EC_e were able to predict Y_r with similar accuracies, with EC_e having slightly better predictions when using the 4PL and linear regression models. This might be explained by the susceptibility of EC_a being biased easily by other inter-field variable edaphic properties, such as moisture or texture, whereas EC_e is a more direct measure of salinity. The 4PL model resulted in the best GOF measurements for both EC_a and EC_e, and is shown to be useful in predicting Y_r. Furthermore, it is shown that the RMSE and RMSPE values generated are small enough to indicate that the model could be viable for sub-regional yield mapping and informing management decisions.

Table 2. Summary of goodness of fits results using saturated paste extract and soil bulk apparent electrical conductivities (EC_e and EC_a, respectively) to predict relative yield losses (Y_r; %).

	Input	**RMSE**	**RMSPE**	**IOA**

Model	Variable	%	%	n/a
4PL	EC_a	16.71	17.02	0.74
Modified Discount	EC_a	21.37	21.48	0.71
Linear Regression	EC_a	18.06	18.29	0.66
4PL	EC_e	14.37	14.70	0.84
Modified Discount	EC_e	24.01	24.12	0.70
Linear Regression	EC_e	15.30	15.47	0.89
Threshold-Slope	EC_e	18.43	n/a	0.75

Where 4PL is sigmoidal four parameter logistic model, RMSE is root mean squared error, RMSPE is root mean squared prediction error, and IOA is index of agreement.

Visual fitting of the 4PL model with both EC_a and EC_e inputs compared to observed Y_r is shown in Figure 1. Although the 4PL model captures the general trend of the data well, much variability exists around each Y_r prediction. This may be due to variability around confounding factors resulting in yield loss outside of soil salinity. Some of these factors include i) differences in maize variety salinity and drought tolerance, ii) differences in field-to-field irrigation and fertilizer management, and iii) spatial differences in soil physiochemical properties. The fitted Y_r -EC_e regression relationships, however, indicate that the threshold EC_e value at which significant maize yield loss commences for these gypsum soils is approximately 2.5 dS/m, which is markedly higher than the 1.7 dS/m threshold reported for halite soils by Maas and Hoffman (1977).

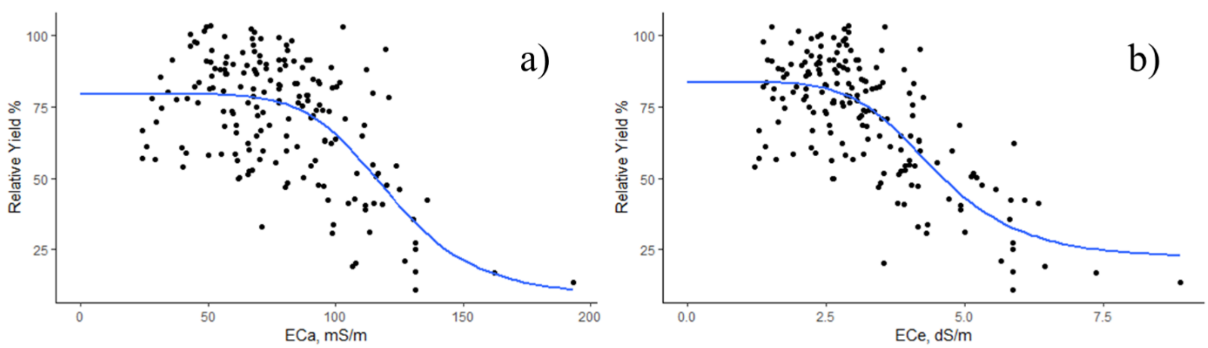

Figure 1.Relationship between a) relative yield % (Y_r) and bulk apparent soil electrical conductivity (EC_a; mS/m) and b) Y_r and soil saturated paste extract electrical conductivity (EC_e; dS/m). Each graph is fitted with a sigmoidal four parameter logistic model, shown in blue.

In summary, this study provides strong evidence to suggest that using EC_a as a predictor for yield losses can be both useful and easily scalable to large areas if it is known that salinity is the dominant yield inhibitor prior to model generation. Additionally, it indicates that EC_e may also be used, but comes with additional labor and cost due to the nature of current soil salinity mapping methods. However, if EC_e can be obtained, it is possible that a calibration might be more temporally stable (unlike EC_a, which would require annual re-calibration) because little changes are seen with EC_e over short periods of time with consistent land management.

REFERENCES

Corwin, D., Kaffka, S., Hopmans, J.W., Mori, Y., Van Groenigen, J., van Kessel, C., Lesch, S., Oster, J., 2003a. Assessment and field-scale mapping of soil quality properties of a saline-sodic soil. Geoderma 114(3-4), 231-259.

Corwin, D., Lesch, S., 2003. Application of soil electrical conductivity to precision agriculture. Agronomy journal 95(3), 455-471.

Corwin, D., Lesch, S., 2017. Validation of the ANOCOVA model for regional-scale ECa to ECe calibration. Soil Use and Management 33(2), 178-190.

Corwin, D., Lesch, S., Shouse, P., Soppe, R., Ayars, J., 2003b. Identifying soil properties that influence cotton yield using soil sampling directed by apparent soil electrical conductivity. Agronomy Journal 95(2), 352-364.

Corwin, D.L., Lesch, S.M., 2014. A simplified regional-scale electromagnetic induction—Salinity calibration model using ANOCOVA modeling techniques. Geoderma 230, 288-295.

Gates, T.K., Burkhalter, J.P., Labadie, J.W., Valliant, J.C., Broner, I., 2002. Monitoring and modeling flow and salt transport in a salinity-threatened irrigated valley. Journal of Irrigation and Drainage Engineering 128(2), 87-99.

Grieve, C.M., Maas, E.V., Grattan, S.R., 2013. Crop Salt Tolerance. In: K.K.t. Wesley W. Wallender (Ed.), Agricultural Salinity Assessment and Management. American Society of Civil Engineers, Online, pp. 405-459.

Jaynes, D., Colvin, T., Ambuel, J., 1995. Yield mapping by electromagnetic induction, Site-specific management for agricultural systems. American Society of Agronomy, Crop Science Society of America, Soil Science Society of America, pp. 383-394.

Lesch, S., Rhoades, J., Corwin, D., Robinson, D., Suarez, D., 2002. ESAP-SaltMapper version 2.30 R. User manual and tutorial guide, Res. Report 149, December (2002). USDA-ARS. George E. Brown, Jr., Salinity Laboratory, Riverside, California.

Maas, E.V., Hoffman, G.J., 1977. Crop salt tolerance–current assessment. Journal of the irrigation and drainage division 103(2), 115-134.

Nachtergaele, F., van Velthuizen, H., Verelst, L., Batjes, N., Dijkshoorn, K., van Engelen, V., Fischer, G., Jones, A., Montanarella, L., Petri, M., 2009. Harmonized world soil database. Wageningen: ISRIC.

Nellemann, C., 2009. The environmental food crisis: the environment's role in averting future food crises: a UNEP rapid response assessment. UNEP/Earthprint.

Qadir, M., Quillérou, E., Nangia, V., Murtaza, G., Singh, M., Thomas, R.J., Drechsel, P., Noble, A.D., 2014. Economics of salt-induced land degradation and restoration, Natural Resources Forum. Wiley Online Library, pp. 282-295.

Rhoades, J., 1996. Salinity: electrical conductivity and total dissolved solids. Methods of Soil Analysis Part 3—Chemical Methods (methodsofsoilan3), 417-435.

Shaner, D., Khosla, R., Brodahl, M., Buchleiter, G., Farahani, H., 2008. How well does zone sampling based on soil electrical conductivity maps represent soil variability? Agronomy Journal 100(5), 1472-1480.

Steppuhn, H., Van Genuchten, M.T., Grieve, C., 2005. Root-zone salinity: I. Selecting a Product–Yield Index and Response Function for Crop Tolerance. Crop Science 45(1), 209-220.