Texture Specific Regression Models for Predicting Soil EC_e Values from $EC_{1:2.5}$ for Effective Soil Salinity Assessment in Tanzania

***Isdory, D.P. and B.H. Massawe**

Department of Soil and Geological Sciences, College of Agriculture, Sokoine University of Agriculture, P.O. Box 3008, Morogoro, Tanzania

*Corresponding author e-mail: *danielisdory@sua.ac.tz or danielisdory@gmail.com*

Abstract

Electrical conductivity of saturated soil paste extract (EC_e) is a standard laboratory soil salinity measurement. However, due to difficulty of ECe measurement, electrical conductivity of soil to water suspensions ($EC_{soil:water}$) such as $EC_{1:2.5}$ are used and its values converted to EC_e for salinity interpretation in crop production. This study was conducted to develop texture specific regression models for predicting EC_e values from $EC_{1:2.5}$ for Tanzanian soils. A total of 198 composite soil samples at 0 – 30 cm depth were collected from Kiwere, Dakawa, Sakalilo and Mwamapuli irrigation schemes in Iringa, Morogoro, Rukwa and Katavi Regions respectively and analyzed for soil texture, $EC_{1:2.5}$ and EC_e using standard laboratory methods. The dominant soil textural classes were clay, sandy clay loam, sandy clay, and clay loam. There were significant differences ($P<0.05$) between mean values of $EC_{1:2.5}$ and EC_e (dS m^{-1}) in all textural classes. The regression models indicated significantly strong linear relationships between values of $EC_{1:2.5}$ and EC_e for all textural classes with $R^2>0.90$ and $P<0.001$ for both regression models with and without intercept. The regression models without intercept performed better in predicting soil EC_e from $EC_{1:2.5}$ than regression models with intercept by having higher P-values, slope value closer to 1.0 and lower RMSE values between measured and predicted EC_e. The study recommends regression models expressed as $EC_e = 2.0963EC_{1:2.5}$ for clay; $EC_e = 2.7714EC_{1:2.5}$ for sandy clay loam; $EC_e = 2.3519EC_{1:2.5}$ for sandy clay and $EC_e = 2.0811EC_{1:2.5}$ for clay loam soils for predicting soil EC_e from $EC_{1:2.5}$ in Tanzania.

Keywords: Soil salinity, regression models, $EC_{1:2.5}$, EC_e, Tanzania

Introduction

Soil salinity, the second major cause of land degradation after soil erosion, has been a cause of global decline in agricultural crop production (Zaman *et al.,* 2018; Hopmans *et al.,* 2021). According to Hopmans *et al.* (2021), approximately 1 billion ha of the global land surface is currently salt affected, representing about 7% of the earth's land surface. Whereas most of it results from natural geochemical processes, an estimated 30% of irrigated lands globally are salt-affected through secondary human-induced salinization (Hopmans *et al.,* 2021). Human induced salinization occurs in irrigated agriculture farms due to poor management of water and soil resources, high water table, poor drainage conditions and the use of saline water for irrigation with less leaching fraction (Shahid, 2013; Hopmans *et al.,* 2021). Therefore, it is an important concern to assess and monitor soil salinity in order to take protective measures against further deterioration of the soil for sustainable crop production (Gorji *et al.,* 2015; Zaman *et al.,* 2018).

The current climate change has increased importance of irrigated agriculture as one of the approaches in ensuring food security in many parts of the world including Tanzania (Kadiresan & Khanal, 2018; Mdemu *et al.,* 2020; Omar *et al.,* 2022). Soil salinity has been reported to be among the key constraints to land productivity in most irrigation schemes of Tanzania, posing a decline in crop yield (Kashenge-Killenga *et al.,* 2016; Isdory *et al.,* 2021; Omar *et al.,* 2022). It has been reported that most irrigation schemes in Tanzania, are already experiencing increasing levels of salt-affected soils due to the mismanagement of the soils, the use of poor quality irrigation water, poor drainage system, poorly designed and managed irrigation infrastructures, excessive use of irrigation water and climate change (Kashenge-Killenga *et al.,* 2016; Dolo *et al.,* 2017; Omar *et al.,* 2022). Therefore, there is a need for accurate assessment and monitoring of soil salinity in the irrigated lands (Kashenge-Killenga *et al.,* 2016; Mdemu *et al.,* 2020; Isdory *et al.,* 2021) and other agricultural soils for informed decision making in reversing land degradation and enhancing sustainability of crop production in the irrigated lands in Tanzania.

Electrical conductivity (EC) of saturated soil paste extracts (ECe) is a standard laboratory measure for soil salinity assessment (Matthees *et al.,* 2017; Seo *et al.,* 2022) whereas soil is considered saline if the EC_e value exceeds 4 dS m^{-1} at 25 ^{0}C (Kargas *et al.,* 2018). The yields of very salt sensitive crops are negatively affected by EC_e values between 2 and 4 dS m^{-1} while yields of most crops are affected by EC_e values between 4 and 8 dS m^{-1} (Shahid, 2013; Zaman *et al.,* 2018). Only salt tolerant crops grow well above EC_e of 8 dS m^{-1} (Zaman *et al.,* 2018). However, due to the difficulty of EC_e laboratory measurement, EC of the extracts of soil to water suspensions ($EC_{soil:water}$) at various ratios such as 1:1 (EC1:1); 1:2 (EC1:2); 1.2.5 ($EC_{1:2.5}$) and 1:5 (EC1:5) are widely used (Aboukila and Norton, 2017; Seo *et al.,* 2022). The conversion of such ECsoil:water values to EC_e is often required because the interpretations of crop tolerance and remediation of salinity are based on values derived from EC_e (Aboukila and Norton, 2017; Isdory *et al.,* 2021; Seo *et al.,* 2022). Several studies have reported that strongly significant linear relationships exist between the values of ECsoil:water and EC_e (Kargas *et al.,* 2018; Seo *et al.,* 2022). Several linear regression models have been established in different countries (; Kargas *et al.,* 2018; Seo *et al.,* 2022) for converting ECsoil:water values mostly based on ratios of 1:1, 1:2 and 1:5 and very few models on 1:2.5 ratios. However, such regression models have shown regional variabilities due to different soil forming factors such as climate and parent materials producing variation in soil properties (Kargas *et al.,* 2018; Isdory *et al.,* 2021). Therefore, it has been suggested in several studies such as by Kargas *et al.* (2018) that there is a need for regional specific models for use in the soils of a particular country for efficient prediction of soil ECe from ECsoil:water values.

According to Isdory *et al.* (2021), most soil laboratories in Tanzania assess soil salinity from $EC_{1:2.5}$ measurements. There are still no adequate studies done to establish regression models for converting $EC_{1:2.5}$ values to EC_e for specific use in the context of Tanzanian soils. Up to the time of this research work, only one published study in Tanzania by Isdory *et al.* (2021) attempted to develop a regression model for predicting values of EC_e from $EC_{1:2.5.}$ However, this study was based on only 60 soil samples from one study location which can limit extent of inference for application to other areas in Tanzania. Moreover, the study by Isdory *et al.* (2021) recommended a regression model for combined soil textural classes. It is well known that soil textural differences affect soil EC values in soil to water extracts and improvements in conversion equation accuracy is realized by differentiating soils by texture (Aboukila & Abdelaty, 2017).

Therefore, there is still a need for extensive studies in Tanzania to develop regression models based on soil textural classes for predicting values of EC_e from $EC_{1:2.5}$ results for effective laboratory soil salinity assessment and monitoring in the country. The development of conversion models in Tanzania for predicting values of EC_e from $EC_{1:2.5}$ will help soil laboratories in the country to reduce the cost and time associated with soil salinity analysis by EC_e (Aboukila & Abdelaty, 2017; Isdory *et al.,* 2021) as well as using the same $EC_{1:2.5}$ extracts for pH measurements while still maintaining high precision and accuracy in soil salinity assessment (Sonmez *et al.,* 2008; Isdory *et al.,* 2021). This study was conducted to develop regression models for predicting values of soil EC_e from $EC_{1:2.5}$ based on dominant soil textural classes from the selected irrigation schemes in Tanzania.

Materials and methods

Study location and soil sampling

A total of 198 composite soil samples at a depth of 0 – 30 cm were collected from four irrigation schemes in Tanzania namely Kiwere

(40 samples), Dakawa (50 samples), Sakalilo (48 samples) and Mwamapuli (60 samples) in Iringa, Morogoro, Rukwa and Katavi Regions, respectively. The map of Tanzania showing the geographic location of the studied irrigation schemes is presented in Fig. 1. The geographic point location of Kiwere Irrigation Scheme is at Latitude 7°39'47.15"S and Longitude 35°34'41.74"E; Latitude 6°23'41.71"S and Longitude 37°35'22.97"E for Dakawa Irrigation Scheme; Latitude 8°11'50.08"S and Longitude 31°59'29.67"E for Sakalilo Irrigation Scheme as well as Latitude 7° 8'23.93"S and Longitude 31°26'14.08"E for Mwamapuli Irrigation Scheme.

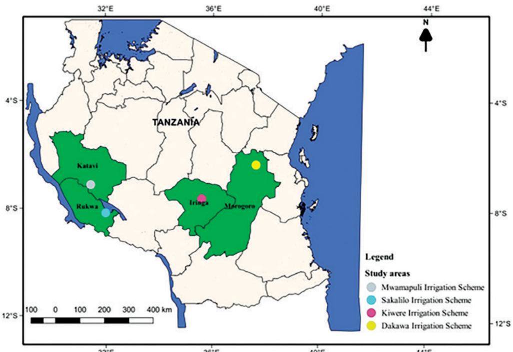

Figure 1: Geographic location of the studied irrigation schemes

The main irrigated crops grown in Kiwere Irrigation Scheme are maize, tomato, onions, and leafy vegetables with small areas under rice cultivation (Mdemu *et al.,* 2020) while rice is the main crop grown in Dakawa, Sakalilo and Mwamapuli Irrigation Schemes (Kashenge-Killenga *et al.,* 2016; Omar *et al.,* 2022). The soil samples collected from the aforementioned irrigation schemes were sent to the Soil Science Laboratory at Sokoine University of Agriculture for analysis of soil texture, $EC_{1:2.5}$ and EC_e.

Laboratory analysis and soil sample selection for model training and validation

The soil samples were air-dried, ground and passed through a 2-mm sieve followed by determination of particle size analysis by hydrometer method after dispersion with 5% sodium hexametaphosphate (Okalebo *et al.,* 2002). The USDA textural triangle was used to identify specific soil textural classes for each soil sample based on the percentage content of sand, silt, and clay particles according to Soil Survey Staff (2014). Soil electrical conductivity ($EC_{1:2.5}$) in dS m^{-1} was measured potentiometrically at a ratio of 1:2.5 soil: water (Okalebo *et al.,* 2002). Soil EC_e was determined by saturated paste extract method using the standard method by US Salinity Laboratory Staff (1954).The soil textural classes obtained from 198 soil samples were sorted and grouped into specific soil textural classes. For each of the soil textural class, 75% of the total number of samples was randomly selected as model training data set and the remaining 25% was retained as model validation data set according to Hassani and Shokri (2020). The sandy loam class was found to have only six samples in this study (Table 1) and therefore all the samples were used as a training data set only.

Statistical analysis

Descriptive statistics on the values of soil $EC_{1:2.5}$ and EC_e

The basic statistics namely minimum, maximum, mean, and standard deviation of the values of $EC_{1:2.5}$ and EC_e were computed in GenStat Software (Snell & Simpson, 2021) using all the samples for each soil textural class. The differences between mean values of soil $EC_{1:2.5}$ and EC_e were statically tested at 0.05 significance level according to Snell and Simpson (2021).

Linear relationships between $EC_{1:2.5}$ and EC_e

Linear regression analysis to establish the relationships between $EC_{1:2.5}$ and EC_e using the training data sets for each soil textural class were conducted using GenStat Software and Microsoft Excel 2013 Analysis ToolPak (Snell & Simpson, 2021). Two types of regression models one with intercept and another without intercept were developed for each soil textural class. The significance in linear relationships between $EC_{1:2.5}$ and EC_e of the developed regression models were assessed for each soil textural class by using coefficient of determination (R^2>0.8) at 0.05 significance level (Matthees *et al.,* 2017).

Model validation and selection

The selection of the best regression model between an equation with and without intercept for a particular soil textural class was done by assessing their performance based on their comparative accuracy in predicting EC_e in the validation data set (Matthees *et al.,* 2017; Kargas *et al.,* 2018). The best model for each identified soil textural class was selected based on the comparative statistical difference of ECe means at 0.05 significance level, slope of the linear relationships, R^2 and root mean square error (RMSE) all between measured and predicted EC^e values (Kargas *et al.,* 2018). The best model was assumed to have comparatively no significant difference in ECe means (P>0.05), slope closer to 1, higher R^2 value as well as smaller RMSE value between measured and predicted EC^e values (Aboukila & Abdelaty, 2017).

Results

Soil texture and values of $EC_{1:2.5}$ and EC_e for individual textural classes

The results indicating the identified soil textural classes and their values of $EC_{1:2.5}$ and EC_e in dS m^{-1} for the studied soils have been presented in Table 1. Five soil textural classes namely clay, sandy clay loam, sandy clay, clay loam and sandy loam were found from the studied soil samples. The clay was the most dominant textural class (35%) followed by sandy clay loam (30%) with sandy loam being the lowest in dominance (3%). In their study, Isdory *et al.* (2020) found the same five soil textural classes in Magozi Irrigation Scheme from Iringa Region in Tanzania where the most dominant textural class was sandy clay loam (36%) followed by clay (20%) with sandy loam (8%) and clay loam (7%) being the lowest in dominance. Other several studies (Kashenge-Killenga *et al.,* 2016; Mbaga *et al.,* 2017; Isdory *et al.,* 2021) have reported clay, sandy clay loam, sandy clay, clay loam and sandy loam as dominant textural classes from various irrigation schemes in Tanzania.

The values of $EC_{1:2.5}$ ranged from 0.23 to 4.74 dS m^{-1} with a mean of 0.83 dS m^{-1} in clay; 0.05 to 3.7 dS m^{-1} with a mean of 0.47 dS m^{-1} in sandy clay loam; 0.17 to 5.25 dS m^{-1} with a mean of 0.69 in sandy clays; 0.28 to 5.29 dS m^{-1} with a mean of 1.58 dS m^{-1} in clay loam and 0.06 to 0.78 dS m^{-1} with a mean of 0.29 dS m^{-1} in sandy loam soils. The measured EC_e values in dS m^{-1} ranged from 0.52 (non-saline) to 9.94 (very saline) with mean of 1.74 (non-saline) in

Table 1: Descriptive statistics of soil textural classes and values of electrical conductivity for the studied soil samples

Soil textural class	No. of samples (n = 198)	Percentage of samples (%)	Type of EC	Statistic				
				Minimum	Maximum	Mean	Standard deviation	P-value for means
				(dS m^{-1})				
Clay	70	35	$EC_{1:2.5}$	0.23	4.74	0.83	0.95	<0.001
			EC_e	0.52	9.94	1.74*	2.01	
Sandy clay loam	59	30	$EC_{1:2.5}$	0.05	3.70	0.47	0.50	<0.001
			EC_e	0.37	9.62	1.47*	1.29	
Sandy clay	48	24	$EC_{1:2.5}$	0.17	5.25	0.69	0.93	0.024
			EC_e	0.49	12.44	1.66*	2.17	
Clay loam	15	8	$EC_{1:2.5}$	0.28	5.29	1.58	1.39	<0.001
			EC_e	0.30	5.69	3.26*	2.94	
Sandy loam	6	3	$EC_{1:2.5}$	0.06	0.78	0.29	0.23	0.024
			EC_e	0.19	2.81	1.13*	0.82	

*Significantly different from $EC_{1:2.5}$ at $\alpha = 0.05$

clay while ranging from 0.37 (non-saline) to 9.62 (very saline) with a mean of 1.47 (non-saline) for the sandy clay loam as well as 0.47 (non-saline) to 12.44 (very saline) with mean of 1.66 (non-saline) for sandy clay soils (Zaman *et al.,* 2018). Also, the values of EC_e (dS m^{-1}) in clay loam ranged from 0.3 (non-saline) to 5.69 (moderately saline) with a mean of 3.26 (slightly saline) while ranging from 0.19 (non-saline) to 2.81 (slightly saline) with a mean of 1.13 in sandy loam soils (Zaman *et al.,* 2018).

Linear relationships between soil $EC_{1:2.5}$ and EC_e values from training data set

The results in Table 2 present the regression equations both with and without intercept showing linear relationships between measured $EC_{1:2.5}$ and EC_e values in dS m^{-1} using the training soil samples for each identified soil textural class. The model estimates (slope) ranged from 2.0552 in clay to 3.519 in sandy loam for the regression models with intercept and 2.0811 in clay loam to 3.7577 in sandy loam for the regression models without intercept.

Table 2: Linear relationships between the values of $EC_{1:2.5}$ and EC_e from the model training soil samples

Soil textural class	Number of training samples (n=149)	Linear model with intercept		Linear model without intercept		P-values for linear correlation
		Regression equation	R^2	Regression equation	R^2	
Clay	52	EC_e=2.0552$EC_{1:2.5}$+0.0277	0.9194	EC_e=2.0963$EC_{1:2.5}$	0.9189	<0.001
Sandy clay loam	44	EC_e=2.4441$EC_{1:2.5}$+0.3729	0.9446	EC_e=2.7714$EC_{1:2.5}$	0.9052	<0.001
Sandy clay	36	EC_e=2.312$EC_{1:2.5}$+0.0873	0.9733	EC_e=2.3519$EC_{1:2.5}$	0.9725	<0.001
Clay loam	11	EC_e=2.1291$EC_{1:2.5}$-0.1451	0.9883	EC_e=2.0811$EC_{1:2.5}$	0.9875	<0.001
Sandy loam	6	EC_e=3.519$EC_{1:2.5}$+0.1128	0.9869	EC_e=3.7577$EC_{1:2.5}$	0.9794	<0.001

Predicted values of soil EC_e in the model validation data set

The comparative results between measured and predicted means of EC_e values along with their P-values, slope, R^2 and RMSE for the trained regression models both with and without intercept for each soil textural class have been shown in Table 3.

Discussion

The results of this study reported strongly significant differences (P<0.05) between the mean values of $EC_{1:2.5}$ and EC_e (dS m^{-1}) in all textural classes of the studied soils in Tanzania. This observation is in agreement with literature on the difference between values of $EC_{1:2.5}$ and EC_e (Aboukila & Abdelaty, 2017; Zaman *et al.,* 2018). The results of minimum, maximum, and mean values of soil electrical conductivities were clearly observed to differ between soil textural classes. Several studies in literature have reported that soil texture affects saturated soil electrical conductivity (Aboukila & Abdelaty, 2017; Zaman *et al.,* 2018). According to Sonmez *et al.* (2008), when more precise results are required, the regression models based on soil texture should be used for predicting soil EC_e from $EC_{1:2.5}$.

The developed regression models from the training soil samples indicated significantly strong linear relationships between the values of $EC_{1:2.5}$ and EC_e for all the soil textural classes with all the R^2>0.90 and P<0.001 for both regression models with and without intercept. Equivalent results on the strong linear relationships between the values of $EC_{1:2.5}$ and EC_e were observed by Isdory *et al.* (2021) in Tanzania and elsewhere by Sonmez *et al.* (2008) in Turkey and in Egypt (Aboukila & Abdelaty, 2017; Aboukila and Norton, 2017).

The results indicate that, the predicted EC_e

Table 3: Prediction results of soil EC_e for regression models with intercept and without intercept on the validation data set

Soil textural class	Number of validation samples (n=49)	Regression model	EC_e means (dS m^{-1})		P-value	Slope	R^2	RMSE
			Measured	Predicted				
Clay	18	EC_e=2.0552$EC_{1:2.5}$+0.0277	3.65	3.62NS	0.80	0.95	0.97	0.57
		EC_e=2.0963$EC_{1:2.5}$	3.65	3.66NS	0.95	0.97	0.97	0.56
Sandy clay loam	15	EC_e=2.4441$EC_{1:2.5}$+0.3729	1.17	1.42*	<0.001	0.84	0.93	0.31
		EC_e=2.7714$EC_{1:2.5}$	1.17	1.18NS	0.72	0.95	0.93	0.18
Sandy clay	12	EC_e=2.312$EC_{1:2.5}$+0.0873	1.03	1.10NS	0.12	1.07	0.92	0.17
		EC_e=2.3519$EC_{1:2.5}$	1.03	1.03NS	0.84	1.02	0.92	0.16
Clay loam	4	EC_e=2.1291$EC_{1:2.5}$-0.1451	1.14	1.01*	0.01	1.16	0.95	0.14
		EC_e=2.0811$EC_{1:2.5}$	1.14	1.12NS	0.54	1.13	0.95	0.05

NS Not significantly different from measured EC_e at α=0.05
**Significantly different from measured EC^e at α=0.05*
RMSE = Root mean square error in dS m^{-1}

means were not significantly different (P>0.05) from the measured EC_e for both regression models with and without intercept across all the textural classes except for the two models with intercept in sandy clay loam and clay loam whose EC_e means were significantly different (P<0.05) from the measured EC_e. The EC_e prediction P-values in the regression equations with intercept ranged from <0.001 in sandy clay loam to 0.8 in clay soils while ranging from 0.54 in clay loam to 0.95 in clay for the regression models without intercept. Therefore, the P-values were higher in the regression models without intercept than in the regression models with intercept. These results imply that, the predicted EC_e means in the regression models without intercept were more not significantly different from the measured EC_e than in the regression models with intercept. These results are in general agreement with Isdory *et al.* (2021) who also reported similar observations for the regression models with and without intercept for the soils samples with combined soil texture.

The slope values between measured and predicted EC_e in all the soil textural classes were closer to 1.0 in the regression models without intercept as compared to the regression models with intercept. Several studies have reported that the regression models with slopes of closer 1.0 between measured and predicted EC_e are considered to be more accurate in prediction.

The R^2 values for the linear relationships between measured and predicted EC_e ranged from 0.92 in sandy clay to 0.97 in clay. The R^2 values were the same between regression model with and without intercept within the soil textural classes which were 0.97, 0.93, 0.92 and 0.95 for clay, sandy clay loam, sandy clay, and clay loam, respectively. The observed R^2>0.9 shows strong linear relationships between the measured and predicted values of EC_e in this study, which is in corresponds with several similar studies within and out of Tanzania (Matthees *et al.,* 2017; Kargas *et al.,* 2018; Isdory *et al.,* 2021). The RMSE values in the regression models with intercept ranged from 0.14 to 0.57 dS m^{-1} in clay loam and clay soils respectively while ranging from 0.05 to 0.56 dS m^{-1} in clay loam and clay soil respectively for the regression models without intercept. Therefore, the RMSE values were comparatively lower in the regression equations without intercept for all the soil textural classes as also reported by Isdory *et al.* (2021).

Under ideal conditions, if the predicted values of EC_e were exactly the same as the measured EC_e values, the slope would equal 1.0,

R^2 would equal 1.0 and lower RMSE (Sonmez *et al.,* 2008). Comparatively, the regression models without intercept in this study performed better in predicting soil EC_e from $EC_{1:2.5}$ than the regression models with intercept in all the soil textural classes due to their higher P-values, slope value closer to 1.0 and lower RMSE values. Therefore, in this research more accuracy in predicting soil EC_e from $EC_{1:2.5}$ values can be attained using the regression models expressed as $EC_e = 2.0963EC_{1:2.5}$; $EC_e = 2.7714EC_{1:2.5}$; $EC_e = 2.3519EC_{1:2.5}$ and $EC_e = 2.0811EC_{1:2.5}$ for clay, sandy clay loam, sandy clay and clay loam soils respectively.

Conclusion

The soil textural classes in 198 soil samples from the studied irrigation schemes were clay, sandy clay loam, sandy clay, clay loam and sandy loam with clay (35%) being the most dominant textural class. There were strongly significant differences ($P<0.05$) between the mean values of $EC_{1:2.5}$ and EC_e (dS m^{-1}) in all textural classes of the studied soils. The regression models indicated significantly strong linear relationships between the values of $EC_{1:2.5}$ and EC_e (dS m^{-1}) for all the soil textural classes with $R^2>0.90$ and $P<0.001$ for both regression models with and without intercept. The regression models without intercept in this study performed better in predicting soil EC_e from $EC_{1:2.5}$ than the regression models with intercept in all the obtained soil textural classes due to their comparatively higher P-values, slope value closer to 1.0 and lower RMSE values all between measured and predicted EC_e values. Therefore, this research recommends that more accuracy in predicting soil EC_e from $EC_{1:2.5}$ values can be attained using the texture specific regression models expressed as $EC_e = 2.0963EC_{1:2.5}$ for clay; $EC_e = 2.7714EC_{1:2.5}$ for sandy clay loam; $EC_e = 2.3519EC_{1:2.5}$ sandy clay and $EC_e = 2.0811EC_{1:2.5}$ for clay loam soils of Tanzania. This research recommends similar studies in Tanzania for the soils dominated by other textural classes.

Acknowledgement

We express our sincere gratitude to the Sokoine University of Agriculture (SUA) Research and Innovation Support for the financial support that made this research work possible through SUARIS 1 Project. We are also thankful to anonymous reviewers and journal editors for their constructive comments.

References

Aboukila, E. and Abdelaty, E. (2017). Assessment of saturated soil paste salinity from 1: 2.5 and 1: 5 soil-water extracts for coarse textured soils. *Alexandria Science Exchange Journal,* 38, 722-732.

Aboukila, E.F. and Norton, J.B. (2017). Estimation of saturated soil paste salinity from soil-water extracts. Soil Science, 182(3), 107-113.

Dolo, J.S., Msolla, S.N. and Msaky, J.J. (2017). Farmer's perceptions on salinity problems in irrigated fields in Kilosa District. *J. Econ. Sust. Devpt,* 14, 194-203.

Gorji, T., Tanik, A. and Sertel, E. (2015). Soil salinity prediction, monitoring and mapping using modern technologies. Procedia Earth and Planetary Science, 15, 507-512.

Hassani, A., Azapagic, A. and Shokri, N. (2020). Predicting long-term dynamics of soil salinity and sodicity on a global scale. Proceedings of the National Academy of Sciences, 117(52), 33017-33027.

Hopmans, J.W., Qureshi, A.S., Kisekka, I., Munns, R., Grattan, S.R., Rengasamy, P., Ben-Gal, A., Assouline, S., Javaux, M., Minhas, P.S. and Raats, P.A.C. (2021). Critical knowledge gaps and research priorities in global soil salinity. Advances in agronomy, 169, 1-191.

Isdory, D.P., Massawe, B.H.J. and Msanya, B.M. (2021). Predicting soil EC_e based on values of $EC_{1:2.5}$ as an indicator of soil salinity at Magozi Irrigation Scheme, Iringa, Tanzania. *Tanzania Journal of Agricultural Sciences,* 20(1), 63-71.

Kadiresan, K. and Khanal, P.R. (2018). Rethinking irrigation for global food security. Irrigation and drainage, 67(1), 8-11.

Kargas, G., Chatzigiakoumis, I., Kollias, A., Spiliotis, D. and Kerkides, P. (2018). An Investigation of the relationship between the electrical conductivity of the soil saturated paste extract EC_e with the respective values of the mass soil/water ratios 1:1 and 1:5 (EC1:1 and EC1:5). In Proceedings (Vol. 2, No. 11, p. 661).

Kashenge-Killenga, S., Meliyo, J., Urassa, G. and Kongo, V. (2016). Extent of Salt-Affected Soils and Their Effects in Irrigated and Lowland Rain-Fed Rice Growing Areas of Southwestern Tanzania. In: Climate Change and Multi-Dimensional Sustainability in African Agriculture. pp. 97 - 126.

Matthees, H.L., He, Y., Owen, R.K., Hopkins, D., Deutsch, B., Lee, J., Clay, D.E., Reese, C., Malo, D.D. and DeSutter, T.M. (2017). Predicting soil electrical conductivity of the saturation extract from a 1: 1 soil to water ratio. Communications in Soil Science and Plant Analysis, 48(18), 2148-2154.

Mbaga, H.R., Msanya, B.M. and Mrema, J.P. (2017). Pedological characterization of typical soil of Dakawa irrigation scheme, Mvomero district, Morogoro region, Tanzania. *International Journal of Current Research in Biosciences and Plant Biology,* 4(6), 77-86.

Mdemu, M.V., Mziray, N., Bjornlund, H. and Kashaigili, J.J. (2017). Barriers to and opportunities for improving productivity and profitability of the Kiwere and Magozi irrigation schemes in Tanzania. *International Journal of Water Resources Development,* 33(5), 725-739.

Mdemu, M., Kissoly, L., Bjornlund, H., Kimaro, E., Christen, E.W., van Rooyen, A., Stirzaker, R. and Ramshaw, P. (2020). The role of soil water monitoring tools and agricultural innovation platforms in improving food security and income of farmers in smallholder irrigation schemes in Tanzania. *International Journal of Water Resources Development,* 36(sup1), pp.S148-S170.

Okalebo, J.R., Gathua, K.W. and Woomer, P. L. (2002). Laboratory methods of soil and plant analysis: A working manual second edition. Sacred Africa, Nairobi. 21pp.

Omar, M.M., Shitindi, M.J., Massawe, B.J., Fue, K.G., Pedersen, O. and Meliyo, J.L. (2022). Exploring farmers' perception, knowledge, and management techniques of salt-affected soils to enhance rice production on small land holdings in Tanzania. Cogent Food & Agriculture, 8(1), 2140470.

Seo, B.S., Lee, K.S., Park, H.J., Jeong, Y.J., Baek, N., Lee, S.I., Yoon, K.S. and Choi, W.J. (2022). Conversion Factors for Electrical Conductivity of 1:5 Soil-Water Extracts to Saturated Paste of Reclaimed Tideland Soils are Affected by Sand Contents. *Korean Journal of Soil Science and Fertilizer,* 55(3), 251-260.

Shahid, S.A. (2013). Developments in soil salinity assessment, modeling, mapping, and monitoring from regional to submicroscopic scales. Developments in soil salinity assessment and reclamation: innovative thinking and use of marginal soil and water resources in irrigated agriculture, 3-43.

Snell, E.J. and Simpson, H. (2021). Applied statistics: handbook of GENSTAT analysis. Chapman and Hall/CRC.

Soil Survey Staff (2014). Keys to soil taxonomy. United States Department of Agriculture, Natural Resources Conservation Service.

Sonmez, S., Buyuktas, D., Okturen, F. and Citak, S. (2008). Assessment of different soil to water ratios (1: 1, 1: 2.5, 1: 5) in soil salinity studies. Geoderma, 144(1-2), 361-369.

US Salinity Laboratory Staff (1954). Diagnosis and improvement of saline and alkali soils. Agriculture Handbook, 60, 83-100.

Zaman, M., Shahid, S.A., Heng, L., Shahid, S.A., Zaman, M. and Heng, L. (2018). Introduction to soil salinity, sodicity and diagnostics techniques. Guideline for salinity assessment, mitigation and adaptation using nuclear and related techniques, 1-42.