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MODELS OF SOIL WATER CHARACTERISTICS CURVES: A REVIEW

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ABSTRACT

Soil water characteristic curve (SWCC) is very important in the study of unsaturated soil because it represents a soil's ability to store and release water as it is subjected to various soil suctions. This storage of moisture in soil is paramount in irrigation engineering, as it determines the irrigation scheduling in dryland. This study reviews some SWCC model's performance to predict the soil from some selected soils in Nigeria from previous work. This previous work contains 7 points between 0 – 1,500 kPa. Seki, which is bimodal, tends to perform better than the rest with R^2 value of 0.99. Generally, the bimodal models performed better than the unimodal, due to the flexibility of the curve. However, with the removal of the reference point of 1,000,000kPa (leaving 7 points), all the unimodal models had good performance in the topsoil. Fredlund and Xing performed best and van Genuchten performed poorly in the subsoil. Also, it was observed with the increase in both the organic matter contents and electrical conductivity, the performance of the models decreased. From this review, it is observable that in analysis of 8 or more points and 3 to 7 points Seki's model and Fredlund and Xing model can be used respectively for further research in the study of dryland soils of Nigeria.

Keywords: bimodal, soil water characteristics curve, subsoil, topsoil, unimodal

INTRODUCTION

Soil and water are two important resources and are intimately related to nature. Soils that exist above the water table are normally in unsaturated conditions (Habasimbi & Nishimura, 2018) and are diverse across the depth. Although, these soils contain water, which is termed 'soil water'. Soil water is defined as the infiltrated water shallow enough to be used by plants (Kern, 1995). Soil water plays a crucial role in ecological balance and in the development of agriculture. There is a need for proper assessment and detailed planning for proper usage of water available to reach the optimum level of utilization. This water, soil water in the vadose zone, is held by different forces gravity, matric, and osmotic forces. Soil water is dependent on soil water retention and soil water potential, these, along with the mechanical behaviours of these soils, have a greater influence on the stability of geotechnical structures such as foundations, road pavements, dams, or even nuclear waste disposal sites (Habasimbi & Nishimura, 2018), and a large number of experimental methodologies has been developed and tested over the years to estimate the water retention, θ(h)*(*Lipovetsky *et al.*, 2020), while in agriculture it is paramount for the study of water availability for plants, plant water stress, infiltration, irrigation scheduling, drainage, and water conductivity.

The soil water characteristics (soil water retention), a critical part of PTFs, can be described as the relationship between the soil suction and either the gravitational water content, w; the volumetric water content, O; or the degree of saturation, S (Vanapalli *et al*, 1998). According to Fredlund *et al* (2012), the most important property in unsaturated soil is soil–water characteristic curve (SWCC) and it represents a soil's ability to store and release water as it is subjected to various soil suctions. Habasimbi and Nishimura (2018) explained that soil water characteristics reflect the behavior of unsaturated soils concerning its hydraulic conductivity, shear strength, and volume change behavior. Therefore, the soil water characteristics relationship has greater meaning if it is presented using the degree of saturation against the suction. Thus, the water characteristics are a measure of water holding capacity (i.e., storage capacity) of the soil as the water content changes when subjected to various values of suction.

The experimental determination of the characteristics curve in the soil is of fundamental importance in the area of geotechnics and it has been used as a tool in the description of the physical-hydric behavior and the mechanics of unsaturated soil (Lafayette et al., 2014). Attempts have been made by various researchers, such as Fredlund *et al*, (2012); to estimate or predict the SWCC of the soil as a function of grain size distribution and other properties of the soil, however, Lafayette *et al.*, (2014) observed there are many limitations, especially at the intermediate values of low water content; often, the curve is completed by extrapolation, especially the fitting parameters (*a*, *n*, *m*) which can lead to instability in the numerical values. This study has reviewed the soils of the dryland zone of Nigeria from a previous study by Ojo & Maina (2019), the relationship between the volumetric water and soil suction, and bimodal models' ability to predict.

The Soil-Water Characteristic Curve Models.

The soil-water characteristic curve (SWCC), also known as soil water retention curve (SWRC) or suction–volumetric water content curve, is the relationship between the matric potential (Φ) (also called capillary pressure or matric suction) and the volumetric soil water content (Θ)(Pham, 2005). The matric potential (Φ) of soil (in the head unit, e.g., cm H_2O) is defined as "the energy per unit volume of water required to transfer an infinitesimal quantity of water from a reference pool of water at the elevation of the soil to the point of interest in the soil at reference air pressure" (Jury & Horton, 2004). The Φ is always negative and its maximum value could be zero under saturated soil conditions (known as the pressure potential). The Θ at any given time can be expressed either as a mass fraction or gravimetric Θ (a ratio of the mass of water per unit mass of dry soil) or as a volume fraction or volumetric Θ (which is calculated from the ratio of the volume of water and total (solids plus pores) volume of soil). The degree of saturation (or relative saturation or saturation ratio) represents the fraction of pore spaces filled with water.

When the Θ on the X-axis and the Φ on the Y-axis or vice versa is plotted, the SWRC is obtained (e.g., Fredlund *et al.*, 1994; Bordoni et al., 2017; Bittelli & Flury, 2009). There are two SWRCs, i.e., desorption curve (or the drying curve) and the adsorption curve (or the wetting curve) and they differ from each other due to hysteresis (Fredlund and Xing, 1994; Tuller & Or, 2004). The drying curse can be approximately divided into three regions such as the air-entry region, the capillary region, and the adsorption region. The air-entry region is the saturation region. In this saturation region, the Θ does not change with the change in the Φ, and the air begins to enter the largest pores. Lv et al., (2021) however, the observed sample prepared by slurry consolidation exhibited a lower air-entry value, faster dehydration rate, and lower residual water content. The capillary region is the intermediate part of the drying curve where the Θ drop after the air begin to enter the soil. Incremental increases in suction on the soil gradually drain water from smaller pores, resulting in a decrease in the Θ. In the adsorption region, all of the water held in pores is drained except for the tightly bound water that is adsorbed on the soil particle surfaces (Fredlund and Xing, 1994).

Kharel et al., (2018) noted that up to 2018, the empirical models are one of the widely used approaches to describe the SWCC and at the same time, statistical models are employed to determine the unsaturated hydraulic conductivity. The determination of the SWRC and the soil unsaturated hydraulic conductivity using combined empirical and statistical models is based on the consideration that both the SWCC and the unsaturated hydraulic conductivity are mainly determined by the pore-size distribution of the given soil. Various empirical models have been used by different researchers such as Brooks and Corey, (1966); van Genuchten, (1980); Fredlund and Xing, (1994) (Jotisankasa and Mairaing, 2010, Thakur, Sreedeep and Singh, 2005) to determine the hydraulic conductivity of an unsaturated soil using the SWRCs.

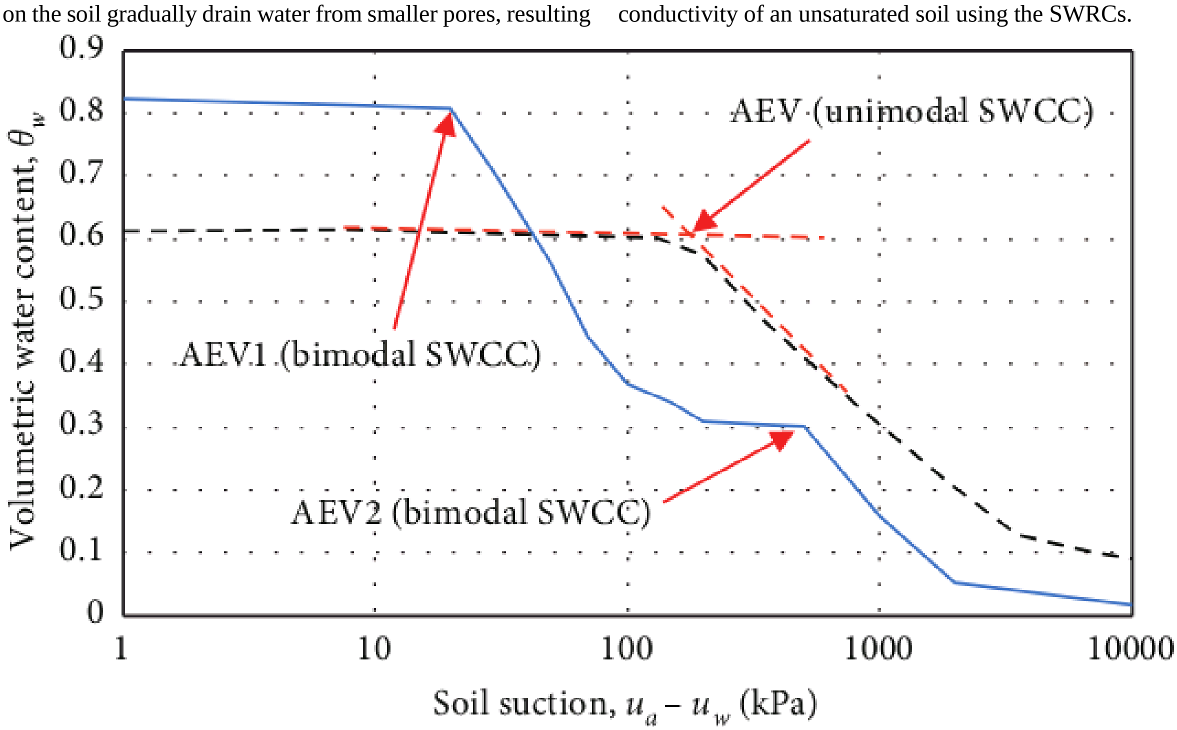


Figure: 1 unimodal and bimodal SWCC (Syarifudin & Satyanaga, 2021)

Brooks and Corey model

One of the earliest and the most widely used modes for describing the SWCC is the equation of Brooks and Corey (1966). The model is assumed to be constant for suctions less than the air entry value. The soil-water characteristic curve is assumed to be an exponentially decreasing function at soil suctions greater than the air entry value. The equation uses two fitting parameters, namely, *a* and *n*. The parameter *a* is related to the air entry value of the soil. The *n* parameter is termed the pore size index and is related to the pore size distribution of the soil. The model is given by the following equations:

$$\begin{cases} S = 1 & \psi < a \\ S = \left(\frac{\psi}{a}\right)^{-n} & \psi > a \end{cases} \qquad 2$$

The normalized water content form of the model gives the volumetric water content at soil suctions higher than the air entry value and can be written as, rated soil behaviour.

$$\Theta = \Theta_r + (\Theta_s + \Theta_r)\left(\frac{\psi}{a}\right)^{-n} \qquad 3$$

However, both parameters have physical meaning and the effect of each parameter on the function, can readily be seen. It is not possible to use the proposed SWCC equation for estimating suctions prior to the air-entry value. The Brooks and Corey equation can be rearranged to compute soil suction corresponding to the measured water content:

$$\psi = a\left(\frac{w_s}{w}\right)^{1/n} \qquad 4$$

Two fitting parameters, *a* and *n*, and the saturated water content w_s are required along with the measured water content for the calculation of soil suction.

Experimental results by some researchers such van Genuchten and Nielsen 1985, and Milly, observed that the BC model promises more suitable results for coarse-grained soils than for fine-grained soils. However, Cuceoglu (2014) further noted that the BC model has drawbacks, for instance, losing applicability at high suction ranges and the absence of an inflection point.

van Genuchten model

The van Genuchten model is a three-parameter continuous soil-water characteristic curve model. The model fits the degree of saturation versus soil suction data over the entire range of soil suctions. The equation uses three fitting parameters; namely, *a, n* and *m.* The parameter *a* is related to the inverse of the air entry value; the *n* parameter is related to the pore size distribution of the soil and the *m* parameter is related to the asymmetry of the model. This model can be described as follows:

$$S = \frac{1}{[1+(a\psi)^n]^m} \quad 1$$

where: *a*, *n* and *m* = fitting parameters.

The equation bears some similarity in form to the Gardner (1958) model. When the *m* parameter is equal to 1.0, the van Genuchten (1980) model is equivalent to the Brutsaert (1966) model with the *a* parameter inverted. This is also true of the Gardner (1958) model.

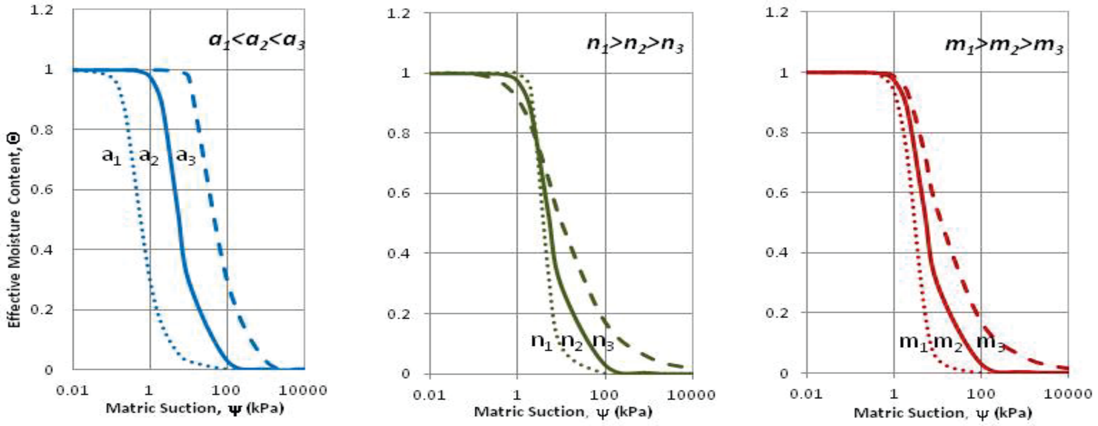


Figure2: Effects of van Genuchten model parameters on the shape of SWCC.(Ellithy, 2017)

The *m* parameter is related to the asymmetry of the curve as stated earlier, thus small values of *m* result in a moderate slope in the low suction range and a steeper slope in the high suction range. The advantages of the van Genuchten model are as follows: It provides a wide range of flexibility, allowing it to better fit data from a variety of soil types; the model parameters have physical meaning; the effect of one soil parameter can be distinguished from the effect of the other two parameters. However, the magnitude of the *n* and *m* best-fit values may vary somewhat depending on the convergence procedure.

The van Genuchten model contains three fitting parameters and this limits the type of correction factors that may be added to the model (Kharel, *et al*, 2018). Increasing the number of free parameters certainly allows more flexibility in the fitting of SWCCs, but constraining the m parameter provides great stability during parameter optimization and permission of a closed-form equation of the SWCC (van Genuchten, 1980). Instead of committing a constant m value and in an attempt to establish a closed-form expression, van Genuchten (1980) proposed the relationships of $m=1-1/n$ ($n>1$, $0<m<1$).

Overall, the VG model has more considerations and advantages than the BC model, for example, taking account an inflection point, applicability on a variety of soil types, and great flexibility within a wide-range of suction (Cuceoglu, 2014).

Fredlund and Xing model

Fredlund and Xing (1994) proposed a three-parameter model for the soil-water characteristic curve and the form of the equations is somewhat similar to that of the van Genuchten (1980) equation. The Fredlund and Xing (1994) model provide a continuous soil-water characteristic curve model over the entire soil suction range. The equation uses three fitting parameters; namely, *a, n* and m. The Fredlund and Xing (1994) model is written as follows (Sillers *et al*, 2001):

$$\Theta = \frac{1}{\left[ln\left[e+\left(\frac{\psi}{a}\right)^n\right]\right]^m} \quad 5$$

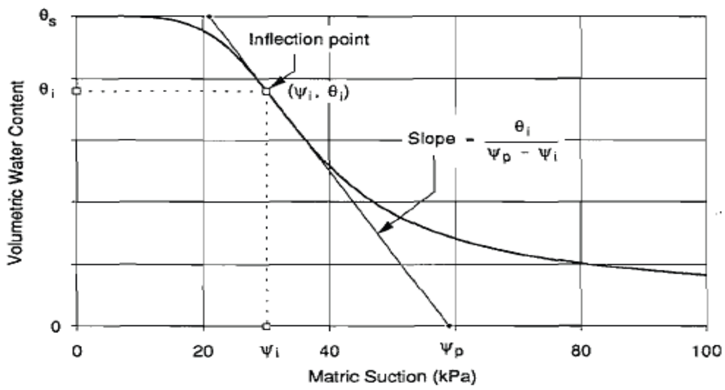


Figure 3: A sample plot of the graphical solution for the three parameters *(a, n,* and *m*) (Fredlund, *et al* 2012)

The advantages of the Fredlund and Xing (1994) model are as follows: There is great flexibility for the model to fit a wide variety of datasets; the soil parameters are meaningful; the effect of one parameter can be distinguished from the effect of the other two parameters. It has been observed that the Fredlund and Xing (1994) model required less iteration to converge to the best-fit parameters than the van Genuchten (1980) three-parameter model (Sillers *et al*, 2001). Fredlund and Xing (1994) also presented a correction factor for use with their model to ensure that the Soil-water characteristic curve goes through 1,000,000 kPa at zero water content. The Fredlund and Xing (1994) corrections are as follows:

$$\Theta = C(\psi)\ \frac{1}{\left[In\left[e+\left(\frac{\psi}{a}\right)^{n}\right]\right]^{m}} \qquad 6$$

$$C(\psi) = \left(1 - \frac{In\left(1+\frac{\psi}{\psi_r}\right)}{In\left(1+\frac{10^6}{\psi_r}\right)}\right) \qquad 7$$

Where α= fitting parameter which is primarily a function of the ai-entry value of soil n = fitting parameter which is primarily a function of the rate of water extraction from the soil once air-entry value has been exceeded, m= fitting parameter which is primarily a function of residual water content $C(\psi)$ = correction factor which is primarily a function of suction corresponding to residual water content.

Kosugi model

By applying three-parameter lognormal distribution laws to the pore-size distribution function and to the pore capillary pressure potential distribution function, Kosugi, (1996) proposed a four-parameter SWRC expression as follows:

$$\Theta = \frac{1}{2}erfc\left[\frac{In(\frac{\Phi}{\Phi_m})}{\sqrt{2n}}\right](\Phi < 0)$$

$$(\Phi \geq 0) \qquad 8$$

Where *erfc* is the complementary error function, Φ is the suction, n is the fitting parameter

Durner model

Durner, (1994) divided the porous medium into two (or more) overlapping regions (dual-porosity media). He suggested a van Genuchten-Mualem (VGM) type function (Mualem, 1976; van Genuchten, 1980) to use for each of these regions. The functions for the composite multimodal pore system, using the linear superposition of the functions for each particular region, are given by the following equation (K Seki, 2007).

SEKI model

Seki (2007) developed the program SWRC Fit. The SWRC Fit performs nonlinear fitting of five SWRC models using the Levenberg-Marquardt method. The SWRC Fit program includes Brooks and Corey or BC model, van Genuchten or VG model, Kosugi's lognormal pore-size distribution or K model, Durner's bimodal pore-size distribution model, and a proposed bimodal log-normal pore-size distribution model. Seki (2007) evaluated the performance of the SWRC Fit model by predicting the soil hydraulic parameters of 420 soils in the Unsaturated Soil Hydraulic Database (UNSODA). Based on the comparisons of the RMSE values of the unimodal models, Seki (2007) reported that the VG and the Kosugi or K models were better than the BC model. The fitting performance of the proposed bimodal log-normal pore-size distribution model was similar to Durner's bimodal pore–size distribution model (Kharel *et al*, 2018)

Types of SWCCs

SWCC can be divided into 4 types:

i. Unimodal (one bending point): A rotated and translated hyperbola was used to represent the first type of SWCC curve: the two straight lines defined by the coordinates (0, 1) (ψ_{aev}, 1) and (10^6, 0) for the hyperbola asymptotes.
ii. Unimodal (two bending points): Two rotated and translated hyperbola are needed to define an entire unimodal SWCC with two bending points. The three straight lines defined by the coordinates (0, 1) (ψ_{aev}, 1) (ψ_{res}, S_r) and (10^6, 0) are the asymptotes of the hyperbola. These two hyperbolae are merged through a third equation to produce a continuous function with a smooth transition.
iii. Bimodal: Four hyperbolae are needed to model a bimodal SWCC delineated by the five asymptotes that are defined by coordinates (0, 1) (ψ_{aev1}, 1) (ψ_{r1}, S_{r1}) (ψ_{aev2}, S_{aev}) (ψ_{r2}, S_{r2}) and 10^6, 0) (Fredlund *et al*., 2012)
iv. Multimodal: this representation is very flexible to describe water retention function and hydraulic conductivity function data, the derived equations are macroporous or aggregated soils over a wide range of pressure heads from capillary water to adsorption water. (Seki *et al.*, 2021)

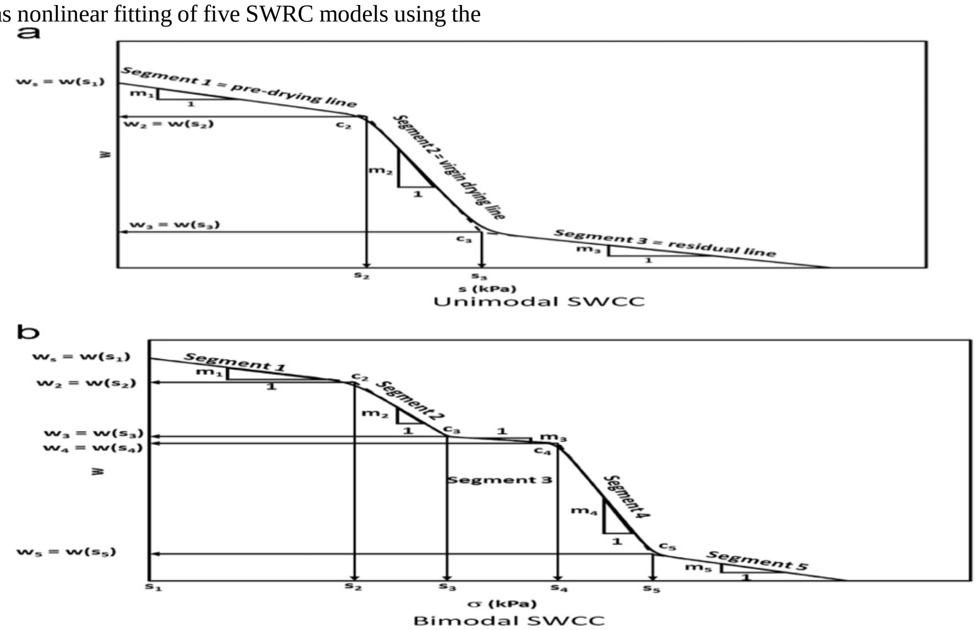


Figure 4: Unimodal and bimodal SWCC and their parameters (Wijaya & Leong, 2016)

It was observed by Seki, (2007) that the bimodal curve needs at least 8 points before the parameters can be estimated. While

Brook and Corey, van Genutchen, Kusogi and Fredlund, and Xing equations are unimodal, Durner and Seki equations are bimodal.

As observed by Zou and Leong (2018), several soils have been found to exhibit bimodal SWCC, hence, commonly used SWCC equations for unimodal SWCC are not as accurate for bimodal as it is for unimodal SWCC, and several SWCC equations have been proposed for bimodal SWCCs. However, they noted that to use these bimodal SWCC equations, it must first be established that soil has a bimodal SWCC, many hypotheses have been advanced to explain the occurrence of the bimodal SWCC. Generally, it is accepted that the cause of bimodal SWCC is the existence of both macropores and micropores in the soil, unimodal models such as standard Brooks and Corey (1964) and van Genuchten (1980), are not appropriate for simulating unsaturated flow in macroporous soils and fractured rock(Seki *et al*., 2021). A bimodal grain size distribution is a pre-requisite for a bimodal SWCC but not all soils with a bimodal grain size distribution (bimodal soils) have a bimodal SWCC (Zou and Leong, 2018; Fredlund *et al*, 2012). The bimodal equations are more accurate than the unimodal due to the flexibility of the curve, however, the mathematical rigidity and high numbers of parameters needed for it make the unimodal more widely accepted by researchers, such as Yamusa *et al* (2019).

STATISTICAL ANALYSIS

The SWCC models' performance was subjected to the coefficient of determination, $R^{2,}$ and AIC

$R^2 = 1 - (RSS/TSS)$ 9

Where R^2 is coefficient of determination, refers to the strength of the linear relationship between measurement and prediction, which indicates the amount of variability explained by the regression equation, RSS = Sum of the square of residual, TSS = total sum of the square.

AIC (Akaike Information Criterion)

$= n\ ln(RSS/n)+2k,$ 10

AIC is used to derive weights for individual models, where n is the sample size, RSS is the residual sum of squares and k is the number of estimated parameters.

3.2 Engaging machine learning

The data were subjected to analyses using Multiple Linear regression (MLR), Random Forest (RF), Support Vector Regression (SVM), Neural Network (NN), Stochastic Gradient Descent, and Decision Tree (DT), to observe how various machine learning models will perform predicting the Vol moisture content. Zhang et al., (2021) observed that multiple regression analysis may be used for SWCC to develop predictive models. The data was divided into categories, the training set which was 80%, and the testing set 20%, this was done to prevent overfitting of the predicted models. The test set was used to observe each model's ability to predict the actual data. The data were first normalized before training. The input values for the soil suction were 3 points, at 0kPa, 33kPa, and 1500kpa. The model's performance on the testing set (20% of the data) was subject to statistical indices to observe their performances.

$R^2 = 1 - (RSS/TSS)$ 11

$$\text{RMSE}= \sqrt{\sum_{i=1}^{n} \frac{Pi-Oi^2}{n}} \quad 12$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Pi - Oi)^2 \quad 13$$

$$\text{MAE}=\sum_{i=1}^{n} \frac{|Pi-Oi|}{n} \quad 14$$

Performance Evaluation of Soil Water Characteristics Models

Data harvested from a previous study done in some selected dryland of Nigeria (Ojo and Maina, 2019). These data have seven suction points 0, 10, 33, 100, 500, 1000, 1500 kPa. It should be noted that 0 kPa was assumed to be 1 kPa during the plotting of lognormal graph for the SWCC. Also, due to the data having 7 points, and according to observation by Seki, (2007), 8 points are needed for bimodal curves. Therefore, the last point 1,000,000 kPa was added when the moisture content of the soil is at zero. Due to no information about the macropores and micropores of the soil (Zou & Leong, 2018b), both the unimodal and bimodal SWCC analyses were performed on the soils.

Table 1: Soil description

Stats	Zone	Depth(cm	%SA	%Si	%CL	(%) OM	Ec (ds/m)
MEAN	SS	0-30	81.38095	10.7619	7.761905	0.672429	0.202571
STDVN	SS	0-30	19.76481	18.06351	2.567192	0.229516	0.196904
MEAN	SS	31-60	78.7619	10.42857	9.666667	0.636762	0.09581
STDVN	SS	31-60	12.13633	9.94772	3.953901	0.290032	0.042941
MEAN	NGS	0-30	46.7619	30.2381	22.28571	1.096476	0.271952
STDVN	NGS	0-30	28.79567	16.77768	17.38431	0.256746	0.188772
MEAN	NGS	31-60	23.28571	37.90476	38.71429	0.761238	0.276
STDVN	NGS	31-60	11.26562	14.18769	15.93783	0.202071	0.217635

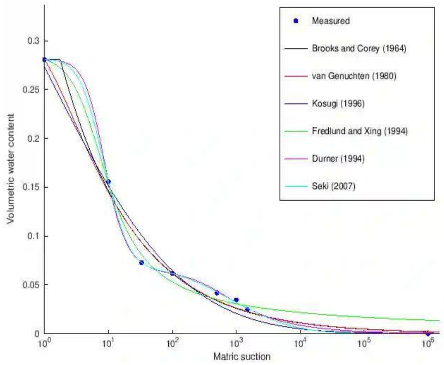
Strength and Weakness of the Various Methods Reviewed

Table 2. Performance of 8 points

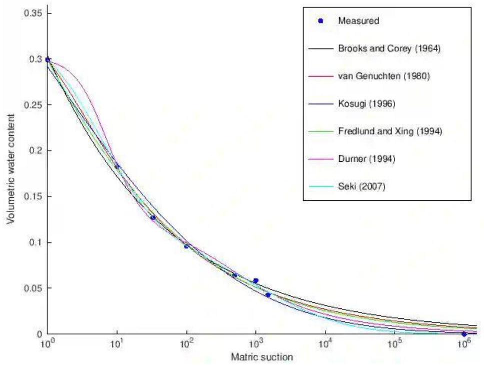
	0- 30 CM		30-60CM	
	R^2	AIC	R^2	AIC
MODEL		SUDAN SAVANNA		
Brooks and Corey	0.98882	-67.188	0.9953	-73.641

van Genuchten	0.988833	-66.846	0.99775	-79.55
Kosugi	0.97875	-62.052	0.9953	-70.89
Fredlund and Xing	0.99315	-69.103	0.99758	76.954
Durner	0.9998	-93.95	0.99858	-77.23
Seki	0.9999	-96.68	0.9994	-84.12
		NORTHERN GUINEA SAVANNA		
Brooks and Corey	0.934	-49.97	0.9495	-50.33
van Genuchten	0.8991	-46.57	0.92761	-47.45
Kosugi	0.8917	-46.01	0.9294	-47.65
Fredlund and Xing	0.9321	-47.74	0.94217	-47.247
Durner	0.9993	-80.19	0.99582	-64.267
Seki	0.99913	-78.59	0.99869	-73.565

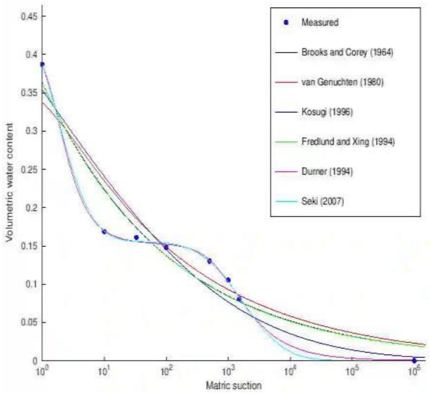
From the table above, it is observable that all the equations have good performance and Seki's model is the best of all. However, it is bimodal which as earlier stated needed 8 points before it could be used to predict the SWCC.



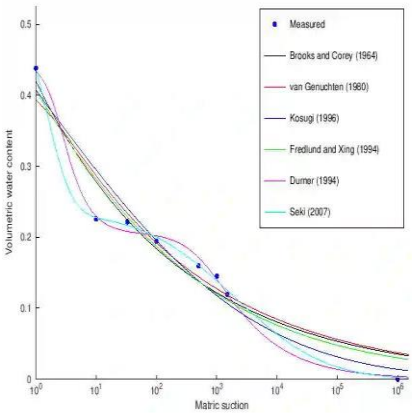
(a) SS topsoil



(b) SS subsoil



(c) NGS topsoil



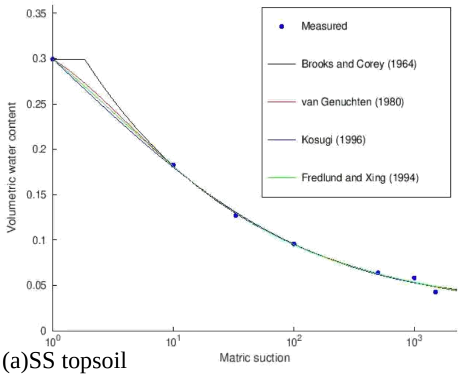
(d) NGS sub soil

Figure 5. The SWCC of bimodal and unimodal. Graphs showing the unimodal and bimodal SWCC of 8 points

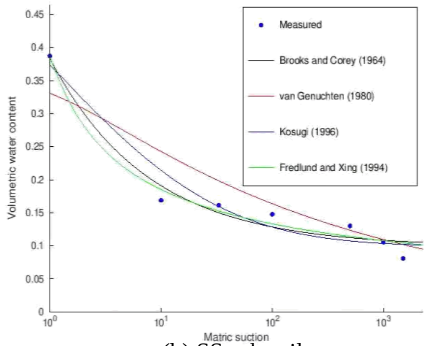
Following the recommendation of Too *et al* (Too et al., 2019), which stated that 3 point is needed for an SWCC, therefore it was analyzed again, without using 1,000,000 kPa. It was noted that Fredlund and Xing equation performed best overall.

Table 3: Performance of unimodal with 7 points

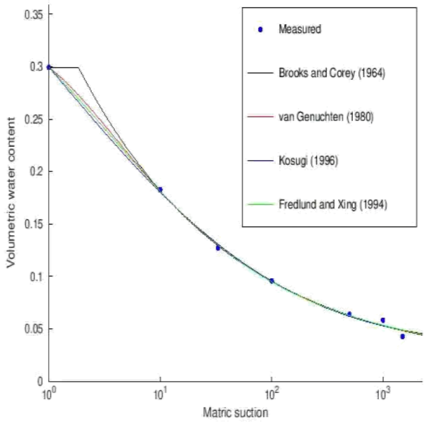
	0- 30 CM		**30-60CM**	
	R^2	**AIC**	**R^2**	**AIC**
MODEL		SUDAN SAVANNA		
Brooks and Corey	0.99507	-63.614	0.99872	-73.281
van Genuchten	0.99451	-62.856	0.99865	-72.92
Kosugi	0.99187	-60.105	0.99824	-71.08
Fredlund and Xing	0.9965	-64.006	0.99856	-70.46
		NORTHERN GUINEA SAVANNA		
Brooks and Corey	0.96766	-49.16	0.95606	-46.36
van Genuchten	0.82406	-37.3	0.8718	-38.87
Kosugi	0.94142	-45	0.9532	-45.92
Fredlund and Xing	0.97758	-49.72	0.98	-49.888



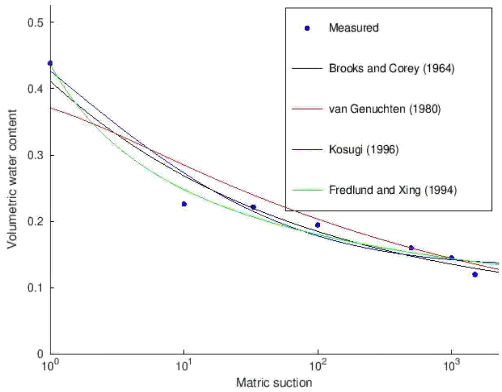
(a)SS topsoil



(b) SS sub soil



(c) NGS topsoil



(d) NGS sub soil

Figure 6: SWCC of the unimodal models

From the AIC values, it was noted that van Genuchten has the lowest values of the models for the NGS soils in the unimodal test. These values show how the models fit on identical samples of soil with more clay content. The range of the values of the models in NGS is higher compared to values from the SS. However, the model has the lowest R^2 of the models tested. It could be noted that the models (in both unimodal and bimodal tests) performed very well in the subsoil of SS. This may be due to the lower quantity of organic composition and electrical conductivity of the soil as compared with its topsoil and the soils from NGS. Also, it was observed, this soil has lower organic matter content mean and higher standard deviation compared to others (SS topsoil = 0.67; 0.23, SS subsoil= 0.637; 0.29, NGS topsoil 1.1; 0.26, NGS subsoil = 0.761; 0.20). From these analyzes, it was observed that the SWCC models' performances decrease with the increase of organic matter contents and electrical conductivity of soils, as Bot and Benites, (2005) noted organic matter also binds soil particles into aggregates and improves the water holding capacity of soil.

Table 4. Statistical indices of Performance of the models on 20% data

MODEL	MSE	RMSE	MAE	R^2
MLR	60.65	7.7878	5.9936	0.7456
NN	44.419	6.665	5.203	0.84
RF	61.896	7.867	5.316	0.778
SGD	72.848	8.535	6.811	0.738
SVM	66.01	8.1246	6.1936	0.7376
Tree	77.074	8.779	5.78	0.723

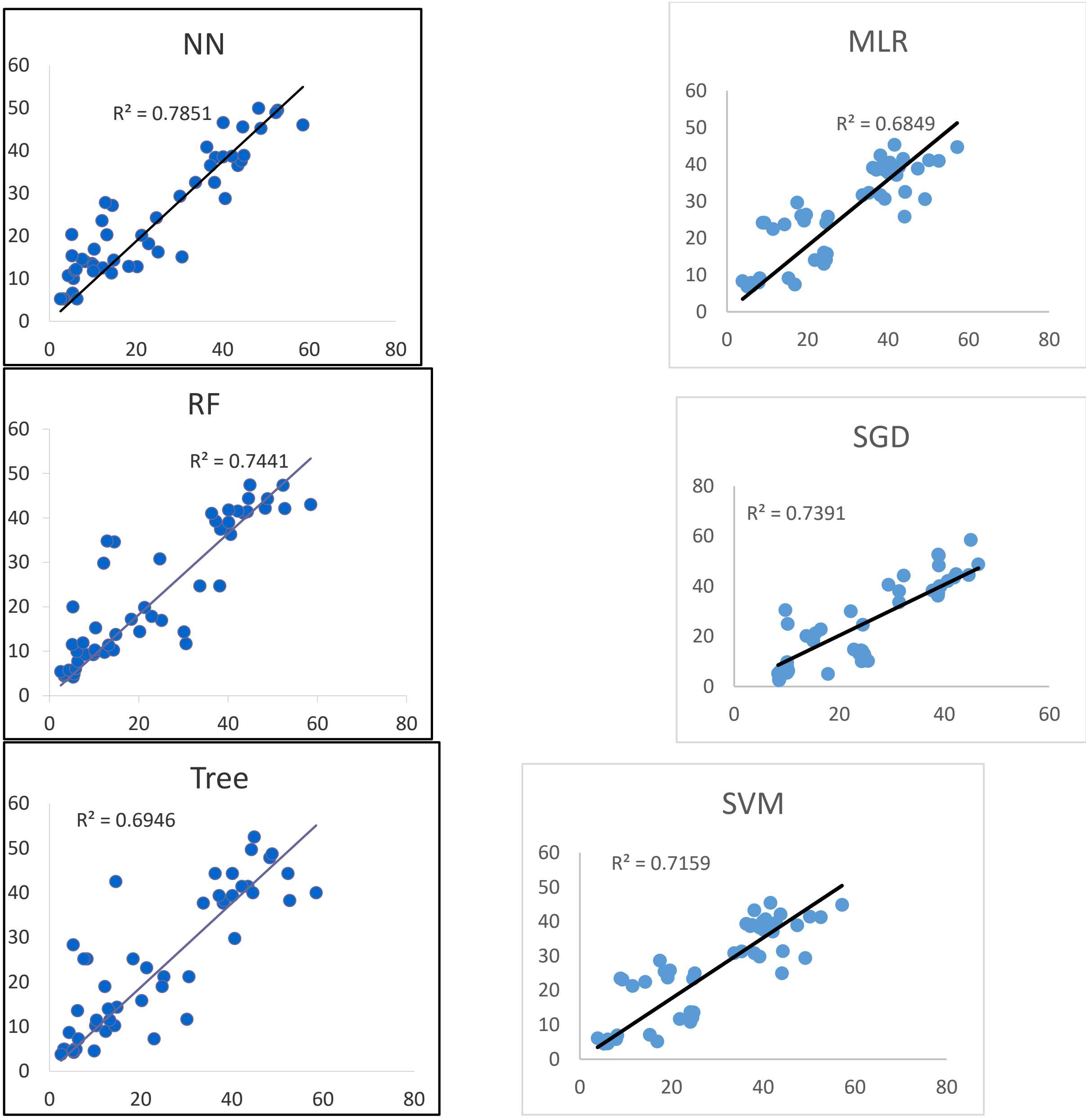


Figure 7: R^2 set at the intercept. X-axes are actual and Y-axes are predicted

Parametric Models developed from the data Output

Artificial Neural Network

θ = 0.81089425 + 0.94200176(OM) - 0.33700547(Ec) + 0.8797987 In(u_a-u_w)

SVM (regression)

θ = 34.8352 + 4.9951 (OM) + 11.4597 Ec - 29.8005In(u_a-u_w)

SGD

θ = 26.5226 + 0.915836(OM) + 2.55268 (Ec) -12.3858 In(u_a-u_w)

MLR

θ = 28.4764 + 2.39126(OM) + 16.8768 (Ec) -0.014866(u_a-u_w)

From the performance of machine learning in predicting the volume of moisture content of an SWCC, it should be noted that for these soil samples, NN scored more than 0.8 in the R^2 test, and the remainders scored more than 0.7 Although, these tests scored low compared to the unimodal models. It should be noted that 3 points of the suction were incorporated in the training and testing procedures, models with more inputs achieved better performance (Li et al., 2022). It should be noted that the test was run on all the samples without taking cognizance of the agro-ecological zones or the depth from which they were obtained.

CONCLUSION

It was observed that generally, the unimodal models' performance is less than the bimodal when the reference point 1,000,000kPa was added to the points to make the numbers of points 8. However, the unimodal models tend to improve with the removal of the reference point (1,000,000 kPa). The unimodal models were able to predict the topsoil of the zones in 7 points than the subsoil as observable by the curves passing through the points, this may be due to the higher clay content and less organic matter content in the subsoil. Also, the unimodal predicted the NGS zone poorly as compared to the SS zone soils. Further tests are needed to understand the behaviours and features of the SWCC of dryland soils concerning the effect of organic matter, electrical conductivity, and the mineralogical composition (i.e clay), such as to provide information about soil structure, microstructure, and macrostructure of the soil, and as observed in the previous section, there may be a correlation between the performance of SWCC and both the electrical conductivity and organic matter content. Due to the cost and impracticability of testing every sample under every condition, basic series of tests are only needed and should be performed to establish the main effects and the influence they have on the SWCC of the soil.

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