UJEAS

UNIZIK JOURNAL OF ENGINEERING AND APPLIED SCIENCES

UNIZIK Journal of Engineering and Applied Sciences 2(1), June 2023, 127-134
Journal homepage: https://journals.unizik.edu.ng/index.php/ujeas
PRINT ISSN: 2992-4383 || ONLINE ISSN: 2992-4391

# Prediction Model for Field Capacity Based on Physicochemical Parameters- A Case Study for Imo State

Ngwangwa. N. V [1]*, Orakwe L. C[2] and Ndukwe S. K.[3]
1 Department of Agricultural and Bio-resources Engineering, Federal University of Technology, Owerri, Imo State.
2 Department of Agricultural and Bio-resources Engineering, Nnamdi Azikiwe University, Awka, Anambra State.
3 Department of Bio-environmental Engineering, Federal Polytechnic Nekede, Owerri, Imo State
*Corresponding Author's E-mail: nkechingwangwa2@gmail.com

**Abstract**
A field capacity model for different soil sub-groups (locations) was developed using statistical analysis based on the stepwise method. In this research study, the independent variables: organic matter content, hydraulic conductivity, exchangeable sodium, soil pH, cation exchange capacity, particle density, bulk density, porosity, percentage clay, percentage silt, percentage sand, electric conductivity, and the dependent variable (field capacity) were measured using standard experimental methods. A high coefficient of determination (R2) of 0.933 was obtained for the developed model at different soil sub-groups using raw data from three locations. The model was verified and validated by comparing the predicted values with the measured field capacity values from the remaining raw data from two locations not used in building the model, and there was no significant difference between the measured and predicted values at the 5% level of significance. The standard error of the model was predicted fairly accurately, judging from the low residual values obtained from the two locations not used in building the model: 16.3% and 10.4%. These results are clear evidence of the goodness of fit of the model between predicted and measured parameters for field capacity in different soil sub-groups.

**Keywords:** Field capacity, model, hydraulic conductivity, statistical analysis, soil sub-groups.

## 1. Introduction

Moisture is one of the most important soil properties and plays a substantial role in energy partitioning between topsoil and atmosphere. This parameter is dramatically affected by the interactions occurring within the soil profile – such as changes in physical and chemical properties of the soil – or by such external factors as evaporation, irrigation, precipitation and vegetation (Alletto, et al., 2022). It is one of the main input parameters fed into Soil-Vegetation-Atmosphere Transfer (SVAT) models (Askary, et al., 2022). Soil moisture (SM) is also a very important indicator in agricultural drought monitoring (Navidi, et al., 2021). Soil moisture data are quite vital in several areas such as runoff estimation, climate modeling, flood control, geotechnical engineering, slope failure prediction and water quality assessment. It is considered one of the principal factors in irrigation scheduling, and determines irrigation water requirement and irrigation timing. Over recent years, the idea of precision agriculture on the farm scale has been very popular among researchers and farmers. One of the approaches in precision agriculture is determination of irrigation water requirement and the appropriate irrigation time, which has been realized with the use of moisture sensors and by accurate determination of SM. However, spatial and temporal variability, which is a characteristic feature of SM, complicates its monitoring (Cousin, et al., 2022). The significance of SM in irrigation scheduling becomes much more apparent on the small scale of a farm. Accordingly, several studies have been conducted to estimate SM at field capacity and permanent wilting point (PWP). Application of moisture sensors for exact irrigation timing based on real-time SM measurement has been also developed under the concept of ‘precision agriculture’ and with the aim of optimizing water consumption and minimizing the water stress imposed on plants (Navidi, et al., 2021; Tasan, & Demir, 2020). The role of this parameter is obvious on a large scale, as in catchments, where it plays a part in controlling such processes as infiltration, runoff and evapotranspiration and eventually the water balance of catchments.

Field capacity (FC) corresponds to the superior limit of available water and represents the moisture of the soil after drainage of the water contained in the macrospores by gravity action (He, et al., 2022 and Robertson, et al., 2021). This moisture condition favors higher absorption of water and nutrients by the plants. It is interchangeably used as water holding capacity and water retention capacity, which is the amount of soil moisture or water content held in soil after excess water has drained away and the rate of downward movement has materially decreased, which usually takes place within 2–3 days after a rain or irrigation in pervious soils of uniform structure and texture. The physical definition of field capacity is the bulk water content retained in soil at −33 J/kg (or −0.33 bar) of hydraulic head or suction pressure. When irrigation is applied to the soil, all the soil pores get filled with water. After the gravitational drainage, the large soil pores are filled with both air and water, while the smaller pores are still full of water. At this stage, the soil is said to be at field capacity. At field capacity, the water and air contents of the soil are considered to be ideal for crop growth.

Worldwide, there are concerns about rising nutrient concentrations in surface and groundwater systems (He, et al., 2022). A leading source of leached nutrients is agricultural land, which has expanded significantly with the global demand for food (Wang, X., et al., 2022). To mitigate nutrient leaching, more effective land management practices operating within an appropriate regulatory environment are necessary, making knowledge of soil water and nutrient retention properties indispensable. However, soil hydraulic properties are costly and time-consuming to measure, making it difficult or impossible to provide representative soil hydraulic properties at the farm scale, let alone regional and national scales. Therefore, models have been developed to provide estimates of soil retention properties like field capacity (FC) using more readily available field data (Robertson, 2021). When applied to soil mapping units, these models (known as pedotransfer functions) can be utilized for management and regulation purposes at the national scale when appropriate uncertainty analysis is included (Shahriari, et al., 2019).

Soil water holding capacity is known to optimize crop production and this is the amount of water that a given soil can hold for crop use. Field capacity is the point where the soil water holding capacity has reached its maximum for the entire field and this is the goal for most if not all agricultural producers. When there is a deficit in the amount of water in the soil, the soil profile needs to be replenished by precipitation or irrigation. According to Robertson, et al., 2021, the best-standardized procedure to evaluate FC is by flooding a square or rectangular plot on a bare field; after irrigation, it is covered with a plastic sheet (He, et al., 2022) to avoid evaporation. The FC profile is defined by the distribution of moisture in the upper half of the soil profile, which will be fully wet at the end of infiltration (quasi-saturated), as measured 2 or 3 days after water application. This FC profile usually depends on the texture and structure of the individual soil layers (Navidi, et al., 2021). Based on this dependence and the operational difficulties of a field test, FC is commonly evaluated in a laboratory setting as the moisture of undisturbed soil samples at a specific matric potential. Swain, et al., 2021, reported that a wide range of matric potentials (from -2.5 kPa to -50 kPa) has been used for this purpose, although suctions of 5 kPa, 6 kPa, 10 kPa, and 33 kPa are more common choices; however, there is no satisfactory general criterion for selection of the suction values for the determination of FC (Ostovari, et al., 2015). The key is for farmers to understand the nuances of soil water holding capacity and how to manage it so that the farm does not need to irrigate or suffer from a drought. Soil Organic Matter (SOM) is another factor that can help increase water holding capacity. Soil organic matter has a natural magnetism to water. If the farm increases the percentage of soil organic matter, the soil water holding capacity will increase (Wang, et al., 2022).

Soil Organic Matter is decayed material that originated from a living organism and can be increased by adding plant or animal material. When irrigation is applied to the soil, all the soil pores get filled with water. After the gravitational drainage, the large soil pores are filled with both air and water, while the smaller pores are still full of water. At this stage, the soil is said to be at field capacity. At field capacity, the water and air contents of the soil are considered to be ideal for crop growth. The persistence of a high field capacity due to water logging, particularly in the presence of bio-available C sources, results in declining soil redox potential and development of anoxic conditions. At “Field Capacity” (FC) the soil is wet and contains all the water it can hold against gravity. At the

"Permanent Wilting Point" (PWP) the soil is dry and the plant can no longer extract any more water. The difference in the water content of soil between field capacity and the permanent wilting point gives the amount of soil water available for uptake by plants. The plant available water is expected to be greater for clayey and organic soils compared to sandy soils. If we know the plant available water and the rate at which this water is being depleted by crops then we can determine the necessary frequency of irrigation. Apart from irrigation scheduling, this information can also be useful in the modeling of crop growth and prediction of yields (Askary, 2022).

Usually, field capacity is determined in the laboratory, by the retention curve method. In this method, the value of the field capacity moisture is represented by the balance moisture with tension of 6–33 kPa, depending on the texture, structure and content of organic matter in the soil. Since the determination of these parameters is expensive and time-consuming, this study aims to develop model for estimating field capacity based on physicochemical properties of soils.

## 2.0 Material and methods

**2.1 The study area** - The study area (Federal University of Technology Owerri, School of Agriculture and Agricultural Technology Farm, Imo State) lies between latitude 4º.45´N and 5º50´N, longitude 6º35´E and 7º30´E located in the Southeastern section of Nigeria and is one of the 36 States of the Nigerian Federation, with Owerri as its capital and largest city. It occupies an area of about 5,329.17 sq. km with a Population of 2,938,708. Imo State derives its name from Imo River, which takes its course from the Okigwe/Awka upland. Imo State is located between the lower River Niger and the upper and middle Imo River. The area experiences a humid, semi-hot equatorial climate (Amanbagara, et al., 2015). The rainfall is heavy, with an average annual rainfall of 2000-2400mm and an average number of 152 rainy days particularly during the rainy season (April - October). Rainfall distribution is bimodal, with peaks in July and September and two weeks break in August. The rainy season begins in March and lasts till October or early November.

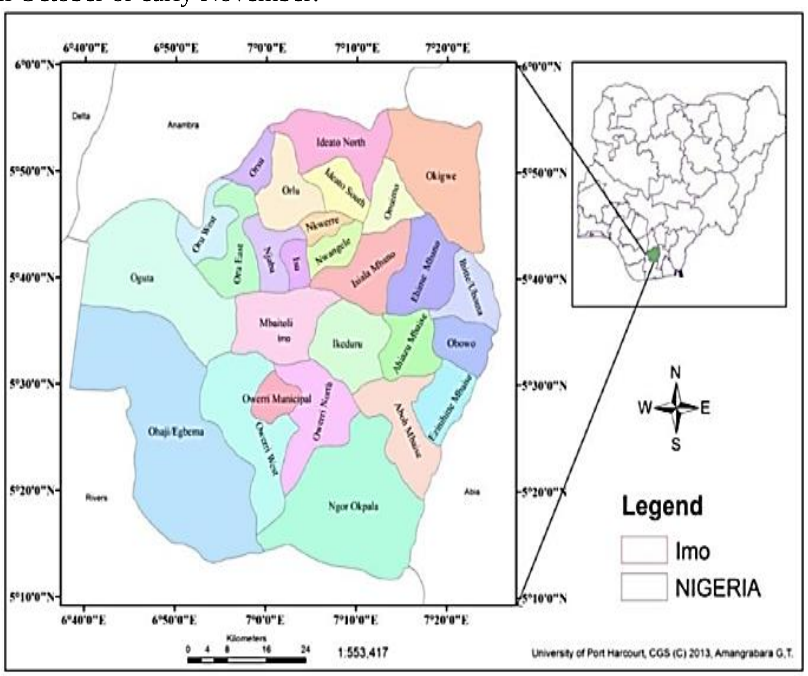


**Figure 1: Map of Imo State showing the local government areas. (Amanbagara, et al., 2015).**

Geologically, Imo State is underlain by the sedimentary sequences of the Benin Formation (Miocene to recent), and the Bende-Ameki Formation (Eocene). The Benin Formation is made up of friable sands with minor intercalations of clay (Amanabagara et al., 2015). The sand units are mostly coarse-grained, pebbly, poorly sorted, and contain lenses of fine-grained sands. In some areas like Okigwe, impermeable layers of clay occur near the surface, while in other areas, the soil consists of lateritic material under a superficial layer of fine-grained sand. Imo State is characterized by three main landform regions: a highland region of elevation of 340m in the northern sections covering Orlu, Ideato, Okigwe, and White Uboma local government areas. The mainstream-Orashi (Ulasi) River, rises near Dikenafai in Imo State, flows northward to Ozubulu in Anambra State, and then turns round in a wide loop and heads for the Atlantic Ocean. The second main landform region is midway between the North and the Southern section of the state and is of a moderate elevation of between 175m - 240m above Medium Sea Level. They provide elevated, well-drained topography with few isolated undulating topography and valleys. The third landform region is the lowland/plains that lie South of the high and moderately elevated highlands; the Orashi River plain, south of Oguta, and the inter-basin area between Oguta and Egbema. The main rivers draining the State are Imo, Otamiri, Njaba, Arashi, Nwaorie, Oraminiukwa, and a couple of other smaller streams all of which have very few tributaries. These rivers constitute the five subbasins in the Imo-Anambra River Basin draining an average area of about 3,777.76km2 of Imo State. The area underlain by the Imo Shales, other rivers rise within the coastal plain sands.

The width and depth of the majority of these rivers ranged between 10m to 350m and 0.5m to 2.8m respectively. Water in excess of that required to maintain field capacity is known as excess winter rainfall and this water leaches through the soil profile and represents the recharge to water sources. The volume of excess winter rainfall varies each year according to factors such as precipitation amount, soil type, antecedent cropping, evaporation, temperature. Random sampling method was adopted during sampling by taking soil samples from areas of the given site chosen at random when there is little previous knowledge of the site.

**2.1.1 Soil pH:** In a mechanical sieve shaker, a 10grams of 2mm sieved air dried soil sample was put into the 100ml beaker, 10ml of distilled water added making the soil-water ratio to be 1:1 and the whole solution is stirred for about 30mins simultaneously. The solution is left to stand and settle for about 6hrs before the glass electrode of the pH meter is immersed deep enough in the clear solution on top of the settled suspension so as to read and record the result shown on the meter.

**2.1.2 Organic matter content:** Organic matter content was determined using Walkley-Black wet oxidation method procedure where the percentage organic carbon was calculated using the Equation (1) below;

$$\%\,Organic\ Carbon\ =\ (B-T)\times M\times 0.003\times 1.33\times \frac{100}{wt} \qquad (1)$$

Where; wt = weight of soil sample in grams

B = Blank titre value in ml

T = sample titre value in ml

M = molarity of actual concentration of $fe^{2+}$

**2.1.3 Particle size:** Particle size distribution of less than 2 mm fractions was determined using hydrometer method and the %clay, %silt and %sand was calculated using the equations below after getting the parameters required from the laboratory

$$\%Sand\ = 100-\%(clay\ + silt) \qquad (2)$$

$$\left\{\frac{[(R_{2hrs}-R_b)+R_d]}{wt}\right\}\times 100 \qquad (3)$$

$$\%(clay+silt) = \left\{\frac{[(R_{40s}-R_a)+R_a]}{wt}\right\}\times 100 \qquad (4)$$

Where; $R_{40s}$ and $R_{2hrs}$ = Hydrometer reading after 40 secs and 2hrs, grams

$R_a$ and $R_b$ = 40secs and 2hrs blank hydrometer reading, grams

$R_e$ and $R_d$ = Temperature readings of the suspension, °c for 40secs and 2hrs

wt = weight of soil sample, grams

Finally, with the results, the textural classes (%clay, % sand and %silt) were determined using textural triangle.

**2.1.4 Bulk density:** The bulk density was determined using core method. The core sampler was driven vertically into the soil to 10cm depth so as to fill the sampler with soil and later it was removed carefully from the hole so as to get an undisturbed soil sample insitu. The soil extending was trimmed from both ends of the sampler with a knife and the weight of the sampler when empty and its weight with the soil sample was recorded as $W_1$ and $W_2$. The volume of the soil sample which is the same as the volume of the core sampler was calculated using the formula;

$$V = \pi^2 h \quad (5)$$

Where; h and r are the height and radius of the core sampler.

Bulk density is then calculated using the equation below;

$$Bulk\ density = \frac{mass\ of\ soil, g}{volume\ of\ soil, cm^3} \quad (6)$$

**2.1.5 Porosity:** Porosity is calculated using the equation below;

$$Porosity = \left[\left(1 - \frac{D_b}{D_p}\right) \times 100\right]\% \quad (7)$$

**2.1.6 Cation Exchange Capacity:** The exchangeable calcium and magnesium were determined using EDTA titration method and after the parameters were gotten in the Lab, the following equations were used to calculate the magnesium and calcium in the soil sample.

$$Calcium, \frac{Mg}{100g} = T \times mol\ of\ EDTA \times \left(\frac{V_1}{V_2}\right) \times \left(\frac{100}{w}\right) \quad (8)$$

$$M_g = (c_a + m_g) - c_a \quad (9)$$

**3.0. Results and Discussions**

A multiple linear regression was run by using each property to relate to the measured Field Capacity by simple correlation and multiple correlation analysis to predict field capacity from Soil ph, Organic matter content, percentage clay, Bulk density, particle density, Exchangeable sodium percentage, Porosity, Percentage sand, Percentage silt, Cation exchange capacity and Electrical conductivity. The correlation coefficients were checked for significance using IBM SPSS software (version 20) in other to determine the order of inclusion of the variables during model building. The model was then developed using stepwise regression method in the statistical package. In stepwise regression method, each variable is entered in sequence and assessed using the observed coefficient of determination ($R^2$) and adj. $R^2$.

**Table 1: Correlation coefficient between field capacity and the selected soil properties**

| Soil properties | Correlation, r | P-value | Remark |
|---|---|---|---|
| Fc &Hc | -0.168 | 0.240 | Not correlated |
| Fc & OMC | -0.389 | 0.045* | Correlated |
| Fc &Bd | -0.490 | 0.014* | Correlated |
| Fc &Pd | -0.245 | 0.149 | Not correlated |
| Fc & ECS | 0.365 | 0 .057 | Not correlated |
| Fc & Soil Ph | 0.554 | 0.006* | Correlated |
| Fc & P | 0.398 | 0.041* | Correlated |
| Fc & %S | -0.455 | 0.022* | Correlated |
| Fc & %Si | 0.176 | 0.229 | Not Correlated |
| Fc & %C | 0.571 | 0.004* | Correlated |
| Fc & CEC | 0.482 | 0.016* | Correlated |
| Fc & EC | 0.465 | 0.019* | Correlated |

If adding a variable increases the $R^2$ and adj. $R^2$ values of the model, then it is retained but all other variables in the model are retested to see if they are still contributing to the success of the model. If they no longer contribute significantly, they are removed. This method ended up in giving the smallest possible set of soil properties one needed to measure so as to predict field capacity within the studied location. The effective variables that influence field capacity that were retained in the model include; Organic matter content, Soil ph, Percentage clay and Bulk density. These variables generally, statistically and significantly predicted field capacity as stated in Table (1) below. This model has variables not originally well correlated with measured Field capacity retained in the model while one originally well correlated was eventually excluded from the model. Based on Table 1, porosity, percentage sand, cation exchange capacity and electrical conductivity, were to appear in the final field capacity model but rather they were excluded. What this suggests is that a variable may not be well correlated with another factor on its own, but its interaction with other variables may enhance its relationship with the variables with which it was not originally well correlated as a single variable. The coefficient of determination, $R^2$ increased generally until it gets to a point where $R^2$ remained unchanged which shows that the best model fit has been achieved. Table (1) shows the result of the correlation analysis of the measured field capacity value against the selected soil properties.

From Table (1), the R-value computed for the correlation between Field Capacity and Percentage Clay exceeds both tabular R-values at 5% and 1% probability levels. It was concluded that the simple linear correlation coefficient is significantly different from zero at 1% probability level. This significantly high R-value indicates that there is strong evidence that the Field Capacity and Percentage Clay in the different soil sub-groups are highly associated with one another in a linear function. This linear association shows that soil sub-groups with high field capacity will have a high Percentage Clay or vice versa. For the linear function of the Percentage Clay in the soil sub-groups of the study, the coefficient of determination, $R^2$ increased gradually until it gets to a point where, $R^2$ remained unchanged which shows that the best model fit has been achieved. Table 2 illustrates the mean comparison for the soil properties in the soil sub-groups.

**Table 2: Mean comparison table using Duncan's Multiple Range Test (DMRT) for the model**

| BLOCKS (Locations) | TREATMENTS (Soil properties) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | FC | Hc | OMC | Bd | Pd | ESP | pH | P | %S | %Si | %C | CEC | EC |
| Egbema | 7.4800<br>(0.4288) | 0.2921<br>(0.0625) | 4.2971<br>(0.0826) | 1.5600<br>(0.0383) | 2.4157<br>(0.0399) | 3.3471<br>(0.0505) | 6.2314<br>(0.0945) | 35.4300<br>(2.4817) | 87.2714<br>(0.4957) | 4.7286<br>(0.6291) | 8.0000<br>(0.6055) | 3.0314<br>(0.2395 | 42.3000<br>(10.6022) |
| Owerri | 9.4850<br>(0.5358) | 0.9557<br>(0.1355) | 7.1129<br>(0.0320) | 1.2243<br>(0.0489) | 2.1157<br>(0.0616) | 2.1743<br>(0.1032) | 5.3671<br>(0.1791) | 42.0671<br>(3.3759) | 50.1857<br>(0.4741) | 28.1857<br>(0.4375) | 21.6286<br>()0.1704 | 3.9343<br>(0.3640) | 82.5750<br>(25.3022) |
| Okwele | 14.010<br>(1.7847) | 0.4433<br>(0.1560) | 4.4814<br>(0.0727) | 1.4500<br>(0.0311) | 2.6214<br>(0.0279) | 3.8586<br>(0.2499) | 6.0771<br>(0.4601) | 44.910<br>(1.3244) | 47.0714<br>(0.2498) | 16.3571<br>(0.5769) | 36.5714<br>(0.4991) | 4.7000<br>(0.1327) | 91.8500<br>(16.3938) |
| Umuna | 17.0350<br>(0.2767) | 0.4218<br>(0.0492) | 4.5929<br>(0.0626) | 1.2714<br>(0.0328) | 2.1657<br>(0.0544) | 2.9129<br>(0.1096) | 6.5186<br>(0.0913) | 41.2514<br>(2.2156) | 62.2857<br>(0.4488) | 16.1000<br>(0.2582) | 21.6571<br>(0.4577) | 3.3729<br>(0.1841) | 84.5000<br>(26.1057) |
| Orlu | 16.4350<br>(1.0702) | 0.4926<br>(0.0241) | 4.2271<br>(0.0776) | 1.2643<br>(0.0446) | 2.0686<br>(0.0578) | 3.9757<br>(0.3552) | 7.4571<br>(0.2613) | 38.8671<br>(1.9469) | 57.4143<br>(1.3146) | 18.2857<br>(1.4369) | 24.3000<br>(0.9399) | 5.4543<br>(0.2622) | 73.2000<br>(8.1343) |

### 3.1Stepwise Regression

Table (3) below listed the best fit equations of the stepwise regression for the different number of model variables including their test characteristics; correlation coefficient, R, coefficient of determination, $R^2$, adjusted coefficient of determination, $R^2$adj, F test and standard error of estimate, S.E.

**Table 3: Stepwise regression equation for different numbers of Model variables**

| S/N | Equation | R | $R^2$ | $R^2$adj | F | SE | Remarks |
|---|---|---|---|---|---|---|---|
| 1. | 7.391 + 0.246%Cl | 0.571 | 0.326 | 0.289 | 8.725 | 3.3621 | Best of 12 one-variable equation. Sig. at 0.01 |
| 2. | -9.643 +0.24%Cl + 2.707pH | 0.786 | 0.618 | 0.573 | 13.754 | 2.6052 | Best of 11 two-variable equation. Sig. at 0.01 |
| 3. | 5.210 + 0.210%Cl + 2.524pH - 9.642Bd | 0.847 | 0.718 | 0.665 | 13.590 | 2.3068 | Best of 10 three-variable equation. Sig. at 0.01 |
| 4. | 82.24 + 0.150%Cl - 1.907pH – 30.074Bd – 4.047OMC | 0.966 | 0.933 | 0.915 | 51.869 | 1.1653 | Best of 9 four-variable equation. Sig. at 0.01 |

*N/B: OMC = Organic Matter Content; %Cl = %Clay; pH = Soil pH; Bd = Bulk density*

From Table (3), the equation that seems to be the optimum of the best fit using statistical analysis in serial number four (4) equation as shown in Equation (10) below.

$$FC = 82.24 + 0.150\%Cl - 1.907pH - 30.074BD - 4.047OMC \qquad (10)$$

Where: Fc =Field capacity; OMC = Organic matter content; %Cl = Percentage clay; BD = Bulk density; pH = Soil pH

Validation of Model:

Table 4 shows the difference between the measured and predicted field capacity values for the two locations not used in building the model.

**Table 4: Measured and predicted field capacity values from the two locations not used in developing the model.**

| Location (soil group) | Measured | Predicted | Residual (%) |
|---|---|---|---|
| Owerri(DystricFerrasol) | 9.485 | 9.648 | 1.72 |
| Orlu(EutricNitosol) | 16.435 | 16.539 | 0.63 |

According to Table 3, the model predicted perfectly with a decent amount of accuracy, going by the low residual values (1.72% and 0.63%) obtained from the two locations not included in the model's development. This concurs with research by Nwakuba et al. (2018) and Ngwangwa et al. (2015) showing the models are more accurate with less percentage error values between measured and predicted results.

## 4.0. Conclusion

A mathematical model was established using statistical analysis; special package for the social sciences, SPSS, based on stepwise method. A functional relationship between some soil properties and Field Capacity was established. The model was tested with data from the two locations (Owerri and Orlu) not used in building the model and low residual values got as 1.72%and 0.63%. There was no significant difference between the measured and predicted Field Capacity values at 5% level of significance. The difference between the actual (measured) and the predicted Field Capacity values were below 20% which implies good model.

## 5.0 Recommendation

Having the knowledge of current values of Field Capacity and other soil properties from the desired area combined with the relevant understanding of water flows within the study area, aids in developing useful information recommended for agriculture and structural maintenance in Soil and Water Engineering practices. I recommend the model (Equation 10) as a better one to use in the study area for the fact that it predicted field capacity well.

## Acknowledgements

My gratitude goes to Laboratory Technologist in the name of Engr. F. O. Nkwazema, the Chief Technologist at Micheal Okpara University of Agriculture, Umudidke, Umuahia in the use of his expertise in the laboratory experiments for all the measurements carried out in the study

## References

Alletto, L., Cueff, S., Bréchemier, J., Lachaussée, M., Derrouch, D., Page, A., Gleizes, B., Perrin, P., & Bustillo, V. 2022. Physical properties of soils under conservation agriculture: A multi-site experiment on five soil types in south-western France. Geoderma.

Askary, R., Najarchi, M. & Mazaheri, H. 2022. Estimating SWRC parameters and unsaturated hydraulic permeability by improved Jaya and hybrid improved jaya optimization algorithms. Earth Sci Inform 15, 2155–2169 (2022). https://doi.org/10.1007/s12145-022-00862-z

Cousin, I., Buis, S., Lagacherie, P., Doussan, C., Le Bas, C., & Guérif, M. 2022. Available water capacity from a multidisciplinary and multiscale viewpoint. A review. Agronomy for Sustainable Development, 42.

He, D., Oliver, Y.M., & Wang, E. 2020. Predicting plant available water holding capacity of soils from crop yield. Plant and Soil, 459, 315-328.

He, D., Oliver, Y.M., Rab, A., Fisher, P.D., Armstrong, R.D., Kitching, M.A., & Wang, E. 2022. Plant available water capacity (PAWC) of soils predicted from crop yields better reflects within-field soil physicochemical variations. Geoderma.

Honarbakhsh, A., Tahmoures, M., Ostovari, Y., & Noroozi, S. 2017. Developing Pedotransfer Functions for Predicting FC and PWP. Communications in Soil Science and Plant Analysis, 48, 2485 - 2495.

Navidi, M.N., Seyedmohammadi, J., & SeyedJalali, S.A. 2021. Predicting soil water content using support vector machines improved by meta-heuristic algorithms and remotely sensed data. Geomechanics and Geoengineering, 17, 712 - 726.

Nwakuba, N. R., Chukwuezie, O. C., Asoegwu, S. N., Nwadikom, G. I. and Okereke, N. A. A. 2018. A predicting model of energy requirements for drying of okro slices in a Hybrid Solar – Electric Dryer. Umudike Journal of Engineering and Technology (UJET), 4 (1) 155 – 163.

Ostovari, Y., Asgari, K., Cornelis, W., &Beigi-Harchegani, H. 2015. Simple methods for estimating field capacity using Mamdani inference system and regression tree. Archives of Agronomy and Soil Science, 61, 851 - 864.

Robertson, B.B., Carrick, S.T., Almond, P.C., McNeill, S.J., Penny, V., Chau, H.W., & Smith, C.M. 2021. Predicting field capacity in undisturbed stony soils. Geoderma, 401, 115346.

Shahriari, M.R., Delbari, M., Afrasiab, P., &Pahlavan-Rad, M.R. (2019). Predicting regional spatial distribution of soil texture in floodplains using remote sensing data: A case of southeastern Iran. CATENA.

Swain, S., Chakraborty, P., Panigrahi, N., Vasava, H.B., Reddy, N.N., Roy, S., Majeed, I., & Das, B.S. 2021. Estimation of soil texture using Sentinel-2 multispectral imaging data: An ensemble modeling approach. Soil & Tillage Research, 213, 105134.

Taşan, S., &Demir, Y. 2020. Comparative Analysis of MLR, ANN, and ANFIS Models for Prediction of Field Capacity and Permanent Wilting Point for Bafra Plain Soils. Communications in Soil Science and Plant Analysis, 51, 604 - 621.

Wang, X., Li, L., Liu, H., Song, K., Wang, L., &Meng, X. 2022. Prediction of soil organic matter using VNIR spectral parameters extracted from shape characteristics. Soil and Tillage Research.

Wang, X., Song, K., Wang, Z., Li, S., Zheng, M., Wen, Z., & Liu, G. 2022. Are topsoil spectra or soil-environmental factors better indicators for discrimination of soil classes? CATENA.

Xing, X., Wang, H., & Ma, X. 2018. Brooks–Corey Modeling by One-Dimensional Vertical Infiltration Method. Water, 10, 593.