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# Assessment of different pedotransfer models using soil texture for predicting saturated water content, Al-Ahsa, Saudi Arabia

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***Abstract*--This study assessed the accuracy of 22 published pedotransfer functions (PTFs) for estimating soil saturation (θs) was evaluated using local soil samples (n=10) in the Al-Ahsa region. The results showed only the PTF model developed by Al-Saeedi (2022) met the applied evaluation performance criteria ($R^2$=0.872, RMSE=0.024, NSE=0.705, and RSR=0.506) Where the $R^2$, RMSE, NSE, and RSR mean correlation coefficient, root mean square, Nash-Sutcliffe efficiency, and the ratio of the RMSE to the standard deviation SD, respectively. The other 21 equations did not meet the required model reliability and validation criteria. This study also produced a crucial result: the demand for additional statistical criteria rather than correlation and error measurements in evaluating and validating the suitable model.**

**Key words: Pedotransfer functions, Al-Ahsa, PTF model, Statistical criteria**

## INTRODUCTION

The saturated water content of soil (θs) is defined as the maximum water content at which all pores are completely filled with water. In soil physics, geotechnical, and environmental studies, θs ($cm^3$ $cm^{-3}$) has emerged as an important and indispensable physical property that is included in almost all soil and liquid formulas and prediction models (Eyo et al., 2022; Fredlund et al., 2012; Zhai et al., 2020a). θs equates to porosity, the total volume of soil unoccupied by solid material and therefore available to liquids within a specific soil body (Hillel, 2013; Kirkham, 2014; Nimmo, 2013). The role of θs (total porosity ) and ϕ ($cm^3$ $cm^{-3}$) is well documented by many scientists in the soil-fluid process and equations in unsaturated media, hydrological studies, agricultural water relations, geotechnical aspects such as soil swelling and soil stability, soil conservation and erosion, and the environment such as contaminant movement (Adiaha et al., 2019; Brooks and Corey, 1964; Campbell and Shiozawa, 1992; Childs, 1940; Eyo et al., 2022; Fredlund and Anqing Xing, 1994; van Genuchten, 1980; Wang et ai., 2021; Zapata et al., 2000; Zhai et al., 2020b).

Over the past three decades, estimating θs using basic soil property information has been widely practiced (Khoshkroudi et al., 2013; Mayr and Jarvis, 1999; Rajkai et al., 2004; Sinowski et al., 1997; Vereecken et al., 1989; Williams et al., 1992; Wösten et al., 1999). Porosity ϕ was originally defined as one minus the solid volume fraction of a sample, which was derived from the bulk density ρb (gm $cm^{-3}$) and particle density ρs (gm $cm^{-3}$). The ratio of bulk density ρb to particle density ρs represents the proportion of total volume occupied by solids (Flint and Flint, 2018; Hillel, 2013; Nimmo, 2004). Total porosity ϕ is therefore equal to:

$$\theta_s = \emptyset = 1 - \frac{\rho_b}{\rho_s} \quad (1)$$

Mathematically, this equation works with idealized soil of packed uniform spheres. Real soil is influenced by irregular particle shape and size, compaction and density, organic carbon content, and clay mineral type and quantity, making the equation less than ideal (Nimmo, 2004; Vereecken et al., 1989). Many researchers have replaced particle density with a fixed number equal to 2.65 gm $cm^{-3}$(Campbell and Shiozawa, 1992; Oosterveld and Chang, 1980; Rawls and Brakensiek, 1985) :

$$\theta_s = \emptyset = 1 - \frac{\rho_b}{2.65} \quad (2)$$

Williams et al. (1992) modified equation 2 to fit their Australian soil samples (n=111), which consisted of a structured soil with a high proportion of clay as follows:

$$\theta_s = 0.93 \times (1 - \frac{\rho_b}{2.65}) \quad (3)$$

This factor (0.93) is used to climatize Equation 2 concerning the soil properties and local conditions; Model results have been validated by (Minasny et al., 1999). Using a simple linear equation Rubio (2008) determined that the best fit for θs with ρb for forest soils contained a silt content of 60%. He then developed the following equation with a high correlation coefficient:

$$\theta_s = 0.857 - 0.247\ \rho_b \quad (4)$$

Abdelbaki (2021) analyzed equation 4 for 2046 soil samples and concluded that the results were unsatisfactory. Liao et al. (2014) found a significant correlation between θs with ρb, and developed the following equation based only on ρb:

$$\theta_s = 1.034 - 0.460\ \rho_b \quad (5)$$

Al-Saeedi (2022) developed a local PTF for Al-Ahsa based on the value of ρb,:

$$\theta_s = 0.966 - 0.44370\ \rho_b \quad (6)$$

As a result of the analysis of data from 544 samples from north Munich, Sinowski et al. (1997) were able to improve the estimation of θs by considering the effect of clay:

$$\theta_s = 0.85 \times \left(1 - \frac{\rho_b}{2.65}\right) + 0.0013\ \text{clay} \quad (7)$$

Varallyay et al. (1982) realized the significance of clay percentage and ρb together as correlative variables with θs, and the following equation was included in the stepwise regression analysis:

$$\theta_s = 0.01\,(-56.4\rho_b + 0.00205\text{clay}^2 + 123.79) \quad (8)$$

Vereecken et al. (1989) applied a stepwise regression approach to 182 soil samples. They showed that clay percentage and ρb contributed significantly to estimating θs with no substantial improvement when other variables were added to the equation:

$$\theta_s = 0.81 - 0.283\,\rho_b + 0.001\,\text{clay} \quad (9)$$

Many researchers have employed this equation in their models and prediction models for estimating SWCC and saturated conductivity value (Guber et al., 2009; Liao et al., 2011; Schaap et al., 2001; Tomasella et al., 2000; Weynants et al., 2009). Weynants et al. (2009) modified Verbeeck's equation to account for soil changes and the characteristics of the soil to improve the results (Mohajerani et al., 2021):

$$\theta_s = 0.6355 + 0.0013\,\text{clay} - 0.1631\rho_b \quad (10)$$

Khoshkroudi et al. (2013) applied evolutionary polynomial regression (EPR) to produce a nonlinear equation linking θs with ρb and clay percentage:

$$\theta_s = 0.842 - 0.34\,\rho_b + 0.035\,\text{clay}^{0.25} \quad (11)$$

Compared to other widely used equations, he recorded a good result in his paper. Zacharias and Wessolek (2007) developed a PTF mode for high sand soils from s and b, which produced a satisfactory result (Mohajerani et al., 2021; Schweppe et al., 2022):

$$\theta_s = 0.890 + 0.001\,\text{clay} - 0.322\rho_b \quad \text{sand} > 66.5\% \quad (12)$$

Stolf et al. (2011) investigated the relationships between 10 soil samples and found that ρb and sand have significant correlations with θs; he also found that high compatibility has been found between measured and estimated θs:

$$\theta_s = 1.030 - 0.345\,\rho_b - 0.082\,\left(\frac{\text{sand}}{100}\right) \quad (13)$$

Cosby et al. (1984) also observed the effects of sand and used multiple linear regression analysis, which was conducted using the average value of 1448 samples distributed across 11 textural classes:

$$\theta_s = 0.505 - 0.00142\,\text{sand} - 0.00037\,\text{clay} \quad (14)$$

Moreover, Liao et al. (2011) found that the regression equation of θs was positively correlated with organic matter (OM) and negatively correlated with ρb. Therefore, ln OM and ln ρb together explained 58% of the variability observed in θs:

$$\theta_s = 0.591 + 0.027\,\ln \text{OM} - 0.651\,\ln\,\rho_b \quad (15)$$

Saxton et al. (1986) used sand and logarithm clay to represent the value of θs:

$$\theta_s = 0.332 - 0.0007251\text{sand} + 0.127\,\log_{10}\text{clay} \quad (16)$$

This equation has been widely used by many researchers with varying accuracy levels according to the soil's type and texture (Gijsman et al., 2002; Han et al., 2019; Sghaier et al., 2022; Silva et al., 2022). Wösten et al. (1999) used the subset selection method developed by Furnival and Wilson (1974) with a polynomial regression analysis of 5521 soil samples. They proposed a continuous pedotransfer function consisting of a variety of basic soil properties and interactions, all of which play an important role in the description of transformed model parameters:

$$\theta_s = 0.7919 + 0.001691\,\text{clay} - 0.29619\rho_b - 0.00000149\text{silt}^2 + 0.000821\text{OM}^2 + \frac{0.0242}{\text{clay}} + \frac{0.01113}{\text{silt}} + 0.01472\,\ln\text{silt} - 0.0000733\,\text{OM}\times\text{clay} - 0.000619\rho_b \times \text{clay} - 0.001183\rho_b \times \text{OM} - 0.0001664\text{Topsoil}\times\text{silt} \quad (17)$$

Several publications have used this equation, albeit with contradictory results (Dai et al., 2013; Guber et al., 2009; Hewelke et al., 2018; Matula et al., 2007; Mohajerani et al., 2021; Tomasella et al., 2000). Mayr and Jarvis (1999) similarly developed the multiple regression equation:

$$\theta_s = 0.2346 + 0.00466\,\text{sand} + 0.0082\text{silt} + 0.00643\text{clay} + 0.303\rho_b + 0.00001797\text{sand}^2 - 0.0000313\text{silt}^2 \quad (18)$$

Rajkai et al. (2004) developed a nonlinear continuous pedotransfer function for Hungary based on soil basic properties and Logarithms, squares, and ratios of original properties:

$$\theta_s = 123.76 - 65.37\rho_b - 0.20\,\text{OM} - 0.000048\text{clay}^2 - 1.99\ln\text{clay} + 12.46{\rho_b}^2 - 0.054\rho_b \times \text{sand} + 0.14\,\frac{\text{sand}}{\text{silt}} + 0.00049{\rho_b}^2 \times \text{clay}^2 \quad (19)$$

Rajkai's equation performed well in fine soils, while in coarse and medium soils, the result was poor (Abbasi et al., 2011; Mohamed and Ahmed, 2011). Al Majou et al. (2007) established a class PTF using 427 soils with high silt and clay with a mean content of 28.9% and 46.2%, respectively. This model was examined with a positive prediction (Abdelbaki, 2021a; Piedallu et al., 2011):

$$\theta_s = 1.1658 - 0.0032\,\text{clay} - 0.4737\rho_b + 0.0000002\text{sand}^2 - 0.0001\text{OM}^2 + 0.0373\text{clay}^{-1} + 0.013\text{sand}^{-1} - 0.0072\ln\text{sand} + .00003\text{OM}\times\text{clay} + 0.0022\rho_b \times \text{clay} - 0.0002\rho_b \times \text{OM} - 0.0001\text{sand} \quad (20)$$

Using 36 soils from China with sandy to loamy textures, Li et al. (2007) developed the following logarithmic multiple regression PTF model:

$$\theta_s = \exp(-1.531 + 0.212\ln\text{sand} + 0.006\text{silt} - 0.051\text{OM} - 0.566\ln\rho_b \quad (21)$$

It was argued by Saxton and Rawls (2006) in their comprehensive paper that the long PTF could be defined as:

$$\theta_s = y - 0.062 - 0.00097\text{sand} + 1.636[0.00278\text{sand} + 0.00034\text{clay} + 0.022\text{OM} - 0.00018\text{sand}\times\text{OM} - 0.00027\text{clay}\times\text{OM} - 0.0000584\text{sand}\times\text{clay} + 0.078] \quad (22)$$

Where:

$$y = x + (1.28x^2 - 0.374x - 0.015) \quad (23)$$

$$x = -0.00251\text{sand} + 0.00195\text{clay} + 0.011\text{OM} + 0.00006\text{sand}\times\text{OM} - 0.00027\text{clay}\times\text{OM} + 0.0000452\text{sand}\times\text{clay} + 0.299 \quad (24)$$

Several researchers have implemented this model (Abdelbaki, 2021a; Dai et al., 2013; De Girolamo et al., 2022; Guber et al., 2009). It is the effective estimation of θs that will have a direct effect on the accuracy of the SWCC prediction since 80% of the variance observed in SWCC prediction can be attributed to the inaccuracy of θs and ρb estimations(Mohajerani et al., 2021; Rajkai and Varallyay, 1992; Vereecken et al., 2010b). Due to the wide variation in soil physical and chemical properties and the high spatial variability, it is difficult to generalize one PTF model to all soils (Saxton and Rawls, 2006; Tomasella et al., 2000; Van Looy et al., 2017; Weynants et al., 2009). This study examined the validity of some of the most popular and commonly used PTFs in estimating θs, as well as their suitability for Al Ahsa soil.

## MATERIALS AND METHODS

Data from ten soil samples were collected from topsoil (0-20cm) from palm tree cultivated land in the eastern part of the Al-Ahsa oasis, Saudi Arabia. The Al-Ahsa oasis lies approximately 70 kilometers from the Arabian Gulf, between the latitudes of 25 21' and 25 37' N and the longitudes of 49 33' and 49 46' E. Available data included soil particle (sand, silt, clay) content, particle density θs, and saturation water content θs. The bulk density ρb was estimated using the localized PTF model developed by Al-Saeedi (2022). A descriptive statistical summary of the soil data is shown in Table 1.

Based on the available basic soil data, this study applied the PTF calculations (eq.1 - eq.22) to estimate θs. The results were subjected to a detailed statistical analysis to assess the validity of each PTF.

TABLE 1. DESCRIPTIVE STATISTICS OF THE PERCENTAGE OF SOIL SIZE CLASS (SAND, SILT, AND CLAY), BULK DENSITY (PS), PARTICLE DENSITY (PS), AND SATURATION (ΘS)

| Statistical# parameter | sand % | silt % | clay % | **$\rho_b$** g $cm^{-3}$ | **$\rho_s$** g $cm^{-3}$ | **$\theta_s$** $cm^3$ $cm^{-3}$ |
|---|---|---|---|---|---|---|
| ***n*** | 10 | 10 | 10 | 10 | 10 | 10 |
| **Max** | 97.50 | 10.00 | 10.00 | 1.597 | 2.053 | 0.421 |
| **Min** | 87.50 | 7.00 | 5.50 | 1.393 | 1.989 | 0.360 |
| **Mean** | 87.40 | 7.00 | 5.60 | 1.393 | 1.989 | 0.309 |
| **SD** | 4.162 | 1.972 | 3.116 | 0.127 | 0.065 | 0.018 |

#: *N*=NUMBER OF SOIL SAMPLES, MAX=MAXIMUM, MIN=MINIMUM, SD=STANDER DEVIATION

## STATISTICAL ANALYSIS

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According to Donatelli et al. (2004), limited testing makes it difficult for modelers to verify that the PTFs selected are sufficiently accurate. The more tests conducted in which the function is not demonstrably incorrect, the greater the degree of confidence in the function (Donatelli et al., 2004; Schaap, 2004). Various PTF models were evaluated using different statistical criteria, including correlation coefficient ($R^2$), root mean square error (RMSE), Nash-Sutcliffe model efficiency coefficient (NSE), a ratio of RMSE to standard deviation SD (RSR), percent bias (PB), and Akaike information criterion (AIC). A Pearson correlation coefficient analysis examined the relationships between laboratory-measured values and estimated values derived from the PTF model using equation. 25:

$$R^2 = \left[\frac{\sum_{i=1}^{N}(x_i-\hat{x})(y_i-\hat{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\hat{x})^2(y_i-\hat{y})^2}}\right]^2 \quad (25)$$

The xi and yi are measured and estimated variables, respectively, x̂ and ŷ mean.

The root mean square (RMSE) is a commonly used metric for computing the variance between predicted and measured values of a model or predictor. Compared with other models, ideal models should have a minimum positive RMSE value (Schaap, 2004).

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n}\frac{(x_i-y_i)^2}{n}} \quad (26)$$

n equals the number of samples.

To provide reliable information on the overall success of a model, an NSE (Nash-Sutcliffe efficiency) is recommended as one of the most appropriate objective functions (Legates and Mccabe, 1999; McCuen et al., 2006; Nash and Sutcliffe, 1970; Willmott, 1981). Nash-Sutcliffe efficiency (NSE) is defined as a normalized statistic that represents the relative magnitude of residual variance ("noise") relative to the predicted data variance (Moriasi et al., 2007b). According to Nash and Sutcliffe (1970), NSE is a measure of how well the plot of observed and predicted data fits a 1:1 curve, ranging from minus infinity to one (-∞ to 1.0), with higher values indicating greater agreement, Table 1 summarizes the level of model validity. Therefore, a zero value indicates that the observed mean is as good a predictor as the model, while negative values indicate the observed mean is a better predictor (Wilcox et al., 1990).

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}(x_i-y_i)^2}{\sum_{i=1}^{n}(x_i-\hat{x_i})^2} \quad (27)$$

Moriasi et al. (2007a) have presented guidelines for assessing the prediction model's accuracy. To assess the validity of the model fitting, he used an equation (26) based on the ratio of the RMSE to the standard deviation SD of the measured data (Table 1).

$$RSR = \frac{MRSE}{SD_{mes}} = \frac{\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2}}{\sqrt{\sum_{i=1}^{n}(x_i-\hat{x_i})^2}} \quad (28)$$

The percent bias (Pb) reflects the tendency for predictions to overestimate or underestimate their measured counterparts. The ideal value is 0.0. Positive values indicate an underestimation bias, whereas negative values indicate an overestimation bias (Gupta et al., 1999; Moriasi et al., 2007b). The form of the PB equation:

$$\text{PB} = \left[\frac{\sum_{i=1}^{n}(y_i-\bar{y}_i)\times 100}{\sum_{i=1}^{n}y_i}\right] \quad (29)$$

The AIC (Akaike Information Criterion) is a statistical tool used for comparing and selecting the best candidate model among several alternatives. In AIC, the goal is to select a model that best explains the variance of the dependent variable using the fewest number of independent variables (parameters). Selecting AIC reduces the complexity of the model, which can lead to overfitting and reduce the number of unwanted parameters, which can result in additional noise affecting the model's fit. (Akaike, 1974).

$$AIC = n \times ln(\frac{SS_e}{n}) + 2k \quad (30)$$

SSe is the sum square of errors, n is the number of observations, and k is the number of parameters.

TABLE 2. THE CLASSIFICATION OF STATISTICAL CRITERIA FOR MODEL VALIDITY, NSE (NASH–SUTCLIFFE EFFICIENCY) AND RSR (RATIO OF RMSE TO THE STANDARD DEVIATION SD)

| Statistical criteria | Very good | Good | Satisfactory | Unsatisfactory |
|---|---|---|---|---|
| NSE [1] | 1-0.75 | 0.75-0.65 | 0.65-0.50 | ≤ 0.50 |
| RSR [2] | 0-0.50 | 0.50-0.60 | 0.60-0.70 | ≥ 0.70 |

1) According to Gupta et al., 1999; Moriasi et al., 2015.
2) According to: Beharry et al., 2021; Carlos Mendoza et al., 2021.

## RESULTS

Based on statistical criteria, the evaluations of all PTFs examined showed unsatisfactory results, except for equation 6 (Table 3 and Figure 1). Table 3 shows that equation 6 found that the $R^2$ value was highly significant (p=0.01), equal to 0.872. The MRSE was low at 0.024, and the NSE was detected with a reliable estimation PTF model of 0.705. The RSR accuracy was good at 0.516. PB% underestimation PTF was detected with 3.269%, and the AIC value was the lowest (-73.003) of all equations.

In spite of the significant correlation coefficients $R^2$ (p=0.05) for equations 10, 11, 16, 18, 21, and 22 with values of 0.401, 0.477, 0.478, 0.391, 0.446, and 0.484 respectively. The low MRSE values were recorded 0.040, 0.051, 0.034, 0.055, 0.097, and 0.100, respectively for the same equations. The results from the other statistical criteria were dissatisfactory, according to Table 3. Low NSE (-0.415) and PB values also struggled between high overestimation for equations 10, 18, 21, and 22 with values of -8.645%, -8.127%, -23.711%, and -25.941%, respectively, and underestimate for equations 11 and 16 with values of 3.243% and 1.892% respectively. Equation 14 showed a low correlation significance (p=0.1), $R^2$ equal to 0.341, MRSE equal to 0.045. However, NSE and RSR were -0.079 and 0.986, respectively, reflected in the PB value with an overestimate of -5.286%. The remainder of equations 1-5, 7-9, 12, 13, 15, 17, 19, and 20 did not demonstrate any statistical significance, nor did they meet any of the statistical criteria used in this study.

TABLE 3. STATISTICAL PERFORMANCES CRITERIA OF ASSESSED PTFS FOR PREDICTING SOIL SATURATION ΘS VALUES USING TEN SOIL SAMPLES PTFS

| PTFs Eq. No[1] | No. of variable | $R^2$ | MRSE | NSE | RSR | PB % | AIC |
|---|---|---|---|---|---|---|---|
| Eq.1 | 2 | 0.045 | 0.177 | -15.735 | 3.881 | 46.676 | -30.634 |
| Eq.2 | 1 | 0.036 | 0.056 | -0.680 | 1.229 | -9.537 | -55.624 |
| Eq.3 | 1 | 0.036 | 0.045 | -0.070 | 0.982 | -1.869 | -60.128 |
| Eq.4 | 1 | 0.036 | 0.110 | -5.439 | 2.407 | -27.965 | -42.185 |
| Eq.5 | 1 | 0.036 | 0.078 | -2.279 | 1.718 | 17.892 | -48.935 |
| **Eq.6** | 1 | 0.872 | 0.024 | 0.705 | 0.516 | 3.269 | -73.003 |
| Eq.7 | 2 | 0.197 | 0.045 | -0.082 | 0.987 | 4.870 | -56.022 |
| Eq.8 | 2 | 0.014 | 0.052 | -0.440 | 1.138 | 7.403 | -58.022 |
| Eq.9 | 2 | 0.152 | 0.042 | 0.059 | 0.920 | -0.393 | -59.420 |
| **Eq.10** | 2 | 0.401 | 0.040 | -0.415 | 1.128 | -8.645 | -55.339 |
| **Eq.11** | 2 | 0.477 | 0.051 | 0.135 | 0.882 | 3.243 | -60.261 |
| Eq.12 | 2 | 0.265 | 0.047 | -0.178 | 1.030 | -2.111 | -57.167 |
| Eq.13 | 2 | 0.174 | 0.061 | -1.010 | 1.345 | -12.396 | -51.827 |
| Eq.14 | 2 | 0.341 | 0.045 | -0.079 | 0.986 | -5.286 | -58.048 |
| Eq.15 | 2 | 0.036 | 0.075 | -1.974 | 1.636 | 16.671 | -47.909 |
| **Eq.16** | 2 | 0.478 | 0.034 | 0.389 | 0.742 | 1.892 | -63.732 |
| Eq.17 | 5 | 0.246 | 0.046 | -0.118 | 1.003 | 1.277 | -51.691 |
| **Eq.18** | 4 | 0.391 | 0.055 | -0.632 | 1.212 | -8.127 | -49.909 |
| Eq.19 | 5 | 0.261 | 0.087 | -3.012 | 1.900 | -17.809 | -38.917 |
| Eq.20 | 4 | 0.193 | 0.054 | -0.544 | 1.179 | -5.215 | -50.462 |
| **Eq.21** | 4 | 0.446 | 0.097 | -3.988 | 2.119 | -23.711 | -38.739 |
| **Eq.22** | 4 | 0.484 | 0.100 | -4.340 | 2.192 | -25.941 | -38.057 |

1) Underline: correlation significant p=0.1, Bold= correlation significant p=0.05, Underline and bold: correlation significant p=0.01 and satisfy for all statistical criteria.

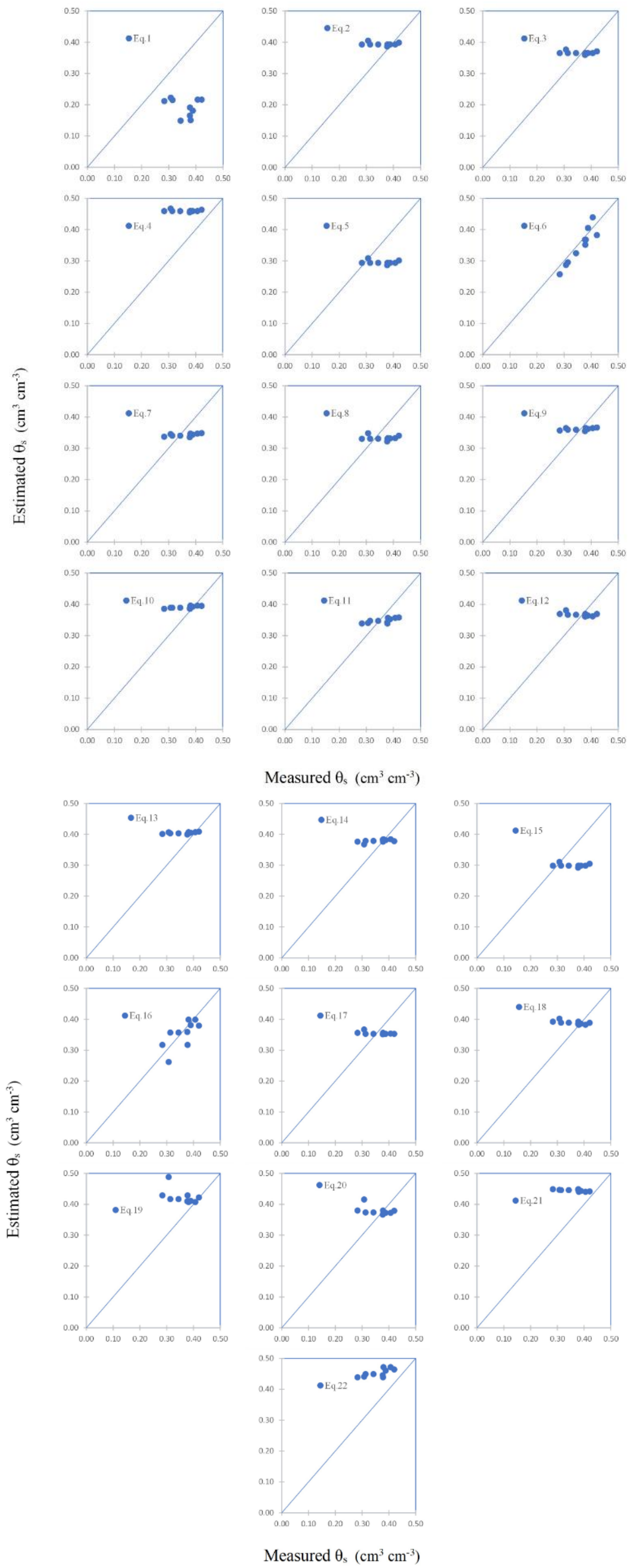


Fig. 1 Estimated versus measured saturation θs using 22 PTFs equation.

## DISCUSSION

This study revealed inconsistent and conflicting results. The only PTF that showed a significant correlation with satisfied statistical criteria was equation 6. This PTF was based on ρb estimated from the silt percentage described with local origin advantage. In his study of Al-Ahsa soil, Al-Saeedi (2022) found a significant relationship between θs and sand, silt, and ρb, whereas clay did not show any significant relationship. Consequently, clay was not a primary elementary estimator for this type of soil, which could explain the poor results of other PTFs based, directly or indirectly, on clay and organic matter as factor estimators.

Equations 1, 2, and 3 were based on ρb, which Ungaro and Calzolari (2001) considered responsible for half of the deviation in PTF models, and the measured or assumed value for ρs (2.65 gm $cm^{-3}$). Both approaches had poor performance due to the only consideration of solid mass occupation being within the solid volume without any consideration of particle irregularities, particle packing (structure), chemical and mineralogical effects, and organic matter effects (Dai et al., 2013; Nimmo, 2013; Perreault et al., 2022). This was attempted through equation 3 by multiplying by 0.930 to overcome these effects, but this customization was not suitable for the used samples, which were dominated by clay (Deng et al., 2009; Williams et al., 1992).

Equations 4 and 5 were derived from a simple linear regression equation model. Rubio (2008) used soil samples with high silt and clay content of approximately 75% and high organic matter content, creating a structure-forming effect (Rawls et al., 2003). That effect played a significant role in increasing the water retention capacity, especially from saturation to the field's capacity Rubio (2008). Thus, the overestimation of equation 4 is due to the equation's high slope and low interception values incorporating the nonphysical effects of low silt and clay content and organic matter in this study.

Equation 5 performed poorly due to the training dataset's clay and silt contents of greater than 50% and OM 1.35%. Equations 7 through 12 included clay as an additional estimator to ρb. The combination of clay and ρb may be effective only if clay is a dominant component of the soil and is significantly related to ρb (Esmaeelnejad et al., 2015; Khoshkroudi et al., 2013; Weynants et al., 2009), which was not the case in this study as sand was predominate.

In related work, the clay percentage and coefficient of variation ρb are the most frequently used predictors in most PTFs (Abdelbaki, 2018; Perreault et al., 2022; Rawls and Brakensiek, 1985; Saxton et al., 1986; Vereecken et al., 1989; Weynants et al., 2009). All PTF samples (equations 7-12) shared high silt and clay content, while all PTFs reported catastrophic estimates which were validated previously (Abbasi et al., 2011; Abdelbaki, 2021a; Botula et al., 2012; Liao et al., 2011; Nasta et al., 2021; Patil et al., 2016; Tomasella et al., 2000; Ungaro and Calzolari, 2001; Vereecken et al., 1992; Weihermüller et al., 2021; Weynants et al., 2009). There was a contradiction in PB%, which indicated that each equation was calibrated with a coefficient to fit its training samples, making it complex to replicate the same results with other soil.

In equations 13 and 14, sand was used as a predictor in a stepwise regression equation with b and clay. The first PTF (equation 13) used ten samples focusing on macro and micropores, which should logically be more affected by sand percentage. Stolf deliberately selected sand rather than clay with six soil samples greater than 50% sand (Stolf et al., 2011). Stolf et al. (2011) showed that the PTF (eq.13) was built around clay and not sand. The low accuracy of Cosby et al. (1984) PTF (eq. 14) can be attributed to its construction, as it was designed on the correlation between groups rather than within the group. It provided a general indication of the group effect but did not apply to individual predictions within the group (Marzban et al., 2013). There is a disagreement between the estimation result of equation 14 and the measured result reported in many previous studies (Dai et al., 2013; Schaap et al., 1998; Sobieraj et al., 2001; Zuo and He, 2021), Liao et al. (2011). As Liao et al. (2011) described, PTF (eq. 15) is based on the inverse relationship between OM and ρb. Consequently, an error in estimating the soil's understudy will occur, especially when OM and ρb are absent.

Saxton et al.'s(1986) PTF (equation 15) model was based on the mean of ten soil texture parameters. As stated previously, the correlation between groups was not always successful in estimating differences between groups. One of the major criticisms of this equation was the use of (eq. 2) to estimate the θs in the training dataset rather than actual measurement (Saxton et al., 1986; Saxton and Rawls, 2006). Tomasella et al. (2000) stated that overestimation errors increased as fine particles percentage decreased, agreeing with this study's findings and other researchers (Abdelbaki, 2021a; Dai et al., 2013; Nasta et al., 2021). Wösten et al. (1999) PTF (eq. 17) showed unsatisfying negative NSE with RSR > 1.0 and confirmed the unreliability of this model in estimating θs, despite a significant correlation with the relatively low MRSE. Despite the large database used to generate the PTF and its wide acceptance, the poor accuracy of estimation was reported by many researchers (Abbasi et al., 2011; Abdelbaki, 2021b; Matula and Špongrová, 2007; Piedallu et al., 2011; Weihermüller et al., 2021; Weynants et al., 2009; Zou et al., 2016). The Mayr PTF (eq. 18) performed well with fine particles, but with coarse and fine sand, a high error rate was observed (Abdelbaki, 2021b; Mayr and Jarvis, 1999).

Equations 19 and 20 used OM, ρb, and clay as the main variables in a polynomial equation. Both PTFs performed poorly with recent soil samples, as other researchers have already reported (Abbasi et al., 2011; Abdelbaki, 2021b; Cueff et al., 2021; Dai et al., 2013; Zou and Leong, 2019). (Li et al., 2007) PTF (eq. 21) Li generated his PTF on soils with low organic matter and 50% sand, implying a significant correlation, but with high MRSE and overestimate results, as evaluated by others (Abdelbaki, 2021a; Zou et al., 2016). Saxton and Rawls (2006) developed the most comprehensive spared continuous PTF for the last fifteen years (eq. 22). OM played an important role in this PTF, which can also be the primary source of deficits. However, other statistical criteria were inadequate and invalid. Despite this, the model has been implemented in many simulation cases. Many researchers have questioned the validity of using (Abdelbaki, 2021a; Antinoro et al., 2008; Castellini and Iovino, 2019; Kalumba et al., 2021; Karim and Fattah, 2020; Mohamed and Ali, 2006; Perreault et al., 2022).

The deviation of the referenced PTFs could be based on the following justifications:

- All PTFs, except Stolf et al. (2011) (eq. 13), were derived from soils with fine particle means greater than 50%. Some PTFs used fine particle means greater than 70% (equations 4, 11, and 19) or soils with organic matter contents greater than 1% and ρb greater than 1.4 gm $cm^{-3}$. According to the above information, the soil is moderately compacted and well-structured. Moreover, the land is either long-term pasture, long-term agriculture, or long-term forest with a few desert areas. These factors significantly influenced water content near and at saturation (Esmaeelnejad et al., 2015; Gupta and Larson, 1979; Minasny and McBratney, 2018; Myeni et al., 2021; Nemes and Rawls, 2006; Vereecken et al., 2010a). Indirectly, these factors, OM and structure, determined the constant values required to calibrate the PTF model (intercept and slope) to match the measured data during regression analysis.
- All PTFs neglected to consider other physiochemical effects, such as CaCO3, pH, and CEC, which are already accepted as major contributors to the value of water content at saturation (Al-Saeedi, 2022; Lake et al., 2009; Tomasella and Pachepsky, 2003).
- Different textural classifications were used to represent particle-size distributions across different countries and institutes, representing a major challenge for validating a single source of particle-size distributions globally (Minasny et al., 1999; Nemes et al., 1999; Xu et al., 2021).
- The adaptation of PTFs to soils other than those under which they were developed leads to high uncertainties and deviations (McBratney et al., 2011; Medeiros et al., 2014; Rubinić et al., 2022; Zhai et al., 2020a). Most PTF models have been derived from linear and stepwise multiple regression equations using backward elimination (equations 3-7, 9, 10 and 12-14) and polynomial regression using a subset of basic soil properties and interactions (equations 8, 11, 15-22). These models are disadvantaged due to highly sensitive to outliers in the data, severely affecting their performance and leading to models with insufficient accuracy (Iqbal, 2021). Consequently, every PTF is worthless as it is based on the specific conditions of the calibration dataset, which reflect local and regional soil properties and conditions.
- Using $R^2$ alone is insufficient to assess the model estimation accuracy without considering other statistical criteria (Hagquist and Stenbeck, 1998; Krause et al., 2005). Not MRSE, since it does not indicate the quality of a fit, as long as it is not zero (Hagquist and Stenbeck, 1998). (Tietje and Tapkenhinrichs, 1993) listed different RMSE values for 13 PTF models as the maximum acceptable value. There is no statistical basis for determining and differentiating these values. Introducing another statistical criterion to evaluate model uncertainty is necessary (de Almeida et al., 2018; Krause et al., 2005; Moriasi et al., 2015). NSE is an effective method of characterizing good points around the identity line in a PTF model. Table 2 indicates that the NSE values (Table 2) ranged from -∞ to 1. A value equal to 1 indicates perfect modeling. A value equal to or below 0 indicates that the mean of measured values is an equivalent or better estimator than the PTF model estimation (Gupta et al., 1999; Moriasi et al., 2015). Additionally, the application of RSR will determine the highest primitive value of MRSE required to qualify the PTF model (Beharry et al., 2021; Carlos Mendoza et al., 2021). Most of these models may be excluded entirely or have their reliability level reduced if these criteria are applied.

## CONCLUSION

Ten soil samples of sandy and loamy sand were subjected to a θs estimation process using 22 PTF models. A detailed statistical analysis of uncertainty was used to assess the validity of these models. Only one PTF model, equation 6, was valid and met all the statistical criteria. The traditional statistical measures of correlation and RMSE values proved they were not enough by themselves to prove the PTF model. This study emphasized the importance of using the locally developed PTF model to eliminate the uncertainty between the general nature of soils to avoid multi subset equations with many variables and avoid error propagation.

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# تقييم لنماذج مختلفة من معادلات التنبؤ بالسعة التشييبعية باستخدام البيانات الاساسية لقوام التربة، الاحساء، المملكة العربية السعودية

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***مستخلص.*** قيمت هذه الدراسة دقة ٢٢ دالة من دوال التنبؤ المنشورة (PTFs) لتقدير تشبع التربة (θs) والتي تم تقييمها باستخدام عينات التربة المحلية (عدد الترب = ١٠ عينات) من منطقة الأحساء. أظهرت النتائج فقط أن نموذج PTF الذي طوره السعيدي (٢٠٢٢ م) يفي بمعايير أداء التقييم المطبقة ( $R^2 = 0.872$، RMSE = 0.024، NSE = 0.705 ، و RSR = 0.506) حيث $R^2$، RMSE، NSE ، و RSR يعني معامل الارتباط ، متوسط الجذر التربيعي ، كفاءة Nash-Sutcliffe ، ونسبة RMSE إلى الانحراف المعياري SD ، على التوالي. لم تستوف المعادلات الـ ٢١ الأخرى المعايير الموثوقة والتحقق من النموذج المطلوبة. أعطت هذه الدراسة أيضًا نتيجة حاسمة: لابد من استخدام معايير إحصائية إضافية بدلاً من قياس الارتباط والخطأ في تقييم والتحقق من صحة النموذج المناسب.

**الكلمات المفتاحية:** دوال Pedotransfer ، الأحساء ، نموذج PTF ، المعايير الإحصائية