

# Pedotransfer functions for estimating saturated hydraulic conductivity of selected benchmark soils in Ghana

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## ABSTRACT

**Aims:** Direct methods of measuring saturated hydraulic conductivity ( $K_s$ ), either in situ or in the laboratory, are time consuming and very expensive. Several Pedotransfer functions (PTFs) are available for estimating  $K_s$ , with each having its own limitations. In this study, the performances of four popular PTFs were evaluated on different soil classes. The PTFs considered herein were Puckett et al. (1985), Campbell and Shiozawa (1994), Dane and Puckett (1994), and Ferrer-Julià et al. (2004). In addition, five local data derived PTFs were used to study the possibility of using local datasets to validate PTF accuracy.

**Materials and methods:** A total of 450 undisturbed soil cores were collected from the 0 – 15 cm depth from a Stagni-Dystric Gleysol, Plinthi Ferric Acrisol and Plinthic Acrisol. The  $K_s$  of samples were measured by falling-head permeameter method in the laboratory. Sand, silt and clay fractions, bulk density, organic matter content, and exchangeable calcium and sodium were measured and used as input parameters for the derived PTFs. Accuracy and reliability of the predictions were evaluated by the root mean square error (RMSE), coefficient of correlation ( $r$ ), index of agreement ( $d$ ), and the Nash-Sutcliffe efficiency (NSE) between the measured and predicted values. The relative improvement ( $RI$ ) of the derived PTFs from this study over the existing ones were also evaluated.

**Results:** The derived PTFs in this study had good prediction accuracy with  $r$ ,  $d$ , RMSE and NSE ranging from 0.80 – 0.99, 0.79 – 0.94, 0.14 – 1.74 and 0.84 – 0.98, respectively, compared with 0.32 – 0.45, 0.27 – 0.50, 4.00 – 4.90 and 0.41 – 0.47 for the tested PTFs. The relative improvement of the derived over the tested PTFs ranged from 56.50 – 95.71% in the Stagni-Dystric Gleysol, 70.73 – 96.89% in the Plinthi Ferric Acrisol, and 65.37 – 95.81% in the Plinthic Acrisol. Generally,  $RI$  was observed to be highest for Model 1 in the Stagni-Dystric Gleysol, and Model 4 in both Plinthic Ferric Acrisol and Plinthic Acrisol, and lowest for Model 5 in all three soils. It was observed that the inclusion of exchangeable calcium and sodium as predictors increased the predictability of the derived PTFs.

11  
12 *Keywords: Clay, Pedotransfer function, Saturated hydraulic conductivity, Sand*

## 1. INTRODUCTION

14 Hydraulic conductivity is a major parameter in all hydrological models, spanning from  
15 physically-based, fully-distributed small-catchment models to land surface parameterizing  
16 schemes of general circulation or global climate models [1, 2]. Hydraulic conductivity in  
17 saturated soils, referred to as the saturated hydraulic conductivity ( $K_s$ ) is very crucial in soil  
18 and water management with regard to ecology, agriculture and the environment [3, 4]. In  
19 addition, it is a very significant parameter in the study of processes such as infiltration,  
20 irrigation and drainage, runoff and erosion, and heat and mass transport in top soils, and  
21 solute transport in soils [5 – 7]. However, direct determination of  $K_s$  under both field and  
22 laboratory conditions can be very tedious, time constraining, and cost inefficient, especially  
23 over large scales [8], and may often result in unreliable data due to soil heterogeneity and  
24 experimental errors. As a result, indirect methods often adopted estimate  $K_s$  from other soil

25 properties. These are categorized into three, namely, pore-size distribution models, inverse  
26 methods, and pedotransfer functions [1, 9].

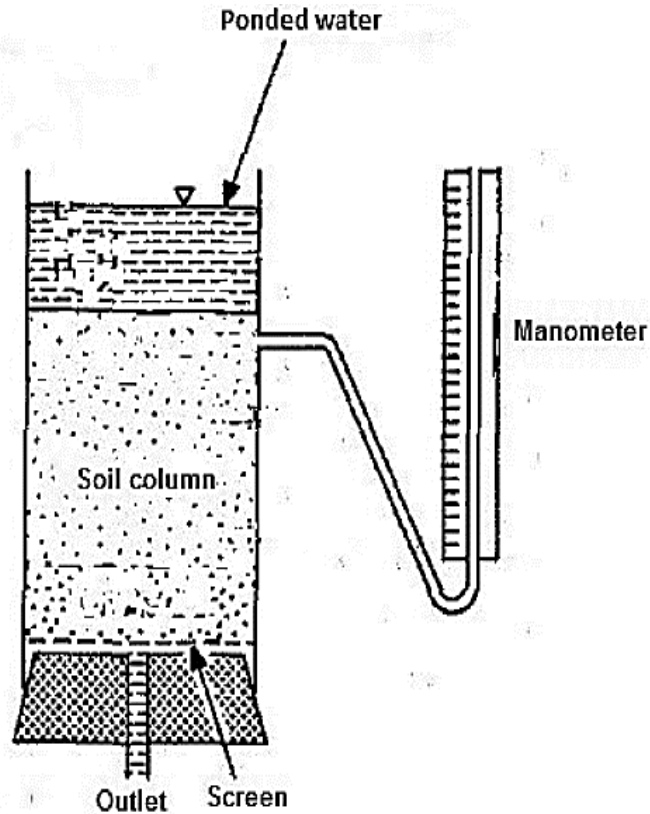
27 Pedotransfer functions are mainly empirical; however, physico-empirical models and fractal  
28 theory models are also available [10]. They are generally employed for estimating hydraulic  
29 properties from soil properties such as soil texture, bulk density, organic matter content, and  
30 water retention [1, 10, 11]. According to Schaap [11] any PTF may belong to one of three  
31 main groups, namely, Class PTFs, Continuous PTFs, and Neural network analysis-derived  
32 PTFs. The Class PTFs [e.g. 12 – 14] are based on the similar media theory [15], wherein,  
33 similar soils are assumed to exhibit similar hydraulic properties. Continuous PTFs, which are  
34 mainly derived from linear and nonlinear regression models, show a continuous trend of  
35 variations among estimated hydraulic properties for defined textural classes [16]. All PTFs  
36 are developed from data obtained from a small number of soil samples, and usually do not  
37 account for soil structural heterogeneities, which may result in less accurate or poor  
38 predictions when applied to soils different from those from which they were developed [7,  
39 17]. This implies that the prediction accuracy of PTFs depends on the similarity between the  
40 soils from which they were developed and tested [18]. Inclusion of extra basic soil  
41 properties, such as bulk density, porosity, organic matter content, water retention  
42 parameters [19 – 22], and exchangeable sodium and calcium may improve the prediction  
43 performance of such models. It is therefore, important to evaluate how well PTFs will  
44 perform when applied outside the range of the data that were used to derive them, and to  
45 make appropriate modifications where necessary. The objectives of the study were to:

- 46 i. Evaluate the general reliability of four most commonly cited PTFs to predict  $K_s$  of  
47 selected Ghanaian soils, where climatic and geological conditions are different from  
48 where they were developed and tested;
- 49 ii. Derive and verify, for selected benchmark soils in Ghana, more accurate PTFs to  
50 estimate  $K_s$ ;
- 51 iii. Test whether the inclusion of exchangeable Na and Ca as input parameters would  
52 improve the accuracy of the derived PTFs.

## 53 **2. MATERIAL AND METHODS**

### 54 **2.1 Soil sampling, analysis and characterization**

55 A set undisturbed soil samples were collected from the surface 0 – 15 cm depth with a core  
56 sampler of 10 cm diameter and 30 cm height. The soils were classified as Stagni-Dystric  
57 Gleysol, Plinthi Ferric Acrisol and Plinthic Acrisol. In total, 450 undisturbed cores and two  
58 sets of 450 disturbed samples were collected. One set of the disturbed samples was oven-  
59 dried and used for the determination of bulk density; the other set was air-dried and sieved  
60 through a 2 mm sieve. The disturbed samples were used for the determination of particle  
61 size distribution, pH, organic matter content, exchangeable sodium, calcium, magnesium,  
62 and potassium, cation exchange capacity, exchangeable sodium percentage and sodium  
63 absorption ratio. The undisturbed cores were used for the laboratory measurements of  
64 saturated hydraulic conductivity. Soil bulk density was estimated based on the weight of soil  
65 core samples after correcting for soil moisture and the mass and volume of roots and stones  
66 [23]. Saturated moisture content was assumed to be equal to the total porosity [24, 25].  
67 Particle size analysis was determined by the hydrometer method. The saturated hydraulic  
68 conductivity was determined on laboratory soil columns with the falling head permeameter  
69 (Figure 1) [2, 26]. Measured properties of the soil classes are presented in Table 1. The soil  
70 textures were sandy, sandy loam, and loamy sand.



71

72 **Figure 1.** Laboratory setup for the determination of saturated hydraulic conductivity  
 73 Source: Tuffour et al. [27]

74 **2.1.1 Collection of soil cores**

75 Soil sampling was done as described by Tuffour [2]. Undisturbed soil cores were collected  
 76 from the fields using a 10 cm diameter PVC pressure sewer pipe and a height of 30 cm and  
 77 beveled on the outer part of one end to provide a cutting edge to facilitate the insertion of  
 78 the core. Soil cores were collected by first digging a circular trench around an intact "pillar"  
 79 of undisturbed soil which was taller and had a slightly larger diameter than the core sampler.  
 80 The core sampler was then inserted directly into the pillar of soil by striking a wooden plank  
 81 positioned across the top of the ring, with a mallet. By this, the edges of the pillar were  
 82 allowed to fall away from the core as it was inserted. Following complete insertion, the core  
 83 was excavated by hand. A sealant (herein, paraffin wax) was used to ensure good contact  
 84 between the soil and core, and thereby minimised any edge flow resulting from an air  
 85 annulus created by the inner ring down the core.

86 **2.1.2 Determination of saturated hydraulic conductivity**

87 Determination of  $K_s$  was done as described by Tuffour [2]. Undisturbed soil cores samples  
 88 were soaked for 24 hours in water until they were completely saturated. The saturated core  
 89 was gently placed on gravel supported by a plastic sieve. The set up was placed in a sink,  
 90 and water was gently added to give hydraulic head in the extended cylinder. The fall of the  
 91 hydraulic head ( $h_t$ ) on the soil surface was measured as a function of time ( $t$ ) using a water  
 92 manometer with a 5-meter scale (Figure 1). Saturated hydraulic conductivity was calculated  
 93 by the standard falling head equation given as:

$$K_s = \left( \frac{aL}{At} \right) \ln \left( \frac{h_o}{h_t} \right); \quad (1)$$

94 where,

95  $a$  = Surface area of the cylinder [ $L^2$ ]

96  $A$  = Surface area of the soil [ $L^2$ ]

97  $h_o$  = Initial hydraulic head [L]

98  $L$  = Length of the soil column [L]

99  $h_t$  = Hydraulic head after a given time  $t$  [L]

100 Rewriting equation (1), a regression of  $\ln\left(\frac{h_o}{h_t}\right)$  on  $t$  with slope  $b = K_s \left(\frac{A}{La}\right)$  was obtained.

101 Since  $a = A$  in this particular case,  $K_s$  was simply calculated as:

$$K_s = bL \quad (2)$$

102 The measurement data on soil properties from the present study are presented in the  
103 following Table 1.

104 **Table 1. Soil property ranges of the datasets soil types**

Soil property	SDG	PFA	PA
Sand (%)	87.73 ± 2.82	68.45 ± 4.89	77.65 ± 4.67
Silt (%)	9.30 ± 2.62	13.74 ± 3.87	12.55 ± 4.03
Clay (%)	3.11 ± 0.93	17.80 ± 2.80	9.79 ± 2.26
Texture	Sandy	Sandy loam	Loamy sand
BD ( $g/cm^3$ )	1.70 ± 0.12	1.40 ± 0.10	1.20 ± 0.08
$K_s$ (cm/min)	4.14 ± 0.40	4.14 ± 0.36	4.12 ± 0.36
OM (%)	0.98 ± 1.52	3.77 ± 1.32	2.40 ± 0.84
Exch. Na (cmol/kg)	0.04 ± 0.018	0.02 ± 0.01	0.04 ± 0.02
Exch. Ca (cmol/kg)	1.50 ± 0.41	4.87 ± 1.25	7.34 ± 1.84

105 SDG = Stagni-Dystric Gleysol; PFA = Plinthi Ferric Acrisol; PA = Plinthic Acrisol; BD = Bulk  
106 density ( $g/cm^3$ );  $K_s$  = Saturated hydraulic conductivity (cm/min); OM = Organic matter (%);  
107 Exch. Na and Ca = Exchangeable sodium and calcium (cmol/kg)

## 108 2.2 Pedotransfer functions (PTFs)

109 Saturated hydraulic conductivity was predicted by relating it to basic soil properties using  
110 PTFs. The commonly cited PTFs evaluated were those developed by Puckett et al. [28],  
111 Campbell and Shiozawa [29], Dane and Puckett [30], and Ferrer-Julà et al. [31] as  
112 presented in equations (3 – 6), respectively:

$$113 K_s = 156.96 \exp[-0.1975Cl] \quad (3)$$

$$114 K_s = 54 \exp[-0.07S_a - 0.167Cl] \quad (4)$$

$$115 K_s = 303.84 \exp(-0.144Cl) \quad (5)$$

$$116 K_s = 2.556 \times 10^{-7} \exp(0.0491S_a) \quad (6)$$

117 Additionally, five new PTFs, (Equations 7 – 11), were derived using multiple linear  
118 regression (MLR) to relate  $K_s$  to particle size distribution, bulk density, exchangeable sodium  
119 and cation, and organic matter content. The derived PTFs (Equations 7 – 11) in this study  
120 are:

121 Model 1:  $K_s = 0.046158S_a + 0.008362S_i + 0.107176Ca - 1.121352Na$  (7)

122 Model 2:  $K_s = 0.02256S_i + 0.06784Cl + 0.29335OM + 0.14592Ca + 33.75189Na$  (8)

123 Model 3:  $K_s = 0.1832Cl + 40.9297Na$  (9)

124 Model 4:  $K_s = 2.743BD + 1.123Na$  (10)

125 Model 5:  $K_s = 0.45615Ca + 37.403333Na$  (11)

126 where,  $K_s$  = Saturated hydraulic conductivity [L/T];  $S_a$  = Sand content;  $S_i$  = Silt content;  $Cl$  =  
 127 Clay content;  $BD$  = Bulk density;  $OM$  = Organic matter;  $Na$  = Exchangeable sodium;  $Ca$  =  
 128 Exchangeable calcium

129 The first model (Model 1) uses sand, silt percentages, and exchangeable calcium and  
 130 sodium contents. The second model (Model 2) uses silt and clay percentages, organic  
 131 matter, and exchangeable calcium and sodium contents. The third model (Model 3) uses  
 132 clay percentage and exchangeable sodium content. The fourth model (Model 4) uses bulk  
 133 density and exchangeable sodium content. The fifth model (Model 5) uses exchangeable  
 134 calcium and sodium contents.

### 135 2.3 Performance evaluation of the PTFs

136 In order to evaluate the performance of the PTFs in predicting  $K_s$ , the  $K_s$  values estimated  
 137 from the derived and tested PTFs were compared to the laboratory measured  $K_s$  values,  
 138 and assessed with the root mean square error (RMSE) (Equation 12), index of agreement  
 139 ( $d$ ) (Equation 13), correlation coefficient ( $r$ ) (Equation 14), relative improvement ( $RI$ )  
 140 (Equation 15), and Nash–Sutcliffe efficiency (NSE) (Equation 16). The  $d$  statistic was used  
 141 to avoid problems related with coefficient of determination ( $R^2$ ).

$$RMSE = \left[ \frac{1}{n} \sum_{i=1}^n (d_s - d_o)_i^2 \right]^{1/2} \quad (12)$$

$$d = 1 - \left( \frac{\sum_{i=1}^n (d_s - d_o)_i^2}{\sum_{i=1}^n [(d_s - \bar{d}_o)_i + (d_o - \bar{d}_o)_i]^2} \right) \quad (13)$$

142 where,  $n$  = Number of observations;  $d_o$  = Observed data;  $d_s$  = Simulated data

$$r = \sqrt{1 - \frac{SSE}{SST}} \quad (14)$$

143 where,  $SSE$  measures the deviations of observations from their predicted values and  $SST$  is  
 144 a measure of the deviations of the observations from their mean.

$$RI = \left( \frac{RMSE_E - RMSE_D}{RMSE_E} \right) \times 100 \quad (15)$$

145 where,  $RMSE_E$  =  $RMSE$  of the existing models;  $RMSE_D$  =  $RMSE$  of the derived models

146 The Nash–Sutcliffe efficiency was estimated as:

$$NSE = 1 - \left[ \frac{\sum_{i=1}^n (d_s - d_o)^2}{\sum_{i=1}^n (d_s - \bar{d}_o)^2} \right] \quad (16)$$

147 where,  $d_s$  = Calculated values of  $K_s$ ;  $d_o$  = Observed values of  $K_s$ ;  $n$  = Number of  
148 observations

### 149 3. RESULTS AND DISCUSSION

150 Saturated hydraulic conductivity was estimated from the above-mentioned PTFs, and  
151 compared to measured  $K_s$  of the 45 spots in each study site. The performance of the tested  
152 PTFs were assessed based on the quality of the estimations when applied on specific soil  
153 data from this study. However, since those PTFs were developed from different soil  
154 datasets, their predictability is always expected to be dependent on the set from which they  
155 were developed and those on which they are tested [18]. The results of scatter plots of  
156 measured versus estimated  $K_s$  for the derived and tested PTFs, and their performance  
157 statistics are presented in Table 2. The input data required for the PTFs varied upon the  
158 parameters used in developing a particular model. This resulted in variations in their  
159 performances in the prediction of  $K_s$ . In general, the performances of the well-known PTFs  
160 were not good as evidenced by the evaluation indices (i.e.,  $r$ ,  $d$ , RMSE and NSE) as shown  
161 in Table 2. This implies that no particular model amongst the well-known PTFs could be said  
162 to have yielded the best quality fit for  $K_s$  in this study. However, estimated  $K_s$  by from the  
163 PTFs showed a positive correlation with measured  $K_s$ . Generally, the  $r$  values observed in  
164 the study were comparable to those reported by Agyare et al. [32], who reported  $r$  in the  
165 range of 0.29 – 0.41 when NN model, a concept that is very similar to PTF was used to  
166 estimate  $K_s$ .

167 **Table 2. Goodness-of-fit indicators for the well-known PTFs**

Soil	Equation	$r$	RMSE	$d$	NSE
Stagni-Dystric Gleysol	P	0.40	4.00	0.45	0.42
	CS	0.35	4.10	0.44	0.41
	DP	0.35	4.90	0.44	0.46
	FJ	0.35	4.30	0.40	0.43
Plinthi Ferric Acrisol	P	0.45	4.10	0.50	0.47
	CS	0.40	4.30	0.39	0.44
	DP	0.43	4.20	0.40	0.44
	FJ	0.41	4.50	0.27	0.46
Plinthic Acrisol	P	0.38	4.10	0.32	0.40
	CS	0.32	4.30	0.36	0.45
	DP	0.32	4.20	0.45	0.42
	FJ	0.32	4.10	0.37	0.44

168  $r$  = Correlation coefficient; RMSE = Root mean square error;  $d$  = Index of agreement; P =  
169 Puckett et al. [28]; CS = Campbell and Shiozawa [29]; DP = Dane and Puckett [30]; FJ =  
170 Ferrer-Julia et al. [31]; NSE = Nash–Sutcliffe efficiency

171  
172 Since the ultimate goal of this study was to find a suitable PTF to include in soil water  
173 management scheduling, it was imperative to also develop PTFs upon the failure of the  
174 tested ones (Table 2) to predict the saturated hydraulic conductivity. A key aspect of this  
175 study, therefore, dealt with the identification of additional soil information that could improve  
176 the accuracy of the PTFs, besides the traditional PTF predictors, viz., sand, silt, and clay  
177 contents, bulk density, and OM content. This implies that PTF development should be site-  
178 specific [33, 34]. From the set of derived PTFs, OM was only applicable in Model 2, even  
179 though it was listed among the essential input parameters to build PTFs in this study. A  
180 possible reason, according to Tomasella et al. [35] is that not only the quantity, but the  
181 quality of organic matter significantly affects soil hydraulic properties. In addition, OM is

182 reported to be an important variable for estimating unsaturated soil hydraulic properties; it  
 183 has less effect in saturated soils, since OM mainly affects retention forces (matric potential),  
 184 which are ca zero in saturated soils [36, 37]. Also, the exchangeable Na and Ca contents,  
 185 and bulk density made the use of OM unnecessary. Thus, the use of bulk density [35, 38],  
 186 and exchangeable Na and Ca were effective substitutes for OM in the development of PTFs  
 187 in this study.

188  
 189 Table 3 presents the performance indices of the derived PTFs. While the performances of  
 190 all the well-known PTFs were generally poor, those of the derived PTFs (Models 1 – 5) were  
 191 highly accurate, as revealed by the very high  $r$ ,  $d$ , NSE, and very low RMSE values.  
 192 Contrary to the tested the PTFs, Models 1 – 5 would allow for the assessment of changes in  
 193 OM, bulk density [39], and exchangeable Na and Ca on saturated hydraulic conductivity.  
 194 Compared to the best predictor amongst the well-known PTFs, herein, Puckett et al. [28]  
 195 model with RMSE between 4.00 and 4.10, the derived PTFs provided high accuracy, with  
 196 RMSE not exceeding 1.741. In addition, the NSE values of the derived PTFs ranged  
 197 between 0.844 – 0.950 in the Stagni-Dystric Gleysol, 0.854 – 0.982 in the Plinthi Ferric  
 198 Acrisol, and 0.892 – 0.972 in the Plinthi Acrisol. This implies that the PTFs developed from  
 199 the local datasets had a superior performance over the well-known ones. The relatively poor  
 200 prediction of the well-known PTFs may be explained by the selection of inappropriate soil  
 201 properties as predictors [40]. This corroborates the reports by several studies [e.g. 5, 41 –  
 202 43] that the performance of PTFs is highly affected by factors such as geographical source  
 203 of data used for its derivation, and differences in methods of measurement. Additionally,  
 204 according to Tuffour [2], most theories in soil hydrology, including these well-known PTFs  
 205 have been developed for standard, clay-rich and organic-rich, and fertile temperate soils.  
 206 This implies that these models are generally successful for moist environments, but do not  
 207 always carry over meaningfully over arid and semi-arid regions as in the present study. The  
 208 derived PTFs, on the other hand, are a simple and suitable approach for the determination  
 209 of  $K_s$  in the absence of instrumentation.

210  
 211 **Table 3. Goodness-of-fit indicators for the derived PTFs**

Soil	Equation	$r$	RMSE	$d$	NSE
Stagni-Dystric Gleysol	Model 1	0.892	0.213	0.794	0.844
	Model 2	0.994	0.584	0.920	0.932
	Model 3	0.993	1.040	0.911	0.950
	Model 4	0.994	0.283	0.923	0.873
	Model 5	0.991	1.741	0.874	0.931
Plinthi Ferric Acrisol	Model 1	0.990	0.154	0.893	0.982
	Model 2	0.993	0.212	0.941	0.963
	Model 3	0.991	0.714	0.844	0.940
	Model 4	0.994	0.143	0.921	0.903
	Model 5	0.992	1.204	0.873	0.854
Plinthic Acrisol	Model 1	0.971	0.203	0.863	0.892
	Model 2	0.992	0.534	0.922	0.930
	Model 3	0.991	0.670	0.874	0.952
	Model 4	0.993	0.181	0.911	0.894
	Model 5	0.991	1.422	0.912	0.972

212  $r$  = Correlation coefficient; RMSE = Root mean square error;  $d$  = Index of agreement; NSE =  
 213 Nash–Sutcliffe efficiency  
 214

215 The observation made in the study is a clear evidence of inter-user variability emanating  
 216 from soil surface characteristics, presence of a protective layer, and land use history of the  
 217 study site [44] and site specificity of PTFs, which are the key limitations of applying PTFs  
 218 developed in one region to other regions [45, 46]. Hence, the prediction of  $K_s$  using PTFs  
 219 could be well improved by adding input variables such as topographic, vegetation, and land  
 220 use and/or by enlarging the datasets [47]. This clearly shows the importance of using local

221 data in the development of  $K_s$  PTFs as corroborated by [46], who assessed the  
 222 performances of four PTFs (Jabro, Puckett, Neurotheta, and Rosetta) with a locally derived  
 223 PTF (Turkey). They reported the lowest RMSE value of 0.74 for the Turkey against Rosetta,  
 224 which performed best among the four well-known PTFs, with RMSE of 1.61. The index of  
 225 agreement ( $d$ ) (Table 3), ranged between 0.79 (for Model 1 in the Stagni-Dystric Gleysol)  
 226 and 0.94 (for Model 2 in the Plinthi Ferric Acrisol), which reflects reasonable performance of  
 227 the derived PTFs. The  $d$  statistic herein reflects the degree to which the observations were  
 228 accurately estimated by the predictions [43, 48]. In all, the results indicate very good  
 229 performance of the derived PTFs in terms of the four statistics used as evaluation indices.

230  
 231 As presented in Table 4, the addition of Ca and Na as input parameters for the derived  
 232 PTFs improved the predictions of  $K_s$  between 57.56% and 95.71% in the Stagni-Dystric  
 233 Gleysol, 70.73% and 96.89% in the Plinthi Ferric Acrisol, and 65.37% and 95.81% in the  
 234 Plinthic Acrisol. Most especially, it was found that  $K_s$  was directly affected by exchangeable  
 235 Na, which was in fact the most important soil property influencing  $K_s$  in the soils in this study.  
 236 The performances of the derived PTFs based on their relative improvements over the well-  
 237 known ones were in the order of Model 1 > Model 4 > Model 2 > Model 3 > Model 5 for the  
 238 Stagni-Dystric Gleysol, and the Plinthi Ferric Acrisol, and Model 4 > Model 1 > Model 2 >  
 239 Model 3 > Model 5 for the Plinthic Acrisol. The large improvement may be attributed to the  
 240 consideration of additional properties, particularly Na as input parameters. The PTF with OM  
 241 as an input variable (Model 2) performed very well in estimating  $K_s$  as reported by Wösten  
 242 [13] and Vereecken et al. [20]. Similar to fine textured soils as reported by Candemir and  
 243 Gülser [49],  $K_s$  depends on both soil physical and chemical properties in coarse textured  
 244 soils. The differences in the results between estimates from the derived and tested PTFs  
 245 may not be exclusively due to the inclusion of OM, exchangeable Ca and Na, but also from  
 246 other factors such as database-related uncertainties and the adopted algorithms [9, 44, 50].

247 **Table 4. Relative improvement of the derived over the tested PTFs**

Soil	Equation	Relative Improvement (%)			
		P	CS	DP	FJ
Stagni-Dystric Gleysol	Model 1	94.75	94.88	95.71	95.12
	Model 2	85.50	85.85	88.16	86.51
	Model 3	74.00	74.63	78.78	75.81
	Model 4	93.00	93.17	94.29	94.65
	Model 5	56.50	57.56	64.49	59.53
Plinthi Ferric Acrisol	Model 1	96.34	96.51	96.43	96.67
	Model 2	94.88	95.11	95.00	95.33
	Model 3	82.68	83.49	83.10	84.22
	Model 4	96.59	94.74	96.67	96.89
	Model 5	70.73	72.09	71.43	73.33
Plinthic Acrisol	Model 1	95.12	95.35	95.24	95.12
	Model 2	87.07	87.67	87.38	87.07
	Model 3	83.66	84.42	84.05	83.66
	Model 4	95.61	95.81	95.71	95.61
	Model 5	65.37	66.98	66.19	65.37

248 P = Puckett *et al* [28]; CS = Campbell and Shiozawa [29]; DP = Dane and Puckett [30]; FJ =  
 249 Ferrer-Julià *et al* [31]

250  
 251

#### 4. CONCLUSION

252 This study tested the application of four well-known Pedotransfer Functions (PTFs) in the  
 253 literature and local data derived PTFs, to identify the level of accuracy to estimate  $K_s$  for  
 254 some selected benchmark soils in Ghana. Multilinear regression analysis was used to derive  
 255 the best relationships between  $K_s$  and some basic soil properties. The derived PTFs  
 256 provided more accurate predictions, whereas the well-known PTFs underestimated  $K_s$   
 257 values for all three soil types. The derived PTFs in this study are highly advantageous over



258 the tested ones due to the overall low error levels (i.e., higher  $r$ ,  $d$  and NSE values, and  
259 lower RMSE values) and simplicity to input parameters. Reliability of the developed PTFs  
260 (Models 1 – 5) against the well-known ones demonstrated the ability of the developed PTFs  
261 to accurately predict  $K_s$ , and also revealed the shortcomings of the well-known PTFs. The  $R^2$   
262 of the derived over the tested PTFs was observed to be highest for Model 1 in the Stagni-  
263 Dystric Gleysol, and Model 4 in both Plinthic Ferric Acrisol and Plinthic Acrisol, and lowest  
264 for Model 5 in all three soils. It was observed that the inclusion of exchangeable Ca and Na  
265 as predictors increased the predictability of the derived PTFs. Thus, inclusion of additional  
266 soil parameters which influence soil aggregation and structure improved the prediction  
267 accuracy of the derived PTFs. Another alternative could be the development of soil class  
268 specific PTF models.  
269

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#### 406 **COMPETING INTERESTS**

408 Authors have declared that no competing interests exist.

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