

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

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.

Keywords: Clay, Pedotransfer function, Saturated hydraulic conductivity, Sand

1. INTRODUCTION

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

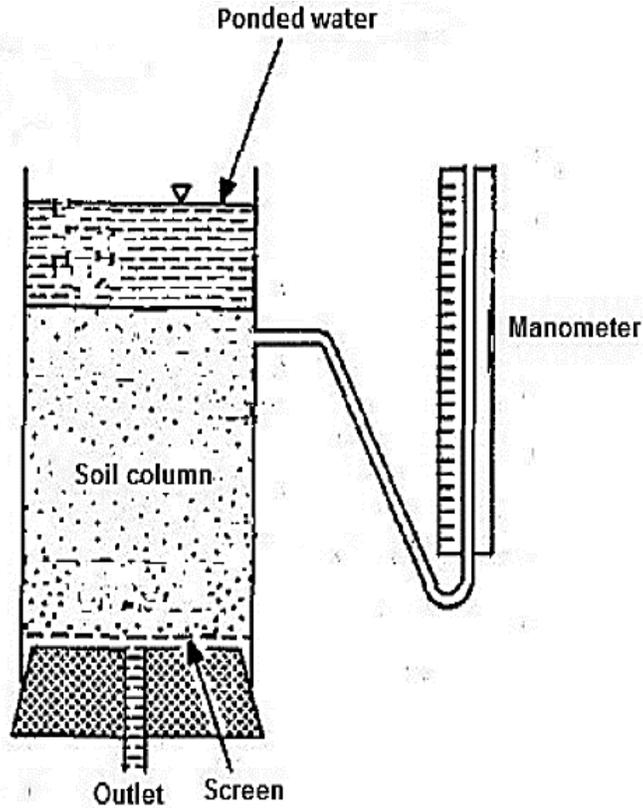
27 Pedotransfer functions are mainly empirical; however, physico-empirical models and fractal
28 theory models are also available [10]. They are generally employed for estimating hydraulic
29 properties from soil properties such as soil texture, bulk density, organic matter content, and
30 water retention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

94
$$K_s = \left(\frac{aL}{At} \right) \ln \left(\frac{h_0}{h_t} \right); \quad (1)$$

95 where,

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

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

98 h_0 = Initial hydraulic head [L]

99 L = Length of the soil column [L]

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

101 Rewriting equation (1), a regression of $\ln\left(\frac{h_0}{h_t}\right)$ on t with slope $b = K_s \left(\frac{A}{La}\right)$ was obtained. Since
102 $a = A$ in this particular case, K_s was simply calculated as:

103
$$K_s = bL \quad (2)$$

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

106 **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

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

110 2.2 Pedotransfer functions (PTFs)

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

115
$$K_s = 156.96 \exp[-0.1975Cl] \quad (3)$$

116
$$K_s = 54 \exp[-0.07S_c - 0.167Cl] \quad (4)$$

117
$$K_s = 303.84 \exp(-0.144Cl) \quad (5)$$

118
$$K_s = 2.556 \times 10^{-7} \exp(0.0491S_c) \quad (6)$$

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

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

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

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

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

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

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

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

137 2.3 Performance evaluation of the PTFs

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

144
$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n (d_s - d_o)_i^2 \right]^{1/2}$$
 (12)

145
$$d = 1 - \left(\frac{\sum_{i=1}^n (d_s - d_o)_i^2}{\sum_{i=1}^n [(d_s - \bar{d}_o)_i + (d_o - \bar{d}_o)_i]^2} \right)$$
 (13)

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

147
$$r = \sqrt{1 - \frac{SSE}{SST}}$$
 (14)

148 where, SSE measures the deviations of observations from their predicted values and SST is
 149 a measure of the deviations of the observations from their mean.

150
$$RI = \left(\frac{RMSE_E - RMSE_D}{RMSE_E} \right) \times 100$$
 (15)

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

152 The Nash–Sutcliffe efficiency was estimated as:

$$NSE = 1 - \frac{\sum_{i=1}^n (d_i - \bar{d}_o)^2}{\sum_{i=1}^n (d_i - \bar{d}_c)^2} \quad (16)$$

153

154 where, \bar{d}_c = Calculated values of K_s ; \bar{d}_o = Observed values of K_s ; n = Number of
 155 observations

156 3. RESULTS AND DISCUSSION

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

174 **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

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

178

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

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

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

217
 218 **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

219 r = Correlation coefficient; RMSE = Root mean square error; d = Index of agreement; NSE =
 220 Nash–Sutcliffe efficiency

221
 222 The observation made in the study is a clear evidence of inter-user variability emanating
 223 from soil surface characteristics, presence of a protective layer, and land use history of the
 224 study site [44] and site specificity of PTFs, which are the key limitations of applying PTFs
 225 developed in one region to other regions [45, 46]. Hence, the prediction of K_s using PTFs
 226 could be well improved by adding input variables such as topographic, vegetation, and land
 227 use and/or by enlarging the datasets [47]. This clearly shows the importance of using local

228 data in the development of K_s PTFs as corroborated by [46], who assessed the
 229 performances of four PTFs (Jabro, Puckett, Neurotheta, and Rosetta) with a locally derived
 230 PTF (Turkey). They reported the lowest RMSE value of 0.74 for the Turkey against Rosetta,
 231 which performed best among the four well-known PTFs, with RMSE of 1.61. The index of
 232 agreement (d) (Table 3), ranged between 0.79 (for Model 1 in the Stagni-Dystric Gleysol)
 233 and 0.94 (for Model 2 in the Plinthi Ferric Acrisol), which reflects reasonable performance of
 234 the derived PTFs. The d statistic herein reflects the degree to which the observations were
 235 accurately estimated by the predictions [43, 48]. In all, the results indicate very good
 236 performance of the derived PTFs in terms of the four statistics used as evaluation indices.
 237

238 As presented in Table 4, the addition of Ca and Na as input parameters for the derived
 239 PTFs improved the predictions of K_s between 57.56% and 95.71% in the Stagni-Dystric
 240 Gleysol, 70.73% and 96.89% in the Plinthi Ferric Acrisol, and 65.37% and 95.81% in the
 241 Plinthic Acrisol. Most especially, it was found that K_s was directly affected by exchangeable
 242 Na, which was in fact the most important soil property influencing K_s in the soils in this study.
 243 The performances of the derived PTFs based on their relative improvements over the well-
 244 known ones were in the order of Model 1 > Model 4 > Model 2 > Model 3 > Model 5 for the
 245 Stagni-Dystric Gleysol, and the Plinthi Ferric Acrisol, and Model 4 > Model 1 > Model 2 >
 246 Model 3 > Model 5 for the Plinthic Acrisol. The large improvement may be attributed to the
 247 consideration of additional properties, particularly Na as input parameters. The PTF with OM
 248 as an input variable (Model 2) performed very well in estimating K_s as reported by
 249 Wösten [13] and Vereecken et al. [20]. Similar to fine textured soils as reported by Candemir
 250 and Gülser [49], K_s depends on both soil physical and chemical properties in coarse textured
 251 soils. The differences in the results between estimates from the derived and tested PTFs
 252 may not be exclusively due to the inclusion of OM, exchangeable Ca and Na, but also from
 253 other factors such as database-related uncertainties and the adopted algorithms [9, 44, 50].
 254

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

255 P = Puckett *et al* [28]; CS = Campbell and Shiozawa [29]; DP = Dane and Puckett [30]; FJ =
 256 Ferrer-Julía *et al* [31]
 257

258 4. CONCLUSION

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

265 the tested ones due to the overall low error levels (i.e., higher r , d and NSE values, and lower
266 RMSE values) and simplicity to input parameters. Reliability of the developed PTFs (Models
267 1 – 5) against the well-known ones demonstrated the ability of the developed PTFs to
268 accurately predict K_s , and also revealed the shortcomings of the well-known PTFs. The R^2
269 of the derived over the tested PTFs was observed to be highest for Model 1 in the Stagni-
270 Dystric Gleysol, and Model 4 in both Plinthic Ferric Acrisol and Plinthic Acrisol, and lowest
271 for Model 5 in all three soils. It was observed that the inclusion of exchangeable Ca and Na
272 as predictors increased the predictability of the derived PTFs. Thus, inclusion of additional
273 soil parameters which influence soil aggregation and structure improved the prediction
274 accuracy of the derived PTFs. Another alternative could be the development of soil class
275 specific PTF models.
276

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412 **COMPETING INTERESTS**

414 Authors have declared that no competing interests exist.

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