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Minding the geotechnical data gap: appraisal of the variability of key soil parameters for slope stability modelling in Saint Lucia

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Abstract

Identification of failure thresholds and critical uncertainties associated with slope stability often requires the specification of geotechnical parameter values for input into a physically-based model. The variation of these parameters (including mechanical soil properties such as effective friction angle and cohesion) can have a significant impact on the computed factor of safety. These uncertainties arise from natural variations in soils, measurement techniques, and lack of reliable information. Researchers may use statistical analysis coupled with numerical simulation to determine possible ranges of slope factors of safety and the relative influence of geotechnical and other parameters, such as topsoil depth and rainfall. This study investigates the variation of geotechnical parameters observed on the island of Saint Lucia in the Eastern Caribbean. A database of particle size distributions, in-situ moisture contents, Atterberg and direct shear box test results is compiled from 91 samples of tropical soils in Saint Lucia. A study of various probability distributions shows that the Weibull distribution may be favoured for the effective friction angle of the Saint Lucian soils considered based on the Akaike information criterion, employed as an estimator of the relative quality of statistical models dealing with the trade-off between goodness-of-fit and simplicity of the model.

Keywords Tropical soils · Friction angle · Probability distributions · Weibull distribution · Landslides · Saint Lucia

Notation

c' cohesion intercept, kPa
CF clay fraction
 k number of parameters in a model

L likelihood
 n number of data points
 PI plasticity index, %
 p p -value; probability of rejecting the null hypothesis and thus concluding that no correlation exists between two parameters
 r correlation coefficient
 R^2 coefficient of determination
 SF silt-clay fraction, % (taken here as percent passing the 0.075mm sieve)
 w_{nat} natural water content, %
 w_L liquid limit, %
 w_P plastic limit, %
 x a variable
 β Weibull shape factor
 δ Weibull scale factor
 μ statistical mean
 σ' effective normal stress, kPa
 τ shear stress, kPa
 ϕ' effective friction angle, degrees
 ϕ'_{crit} effective critical state friction angle, degrees
 ϕ'_{peak} effective peak friction angle, degrees

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Introduction

Landslides and geotechnical data

Landslides triggered by rainfall and seismic events affect people, the built environment and economies worldwide. The susceptibility of slopes to landslides is due to a combination of preparatory factors including slope angle, geology, soil properties, groundwater conditions and vegetation cover. Human actions such as the construction of buildings and roads or changes to natural vegetation can affect these preparatory factors and decrease the stability of a slope. Rapid rates of urbanisation and land use change (both planned and informal) in landslide-prone developing countries mean that they are disproportionately affected by landslide hazards and their consequences (Petley, 2009). In such locations, landslides frequently occur due to a combination of localised factors such as slope-cutting, surcharge loading, altered surface water drainage patterns, and leakage from water services, water tanks and latrines – as reported in the city of São José dos Campos, Brazil, by Mendes et al. (2018), for example.

Implementation of landslide hazard assessments at the required resolution to inform landslide exposure, vulnerability and risk assessments, and risk management are often hindered by the limited availability of data in such regions. Acquisition of soil geotechnical information poses a particular challenge due to the expense of soil sampling in relevant locations and laboratory testing, the inherent heterogeneity of soils, the disturbance of in-situ soil structure and moisture content that occurs with sample extraction, and the resulting uncertainties associated with parameter values and sparse data. Furthermore, any such data from previous studies and projects tend to be inaccessible or undocumented. Thus, engineers and slope stability modellers encounter a geotechnical data gap when attempting to use physics-based models to investigate highly localised urban landslide processes (and potential mitigation measures) and when parameterising spatially-distributed landslide hazard models in Geographical Information Systems (GIS) at city or regional scales (e.g., Mutekanga et al. 2010; Ringrose-Voase et al. 2017; Du et al. 2018).

Effective friction angle

Slope stability calculations are sensitive to soil strength parameters such as the effective friction angle (ϕ' , degrees), which is a measure of the resistance of the soil sample to shear stress, as defined by the Mohr-Coulomb failure criterion, Eq. 1 (e.g., Parry, 2004):

$$\tau = c' + \sigma' \sin(\phi') \quad (1)$$

where τ is the shear stress, c' the cohesion intercept, and σ' the effective normal stress. Simple factor of safety calculations

(and the associated design charts) used by engineers for rapid slope stability assessments require input values for the soil effective friction angle, effective cohesion intercept, unit weight, slope geometry and groundwater conditions (e.g., Taylor, 1937; Anderson and Lloyd, 1991; Anderson et al. 1997; Michalowski, 2002 and Li et al. 2008). The c' and the ϕ' can also be back-calculated from field observations (e.g., van Asch, 1984). During shearing, a dense soil sample reaches a peak effective angle of friction (ϕ'_{peak}) at a relatively low strain; as strain increases the angle drops to a critical effective angle of internal friction (ϕ'_{crit}) (c.f. Craig, 2004, p.103) which should be used if designing against slope failure (Take and Bolton, 2011). However, ϕ'_{crit} is still rarely reported in geotechnical characterisation studies.

More sophisticated models representing dynamic hydrological processes of rainfall infiltration, sub-surface flow, pore water pressure and slope stability response have shown that in certain cases the choice of friction angle design values can affect computed factors of safety to the same extent as variations in rainfall for deeply weathered residual soil slopes in the humid tropics (e.g., Holcombe et al. 2016, Beesley et al. 2017 and Shephard et al., 2018a, 2018b). Physically-based models can also be applied using reliability or stochastic approaches, in which input parameters are described using probability distributions rather than discrete values. Sensitivity analysis of model inputs and outputs may then be performed to identify dominant slope stability mechanisms for different classes of slope, system behavioural thresholds and ultimately data acquisition priorities.

Geotechnical correlations and classification systems

Where extensive laboratory testing is not available or affordable, it is common practice to use comparisons with other soil index properties, such as the plasticity index (PI) as a proxy for friction angle (e.g., Kenney, 1959; Brooker and Ireland, 1965, Ladd et al. 1977 and Sorensen and Okkels, 2013). Such relationships allow geotechnical engineers to draw additional information from the routine soil tests carried out as part of civil engineering design and construction of foundations and transport infrastructure.

Another source of proxies for soil mechanical properties can be agricultural soil maps and databases developed at national and worldwide scales. Agricultural soil data often include soil indices such as particle size distribution and soil bulk density and aspects of soil chemistry relating to clay particles, though not always the PI . Current engineering and agricultural databases of soil properties are most representative of North America, Europe and other regions with resources for soil testing. The most landslide-prone areas, typically encompassing developing countries in sub-tropical and tropical climatic zones, are less well represented. On the other hand, more recently, studies based in developing countries are

becoming available (e.g., Roopnarine et al. 2012, Havaee et al. 2015). Roopnarine et al. (2012) reported the results of a study of Trinidadian soils and used soil physical properties to predict friction angle, reporting that the sand and clay fractions were the key predictors of residual and peak friction angle. Havaee et al. (2015) obtained significant positive correlation between friction angle and gravel content for Central Iran, and they also observed improvement in prediction models of soil shear strength derived using basic soil properties and normalized difference vegetation index.

Study aims

This paper investigates the extent to which the gap between available and required geotechnical data, specifically friction angle, can be reduced using soil data typically available in a landslide-prone humid tropical country. The first step was the collation of non-georeferenced hard copies of soil test results routinely undertaken by the Government of Saint Lucia, including soil classification and indexing, and direct shear test data. The resulting database is analysed with the following research objectives:

- (i) Based on preliminary work by Shephard et al. (2018b) and Vardanega et al. (2018), to investigate whether significant soil property correlations can be derived to link soil friction angle to basic soil parameters for the Saint Lucia database (hereafter referred to as the 'SL database');

- (ii) To distinguish different classes of Saint Lucia's soils using both a soil type classification framework and the well-known Casagrande approach (Casagrande 1947);
- (iii) To fit probability distribution curves to the soil properties, the functions that best fit the available data.

The overall aim is to provide local engineers and landslide researchers with information to make *a priori* estimates of key geotechnical parameters based on available local data instead of (or in addition to) more generic probability distributions derived from regional or global datasets.

Materials and methods

The Saint Lucia soil data were made available by the Government of Saint Lucia materials testing laboratory in 2016 as part of collaboration on the landslide hazard assessment component of a World Bank funded public infrastructure asset risk management project ('Vision 2030'). The database contains the results of a variety of historical laboratory tests carried out on soil samples from across the island. These data represent a subset of the laboratory's historic soil test records, which are currently archived in largely analogue format. Tests typically included the determination of field moisture content, particle size distribution and Atterberg limits as well as direct shear tests on partially-disturbed samples. The direct shear apparatus (DSA) in Saint Lucia has previously been

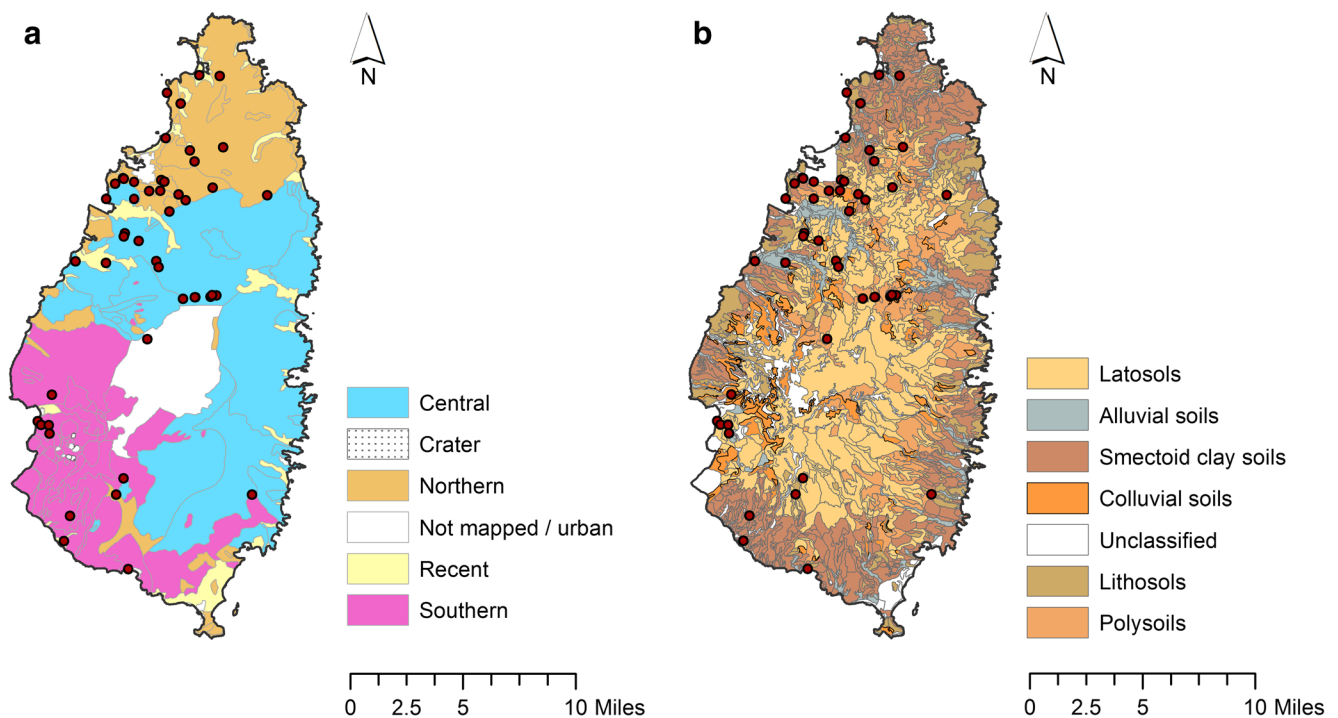
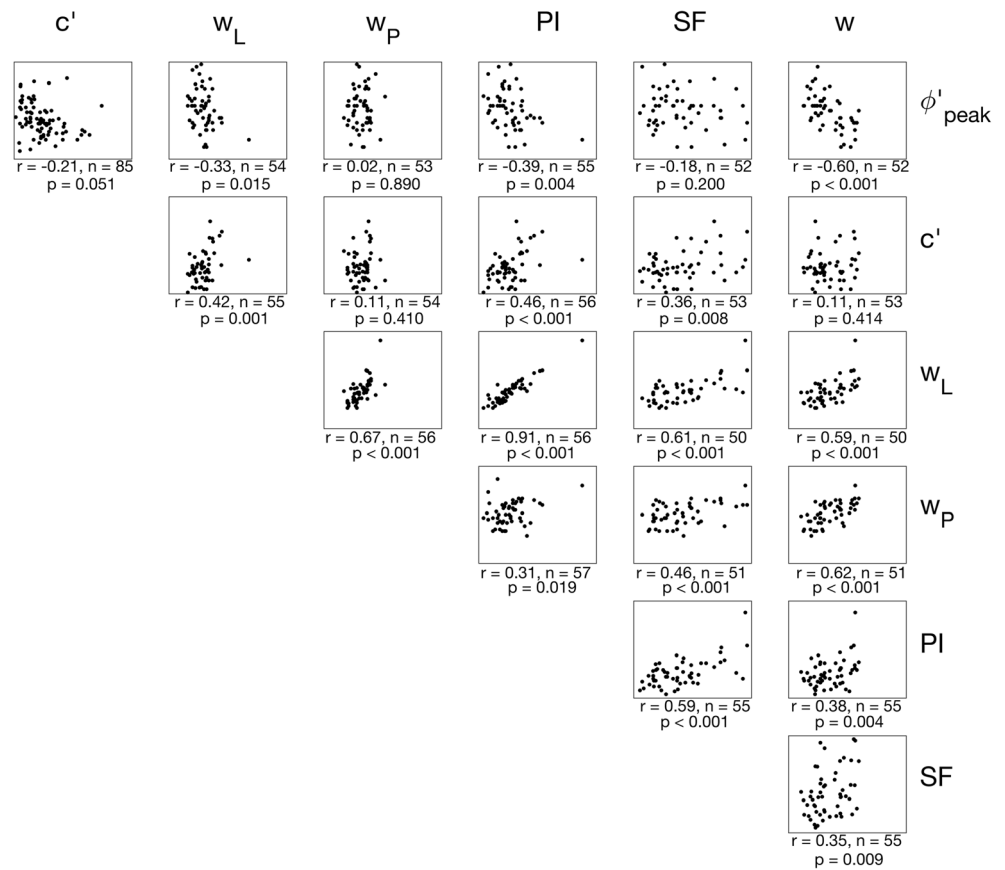


Fig. 1 (a) Geological series, and (b) Soil group maps for Saint Lucia (CHaRIM, 2013 see <http://charim-geonode.net/people/profile/lucia/?content=layers>; with soil map digitised from the original RRL, 1966, survey). Approximate soil sample locations marked by dots

Fig. 2 Scatter plots of the key parameters in the Saint Lucia database regressed linearly against each other (plot adapted from Shephard et al. 2018b) (original source: On the variability of Effective Friction Angle of Saint Lucian Soils: investigations through a Laboratory database, Shephard et al., ce/papers-Online collection for conference papers in civil engineering (c) [2018], John Wiley and Sons)



satisfactorily benchmarked against a modified DSA at the University of Bristol by repeating the tests reported in Lings and Dietz (2004), using loosely and densely compacted samples of Leighton Buzzard sand. The DSA testing procedure for

Saint Lucia was also reviewed as part of the Vision 2030 project and found to have been consistently applied by the laboratory technicians. The Saint Lucia procedure is to extract samples from the field and place them into the direct shear

Fig. 3 ϕ'_{peak} plotted against PI, see the section "Classification of soils from Saint Lucia" for soil classes

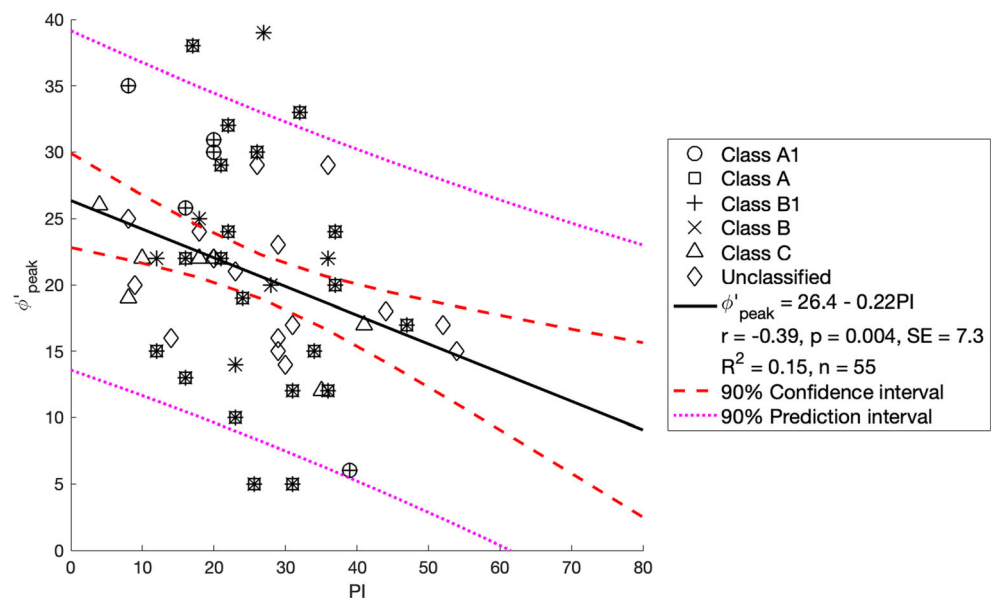
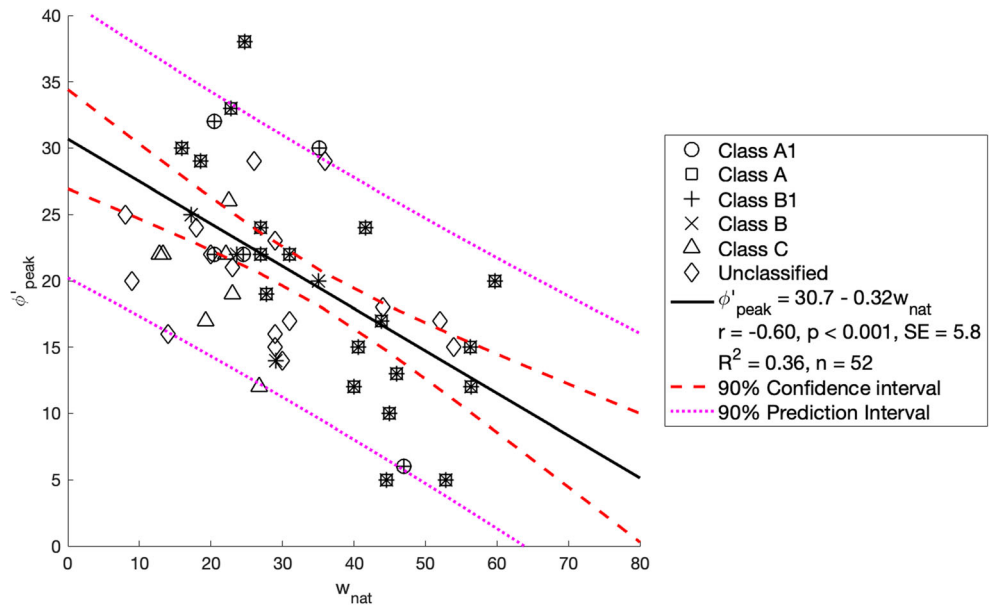


Fig. 4 ϕ'_{peak} plotted against sample w_{nat} , the section "Classification of soils from Saint Lucia for soil classes, (plot adapted from Shepherd et al. 2018b) (original source: On the variability of Effective Friction Angle of Saint Lucian Soils: investigations through a Laboratory database, Shepherd et al., ce/papers-Online collection for conference papers in civil engineering (c) [2018], John Wiley and Sons)



box, without sieving or remoulding in the classical sense, although some degree of disturbance is inevitable during extraction and transportation.

The first stage of data processing was the creation of a digital database of the soil test records and the estimation of the location from which each sample was obtained. Of the 91 database entries there were 70 samples, taken from 44 sites, for which approximate map co-ordinates could be determined (assigned). Figure 1 indicates the 44 approximate sample locations associated with parent material geologies and the soil groups identified in the 1966 Saint

Lucia soil and land-use survey (Regional Research Laboratory, 1966). The next stage was to identify classes of soils that might be expected to show distinct geotechnical properties and that could be distinguished from a combination of field observations, basic (often incomplete) soil descriptions in the original soil test records, and locations of the samples with respect to a particular parent material or soil type. The rationale for this classification is described in the next section along with the interpretation of the Saint Lucia soil data, the 1966 soil survey and local expert knowledge.

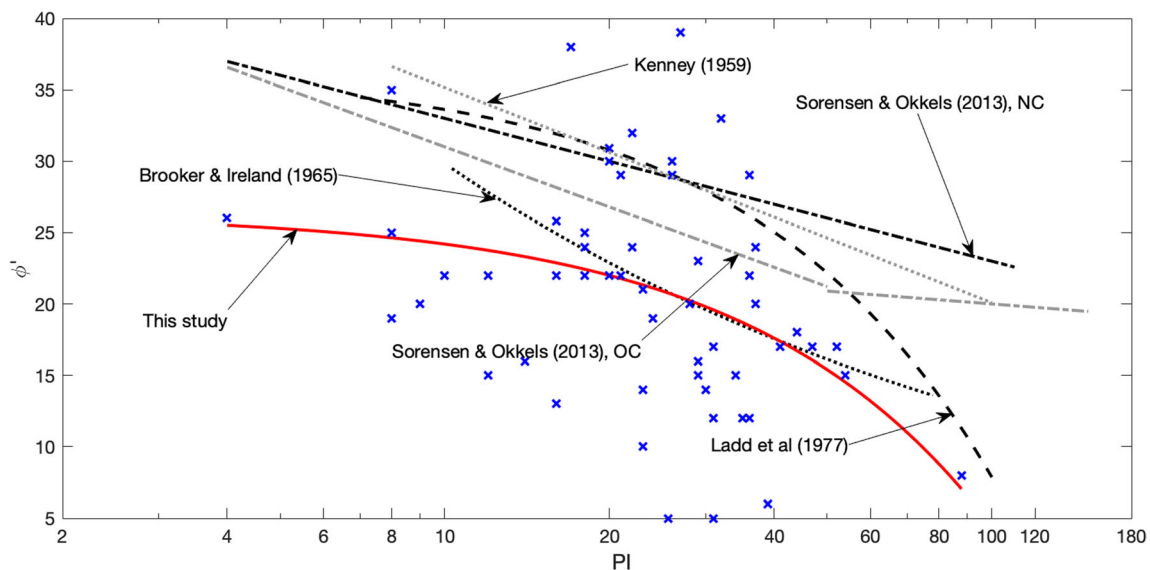
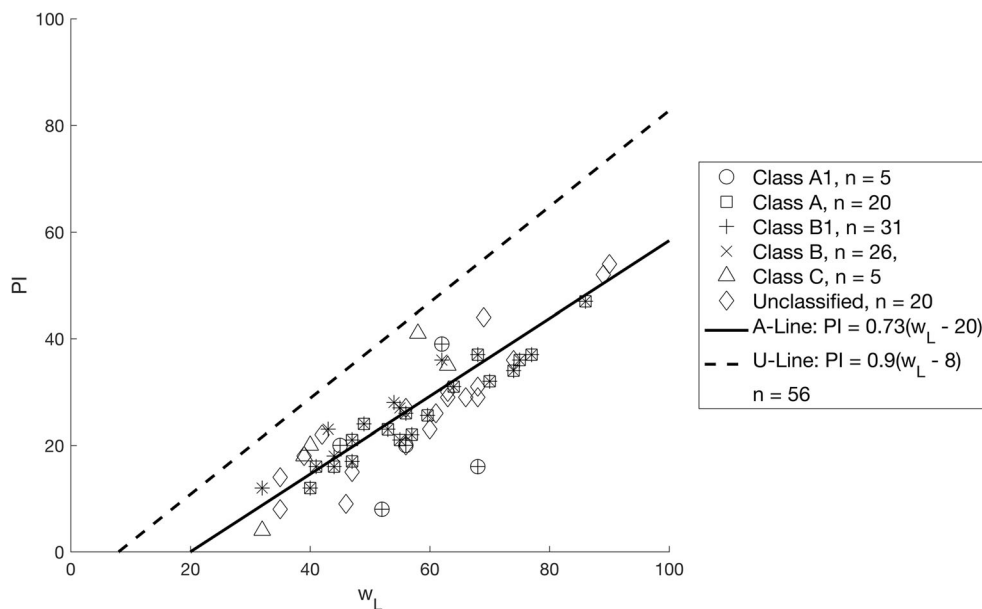


Fig. 5 Comparison of friction angle with varying plasticity index for Saint Lucian soils (data points shown on plot) compared with the trends given in Kenney (1959); Ladd et al. (1977) [the trend-line shown in Ladd

et al. 1977 is attributed to NAVDOCKS DM-7]; Brooker and Ireland (1965) and Sorensen and Okkels (2013) [trends for normally consolidated (NC) and overconsolidated clays (OC) are shown]

Fig. 6 Soils from the SL database plotted on the Casagrande chart (chart design based on Casagrande 1947 and Howard 1984)



Results and discussion

Geotechnical correlations

In soil engineering and geotechnics it is common to estimate engineering parameters that are complex or hard to measure by using a simpler property, or combination of properties (e.g., Kulhaway and Mayne, 1990; Ching and Phoon, 2014a, 2014b; Havaee et al. 2015; Zolfaghari, et al. 2016; Ahmed (2018), Bayat et al. (2018); Jie et al. (2018); Pham et al. (2018) and Schjøning and Lamandé, 2018). Preliminary statistical analysis of this database has been reported in Shephard et al. (2018b) and Vardanega et al. (2018).

Figure 2 shows the soil friction angles (and apparent cohesion intercepts) in the database plotted against the liquid limit (w_L), plastic limit (w_p), PI , silt-clay fraction (SF) and natural water content (w_{nat}). As clay fraction (CF) is not routinely available from the Saint Lucia geotechnical laboratory, SF is used in place of this more common parameter, which is defined as the percentage of material passing the 0.075 mm sieve. The effective friction angles are assumed to correspond to a normal stress range of 37.2 kPa to 112.4 kPa based on examination of local working practice in Saint Lucia. This is analogous to reports by Rouse et al. (1986) and Rouse (1990) of a series of effective friction angles of Dominican soils obtained from reversible shear box testing using a normal stress range of 41.8 kPa to 229.8 kPa.

In Fig. 2 the number of data-points available for each sub-correlation (n); the correlation coefficient (r) and the p -value (p) are shown underneath each sub-plot. The p -value represents the probability value estimated to test the null hypothesis that the coefficient of correlation between the variables is zero (no effect). A low p -value leads to the rejection of the null

hypothesis, suggesting that the tested variable can be a meaningful addition for the prediction of friction angle. Examination of Fig. 2 shows that the two best correlations with effective friction angle are the natural water content ($r = -0.60, n = 52$) and the plasticity index ($r = -0.39, n = 55$), where the water content (w) is characterised by $p < 0.001$ and the plasticity index (PI) by $p < 0.004$, making these two parameters good candidates for a regression model for predicting the friction angle. Figure 3 shows the regression of ϕ'_{peak} with PI used to construct Eq. (2). Figure 4 shows the regression of ϕ'_{peak} with w_{nat} to derive Eq. 3.

$$\phi'_{peak} = 26.4 - 0.22PI \tag{2}$$

Equation 2 was found to have an $R^2 = 0.15$ for $n = 55$ with $p = 0.004$.

$$\phi'_{peak} = 30.7 - 0.32w_{nat} \tag{3}$$

Equation 3 was found to have an $R^2 = 0.36$ for $n = 52$ with $p < 0.001$.

Table 1 Anderson-Darling test statistics for the exponential, normal, lognormal and Weibull distributions fitted to the SL database, including unclassified data (strongest fits shown in bold type)

	Exponential	Normal	Lognormal	Weibull	n
ϕ'_{peak}	13.37	0.93	1.03	0.61	85
c'	5.43	1.78	1.26	0.47	86
PI	7.06	1.00	0.68	0.49	61
w_{nat}	9.59	0.99	0.68	0.79	58

Table 2 Akaike information criterion values modified for small samples for the exponential, normal, lognormal, Weibull and Generalised Extreme Value distributions fitted to the SL database, including unclassified data (strongest fits shown in bold type)

	Exponential	Normal	Lognormal	Weibull	Generalised Extreme Value	<i>n</i>
ϕ'_{peak}	714	639	643	635	636	85
c'	715	712	697	690	694	86
PI	519	497	484	485	483	61
w_{nat}	529	470	470	467	470	58

The reduction of effective friction angle with increasing plasticity index has been identified previously by many researchers (e.g., Kenney, 1959; Brooker and Ireland, 1965, Ladd et al. 1977 and Sorensen and Okkels, 2013). The data are highly scattered for all the correlations of basic soil parameters with ϕ'_{peak} and c' . Figure 2 shows only basic soil parameters that do not capture the effects of sample disturbance. Figure 5 illustrates how the regression of ϕ'_{peak} with PI for the SL database compares with some previously quoted by Kenney (1959), Ladd et al. (1977), Brooker and Ireland (1965) and Sorensen and Okkels (2013). The Saint Lucia trend-line correlates with a lower ϕ'_{peak} than other sources. This may be due to sample disturbance effects. The line from Brooker and Ireland (1965) is closest to that for the SL data.

Shepherd et al. (2018b) performed multiple-linear-regression analysis and found the following relationship to predict ϕ'_{peak} (to within about $\pm 50\%$) from basic soil properties:

$$\phi'_{peak} = 19.8 - 0.14w_L + 0.77w_P - 0.46w_{nat} \quad (4)$$

Equation 4 was found to have an $R^2 = 0.56$ for $n = 47$ with $p < 0.001$. Vardanega et al. (2018) found that when ϕ'_{peak} was regressed against liquidity index for the SL database a R^2 of 0.43 was obtained.

Classification of soils from Saint Lucia

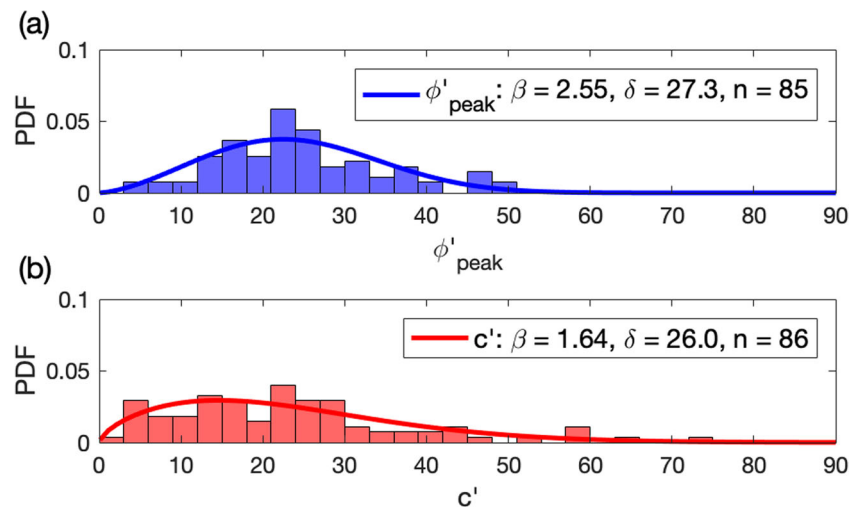
Classification of soils based on formation and weathering

The natural structure of soil, and thus its geotechnical behaviour, is dependent on its parent material and the climate, topography, biological factors (micro-organisms, plants and animals) and time. The formation process for many fine-grained soils can be categorised simply as either 'residual' or 'sedimentary'. Sedimentary soils are formed from minerals and organic materials that have been eroded (or produced by a volcanic eruption), transported and deposited by air, water or ice, and become consolidated (Wesley, 1990). Over time, sedimentary soil horizons may develop, and bonds can form between particles so that the material eventually behaves more like intact rock. For engineers, the stress history of sedimentary soils is recognised to be an important factor in

determining their geotechnical behaviour. Conversely, taking the definition of The Geological Society Professional Handbook on Tropical Residual Soils (Fookes, 1997a, p10), residual soil profiles are formed from the in situ physical and chemical weathering of rock, leaching and accumulation of insoluble minerals and movement of fine particles, animal activity, plant root growth, and incorporation of organic materials, typically leading to cohesive soils and in some cases the cementation of the soil (e.g. laterites); essentially the reverse of the sedimentary soil formation process (Wesley, 1990). Large areas of the earth are mantled by residual soils, and deep profiles can form in humid tropical regions, such as the Caribbean, where readily available moisture and high temperatures lead to aggressive weathering. Both the mineralogy and structure of the parent material and the degree of weathering decomposition strongly influence the geotechnical behaviour of residual soils (cf. Wesley, 2009).

The 1966 soil survey of Saint Lucia (Regional Research Laboratory, 1966) primarily focuses on soils regarding their agricultural usage. It names 53 soil types based on parent material, geomorphological or topographical context, estimated particle size distribution, mineralogy, chemistry, nutrient availability, drainage, erodibility and depth. These soils are grouped into six classes according to the prevailing soil science taxonomy of the time (see legend of Fig. 1b). Although soil science terms such as 'latosols' are not often used by engineers (Wesley, 2009), they do encapsulate information on the soil formation process, parent material and structure. Thus, the soil series and classes defined in global and national soil maps, such as those compiled by FAO-UNESCO and reported by Hartemink et al. (2013), for example, can provide a starting point for investigating potential soil strength properties (e.g., Bonilla and Johnson, 2012). When the 1966 Saint Lucia soil survey information was combined with field observations, soil sample descriptions and depths, and local geotechnical engineering knowledge of the soils, it was possible to identify three distinct soil classes for this study: A) residual soils B) agglomerate soils and C) ash-derived soils, the second two classes having been formed through the weathering of sedimentary materials that were originally deposited by volcanic activity.

Fig. 7 Weibull probability density function (PDF) fitted to (a) ϕ'_{peak} , (b) c' for the SL database



As well as identifying which of the three classes each soil sample in the SL database belonged to, a further distinction was made based on the degree of weathering of the residual soils (A) and the soil matrix from the agglomerate material (B). For residual soils the weathered state of rock is often defined in terms of gradations from rock to soil, numbered from the fresh parent rock, Grade I, to completely weathered residual soil, Grade VI (GCO Geotechnical Control Office, 1982; Fookes, 1997a, 1997b; Toll, 2012). In this paper, the term ‘residual soil’ is used to describe soil samples in the Saint Lucia dataset that are likely to fall within both weathering Grade V (completely decomposed rock) and weathering Grade VI (soil) classes; due to the weathering grade classification being based largely upon visual inspection of samples (GCO Geotechnical Control Office, 1982), and the fact that the Saint Lucia soil sample descriptions did not explicitly record the weathering grade. This is also in keeping with Fookes (1997a, p12) who recognised that using the term ‘soil’ for weathering Grade VI only is “... somewhat restrictive for engineering purposes as much material normally described as ‘soil’ occurs below this Grade in the weathered profile”.

The three classes of soils, and weathering subsets, identified for this study are as follows:

- **Class A: Tropical residual soils** are the classical ‘tropical residual soils’. They are reddish-brown, clayey soils with deep weathering profiles, and are particularly associated with the latosolic soils and andesitic polysols of the 1966 Regional Research Laboratory soil survey. Colluvium derived from these soils is also included as Grade VI material, based on field observations. Two subsets are defined, where ‘A1’ ($n = 17$) describes the upper layer of weathering Grades V and VI (soil), and ‘A’ ($n = 23$) is the underlying layer of weathered Grade IV material in which some of the relict rock structure and cementation is still present (which, in turn is underlain by Grades III, II

and the Grade I parent material). Subset ‘A1’ contains only data which are known to pertain to the topsoil layer based on knowledge of the original samples. Subset ‘A’ contains all other ‘A’ data, excluding ‘A1’.

- **Class B: Agglomerate soils** derived from poorly sorted pyroclastic deposits. This soil is recognisable by the presence of boulders and gravels with a weakly cemented (and sometimes clayey) weathered soil matrix. Two subsets are defined, where ‘B1’ describes the most weathered layer in which the soil matrix is fully weathered and few large particles remain (large particles are manually removed from samples before direct shear testing), and ‘B’ the underlying less weathered layer. Because the soil matrix of Soil ‘B’ tested in the DSA is thought to be similar to that of Soil ‘A’, Soil ‘A’ is included in the statistical analysis of angle of friction: Subset ‘B1’ contains all data for Soil ‘A’, ‘A1’ and ‘B’ ($n = 47$). Subset ‘B’ contains all data for Soil ‘A’ (excluding A1) and Soil ‘B’ ($n = 30$).
- **Class C: Volcanic ash soils** derived from pumice or tuff. This class contains only data points described recognised as a distinctive grey ash (or tuff) soil, sometimes highly cemented, but otherwise friable ($n = 14$). It is typically associated with the southern geological series (Fig. 1). Wright et al. 1984 give further commentary on the soils of Saint Lucia and is part of the so called ‘Belfond Pumice’.

Of the 91 samples collected, 47 can be classed as residual soils (‘A1’, ‘A’, ‘B1’ and ‘B’), according to these geological maps and soil descriptions (see column 2, Table 4).¹

¹ Some soils in the database were classified as being comprised of multiple soil classes.

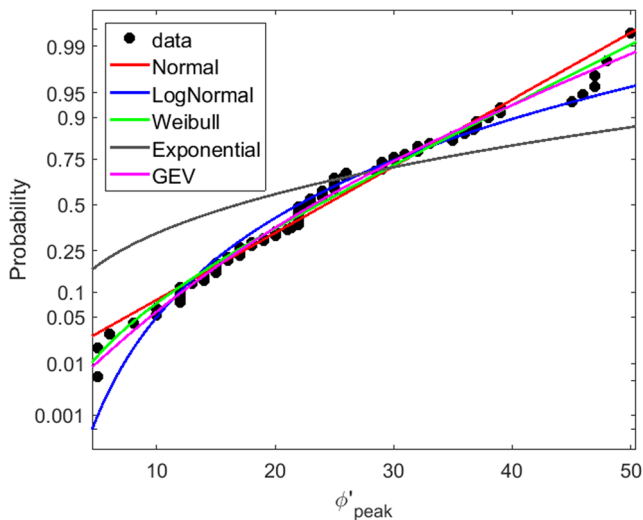


Fig. 8 Probability plots for ϕ'_{peak} data considering Normal, Lognormal, Weibull, Exponential and Generalised Extreme Value (GEV) fits

Classification of soils based on soil index parameters

The data from Saint Lucia (Table 4) have been classified using the Casagrande chart in Fig. 6. The number of data points shown in Fig. 6 is below that in the whole database, as for many samples both a liquid limit and plasticity index are not available. The residual soils plot close to the A-line. According to the chart, 32 soils were classified as silts and 24 as clays. All data plot below the U-line.

Statistical Models

Probability density functions can be used to describe the variability of soil parameters and account for parametric uncertainty in reliability-based design, the development of decision-support tools, and stochastic physics-based modelling. When data for a particular site or region are limited, a geotechnical database and derived probability distributions, can provide useful information. Vardanega and Bolton (2016) suggest that reliability-based design analysis is best used for assessing the performance of geo-structures, as opposed to failure analysis. For instance, analysis of various predictors of undrained shear strength using a database and probability density function has been recently reported (Ching and Phoon, 2014a, 2014b). Pham et al. (2016) and Pham et al. (2017) have used decision support trees for landslide susceptibility assessments in Vietnam and India. Chen et al. (2018a, 2018b) used data-mining approaches to develop landslide susceptibility maps for the Shangnan County and Shangzhou district in China. Numerical models can be coupled with probability distributions when studying the effects of different sources of uncertainty on computed slope factors of safety, and the sensitivity of the system to different model inputs (e.g., Singh et al., 2014; Pianosi et al., 2016; Almeida et al., 2017). Recent work by Almeida et al. (2017) used Classification and Regression

Tree (CART) Analysis (Breiman et al. 1984) in conjunction with the CHASM model (see Anderson and Howes, 1985; Wilkinson et al., 2002) to evaluate thresholds for slope failure due to parameter variation. Almeida et al. (2017) assigned uniform, normal and lognormal distributions to the parameter inputs for CHASM simulations in order to investigate the effects of various parameters on the failure of a modelled slope in Saint Lucia.²

Lumb (1966) suggested the normal distribution gives a good fit for the w_L and w_P (and thus also PI), and the strength parameters ϕ' and c' for some Hong Kong soils. A review by Scott et al. (2003) noted that while the normal distribution may be the “least biased” model, many soil parameters cannot have negative values – therefore the lognormal distribution may be more appropriate. Similarly, Lumb (1970) used the beta distribution to adapt the normal distribution to skewed data. However, to fit a beta distribution the data must be transformed into the range $[0,1]$, thus increasing the number of computational steps required.

Goodness of fit tests

The goodness of fit of a probability distribution can be evaluated using the Anderson-Darling test statistic (Anderson and Darling, 1954), for which a smaller test statistic indicates a better fit (Minitab 17 Support, 2017). For the parameters in the SL database, Anderson-Darling tests have been calculated using Minitab (Minitab 17 Support, 2017), and the results quoted in Table 1. The ranking of different SL database candidate distributions can be done by directly comparing the Anderson-Darling tests statistics because they are all two-parameter distributions. Note that this comparison excludes the exponential distribution, which is a one-parameter distribution and shows relatively poor performance with respect to the other distributions. Table 1 shows that based on the Anderson and Darling criterion the Weibull is the preferred model for ϕ'_{peak} , c' and PI . The lognormal distribution is favoured for w_{nat} .

Another suitable approach is to rank distributions according to the maximum likelihood (e.g., Faber, 2012). Such ranking approaches are effective for the cases in which the candidate family distributions have the same number of parameters. For the cases in which the number of parameters is different, criteria employed in the information theory are more suitable as they “weight” the number of parameters considered allowing a trade-off between the goodness-of-fit of the model and its simplicity (i.e., the number of parameters). The corrected Akaike information criterion (AICc) is employed herein to rank the different fits (Akaike, 1974), to take into account the size of the sample and also to include a three-parameter distribution – in this case the Generalised Extreme value (GEV). In general,

² Almeida et al. (2017) used a normal distribution to model the variability of ϕ' and c' .

Table 3 Anderson-Darling results of fitting the normal, lognormal, Weibull and exponential distributions to the ϕ'_{peak} and c' data from the SL database subdivided by soil class

Distribution	Saint Lucia soil type (number of data points)											
	A1 ($n=17$)		A ($n=23$)		B1 ($n=47$)		B ($n=30$)		C ($n=14$)		U ($n=24$)	
	ϕ'_{peak}	c'	ϕ'_{peak}	c'	ϕ'_{peak}	c'	ϕ'_{peak}	c'	ϕ'_{peak}	c'	ϕ'_{peak}	c'
Normal	0.35	0.69	0.28	0.80	0.31	1.45	0.25	0.73	0.65	0.21	1.15	0.64
Lognormal	1.33	0.49	0.56	0.64	1.72	0.55	0.74	0.78	0.42	0.94	0.34	0.42
Weibull	0.36	0.50	0.27	0.42	0.44	0.41	0.25	0.38	0.60	0.60	0.77	0.28
Exponential	4.16	1.96	3.03	1.99	8.04	2.29	4.54	2.42	2.65	1.28	3.14	2.46

the GEV distribution is the one with maximum likelihood, but the Akaike criterion accounts for the risk of ‘over-fitting’ the data (De Risi et al. 2017). The sample of data considered is not large enough, so the corrected Akaike formulation is considered as shown in Eq. (5), where k is the number of parameters, L is the likelihood and n is the size of the data sample considered.

$$AIC_C = 2k - 2\ln(L) + \frac{2k^2 + 2k}{n - k - 1} \quad (5)$$

As previously mentioned, from the comparison of Anderson-Darling statistics for each candidate distribution, it appears quite clear that, of the distributions assessed, the two-parameter Weibull (Eq. 6) (Montgomery et al., 2007, p.80) is the best-fitted for most of the data and, even when not ranked as the most suitable, it has test statistics that are relatively close to those of the best distribution (i.e., normal and lognormal), see Table 2. The same results are obtained if the fits are ranked using the corrected AICc: the Weibull always represents the best fit with the exception of the *PI* in which the GEV distribution provides a slightly better result.

The probability density function of Weibull is presented in Eq. 6, where β is a shape factor and δ is a scale factor, (e.g., Murthy et al., 2004, p.10).

$$f(x) = \frac{\beta}{\delta} \left[\frac{x}{\delta} \right]^{\beta-1} e^{-\left(x/\delta\right)^\beta} \quad (6)$$

These fitting parameters make the Weibull distribution highly adaptable to data. The Weibull model has been used to model aggregate size (e.g., Nimmo and Perkins, 2002). Fig. 7 shows that the shape factor β estimated for the variables are higher than 1.

The Weibull distribution appears to be a sensible choice of fit for the soils in the SL database. Like the lognormal distribution, the Weibull does not allow for values below zero; while the shape parameter in Eq. 6 allows the skewness to be represented (Weibull, 1951; Murthy et al., 2004). Figure 8 shows the comparison of the probability plots for the effective friction angle data fitted with normal, lognormal, Weibull, exponential and GEV. From the plots it is can be seen that the Weibull and GEV fit the data best. However, the Weibull is preferred, as it

gets a result similar to the GEV, but with just two parameters, and is more efficient with respect to the size of the database. Table 3 shows the best fit distributions for the ϕ'_{peak} and c' parameters when the database is divided by soil type (i.e. A1, A, B1, B, C and U), and again the Weibull distribution is either the most favoured or second most favoured based on the Anderson-Darling test statistics.

Conclusions

A database comprising information on 91 soil samples from Saint Lucia has been presented and classified according to soil type and formation. Simple regression analysis has been performed for some soil parameters, and it is seen that the strongest correlation for the friction angle is found with the natural water content. Additionally, a variety of probability distributions have been fitted to key parameters from the SL database. According to two ranking criteria (i.e. Anderson-Darling and Akaike), the Weibull distribution is preferred for ϕ'_{peak} and c' .

These results are directly applicable for slope stability assessments in Saint Lucia. For local engineers, the database, soil property correlations and statistical distributions provide a basis for estimating soil properties in preliminary geotechnical analyses and for prioritising data acquisition (from basic soil sampling to potentially costly geotechnical investigations). For slope stability modellers the identification of appropriate parameter ranges and probability distributions can inform parametric studies at specific sites (e.g. Holcombe et al., 2016) or stochastic physics-based modelling of slope stability or over wide areas (Almeida et al., 2017), thus accounting for the effect on slope factor of safety of uncertainties in geotechnical and other slope properties.

In broader terms, this paper demonstrates that even in locations where traditional, well-curated geotechnical data are relatively scarce, it can be possible to compile useful databases of soil properties. Where statistically significant correlations and probability distributions fitted, this can provide a basis for geotechnical analysis and reliability-based design. In this paper, based on the available data, the Weibull distribution is shown

to be more appropriate for certain geotechnical parameters in Saint Lucia. This contrasts with the usual assumption by engineers and environmental modellers that the lognormal distribution is often the best representation for soil parameters (Kulhawy, 2010, Hamm et al., 2006). It is suggested that while the selection of a lognormal distribution has a strong precedent and is the default choice for “operational reasons” (Rackwitz, 2000, p201), if sufficient local soil data can be compiled, it is worthwhile exploring the possibility that another distribution may give a better fit.

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Appendix

Table 4 Summary of the SL database (where ‘U’ represents the unclassified samples)

Entry	Class	ϕ'_{peak}	c'	PI	w_L	w_P	w_{nat}	SF
1	A, B, B1	24	30.3	37	68	31	27	41.5
2	A, B, B1	30	26.2	26	56	30	15.9	28.7
3	A, B, B1	32	10.0					
4	A, B, B1	22	29.6	21	55	34	31	48.8
5	A, B, B1	33	74.5	32	70	38	22.8	68.4
6	A, B, B1	24	33.0	22	57	35	41.6	27.4
7	A, B, B1	12	53.8	36	75	39	40	61.5
8	A, B, B1	22	21.4	16	44	28	27	50.5
9	A, B, B1	29	27.6	21	47	26	18.6	37.1
10	A, B, B1	38	12.4	17	47	30	24.7	7.2
11	A, B, B1	19	31.0	24	49	25	27.8	55
12	A, B, B1	20	42.1	37	77	40	59.7	73.7
13	A, B, B1	15	57.2	34	74	40	56.3	48.8
14	A, B, B1	17	60.0	47	86	39	43.8	73.8
15	A, B, B1	32	16.5	22	57	35		47.7
16	A, B, B1	5	4.8	25.6	59.6	34	52.8	49.1
17	A, B, B1	5	4.8	31	64	33	44.6	37
18	A, B, B1	13	22.8	16	41	25	46	43.9
19	A, B, B1	10	21.4	23	53	30	45	16.6
20	A, B, B1	15	29.0	12	40	28	40.6	17.2
21	A, B, B1	23	24.1					
22	A, B, B1	12	26.9					
23	A, B, B1	12	16.5	31	64	33	56.4	
24	A1, B1	36	5.5					
25	A1, B1	29	11.0					
26	A1, B1	25	14.0					

Table 4 (continued)

Entry	Class	ϕ'_{peak}	c'	PI	w_L	w_P	w_{nat}	SF
27	A1, B1	30.9	6.0	20	45	25		
28	A1, B1	25	14.0					
29	A1, B1	18	20.0					
30	A1, B1	22	22.0				24.5	68
31	A1, B1	22	5.0				20.5	34
32	A1, B1	32	5.0				20.5	34
33	A1, B1	30	31.7	20	56	36	35.1	16.6
34	A1, B1	35	6.35	8	52	44		
35	A1, B1	25.8	13.8	16	68	52		
36	A1, B1	36.7	6.8		40			
37	A1, B1	22.7	13.0					
38	A1, B1	21.4	10.0					
39	A1, B1	28.4	15.0					
40	A1, B1	6	13.8	39	62	23	47	77.2
41	B, B1	25	38.0	18	44	26	17.2	17.2
42	B, B1	25	23.0					
43	B, B1	14	24.8	23	43	20	29.1	12.6
44	B, B1	22	20.7	12	32	20	23.6	21.7
45	B, B1	22	42.7	36	62	26		57.3
46	B, B1	39	6.9	27	55	28		26.3
47	B1	20	7.0	28	54	26	35	16.4
48	C	26	1.4	4	32	28	22.5	27.5
49	C	22	26.2	10			22.1	8.5
50	C	19	23.4	8			23	5.3
51	C	17	44.1	41	58	17	19.3	42.4
52	C	22	22.1	18	39	21	13.3	18.6
53	C	12	41.4	35	63	28	26.8	18.6
54	C	22	26.9	20	40	20	12.8	33.4
55	C	39	16.5					
56	C	37	17.2					
57	C	37	14.5					
58	C	23	11.0					
59	C	46	5.5					
60	C	24	24.8					
61	C	47	29.6					
62	U	25	19.3	8	35	27	30.3	23.5
63	U	24	22.1	18	39	21	28.6	36.9
64	U	15	25.0	29	66	37	58	25
65	U	29	13.8	36	74	38	30.6	21.8
66	U	17	22.1	31	68	37	44.3	36.4
67	U	8	35.2	88	136	48	56.7	94.9
68	U	22	27.6	20	56	36	27	92.7
69	U	16	36.0	29	68	39	54	19
70	U	25	10.0					
71	U	10	4.3					
72	U	14	23.0	30	63	33	44	20
73	U	48	17.0					
74	U	29	22.1	26	61	35	30.7	87.1
75	U	17	29.6	52	89	37	53.3	74.5
76	U	15	64.1	54	90	36	55.5	96.4
77	U	23	14.0	29	63	34	43.5	
78	U	16	41.4	14	35	21	18.6	13.4
79	U		20.7	22	42	20	21.8	28.4
80	U	20	15.0	9	46	37	36	
81	U	21	27.6	23	60	37	30	47.5
82	U	18	57.9	44	69	25	25.3	36.5
83	U	47	29.6					
84	U	50	45.0					
85	U	45	5.5					
86	U	35	15.0					
87	U			27	56	29	10.7	42
88	U			15	47	32	39.2	54.5
89	U			9			48.7	37.5
90	U			15			43.9	39.5
91	U			7		31	51.7	34.8

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References

- Ahmed S (2018) Assessment of clay stiffness and strength parameters using index properties. *J Rock Mech Geotech Eng* 10(3):579–593. <https://doi.org/10.1016/j.jrmge.2017.10.006>
- Akaike H (1974) A new look at the statistical model identification. *IEEE Trans Auto Control* 19(6):716–723
- Almeida S, Holcombe EA, Pianosi F, Wagener T (2017) Dealing with deep uncertainties in landslide modelling for disaster risk reduction under climate change. *Nat Hazards Earth Syst Sci* 17:225–241. <https://doi.org/10.5194/nhess-17-225-2017>
- Anderson TW, Darling DA (1954) A test of goodness of fit. *J Am Stat Assoc* 49(268):765–769. <https://doi.org/10.1080/01621459.1954.10501232>
- Anderson MG, Howes S (1985) Development and application of a combined soil water-slope stability model. *Q J Eng Geol Hydrogeol* 18(3):225–236. <https://doi.org/10.1144/GSL.QJEG.1985.018.03.04>
- Anderson MG, Lloyd DM (1991) Using a combined slope hydrology-stability model to develop cut slope design charts. *Proc Inst Civ Eng* 91(4):705–718. <https://doi.org/10.1680/iicep.1991.17486>
- Anderson MG, Lloyd DM, Kemp MJ (1997) Overseas road note 14: hydrological design manual for slope stability in the tropics. Transport Research Laboratory, Crowthorne
- Bayat H, Ebrahimi E, Fallah M (2018) Estimation of soil moisture using confined compression curve parameters. *Geoderma* 318:64–77. <https://doi.org/10.1016/j.geoderma.2017.12.034>
- Beesley MEW, Holcombe EA, Shephard CJ, Vardanega PJ, Michaeliedis K (2017) Modelling dynamic drivers and uncertain soil parameters in tropical urban slopes. In: Lee W, Lee J-S, Kim H-K, Kim D-S (eds) Proceedings of the 19th international conference on soil mechanics and geotechnical engineering (ICSMGE 2017): unearth the future, connect beyond. Republic of Korea: Korea Geotechnical Society, Seoul, pp 3365–3368
- Bonilla CA, Johnson OI (2012) Soil erodibility mapping and its correlation with soil properties in Central Chile. *Geoderma* 189–190:116–123. <https://doi.org/10.1016/j.geoderma.2012.05.005>
- Breiman L, Friedman J, Stone CJ, Olshen RA (1984) Classification and regression trees. CRC Press, USA
- Brooker EW, Ireland HO (1965) Earth pressure at rest related to stress history. *Can Geotech J* 2(1):1–15. <https://doi.org/10.1139/t65-001>
- Casagrande A (1947) Classification and identification of soils. *Proc Am Soc Civ Eng* 73(6):783–810
- CHaRIM (2013) Saint Lucia GeoNode. Caribbean Handbook on Risk Management. Available online at <http://charim-geonode.net/people/profile/lucia/?content=layers> (last accessed 13/12/2018)
- Chen W, Pourghasemi HR, Naghibi SA (2018a) Prioritization of landslide conditioning factors and its spatial modeling in Shangna County, China using GIS-based data mining algorithms. *Bull Eng Geol Environ* 77(2):611–629. <https://doi.org/10.1007/s10064-017-1004-9>
- Chen W, Pourghasemi HR, Naghibi SA (2018b) A comparative study of landslide susceptibility maps produced using support vector machine with different kernel functions and entropy data mining models in China. *Bull Eng Geol Environ* 77(2):647–664. <https://doi.org/10.1007/s10064-017-1010-y>
- Ching J, Phoon K-K (2014a) Transformations and correlations among some clay parameters – the world database. *Can Geotech J* 51(6):663–685. <https://doi.org/10.1139/cgj-2013-0262>
- Ching J, Phoon K-K (2014b) Correlations among some clay parameters – the multivariate distribution. *Can Geotech J* 51(6):686–704. <https://doi.org/10.1139/cgj-2013-0353>
- Craig RF (2004) *Craig's soil mechanics*, 7th edn. Taylor & Francis, Abingdon
- De Risi R, Goda K, Yasuda T, Mori N (2017) Is flow velocity important in tsunami empirical fragility modeling? *Earth Sci Rev* 166:64–82. <https://doi.org/10.1016/j.earscirev.2016.12.015>
- Du G, Zhang Y, Yang Z, Guo C, Yao X, Sun D (2018) Landslide susceptibility mapping in the region of the eastern Himalayan syntaxis, Tibetan plateau, China: a comparison between analytical hierarchy process information value and logistic regression – information value methods. *Bull Eng Geol Environ*. <https://doi.org/10.1007/s10064-018-1393-4>
- Faber, M. H. (2012). *Statistics and probability theory: in pursuit of engineering decision support* (Vol. 18). Springer Science & Business Media
- Fookes PG (1997a) Tropical residual soils. A Geological Society Engineering Group Working Party Revised Report. Geological Society, London
- Fookes PG (1997b) Geology for engineers: the geological model, prediction and performance. *Q J Eng Geol Hydrogeol* 30(4):293–424. <https://doi.org/10.1144/GSL.QJEG.1997.030.P4.02>
- GCO (Geotechnical Control Office) (1982) Mid-levels study report on geology, hydrology, and soil properties. GCO, Public Works Department, Hong Kong
- Hamm N, Hall J, Anderson MG (2006) Variance-based sensitivity analysis of the probability of hydrologically induced slope instability. *Comput Geosci* 32(6):803–817. <https://doi.org/10.1016/j.cageo.2005.10.007>
- Hartemink AE, Krasilnikov P, Bockheim JG (2013) Soil maps of the world. *Geoderma* 207:256–267. <https://doi.org/10.1016/j.geoderma.2013.05.003>
- Havaee S, Mosaddeghi MR, Ayoubi S (2015) In situ surface shear strength as affected by soil characteristics and land use in calcareous soils of Central Iran. *Geoderma* 237:137–148. <https://doi.org/10.1016/j.geoderma.2014.08.016>
- Holcombe EA, Beesley MEW, Vardanega PJ, Sorbie R (2016) Urbanisation and landslides: hazard drivers and better practices. *Proc Inst Civil Eng – Civil Eng* 169(3):137–144. <https://doi.org/10.1680/jcien.15.00044>
- Howard AK (1984) The revised ASTM standard on the united classification system. *Geotech Test J* 7(4):216–222. <https://doi.org/10.1520/GTJ10505J>
- Jie W, Binglin S, Jinlin L, Shasha L, Xiubin H (2018) Shear strength of purple soil bunds under different soil water contents and dry densities: a case study in the three gorges reservoir area, China. *Catena* 166:124–133. <https://doi.org/10.1016/j.catena.2018.03.021>
- Kenney TC (1959) Discussion on geotechnical properties of glacial Lake clays. *J Soil Mech Found Div (ASCE)* 85(SM3):67–79
- Kulhawy FH (2010) Uncertainty, reliability, and foundation engineering: the 5th Peter Lumb lecture. *HKIE Trans* 17(3):19–24. <https://doi.org/10.1080/1023697X.2010.10668200>
- Kulhawy, F. H. and Mayne, P. W. (1990). Manual on estimating soil properties for foundation design. *Report. No. EL-6800*, Electric Power Research Institute, Palo Alto, California, USA
- Ladd CC, Foott R, Ishihara K, Schlosser F, Poulos HG (1977) Stress-deformation and strength characteristics. In Proceedings of the Ninth International Conference on Soil Mechanics and Foundation

- Engineering: Tokyo 1977. Tokyo, 10–15 July 1977. Japanese Society of Soil Mechanics and Foundation Engineering, Tokyo, Japan Vol.2, pp. 412–494
- Li AJ, Merifield RS, Lyamin AV (2008) Stability charts for rock slopes based on the Hoek–Brown failure criterion. *Int J Rock Mech Min Sci* 45(5):689–700. <https://doi.org/10.1016/j.ijrmms.2007.08.010>
- Lings ML, Dietz MS (2004) An improved direct shear apparatus for sand. *Géotechnique* 54(4):245–256. <https://doi.org/10.1680/geot.2004.54.4.245>
- Lumb P (1966) The variability of natural soils. *Can Geotech J* 3(2):74–97. <https://doi.org/10.1139/t66-009>
- Lumb P (1970) Safety factors and the probability distribution of soil strength. *Can Geotech J* 7(3):225–242. <https://doi.org/10.1139/t70-032>
- Mendes, R. M., de Andrade, M. R. M., Graminha, C. A., Prieto, C. C., de Áila, F. F. and Camarinha, P. I. M. (2018). Stability analysis on urban slopes: case study of an anthropogenic-induced landslide in São José dos Campos, Brazil. *Geotech Geol Eng*, 36(1): 599–610, <https://doi.org/10.1007/s10706-017-0303-z>
- Michalowski RL (2002) Stability charts for uniform slopes. *J Geotech Geoenviron* 128(4):351–355. [https://doi.org/10.1061/\(ASCE\)1090-0241\(2002\)128:4\(351\)](https://doi.org/10.1061/(ASCE)1090-0241(2002)128:4(351))
- Minitab 17 Support (2017). *The Anderson Darling Statistic*, [online]. See: <http://support.minitab.com/en-us/minitab/17/topic-library/basic-statistics-and-graphs/introductory-concepts/data-concepts/anderson-darling/> (accessed 21/04/2018)
- Montgomery DC, Runger GC, Hubele NF (2007) *Engineering statistics*, 4th edn. Wiley, USA
- Murthy DNP, Vie M, Jiang R (2004) Weibull models. Wiley, USA
- Mutekanga FP, Visser SM, Stroosnijder L (2010) A tool for rapid assessment of erosion risk to support decision-making and policy development at the Ngenge watershed in Uganda. *Geoderma* 160(2):165–174. <https://doi.org/10.1016/j.geoderma.2010.09.011>
- Nimmo JR, Perkins KS (2002) Aggregate stability and size distribution. In: Dane JH, Topp GC (eds) *Methods of soil analysis*, part 4 – physical methods. Soil Science Society of America, Madison, pp 317–328
- Parry RGH (2004) *Mohr circles, stress paths, and geotechnics*, 2nd edn. Spon Press, UK
- Petley DN (2009) On the impact of urban landslides. In: *Engineering Geology for Tomorrow's Cities* (Culshaw, M. G., Reeves, H.J., Jefferson, I. and Spink, T. W. eds.) – Engineering Geology Special Publications, 22: 83–99, <https://doi.org/10.1144/EGSP22.6>
- Pham BT, Bui DT, Dholakia MB, Prakash I, Pham HV (2016) A comparative study of least square support vector machines and multiclass alternating decision trees for spatial prediction of rainfall-induced landslides in a tropical cyclones area. *Geotech Geol Eng* 34(6):1087–1824. <https://doi.org/10.1007/s10706-016-9990-0>
- Pham BT, Bui DT, Prakash I (2017) Landslide susceptibility assessment using bagging ensemble based alternating decision trees, logistic regression and J48 decision trees methods: a comparative study. *Geotech Geol Eng* 35(6):2597–2611. <https://doi.org/10.1007/s10706-017-0264-2>
- Pham BT, Son LH, Hoang T-A, Nguyen D-C, Bu DT (2018) Prediction of shear strength of soft soil using machine learning methods. *Catena* 166:181–191. <https://doi.org/10.1016/j.catena.2018.04.004>
- Pianosi F, Beven K, Freer J, Hall JW, Rougier J, Stephenson DB, Wagener T (2016) Sensitivity analysis of environmental models: a systematic review with practical workflow. *Environ Model Softw* 79:214–232. <https://doi.org/10.1016/j.envsoft.2016.02.008>
- Rackwitz R (2000) Reviewing probabilistic soil modelling. *Comput Geotech* 26(3–4):199–223. [https://doi.org/10.1016/S0266-352X\(99\)00039-7](https://doi.org/10.1016/S0266-352X(99)00039-7)
- Regional Research Laboratory (RRL) (1966). *Soils and Land-Use Surveys No.20. St Lucia*. Regional Research Laboratory of the British Caribbean, at The Imperial College of Tropical Agriculture, Trinidad, University of the West Indies
- Ringrose-Voase AJ, Grealish GJ, Thomas M, Wong MTF, Glover MR, Mercado A, Nilo GP, Dowling TI (2017) Four pillars of digital land resource mapping to address information and capacity shortages in developing countries. *Geoderma*. <https://doi.org/10.1016/j.geoderma.2017.10.014>
- Roopnarine R, Eudoixe G, Gay D (2012) Soil physical properties as predictors of soil strength indices: Trinidad case study. *Geomaterials* 2(1):1–9. <https://doi.org/10.4236/gm.2012.21001>
- Rouse WC, Reading AJ, Walsh RPD (1986) Volcanic soil properties in Dominica, West Indies. *Eng Geol* 23(1):1–28. [https://doi.org/10.1016/0013-7952\(86\)90014-1](https://doi.org/10.1016/0013-7952(86)90014-1)
- Rouse C (1990) The mechanics of small tropical flowslides in Dominica, West Indies. *Eng Geol* 29(3):227–239. [https://doi.org/10.1016/0013-7952\(90\)90052-3](https://doi.org/10.1016/0013-7952(90)90052-3)
- Schjønnning P, Lamandé M (2018) Models for prediction of soil precompression stress from readily available soil properties. *Geoderma* 320:115–125. <https://doi.org/10.1016/j.geoderma.2018.01.028>
- Scott B, Kim BJ, Salgado R (2003) Assessment of current load factors for use in geotechnical load and resistance factor design. *J Geotech Geoenviron* 129(4):287–295. [https://doi.org/10.1061/\(ASCE\)1090-0241\(2003\)](https://doi.org/10.1061/(ASCE)1090-0241(2003))
- Shepherd CJ, Vardanega PJ, Holcombe EA, Michaelides K (2018a) Analysis of design choices for a slope stability scenario in the humid tropics. *Proc Inst Civil Eng-Eng Sustain* 171(1):37–52. <https://doi.org/10.1680/jensu.16.00081>
- Shepherd CJ, Vardanega PJ, Holcombe EA, Hen-Jones R, De Luca F (2018b) On the variability of the effective friction angle of Saint Lucian soils: investigations through a laboratory database. *ce/papers* 2(2–3):779–784. <https://doi.org/10.1002/cepa.765>
- Singh R, Wagener T, Crane R, Mann ME, Ning L (2014) A vulnerability driven approach to identify adverse climate and land use change combinations for critical hydrologic indicator thresholds: application to a watershed in Pennsylvania, USA. *Water Resour Res* 50: 3409–3427. <https://doi.org/10.1002/2013WR014988>
- Sørensen KK, Okkels N (2013) Correlation between drained shear strength and plasticity index of undisturbed overconsolidated clays. In: P Delage, J Desrues, R Frank, A Puech & F Schlosser (eds), *Proceedings of the 18th International Conference on Soil Mechanics and Geotechnical Engineering: vol. 1: Challenges and innovations in geotechnics / Défis et innovations en géotechnique*. Presses des Ponts, pp. 423–428
- Take WA, Bolton MD (2011) Seasonal ratcheting and softening in clay slopes, leading to first time failure. *Géotechnique* 61(9):757–769. <https://doi.org/10.1680/geot.9.P.125>
- Taylor DW (1937) Stability of earth slopes. *Journal of the Boston Society of Civil Engineers* 24(3). Reprinted in: *Contributions to Soil Mechanics 1925–1940*, Boston Society of Civil Engineers, Boston, 337–386
- Toll DG (2012) Tropical soils. In: *ICE manual of geotechnical engineering*. ICE Publishing, London, pp 341–361
- van Asch, W. J. Th. (1984). Landslides: the deduction of strength parameters of materials from equilibrium analysis. *Catena*, 11(1): 39–49, [https://doi.org/10.1016/S0341-8162\(84\)80004-1](https://doi.org/10.1016/S0341-8162(84)80004-1)
- Vardanega PJ, Bolton MD (2016) Design of Geostructural systems. *ASCE-ASME J Risk Uncert Eng Syst, Part A: Civil Eng* 2(1): 04015017. <https://doi.org/10.1061/AJRU6A.0000849>
- Vardanega PJ, Crispin JJ, Gilder CE, Voyagaki E, Shepherd CJ, Holcombe EA (2018) Geodatabases to improve geotechnical design

- and modelling. *ce/papers* 2(2–3):401–406. <https://doi.org/10.1002/cepa.704>
- Weibull W (1951) A statistical distribution function of wide applicability. *J Appl Mech* 18:293–297
- Wesley LD (1990) Influence of structure and composition on residual soils. *J Geotech Geoenviron* 116(4):589–603. [https://doi.org/10.1061/\(ASCE\)0733-9410\(1990\)116:4\(589\)](https://doi.org/10.1061/(ASCE)0733-9410(1990)116:4(589))
- Wesley LD (2009) Behaviour and geotechnical properties of residual soils and allophane clays. *Obras y Proyectos* 6:5–10
- Wilkinson PL, Anderson MG, Lloyd DM (2002) An integrated hydrological model for rain-induced landslide prediction. *Earth Surf Process Landf* 27(12):1285–1297. <https://doi.org/10.1002/esp.409>
- Wright JV, Roobol MJ, Smith AL, Sparks RSJ, Brazier SA, Rose WI, Sigurdsson H (1984) Late quarternary explosive silicic volcanism on St Lucia, West Indies. *Geol Mag* 121(1):1–15. <https://doi.org/10.1017/S0016756800027904>
- Zolfaghari Z, Mosaddeghi MR, Ayoubi S (2016) Relationships of soil shrinkage parameters and indices with intrinsic soil properties and environmental variables in calcareous soils. *Geoderma* 277:23–34. <https://doi.org/10.1016/j.geoderma.2016.04.022>