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Soil databases to assist slope stability assessments in the Eastern Caribbean

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Abstract

Rainfall-triggered landslides are an ‘everyday risk’ to Small Island States, such as Saint Lucia in the Caribbean, and have the potential to destroy or damage buildings and disrupt lifelines such as roads and pipelines. To better evaluate these landslide hazards, efforts have been made to develop decision-support tools linking rainfall scenarios to stability for different types of road cut slope. Many thousands of stochastic simulations can be performed using a combined hydrology and slope stability model (CHASM) which requires inputs of slope cross-sectional geometry, soil and hydrological parameters which allows representative rainfall-triggered landslide scenarios to be produced. To use CHASM for this purpose the statistical variation of the relevant geotechnical properties such as friction angle needs to be assessed. This paper presents the analysis of an updated database for Saint Lucian soils that has been compiled using data supplied by the Government of Saint Lucia Ministry of Infrastructure, Port Services and Transport. The Coefficient of Variation values of the key soil mechanics parameters are reported and previously developed transformation models for estimating effective friction angle are updated. The Weibull statistical distribution is shown to be the best fit to the friction angle data.

Keywords

Coefficient of Variation, Soil Database, Soil Variability, Transformation Models; Statistical Distributions; Tropical Soils

Introduction

Landslides in the humid tropics are typically rainfall triggered (e.g. Lumb 1975, Toll 2001). Considerable research has focused on modelling rainfall triggered landslides in the Eastern Caribbean (Anderson & Kemp 1991, Holcombe et al. 2016, Shepheard et al. 2018a). As a developing country, Saint Lucia is more vulnerable to the effects of natural disasters than other nations (Alcantara-Ayala et al. 2002) with socio-economically vulnerable communities and lifeline infrastructure (Fig. 1) particularly affected (Bull-Kamanga et al. 2003, Larsen & Parks, 1997).

Methods to better assess geotechnical variability are needed to enhance geotechnical design (e.g. Lumb 1966, Lumb 1970). Geotechnical databases are needed to enable measures of geotechnical variability of a soil parameter to be determined, such as the coefficient of variation (COV); or the best-fit probability density functions; or to develop transformation models allowing a more complex soil parameter to be estimated from basic ones (e.g. Kulhawy & Mayne 1990, Phoon & Kulhawy 1999a, Phoon & Kulhawy 1999b, Phoon 2017).

Fig. 1 Road cut slope, Saint Lucia primary road network, after landslide debris cleared (photo: E A Holcombe)

Recent efforts to develop a geotechnical database for Saint Lucia have been reported by Vardanega et al. (2018) and Shepheard et al. (2018b, 2019). In Shepheard et al. (2019), the first 91 entries in the database were reported and analysed. In this paper the database is expanded using data collected during a 2018 research visit. This database was then expanded and further analysed in the thesis of Savva (2019).

Such geotechnical data are necessary for mechanistic slope stability analyses such as those performed using CHASM (e.g. Wilkinson et al. 2002), and more recently by placing such models within a stochastic high-performance computing framework (e.g. Almeida et al. 2017). Potential decision-support outputs include synthetic rainfall thresholds for landslide triggering (cf. Larsen & Simon's, 1993, empirical-statistical thresholds for Puerto Rico). These can be used to assess whether a region will experience landslides for a given storm event (this topic is discussed further in Holcombe et al. 2020).

Soil Classification Parameters

The use of basic soil classification parameters (e.g. plasticity index) to develop transformation models is the subject of many studies (e.g. Kulhawy & Mayne 1990). In this paper the COV of the liquid limit (w_L), plastic limit (w_P), plasticity index (I_P), the silt-clay fraction (SCF) (which is defined in this work as the percentage passing the 0.075mm sieve) and field water content (w) are studied along with the soil effective peak friction angle (ϕ'_p or ϕ'_{peak}) and apparent cohesion (c').

Soil friction angle

The effective friction angle has been studied for soils from various Caribbean islands e.g. Dominica (Rao 1996, Reading 1991, Rouse et al. 1986, Rouse 1990) and Trinidad (Roopnarine et al. 2012). To ensure long-term stability of slopes the critical state friction angle (Take & Bolton 2011) or the fully softened or residual friction angle (e.g. Eid & Rabie 2017, Hayden et al. 2018) would be preferred.

However, in Saint Lucia only the ϕ'_p is typically available from hand-powered direct shear tests in the government materials laboratory. Shepheard et al. (2019) describe the details of the testing process in which the stress increment is believed to have been constant for all the tests in the database (37.2 kPa to 112.4 kPa). Field samples are placed directly into the shear box without sieving, but with inevitable disturbance and change in moisture content due to sample extraction, transporting and testing (Shepheard et al. 2019). Further verification of the shear box testing procedure would be required if individual test data were intended for site-specific analysis and design rather than for stochastic modelling and diagnosis of general slope behaviour thresholds (see Almeida et al. 2017).

Soil friction angle is related to changes in the Atterberg limits (e.g. Brooker & Ireland 1965, Sorensen & Okkels 2013, Stark & Eid 1997, Stark & Hussain 2013, Wesley 1977, Wesley 2003) and clay fraction (Skempton 1985).

Building the Saint Lucia Soils Database

In 2016 a field trip was undertaken by the first two authors to Saint Lucia where data was obtained from the digitised records from the Saint Lucia Ministry of Infrastructure, Port Services and Transport. This data along with other information from past projects undertaken by the second author was used to produce the database with 91 data entries presented in detail in Shepheard et al. (2019) and analysed in Shepheard (2017), Vardanega et al. (2018), Shepheard et al. (2018b).

In 2018, a follow-up visit was undertaken by another research team from the University of Bristol (again the first two authors were involved). In this visit, further data was collected by scanning past data reports. This new data was processed, added to the database and the statistical analysis methodology presented in Shepheard et al. (2019) was re-run. Preliminary results of this new analysis are presented in Savva (2019). In the analysis that follows the number of data-points (n) on each chart can vary, as for each entry in the expanded database not all the parameters of interest were available.

Statistical Analysis

Computation of COV can be used to assess relative variability of different soil parameters (Phoon & Kulhawy 1999a, Phoon & Kulhawy 1999b). Phoon (2017) gives the COV values for many transformation models from the literature. Tab. 1 shows the relevant summary statistics for the updated Saint Lucia database. A range of soil types are present on the island of Saint Lucia (see Shepheard et al. 2019). Fig. 2 shows the soils from the expanded database plotted on the Casagrande chart: a range of plasticity levels is shown with both silts and clays present in the database. Fig. 3 shows the pairs of ϕ'_p and c' with a high degree of scatter shown (the COV for c' is about 2.7 times that of ϕ'_p: see Tab. 1).

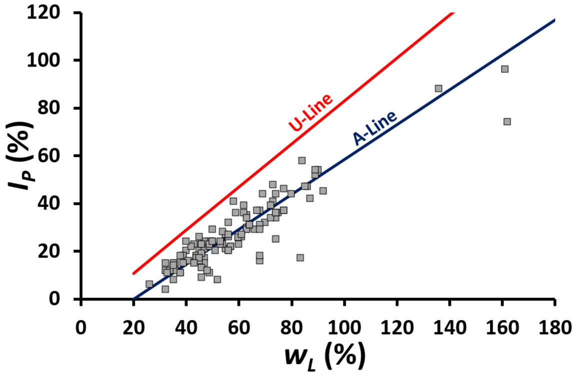

Fig. 2 Expanded Saint Lucia Database (n=114) plotted on the Casagrande-style classification chart

Table 1 Summary statistics for the updated Saint Lucia soils database (all soil types) (*SD* = standard deviation)

	c' (kPa)	ϕ'_p (°)	w_L (%)	w_P (%)	I_P (%)	w (%)	*SCF* (%)
n	153	152	115	115	120	132	119
max	350	55	162	88	96	117	96
average	25	24	59	31	27	32	40
min	0	1	26	16	3	8	3
SD	31	11	22	10	15	16	24
COV (%)	125	46	38	32	58	49	59

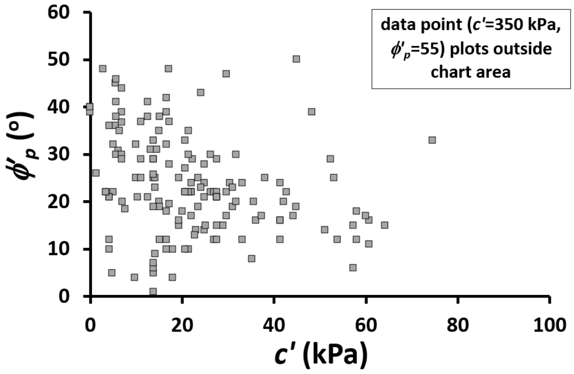

Fig. 3 ϕ'_p plotted against c' (kPa) (expanded database)

Regression Analysis

Past transformation models have been developed for early versions of the Saint Lucia database. I_P is often used to estimate ϕ'_p (e.g. Brooker & Ireland 1965, Sorensen & Okkels 2013). The coefficient of determination (R^2) and the number of data-points used to generate the regression (n) are quoted for each transformation model presented. For the Saint Lucia soils (data from the 2016 field work) the following transformation model was developed (Shepheard et al. 2018b):

$$\phi'_p = 26.4 - 0.22(I_P) \quad [R^2 = 0.15, n=55, p = 0.004] \quad [1]$$

However, for the Saint Lucia soils Shepheard et al. (2018b) also showed a superior correlation using w:

$$\phi'_p = 30.7 - 0.32(w) \quad [R^2 = 0.36, n=52, p < 0.001] \quad [2]$$

Vardanega et al. (2018) showed further improvement in R^2 when ϕ'_p was regressed against liquidity index (I_L):

$$\phi'_p = 20.8 - 10.2(I_L) \quad [R^2 = 0.43, n=48, p < 0.001] \quad [3]$$

Equations 1-3 are compared with updated transformation models in the following section.

Updated Regressions

Fig. 4 shows ϕ'_p plotted against w_L for the expanded database (the number of available data-points for the new regressions is about double that from the previous studies). An exponential model was found to be the best fit to the ϕ'_p versus w_L data:

$$\phi'_p = 37.2e^{-0.011(w_L)} \quad [R^2 = 0.23, n=102, p < 0.001] \quad [4]$$

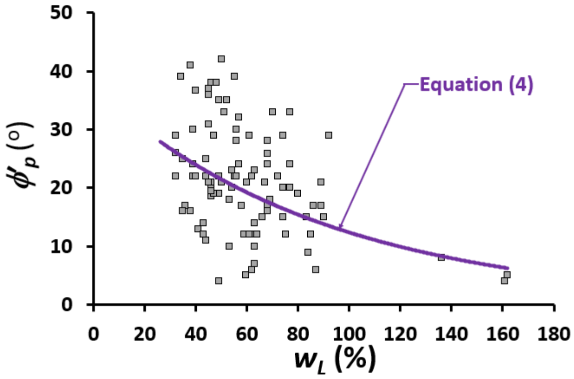

Fig. 4 ϕ'_p plotted against w_L (%) (expanded database)

Fig. 5 shows ϕ'_p plotted against w_p for the expanded database with an exponential relationship:

$$\phi'_p = 31.0e^{-0.015(w_P)} \quad [R^2 = 0.088, n=101, p < 0.01] \quad [5]$$

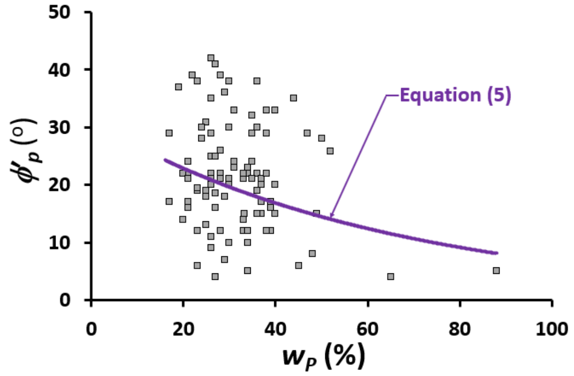

Fig. 5 ϕ'_p plotted against w_P (%) (expanded database)

Fig. 6 shows ϕ'_p plotted against I_p compared with Eq. 1 and the following exponential relationship developed for the updated database (reasonable agreement between Eq.1 and Eq.6 is shown):

$$\phi'_p = 29.6e^{-0.016(I_P)} \quad [R^2 = 0.23, n=104, p < 0.001] \quad [6]$$

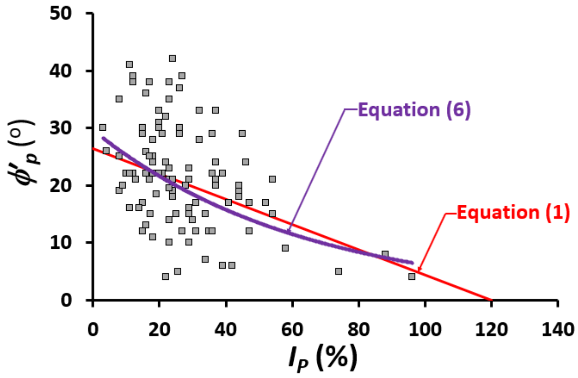

Fig. 6 ϕ'_p plotted against I_P (%) (expanded database)

Fig. 7 shows ϕ'_p plotted against w compared with Eq. 2 and with the following exponential relationship developed for the updated database (reasonable agreement between Eq.2 and Eq.7 is shown):

$$\phi'_p = 39.0e^{-0.020(w)} \qquad [R^2 = 0.39,\ n=114,\ p < 0.001] \quad [7]$$

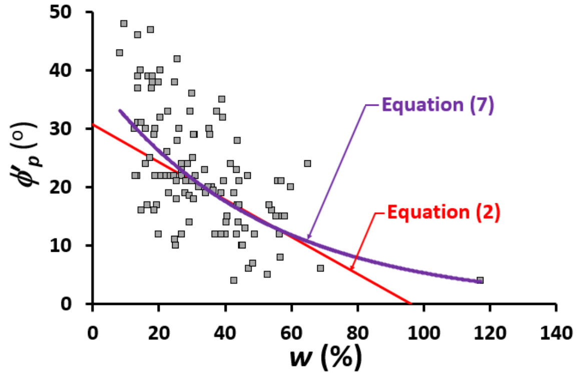

Fig. 7 ϕ'_p plotted against w (%) (expanded database)

Fig. 8 shows ϕ'_p plotted against SCF for the expanded database with the following exponential relationship:

$$\phi'_p = 26.6e^{-0.0079(SCF)} \qquad [R^2 = 0.14,\ n=101,\ p < 0.001] \quad [8]$$

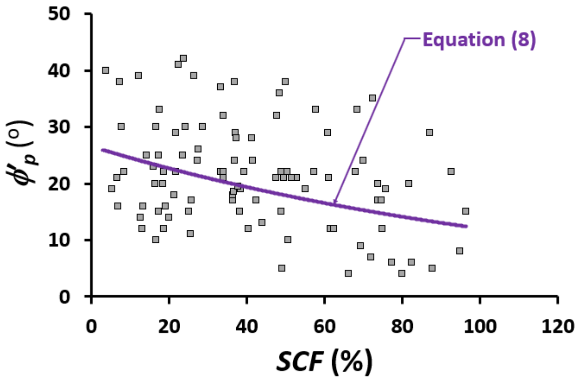

Fig. 8 ϕ'_p plotted against SCF (%) (expanded database)

Fig. 9 shows ϕ'_p plotted against I_L compared with Eq. 3 and the following linear relationship developed for the updated database:

$$\phi'_p = 21.4 - 6.6(I_L) \qquad [R^2 = 0.21,\ n=94,\ p < 0.001] \quad [9]$$

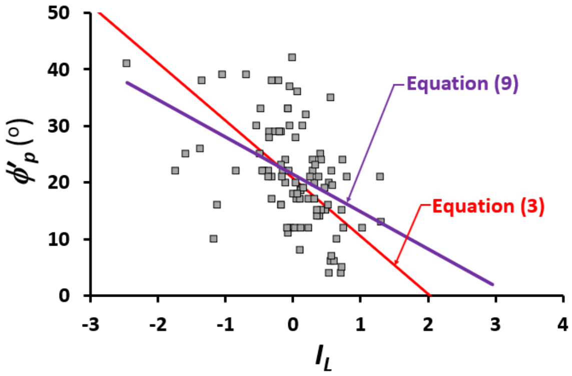

Fig. 9 ϕ'_p plotted against I_L (expanded database)

The slope of Eq. 9 is smaller than Eq. 3 and the R^2 is considerably lower. Of the studied correlations Eq. 7 has the highest R^2 and is higher than for the correlation with I_L (Eq. 9). Fig. 10 shows the predicted measured plot for Eq. 7 with ±50% bounds shown.

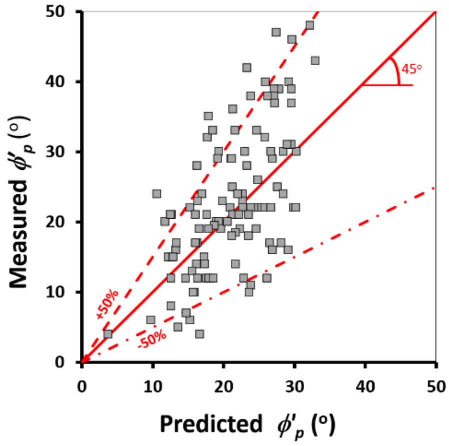

Fig. 10 Predicted versus measured plot for Eq. 7

Multiple Linear Regression (MLR) analysis

MLR studies of the early database were reported in Shepheard (2017) and Shepheard et al. (2018b). The following correlation was found:

$$\phi'_p = 19.8 - 0.14(w_L) + 0.77(w_P) - 0.46(w) \quad [10]$$

$$[R^2 = 0.56,\ n=47,\ p < 0.001]$$

The same analysis was re-run for the expanded database:

$$\phi'_p = 23.6 - 0.078(w_L) + 0.42(w_P) - 0.31(w) \quad [11]$$

$$[R^2 = 0.28,\ n=84,\ p < 0.001]$$

Statistical Models

Distributions of soil parameters are needed for stochastic slope stability analysis. Fits of statistical distributions to the early database were presented in Shepheard et al. (2019) in which it was found that the Weibull distribution was the best fit. With the ϕ'_p data in the extended database (n=152), the Weibull distribution is again shown to be the most appropriate (Fig. 11, Table 2). Table 2 provides a summary of the Akaike Information Criteria (AIC) (Akaike 1974) and Anderson Darling (AD) (Anderson & Darling 1954) test statistics confirming the suitability of Weibull distribution over the others. For the AIC also the Generalised Extreme Value (GEV) fit was tested giving a value of 1278 (still higher than the 1153 obtained using the Weibull fit being the best option).

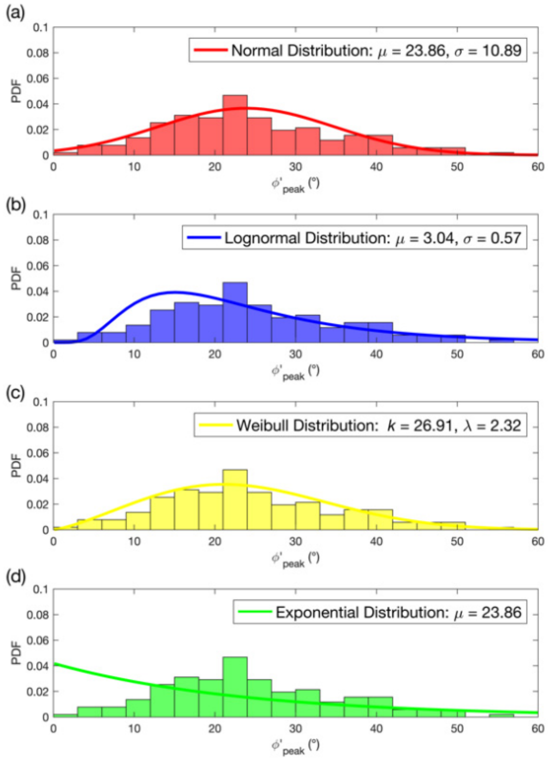

Fig. 11 Normal (a), Lognormal (b), Weibull (c) and Exponential (d) probability density functions fitted to ϕ'_p data from the extended database (fitting parameters for each distribution shown on the figure)

Table 2 AIC and AD statistics for the distributions fitted to the Saint Lucia ϕ'_p data from the extended database

	Normal	Lognormal	Weibull	Exponential
AIC	1160	1190	**1153**	1270
AD	1.0154	2.4775	**0.4210**	19.9490

Summary and Conclusions

This paper has presented preliminary analysis of an expanded geotechnical database for Saint Lucia. The new database has approximately doubled the number of data-points available to develop transformation models to predict ϕ'_p. Future work will analyse classes of soils within the database. Interestingly, the relative strength of the previous correlations with I_P and w has remained consistent with slightly higher computed R^2 values for the correlations developed using the expanded dataset. However, the models developed using I_L and a combination of w_L, w_P and w have reduced R^2 values compared with those for the earlier version of the database. The best predictor of ϕ'_p appears to be w, and Weibull the best statistical distribution.

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