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ORIGINAL PAPER

Predicting nanocomposite binder improved unsaturated soil UCS using genetic programming

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Abstract

The ability of the compacted soils and treated/compacted soils to withstand loads as foundation materials depends on the stability and durability of the soils. The design of such phenomena in treated soils whether as subgrade of pavements or embankments, backfills, etc., is a crucial phase of foundation constructions. Often, it is observed that soil mechanical and structural properties fall below the minimum design and construction requirements and this necessitates the stabilization in order to improve the needed properties. It can be observed that for this reason, there is a steady use of the laboratory and equipment prior to any design and construction as the case may be. In this work, genetic programming (GP) has been employed to predict the unconfined compressive strength of unsaturated lateritic soil treated with a hybridized binder material called hybrid cement (HC), which was formulated by blending nanotextured quarry fines (NQF) and hydrated lime activated nanotextured rice husk ash. Tests were conducted to generate multiple values for output and inputs parameters, and the values were deployed into soft computing technique to forecast UCS adopting three (3) different performance complexities (2, 3 and 4 levels of complexity). The results of the prediction models show that the four (4) levels of complexity GP model outclassed the others in performance and accuracy with a total error (SSE) of 2.4% and coefficient of determination (R^2) of 0.991. Generally, GP has shown its robustness and flexibility in predicting engineering problems for use in design and performance evaluation.

Keywords Hybrid cement (HC) · Nanostructured rice husk ash (NRHA) · Unsaturated lateritic soil · Soft computing (genetic programming) · Unconfined compressive strength · Soil stabilization · Nanostructured quarry fines (NQF)

Introduction

Soil improvement and stabilization: potentials and techniques

The practice of harnessing various soil improvement and stabilization techniques has heavily augmented for the lack of suitable materials used on site for various geotechnical and structural applications [9, 26, 46, 70]. Just as the practice of using locally made available waste materials to partial replace cement in concrete has attracted many research attentions, soil stabilization techniques in the field of geotechnical engineering are not a left out [20, 67]. Enormous benefits are associated with soil improvement practices such as enhancing the physical, chemical, mechanical and even electrical properties of soil [3, 32]. Other uses may include increase in soil strength, durability or even to prevent erosion and environmental pollution [10, 27, 46]. Meanwhile, the structural, mechanical and geotechnical engineering

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applications and uses of soil stabilization such as construction of buildings, roads, railways, embankments, stabilization of slopes, improvement of critically desirable properties like bearing capacity, shear strength and permeability characteristics of soil [44], are of paramount concern to civil engineers [4, 5, 22, 59]. As stated by Perloff [55], stabilization may be realized by mechanically blending the natural soil and a stabilizing agent in order to form a homogeneous mixture or by adding a stabilizing material to an undisturbed soil deposit and allowing it permeate through soil voids. For Saeed et al., [59] and Gopal et al. [30], chemical stabilization entails the blending of admixtures of powder, slurry or liquid, fundamentally for enhancing or controlling its volume stability, strength and stress–strain behavior, permeability and durability [15, 19]. Overall, the alteration of any property of a soil to improve its engineering performance such as strength, reduced compressibility, reduced permeability or improved ground water condition, known as soil improvement has been so far performed using various stabilizing agents [49]. This has been done relying on such factors as; soil type and layering, degree of the expected load, situation and type of the project, and the general critical parameters whose properties are to be enhanced [1, 17, 20, 36, 38, 48, 51, 52, 57, 58].

Enhanced unconfined compressive strength and associated mechanical and physical properties induced by soil improvement practices

Owing to its criticality and varying tendencies at various degrees of blending of stabilizing materials or even the type of stabilizing agent used, many research efforts performed on soil improvement have been centered on the determination for acceptability of the unconfined compressive strength (UCS) of soils, particularly lateritic soil which has been a paramount material used in various geotechnical and structural applications [14, 28]. Due to the intricacies of its water table being very deep, making its upper part usually unsaturated, lateritic soil needs constant enhancement mechanisms [31, 33], while the accompanying properties deserve consistent estimation [10, 42]. UCS has been defined as the maximum axial compressive stress that a right-cylindrical sample of material can withstand under unconfined conditions if the confining stress is zero. It can also be rephrased as the maximum load per unit average cross-sectional area at which the cylindrical specimen of soil falls in compression.

UCS is affected by a host of many factors such as clay activity, unsaturated or bulk unit weight, plasticity index, coefficient of uniformity and the friction angle of the soil specimen [13]. Naein et al. [46] observed that the UCS of soil reinforced with waterborne polymer decreased as the plasticity index improved, whereas the strength property increased markedly. Piratheepan et al. [56] reported that for soil whose mechanical properties were using improved cement, gypsum and limestone, the internal friction and the cohesion factor were traceable using the UCS estimation. As a shear strength parameter, friction angle, φ is of paramount importance in slope stability analysis, and other important soil analysis [31]. In this study also, Xia [68] analyzed the correlation between bulk density, moisture content, cohesion, friction angle and unconfined compressive strength via laboratory experiments. He found out that there exists a strong relationship between soil cohesion, friction angle and UCS, and generated models based on these influencing parameters which in turn can be used to predict UCS. Liu et al. [41] performed a series of unconfined compressive strength tests in order to ascertain the usability of organic polymer as a soil stabilizing agent. From their experiment, they observed that the USC was always at response to the type and degree of stabilization agent used at various geotechnical conditions. Xing et al. [69] developed models for predicting the unconfined compression strength of samples based on cement content, wheat straw content and curing periods.

In areas of variable and inconsistent water table, and based on the intricacies of seasonality effects, including enhancement of the soil by the use of stabilizing agent like hybrid cement, there becomes additional dynamics in the behavior of unsaturated lateritic soil. This, however, affects the factors or parameters in which the UCS of the subgrade depends on, such as bulk unit weight, coefficient of uniformity, plasticity index, internal friction and unsaturated unit weight. The hydraulic properties of unsaturated laterite soils show that when analyzed, the water retention curve and the unsaturated hydraulic conductivity were functions of matrix suction [21]. The unconfined compressive strength of unsaturated soils is significantly influenced by the matric suction, a function of hydraulic conductivity, which in turn has influence on the frictional angle, UCS and bulk unit weight as two important variables being considered in the present work [66]. A previous research [70], which evaluated three soils, viz. pink kaolin silty soil, Botucatu weathered sandstone residual soil and Osorio uniform sand, stabilized with Portland cement type III, did not only show that hydraulic conductivity has relationship with unconfined compressive strength, it further demonstrated an increase in UCS, which is suitably labeled as a linear increase with the rise in cement content and its associated hydration reaction, and as an exponential function as porosity drops. Their computed hydraulic conductivity had an overall reduction, in the same vein, with a linear reduction triggered by raising cement content and reduced as a power function in regard to reducing porosity. Hence, the relationship between hydraulic conductivity and UCS can be said to be negatively bounded. Research results have also presented a study which was focused on evaluating the effects of porosity, dry unit weight of molding, cement content and porosity/volumetric cement content ratio void/cement ratio on the unconfined compressive strength of silty soil–roof tile waste (RT) mixtures. As the dry unit weight has a linear relationship with bulk unit weight, their findings could be concluded with the inclusion of cement; the strength of the RT soil mixtures improved appreciably in a trend. Conversely, the incorporation of RT reduces UCS of the tested cases at a stable percentage of cement, and the reduction on porosity adjusted the UCS upward. Hence, various interconnectedness really exist between the influencing factors of UCS, with some having lesser effects and many others having more holistic implications. As a numerical expression of the degree in particle sizes which enables soil to be classified as either poorly graded or well graded, the coefficient of uniformity (Cu) plays a critical role in fixing the various strength properties of unsaturated laterite soils. Poorly graded soils are more vulnerable to soil liquefaction than well-graded soil, due to the dominance of void ratio [44, 55]. The influence of clay activity is a significant factor that affects the overall soil behavior, particularly UCS of soil. There is also strong interconnectedness between various factors that affect soil behavior, with some factors having direct relationship with the others, while some may have indirect influence on the soil's performance. As a small particle size characterization that does not always ensure that its constituents will be plastic, clay activity has undoubtedly strong relationship with plasticity index which also have influence on the UCS performance. Prediction of these global relationship and interconnectedness is should therefore be extremely suitable using evolutionary computational techniques.

Nanostructured ash/binder additives and soil UCS improvement

There are unquantifiable benefits which the engineering and industrial communities experience owing to the utilization of nanostructured materials such as ash and binder additives to enhance the properties of soil for construction and foundation purposes. In the first place, judging from the fundamental clay structure and water molecule which presents adjustment in plasticity, cohesiveness and lots more, the field of soil engineering has largely explored the potential of the use of nanoscale materials such as nanosoil, nanoclay, nanosilica, nanoalumina, nanomagnesium, carbon nanotube and nanofibers, and nanolime, in performing various soil improvement, stabilization or remediation functions [40, 65]. In addition, nanomaterials are generally envisaged to be small fraction of the general soil medium, such as 0.1–0.5% of total weight of soil, and are basically between the range of 1 and 100 nm [2, 11, 29]. Ibrahim et al. [34] evaluated the environmental applications of nanotechnology in air, soil and water specializations. The use of various ash and binder additives to improve the soil properties such as UCS and other strength characteristics has been a dominant technique investigated by numerous researchers. Owosoni and Atigro [53] treated soil with rice husk ash targeting at determining their effects on the engineering properties of the analyzed different soils for use in various geotechnical and structural problems. Their experimental findings demonstrated significant reduction of plasticity indices of the soils, suggesting a lowered swelling potential which implied enhanced soil strength [14]. They also reported improved California bearing ratio and shear strength characteristics with significant positive correlations. In their own contribution to the improvement of soil properties using the nanostructured ash, Batari et al. [12] observed that the addition of bagasse ash (BA) to cement stabilized black cotton soil (BCS) adjusted its compaction properties, and enhanced both the soaked CBR and the UCS. In the same light, Lakshmi et al. [40] improved the UCS and soaked CBR characteristics of soil by employing rice husk ash (RHA) along with quick lime as the nanostructured admixture with clayey sand subgrade. However, Bello and Grace [13] shifted gear by investigating the stabilization and compaction effects on lateritic soil rather than purely silty and clayey soils. They blended cement with rise husk ash, while observing an improved UCS and CBR properties.

Meanwhile, most of the existing studies on soil improvement techniques are solely performed experimentally [7, 8, 47]; hence, the prediction potentials offered by the use of artificial intelligent techniques were not harnessed. Fortunately, recent researchers that are evolutionary computationally compliant have been exploring this field of machine learning approaches such as artificial neural networks (ANN), support vector machines (SVM), genetic algorithms, genetic programming and many more to predict important soil parameters such as UCS while considering myriads of associated parameters and factors influencing them [6, 50, 60, 62, 64]. From the results of such application of machine learning approaches so far made in the area of nanotechnology, it becomes evident that the degree of enhancement of various soil properties achieved owing to the utilization of nanostructured materials can be effectively ascertained and predicted.

Genetic programming (GP): An outstanding artificial intelligent technique for various engineering parameter prediction

One recent robust evolutionary computational technique for making engineering predictions and developing model equations is the use of genetic programming. Just as the humans search for their own comfort and survival, genetic programming searches for an optimal or at least appropriate program among the space of all programs to solve a given inputted problem. Koza and Poli [39] described it as a domain-independent technique that sorts a population of computer programs genetically to resolve a problem [61]. Precisely, GP transmutes an assembly of computer programs into a new scheme by iteration and then engaging the services of genetic operations. Many researches in civil engineering have consulted the services of GP for making their predictions. Pérez et al. [54] enhanced the norms and codes utilized in civil engineering using GP. Also, Cladera et al. [18] obtained symbolic regression from an experimental dataset by looking into the relationships among precision, accuracy, safety and simplicity. They evaluated the magnitude and implications of the degree of shear reinforcement induced. Another researcher and his team, Mehr et al. [43] performed a state-of-the-art review on the various applications of GP in water resources engineering. Consequently, GP technique was utilized as a rainfall–runoff model induction toolkit rather than as a short-term forecasting mechanism [45, 49]. Shashin critically performed review studies on the application of GP solving geotechnical engineering problems. Onyelowe et al. [16] predicted and evaluated the compression index of multiple-binder treated unsaturated soil for various geotechnical and structural purposes.

While strong attentions keep emerging to predict UCS of enhanced unsaturated soils, little or no study has been directed to the use of hybrid cement while intensively considering critical mechanical and physical properties such as coefficient of uniformity if soil, plasticity index, hydraulic conductivity, clay activity, friction angle and bulk unit weight. For instance, Jiankang et al. [37] predicted the UCS of a rock mass by employing a hybrid model of artificial neural network (ANN) featured on genetic algorithm (GA) optimization, without looking into the mentioned critical mechanical and physical properties. Soleimani et al. [63] predicted the unconfined compressive strength (UCS) of geopolymer stabilized clayey soils by utilizing a multi-gen genetic programming (MGGP), which is an enhanced GP technique. They, however, based their program formulation on the percentages of fly ash, ground granulated blast furnace slag, liquid limit, plastic limit, plasticity index, molar concentration, alkali to binder ratio, and ratios of sodium and silicon to aluminum factors. Obviously, more research on the use of GP in predicting the real critical parameters is still of esteemed engineering importance. The present study aims at predicting the unconfined compressive strength of hybrid cement treated unsaturated lateritic soil using a total of 121 soil samples (treated and untreated) based on the tested mechanical and physical properties which include: clay activity (Ac), unsaturated unit of weight (γb), plasticity index (Ip), coefficient of uniformity (Cu), hybrid cement percentage by weight (HC) and friction angle (φ) by utilizing genetic programming technique of machine learning.

Materials and methods

Materials

This reference soil at 60% saturation collected from the location as presented in the GIS map in Fig. 1 was used in this research work. Rice husk was collected from rice farm area dumbs and milling factories in Abakaliki, Nigeria, and was combusted to produce considerable amount of rice husk ash (RHA) needed for the laboratory soil treatment. The RHA was sieved through 200 nm aperture sieve to generate the nanostructured rice husk ash (NRHA) fines. In order to improve the binding ability of NRHA having increased its reactive and nucleating surface through nanostructuring, 5% hydrated lime by weight of the NRHA was mixed with the NRHA under laboratory room temperature conditions and allowed for a day. This procedure generated hydrated lime activated nanostructured rice husk ash (HANRHA). Nanostructured quarry fines (NQF); a nanotextured solid waste from rock quarrying was produced by completely grinding quarry dust (QD) and passing the powder through 200 nm size sieve. The HANRHA and NQF were finally mixed at room temperature and allowed for another one day to obtain hybrid cement (HC), which was considered as a supplementary cementing material, a cementitious composite meeting the requirements of design and materials standard according to ASTM C618 (1978). The generated HC was further utilized at increasing proportions to stabilize the unsaturated soil, and multiple tests were conducted to produce datapoints for the model protocol.

The materials handling conditions of the British Standard International (BSI) (BS1377, 1990) were adhered to in carrying out the preliminary tests on the reference soil for the purpose of characterization. Under the above standard conditions, the distribution of particle of the soil, compaction, consistency limits, specific gravity and potential for swelling were conducted. In order to determine the composition of oxides of the constituent cementitious composite binder materials (NRHA, NQF and HC), the X-ray fluorescence (XRF) tests were carried out adhering to the standard conditions of the ASTM E1621-13 (2013), and in order to achieve more reliable and accurate outcomes, the specimens were prepared and mixed to considerable homogeneity. Also, the ultraviolet visual spectrophotometer test was conducted on the Soil, NRHA and NQF to observe and record the textured absorbance of the nanoparticle exposures. Further, generated HC stabilization exercise of the soil was conducted adhering to the

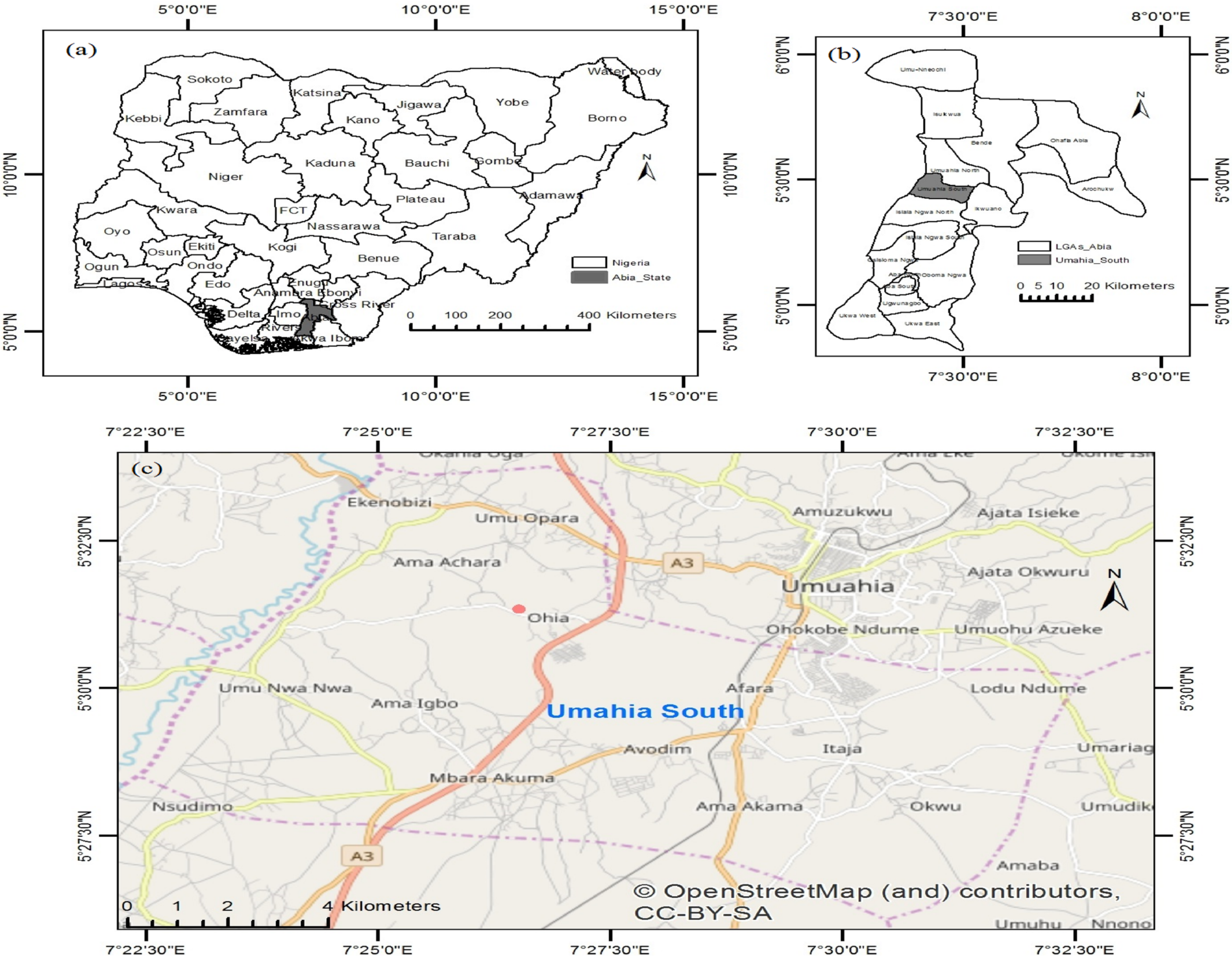


Fig. 1 Location map of borrow pit [50]

standard conditions of the BS1924 (1990) and multitude of data values were generated for various proportions of HC between 0 and 12% by weight of dry soil at the rate of 0.1%. The studied parameters of the treated soil were the predictors; clay activity (Ac), unsaturated (bulk) unit weight (γb) in g/cm^3, plasticity index (Ip), coefficient of uniformity (Cu), friction angle (φ°) and target; unconfined compressive strength (UCS). Furthermore, the generated datasets (see Supplementary Table 1) were deployed in the intelligent prediction exercise employing genetic programming (GP) technique.

Collected database and statistical analysis

A total of 121 soil samples were tested to determine the following physical and mechanical proprieties:

- Hybrid cement percent by weight (HC),
- Clay activity (Ac),
- Unsaturated (bulk) unit weight (γb) in g/cm^3
- Plasticity index (Ip),
- Coefficient of uniformity (Cu),
- Friction angle (φ°) in degrees,
- The corresponding unconfined compressive strength (UCS) in kg/cm^2

The measured records were divided into training set (81 records) and validation set (40 records). Supplementary Table 1 includes the complete dataset, while Table 1 summarizes their statistical characteristics showing the variances and deviations between input and output variables.

Model research program

Three GP models were developed to predict unconfined compressive strength (UCS) values using the measured hybrid cement percent by weight (HC), clay activity (Ac), unsaturated (Bulk) unit weight (γb), plasticity index (Ip),

Table 1 Statistical analysis of collected database

	HC %	Ac -	γb g/cm^3	Ip %	Cu -	φ degree	UCS kg/cm^2
Training set							
Max	0.0	0.6	1.4	0.1	2.1	15.0	1.3
Min	11.9	2.0	2.1	0.5	5.9	21.6	2.8
Avg	5.7	1.4	1.7	0.3	3.7	18.0	1.8
SD	3.3	0.4	0.2	0.1	1.3	2.0	0.4
Var	0.6	0.3	0.1	0.3	0.3	0.1	0.2
Validation set							
Max	0.4	0.6	1.4	0.1	2.1	15.1	1.3
Min	12.0	1.9	2.1	0.4	5.9	21.6	2.9
Avg	6.6	1.3	1.7	0.3	4.0	18.6	2.0
SD	3.8	0.4	0.2	0.1	1.4	2.3	0.6
Var	0.6	0.3	0.1	0.3	0.3	0.1	0.3

coefficient of uniformity (Cu) and friction angle (φ). The developed models started with the simplest (two level of complexity) and graded in the complexity until acceptable prediction accuracy is achieved (at four levels of complexity). Prediction accuracy was evaluated in terms of sum of squared errors (SSE). Because simple formulas allow for limited rooms for variables, the appeared variables are the most effective ones, on the other hand, complicated formulas allow for more rooms for the less effective variables. And hence, the considered variables could be ranked according to their impact on the output. Table 2 shows the characteristics of the developed GP models.

The following section discusses the results of each GP model. The accuracies of developed models were evaluated by comparing the (SSE) between predicted and calculated (UCS) values. The results of all developed GP models are summarized in Table 3.

Results and discussions

Materials characterization

Table 3 and Fig. 2 show the preliminary properties of the soil, which show the soil's potential for swelling, highly plasticity and lack of strength that shows its inability to be adopted as a foundation material are presented. Figures 3, 4 and 5 present the ultraviolet visual spectrophotometric nanograph of soil, NRHA and NQF, which shows the absorbance of the HC constituent materials and their ability to form homogenous mixture with soil in HC composite. Lastly, in

Table 2 Characteristics of developed GP models

Model No	No. of levels	Used variables	Population size	Survivors size	No. of generations	Mutation present
1	2	HC, Ac, γb, Ip, Cu, φ, UCS, 1, 3, 5, 7, 11	30,000	10,000	50	5%
2	3		60,000	20,000	100	
3	4		90,000	30,000	150	

Table 3 Preliminary properties of the reference soil at 60% saturation

Property	% Passing 0.075 mm	NMC	LL	PL	PI	SP	SG	AASHTO	MDD	OMC
Value	45	14	66	21	45	23	1.24	A-7–6	1.25	16
Unit	%	%	%	%	%	%	–	–	g/cm^3	%

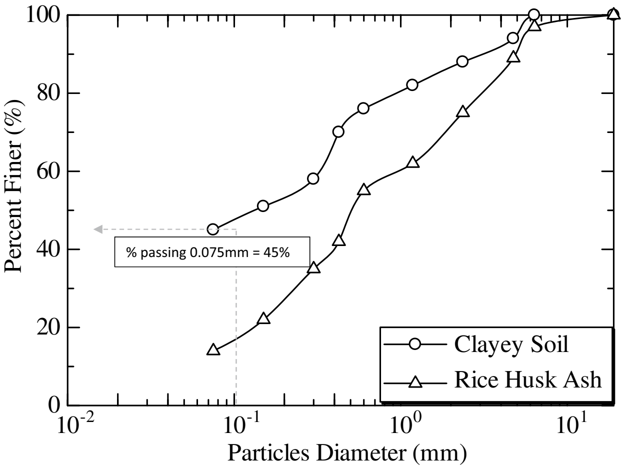


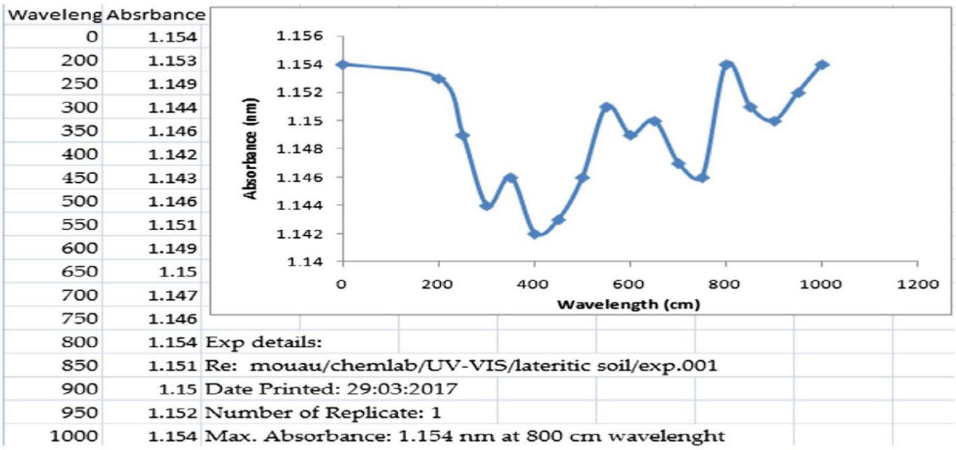
Fig. 2 Particle size distribution curve of clayey soil and rice husk ash [35, 50]

Fig. 6, the compaction characteristics of the lateritic soil sample is presented [50].

In previous research results [50], it was observed that "RHA exhibited gel-like porous-valve structure at a magnification level of 100 µm. Additionally, the presence of bigger voids could be observed in the SEM micrograph, which illustrates the lightweight structure and porous structure of the agricultural waste. Similarly, the SEM image of the soil depicts a laminar structure with dispersive, larger and thinner clay platelets. The smectites are seen to conform plate-like structures with the presence of thin hairline cracks. Additionally, the aggregates are mostly arranged in a face-to-face contact style." These morphological characteristics contribute to the reactive and pozzolanic capacity of the test materials in their nanoscale texture used in this study.

Table 4 shows the aluminosilicate composition of the experimental materials from XRF tests. This shows that

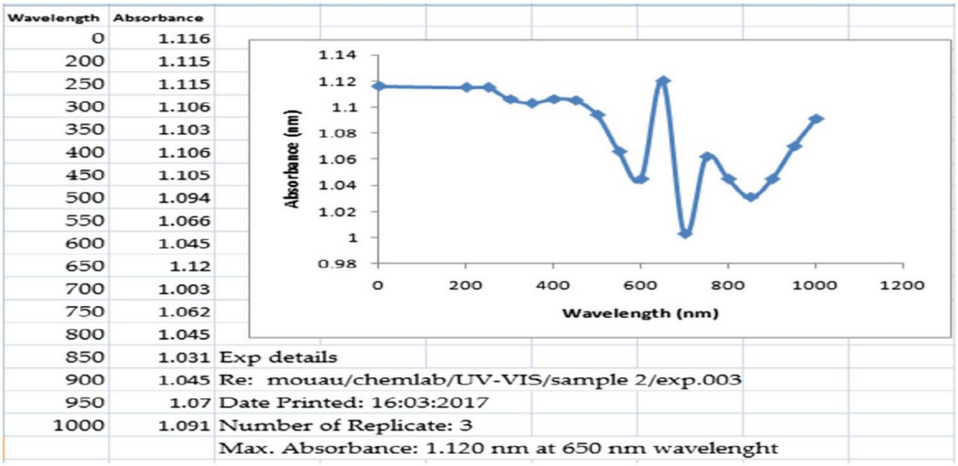
Fig. 3 Absorbance and wavelength variation for the lateritic soil using ultraviolet visual spectrophotometer at 25 °C



Waveleng	Absrbance
0	1.154
200	1.153
250	1.149
300	1.144
350	1.146
400	1.142
450	1.143
500	1.146
550	1.151
600	1.149
650	1.15
700	1.147
750	1.146
800	1.154
850	1.151
900	1.15
950	1.152
1000	1.154

Exp details:
Re: mouau/chemlab/UV-VIS/lateritic soil/exp.001
Date Printed: 29:03:2017
Number of Replicate: 1
Max. Absorbance: 1.154 nm at 800 cm wavelenght

Fig. 4 Absorbance and wavelength variation for the NRHA using ultraviolet visual spectrophotometer at 25 °C



Wavelength	Absorbance
0	1.116
200	1.115
250	1.115
300	1.106
350	1.103
400	1.106
450	1.105
500	1.094
550	1.066
600	1.045
650	1.12
700	1.003
750	1.062
800	1.045
850	1.031
900	1.045
950	1.07
1000	1.091

Exp details
Re: mouau/chemlab/UV-VIS/sample 2/exp.003
Date Printed: 16:03:2017
Number of Replicate: 3
Max. Absorbance: 1.120 nm at 650 nm wavelenght

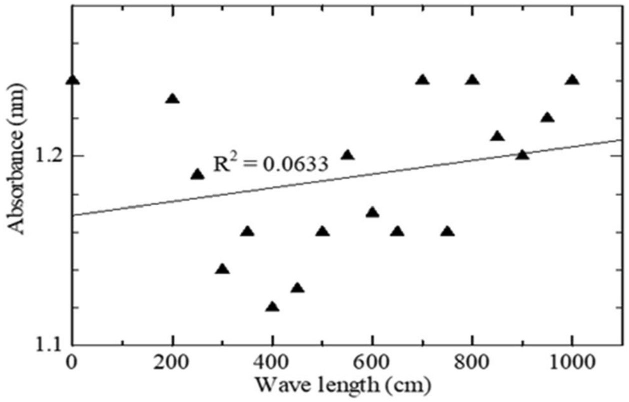


Fig. 5 Ultraviolet visual spectrophotometric graph of NQF [50]

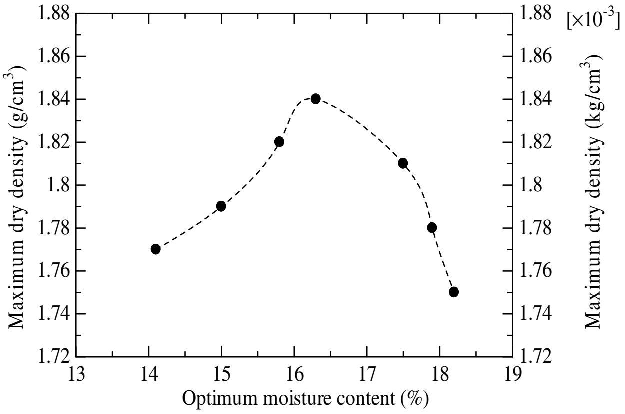


Fig. 6 Compaction characteristics of lateritic soil sample [50]

the HC, presently constituted from blending HANRHA and NQF, is observed with the highest aluminosilicate content of 97.15% compared to NQF with 87.74% and NRHA with 83.97% corresponding to the total of Al_2O_3, SiO_2 and Fe_2O_3 compositions. Accordingly, the supplementary cementitious materials (SCMs) design conditions proposed by ASTM C618 (1978) show that HC is highly cementitious and can be utilized as a binder in the soil treatment experiment. From the foregoing requirements, it can be seen that HC is a hybridized composite of NRHA and NQF with higher capacity to bind materials. It can be observed that the increased varying proportion of the multiple binders consistently improved the studied treated soil parameters, which was due to hydration, pozzolanic reaction, cation exchange and densification of the treated soil with increased binders and fundamentally due to the nanostructuring of the binder constituents thereby increasing the reactive surface. The increased nucleating and reactive surface achieved through nanotexturing of the quarry dust and RHA through complete pulverization and nanosieving has proven to be of great addition to the geotechnics of this exercise. This linear improvement on the studied parameters of the unsaturated soil has a huge influence on the proposed models' performance.

Prediction of (UCS) value using (GP)

Two levels of complexity UCS GP model

With only two level of complexity, this model is the simplest one. Equation 1 presents the output of this model, while Fig. 7a shows its fitness. The error % for training, validation and total sets are (5.1%), (3.3%) and (4.5%), respectively, while the (R^2) values of (0.970), (0.975) and (0.972), which agrees with previous findings [23–25, 61], respectively.

$$\mathrm{UCS} = \frac{e^{\gamma b}}{\mathrm{Ac} + \gamma b} \tag{1}$$

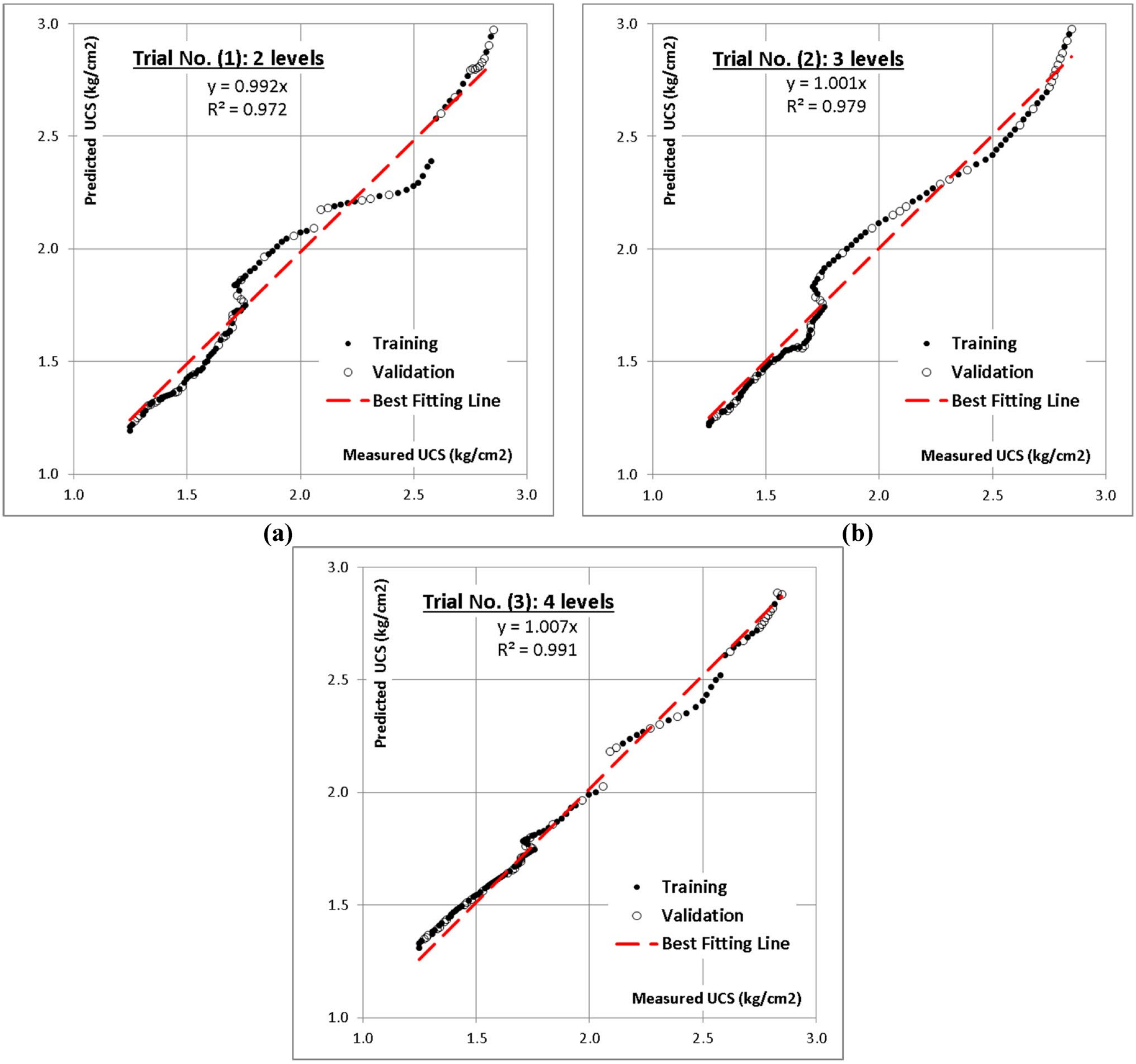
Three levels of complexity UCS GP model

The next step was to increase the level of complexity to enhance the prediction accuracy; hence, three levels of

Table 4 Chemical oxide composition of the additive materials

Materials	Oxides' composition (content by weight, %)												
	SiO_2	Al_2O_3	CaO	Fe_2O_3	MgO	K_2O	Na_2O	TiO_2	LOI	P_2O_5	SO_3	IR	free CaO
Clay Soil	12.45	18.09	2.30	10.66	4.89	12.10	34.33	0.07	–	5.11	–	–	–
NRHA	57.48	22.72	4.56	3.77	4.65	2.76	0.01	3.17	0.88	–	–	–	–
NQF	62.48	18.72	4.83	6.54	2.56	3.18	–	0.29	1.01	–	–	–	–
HC	66.5	27.8	1.3	2.85	1.5	0.03	–	0.02	–	–	–	–	–

*IR is insoluble residue; LOI is loss on ignition



(a) (b)

(c)

Fig. 7 Relation between predicted and calculated (UCS) values using the developed GP models

complexity were used in this model. The output and its fitness are illustrated in Eq. 2 and Fig. 7b. The error % and (R^2) values were improved to (4.2%) – (0.974), (3.3%) – (0.982) and (3.9%) – (0.979) for training, validation and total sets, in line with the results of literature [23–25, 61], respectively.

$$\mathrm{UCS} = e^{\left(\frac{HC}{11} + Ip^{Cu}\right)} \tag{2}$$

Four levels of complexity UCS GP model

Finally, four levels of complexity GP model were used to developed Eq. 3 with error % of (2.5%), (2.1%) and (2.4%) and (R^2) values of (0.989), (0.993) and (0.991) for training, validation and total sets, respectively. The relation between calculated and predicted values of (UCS) is shown in Fig. 7(c). Generally, the performance accuracies of the developed GP models are presented in Table 5.

Table 5 Performance accuracies of developed (GP) models

Model No	No. of levels	Output formula	Error %			R^2		
			Training	Validation	Total	Training	Validation	Total
1	2	Equation (1)	5.1	3.3	4.5	0.970	0.975	0.972
2	3	Equation (2)	4.2	3.3	3.9	0.974	0.982	0.979
3	4	Equation (3)	2.5	2.1	2.4	0.989	0.993	0.991

$$\mathrm{USC} = \mathrm{Ln}(11\ \mathrm{Ln}(\gamma b)) + \left(\frac{\gamma b(\mathrm{HC} - 7) + 1}{\gamma b(\mathrm{Ac}^{*\varphi} + \mathrm{Cu} + 1)}\right) \tag{3}$$

Conclusions

This research presents three GP models to predict the unconfined compressive strength (UCS) values using the measured hybrid cement percent by weight (HC), clay activity (Ac), unsaturated (bulk) unit weight (γb), plasticity index (Ip), coefficient of uniformity (Cu) and friction angle (φ). The results of comparing the accuracies of the developed models could be concluded in the following points:

- The prediction accuracy of the 1st model (the simplest one) was 95.5% and it enhanced in the 2nd model to 96.1%, and finally, it settled to 97.6% in the 3rd model (the most complicated one). This indicates that prediction accuracy was enhanced by increasing the model complexity up to acertain level, apart from this reason, the enhancement in the accuracy doesn't worth the increase in thecomplexity of the model.
- The output formula of the 1^{st} model contains only two parameters (Ac & γb), while the formula of the 2^{nd} model contains three parameters (HC, Ip and Cu); finally, the generated formula from the 3^{rd} model contains all the considered parameters except (Ip). This indicates that no specific parameter has a major impact on (UCS) value.
- Because the prediction accuracies of the three developed formulas are so close, any one of them could be used to predict the (UCS) value depending on the available soil parameters.
- Like any other (AI) or mathematical regression technique, the generated formulas from GP models are valid within the considered range of parametric values; beyond this range, the prediction accuracy should be verified.

Data Availability The supporting data in this research have been reported in the manuscript.

Declarations

Conflict of interest None.

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