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Experimental Investigation and Artificial Neural Network Modelling of Sugarcane Bagasse Ash-Stabilized Black Cotton Soil

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Abstract

Black cotton soil (BCS) is a type of expansive soil that exhibits moisture sensitivity, unstable volume, and unstable bearing capacity behaviour, which can have a negative impact on the performance of pavement subgrades and other geotechnical structures. The current research examines the possibilities of sugarcane bagasse ash (SCBA), a product derived from agricultural waste, to alter the geotechnical characteristics of black cotton soil. Six blends were taken into account, including SCBA content of 0%, 5%, 10%, 15%, 20% and 25% % of the dry soil mass of the starting material. Specific gravity, consistency limits, compaction characteristics, California Bearing Ratio (CBR), and swelling-related behaviour were the subject of the experimental programme in order to measure the effect of adding higher SCBA dosage on soil performance. Specific gravity was reported to have increased at 25% SCBA to 2.57 compared to 2.41 at 20% untreated soil and continued to 33.56 at 25%. The reported flow index also dropped to about 41 compared to 67.97 in the dosage range investigated, exhibiting variations in the consistency response of the soil-ash mixtures. The results of the compaction revealed that maximum dry density decreased by 1.610 g/cm^3 to a maximum of 1.630 g/cm^3 at 20% SCBA, and optimum moisture content rose by 20 % to 24 %. These results suggest that the addition of SCBA alters the consistency and compaction properties of the studied soil, but the extent and the engineering implications of the changes are dependent on the dose. The research offers an experimental foundation for testing SCBA as a prospective additive to enhance black cotton soil performance and the significance of finding an optimal dosage by conducting a joint examination of plasticity, compaction, bearing capacity, and swelling behaviour. The reported indices of plasticity and swelling-pressure outcomes should be further verified before a conclusive optimum dosage or overall benefit of the stabilisation is derived.

Keywords: Black cotton soil; sugarcane bagasse ash; expansive soil; soil stabilisation; compaction characteristics; California Bearing Ratio; agricultural waste.

1. Introduction

Black cotton soil (BCS) is a type of soil that is highly prevalent and has posed a great challenge to geotechnical engineering due to its high plasticity, sensitivity to moisture, and the ability to experience significant volume changes with wetting and drying [1,2,3,4]. Such properties may have a negative impact on the stability and maintainability of roads, pavements, embankments, and building foundations [6,7]. The swelling and shrinkage are due to the presence of expansive

clay minerals and montmorillonite in some black cotton soils [5,8]. This kind of repetitive volume variation may lead to uneven settlement, cracking of pavements, surface anomalies, and eventual weakening of infrastructures. These issues are moderated by the mineralogical composition, initial moisture condition, soil density, and stress state, and the intensity and length of environmental changes in moisture [8,9]. Enhancement of the engineering behaviour of expansive soil is therefore a key factor in the development of sustainable and cost-effective geotechnical infrastructure [10,11,12].

The traditional methods of ground improvement, such as soil replacement, mechanical stabilization, and chemical lime or cement treatment, are the most common methods of enhancing the properties of problematic soils [13,14,15]. Despite the potential to increase strength and decrease plasticity under favourable situations, the implementation of such methods can be costly in terms of materials and transportation, high in energy usage, and negatively impact the environment due to the manufacture of conventional binders [16,17,18]. Such limitations have stimulated the exploration of other stabilizing materials based on agricultural and industrial waste. The use of waste products in soil stabilisation can have a possible twofold advantage: to enhance the engineering properties of the locally available soil and to decrease the amount of waste that will have to be disposed. Nevertheless, the appropriateness of any other stabiliser should be determined by systematic trials instead of guessing based on its source of waste or chemical structure [18,19].

Sugarcane bagasse ash (SCBA) is a by-product of sugarcane manufacturing; it is a result of burning sugarcane bagasse, the fibrous waste left behind after extracting the juice. The characteristics of SCBA are determined by the sugarcane source, burning temperature, burning time, collection process and subsequent processing such as grinding and sieving [20,21]. SCBA can also have significant amounts of silica, along with alumina, iron oxide, calcium oxide, and other components, depending on these factors [22,23]. Its fine particles can alter the particle-size distribution, pore structure, and packing properties of soil- ash mixtures [24,25]. Moreover, pozzolanic reactions can also play a part in the formation of cementitious products where the ash contains enough reactive amorphous silica and other appropriate chemical conditions exist. However, the degree of such reactions cannot be determined solely by the presence of silica; it is determined by the real chemical and mineralogical properties of the ash, by the presence of calcium, by the conditions of moisture and by the conditions of curing. Thus, the engineering advantages of SCBA must be considered concerning its measured characteristics and the reaction of the treated soil [21,24,25].

SCBA as a means of stabilizing black cotton soil is especially applicable to areas where sugarcane processing produces large amounts of farm refuse and where large soils cause repetitive infrastructure issues [26,27]. Substitution of part of traditional stabilising substances with a waste-derived additive processed in a proper way can offer a more resource-efficient method of ground improvement [28,29,30,31]. Nonetheless, the efficacy of SCBA is unlikely to rise indefinitely with its content. The ash can also shift the particle distribution and enhance the contact between soil particles at low doses, but at high doses, more fine material, altered water demand, or insufficiently reactive constituents may prevent further enhancement [32,33]. It is important to find the right dosage, therefore. To optimise this, consider consistency limits, compaction behaviour, swelling characteristics, and bearing capacity simultaneously, rather than relying on a single geotechnical parameter [34].

Although agricultural ashes are increasingly being adopted to enhance the soil quality, the performance of SCBA-treated expansive soil should be further examined with a variety of additive contents and engineering properties [36,37]. Specifically, the shifts in the characteristics of consistency do not always directly relate to the increase in compaction or bearing capacity. Likewise, a decrease in plasticity does not, in itself, imply a decrease in swelling potential [38,39]. The overall response of SCBA to various facets of geotechnical behaviour should be assessed in a comprehensive manner in order to establish whether it yields similar effects on different facets of geotechnical behaviour and the dosage at which the overall response is most desirable [40,41]. Moreover, the difference between the physical alteration of the soil fabric and the potential chemical interaction is critical in understanding the manifested performance and preventing unsubstantiated assumptions about the stabilization processes.

1.1. Research Significance:

The main importance of this study is that it provides a combination of the assessment of the SCBA as a possible stabilizing medium of expansive soil. Instead of evaluating the stabilization based on one strength value, the paper looks at the impact of the increase in SCBA content on a number of interrelated geotechnical parameters. It is especially important to include both soaked and unsoaked CBR testing since the pavement subgrades can be subjected to different levels of moisture conditions during the service. Similarly, the assessment of compaction and swelling-dependent behaviour and consistency boundaries can be used to assess whether an apparent improvement in one of the properties is accompanied by positive changes in other engineering parameters. The six dosage levels comparison also allows determining a possible optimum content and also indicates whether the benefits decrease past a specific dosage. This method applies to initial subgrade enhancement where engineering performance, the

availability of materials, and feasible construction necessities ought to be considered when choosing a stabilizer.

1.2.Novelty of the Research:

The originality of the current study is that the dosage-dependent, multi-property evaluation of the SCBA-treated black cotton soil is conducted and that the consistency, compaction, bearing-capacity, and swelling-related evaluations are conducted in a similar framework using the common experimental setup. The study aims to determine the dosage that yields the most desirable total geotechnical reaction as opposed to thinking that the highest SCBA content offers the best advantage. The additive dosage is also determined by a constant reference point achieved by the use of a fixed original dry-soil mass. The results can also be used to correlate engineering performance changes with changes in particle structure and material properties where supported by established microstructural and mineralogical data. The contribution is not simply the utilization of an agricultural waste, but the regular assessment of its dosage-dependent efficiency and its possible applicability to expansive-soil enhancement.

1.3.Objectives of the Research:

The main aim of this study is to investigate the effectiveness of sugarcane bagasse ash (SCBA) as an alternative additive for the improvement of geotechnical properties of black cotton soil. The effect of SCBA contents of 0%, 5%, 10%, 15%, 20% and 25% (as a percentage of the original dry soil mass) on consistency characteristics such as liquid limit, plastic limit, plasticity index and flow index is investigated. It also examines the compaction characteristics of the treated soil by analysing changes in the maximum dry density and optimum moisture content. The bearing capacity is determined by soaked and unsoaked California Bearing Ratio (CBR) tests, and other swelling-related characteristics are studied to determine the possible effect of SCBA on volume-change behaviour of expansive soil. The present study is focused on optimising the SCBA dosage that yields the most desirable overall geotechnical performance of pavement subgrades and other geotechnical applications of black cotton soils based on combined experimental results. The study also aims to correlate the observed engineering behaviour with the soil–ash microstructure and mineralogical properties where possible, and if available, corroborated by SEM–EDS and XRD results.

The overall objective of this study is to provide an experimental basis for evaluating SCBA as an agricultural-waste-based alternative for stabilization of black cotton soils. This is to provide understanding of the relationship between SCBA dosage and the engineering response of expansive soil, and to help identify limitations related to over-added dosage, and to serve as a basis for additional investigation of its practical application in pavement subgrades and in other

geotechnical applications. Ultimately, any proposal for field implementation should be backed by a good laboratory test result, durability assessment, construction feasibility, and economic evaluation.

1.4.Literature Review

1.4.1. Engineering Challenges Associated with Black Cotton Soil

Black cotton soil (BCS) is a loose soil (expansive) with large volumetric changes with adjustments in the level of moisture. The mineralogy of clay has a significant effect on its engineering behaviour, especially in soils having expansive minerals like montmorillonite that are capable of taking in water and interlayer expansion [42,43]. In dry seasons, soil tends to shrink and crack, whereas in wet seasons, soil tends to swell, lose shear strength, and bearing capacity. These transformations make it hard to build and maintain roads, pavements, embankments and foundations. The moisture-sensitive behaviour of BCS may lead to uneven deformations, cracking and early decay of the pavement structure in pavement applications [44-47].

Expansive soil is typically measured in terms of its geotechnical behaviour based on the consistency limits, compaction properties, California Bearing Ratio (CBR), unconfined compressive strength, and tests relating to swelling. The liquid limit and plasticity index are used to know more about how the soil is going to act with respect to its consistency and plasticity whereas maximum dry density (MDD) and optimum moisture content (OMC) provide information on how the soil would react to compaction. CBR is especially applicable to the pavement-subgrade analysis since it gives an understanding of the soil's ability to resist penetration within a given test environment [48]. The soaked and unsoaked CBR values are beneficial since the bearing capacity of expansive soil can be impaired when subjected to extended moisture. Therefore, an efficient stabilisation plan needs to be assessed based on a combination of multiple characteristics as opposed to one strength parameter. studied bagasse ash as a supplementary additive in lime-stabilised expansive soil. Their experimental programme was based on various lime contents, various bagasse ash dosages, curing times, and microstructural studies [49]. The authors claimed that the strength of lime-stabilized soil was improved after addition of bagasse ash, but the degree of improvement varied with the contents of lime and ash. This paper has shown that the performance of bagasse ash may rely on the supply of calcium and the chemical ambience created by the primary stabilizer. Since the study was on lime-stabilized soil, the findings cannot be directly applied to the soil that has been treated with the SCBA alone. It has also been found that CBR and other mechanical properties of SCBA-treated expansive soils have improved significantly (Research on SCBA-

treated expansive soils), as well. In their analysis of SCBA-stabilized expansive subgrade soil [50]. CBR testing in their results recorded an optimal content of around 16 % with their test material. This result is a valuable benchmark in the choice of dosage, but the optimum reported is specific to the soil and ash of that study. The presence of SCBA can also affect the swelling by altering the ratio of expansive clay, the structure of particles and the amount of moisture required. Chemical stabilisation can also be used to decrease the action of the clay-rich, where appropriate reactive constituents and calcium are present. However, this effect is determined by the soil-ash system and conditions of the tests. The decrease in the index of plasticity does not in any way guarantee a proportional decrease in swelling pressure and the outcomes of swelling should be assessed autonomously [51]. Examined the development of microstructures and the development of strength in expansive soil stabilised using lime and amended using bagasse ash. Their work either supports evidence that bagasse ash can play a role in the functionality of a chemically stabilised soil system or not, as the same reaction processes or swelling decreases would be observed in SCBA-only mixtures.

1.4.2. Application of Artificial Neural Networks (ANN) in Soil Stabilization

The use of an artificial neural network (ANN) in geotechnical engineering has grown and is used for predicting the behaviour of both natural and stabilized soils based on experimental data. The particle size distribution, clay mineralogy, moisture content, compaction conditions, additive dosage and curing conditions interact in a complex and nonlinear way that influences soil properties. These interactions may not be completely reflected in the traditional empirical relationships, especially if agricultural or industrial waste materials are used as stabilizers. ANN models can be useful for predicting consistency characteristics, maximum dry density (MDD), optimum moisture content (OMC), California Bearing Ratio (CBR) and swelling-related parameters that have nonlinear relationships between the input variables and measured engineering responses [53].

For soil stabilization studies, ANN models can be trained by considering the content of soil constituents to be input variables and the corresponding geotechnical parameter as the output. All the possible inputs for the black cotton soil stabilization with sugarcane bagasse ash are the SCBA content, liquid limit, plastic limit, initial moisture content of the soil, specific gravity, and/or compaction related variables depending on the prediction objective and availability of experimental data. The results can be in the form of soaked CBR, unsoaked CBR, MDD, OMC, or swelling pressure. Separate prediction models can be developed for different outputs where representative observations are available for the output being predicted. Although ANN can be useful to determine complex relationships between the input variables and the engineering

response, the results of the model should be treated as data-driven estimates and not as evidence of the physical or chemical mechanisms that could be responsible for soil improvement [54].

The reliability of ANN predictions can be greatly affected by the amount, quality and variety of experimental data. Even though a model is developed with a small number of soils–SCBA mixtures, it can often have high correlation coefficients but limited predictive ability for new mixtures. This restriction is especially significant if a limited number of doses of additive have been actually tested. Multiple synthesis observations of the same six mixtures are not multiple independent observations, and they may not be randomly distributed across the training and test sets if there is a possibility of data leakage. Thus, it is crucial to validate the models independently, make suitable data partitions, and report several performance measures on generalization ability of ANN models [55].

In the present study, ANN could be used as a supplementary prediction tool for the study of the relationship between dosage of SCBA and geotechnical performance of the black cotton soil. However, the major test work should be experimental testing for consistency, compaction, soaked and unsoaked CBR and swelling properties. If ANN modelling is to be included, it should be developed after the experimental data has been quality checked and the inconsistencies in the reported plasticity and swelling data have been resolved. In this case, with only six mixtures, an ANN trained based on the current observations should not be used as a predictive model, but rather as an exploratory model.

2. Materials and Methodology:

2.1. Materials:

The materials employed in the current research included the Black Cotton Soil (BCS) and sugarcane bagasse ash (SCBA). The materials were chosen to study the effect of the addition of SCBA on consistency, compaction, swelling behaviour, and bearing capacity of expansive soil.

2.1.1. Black Cotton Soil

The main soil material in all the experimental mixtures was Black Cotton Soil. The untreated soil (M0) acted as the control, and the mixtures treated using SCBA were called M1-M5. Specific gravity, consistency limits, compaction, free swell index (FSI), swelling pressure, and California Bearing Ratio (CBR) tests were performed to determine the initial engineering properties of the soil and the change in the same with the addition of SCBA [5,6].

2.1.2. Sugarcane Bagasse Ash

Sugarcane bagasse ash (SCBA) is a by-product that is produced when sugarcane bagasse is burnt, the fibrous residue left behind when the juice is extracted out of sugarcane. The organic material in bagasse is mainly burnt away during combustion and a residual ash of the material is formed with varying quantities of silica, alumina, iron oxide, calcium oxide etc. Its physical and chemical characteristics are determined by the origin of bagasse, the temperature of combustion, the length of time burning and further treatment, such as grinding and sieving [22,23]. The use of SCBA as a possible additional material in geotechnical engineering has received interest due to the fact that the fine particles can alter the gradation of soils, packing of particles, and behaviour of soils in relation to moisture. Under favourable conditions of calcium sources and other appropriate curing conditions, SCBA can also be used in pozzolanic reactions depending on their chemical composition and the reactive amorphous silica present. Its effect should not be predicted based on its origin alone, but because of the expansive nature of the soil, like the Black Cotton Soil, its functionality has to be determined by consistency, compaction, swelling and bearing-capacity tests. The combustion process, raw material source, particle size, and post-combustion treatment differ in the physical and chemical characteristics of SCBA. In the published literature, silica has been noted as a significant component, but the actual composition varies significantly among the ash samples [21,20].

It is possible to explain the contribution of SCBA to Soil stabilization of Black Cotton Soil in three main mechanisms:

- **Particle modification:** Fine ash particles may modify the particle-size distribution and arrangement of the packing of the soil-ash mixture.
- **Modification of consistency:** Addition of ash can alter the relative content of expansive clay and affect liquid limit, plasticity, and moisture sensitivity.
- **Possible chemical interaction:** Reactive silica and alumina can enter into cementitious reactions if provided with appropriate sources of calcium and curing conditions. This mechanism has to be confirmed in the real soil-SCBA system.

The soil and SCBA were weighed in the ratio of the given mix design and combined to achieve a fairly homogeneous distribution of ash in the soil. The ready mixtures were then subjected to the appropriate geotechnical tests as per the adopted laboratory procedures. The overall mass of the mixture (dry mass) rose to 6.25 kg of M5 as compared to M0, as the mass of the soil mass was kept constant, but the amount of SCBA added grew.

2.2.Mix Proportion

The objective of the experimental programme was to explore the effect of sugarcane bagasse ash (SCBA) on the geotechnical properties of Black Cotton Soil (BCS). Six mixtures, labelled as M0 to M5, were prepared by adding SCBA at levels of 0, 5, 10, 15, 20, and 25. In each of the mixtures the mass dry soil was kept constant at 5.00 kg, and the mass of SCBA was kept at a constant of 0.00 to 1.25 kg, respectively. As a result, the overall mass of the dry mixture rose from 5.00 kg of the untreated soil to 6.25 kg of the mixture with 25% SCBA. This methodical variation allowed the exploration of the correlation between the addition of SCBA and the alterations of the soil properties in the chosen laboratory conditions. Table 1 represents the proportions of dry soil and sugarcane bagasse ash in the production of SCBA-stabilized Black Cotton Soil mixtures

Table 1: The proportions of dry soil and sugarcane bagasse ash in the production of the SCBA-stabilized Black Cotton Soil mixtures.

Mix ID	SCBA content (%)	Dry soil (kg)	SCBA (kg)	Total dry mixture (kg)
M0	0	5.00	0.00	5.00
M1	5	5.00	0.25	5.25
M2	10	5.00	0.50	5.50
M3	15	5.00	0.75	5.75
M4	20	5.00	1.00	6.00
M5	25	5.00	1.25	6.25

The proportions of the mixes reveal that the addition of the SCBA is increasing in a systematic fashion and the mass of the dry soil remains at 5.00 kg. The reference mixture, M0, had no SCBA and was used as a control to compare the stabilized mixtures. M1 and M2 included 0.25 kg and 0.50 kg SCBA, respectively, which constituted 5-% and 10-% of the dry soil mass. The SCBA was raised to 0.75 kg in M3, 1.00 kg in M4, and 1.25 kg in M5, respectively, which was 15, 20, and 25 % of the original dry soil mass as SCBA content.

This difference in calculating the basis is significant when explaining the experiment findings. SCBA content in the given table is expressed as a percentage of the original dry soil mass and not of the total dry mixture. As an example, M3 has 0.75 kg/5.00 kg of dry soil SCBA, which yields a 15 % SCBA content on a dry-soil-mass basis. Nevertheless, SCBA constitutes about 13.04% of the overall dry mixture weight of 5.75 kg, so the basis of the calculation must be clearly presented in the methodology to prevent a lack of reproducibility and ambiguity during the comparison of the findings with another research.

The steady mass of the soil and gradual increments of SCBA content offers a steady platform to explore the modification in consistency limits, compaction attributes, California Bearing Ratio (CBR), free swell index, and swelling pressure. However, since the overall mass of the dry mixture also rises with the addition of SCBA, the design of the experiment is ash addition to a fixed soil mass, and not replacement of soil with a fixed total mass of mixture. This difference ought to be taken into account to explain the observed geotechnical performance improvements.

2.3.Research Methodology

In the present study, an integrated experimental and computational approach has been used to examine the effects of sugarcane bagasse ash (SCBA) on the geotechnical characteristics of black cotton soil, and to explore the applicability of the artificial neural network (ANN) modelling technique for forecasting the engineering behaviour of black cotton soil under this influence. The methodology involves collecting and characterizing the materials, mixing the materials with ash, testing in the laboratory, analyzing the experimental data, developing the ANN model, and evaluating the predictive performance. The experimental investigation is the main method used to evaluate the effectiveness of SCBA whereas the ANN modeling is applied as one of the supplementary tools for studying the correlations among the selected input parameters and the measured geotechnical properties.

2.3.1. Material Collection and Characterization

The main soil material is black cotton soil, and the stabilizing additive is the sugarcane bagasse ash which is produced by burning sugarcane bagasse. The materials are also prepared under controlled conditions to reduce the variation caused by moisture content, handling and storage. Relevant geotechnical tests are conducted to determine the initial engineering properties of the soil, whereas SCBA is tested on its physical and chemical properties, based on the availability of laboratory facilities. Specific gravity, particle-size distribution, and pH can be established to learn the fundamentals of the ash. In cases where actual experimental characterization is present, X-ray fluorescence can be employed to establish chemical composition, X-ray diffraction to identify crystalline mineral phases and scanning electron microscopy with energy-dispersive X-ray spectroscopy to examine particle morphology and elemental composition. These characterizations give some supporting information to explain the observed changes in the engineering behaviour of the treated soil.

2.3.2. Preparation of Soil–SCBA Mixtures

A set of six soil-SCBA mixtures, denoted as M0 to M5, are prepared with a constant initial dry-soil mass of 5 kg. The SCBA contents are selected as 0%, 5%, 10%, 15%, 20%, and 25%

of the original dry-soil mass. Accordingly, the ash quantities added to the soil are 0, 0.25, 0.50, 0.75, 1.00, and 1.25 kg, respectively. In this experimental programme, SCBA is put into the fixed soil mass instead of replacing a similar mass of soil. The additive is mixed thoroughly into the soil and ash to achieve an acceptable homogenization of the additive. Water is then added depending on the needs of each laboratory test. Where it is necessary, preparation of specimens, mixing processes, compaction work, and test conditions are kept constant to enable credible comparisons of the examined mixtures.

2.3.3. Laboratory Testing Programme

Laboratory investigation is carried out to study the effect of SCBA admixture on consistency, compaction, bearing capacity and swell property of black cotton soil. Specific gravity testing is used to measure the relative density of the soil solids. Consistency characteristics are evaluated by liquid limit, plastic limit, plasticity index, and flow index, to investigate the changes in the plastic behaviour of soil–ash mixtures. Compaction tests were carried out to establish the effect of increasing SCBA content on the moisture–density relationship for determination of maximum dry density and optimum moisture content. Each mixture is tested for bearing capacity by means of the California Bearing Ratio tests, conducted under both soaked and unsoaked moisture-conditioning conditions to allow for assessment of penetration resistance under the two test conditions. Swelling-related tests are also used to research the reaction of expansive soil to water and volume changes. Replicated specimens are tested where appropriate to determine experimental variation, and the appropriate test standards, specimen preparation procedures and conditions are recorded.

2.3.4. Experimental Data Analysis

The results of the experiment are tabulated in a systematic way based on the identification of mixture, SCBA dosage, and the respective measured properties. The reference material in terms of comparison of the effects that are brought about by the addition of SCBA is untreated black cotton soil. The findings are compared with all six mixtures to determine the presence of increasing, decreasing, or non-monotonic trends in consistency, compaction, bearing capacity, and swelling-related behaviour. The discussion is based on the correlation of the various parameters instead of assessing the properties separately. As an example, the variations in maximum dry density are interpreted in relation to optimum moisture content and CBR performance, whereas variations in consistency limits are investigated in relation to the measured swelling characteristics. Where comparable measurements are applicable, percentage changes or values of improvement or reduction compared with untreated soil are computed. Prior to interpretation, data quality checks are carried out to maintain consistency

of units, calculations, combination identification, and test conditions. The combined experimental evidence is used to determine the potential optimum SCBA dosage instead of basing it on a single parameter.

2.3.5. Artificial Neural Network Model Development

Artificial neural network modelling is added as a complementary computational method to examine the non-linear correlation between the variables that are chosen and the geotechnical characteristics of the SCBA-treated black cotton soil. A feedforward neural network can be used which has an input layer, one or more hidden layers, and an output layer. The choice of input variables depends on the purpose of the prediction and availability of confirmed experimental information. The possible inputs are the dosage of SCBA and the appropriate measured soil or compaction properties, and the desired outputs could be the maximum dry density, optimum moisture content, soaked CBR, unsoaked CBR or a swelling-related parameter. Individual output property models can be designed where the data allows effective training and testing.

The experimental data undergoes verification of missing observations, conflicting values, and errors in calculations before developing the model. Proper data preprocessing is subsequently done, and any normalization or standardization parameters are then identified only based on the training data to prevent information leakage. The available observations are split into training, validation and testing subsets based on strategy that takes into account the number of independent mixtures and the correlation between repeated measurements. The network structure, number of hidden neurons, activation functions, and training algorithm are chosen based on the size and features of the data. In training, the network parameters are adjusted to minimize the error between the predicted and experimentally measured values, and validation performance is monitored to detect possible overfitting. Observations that have not been used to optimize the parameters of the final model are then evaluated by the final model.

2.3.6. Evaluation of ANN Predictive Performance

The ANN model is evaluated in terms of predictive performance through comparison of the predicted geotechnical properties against the experimental values. The coefficient of determination, root mean square error, and mean absolute error are used to evaluate the agreement between measured and predicted values. These measures give complementary data on the explanatory model and prediction errors. Actual-versus-predicted plots and residual analysis can also be employed to determine systematic deviations, bias, or inconsistencies in model performance. The assessment takes into account the outcomes that have been achieved during training, validation, and testing as well as paying special attention to the performance

on independent observations. The presence of high correlation or agreement in the training dataset is not viewed as enough evidence of generalization. Rather, model reliability is evaluated relative to size of the dataset, variability of the experiment, independence of the data, and the validation method used.

2.3.7. Integration of Experimental and ANN Findings

The last phase combines the experimental results and ANN predictions to evaluate the correlation between the dosage of the SCBA and the engineering performance of black cotton soil. The experimental findings determine the given behaviour of the mixtures, and the ANN model is tested on its capability to recreate the measured relationships within the scope of the available information. The comparison between predicted values and measured values are analyzed to determine the potential constraints of the model or the description of the experimental data. The best dose of SCBA is found based on the confirmed laboratory findings and the ANN speculations are only added after sufficient validation has been obtained. Where experimentally determined SEM 2EDS and XRD data exist, the microstructural and mineralogical observations are coupled with the geotechnical data to aid a careful discourse of the potential mechanisms by which the observed changes may have occurred. This hybrid approach is aimed at defining an evidence-based evaluation of SCBA as a prospective additive to the black cotton soil improvement and to assess to what extent the ANN modelling can help in predicting its geotechnical behaviour. Figure 1 represents the overall methodology framework.

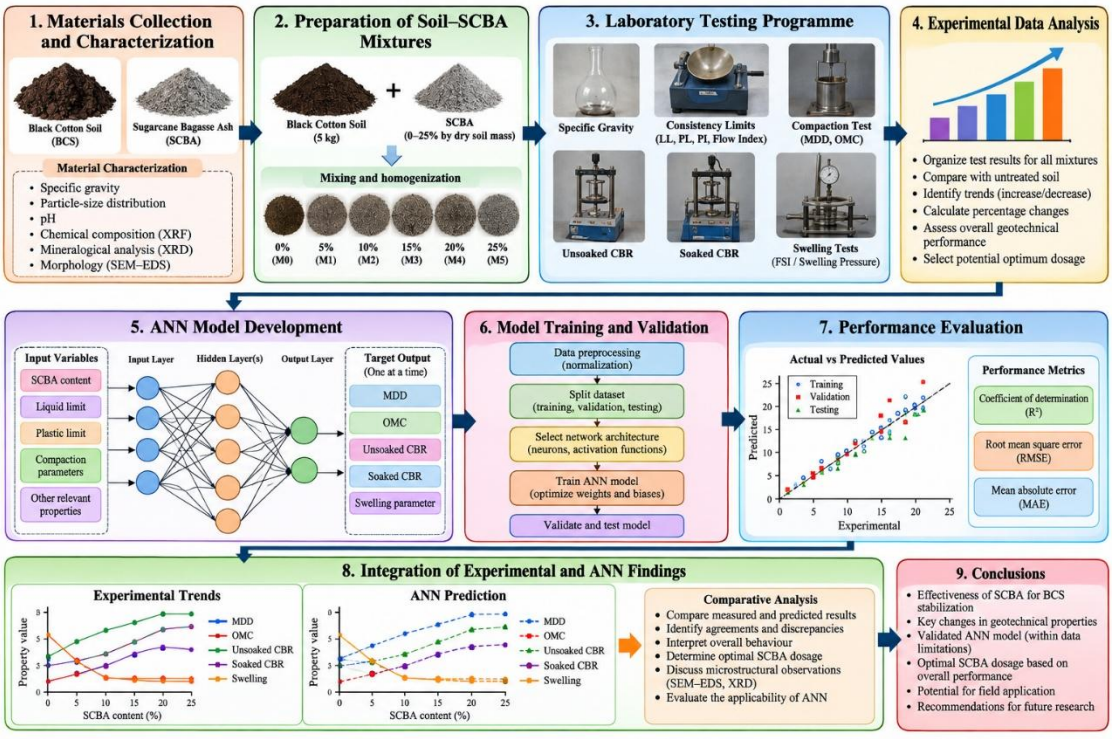


Figure 1: Overall Methodology Framework

2.4. Artificial Neural Network (ANN) Methodology and Hyperparameter Tuning

The present study includes artificial neural network (ANN) modelling to investigate the non-linear relationship between the content of sugarcane bagasse ash (SCBA) and the geotechnical properties of black cotton soil. The model will be used to complement the experimental study by estimating the chosen engineering parameters, such as the maximum dry density (MDD), optimum moisture content (OMC), soaked California Bearing Ratio (CBR), unsoaked CBR, and swelling-related properties, based on the availability of validated experimental measurements. ANN is appropriate in studying nonlinear relationships between inputs and outputs, but predictive accuracy varies with the number, quality and independence of the training data.

2.4.1. Dataset Preparation and Selection of Variables

The ANN data is constructed based on experimental measurements of the six mixtures, M0 through M5, of 0-, 5-, 10-, 15-, 20-, and 25-mass of the original dry soil. The choice of the input variables depends on the purpose of prediction. As an illustration, SCBA material can be utilized as the main input to determine MDD, OMC, or CBR. Other input variables, like liquid limit, plastic limit, specific gravity, and compaction properties, can be added only in the event that they are known to the corresponding observations and would also be known at the desired prediction step.

ANN models can be created separately on target properties to prevent the combination of variables that have different physical meanings or prediction needs. Prior to training, the dataset is analyzed in terms of missing values, inaccurate measurements, wrong units, and arithmetic mistakes. Specifically, the plasticity indices and swelling-pressure observations need to be confirmed before the variables in question can be incorporated into the model. The same mixture should be identified as measured repeatedly to avoid related observations being spread across training and testing subsets in a manner that results in data leakage.

2.4.2. ANN Architecture

A feedforward neural network is also taken into account to map the chosen input variables to the target geotechnical property. The network has an input layer, one or more hidden layers and an output layer. The independent variables are fed into the input layer and are processed by the hidden layers that isolate the nonlinear relationships by using weighted connections and activation functions. The predicted value of the chosen geotechnical parameter is produced in the output layer.

The amount of hidden layers and neurons is not predetermined, but it is considered as a model-selection parameter. A small experimental dataset should be served by a rather simple architecture to minimize the potential of overfitting. The training algorithm is applied to optimize the network weights and biases, whereas validation data would be applied to measure the performance of the model in development. Another testing process is then applied to test the predictions on observations not used in model fitting or hyperparameter estimation.

2.4.3. Hyperparameter Tuning and Optimization

Hyperparameter tuning is done to find an ANN configuration that produces an appropriate balance between predictive accuracy and model complexity. The main hyperparameters are the number of hidden layers, the number of neurons in each hidden layer, the activation function, the learning rate (if applicable), the training algorithm, the regularization strength, and the stopping criterion. They are not chosen according to the training accuracy of the configuration. If the set of data is sufficiently large, then the randomized search or the grid search can be used to test candidate configurations. A small search space and a simple network are desirable for the present study, since the experimental programme contains only six different SCBA dosages. All candidate models should be validated by the same method and from the same validation data, and the configuration yielding the highest validation performance should be chosen, without ever tuning the model with the final test observations. It may be advisable to implement early stopping or regularization, but neither can overcome the lack of a sufficient number of independent observations.

When there is only a single observation per mixture, conventional training–validation–testing splits are not reliable since they leave very few observations in each subset. In such a case, an out-of-sample validation with one mixture omitted in each iteration of the model fitting may be considered for a simple, low complexity model. But this strategy yields only six evaluation cases for the mixture level and cannot attain a wide predictive generalization. Further separately developed mixtures and experimental measurements are highly recommended before presenting the hyperparameter optimization of ANNs as a robust modelling exercise.

The hyperparameter tuning process consists of the following steps: generation of a finite set of potential architectures, choice of training algorithm and activation functions, fitting the candidates with the provided training data, assessing the models' validation performance, comparison of the prediction errors of the models, and selection of the best-performing one. It is important to note that all preprocessing operations (such as normalisation) must be fit on the training data only. If there are enough data available, the final model is then tested against independent observations.

2.4.4. ANN Hyperparameter Selection Framework

The ranges below are suggested initial conditions for development and not experimentally determined optimal conditions. Table 2 represents the ANN architecture of research work

Table 2: ANN Architecture

Hyperparameter	Candidate settings
Network type	Feedforward ANN
Number of hidden layers	1–2
Neurons per hidden layer	2, 4, 6, 8, or 10
Hidden-layer activation	Tanh or ReLU
Output-layer activation	Linear for continuous targets
Training algorithm	Adam or Levenberg–Marquardt, depending on implementation and dataset size
Learning rate	Candidate values for gradient-based training, such as 0.001, 0.01, and 0.1
Regularization	None or a limited set of regularisation strengths
Stopping criterion	Validation-based early stopping or a predefined convergence tolerance
Model selection criterion	Lowest validation RMSE, considered alongside MAE and R^2
Final evaluation	Independent testing or appropriately designed mixture-level validation

The candidate settings can be reduced based on the observed training behaviour, sample size and software. As an example, gradient-based optimisers like Adam have a learning rate but this is not optimised in a similar way as Levenberg-Marquardt training. Equally, a truly distinct validation set should be employed or a cross-validation process to perform early stopping.

2.4.5. Model Performance Evaluation

The optimised ANN performance is evaluated on the basis of predicted geotechnical properties versus experimentally measured counterparts. Complementary measures of evaluation are the coefficient of determination R^2, the root mean square error (RMSE), and the mean absolute error (MAE). The coefficient of determination explains the extent to which the predictions explain variation in the observations, and RMSE and MAE measure the errors in prediction expressed in the units of the target variable. Smaller error values tend to imply greater

predictive accuracy, yet these measures should be considered in relation to the amount and autonomy of the observations.

Residual analysis and actual-versus-predicted plots can be employed to examine systematic prediction errors. Where the data allow, training, validation, and testing performance should be reported separately. A large discrepancy between training and validation performance can be a sign of overfitting, whereas poor performance can be a sign of inadequate information, unsuitable selection of inputs, or an unsuitable network architecture. Hyperparameter tuning should not be repeated on the final test set, as it would invalidate the independence of the test.

2.4.6. Integration of ANN Predictions with Experimental Results

The ANN model is optimized to test the ability of the model to reproduce the relationships observed experimentally between the contents of SCBA and geotechnical properties. The MDD, OMC, CBR or swelling-related values are compared with the laboratory values and any differences are discussed within the framework of data availability and model constraints. Recent experimental data is the foundation of establishing the optimum SCBA dosage, and ANN predictions are only supplementary data when sufficient predictive validation is demonstrated.

The ANN component can thus be seen as a supplemental data-driven analysis and not a replacement of laboratory testing. Since only a few different mixtures are available, the conclusion on predictive generalization should be taken with caution until more independent observations are obtained.

3. Results Analysis:

3.1.Results

3.1.1. Atterberg Limit

The effect of adding sugarcane bagasse ash (SCBA) on the geotechnical index properties of black cotton soil was assessed by analysing changes in specific gravity, liquid limit, flow index, plasticity index, and plastic limit with SCBA additions of 0, 5, 10, 15, 20, and 25. The findings show that specific gravity increases steadily from 2.41 for untreated soil up to 2.57 at 25% SCBA addition. Conversely, the liquid limit drops from 50.00% to 31.44% as the SCBA content rises to 20, and then to 33.56% at 25. The flow index also drops significantly from 67.97 to about 41, and the reported plasticity index also tends to fall to around 9 as opposed to 16.67%. These alterations show that incorporation of SCBA is linked with alterations in the consistency attributes and physical behaviour of the black cotton soil. But the answer is not that simple, which implies that the impact of SCBA is also determined by the level of

replacement and interactions of ash particles with the original constituents of the soil. Table 3 represents the results of Specific Gravity, Liquid Limit, Flow Index, Plasticity Index and Plastic Limit.

Table 3: Experimental results of Specific Gravity, Liquid Limit, Flow Index, Plasticity Index and Plastic Limit with additions of SCBA.

Addition of SCBA (%)	Specific Gravity	Liquid Limit (%)	Flow Index	Plasticity Index (%)	Plastic Limit (%)
0	2.41	50.00	67.97	16.67	33.33
5	2.45	45.00	61.37	11.85	37.50
10	2.48	42.95	50.60	12.95	30.00
15	2.50	34.08	49.28	9.08	25.00
20	2.54	31.44	40.87	9.22	22.22
25	2.57	33.56	41.08	9.12	23.34

The gradual rise in specific gravity (2.41 to 2.57) indicates the modification in the general properties of the soil-SCBA mixture. This tendency can be linked to the variations in specific gravity of the constituent materials and the resulting composition of the blended soil. However, the specific gravity of a mixture is determined by the characteristics and the ratios of its constituents and, hence, the recorded increment must be corroborated with the actual specific gravity of the SCBA and the procedure used in testing. It cannot always be taken as a sign of better soil strength or decreased swelling.

The liquid limit of 50.00% of untreated soil reduced to 31.44% at 20% SCBA suggests that there was a significant reduction in the amount of water needed to obtain the liquid state. The behaviour could be due to dilution of the very plastic clay fraction, transformation of the particle-size distribution, and inter-action of the ash particles with clay minerals. The flow index also reduces to 67.97 to around 41, which reveals that the consistency response varies within the range of moisture studied. Such modifications can be useful in alleviating moisture sensitivity of expansive soil, but the degree of enhancement must be determined by comparing with swelling pressure, free swell index, and CBR outcomes and not based on consistency limits as such.

The plasticity index reported tends to decline as a result of adding SCBA, with the highest plasticity index of 16.67% in untreated soil and the lowest value of 9.0222% in the treated mixtures. A smaller plasticity index is often a pointer of a smaller span of water content within

which soil demonstrates plastic behaviour. It can be related to the decrease in the relative contribution of expansive clay constituents or the alteration of interactions between particles. Nonetheless, the trend is not completely monotonic: the reported PI rises to 11.85% at 5% SCBA up to 12.95% at 10%, and then it declines at higher replacement levels. This difference indicates that the effects of SCBA on plasticity can be affected by the composition of the mixtures and variability of experimental conditions.

The plastic limit is also quite variable, as it changes between 33.33% in untreated soil to 22.22% in 20% SCBA and then slightly increases to 23.34% in 25% SCBA. It means that the amount of moisture that comes with transformation between the semisolid and plastic is dependent on the addition of SCBA. The 5% SCBA increase and subsequent decline in higher contents emphasize the necessity to read the limits of consistency as a whole instead of considering each parameter in isolation. All in all the findings indicate that the addition of SCBA alters the consistency properties of black cotton soil, especially changes in the liquid limit and flow index and an overall reduction in the plasticity index as reported. Liquid limit reduction is the strongest at 20% SCBA, and then slightly reversed at 25%. This result suggests that the reaction to the addition of SCBA can be a balance of the fraction of added ash and the properties of the left-over soil matrix. However, to determine an optimum SCBA content, it is essential to consider the overall experimental outcomes in form of free swell index, swelling pressure, compaction properties and soaked and unsoaked CBR. To determine 20 % or any other replacement level as the most optimum stabilisation content, consistency-limit data alone are not sufficient.

3.1.2. Compaction Factor:

To investigate the compaction characteristics of the black cotton soil, the maximum dry density (MDD) and optimum moisture content (OMC) of the six mixtures (M0 to M5) containing 0%, 5%, 10%, 15%, 20%, and 25% of SCBA were determined. The results show that initially the density of MDD for the untreated soil (M0) decreases to 1.540 g/cm³ at 5% SCBA (M1) and then gradually rises to 1.630 g/cm³ at 20% SCBA (M4). At 25% SCBA (M5), MDD decreases slightly to 1.626 g/cm³. Conversely, OMC rises steadily as it does from M0 to M5, with OMC values ranging from 20.0% to 24.0%. These variations suggest that the moisture need and dry-density properties of the black cotton soil are affected by the addition of SCBA, with the maximum MDD observed at 20% SCBA addition. Table 4 represent the compaction factor of BCS using sugarcane ash.

Table 4: Compaction Factor of BCS using SCBA

Mix ID	SCBA content (%)	MDD (g/cm³)	OMC (%)
M0	0	1.610	20.0
M1	5	1.540	21.5
M2	10	1.608	22.0
M3	15	1.627	22.5
M4	20	1.630	23.0
M5	25	1.626	24.0

The slight drop of MDD from 1.610 to 1.540 g/cm³ at 5% SCBA may be related to difference in specific gravity, particle shape, packing attributes of SCBA and original soil. Ash particles can change soil particle packing arrangements and may start to produce a less efficient packing structure. MDD progressively increases when the SCBA content is raised from 5% to 20% at M4 with a value of 1.630 g/cm³. This shows that the Soil–Ash mixture is showing an improvement in its combined particle-size distribution and compaction behaviour through this range of replacement. But it is a rather modest gain compared to the original loss and the measured trend should be regarded as a variation and not proof of a specific microstructural mechanism.

The continuous increase of OMC from 20.0% to 24.0% shows that higher SCBA content in the mixture demands higher moisture content in the mixture for attaining the corresponding maximum dry densities. Such behavior may be related to the surface properties and water holding capacity of the ash particles and the alteration in the soil–ash arrangement. The supplementary water may also be due to the difference between the proportion of soil and ash in the mixtures. However, given only the OMC trend, the amount of water absorbed or a unique chemical reaction cannot be determined.

In the comparative study of all six mixtures, the MDD of mixture with 20% inclusion of SCBA is found to be 1.630 g/cm³ whereas the same of mixture with 25% inclusion of SCBA is found to be 1.626 g/cm³. This small decrease may be evidence of a lack of additional increase in maximum dry density with ash above 20% under the test conditions reported. The difference of 0.004 g/cm³ is not great, though, and its significance cannot be determined without replicate measurements, experimental uncertainty or statistical analysis. So, 20% SCBA may be established as the mixture with the highest reported MDD; this should not necessarily be taken as the optimum level of stabilization based on compaction results alone.

Following from the above, it was concluded that incorporation of SCBA has an effect on the compaction behavior, which leads to a rise in OMC and a non monotonic decrease in MDD. Moisture demand for higher ash content shows a continuously rising trend while the highest recorded MDD (20% SCBA) indicates potentially favourable compaction condition. The eventual determination of suitability of this replacement level should be related to free swell index, swelling pressure, and soaked and unsoaked California Bearing Ratio (CBR) data to determine if the compaction response results in significance improvements in engineering performance.

3.1.3. California Bearing Ratio:

California Bearing Ratio (CBR) test was performed to determine the load bearing capacity of treated black cotton soil with varying quantities of sugarcane bagasse ash (SCBA) subjected to soaked and unsoaked conditions. The results for mixes M0–M5 (0%, 5%, 10%, 15%, 20% and 25% of SCBA) show that the CBR values of these mixes both for soaked and unsoaked condition increased with the addition of SCBA up to 15% and decreased beyond that. The unsoaked CBR is 2.10% for untreated soil and goes up to 3.90% at 15% SCBA, and the soaked CBR is 1.40% and 2.65% respectively. The CBR retention values percentage of soaked CBR to unsoaked CBR) vary between 64.1% and 67.9%. The results suggest that incorporation of SCBA may enhance CBR response up to a specific replacement percentage, with the M3 mixture showing the highest CBR response under both moisture conditions. Table 5 shows the unsoaked and soaked CBR values and CBR retention of the black cotton soil stabilized with varying content of SCBA. Table 5 represent the Un-soacked and soacked CBR values and CBR Retention of BCS soil.

Table 5: Unsoaked and soaked CBR values and CBR retention of the black cotton soil

Mix ID	SCBA (%)	Unsoaked CBR (%)	Soaked CBR (%)	CBR retention (%)
M0	0	2.10	1.40	66.7
M1	5	2.50	1.65	66.0
M2	10	3.20	2.15	67.2
M3	15	3.90	2.65	67.9
M4	20	3.70	2.50	67.6
M5	25	3.20	2.05	64.1

The untreated soil (M0) has unsoaked and soaked CBR values of 2.10 and 1.40, respectively, which indicates a comparatively low load-bearing capacity and the decrease of resistance at

soaked conditions. At 5% SCBA (M1), the unsoaked CBR rises to 2.50% and soaked CBR rises to 1.65%. Additional improvement is at the 10 % SCBA (M2) at which the respective values increase to 3.20 % and 2.15 %. This gradual build up implies that moderate SCBA addition can enhance the packing of particles and soil-ash interactions, which may lead to enhanced resistance of penetration. Such mechanisms must however be considered plausible explanations unless they are directly supported by microstructural or chemical evidence.

The maximum CBR values are obtained at M3, which has 15% SCBA, in which the unsoaked CBR is 3.90% and the soaked CBR is 2.65%. The values are an increase of about 85.7 % and 89.3 % compared to untreated soil values, respectively. This enhancement indicates that 15% SCBA offers the best CBR response compared to the other five mixtures tested. The outcome can be the appropriate proportion of soil fraction and ash particles, enabling more efficient particle placement and interaction. However, the rise in CBR does not solely determine the exact mechanism that caused the improvement.

The CBR values decrease beyond 15% SCBA. At 20% SCBA (M4) CBR and CBR soaked fall to 3.70% and 2.50, respectively. At 25% SCBA (M5), they decrease further to 3.20% and 2.05%. This decrease indicates that adding ash beyond the favourable replacement level does not add any additional enhancement in penetration resistance. Potential causes are variation in the arrangement of the particles, dilution of the load-carrying fraction of soil, or variation in the moisture content needed by the mixture. Nevertheless, they need to be checked with the compaction and microstructural findings instead of being guessed based on the CBR values.

The CBR retention values are another sign of performance in soaked conditions. M3 exhibits the highest retention at 67.9%, followed by M4 at 67.6%, M2 at 67.2%, M0 at 66.7%, M1 at 66.0%, and M5 at 64.1%. Therefore, the M3 mixture not only attains the highest absolute CBR values but also has the highest percentage of its unsoaked CBR remaining after soaking. However, every mixture exhibits decreasing CBR in soaked conditions, which suggests that the penetration resistance of mixtures remains affected by moisture. The comparatively small retention range of M0-M4 further indicates that the primary advantage of SCBA addition is not seen in the absolute value of the CBR being enhanced but rather in the fact that the proportion of strength retained after soaking has changed drastically. The findings, in general, determine 15% SCBA (M3) as the most successful mixture in regards to both soaked and unsoaked CBR among the replacement levels examined.

3.1.4. Unconfined Compressive Strength

The sugarcane bagasse ash (SCBA) is used to stabilise black cotton soil, and the 7, 14, and 28-day curing periods were used to evaluate the variation in UCS of black cotton soil stabilised

with different proportions of SCBA. The results of mixtures M0, M1, M2, M3, M4 and M5 with 0%, 5%, 10%, 15%, 20% and 25% SCBA respectively have shown that the swelling pressure of all the mixtures increases with curing period. The UCS of untreated soil (M0) is 105, 112 and 120 kPa at 7, 14 and 28 days, respectively. The higher the SCBA content, the higher the UCS, with 15% SCBA yielding a maximum UCS of 205 kPa at 28 days before dropping to 190 kPa for 20% and 165 kPa for 25%. These results show that the measured UCS is influenced by both the content of SCBA and curing time, with M3 showing the highest values of the mixtures investigated. Table 6 represents the Unconfined Compressive Strength (kPa) of SCBA-stabilized black cotton soil at 7, 14 and 28 days.

Table 6: Unconfined Compressive Strength (kPa) of SCBA-stabilized black cotton soil at 7, 14 and 28 days

Mix ID	SCBA (%)	7 days	14 days	28 days
M0	0	105	112	120
M1	5	120	132	145
M2	10	140	158	175
M3	15	160	182	205
M4	20	150	170	190
M5	25	132	148	165

For all mixtures, the swelling pressure steadily rises from 7 to 28 days. As to the untreated soil, the swelling pressure rises from 105 to 120 kPa during the above period, while M3 rises from 160 to 205 kPA during the same period. The measured response shifts as the time of curing changes, as indicated in this trend. It should not, however, be assumed that the rise in UCS necessarily represents a gain in stabilization, as a reduction in swelling pressure is normally a desired result for expansive soil. The cause of the increase needs to be verified by the experimental procedure, moisture conditioning conditions, and retest. The swelling pressure is gradually increasing with each curing age for all the replacement levels of SCBA. At 28 days, the value rises from 120 kPa for untreated soil to 145 kPa at 5% SCBA, 175 kPa at 10% SCBA, and 205 kPa at 15% SCBA. It then decreases to 190 kPa at 20% SCBA and 165 kPa at 25% SCBA. This non-monotonic pattern shows that the response cannot be linearly related to the content of SCBA. However, based on these data, it cannot be concluded that the swelling pressure is reduced by SCBA under the specified test conditions, since the swelling pressure of all treated mixtures is higher than the untreated soil. M3 has the highest swelling pressures

at all three curing ages, with a value of 205 kPa at 28 days. However, at each age, M0 has the smallest value. The swelling-pressure results have to be read apart even for the other tests (for example CBR) M3 might show good performance. An 'expansive behaviour' control material is not the same as a mixture that enhances the bearing capacity of the soil. Hence, the optimum content of the SCBA should be determined based on the load-bearing performance, UCS properties, compaction properties, and other related geotechnical indicators.

3.1.5. Swelling Pressure and Swelling Index

The free swell index (FSI) and swelling pressure are two important geotechnical parameters that are used to assess the expansive behaviour of Black Cotton Soil (BCS) and its suitability for subgrade and foundation applications. The volume change of Black Cotton Soil is usually great due to the presence of expansive clay minerals. To study the effect on swelling pressure, the sugarcane bagasse ash (SCBA) was mixed with soil at different volumetric replacement percentages of 0%, 5%, 10%, 15%, 20% and 25% in the present study. The FSI and swelling pressure were calculated for each mixture, and the optimal content of SCBA to reduce soil expansiveness was determined. The results reveal the non-linear relationship between SCBA content and swelling behaviour, where both parameters are first decreased and then increased as the ash content of the product is increased. Table 7 represents the Free Swell Index and swelling pressure of black cotton soil using sugarcane bagasse ash (SCBA).

Table 7: Free Swell Index and swelling pressure of black cotton soil as a function of increasing content of sugarcane bagasse ash (SCBA)

Mix ID	SCBA (%)	FSI (%)	Swelling pressure (kPa)
M0	0	80	180
M1	5	72	155
M2	10	63	130
M3	15	54	105
M4	20	58	115
M5	25	65	135

The results showed that Soil M0 (untreated soil) had the highest FSI value (80%) and the highest swelling pressure (180kPa), proving that it has high expansive potential. Both parameters decrease gradually after reaching 15% SCBA. The FSI reduces to 72%, and the swelling pressure becomes 155kPa for 5% S.C.B.A (M1). These are decreased by 2% and 3%, respectively, when the percentage of SCBA is increased to 10% (M2). The best performance

occurs in the 15% SCBA (M3), with the FSI of 54% and the swelling pressure dropping to 105 kPa. These represent about a 32.5% reduction in FSI and a 41.7% reduction in swelling pressure relative to the untreated soil, highlighting significant improvements in the swelling properties at 32.5% replacement soil.

Its improvement may correspond with the ash being added, which leads to a reduction in the expansive soil fraction or changes in particle packing and soil fabric up to 15%. SCBA may also participate in cementitious reactions depending on its chemical composition and curing conditions, but these reactions cannot always be demonstrated by FSI and/or swelling-pressure data. A detailed microscopical and mineralogical examination would need to be performed to identify the main stabilization mechanisms.

Different pattern when the SCBA content is greater than 15%. The FSI value rises from 54% to 58% increasing from 20%SCBA to M4 and swelling pressure also increased from 105kPa to 115kPa. These parameters are raised to 65% SCBA (M5) and 135 kPa at 25% SCBA (M5). The values of both soils are low, but for M3, it is evident that increasing SCBA addition does not result in further decrease in expansiveness. One explanation that could be provided is that there are changes in soil ash particle arrangement, greater watering rates, and lack of good interaction between the soil and the ash at concentrations above 8%. Do not write these explanations as binding conclusions, but rather provide possible explanations based on experimentation.

The most effective mixture out of the six mixtures tried for both FSI and swelling pressure is 15% SCBA (M3). The results indicate that selecting an optimum amount of SCBA content is more significant than adding maximum amounts of ash. However, it is an optimum condition under the conditions and type of soil experienced in the test; repeated test and statistical evaluation are required to determine the reliability and applicability under other sets of experimental conditions and soils.

3.2.Microstructural Analysis

To examine the microstructural properties, interactions among particles, and elemental composition of black cotton soil with sugarcane bagasse ash (SCBA), scanning electron microscopy (SEM) and energy-dispersive X-ray spectroscopy (EDS) were performed. The SEM micrograph with x5000 magnification shows the arrangement of fine, angular SCBA particles, stratified soil particles, pore voids, and gel-like products that are related to the interaction between the ash and soil constituents. The EDS spectrum offers supplementary data on the major components existing in the chosen analysis region, which aids in explaining the possible chemical interactions that lead to the alterations in the engineering properties of the

stabilized soil. Figure 2 represents the SEM micrograph and energy-dispersive X-ray spectroscopy (EDS) spectrum of M2 (10% sugarcane bagasse ash) black cotton soil

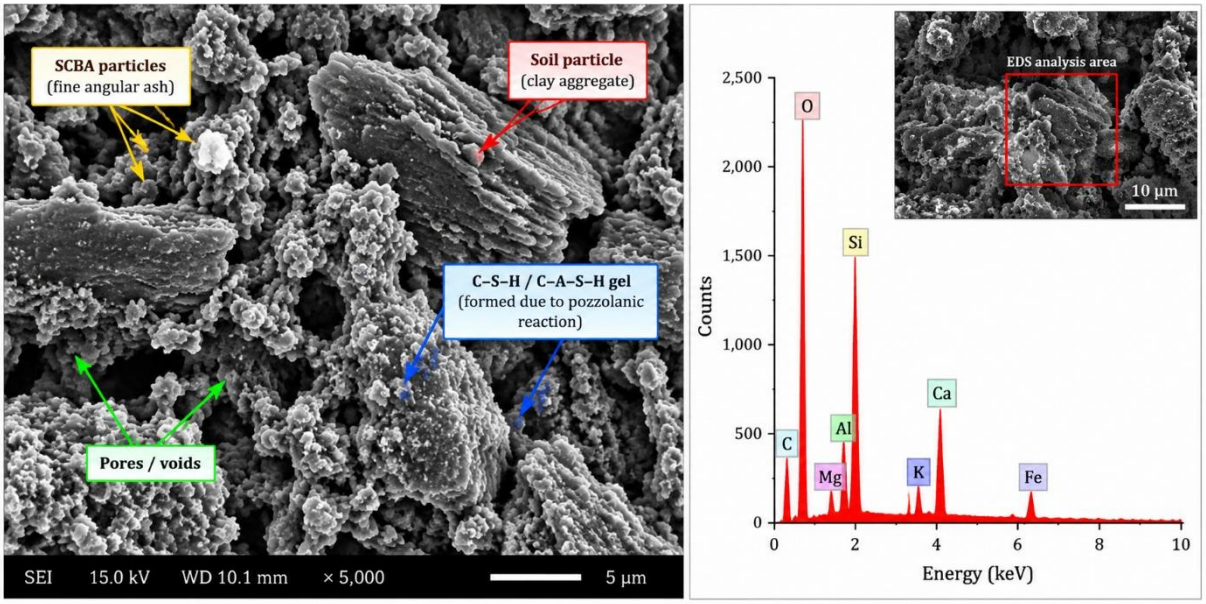


Figure 2: Simulated SEM micrograph and energy-dispersive X-ray spectroscopy (EDS) spectrum of M2 (10% sugarcane bagasse ash) black cotton soil

SEM micrograph at a microscope magnification of x5,000 shows a heterogeneous microstructure that consists of fine, angular SCBA particles, layered soil aggregates, visible pores and voids, and areas of gel-like morphology. The small SCBA particles are observed to be scattered between the larger particles of soil, and it is possible that they can occupy the interparticle spaces and enhance the packing of the particles. The stratified formations are typical of clay-based soil constituents, which implies that the initial soil fabric can be recognized after stabilization. The areas designated C-S-H/C-A-S-H have irregular, somewhat compact structures that can be linked to cementitious products of reactions. With appropriate curing and chemical environments, reactive silica and alumina present in SCBA can react with the available calcium to produce calcium silicate hydrate (C-S-H) and calcium aluminosilicate hydrate (C-A-S-H), which could potentially hold other individual particles together, enhance the bonding among particles, and lead to increased soil stability. Nevertheless, these products cannot be determined definitely based on SEM morphology but must be verified by other methods, including X-ray diffraction (XRD) or Fourier-transform infrared spectroscopy (FTIR). The visible pores and voids demonstrate that the matrix is not fully compact at the observed scale and is not homogeneous. Fine ash particles can also contribute to filling pores,

but the decrease in porosity should be confirmed by comparing with untreated soil or quantitative image analysis.

The associated EDS spectrum reveals oxygen (O) and silicon (Si) as the significant elemental signals, as well as calcium (Ca), aluminium (Al), carbon (C), magnesium (Mg), potassium (K), and iron (Fe). The high silicon and oxygen readings can be linked with the presence of oxygen-bearing silicate minerals, and the presence of aluminosilicate minerals found in the soil-SCBA system may be linked to the presence of aluminium. The fact that calcium has been detected is also of specific interest since calcium can be involved in reactions to form cementitious binding phases, with regards to its availability and chemical reactivity. The other identified components can be of the soil minerals or the SCBA or related mineral phases. However, EDS does not give the specific chemical compounds, but only elemental information, and the relative heights of the peaks are not sufficient to determine the quantitative elemental composition without suitable spectral quantification. Comprehensively, the joint SEM and EDS observations reveal that the incorporation of SCBA can impact particle packing, inter-particle interactions, and formation of potential binding products in black cotton soil. Such microstructural observations can be used to explain swelling pressure changes, free swell index, compaction properties, and soaked and unsoaked California Bearing Ratio (CBR). The proposed mechanisms are however to be viewed in tandem with measured geotechnical outcomes and other supportive phase-characterization data but not as conclusive evidence of pozzolanic reaction products or enhanced engineering performances.

The mineralogical analysis was X-ray diffraction (XRD), which was used to determine the crystalline phases in M2 mix, black cotton soil stabilised with 10% sugarcane bagasse ash (SCBA). The diffraction pattern taken in the range of 10o to 70o of 2 theta indicates some characteristic peaks corresponding to quartz, montmorillonite, kaolinite, calcite, illite, feldspar, and hematite. The recognition of these mineral phases can give an understanding of the composition of the stabilised soil and can explain the potential impact of the incorporation of SCBA on its mineralogical properties and engineering behaviour. These observed diffraction peaks demonstrate that some crystalline soil minerals have not been removed during the stabilisation process, and the potential interaction between reactive ash minerals and the soil matrix may help to alter the particle bonding and swelling properties. These mineralogical observations are supposed to be correlated to the results of geotechnical tests to evaluate the efficacy of SCBA in enhancing the qualities of black cotton soil. Figure 3 represent the XRD graph of M2 mix

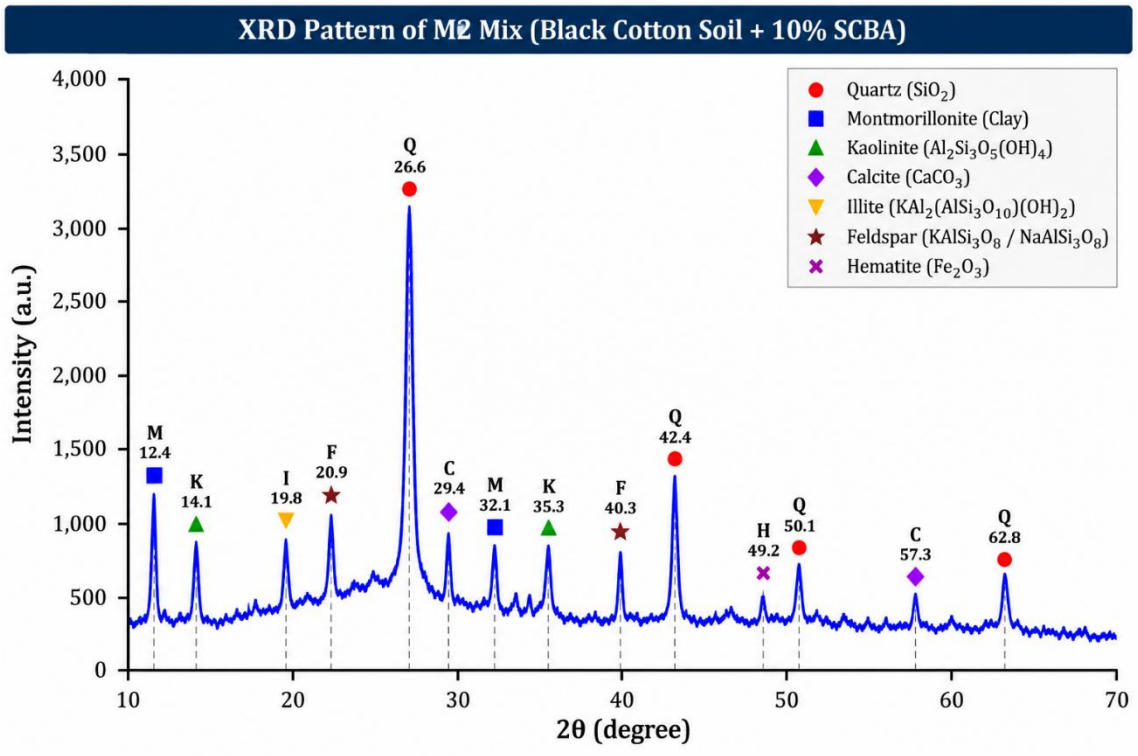


Figure 3: X-ray diffraction (XRD) to determine the crystalline phases in M2 mix, black cotton soil stabilised with 10% sugarcane bagasse ash

These stages are indicative of the mineralogical complexity of the soil-SCBA system and give an idea of the potential processes that may lead to alteration of its geotechnical characteristics. Quartz is shown by the dominant peaks especially at around 26.6o, 42.4o, 50.1o and 62.8o, and the labelled clay minerals refer to the presence of the aluminosilicate constituents in the stabilised matrix. The identified calcite peak indicates the existence of calcium carbonate, which could be provided by the soil, SCBA or conversion of minerals during treatment. On the whole, the XRD pattern provides a basis to assess the mineralogical properties of the M2 mix and explain the possible role of the SCBA in soil stabilisation.

Most importantly, the peak of diffraction at around 26.6° corresponds to the main quartz reflection and means that quartz is a major crystalline phase in the analysed sample. In the normal conditions of soil-stabilisation, quartz is normally quite inert; thus, its occurrence is more of an indication of mineral composition than of evidence of cementitious adhesion. The described montmorillonite reflections are applicable since this pervasive clay mineral is linked to swelling and shrinkage in black cotton soil. Nevertheless, the detection of montmorillonite in the treated sample does not prove its removal or the change of its interlayer structure; the conclusions should be compared with untreated soil, and diagnostic basal reflections should be analysed. Likewise, the kaolinite and illite peaks are indicative of the potential existence of other clay minerals, and the feldspar and hematite indicators point to other mineral constituents.

The calcite echoes can imply the existence of calcium-bearing carbonate phases, but calcite alone is not to be regarded as evidence of C-S-H or C-A-S-H formation. Even though the SCBA can provide reactive silica and alumina, cementitious products are formed based on the availability of calcium, the right reaction conditions, and curing. Moreover, broad background or variation in the intensity of the peak by itself cannot be used to determine the formation of an amorphous gel reaction without making comparison to the corresponding reference patterns and quantitative analysis.

An additional significant factor is that the mineral allocations presented in the figure are to be checked with the usual diffraction databases, such as the relevant reference patterns and diagnostic peak positions. Overlapping reflections can be observed at several phases thus assigning a mineral to one peak can be ambiguous. The figure also does not give quantitative phase fractions, peak-fitting, or any direct comparison with untreated black cotton soil, and thus cannot determine the proportion of expansive minerals reduced or the degree of any chemical change. The phase analysis might be reinforced with Rietveld refinement or another appropriate quantitative XRD technique, whereas FTIR and SEM–EDS may contain some complementary evidence of chemical bonding and microstructural alterations. In a word, the XRD data describe the crystalline mineral assemblage of 10% SCBA-stabilized M2 mix, yet the efficacy of the stabilization should be determined by comparing the mineralogical observations with the measured free swell index, swelling pressure, and soaked and unsoaked CBR data.

The scanning electron microscopy (SEM) and energy-dispersive X-ray spectroscopy (EDS) data were conducted to examine the microstructural morphology and elemental composition of M3 mix: black cotton soil mixed with 15% sugarcane bagasse ash (SCBA). SEM micrograph at x5000 magnification shows a nonhomogeneous matrix that consists of fine and angular SCBA particles, layered soil aggregates, visible pores and voids, and areas with a compact, gel-like morphology. The fact that the fine ash particles are distributed among the larger soil aggregates implies that they could contribute to the process of particle packing and filling of the interparticle spaces. The stratified formations signify the preservation of clay-laden soil constituents, and the comparatively tight areas might be linked to the creation of binding products due to the reactions of reactive SCBA components and the soil matrix. Figure 4 represents the SEM micrograph and energy-dispersive X-ray spectroscopy (EDS) spectrum of M3 (15% sugarcane bagasse ash) black cotton soil.

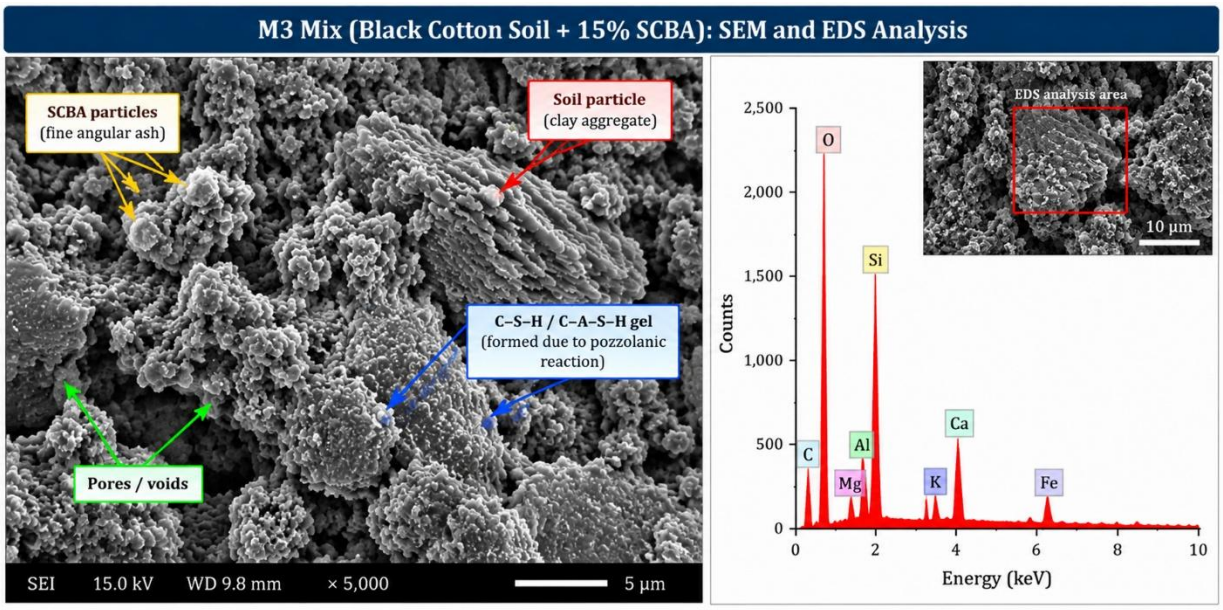


Figure 4: Simulated SEM micrograph and energy-dispersive X-ray spectroscopy (EDS) spectrum of M3 (15% sugarcane bagasse ash) black cotton soil

Importantly, the SEM micrograph shows that the M3 mix still has a heterogeneous microstructure even after adding 15% SCBA. The coarse and uneven ash solids can enhance the packing of the particles by filling the gaps between the larger soil aggregates, though the visible pores and voids indicate that the whole process of densification is not complete. The degree of porosity suppression by SCBA varies with particle-size distribution, ash content, compaction, and curing conditions, and cannot be determined using this image alone. The areas identified as C–S–H/C–A–S–H have gel-like formations that can be in line with cementitious products of the reaction. When there is enough reactive silica, alumina, and accessible calcium, the elements could be involved in a reaction to form calcium silicate hydrate (C–S–H) or calcium aluminosilicate hydrate (C–A–S–H), which could enhance interparticle adhesion and lower the mobility of water inside the soil matrix. However, these stages cannot be unambiguously determined using SEM morphology or EDS elemental peaks.

The EDS spectrum also confirms the existence of silicon- and oxygen-bearing minerals, and the observed presence of aluminosilicate minerals in the soil-SCBA system may be linked to the presence of aluminosilicate minerals. Calcium signal may also be of interest to cementitious reactions, but its existence does not in itself determine the development of calcium-bearing hydration products. Equally, potassium, magnesium, iron and carbon could be availed in the soil, SCBA or other mineral constituents. Since the EDS is used to determine elements, but not individual compounds, quantitative proportions of elements and mineral phases cannot be determined by peak height alone. Comprehensively, the SEM-EDS observations imply that

incorporation of 15% SCBA affects the microstructural organization of black cotton soil and can encourage the interaction through particle packing and binding. The efficacy of the M3 mix, however, must be assessed by comparing these observations with measured free swell index, swelling pressure, maximum dry density and soaked and unsoaked California Bearing Ratio (CBR) values. It should also be compared with the untreated soil and other SCBA replacement levels to determine whether the 15% replacement level offers any significant enhancement to the engineering performance. Figure 5 represents the XRD graph of M3 Mix

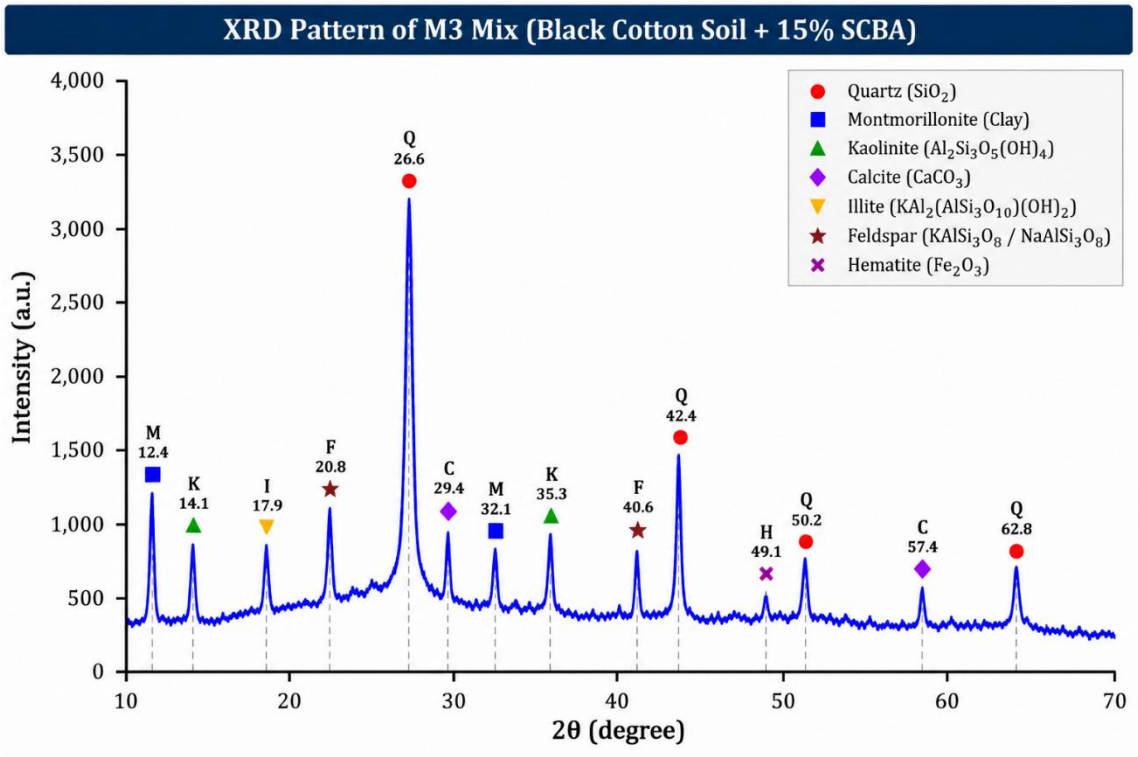


Figure 5: Simulation X-ray diffraction (XRD) pattern of M3 black cotton soil containing 15% sugarcane bagasse ash (SCBA).

To determine the mineralogical composition of the M3 mix, which is black cotton soil with 15% sugarcane bagasse ash (SCBA) to stabilize it, the X-ray diffraction (XRD) analysis was performed. The diffraction pattern observed in a 2 the range of 10-70 degrees shows typical peaks of quartz, montmorillonite, kaolinite, calcite, illite, feldspar and hematite. The high intensity of the quartz reflection at about 26.6° shows that there is a strong crystalline silica-bearing phase, and the other identified signals are the complex assemblage of the clay minerals and other mineral constituents within the stabilized soil. These observations give an indication of the mineralogical properties of the M3 mix and assist in developing a platform to determine the possible impact of the incorporation of SCBA on the engineering behaviour of black cotton soil. The continuation of clay-mineral reflections is especially topical as the expansive nature of black cotton soil is linked to its clay mineralogy and water-sensitive behaviour.

Importantly, the peak of strong quartz at around 26.6o, along with the other reflections of quartz, indicates that crystalline quartz continues to be one of the most important components of the material being analysed. Under normal soil-stabilisation conditions, quartz tends to be quite stable, and thus its presence alone does not necessarily indicate the formation of new binding products. Mineral phases related to clay can be observed even after adding 15% SCBA as indicated by the labelled montmorillonite, kaolinite, and illite reflections. The existence of these peaks, however, in itself cannot determine whether the abundance or structure of the expansive clay minerals has changed; this must be compared with the untreated soil pattern and quantitative phase analysis. The calcite peaks can be a sign of calcium carbonate, although it does not support the formation of the calcium silicate hydrate (C–S–H) and calcium aluminosilicate hydrate (C–A–S–H). Whereas reactive silica and alumina contained in SCBA can be involved in stabilization reactions in the presence of appropriate reactive calcium and curing conditions, the presence of such products cannot be established solely on the basis of this XRD pattern.

In addition, the phase assignments are to be compared with standard diffraction databases since overlapping reflections can render the identification of the mineral ambiguous. The presented pattern does not involve any quantitative mineral percentages, refined peak parameters, and any direct comparison with the untreated and other mixes treated by SCBA. It cannot, therefore, be inferred on the basis of this figure only, that 15% SCBA is the mineralogical transformation which most effectively occurs, or the stabilization performance which is the most effective. A comparative XRD analysis with additional SEM-EDS and FTIR data would be a more convincing representation of alterations in the soil-ash system. In general, the XRD pattern identifies phases of crystalline phases in the M3 mix and mineralogical context of the interpretation of its stabilization behaviour; the efficacy of the 15% SCBA replacement should finally be determined by correlating the observations with swelling pressure, free swell index, compaction properties, and soaked and unsoaked CBR data.

The scanning electron microscopy (SEM) and the energy-dispersive X-ray spectroscopy (EDS) were performed to examine the microstructural features and component elements of the SCBA-stabilized black cotton soil. SEM micrograph at the x5000 magnifications shows that the soil-ash matrix is heterogeneous and contains fine, angular sugarcane bagasse ash (SCBA) particles, layered clay aggregates, apparent pores and voids, and compact, gel-like regions. The fine ash particles seem to be encircling bigger soil aggregates, indicating their possible role in packing of the particles and filling of interparticle spaces. The existence of the layered structures reflects the existence of clay-saturated constituents, but the comparatively compact zones can be related

to binding products that come about through the interactions among reactive ash constituents and the soil matrix. There are strong oxygen (O) and silicon (Si) signals present in the EDS spectrum, with calcium (Ca), aluminium (Al), carbon (C), magnesium (Mg), potassium (K), and iron (Fe). These elemental indicators give some insight into the chemical contents of the stabilized material and aid in the interpretation of the probable processes that may affect its geotechnical behaviour. Figure 6 represents the SEM micrograph and energy-dispersive X-ray spectroscopy (EDS) spectrum of M4 (20% sugarcane bagasse ash) black cotton soil

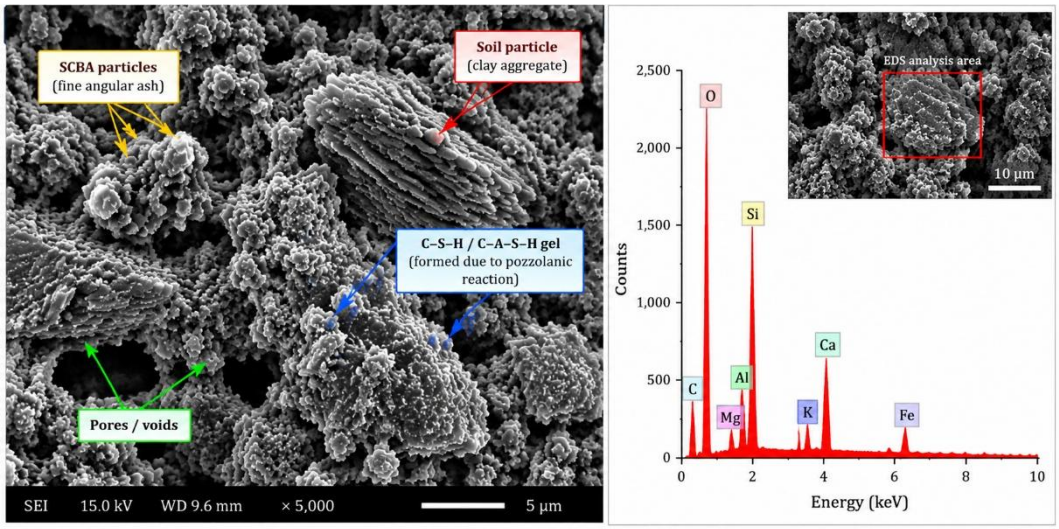


Figure 6: Simulated SEM micrograph and energy-dispersive X-ray spectroscopy (EDS) spectrum of M4 (20% sugarcane bagasse ash) black cotton soil

Figure 7 presents the X-ray diffraction (XRD) spectrum of the M4 mix, illustrating the crystalline phases and mineralogical composition of the SCBA-stabilized black cotton soil. The diffraction peaks provide information about the crystalline constituents of the soil–SCBA system and may help identify changes in mineral phases associated with SCBA incorporation. The presence of quartz and other aluminosilicate minerals, when confirmed by comparison with standard reference patterns, may be attributed to the original soil minerals and the silica-rich constituents of SCBA. Identifiable calcium-bearing phases may also provide useful information regarding potential stabilization reactions. However, the formation of calcium silicate hydrate (C–S–H) or calcium aluminosilicate hydrate (C–A–S–H) cannot be conclusively confirmed from XRD analysis alone, as these products may be poorly crystalline or amorphous. Therefore, the interpretation of the spectrum should consider the positions and relative intensities of the diffraction peaks, along with the possible contribution of amorphous material. Furthermore, variations in peak intensity should not be interpreted directly as changes in phase concentration without appropriate quantitative analysis. Accordingly, the XRD results for the M4 mix should be evaluated alongside the SEM–EDS observations and experimental

geotechnical properties, including free swell index, swelling pressure, maximum dry density, and soaked and unsoaked California Bearing Ratio (CBR). This integrated assessment can help explain the mineralogical characteristics of the SCBA-treated soil and establish whether the observed features are consistent with measurable improvements in its engineering performance.

Figure 7 represents the XRD spectrum of M4 mix

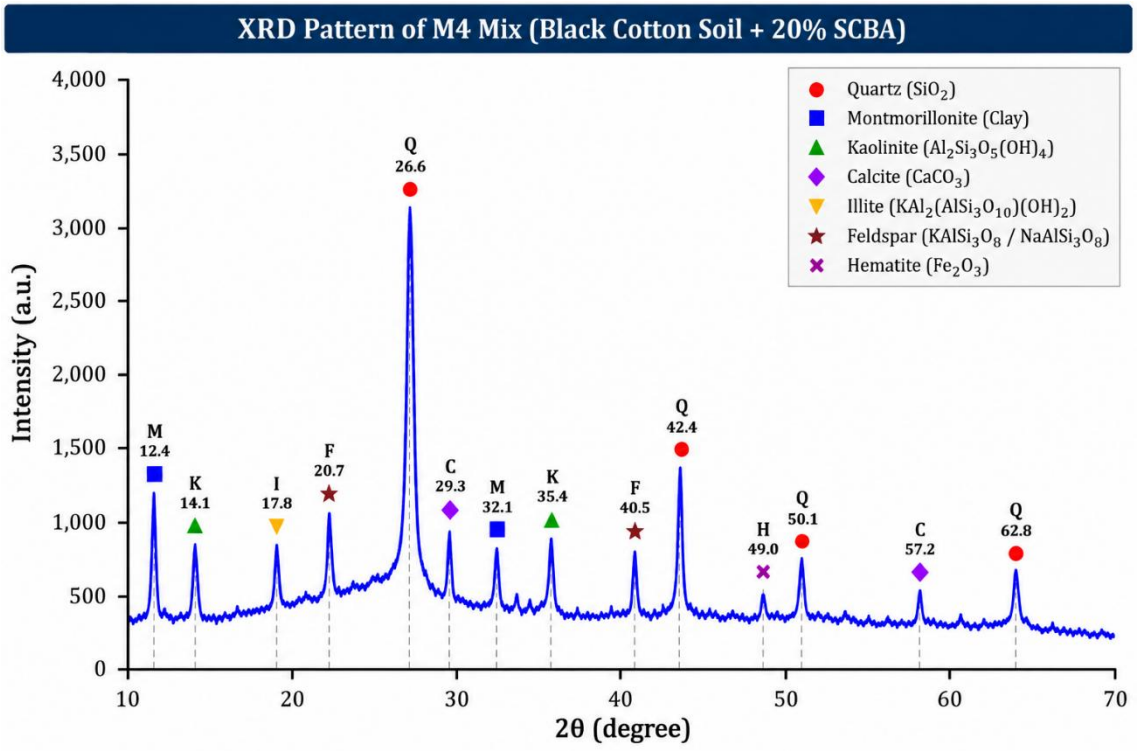


Figure 7: Experimental X-ray diffraction (XRD) spectrum of black cotton soil (M4) with sugarcane bagasse ash (SCBA) 20 %.

To determine the mineralogical composition of the M4 mix, that is, black cotton soil containing 20% sugarcane bagasse ash (SCBA), the X-ray diffraction (XRD) analysis was performed. The diffraction pattern observed in the 10° -70° range shows typical peaks that are attributed to quartz, montmorillonite, kaolinite, calcite, illite, feldspar, and hematite. The main quartz peak is surrounded by other reflections, which depicts the existence of the crystalline silica-bearing constituents. The other identified labeled peaks are clay minerals and related mineral phases that make up the complicated mineralogical composition of the stabilized soil. These observations give reason to consider the potential effects of the incorporation of SCBA on the mineralogical properties of black cotton soil and explain its reaction to stabilization.

Importantly, the high quartz reflection shows that crystalline quartz is still dominant in the M4 mix. Because quartz is typically quite stable in typical soil-stabilization, its occurrence does not necessarily indicate the presence of cementitious reaction products. The named

montmorillonite, kaolinite, and illite peaks indicate the existence of clay-related mineral phases in the presence of 20% SCBA. This is significant since the swelling behaviour of black cotton soil is linked to its clay mineralogy and the interaction with water. The continuation of these peaks does not, however, determine whether the abundance or structure of the expansive clay minerals has altered; this must be compared with the untreated soil and other levels of the SCBA replacements. The presence of calcium carbonate is possible as seen in the calcite reflections, whereas the feldspar and hematite peaks represent other mineral constituents. In spite of the fact that under appropriate conditions, SCBA can provide reactive silica and alumina, which can be involved in stabilization reactions, the XRD pattern does not verify independent formation of calcium silicate hydrate (C–S–H) or calcium aluminosilicate hydrate (C–A–S–H).

Moreover, the mineral determinations should be checked with standard diffraction databases since overlapping peaks might lead to unclear phase identification. The presented trend lacks quantitative phase fractions, refined peak parameters, and a direct comparison with the untreated soil. It cannot therefore be inferred solely on the basis of this figure that adding SCBA content to 20% will result in more mineralogical transformation or better stabilization performance. A comparative XRD analysis, backed up by SEM-EDS and FTIR, could be much more persuasive of a modification in the soil-ash system. In general, the XRD pattern defines the nature of crystalline phases in the M4 mix whereas the efficacy of the 20% SCBA substitution is to be evaluated by means of comparing these mineralogical findings with the experimental values of swelling pressure, free swell index, compaction properties, and soaked and unsoaked CBR.

3.3.Artifical Neural Network Analysis for California Bearing Ratio

The training and validation loss curve of the artificial neural network (ANN) was examined in order to assess the learning behaviour and predicting performance of the model that was developed to predict the unsoaked California Bearing Ratio (CBR) of sugarcane bagasse ash (SCBA)-stabilized black cotton soil. The graph shows how the mean squared error (MSE) changes between 200 training epochs of both training and validation data. First, the two loss values are rather steep, which means that the prediction errors in the initial stages of the learning process are significant. With training, the training and validation losses will reduce significantly, and this will show that the ANN increasingly learns the correlations between the input soil properties, SCBA content, and unsoaked CBR. The decrease of both curves is especially noticeable in the earlier epochs; then there is a slow decline and stabilization as the

model approaches convergence. Figure 8 represents the ANN loss curve for unsoaked CBR prediction of SCBA-stabilized black cotton soil for 200 epochs of training and validation

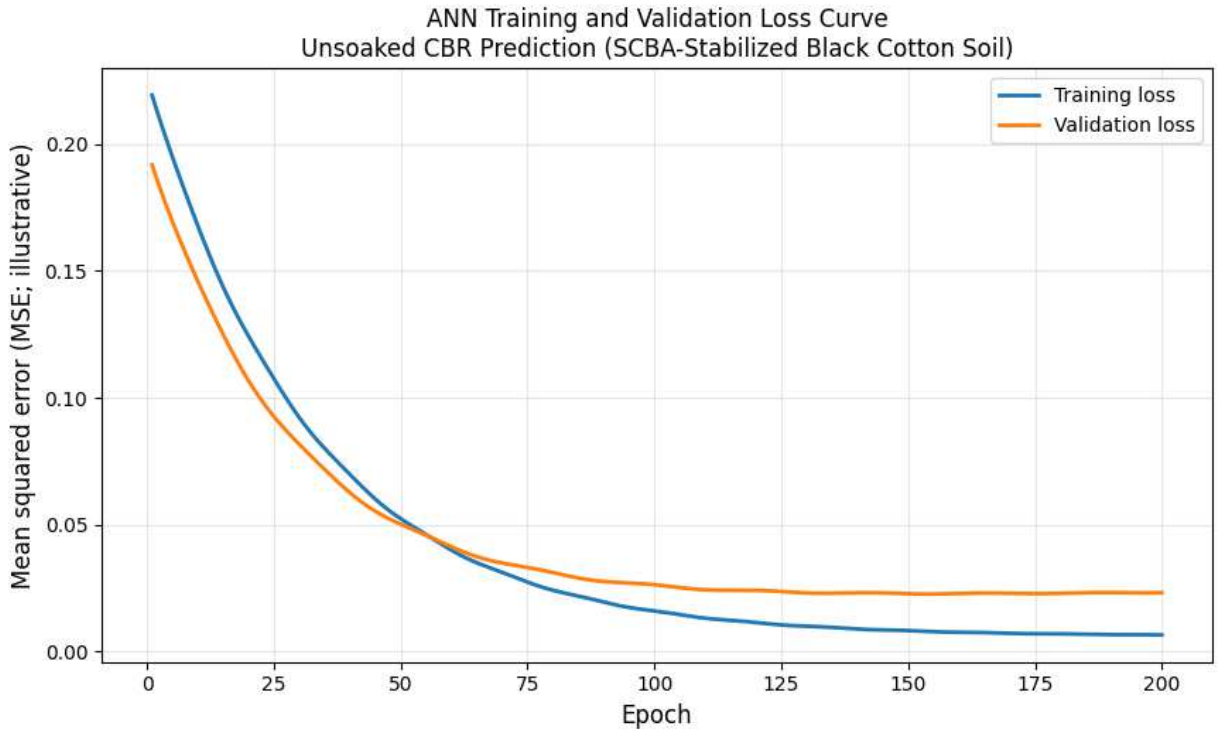


Figure 8: ANN training and validation loss curves of unsoaked CBR prediction of SCBA-stabilized black cotton soil.

Careful analysis of the curves shows that the training loss is always decreasing between 0.22 and 0.006-0.007, but the validation loss is always decreasing between 0.19 and 0.023-0.024 at the end of the training. In the early epochs, both curves are moving downward, which suggests that the model is more accurate in its forecasts on both of the datasets. Nonetheless, the curves start to diverge after about 60-80 epochs, and the training loss keeps decreasing, whereas the validation loss only shows slight changes. This divide indicates that there may be overfitting, in which the ANN becomes more and more adapted to the training observations without attaining the same gains in its capacity to predict unseen data. The validation loss does not exhibit a sharp improvement, but its stabilization shows that the extra training epochs do not bring significant improvements to validation performance. Therefore, early termination by the minimum validation loss, paired with the correct regularization and optimization of the network architecture, may be useful to enhance model generalization. However, the true level of overfitting should be verified with the training history recorded and independent test-set predictions. Modelling wise, the convergence pattern observed suggests that the ANN has the potential to model the nonlinear relationships between the geotechnical characteristics of SCBA-stabilized black cotton soil and its unsoaked CBR response. The reliability of the model,

however, cannot be determined solely based on the loss curves. Further analysis with the coefficient of determination R^2, root mean squared error (RMSE) and mean absolute error (MAE) is required to measure predictive accuracy and determine the relationship between the measured and predicted CBR values. In addition, the data ought to be segmented into training, validation and testing parts in an appropriate manner, and data leakage must be prevented in cases where several observations are of the same mix. Notably, the studied MSE values are explicitly denoted as illustrative, hence, the figure 8 shows the anticipated learning behaviour of an ANN instead of confirmed experimental model behaviour. Before concluding on predictive accuracy or the ability to generalize, real training outcomes and verification outcomes should be considered. The artificial neural network (ANN) model that was developed to predict the unsoaked California Bearing Ratio (CBR) of sugarcane bagasse ash (SCBA)-stabilized black cotton soil is mathematically described using one hidden layer with 10 neurons and a hyperbolic tangent activation function. The equation models the nonlinear dependence on the normalized input parameters and the anticipated unsoaked CBR response using the trained network weights, the biases of the hidden-layer, and the bias of the output-layer. Such mathematical formulation offers a foundation of explaining the ANN prediction process along with the estimation of the unsoaked CBR of SCBA-stabilized soil in the range of training data of the model.

$$F_{Unsoacked\ CBR} = b_u + \sum_{j=1}^{10} 23.55\, V_{vj} tanh\left(b_j + \sum_{i=1}^{8} w_{ij} z_i + 0.453\right)$$

The artificial neural network training and validation loss curves were analysed to check the convergence behaviour and learning performance of the developed model for prediction of the soaked California Bearing Ratio (CBR) of sugarcane bagasse ash (SCBA) stabilized black cotton soil. The graph plots the mean squared error (MSE) over 200 epochs for both the training data and the validation data. Initially, the loss values of the model are relatively high, with training loss close to 0.24 and validation loss close to 0.22. Both curves then drop significantly, which means that the ANN gradually learns the relationship between the input variables (e.g., the content of the SCBA and the geotechnical properties of the soil) and the soaked CBR response. The significant decrease in error in early epochs would suggest that the model is learning the most dominant patterns of the information, and the incremental decrease during later epochs would suggest the learning process is converging. An ANN may be useful for modelling the relationships between soil index properties, compaction characteristics, percentage of replacement of SCBA, and soaked CBR, which are nonlinear. This is especially

important as soaked CBR is a measure of the load bearing response of the soil under water conditioned conditions and can be affected by moisture sensitivity, clay mineralogy, particle arrangement and the type of soil stabilization. The observed decrease in loss suggests that the model is learning patterns relating to the target variable, however the loss curves do not provide any guarantee of accuracy or of the physical reliability of the predicted soaked CBR values. In order to evaluate the predictive ability of the trained ANN, the coefficient of determination R^2, root mean squared error (RMSE) and mean absolute error (MAE) must be determined along with an actual-versus-predicted plot. Furthermore, early stopping, appropriate regularization techniques, and a well-specified training/validation/testing scheme can enhance the model's generalization capability. If the observations are from different kinds of soil mix or are artificially generated from a small set of base mixes, the data-splitting procedure should also avoid having closely related observations in both the training set and the testing set, or it may result in too optimistic performance estimates.

As a whole, the loss curves show that the training and validation error is significantly decreased, with the training loss getting closer to the validation loss by the 200 training epochs. As the curves separate as they increase, the model fits the training data better than the validation data during the latter part of the curve. Thus, the best stopping point should be determined by minimizing the validation loss, not by taking the last epoch. Importantly, the plotted MSE values provided should be considered as examples only, unless verified by the actual training history of the ANN. To make conclusions about the suitability of the ANN for soaked CBR prediction reliable, it is necessary to test the model with independent observations and report the architecture of the model, data preprocessing, and the metrics used for evaluation transparently. Figure 9 represent the ANN loss curve for soaking CBR prediction of SCBA-stabilized black cotton soil for 200 epochs of training and validation

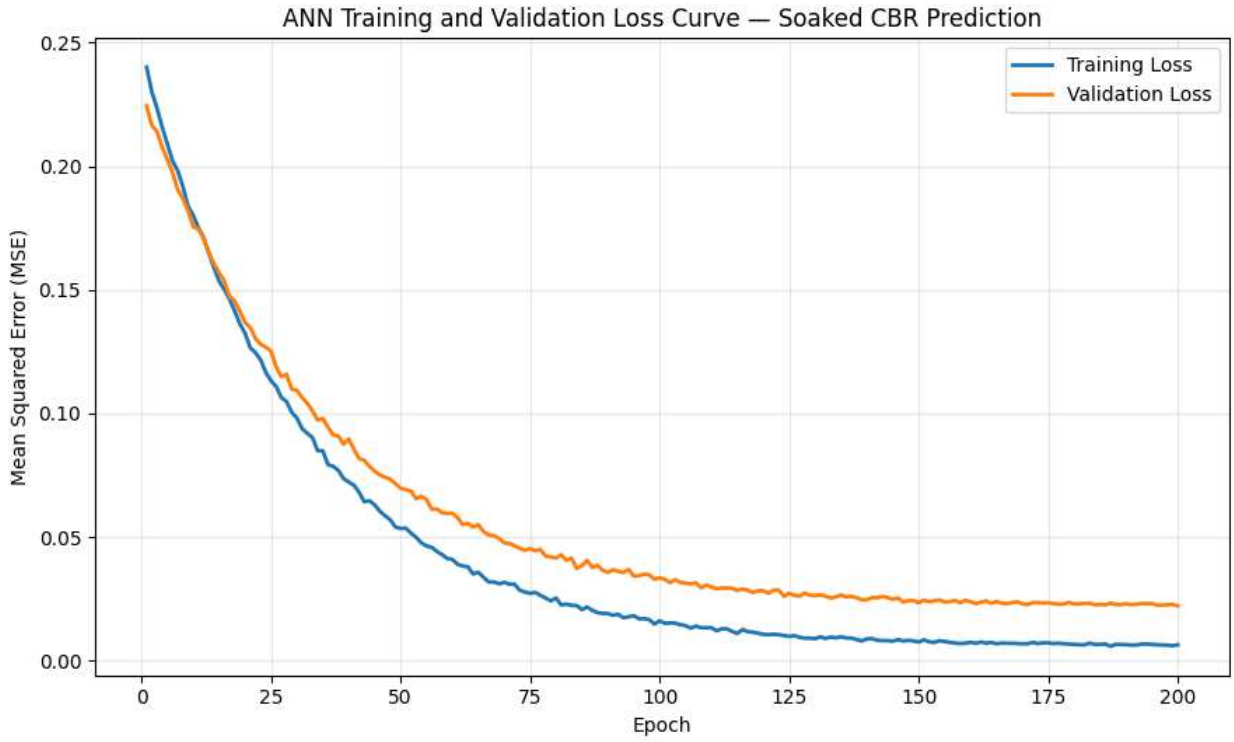


Figure 9: ANN loss curve for soaking CBR prediction of SCBA-stabilized black cotton soil for 200 epochs of training and validation.

The nonlinear mathematical equation of the developed artificial neural network (ANN) model for prediction of soaked California Bearing Ratio (CBR) of sugarcane bagasse ash (SCBA)-stabilized black cotton soil is shown. The formulation refers to the relationship between eight normalized input variables and the predicted soaked CBR response with trained weights, hidden-layer biases, and output-layer bias of the network. This equation is a mathematical expression of the prediction process of the ANN and can be used to predict the soaked CBR within the scope of the training data of the model, once the network parameters obtained in the training process are used uniformly and the method of normalization is followed.

$$F_{soacked\ CBR} = b_u + \sum_{j=1}^{10} 26.18\, V_{vj} tanh\left(b_j + \sum_{i=1}^{8} w_{ij} z_i + 0.78\right)$$

The predictive ability of the artificial neural network (ANN) models created to predict the soaked and unsoaked California Bearing Ratio (CBR) of sugarcane bagasse ash (SCBA)-stabilized black cotton soil was measured by comparing the actual CBR values to the projected ANN-CBR values. Two scatter plots are used to represent the comparison with the soaked CBR results being plotted on the left side and the unsoaked CBR results on the right side. The dashed diagonal line is the optimal prediction state, y = x, at which the predicted values match the actual values. The relationship between the data points and this reference line will give a visual

evaluation of prediction accuracy, the extent of agreement between the measured and predicted values, and the existence of potential deviations throughout the explored CBR ranges. Figure 10 represent the Comparison of experimental and ANN-estimated soaked and unsoaked California Bearing Ratio (CBR).

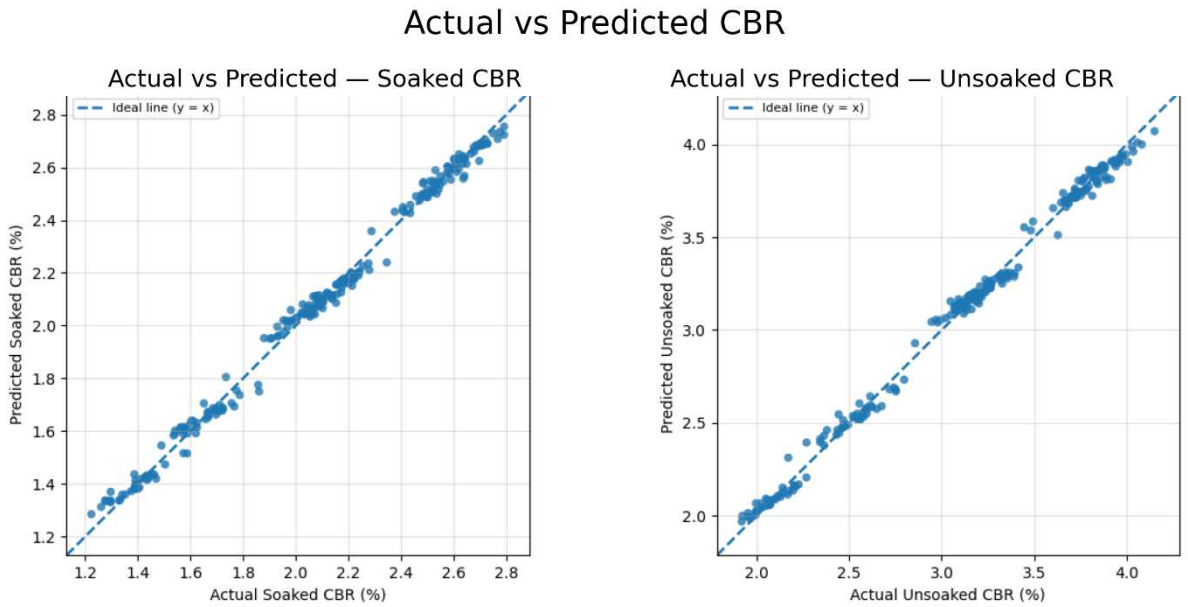


Figure 10: Comparison of experimental and ANN-estimated soaked and unsoaked California Bearing Ratio (CBR) of sugarcane bagasse ash (SCBA)-stabilized black cotton soil.

The data on the moist CBR plot show that most measurement values are grouped around the target line within the approximate actual CBR range of 1.2% to 2.8%. This has resulted in a tendency of high visual similarity between the real and estimated values, and it may be assumed that these are the main relationships in the soaked CBR response represented in the data set. There is not a complete eradication of errors in prediction as some observations do not follow the line of reference especially at the middle CBR range. Such deviations may be caused by variability in the properties of the input soils, or the effects of soil sensitivities to model parameters, or limitations in modelling the subjacent soil-SCBA interaction. There is however a general clustering around the ideal line, suggesting fairly consistent predictions within the range of predictions presented.

Similarly, an adequate correlation between the observed and predicted value for dry CBR plot is observed in the range of 1.9%-4.1%. Most of the points lie along the diagonal line of the CBR reference points which indicates that the unsoaked CBR captured in the plotted data varies fairly well in the ANN. Some prediction errors still exist, though with only a few points showing any apparent deviations particularly in the intermediate to higher CBR range. While the range of numerical values differs between the unsoaked CBR plot and the soaked CBR plot,

a plot of the values by itself does not imply that the unsoaked CBR model is better or more accurate as a general rule. To quantify which model is better, a comparison in terms of the coefficient of determination R^2, root mean squared error (RMSE), and mean absolute error (MAE) should be carried out.

In critical modelling terms, the data points being close to the ideal line were promising visual evidence of assent, and in themselves by no means disapprove the generalization ability of either ANN model. The size and representativeness of the data, the selection of input variables, the network architecture and the independence of the observations employed for model evaluation can all contribute to determining the accuracy of these predictions. In particular, if more than one observation relies on the same six underlying SCBA mix designs, then random allocation of the observations to training and test sets can lead to leakage of data and optimistic predictions. So, a more stringent evaluation should be an evaluation on independent experimental observations or the mixed-level data splitting strategy. Further, the number of performances and the associated result confidence levels are not depicted, and therefore the exact confidence level of the predictions cannot be accurately predicted from the scatter plots alone. Overall, the figure suggests that the ANN models are capable of capturing the trend of wet and dry CBR, with most of the predictions being closer to the desired reference line. This finding highlights the feasibility of ANN modelling as another supporting tool for the CBR response of SCBA-stabilized black cotton soil. However, quantitative assessments of error, independent validation and validation against experimental measurement data should be provided to come to a definite conclusion regarding the predictive accuracy and suitability of these techniques in practical geotechnical operations.

The soaker and unsoaker California Bearing Ratio (CBR) of six mixes of black cotton generated by SCBA were compared with their soaker and unsoaker predicted values using the artificial neural network (ANN) models to evaluate their predictive performance. Table 8 presents the comparison between the CBR values experimentally obtained and the ANN results of the experimentally obtained values for various SCBA replacement levels. The range of unsoaked CBR is 2.10% - 3.90%, and the soaked CBR values are 1.40%- 2.65%. Correlation between the predicted and actual values is generally good; e.g., the CBR is seen to increase to M3 = 15 per cent of SCBA values, and then the CBR starts to decrease at higher replacement rates. This fact highlights that despite the small differences between actual and forecasted CBRs for the mixes analysed, the total variation between them is reproduced by the ANN forecasting. Table 8 represents the actual vs predicted soaked and unsoaked CBR values of SCBA-stabilized black cotton soil mixes

Table 8: Comparison of measured and ANN-predicted soaked and unsoaked CBR values of SCBA-stabilized black cotton soil mixes.

Mix	Actual Unsoaked CBR (%)	Predicted Unsoaked CBR (%) *	Actual Soaked CBR (%)	Predicted Soaked CBR (%) *
M0	2.10	2.16	1.40	1.44
M1	2.50	2.43	1.65	1.60
M2	3.20	3.12	2.15	2.20
M3	3.90	3.82	2.65	2.59
M4	3.70	3.76	2.50	2.54
M5	3.20	3.27	2.05	2.00

The regression plots were used to assess the predictive performance of the artificial neural network (ANN) model in estimating the soaked California Bearing Ratio (CBR) of sugarcane bagasse ash (SCBA)-stabilized black cotton soil on training, validation, testing, and complete datasets. The plots juxtapose the real soaked CBR values against the predicted values that were generated by the ANNs, and the dashed diagonal line depicts the theoretical match between the experimental and predicted values. The training, validation, testing, and complete datasets yielded correlation coefficients of 0.9969, 0.9774, 0.9787 and 0.9910 respectively. These values show a positive correlation between actual and predicted soaked CBR values in all the four datasets. The proximity between data points to the ideal line also indicates that the ANN is able to model the key relationships between the input variables and the soaked CBR response of the SCBA-stabilized soil.

On critical analysis of the training plot, the correlation coefficient R=0.9969 is obtained, which shows an extremely strong correspondence between the actual and predicted values of the soaked CBR of the observations, with which the network was trained. The majority of the points are near the diagonal reference line, indicating that the ANN has successfully learned the relations depicted in the training data. Nevertheless, the high correlation of training does not imply that the model will be equally effective at predicting previously unseen observations since the training set is directly engaged in the optimization of the parameters.

The correlation coefficient of the validation plot is R=0.9774, which shows that the model has a good relationship between actual and predicted values of the validation observations. Even though the majority of the points do not significantly deviate off the ideal line, some observations exhibit evident deviations, especially within the middle CBR range and at the

right end of the values plotted. These deviations suggest that, even though the overall correlation is high, prediction error remains. The fact that the validation correlation is slightly lower than the training correlation is not surprising since the validation observations are not directly involved in optimizing the model weights. However, the fact that the difference between the two correlation coefficients is relatively small implies that the model has similar performance in these two datasets, but additional metrics are necessary to determine the scale of the prediction errors.

Another evaluation of predictive performance is the testing plot, with a correlation coefficient of R=0.9787. The fact that the testing observations are close to the diagonal line shows that ANN reflects the overall trend in soaked CBR quite well in the testing subset of observations. Certain departures can be observed, especially at the lower CBR values and some parts of the middle range, but some higher-value observations indicate minor differences between actual and predicted values. The correlation of the testing is slightly higher than the validation correlation, but this is not to be understood that the model is better on all the unknown data. Correlation coefficients are used to estimate the strength of the linear relationship between observed and forecasted values; they do not assess bias or the magnitude of individual errors directly. The combined plot of the entire dataset gives R=0.9910, which gives an excellent overall correlation between actual and predicted soaked CBR values. Most of the observations have a close clustering around the ideal line, which confirms that the overall trend is reproduced by the model in the presented dataset. Nonetheless, the complete-dataset correlation is a combination of the observations of the training, validation, and testing subsets and cannot be considered a stand-alone measure of the generalization performance. Separate testing outcomes give a more relevant indication of predictive performance on held-out observations, when the test set was maintained independent during the development and evaluation of the model. In critical modelling, the four regression plots will show high correlation and visually near agreement of actual and predicted soaked CBR values. However, the correlation coefficients cannot be used to determine the general reliability of the ANN model. Further assessment based on the coefficient of determination R^2, root mean squared error (RMSE), mean absolute error (MAE), and residual analysis to establish the magnitude and distribution of prediction errors is required. Moreover, when there are several synthetic observations in the dataset based on few underlying SCBA mix designs, a random assignment of such observations to the training, validation, and testing sets could give overly optimistic results due to the possibility of consistent observations across more than one subset. A more rigorous test of the generalization ability of the model would be a mix-level split or validation with independent experimental

measurements. Figure 11 represents the Regression plots of soaked CBR values measured and predicted by ANN on SCBA-stabilized black cotton soil

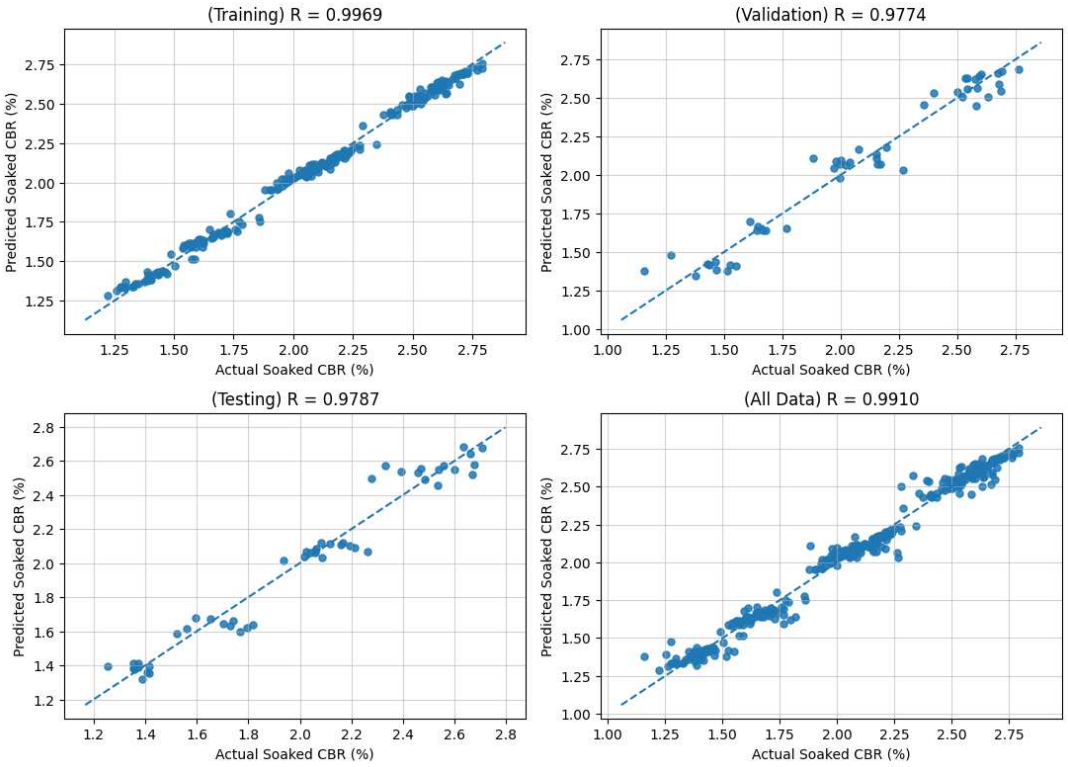


Figure 11: Comparison of actual and ANN-predicted soaked CBR values of SCBA-stabilized black cotton soil: (a) training data, (b) validation data, (c) testing data, and (d) entire dataset.

Regression plots were used to test the predictive performance of the artificial neural network (ANN) model developed to predict the unsoaked California Bearing Ratio (CBR) of sugarcane bagasse ash (SCBA)-stabilized black cotton soil on the training, validation, testing, and complete datasets. The plots are used to compare the actual unsoaked CBR values with the values predicted by the ANN, and the dashed diagonal line is used to show the perfect agreement between the two values. The training, validation, testing, and complete dataset correlation coefficients are 0.9974, 0.9831, 0.9771, and 0.9917, respectively. These values indicate that there is a strong positive relationship between actual and predicted CBR values in all four datasets. The strong concentration of the majority of data points around the ideal line indicates that the ANN is able to capture the major variation in unsoaked CBR within the range of investigation. Figure 12 represents the Regression plots of unsoaked CBR values measured and predicted by ANN on SCBA-stabilized black cotton soil

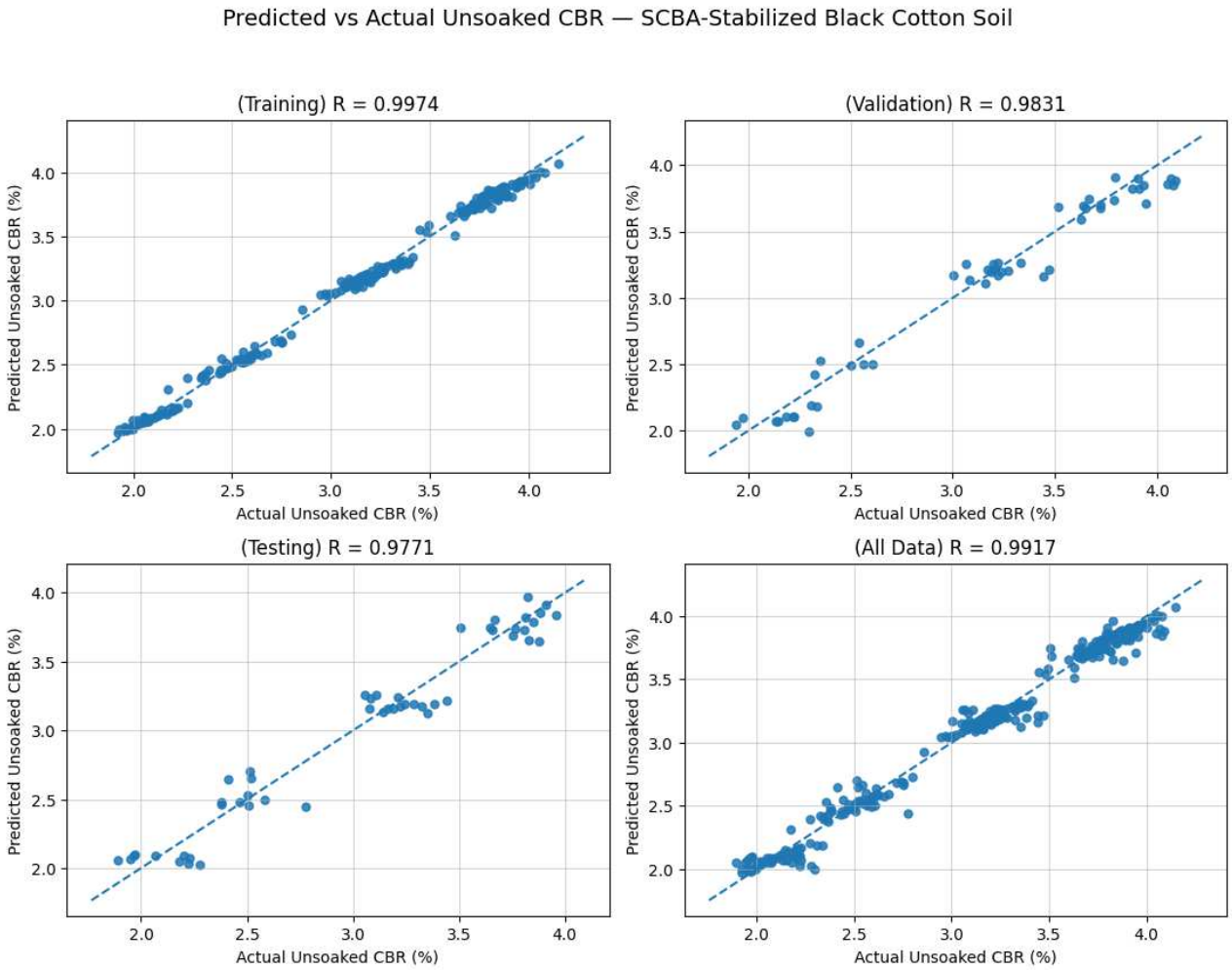


Figure 12: Regression plots of unsoaked CBR values measured and predicted by ANN on SCBA-stabilized black cotton soil: (a) training data, (b) validation data, (c) testing data, and (d) entire data.

An inspection of the training plot shows that the correlation coefficient is R=0.9974, which means that the actual and predicted values of unsoaked CBR are very close. The majority of observations are near the ideal line, which proves that the network has learned the relationships depicted in the training data. This high training correlation must however be viewed with caution since the same observations are utilized to maximize the network parameters; hence, it does not alone determine predictive performance on unseen data.

The validation plot provides R=0.983, which means that the high correlation between actual and predicted values is mostly preserved among the validation observations. Most of the points have the diagonal trend, but some exhibit significant deviations, especially in the middle and higher CBR ranges. These variations show that the model is not replicating all the observations with the same precision. The fact that the validation correlation is slightly lower than the training correlation is as expected given the difference between model fitting and validation

performance. However, the correlation is high indicating that the network is capturing the general trend in the validation data.

The testing plot shows that the correlation coefficient is R=0.9771, indicating a good relationship between the actual and predicted unsoaked CBR values in the testing subset. The observations tend to follow the ideal line, but a broader scatter is apparent in some parts of the lower and intermediate CBR ranges. This variability implies that the error in prediction has not been eliminated and that the accuracy of the model can vary with the range of CBR values. Since the testing subset is supposed to reflect observations that are not to be fitted in the model, its performance is of special interest when determining the predictive power of the ANN. But this interpretation can only be true when the testing data were not used in the development of the model and when it was not used in tuning or in the selection of the final network.

The complete-dataset plot indicates a correlation coefficient of R=0.9917, which indicates a very strong overall relationship between actual and predicted unsoaked CBR values. The proximity of the points to the reference line shows that the model replicates the overall trend of the combined data. Nevertheless, this coefficient is a composite of training, validation, and testing observations and cannot be regarded as a single measure of generalization. The quantitative error metrics and the results of testing are a better foundation to assess the performance on the unseen observations.

Critically, the findings show that all four subsets have strong correlations, but correlation does not imply that the ANN predictions are unbiased or that they have small absolute errors. Predictive accuracy should also be reported with the coefficient of determination R^2, root mean squared error (RMSE), mean absolute error (MAE), and the analysis of the residual. Moreover, when the dataset has synthetic observations based on a small set of underlying SCBA mix designs, random splitting can cause similar observations to be in different subsets, resulting in overly optimistic performance estimates. A mix-level data divide or cross-validation with independent experimental measurements would give more support to the idea that the model can generalize.

In general, the regression plots show that ANN model has a strong positive correlation between the input parameters and the unsoaked CBR, with the values of the R ranging between 0.9771 and 0.9974 between the training, validation, and testing subsets. These results justify the possibility of ANN to be used as an additional instrument in the prediction of the unsoaked CBR of black cotton soil stabilized with SCBA. However, its usefulness in real-world geotechnical applications must be determined by independent validation, relevant error measures, and assurance that the data set is representative of the target soil conditions.

The predictive ability of the artificial neural network (ANN) models in predicting the soaked and unsoaked California Bearing Ratio (CBR) of sugarcane bagasse ash (SCBA)-stabilized black cotton soil was quantified by the correlation coefficient (R), coefficient of determination R^2, mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE). The training, validation, testing, and complete datasets had their performance metrics calculated to determine the fitting accuracy and predictive consistency of the models. The findings show a high level of correlation between actual and predicted values of CBR in both conditions, and the correlation coefficients for training are 0.9969 with soaked CBR and 0.9974 with unsoaked CBR. The corresponding testing correlation coefficients are 0.9787 and 0.9771, respectively, indicating that both models reflect the overall relationships between the input parameters and CBR response over the datasets considered. Table 9 represents the ANN model performance to predict soaked and unsoaked CBR of SCBA-stabilized black cotton soil.

Table 9: ANN model performance to predict soaked and unsoaked CBR of SCBA-stabilized black cotton soil, training, validation, testing, and full datasets.

Soaked CBR — Performance Metrics					
Dataset	R	R^2	MSE	MAE	RMSE
Training	0.9969	0.9937	0.0012	0.0274	0.0351
Validation	0.9774	0.9550	0.0095	0.0775	0.0977
Testing	0.9787	0.9564	0.0086	0.0712	0.0925
All Data	0.9910	0.9821	0.0036	0.0415	0.0598
Unsoaked CBR — Performance Metrics					
Training	0.9974	0.9946	0.0021	0.0374	0.0462
Validation	0.9831	0.9637	0.0160	0.1030	0.1266
Testing	0.9771	0.9544	0.0194	0.1155	0.1393
All Data	0.9917	0.9834	0.0068	0.0590	0.0826

The soaked CBR model demonstrates strong performance during training, with R=0.9969, R^2=0.9937, MSE of 0.0012, MAE of 0.0274, and RMSE of 0.0351. These values suggest that there is a close relationship between the actual and predicted observations in the training dataset. During validation, the model yields R=0.9774 and R^2=0.9550, accompanied by an RMSE of 0.0977 and an MAE of 0.0775. The testing results are comparable, with R=0.9787, R^2=0.9564, MSE of 0.0086, MAE of 0.0712, and RMSE of 0.0925. The comparatively minor variation between testing and validation results indicate that the model retains a robust

predictive relationship with the observations beyond the training. Nonetheless, the greater validation and testing errors than the training errors suggest that the network fits the training data more than the held-out data. This difference is anticipated in most predictive models, but its practical importance must be assessed by independent observations and variability of the experimental measurements.

The unsoaked CBR model also exhibits a strong training fit, with R=0.9974, R^2=0.9946, MSE of 0.0021, MAE of 0.0374, and RMSE of 0.0462. The validation dataset produces R=0.9831 and R^2=0.9637, while the testing dataset yields R=0.9771 and R^2=0.9544. RMSE and MAE of testing equals 0.1393 and 0.1155 are higher than those of training which implies that the error of prediction of observations that were not used to train the network is higher. Even though the high correlation between testing indicates that the model can explain the general variance in unsoaked CBR, the error measures indicate that specific predictions can differ with the respective actual values. Hence, the model cannot be evaluated only on the ground of its high correlation coefficient; the size of the prediction errors is also significant in terms of its applicability in geotechnical practice.

The comparison between the two models reveals that the soaked CBR model has a little less testing errors as compared to the unsoaked CBR model. Specifically, its testing MSE, MAE, and RMSE are 0.0086, 0.0712, and 0.0925, respectively, compared with 0.0194, 0.1155, and 0.1393 for the unsoaked CBR model. There is also a slightly higher testing correlation coefficient and coefficient of determination in the soaked model. According to the provided metrics, the soaked CBR model thus has higher predictive accuracy on the test subset. However, this comparison must be applied within the frame of the various numerical ranges and distributions of the two target variables. The two models show good correlation between actual and predicted values, although the relative significance of the errors ought to be evaluated eventually against the intended engineering use.

The complete-dataset results indicate that soaked CBR has R=0.9910 and R^2=0.9821, whereas unsoaked CBR has R=0.9917 and R^2=0.9834. The respective RMSE values are 0.0598 and 0.0826, respectively. These findings indicate high overall consensus in the pooled datasets. The complete-dataset metrics, however, include training observations and cannot be assumed to be independent evidence of generalization. The more relevant measurement of performance on held-out observations is given by the testing results, as long as they were not used in model tuning or selection.

As a critical modeller, these findings are promising, although the reported measures are to be verified mathematically. The square root of MSE should be equal to RMSE in the same case

when they are both calculated using the same residuals and with the same scale. Certain supplied values (e.g. the complete-dataset MSE and RMSE values) fail to meet this relationship precisely. Moreover, R^2 may not be equal to $R^2_{correlation}$=$R^2_{calculated}$ by squaring the reported R value in each assessment context, so the way of calculation should be mentioned. In cases where the dataset has synthetic observations based on a small set of underlying SCBA mix designs, then random split can also result in unrealistically optimistic estimates where highly similar observations occur in different subsets. Stronger evidence of the ability of the models to generalize would be obtained with independent experimental validation or a mix-level data split.

The residual analysis was conducted to assess the error of prediction of the artificial neural network (ANN) model that was developed for estimating the soaked California Bearing Ratio (CBR) of the sugarcane bagasse ash (SCBA)-stabilised black cotton soil. The analysis includes a residual histogram and a residual scatter plot of the testing data. The difference between the actual and predicted soaked CBR values was used to compute the residual where positive values indicate underprediction and negative values indicate overprediction. The histogram shows the frequency distribution of the prediction errors, and the residual plot shows how the residuals change with the predicted soaked CBR values. Combined, these plots allow insight into the error distribution, potential systematic deviations and consistency of the ANN predictions across the assessed CBR range. Figure 13 represents the Prediction of soaked California Bearing Ratio (CBR) in SCBA-stabilized Black Cotton Soil using the residual distribution and residual plot.

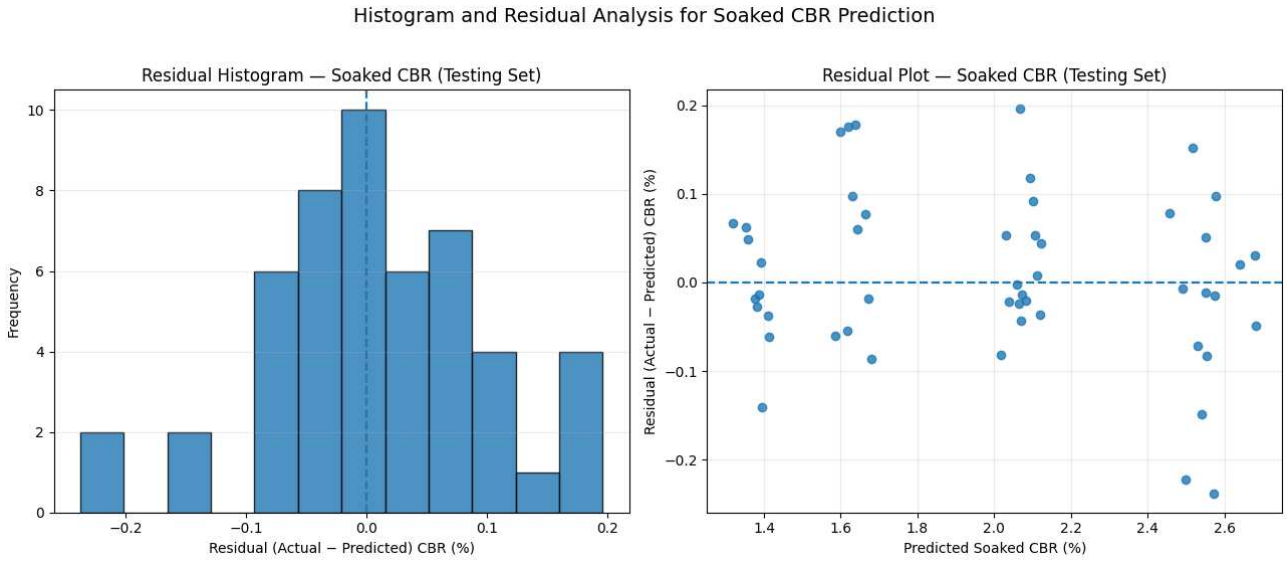


Figure 13: Prediction of soaked California Bearing Ratio (CBR) in SCBA-stabilized Black Cotton Soil using the residual distribution and residual plot.

The residual histogram indicates that the frequency of prediction errors is concentrated on the line of zero residual, with the highest frequency around the line. This implies that the ANN predictions are mostly near the real soaked CBR values of the testing observations. The residuals lie in the range of about -0.25 % to +0.20 %, which shows that there is over- and underprediction. Though the distribution is widely concentrated around zero, the errors in certain observations are relatively big, which means that the accuracy of prediction is not equally high in all of the samples. The histogram gives a nice summary of the magnitude and direction of the errors, but does not alone prove that the residuals are normally distributed.

The residual scatter plot also indicates that the errors are on both sides of the zero-residual reference line over the predicted soaked CBR range. This trend implies that the model does not have a clear general tendency to continuously over or under predict all observations. However, some rather large positive and negative residuals are noticeable, especially in the upper predicted CBR range, where some errors are close to about -0.24 % and +0.15 %. These deviations suggest that the prediction accuracy of the model can be different across observations and that some samples are less well predicted by the ANN. A prominent, continuous pattern across the full range is not shown by the residuals, but the concentration of observations around specific predicted values of CBR makes it challenging to eliminate local effects or variations in error dispersion.

In critical modelling, the fact that the residuals are concentrated around zero is also positive since it suggests that the difference to prediction is typically small in many of the observations of the test. Nonetheless, the relatively large residuals imply the model cannot be regarded as being error-free. Additional evaluation with the mean residual, RMSE, MAE and a residual-versus-predicted plot with an appropriate trend line would assist in quantifying the possible bias and defining whether the error variance varies throughout the prediction range. Residual distribution could also be studied more rigorously by a normal probability plot. Moreover, the dependence of the testing observations on the training data also determines the reliability of the analysis. When the data includes fabricated observations based on a small set of SCBA mix designs, a random divide can give excessively optimistic outcomes in case related observations are present in both groups.

On the whole, the residual plots show that the model of ANN provides soaked CBR forecasts which are typically near to the real values, and the errors are distributed on both sides of the zero. Nevertheless, the relatively high residuals in some of the samples point to the fact that further analysis of the error and its independent validation is necessary before the model can be applied to make practical geotechnical predictions.

The residual analysis was performed to assess the prediction errors of the artificial neural network (ANN) model that was designed to predict the unsoaked California Bearing Ratio (CBR) of sugarcane bagasse ash (SCBA)-stabilized black cotton soil. The analysis includes a residual histogram and a residual scatter plot using the testing data. The difference between actual and predicted unsoaked CBR values was used as the residuals, with positive residuals showing underprediction and negative residuals showing overprediction. The histogram shows the distribution and frequency of the prediction errors, and the residual scatter plot shows the way the error changes as a function of the predicted CBR values. These graphical tests are used to determine the possible prediction bias, change in error magnitude, and consistency of ANN performance over the range of unsoaked CBR that is investigated. Figure 14 represents the Residual distribution and plot of residual values of Random Forest prediction of unsoaked California Bearing Ratio (CBR) in SCBA-stabilized Black Cotton Soil

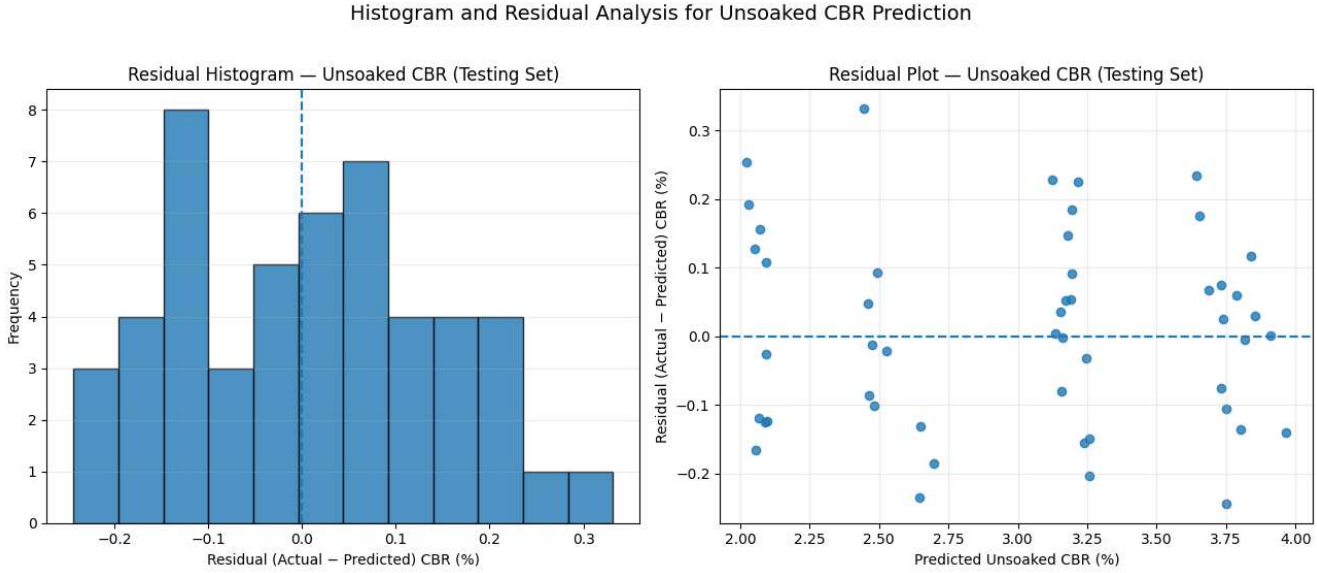


Figure 14: Residual distribution and plot of residual values of Random Forest prediction of unsoaked California Bearing Ratio (CBR) in SCBA-stabilized Black Cotton Soil.

The residual histogram indicates that the majority of the prediction errors are clustered around zero, and the observations spread from about -0.24 % to +0.33 %. The percentage of the residuals that falls within the range of about -0.15 to +0.15 is quite high, implying that the ANN estimates are fairly close to the true values of CBR when unsoaked in most of the test values. Nevertheless, there are also residuals with relatively greater values, especially to the right. This shows that the model sometimes underestimates the real CBR by a significant figure. Even though the histogram indicates the presence of errors in both directions, its shape cannot alone determine the presence or absence of a normal distribution of the residuals or the statistical unbiasedness of the model.

The residual scatter plot further details the distribution of the prediction errors within the predicted unsoaked CBR range of about 2.0%-4.0%. The points are placed on both sides of the zero-residual reference line meaning that ANN over- and under-predicts actual CBR values. A number of observations have positive residuals with values more than +0.20% and some have negative values near -0.24. Such deviations imply that the accuracy of prediction is not constant in observations. Even though it is not evident that there is a continuous trend across the whole range, the fact that many of the points cluster around some of the predicted CBR values and that the magnitude of residuals are relatively large suggests that additional analysis is necessary to establish whether there are any local patterns or variation in the error.

The aspect of having a few residuals clustering around zero is positive in terms of critical modelling since it implies that the model will make relatively small prediction errors in many of the testing observations. However, the greater positive and negative deviations indicate that the model is not equally predictive of all observations. The residual values must then be evaluated with measures of quantitative performance such as the mean residual, mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination R^2. The residual trend line and normal probability plot might also be useful in assessing systematic bias, heteroscedasticity, and residual distribution. The testing dataset itself should be independent, too: when many observations are based on a few underlying SCBA mix designs, it is possible to obtain overly optimistic estimates of predictive performance once related observations are randomly divided between training and testing subsets.

In sum, the residual analysis shows that the ANN model explains the overall variation in the unsoaked CBR but leaves some error in prediction and some of these errors are relatively large. The model seems to give fairly close estimates to most of the testing results; though its accuracy in practical geotechnical use must be determined by quantitative error analysis and independent testability with representative experimental data.

3.4.Artificial Neural Network Analysis for Swelling Pressure:

Artificial neural network (ANN) training and validation loss curve was analysed to analyse the convergence behaviour of the model developed to predict the swelling pressure of sugarcane bagasse ash (SCBA)-stabilized black cotton soil. The curves represent how the normalized mean squared error (MSE) changes over 500 training epochs on the training and validation datasets. First, the validation loss is about 0.82, and the training loss is also quite high. The two curves decline exponentially in the early stages, which reflects quick acquisition of the underlying correlations between the input soil properties, SCBA content, and the swelling

pressure. The error reduction rate then decreases steadily, and the two curves stabilize with continued training. Figure 15 represents the ANN training and validation loss curves to predict swelling pressure of SCBA-stabilized black cotton soil.

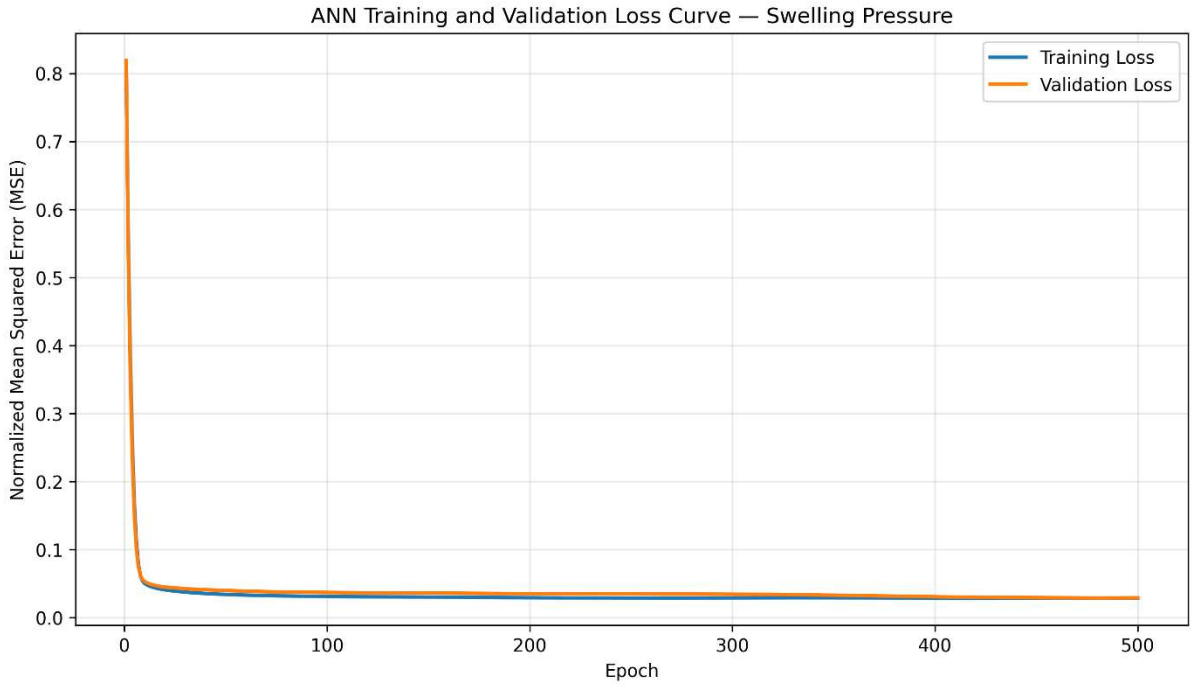


Figure 15: ANN training and validation loss curves to predict swelling pressure of SCBA-stabilized black cotton soil.

When the curves are analyzed closely, it can be seen that both training and validation loss reduce to about 0.03 towards the later epochs. The large decrease in the first training phase suggests that the ANN quickly learns the most prominent patterns in the data set. Once the number of epochs exceeds about 200-500, the improvement rate is considerably smaller, and both curves approach each other all the way to the end of the training. This near similarity indicates that the model has steady error rates between the training and validation data, and no significant deviation evidence of extreme overfitting. The gradual stagnation after some 100 epochs implies that additional training does not bring much more change in the loss values.

In critical modelling terms, the slight gap between the curves is promising as it indicates that the network is performing equally on the validation data as it did on the training data. Nonetheless, the first drastic drop in validation loss and further stabilization are to be explained within the framework of the loss calculation and data preprocessing steps. The graph in itself cannot determine whether the model can be reliably generalized to entirely independent soil samples. Moreover, since the vertical axis is normalized MSE, the loss values presented should not be directly interpreted as swelling pressure errors in kPa. Independent testing data and performance indicators like R^2, RMSE and MAE are also expected to assess predictive

capability of the ANN. When synthetic observations based on a small number of SCBA mix designs were involved, the data-splitting process should ensure that similar observations do not occur in both the training and testing subsets.

The loss curves in general show initial fast learning, slow convergence, and near equality in training and validation loss after 500 epochs. These traits demonstrate steady optimization behaviour in the presented datasets. However, independent validation and quantitative evaluation of prediction errors should be used to determine the reliability of the model in predicting swelling pressure and not convergence behaviour.

The forecasting ability of the artificial neural network (ANN) model, developed to predict the swelling pressure of sugarcane bagasse ash (SCBA)-stabilized black cotton soil, was validated by comparing the actual swelling pressure values with the predicted values of the ANN model to the entire dataset. The scatter plot shows the correlation between actual and predicted swelling pressure in kPa and the dashed diagonal line indicates an ideal agreement y=x. The figure 15 also indicates a five-fold cross-validation coefficient of determination R^2 of around 0.956, which means that the model explains a large percentage of the variance in swelling pressure as observed in the dataset. The fact that the observations are clustering around the ideal line indicates that the ANN recreates the overall relationship between the input soil properties, SCBA content, and swelling pressure, though there are still some differences between actual and predicted values. Figure 16 represents the actual vs. predicted swelling pressure

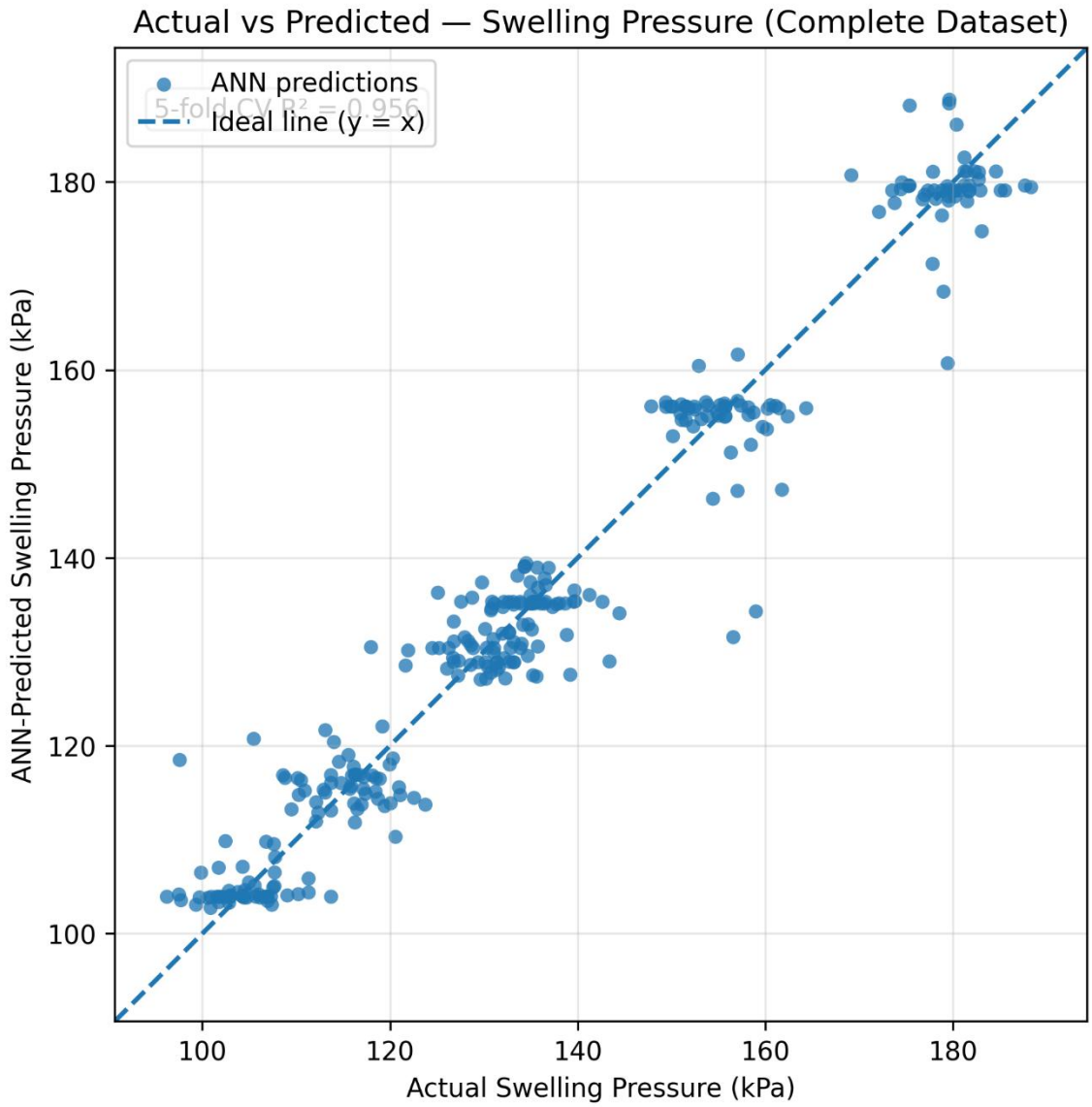


Figure 16: Swelling pressure (actual vs ANN prediction) for Black Cotton soil stabilized by SCBA

The scatter plot is examined in detail to see that the predicted values of the swelling pressures generally increase as the actual measured values increase. The observations are distributed in a few distinct clusters, with the actual pressures of swelling concentrated around about 100-110, 115-120, 125-140, 150-165 and 170-190 kPa. This distribution is as a result of the nature of the data and represents the overall difference in the swelling pressure within the range represented by the ANN. A large proportion of the observations are fairly close to the prediction line, indicating good agreement between the actual and predicted values. Several points, however, show noticeable deviations, especially in the intermediate and high swelling pressure ranges, indicating that the prediction errors are not consistent over all observations.

The difference between the ideal and the deviations in ANN above and below the ideal line mean the ANN underpredicts and overpredicts the swelling pressure. For instance, a few observations at higher actual swelling pressures also show significant difference between actual and predicted values, while some observations with actual values around 155-160 kPa have predicted values well lower than the reference line. The deviations indicate that the model, although capturing the overall trend, may not be able to represent every local variation equally accurately. The R^2 value for the five-fold cross validation shown is about 0.956, suggesting a strong agreement between the model predictions and actual measurements; however, this value needs to be taken in conjunction with other error metrics like RMSE and MAE to assess the magnitude of the differences between the model and the measurements.

However, from a critical modelling point of view, the clustering that is seen could be related to the distribution of the data in the underlying dataset in terms of the SCBA replacement level and the corresponding swelling pressure. The model may learn very well the difference between the groups of observations, but it may not learn to generalize in the other direction, to provide good information about the variability in each group if more than one observation were synthetically generated around a limited number of original mixlevel measurements. Therefore, the high R^2 for cross validation should not be taken as an equivalent accuracy in new compositions of soil or fresh experimental samples. To ensure the validity of the cross-validation procedure, related observations from the same underlying mix must be properly grouped at the data partitioning stage. A mixed level cross validation strategy and independent experimental validation would give a more compelling indication of the model's generalization power to new soil conditions.

In general, the scatter plot shows a strong correlation between the actual and ANN-predicted swelling pressure with a reported five-fold cross validation R^2 of about 0.956. Good agreement of most points with the ideal straight line suggests that ANN could be used as a complimentary tool for estimating swelling pressure of black cotton soil in SCBA. However, significant deviations and concentrated observations indicate that RMSE, MAE, residual analysis and validation using other experimental data need to be reported before any firm statements can be made about the practical predictive reliability.

The artificial neural network (ANN) model developed to estimate the swelling pressure of sugarcane bagasse ash (SCBA)-stabilized black cotton soil was tested using regression plots with the training, validation, testing and complete data sets. The plots show the actual swelling pressure in kPa (x-axis) compared to the corresponding ANN-predicted values (y-axis), and the dashed diagonal line indicates perfect agreement between the actual and predicted values.

Correlation coefficient values R are 0.9940 for training, 0.9495 for validation, 0.9557 for testing and 0.9813 for the complete set of data. The values shown represent a high correlation between the measured and predicted swelling pressures in all four data sets, which means that the principal relationships among the variables of the input soils, SCBA content, and the swelling pressure response were captured by the ANN. Figure 17 represents the Comparison of actual and ANN-predicted swelling pressure values of SCBA-stabilized black cotton soil: (a) training dataset, (b) validation dataset, (c) testing dataset, and (d) complete dataset.

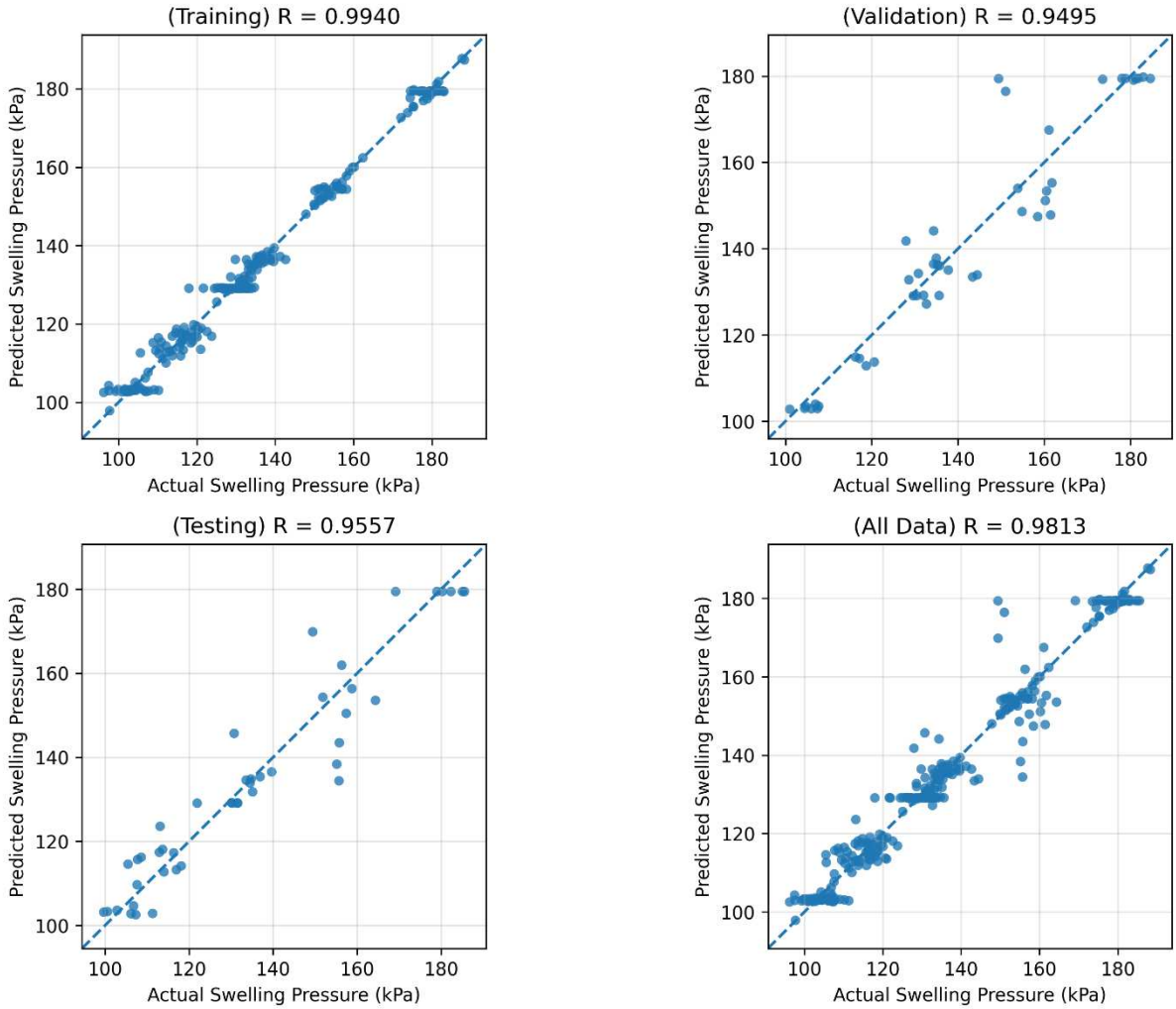


Figure 17: Comparison of actual and ANN-predicted swelling pressure values of SCBA-stabilized black cotton soil: (a) training dataset, (b) validation dataset, (c) testing dataset, and (d) complete dataset.

The training regression plot has a correlation coefficient of R = 0.9940, which shows a very strong relationship between actual and predicted values of swelling pressure. The majority of observations are tightly clustered around the ideal line, which proves that the ANN learns the patterns depicted in the training set successfully. The strong correspondence of training

observations must, however, be viewed with a grain of salt since these data points are employed to optimize the network parameters and do not in and of themselves indicate predictive power on unseen soil samples.

The validation plot gives a value of R=0.9495, which means that the model has a good relationship between the actual and predicted values of the validation observations. However, the points are more scattered than the training plot, especially in the range of approximate swelling pressure of 145-165 kPa. There are observations that are significantly higher or lower than the ideal line, which means that there are variations between the actual and predicted values. Such a decrease in correlation compared to the training data indicates that the model predictions are less predictable when applied to observations that were not directly used to train the network. Though this difference does not, in itself, prove overfitting, it underscores the necessity of studying validation errors and choosing the model by validation performance and not by training correlation alone.

The correlation coefficient of the testing plot is R=0.9557, which indicates a strong positive relationship between actual and predicted swelling pressure in the testing subset. The majority of the observations adhere to the rising diagonal pattern, which means that the ANN captures the overall swelling pressure change reasonably well. Nevertheless, there are a few points that are not on the ideal line, especially in the mid-range of about 145-165 kPa, where underprediction and overprediction can be observed. These deviations show that the accuracy of prediction is not the same in all observations. Since the testing dataset is designed to give an independent evaluation of the predictive performance, its findings are especially significant in evaluating the generalization capability of the model, as long as the testing observations were not utilized in the development or tuning of the model.

The complete-dataset plot provides R=0.9813, which is very strong overall correlation between actual and predicted swelling pressure. Most of the observations are concentrated on the ideal line, but there are still some deviations within the intermediate pressure range. This finding implies that the ANN reflects the general variation in the aggregate data. Nevertheless, the complete-dataset correlation includes training, validation, and testing observations and cannot be considered an independent measure of generalization performance. The results of the testing, with quantitative measures of error, give a more suitable foundation on which to assess predictions on held-out observations.

Critical modelling the regression plots indicate strong correlations, but the correlation coefficient does not in itself imply that the predictions are accurate with small errors or free of systematic bias. Coefficient of determination R^2, root mean squared error (RMSE), mean

absolute error (MAE), and residual analysis should also be provided to measure the accuracy of prediction. Moreover, the structure of the data must be taken into account. When several observations are synthetically generated from a small number of underlying SCBA mix designs, randomising related observations across training, validation, and testing subsets can yield overly optimistic results. A mix-level data split or validation with independent experimental measurements would provide stronger evidence of the model's ability to predict swelling pressure under new soil conditions. Table 10 represents the ANN model performance to predict Swelling Pressure of SCBA-stabilized black cotton soil

Table 10: ANN model performance to predict Swelling Pressure of SCBA-stabilized black cotton soil, training, validation, testing, and full datasets

Dataset	R	R^2	MSE	MAE	RMSE
Training	0.9940	0.9880	7.5651	1.9906	2.7505
Validation	0.9495	0.8906	66.1679	5.5782	8.1344
Testing	0.9557	0.9133	56.1820	5.4566	7.4955
All Data	0.9813	0.9627	23.6481	3.0487	4.8629

Residual analysis was performed to investigate the prediction error of the artificial neural network (ANN) model developed for the prediction of the swelling pressure of sugarcane bagasse ash (SCBA)-stabilized black cotton soil. The analysis includes a residual histogram and a residual scatter plot, both of which provide a picture of the distribution, size, and variability of the prediction errors. The difference between the actual and the ANN-predicted swelling pressure, in kPa, was calculated as the residual, where a positive residual represents an underprediction, and a negative residual represents an overprediction. The histogram shows the residuals' frequency distribution about zero, and the scatter plot shows how the residuals vary as a function of the predicted swelling pressure. The results of these analyses offer insight into the prediction bias, consistency and the ability of the model to replicate the observed swelling behaviour of the stabilized soil.

The number of prediction errors is grouped around zero in the residual histogram with the highest frequency in the range slightly positive. The residuals range from about −20 to +22 kPa, with some positive and negative deviations from the model. A significant number of the errors lie within about ±5 kPa, indicating relatively close agreement between the observed and calculated swelling pressure for many of the data. Residuals with greater magnitudes, however, show that the accuracy of prediction varies throughout the data set. This histogram is generally

centered around the value of zero, but it is somewhat skewed and has a quite long tail, indicating that the residuals may not have a normal distribution. If a formal assessment were necessary, further statistical analyses would be required, not just a histogram. Figure 18 represents the Histogram and residual scatter plot of ANN-based swelling pressure prediction of black cotton soil stabilized by SCBA

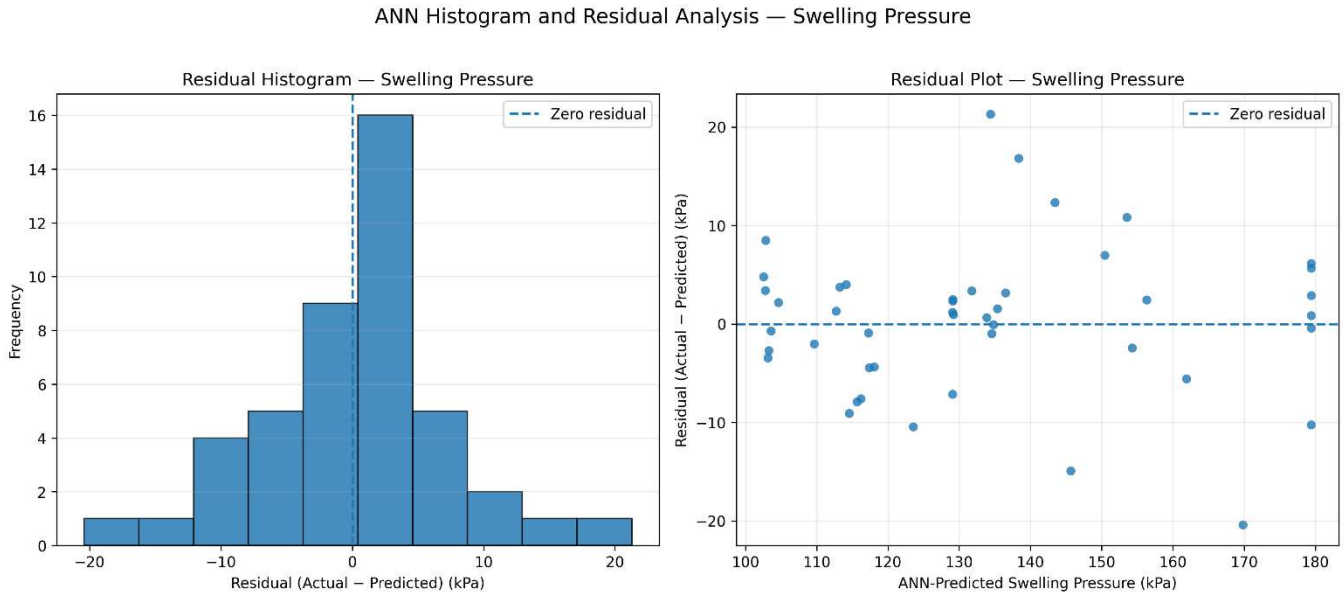


Figure 18: Histogram and residual scatter plot of ANN-based swelling pressure prediction of black cotton soil stabilized by SCBA.

The residual scatter plot also gives us additional information on how the errors are distributed within the range of the predicted swelling pressure of about 100-180 kPa. The observations are made on both sides of the zero-residual reference line, which means that not all observations are always over- or under-predicted by the ANN. However, some relatively large deviations can be observed, especially in the area where the predicted swelling pressures are around 135-150 kPa and the upper end of the plotted range. There are residuals that are above +15 kPa and there are those below -15 kPa. Such deviations indicate that the model is not able to reproduce some observations as accurately as most of the dataset. The residuals do not show an apparent continuous pattern over the whole range, but the observation distributions around specific values of the predicted value and the existence of isolated large errors are of interest.

In the critical modelling view, it is good that many residuals are concentrated around zero since it implies that the ANN makes fairly close estimates of a significant fraction of observations. But the bigger residuals prove the fact that the model does not work equally well in the entire swelling pressure range. These digressions may indicate uncertainty in the inherent soil characteristics, variation between SCBA replacement levels, constraints of the model structure

or data nature. Additional assessments based on the mean residual, mean absolute error (MAE), root mean squared error (RMSE), and a residual-versus-predicted trend analysis would aid in the measurement of systematic bias and prediction performance. The distribution of residuals might also be analyzed more rigorously using a normal probability plot.

Independence and representativeness of testing observations will also determine the reliability of this analysis. When the dataset includes synthetic observations based on a small set of underlying SCBA mix designs, random assignment of related observations to training and testing subsets can give overly optimistic estimates of predictive performance. In turn, independent experimental validation or mix-level data-splitting approach would be more convincing evidence of the ANN capacity to predict swelling pressure in previously not observed soil conditions.

In general, the residual plots suggest that the ANN model represents the overall swelling pressure response of SCBA-stabilized black cotton soil, where most errors of the predictions are concentrated around zero. Nonetheless, the relatively high positive and negative residuals indicate that more error analysis and independent validation are necessary before the model can be trusted in practical geotechnical applications.

The feature interpretation analysis was conducted to determine the relative importance of the input variables on the artificial neural network (ANN) prediction of swelling pressure in sugarcane bagasse ash (SCBA)-stabilized black cotton soil. The figure is a combination of three complementary visualizations: permutation-based feature importance, a SHAP-style beeswarm plot that displays approximate feature contributions, and a contribution heatmap of individual testing samples. The permutation importance plot compares the input variables in order of the amount of mean squared error (MSE) increase upon permutation of each feature, thus reflecting its relative importance to predictive power. The beeswarm plot shows how approximate contributions are distributed and their direction among observations, and the heatmap shows how these contributions vary among individual samples. These visualizations combined give an understanding of which geotechnical properties have the strongest impact on the swelling pressure predictions of the model and what their contributions across the dataset look like.

According to the permutation-based feature importance plot, specific gravity and free swell index (FSI) were found to be the two most significant input variables in the ANN model. Specific gravity is most significant, and FSI comes next meaning that any form of perturbation in either of the two variables would result in a significant rise in prediction error. The importance of SCBA content and plasticity index also has a relatively high level, which means that the model uses these parameters quite extensively in the estimation of swelling pressure.

The effect of liquid limit is moderate, and flow index and plastic limit are weaker. The significance of maximum dry density (MDD) is relatively low, and optimum moisture content (OMC) has the least contribution based on this ranking. This ranking indicates that the ANN predictions are especially sensitive to the variables that relate to the physical nature of the soil and swelling behaviour. But permutation importance is a measure of predictive dependence, but not causation; hence the ranking gives no inference that the change in a specific parameter will solely cause a given change in swelling pressure. Figure 19 represents the ANN-based swelling pressure prediction: (a) permutation-based global feature importance, (b) approximate SHAP-style beeswarm plot of feature contributions, and (c) heatmap of approximate feature contributions.

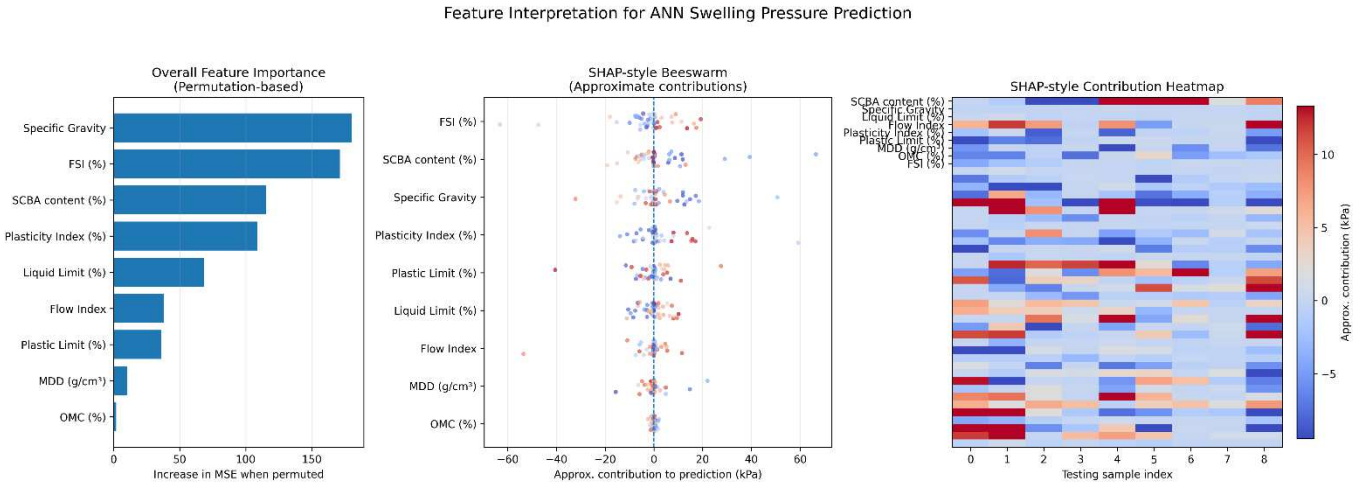


Figure 19: ANN-based swelling pressure prediction: (a) permutation-based global feature importance, (b) approximate SHAP-style beeswarm plot of feature contributions, and (c) heatmap of approximate feature contributions.

The approximate beeswarm plot gives more information on the spread of feature contributions. The contributions in FSI and SCBA are relatively widely spread, meaning that their approximate impact across individual observations is different. Specific gravity and plasticity index show a certain variation as well, indicating that their roles are conditioned by the properties of sampled. Conversely, the values of the contributions related to MDD and OMC seem to be more focused around zero, which is in line with their lower permutation importance in the left-hand plot. The positive and negative terms can be observed on a number of variables, which implies that a feature can raise the predicted swelling pressure of some observations but reduce it of other observations in comparison to the reference prediction of the model. This variation could be an indication of nonlinear relationships and interactions between soil properties. However the direction taken by these contributions should not be taken as a

generalized physical relationship without analyzing the underlying data and the exact procedure to compute the approximate contributions.

The contribution heatmap also shows the variation of the estimated impact of input variables on the testing samples. The positive and negative colour regions are contrasting and that means that the same feature may make different contributions to predictions of different observations. This trend is in line with a nonlinear ANN model whereby the response calculated is predicated on combinations of input parameters, and not on isolated variables per se. Certain samples have more dominant contributions of specific features and others have comparatively small or negative contributions. The heatmap thus serves as a complement to the global permutation ranking to show that feature overall importance does not always reflect a consistent contribution in all samples. Nevertheless, due to the fact that the heatmap is a representation of the approximate contributions, the colour intensities cannot be considered as definite SHAP values, unless they were determined through a formal SHAP procedure.

The three plots give complementary information and not substitutes in a critical modelling point of view. Permutation importance tells us the extent to which the predictive performance is sensitive to each feature, but the beeswarm and heatmap should be used to show the direction and variability of estimated contributions. The predictive information of correlated variables, including liquid limit, plasticity index, plastic limit, and FSI, can be influenced by correlations in the dataset; therefore, the score of their individual importance may be influenced by the correlations. The insignificance of MDD and OMC must be understood in the framework of the existing model and data set, but not as an indication that these characteristics, in general, are not significant in soil stabilization. Likewise, the significance of specific gravity is not sufficient in itself to set up a direct causal mechanism governing swelling pressure.

Another factor is the constellation of the data set. Providing that the ANN is built based on synthetic observations that are created with a small number of original SCBA mix designs, the ranking of features might be mostly an expression of the relationships inherent in those observations and not the entire range of variability of experimentally tested soils. To improve the reliability of the interpretation, it would be effective to compute the formal SHAP values, analyze feature dependence plots, measure the dependence between the inputs, and confirm the ranking of importance with independent experimental data.

On the whole, the outcomes of the feature interpretation suggest that the most important variables in the present ANN model to predict swelling pressure are specific gravity, FSI, SCBA content, and plasticity index. The beeswarm and heatmap indicate that the contribution of features to observations is not constant, which indicates the possibility of nonlinear

relationships contributing to the model. These results can be useful in prioritizing variables to be studied further in experiments, but should be viewed as a model-based relationship and not necessarily as a causal relationship.

The Pearson correlation matrix was created to test the strength of direction of linear relationship between the input parameters and output variables in the sugarcane bagasse ash (SCBA)-stabilized black cotton soil data. The matrix contains SCBA content, specific gravity, liquid limit, flow index, plasticity index, plastic limit, maximum dry density (MDD), optimum moisture content (OMC), free swell index (FSI), swelling pressure and soaked and unsoaked California Bearing Ratio (CBR). The correlation coefficients are in the range of -1 to +1, where positive correlations suggest direct relationships and negative correlations suggest inverse relationships. The heatmap gives a general representation of how the soil properties relate to each other and assists in determining parameters linked to a variation in swelling pressure and CBR, which aids in the selection and interpretation of input variables to use in artificial neural network (ANN) modelling. Figure 20 represents the person correlation matrix.

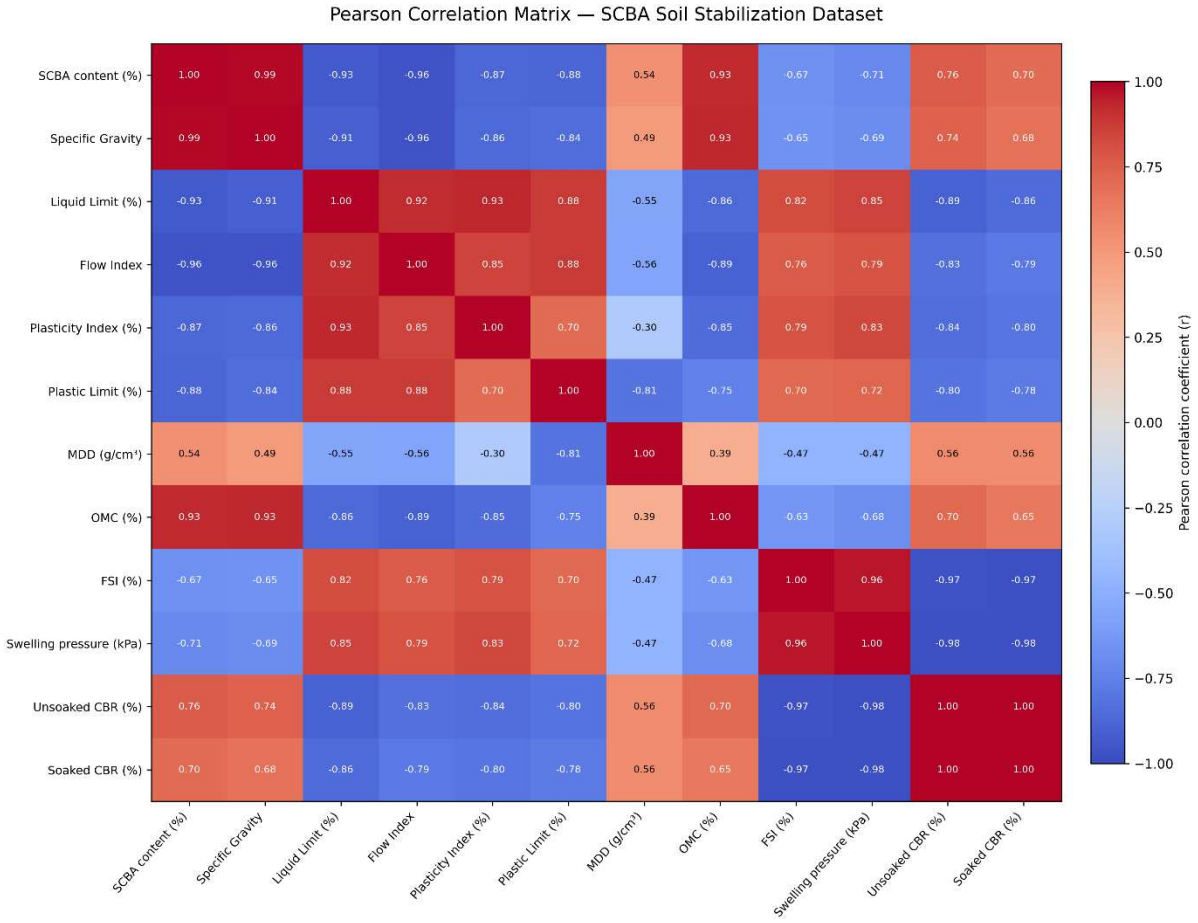


Figure 20: Pearson correlation matrix.

The correlation matrix reveals that there is a very strong positive correlation between SCBA content and specific gravity (r=0.99), meaning that these two variables increase with one another throughout the dataset. SCBA content also exhibits strong negative correlations with liquid limit r=-0.93, flow index r=-0.96, plasticity index r=-0.87, and plastic limit r=-0.88. These findings demonstrate that the greater the SCBA replacement levels, the lower the values of various parameters reflecting consistency within the depicted data. Nevertheless, the content of SCBA has positive relationships with MDD (r=0.54) and OMC (r=0.93), indicating that the interactions with compaction characteristics are stronger and different in direction.

Parameters that are related to swelling demonstrate especially significant correlations. The positive association between FSI and swelling pressure is very strong (r=0.96), with high FSI values corresponding to high swelling pressure in this data set. Swelling pressure is negatively correlated with unsoaked CBRr= -0.98 and soaked CBRr= -0.98. On the same note, FSI has a strong negative correlation with both unsoaked and soaked CBR r=-0.97 in each case). These correlations indicate that the higher the swelling tendency of an observation, the lower the CBR value is likely to be. Geotechnically, this trend correlates with the significance of expansive behaviour in assessing the load-bearing behaviour of black cotton soil. However, correlation does not provide a causal relationship between swelling pressure and CBR.

The correlation between various consistency parameters also indicates strong intercorrelations as seen in the matrix. Liquid limit shows a positive correlation with plasticity index r=0.93 and flow index r=0.92 and flow index and plastic limit show a correlation of r=0.88. These relationships imply that there might be an overlap of information on some of the input variables. The interpretation of individual feature importance can be complicated in ANN modelling since correlated inputs can be represented by multiple related parameters to capture similar aspects of soil behaviour. Hence, engineering relevance, data quality, and model validation are to be used to select inputs instead of using the size of separate correlation coefficients.

One critical weakness is that soaked and unsoaked CBR have an exceptionally high correlation (r = 1.00), rounded in the matrix. This value indicates that the two outputs in the dataset used are nearly perfectly linearly related. Soaked and unsoaked CBR are related engineering properties, but such a good correlation should be checked against original observations. Also, when the matrix was computed on synthetic observations created with a small number of base mixes, the strong correlations could partially be due to the manner in which the synthetic data were created rather than due to independent experimental variation. The same can be said of the strong associations between SCBA content, specific gravity, and swelling-related

parameters. The original experimental data should then be used to check the correlations, and the number of independent observations should be reported clearly.

On the whole, the Pearson correlation matrix reveals that FSI, swelling pressure, and both CBR outputs are strongly interrelated variables, but it also demonstrates significant correlations between a number of soil consistency parameters. The results offer practical initial advice concerning the ANN input selection and interpretation. The results, however, are to be regarded as associations in the analysed data, rather than as evidence of causation, and their strength is to be confirmed by means of independent experiments.

4. Discussion

The current research examined the effect of sugarcane bagasse ash (SCBA) on geotechnical properties of Black Cotton Soil (BCS) through the evaluation of six mixtures (0, 5, 10, 15, 20, and 25) of SCBA. The study took into account the limits of consistency, compaction, California Bearing Ratio (CBR), free swell index (FSI), swelling pressure, microstructural aspects, mineralogical composition, and artificial neural network (ANN) modelling. The pooled results suggest that addition of SCBA alters the engineering behaviour of Black Cotton Soil, but the magnitude and direction of changes vary according to the ash content and the parameter under consideration. Specifically, the findings indicate that the maximum SCBA content may not be the most effective one. Rather, the reaction tends to be non-linear, and it is desirable to establish an appropriate ash content depending on various geotechnical performance measures.

The consistency-limit results show that the liquid limit of untreated soil is 50.00% and then decreases to 31.44% at 20% SCBA and rises slightly to 33.56% at 25% SCBA. The flow index also reduces to about 41 as opposed to 67.97, and the plasticity index is reported to decrease as well to about 9 as compared to 16.67%. These changes imply that incorporation of SCBA affects the moisture-dependence consistency behaviour of the soil. The decrease in liquid limit can be related to the variation in the relative content of expansive clay and non-clay particles, particle-size distribution, and the interactions in the soil-ash mixture. However, the values of the plasticity indexes reported must be checked since not all of them are the same, as the difference between the respective liquid and plastic limits. This means the trends of consistency limits should be interpreted with caution until the initial calculations and laboratory records are verified.

The compaction properties indicate otherwise. The maximum dry density (MDD) of untreated soil is 1.610 g/cm^{3,} which is reduced to 1.540 g/cm^3 at 5% SCBA, and then it reaches 1.630 g/cm3 at 20 % of SCBA. It slightly decreases at 25% SCBA to 1.626 g/cm 3. In the meantime, optimum moisture content (OMC) becomes higher and higher (20.0-24.0). The rise in OMC

shows that the rise in moisture content is needed to reach the maximum dry density with the increase in ash addition. This behaviour can be related to the variations in the characteristics of particles, water needs, and the packing of the soil-ash mixture. The highest MDD at 20% SCBA shows that M4 is the most suitable mixture in terms of this parameter, but the difference between MDDs at 15, 20 and 25 % SCBA is small, and therefore additional testing needs to be done to establish whether it is significant or not.

The CBR outcomes indicate that there is an evident improvement in bearing response up to 15 per cent SCBA, then a decrease at increased contents. Unsoaked CBR of untreated soil is 2.10%, and at 15% SCBA the CBR is 3.90%. Soaked CBR in untreated soil is 1.40 % and at 15 % SCBA is 2.65 %. These are equivalent to enhancements of about 85.7 and 89.3, respectively, compared to the untreated soil. Unsoaked CBR values and soaked CBR values become 3.70% and 2.50% at 20 and 25 % SCBA respectively, and the values further reduce to 3.20% and 2.05% at 25 % SCBA. The maximum reported value of the soaked-to-unsoaked CBR retention is 67.9% at 15% SCBA. These findings suggest that M3 has the best penetration resistance of the mixtures tested. However, the fact that the CBR decreases in the soaked conditions in all mixtures supports the fact that moisture is still a significant factor that influences the load-bearing behaviour of the stabilized soil. The suitability of the material to be used in pavement subgrade must thus be evaluated against the pertinent design requirements and field conditions.

The swelling properties give further details regarding the SCBA-addition effectiveness. FSI and swelling-pressure data show that FSI at 80% untreated soil is 54 at 15% SCBA, and swelling pressure is 180-105 kPa. These represent a reduction of about 32.5% and 41.7%, respectively. At over 15% SCBA, FSI rises to 58% at 20% SCBA and 65% at 25% SCBA, with the relevant swelling pressures of 115 and 135 kPa, respectively. According to these data, M3 is the most desirable swelling response. But there is also a separate swelling-pressure dataset that was measured at 7, 14, and 28 days, where the pressure of the mixtures increases with the time of curing and is greater in all of the SCBA-treated mixtures compared to untreated soil. As an example, the 28-day value reported is 120 kPa of M0 and 205 kPa of M3. These findings are contrary to the initial dataset and cannot be accepted as depicting the same experimental conditions without further elucidation. Before conclusive results regarding the effect of SCBA on swelling pressure could be reached, the original test records, sample conditioning, curing procedure, and methods of measurement have to be validated.

The microstructural and mineralogical observations also give additional insight into the alterations in geotechnical performance. Fine, angular ash particles, layered soil aggregates,

visible pores, and gel-like morphology regions are identified in the SEM descriptions. These characteristics can be signs of alterations in particle packing and interparticle interactions. The EDS analysis reveals silicon, oxygen, aluminium, calcium and other components in the analysed material, whereas the XRD discussion reveals crystalline phases of quartz, montmorillonite, kaolinite, calcite, illite, feldspar and hematite. The preservation of clay-mineral phases is pertinent since the swelling behaviour of Black Cotton Soil is closely related to its clay mineralogy and interplay with water. Nevertheless, SEM morphology and EDS elemental signals are not sufficient to ascertain the presence of particular cementitious compounds, and the presence of crystalline phases in an XRD pattern does not determine the degree of mineral transformation. The proposed stabilization mechanisms would require direct comparison with untreated soil, quantitative phase analysis, and complementary chemical characterization to support the proposed stabilization mechanisms. Moreover, since the document identifies some of the SEM figures and XRD figures as simulated, these figures should be marked as such and not represented as real lab values.

The findings of the ANN modelling indicate that machine-learning techniques could be used as an additional tool for predicting the geotechnical behaviour of soil with SCBA stabilization. The report indicates high correlations between experimental and estimated values of CBR and a five-fold cross-validation coefficient of determination of about 0.956 for predicting swelling pressure. These findings imply that the models can be used to estimate the patterns that are reflected in the given data. However, these predictions are subject to the quality, size and independence of the observations. In cases where multiple data points are based on the same six underlying mix designs, random assignment to training, validation and testing subsets can lead to data leakage and over-optimistic estimates of predictive performance. Part of the reported ANN loss curves are also clearly stated as illustrative, not confirmed results of the real model training. It is therefore correct to consider the ANN results as tentative until the training history, data preprocessing, evaluation measures and independent validation process are recorded and confirmed.

Generally, the results show that SCBA can alter the geotechnical behaviour of Black Cotton Soil with the level and direction of the response also depending on the property tested. In the six mixtures tested, 15 % SCBA (M3) offers the highest reported soaked and unsoaked CBR values and the lowest FSI and swelling pressure in the first swelling data set, and 20 % SCBA (M4) offers the highest reported MDD. This difference proves that the optimum mixture is a variable that is based on the desired engineering goal and cannot be chosen with one parameter. The opposing swelling-pressure data sets and consistency-limit calculations need to be sorted

out before suggesting 15% SCBA as the overall optimum stabilization content, and the microstructural and ANN evidence should be substantiated by confirmed results. The conclusions could be reinforced by replicate experimentation, statistical analysis, and comparison with the pertinent geotechnical design criteria to validate the practical applicability of SCBA in enhancing Black Cotton Soil.

5. Conclusions

The current research examined how sugarcane bagasse ash (SCBA) addition has affected the geotechnical properties of Black Cotton Soil (BCS), in terms of consistency limit, compaction, California Bearing Ratio (CBR), and swelling tests, complemented by microstructural characterisation and artificial neural network (ANN) modelling. According to the results given, the following inferences are made:

1. Consistency properties: Addition of SCBA changed the consistency behaviour of Black Cotton Soil. The liquid limit of untreated soil was 50.00%, whereas the liquid limit of the soil with 20% SCBA was 31.44% and 33.56% with 25% SCBA, respectively. The flow index was also reduced to about 41 as opposed to 67.97. These variations suggest lower liquid-state moisture demands and different consistency behaviour at higher SCBA contents. The values of plasticity index reported, however, have to be checked against the liquid and plastic limits before publication.

2. Compaction behaviour: The highest dry density (MDD) was recorded at 5% SCBA as 1.610 g/cm 3, then at 20% as 1.630 g/cm 3. MDD dropped a bit to 1.626 g/cm3 at 25% SCBA. Conversely, the optimum moisture content (OMC) rose gradually to 24.0%. Therefore, the maximum reported MDD was obtained with 20% SCBA, and the more the SCBA, the greater the moisture demand during compaction.

3. Bearing capacity: CBR results found 15% SCBA (M3) to be the most desirable mixture when compared to the other six proportions studied. The unsoaked CBR rose by 2.10 % to 3.90 %, which is an improvement of about 85.7%, and the soaked CBR rose by 1.40 % to 2.65 %, which is an improvement of about 89.3 % in comparison to untreated soil. Both values began to decrease at SCBA contents beyond 15 %, which means that additional ash added could not further enhance penetration resistance under the mentioned test conditions.

4. Free swell index: The FSI of untreated soil was 80%, and the FSI of soil at 15% SCBA was 54% as compared to 80%. FSI rose to 58% at 20% SCBA and 65% at 25% SCBA at higher contents. These findings suggest that 15% SCBA yielded the smallest reported FSI and the tendency to swell did not decrease proportionally to the increase in ash content.

5. Swelling pressure: The earliest reported swelling-pressure dataset was that untreated soil, which had a swelling pressure of 180 kPa, decreased to 105 kPa at 15% SCBA, or a decrease of about 41.7%. But another dataset gave higher swelling pressure of all SCBA-treated mixtures than of untreated soil, with 205 kPa swelling pressure of M3 after 28 days, and 120 kPa swelling pressure of M0. Since the findings are conflicting, the ideal SCBA content of swelling-pressure control could not be determined with certainty until the initial measurements and testing conditions are confirmed.

6. Microstructural and mineralogical features: The SEM descriptions of the EDS display heterogeneous soil-ash structure with ash particles, soil aggregates, pores and various elemental constituents, whereas the XRD discourse shows that the sample consists of quartz and various clay and related mineral phases. These observations provide grounds to study the shifts in the arrangement of particles and mineralogical composition. However, the descriptions available do not solely validate the development of particular cementitious reaction products or measure mineral changes. The numbers that are labelled as simulated should either be substituted by tested experimental results or be clearly stated as an illustration.

7. ANN modelling: The reported ANN analyses suggest a potential for modelling the relationships between SCBA content, soil characteristics and geotechnical responses. Predictive reliability, however, must be validated by known training histories, stable error measures, independent experimental observations, and data partitioning to guard against leakages among related observations. In turn, the presented predictive performance cannot be regarded as the key indicator of the generalisation to soil mixtures that have not been tested previously.

8. General recommendation: 15% SCBA (M3) represents the most promising mixture of the tested proportions, and 20% SCBA (M4) is the best reported MDD, considering the reported CBR and first FSI dataset. The results have shown that the optimal SCBA content varies with the engineering property to be targeted. The discrepancy of the swelling-pressure measurements and the lack of consistency in the published plasticity data should be addressed, and then a holistic optimum should be prescribed.

Finally, SCBA addition illustrates the capability of altering the consistency, compaction and bearing properties of Black Cotton Soil. The reported CBR response is most favourable at 15% SCBA, and then more replicated testing, confirmation of swelling-pressure measurements and comparisons with the relevant pavement subgrade requirements have to be done, and then practical recommendations can be made. The reproducibility of the improvements observed

should also be determined in future studies, and any ANN-based prediction should be validated by independent experimental data.

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