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Empirical Modeling and Correlation Analysis of Soil Properties for Alkali-Activated Blended Soils

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Abstract

This research paper presents a comprehensive investigation of the development of mathematical models and correlation analysis to establish empirical relationships between the Unconfined Compressive Strength (UCS) and California Bearing Ratio (CBR) of alkali-activated blended soils with various engineering properties. The study focuses on alkali-activated Rice Husk Ash (RHA) blended with Fly Ash (FA), Metakaolin (MK), and Sugar Cane Bagasse Ash (SCBA). A meticulous review of existing literature guided the determination of mix proportions, wherein soil samples were admixed with RHA-FA, RHA-MK, and RHA-SCBA at different proportions ranging from 0% to 30%. The binder combination employed a fixed ratio of RHA to FA/MK/SCBA at 1:3, with 25% RHA and 75% FA/MK/SCBA, while the alkali activator ratio (Na_2SiO_3: NaOH) was fixed at 2.5. The development of mathematical models was facilitated by linear regression and multiple regression analyses, with dedicated computer programs created using Python programming language. The efficacy of the proposed models was examined by comparing measured and predicted values of UCS and CBR for various blended soil specimens encompassing different curing durations. To validate the findings, a series of laboratory tests, including compaction, UCS, CBR, free swell index, and Atterberg's limits, were conducted on both natural black cotton soil and admixed soil specimens, complying with the relevant IS Code.

Keywords- Cost analysis, California Bearing Ratio (CBR), Expansive soil, Geopolymers, Soil stabilization

INTRODUCTION

Expansive soils are naturally occurring soils that exhibit significant volume changes upon wetting and drying [1], [2]. These soils, commonly composed of clay minerals with high plasticity, can cause substantial problems [3] in road construction and other geotechnical applications. The expansive nature of these soils leads to detrimental effects such as swelling, shrinkage, and differential settlements [4], which can compromise the stability and performance of infrastructure.

Road construction is particularly [5] susceptible to issues caused by expansive soils. When expansive soils come into contact with moisture [3], they can undergo substantial swelling, exerting significant pressure on overlying structures and causing cracks and deformation. Conversely, during dry periods, these soils shrink [6], leading to settlement and the development of voids beneath the road surface. Such movements and deformations pose serious challenges to road infrastructure's durability, functionality, and safety.

There has been a growing interest in

utilizing waste materials as potential stabilizers for expansive soils to address these challenges. Waste materials, such as Rice Husk Ash (RHA), Fly Ash (FA), Metakaolin (MK), and Sugar Cane Bagasse Ash (SCBA), are abundantly available [7]-[10] as by-products from various industries. However, the disposal of these waste materials poses environmental concerns and can lead to land and water pollution [11]. Therefore, finding beneficial uses for these waste materials in geotechnical applications, such as road construction, offers a sustainable solution while mitigating the environmental impact.

Geopolymer technology has emerged as a promising approach to utilize waste materials as stabilizers for expansive soils [12]. Geopolymers are formed by the alkali activation [13] of waste materials, which triggers a chemical reaction to create a solid binder. This binder can effectively stabilize the expansive soils and improve their engineering properties. The geopolymerization process offers numerous advantages, including reduced environmental impact, enhanced durability, and improved mechanical properties [14].

To optimize the use of geopolymers in expansive soil stabilization, the development of mathematical models becomes crucial. These models allow for establishing empirical relationships between the geopolymers properties, soil characteristics, and engineering performance. The mathematical models can capture the complex interactions and dependencies between various parameters by utilizing regression analysis, such as linear regression and multiple regressions. This enables the prediction and optimization of the geotechnical behavior of alkali-activated blended soils, aiding in the design and implementation of sustainable geotechnical engineering practices.

Therefore, this research explores the potential of utilizing waste materials through geopolymers technology to stabilize expansive soils in road construction. The investigation includes developing mathematical models using regression analysis to establish empirical relationships between geopolymers properties, soil behavior, and engineering performance. This research seeks to optimize alkali-activated blended soils and contribute to sustainable geotechnical engineering practices by understanding these relationships.

MATERIALS AND METHODOLOGY

Black Cotton Soil

The Black Cotton Soil sample was collected using the disturbed sampling method, whereby the topsoil was removed down to a depth of 1 meter from a pit located in the Kakaddati village region near the Babasaheb Naik College of Engineering, Pusad, in the Yavatmal district of Maharashtra State, India. The physical properties of natural black cotton soil are shown in Table 1.

Table 1: *Physical properties of natural soil.*

Property	Value
Specific Gravity	2.68
Liquid Limit (%)	68.29
Plastic Limit (%)	25.43
Shrinkage Limit (%)	21.70
Plasticity Index (PI)	42.86
Unified Soil Classification	CH
AASHTO Soil Classification	A-7-6
Indian Standard Classification (ISC) System	CH (Inorganic Clay of High Plasticity)

Rice Husk Ash (RHA)

The processed RHA was obtained from Manikji Metachem Pvt. Ltd., located in Murtijapur - 444107, Maharashtra, India. The RHA was fine-grained, siliceous in nature, light in weight, and had a grey color. The physical properties of RHA are presented in Table 2, while Table 3 provides information on its chemical properties.

Table 2: *Physical properties of rice husk ash.*

Property	Value
Color	Grayish-Black
Odor	Odorless
Specific Gravity	2.02
Liquid Limit (%)	76
Plastic Limit (%)	Non-Plastic
Optimum Moisture Content (%)	47
Maximum Dry Density (g/cm^3)	1.65

Table 3: *Chemical properties of rice husk ash.*

Constituent	Value (%)
SiO_2	91.00
Al_2O_3	0.1
Fe_2O_3	0.1
CaO	0.4
MgO	0.9
SO_3	0.5
K_2O	3.3
Loss on Ignition	2.0

Fly Ash (FA)

The study employed "Pozzocrete 100," a highly efficient and fully processed pozzolanic material obtained from the Dirk Pozzocrete plant in Nashik, Maharashtra, India (Table 4).

Table 4: *Typical primary oxide composition and various properties of fly ash.*

Property	Value
SiO_2	57.2
Al_2O_3	31.1
Fe_2O_3	3.3
CaO	2.3
Loss on Ignition	< 2.5%
Color	Greyish white
Bulk Weight	0.65 tons/m^3
Specific density	2.3 metric tons per cubic meter
Particle Size	
Retention on 45µSieve	0%
Retention on 25µSieve	<0.25%
Particle Shape	Spherical

(Source: Manufacturer)

Metakaolin (MK)

For the present investigation, metakaolin marketed as "Metacem 85-C" (a trading name for calcined China clay) was obtained from 20 Microns Limited, Mumbai. The physical and chemical properties of metakaolin Metacem 85-C are shown in Table 5 and 6, respectively.

Table 5: *Physical properties of metakaolin.*

Property	Value
Average Particle Size, µm	1.5
Residue 325 Mesh (% max)	0.5
B. E.T. Surface Area m^2 /gm	15
Pozzolanic Reactivity in mg $Ca(OH)_2$ /gm	1050
Specific Gravity	2.5
Bulk Density (gm/ltr)	300 ± 30
Brightness	80 ± 2
Physical Form	Off-white powder

Table 6: *Physical properties of metakaolin.*

Property	Value (%)
$SiO_2+Al_2O_3+Fe_2O_3$	96.88
CaO	0.39
MgO	0.08
TiO_2	1.35
Na_2O	0.56
K_2O	0.06
Li_2O	Nil
Loss on Ignition	0.68

Sugarcane Bagasse Ash (SCBA)

The SCBA used in this work was obtained from a Sugar Factory in the nearby area. Approximately 50% of cellulose, 25% of lignin and 25% of hemicellulose in a typical sample of SCBA [15]. The properties of SCBA are illustrated in Table 7 and 8.

Table 7: *Physical properties of SCBA.*

Property	Value
Color	Black
Specific Gravity	2.18
Bulk Density (gm/cm^3)	1.85
Particle Shape	Spherical
Physical Form	Blackish Powder

Table 8: *Chemical composition of SCBA [15].*

Property	Value (%)
SiO_2	62.43
Al_2O_3	04.28
Fe_2O_3	06.98
CaO	11.80
K_2O	03.53
MgO	02.51
SO_3	01.48
Loss on Ignition	04.73

Alkali Activators

In this study, an alkaline activator was prepared using a mixture of sodium silicate solution and sodium hydroxide solution. Many researchers have suggested that the alkaline liquid used in the study should be prepared by agitating both solutions for at least 24 hours before application. The typical sodium silicate solution used for alkaline activation has a SiO_2-to-Na_2O mass ratio of about 2, with

SiO_2 making up 29.4% of the solution, Na_2O making up 14.7%, and water making up 55.9%. The sodium hydroxide used in this study was in flaky form and had a purity of 98.1%. After reviewing previous research studies, the concentration of sodium hydroxide solution was established as 12 molar. Additionally, the ratio of sodium silicate to sodium hydroxide was determined to be 2.5, and the ratio of the alkali activator solution (composed of Na_2SiO_3 and NaOH) to the binders (RHA+FA/ MK/SCBA) was set at 0.45.

- The sodium hydroxide was procured from MIDC Nagpur in flake form with 98.1% purity and was one of the ingredients to prepare an alkaline solution.
- Liquid sodium silicate used in this investigation was procured from the Khamgaon MIDC area, Maharashtra, India.

Mix Proportioning and Nomenclature

The soil samples were mixed with alkali-activated RHA-FA/MK/SCBA at different percentages (0%, 5%, 10%, 15%, 20%, 25%, and 30%) based on the dry unit weight of the soil. The mix design was based on a review of various literature sources, and the ratio of the alkali activator (a combination of Na_2SiO_3 and NaOH) to the binders (a combination of RHA and FA/MK/SCBA) was fixed at 0.45. The binder combination was made using RHA and FA/MK/SCBA with a ratio of RHA: FA/MK/SCBA = 1:3, where 25% of RHA was mixed with 75% of FA/MK/SCBA. The ratio of activator ingredients (a mixture of Na_2SiO_3 and NaOH) was fixed at Na_2SiO_3: NaOH = 2.5. The samples were labeled according to Table 9 for identification and representation of results.

Table 9: *Proportioning and nomenclature of soil-alkali activated RHA- FA/MK/SCBA admixtures for various replacement levels.*

S. No.	Soil (%)	Quantity of Stabilizers (Activator: Binder = 0.45)					Nomenclature
		Binder (RHA: FA/MK/SCBA = 1: 3)		Activator (Na_2SiO_3 : NaOH = 2.5)		Total Quantity (%)	
		RHA (%)	FA/MK/ SCBA (%)	NaOH (%)	Na_2SiO_3 (%)		
01	100	0	0	0	0	0	S100R FA/MK/SB 0
02	95	0.86	2.59	0.44	1.11	05	S95R FA/MK/SB 05
03	90	1.72	5.18	0.88	2.22	10	S90R FA/MK/SB 10
04	85	2.58	7.77	1.32	3.33	15	S85R FA/MK/SB 15
05	80	3.44	10.36	1.76	4.44	20	S80R FA/MK/SB 20
06	75	4.30	12.95	2.20	5.55	25	S75R FA/MK/SB 25
07	70	5.16	15.54	2.64	6.66	30	S70R FA/MK/SB 30

RESULTS AND DISCUSSION

The following section presents the findings and analysis from the experimental investigation to evaluate the geotechnical performance of alkali-activated blended soils in stabilizing expansive soils for road construction. The study examined the effects of different binder combinations, activator ratios, and curing durations on the engineering properties of the stabilized soil specimens. The relationships between the Unconfined Compressive Strength (UCS), California Bearing Ratio (CBR), and other key geotechnical parameters were established through comprehensive data analysis and correlation assessments.

Sample Python Programs for Regression

Python programs were developed to conduct regression analysis between Unconfined Compressive Strength (UCS) and Liquid Limit (LL) in alkali-activated blended soils. These programs utilized statistical functionalities in Python, including libraries such as NumPy and Scikit-learn, to preprocess the data, build regression models, and evaluate their performance. The programs provided valuable insights into the empirical relationship between UCS and LL, enabling accurate predictions of UCS based on LL values. Visualizations such as scatter plots and regression lines were utilized to enhance the interpretation of the correlation between the variables. Overall, these Python programs served as essential tools for understanding the influence of other soil properties on UCS in alkali-activated blended soils.

Developed Python Program for Linear Regression Analysis between Unconfined Compressive Strength (UCS) and Liquid Limit (LL)

```
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

# Prompt user for input data
print("Enter UCS values of soil:")
UCS = [float(x) for x in input().split()]
print("Enter liquid limit values of soil:")
liquid_limit = [float(x) for x in input().split()]

# Create data frame from input data
data = {'UCS': UCS, 'liquid_limit': liquid_limit}
df = pd.DataFrame(data)

# Perform regression analysis
X = df[['UCS']]
y = df['liquid_limit']
reg = LinearRegression().fit(X, y)

# Generate correlation equation
coefficients = reg.coef_
intercept = reg.intercept_
equation = f'y = {coefficients[0]:.2f}x + {intercept:.2f}'

# Generate R-value, R-squared, standard error estimate, sum of squares, F-value, and t-value
r_value = reg.score(X, y)
r_squared = r_value**2
standard_error = mean_squared_error(y, reg.predict(X))**0.5
sum_of_squares = sum ((reg.predict(X) - y) ** 2)
f_value = (r_squared / (1 - r_squared)) * ((len(UCS) - 2) / 1)
t_value = r_value / (standard_error / (len(UCS)**0.5))

# Print results
print(f'Correlation equation: {equation}')
print(f'R-value: {r_value:.2f}')
print(f'R-squared: {r_squared:.2f}')
print(standard error estimate: {standard_error:.2f}')
print(sum of squares: {sum_of_squares:.2f}')
print(f'F-value: {f_value:.2f}')
print(f't-value: {t_value:.2f}')
```

```
Output:
Enter UCS values of soil:
107.01 132.48 152.87 183.44 203.82 219.11 254.78
Enter liquid limit values of soil:
68.29 61.51 58.02 53.73 52.59 47.95 43.59
Correlation equation: y = -0.16x + 83.62
R-value: 0.98
R-squared: 0.96
standard error estimate: 1.13
sum of squares: 8.93
F-value: 112.58
t-value: 2.29
```

Developed Python Program for Multiple Regression Analysis

```
from sklearn.linear_model import LinearRegression
import pandas as pd
# Input data
UCS = float(input("Enter UCS value: "))
LL = float(input("Enter Liquid Limit value: "))
```

```
PL = float(input("Enter Plastic Limit value: "))
PI = float(input("Enter Plasticity Index value: "))
SL = float(input("Enter Shrinkage Limit value: "))
MDD = float(input("Enter maximum dry density value: "))
OMC = float(input("Enter optimum moisture content value: "))
# Create data frame
data = {'UCS': [UCS], 'LL': [LL], 'PL': [PL], 'PI': [PI], 'SL': [SL], 'MDD': [MDD], 'OMC': [OMC]}
df = pd.DataFrame(data)
# Define independent and dependent variables
X = df[['UCS,' 'LL,' 'PL,' 'PI,' 'SL,' 'MDD,' 'OMC']]
y = df['UCS']
# Fit the model
reg = LinearRegression().fit(X, y)
# Coefficients
Coefficients = reg.coef_
 Intercept
intercept = reg.intercept_
# R-squared value
r2 = reg.score(X, y)
# Print results
print("Coefficients:", coefficients)
print("Intercept:", intercept)
print("R-squared:", r2)
```

Model Summary of UCS Values for Admixed Soil Specimens by Linear Regression Analysis

The summary of developed mathematical model for soil admixed with alkali-activated rice husk ash-fly ash/metakaolin/sugarcane bagasse ash (AARHA-FA/MK/SCBA) considering UCS as independent variable and Liquid Limit (LL), Plastic Limit (PL), Plasticity Index (PI), Shrinkage Limit (SL), Free Swell Index (FSI), Optimum Moisture Content (OMC) and Maximum Dry Density (MDD) as dependent variables is presented in this section (Table 10, 11 and 12).

Table 10: *Model summary of UCS values for soil-AARHA-FA admixed specimens with other soil properties.*

UCS	Model	Correlation Equation	R-Value	R^2	Standard Error Estimate
Without Curing	LL	- 0.1638 LL + 85.9415	0.98	0.96	1.13
	PL	0.0814 PL + 17.4308	0.97	0.94	0.69
	PI	- 0.2452 PI + 68.5106	0.97	0.94	2.15
	SL	0.0838 SL + 12.7706	0.99	0.98	0.38
	OMC	0.0753 OMC + 12.7067	0.94	0.88	0.91
	MD	-0.0018 MDD + 1.7672	0.98	0.97	0.01
03 Days Curing	LL	-0.1565 LL + 85.8895	0.95	0.90	1.85
	PL	0.0783 PL + 17.3612	0.98	0.95	0.61
	PI	-0.2348 PI + 68.5282	0.97	0.93	2.21
	SL	0.0799 SL + 12.8304	0.98	0.96	0.56
	OMC	0.0729 OMC + 12.5607	0.96	0.92	0.76
	MD	-0.0017 MDD + 1.7668	0.98	0.96	0.01
07 Days Curing	LL	-0.1493 LL + 86.0646	0.94	0.89	1.90
	PL	0.0750 PL + 17.2117	0.98	0.96	0.54
	PI	-0.2243 PI + 68.8529	0.97	0.93	2.22
	SL	0.0762 SL + 12.7571	0.98	0.95	0.63
	OMC	0.0701 OMC + 12.3628	0.97	0.94	0.63
	MD	-0.0016 MDD + 1.7686	0.98	0.95	0.01
28 Days Curing	LL	-0.1340 LL + 84.7990	0.94	0.89	1.90
	PL	0.0674 PL + 17.8351	0.98	0.97	0.51
	PI	-0.2013 PI + 66.9639	0.97	0.93	2.19
	SL	0.0683 SL + 13.4043	0.98	0.95	0.63
	OMC	0.0633 OMC + 12.8783	0.98	0.97	0.48
	MDD	-0.0015 MDD + 1.7551	0.98	0.96	0.01

Table 11: *Model summary of UCS values for soil-AARHA-MK admixed specimens with other soil properties.*

UCS	Model	Correlation Equation	R-Value	R^2	Standard Error Estimate
Without Curing	LL	-0.1676 LL + 86.6978	0.96	0.92	1.55
	PL	0.0865 PL + 15.6657	0.92	0.84	1.13
	PI	-0.2541 PI + 71.0321	0.95	0.90	2.63
	SL	0.0723 SL + 13.9893	0.97	0.94	0.56
	OMC	0.0859 OMC + 10.4298	0.98	0.96	0.57
	MD	-0.0018 MDD + 1.7750	0.98	0.97	0.01
03 Days Curing	LL	-0.1575 LL + 86.6902	0.97	0.94	1.30
	PL	0.0812 PL + 15.6884	0.93	0.86	1.06
	PI	-0.2387 PI + 71.0018	0.96	0.92	2.32
	SL	0.0678 SL + 14.0292	0.98	0.95	0.49
	OMC	0.0803 OMC + 10.5113	0.98	0.96	0.54
	MD	-0.0017 MDD + 1.7735	0.99	0.97	0.01
07 Days Curing	LL	-0.1427 LL + 86.6184	0.90	0.81	2.38
	PL	0.0725 PL + 15.9340	0.83	0.70	1.60
	PI	-0.2153 PI + 70.6844	0.88	0.77	3.96
	SL	0.0616 SL + 14.0272	0.91	0.83	0.96
	OMC	0.0742 OMC + 10.2661	0.94	0.89	0.90
	MD	-0.0015 MDD + 1.7749	0.93	0.86	0.02
28 Days Curing	LL	-0.1169 LL + 84.1909	0.75	0.57	3.72
	PL	0.0581 PL + 17.4587	0.67	0.45	2.27
	PI	-0.1750 PI + 66.7322	0.73	0.53	5.98
	SL	0.0506 SL + 15.0468	0.77	0.59	1.55
	OMC	0.0625 OMC + 11.1400	0.84	0.70	1.54
	MDD	-0.0013 MDD + 1.7531	0.80	0.64	0.04

Table 12: *Model summary of UCS values for soil-AARHA-SCBA admixed specimens with other soil properties.*

UCS	Model	Correlation Equation	R-Value	R^2	Standard Error Estimate
Without Curing	LL	-0.2049 LL + 87.6104	0.90	0.81	2.44
	PL	0.1134 PL + 13.0492	0.83	0.70	1.80
	PI	-0.3183 PI + 74.5612	0.89	0.80	3.92
	SL	0.1194 SL + 8.6522	0.91	0.83	1.31
	OMC	0.1101 OMC + 8.7961	0.93	0.87	1.04
	MD	-0.0023 MDD + 1.8289	0.89	0.79	0.03
03 Days Curing	LL	-0.1738 LL + 85.3291	0.96	0.92	1.53
	PL	0.0969 PL + 14.1824	0.90	0.82	1.37
	PI	-0.2707 PI + 71.1467	0.96	0.92	2.43
	SL	0.1001 SL + 10.1926	0.95	0.91	0.97
	OMC	0.0931 OMC + 10.0690	0.99	0.98	0.37
	MD	-0.0019 MDD + 1.8027	0.94	0.89	0.02
07 Days Curing	LL	-0.1780 LL + 88.0147	0.95	0.91	1.66
	PL	0.0952 PL + 13.4521	0.82	0.68	1.86
	PI	-0.2732 PI + 74.5627	0.92	0.85	3.31
	SL	0.0983 SL + 9.4302	0.87	0.76	1.61
	OMC	0.0955 OMC + 8.6120	0.99	0.97	0.47
	MD	-0.0019 MDD + 1.8192	0.87	0.76	0.03
28 Days Curing	LL	-0.1647 LL + 87.7112	0.94	0.89	1.82
	PL	0.0864 PL + 13.9383	0.79	0.62	2.05
	PI	-0.2511 PI + 73.7729	0.90	0.82	3.74
	SL	0.0889 SL + 9.9913	0.82	0.68	1.87
	OMC	0.0872 OMC + 9.0089	0.95	0.90	0.90
	MDD	-0.0017 MDD + 1.8080	0.82	0.68	0.04

Model Summary of CBR Values for Admixed Soil Specimens by Linear Regression Analysis

The summary of developed mathematical model for soil admixed with alkali-activated rice husk ash-fly ash/metakaolin/ sugarcane bagasse ash (AARHA-FA/MK/SCBA), considering CBR as independent variable and Liquid Limit (LL), Plastic Limit (PL), Plasticity Index (PI), Shrinkage Limit (SL), Free Swell Index (FSI), Optimum Moisture Content (OMC) and Maximum Dry Density (MDD) as dependent variables is presented in this section (Table 13).

Table 13: *Model summary of CBR values for soil-AARHA-FA/MK/SCBA admixed specimens with other soil properties.*

Type of Specimens	Model	Correlation Equation	R-Value	R^2	Standard Error Estimate
Soil-AARHA-FA	LL	-5.0547 LL + 82.7873	0.96	0.92	1.62
	PL	2.5005 PL+ 19.0554	0.97	0.94	0.72
	PI	-7.5551 PI + 63.7319	0.97	0.94	2.02
	SL	2.5199 SL + 14.7333	0.95	0.90	0.93
	OMC	2.3275 OMC + 14.1368	0.95	0.90	0.83
	MDD	-0.0539 MDD+ 1.7263	0.95	0.90	0.02
Soil-AARHA-MK	LL	-5.0507 LL + 82.2619	0.98	0.95	1.17
	PL	2.6458 PL + 17.7712	0.96	0.93	0.76
	PI	-7.6964 PI+ 64.4907	0.97	0.95	1.82
	SL	2.1730 SL + 15.9382	0.98	0.96	0.43
	OMC	2.4786 OMC + 13.2336	0.91	0.83	1.12
	MDD	-0.0532 MDD + 1.7212	0.96	0.91	0.02
Soil-AARHA-SCBA	LL	-5.2716 LL + 78.9322	0.95	0.90	1.76
	PL	3.0811 PL + 17.1174	0.98	0.96	0.63
	PI	-8.3527 PI + 61.8149	0.98	0.96	1.73
	SL	3.0847 SL+ 13.6541	0.97	0.94	0.76
	OMC	2.7233 OMC + 13.9526	0.91	0.83	1.22
	MDD	-0.0606 MDD+ 1.7384	0.98	0.97	0.01

Model Summary of CBR vs. UCS Values for Admixed Soil Specimens by Linear Regression Analysis

The summary of the developed mathematical model for soil admixed with alkali-activated rice husk ash - fly ash/metakaolin/sugarcane bagasse ash (AARHA-FA/MK/SCBA), considering CBR as the independent variable and UCS as the dependent variable are presented in this section (Table 14).

Table 14: *Model summary of CBR vs. UCS values for soil-AARHA-FA/MK/SCBA admixed specimens with other soil properties.*

Type of Specimens	Model	Correlation Equation	R-Value	R^2	Standard Error Estimate
Soil-AARHA-FA	CBR vs. UCS0	30.1854 UCS0 + 22.7558	0.96	0.93	9.19
	CBR vs. UCS3	31.6099 UCS3 + 23.3843	0.97	0.94	8.59
	CBR vs. UCS7	33.3404 UCS7 + 24.6142	0.99	0.97	6.27
	CBR vs. UCS28	37.1200 UCS28 + 18.1471	0.98	0.97	7.45
Soil-AARHA-MK	CBR vs. UCS0	29.0114 UCS0 + 31.8271	0.94	0.89	10.28
	CBR vs. UCS3	31.5089 UCS3 + 30.7918	0.97	0.94	7.98
	CBR vs. UCS7	32.7618 UCS7 + 43.0400	0.93	0.87	13.06
	CBR vs. UCS28	34.2005 UCS28 + 59.4658	0.81	0.66	23.98
Soil-AARHA-SCBA	CBR vs. UCS0	22.7998 UCS0 + 55.6025	0.83	0.68	14.82
	CBR vs. UCS3	29.3558 UCS3 + 41.2469	0.92	0.85	11.97
	CBR vs. UCS7	27.9289 UCS7 + 58.6171	0.88	0.78	14.37
	CBR vs. UCS28	29.5316 UCS28 + 64.4751	0.85	0.73	17.32

Prediction of UCS and CBR Values by Multiple Regression Analysis

A total of 15 models were developed using multiple regression analysis to predict CBR value and the UCS for various curing periods using specific geotechnical parameters and established regression analysis correlations for all parameters found in laboratory experimental test data for soil admixed with alkali-activated rice husk ash-fly ash/metakaolin/sugarcane bagasse ash (AARHA-FA/MK/SCBA) as shown in the corresponding tables of this section (Table 15).

Table 15: *Developed correlations by multiple regression analysis for soil-AARHA-FA/MK/SCBA admixed specimens.*

Type of Specimens	Model	R^2
Soil-AARHA-FA	UCS0=−2158.8009−0.9661·LL+3.4905·PL+27.3983·SL+1.2412·OMC+1027.6406·MDD	0.9962
	UCS3=−2348.903−0.6598·LL+5.0473·PL+24.745·SL+5.2837·OMC+1095.9025·MDD	0.9885
	UCS7 = − 4419.759 − 0.9161 · LL + 6.1836 · PL + 38.9415 · SL + 12.5116 · OMC + 2115.4824 · MDD	0.9967
	UCS28 = − 4526.4576 − 0.9533 · LL + 5.1589 · PL + 38.946 · SL + 16.1301 · OMC + 2156.8141 · MDD	01
	CBR = − 199.3422 − 0.132 · LL + 0.1891 · PL + 1.627 · SL + 0.5291 · OMC + 101.5004 · MDD	0.9994
Soil-AARHA-MK	UCS0 = 166.2834 + 10.4114 · LL + 4.3932 · PL + 12.1182 · SL + 1.6164 · OMC − 745.8732 · MDD	0.9989
	UCS3 = 804.5516 − 4.6069 · LL − 13.7294 · PL + 17.6324 · SL − 2.4735 · OMC − 231.7315 · MDD	0.999
	UCS7 = 1884.2644 − 27.5862 · LL − 51.5659 · PL + 36.4471· SL − 8.9778 · OMC + 513.2798 · MDD	0.9837
	UCS28 = 3697.3377 − 52.3007 · LL − 98.5122 · PL + 61.1424 · SL −20.0891 · OMC + 992.6883 · MDD	0.952
	CBR = 47.7977 − 0.4909 · LL − 0.8236 · PL + 0.858· SL − 0.4733 · OMC −0.1052 · MDD	0.9973
Soil-AARHA-SCBA	UCS0 = − 1481.972 + 0.7145 · LL − 11.1882 · PL + 30.0996 · SL +3.7969 · OMC + 695.3231 · MDD	0.999
	UCS3 = − 746.3374 + 0.8867 · LL − 0.2417 · PL + 8.6722 · SL + 9.0571 · OMC + 274.338 · MDD	0.9997
	UCS7 = −14.7633 − 1.8193 · LL + 4.2487 · PL − 7.7733 · SL + 11.8214 · OMC + 49.1972 · MDD	0.9986
	UCS28 = 127.7632 − 5.2029 · LL + 6.5004 · PL − 12.0647 · SL + 10.3549 · OMC + 147.5772 · MDD	0.992
	CBR = 41.7401 − 0.048 · LL + 0.2818· PL − 0.4955 · SL + 0.047 ·OMC− 21.0898 · MDD	0.9998

Measured and Predicated Values of Admixed Specimens

This section presents and analyzes the measured and predicted values of soil-admixed specimens. The admixed specimens included soil combined with alkali-activated binders derived from rice husk ash and fly ash (soil-AARHA-FA), rice husk ash and metakaolin (soil-AARHA-MK), and rice husk ash and sugar cane bagasse ash (soil-AARHA-SCBA). This analysis aims to evaluate the accuracy and reliability of the developed regression models in predicting the Unconfined Compressive Strength (UCS) and California Bearing Ratio (CBR) values for these admixed specimens.

Table 16 displays the measured and predicted values of UCS and CBR for the soil-AARHA-FA admixed specimens. The measured values were obtained through laboratory testing using standard protocols, while the predicted values were calculated using the regression models developed in previous sections. A comprehensive comparison and analysis of the measured and predicted values are provided, highlighting their degree of agreement.

Similarly, Table 17 presents the measured and predicted values of UCS and CBR for the soil-AARHA-MK admixed specimens. This table allows for a thorough assessment of the regression models' accuracy and performance in predicting this specific admixture's strength characteristics.

Furthermore, Table 18 displays the measured and predicted values of UCS and CBR for the soil-AARHA-SCBA admixed specimens. The measured values were obtained through laboratory testing, while the predicted values were derived from the regression models. A detailed examination of these values provides insights into the regression models' effectiveness in capturing the soil-AARHA-SCBA admixture's behavior.

The comparison between the measured and predicted values of UCS and CBR in these tables enables the assessment of the regression models' reliability and ability to capture the variations in strength characteristics due to different admixture compositions. Any discrepancies or deviations between the measured and predicted values will be critically analyzed and discussed, shedding light on the limitations and potential areas for improvement of the regression models.

Overall, analyzing the measured and predicted values of admixed specimens provides valuable insights into the performance and applicability of the developed regression models in predicting the strength characteristics of alkali-activated blended soils. These findings contribute to the understanding and optimizing the geotechnical performance of these sustainable soil admixtures in various engineering applications.

Table 16: *Measured and predicted values of soil-AARHA-FA admixed specimens.*

S. No.	**Soil Property**	**Stabilizer Content (%)**						
		0	**5**	**10**	**15**	**20**	**25**	**30**
01	UCS (without curing) Measured	107.01	132.48	152.87	183.44	203.82	219.11	254.78
	UCS (without curing) Predicted	106.41	135.05	150.21	182.17	203.67	224.80	251.17
02	UCS (03 Days Curing) Measured	107.01	137.58	168.15	193.63	214.01	224.2	264.97
	UCS (03 Days Curing) Predicted	105.92	142.24	163.34	191.33	213.75	234.51	258.44
03	UCS (07 Days Curing) Measured	107.01	152.87	178.34	203.82	224.2	239.49	275.16
	UCS (07 Days Curing) Predicted	106.40	155.50	175.64	202.53	224.06	245.30	271.48
04	UCS (28 Days Curing) Measured	107.01	163.06	188.54	219.11	239.49	264.97	290.45
	UCS (28 Days Curing) Predicted	107.06	162.84	188.77	219.22	239.51	264.48	290.77
05	CBR Measured	2.45	4.06	4.75	5.14	5.67	6.59	7.59
	CBR Predicted	2.26	3.89	4.50	4.90	5.42	6.41	7.28

Table 17: *Measured and predicted values of soil-AARHA-MK admixed specimens.*

S. No.	**Soil Property**	**Stabilizer Content (%)**						
		0	**5**	**10**	**15**	**20**	**25**	**30**
01	UCS (without curing) Measured	107.01	122.29	147.77	178.34	193.63	203.82	239.49
	UCS (without curing) Predicted	105.00	124.51	147.37	177.74	194.89	204.85	238.00
02	UCS (03 Days Curing) Measured	107.01	132.48	163.06	188.34	203.8	224.2	249.68
	UCS (03 Days Curing) Predicted	109.06	130.22	163.47	188.96	202.51	223.15	251.21
03	UCS (07 Days Curing) Measured	107.01	152.87	193.63	214.01	224.2	244.59	259.87
	UCS (07 Days Curing) Predicted	115.90	143.05	195.41	216.68	218.61	240.02	266.48
04	UCS (28 Days Curing) Measured	107.01	178.34	234.39	244.59	254.78	264.97	275.16
	UCS (28 Days Curing) Predicted	124.06	159.52	237.80	249.72	244.07	256.21	287.83
05	CBR Measured	2.45	3.53	4.29	4.68	5.06	6.36	7.05
	CBR Predicted	2.55	3.41	4.31	4.71	4.99	6.30	7.13

Table 18: *Measured and predicted values of soil-AARHA-MK admixed specimens.*

S. No.	Soil Property	Stabilizer Content (%)						
		0	5	10	15	20	25	30
01	UCS (without curing) Measured	107.01	117.2	132.48	178.34	183.44	193.63	198.73
	UCS (without curing) Predicted	108.12	115.56	133.28	178.82	182.24	192.76	200.04
02	UCS (03 Days Curing) Measured	107.01	122.29	157.96	183.44	198.73	219.11	229.3
	UCS (03 Days Curing) Predicted	106.32	123.31	157.46	183.14	199.47	219.65	228.49
03	UCS (07 Days Curing) Measured	107.01	142.68	183.44	193.63	208.92	224.2	234.39
	UCS (07 Days Curing) Predicted	108.61	140.32	184.60	194.33	207.19	222.94	236.28
04	UCS (28 Days Curing) Measured	107.01	163.06	198.73	208.92	219.11	239.49	249.68
	UCS (28 Days Curing) Predicted	111.05	157.09	201.66	210.69	214.74	236.31	254.45
05	CBR Measured	2.45	3.3	3.91	4.06	5.06	6.13	6.74
	CBR Predicted	2.47	3.27	3.92	4.07	5.04	6.11	6.76

Correlations of Measured and Predicated Values

This section examines the correlations between the measured and predicted values of Unconfined Compressive Strength (UCS) and California Bearing Ratio (CBR) for the various admixed soil specimens. The correlations are illustrated through figures, highlighting the variations between the measured and predicted values under different curing conditions.

Fig. 1 depicts the variation of measured UCS values versus predicted UCS values for all specimens without curing conditions. Similarly, Fig. 2 represents the variation of measured UCS values versus predicted UCS values for specimens with a 3-day curing condition. Fig. 3 displays the variation of measured UCS values versus predicted UCS values for specimens cured for 7 days, while Fig. 4 showcases the same variation for specimens cured for 28 days. Furthermore, Fig. 5 presents the compiled variation of measured and predicted UCS values for all blends under different curing conditions. The measured UCS values were obtained through experimental procedures, while the predicted values were calculated using the developed regression models. This figure highlights the relationship between experimental and modeled results, providing insights into the reliability and accuracy of the predictive models across various soil compositions and curing durations. The trends observed validate the effectiveness of the geopolymers stabilization method for enhancing the UCS properties of the studied soil blends.

Additionally, Fig. 6 demonstrates the variation of measured CBR values versus predicted CBR values for all admixed soil samples. These figures visually represent the relationship between the measured and predicted values, offering insights into the accuracy and reliability of the regression models developed.

The coefficient of determination (R2) is employed to quantify the goodness of fit between the measured and predicted values. For the variation of measured UCS values versus predicted UCS values without any curing condition, the R2 value is determined to be 0.9979. Similarly, for the variation of measured UCS values versus predicted UCS values with 3, 7, and 28 days of curing, as well as for all samples combined, the R2 values are found to be 0.9953, 0.9927, 0.9814, and 0.9916, respectively. Moving on to the variation of measured CBR values versus predicted CBR values, the obtained R2 value is 0.994, as shown in Fig. 6.

These results indicate a strong relationship between UCS and CBR values, as well as other parameters associated with the engineering properties of soil. The high R^2 values obtained from the developed multiple regression models, ranging from 0.992 to 1, demonstrate the reliability of the models in predicting UCS and CBR values. The correlations and regression analyses of the measured and predicted values further contribute to understanding the geotechnical behavior of the alkali-activated blended soil specimens and validate the effectiveness of the developed models.

Overall, the findings from the correlations of measured and predicted values of UCS and CBR provide valuable insights into the relationships between these properties and other relevant engineering parameters. These insights contribute to optimizing and applying alkali-activated blended soils in sustainable geotechnical engineering practices.

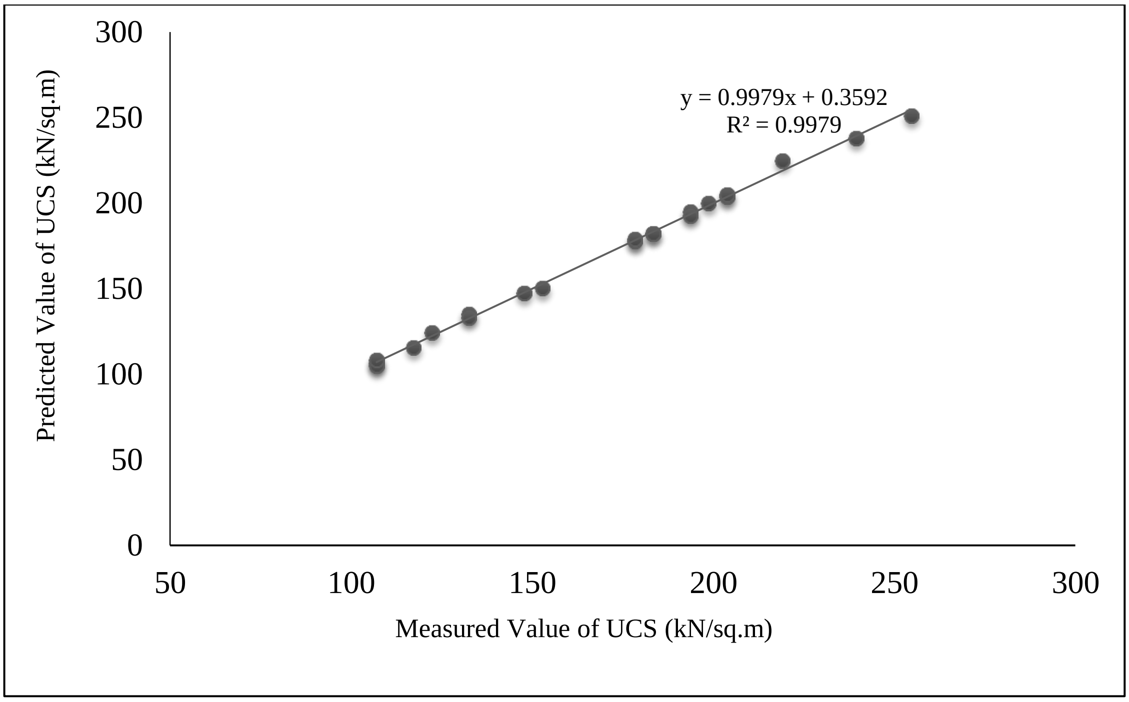

Figure 1: *Variation of measured vs. predicted UCS value for all types of specimens (without curing condition).*

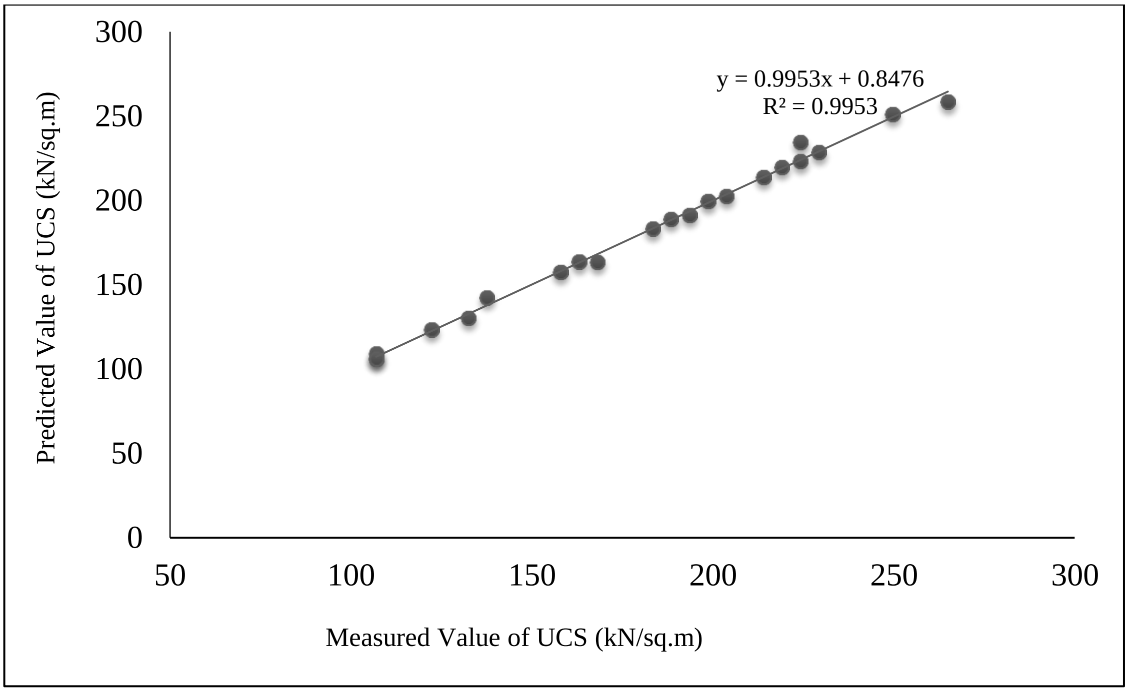

Figure 2: *Variation of measured vs. predicted UCS value for all types of specimens (03 days curing condition).*

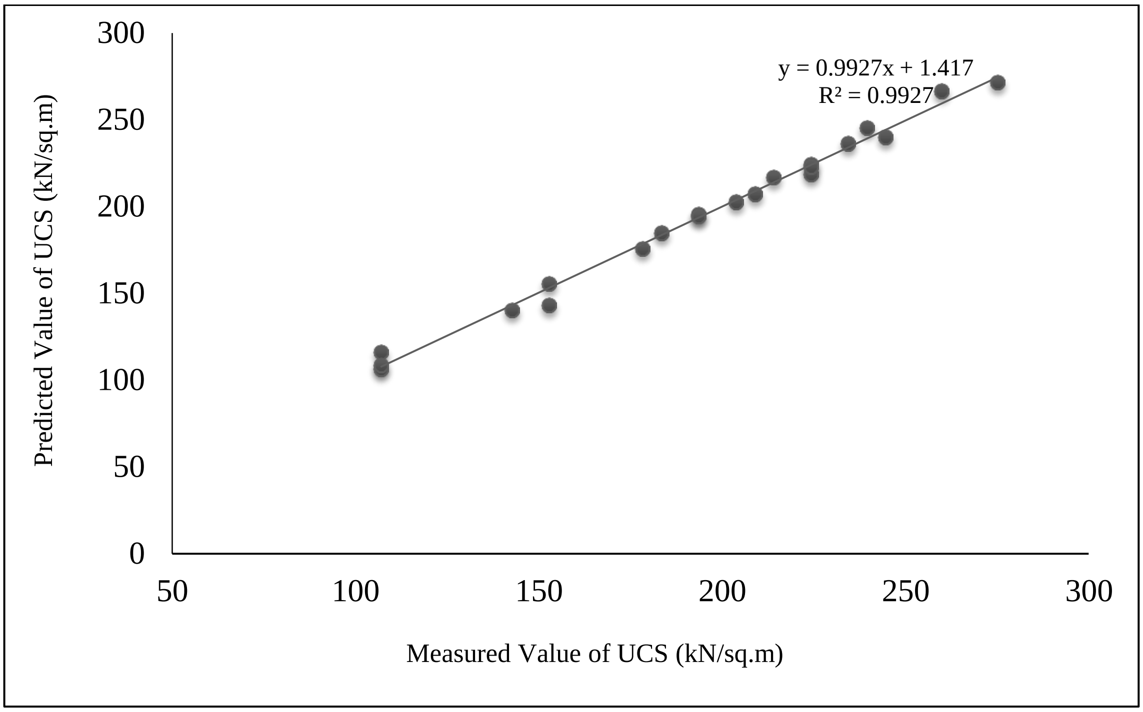

Figure 3: *Variation of measured vs. predicted UCS value for all types of specimens (07 days curing condition).*

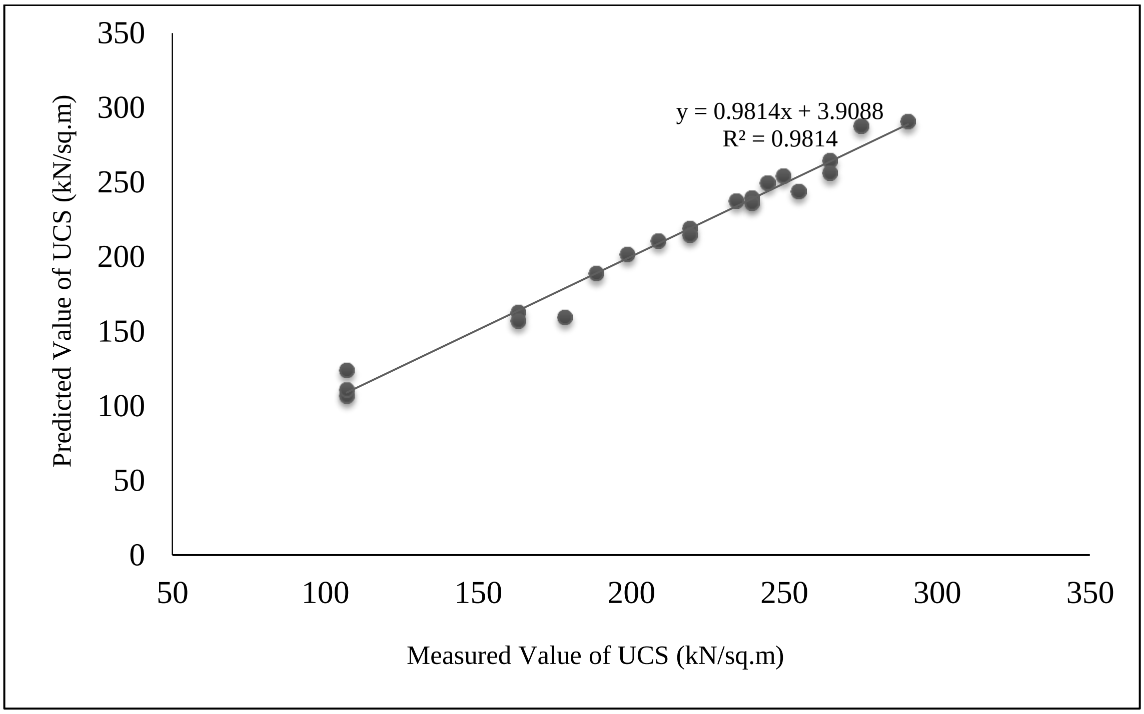

Figure 4: *Variation of measured vs. predicted UCS value for all types of specimens (28 days curing condition).*

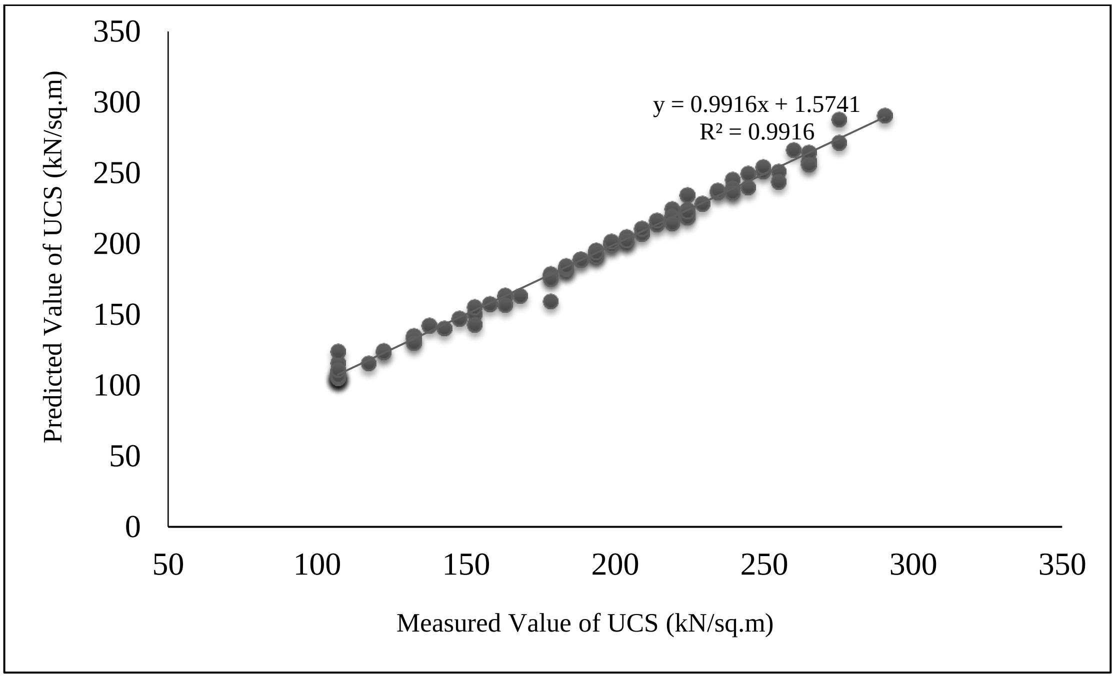

Figure 5: *Variation of measured vs. predicted UCS value for all specimens (for various curing conditions).*

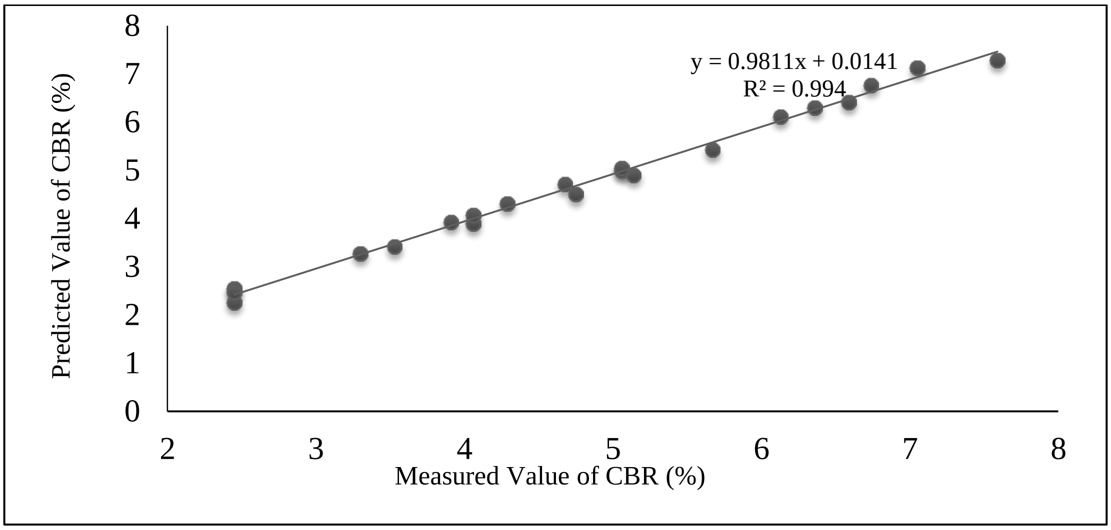

Figure 6: *Variation of measured vs. predicted CBR value for all specimens.*

CONCLUSION

- The research paper highlighted the importance of regression analysis in understanding the relationship between soil properties and engineering characteristics. Regression analysis provides valuable insights into the factors influencing soil behavior, leading to more effective soil stabilization techniques.
- Soil index properties, including Liquid Limit (LL), Plastic Limit (PL), Plasticity Index (PI), shrinkage limit, Optimum Moisture Content (OMC), and Maximum Dry Density (MDD), were identified as crucial factors in soil engineering. Understanding their correlation with engineering properties allows for better prediction and control of soil behavior.
- The presented Python program showcased the practical implementation of regression analysis. By taking user

input for California Bearing Ratio (CBR) and Unconfined Compressive Strength (UCS) values, the program demonstrated how regression analysis can be used to predict the Liquid Limit (LL) as the dependent variable. Data cleaning and preprocessing techniques were emphasized to ensure accurate and reliable results.

- The research paper provided model summaries for UCS values in admixed soil specimens with different curing periods. These models incorporated various soil properties as dependent variables, allowing for a comprehensive understanding of the relationship between soil properties and strength characteristics. The correlation equations, R-values, R-squared values, and standard error estimates provided valuable insights into the influence of different soil properties on the strength behavior of the soil.
- The regression results indicated significant correlations between soil properties and engineering characteristics. By analyzing the coefficients and statistical measures of the models, the research paper unveiled the quantitative relationships between soil properties and strength behavior. This information can assist engineers and researchers in making informed decisions and developing effective strategies for soil improvement and construction projects.
- The findings presented in this research paper contribute to the body of knowledge in soil engineering. The paper simplifies soil stabilization tasks for problematic soils by establishing empirical relationships through regression analysis. The practical implications of the research provide engineers with tools to predict better and control soil behavior, ultimately leading to improved construction practices.

In summary, the research paper underscores the importance of regression analysis in soil engineering. Through the presented models and regression results, the paper offers valuable insights into the relationship between soil properties and engineering characteristics. The findings contribute to the field of soil engineering and provide practical implications for soil stabilization and construction projects.

CONFLICTS OF INTEREST/COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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