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Numerical Modelling for Prediction of Compression Index from Soil Index Properties in Jimma town, Ethiopia

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Abstract

In this study, correlations are developed to predict compression index (Cc) from index parameters so that one can be able to model Jimma soils with compression index using simple laboratory tests. Undisturbed and disturbed soil samples from twelve different locations in Jimma town were collected. Laboratory tests like specific gravity, grain size analysis, Atterberg limit, and one-dimensional consolidation test for a total of twenty-four test samples were conducted. From one-dimensional consolidation tests, compressibility soil parameters (Cc and Cs) are determined. From the results of limited tests, an indicative good correlation is observed between Cc and LL, PL, and PI. However, a Poor correlation is developed between Cc and PL when related to the other parameters. The developed correlations will be important inputs in modeling Jimma clay soils with regression model and Artificial neural networks (ANN) analysis using simple index tests. In addition, the results of this study can serve as a basis for further study of such correlations on different clay soils in the country. In this study, regression analysis was used to explore the significance of individual independent (index) soil properties. Regression model and correlation of compression index for liquid limit, plastic limit, and plasticity index were obtained from the linear regression analysis and ANN. This correlation will be helpful for geotechnical engineers in developing the coefficient of compression (Cc) value of expansive/clay soil from index properties. Finally, based on the general findings of the study, suitable recommendations have been forwarded.

Author Keywords. ANN Model. Regression Model. Atterberg Limits. Compression Index. Correlation.

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1. Introduction

Settlement can occur because of a construction foundation built on a compressible soil layer. Compression index (Cc) is a compressibility parameter calculated from the oedometer test and used to estimate the magnitude of settlement. It is important to consider soil compression purposes. The process of consolidation test proceeds longer durations. Therefore, it is constructive if the value of the compression index can be interrelated with index properties such as liquid limit, plastic limit, and plasticity index. The correlations between the engineering and index properties of soils will reduce the workload of a soil investigation program in case of urgency. The nature of the soil has always been an important part of civil engineering. Soil properties, such as plasticity, the capability of existing, or soil strength, always influence the design of the structure (Akayuli and Ofosu 2013). Failure to understand soil characteristics can result in significant construction errors. Soil applicability for a specific application must be determined by its engineering characteristics and not only by visual inspection or obvious similarities with other soil. It takes two weeks to complete the oedometer test, but it is expensive, stressful, and time-consuming (Jain, Dixit, and Chitra 2015).

Engineers need a lot of maturities and the ability to interpret application results with local conditions. Due to these factors, several attempts were made in the past to predict the compression index based on the properties of the soil index, which is rather convenient to decide and requires much less time in the laboratory. Soil index properties, which include Atterberg Limit values and moisture content, are physical soil properties. Therefore, the characteristics of this index are used to determine the soil compression index (Cc).

The objective of the research was to determine the relationship between the compression index (Cc) and the index properties of the soil. The compression tendencies of expansive soils are quantified by the compressibility parameters. Determination of compressibility of expansive soils, namely, recompression index and compression index (Cc), is important for the design of foundations (Abbasi, Javadi, and Bahramloo 2012). The swell percent or volume change of soil compression is the percentage of soil load for a particular load with an additional surcharge load. The external pressure that has been applied to the expanded soil to prevent an increase in volume is called soil pressure (Zumrawi 2012). A major concern of the foundation engineer is to predict the behavior of changes in the volume of soil stress when exposed to changes in a stressful environment. Geotechnical engineers practicing in such areas are involved in a better understanding of relationships between the physical and chemical properties of active clay. The soil is mostly selected fine-grained and clayey/silt inherited with compressibility. Selected samples have been checked for index and engineering properties.

Numerical modeling is an approach or method that is used to estimate, correlate, model, and analyze the relationships between dependent and independent variables (Namdarvand, Jafarnejadi, and Sayyad 2013). This study focuses on the correlation between compression index and Atterberg limit (i.e., liquid limit, plasticity index) by using numerical modeling (regression analysis and Artificial neural networks approaches). Regression analysis uses extremely complicated equations to evaluate large datasets and interprets them into coordinates on a line or curve, whereas artificial neural networks (ANN) are computational methodologies that carry out multifactorial attempts.

In the MATLAB software, 70 percent of both normalized output and input data were entered into the network as training and the remaining 30 percent entered as a test (the training is an observer one). If the value of predicated output is close to the actual one entered into the output part, indicate the ideal prediction of the network and ensure that the MSE is low and R is high. Therefore, in this study, the predicted output of the network is close to the target. The predicted values of Cc depend on the test results. One-dimensional consolidation was done on twenty-four test samples at loading intensities of 50 kPa to 800 kPa. The compression index (Cc) is one of the very important compressibility parameters in settlement estimation for engineering design purposes. There were a lot of formulas that were developed by different scholars (Ibrahim et al. 2012; Rashed, Salih, and Abdalla 2017; Giasi, Cherubini, and Paccapelo 2003; Ng, Chew, and Lazim 2018) for the correlation between Cc and other soil properties. However, most of the researchers recommended Cc = 0.009 (LL-20) (Vinod and Bindu 2010); but the best correlation of compression index with Atterberg limits was suggested by Giri (2019). The compression index (Cc) values of medium to soft soil are in the ranges of 0.15 to 1.0 (Hermans and Irving 2017). The correlation results of the compression index (Cc) for this study are between 0.227 and 0.33. Coefficient of compressibility (Cc) values are found to be relatively almost similar to those obtained for undisturbed soil samples by Jayalekshmi and Elamathi (2020) and according to Alptekin and Taga (2019), the soils are soft clay that is highly compressible when comparison with the current study.

Hence, many researchers have used these approaches to determine the value of Cc from basic soil properties (Yoon, Kim, and Jeon 2004; Dwivedi, Kumar, and Jain 2016; Onyejekwe, Kang, and Ge 2015). They used ANN and regression analysis to predict the compression behavior of normally consolidated fine-grained soil (Işik 2009). They concluded that, for predicting the compression index from index soil properties: Liquid limit (LL), water content (w), and void ratio (e), which are given as input data to provide good correlation models for different soil and also a comparison with the existing Cc empirical equation (Tiwari and Ajmera 2012).

2. Materials and Methods

The study was conducted in Jimma town, which is located in southwest Ethiopia at a distance of 335 km from the capital of Ethiopia, Addis Ababa. Jimma town is one of the special towns of the Oromiya National Regional State and is surrounded by Jimma Zone. The representative and purposive sampling techniques were used by selecting particular parameters to make sure that the settings have specific characteristics as indicated for this study. The size of soil collected is specified in the sample collection procedure according to the ASTM Standard Test Manual. The sample collection procedure has been according to the ASTM Standard Test Manual for all different types of laboratory tests. A series of Geotechnical laboratory tests, including Atterberg Limits, Natural moisture content, particle size distribution (wet sieving), and one-dimensional consolidation tests, have been conducted. The data processing and analysis to be carried out in this study were presented and explained using tables, charts, and graphs. The results of laboratory tests were analyzed and compared to the standards and current specifications (Legget 1964) proposed by ASTM. The result obtained was organized and interpreted using MS Excel and numerical modeling according to the established objective and presented as a chart, table, and graph. There are two different approaches to Numerical Modeling, namely Regression analysis and Artificial Neural Network (ANN), to obtain the correlation between compression indexes (Cc) and liquid limit (LL). Similar approaches can also be used to predict the correlation between compression index (Cc) and plasticity index (PI).

In order to examine the data based on regression, storing and normalization of the data was done by SPSS 17 (Namdarvand, Jafarnejadi, and Sayyad 2013) packages. The relation between the compression coefficient and the other properties was carried out by stepwise regression. To investigate being interdependent of the factors, the Pearson correlation coefficient was measured and the properties which had a significant correlation were specified.

In neural network modeling, MATLAB software, as well as the multilayer perceptron (MLP) model, was used. These networks have the potential to be evolved by input vectors and include a series of sensory units (base neuron) comprising an input layer, one or more latent layers and an output layer. The input signals are released as layer by layer through network and follow a forward route (Sarmadian, Taghizadeh Mehrjardi, and Akbarzadeh 2009). It is through trial-and-error method, that is, replacement of transfer functions and modification of the number of neurons that the results can be obtained at best, having the highest correlation coefficient (R) and the least mean square error (MSE).

3. Index Properties Test Results

3.1. Natural moisture content

For the correlation of soil characteristics within index properties, the natural moisture content is the significant index soil property. The natural moisture content of the soil examined was determined according to ASTM D2216-98 (ASTM 1998). The natural moisture content of the soils in the study area is between 39.14% and 68.78%. Table 1 shows a test specimen dehydrated at a temperature of 110° ± 5°C to a constant mass using oven-dried.

3.2. Specific gravity

The specific gravity of solids in a soil particle was defined as the ratio of the unit weight of solid matter to the unit weight of water. The specific gravity of the solid is a measure of and a means of expressing the heaviness (weight) of the material. By ASTM -D 854-06 (ASTM 2006), two procedures were provided to perform specific gravity. These are Method A, procedures for oven-dried samples, and Method B, procedures for wet samples. In this study, the specific gravities are determined using Method-A procedures. Specific gravity test results are shown in Table 1. The specific gravity of the solid of the light-colored sand, which is composed mainly of quartz, can be estimated at 2.65: for clayey and silty soil, it can vary from 2.6-2.9 (Onyejekwe, Kang, and Ge 2015). Table 1 summarizes the specific gravity of the soil samples. The results indicate that all soil samples conform to specifications. The specific gravity of clay is between 2.60-2.76 and for silty it varies from 2.68-2.73. The specific gravity values showed a variation within a limited range at different depths and different locations. The specific gravity should be a lower value when a high organic content exists", while the presence of heavy minerals can lead to higher values.

Sample No	Moisture content (%)	Specific Gravity (Gs)	Sample No	Moisture content (%)	Specific Gravity (Gs)	Sample No	Moisture content (%)	Specific Gravity (Gs)
1	43.90	2.72	9	45.91	2.69	17	43.26	2.69
2	47.41	2.7	10	66.62	2.66	18	44.78	2.65
3	57.00	2.62	11	39.14	2.7	19	45.51	2.65
4	44.45	2.6	12	45.70	2.68	20	47.50	2.61
5	43.96	2.76	13	40.89	2.69	21	43.57	2.61
6	47.50	2.73	14	57.07	2.65	22	39.98	2.65
7	47.39	2.73	15	43.00	2.64	23	60.82	2.68
8	47.50	2.71	16	46.88	2.61	24	68.78	2.71

Table 1: Natural moisture content of soil samples

3.3. Atterberg limits

Atterberg limits were determined for air-dried samples. It was carried out based on the standard according to ASTM (2000). Air-dried soil samples were prepared by spreading the material out in trays and leaving them open in the air for at least 5-7 days until completely dry. The room temperature was approximately 25º C. Atterberg limit values for soils in the study area are summarized in Table 2.

The result of the Atterberg limit of soil sample used presented in Table 2 shows which were determined by using Casagrande's and plastic limit method is performed. From this, it is observed that the liquid limit is between 58% and 106%; the plastic limit ranges from 24.8-52.3%, and the plastic index is between 31% and 61%. The test outcome displays that the soils in the study area are highly plastic with high plasticity index values.

Sample No	Liquid Limit, LL (%)	Plastic Limit, PL (%)	Plasticity Index, PI (%)	Sample No	Liquid Limit, LL (%)	Plastic Limit, PL (%)	Plasticity Index, PI (%)
1	81.30	36.60	44.70	13	65.00	25.00	40.00
2	77.30	37.30	40.00	14	90.00	40.00	50.00
3	59.50	28.50	31.00	15	77.00	37.00	40.00
4	59.80	24.80	35.00	16	75.60	33.60	42.00
5	61.00	30.00	31.00	17	65.70	30.70	35.00
6	60.00	29.00	31.00	18	83.50	38.50	45.00
7	79.70	44.70	35.00	19	67.40	31.40	36.00
8	87.00	46.00	41.00	20	79.20	32.20	47.00
9	67.00	32.50	34.50	21	70.20	33.20	37.00
10	72.30	34.80	37.50	22	71.00	32.00	39.00
11	63.00	32.00	31.00	23	101.00	52.30	48.70
12	58.00	27.00	31.00	24	106.00	45.00	61.00

Table 2: Atterberg limits of soils of the study area

3.4. Particle size analysis

The test was conducted according to ASTM D422-63(2007) (ASTM 2007) particle distribution finer than 75µm can be done by hydrometer test and courser than 75µm can be done by mechanical sieve. Therefore, the samples collected from the site were first air-dried and a representative sample was taken by quartering. The weight of the sample was measured and then washed in sieve No.200. The mechanical sieve was performed on soil samples retained by No. 200 sieve after oven drying for 24 hours. In the hydrometer test, 50 g of soil has taken and soaked for 24 hours by adding a sodium hexametaphosphate that is used as a dispersing agent. Then, soaking the sample was further dispersed using a stirring apparatus. Then it was poured into a 1000 ml cylinder and mixed again for one minute by covering it with the palm (glove). The hydrometer reading and the test temperature were taken for 1, 2, 4, 8, 15, 30, 60, 120, 240, 480 and 1440 minutes. The summarized combined grain size and hydrometer analysis curves are shown in Figure 1. From the particle size results, it was observed that there are several particle size variations. Grain size analysis yielded a clay content ranging from 6.38-22.97%, silt fraction 74.98-90.86%, sand fraction 0.67-12.89% and gravel content from 0.0 – 0.41%.

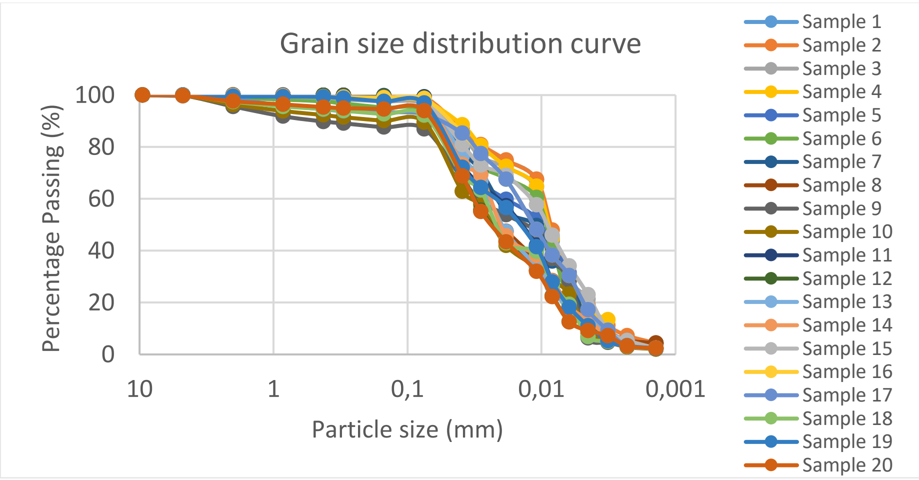


Figure 1: Summary of combined grain size distribution curves from sieve and hydrometer analysis

3.5. Soil classification

The soils under investigation have been classified according to USCS (Das and Sobhan 2012) and AASHTO (2000). For both, the classification test results are summarized in the following figures. Most of the soil of the study area falls in Highly plastic clay (CH) and three soil samples fall in the MH region as USCS classification scheme (Das and Sobhan 2012). From visual observations and field tests, the soils of the study area are classified as clay with high plasticity. The soils are classified as CH or MH (clay with high plasticity, clay with high elasticity) conducted as USCS. According to AASHTO classification, the soil is classified as A-7-5 and A-7-6, which are clayey soils.

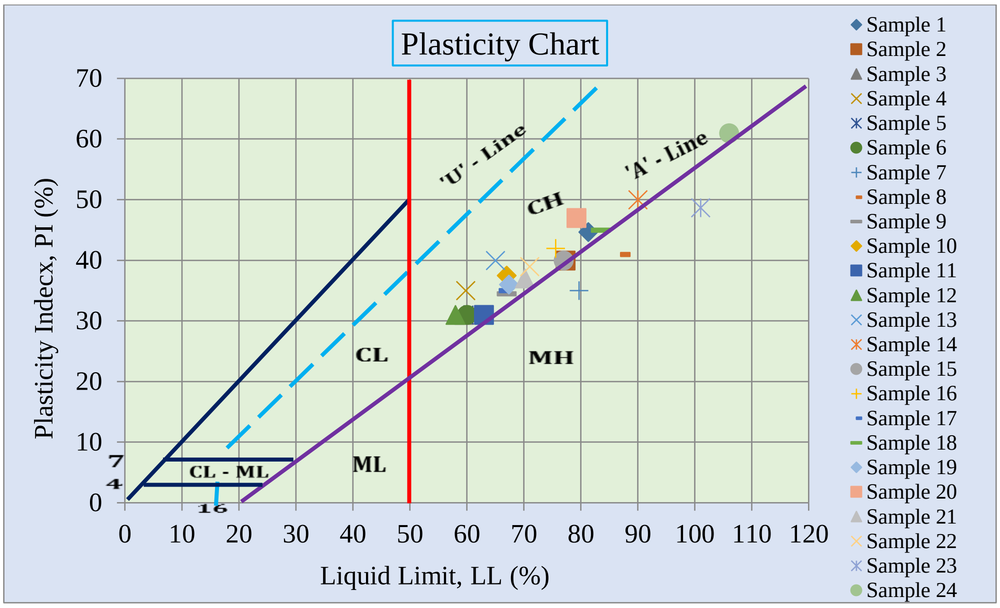


Figure 2: Unified soil classification systems of the soil in the study area using a plasticity chart

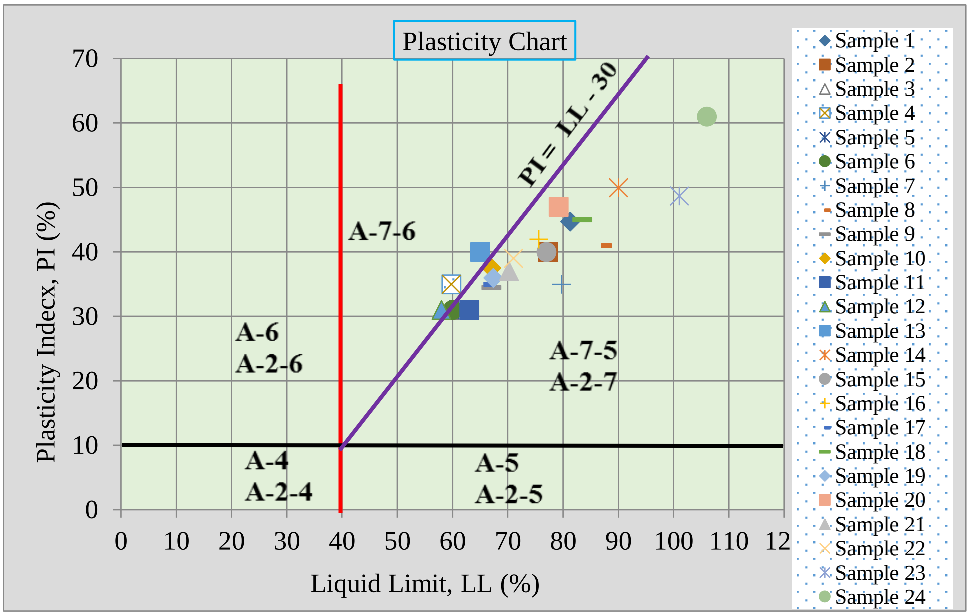


Figure 3: Plasticity chart of soil in the study area according to AASHTO system of classification

From the plot of the plasticity chart in Figure 2, the soils found in Jimma town are highly plastic clay except for samples 7, 8, and 23, which are highly elastic. Figure 3 also shows that most soil samples of the study area fall in the A-7-5 subgroup, in which the plasticity index is equal to or less than the liquid limit minus 30 (LL-30) and below the A-line. In addition, some soil samples fall in the A-7-6 subgroup, in which the plasticity index is greater than the liquid limit minus 30 and above or equal to the A-line.

3.6. Consolidation test

Consolidation properties of soils test were done on the ASTM standard, Designation (ASTM 2011). A small representative undisturbed soil sample is carefully trimmed and fitted into the rigid metal ring. The specimen was mounted on a bottom porous stone base, and a similar porous stone was placed on top to permit water, which has squeezed out of the sample, to escape freely at the top and bottom and a sitting load of 7 kPa was applied. A consolidation test was carried out to study the compressibility of the soil using the apparatus called oedometer. Diameters of 50 mm soil samples having a height of 20 mm were loaded from 50 kPa to 800 kPa by doubling the loading. The loads were doubled every 24 hours, starting from 50 kPa to 800 kPa. Similarly, for all samples, the procedure is followed.

The undisturbed soil samples are performed for all the twelve test pits; twenty-four oedometer tests (i.e., 1.5 m and 3.0 m depths) are conducted. Then, the compression index (Cc), which is used in establishing correlations with index properties and reconsolidation pressure (Pc), is determined from the consolidation test. Results of compressibility parameters for the twenty-four undisturbed soil samples collected from test pits around Jimma town are summarized in Table 3. The results revealed that clays in the study area are highly plastic with a marginal degree of expansion. They also have relatively moderate to high free swell values. Correlation between the results of the twelve stations and collected data shows that the Cc values, in general, increase with increasing liquid limit and plastic index of soil. This serves to suggest that soil compressibility generally increases with plasticity and vice versa. Generally, void ratios for all samples were reduced to lower values since the increasing intensity of loadings at each step of loading brought soil grains closely to each other. The test results of the collected data test in the study area are conducted for the oedometer test. The compression index (Cc) range is 0.227 to 0.33 and the swelling index (Cs) lies in a range of 0.02 to 0.11.

Sample No	Compression index (Cc)	Swelling index (Cs)	Sample No	Compression index (Cc)	Swelling index (Cs)
1	0.287	0.02	13	0.256	0.11
2	0.274	0.06	14	0.305	0.05
3	0.232	0.05	15	0.296	0.04
4	0.227	0.07	16	0.294	0.04
5	0.248	0.03	17	0.26	0.04
6	0.244	0.03	18	0.29	0.04
7	0.286	0.03	19	0.264	0.07
8	0.31	0.03	20	0.324	0.07
9	0.264	0.06	21	0.267	0.02
10	0.243	0.05	22	0.272	0.02
11	0.252	0.04	23	0.321	0.06
12	0.241	0.04	24	0.33	0.07

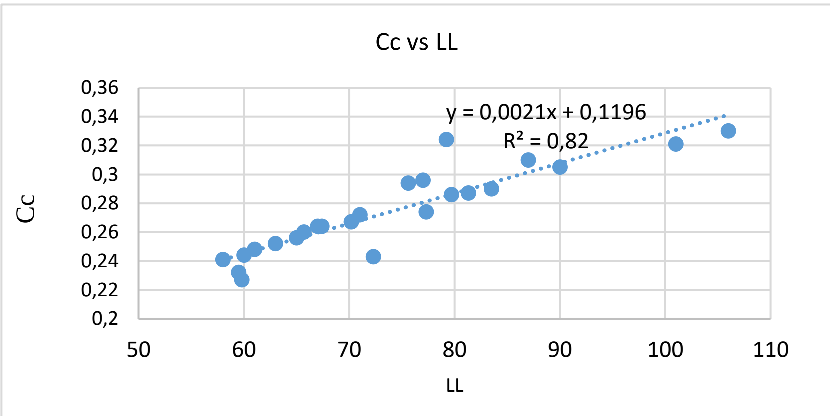
Table 3: Results of Consolidation Test for twenty-four soil samples for the study area

4. Numerical Modelling

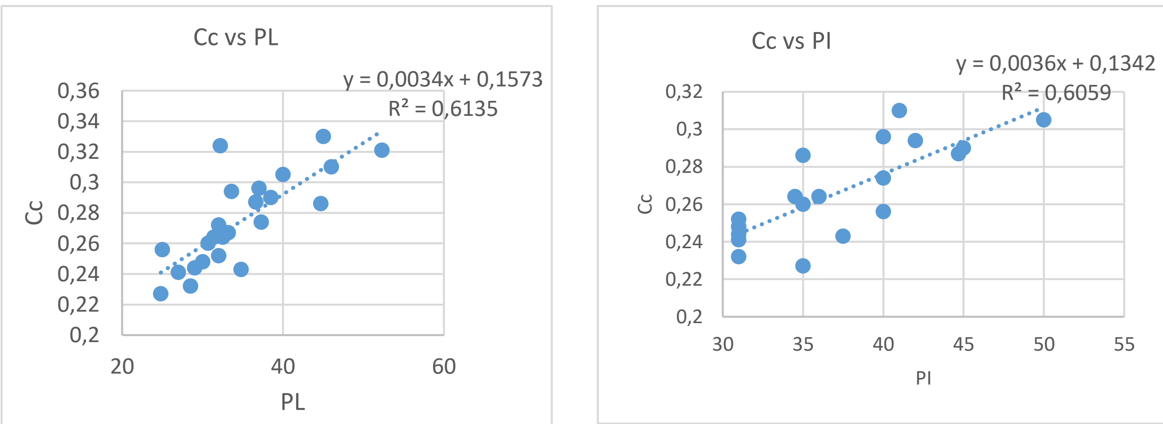
Artificial neural networks and regression analysis are the two approaches to get the correlation between compression index (Cc) and soil index properties (Nesamatha and Arumairaj 2015). Determination of the parameter model needs various premises, which the residuals (observed value small estimated values) corresponding to different observations are uncorrelated random variables with zero mean and constant variance (Danial Mohammadzadeh et al. 2019). In addition, one assumes that the order of the model is correct; that is, if one fits a simple linear regression model, one is assuming that the phenomenon behaves in a linear or first-order manner (Chen 1975). During regression analysis, a regression model with a higher value of R^2 (coefficient of determination), which quantifies the proportion of the variance of one variable by the other, is usually accepted. In this study, the compression index (Cc) is the dependent variable, whereas the LL, PL, and PI are regressor variables. To carry out statistical analysis, Microsoft® Excel and SPSS-20 (Gabrosek 2013) were used. Twenty-four numbers of samples are used in correlating Cc with LL, PL, and PI, and seven numbers of secondary samples are used in correlating Cc with LL, PL, and PI. While carrying out the statistical analysis, different regression models are used and those models with a higher value of the coefficient of determination (R^2) are accepted.

4.1. Scatter plot

In developing correlations, the first step is creating a scatter plot of the data to visually assess the strength and form of the relationship. In Figure 4, the scatter plot of Cc with LL, PL, and PI is presented.



(a)



(b) (c)

Figure 4: (a), (b), (c): Scatter plot of Cc versus LL, PL and PI

From Figure 4, the available test points are not sufficient to give reliable relationships between the independent and dependent variables. Nevertheless, different models (linear and non-linear) have been employed to examine the trend of the scatter. Figure 4(a) shows that the compression index is increased with the increment of liquid limit and has a good relationship between Cc and LL as R2 = 0.84. Figure 4(c) indicates the compression index is increased with the plasticity index increased and has a positive relationship between Cc and PI as the value of R2 = 0.6059. Figure 4(b) shows that the compression index is increased with the increment of plastic limit, but it is not an intrinsic variable on Cc value as LL and PI. Three different values of compression index predicted when liquid limit, plastic limit, and plasticity index are given as input are shown in Table 4.

Sample No	Cc actual	Pred. Cc LL as input	Pred. Cc PL as input	Pred. Cc PI as input	Sample No	Cc actual	Pred. Cc LL as input	Pred. Cc PL as input	Pred. Cc PI as input
1	0.287	0.290	0.281	0.293	13	0.241	0.241	0.248	0.246
2	0.274	0.281	0.283	0.277	14	0.256	0.256	0.242	0.277
3	0.232	0.244	0.253	0.246	15	0.305	0.308	0.292	0.311
4	0.227	0.245	0.241	0.260	16	0.296	0.281	0.282	0.277
5	0.248	0.247	0.258	0.246	17	0.294	0.278	0.271	0.284
6	0.244	0.245	0.255	0.246	18	0.26	0.257	0.261	0.260
7	0.286	0.286	0.308	0.260	19	0.29	0.294	0.287	0.294
8	0.31	0.302	0.312	0.280	20	0.264	0.261	0.263	0.263
9	0.264	0.260	0.267	0.258	21	0.324	0.285	0.266	0.301
10	0.243	0.271	0.275	0.268	22	0.267	0.266	0.269	0.267
11	0.252	0.251	0.265	0.246	23	0.272	0.268	0.265	0.273
12	0.287	0.290	0.281	0.293	24	0.321	0.331	0.334	0.307

Table 4: Predicted values of compression index (Pred. Cc) using regression model

4.2. Summary of correlation between Cc and LL, PL and PI for soils of Jimma

A linear model is used. The correlation coefficient with least standard error is considered, and the following relationships are found in Table 5.

Ser. No.	Model equation	R2 (coefficient of determination)	No. of samples, n
1	Cc = 0.164ln(LL-0.4296)	0.8418	24
2	Cc = 0.1233ln (PL) -0.161	0.6282	24
3	Cc = 0.145ln (PI) – 0.2556	0.7395	24

Table 5: Summary of the regression analysis by Microsoft excel and SPSS-20

4.3. Artificial Neural Network (ANN)

Atterberg limits that are detected (i.e., LL, PL, and PI) are given as input and the observed compression index is given as a target for the ANN modeling. After the values are given as input, the training process will take place in the developed hidden layer to predict the R-value. From the trained results, the output values are obtained. By changing the number of the hidden layer, the R-value changes. In this training, the maximum R-value is obtained by giving 20 hidden layers for the ANN modeling. The correlation coefficient value (R^2) obtained from the output is 0.961.

Three different types of predicted values of compression index (Cc) using regression model when liquid limit, plastic limit as input, and plasticity index as input are shown in Table 6. The output of the software after the training is shown in Figure 5.

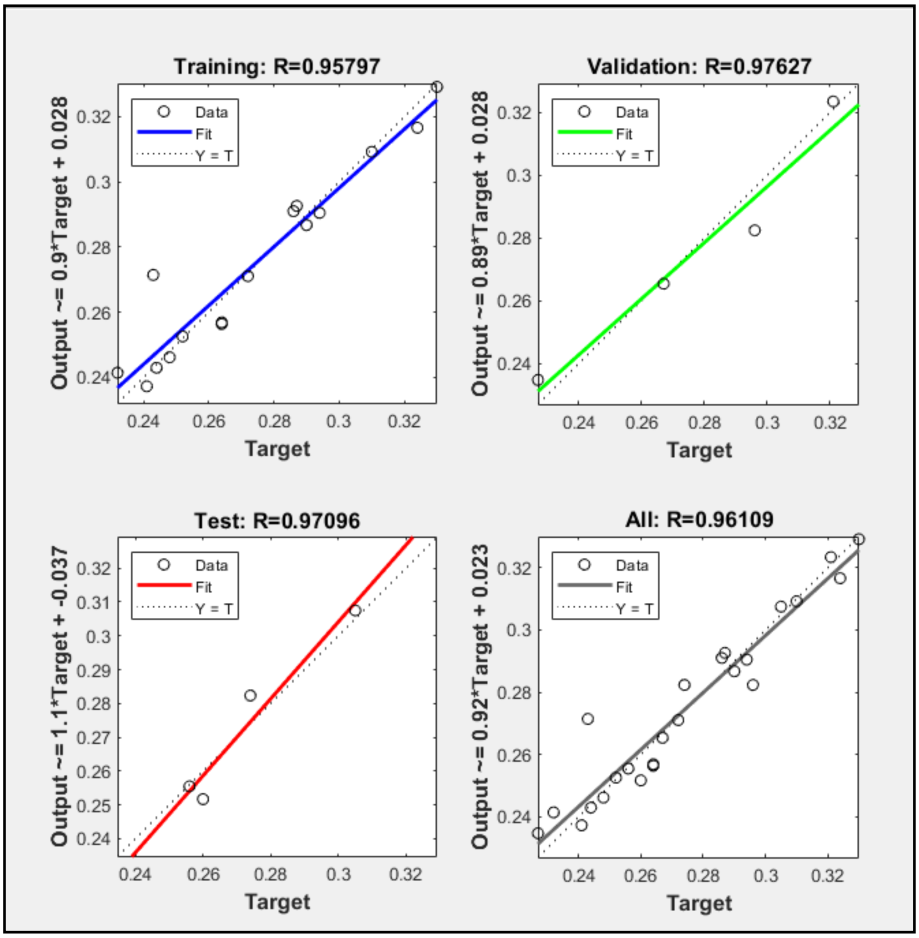


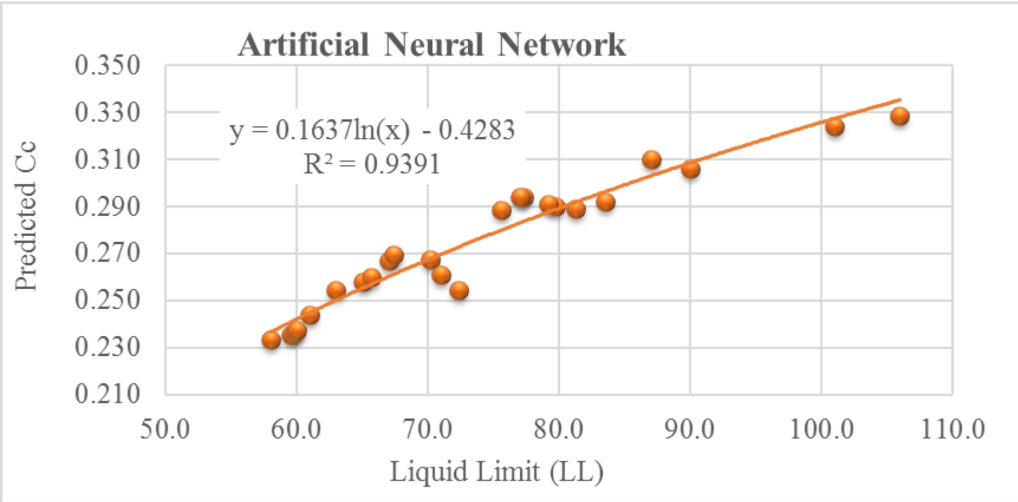
Figure 5: Output after training

Sample No	Cc actual	Pred. Cc LL as input	Pred. Cc PL as input	Pred. Cc PI as input	Sample No	Cc actual	Pred. Cc LL as input	Pred. Cc PL as input	Pred. Cc PI as input
1	0.287	0.289	0.293	0.285	13	0.241	0.258	0.247	0.278
2	0.274	0.294	0.273	0.278	14	0.256	0.306	0.294	0.305
3	0.232	0.236	0.234	0.243	15	0.305	0.294	0.329	0.278
4	0.227	0.237	0.248	0.252	16	0.296	0.289	0.275	0.295
5	0.248	0.244	0.246	0.243	17	0.294	0.260	0.263	0.252
6	0.244	0.237	0.232	0.243	18	0.26	0.292	0.295	0.289
7	0.286	0.290	0.288	0.252	19	0.29	0.269	0.253	0.263
8	0.31	0.310	0.330	0.308	20	0.264	0.291	0.297	0.322
9	0.264	0.267	0.293	0.252	21	0.324	0.267	0.281	0.260
10	0.243	0.254	0.261	0.245	22	0.267	0.261	0.262	0.272
11	0.252	0.254	0.262	0.243	23	0.272	0.324	0.323	0.321
12	0.287	0.234	0.240	0.243	24	0.321	0.329	0.330	0.330

Table 6: Predicted values of compression index using ANN Model

4.4. Correlations from the Artificial Neural Network

Figure 6 shows the relation between the observed and predicted compression index with liquid limit as input.



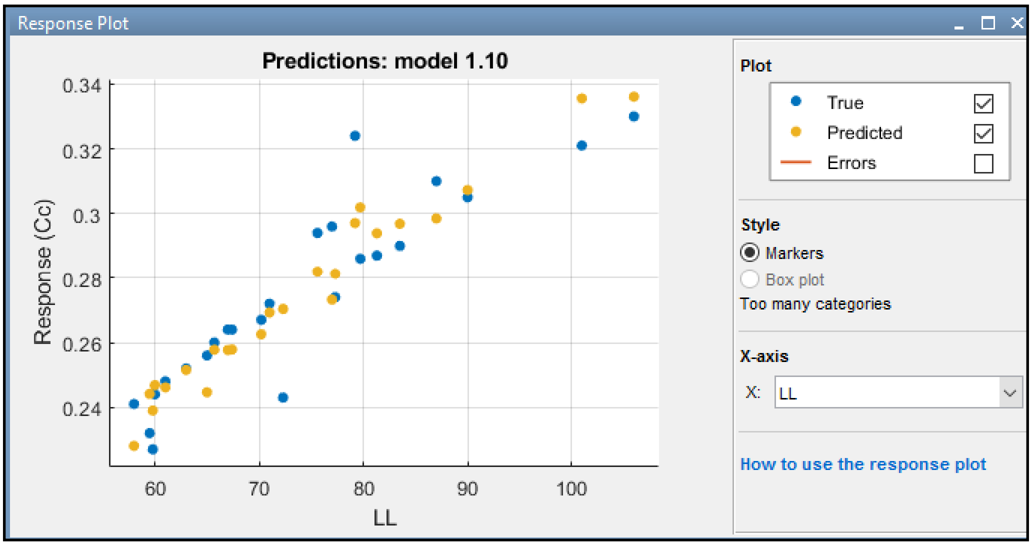
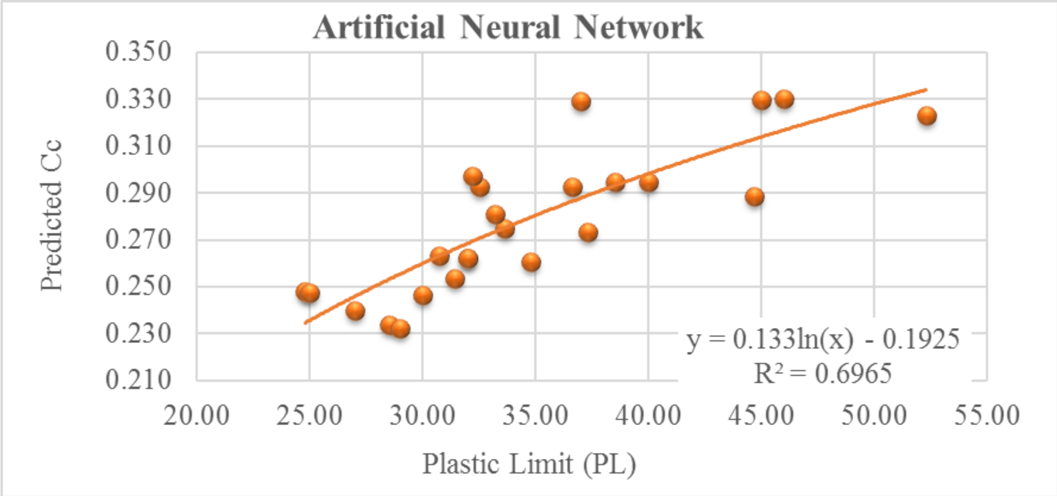


Figure 6: Predicted and observed compression index from ANN model using liquid limit (LL). A relationship between compression index and liquid limit was arrived based on the above plot

Figure 7 shows the relation between the observed and predicted compression index with plastic limit as input.



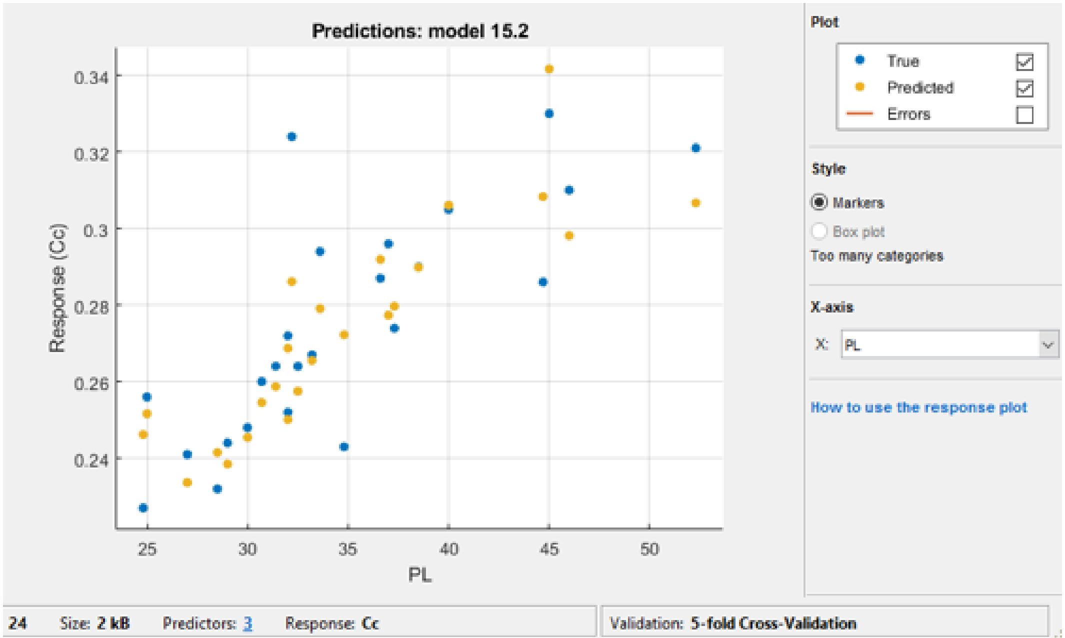


Figure 7: Predicted and observed compression index from ANN model using plastic limit (PL)

A relationship between the compression index and liquid limit was arrived based on the above plot. Figure 8 shows the relation between the observed and predicted compression index with the plasticity index as input.

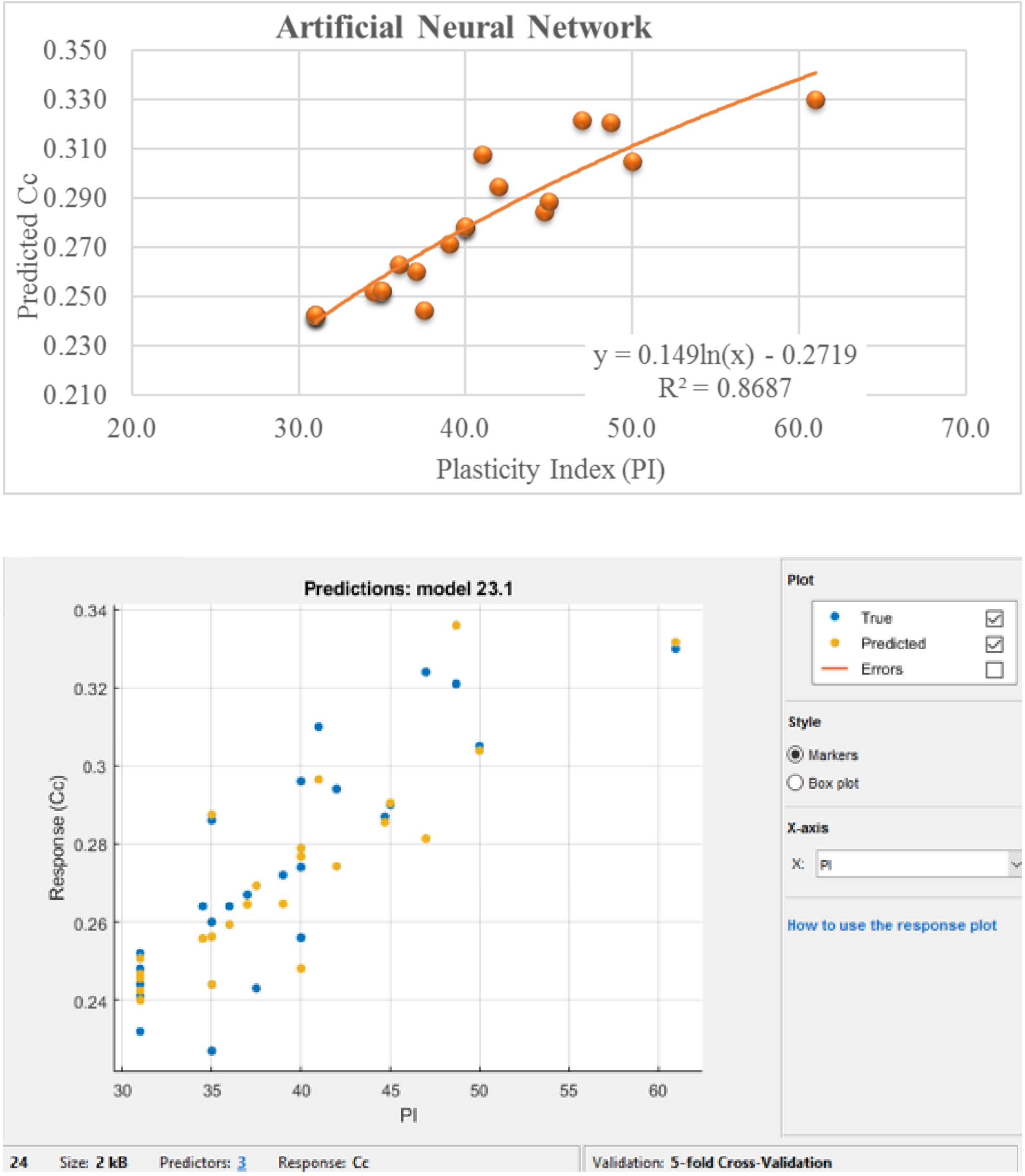
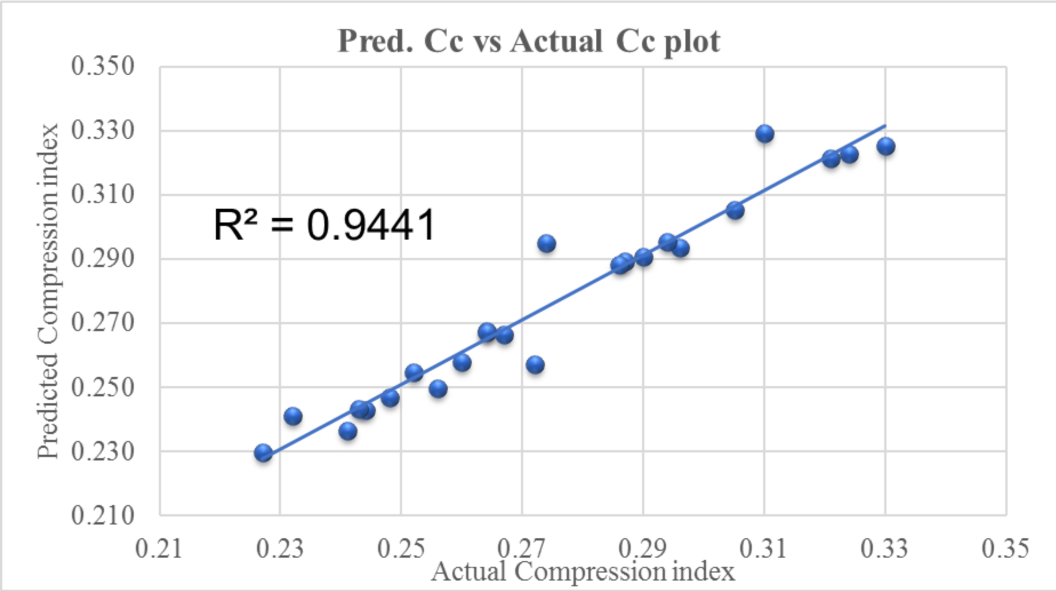


Figure 8: Predicted and observed compression index from ANN model using plasticity index (PI)

A relationship between the compression index and plasticity index was arrived based on the above plot. The predicted Cc vs. actual Cc that was obtained through ANN trained model is shown in Figure 9.



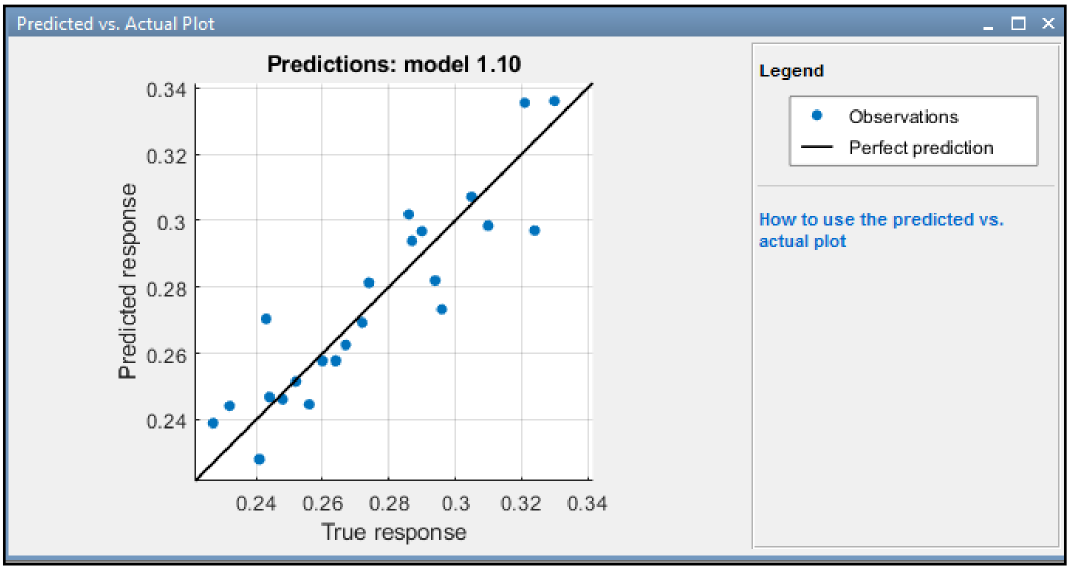


Figure 9: The predicted compression index versus the observed compression index by ANN trained model

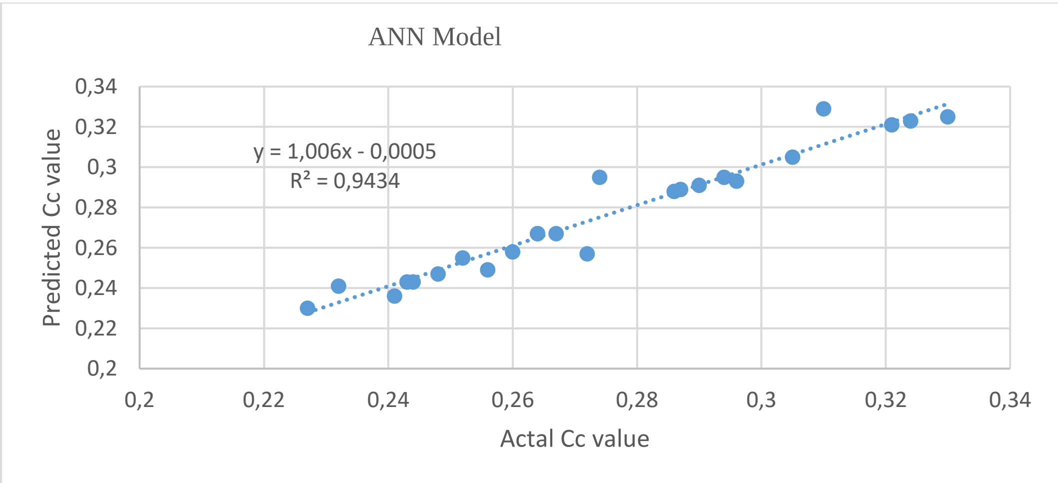
4.5. Comparison of predicted Cc by Microsoft Excel, SPSS-20 and MATLAB-ANN

In this study the value of Cc found from Oedometer tests and the predicted Cc are almost similar as it is shown in Table 7 below.

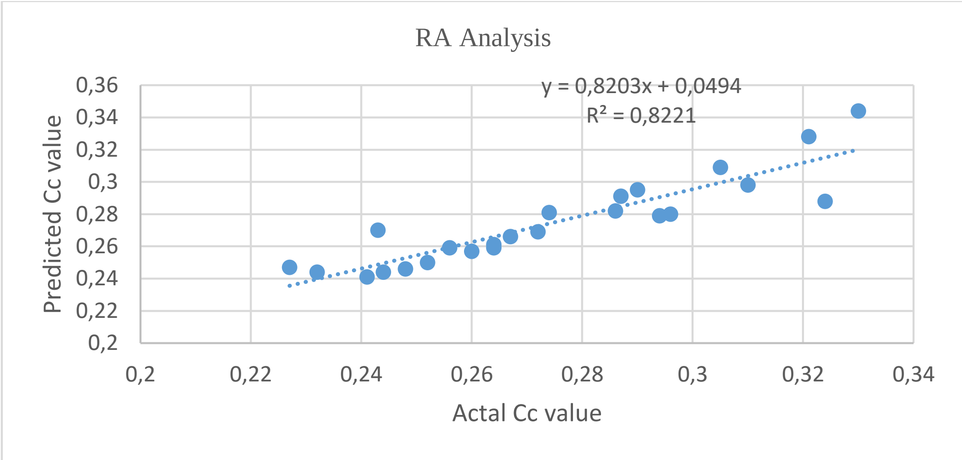
Ser. No	Laboratory test	RA	MLP	ANN	Ser. No	Laboratory test	RA	MLP	ANN
1	0.287	0.291	0.290	0.289	13	0.256	0.259	0.256	0.249
2	0.274	0.281	0.274	0.295	14	0.305	0.309	0.330	0.305
3	0.232	0.244	0.248	0.241	15	0.296	0.280	0.274	0.293
4	0.227	0.247	0.256	0.230	16	0.294	0.279	0.294	0.295
5	0.248	0.246	0.248	0.247	17	0.26	0.257	0.264	0.258
6	0.244	0.244	0.248	0.243	18	0.29	0.295	0.290	0.291
7	0.286	0.282	0.274	0.288	19	0.264	0.261	0.264	0.267
8	0.31	0.298	0.274	0.329	20	0.324	0.288	0.330	0.323
9	0.264	0.259	0.264	0.267	21	0.267	0.266	0.264	0.267
10	0.243	0.270	0.264	0.243	22	0.272	0.269	0.272	0.257
11	0.252	0.250	0.264	0.255	23	0.321	0.328	0.290	0.321
12	0.241	0.241	0.244	0.236	24	0.33	0.344	0.330	0.325

Table 7: Comparison of the value of Cc found from the oedometer test and predicted Cc by LR (Microsoft Excel), NN- MLP (SPSS-20) and MATLAB-ANN analysis

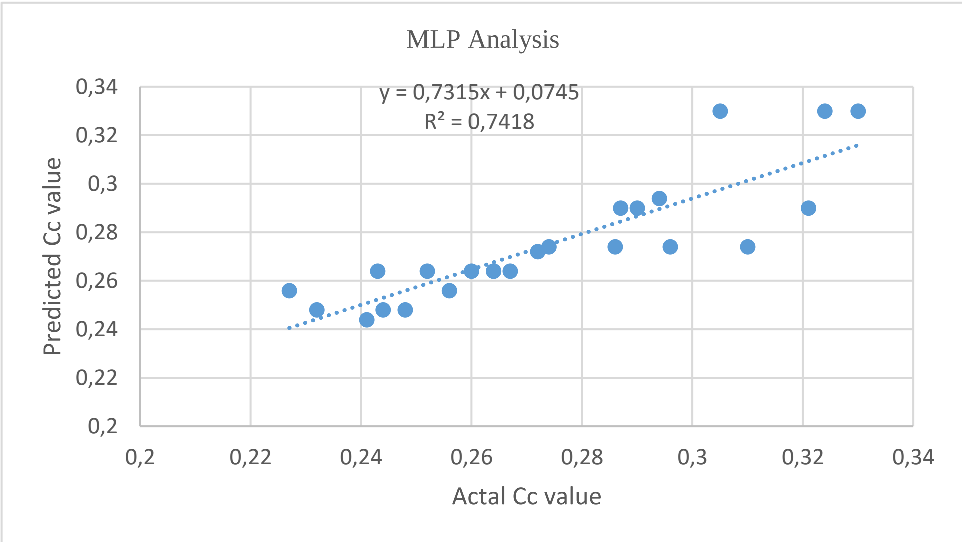
From Table 7 and shown in Figure 10, the accuracy of the present ANN model was checked by comparing the laboratory values of Cc with predicted values of Cc. It was found that the mean target value for input data was 0.274, whereas the mean target value for ANN output was 0.276. But the mean target value using regression analysis and Multilinear perception is similar, which is 0.275. The accuracy of the proposed model was also checked by calculating the correlation coefficient (R-value) and it was found that the ANN model was 0.944, whereas for models proposed using regression analysis and Multilinear perception were 0.822 and 0.742. It was found that compression index values predicted using the ANN model have better distribution around the trend line in comparison to another model (Nesamatha and Arumairaj 2015). It can be calculated that the proposed models are much more accurate and are in good agreement with laboratory values.



(a)



(b)



(c)

Figure 10: (a), (b) and (c): The plot of different mathematical model for relationship between predicted and observed target values of the study

Ser. No.	Model equation	R2 (coefficient of determination)	No. of samples, n	Mathematical model used
1	Cc = 0.164ln (LL) - 0.4296	0.8418	24	Regression analysis (LR)
2	Cc = 0.1233ln (PL) -0.161	0.6282	24	Regression analysis (LR)
3	Cc = 0.145ln (PI) – 0.2556	0.7395	24	Regression analysis (LR)
4	Cc = 0.1637ln (LL) - 0.4283	0.939	24	Artificial neural network (ANN)
5	Cc = 0.1637ln (LL) - 0.4283	0.696	24	Artificial neural network (ANN)
6	Cc = 0.149ln (PI) - 0.2719	0.869	24	Artificial neural network (ANN)

Table 8: R^2-Value for Regression and ANN Model

Table 8 shows the variation of R^2 for both Regression analysis (LR) and Artificial neural network (ANN). ANN model shows more goodness of fit and it has higher reliability than the regression analysis from these two correlations. Figure 11 shows a comparison of different mathematical models in one plot.

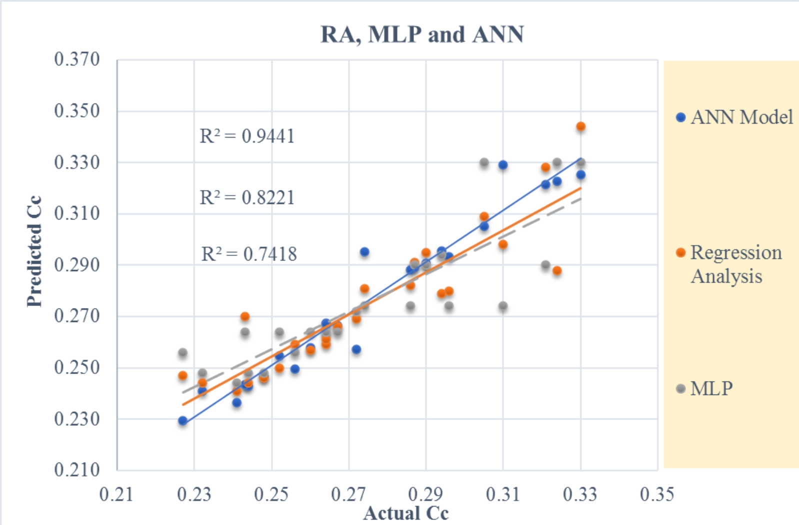


Figure 11: Comparison of different mathematical models in one plot

5. Conclusions

The main objective of this paper was to obtain valid relationships between index properties and compression index of Jimma clay soil. However, from regression analysis, Cc has a very strong correlation with Atterberg limits by achieving a coefficient of determination of 84%, 63%, and 74% using ANN model, Regression and analysis and MLP, respectively, while parameters like void ratio, dry unity weight, and natural moisture content have little influence on the compression index in this study. The R^2 (correlation coefficient) of the ANN model for LL, PL, and PI is 93%, 69%, and 86%, respectively, indicating that the Cc has a very strong correlation with Atterberg limits. In this study, the ANN model is the best fit to achieve a greater R-value than the regression analysis model. Therefore, the compression index can be computed from the known value of LL, PL, and PI by the correlation equations.

From the statistical analysis and ANN analysis, one observes a relatively good indicative correlation between Cc and liquid limit (LL), Cc and plastic limit (PL), and Cc and plasticity index (PI), while parameters like void ratio, dry unity weight, and natural moisture content have little influence on the compression index in this study. From the developed correlations, one would be in a position to determine the compression index from the index properties for undisturbed soil samples of Jimma town. The compression index is influenced by LL and PI for this category; Cc can be estimated from the oedometer by:

$$Cc = 0.1641n\,(LL) - 0.4296, R2 = 0.84, n = 24, and\ Cc = 0.145ln\,(PI) - 0.2556, R2 = 0.74, n = 24 \quad (1)$$

The corresponding settlement equation of:

$$Sc = Ho + \frac{Cc\ log10\ ((\sigma\prime v + \Delta\sigma\prime v)/\sigma\prime v)}{1+eo} \quad (2)$$

In this study, ANN's (curve fitting) practice has been made to predict the compression index based on the geotechnical characteristics of different test pits data collected from Jimma town. ANN is a powerful tool in predicting the consolidation parameters and the best fit model than conventional methods are obtained. In the proposed ANN model, the soil properties, such as the liquid limit, plastic limit, and plasticity index, are input parameters. The proposed model of the ANN results compared with the experimental values and the predicted compression index values have been found close to the experimental values. In this research, the observed compression index is performed by ANN proposed model to obtain the predicted Cc.

$$Cc = 0.1637ln\,(LL) - 0.4283, R2 = 0.939\ and\ Cc = 0.149ln\,(PI) - 0.2719, R2 = 0.869. \quad (3)$$

By engineer judgment, one of the formulae given above may be used for computing Cc due to the absence of consolidation test data.

References

AASHTO. 2000. *Classification of soil and soil-aggregate mixtures for highway construction purposes*. AASHTO M-145-91. American Association of State Highway and Transportation Officials.

Abbasi, N., A. A. Javadi, and R. Bahramloo. 2012. "Prediction of compression behaviour of normally consolidated fine-grained soils". *World Applied Sciences Journal* 18, no. 1: 6-14. https://doi.org/10.5829/idosi.wasj.2012.l8.01.2675.

Akayuli, C. F. A., and B. Ofosu. 2013. "Empirical model for estimating compression index from physical properties of weathered Birimian phyllites". *Electronic Journal of Geotechnical Engineering* 18 Z: 6135-44.

Alptekin, A., and H. Taga. 2019. "Prediction of compression and swelling index parameters of quaternary sediments from index tests at mersin district". *Open Geosciences* 11, no. 1: 482-91. https://doi.org/10.1515/geo-2019-0038.

ASTM International. 1998. *Standard test method for laboratory determination of water (moisture) content of soil and rock by mass*. ASTM D2216-98. ASTM International. https://doi.org/10.1520/D2216-98.

———. 2000. *Standard test methods for liquid limit, plastic limit, and plasticity index of soils*. ASTM D4318-00. ASTM International. https://doi.org/10.1520/D4318-00.

———. 2006. *Standard test methods for specific gravity of soil solids by water pycnometer*. ASTM D854-06e1. ASTM International. https://doi.org/0.1520/D0854-06E01.

———. 2007. *Standard test method for particle-size analysis of soils*. ASTM D422-63(2007). ASTM International. https://doi.org/10.1520/D0422-63R07.

———. 2011. *Standard test method for one-dimensional consolidation properties of soils*. ASTM D2435-96. ASTM International. https://doi.org/10.1520/D2435_D2435M-11.

Chen, F. H. 1975. *Foundations on Expansive Soils*. Developments in Geotechnical Engineering. https://doi.org/10.1016/B978-0-444-41393-2.50002-8.

Danial Mohammadzadeh, S., S. F. Kazemi, A. Mosavi, E. Nasseralshariati, and J. H. M. Tah. 2019. "Prediction of compression index of fine-grained soils using a gene expression programming model". *Infrastructures* 4, no. 2. Article number infrastructures4020026. https://doi.org/10.3390/infrastructures4020026.

Das, B. M., and K. Sobhan. 2012. *Principles of Geotechnical Engineering*. 8th ed. Cengage Learning.

Dwivedi, P., R. Kumar, and P. K. Jain. 2016. "Prediction of compression index (C_c) of fine grained remolded soils from basic soil properties". *International Journal of Applied Engineering Research* 11, no. 1: 592-98.

Gabrosek, J. 2013. *SPSS manual for introductory applied statistics: A variable approach*. John Gabrosek.

Giasi, C. I., C. Cherubini, and F. Paccapelo. 2003. "Evaluation of compression index of remoulded clays by means of Atterberg limits". *Bulletin of Engineering Geology and the Environment* 62, no. 4: 333-40. https://doi.org/10.1007/s10064-003-0196-3.

Giri, S. 2019. "Correlation of compression index (Cc) with liquid limit (LL) and plasticity index (Ip) for white soil deposit (CL, low plastic inorganic clays)". *Journal of Advances in Geotechnical Engineering* 2, no. 1: 1-8. https://doi.org/10.13140/RG.2.2.33725.69605.

Hermans, T., and J. Irving. 2017. "Facies discrimination with electrical resistivity tomography using a probabilistic methodology: Effect of sensitivity and regularization". *Near Surface Geophysics* 15: 13-25. https://doi.org/10.3997/1873-0604.2016047.

Ibrahim, N. M., N. L. Rahim, R. C. Amat, S. Salehuddin, and N. A. Ariffin. 2012. "Determination of plasticity index and compression index of soil at perlis". *APCBEE Procedia* 4: 94-98. https://doi.org/10.1016/j.apcbee.2012.11.016.

Işik, N. S. 2009. "Estimation of swell index of fine grained soils using regression equations and artificial neural networks". *Scientific Research and Essays* 4, no. 10: 1047-56.

Jain, V. K., M. Dixit, and R. Chitra. 2015. "Correlation of plasticity index and compression index of soil". *International Journal of Innovations in Engineering and Technology* 5, no. 3: 263-70.

Jayalekshmi, S., and V. Elamathi. 2020. "A review on correlations for consolidation characteristics of various soils". *IOP Conference Series: Materials Science and Engineering* 1006: Article number 012007. https://doi.org/10.1088/1757-899X/1006/1/012007.

Legget, R. F. 1964. "American society for testing and materials". *Nature* 203, no. 4945: 565-68. https://doi.org/10.1038/203565a0.

Namdarvand, F., A. Jafarnejadi, and G. Sayyad. 2013. "Estimation of soil compression coefficient using artificial neural network and multiple regressions ". *International Research Journal of Applied and Basic Sciences* 4, no. 10: 3232-36.

Nesamatha, R., and P. D. Arumairaj. 2015. "Numerical modeling for prediction of compression index from soil index properties". *IOSR Journal of Mechanical and Civil Engineering* 12, no. 3: 68-76. https://doi.org/10.9790/1684-12316876.

Ng, K. S., Y. M. Chew, and N. I. A. Lazim. 2018. "Prediction of consolidation characteristics from index properties". In *E3S Web of Conferences*, Article Number 06004. https://doi.org/10.1051/e3sconf/20186506004.

Onyejekwe, S., X. Kang, and L. Ge. 2015. "Assessment of empirical equations for the compression index of fine-grained soils in Missouri". *Bulletin of Engineering Geology and the Environment* 74, no. 3: 705-16. https://doi.org/10.1007/s10064-014-0659-8.

Rashed, K. A., N. B. Salih, and T. A. Abdalla. 2017. "Correlation of consistency and compressibility properties of soils in Sulaimani city". *Sulaimani Journal for Engineering Sciences* 4, no. 5: 86-94. https://doi.org/10.17656/sjes.10061.

Sarmadian, F., R. Taghizadeh Mehrjardi, and A. Akbarzadeh. 2009. "Modeling of some soil properties using artificial neural network and multivariate regression in Gorgan Province, North of Iran". *Australian Journal of Basic and Applied Sciences* 3, no. 1: 323-29.

Tiwari, B., and B. Ajmera. 2012. "New correlation equations for compression index of remolded clays". *Journal of Geotechnical and Geoenvironmental Engineering* 138, no. 6: 757-62. https://doi.org/10.1061/(ASCE)GT.1943-5606.0000639.

Vinod, P., and J. Bindu. 2010. "Compression index of highly plastic clays–an empirical correlation". *Indian Geotechnical Journal* 40, no. 3: 174-80.

Yoon, G. L., B. T. Kim, and S. S. Jeon. 2004. "Empirical correlations of compression index for marine clay from regression analysis". *Canadian Geotechnical Journal* 41, no. 6: 1213-21. https://doi.org/10.1139/T04-057.

Zumrawi, M. M. E. 2012. "Prediction of swelling characteristics of expansive soils". *Sudan Engineering Society Journal* 58, no. 2: 55-62.