STATISTICAL EVALUATION OF EMPIRICAL CORRELATIONS FOR THE COMPRESSION INDEX (CC) IN BRAZILIAN SOFT SOILS

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Abstract. One-dimensional laboratory consolidation test is used to discover one of the most important parameters of consolidation of cohesive soils, the compression index (Cc). However, it is a long test and requires the utmost care to obtain reliable samples. Geotechnical correlations are largely used because it can give fast means of parameter prediction using simple tests. These correlations are constructed from local data and need to be evaluated before used in other regions. This paper reports on laboratory tests conducted in soft soils of Brazil and shows a more complete form of statistical evaluation for the correlation of the Cc. The database is formed by 430 results of Cc and moisture content (w_n) collected in the national literature. The correlations analyzed are exclusively in function of w_n. The equations were evaluated using 17 statistical tools for each of the 11 compression index correlations. Comparison between the results showed the best correlations and the less suitable correlations for the database in this study. In this paper an attempt has been made to present the empirical correlations proposed by various researchers for compression index in function of moisture content. The results will be useful in identifying empirical equations to estimate the compression index of Brazilian soft soils.

Keywords: Empirical correlations, Statistical evaluation, Compression index

1 Introduction

In the world, cities such as: Shanghai, Bangkok, Kuala Lumpur, Singapore, Bogota and Mexico City are developing in soil composed of thick layers of soft soils (Pacheco [1]). In Brazil it is common to find this soil in cities such as Recife, Maceió, Salvador, Rio de Janeiro, Campinas, Santos, Porto Alegre, Belém and others.

For the occupation of these lands, where there is presence of soft soils, aiming at construction of houses, roads and implementation of enterprises, landfill is commonly built, generating overload to the land. These constructions are subject to problems, from the geotechnical point of view, of the rupture of the soil mass and of high settlements.

With regard to Geotechnical Engineering, the study of soil behavior is fundamental to understand the deformations starting from addition or relief of tensions. The occurrence of excessive displacements, above the limits allowed by norm, compromise the aesthetics of the construction and the performance of the structure.

The present work cites a particular case of deformation, in which the soil is subjected to a state of geostatic stresses and the load causes only vertical displacements. For this case, it is said that there was as one-dimensional displacement, also known as Oedometric compression.

For the study of Oedometric compression, the Oedometric test is performed. In this test, the variation of height (vertical displacement) of a soil sample is determined while it undergoes vertical loading by modeling a graph of voids index (e) x vertical effective tension log (σ'_v), called compression curve. By means of this graph soil compressibility parameters are obtained which are called: Compression Index (Cc), Recompression (Cr) and Decompression (Cs).

These indices provide us information about the deformation presented by the soil when it is being subjected to a tension or relief. By means of them they estimate the settlements that the soils take to happen, being able to predict the displacements and to develop suitable measures to fight them.

The assay requires some prudence, the same must be done in undisturbed samples, where the structure of the sample brought to the laboratory presents "fidelity" to the structure of the soil in field conditions, and the modifications suffered by the handling is minimal, in such a way that the modifications of their properties are despicable.

Samples for the Oedometric test are carried out in the field by mechanical machinery, and a good process control is required in the extraction and in the laboratory to obtain satisfactory results. Therefore, for the pre-project phase or initial studies, this test becomes expensive and time-consuming.

To facilitate this process it is possible to use correlations. The use of correlations in Geotechnics is a quick way to predict parameter values whose derivation comes from long-term and/or high-cost methods. Researchers (Azzouz [2], Herrero [3], Almeida et alli [4] and others) have sought mathematical-statistical methods to determine the parameters obtained in the Oedometric test, aiming at more agility for the calculation of settlements, creating correlations between these coefficients with more practical physical index (natural moisture content, liquidity limit, plasticity index, among others).

The choice for moisture is given by this parameter, together with the grain density and total specific gravity, are the first indices to be determined when analyzing undeformed samples.

However, many equations cannot be considered valid for any soil conditions, they have their limitations. This affects its use in certain situations, such as moisture content limit and soil type, generating non-reliability in the result for a wide range of parameters.

Therefore, is a need to verify the optimal use of these relationships to determination the Cc to a local in order to verify their consistency with real data.

In this study, are investigated the reliability of some of the empirical relationships in the literature related to the compression index using a statistical evaluation criterion for Brazilian soil data, where the presence of soft soil is significant.

2 Oedometric Compression Test

At the moment the sedimentation process occurs for the formation of soft soil massif, the lower layers are overloaded by the sediments deposited on the subsequent layers. In this case, the soil's own weight provides stress states called geostatic stresses.

The displacement imposed by its own weight is one-dimensional, occurring only in the vertical direction. In this situation it is said that the soil is undergoing confined or Oedometric compression.

The Oedometric compression test seeks to reproduce, in the laboratory, the one-dimensional displacement that occurs in the soil massif after loading.

It consists of molding a specimen in a steel ring, with a diameter/height ratio equal to or greater than three (due to Terzaghi's assumption), from an undeformed sample extracted in the field. The specimen is placed in the test apparatus and compressed vertically (Figure 1).

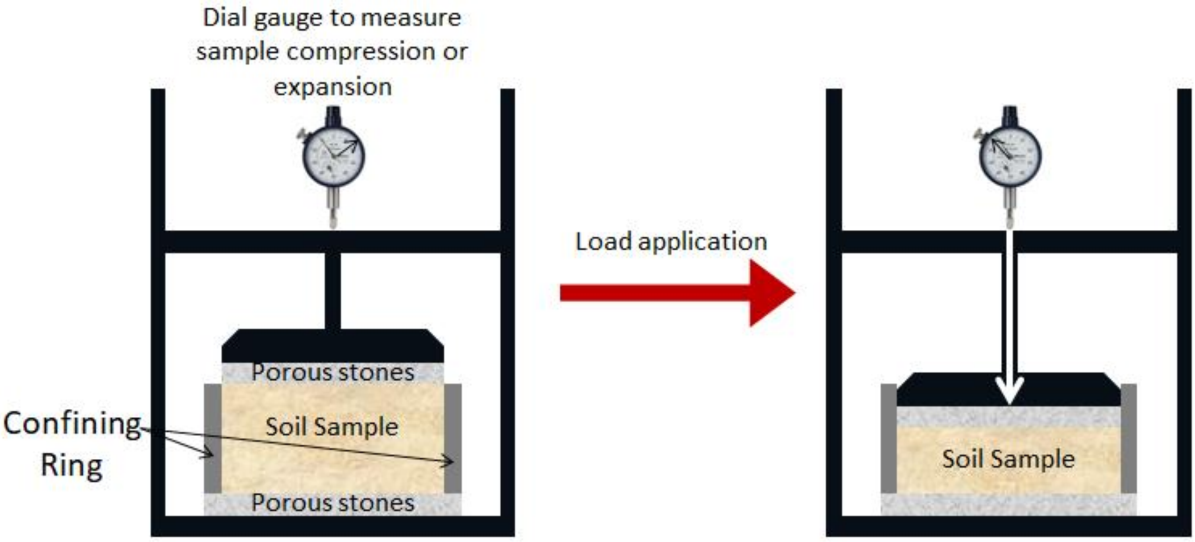

Figure 1. Oedometric Compression Test

The steel ring nullifies the lateral displacements, confining the sample, causing the water flow to occur exclusively vertically. The porous stones act as upper and lower draining boundaries. The lower boundary may or may not exist in the field, a fact that can be seen after site exploration.

The load is applied to the entire surface of the specimen, the relationship between the load and the surface area is the effective vertical stress - σ'_v, at a given loading stage representing the overload imposed on the ground layer.

The application of axial loads is performed in stages. In each step the vertical deformations are read over time with the aid of an extensometer for each load increment. This device is in contact with the upper surface of the soil sample throughout the loading stage. After the deformations of each load cease, loads are applied at twice the intensity of the previous stage.

At each loading stage there is an increase of pore pressure generated by the increased vertical tension. Excess pore pressure, equal to the increase in total vertical tension applied, causes water to flow into the draining boundaries (porous stones). The consolidation of the sample is caused by the reduction of the voids index (e) after water outflow.

One of the objectives of the test is the construction of the Oedometric compression curve e x $log(\sigma'_v)$ presented in Figure 2.

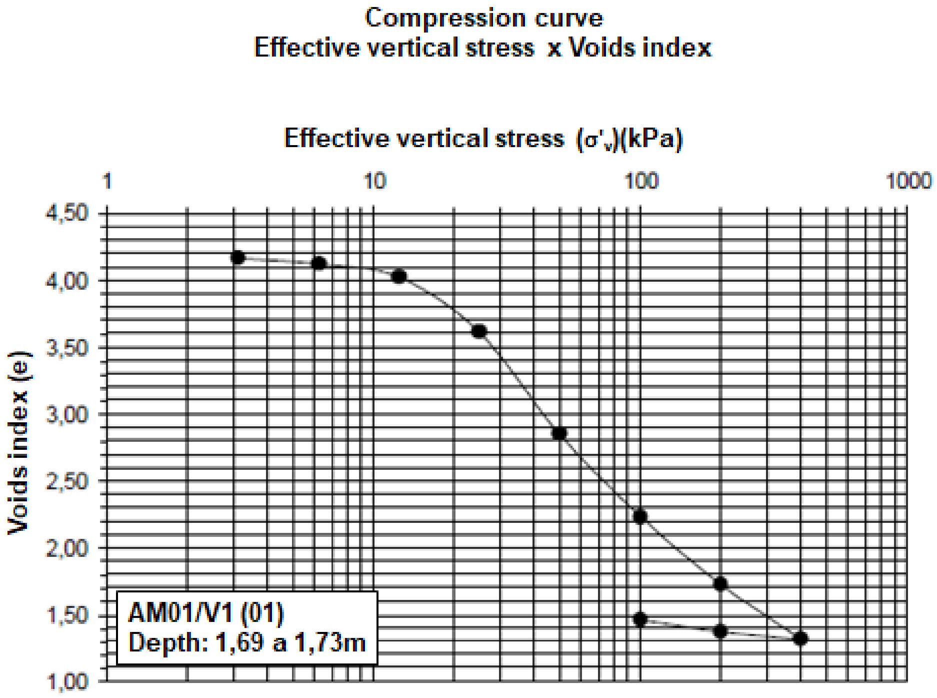

Figure 2. Compression curve e x log (σ'_v) Test - Sarapuí II Clay. Source: Silva [5]

The σ'_v axis is logarithmic so that the virgin compression stretch has a rectilinear shape (Martins [6]). The sequence of applied loads (σ'_v) is double the previous one so that a better distributed spacing is obtained in the graph.

After all load increments have ceased and the data are computed, the $e\ x\ log\ \sigma'_v$ shown in Figure 2 is plotted. From it, it is possible to obtain the compressibility parameters known as compression index (Cc), recompression index. (Cr) and decompression index (Cs), as shown in Figure 3.

All curve indices are angular coefficients of the lines representing recompression (Cr), virgin compression (Cc) and soil decompression (Cs).

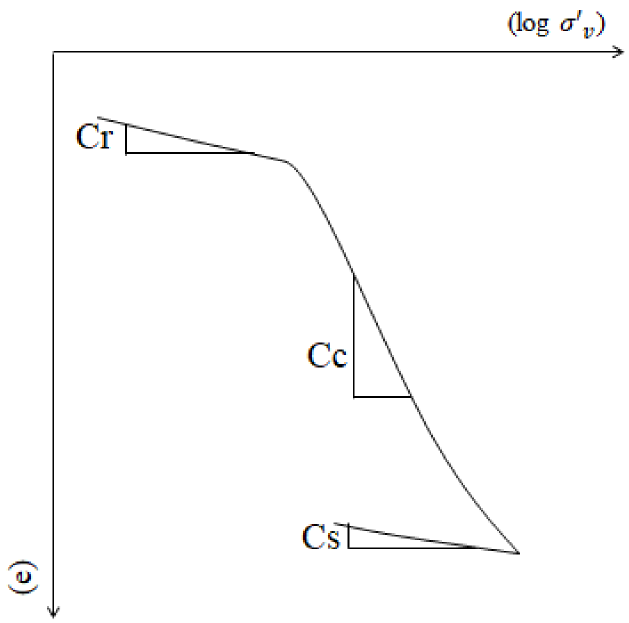

Figure 3. Graph $e\ x\ \sigma'_v\ (log)$

3 Sample reliability

In order to obtain significant results in the assay, the field samples must be of good quality undeformed, in which the structure that arrives in the laboratory is the most faithful to the structure in the field. For this, the soil collection should be done following the procedures described in NBR 9820/1997, which gives the procedures for the collection of undisturbed samples of low consistency soils in drillholes.

Nevertheless, Louvise [7] and Brazil [8] state that most of the undisturbed samples are still of questionable quality due to the low seriousness with which the procedures are performed in the collection, transport, handling and laboratory tests. This directly implies a change in soil properties, causing the sample to soften, masking the correct value of pre-compaction stress and influencing the final value of Cc.

In saturated soft clays, denting is an undrained process that occurs only due to distortions in the sample as no volumetric variation occurs.

Studies by Coutinho [9] showed the denting of tested samples by observing the graph obtained in the Oedometric test (Figure 7). Their study showed that the behavior of the compression curve differs for the cases of good quality undisturbed, poor quality undisturbed and dented specimens.

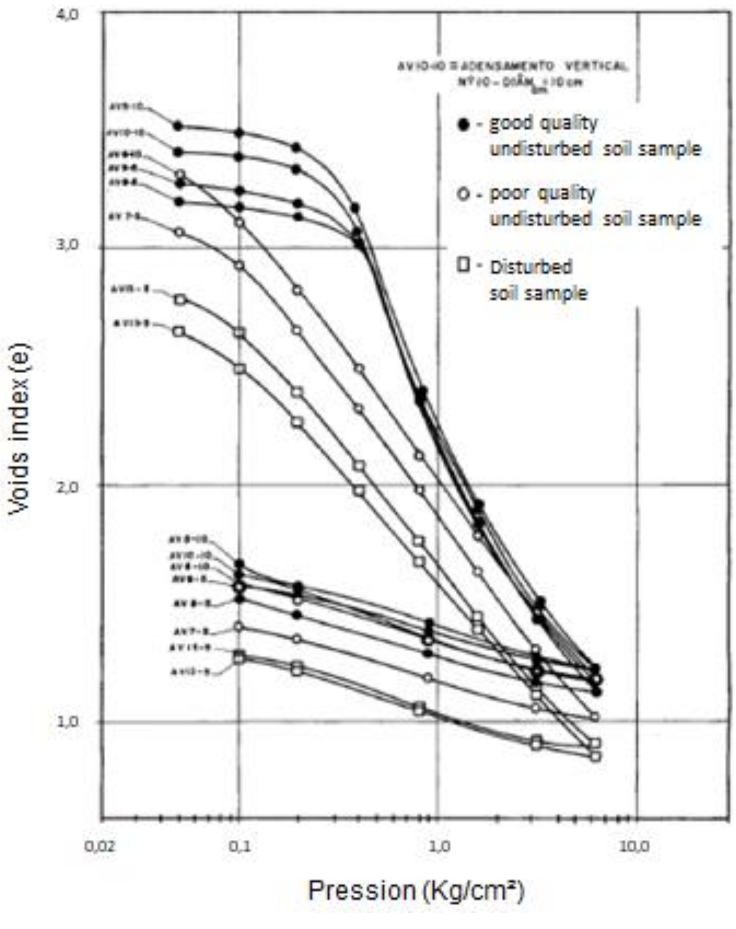

Figure 4. One-dimensional compression curves for Sarapuí clays obtained from good quality, poor quality undisturbed samples and remolded samples. Source: Coutinho [9]

Figure 4 shows that:

• For any value of σ'_v the void index of undeformed samples is always greater than that of deformed ones;

• The curvature of the virgin stretch is less pronounced for so-called dented samples;

• Lower will be the value of the pre-tensioning voltage;
• Increased compressibility in the recompression stretch.

4 Compression index equations as a function of natural moisture content

According to Herrero [3], Helenelund in 1951 proposed an expression relating the compression index to the natural moisture (w_n), being the first author to use this parameter for correlation. From there, many researchers looked for equations that best represented their local soils in function of the natural moisture content.

Azzouz *et alli* [2] cites Moran *et alli* as the precursors, in 1958, to launch an equation for organic soils and Osterberg, in 1972, for Chicago Clay. In their work, Azzouz *et alli* [2] proposed equations for clays from Greece and the United States (USA)

Herrero [3] established a formulation for clays in general. The study of Koppula [10] obtained a similar result to that of Osterberg for cohesive soils. Yoon *et alli* [11] studied clays and silts from Bangladesh, Touiti *et alli* [12] soft clays of Tunisia, Solanki [13] Aluviares deposits of India, Park & Lee [14] soils of Korea, Kalantary & Kordnaiej [15] of Iran.

Almeida *et alli* [4] and Silva [5] obtained their equations from results based on the national literature on soft clays, with clays from Rio de Janeiro.

Table 1 presents the empirical expressions developed by these authors used in the analysis of this work, as well as their applicability criteria. When applying the equations, there are important information that must be seen for the correct use of them, for example: for which horizon of values each expression was idealized.

Table 1. Compression index equations as a function of natural moisture*; $Cc = f(w_n)$*

Reference	Correlation	Applicability
*Moran *et alli* (1958)	$C_c = 0,0115w_n$	Solos Orgânicos
*Osterberg (1972)	$C_c = 0,01w_n$	Argila de Chicago
**Koppula (1981)	$C_c = 0,01w_n$	Solos coesivos
Azzouz *et alli* (1976)	$C_c = 0,01(w_n - 5)$	Argila da Grécia e EUA
Herrero (1980)	$C_c = 0,01(w_n - 7,549)$	Argilas
Yoon *et alli* (2004)	$C_c = 0,013(w_n - 3,85)$	Argila e Silte de Bangladesh
Touiti *et alli* (2007)	$C_c = 0,00667w_n + 0,19034$	Argila mole da Tunísia
Solanki (2008)	$C_c = 0,0091w_n + 0,0522$	Depósitos Aluviares da Índia
Almeida *et alli* (2008)	$C_c = 0,013w_n$	Argila mole do Brasil
Park & Lee (2011)	$C_c = 0,013w_n + 0,115$	Solos da Coreia
Kalantary & Afshin (2012)	$C_c = 0,0074w_n - 0,007$	Argilas de Mazandaran
Silva (2013)	$C_c = 0,0115w_n + 0,8$	Argila mole do Brasil

Not all authors present a significant amount of information about their equations. This lack of data can mislead applications, not representing the behavior of the ranges of values of the variables calculated in the process. The formulations used in this work do not represent all the equations that estimate the compression index, they are only those that correlate it exclusively with the natural moisture and that have a determination index above 0.7 and/or that are very widespread in the scientific environment together with the two Brazilian (Almeida *et alli* [4] and Silva [5]).

5 Statistical Tools for Model Evaluation

To ascertain how well a model describes the behavior of the study variable, it is essential to use statistical tools that can quantify the accuracy and precision of the model. After data collection a central measurement is observed, the average value estimated by the model should approach the measured value (true) for the model to have good accuracy. It has its accuracy assumed if the model is able to estimate values without presenting large dispersions. Standard deviation is the model variability estimator.

To evaluate the model to be built in the present work and the other models found in the literature, seventeen statistical tools were used. The choice for this total of tools was due to the fact that there is no single definitive one in the evaluation of the fit between calculated (predicted) and measured values of any magnitude. Thus, it was decided to evaluate the models in the form of ranking after the analysis with the tools. To understand the formulas, the following statistical metrics are described below:

k: Ratio between calculated and measured value;
Q_c: Calculated (predicted) value;
Q_m: Measured value;
μ_k: Arithmetic mean of k values;
σ_k: Standard deviation of the values of k;
$\mu_{\ln (k)}$: Arithmetic mean of the values of ln (k);
$\sigma_{\ln (k)}$: Standard deviation of the values of ln (k);
n: Number of data;
MA: Mean
MED: Median;
x: Variable (k values);
f(x): probability density function;
$\mu(Q_m)$: Arithmetic mean of Q_m values:

The analysis of the tools starts from the concepts of Mean and/or Standard Deviation.

In this work the calculated and measured values can be compared using the synthetic probabilistic method described by Cherubini & Greco [16]. We then use the “bias factor” k, where in a database of n calculated values (Q_c) and their corresponding measured values (Q_m), k can be calculated by:

$$k = \frac{Q_c}{Q_m}. \tag{1}$$

A value of k greater than 1 means that the calculated value is greater than the measured value (determined in the test). Values less than 1 means that the measured values are greater than those determined by the formulations.

If different methods are being analyzed, such as in this work, different sets of k values can be calculated for a single set of Q_m. In this case, to determine which model better fits the behavior of the measured values, it is necessary to statistically evaluate the predicted values.

5.1 Arithmetic mean

The arithmetic mean indicates the accuracy of a model, ie how well this model describes the data. It is a central trend measure of the data set and is considered the simplest way to describe it. Its expression is given by:

$$\mu_k = \frac{1}{n}\sum_{i=1}^{n} k_i. \tag{2}$$

5.2 Standard deviation

Standard deviation is a measure indicative of accuracy (data set dispersion) relative to the mean.

$$\sigma_k=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(k_i - \mu_k\right)^2}. \tag{3}$$

5.3 Other Tools

Table 2. Statistical Tools

Tool	Equation	Eq.
Determination coefficient (r^2)	$r^2 = \left[\frac{n\sum Q_c Q_m - \sum Q_c \sum Q_m}{\sqrt{n\sum Q_c^{\,2} - \left(\sum Q_c\right)^2}\sqrt{n\sum Q_m^{\,2} - \left(\sum Q_m\right)^2}}\right]^2$	(3)
Ranking Index (RI)	$RI = \left\|\mu_{\ln(k)}\right\| + \sigma_{\ln(k)}$	(4)
Ranking Distance (RD)	$RD = \sqrt{[1 - \mu_k]^2 + [\sigma_k]^2}$	(5)
Mean Absolut Error (MAE_MA)	$MAE\_MA = \frac{1}{n}\sum_{i=1}^{n}\left\|Q_m - Q_c\right\|$	(6)
Median Absolut Error (MAE_MED)	$MAE\_MED = MED\left(\left\|Q_m - Q_c\right\|\right)$	(7)
Mean Square Error (MSE)	$MSE = \frac{1}{n}\sum_{i=1}^{n}(Q_{mi} - Q_{ci})^2$	(8)
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{mi} - Q_{ci})^2}$	(9)
Mean Absolute Percentage Error (MAPE_MA)	$MAPE\_MA\ (\%) = \frac{100}{n}\sum_{i=1}^{n}\left\|\frac{Q_{mi} - Q_{ci}}{Q_{mi}}\right\|$	(10)
Median Absolute Percentage Error (MAPE_MED)	$MAPE\_MED(\%) = 100.MED\left(\left\|\frac{Q_{mi} - Q_{ci}}{Q_{mi}}\right\|\right)$	(11)
Root Mean Squared Prediction Error (RMSPE)	$RMSPE(\%) = 100.\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{Q_{mi} - Q_{ci}}{Q_{mi}}\right)^2}$	(12)
Normal probability (P)	$f(x)=\frac{1}{\sigma_k\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{x - \mu_k}{\sigma_k}\right)^2\right]$	(13)
LogNormal probability (P_ln)	$f(x)=\frac{1}{x\sigma_{\ln(k)}\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{\ln(x) - \mu_{\ln(k)}}{\sigma_{\ln(k)}}\right)^2\right]$	(14)
Nash-Sutcliffe efficiency coefficient (COE)	$E = 1 - \left[\frac{\sum_{i=1}^{n}\left(Q_{c_i} - Q_{m_i}\right)^2}{\sum_{i=1}^{n}\left(\mu(Q_m) - Q_{m_i}\right)^2}\right]$	(15)
Coefficient of residual mass (CMR)	$CMR = \left\|\frac{\sum_{i=1}^{n} Q_{c_i} - \sum_{i=1}^{n} Q_{m_i}}{\sum_{i=1}^{n} Q_{m_i}}\right\|$	(16)
Index of Agreement of Willmott (d)	$d = 1 - \left[\frac{\sum_{i=1}^{n}\left(Q_{c_i} - Q_{m_i}\right)^2}{\sum_{i=1}^{n}\left(\left\|Q_{c_i} - \mu(Q_m)\right\| + \left\|Q_{m_i} - \mu(Q_m)\right\|\right)^2}\right]$	(17)

6 Database

The database of this paper is quantitative and composed by 430 pairs of results of natural moisture and compression index (w_n - Cc) from tests performed on undisturbed soft soil samples found in Brazil. The data was collected from papers, journals, dissertations and theses by national authors.

Of this total, 135 correspond to tests performed on clay samples from Rio de Janeiro, 94 from Santa Catarina, 66 from Pernambuco, 58 Rio Grande do Sul, 54 from Santos, 15 from Maranhão, 5 from Espirito Santo and 3 from Minas Gerais. Table 3 presents statistical descriptive measures of the database.

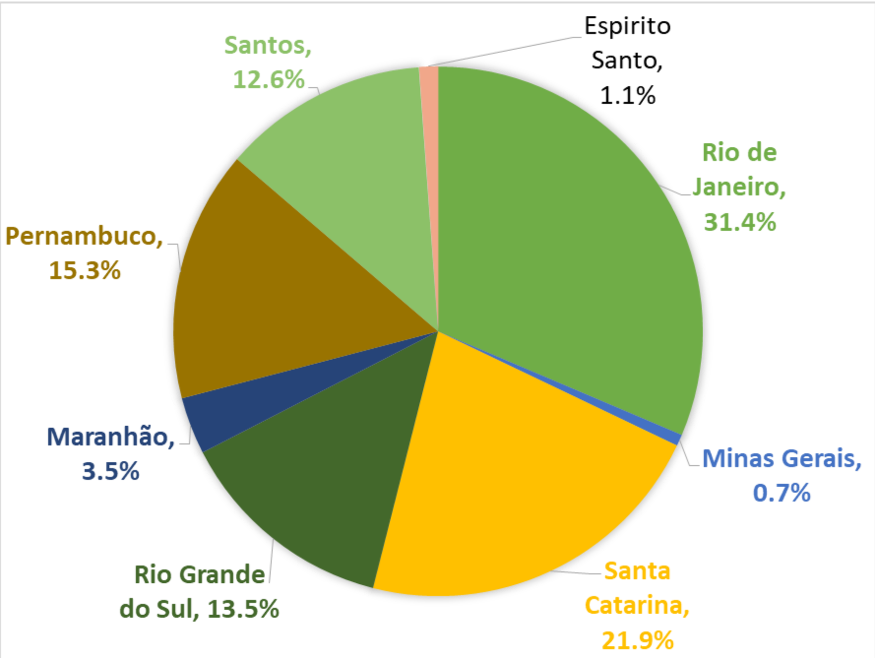

Figure 5. Brazilian sampling

Figure 5 shows the locations from which the data comes and the percentage that each location contributed to the database of this work. Plainly, the absence of data in most of the Brazilian territory is clear, several reasons may explain this fact, as few publications in the area, lack of research / works in the region, lack of infrastructure to perform the tests, difficulty of access to data. by the authors, among others. The states Rio de Janeiro and Santa Catarina are the ones that most contribute for the database to this paper.

Table 3. Descriptive measures of the database

Reference	w_n (%)	Cc
Nº of Data	430	430
Minimum	23.30	0.090
Maximum	784.48	7.270
Mean	120.97	1.550
Median	98.24	1.459
Standard deviation	93.564	1.064
Kurtosis	17.556	6.855
Asymmetry	3.694	2.074

The mean values different from the median values indicate asymmetry, this fact proved by the calculated asymmetry values. Asymmetry greater than 0 reveals that the distribution is asymmetric on the right, also called positive, and can be seen more clearly in Figure 6 obtained from the SPSS (*Statistical Product and Service Solution*) program. Kurtosis shows high values above zero, which indicates a Leptocurtic frequency distribution with tapered curve.

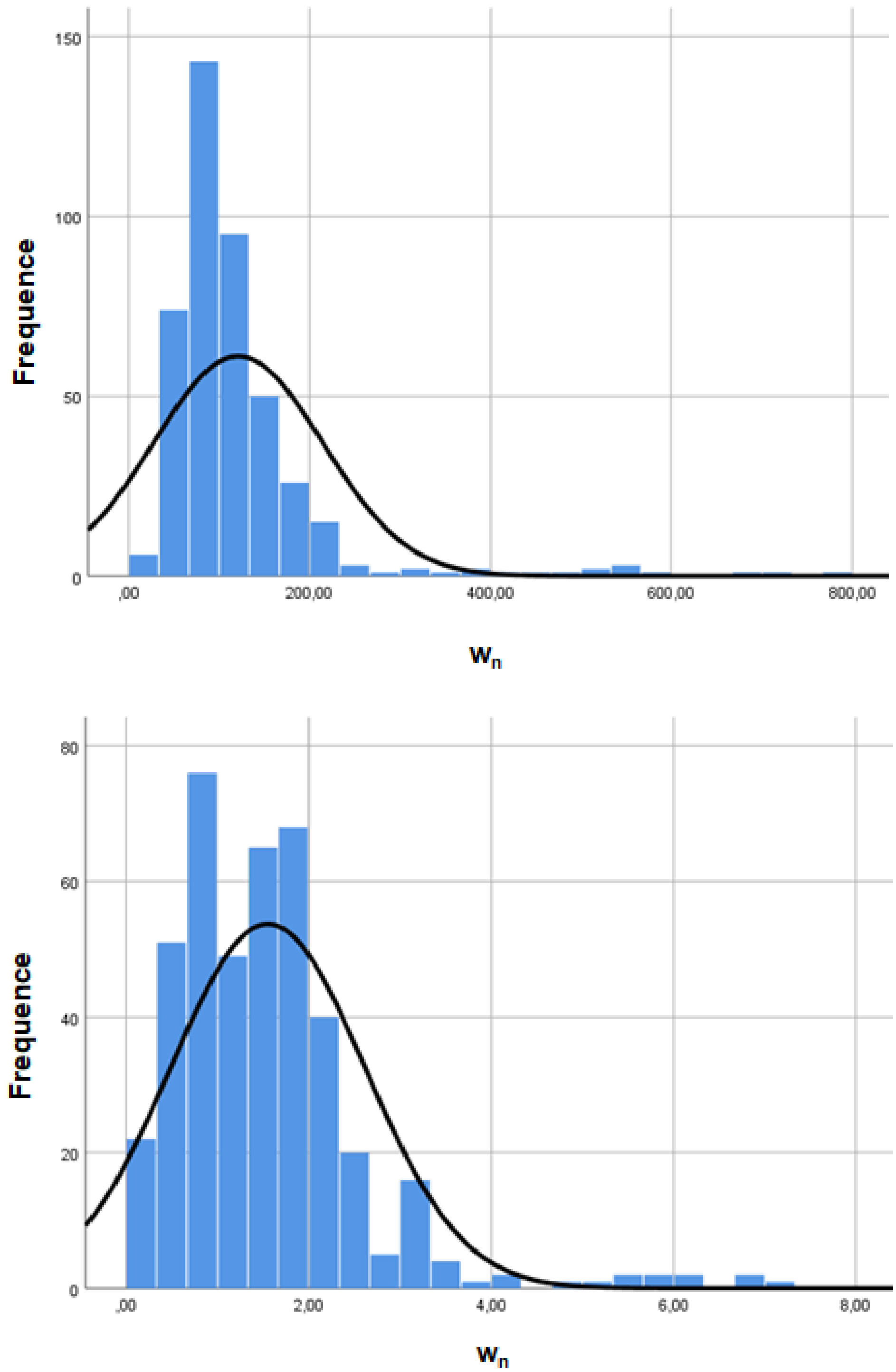

Figure 6. Database Histogram

7 Model Analysis

The statistical analysis tools presented in this paper are used as performance meters of the prediction models seen in this study. All 11 expressions found in the literature, in the universe of 430 w_n x Cc pair data, were analyzed with each of the 17 tools (Figure 7).

The methods were then sorted in ascending order for each tool. The cumulative sum of the ratings (Sum) is used in the overall rating to determine the best expressions. The prediction models that presented the best scores among all the statistical tests accumulated smaller sum, therefore, they have better adjustments to the data. The classification of the original methods can be seen in Table 3. It is important to note that rank prompts the analysis of numerous statistical tools, such as model evaluation, rather than one or three as usual.

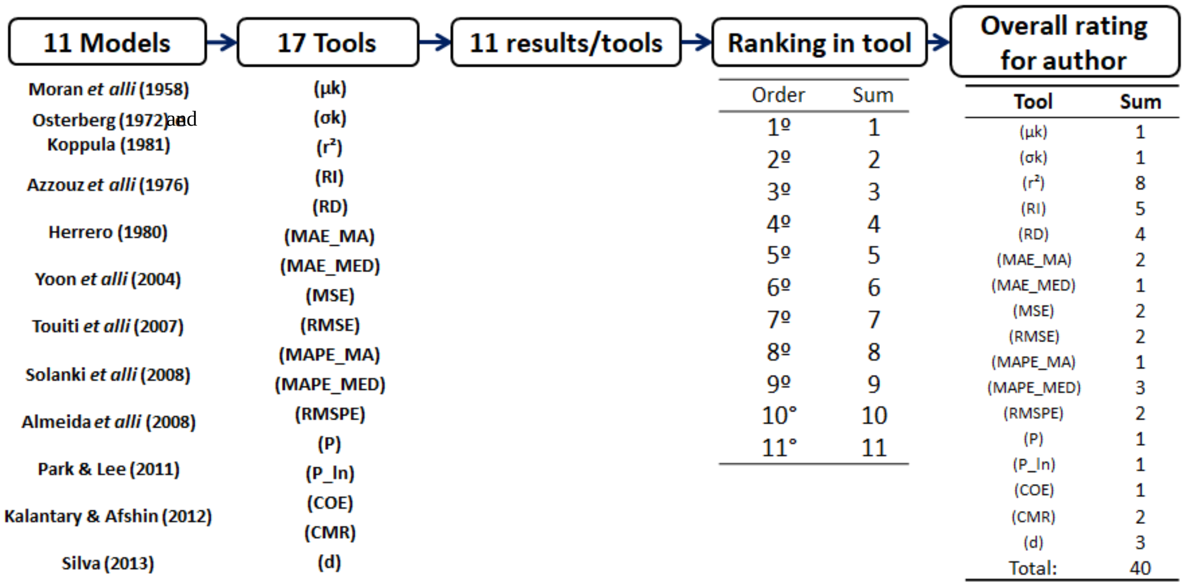

Figure 7. Calculation Scheme

Table 3. Overall Rating - Forecasting Models

Order	Model	Sum
1	Park & Lee (2011)	698
2	Moran *et alli* (1958)	783
3	Yoon *et alli* (2004)	845
4	Almeida *et alli* (2008)	987
5	Osterberg (1972) and Koppula (1981)	1252
6	Azzouz *et alli* (1976)	1515
7	Herrero (1980)	1785
8	Solanki *et alli* (2008)	2324
9	Touiti *et alli* (2007)	2857
10	Kalantary & Kordnaeij (2012)	3101
11	Silva (2013)	3352

Among the models found in the literature, the Park & Lee [14] model best represents the compression index behavior. It is noteworthy that each formulation is made from local data that may differ from the parameters found in Brazilian soils, so the importance of finding out which model can best estimate the compression index for national soils and which models should not be used.

A better view of the behavior of the calculated and measured set of values for the 11 equations can be seen in Figure 8.

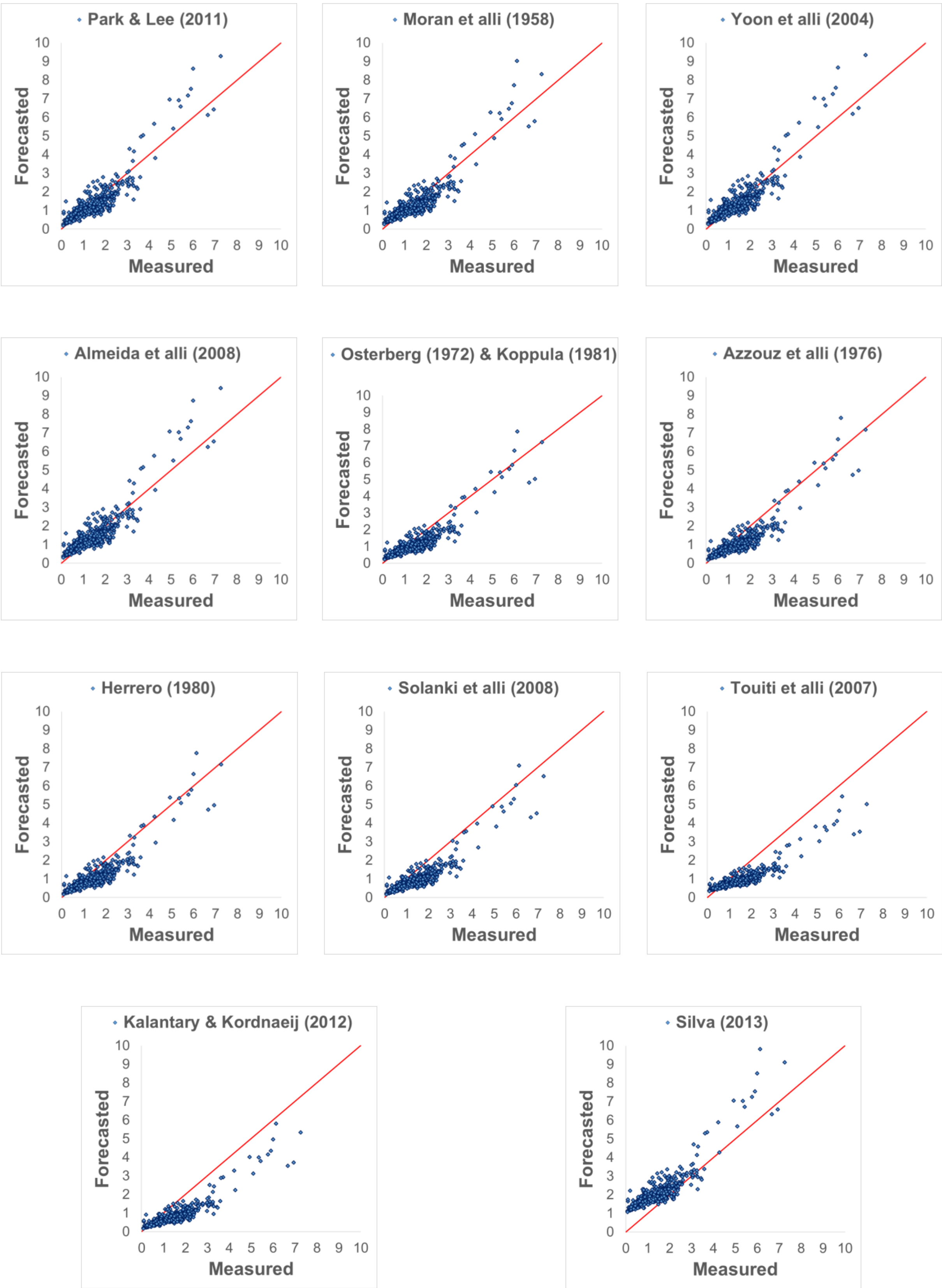

Figure 8. Cc forecasted x measured of formulations

Figure 8 shows a better distribution around the line k = 1 (calculated values equal to measured values) for the expression proposed by Park & Lee [11], Moran *et all* cited by Azzouz *et alli* [2] and Yoon *et alli* [11] compared to the others. The Herrero, Osterberg and Koppula models calculate many values below those measured in the laboratory. This implies a lowering of settlements values as lower Cc values imply lower settlements values.

Almeida et alli [4] present initial calculated values above those found in the database. Among the 11 models analyzed, Touiti et alli [12] and Silva [5] presented the largest dispersions in comparison to the other models (clearly noticeable when the calculated and measured data were presented).

8 Conclusions

The study of correlations is not intended to replace the Oedometric test, it aims only to fasten implementation feasibility of projects since they allow to predict the parameters more quickly and simply than conventional ones. Such formulations should always be implemented within the scope of their applicability, taking into consideration their limitations as presented in this paper, for projects with greater safety criteria or lower cost.

The use of different statistical tools helps in the decision of choosing prediction models, since they show more succinctly errors and concordances between measured (observed) and calculated (predicted) values, so that more accurate equations are employed.

The analysis of the 430 Cc x w_n data pairs of soft soil samples performed in this work indicated that the estimation models of Park & Lee [11], Moran *et all* cited by Azzouz *et alli* [2] and Yoon *et alli* [11] stand out positively for the Cc prediction for Brazilian soft soils.

Correlations can also be employed to predict the results of laboratory tests. This way, it is possible to have a better quality control and confidence in the final result.

References

[1] D. C. Cárdenas Pacheco. Análise numérica da interação de estruturas subterrâneas em solos moles em processo de adensamento, estudo de caso: usina de bombeamento "Casa Colorada". *Dissertation (Master in Geotechnics),* University of Brazilia, 2017.

[2] A. S. Azzouz, et alli. Regression Analysis of Soil Compressibility. *Soils and Foundations, Japanese Society of Soil Mechanics and Foundation Engineering*. vol. 16, n. 2, pp. 19–29, 1976.

[3] O. R. Herrero. Universal compression index equation: Closure. *Journal of Geotechnical Engineering, ASCE,* vol. 109, pp. 755–761, 1983.

[4] M. S. S. Almeida, et alli. Laboratory Behavior of Rio de Janeiro Soft Clays. Part 1: Index and Compression Properties. *Soils and Rocks*. vol. 31, n. 2, pp. 69–75, 2008.

[5] D. M. Silva. Estimativa do Índice de Compressão de Argilas Moles da Costa Brasileira a partir de Ensaios de Caracterização. *Dissertation (Master in Geotechnics), COPPE,* University of Rio de Janeiro, 2013.

[6] I. S. M. Martins. Settlements class notes. *Polytechnic School*, UFRJ, 2011.

[7] R. B. Louvise. Estimativa da curva de compressão de argilas moles a partir de amostras deformadas e ensaios de caracterização. *Dissertation (Master in Geotechnics), COPPE,* University of Rio de Janeiro, 2015.

[8] M. R. Brasil. Cálculo de recalques por adensamento unidimensional. *Dissertation (Master in Geotechnics), COPPE,* University of Rio de Janeiro, 2015.

[9] R. Q. Coutinho. Características de Adensamento com Drenagem Radial de uma Argila Mole da Baixada Fluminense. *Dissertation (Master in Geotechnics), COPPE,* University of Rio de Janeiro, 1976.

[10] S. D. Koppula. Statistical Estimation of Compression Index. *Ceotechnical Testing Journal*, vol. 4, n. 2, pp. 68–73, 1981.

[11] G. L. Yoon, et alli. Empirical correlations of compression index for marine clay from regression analysis. *Canadian Geotechnical Journal*, vol. 41, pp. 1213–1221, 2004.
[12] L. Touiti. Geotechnical Study of Tunis Soft Clay. *14th ARC SMGE*. pp. 177–184, 2007.
[13] C. H. Solanki, et alli. Statistical Analysis of Index and Consolidation Properties of Alluvial Deposits and New Correlations. *International Journal of Applied Engineering Research*, vol. 3, n. 5, pp. 681–688, 2008.
[14] H. I. Psrk and S. R. Lee. Evaluation of the compression index of soils using an artificial neural network. *Computers and Geotechnics, Elsevier*, vol. 38, n. 4, pp. 472–481, 2011.
[15] F. Kalantary and A. Kordnaeij. Prediction of compression index using artificial neural network. Scientific Research and Essays, vol. 7, n. 31, pp. 2835–2848, 2012.
[16] C. Cherubini and V. R. Greco A comparison between measured and calculated values in geotechnics: An application to settlements. In *G. N. Frantziskonis (Ed.), Probabilities and materials: Proceedings of the workshop Probamat*, *21st century, Kluwer Academic Publishers*, pp. 481–498, 1998.