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Recalibrated Correlations between Dynamic Cone Penetrometer (DCP) Data and California Bearing Ratio (CBR) in Subgrade Soil

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Abstract: This study investigates the correlation between the California Bearing Ratio (CBR) and the Dynamic Cone Penetrometer (DCP) for subgrade soil analysis. The paper aims to provide practical equations for predicting CBR values from DCP test results, therefore enhancing the efficiency of soil assessments in engineering practice. By analyzing test data and proposing correlations for different soil groups, the study introduces recalibrated correlations that demonstrate high accuracy in predicting CBR values. The newly proposed equations offer reliable predictions with R^2 values of 0.89, 0.92, and 0.94 for clean sand, silty sand or sandy silt, and cohesive soil, respectively. These correlations serve as valuable tools for engineers, enabling rapid and accurate CBR estimations for improved decision-making in various engineering projects.

Keywords: California Bearing Ratio; CBR; Dynamic Cone Penetrometer; DCP; estimation; prediction; subgrade; sand; soil; cheap and fast

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1. Introduction

The California Bearing Ratio (CBR) is one of the most important characteristics representing the shear strength of subgrade material in pavement structures. To conduct the CBR test, samples must be transported from the borrow pit, prepared, compacted, and soaked in the laboratory, and then penetrated with CBR equipment. Consequently, a truly representative CBR value is difficult to obtain because it takes a long time and is not readily determined in the field. In addition, civil engineers are often faced with the urgent need for the CBR of soil in a short amount of time. A survey of large amounts of material resources for road construction is a good example. Therefore, in the literature, a number of correlations between CBR and other strength properties of soil, such as density, unconfined compressive strength, and DCP, have been established [1–35]. Among these techniques, one of the tests that can provide a highly reliable correlation with the CBR is the Dynamic Cone Penetration (DCP) test [3,4,13,14,17–29,35]. In addition, a CBR prediction from multivariate data analysis and/or method of neural network can also provide highly reliable results [36–42]. However, the multivariate data analysis and neural network method always require input soil parameters that are not already determined in the field. Therefore, DCP equipment, which is considered compact, accurate, and lightweight, is a powerful tool to achieve an efficient onsite correlation between CBR and DCP.

The correlations between CBR and DCP for local materials proposed by many researchers are usually in the form of logarithmic equations, as summarized in Table 1, and the trends of all graphs are depicted in Figure 1. According to the equations in Table 1, a typical form of the DCP–CBR equation can be expressed as shown in Equation (1), where α and β are the fitting parameters. Using the same form of equation, all graphs have the same tendency. It should be noted that when DCP reaches approximately 30 mm/blow, the CBR varies in a narrow range, around approximately 6%. Furthermore, a wide possible range of CBR was found when DCP was less than 30 mm/blow. For instance, when DCP is 10 mm/blow, the possible value of CBR can be approximately 13–32%. In this situation, it is very difficult for engineers to make decisions when selecting the proper CBR. In addition, inconsistency was found in the literature. Wilcesh et al. (2018) [19] reported a single equation that predicted well for various groups of soil (USCS system), i.e., SC, ML, MH, CL, and CH for DCP ranging between 20 and 120 mm/blow. On the other hand, it was revealed from the test data for soil type SM, SP, SP–SM, ML, and CL (USCS system) obtained by Al-Refeai and Al-Suhaibani (1996) [17] that the correlations could predict well for some groups of soil but the data points for all groups of soil were scattered. However, consistency was found from the test results of Feleke and Araya (2016) [18] and the soil type CL of Al-Refeai and Al-Suhaibani (1996) [17]. It was evident that what was available was not enough. However, this was due to the existing test data, which was used to obtain reliable correlations for CBR predictions for general purposes.

Table 1. Existing correlation between CBR and DCP.

Equation No.	Correlation CBR (%), DCP (mm/Blow)	Researchers
1	$Log(CBR) = 2.494 - 1.0672Log(DCP)$	Al-Refeai, Al-Suhaibani (1996) [17]
2	$Log(CBR) = 2.015 - 0.906Log(DCP)$	Feleke & Araya (2016) [18]
3	$Log(CBR) = \frac{112.03}{DCP^{0.808}}$	Wilcesh et al. (2018) [19]
4	$Log(CBR) = 2.81 - 1.32Log(DCP)$	Harrison (1986) [20]
5	$Log(CBR) = 2.20 - 0.71Log(DCP)^{1.5}$	Livneh (1989) [21]
6	$Log(CBR) = 2.465 - 1.12Log(DCP)$	U.S. Army Corps of Engineers (1992) [22]
7	$Log(CBR) = 2.48 - 1.057Log(DCP)$	TRL [23]
8	$Log(CBR) = 2.954 - 1.496Log(DCP)$	Yitagesu (2012) [24]
9	$Log(CBR) = 0.84 - 1.26Log(DCP)$	IDOT (1997) [25]

TRL denotes Transport Research Laboratory, Huntingdon, UK; IDOT denotes Illinois Department of Transportation, US.

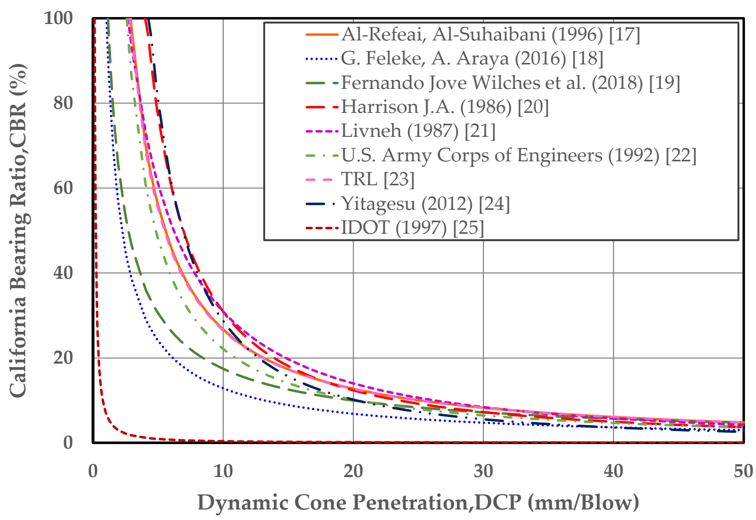

Figure 1. Graphs of the existing correlation between CBR and DCP.

In this paper, the existing test data for various soil types were investigated, and the correlations were recalibrated. Four distinct sets of test results (three existing test results [17–19] and one additional set from this study) were used in the analyses. The coefficient of determination (R^2) was used to evaluate the proposed correlations. Useful recommendations were also provided for practical application with no additional testing.

$$Log(CBR) = \alpha - \beta \cdot Log(DCP) \quad (1)$$

2. Materials and Methods

To recalibrate the existing correlations between CBR and DCP, the test results of soils from many regions and soil groups are required. As mentioned earlier, three existing test results [17–19] were included in the analyses, with one extra test result from five provinces in northeast Thailand. Figure 2 shows the location map for material resources in northeast Thailand. The three existing soil testing datasets [17–19] are not repeated here. On the other hand, soil data from tests conducted in Thailand are shown in Table 2.

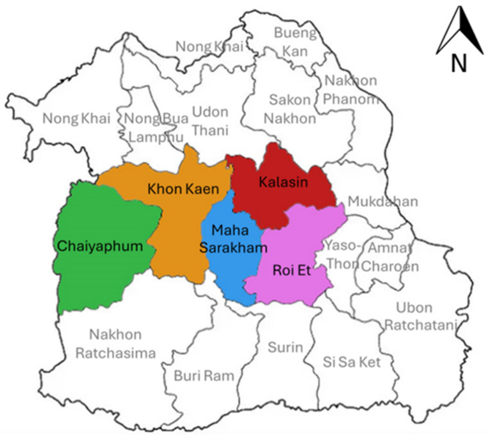

Figure 2. Location map for local material from five provinces of northeast Thailand (Chaiyaphom, Khon Kaen, Maha Sarakham, Kalasin, and Roi Et).

Table 2. Basic soil test properties of soil in northeast Thailand.

Sample No.	LL (%)	PI (%)	G_s	Soil Classification	
				AASHTO	USCS
1	18.27	5.54	2.69	A-2-4	SC–SM
2	24.50	13.21	2.67	A-2-6	SC
3	15.99	4.51	2.65	A-2-4	SC–SM
4	17.43	9.04	2.65	A-2-4	SC
5	19.27	9.75	2.67	A-2-4	SC
6	20.12	11.15	2.65	A-2-6	SC
7	19.50	15.48	2.66	A-2-6	SC
8	18.02	9.57	2.68	A-2-4	SC
9	21.89	16.44	2.63	A-2-6	SC
10	15.78	10.84	2.67	A-2-6	SC
11	20.56	8.86	2.67	A-2-4	SC
12	27.56	20.04	2.66	A-2-6	SC
13	19.95	8.22	2.64	A-2-4	SC
14	23.21	14.61	2.63	A-2-6	SC
15	18.27	6.08	2.62	A-2-4	SC–SM
16	20.32	14.69	2.65	A-2-4	SC
17	19.81	14.92	2.66	A-2-4	SC
18	17.23	10.98	2.68	A-2-6	SC
19	16.72	5.56	2.63	A-2-4	SC–SM
20	17.25	6.12	2.62	A-2-4	SC–SM
21	18.33	11.23	2.64	A-2-4	SC

According to Table 2, most soils are classified as clayey sand (SC), and some of the samples are silty–clayey sand (SC–SM) in the USCS system, while soils are classified as A-2 group in the AASHTO system for all samples.

CBR and DCP testing are two significant tests in addition to the testing of basic properties. The standard for conducting the CBR and DCP were ASTM D1883-21 and ASTM D6951/D6951M-18, respectively. The CBR test method involves several key steps to determine the strength of a soil sample. The soil sample is initially passed through a 19-millimeter sieve. The portion passing through the sieve is used for testing, while the retained soil is replaced with an equal amount of fresh soil. Samples of 6.8 kg are prepared. Compaction is performed to achieve maximum dry densities specific to each specimen. Each specimen is mixed with water to achieve its optimum moisture content (OMC). The soil is compacted in the mold in five layers, with each layer being compacted thoroughly. The number of rammer blows is 56 blows/layer. After compaction, the weight of the mold and compacted soil is measured. In the loading step, the mold with the specimen is placed in a compression testing machine (CTM) under a surcharge load of 4.54 kg. The CTM is operated at a controlled rate of penetration (1.25 mm/minute). During the test, the penetration of the piston into the soil and the corresponding load applied are measured using a dial gauge and a proving ring, respectively. The load applied at various levels of penetration is recorded.

A steel rod with a 60-degree conical tip and a diameter of 20 mm makes up the DCP apparatus. An anvil attached to a second steel rod sits above the rod. This rod serves as a guide so that an 8-kilogram hammer may be raised and lowered from a height of 57.5 cm on several occasions. The anvil is used as the connecting point between the two rods to provide rapid couplings and effective energy transmission from the falling weight to the penetrating rod. After the test gear is put up, the DCP is set up at the test site, and a zeroing scale is created by recording the rod's initial penetration. The weight is hoisted to the top of the rod, 57.5 cm above the anvil, and then dropped while the rod is held vertically. Following each drop, the rod's penetration is measured. To avoid soil binding and the penetration rod affecting test findings, the rod may be gently rotated in cohesive soils. If the target depth is attained or the rod penetrates less than 3.18 mm 10 drops, the test will be declared over. The DCP's dimensions are shown in Figure 3. The penetration depth (D) in millimeters per single drop of the hammer is the definition of the DCP value.

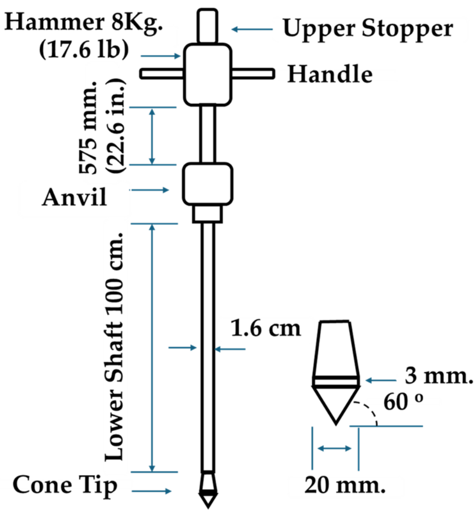

Figure 3. The dynamic cone penetrometer (DCP).

3. Results and Discussions

In this section, the results of both DCP and CBR testing from 21 soil samples in northeast Thailand are presented, and then the analyses for the correlation are described.

3.1. Test Results for Strength Parameters of Subgrade Soils

Prior to the test of CBR, a compaction test had to be performed to obtain the optimum moisture content (OMC) and the maximum dry density (MDD), which is required in the CBR testing procedure. Therefore, the results of DCP and CBR, as well as the MDD, are presented in this section. It is worth noting that MDD is one of the most effective factors that can provide a reliable correlation to the CBR. However, the process of MDD testing has a drawback in that it is time-consuming compared to the DCP test.

Table 3 summarizes the test results of the 21 soil samples in northeast Thailand. The relationship between the DCP and CBR is demonstrated in Figure 4. It is indicated from Table 3 that the DCP values range from 7 to 40 mm/blow, and it is observed that the tendency of the DCP–CBR is similar to those of the DCP–CBR presented in Figure 1. Using Equation (1), the best-fit parameters α and β for soil in northeast Thailand were evaluated, as shown in Equation (2) with R^2 of 0.94. Notably, although Equation (2) can predict well in northeast Thailand, there is no guarantee that the equation for local material is applicable to material in other regions. Therefore, a recalibration process is required and is described in the next section.

$$Log(CBR) = 2.58 - 1.18Log(DCP) \tag{2}$$

Table 3. Test results of 21 soil samples in northeast Thailand.

Sample No.	Soil Classification	MDD (g/cm^3)	DCP (mm/Blow)	CBR (%)
1	SC–SM	1.84	20.83	14.18
2	SC	1.79	13.10	12.92
3	SC–SM	1.71	31.25	5.32
4	SC	1.75	20.00	8.66
5	SC	1.74	25.00	8.13
6	SC	1.79	30.00	7.88
7	SC	1.89	16.67	15.44
8	SC	1.64	30.00	4.54
9	SC	1.76	10.70	21.42
10	SC	1.73	27.50	8.82
11	SC	1.78	22.00	11.50
12	SC	1.86	15.71	13.02
13	SC	1.94	12.50	20.37
14	SC	1.86	17.86	13.55
15	SC–SM	1.85	11.09	14.28
16	SC	1.76	30.64	8.65
17	SC	1.93	10.42	25.87
18	SC	1.70	33.33	5.25
19	SC–SM	1.95	8.93	30.36
20	SC–SM	1.94	7.35	35.46
21	SC	1.69	39.82	5.04

3.2. Recalibration of the Correlations

The recalibration process starts by investigating all test results of DCP–CBR from all types of soil. The data points extracted from [17–19], including from this study, are depicted in Figure 5 with the upper and lower bound lines. Data points can be divided into two ranges of DCP value: (1) DCP less than 30 mm/blow; and (2) DCP greater than 30 mm/blow. For DCP less than 30 mm/blow, CBR decreased with DCP, and the data points were scattered in a wide range. Within this range, it is impossible to determine a unique correlation. This confirmed that test results from local material could not be used in the CBR prediction without any special conditions. For DCP greater than 30 mm/blow, the CBR varied in a narrow range for all types of soil. Therefore, a unique correlation can be established. This agreed with the finding of Wilcesh et al. [19], who suggested a single equation for describing the DCP–CBR relationship in this range of DCP. In addition, despite having the equation of Wilcesh et al. [19], a constant value of CBR of 6% is enough for the estimation of DCP greater than 30 mm/blow. Moreover, when trying to evaluate the existing correlations presented in Table 1 by four sets of test data, the finding showed that the equation proposed by Wilcesh et al. [19] provided the highest R^2 in three cases (i.e., Feleke & Araya (2016), Wilches et al. (2018) and the soil test in this paper), but gave low R^2 for data from Al-Refeai & Al-Suhaibani (1996). Table 4 summarizes the R^2 described above. The numbers in rectangles represent the considered low value of R^2.

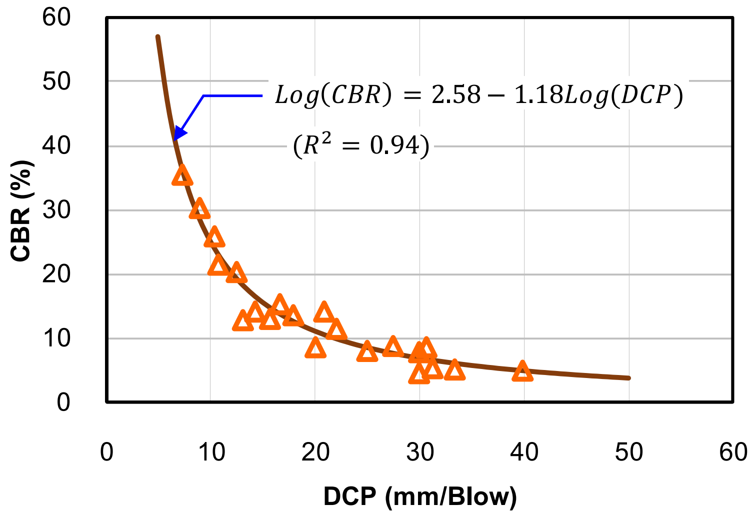

Figure 4. Relationship between the DCP and CBR of soil samples in northeast Thailand.

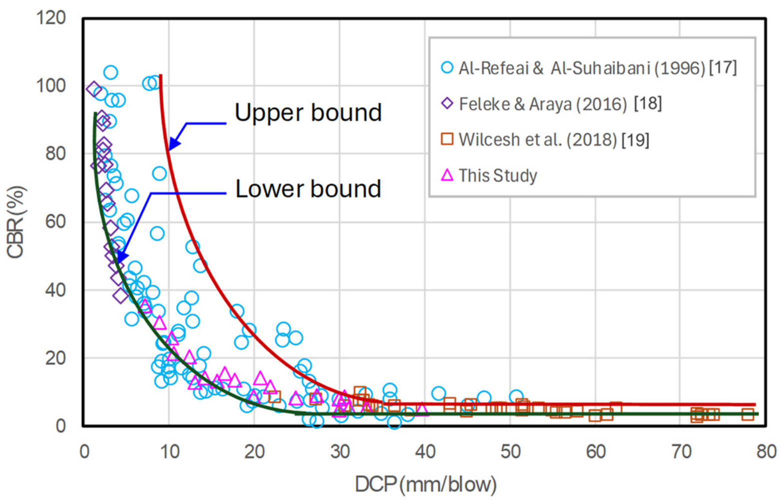

Figure 5. Data plot between the DCP and CBR of subgrade soils.

The special conditions for recalibration are addressed here. It should be kept in mind that no extra testing should be required, and the identifying procedure of soil samples during DCP testing by visual inspection should be enough in the case of the soil type involved. The special conditions added in the analyses are as follows:

(1) The proposed correlations should be in the form of Equation (1) and provide fewer changes or a constant value of CBR when DCP is greater than 30 mm/blow;
(2) The correlation should be separated for the cohesionless and cohesive soil;
(3) For cohesionless soil in which the data points were more scattered, the subgroup, such as clean sand or sand mixed with non-plastic silt (both silty sand and sandy silt), could be an important condition.

Table 4. Coefficient of determination (R^2) of Equations in Table 1 for various soil datasets.

Equation Number	Al-Refeai & Al-Suhaibani (1996) [17]	Feleke & Araya (2016) [18]	Wilches et al. (2018) [19]	This Study
1	0.82	$\boxed{0.45}$	0.96	0.97
2	$\boxed{0.59}$	0.85	0.83	$\boxed{0.77}$
3	$\boxed{0.78}$	0.92	0.97	0.91
4	0.43	$\boxed{0.00}$	0.92	0.93
5	0.85	$\boxed{0.74}$	0.93	0.92
6	0.82	$\boxed{0.67}$	0.92	0.97
7	0.83	$\boxed{0.51}$	0.96	0.97
8	$\boxed{0.09}$	$\boxed{0.00}$	0.81	0.95
9	$\boxed{0.03}$	$\boxed{0.06}$	0.02	0.03

TRL denotes Transport Research Laboratory, Huntingdon, UK; IDOT denotes Illinois Department of Transportation, US.

With these conditions, the proposed correlations can be derived in three subgroups, as shown in Equations (3)–(5) and Figure 6. In analyzing data using the aforementioned conditions, it was also assumed that soils in the same group should yield consistent results independently of the data source. However, it should be noted in grouping that there should be no additional tests to maintain the ease of practical application of the obtained equations. Therefore, SP and SP–SM were grouped as clean sand, SM, ML, and MH were grouped as silty sand or sandy silt, and SC and SC–SM were grouped as cohesive soil.

$$\text{Log(CBR)} = 3.47 - 1.68\text{log(DCP)} \text{ (for soil SP, SP-SM)} \tag{3}$$

$$\text{Log(CBR)} = 2.53 - 1.13\text{log(DCP)} \text{ (for soil SM, ML, MH)} \tag{4}$$

$$\text{Log(CBR)} = 2.32 - 1.03\text{log(DCP)} \text{ (for soil SC, SC-SM)} \tag{5}$$

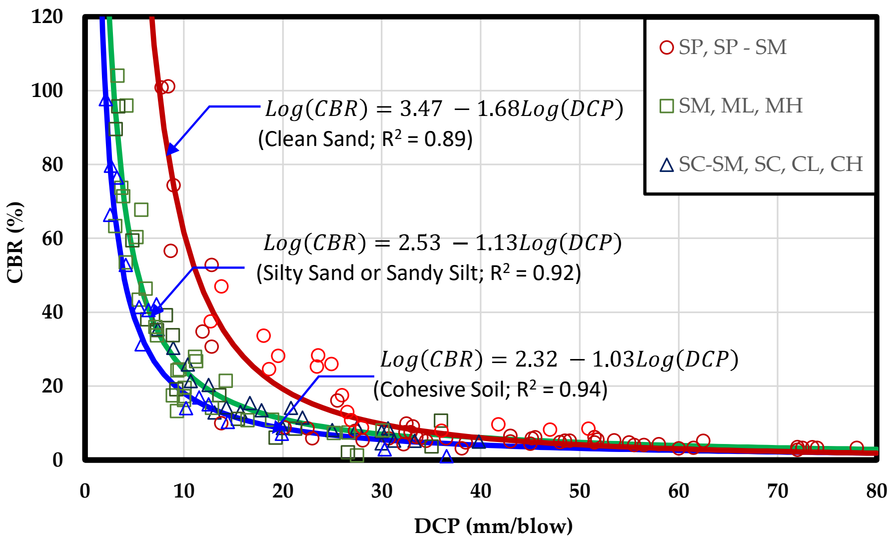

Figure 6. Graphs of new correlations proposed in this paper.

In Figure 6, data points representing soil groups SP, SP–SM, SM, ML, MH, SC, and SC–SM were plotted against the proposed correlations. These correlations were established based on the conditions mentioned earlier, yielding R^2 values of 0.89, 0.92, and 0.94 for clean sand, silty sand or sandy silt, and cohesive soil, respectively. With an R^2 of approximately 0.9, these correlations provided sufficient accuracy for rapid prediction. It was emphasized that visually inspecting the soil before applying the correlations was crucial. Engineers could distinguish between clean sand and sand mixed with silt by observing the particle sizes. If the soil appeared predominantly sandy with visible particles, it was likely clean sand. However, if there were clearly visible portions of finer soil mixed in, it indicated a mixture of sand and silt. Additionally, if the soil exhibited cohesive properties or could be molded into threads when mixed with water, akin to the plastic limit (PL) test, it was classified as cohesive soil. Hence, visual inspection could be effectively combined with the new correlation method.

4. Conclusions

This study focuses on predicting the CBR from the DCP for subgrade soil. By analyzing test data and proposing correlations between CBR and DCP for different soil groups, the researchers aimed to provide simple and practical equations for accurately predicting CBR values in general engineering practice. The findings of the study highlight the importance of recalibrating the existing correlations to ensure applicability across different regions and emphasize the significance of visually inspecting soil characteristics before applying the proposed correlations. The newly proposed correlations demonstrated high accuracy with R^2 values of 0.89, 0.92, and 0.94 for clean sand, silty sand or sandy silt, and cohesive soil, respectively. These correlations offer a valuable tool for engineers to rapidly obtain CBR values, ultimately enhancing the efficiency and reliability of subgrade soil assessments in various engineering projects.

Furthermore, the authors advise future research on the application of multivariate data analysis and neural network modeling if more trustworthy findings in the prediction of CBR are needed and if testing for CBR values should not be rushed.

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