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Predicting the phase composition curve in frozen soils using index properties: A physico-empirical approach

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ABSTRACT

The relationship between unfrozen water content and temperature in frozen soils, which is referred to as the phase composition curve (PCC), is a fundamental relationship in cold regions engineering. In a previous study, the authors succeeded in developing a physical description and a physically-based equation for the PCC, which overcomes the limitations of the existing empirical approaches. Here, the authors propose a physico-empirical approach to predict the parameters in this equation to facilitate the calculation of the PCC in practice. An accurate prediction of the PCC will only need simple soil index properties and one measured data point for constraint. In this approach, the four parameters in the PCC equation are first calculated from soil index properties using accepted formulas. Two selected parameters are then adjusted by a curve fitting process using the measured data point. A criterion was suggested for obtaining the best point. This new approach was implemented using a computer program to automate the process. Validations with data from several soils indicated that the approach offers consistent and accurate predictions of PCCs when used with Zapata's model for plastic soils and with the Mechanistic–Empirical Pavement Design Guide (MEPDG) model for non-plastic soils. This study thus bridges an important gap between the theory and application of PCCs.

1. Introduction

The relationship between unfrozen water content and temperature in frozen soils has been repeatedly confirmed since its first observation in the early 20th century (Buckingham, 1907). In geotechnical engineering, this relationship was extensively studied in terms of phase composition curves (PCCs) in 1960s (Koopmans and Miller, 1966; Williams, 1964). A typical outcome is the considerable number of data published in the First International Permafrost Conference in 1966 (Anderson and Tice, 1972). This relationship has been recognized as fundamental in cold regions engineering due to its essential role as a constitutive relationship between two fundamental quantities in frozen soils, i.e., unfrozen water content and temperature (Anderson and Morgenstern, 1973). The relationship thus links the degree of phase transition to the sub-freezing temperature. As a result, many important parameters in cold regions engineering practice, such as the segregation potential for frost heave (Konrad, 2001), resilient modulus (Bigl and Berg, 1994), and strength (Agergaard and Ingeman-Nielsen, 2012; Akagawa and Nishisato, 2009), can be calculated using PCCs.

Meanwhile, the relationship has also been studied indirectly by soil scientists to obtain the Soil Freezing Characteristic Curve (SFCC), which can be related to the PCC via the Clapeyron equation. The SFCC is the relationship between unfrozen water content and suction in frozen soils. Due to the similar energy relationships in thermal and drying processes (Liu and Yu, 2013; Schofield, 1935), the SFCC is essentially analogous to the Soil Water Characteristic Curve (SWCC) in unsaturated soils. A considerable amount of experimental work has been conducted to explore this similarity (Gardner, 1919; Koopmans and Miller, 1966). Based on this similarity, numerous methods have been suggested for obtaining SWCCs by measuring PCCs (Bittelli et al., 2003; Croney and Coleman, 1961; Schofield, 1935; Spaans and Baker, 1996). Within these studies, the two components of PCC, temperature and unfrozen water content, were usually measured using a thermometer and a liquid water measurement method (e.g., time domain reflectometry, nuclear magnetic resonance, and transmission line), respectively. In more recent studies, PCCs have been measured to obtain other properties of frozen soils, such as the hydraulic conductivity (Arenson et al., 2008; Azmatch et al., 2012).

Despite its long research history and essential role, this relationship has not been studied and applied as intensively as the SWCC in unsaturated soils. One possible reason is that a physical understanding of this relationship had long been absent until recently. As a result, empirical equations were usually used to formulate the PCC. Anderson and Tice (1972) found that the unfrozen water contents of most frozen soils

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can be conveniently expressed as a function of temperature by a simple power curve. Dillon and Andersland (1966) proposed a prediction equation by incorporating the specific surface area, the Atterberg limits, temperature, the clay mineral type, and a defined activity ratio for soils. Similarly, Anderson and Tice (1972) suggested an equation based on a regression analysis of phase composition data for various soils. This equation predicted that water content was a function of the specific surface area and temperature. All of these equations are empirical and thus can hardly guarantee satisfactory predictions under various conditions. This situation caused the nature of the PCC to remain obscured and the relevant research to seriously lag behind.

In a recent study (Liu and Yu, 2013), the authors succeeded in presenting a physical description for the PCC in frozen soils and, for the first time, obtaining a closed-form physically-based equation for this relationship. The proposed prediction equation was proven to yield excellent fitting results for both PCCs measured by the authors (Fig. 1a) and published data for a variety of soils (Fig. 1b), in a large temperature range (Fig. 1c), and in both freezing and thawing processes (Fig. 1d). In spite of these achievements in advancing the PCC research, one more issue still needs to be addressed to facilitate the application of the PCC in engineering practice: how to predict the PCC using soil properties that can be easily obtained, such as the index properties? To address this knowledge gap, this paper presents a physico-empirical approach to predict PCCs using soil index properties. This method can accurately predict the PCC with only one measured data point. The effort overcomes an important barrier for the application of PCCs due to demanding experimental work, and further develops the theoretical framework into a reliable research and engineering tool.

2. Physico-empirical prediction approach

The physical mechanisms necessary for developing the physico-empirical approach, which were described in detail by Liu and Yu (2013), are briefly introduced here. The existence of the PCC is attributed to two physical mechanisms. The first mechanism is the SFCC (Koopmans and Miller, 1966; Liu et al., 2013; Spaans and Baker, 1996), which establishes a relationship between the suction and unfrozen water content in frozen soils. This relation can be expressed as follows,

$$\psi = \psi(S) \tag{1}$$

where ψ is the soil suction and S is the saturation. S is equivalent to the unfrozen water content in a freezing/thawing process. The second mechanism is described by the Clapeyron equation. This equation predicts that the freezing point of pore water will decrease to somewhat below the freezing point of bulk water due to the presence of suction:

$$T = T_0 \exp\left(\frac{\psi}{-\rho_w L}\right) \tag{2}$$

where T_0 is the freezing point of bulk water (273.15 K), ρ_w is the water density (10^3 kg/m^3), and L is the latent heat of water fusion (3.34×10^5 J/kg). Eq. (2) was obtained based on the original equation (Hansson, 2005; Kay and Groenevelt, 1974) by assuming that the ice pressure is zero, which is more a rule than an exception when ice lenses are absent.

A prediction equation can be obtained based on the aforementioned physical mechanisms. In the previous study (Liu and Yu, 2013), the

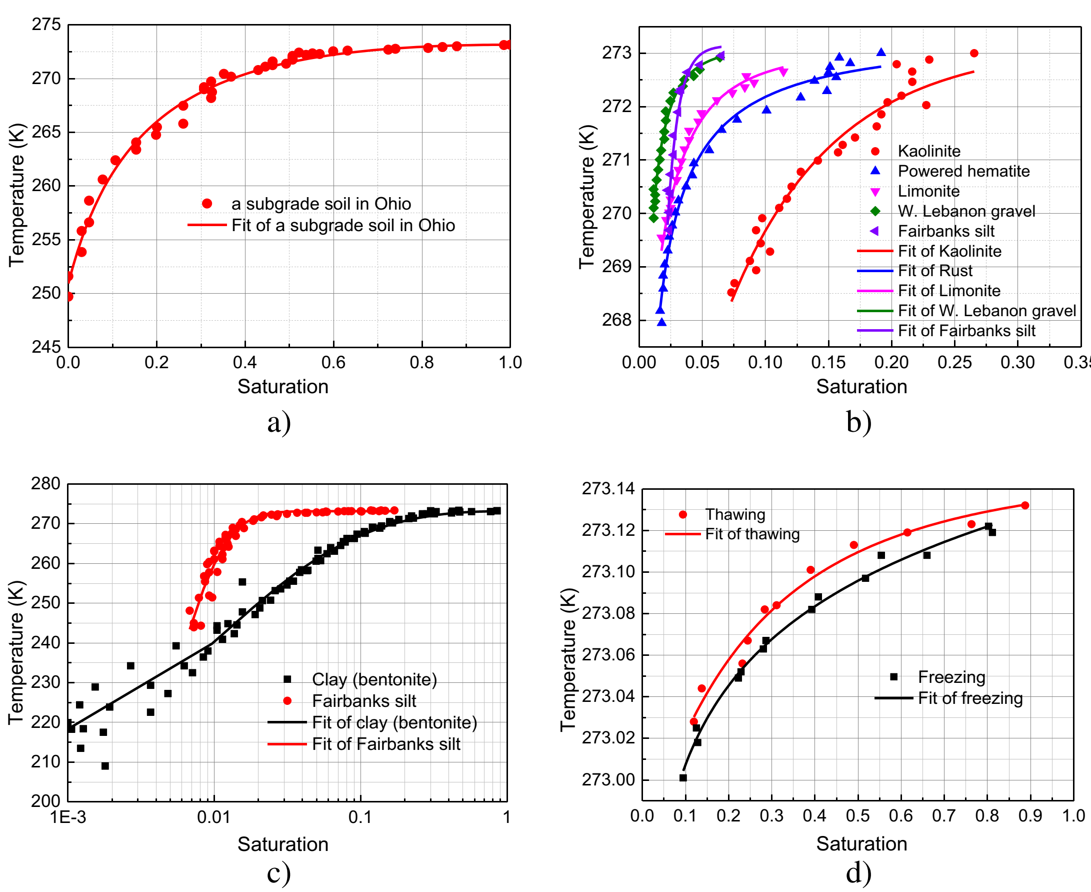

Fig. 1. Validations of the physics-based equation for PCC on various types of soils: a) experimental measured data by the authors; b) published data in literature; c) data in large temperature range; d) freezing and thawing processes (Liu and Yu, 2013).

equation proposed by van Genuchten (1980) was employed for the SFCC, and based on that, a prediction equation for the PCC was obtained. In this paper, the equation presented by Fredlund and Xing (1994) is adopted instead considering that this equation was developed for use over the entire soil suction range. Additionally, the equation achieves good performance at the high suction range (greater than 1500 kPa), which corresponds to temperatures lower than 271.9 K. This equation is therefore expected to support the major range of PCC applications (from several degrees to 20° below the freezing point). The equation proposed by Fredlund and Xing (1994) is as follows:

$$S(\psi) = \frac{C(\psi)}{\left[\ln\left[e + \left(\frac{\psi}{a}\right)^{b}\right]\right]^{c}} \tag{3}$$

$$C(\psi) = \left[1 - \frac{\ln\left(1 + \frac{\psi}{\psi_r}\right)}{\ln\left(1 + \frac{10^9}{\psi_r}\right)}\right] \tag{4}$$

where a is a parameter dependent on the air entry value in Pa, b is a parameter dependent on the slope of SWCC curve after the air entry value is exceeded, C is a parameter dependent on the suction at the residual water content, and ψ_r is a parameter dependent on the suction at the residual water content in Pa. An explicit equation for the PCC cannot be obtained as was done by Liu and Yu (2013), because the inverse of Eqs. (3)–(4) is not available. Alternatively, the PCC is obtained using numerical tools for implementing Eqs. (2)–(4). Typical PCCs for fine- and coarse-grained soils are presented in Fig. 2 using parameters typical of each type of soil.

In order to predict PCCs based on soil index properties, correlations between the fitting parameters (a, b, c, ψ_r) in the PCC prediction equation (Fredlund and Xing, 1994) and soil index properties need to be identified. In fact, many studies have been carried out for partially saturated soils to establish these correlations based on a regression analysis and a considerable pool of data (Chin et al., 2010; Ganjian et al., 2007; Perera et al., 2005; Sung et al., 2005; Torres-Hernandez, 2011; Witczak et al., 2006; Zapata et al., 2000). Three typical models to link the fitting parameters and index properties, which are used in this paper, are summarized in Table 1. Based on the similarity between freezing/thawing and drying/wetting processes, it is hypothesized that the correlations in these models can be applied to partially frozen soils as well. As shown in Fig. 3, the chain-dotted line is the PCC predicted with the correlations proposed by Zapata et al. (2000). As can be seen, the direct prediction using only index properties (chain-dotted line) failed to provide a good estimate of the PCC, and the difference between predicted and measured results is too big to be acceptable in engineering practice.

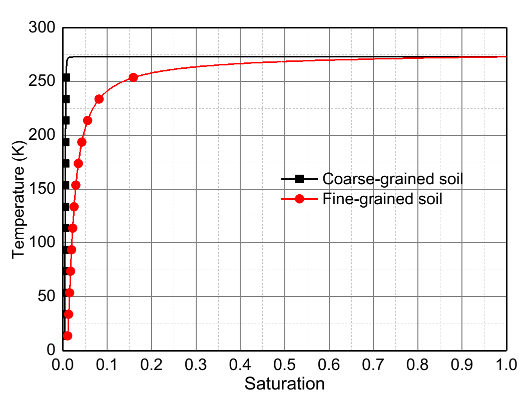

Fig. 2. Typical phase composition curves for coarse- and fine-grained soils.

One possible way to improve the prediction is to incorporate a few measured data points, just like the 'one-point calibration' technology used in the estimation of soil compaction curves (Chin et al., 2010). Also, in SWCC studies, there seems to be a trend that SWCC estimation methods in geotechnical engineering have been extended from being solely based on basic index properties to being based on basic index properties coupled with one-point SWCC measurements (Chin et al., 2010). In the case of PCCs, one unique feature is that values at two special points are pre-determined based on physics, i.e., the point at the start of freezing (approximately the freezing point of bulk water) and the one at absolute zero. With those two known points, we propose to use one additional measured data point to improve the prediction of PCCs. The purpose is to improve the accuracy without requiring a significant amount of experimental effort. A curve fitting process with these three known points in the PCC curve is then used to adjust the fitting parameters that have been calculated previously using the index properties. In such a way, the error of the prediction using only index properties is reduced by taking advantage of information carried by the three known points.

Four parameters need to be determined for the PCC, i.e., a, b, c and ψ_r. As we know, three known points can theoretically guarantee a unique solution to an optimization with up to three fitting parameters. Therefore, we can choose to have one, two, or three parameters as the adjustable fitting parameters and the rest fixed. Our preliminary calculations indicated that curve fitting with only one fixed fitting parameter (calculated using index properties) made it difficult to identify optimal values for the other three fitting parameters, regardless of which three parameters were chosen. In contrast, curve fitting with three fixed fitting parameters (calculated using the index properties) does not provide sufficient flexibility to make predicted results approach measured data satisfactorily. The best curve fitting is achieved by fixing two fitting parameters and adjusting the other two via curve fitting. The values calculated using the index properties serve as the initial guess for the parameters. Within these four parameters, ψ_r is chosen to be one of the fixed parameters considering the lower sensitivity of the SWCC to this parameter than to the others (Torres-Hernandez, 2011). The parameter b is selected as the other fixed parameter because it controls the slope of the SWCC and also because another parameter c was found to be related to it to some extent. Preliminary calculations suggested that the use of a and c as the adjustable fitting parameters yielded satisfactory results in most cases.

Calculations were made for a typical subgrade soil (sample name is S5) from Ohio, whose PCC was measured by the authors using a thermo-time-domain-reflectometry sensor. More details regarding the materials and procedure can be found in Liu et al. (2013). As shown in Fig. 3, the square points are the measured PCC data. The chain-dotted line represents the predicted PCC using index properties alone. The red lines are results obtained by the one-point calibration method discussed above. Each red line corresponds to one data point employed in the curve fitting, which is marked using a cross. In general, a prediction calibrated with a measured data point significantly improved over what was predicted with only index properties. However, as shown in Fig. 3a, the deviations from the measured PCC curve are still significant in some cases, especially for those predictions using measured data close to the freezing point. The major reason is that the absolute value of the sub-freezing temperature (freezing point minus temperature) at such a data point is small. As a result, an error occurring during the measurement at such a point is comparatively large when compared with the absolute value of the sub-freezing temperature. This resultant large relative error carried by this data point will be transferred to the whole range when this point is used in the curve fitting. Therefore, it is concluded that a data point with a lower temperature or a smaller degree of saturation is generally a better choice for ensuring accurate PCC predictions. However, such a data point in the low temperature range of the PCC is usually experimentally demanding to achieve either in the laboratory or in the field. A criterion is thus necessary for defining a

Table 1
Typical models for correlations between the fitting parameters and index properties.

Model 1	Zapata's model (2000)	
Parameter	Plastic soils	Non-plastic soils
a (unit: Pa)	$3.64(WPI)^{3.35} + 4000(WPI) + 11,000$	$862.7(D_{60})^{-0.751}$
b	$[-2.313(WPI)^{0.14} + 5] \cdot c$	7.5
c	$0.0514(WPI)^{0.465} + 0.5$	$0.1772 \ln(D_{60}) + 0.7734$
ψ_r (Pa)	$32.44e^{0.0186WPI} \cdot a$	$a/(D_{60} + 9.7e^{-4})$
Constraints	None	None
Model 2	**MEPDG model (Witczak et al., 2006)**	
Parameter	Plastic soils	Non-plastic soils
a (unit: Pa)	$32,835 \ln(WPI) + 32,438$	$1140a_1 - 500$ $a_1 = -2.79 - 14.1 \ln(D_{20}) - 1.9 \times 10^{-6}P_{200}^{4.34} + 7 \ln(D_{30}) + 0.055a_2 a_2 = 10^{40/m_1 + \ln(D_{60})}$ $m_1 = 30/[\ln(D_{90}) - \ln(D_{60})]$
b	$1.421(WPI)^{-0.3185}$	$0.936b_1 - 3.8$ $b_1 = \left[5.39 - 0.29 \ln(P_{200}D_{90}/D_{10}) + 3b_2{}^{0.57} + 0.021P_{200}^{1.19}\right] m_1^{0.1} b_2 = 10^{-30/m_2 + \ln(D_{30})}$ $m_2 = 20/[\ln(D_{30}) - \ln(D_{10})]$
c	$-0.2154 \ln(WPI) + 0.7145$	$0.26e^{0.758c_1} + 1.4D_{10}$ $c_1 = \ln(m_2^{1.15}) - (1 - 1/b)$
ψ_r (unit: Pa)	5×10^5	1×10^5
Constraints	$a > 5000$, $c > 0.01$	If $a < 1$, then $a = 2250P_{200}^{0.5} + 5000$; $0.3 < b < 4$
Model 3	**Chin's model (2010)**	
Parameter	Fine-grained soils (P200 > 30)	Coarse-plastic soils (P200 ≤ 30)
a (unit: Pa)	$-2400eP_{200} + 7.2 \times 10^5$	$530(D_{50})^{-0.96}$
b	$0.07(eP_{200})^{0.4}$	eP_{200}
c	$0.015(eP_{200})^{0.7}$	$-0.23 \ln(eP_{200}) + 1.13$
ψ_r (unit: Pa)	$9.14 \times 10^5 \cdot \exp(-0.002eP_{200})$	1×10^5
Constraints	None	None

Note: $WPI = P_{200} * PI/100$, in which P_{200} is the percentage in mass passing U.S. standard sieve #200 and PI is the plasticity index; $D_{\#}$ is the grain diameter in mm corresponding to #% of passing by weight; e is the void ratio.

range within which a measured data point (temperature or saturation) is relatively easy to achieve while producing acceptable prediction of PCCs.

Based on intuitive observations, the point corresponding to the maximum curvature in the normalized curve of the PCC predicted with the index properties is tentatively proposed as the critical point. Any point with a temperature lower than that of the critical point is regarded as an acceptable point. The curvature of the normalized PCC can be calculated using Eq. (5),

$$\kappa = \frac{dT/dS}{259.47 \cdot \left[1 + (dT/dS)^2/259.47^2\right]^{3/2}} \qquad (5)$$

where κ is the curvature of the normalized PCC, 259.47 is obtained by subtracting the temperature corresponding to 10^9 Pa, which is used in Fredlund and Xing's (1994) equation, from the freezing point of bulk water (273.15 K).

This criterion restrains the range of temperature or saturation where the one data point for assisting predictions should be measured. For the PCC in Fig. 3b, calculations were conducted on predicted PCC using index properties with Eq. (5) for the point with the maximum curvature. As shown in Fig. 3b, only six data points whose temperature value is lower than 262.5 K satisfy this criterion. All of the six predicted PCCs using the corresponding measured data points agree very well with the measured PCC. Therefore, the proposed criterion further improves the reliability and accuracy of PCC predictions. It is noted that all predictions with one measured point shown in the rest of this paper are conducted with this criterion in place. It must be noted however, that the proposed criterion helps ensure a better prediction for the whole PCC but not necessarily for every single point. A prediction with a measured point can usually offer a better estimate at PCC points close to this point, which could be even better than that predicted using points chosen with the proposed criterion, e.g., in a lower temperature/saturation range.

3. Validation and discussion

A MATLAB program, PCCP, was developed to automatically implement the proposed approach described in the previous section. Calculations were conducted using PCCP to test the performance of the proposed approach for predicting PCCs based on index properties and one measured data point. The proposed approach was applied to predict PCCs of various soils with three different types of correlations presented by Zapata et al. (2000), MEPDG (Mechanistic–Empirical Pavement Design Guide) (Witczak et al., 2006), and Chin et al. (2010), respectively. The first two models were chosen because they are two of the most widely used models; and the third one was adopted because it has also been used in predictions coupled with one measured data point. Validations and discussions were made with respect to the types of the correlations. For each type of correlation, comparisons were made between typical results obtained by direct prediction (with index properties), prediction using one measured point, and that by experiments. Whenever possible, the same soils are used for different types of correlations for comparison purpose. The properties of all soils used in this modeling are listed in Table 2.

3.1. Predictions with the correlations in Zapata's model

Shown in Fig. 4 are the predictions of PCCs for two plastic soils using the proposed approach. Zapata's correlations between soil index properties and the parameters were employed with the prediction equation of the PCC. It can be seen that, for both soils, the predicted results match the measured PCC data very well. One typical application of PCCs is to estimate the unfrozen water content based on measured temperature because temperature is easier to measure. If the predicted PCCs for these two soils are used for that purpose, the maximum and average relative errors for the S3 soil are less than 25% and 7%, respectively; and 16% and 3.9% for QT. Moreover, the error level for some predictions (lines) is actually much less than the above values. Considering that

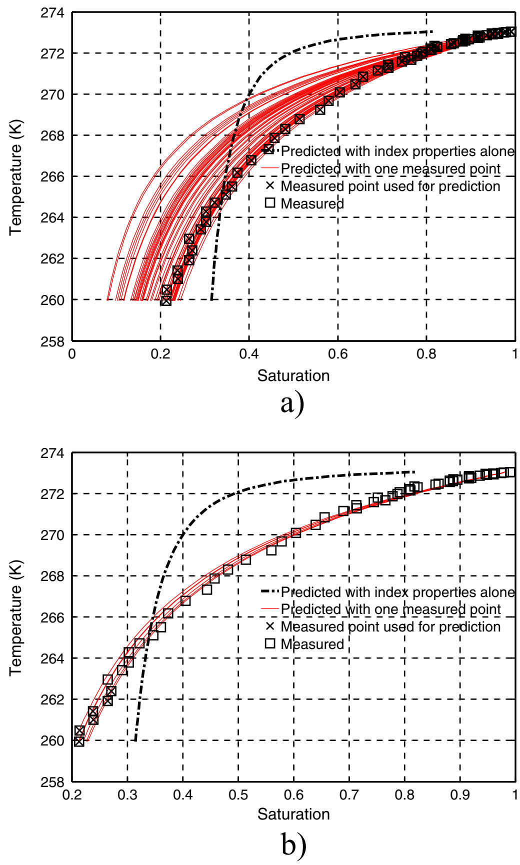

Fig. 3. Comparison between measured and predicted results for a) all data and b) marked data used for each prediction (*square*: measured data; *chain-dotted line*: predicted PCC using index properties alone; *red line*: each line represents a predicted PCC with one measured point; *cross*: data points used for assisting PCC predictions).

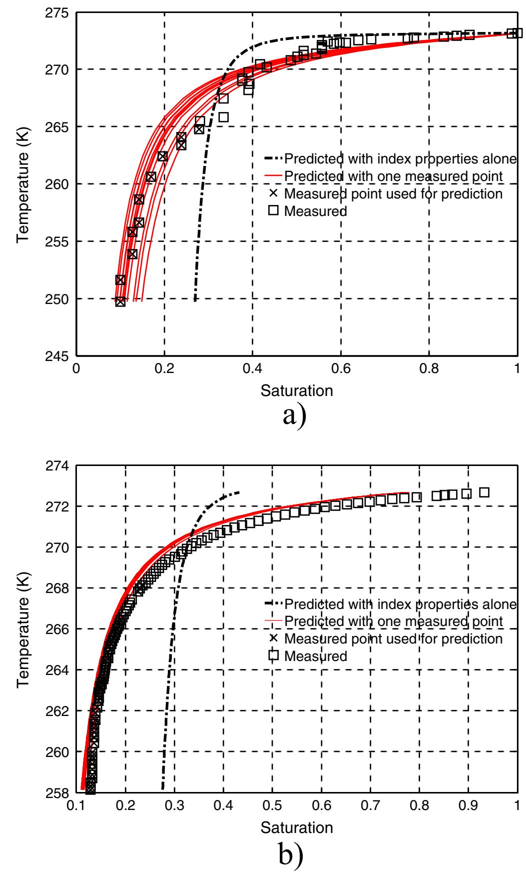

Fig. 4. Predictions with Zapata's model for plastic soils: a) Ohio subgrade soil S3 (Liu and Yu, 2013) and b) Qinghai–Tibet silty clay (QT) (Wen et al., 2012).

only plasticity index, percentage of soil mass passing No. 200 sieve, and one measured data point were used, the results are very satisfactory.

The predictions for non-plastic soils using the correlations in Zapata's model are illustrated in Fig. 5. The predicted curves are not far from the measured data. The predicted unfrozen water content decreases dramatically within a very small temperature range and then stays relatively stable as temperature decreases. That is, the absolute error is not significant at most points; however, the relative error is very large because the unfrozen water content is small enough in most of the temperature range. In addition, the calibration process using a measured data point failed to improve the prediction results for the Wellgreen tailing. This indicates that the fitting parameters predicted with Zapata's model for the non-plastic soil, especially these two fixed during curve fitting (b, ψ_r), are possibly far from their true values.

3.2. Predictions with the correlations in the MEPDG model

The correlations in the MEPDG model for plastic soils use the same index properties as those used in Zapata's model. As shown in Fig. 6, the predicted results obtained by the proposed approach with the MEPDG model are close to the measured PCC, although not as good as those obtained with Zapata's model. This is because parameters used for fitting, i.e., a, c and ψ_r, have a relatively small influence on the shape of PCC, whereas the value of b is believed to be the major factor determining the accuracy of the prediction. Calculations showed that b calculated using the MEPDG model was much smaller than that obtained by Zapata's model when *WPI* was larger than 1.1. And when *WPI* is larger than 1.1, Zapata's model offers a better prediction. According to Table 2, the values of *WPI* for these two soils are above 3. This may explain the relatively poor performance of the MEPDG model than that of Zapata's model when the models were used with the proposed approach for the PCC estimations for plastic soils.

The PCCs for non-plastic soils predicted using the proposed approach with the MEPDG model are compared with measured data

Table 2
Properties of soils used in this modeling.

Soil	Description	*PI*	P_{200} (%)	*e*	D_{10} (mm)	D_{20} (mm)	D_{30} (mm)	D_{50} (mm)	D_{60} (mm)	D_{90} (mm)
S3	Subgrade	11	73	0.51						
S5	Subgrade	22	78	0.54						
QT	Silty clay	10.9	36.1							
Crumbs	Tailing	0	22	0.48	0.011	0.053	0.09	0.25	0.35	1.5
Windsor A	Sandy loam	0	15	0.477	0.047	0.1	0.12	0.24	0.32	0.9
Windsor C	Sandy loam	0	28	0.438	0.034	0.052	0.08	0.13	0.19	0.64

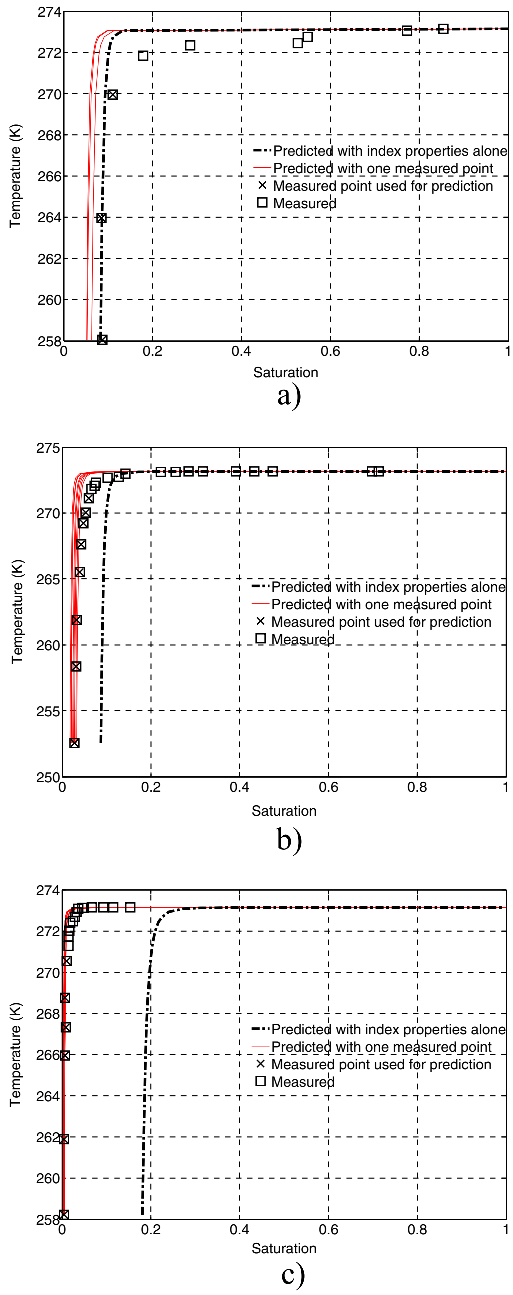

Fig. 5. Predictions with Zapata's model for non-plastic soils: a) Wellgreen tailing (Crumbs) (Northwest Mine Services Ltd., 1998), b) Windsor sandy loam A in freezing (Black and Tice, 1989) and c) Windsor sandy loam C in thawing (Black and Tice, 1989).

in Fig. 7. As can be seen, the direct predictions with only index properties provide better results than average. This makes sense since the correlations consider several index properties including P_{200} and five critical diameters to represent the grain size distribution. The employment of one measured data point also effectively improved the accuracy of the predictions. For all of the three soils, the differences between predicted and measured results are very small. By comparison, it can be clearly seen that the predictions made with the MEPDG model obtained much better results than that made with Zapata's model for the non-plastic soil. The results confirmed the viewpoint that Zapata's model is better than the MEPDG model for plastic soils while the MEPDG model has better performance in non-plastic soils (Torres-Hernandez, 2011). Therefore, the proposed approach for PCC predictions is suggested to be used with Zapata's model for plastic soils and the MEPDG model for non-plastic soils.

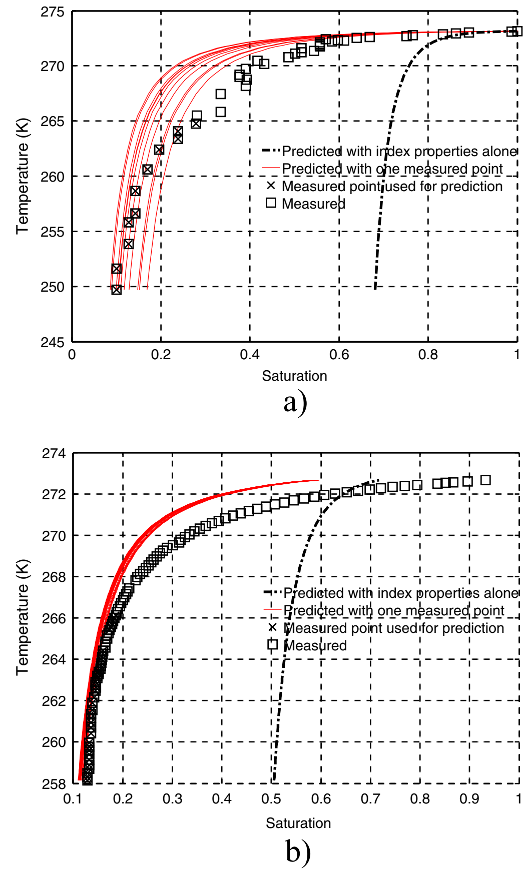

Fig. 6. Predictions with the MEPDG model for plastic soils: a) Ohio subgrade soil S3 (Liu and Yu, 2013) and b) Qinghai–Tibet silty clay (Wen et al., 2012).

3.3. Predictions with the correlations in Chin's model

The proposed approach for PCC estimations was also applied with the correlations in Chin's model. This model was chosen because it had also been employed for SWCC predictions calibrated with measured data. However, results shown in Fig. 8 for both fine- and coarse-grained soils are not as good as those obtained with Zapata's model and the MEPDG model. Hence this model is not recommended in the application of the new approach. We can still obtain two beneficial conclusions for fine- and coarse-grained soils, respectively. Firstly, Zapata's model uses plasticity index for fine-grained soils while Chin's model does not. The better predictions obtained with Zapata's model may imply that plasticity index a helpful quantity for characterizing fine-grained soils, such as the amount of clays and silts. These characteristics may play an essential role in the PCCs of fine-grained soils. Secondly, the MEPDG model includes more index properties than Chin's model. The results indicate that the use of more index properties for coarse-grained soils will yield a better correlation between the index properties and parameters in the prediction equation of PCCs for coarse-grained soils. These two conclusions will be helpful in the formulation or choice of the correlations between soil index properties and the parameters in the prediction equation of PCCs.

4. Conclusion

This paper presents a physico-empirical approach to accurately predict the PCCs of frozen soils. The approach can be used to predict PCCs with only simple soil index properties and one measured data point. A criterion was proposed for determining the measured data point in order to balance accuracy and experimental effort. The

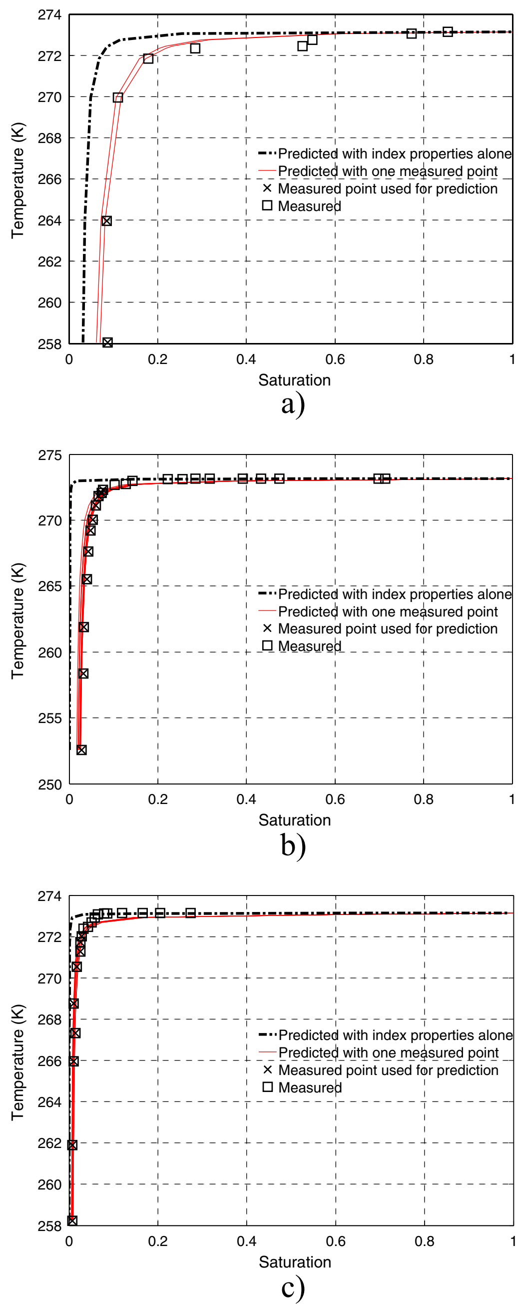

Fig. 7. Predictions with the MEPDG model for non-plastic soils: a) Wellgreen tailing (Crumbs) (Northwest Mine Services Ltd., 1998), b) Windsor sandy loam A in freezing (Black and Tice, 1989) and c) Windsor sandy loam C in thawing (Black and Tice, 1989).

implementation of the approach was automated using a computer program. Predictions have been made with different correlations between soil index properties and parameters in the prediction equations. The comparisons between predicted and measured results for more than ten soils indicated that predictions with only soil index properties are not able to guarantee an acceptable result in most cases. However, the employment of one measured data point significantly improves the accuracy. Good predictions can be ensured when the new approach is used with Zapata's model and the MEPDG model for plastic and non-plastic soils, respectively. The criterion for choosing a measured data point was proven to be capable of effectively ensuring the accuracy of PCC predictions.

It is thus concluded that the new approach provides a practical way to determine the PCC accurately without resorting to extensive

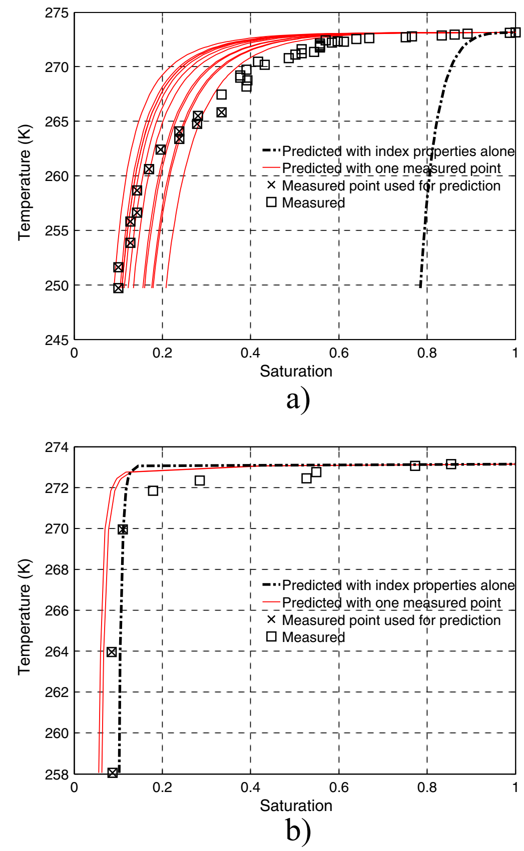

Fig. 8. Predictions of PCCs using the proposed method with Chin's model for a) Ohio subgrade soil S3 (fine-grained) (Liu and Yu, 2013) and b) Wellgreen tailing (Crumbs) (coarse-grained) (Northwest Mine Services Ltd., 1998).

sophisticated experiments. The method can be used by both practitioners and researchers to conveniently predict the relationship between temperature and unfrozen water content in frozen soils with only simple soil index properties and limited measured data. Therefore, this study bridges the gap between the scientific understanding the PCC and the convenient prediction of this relationship with a convenient and reliable engineering and research tool. In addition to the previous work (Liu and Yu, 2013), a framework including a solid physical basis, a mathematical description, an implementing procedure, and a computer program has been well finished.

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