Cite this article

Wang B, Hou H and Zhu Z (2021)
Transparency and applications of transparent soil: a review.
Geotechnical Research 8(4): 130–138,
<https://doi.org/10.1680/jgere.21.00016>

Research Article

Paper 2100016

Received 23/06/2021; Accepted 22/07/2021

Published online 27/10/2021

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Transparency and applications of transparent soil: a review

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The effects of particle size, pore fluid ratio, solution ratio, temperature, time and other preparation factors on the transparency of transparent soil are discussed. The quality of transparency determines the effectiveness of transparent soil in model tests. Also, existing methods cannot quantify transparency in real-time. The history of transparent soil development and the problems encountered in preparation are reviewed; the existing transparency testing methods are scrutinised; and the problems of transparency testing are described. On the basis of progress in the application of machine learning methods to geotechnical engineering, the advantages and technical issues of the method to predict soil transparency are discussed. Lastly, issues that require further research are considered.

Keywords: machine learning/model test/transparency/transparent soil

Notation

A	absorbance
C	concentration of the light-absorbing substance (in g/l)
d_1	distance between the laser incident plane and the boundary of the model box
d_2	laser depth
I_0	incident light intensity
I_t	transmitted light intensity
K	coefficient
L	thickness of absorption medium (in cm)
P_i	transmission power measured by without transparent soil in the glass
P_t	transmission power measured with transparent soil in the glass box
T	transmittance of the transparent soil
Y	transparency of transparent soil
X_1	solute ratio
X_2	solution ratio
X_3	particle ratio

Introduction

Recent research approaches for geological disasters have been predominantly either qualitative or quantitative. Examples include traditional field monitoring (Zhong *et al.*, 2021), numerical simulation (Ji *et al.*, 2016) and model testing (Loveridge *et al.*, 2020). Field monitoring is the most accurate, and the monitoring plan can be adjusted over time depending on the actual situation. However, there are issues such as long distance, difficulty in implementation, inconvenient data, not enough material resources and, of course, lack of time. In contrast, numerical simulation can be implemented easily with minimum manpower and material resources, less time is required and the method returns results quickly. A numerical simulation process needs to establish a simplified model by assuming various ideal parameters that are

different from the actual situation. The model test can be simulated with field rock and soil parameters. The model test data can be collected easily, with less complexity and implementation cost, and the experimental results are more reliable compared with field monitoring. Hence, the model test has been used widely in solving several geotechnical engineering problems.

In the geotechnical model test, the internal deformation of the model is observed mainly by pre-embedded sensors; the observation is point-type, and it is challenging to measure the stress and strain information of continuous lines or surfaces. Thus, a non-intrusive geotechnical model (Qi *et al.*, 2015) is urgently required, one that can observe the continuous deformation of rock and soil without implanting a sensor, which is restricted in non-transparent material.

The deformation of the contact surface between the soil and the box can be detected in the model test by replacing the model box with transparent glass. However, it is not possible to observe the internal deformation of the soil. Thus, the concept of transparent soil has emerged. Not only does transparent soil have the geotechnical properties of soil, but it also enables observation of the internal deformation. Transparent soils are used as a new type of material for model experiments (Iskander 2018). Identification of a similar kind of material for transparent soil has become a new research topic for simulating natural soils.

The transparent soil itself has a transparent state, and the selected material has a refractive index identical or similar to the corresponding pore fluid. Light can pass through the soil without being refracted. Internal soil analysis can be performed externally without ‘intrusive’ treatment such as drilling or embedding sensors. Experiments show that the transparent soil has geotechnical properties similar to those of natural soil. Continuous

deformation inside the soil can be observed by laser speckle and digital image processing techniques (Sadek *et al.*, 2002). For in-depth study of the laws and mechanisms of internal soil deformation, this method has immense importance (Sui *et al.*, 2011).

According to existing research, new problems have emerged during the preparation of transparent soil and model tests. The main problem to be solved urgently is the effect of factors that arise during the preparation of transparent soil, such as particle size, pore fluid ratio and concentration of solutions. Therefore, it is crucial to analyse and evaluate the transparency of transparent soil due to its great theoretical significance and the value of its practical application.

In this paper, the development of transparent soil is reviewed. On the basis of factors that influence transparency, transparency analysis and evaluation methods are discussed. Additionally, machine learning methods to assess transparency are proposed. Existing problems and additional research directions are also discussed.

Development of research based on the preparation of transparent soil

The study of transparent soil began about three decades ago. Allersma (1982) first used transparent materials composed of broken glass to study the stress and strain distribution of materials under single shear conditions. Konagai *et al.* (1992) studied the changes in stress within saturated dykes under seismic loads. Since broken glass has no adsorptive capacity, the air in transparent soil made of broken glass cannot be eliminated from the glass voids. Hence, the transparency effect was poor and could not accurately simulate the soil strength and deformation. Iskander *et al.* (2002) concluded that transparent soils were made by consolidating suspensions of amorphous silica in a pore fluid with a matching refractive index. Sadek *et al.* (2002) concluded that transparent silica gels and amorphous silica have macroscopic geotechnical properties consistent with those of sands and clays. Consequently, the corresponding refractive indices of calcium bromide, mineral oil, and other solutions were considered to be pore fluids. At about 20°C, transparent soil was mixed in a colourless and transparent state, and a laser was used to test the deformation of the spotted surface. To confirm synthesis of the transparent soil, digital imaging technology was used to acquire images. The physical parameters of the soil material were measured in which the internal friction angle was between 19° and 21°. This experiment showed that the geotechnical properties were similar to those of natural soil, thereby establishing the foundation for the follow-up study of transparent soil (Zhong *et al.*, 2021).

Subsequently, other researchers used various materials to prepare different types of transparent soil. Ezzein and Bathurst (2011) developed a new transparent soil by using fused silica sand, Krystol 40 and Puretoll 7. Guzman *et al.* (2014) synthesised transparent soil with fused silica sand and sucrose. By exploring new methods, investigators have evolved the development of transparent soil from preparation to model applications.

With the emergence of new materials and the rapid development of computer programming, investigators have used optical measuring equipment to accurately measure data, and thereby enhance the applications of transparent soil. Researchers have started using transparent soil for their experimental work. In this context, Sadek *et al.* (2003) conducted a series of experiments for observing transparent soil and developed a non-interventional measurement system. They used a digital camera to capture the changes in soil structure and used digital image technology for the analysis, providing technical support for the simulation of natural soil with transparent soil. Subsequently, others used embedded particles in combination with transparent soil in model experiments to achieve the transparency and visualisation in those experiments (Nemat-Nasser and Okada, 2001). Iskander and Liu (2010) improved the modelling for geotechnical and geological environmental engineering by combining optical and image-processing technologies such as particle image velocimetry. The advantages of transparent soil far exceed those of traditional model test materials, and transparent soil can simulate engineering problems under relatively complex geological–engineering conditions. Transparent soil provides strong technical support for the model test, especially the study of the internal mechanism of geological disasters caused by rock and soil mass.

Research on the properties of transparent soil has confirmed that its performance is consistent with natural soil (Cao *et al.*, 2011). Earlier researchers performed a significant amount of work regarding compressive deformation, soil element movement, shear strain, surface uplift, pile foundations, embankments and tunnels. Qi *et al.* (2015) used particle image velocimetry and close-range photography technology to compare the soil unit motion, shear strain and surface uplift of soil elements in transparent soil and natural sand. This method has specific applications in solving some geotechnical engineering problems. Li and Bin (2015) developed a loading system suitable for testing transparent rock samples. By analysing the factors that influence the transparent rock mass of similar materials, the investigators found that engineering characteristics were similar to soft rock. Liu and Iskander (2010) studied the spatial deformation of transparent soil; the investigators considered that transparent soil can be used to study the interaction between soil and structure.

On the basis of the continuous development of transparent soil technology and the necessity to simulate different test conditions, the development of preparation and the properties of transparent soil were summarised. Transparent soils are becoming refined in preparation to meeting particular requirements, and factors that affect preparation are increasingly being identified. The level of preparation determines whether transparent soil can be used successfully in a model test. The basic principle of preparation is to mix two or more materials with the same refractive index (Ezzein and Bathurst, 2011). At the preparation level, the main factors that affect the success of transparent soil are selection of solid particles (aggregate) (Kelly and Black, 2012; Sivakumar *et al.*, 2007), pore solution selection (Zhao *et al.*, 2010), gas content in the mixture (Iskander and Liu, 2010; Sadek *et al.*,

2002) and the ratio of solid particles to pore solution (Ezzein and Bathurst, 2011).

For the selection of solid particles, it is noted that amorphous silica powder and amorphous silica are fused silica with different particle sizes, which are allotropes of silicon. Silica has a range of atomic arrangements. To better simulate natural soil, only transparent particles with small particle sizes were selected. In terms of the pore solution selection, the refractive index for pore fluid should be treated as the primary match, with the solution being colourless, transparent, stable and non-volatile. From the aspect of the gas content in the mixture, during preparation of transparent soil, air in the solid particles or pore solutions will affect the transparency of the soil. For the ratio of solid particles to pore solution, the transparent effect of transparent soil differs from that of various proportional systems.

The preceding four items are the main factors that affect the transparency of transparent soil. For the preparation of high-quality transparent soil, it is necessary to select raw materials with reasonable control of air, temperature and humidity. How do these factors influence the transparency of transparent soil? The establishment of these mathematical relationship models requires a quantitative description of variables; these mathematical relationship models can provide data analysis for the preparation of transparent soil. Hence, the mathematical expression and definition of transparent soil and its constituents are an inevitable choice.

Progress in soil transparency research

Continuous use of transparent soil in model tests and the increasing size of models may cause serious optical errors in the experimental data of transparent soil, and the distortions caused by these observations are often unexplained. How can investigators evaluate the transparency of diaphanous soil? Current methods mainly include grid, digital and letter observations, also visual acuity chart observation, modulation transfer function (MTF) calibration, laser dual-parameter evaluation, transmittance and imaging.

Grid observation method

A grid with a certain spacing is drawn on an A4 size piece of paper to judge the clarity of transparent soil. The grid is placed on the side of a transparent glass box for naked-eye observation (Iskander and Liu, 2010). Sun and Liu (2014) also adopted this method (Figure 1).

Character observation method

The character observation method is similar to the grid observation method. Character observation was used to judge the transparency of transparent soil by printing numbers, letters and other characters on test cards and by placing the cards on the side of a glass box; the box contained a certain thickness of transparent soil, and researchers observed the font size. This method differs from person to person. For example, Ni *et al.* (2010) printed random numbers in Times New Roman on A4

Figure 1. Gridline method

Figure 2. Character observation method

paper to produce test cards. Stanier *et al.* (2014) created test cards with words or phrases having letters of different sizes. Guzman *et al.* (2014) made a similar visual chart using words or phrases of various sizes. All these methods require one to place a card on the side of the glass box to visually observe transparency, as shown in Figure 2.

Thus, transparent soil samples can be compared and judged by visual observation, which is simple, quick, intuitive and easy to operate. Moreover, a visual observation of character size or definition can quickly judge the analytical range of the transparency of transparent soil. Although this method has been used extensively in transparent soil experiments, the method has a few shortcomings.

- Subjective factors have a great effect. The different visual acuities and operating experiences of each investigator cause different evaluations of transparency.
- Because of various types and thicknesses of plexiglass boxes, the observed results are not the same between tests, leading to insufficient actual resolution.
- Relatively large interference factors such as light and temperature affect observation.

MTF calibration method

Because the method of measuring soil transparency with the naked eye is highly subjective and operator-dependent, several investigators have tried to evaluate transparency with mathematical functions. Black *et al.* (2015) proposed an optical calibration method based on MTF to quantitatively evaluate the optical quality of transparent soils.

Black and Take (2015) discussed the possibility of using MTF to quantify the optical quality of transparent soil. They used MTF and digital image correlation to study the correlation between the reduction of the transparency of transparent soil and the accuracy of speckle pattern tracking in transparent soil. On the basis of transparency and the relationship between tracked speckle patterns, investigators can improve the measurement resolution and perform displacement measurement. However, the relationship between transparent soil and influencing factors has not been studied.

Laser dual-parameter evaluation

On the basis of the continuing development of laser technology, Gong *et al.* (2016) proposed a two-parameter method to evaluate the transparency index, as illustrated in Figure 3. This method employs numeric values to measure the transparency of the transparent soil samples, whereas the model test requires specific conditions. Naturally, the observation of the transparent soil was predicted by trial and error and also proved by experimental methods. Furthermore, subjective factors exist in the measurement of incident depth. The distance was also measured by the naked eye and a ruler. Subjective factors arose in observation because of the different refractive indices of the glass box and transparent

Figure 3. Laser two-parameter observation method

soil. Hence, this method will not be easy to implement and has no potential for broader application.

Transmittance observations and imaging method

Transmittance observation and imaging methods are used to determine the transparency of the medium, as shown in Figure 4.

The transmitted light power measured with transparent soil in the glass box is defined as P_t and the transmitted light power measured without transparent soil in the glass box is defined as P_i . The transmittance T of the transparent soil becomes:

$$1. \quad T = \frac{P_t}{P_i}$$

The method mainly evaluates the systematic and random errors of the results obtained by visual measurements. It also analyses the influence of transparency based on visual measurement precision, and it yields the relationship between transparency and the visual measurement. However, this method does not establish a connection between transparency and factors that affect preparation. Lastly, the

Figure 4. Transmittance measuring instrument arrangement

method lacks objective evaluation of parameterisation. In addition, the measurement results are somewhat random because the quality of the sample cell cannot be guaranteed.

The main issues of current transparency research

Transparent soil has been gradually developed to substitute for ordinary soil as a model to visualise rock and soil. The clarity of transparent soil is determined by the analysis of previous studies. Although reported methods of transparency analysis have made progress, the methods of evaluating transparency are highly subjective and dependent on the skill level and subjective judgment of the operator; this subjectivity results in limitations for many methods. Besides transparency, the preparation of a transparent soil environment involves other factors. Existing research focuses on the subjective evaluation of transparency or model tests. However, more factors that affect transparency during preparation need to be considered. Of course, the formation process of transparent soil is always complicated and dynamic, thus a comprehensive analysis of the factors influencing the transparency of transparent soil can be used more widely in model tests. The common problems in the preparation and model testing of transparent soil are summarised below.

- Many factors affect the transparency of transparent soil, for example, subjective factors such as the experience and proficiency of operators, and objective factors, such as material properties, preparation ratio, temperature and humidity. To achieve quantification of all influencing factors, one should also consider operational problems. At present, different particle size ratios, solution ratio and solute ratio are easy to arrange, but the change in transparency, temperature, humidity, time and other factors are not easy to measure.
- Accurate measurement of transparency: transparency is easily affected by the experimenters and other factors (their experience and operation methods). Human subjective error may inevitably occur during measurement. Although removing these errors is important, rapid measurement of transparency is an urgent problem. At present, the UV-2100 UV-visible spectrophotometer can quickly measure transparency, enabling investigators to reduce the negative effect of time on final transparency.
- The third problem is data collection. Big data approaches are being used in geology, and machine learning algorithms have been used in the field of geotechnical engineering. However, the introduction of machine learning in the preparation of transparent soil needs a better experimental basis, and data collection requires considerable time and effort.
- Selection of materials: transparent soil prepared with different aggregates, pore solutions and proportions have different macroscopic properties. Hence, proper material selection is crucial.
- Cost has been an issue. Because different materials with different prices are used, the nature of transparent soils is not uniform.

Feasibility of applying machine learning to transparent soil

Recently, machine learning has been used widely in engineering, material science and other fields. However, many geotechnical engineering problems are non-linear and complex, with numerous random and uncertain factors. Geotechnical engineering problems are entirely influenced by environmental and engineering factors with unpredictable characteristics such as randomness, fuzziness and variability. Machine learning methods can also be represented by a neural network and support vector machine that includes slope stability evaluation and prediction (Guo and Ghee, 2006). Samui (2008) used support vector regression to predict the friction resistance of driven piles in clay. Kuo *et al.* (2009) and Padmini *et al.* (2008) used an artificial neural network to predict the bearing capacity of shallow foundations. Kanungo *et al.* (2014) compared the shear strength parameters predicted by an artificial neural network and regression tree methods. Kiran *et al.* (2016) also proposed a probabilistic neural network to predict the parameters of shear strength in the soil. Pingping (2012) proposed the support vector machine method to analyse geological mining factors and geological environment factors. A satisfactory research effort was achieved by building a non-linear model for comprehensive evaluation and prediction of the quality of the geological environment and by demonstrating examples.

Several new computing methods have emerged with the development of machine learning and optimisation technology. For example, the XGBoost software library, the particle swarm optimisation adaptive network fuzzy reasoning system and genetic algorithm adaptive network fuzzy reasoning systems are useful tools for predicting engineering problems such as flood (Bui *et al.*, 2016; Ostadaliaskari *et al.*, 2016), forest fire (Bui *et al.*, 2017; Dieu Tien *et al.*, 2017), displacement of a hydropower station (Kien-Trinh Thi *et al.*, 2018; Pirnazar *et al.*, 2018), landslide (Chen *et al.*, 2017) and shear strength of soft soil (Binh Thai *et al.*, 2018).

Because transparent soil is a synthetic soil, its transparency is affected by solid particles, pore fluids, time, temperature changes and air in the mixture. Konagai *et al.* (1992) described the evaporation of a component in the pore fluid mixture that changed the refractive index to make the transparent soil completely translucent. However, they did not show how these factors affected the transparency. With the application of a machine learning model and the quantitative concept of transparency of transparent soil, the machine learning method has been used to identify and analyse the transparency data by determining the relationship between transparency and various influencing factors. It is possible to analyse the model test of transparent soil by predicting the transparency.

A fundamental problem of visualisation technology is the definition of the transparency of transparent soil, which often relies on a spectrophotometer. The first spectrophotometer was a colorimeter,

was based on the Lambert–Beer theory for quantitative analysis. It was based on the Beer–Lambert law. The relationship is as follows:

$$2. \quad A = \log_{10} \frac{I_0}{I_t} = \log_{10} \frac{1}{T} = K * L * c$$

where A is absorbance; I_0 is the incident light intensity; I_t is the transmitted light intensity; T is transmittance; K is the coefficient; L is the thickness of absorbing medium (in cm); and C is the concentration of the light-absorbing substance (in g/l).

Problems with machine learning in transparency test

Cuvettes in the UV-visible spectrophotometers can measure changes in the transparency of the transparent soil. In the experiment, data collection is performed based on concepts such as transparency, solute ratio, solution ratio and particle ratio. A database is created, and then a complete mathematical prediction model is established in conjunction with machine learning artificial intelligence methods. This method can provide necessary data support for the preparation and analysis of transparent soil by enabling scientific and reasonable data support, and by establishing a suitable machine learning prediction model.

To verify the rationality of using machine learning to characterise soil transparency, a three-factor and five-level transparency experiment was initially designed, and 125 data sets were collected for machine learning. Transparency was measured by putting transparent soil in a cuvette, with external dimensions of $12.5 \times 12.5 \times 45$ mm (length, width, height) and a rectangular cross-section, and the internal square size was 10×10 mm (Figure 5(a)). The cuvette was placed in a UV-2100 spectrophotometer to collect data (Figure 5(b)). The incident wavelength was 800 nm. The transparent soil was taken as the

dependent variable (Y), and solute ratio solution ratio and particle ratio were considered as independent variables X_1 , X_2 , and X_3 , respectively, to generate a data set for modelling in the transparency test. Figure 6 shows the statistical data used for the experiment.

While using machine learning for transparency testing, the following issues should be considered.

- Simplification of transparency measurement
Methods of testing transparency have been diversified with the continuous development of testing equipment. A UV-visible spectrophotometer can monitor changes in transparency. Support

Figure 6. Transparency data map of 125 groups of transparent soil samples

(a)

(b)

Figure 5. Transparency measuring equipment: (a) cuvette, with external dimensions of $12.5 \times 12.5 \times 45$ mm (length, width, height); (b) UV-2100 spectrophotometer

for the machine learning application requires obtaining appropriate data such as transparency to accurately reflect the characteristics of the soil.

■ Data sources

With the improvement of machine learning technology and the development of measuring equipment, investigators can introduce machine learning into the evaluation of transparent soil preparation. Machine learning will also have a significant function in the field of a model test of transparent soil, and its prediction level can expand the application of artificial intelligence systems. However, compared with traditional methods, existing machine learning models require more data and other test information; these requirements limit applications to indoor model tests of rock and soil mass.

■ Algorithm optimisation

A machine learning algorithm combined with a mathematical algorithm has to be continuously optimised according to experimental requirements. Also, the technical limitations of a machine learning algorithm need to be overcome. To achieve performance optimisation, the super parameter adjustment needs to be conducted constantly. Traditional parameter tuning methods, such as trial and error, are complicated and time-consuming (Snoek *et al.*, 2012). Hyper-parameter tuning of the machine learning algorithm can not only obtain a better model, but can also save time.

■ Coupling of multiple factors

The factors influencing transparency are complex and changeable. The ultimate transparency of transparent soil is not usually determined by a single factor during preparation, and they usually do not appear in a single process, but in an interactive process. In the analysis of transparent soils, machine learning should not only study the influence of various materials on transparency, but also consider multi-field coupling of materials.

■ Establishment of an evaluation and forecast system

On the basis of machine learning technology, the transparency of transparent soil was judged. After the necessary improvement of the algorithm, an evaluation and prediction system must be realised based on transparency and the relationship between various factors. Limitations of machine learning algorithms will be overcome and the algorithms will exert greater potential by combining shear strength and transparency to define the characteristics of transparent soil.

Conclusions

Transparent soil has gradually become an ideal model because of its transparency, lack of internal damage and good simulation results. The development of transparent soil and of transparency testing, and the application of machine learning to existing geotechnical problems have been reviewed and summarised. The feasibility of using machine learning in evaluating transparency has been explained, and the following conclusions have been drawn.

- The basic principle of preparation is the use of two or more materials with the same refractive index. In the preparation

process, the main factors that affect the success or failure of transparent soil are effects of particle size, pore fluid ratio, solution ratio, temperature and time. To measure transparency, current methods mainly include grid observation, digital observation, letter observation, visual acuity chart observation, MTF calibration, laser dual-parameter evaluation, transmittance observation evaluation and imaging.

- Machine learning has been used widely with good results to examine geotechnical engineering problems, but machine learning has not been used to analyse transparent soil. This situation is mainly because machine learning requires a large amount of real-time data, and the observation of the transparency of transparent soil is currently unable to achieve rapid quantification; in addition, an unsolved problem is how rapid quantification could be achieved.

- The concepts of transparency and rapid measurement have been introduced with the development of machine learning technology in the assessment of the preparation of transparent soil. With continuous development of testing equipment, investigators can collect transparency data with UV-visible spectrophotometer instruments, to reflect the transparency characteristics of transparent soil accurately, and to provide a wider range of applications for machine learning. Machine learning analysis will further improve the success of preparation; it will have a significant effect in the model testing of transparent soil; and its prediction capability will be expanded to the implementation of artificial intelligence systems.

Acknowledgements

This work was supported by the Fundamental Research Funds for the Central University (2018CDYJSY0055), the National Natural Science Foundation of China (51478066), and the Chongqing Natural Science Foundation of China (cstc2018jcsx-msybX0271). The authors thank AiMi Academic Services for English language editing and review services.

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