Availability of the particle filter methods on identification of soil hydraulic parameters based on field measurement

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ABSTRACT

The identification of soil hydraulic parameters is of great importance on the study and simulation of rainwater infiltration. Recently, due to the development of sensing technology, field measurement systems have been largely spread. In the systems, volumetric water contents or matric suction are measured, and a large number of field measurement data are accumulated. In this study, the authors tried to identify the soil hydraulic parameters based on the field measurement data, by using the Particle Filter method. As a result, the numerical simulations using the identified parameters were in excellent agreement with field measurement data. Therefore, the availability of the Particle Filter method on identification of soil hydraulic parameters based on field measurement was verified.

Keywords: particle filter; soil hydraulic parameters; field measurement

1 INTRODUCTION

The changes in climate all over the world have been brought an increase of heavy rain. As a result, a large number of landslide disasters occur every year. The landslide disasters are caused by infiltration of too much rainwater into the slope. Therefore, both present monitoring and future prediction of the soil hydraulic conditions in the fields are required, in the prevention of the landslide disasters.

Some field monitoring systems have been developed to assess the risk of landslides under conditions of heavy rain in Japan (Koizumi et al., 2012). In the systems, present soil hydraulic conditions, such as volumetric water contents or matric suction can be measured in real time. Moreover, they are accumulated automatically, and can be reused. However, the systems cannot predict the future soil hydraulic conditions.

Data assimilation methods are one of the inverse analysis methods originated from modifying numerical simulation model based on measurement data. They have been developed in the field of meteorology and oceanography. Several kinds of data assimilation methods, such as 4D-VAR (Talagrand and Courtier, 1987), Ensemble Kalman Filter method (Evensen, 1994), and Prticle Filter method (PF) (Gordon et al., 1993; Kitagawa, 1996) have been proposed. In the Geotechnical Engineering, the PF was applied to identify the mechanical parameters of elasto-plastic constitutive model based on the data of consolidation settlement (Shuku et al., 2012; Murakami et al., 2013).

In this study, the availability of the PF on identification of soil hydraulic parameters based on field measurement is discussed. Firstly, an inverse analysis, in which the PF is applied, is proposed. In the analysis, seepage analysis methods and data assimilation methods by the PF are combined. Secondly, the soil hydraulic parameters are identified by applying the proposed inverse analysis at three slopes which have different types of soils. Finally, the availability of the identified parameters is discussed through the numerical simulations.

2 ANALYTICAL METHODS

2.1 Seepage analysis methods

In this study, an unsaturated-saturated seepage finite element analysis is used to reproduce the infiltration behavior of rainfall into the ground. The following equation, Richards equation (Richards, 1931), is applied in numerical analysis:

$$C \cdot \frac{\partial \psi}{\partial t} = \frac{\partial}{\partial x}\left(k \frac{\partial \psi}{\partial x}\right) + \frac{\partial}{\partial y}\left(k \frac{\partial \psi}{\partial y}\right) + \frac{\partial}{\partial z}\left\{k\left(\frac{\partial \psi}{\partial z} + 1\right)\right\} \tag{1}$$

where C ($=\partial\theta/\partial\psi$) is hydraulic capacity function, θ is volumetric water contents, ψ is matric suction, and k is unsaturated hydraulic conductivity. The following van Genuchten model (van Genuchten, 1978) is adopted to express the soil water characteristic curve, and Mualem model (Mualem, 1976) is adopted to estimate the unsaturated hydraulic conductivity:

$$S_e = \frac{\theta-\theta_r}{\theta_s-\theta_r} = \left\{\frac{1}{1+\left(-\alpha\cdot\psi\right)^n}\right\}^{1-\frac{1}{n}} \quad (2)$$

$$k = k_s\cdot S_e^{0.5}\cdot\left\{1-\left(1-S_e^{\frac{n}{n-1}}\right)^{1-\frac{1}{n}}\right\}^2 \quad (3)$$

where the following notations are employed. S_e: effective soil water saturation, θ_r: residual volumetric water contents, θ_s: saturated volumetric water contents, α, n: material parameters, k_s: saturated hydraulic conductivity. In this study, θ_s, θ_r, α, n, k_s are unknown soil hydraulic parameters.

2.2 Particle filter methods

The PF is one of the sequential data assimilation methods. In the PF, a probability distribution of physical quantity is approximated with its realizations. Each realization is called a particle, and each set is called an ensemble. The PF evaluates the number of particles at a discrete time, using the Bayes' theorem. Fig. 1 shows the computational procedure of the PF. Firstly, a large number of numerical simulations, in which different sets of soil hydraulic parameters are applied for each particle, are carried out ((a) Prediction in Fig. 1). Then, the likelihood is evaluated for each particle through a comparison of measurement data and simulated data ((b) Filtering in Fig. 1). Finally, the number of particles is updated ((c) Resampling in Fig. 1). That is, the particles with high likelihood should be replicated. On the other hand, those with low likelihood should be eliminated. In the PF, the particles which have higher compatibility to the field measurement data could be remained through iteration of those three steps.

3 ANALYTICAL RESULTS

In this study, the availability of the PF on identification of soil hydraulic parameters was discussed thorough the numerical simulations at three slopes which have different types of soils.

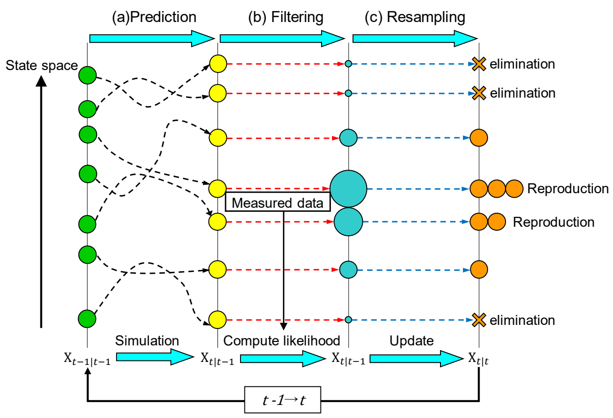

Fig. 1. Computational procedure of the PF.

3.1 Cut slope composed of clayey silt

The target slope in this section is a cut slope composed of clayey silt. The volumetric water contents and rainfall were measured at the slope. Fig. 2 shows the field measurement data of volumetric water contents and rainfall which are used to inverse analysis. A soil moisture sensor was installed at GL-50cm, and the volumetric water contents were measured at 10 minutes' interval.

Fig. 3 shows the analytical model. The variable flux boundary was provided with the top surface, and the free drainage boundary was provided with the bottom surface. It is known that rainwater infiltrates into slope in the direction of gravitational force, until the fully saturated zone generates. Therefore, rainwater infiltration was assumed only in the vertical direction in the model.

The probability distribution of each unknown soil hydraulic parameters is estimated thorough data assimilation by the PF based on field measurement data. In this study, the weighted mean values $\tilde{x}_{t|t}$ are referred to as identified parameters, and the values are obtained by the following equations:

$$\tilde{x}_{t|t} = \sum_{i=1}^{N} w_t^{(i)}\cdot x_{t|t}^{(i)} \quad (4)$$

where N is the number of particles, $w_t^{(i)}$ is the likelihood of each particle, and $x_{t|t}^{(i)}$ is the value of each parameter. Table 1 shows the identified soil hydraulic parameters, and Fig. 4 shows the soil water characteristic curve based on the identified parameters.

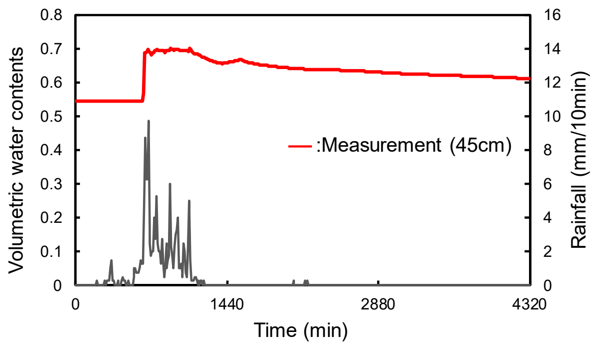

Fig. 2. Field measurement data (clayey silt).

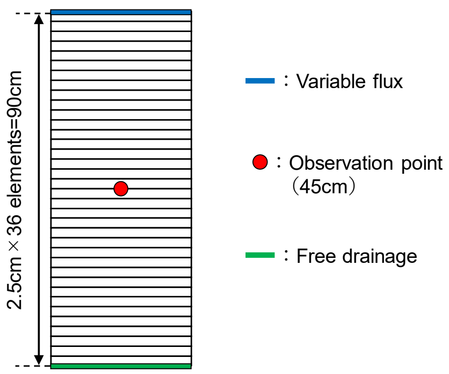

Fig. 3. Analytical model.

Fig. 5 shows the comparison of the simulated results using the identified parameters with the field measurement data as shown in Fig. 1. The numerical simulation was in good agreement with the field measurement data. From the results, the numerical simulation using the identified parameters by the PF could reproduce the field measurement data at the cut slope of clayey silt.

3.2 Cut slope composed of weathered granite

The target slope in this section is a cut slope composed of weathered granite. The volumetric water contents and rainfall were measured at the slope. A soil moisture sensor was installed at GL-45cm, and the volumetric water contents were measured at 10 minutes' interval. Fig. 6 shows the field measurement data at the slope.

Table 2 shows identified soil hydraulic parameters, and Fig. 7 shows the soil water characteristic curve based on the identified parameters. There was a big difference in shape of soil water characteristic curve between Fig. 4 and Fig. 7. The simulated results using the identified parameters by the PF are shown in Fig. 8. The simulation reproduces the field measurement data with high accuracy.

Table 1. Identified parameters (clayey silt).

θ_s	θ_r	α (1/cm)	n	k_s (m/s)
0.782	0.431	0.036	1.343	2.8.E-03

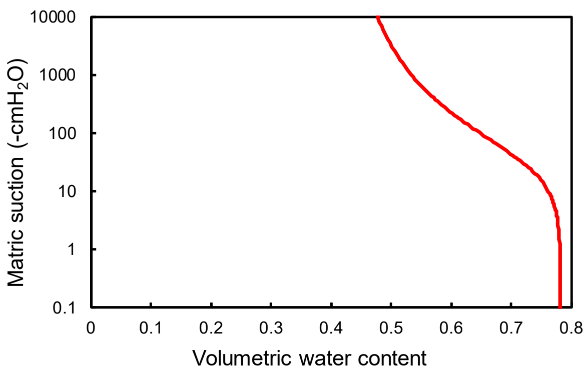

Fig. 4. Soil water characteristic curve (clayey silt).

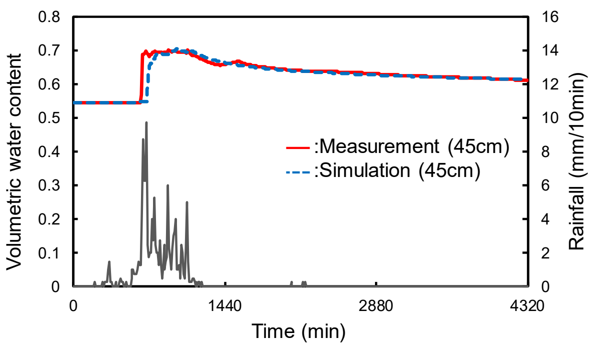

Fig. 5. Simulated results (clayey silt).

3.3 Natural slope

The target slope in this section is a natural slope along road. The base rock of the slope is granite, and the surface layer is forest soil. A tensiometer was installed at GL-20cm, and the matric suction were measured at 10 minutes' interval. Fig. 9 show the field measurement data at the slope.

Table 3 shows the identified parameters, and Fig. 10 shows the soil water characteristic curve. Fig. 11 shows the simulated results using the identified parameters. The simulation could reproduce the field measurement data of matric suction with high accuracy.

3.4 Discussion

The soil hydraulic parameters could be identified based on the data measured at three slopes which have different types of soils. Moreover, they could be identified based on field measurement data of not only volumetric water contents but also matric suction. In addition, the simulated results using the identified parameters were in excellent agreement with the field measurement data. Therefore, it was found that the PF is an available approach to identify the soil hydraulic parameters based on field measurements.

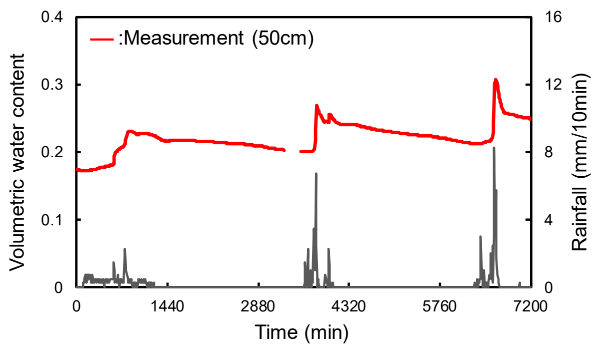

Fig. 6. Field measurement data (weathered granite).

Table 2. Identified parameters (weathered granite).

θ_s	θ_r	α (1/cm)	n	k_s (m/s)
0.412	0.095	0.040	1.443	1.0.E-02

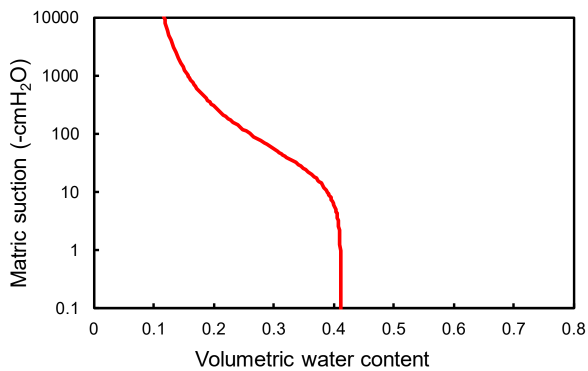

Fig. 7. Soil water characteristic curve (weathered granite).

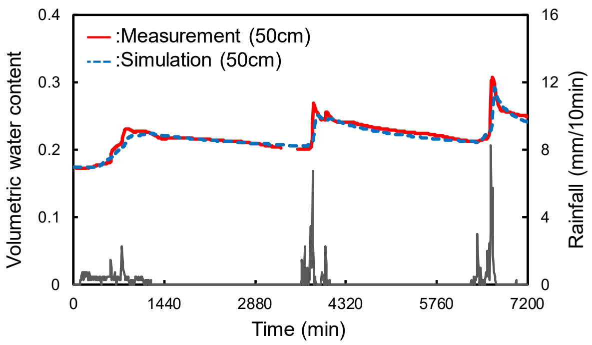

Fig. 8. Simulated results (weathered granite).

4 CONCLUSIONS

In this study, the availability of the PF on identification of soil hydraulic parameters based on field measurement data was discussed. The main conclusions of this study are summarized as follows.

1. With the PF, the soil hydraulic parameters could be identified based on field measurement data of not only volumetric water contents but also matric suction.
2. The numerical simulations using the identified parameters were able to reproduce the field measurement data with high accuracy.
3. The availability of the PF on identification of soil hydraulic parameters based on field measurement were verified.

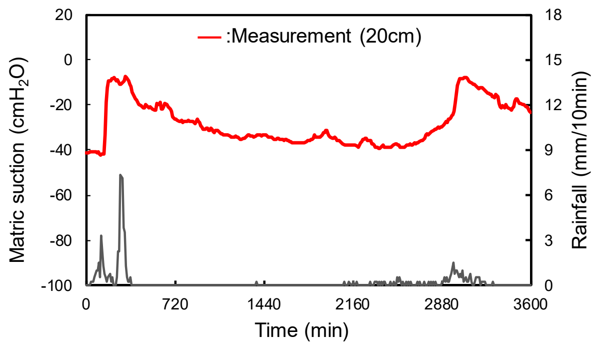

Fig. 9. Field measurement data (natural slope).

Table 3. Identified parameters (natural slope).

θ_s	θ_r	α (1/cm)	n	k_s (m/s)
0.592	0.357	0.129	1.456	7.6.E-04

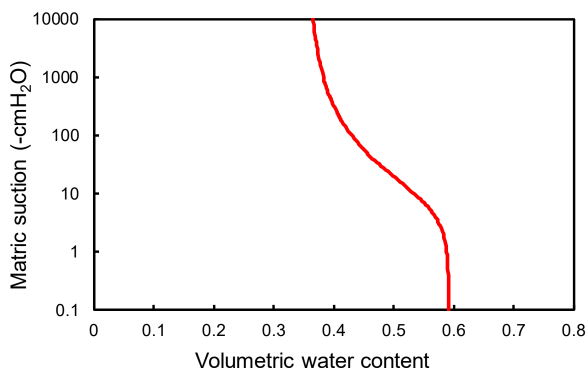

Fig. 10. Soil water characteristic curve (natural slope).

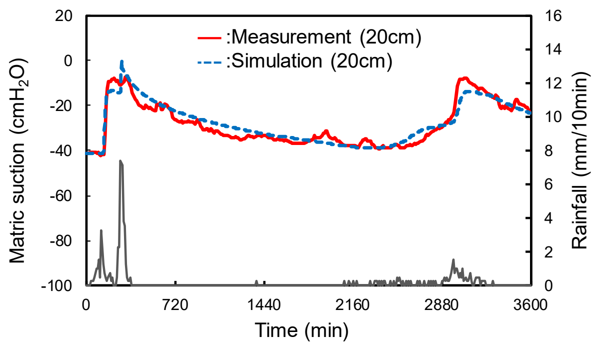

Fig. 11. Simulated results (natural slope).

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