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Applicability of digital twin with merging particle filter to predictions of volumetric water contents of soils

Applicabilité du Twin numérique avec filtre à particules fusionnées aux prédictions du contenu en eau volumétrique des sols

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ABSTRACT: Simulations of soil moisture conditions prevent disaster due to slope failures. A digital twin simulation for accurately predicting soil moisture conditions, in which data assimilation is applied, is proposed. Application to field measurements of volumetric water content in heavy rain was performed. The soil moisture conditions in heavy rains at 240 min intervals were predicted. The simulation model, based on measurements without rain, can predict the soil moisture conditions in heavy rain. It was confirmed that the digital twin simulation with Merging Particle Filter is applicable to predictions of soil moisture conditions.

RÉSUMÉ : Les simulations des conditions d'humidité du sol empêchent la catastrophe en raison de pentes défaillantes. On propose une simulation numérique de jumeaux pour prédire avec précision les conditions d'humidité du sol, dans lesquelles l'assimilation des données est appliquée. L'application à des mesures sur le terrain de la teneur en eau volumétrique dans les fortes pluies a été effectuée. Les conditions d'humidité du sol dans les fortes pluies à intervalles de 240 min ont été prédites. Le modèle de simulation, basé sur des mesures sans pluie, peut prédire les conditions d'humidité du sol dans les fortes pluies. Il a été confirmé que la simulation numérique de jumeaux avec le filtre à particules fusionnantes s'applique aux prédictions des conditions d'humidité du sol.

KEYWORDS: Numerical analysis, soil water condition, data assimilation, prediction, digital twin.

1 INTRODUCTION

Industrial and social reforms by IT technology, such as Industry 4.0 in Germany and the Industrial Internet Consortium in America, have gained worldwide attention. Society 5.0 (Cabinet Office 2018) is a concept of industrial and social reform advocated by the Japanese government. In Society 5.0, a system merges a cyberspace, built mainly of computers and networks, with a physical space, corresponding to the real world. The economic development and solutions of social problems are compatible with the system. The "digital twin" is used to achieve this. In a digital twin, events in a physical space are reproduced in cyberspace. Simulations of the events in cyberspace have been carried out. The simulation results were fed back to a physical space to solve these problems. For example, for ground deformation problems, the ground behavior is measured by sensors. The measured values are sent to cyberspace in real time. Next, a simulation model that can reproduce the measurement results is updated. Finally, the deformation behaviors in the near future can be obtained using the updated simulation model. In other words, TYPE-B prediction (Lambe 1973) is performed in real time.

The slope failure caused by heavy rain depends on soil moisture conditions. To prevent slope failure, it is necessary to elucidate the soil moisture conditions. Therefore, real-time monitoring technology for soil moisture conditions have been developed (Koizumi et al 2018, Sakuradani et al 2018). Furthermore, the application of data assimilation to the infiltration of rainwater into soils has been studied to develop a simulation model that can reproduce soil moisture conditions (Ito et al 2016, Fujimoto et al 2017). In particular, Merging Particle Filter (MPF) (Nakano et al 2007), a data assimilation technique, automatically and sequentially updates the simulation model to reproduce field measurements (Ito et al 2017).

In this study, a digital twin simulation for predicting soil moisture conditions is proposed. Its applicability was verified through a case study on rainwater infiltration into soils. First, the concept of a digital twin based on the issue of rainwater infiltration into soils is described. A comprehensive description of MPF is presented. Next, the unsaturated and saturated seepage analyses used in the simulation model are described. The field measurements of soil moisture conditions and associated modeling are presented. Further, a digital twin simulation for predicting soil moisture conditions is proposed. Finally, the digital twin simulation is applied to reproduce the soil moisture conditions in heavy rain. The identification of the soil moisture parameters in the simulation model is discussed. Moreover, the importance of the accuracy of field measurements in the data assimilation is highlighted. Consequently, the applicability of the proposed digital twin simulation is verified.

2 MERGING PARTICLE FILTER

Data assimilation is a technique used to identify simulation models using field measurements and determine the reliability of numerical simulations. Figure 1 shows the role of data assimilation in soil moisture behavior due to rainwater infiltration into soils. In field measurements, the soil moisture conditions are determined at the measurement position. However, spatial variations in soil moisture conditions cannot be determined. Moreover, changes in the soil moisture conditions cannot be predicted. It is possible to obtain the spatial variation of the soil moisture conditions by numerical simulations, such as unsaturated or saturated seepage analyses. It is also possible to predict the progress of soil water conditions using numerical simulations in combination with precipitation forecasts. However, the numerical simulation results, which are produced by simulation models, are not reliable.

Field measurements and numerical simulations are highly merged in a data assimilation. The defects of both are canceled by the advantages of data assimilation. That is, the reliability of numerical simulations is verified by updating the simulation model. The simulation model must be updated to reproduce field measurements, whenever field measurements are carried out. Numerical simulations can supplement field measurements to reveal the spatial variations in soil moisture conditions. Moreover, a reliable prediction of soil moisture conditions is provided.

In this study, the digital twin simulation predicts soil moisture conditions using a simulation model, which was verified with data assimilation. An MPF was applied, which is a sequential data assimilation method. In this method, the probability distribution of a physical quantity and its realizations are approximated. Each realization is called a particle, and each set is called an ensemble. Each particle has a simulation model (with initial conditions, boundary conditions, and soil moisture parameters) and information on the physical quantity at each time, providing a simulation result. The particle filter method evaluates the number of particles at a discrete time using Bayes' theorem.

Figure 2 shows the computational procedure for MPF. In MPF, data assimilation is carried out by repeating four calculation steps: (a) first stage prediction, (b) filtering, (c) resampling, and (d) merging. For example, seven particles are prepared in Figure 2. For (a), the first-stage prediction, numerical simulations are carried from *t-1* to *t*. When the field measurements are performed and measurement results given to the numerical simulations, (b) filtering is performed. In this process, the weight of each particle is calculated by Bayes' theorem based on the degree of fitness of the numerical simulation results of the field measurement results. In Figure 2, the weight is expressed by the size of the circles. That is, the red and orange circles are large because the numerical simulation results for both particles are similar to the field measurement results. Conversely, the yellow and black circles are small, which differ from the field measurement results. In (c) resampling occurs; the particles are extracted and restored according to the weight assigned by (b) during filtering. In Figure 2, the particles are restored according to the weight, so that the total number of particles is 21. Therefore, the number of red circles is 5, and the number of orange circles is 4. Conversely, the number of both yellow and black circles, is 1. Finally, in (d) merging occurs; 21 circles are grouped into three sets and weighted sums performed for each set. Thus, the seven particles were regenerated. The regenerated particles have a higher probability of containing information from the red and orange circles, which will provide more similar numerical simulation results to the field measurement results. Conversely, the regenerated particles have a lower probability of containing information on both the yellow and black circles. As a result, the particle probability of producing the field measurement results increases. By repeating the above calculation step, the particles are automatically updated in the simulation model with a high fitness for the field measurement results.

3 SIMULATION MODEL

In this study, an unsaturated-saturated seepage finite element analysis was applied as the simulation model for water in slopes. The following equation (Akai et al 1977) was applied in the numerical simulations.

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

where $C(=\partial\theta/\partial x)$ is the hydraulic capacity function, Ψ is the matric potential, and k is the unsaturated hydraulic conductivity. The Van Genuchten model (Van Genuchten 1978), given in Equation (2), was adopted to express the soil water retention behavior. The Mualem model (Mualem 1976), given by Equation (3), was adopted to estimate the unsaturated hydraulic conductivity, *k*.

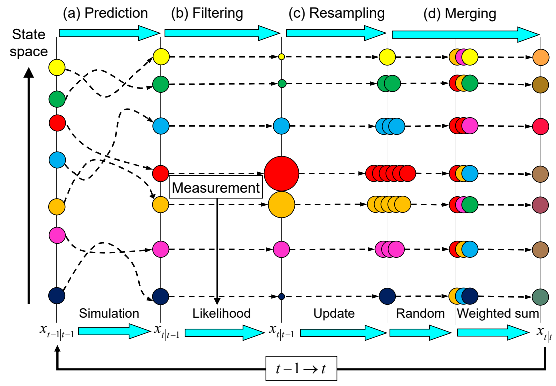

Figure 2. Computational MPF procedure.

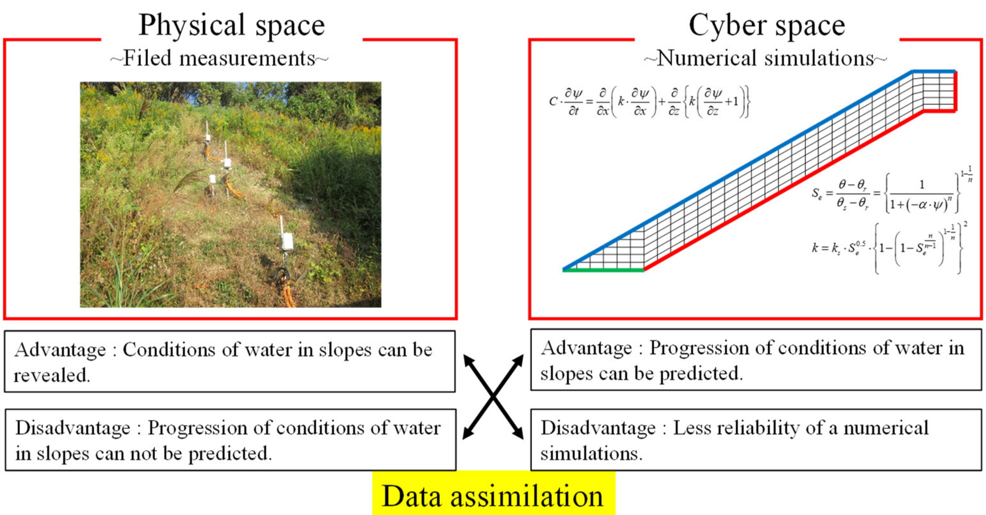

Figure 1. Role of data assimilation in soil moisture behavior due to rainwater infiltration into soils.

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

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

Here, S_e is the effective soil water saturation, θ is the volumetric water content, θ_r is the residual volumetric water content, θ_s is the saturated volumetric water content, α and n are material parameters, and k_s is the saturated hydraulic conductivity. In this study, θ_s, θ_r, α, n, and k_s are unknown soil moisture parameters corresponding to unsaturated soil hydraulic properties.

4 FIELD MEASUREMENT AND SIMULATION MODEL

Measurements of both the volumetric water content and rainfall at a cut slope in Kyushu were performed in May 2015 (Ito et al., 2016). The base rock of the slope is granite, and the surface layer is composed of weathered granite containing gravel. Four sensor nodes were placed on the slope, and three soil moisture sensors were installed at each position. Photo 1 shows the installation of the soil-moisture sensors. The three moisture sensors were installed at GL-30, GL-70, and GL-100 cm, and the volumetric water content was measured at 10 min intervals. Moreover, rainfall at the site was measured at the same intervals.

Figure 3 shows the field measurements of the rainfall used in the sequential data assimilation. Field measurements from 25 days (between June 21 to July 15, 2018) were applied to the data assimilation. The total amount of rainfall was 790 mm. Heavy rainfall was measured five times: 137 mm/day on June 29, 75 mm/day on June 30, 82 mm/day on July 3, 113 mm/day on July 5, and 338 mm/day on July 6. The rainfall on July 6 was the heaviest in 2018 at this site.

Figure 4 shows the analytical model. It is known that rainwater infiltrates the soil in the direction of the gravitational force until a fully saturated zone is generated. Therefore, rainwater infiltration was assumed only in the vertical direction of the model. Three types of soil moisture parameters corresponding to the soil moisture sensor positions were applied in the model.

Table 1 lists the minimum and maximum values of each soil moisture parameter. Each particle has randomly generated soil moisture parameters within these ranges. Five hundred particles were used to prepare 500 sets of soil moisture parameters.

An observation noise variance of of 0.0025 was applied, controlling the weight of each particle. Figure 5 shows a conceptual diagram for the determination of a particle weight. The weight of each particle is calculated by Bayes' theorem based on the degree of fitness of the numerical simulation results for the field measurement results. The smaller the difference between the field measurement and numerical simulation results, the larger the weight. A Gaussian distribution was applied to calculate the weight. The observation noise variance controls the shape of the Gaussian distribution. The smaller the observation noise variance, the sharper the shape of the Gaussian distribution. Only particles that can reproduce the field measurements remain so that the shape of the Gaussian distribution becomes sharp. Therefore, if the observation noise variance is too small, each particle has the same set of soil moisture parameters. Conversely, data assimilation cannot be carried out adequately if the

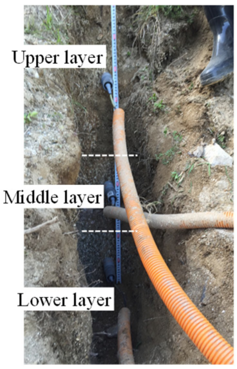

Photo 1. Installation of soil moisture sensors.

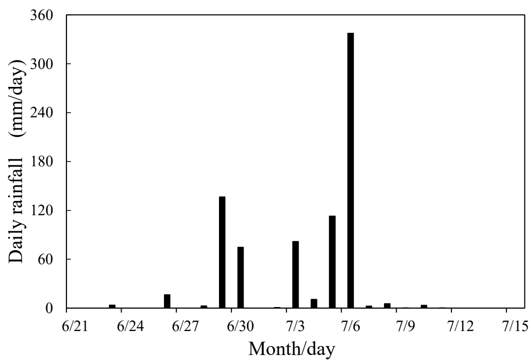

Figure 3. Field measurements of rainfall used in data assimilation.

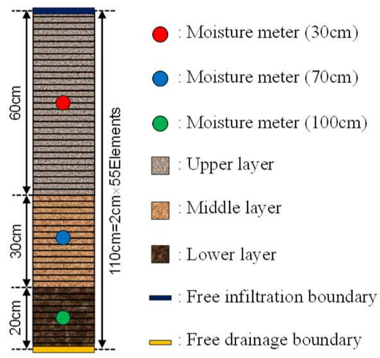

Figure 4. Analytical model.

Table 1 Soil moisture parameters.

		θ_s	θ_r	α	n	k_s
Upper	Max.	0.52	0.16	0.10	2.10	5.00
	Min.	0.42	0.08	0.01	1.10	1.00
Middle	Max.	0.58	0.30	0.10	2.10	5.00
	Min.	0.48	0.10	0.01	1.10	1.00
lower	Max.	0.53	0.30	0.10	2.10	5.00
	Min.	0.43	0.10	0.01	1.10	1.00

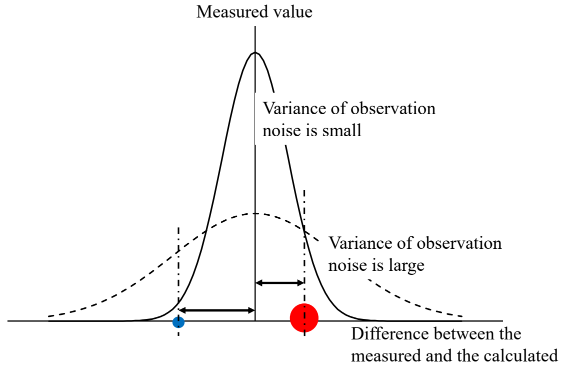

Figure 5. Conceptual diagram for the determination of the particle weight.

observation noise variance is too large.

Figure 6 shows a conceptual diagram of the digital twin simulation. In the digital twin simulation, data assimilation was performed every 240 min. Therefore, the soil moisture conditions are predicted by the simulation model, which is updated at time *t-1* for 240 min.

5 DIGITAL TWIN SIMULATION

Figure 7 shows a comparison of the volumetric water contents in field measurements to those in the numerical simulations, for which data assimilation was not applied. The volumetric water contents in the numerical simulations are given as the average of 500 particles in Figure 8. In the numerical simulation without data assimilation, the simulation models were not updated, and the soil moisture parameters were constant. The difference between the field measurement and numerical simulation results is considerable for each measurement position. In particular, the difference at the middle position was significant.

Figure 8 shows the variation in the volumetric water content in the numerical simulation as a function of time, without data assimilation. The solid lines represent the average numerical simulation results for 500 particles. The dotted lines represent the average ± standard deviation. The difference between the dotted lines is large at each measurement position because the soil moisture parameters were widely extended. The numerical simulations in which the soil moisture parameters at the initial condition were applied could not predict the soil moisture conditions.

Figure 9 shows a comparison of the volumetric water contents in field measurements to those in the digital twin simulations, with data assimilation. The volumetric water contents in the numerical simulations are given as the average of 500 particles, as shown in Figure 10. Apart from the beginning of the digital twin simulation, the numerical analysis reproduced the field measurements. The volumetric water contents at all measurement positions decreased before June 29, because the water in the soil infiltrated vertically, owing to the gravitational force. The digital twin simulation can reproduce a slight decrease in the volumetric water content. The digital twin simulation predicted the rapid increase in volumetric water content on June 29. Heavy rainfall and no rainfall occurred alternately from June 29 to July 6. The digital twin simulation reasonably predicted both an increase and decrease in volumetric water content. In particular, the digital twin simulation reproduced the behavior of the volumetric water content on July 6, at which 338 mm/day of rainfall occurred.

Figure 10 shows the variation in volumetric water content with the digital twin simulation as a function of time. The solid lines represent the average volumetric water content of 500 particles. The dotted lines represent the average ± standard deviation. The difference between the dotted lines decreased from June 21 to June 29, because the extent of the soil moisture parameters narrowed due to data assimilation. This difference was not significant after June 29. Therefore, the standard deviations of the volumetric water content for 500 particles was small. It is suggested that the soil moisture parameters can be identified by data assimilation.

As shown in Figure 7, data assimilation was carried out every 240 min in this study. Therefore, the soil moisture conditions were predicted by the simulation model, which was updated every 240 min. The measured rainfall was applied in the numerical simulations at intervals of 240 min. If the rainfall given by the precipitation forecast was applied, the soil moisture conditions could be predicted by the digital twin simulation.

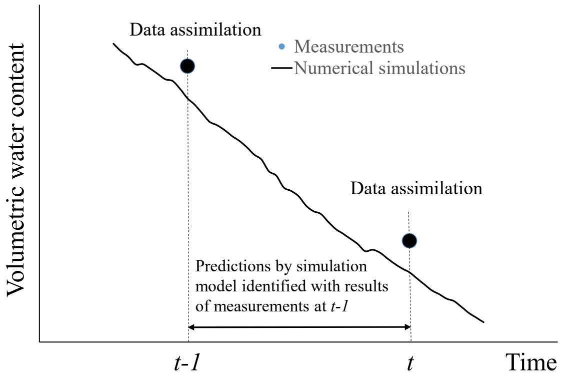

Figure 6. Conceptual diagram of digital twin simulation.

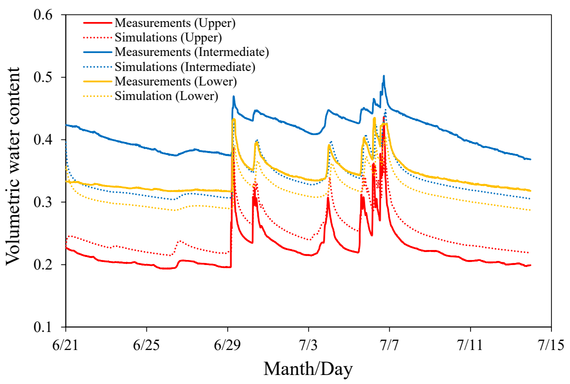

Figure 7. Comparison of volumetric water contents in the field measurements to those in the numerical simulations without data assimilation.

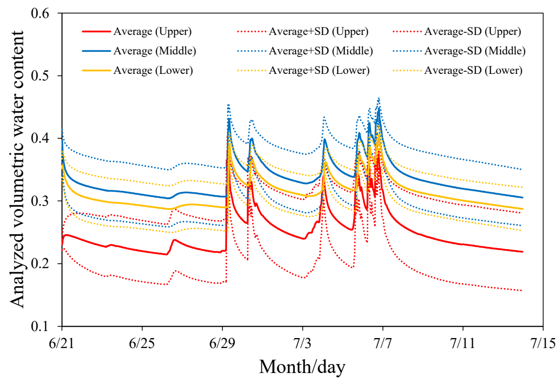

Figure 8. Variation of volumetric water content in the numerical simulation without data assimilation

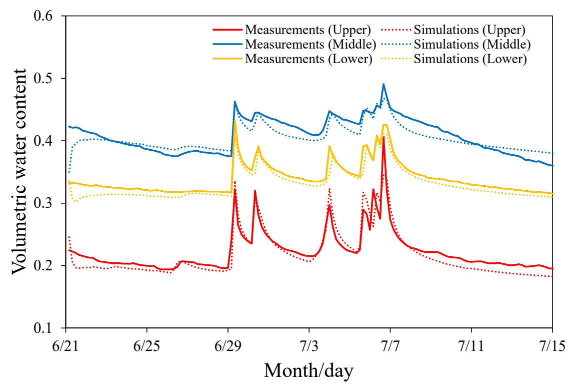

Figure 9. Comparison of volumetric water contents in the field measurements to those in the digital twin simulations.

Figures 11 to 15 show the variations in soil moisture parameters θ_s, θ_r, α, n, and k_s with time. SD in these figures denote the standard deviation. θ_s is the saturated water content, which is equivalent to the porosity. The volumetric water content at each position was less than θ_s, which was obtained by data assimilation. The unsaturated conditions were maintained and groundwater was not generated at this site. This is shows the importance for the implementation of an appropriate data assimilation, because the simulation model applied in this study cannot reproduce the generation of groundwater.

At the beginning of the digital twin simulation, all soil moisture parameters decreased. However, they remained essentially constant after June 23. Moreover, the difference between the dotted lines in all soil moisture parameters decreased with time. Their differences were insignificant after June 29, and therefore all soil moisture parameters were identified.

As the average soil moisture parameters were constant after June 23, the simulation model (in which Equations (1), (2), and (3) were applied) appropriately reproduced the soil moisture conditions. Moreover, the standard deviations of the soil moisture parameters were almost zero, and one set of soil moisture parameters was identified. It was not necessary to update the soil moisture parameters by data assimilation after June 23 (especially after June 29). The digital twin simulation with 240 min intervals was carried out appropriately after June 23, because one set of soil moisture parameters could be identified. No rain occurred from June 21 to 23. Therefore, the variation in the volumetric water content was insignificant. However, the soil moisture parameters were identified with data assimilation. That is, the field measurements at this site were performed with a very high accuracy. The results of the field measurements with rainfall are not necessarily required to

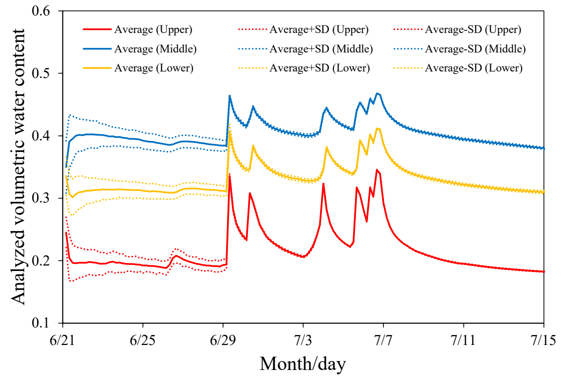

Figure 10. Variation of volumetric water contents with time in the digital twin simulation.

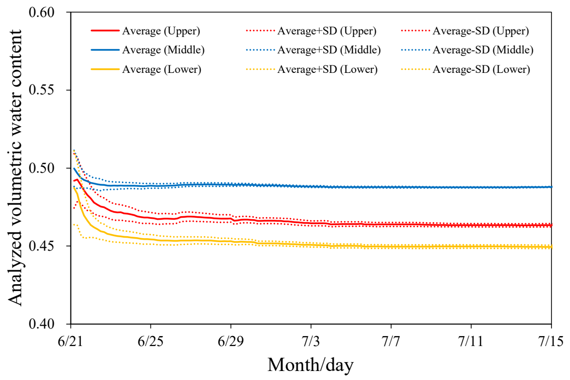

Figure 11. Variation of saturated water contents with time in the digital twin simulation.

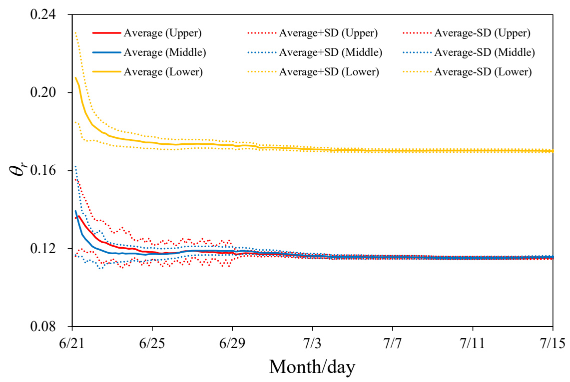

Figure 12. Variation of residual water contents with time in the digital twin simulation.

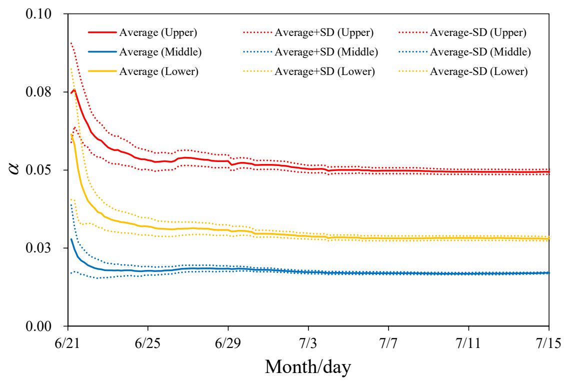

Figure 13. Variation of α with time in the digital twin simulation.

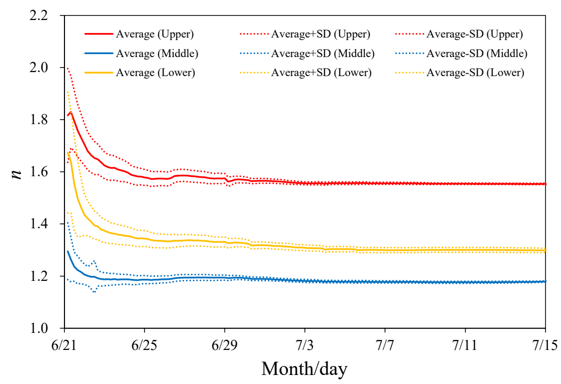

Figure 14. Variation of n with time in the digital twin simulation.

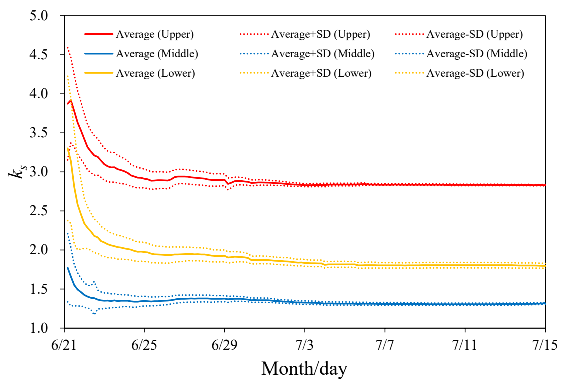

Figure 15. Variation of saturated hydraulic conductivity with time in the digital twin simulation.

identify the soil moisture parameters. If the field measurements are highly accurate, the data assimilation analysis can appropriately identify the soil moisture parameters with the results of field measurements without rainfall.

6 CONCLUSIONS

In this study, a digital twin simulation for predicting soil moisture conditions was proposed. It was applied to the field measurement of volumetric water content in heavy rain. The main findings are summarized as follows:

1. The soil moisture parameters were identified by data assimilation, which was carried out every 240 min.
2. The soil moisture conditions at the site were reproduced using the simulation model.
3. The digital twin simulation used the soil moisture parameters identified by the data assimilation to predict the soil moisture conditions after 240 min.
4. The accurate measurement of volumetric water content in the absence of rainfall was used to identify the soil moisture parameters, and further reproduce the soil water conditions in heavy rain.

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