Soil Water Content Regression Analysis of Measurement Data from Hyperspectral Camera in Weathered Granite Soils

Hwan-Hui Lim[1*], *Seung-Rae* Lee[1], *Enok* Cheon[1], and *Yeeun* Nam[1]

[1]Department of Civil and Environmental Engineering, Korea Advanced Institute of Science and Technology, Daejeon

Abstract. Soil water content is one of the most common physical parameters that cause landslides or debris flow. Therefore, it is of very importance to determine or predict the water content quickly and non-destructively. This study investigates the hyperspectral information in the visible near-infrared regions (VNIR) of different samples of granite soils possessing varying water content. Totally 162 granite samples were taken from each mountain area. The samples with different water contents were examined using a hyperspectral radiometer operating in the 400~1000nm range by obtaining the spectral curves. It was found that the variation of VNIR is consistent with the water content variation of weathered granite soils, and the hyperspectral camera was able to detect it. A Partial Least Squares Regression (PLSR) analysis was applied to develop a calibration-model. The PLSR model resulted in a good correlation between the water content and VNIR profile. The results demonstrate that the hyperspectral camera combined with the PLSR model can be a useful and non-destructive tool for determining soil water contents in the weathered granite soils.

1 Introduction

Soil water content seriously affects soil's physical and chemical properties, and changes in soil properties can lead to landslides or debris flow. The prediction of soil water content plays a decisive role in landslides and debris flow monitoring. Existing water content measurement has been instruments made based on field tests or field sensor-based measurements.

However, both methods have limitations in that they can measure water content in relatively local areas. Therefore, it is necessary to develop a technology that can measure a large area's water content variation. During the last two decades, near-infrared (NIR) spectroscopy has been widely employed as a useful tool for analyzing soil properties. NIR spectroscopy can be used to evaluate the properties of soil that are not disturbed by light [7, 11]. Mouazen et al. [5] used visual and near-infrared (VNIR) hyperspectral imaging to determine the presence of chemicals (carbon and phosphorous) in soil and to measure soil parameters, such as moisture content and pH. Zhang et al. [13] developed a technique for the classification of soil using NIR hyperspectral images. Wang et al. (2018) [12] developed a technique for analyzing the degree of heavy metal contamination of soil using remote sensing and hyperspectral images in NIR.

In this study, we developed a variation of the soil water content prediction model using the hyperspectral technique to overcome the limitations of existing measurement techniques. The objectives of this study are to develop a water content prediction model using

hyperspectral images. For this purpose, the change of reflectance according to the water content in the near-infrared region was confirmed, and the most relevant parameter was analyzed. Finally, the water content prediction model developed with the corresponding parameters is compared with the actual soil water content. Based on these findings, we intend to provide reference materials that can be used for analyzing the water content of soil using hyperspectral near-infrared images to decide the susceptibility of landslides in a mountainous area.

2 Materials and methods

2.1 Study area

The study areas are placed in Seoul's southern part (Mt. Umyeon: 37.45° N, 126.9° E; Mt. Guryong: 37.47° N, 127.06° E; Mt. Daemo: 37.48° N, 127.08° E), as shown in Figure 1. The study areas are comprised of granitic gneiss.

A total of 162 granite soil samples were collected from the study areas within a depth of 30 cm from the surface. First, a sieve analysis was conducted using soil that passed through a No. 40 sieves (0.425 mm). The soils were also dried at 110 ℃ in an oven for 24 hours. And the water was added step by step to measure the water content. Soil water content was calculated by the following equation (Equation 1). Table 1 shows the material properties of the 162 soils.

$$water\ content\ (\%) = \frac{mass\ of\ wet\ woil - mass\ of\ dry\ soil}{mass\ of\ wet\ soil} \tag{1}$$

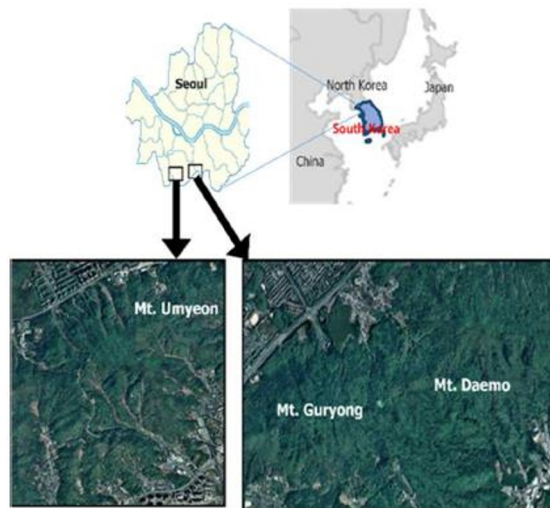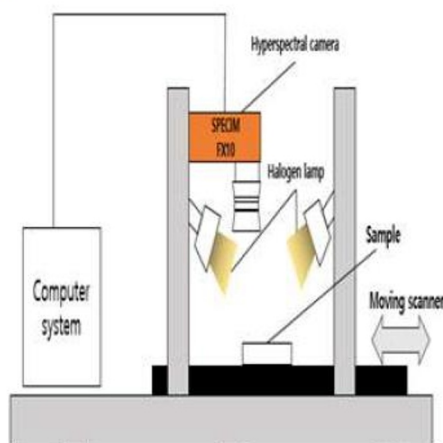* Corresponding author: hwanhui@kaist.ac.kr

Fig. 1. Location map showing the study area of 162 granite soil samples.

Table 1. Material properties of soils

Sample name	Specific gravity	Coeff. of uniformity	Coeff. of curvature	Dry unit weight (kN/m^3)
Mt. Umyeon	2.64	10.76	0.81	13.13
Mt. Guryong	2.57	5.12	1.65	12.0
Mt. Daemo	2.43	12.74	1.22	12.3

(a)

(b)

Fig. 2. Hyperspectral camera system: (a) Hyperspectral camera in the laboratory and (b) Design of the hyperspectral camera.

2.2 Hyperspectral camera system

The hyperspectral camera system consists of a hyper spectral camera, a complementary metal-oxid semiconductor (CMOS) sensor, six 150W Halogen lamps, and a 40 x 20 Lab-scanner (Spectral Imaging Ltd., Oulu, Finland, Figure 2a). The software for scanning speed (CNC USB controller) and hypercube data recorder (Lumo Recorder) provides exposure time, binning mode, wavelength range, and image acquisition [8]. Hyperspectral cameras were placed in a dark room to minimize errors. The design of the hyperspectral camera is shown in Figure 2b.

2.3 Image correction

Hyperspectral images were acquired using the line scanning technique of the hyperspectral camera system. Each sample was placed on a slider table and scanned line by line to get an initial hyperspectral image. After capturing the hyperspectral image, a dark reference and a white reference were obtained. The normalization process is essential. We can remove noise values from hyperspectral images and convert them to relative values using 100% reflectance of the white reference through this process. The white reference was acquired from a Teflon whiteboard with 99% reflectivity. The dark reference was obtained by turning off the light source and completely covering the camera lens with a cap. The reflectance (%) of the sample acquired based on the white reference was calculated using the following equation.

$$Reflectance = \frac{Raw^{t1}-Dark^{t1}}{White^{t2}-Dark^{t2}} \, x \, \frac{t2}{t1} \qquad (2)$$

where the Raw reflectance is the reference measured on an actual object, Dark is the dark reference, and White is the white reference, t1 is the integration time in a white reference, and t2 the integration time in a dark reference [10].

3 Result and discussion

3.1 Investigation of parameters related to water content variation

The near-infrared regions (NIR, 800~1000 nm) are suggested as having a strong correlation with soil water content variation [4]. Three parameters related to water content variation were selected in NIR: the water index (R970/R900, Figure 3a), which is one of the spectral vegetation indices; the depth of 800nm to 1000nm (Figure 3b); and the area of reflectance (Figure 3c). Partial Least Square Regression (PLSR) analysis was performed by setting each parameter and variation of water content as variables. Figure 4 shows the relationship between water content variation and the selected three parameters from each of Mt. Umyeon, Mt Guryong, and Mt. Daemo weathered granite soils.

Among the parameters, the area of reflectance in NIR showed the highest coefficient of determination, and the water index and depth at 1000nm showed the lower coefficient of determination overall. In all 162 weathered granite soils, it was confirmed that the area of reflectance in NIR is the parameter most correlated with the water content variation in VNIR.
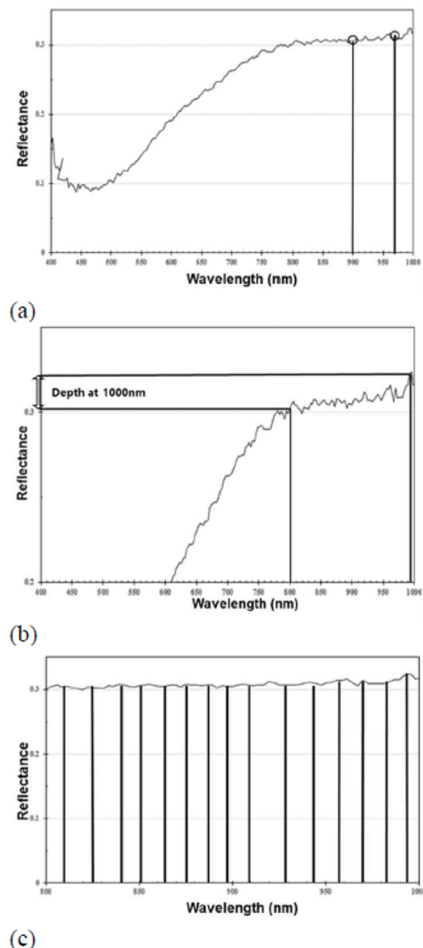

(a)

(b)

(c)

Fig. 3. Parameters of soils related to water content variation: (a) Water Index, (b) Depth at 1000nm, and (c) Area of reflectance.

3.2 Estimation of water content variation of soil according to reflectance

In general, the indicators used to evaluate the goodness of fit of predictive models are mean absolute percentage error (MAPE), root mean square error (RMSE), mean absolute error (MAE), and maximum absolute percentage error (Max-APE) [9]. MAPE has become increasingly popular as a performance measure in forecasting [1, 2, 6], as it is easy to interpret and understand in addition to being highly reliable [3]. All data points, both predicted values and results from laboratory tests, were used to compute the coefficient of determination (R^2).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \qquad (3)$$

where A_t is the predicted value, F_t is the actual value, and n is the duration of the observed value. The 162 weathered granite soils were randomly assigned to the calibration and the validation sets with a 7:3 ratio, which
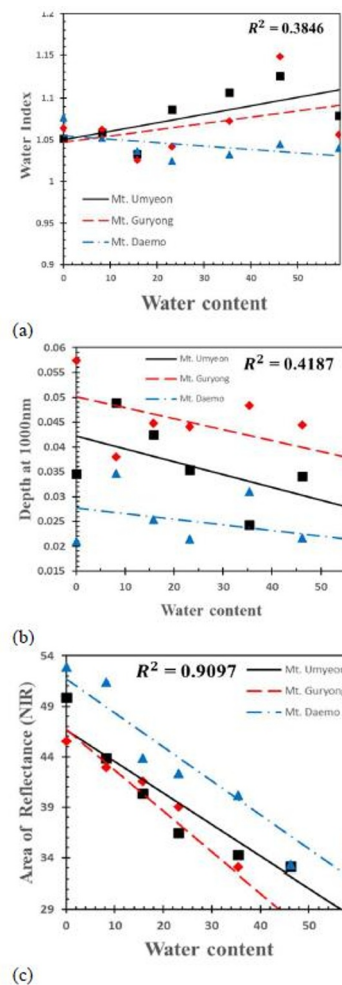

(a)

(b)

(c)

Fig. 4. Relationship between water content variation and parameters of granite soils (Mt. Umyeon, Mt. Guryong, Mt. Daemo): (a) Water Index and (b) Depth at 1000nm and (c) Area of reflectance.

is equivalent to a total of 40 calibration samples and 17 validation samples for Mt. Umyeon soil samples; 38 calibration samples and 16 validation samples for Mt. Guryong soil samples; and 36 calibration samples and 15 validation samples for Mt. Daemo soil samples.

Figure 5 shows the MAPE analysis results of the regression analysis model. The MAPE of Mt. Umyeon is 7.3%, the MAPE of Mt. Guryong is 10.2%, and the MAPE of Mt. Daemo is 7.1%, which is a relatively accurate prediction.

4 Conclusions

In this study, we demonstrated the potential of hyperspectral techniques to estimate the variation of soil water content. The parameter most correlated with the water content in the VNIR was determined from the hyperspectral reflectance data.
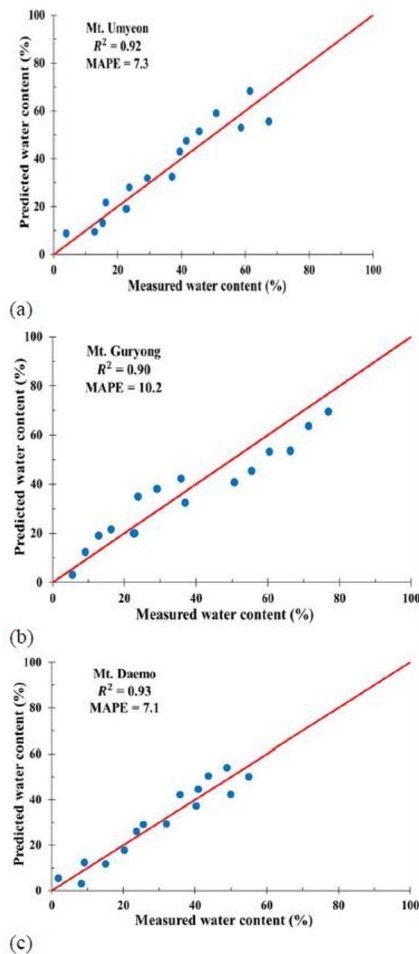
Fig. 5. Comparison of measured water content versus predicted water content using regression analysis: (a) Mt. Umyeon and (b) Mt. Guryong and (c) Mt. Daemo.

We also developed a regression analysis model for predicting the variation of the water content of each weathered granite soils. The research can be summarized as follows:

1) A total of 162 granite weathered soil samples were collected from Mt. Umyeon, Mt. Guryong, and Mt. Daemo in Seoul. Hyperspectral near-infrared images were acquired in 224 bands from 400 to 1000nm.

2) Water index (R970/R900), the depth at 1000nm, and the area of reflectance in NIR were used to find the parameters most relevant to water content variation in VNIR. The regression analysis result of the regression analysis showed that the area of reflectance in NIR is the best parameter correlating to the soil water content variation.

3) The variation of soil water content regression model was developed using the area of reflectance in NIR parameter. As a result of comparing and verifying with the actual soil water content variation, it was confirmed that the MAPE of each soil was less than 11%. Therefore, it can be concluded that the regression model can be successfully used to predict variations in soil water content accurately.

This study aimed to classify soil types and predict soil water content over large areas to detect landslide hazards, which traditionally require a considerable time and human power, by implementing a simple method using the hyperspectral technique. A total of 162 granite soils (Mt. Umyeon, Mt. Guryong, and Mt. Daemo) were examined by applying the hyperspectral technique. The results demonstrated that the developed models were capable of variation of water content prediction.

There are not many studies on the acquisition of soil properties for a wide area using hyperspectral reflectance; therefore, it is expected that it can be used as primary data for a later study on obtaining properties of a wide area using the hyperspectral technique. The accuracy may be somewhat inferior to the existing measurement method. However, it is expected that the variation of the water content of the wide-area can be measured using a drone in the future, so active disaster prevention is likely possible. Finally, for modeling the acquisition of soil property values, research is needed to estimate different characteristics according to the type of soil. It is determined that an applicability study using drone and satellite images is necessary for future research.

References

1. B.E. Flores, E.M. White, Journal of Forecast **8** (1989)

2. S.I. Gunter, C. Aksu, Journal of Forecast **8** (1989)

3. K.F. Lam, H.W. Mui, H.K.Yuen, Computer & Operations Research **28** (2001)

4. H. Lim, E. Cheon, D. Lee, J. Jeon, S. Lee, Journal of Korean Geotech 3**5** (2019)

5. A.M. Mouazen, M.R. Maleki, J. De Baerdemaeker, H. Ramon, Soil Tillage Res **93** (2007)

6. H.W. Mui, C.W. Chu, C.W. Journal of Applied Statics **20** (1993)

7. E.G. Njoku, D. Entekhabi, Journal of Hydrol. **184** (1996)

8. Perception Wiki. Available online: https://wiki.perceptionpark.com/display/MAN/LUMO+Scanner+Setup (accessed on 28 February 2020).

9. K. Sim, H. Kwon, H. Journal of Korean Society of Forest Science **100** (2011)

10. SPEIM IQ User Manual. Available online: https://www.specim.fi/iq/manual/index.html (accessed on 25 November 2019)

11. F.T. Ulaby, P.C. Dubois, J. Van Zyl, Journal of Hydrol **184** (1996)

12. F. Wang, J. Gao, Y. Zha, Journal of Photogrammetry and Remote Sensing **136** (2018)

13. X. Zhang, N. Younan, C. O'Hara, IEEE Transactions on Geoscience and Remote Sensing **43**, 3 (2005)