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Development of Landsat-based Downscaling Algorithm for SMAP Soil Moisture Footprints

SMAP 토양수분을 위한 Landsat 기반 상세화 기법 개발

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Abstract

With increasing satellite-based RS(Remotely Sensed) techniques, RS soil moisture footprints have been providing for various purposes at the spatio-temporal scales in hydrology, agriculture, etc. However, their coarse resolutions still limit the applicability of RS soil moisture to field regions. To overcome these drawbacks, the LDA(Landsat-based Downscaling Algorithm) was developed to downscale RS soil moisture footprints from the coarse- to finer-scales. LDA estimates Landsat-based soil moisture(30m×30m) values in a spatial domain, and then the weighting values based on the Landsat-based soil moisture estimates were derived at the finer-scale. Then, the coarse-scale RS soil moisture footprints can be downscaled based on the derived weighting values. The LW21(Little Washita) site in Oklahoma(USA) was selected to validate the LDA scheme. *In-situ* soil moisture data measured at the multiple sampling locations that can reprent the airborne sensing ESTAR(Electronically Scanned Thinned Array Radiometer, 800m×800m) scale were available at the LW21 site. LDA downscaled the ESTAR soil moisture products, and the downscaled values were validated with the *in-situ* measurements. The soil moisture values downscaled from ESTAR were identified well with the *in-situ* measurements, although uncertainties exist. Furthermore, the SMAP(Soil Moisture Active & Passive, 9km×9km) soil moisture products were downscaled by the LDA. Although the validation works have limitations at the SMAP scale, the downscaled soil moisture values can represent the land surface condition. Thus, the LDA scheme can downscale RS soil moisture products with easy application and be helpful for efficient water management plans in hydrology, agriculture, environment, etc. at field regions.

Keywords: LDA; SMAP; remotely sensed soil moisture; downscaled soil moisture

Ⅰ. Introduction

Soil moisture is a pivotal variable for hydrology, agriculture, environment, etc., because the soil moisture variable plays the key role as a media that connects between the atmosphere and the subsurface soil layers. Usually, soil moisture can be measured using the TDR(Time Domain Reflectrometry) probe sensor at the point-scale, but the *in-situ*(point-scale) data have limitations in representing spatially-distributed soil moisture values. With improving RS(Remotely Sensed) techniques, RS soil moisture products such as AMSR-E(Advanced Microwave Scanning Radiometer-Earth Observing System, Njoku et al. 2003), SMOS(Soil Moisture and Ocean Salinity, Kerr et al., 2001), SMAP(Soil Moisture Active and Passive, Entekhabi et al. 2010), etc. have been using at various research areas. RS soil moisture products have advantages that can represent large areas at the global-scale with the finer time scales(1～3 days), but these also have limitations due to their coarse resolutions(25～40 km × 25～40km) in a spatial domain. Considering that land uses are highly complicated at the real world, course resolutions might have limitations in representing the complexity of land surface conditions. To resolve coarse resolution limitations, several downscaling algorithms have been developed. Kim and Lee(2004) downscaled RS soil moisture products based on the artificial neural network and land surface information. Merlin et al.(2005; 2012) downscaled SMOS soil moisture products using optical high-resolution land surface images, while Shin and Mohanty(2013) developed the deterministic downscaling algorithm based on high-resolution LANDSAT-based

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evapotranspiration. Also, Na et al.(2003) downcaled AMSR2(Advanced Microwave Scanning Radiometer 2) soil moisture footprints based on soil texture and field measurements. Although several downscaling algorithms have been developed to improve resolution limitations of RS products, downscaling algorithms still require various land surface information (e.g., soil texture, crops, topography, etc.) and excessive pre-/post-processes with uncertainties.

Our research works aim to improve the availability of coarse-scale RS soil moisture products using the high resolution(30m × 30m) imageries of LANDSAT. The research objectives are three-folds: 1) to develop the LANDSAT-based Downscaling Algorithm(LDA) to downscale coarse-scale RS soil moisture footprints, 2) to validate the LDA scheme with *in-situ* soil moisture measurements at the airborne sensing(800m × 800m) scale, and 3) to assess the applicability of LDA scheme to SMAP(>9～39km) products. The newly developed LDA could be useful in various areas such as hydrology, agriculture, environment, etc.

Ⅱ. Material and Methods

In this study, the LDA(LANDSAT-based Downscaling Algorithm) was developed to downscale coarse-scale(SMAP) soil moisture footprints to the finer-scale(30m × 30m). Usually, the SMAP satellite provides soil moisture data at the finer-time scale(intervals of 2 or 3 days) with the spatial resolutions of 3, 9, and 39 km, while the LANDSAT data have a finer spatial-resolution(30m × 30m) with a coarse time-scale(interval of about 3 weeks). As the LDA scheme with the finer spatial-resolution of LANDSAT is applied to SMAP(which have the finer time-scale), SMAP products can be downscaled with the spatial(30m × 30m) and temporal(intervals of 2～3 days) scales at the global scale.

Scott et al.(2003) derived the relationship between LANDSAT-based soil evaporations and field-scale soil moisture measurements. Based on the relationship, the regression model was suggested to convert soil evaporations to soil moisture values in Eq. (1). Thus, we estimated LANDSAT-based soil moisture values using the regression model suggested by Scott et al.(2003).

$$R_n = G_o + H + \lambda E \tag{1}$$

$$\Lambda = \frac{\lambda E}{\lambda E + H} = \frac{\lambda E}{R_n - G_o}$$

$$\theta / \theta_{sat} = \exp(\Lambda - a)/b$$

$$a = 1.0, b = 0.421$$

Here, R_n: the net radiation [W/m^2], G_0: the soil heat flux [W/m^2], H: the sensible heat flux [W/m^2], λE: the latent heat flux [W/m^2], Λ: the soil evaporation, θ: the soil moisture [cm^3/cm^3], θ_{sat}: the saturated soil moisture [cm^3/cm^3], and a,b: the curve-fitting parameters, respectively.

To downscale SMAP products based on the LANDSAT-based soil moisture(30m × 30m) values, LDA derives the weighting values($w_{i,j}$) of individual(sub-pixel) Landsat-based soil moisture products (pixels) based on Eq. (2). Here, the estimated weighting values mean the rates of how the individual pixels are biased from the average of all of sub-pixels.

As we applied the derived weighting values to SMAP soil moisture product in Eq. (3), SMAP can be downscaled with both the finer spatial(30m × 30m)/temporal(intervals of 2 or 3 days) resolutions. Note that the SMAP satellite currently only provides soil moisture data with the spatial resolution of 39 km due to its own malfunction of active sensor since July, 2015, but soil moisture data are available with the spatial resolution of 3km × 3km by combining SMAP and SENTINEL.

$$w_{i,j} = \frac{\theta_{i,j}^{Landsat}}{\overline{\theta}^{Landsat}} \tag{2}$$

$$\theta_{i,j}^{Down} = w_{i,j} \times \theta^{SMAP} \tag{3}$$

Here, i,j: the location of Landsat pixels, $\theta_{i,j}^{Landsat}$: the Landsat-based soil moisture pixels with i and j, $\overline{\theta}^{Landsat}$: the average of Landsat-based soil moisture pixels, $w_{i,j}$: the weighting values corresponding to individual Landsat-based soil moisture pixels with i and j, θ^{SMAP} : the satellite-based SMAP soil moisture products, and $\theta_{i,j}^{Down}$: the downscaled soil moisture pixels with i and j, respectively.

1. Study area

The LW21(Little Washita) site comprised of the wheat and native grass covers in Oklahoma (United States of America, USA) was selected to validate the LDA scheme in Fig. 1. The airborne sensing-based ESTAR(Electronically Scanned Thinned Array Radiometer, 800m × 800m) soil moisture products were taken during the SGP97(Southern Great Plains 1997) campaign. The TDR-based soil moisture data at the multiple sampling locations of 49(7 × 7) within the boundary of ESTAR pixel(LW21 site) were also measured during the SGP97 campaign from 18th June to 19th July in 1997, except of the heavy rainfall days(Mohanty and Skaggs, 2001).

Then, SMAP soil moisture products were downscaled from the course(9km)- to finer(30m)-resolutions based on the LDA scheme at the SMAP-ok, ARM-1, and Stillwater regions in Oklahoma. Then, the downscaled(30m × 30m) soil moisture values were compared with the TDR-based soil moisture measurements at these study sites. The TDR-based soil moisture measurements are available from the International Soil Moisture Network-ISMN(https://ismn.geo.tuwien.ac.at/). As the SMAP satellite provides soil moisture products with the resolution of 9km × 9km by combining the active(3km × 3km) and passive(39km × 39km) sensors, the combined soil moisture products(9km × 9km) were downscaled to the finer-scale(30m × 30m) soil moisture based on the LDA scheme. The performance of LDA scheme was evaluated using the Pearson(*R*) and Root Mean Square Error(*RMSE*) as shown in Eqs. (4) and (5).

$$R_t = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J}(\theta_{i,j}^{Down} - \overline{\theta}^{Down})(\theta_{i,j}^{obs} - \overline{\theta}^{obs})}{\sqrt{\sum_{i=1}^{I}\sum_{j=1}^{J}(\theta_t^{sim} - \overline{\theta}_t^{Down})^2 \sum_{i=1}^{I}\sum_{j=1}^{J}(\theta_{i,j}^{obs} - \overline{\theta}^{obs})^2}} \qquad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{I}\sum_{j=1}^{J}(\theta_{i,j}^{obs} - \theta_{i,j}^{Down})^2}{I \times J}} \qquad (5)$$

Here, $\theta_{i,j}^{obs}$: the *in-situ* soil moisture measurements with *i* and *j*, and $\overline{\theta}^{obs}$: the average of *in-situ* soil moisture measurements, respectively. Table 1 showed the information of SMAP and LANDSAT imageries.

Table 1 The information of SMAP and LANDSAT imageries

	Image characteristic	Values
SMAP	Satellite	SMAP
	Coordinate system	Latitude, Longitude
	Resolution	Combined resolution (9km × 9km) of the active and passive sensors
LANDSAT	Satellite	LANDSAT 3, 4, 6
	Coordinate system	Latitude, Longitude
	Resolution	Bands 1–7(30m × 30m)

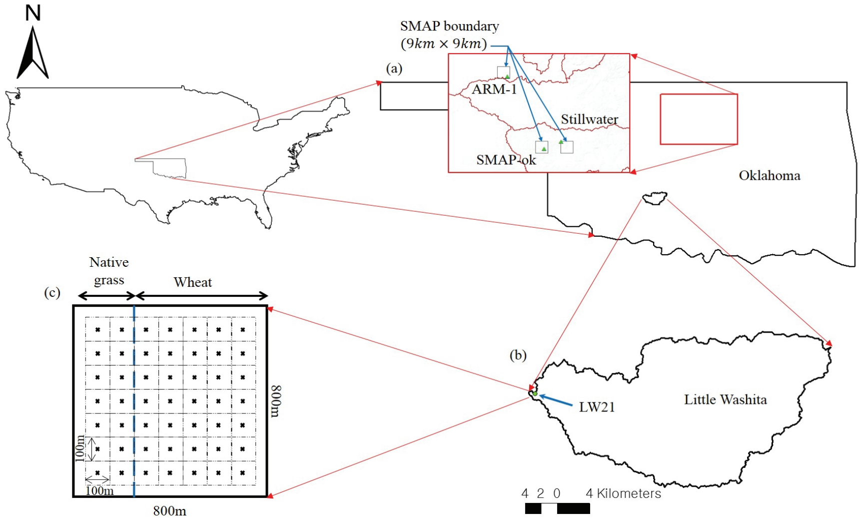

Fig. 1 (a) The SMAP–ok, ARM–1, and Stillwater regions and (b–c) Little Washita (LW 21) site with 49 soil moisture measuring locations within the boundary of ESTAR(800m × 800m) soil moisture products in Oklahoma(USA)

Ⅲ. Results

1. Validation of LANDSAT-based Downscaling Algoritm

The LDA scheme was validated at the LW21 site with the *in-situ* soil moisture data measured at the multiple sampling locations that can represent the airborne sensing(ESTAR) scale in Fig. 2. Note that the Landsat-based soil moisture estimates based on Scott et al.(2003) were validated with the *in-situ*/ESTAR vaues, although the validation results were not shown for the brevity. Unfortunately, the dates of Landsat image(July 9th) taken by the satellite and *in-situ* soil moisture(June 18th to July 18th) measured by the TDR probe sensor were not matched. For this reason, the *in-situ* soil moisture measurements(July 11th) closer to the date of Landsat image taken were used for validation. We downscaled the ESTAR soil moisture(0.260 cm^3/cm^3) product(taken in June 11th), and the downscaled soil moisture values were compared with the *in-situ* measurements. Note that the downscaled soil moisture sub-pixels with the resolution of 30m × 30m were resampled to meet the resolution of *in-situ*(point-scale) measurements. Here we assumed that individual *in-situ* value represents the resolution of 100m × 100m within the LW 21 site(800m × 800m) as shown in Figs. 1b-c. The downscaled(resampled, 100m × 100m) soil moisture values(R: 0.496 and $RMSE$: 0.010) were identified with the *in-situ* soil moisture measurements. Uncertainties might be due to measuring errors, mismatched dates of Landsat, ESTAR and *in-situ* data taken, complexity of land surface conditions, etc. Especially, the scale discrepancy of resampled sub-pixels and *in-situ*(point-scale) might cause significant uncertainties in the downscaled results. However, these uncertainties might be reasonable in comparisons, when we consider the scale discrepancy. Although uncertainties exist, the downscaled soil moisture values from the ESTAR soil moisture products were comparable to the *in-situ* soil moisture measurements at the LW 21 site comprised of the wheat and native grass(shown in the google image and Normalized Difference Vegetation Index-NDVI in Figs. 2(c-d).

2. Downscaling of SMAP soil moisture footprints

Using the LDA scheme the SMAP soil moisture footprints were downscaled from the coarse(9km × 9km)- to finer(30m × 30m)-scales across the Oklahoma regions in Fig. 3. Overall, the SMAP-ok, ARM-1 and Stillwater sites showed the complexity of land surface conditions within the SMAP scale, but the SMAP soil moisture values only provide the single(averaged) values(SMAP-ok: 0.148 cm^3/cm^3, ARM-1: 0.079 cm^3/cm^3, Stillwater: 0.144 cm^3/cm^3), respectively. Although the LDA scheme was not validated at the SMAP scale due to limitations of the *in-situ* measurements available, the downscaled soil moisture values presented the similar trends of land surface condition at the spatial-scale as shown in the Google images. These findings indicated that the derived weighting values successfully represent the land surface conditions using the Landsat imageries.

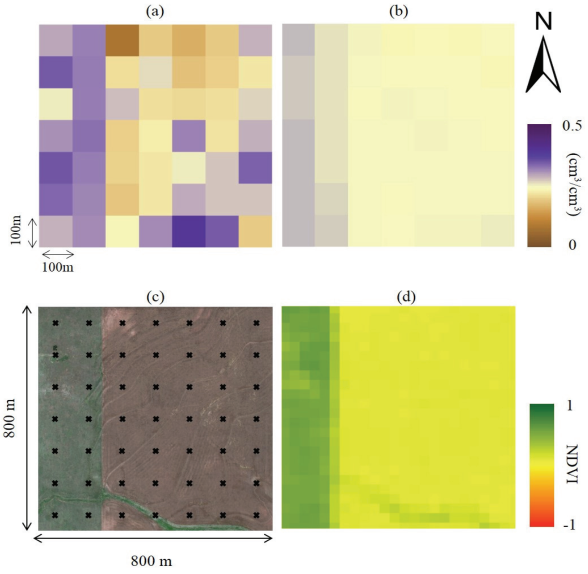

Fig. 2 (a) The *in-situ* soil moisture distributions, (b) downscaled results by the Landsat-based Downscaling Algorithm(LDA), (c) google image, and (d) normalized difference vegetation index (NDVI) at the LW 21 site in Oklahoma(USA)

Fig. 4 showed the comparison of downscaled(30m × 30m) and *in-situ*(point-scale) soil moisture values at the SMAP-ok, ARM-1 and Stillwater sites across the daily time step. Note that the Landsat products are usually taken with the interval of about 3 weeks at the global scale. For this reason, we assumed that the Landsat image taken in the specific date (t) represents up to half of the periods indicating that the previous/next Landsat imageries were taken before/after 3 weeks. The *in-situ* soil moisture dynamics measured at the SMAP-ok and ARM-1 sites were relatively lower than those of the SMAP and downscaled soil moisture values, while the *in-situ* values at the Stillwater

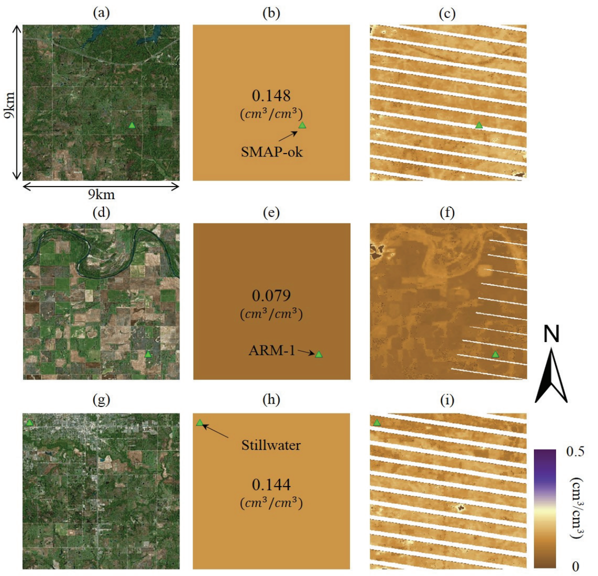

Fig. 3 Comparison of the google image, SMAP soil moisture products, and downscaled soil moisture values at the Oklahoma regions(USA); (a–c) SMAP–ok, (d–f) ARM–1, (g–i) Stillwater

site was higher than that of the SMAP and downscaled soil moisture. Differences between the *in-situ* and SMAP(9km × 9km)/downscaled(30m × 30m) soil moisture values might be due to the heterogeneity of land surface condition, scale discrepancy, measuring errors, etc. Overall, the trends of *in-situ* soil moisture measurements at the time scale were similarly shown compared to the SMAP/downscaled soil moisture values with different quantities of soil moisture. Also, the downscaled soil moisture values showed differences compared to the SMAP data due to the impacts of weighting values(meaning the heterogeneity of land surface conditions), especially for the ARM-1 site. Although the validation works have limitations at the SMAP scale, the downscaled soil moisture values can represent the complexity of land surface conditions with the good match of *in-situ* measurements at the time-scale.

Ⅳ. Discussion

In this study, the LDA scheme was developed to downscale satellite-based SMAP soil moisture footprints from coarse(9km × 9km)- to finer(30m × 30m)-scales. The LDA scheme estimated the Landsat-based soil moisture based on the regression model suggested by Scott *et al.*(2003) and derived their weighting values(30m × 30m). Based on the derived weighting values, coarse-scale(SMAP) soil moisture footprints can be downscaled to the finer-scale. The LW 21 site was selected to validate the LDA scheme with the *in-situ* soil moisture measured at the multiple sampling locations and airborne sensing-scale ESTAR soil moisture footprints. We downscaled the ESTAR soil moisture footprints, and then the downscaled soil moisture values were compared with the *in-situ* measurements. The downscaled results(*R*: 0.496 and *RMSE*: 0.010) were comparable with the *in-situ* measurements, although uncertainties exist. Uncertainties might be due to several reasons such as measuring errors, mismatched dates of Landsat, ESTAR, and *in-situ* data taken, complexity of land surface condition, etc. Especially, the scale discrepancy of resampled sub-pixels of downscaled soil moisture and *in-situ*(point-scale) measurements might cause significant uncertainties. Although uncertainties exist, the downscaled soil moisture values were comparable to the *in-situ* data measured at the LW 21 site comprised of wheat and native grass covers. Then, the SMAP soil moisture footprints were downscaled at the Oklahoma(SMAP-ok, SRM-1, and Stillwater) regions. The

Fig. 4 Comparison of the *in–situ*, SMAP, and downscaled soil moisture values in time at the Oklahoma regions (USA); (a–c) SMAP–ok, (d–f) ARM–1, (g–i) Stillwater

downscaled soil moisture values from SMAP were not fully validated due to the lack of *in-situ* measurements, but the results were similarly shown with the land surface conditions. Furthermore, the trends of SMAP/downscaled soil moisture values were comparable with the *in-situ* measurements at the time-scale. Although the newly developed LDA scheme was validated in limited conditions, our findings demonstrated the applicability of LDA scheme to downscale ESTAR/SMAP soil moisture footprints with easy application. Thus, the LDA scheme could be useful for establishing efficient water management plans in hydrology, agriculture, environment, etc.

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