Spatial composition of AMSR2 soil moisture products by conditional merging technique with ground soil moisture data

Dongkyun Kim, Jaehyeon Lee, Hyunglok Kim & Minha Choi

Stochastic Environmental Research and Risk Assessment

ISSN 1436-3240
Volume 30
Number 8

Stoch Environ Res Risk Assess (2016)
30:2109-2126
DOI 10.1007/s00477-016-1300-0

Stoch Environ Res Risk Assess (2016) 30:2109–2126
DOI 10.1007/s00477-016-1300-0

ORIGINAL PAPER

Spatial composition of AMSR2 soil moisture products by conditional merging technique with ground soil moisture data

Dongkyun Kim[1] · Jaehyeon Lee[1] · Hyunglok Kim[2] · Minha Choi[2]

Published online: 3 August 2016

Abstract The conditional merging (CM) spatial interpolation technique was applied to obtain the composite soil moisture products using the AMSR2 and in situ soil moisture for the 51 days of the summer through the late fall season of the year 2012 in Korean Peninsula. The 'leave one out cross-validation' analysis was conducted to assess the performance of the composite soil moisture products in estimating the soil moisture in ungagged locations. The control variable for comparison was the soil moisture products obtained by spatially interpolating the in situ soil moisture data measured at eight gage locations using the Ordinary Kriging (KR) technique. The results show that the composite soil moisture products are more accurate than the in situ only soil moisture products in estimating the soil moisture for the following cases: (1) when the spatial correlation of in situ soil moisture data is low. Such case includes when there is little rainfall and where the altitude is high (mountainous area) and (2) where the gage density is low or the area located further away from the in situ gages. For both cases, the KR method cannot use enough information due to the low spatial correlation of the in situ measurement for interpolation, while the CM method can take advantage of the satellite soil moisture measurement not affected by the spatial correlation of the in situ data.

Keywords Soil moisture · AMSR2 · Remotely sensed soil moisture · Conditional merging technique · Kriging

✉ Minha Choi
mhchoi@skku.edu

Dongkyun Kim
dekaykim@gmail.com

Jaehyeon Lee
jhl1782@gmail.com

Hyunglok Kim
hlkim@skku.edu

[1] Department of Civil Engineering, Hongik University, Seoul, Republic of Korea

[2] Water Resources and Remote Sensing Laboratory, Graduate School of Water Resources, Sungkyunkwan University, Suwon, Gyeonggi-do 440-746, Republic of Korea

1 Introduction

Soil moisture has been regarded as one of the most important variables in hydrological, biological and metrological systems and plays a major role in the mass and energy transfers between the land and the atmosphere (Wagner et al. 1999; Kerr et al. 2001; Njoku et al. 2003; Choi and Jacobs 2008; Albergel et al. 2009; Entekhabi et al. 2010; Dorigo et al. 2010; Brocca et al. 2011; Al-Yaari et al. 2014). Moreover, soil moisture is a key variable in climate change and natural disaster prediction such as drought, sand dust storms, and flooding. Therefore, soil moisture variable was identified as one of the "Essential Climate Variables" (Li et al. 2015; Crow et al. 2005; System GCO 2010; Bolten et al. 2010; Yoo et al. 2006; Kim and Choi 2015). For these reasons, the investigation of measuring and estimating soil moisture are all very important (Dorigo et al. 2011).

Soil moisture has been measured with different temporal and spatial resolutions including ground-based measurements (i.e., point scale) and satellite-based remote sensing techniques (i.e., global scale) (Köhli et al. 2015; Schmugge et al. 2002). There are three major measurement technics are widely used for the ground-based soil moisture measurement. First of all, soil moisture content are measured by employing the gravimetric method and this method is the standard procedure of soil water content determination (Reynolds 1970). The second, soil moisture information can be obtain through the various electronic sensor instruments such as time domain reflectometry (TDR) or frequency domain reflectometry (FDR) methods. TDR and FDR methods are commonly used for their simplicity and high accuracy of determining soil moisture. Furthermore, the latest technology for measuring ground-based soil moisture is by cosmic-ray neutron, which has footprint radius of about 300 m and proved to be efficient in measuring soil moisture content at larger scale compared point-wise measurements (Zreda et al. 2008, 2012). These ground-based soil moisture value measurements have been frequently used to validate and calibrate remotely sensed and model estimates of soil moisture products.

The in situ soil moisture dataset is regarded as a true value of soil moisture and commonly used as a reference value to validate remotely sensed soil moisture retrieval (Dorigo et al. 2011; Mittelbach and Seneviratne 2012; Yoo 2002; Topp et al. 1980). However, previous research has not applied ground measurements of soil moisture to revise satellite-based soil moisture products (Brocca et al. 2009; Cosh et al. 2008; Wagner et al. 2008). Ground measurements as an ancillary dataset to support satellite-based soil moisture products is has been likely due to a scale discrepancy between ground measurements and satellite-based products. To overcome the scale discrepancy of a dataset, geostatistical methods (e.g. Kriging, inverse distance weighting and spline) for ground measurements can be applied to match the spatial scale with satellite-based soil moisture products for disaggregation analysis (Dani and Hanks 1992; Mohanty et al. 2000). Kriging is a geostatistical method that provides estimates for ungauged areas using the weighted average of neighboring area values in the range of influence (Azimi-Zonooz et al. 1989). Kriging is an effective method for inferring soil moisture estimations and variance, since it provides the optimal interpolation of an estimated soil moisture value by distributed pixels.

Most previous work using Kriging-based soil moisture prediction has been performed by directly interpolating ground measurements (Bardossy and Lehmann 1998). However, soil moisture has high variability even within short distances. The Kriging method is limited in predicting soil moisture products when the study areas have ground condition heterogeneity, such as different types of land use regions, soil texture areas and mountainous areas with varying elevation levels (Pandey and Pandey 2010). In this respect, the Kriging method should be applied in small catchment scale for reasonable results of interpolated soil moisture products (Anctil et al. 2002; Bardossy and Lehmann 1998; Herbst and Diekkruger 2003; Wang et al. 2001). In the rainfall research, the strategies of combining the satellite-based and Kriging ground datasets have been widely used to overcome the limitation of area representativeness of point scale measurements and high variability of satellite-based datasets; this is called the "Conditional Merging (CM)" technique. Ebert (2007) applied a CM technique proposed by Ehret (2003) to combine a mean precipitation field interpolated from rain gauge observations with radar-based products with the spatial variability of precipitation. In general, previous rainfall research applying the CM method presented reasonable results compared with ground based measurements and showed improved spatial and temporal variability of rainfall fields. Despite these benefits of CM strategies, the CM method has not been applied in remotely sensed soil moisture data analysis.

In this study we used ground measurements and satellite-based products to estimate the applicability of CM method applied in a soil moisture dataset. Since point-wise measurement and cosmic-ray neutron methods limit spatial representation of remotely sensed soil moisture datasets, so satellite-based soil moisture retrievals were applied for assessing the area soil moisture content.

Previous studies investigated surface soil moisture from remote sensing instruments onboard satellites to overcome spatial and temporal variability of soil moisture (Kerr et al. 2010; Njoku et al. 2003). The National Aeronautics and Space Administration (NASA) launched the Soil Moisture Active Passive (SMAP) Earth satellite mission in January 2015 (Entekhabi et al. 2010) to measure and map the Earth's soil moisture. The European Space Agency (ESA) launched the Soil Moisture Ocean Salinity (SMOS) in November 2009 (Kerr et al. 2001) and the Japan Aerospace Exploration Agency (JAXA) launched Advanced Microwave Scanning Radiometer 2 (AMSR2, the successor mission of the AMSR for the EOS, AMSR-E) in March 2012 (Imaoka et al. 2010) to monitor soil moisture at a global scale. Other promising satellites (e.g. MetOp-A, -B, Aquarius, and Fengyun-3B) are also making global soil moisture observations (Parinussa et al. 2015; Brocca et al. 2010) using microwave instruments.

The 1–11 GHz low-frequency microwave-based remote sensing can provide quantitative information about few centimeters of soil moisture from the surface depending on its wavelength (Schmugge et al. 2002). In this study, we used the AMSR2 soil moisture dataset to supplement the Kriging method when it is applied to the ground-based measurement of soil moisture through the CM merging methodology. The AMSR2 sensor onboard the Global Change Observation Mission1-Water (GCOM-W1) is a passive microwave sensor that provides almost real-time observation of soil moisture with high accuracy (Imaoka et al. 2010). AMSR2 frequency bands include 6.925, 7.3, 1065, 18.7, 23.8, 36.5 and 89.0 GHz to retrieve surface soil moisture content from the Earth every 1–3 days (Imaoka et al. 2010). JAXA's soil moisture retrieval algorithm and land parameter retrieval model (LPRM) are commonly used to retrieve the surface soil moisture from the brightness temperature (Tb) obtained from the AMSR2 sensor (Cho et al. 2015; Fujii et al. 2009). In this study, we use LPRM products since it documents a reasonably accurate soil moisture value throughout the world (Kim et al. 2015).

To summarize, our study assessed the following: First, the CM method was applied to study soil moisture products using point measurements and remotely sensed soil moisture products. Second, we compared the CM method with the original Kriging method through the statistical analysis. Last, both the CM and original Kriging strategies were analyzed based on hydrological variable characteristics such as precipitation, seasonality, geomorphology and observation density to investigate the application of the CM strategy to combine different characteristics of soil moisture products.

2 Methodology

2.1 Study area and period

The study area chosen was Korean Peninsula, located at 34°–39°N latitude and 26°–130°E longitude (Kyoung et al. 2011). The Korean Peninsula is highly influenced by the east-Asian monsoon climate, so it has a high annual rainfall, varying between 1000 and 1900 mm depending on the region. Approximately 70% of the entire annual rainfall is concentrated during the summer season, starting from early June and ending early in September (Kim et al. 2002). The soil of Korean Peninsula is composed of sandy loam, loam, and sand. Major land use of Korean Peninsula is composed of mixed forest and cropland (Cho and Choi 2014). Figure 1a shows the location of the Korean Peninsula on a world map. The satellite and in situ soil moisture data starting from July 2012 to October 2012 was used for this study, yielding 121 days' worth of data. The satellite soil moisture data was available for 51 of those days. Therefore, the analysis performed in this study covers the 51 days of soil moisture data collected by the AMSR2.

2.2 Satellite soil-moisture data

The satellite soil moisture data used in this study was obtained from the measurement from the AMSR2 sensor installed on the Global Change Observation Mission 1 (GCOM-W1) satellite launched on May 18, 2012 by Japan Aerospace Exploration Agency (JAXA). The soil moisture products based on the AMSR2 sensor measurements was provided starting from July 2012 using the JAXA algorithm and providing near-surface soil moisture information (1–2 cm) (Fujii et al. 2009; Parinussa et al. 2015). NASA also used the LPRM algorithm (Owe et al. 2008) to calculate the soil moisture products from AMSR2 sensor measurements.

Kim et al. (2015) compared the soil moisture products using these two different algorithms and concluded that the LPRM algorithm produced a smaller overall bias and root mean square error (RMSE) compared to the JAXA algorithm. However, the JAXA algorithm performed better in dry conditions. Currently, the JAXA algorithm calculated soil moisture products can be obtained from the JAXA website (https://gcom-w1.jaxa.jp/) and the LPRM algorithm based soil moisture products can be obtained from the NASA website (http://gcmd.gsfc.nasa.gov/). This study used the LPRM algorithm based soil moisture product, since Korean Peninsula has a temperate humid climate. Also we did not consider the cold season since the microwave retrieved soil moisture products in the frozen season is known to have accuracy issue due to land freeze especially the LPRM-based soil moisture retrievals showed an unusual pattern of soil moisture variability when surface temperature drops to 280 K (Schmugge et al. 2002; Kim et al. 2015).

Figure 1a, b shows the snapshot of the Level 3 Surface Soil Moisture Product across the world and of the Korean Peninsula used in this study, respectively.

2.3 In-situ soil-moisture data

Many of previous studies showed that point based ground measurements can be used as a representative value of larger areas (Vachaud et al. 1985; Brocca et al. 2009; Wagner et al. 2008). Even if Jackson et al. (2010) mentioned the limitation of representativeness of ground-based soil moisture observations for filed-mean soil moisture, most of soil moisture dataset used in this study showed specific data distribution such as normal and lognormal distribution. This normality of dataset indicated that point-scale soil moisture variability can capture the variability of filed-mean soil moisture even the scale mismatch between point based and satellite-based soil moisture dataset as described in various previous research (Famiglietti et al. 1999; Choi and Jacobs 2007; Brocca et al. 2009).

In this study, we used the in situ soil moisture products provided by the Rural Development Administration (RDA) of the Korean Government. The RDA has been managing the soil-moisture measurement network in the Korean Peninsula since 2000. Each gauge in the network measures the soil moisture contents at a soil depth of 10 cm using the CS615 and CS616 water content reflectometers (Campbell Scientific Inc. 1996, 2012). Due to the agricultural and meteorological purposes of the network, all of RDA sites

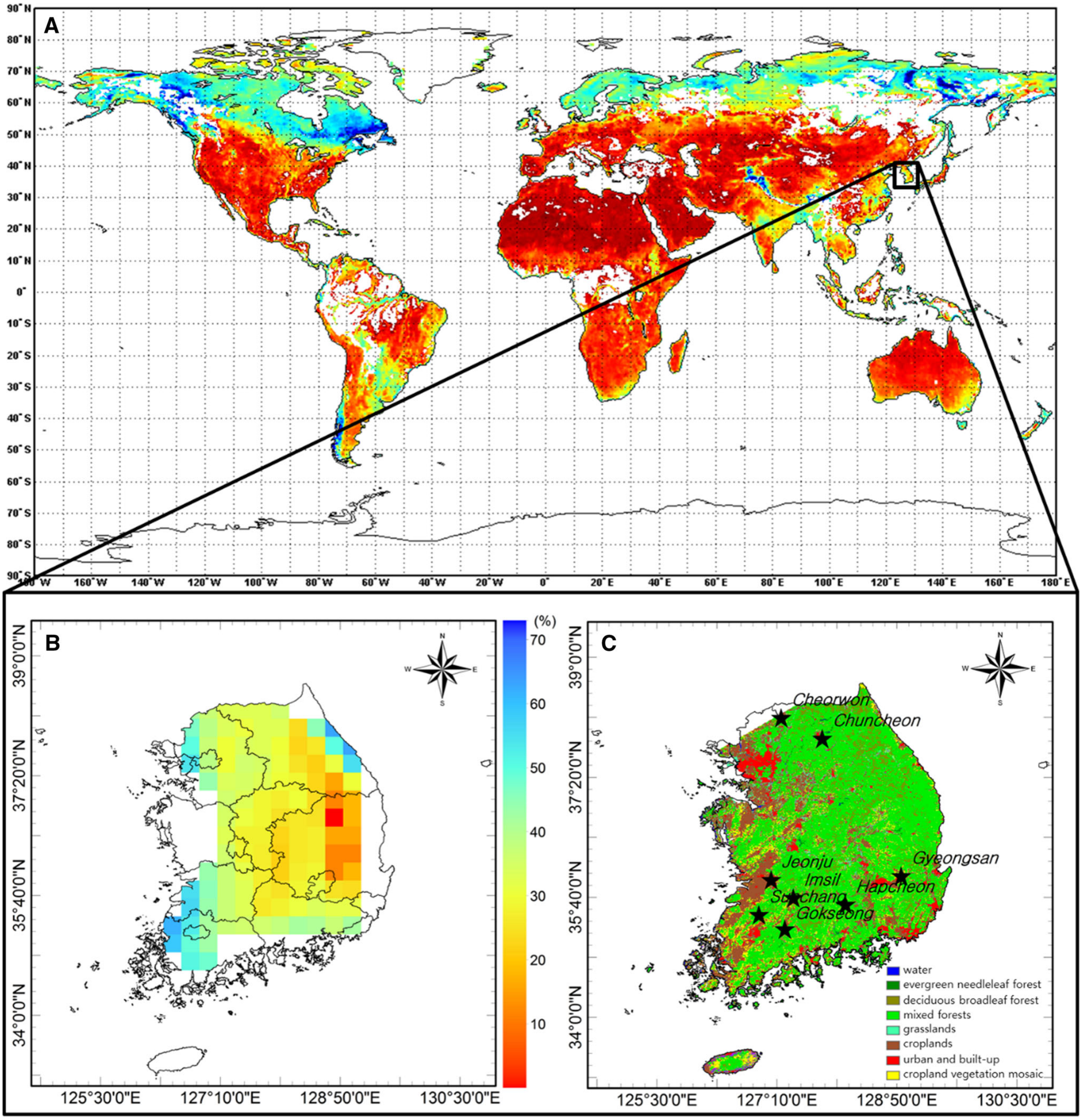

Fig. 1 **a** The world map of soil moisture samples and the location of Korean Peninsula, **b** the sample soil moisture map of the Korean Peninsula and **c** the locations of the in situ soil moisture observation stations and land cover classification on the Korean Peninsula

were located in cropland. Unlike other in situ soil moisture measurements which were designed for validation of remotely sensed data (Jackson et al. 2010), RDA sites were not planned for the satellite-based soil moisture validation purpose. Additionally, in contrast with satellite-based soil moisture dataset in situ dataset provide a deeper layer of soil moisture information ($\sim$10 cm). However, as it is mentioned in AMSR2 dataset section 2.1, the microwave-based soil moisture retrievals represent the near-surface soil moisture information (1–2 cm). Numerous previous studies indicated that soil moisture observation with 5–10 cm depth can be used for validation and estimation of satellite-based soil moisture retrievals if the satellite-based soil moisture dataset are corrected by utilizing the method of normalization (Draper et al. 2009; Su et al. 2013).

In this study, we used soil moisture dataset measured from the eight stations. The geographical characteristics of the stations are summarized in Table 1. The locations of

Table 1 The geographical characteristics of the eight in situ soil moisture gauges

Site Name	Latitude (°)	Longitude (°)	Elevation (El. m)	Annual rainfall (mm)	Annual mean temperature (°C)	Mean relative humidity (%)	Land cover
Gyeongsan	35.82	128.81	58	1046.8	12.4	65.1	Crop land
Gokseong	35.27	127.30	60	1391.0	13.8	69.5	Crop land
Sunchang	35.44	127.04	253	1380.4	12.3	71.7	Mixed forest
Imsil	35.66	127.27	256	1351.9	11.2	73.3	Mixed forest
Jeonju	35.83	127.10	41	1313.1	13.3	69.4	Urban
Cheorwon	38.20	127.25	156	1347.3	11.1	71.0	Crop land
Chuncheon	37.93	127.25	79	1391.2	10.2	70.4	Urban
Hapcheon	35.55	128.11	44	1275.6	13.0	67.6	Crop land

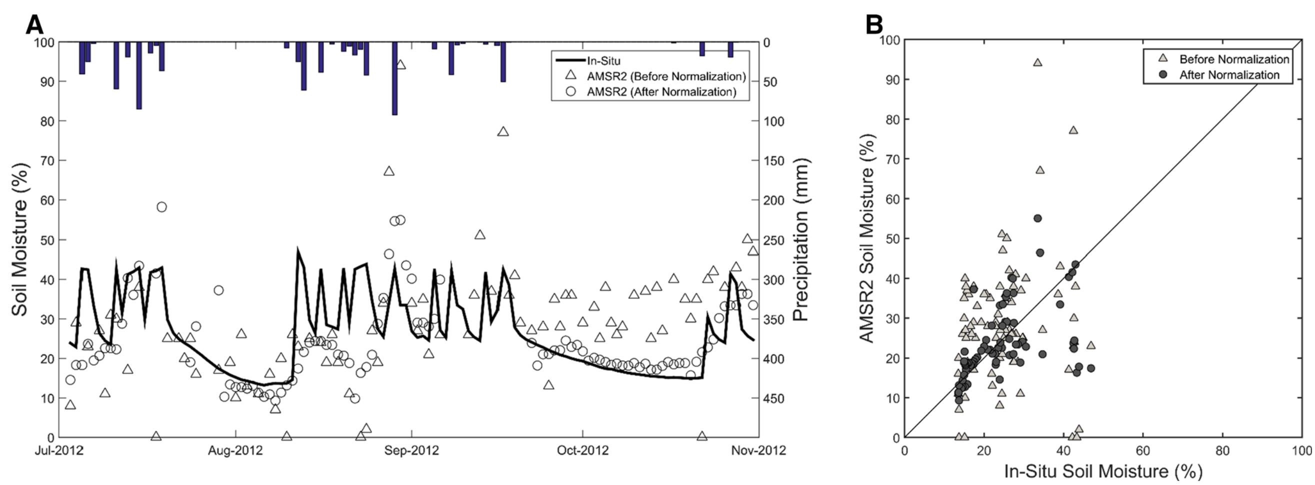

Fig. 2 **a** Time series of AMSR2 satellite soil moisture data before and after the normalization process. In-situ soil moisture data is shown together for reference. The daily hyetograph is shown in the plot on the *top axis*. **b** Scatter plot comparing the in situ soil moisture data (x) and the AMSR2 satellite soil moisture data before and after the normalization process (y)

the eight stations and land cover classification are shown in Fig. 1c.

2.4 Normalization of the satellite soil moisture data

The soil moisture content data obtained by the satellite may be systematically different from the data obtained using a ground sensor because of the discrepancy of the measuring depth and the spatial scale (Kim et al. 2015). For this reason, satellite soil moisture data is often corrected to match the ground soil moisture data using a normalization technique (Draper et al. 2009; Cho et al. 2015). This study applied the average-standard matching method to correct the systematic bias from the satellite soil moisture data. Equation (1) describes the method

$$\theta_S' = \frac{\sigma_i}{\sigma_S}(\theta_S - \mu_S) + \mu_i, \tag{1}$$

where θ_S' is the normalized satellite data, θ_s is the original satellite data, σ_s is the standard deviation of the in situ data, μ_i is the standard deviation of the satellite data, μ_s is the average of the in situ data and is the average of satellite data. In addition, the 5-day moving average filter was applied to the satellite data to reduce the noise before the normalization process. Figure 2 shows the satellite soil moisture data before and after the normalization process.

2.5 Synthesis of ground and satellite based soil moisture data

The CM technique (Ehret 2002; Pegram 2002; Sinclair and Pegram 2005) is a method of spatial interpolation suited for merging the spatially continuous grid-based measurement (e.g. radar rainfall imagery) and the point measurement (e.g. point rainfall measurement). The method has the advantage of precisely preserving the spatial covariance structure of the spatially continuous grid-based measurement while keeping the accuracy of the point-based measurement. The algorithm has been applied and showed superior performance to the traditional geostatistical approaches, especially in obtaining spatial rainfall fields in several regions across the world (e.g. Sinclair and Pegram 2005; Goudenhoofdt and Delobbe 2009 for UK; Delobbe et al. 2009 for Belgium; Kim et al. 2007 for Korea; Berndt et al. 2014 for Germany). The method is also known as Kriging with radar-based error correction because it is frequently used in merging the radar-based rainfall field and point-based rainfall data.

Figure 3 describes the processes of the conditional merging technique applied in this study. The technique has the following six processes: (a) Soil moisture is measured at eight ground gauges; (b) The soil moisture values measured at the eight ground gauges are interpolated using the Ordinary Kriging (KR) technique; (c) Soil moisture is measured from the satellite; (d) The satellite soil moisture values at the eight ground gauge locations are collected and are spatially interpolated using the KR technique; (e) The residual between the data of (c) and the data of (d) is calculated; (f) The residual values of (d) are added to the data of (b) to obtain the final satellite-ground composite soil moisture data. This study is particularly interested in comparing the accuracy of the soil moisture map obtained by spatially interpolating the in situ soil moisture data only using the KR technique—Fig. 3b and the one obtained by merging the satellite and in situ soil moisture data using the CM technique (Fig. 3f).

2.6 Comparison of the spatial interpolation techniques

The leave-one out cross-validation calculation was used to compare the performance of the two spatial interpolation techniques in predicting the soil-moisture values at the

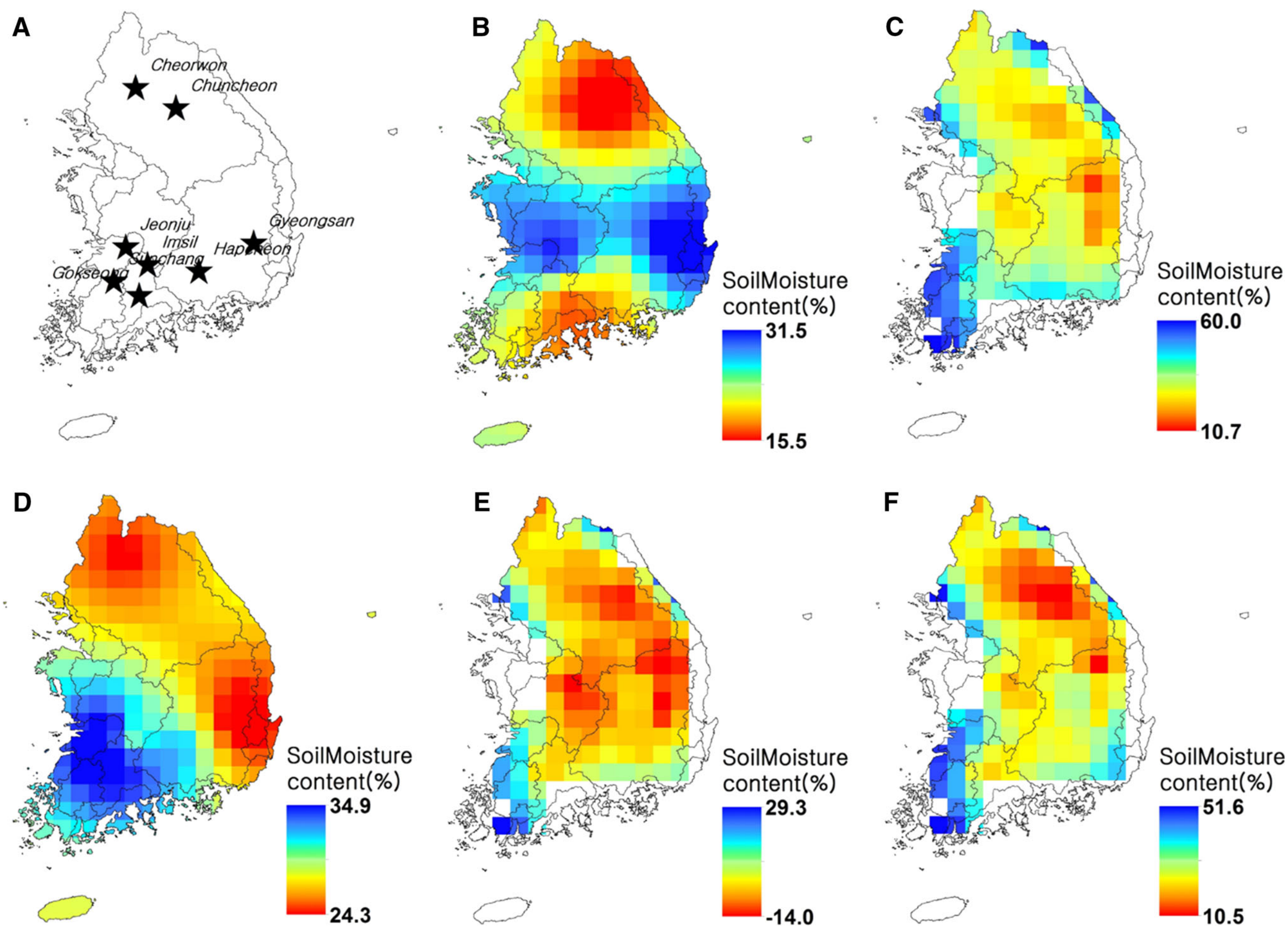

Fig. 3 The processes of the conditional merging technique: **a** soil moisture is measured at eight ground gauges; **b** the soil moisture values measured at the eight ground gages are interpolated using the Ordinary Kriging technique; **c** soil moisture is measured from the satellite and is normalized according to the in situ soil moisture data; **d** the satellite soil moisture values at the eight ground gauge locations are collected and are spatially interpolated using the Ordinary Kriging technique; **e** the residual between the data of **c** and the data of **d** is calculated; **f** the residual values of **e** added to the data of **b** to obtain the final satellite-ground composite soil moisture data

ungauged locations. In the leave-one out cross-validation technique, the in situ soil moisture measurement at a given gauge locations is assumed to be non-existent and the spatial interpolation technique (e.g. CM or KR) is applied to obtain the value at the same point location. Then, the estimated value obtained from the spatial interpolation technique is compared to the original value. Lastly, this process is repeated for all point measurement locations. Figure 4 shows the scatter plot comparing the soil moisture value observed at the ground gauge location on August 2, 2012 and the one obtained from leave-one out cross-validation based on the CM technique (triangles) and the KR technique (circles). If the scatter of the triangles are closer to the 1:1 line in the plot compared to scatter of the circles, the performance of the CM technique can be considered to be better than that of KR technique in estimating soil moisture value at ungaged locations. This also means that the satellite reported soil moisture information enhances the predictability of the soil moisture values at ungauged locations. The arrows shown in the plot shows the effect of adding satellite reported soil moisture information using the CM technique. The scatter of the soil moisture estimate based on the KR method has the correlation coefficient of −0.79 with respect to the zero-intercept least-fit regression line. The soil moisture information derived from the satellite observation is reflected in the soil moisture estimate based on the CM method, enhancing the same correlation coefficient value up to 0.79. However, this result is valid only for the specific date analyzed in the plot (August 2, 2012). This study repeated this cross-validation process for all 51 days of data in this study to draw more general conclusion.

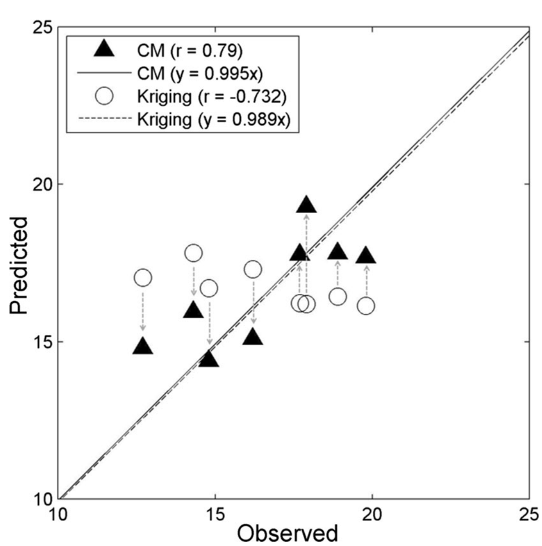

Fig. 4 Scatter plot comparing the soil moisture value observed at the ground gauge locations on August 2, 2012 and the value obtained from leave-one out cross-validation based on the CM (*triangles*) and the KR (*circles*) techniques. The *gray dotted arrow line* indicates the enhancement of the soil-moisture estimate by including the soil-moisture information reported by the satellite. The length and the direction of the *arrow* corresponds to the residual value explained in Fig. 3e

3 Result

3.1 Spatial characteristics of the satellite and in situ soil moisture data

It is important that the satellite and in situ dataset merged using the conditional merging technique have similar spatial characteristics. Regarding this, Cho et al. (2015) provided the result of the direct comparison of the two data sets and concluded that the correlation coefficient is, on average, 0.31. In addition, this study is particularly interested in whether the two data sets have similar spatial covariance structures, which can be measured by comparing the variograms of the two data sets.

Figure 5 shows the daily variation of the spherical model variogram ranges. While it can be noted that the variogram range of both data sets are similar, especially for the period from September through mid-October, no other notable temporal similarity patterns of the model variogram range were identified.

Figure 6 shows the relationship between the squared difference of the model variogram ranges and the average rainfall on the same day. No remarkable relationship has been identified; however, the absence of the scatter points on the upper right side of the plot indicates that when large amount of rainfall occurs, the model variogram range of the in situ soil moisture value and that of the satellite soil moisture value does not tend to be significantly different. Table 2 summarizes the statistics of the model variogram ranges. The average of the in situ and satellite model variogram range was 334 and 363 km, respectively. The average of the model variogram range difference was 54 km.

3.2 Comparison of the satellite-in situ soil moisture composite data (conditional merging) and the in situ only data (Ordinary Kriging)

Figure 7 shows the result of the leave-one-out cross validation for the date of (a) July 3rd, (b) August 2nd, (c) September 1st and (d) October 1st. The scatter plot compares the in situ soil moisture value to the satellite-in situ composite soil moisture value obtained by applying the CM technique (solid squares) and to the in situ only soil moisture value obtained by applying the KR technique (empty squares). The y coordinates of the scatter plots were obtained from the leave-one out interpolation.

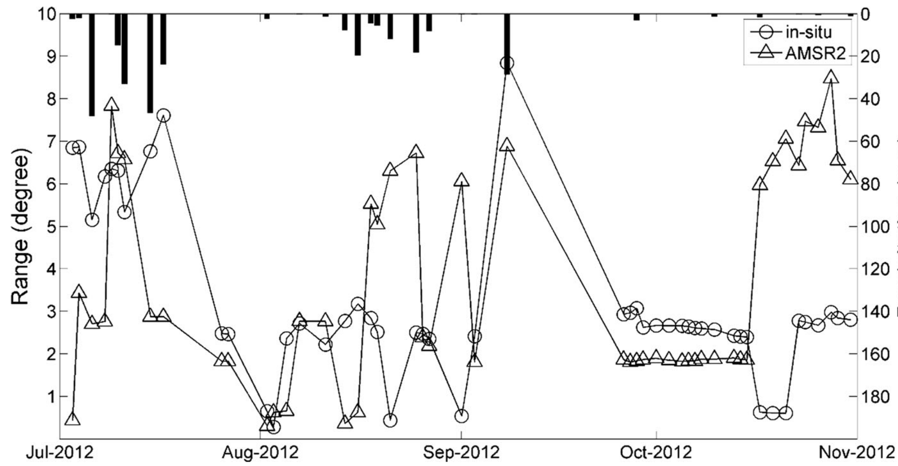

Fig. 5 Daily variation of the spherical model variogram range of the in situ and AMSR-2 soil moisture data

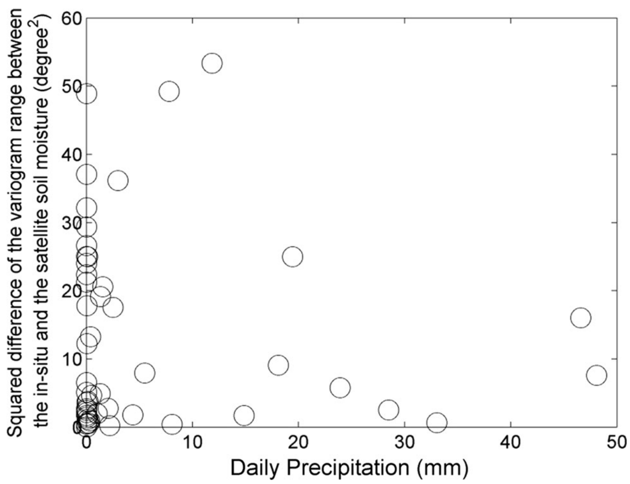

Fig. 6 Scatter plot comparing the squared residual between the in situ and satellite model variogram ranges

For all plots, the zero-intercept least square fit linear regression line, the corresponding equation and the correlation coefficient are shown together. The regression line was set to pass through the origin of the coordinate system because the overall similarity of the dataset to the 1:1 line passing through the origin represents the perfect prediction of the soil moisture value at ungauged location. The performance of the interpolation technique can be considered as the slope of the regression line as the correlation coefficient approaches to the value of one.

For all dates analyzed in Fig. 7, the predictability of the CM method in estimating the soil-moisture at ungauged locations is enhanced compared to the predictability of the KR method; the KR method has the regression line slope and the correlation coefficient closer to the unity. Figures 9 and 10 show the daily variation of the correlation coefficients and the slopes. The correlation coefficient is greater using the KR method in 69 % of the 51 days investigated. However, for several days especially, during the period from late July through early October, the KR method showed drastically low correlation coefficients. The CM method did not have low correlation coefficients for most dates investigated. In addition, the difference between the two correlation coefficients is not significant when the KR method has a greater correlation coefficient compared to the CM method.

The hatched area in Fig. 8 shows the degree of improved correlation coefficients, when the CM method outperforms the KR method. The shaded area in the plot shows when the KR method outperforms the CM method. The first is significantly larger than the latter. The sum of the correlation coefficients for all 51 days when applying the CM and the KR method are 22.6 and 12.6, respectively. In Fig. 9, the slope of the regression line was

Table 2 The statistics of the model variogram range

Month	Monthly average variogram range (°)					
	In-situ			AMSR2		
	Spherical	Exponential	Gaussian	Spherical	Exponential	Gaussian
JUL	5.6701	2.8223	2.3637	3.6255	2.7958	1.4933
AUG	2.1001	1.1078	0.9169	2.7919	1.5189	1.2512
SEP	3.2756	2.6900	1.4742	3.8615	1.8305	1.3524
OCT	2.3330	1.4068	1.2049	4.2410	2.1242	1.7227
Total	3.3447	2.0067	1.4899	3.6300	2.0673	1.4549

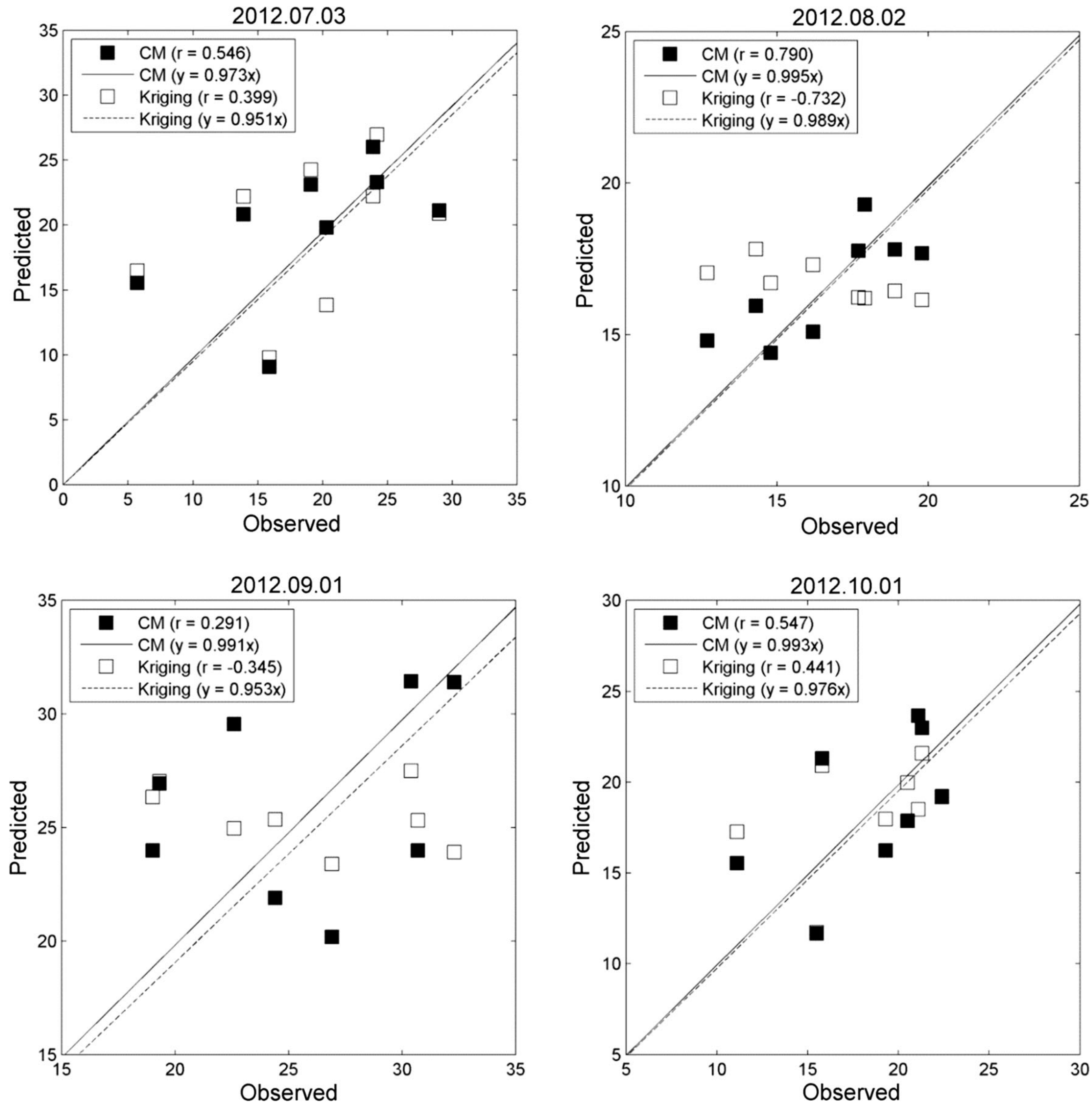

Fig. 7 Results of the leave-one out cross-validation. The scatter of the *filled squares* in the plots compares the in situ soil moisture value (x) and the satellite-in situ composite soil moisture value, obtained by applying the conditional merging technique to (y). The scatter of the *hollow squares* in the plots compares the in situ soil moisture value (x) and the in situ only soil moisture obtained by applying the Ordinary Kriging technique (y)

greater using the CM method for 80 % the 51 days investigated. The hatched area in the plot shows the degree of improved regression line slope when the CM method outperforms the KR method. The shaded area shows time points where the KR method outperforms the CM method. For Figs. 8 and 9, the hatched area is greater than the shaded area, which generally means the CM method yields more certain (greater correlation coefficient) and less biased (regression line slope closer to the unity) soil moisture estimates at ungauged locations compared to the KR method.

While Fig. 7 compares the cross-validation result for a specific date, Fig. 10 compares the cross-validation results for all dates considered in this study at individual gauges. The result corresponding to all eight in situ gauges are shown. Each plot shows the observed (x) versus an estimated (y) soil moisture value obtained through cross validation using the CM method (black solid square) and the KR method (hollow square). The CM method outperforms the KR method using the Gyeongsan gauge (Fig. 10a). Conversely, the KR method outperforms the CM method at Cheorwon (Fig. 10e) and Chuncheon (Fig. 10f) gauges.

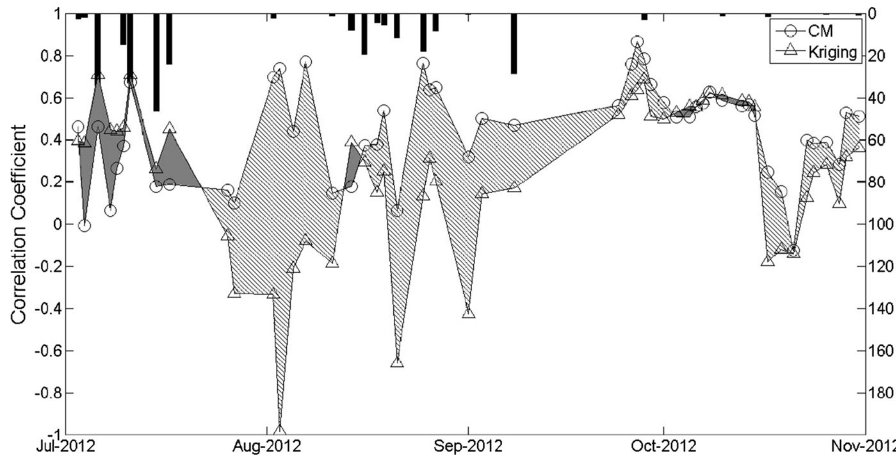

Fig. 8 Daily variation of the correlation coefficient of the regression line relating the in situ soil moisture value and the soil moisture value obtained by applying the leave-one-out interpolation. The *hatched area* in the plot shows the degree of improved correlation when the CM method outperforms the KR method. The *shaded area* in the plot shows when the KR method outperforms the CM method

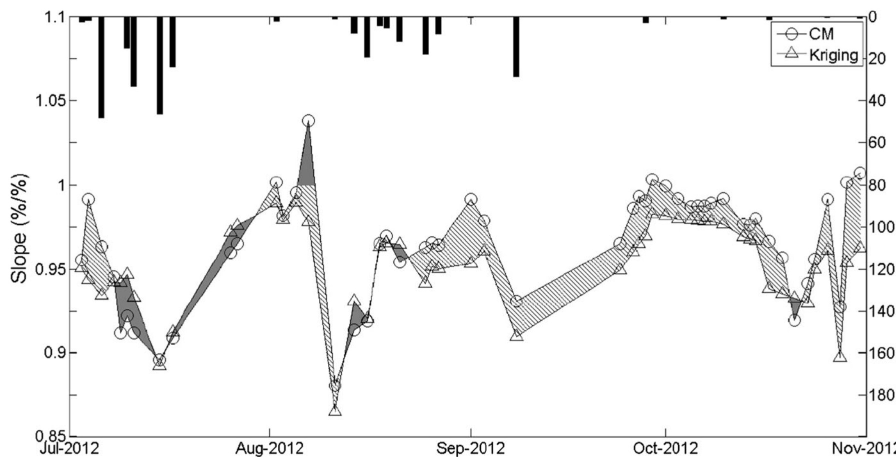

Fig. 9 Daily variation of the slope of the regression line relating the in situ soil moisture value and the soil moisture value obtained by applying the leave-one-out interpolation. The *hatched area* in the plot shows the degree of improved regression line slope, when the CM method outperforms the KR method. The *shaded area* in the plot shows when the KR method outperforms the CM method

The performances of both methods were similar at the remaining five gauges. This notable difference of the relative performance of the two methods is because the CM method is affected by the accuracy of the KR estimate of the in situ data (see Fig. 3b). In the CM method, the satellite data adjusts the KR estimate of the in situ soil moisture data (see Fig. 3f). Consequently, if the KR estimate of the in situ soil moisture value is not accurate, the estimate based on the CM method will be inaccurate as well. This can be proven by the correlation coefficients of both interpolation methods being closely related with each other.

Both Cheorwon and Chuncheon gauges are located further away from the remaining six gauges, which means that the KR estimate of those two locations tend to be inaccurate, especially for the days with low variogram range. In addition, both Cheorwon and Chuncheon gauges are located in mountainous areas where the difference between the in situ and the satellite soil-moisture data is known to be significant. This subsequently yields an inaccurate estimate of the residual value (Fig. 3e) used by the CM method to adjust the KR in situ soil moisture value estimate.

The correlation coefficient and slope of the regression analysis is provided in Fig. 10. This figure cannot thoroughly represent the absolute performance of the applied interpolation technique, because each of the data point may have a unique reason of being optimal estimate. The data points still work as a standard to measure the general performance of each interpolation technique.

Figure 11 shows the map of the correlation coefficients of the regression line shown in Fig. 10 while comparing the observed (x) versus cross-validated soil moisture value estimates based on the (a) CM method and the (b) KR method. For both maps, the lighter area indicates a more optimal performance of the applied interpolation technique. The general spatial trend of both maps is similar showing greater correlation coefficient values at the southwestern regions of the Korean Peninsula. The correlation coefficient decreased toward the north.

Figure 12 shows the map of the relative performance of both methods measured in terms of (a) the regression line

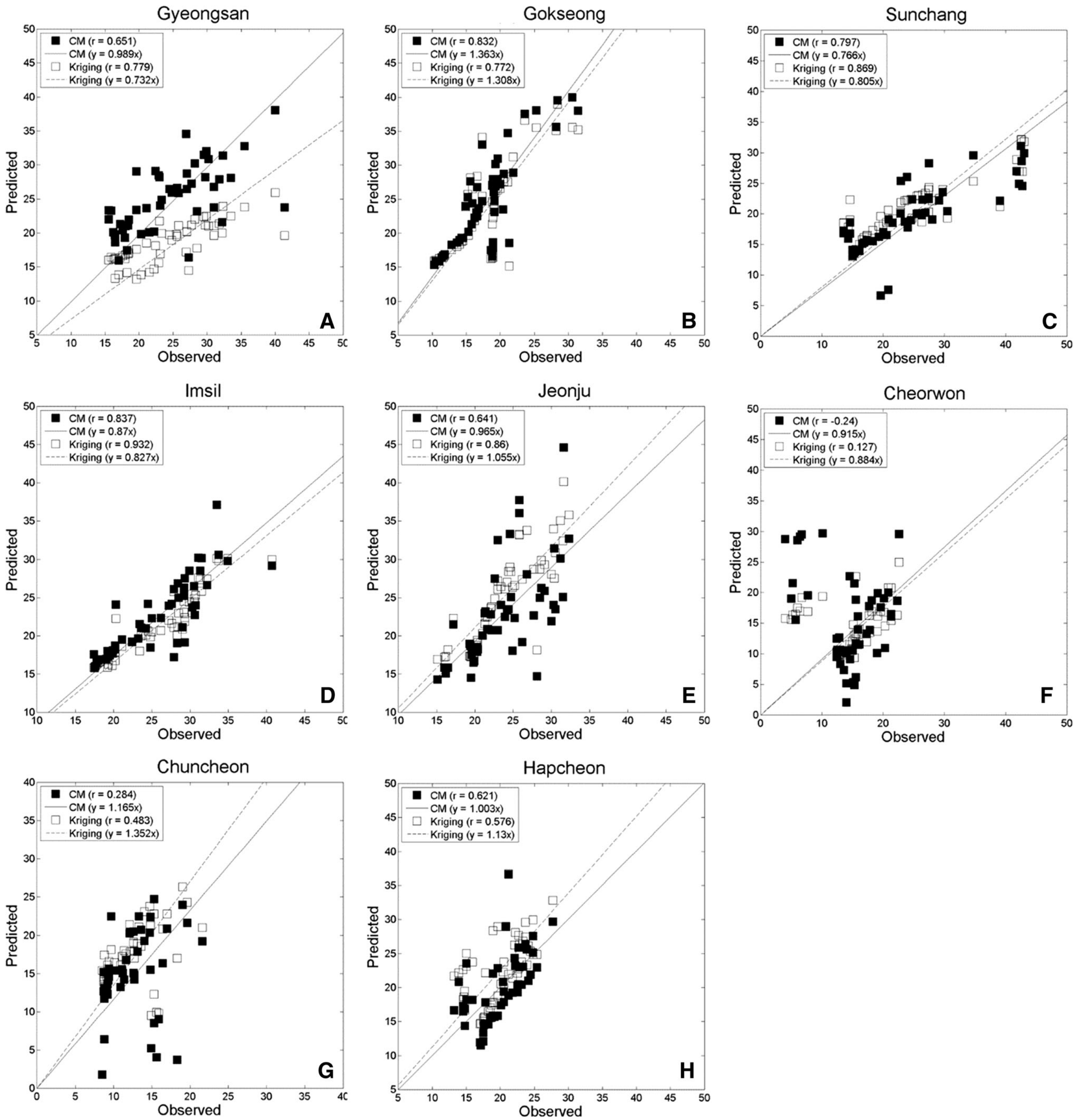

Fig. 10 In-situ soil-moisture value (x) versus the soil moisture value obtained from leave-one-out interpolation for all dates considered in this study at individual gauges

slope and (b) the correlation coefficient. Specifically, Eq. (2) was used to calculate the value at each of the eight gauges to be used for the spatial interpolation:

$$\text{KR-CM}_a = |1 - a_{KR}| - |1 - a_{CM}|, \qquad (2)$$

where a_{CM} is the slope of the zero-intercept least-square fit regression line of the cross-validation plot using the CM method for a given gauge; a_{KR} is the slope of the zero-intercept least-square fit regression line of the cross-validation plot using the KR method for a given gauge.

The first and the second term on the right hand side of the equation, which are $|1 - a_{KR}|$ and $|1 - a_{CM}|$, represent the closeness of the slope of the regression line of each interpolation method to the unity. The difference of $|1 - a_{KR}| - |1 - a_{CM}|$ or KR-CM$_a$ calculates which method has the slope of the regression line closer to the

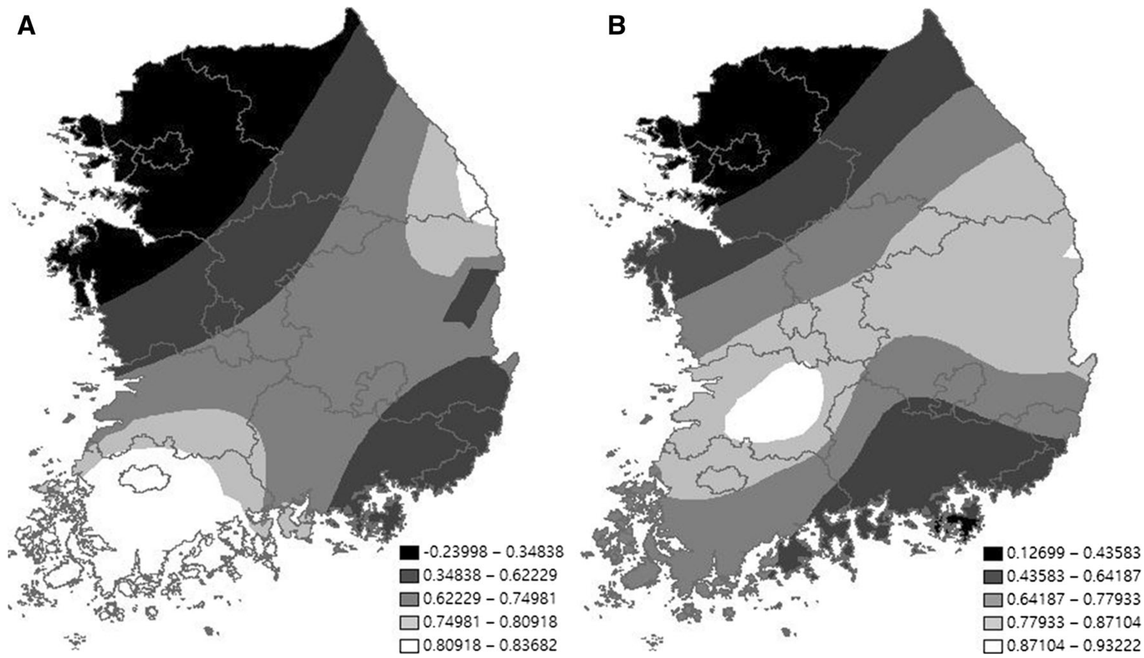

Fig. 11 The map of the correlation coefficient of the regression analysis comparing the observed (x) versus cross-validated soil moisture value estimates based on the **a** CM method and the **b** KR method

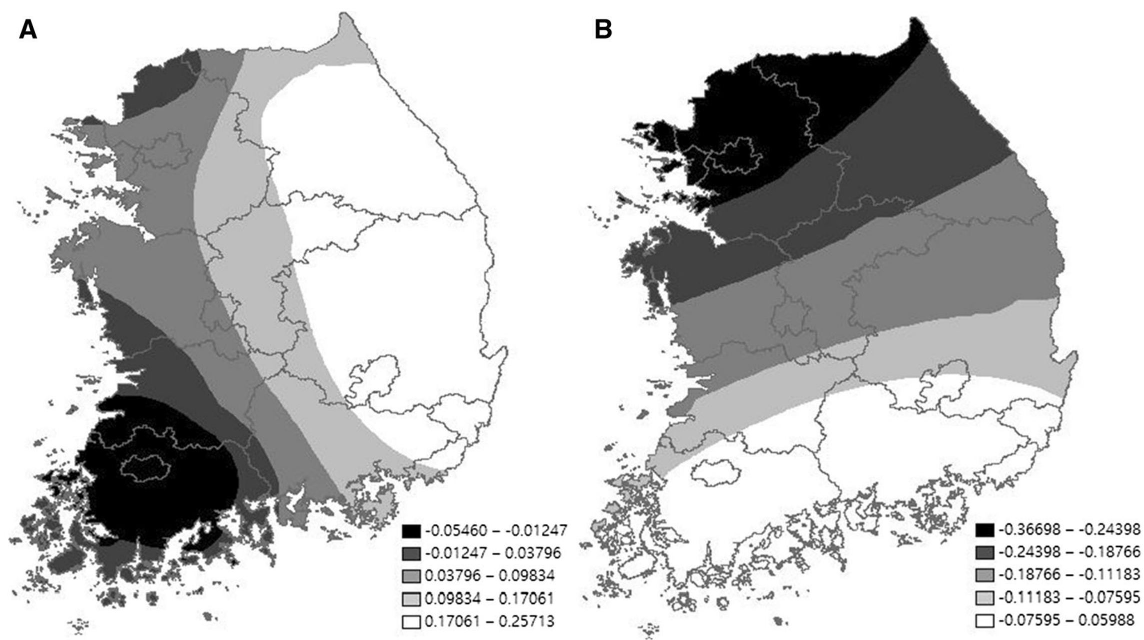

Fig. 12 Maps of the differences between the slope of the regression line (**a**) and correlation coefficient (**b**). *Bright colors* mean CM showed increased predictability compared to the Kriging method, and *dark colors* mean the opposite

unity. The positive value means that the CM method has the regression line closer to the unity compared to the Kriging method and vice versa.

For example, the cross-validation plot of Fig. 10a has the two zero-intercept regression lines for the KR method and the CM method, which has the slope of 0.65 and 0.98, respectively. According to Eq. (2), KR-CM_a has the positive value of 0.33 which means that the CM method has the regression line closer to the unity compared to the Kriging method. Therefore, when the map value increases, the predictability of the CM method increases at the corresponding location. Conversely, when the map value decreases, the predictability of the KR method increases. Figure 12b was produced using a similar value based on

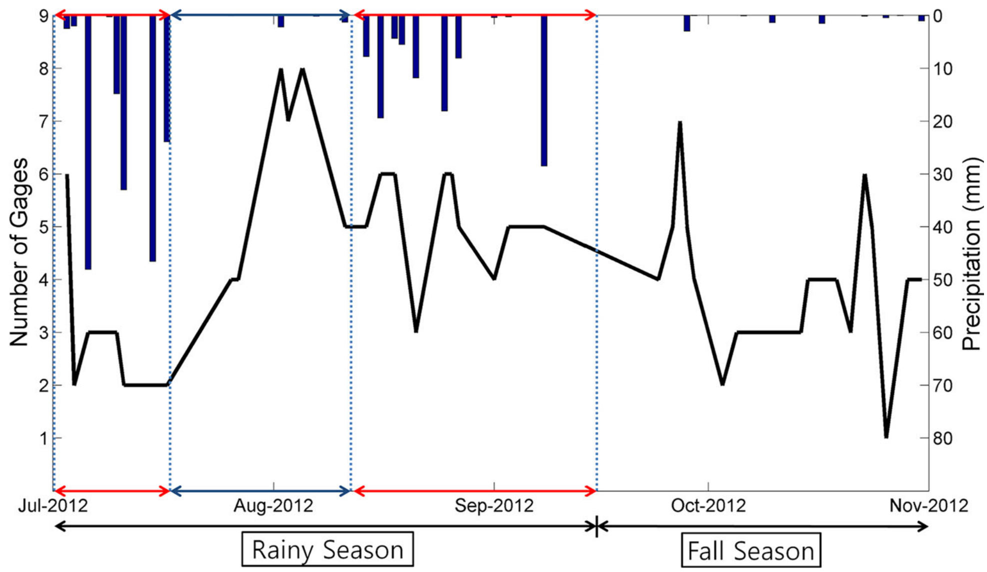

Fig. 13 Daily variation of the number of the gauges where the CM method outperformed the Kriging method. At these gauges, the residual between the CM-based soil moisture value and the observed soil moisture value was lower than the residual between the Kriging-based soil moisture value and the observed soil moisture value. On the *top side* of Fig. 14 (*right axis*) shows the average areal daily rainfall in the study area

the correlation coefficient of the regression analysis. Specifically, Eq. (3) was used:

$$\text{KR-CM}_r = |1 - r_{KR}| - |1 - r_{CM}|, \quad (3)$$

where r_{CM} is the correlation coefficient of the zero-intercept least-square fit regression line of the cross-validation plot using the CM method for a given gauge; r_{KR} is the correlation coefficient of the zero-intercept least-square fit regression line of the cross-validation plot using the CM method for a given gauge.

The CM method outperforms the KR method at eastern part of the Korean Peninsula in terms of the regression line slope. The opposite is true for the western part of the Korean Peninsula. The spatial trend of the relative performance in terms of correlation coefficient was different from the one based on the regression line slope. The CM method outperforms the KR method in the southern part of the Korean Peninsula. The opposite is true for the northern part of the study area.

4 Discussion

4.1 Influence of the rainfall on the relative performance of the interpolation methods

As soil moisture is directly influenced by rainfall, the relative performance of the two interpolation methods is expected to be influenced by the amount of rainfall. Figure 13 shows the daily variation of the number of the gauges where the CM method outperformed the KR method. At these gauges, the residual between the CM-method-based soil moisture value and the observed soil moisture value was lower than the residual between the KR-method-based soil moisture value and the observed soil moisture value. The bars on the top side of Fig. 13 show the average areal daily rainfall in the study area. The amount of this areal daily rainfall is shown in the right axis of the plot. During the rainy season (July through September), the number of the gauges at which CM method outperforms the KR method decreases when the rainfall occurs (period specified by the red arrow). Conversely, the number of the gauges at which CM method outperforms the Kriging method increases when no rainfall occurs (period specified by the blue line). This contrast is caused by the spatial correlation of the in situ soil moisture value increasing when a large amount of rainfall occurs. In other words, the soil moisture value at different in situ gauges is similar with each other. This allows the KR method to use the information from nearby gages to estimate the soil moisture value.

Conversely, when there is little rainfall, the soil moisture values at different gauges are completely different. Then, the KR method cannot use information as many as the date with large rainfall. Instead, the CM method, which can use the data from the satellite to overcome this low spatial correlation of the in situ gage measurements. The reason why the CM method, which takes advantage of soil moisture information from both satellite and in situ measurement, is not always better than the KR method is because the satellite measurements have low accuracy. To support this argument, the spatial correlation of the in situ soil moisture value should increase as the average areal rainfall across the study area increases. Figure 14 shows the relationship between the average rainfall across the study area (x) and the variogram range of the in situ soil moisture value (y). By the definition of the variogram range, a soil moisture value from one in situ gauge does not

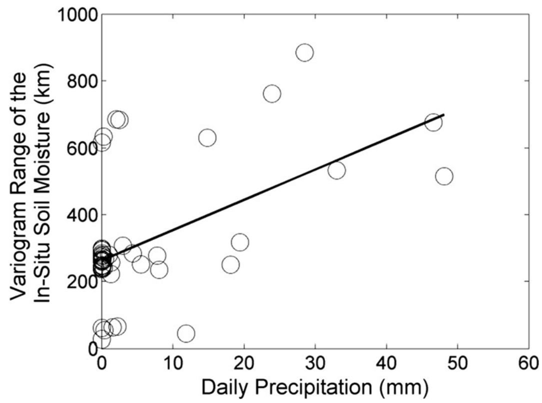

Fig. 14 The relationship between the average rainfall across the study area and the variogram range of the in situ soil moisture values

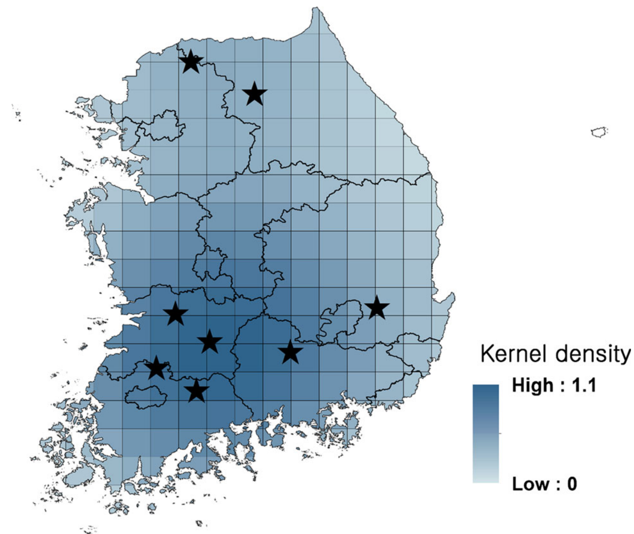

Fig. 15 The Kernel density field of the study area along with the location of the in situ soil moisture gauges

affect the soil-moisture value of another area located further than the variogram range shown in the plot. The variogram range generally increases with precipitation increase, while variation is significant when there is little rainfall. This implies the spatial correlation of in situ soil moisture value varies when there is little rainfall, but it tends to be high when a large amount of rainfall occurs across the study area. This eventually increases the predictability of the KR method.

4.2 Influence of the gage density

Both the KR method and the CM method are based on the KR interpolation technique, and the performance of the KR interpolation technique are influenced by the spatial density of the observations (Hofstra et al. 2010). The area with greater observation density has increased accurate variable estimates because more information can be obtained from nearby observations. To find out whether the spatial density of the in situ soil moisture observation influences the relative performance of the two methods applied in this study, we compared the spatial density of the in situ soil moisture gauges and the relative performance of the in situ Kriging and the CM methods. Here, the spatial density of the in situ gauges were obtained by the Kernel density method (Silverman 1986). Figure 15 shows the Kernel density field of the study area along with the grid setting designed for the comparison. The grid cell shown in Fig. 15 overlapped with Fig. 12a, b to obtain the grid cell values from the corresponding maps.

Figure 16 shows the result of the comparison. Figure 16a compares the Kernel density of in situ gauge (x) and the relative performance of the KR and the CM method in terms of the slope of the regression line (y). The y value of the scatter in the plot was calculated using Eq. (2). The positive y-value means that the CM method performs better than the Kriging method at the corresponding grid cell location in terms of regression line slope. Even though the variability of the scatter is high, the relative performance of the CM method generally decreases as the gauge density increases (shown by the black solid line; the moving average of the scatter in the plot).

Figure 16b shows the same plot with the variation of the relative performance of the CM method and the Kriging method in terms of the correlation coefficient. The y value of the scatter in the plot was calculated using Eq. (3). Note that the y-values of the scatter are mostly below 0, meaning that the correlation coefficient of the Kriging method is greater than that of the CM method at most of the grid cell locations in the study area. Note that as the gauge density increases, the relative performance of the CM method, in terms of correlation coefficient, increases.

These findings lead to the conclusion that as the gauge density decreases, the CM method tends to yield a less-biased estimate of the soil moisture value with greater uncertainty, compared to the Kriging method. This is because as the gauge density decreases or there are not sufficient nearby gages, the soil-moisture information that the Kriging method can use decreases yielding biased estimate. However, the CM method still can use the satellite-derived soil moisture information, even when there are no nearby in situ gauges.

4.3 Influence of terrain and land use

The accuracy of the AMSR2 soil moisture product is influenced by terrain and land use (Yuan et al. 2015). Therefore, the relative performance of the two

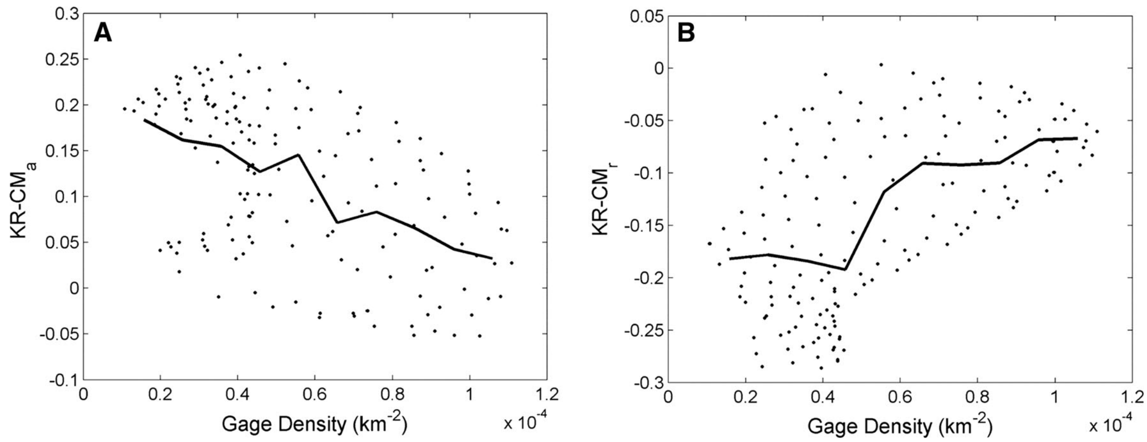

Fig. 16 The relationship between the gauge Kernel density and the relative performances of the KR method and the CM method, measured in terms of the **a** regression line slope and the **b** correlation coefficient

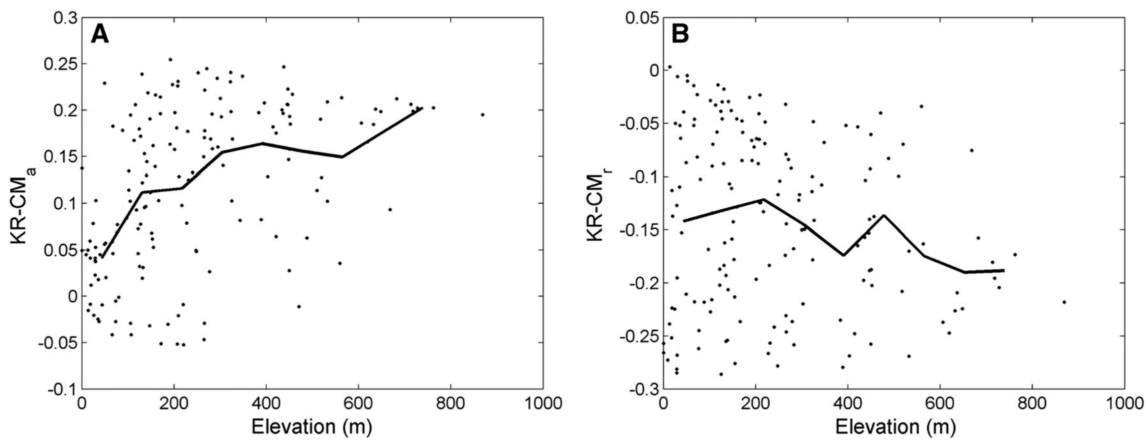

Fig. 17 The relationship between the altitude and the relative performance of the KR method and the CM method measured in terms of **a** the regression line slope and **b** the correlation coefficient. The y-value of the scatter in plot **a** and plot **b** was calculated using Eqs. (2) and (3), respectively

interpolation methods applied in this study can be influenced by terrain and land use. Figure 17 compares the relative performances of the interpolation methods varying with altitude. Here, the Normalized Difference Vegetation Index (NDVI) is considered as the explanatory variable along with altitude; however, it has a very high positive correlation with altitude. Therefore, only the analysis based on altitude is presented in this study. In addition, the Kernel density of the in situ gauges investigated in Sect. 4.2 does not have notable correlation with altitude. The same grid setting shown in Fig. 15 was used for comparison.

The y value of the scatter in both plots in Fig. 17 is the relative performance of the KR and CM method in terms of regression line slope (Eq. 2) and correlation coefficient (Eq. 3). Figure 17a shows the relative performance of the two interpolation methods in terms of regression line slope. As the altitude increases, the CM method performance increases when compared to the Kriging method. Figure 17b shows the relative performance of the two interpolation methods in terms of correlation coefficient. The y value of the scatter was calculated using Eq. (3). While the Kriging method shows improved performance compared to the CM method as altitude increases, the degree of improvement was not as dramatic as that of the comparison based on the regression line slope.

These findings lead to the conclusion that the CM method yields a less biased but more uncertain estimate of soil moisture value compared to the Kriging method as the altitude of the area increases. As the altitude of the area increases, the spatial correlation of the in situ soil moisture value decreases (Western et al. 1999), this yields little information for interpolation for the KR method. On the contrary, the CM method uses the soil-moisture information derived from satellite for the area where even in situ data cannot provide information due to low spatial correlation, which is the reason why the CM method shows improved performance in terms of regression line slope.

5 Conclusion

This study investigated the applicability of the conditional merging (CM) spatial interpolation technique to obtain the AMSR2-satellite-in situ composite soil moisture value in Korean Peninsula. The performance of the composite product was compared to the soil moisture value obtained by spatially interpolating the in situ soil moisture data measured at eight gauge locations using the KR technique. The leave-one out cross-validation technique was used to estimate both methods' ability to estimate soil moisture values at ungauged locations.

We conclude the performance of the KR method is highly influenced by the spatial correlation of the in situ soil moisture content. When the spatial correlation of the in situ data is high, the KR method can use the soil moisture information from many nearby gauges, yielding a more accurate soil moisture estimate. Conversely, when the spatial correlation of the in situ data is low, the CM method is likely to outperform the KR method because the CM method overcomes this issue by taking advantage of the satellite-soil moisture measurement. This case includes when there is little rainfall and where the altitude of the area is high (mountainous area). However, the CM method does not always outperform the KR method, even if there is low spatial correlation. This is because the satellite measurement is not always accurate.

We further conclude that the CM method outperforms the KR method for locations with low gauge density (areas further away from in situ gauges). This is due to the accuracy of the KR method increasing as in situ gauge density increases.

Acknowledgments This research was supported by the Basic Research Laboratory Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT & Future Planning. (Grant ID: NRF-2015041523). This research was also supported by Space Core Technology Development Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT and Future Planning (NRF-2014M1A3A3A02034789). The AMSR2 data was supplied by the GCOM-W1 Data Providing service, Japan Aerospace Exploration Agency. We would like to thank the Rural Development Administration of the Korean Government for providing ground soil moisture data.

References

Albergel C, Rüdiger C, Carrer D et al (2009) An evaluation of ASCAT surface soil moisture products with in situ observations in Southwestern France. Hydrol Earth Syst Sci 13(2):115–124. doi:10.5194/hess-13-115-2009

Al-Yaari A, Wigneron JP, Ducharne A et al (2014) Global-scale evaluation of two satellite-based passive microwave soil moisture datasets (SMOS and AMSR-E) with respect to Land Data Assimilation System estimates. Remote Sens Environ 149:181–195. doi:10.1016/j.rse.2014.04.006

Anctil F, Mathieu F, Parent L-E et al (2002) Geostatistics of near-surface moisture in bare cultivated organic soils. J Hydrol 260(1):30–37. doi:10.1016/S0022-1694(01)00600-X

Azimi-Zonooz A, Krajewski WF, Bowles DS, Seo DJ (1989) Spatial rainfall estimation by linear and non-linear co-Kriging of radar-rainfall and raingage data. Stoch Hydrol Hydraul 3(1):51–67. doi:10.1007/s00477-010-0398-8

Bardossy A, Lehmann W (1998) Spatial distribution of soil moisture in a small catchment. Part 1: Geostatistical analysis. J Hydrol 206(1):1–15. doi:10.1016/S0022-1694(97)00152-2

Berndt C, Rabiei E, Haberlandt U (2014) Geostatistical merging of rain gauge and radar data for high temporal resolutions and various station density scenarios. J Hydrol 508:88–101. doi:10.1016/j.jhydrol.2013.10.028

Bolten JD, Crow WT, Zhan X et al (2010) Evaluating the utility of remotely sensed soil moisture retrievals for operational agricultural drought monitoring. IEEE J Select Top Appl Earth Obs Remote Sens 3(1):57–66. doi:10.1109/JSTARS.2009.2037163

Brocca L, Melone F, Moramarco T et al (2009) Assimilation of observed soil moisture data in storm rainfall-runoff modeling. J Hydrol Eng 14(2):153–165. doi:10.1061/(asce)1084-0699(2009)14:2(153)

Brocca L, Melone F, Moramarco T et al (2010) ASCAT soil wetness index validation through in situ and modeled soil moisture data in central Italy. Remote Sens Environ 114(11):2745–2755. doi:10.1016/j.rse.2010.06.009

Brocca L, Hasenauer S, Lacava T et al (2011) Soil moisture estimation through ASCAT and AMSR-E sensors: an intercomparison and validation study across Europe. Remote Sens Environ 115(12):3390–3408. doi:10.1016/j.rse.2011.08.003

Campbell Scientific Inc. (1996) CS615 water content reflectometer instruction manual. Campbell Scientific Inc., Utah

Campbell Scientific Inc. (2012) CS616 and CS625 water content reflectometers instruction manual. Campbell Scientific Inc., Utah

Cho E, Choi M (2014) Regional scale spatio-temporal variability of soil moisture and its relationship with meteorological factors over the Korean peninsula. J Hydrol 516:317–329. doi:10.1016/j.jhydrol.2013.12.053

Cho E, Moon H, Choi M (2015) First assessment of the advanced microwave scanning radiometer 2 (AMSR2) soil moisture contents in Northeast Asia. J Meteorol Soc Jpn 93(1):117–129. doi:10.2151/jmsj.2015-008

Choi M, Jacobs JM (2007) Soil moisture variability of root zone profiles within SMEX02 remote sensing footprints. Adv Water Resour 30(4):883–896

Choi M, Jacobs JM (2008) Temporal variability corrections for advanced microwave scanning radiometer E (AMSR-E) surface soil moisture: case study in Little River region, Georgia, US. Sensors 8(4):2617–2627. doi:10.3390/s8042617

Cosh MH, Jackson TJ, Moran S et al (2008) Temporal persistence and stability of surface soil moisture in a semi-arid watershed. Remote Sens Environ 112(2):304–313. doi:10.1016/j.rse.2007.07.001

Crow WT, Bindlish R, Jackson TJ (2005) The added value of spaceborne passive microwave soil moisture retrievals for forecasting rainfall-runoff partitioning. Geophys Res Lett. doi:10.1029/2005GL023543

Dani OR, Hanks RJ (1992) Spatial and temporal soil moisture estimation considering soil variability and evapotranspiration on uncertainty. Water Resour Res 28(3):803–814. doi:10.1029/91WR02585

Delobbe L, Bastin G, Dierickx P et al (2009) Evaluation of several radar-gauge merging techniques for operational use in the Walloon region of Belgium. In Proceedings of the international symposium on weather radar and hydrology, Grenoble, France, 10–15 March 2008

Dorigo WA, Scipal K, Parinussa RM et al (2010) Error characterisation of global active and passive microwave soil moisture datasets. Hydrol Earth Syst Sci 14(12):2605–2616. doi:10.5194/hess-14-2605-2010

Dorigo WA, Wagner W, Hohensinn R et al (2011) The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements. Hydrol Earth Syst Sci 15(5):1675–1698. doi:10.5194/hess-15-1675-2011

Draper CS, Walker JP, Steinle PJ et al (2009) An evaluation of AMSR-E derived soil moisture over Australia. Remote Sens Environ 113(4):703–710. doi:10.1016/j.rse.2008.11.011

Ebert EE (2007) Methods for verifying satellite precipitation estimates. In: Levizzani V, Bauer P, Turk FJ (eds) Measuring precipitation from space. Springer, Dordrecht, pp 345–356

Ehret U (2002) Rainfall and flood nowcasting in small catchments using weather radar. PhD thesis, University of Stuttgart

Ehret U (2003) Rainfall and flood nowcasting in small catchments using weather radar. PhD thesis, University of Stuttgart

Entekhabi D, Njoku EG, Neill PE et al (2010) The soil moisture active passive (SMAP) mission. Proc IEEE 98(5):704–716. doi:10.1109/JPROC.2010.2043918

Famiglietti JS, Devereaux JA, Laymon CA et al (1999) Ground-based investigation of soil moisture variability within remote sensing footprints during the Southern Great Plains 1997 (SGP97) Hydrology Experiment. Water Resour Res 35(6):1839–1851

Fujii H, Koike T, Imaoka K (2009) Improvement of the AMSR-E algorithm for soil moisture estimation by introducing a fractional vegetation coverage dataset derived from MODIS data. J Remote Sens Soc Jpn 29(1):11. doi:10.11440/rssj.29.282

Goudenhoofdt E, Delobbe L (2009) Evaluation of radar-gauge merging methods for quantitative precipitation estimates. Hydrol Earth Syst Sci 13(2):195–203. doi:10.5194/hess-13-195-2009

Herbst M, Diekkruger B (2003) Modelling the spatial variability of soil moisture in a micro-scale catchment and comparison with field data using geostatistics. Phys Chem Earth A/B/C 28(6):239–245. doi:10.1016/S1474-7065(03)00033-0

Hofstra N, New M, McSweeney C (2010) The influence of interpolation and station network density on the distributions and trends of climate variables in gridded daily data. Clim Dyn 35(5):841–858. doi:10.1007/s00382-009-0698-1

Imaoka K, Kachi M, Fujii H et al (2010) Global Change Observation Mission (GCOM) for monitoring carbon, water cycles, and climate change. Proc IEEE 98(5):717–734. doi:10.1109/JPROC.2009.2036869

Jackson TJ, Cosh MH, Bindlish R et al (2010) Validation of advanced microwave scanning radiometer soil moisture products. IEEE Trans Geosci Remote Sens 48(12):4256–4272

Kerr YH, Waldteufel P, Wigneron JP et al (2001) Soil moisture retrieval from space: the Soil Moisture and Ocean Salinity (SMOS) mission. IEEE Trans Geosci Remote Sens 39(8):1729–1735. doi:10.1109/36.942551

Kerr YH, Waldteufel P, Wigneron JP et al (2010) The SMOS mission: new tool for monitoring key elements of the global water cycle. Proc IEEE 98(5):666–687. doi:10.1109/JPROC.2010.2043032

Kim H, Choi M (2015) Impact of soil moisture on dust outbreaks in East Asia: using satellite and assimilation data. Geophys Res Lett 42(8):2789–2796. doi:10.1002/2015GL063325

Kim BJ, Kripalani RH, Oh JH et al (2002) Summer monsoon rainfall patterns over South Korea and associated circulation features. Theor Appl Climatol 72(1–2):65–74. doi:10.1007/s007040200013

Kim BS, Hong JB, Kim HS et al (2007) Combining radar and rain gauge rainfall estimates for flood forecasting using conditional merging method. In: Proceedings of the world environmental and water resources congress. ASCE, Reston, pp 1–16

Kim S, Liu YY, Johnson FM et al (2015) A global comparison of alternate AMSR2 soil moisture products: why do they differ? Remote Sens Environ 161:43–62

Köhli M, Schrön M, Zreda M et al (2015) Footprint characteristics revised for field-scale soil moisture monitoring with cosmic-ray neutrons. Water Resour Res 51(7):5772–5790. doi:10.1016/j.rse.2015.02.002

Kyoung MS, Kim HS, Sivakumar B, Singh VP, Ahn KS (2011) Dynamic characteristics of monthly rainfall in the Korean Peninsula under climate change. Stoch Environ Res Risk Assess 25(4):613–625. doi:10.1007/s00477-010-0425-9

Li Q, Li P, Li H, Yu M (2015) Drought assessment using a multivariate drought index in the Luanhe River basin of Northern China. Stoch Environ Res Risk Assess 29(6):1509–1520. doi:10.1007/s00477-014-0982-4

Mittelbach H, Seneviratne SI (2012) A new perspective on the spatio-temporal variability of soil moisture: temporal dynamics versus time-invariant contributions. Hydrol Earth Syst Sci 16(7):2169–2179. doi:10.5194/hess-16-2169-2012

Mohanty BP, Skaggs TH, Famiglietti JS (2000) Analysis and mapping of field scale soil moisture variability using high resolution ground based data during the Southern Great Plains. Water Resour Res 36(4):1023–1031. doi:10.1029/1999WR900360

Njoku EG, Jackson TJ, Lakshmi V et al (2003) Soil moisture retrieval from AMSR-E. IEEE Trans Geosci Remote Sens 41(2):215–229. doi:10.1109/TGRS.2002.808243

Owe M, de Jeu R, Holmes T (2008) Multisensor historical climatology of satellite-derived global land surface moisture. J Geophys Res Earth Surf. doi:10.1029/2007JF000769

Pandey V, Pandey PK (2010) Spatial and temporal variability of soil moisture. Int J Geosci 1(02):87. doi:10.4236/ijg.2010.12

Parinussa RM, Holmes TR, Wanders N, Dorigo WA, de Jeu RA (2015) A preliminary study toward consistent soil moisture from AMSR2. J Hydrometeorol 16(2):932–947

Pegram GGS (2002) Spatial interpolation and mapping of rainfall: 3. Optimal integration of rain gauge, radar & satellite-derived data in the production of daily rainfall maps. Water Research Commission, Pretoria

Reynolds SG (1970) The gravimetric method of soil moisture determination. Part III: An examination of factors influencing soil moisture variability. J Hydrol 11(3):288–300. doi:10.1016/0022-1694(70)90068-5

Schmugge TJ, Kustas WP, Ritchie JC et al (2002) Remote sensing in hydrology. Adv Water Resour 25(8):1367–1385. doi:10.1016/S0309-1708(02)00065-9

Silverman BW (1986) Density estimation for statistics and data analysis, vol 26. CRC Press, Boca Raton

Sinclair S, Pegram G (2005) Combining radar and rain gauge rainfall estimates using conditional merging. Atmos Sci Lett 6(1):19–22. doi:10.1002/asl.85

Su CH, Ryu D, Young RI, Western AW, Wagner W (2013) Inter-comparison of microwave satellite soil moisture retrievals over the Murrumbidgee Basin, southeast Australia. Remote Sens Environ 134:1–11

System GCO (2010) Implementation plan for the global observing system for climate in support of the UNFCC, p 180

Topp GC, Davis JL, Annan AP (1980) Electromagnetic determination of soil water content: measurements in coaxial transmission lines. Water Resour Res 16(3):574–582

Vachaud G, Passerat de Silans A, Balabanis P, Vauclin M (1985) Temporal stability of spatially measured soil water probability density function. Soil Sci Soc Am J 49(4):822–828

Wagner W, Lemoine G, Rott H (1999) A method for estimating soil moisture from ERS scatterometer and soil data. Remote Sens Environ 70(2):191–207

Wagner W, Pathe C, Doubkova M et al (2008) Temporal stability of soil moisture and radar backscatter observed by the Advanced Synthetic Aperture Radar (ASAR). Sensors 8(2):1174–1197

Wang J, Fu B, Qiu Y et al (2001) Geostatistical analysis of soil moisture variability on Da Nangou catchment of the loess plateau, China. Environ Geol 41(1–2):113–120. doi:10.1029/WR016i003p00574

Western AW, Grayson RB, Blöschl G et al (1999) Observed spatial organization of soil moisture and its relation to terrain indices. Water Resour Res 35(3):797–810. doi:10.1029/1998WR900065

Yoo C (2002) A ground validation problem of remotely sensed soil moisture data. Stoch Environ Res Risk Assess 16(3):175–187. doi:10.1007/s00477-002-0092-6

Yoo C, Kim S, Kim TW (2006) Assessment of drought vulnerability based on the soil moisture PDF. Stoch Environ Res Risk Assess 21(2):131–141. doi:10.1007/s00477-006-0050-9

Yuan X, Ma Z, Pan M et al (2015) Microwave remote sensing of short-term droughts during crop growing seasons. Geophys Res Lett. doi:10.1002/2015GL064125

Zreda M, Desilets D, Ferré TPA et al (2008) Measuring soil moisture content non-invasively at intermediate spatial scale using cosmic-ray neutrons. Geophys Res Lett. doi:10.1029/2008GL035655

Zreda M, Shuttleworth WJ, Zeng X et al (2012) COSMOS: the cosmic-ray soil moisture observing system. Hydrol Earth Syst Sci 16(11):4079–4099. doi:10.5194/hess-16-4079-2012