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Key Points:
- Two existing remote sensing products were combined based on a reference
- The combination maximizes the temporal correlation coefficient of the products
- A global comparison revealed superior results of the combined product

Supporting Information:
- Text S1, Tables S1–S3, and Figures S1–S15

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A framework for combining multiple soil moisture retrievals based on maximizing temporal correlation

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Abstract A method for combining two microwave satellite soil moisture products by maximizing the temporal correlation with a reference data set has been developed. The method was applied to two global soil moisture data sets, Japan Aerospace Exploration Agency (JAXA) and Land Parameter Retrieval Model (LPRM), retrieved from the Advanced Microwave Scanning Radiometer 2 observations for the period 2012–2014. A global comparison revealed superior results of the combined product compared to the individual products against the reference data set of ERA-Interim volumetric water content. The global mean temporal correlation coefficient of the combined product with this reference was 0.52 which outperforms the individual JAXA (0.35) as well as the LPRM (0.45) product. Additionally, the performance was evaluated against in situ observations from the International Soil Moisture Network. The combined data set showed a significant improvement in temporal correlation coefficients in the validation compared to JAXA and minor improvements for the LPRM product.

1. Introduction

Soil moisture plays a key role in the water, energy, and carbon cycles through soil-vegetation-atmosphere interactions [e.g., *Guillod et al.*, 2015; *Taylor et al.*, 2012]. A number of satellite-based soil moisture products are now available in near real time (~3 h delay), and an important factor influencing the applications of these soil moisture products lies in their uncertainty [e.g., *Brocca et al.*, 2014; *Crow et al.*, 2011; *Wanders et al.*, 2014].

Significant efforts have been made to validate existing satellite soil moisture products through comparisons with ground-based measurements [e.g., *Wagner et al.*, 2007; *Gruhier et al.*, 2010; *Brocca et al.*, 2011; *Kim et al.*, 2015] or other large-scale verification techniques such as the triple collocation and *R* value method [*Parinussa et al.*, 2011a]. Traditionally, the quality of a soil moisture product is assessed by comparing with ground-based observations which serve as an assumed truth, and generally, metrics such as bias, root-mean-square error (RMSE), standard error, and correlation coefficient are then determined [*Entekhabi et al.*, 2010; *Yilmaz and Crow*, 2013]. There are often systematic differences between the assumed truth and the satellite soil moisture products. The systematic differences come from the spatial representativeness of the ground-based (point-scale) observations [e.g., *Crow et al.*, 2012], different measurement depths of the in situ sensors and the uncertainties in the (limited) parameterization of the land surface for the soil moisture retrieval algorithm [*Parinussa et al.*, 2011b]. To minimize systematic differences, preprocessing steps such as decomposing the signal into anomalies and scaling to a reference data set are common practice for the majority of applications of remotely sensed soil moisture [*Reichle and Koster*, 2004].

It is also common to consider the temporal correlation of the satellite soil moisture and reference data sets. Temporal correlations are attractive because they are insensitive to bias or the dynamic range of the two products being compared [*Entekhabi et al.*, 2010] and are thus likely to be the most important statistics in many studies of remotely sensed soil moisture [e.g., *Brocca et al.*, 2010; *Draper et al.*, 2009; *Liu et al.*, 2011, 2012]. To this end, this study develops a methodology to improve the temporal correlation coefficients of satellite soil moisture products compared to a reference data set.

Recently *Kim et al.* [2015] assessed two surface soil moisture products from Advanced Microwave Scanning Radiometer 2 (AMSR2) observations, retrieved using the Japan Aerospace Exploration Agency (JAXA) [*Fujii et al.*, 2009] and the Land Parameter Retrieval Model (LPRM) algorithm [*Owe et al.*, 2008], respectively. The JAXA and LPRM algorithms share a common background in the radiative transfer model [*Mo et al.*, 1982], but there exist key differences in their parameterizations. For example, surface temperature, roughness, and vegetation are treated differently within both algorithms and they also use different dielectric mixing models to convert the dielectric constant into soil moisture [*Kim et al*., 2015]. As a result of these differences, it was shown that the performance of the two products is complementary in many locations in terms of bias, RMSE, and, most importantly, correlation coefficients. This complementary behavior arises because each product has different skill under different conditions such as soil temperature, surface roughness, vegetation, and ground wetness. This study develops a methodology to combine these two AMSR2-based soil moisture products into one product which improves the temporal correlation coefficient by leveraging the strengths of both the AMSR2 products. This new product is linearly combined by applying an optimal weighting factor, calculated based on statistics of two AMSR2 products, specifically variance and correlation coefficients against a reference data set. The purpose of this paper is to develop and test the optimum weighting factors.

2. Data

2.1. Soil Moisture Data Sources

The Global Change Observation Mission-Water (GCOM-W) is a satellite launched by JAXA in May 2012 and flies in a Sun-synchronous orbit. AMSR2 is one of the sensors on board GCOM-W observing seven microwave frequencies (including 6.9, 7.3, and 10.7 GHz which are relevant for soil moisture retrievals) in both vertical and horizontal polarization. The swath width of AMSR2 is 1450 km which results in a revisit time of approximately 2–3 days for a fixed point on the ground. AMSR2 observations have been used to estimate surface soil moisture through two retrieval algorithms—the JAXA algorithm [*Fujii et al*., 2009] and the LPRM algorithm [*Parinussa et al*., 2014]. In this study, we used the daily JAXA (version 1.0) and LPRM soil moisture products at 0.25° for a 2 year period from 1 August 2012 to 31 July 2014. The JAXA algorithm only links microwave observations in the X-band (10.7 GHz) frequency to soil moisture, whereas the LPRM also retrieves soil moisture through the lower C-band (6.9 and 7.3 GHz) frequencies. Even though it is expected that the soil moisture retrieved from C-band will be more accurate [*Parinussa et al*., 2011b], in this study we use the AMSR2 soil moisture products based on the X-band brightness temperatures because it is available from both algorithms. This means that the proposed approach will be tested by combining two evenly matched products in terms of their ability to retrieve soil moisture. However, there is no reason that the combination approach could not be used with C-band observations as well as the X-band ones in future work.

The soil moisture retrieval algorithms rely on the large contrast between the dielectric constants of dry soil material and liquid water. This contrast changes dramatically when water freezes. LPRM relies on an internal algorithm that retrieves land surface temperature by using brightness temperatures observed at the Ka-band (36.5 GHz) channel [*Holmes et al*., 2009]; however, the JAXA algorithm assumes that surface temperature is constant throughout the year [*Koike*, 2013]. In order to account for frozen conditions, additional soil temperature data from the ERA-Interim reanalysis product of the European Centre for Medium-Range Weather Forecasts were used (http://apps.ecmwf.int/datasets/) [*Dee et al*., 2011]. When the ERA-Interim soil temperature in the top soil layer (0–0.07 m) is below freezing, the corresponding AMSR2 soil moisture retrievals (both LPRM and JAXA) were masked out.

To calibrate the weights for the combination approach, a reference soil moisture product is required. In this study we use the volumetric water content in the topmost soil layer (0–0.07 m) from the ERA-Interim reanalysis at 0.25° as the reference. Data at the local satellite overpass time was obtained by linearly interpolating the 6-hourly reanalysis. The final combination depends on the choice of reference data set, which is an arbitrary but unavoidable choice. In this study, ERA-Interim was chosen because of its availability over the entire study period, global coverage and temporal consistency. However, it should be noted that the combination approach has the flexibility to be applied with any other appropriate reference data set.

To validate the combined product, an independent data source is required. In this work, ground-based observations from the International Soil Moisture Network (ISMN, http://ismn.geo.tuwien.ac.at/ismn/) [*Dorigo et al*., 2011] were used to evaluate the performance of the combined remotely sensed soil moisture product. To evaluate the suitability of the ground stations for satellite validation purposes, topographic complexity and wetland fraction data from European Space Agency Climate Change Initiative (ESA CCI http://www.esa-soilmoisture-cci.org/) [*Liu et al*., 2011, 2012; *Wagner et al*., 2012] were used.

2.2. Data Preprocessing

A number of preprocessing steps are required to allow the three data sets (remote sensing, reanalysis, and ground-based observations) to be compared. Commonly applied masking procedures [*De Jeu et al*., 2008; *Liu et al*., 2011] were adopted as follows to remove conditions unfavorable for soil moisture retrievals. First, land adjacent to the ocean or large lakes that may be sensitive to open water fluctuations was masked (i.e., center of grid cells within 25 km from the coast or large lake). Next, as the emitted soil (moisture) radiation is totally masked under dense canopies, these regions were excluded when annual mean vegetation optical depth is greater than 0.8 at 6.9 GHz from LPRM [*De Jeu et al*., 2008]. Results from the soil moisture retrievals from the nighttime observations (descending satellite path) are presented here as they are generally considered to be of higher quality than the daytime observations (ascending satellite path) [*De Jeu et al*., 2008]. Results from these daytime observations are available in the supporting information.

For the ground-based observations, the data set was filtered to ensure only high-quality stations were used in validation. The ISMN provides access to 915 ground stations which have at least 365 days overlapping with the study period and measurement depths of 10 cm or shallower, available over 10 different monitoring networks, mainly located in the USA and Europe. Systematic differences between remotely sensed observations and the ISMN are known to be caused by their different measurement depths and the spatial heterogeneity of soil moisture that affects the comparison of point observations against coarse-scale satellite footprint [*Crow et al*., 2012; *Gruber et al*., 2013]. To overcome the first issue, we only considered in situ measurements from the shallowest soil layer in locations with multiple-measurement depths (e.g., 10 cm and 5 cm) and applied the standard quality control (QC) flags from the ISMN [*Dorigo et al*., 2013]. These QC flags exclude doubtful observations such as spikes and sudden breaks in the ground-based observations. Second, only ground stations in grids with low wetland fraction ($<$10%) and topographic complexity ($<$10%) were considered for further analysis as these are known as factors contaminating the microwave signal [*Draper et al*., 2012]. Furthermore, a simple test was performed to check the spatial representativeness of two or more ground-based stations within a coarse-scale satellite footprint according to *Dorigo et al*. [2014]. The area representativeness was defined as the average of three correlation coefficients between in situ data and ERA-Interim data ($R_{\text{ERA-in situ}}$), the JAXA, and LPRM products ($R_{\text{JAXA-in situ}}$ and $R_{\text{LPRM-in situ}}$). The station with the highest area representativeness was selected. Additionally, when two or more correlation coefficients including $R_{\text{ERA-in situ}}$ are significantly ($p \leq 0.05$) negative at a station, the station was considered to be unrepresentative and discarded. The Snow Telemetry and Atmospheric Radiation Measurement networks were excluded since their primary purposes are not soil moisture measurements (W. A. Dorigo, personal communication, 2014). For the soil climate analysis network, only stations which have suitable topography and vegetation characteristics, and which were used for the Soil Moisture and Ocean Salinity data assimilation experiments, were adopted in this study (G. J. M. De Lannoy, personal communication, 2014). Finally, in order to ensure statistically robust results, we have only used stations that have at least 100 observations over the entire study period. The geographic distribution of the selected 159 stations over eight networks used in this study can be found in Figure S1 in the supporting information.

3. Methodology

The original linear combination of forecasts was developed by *Bates and Granger* [1969] and created a product that minimized the mean square error (MSE) from two parent forecasts. The rationale behind forecast combination is that if one forecast is based on variables or information that the other forecast has not considered, or/and the forecast makes a different assumption about the form of the relationship between the variables then the combined product is likely to have lower overall error than any of the individual components. A follow-up study [*Granger and Ramanathan*, 1984] showed that the idea could be extended to multiple forecasts and the optimal weights using a restricted least squares regression by assuming the total sum of weights is restricted to 1. During the past decades, the combination concept has been widely applied to various disciplines dealing with time series of forecasts or other products [*Clemen*, 1989; *Timmermann*, 2006; *Wasko et al*., 2013]. For a recent example, *Khan et al*. [2014] proposed an approach combining five global sea surface temperature forecasts by seasonality-based dynamic weighting factors. The following is a summary of the original forecast combination. Given two sets of unbiased forecasts or products ($\boldsymbol{f_1}$ and $\boldsymbol{f_2}$, $n \times 1$) a combination ($\boldsymbol{f_c}$) can be expressed with a weight (w), ranging from 0 to 1, as follows

$$\boldsymbol{f}_c = w\boldsymbol{f}_1 + (1-w)\boldsymbol{f}_2 \tag{1}$$

where n is the length of the forecasts. The optimal weight w, which leads to the minimum MSE for the combined $\boldsymbol{f_c}$ against a reference, is expressed as

$$w = \frac{\sigma_{\varepsilon_2}^2 - \rho_\varepsilon \sigma_{\varepsilon_1}\sigma_{\varepsilon_2}}{\sigma_{\varepsilon_1}^2 + \sigma_{\varepsilon_2}^2 - 2\rho_\varepsilon \sigma_{\varepsilon_1}\sigma_{\varepsilon_2}} \tag{2}$$

where $\sigma_{\varepsilon_1}^2$ and $\sigma_{\varepsilon_2}^2$ are the error variances of $\boldsymbol{f_1}$ and $\boldsymbol{f_2}$ against the reference, respectively, and ρ_ε is the correlation between the two sets of errors.

As the remotely sensed soil moisture products are retrieved by various algorithms which are based on different variables, information, and assumptions [*Kim et al.*, 2015], we believe it is valid to extend the combination scheme to soil moisture data sets. As discussed previously, the temporal correlation coefficient is the most important indicator of the utility of remotely sensed soil moisture products. However, existing combination approaches focus on the minimization of the MSE. Minimizing the MSE will also improve the temporal correlation coefficients because MSE consists of three components contributed by bias (differences in temporal mean), variance (dynamic range), and correlations (temporal pattern) [*Su et al.*, 2013]. However, given the importance of the temporal patterns in soil moisture analysis, we aim to answer the following question: Can we develop a combination framework to solely maximize the temporal correlation coefficients rather than minimizing MSE and apply this to the remotely sensed soil moisture products?

One can consider that two sets of unbiased soil moisture retrievals $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ ($n \times 1$) are linearly combined into $\boldsymbol{\theta}_c$ by applying a weighting factor w, 0 to 1.

$$\boldsymbol{\theta}_c = w\boldsymbol{\theta}_1 + (1-w)\boldsymbol{\theta}_2 \tag{3}$$

The Pearson correlation coefficient (R) between θ_c and a reference (θ_R) can be expressed as a function of w according to the definition of R and equation (3), and this is an optimization problem of the following function.

$$\text{Maximize } R = f(w) = \frac{E[(\boldsymbol{\theta}_c - \mu_c)(\boldsymbol{\theta}_R - \mu_R)]}{\sigma_c \sigma_R} \quad \text{Subject to } 0 \le w \le 1 \tag{4}$$

where μ_C and μ_R are the mean values and σ_c and σ_R are the standard deviations of $\boldsymbol{\theta}_c$ and $\boldsymbol{\theta}_R$, respectively. For this case with only two parent products which have positive correlation coefficients against the reference, differentiating equation (4) with respect to w, the maximum R is found when

$$w = \frac{\sigma_2(\rho_{1R} - \rho_{12}\cdot\rho_{2R})}{\sigma_1(\rho_{2R} - \rho_{12}\cdot\rho_{1R}) + \sigma_2(\rho_{1R} - \rho_{12}\cdot\rho_{2R})} \tag{5}$$

where each σ presents the standard deviation of each product and ρ is the temporal correlation coefficient between two products. The details of the derivation of equation (5) are available in the supporting information. When applying the weighting factor which is calculated by equation (5) and in the constrained range (0 to 1), the correlation coefficient between the combined product and the reference will always be larger than or equal to the correlation coefficients between each original product and the reference. In the case of a negative correlation coefficient for either of the parent products, the weights can be optimized numerically to maximize R and ensure that the weights are between zero and one.

To apply the proposed methodology, the first requirement is to remove the systematic differences among the data sets. This was achieved by normalizing the two parent products (i.e., JAXA and LPRM) against the chosen reference through equation (6) [*Draper et al.*, 2009].

$$\boldsymbol{\theta}_{\mathbf{NORMAL}} = \left(\boldsymbol{\theta}_{\mathbf{RAW}} - \overline{\theta_{\mathrm{RAW}}}\right) \times \frac{\mathrm{std}(\theta_{\mathrm{REF}})}{\mathrm{std}(\theta_{\mathrm{RAW}})} + \overline{\theta_{\mathrm{REF}}} \tag{6}$$

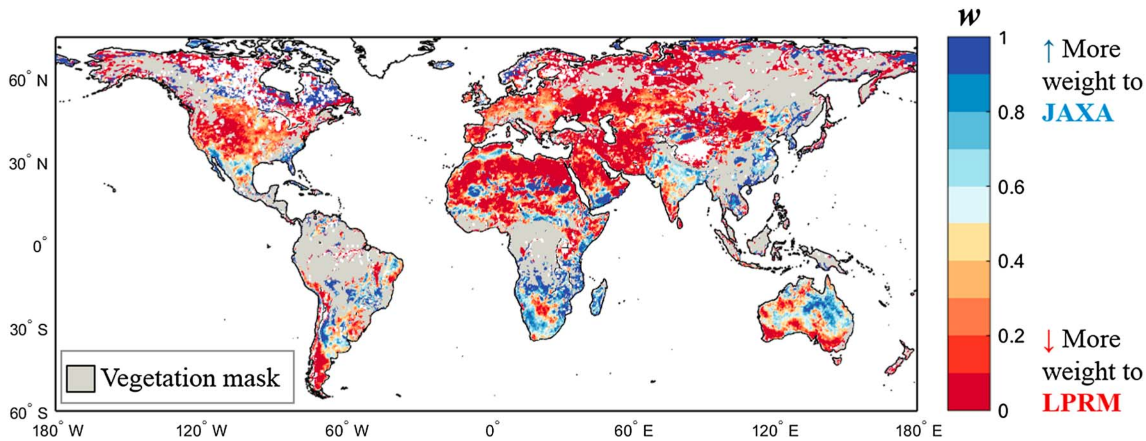

Figure 1. The spatial distribution of the optimal weights for the JAXA and LPRM soil moisture products using ERA-Interim as the reference product.

where $\theta_{\mathbf{NORMAL}}$ is normalized soil moisture, $\theta_{\mathbf{RAW}}$ is raw soil moisture, $\theta_{\mathbf{REF}}$ is reference soil moisture, $\overline{\theta}$ is mean of θ, and std is standard deviation. When the two parent products are normalized against the same reference, equation (5) can be simplified to

$$w = \frac{\rho_{1R} - \rho_{12} \cdot \rho_{2R}}{\rho_{2R} - \rho_{12} \cdot \rho_{1R} + \rho_{1R} - \rho_{12} \cdot \rho_{2R}} \tag{7}$$

The optimal weighting factors can now be calculated through equation (7). Finally, the parent products are combined into a single product by using the calculated optimal weighting factors.

4. Results and Discussions

4.1. Global Optimal Weighting Factors

The proposed correlation-based combination approach was applied to the remotely sensed soil moisture products from AMSR2 over the 2 year study period. As discussed above, the volumetric water content in the topmost soil layer (0–0.07 m) of ERA-Interim was chosen as reference data set. Based on this reference data, the global optimal weighting factors were determined using the approach presented in the previous section. The global map of the optimal weighting factors for the two remotely sensed soil moisture products from AMSR2 is presented in Figure 1.

The dark red color indicates that the majority of the weight comes from the LPRM product whereas the dark blue color is where the JAXA product is most effective. For the colors in between the combination product is a more even mix of the two parent products. This global map of optimal weights provides information on the relative strengths (and weaknesses) of the remotely sensed soil moisture products against each other under the assumption that ERA-Interim reanalysis soil moisture represents the true soil moisture. As shown in Figure 1, the JAXA product has strengths over humid subtropical regions, such as the southeastern USA, northern India, and the southeastern Asia. The LPRM product generally shows strengths in the more temperate areas which is in line with the results from previous studies [*Crow et al*., 2010; *Dorigo et al*., 2010].

After applying the weighting factors, the two AMSR2 products are combined into a single product, and correlation coefficients of the combination product and the two parent products against the reference are presented in Figure 2. The correlation coefficients for the combined product are higher in all cases than either of the parent products (Figures 2d and 2e), demonstrating that the combination method assures improved (or at least equal) performance. The global mean correlation coefficients are 0.35 for the JAXA product, 0.45 for the LPRM product, and 0.52 for the combined product.

Again, the results and actual values of the weights in Figures 1 and 2 depend on the choice of reference data set which is an assumed truth. The optimal combination is considered independently for each location so a reference data set with smaller spatial domain or even at a point would still allow a combination product to be constructed. The presented combination approach is general enough to be applied with any other appropriate reference data set, which could be reanalysis, ground-based or remotely sensed data sets, and

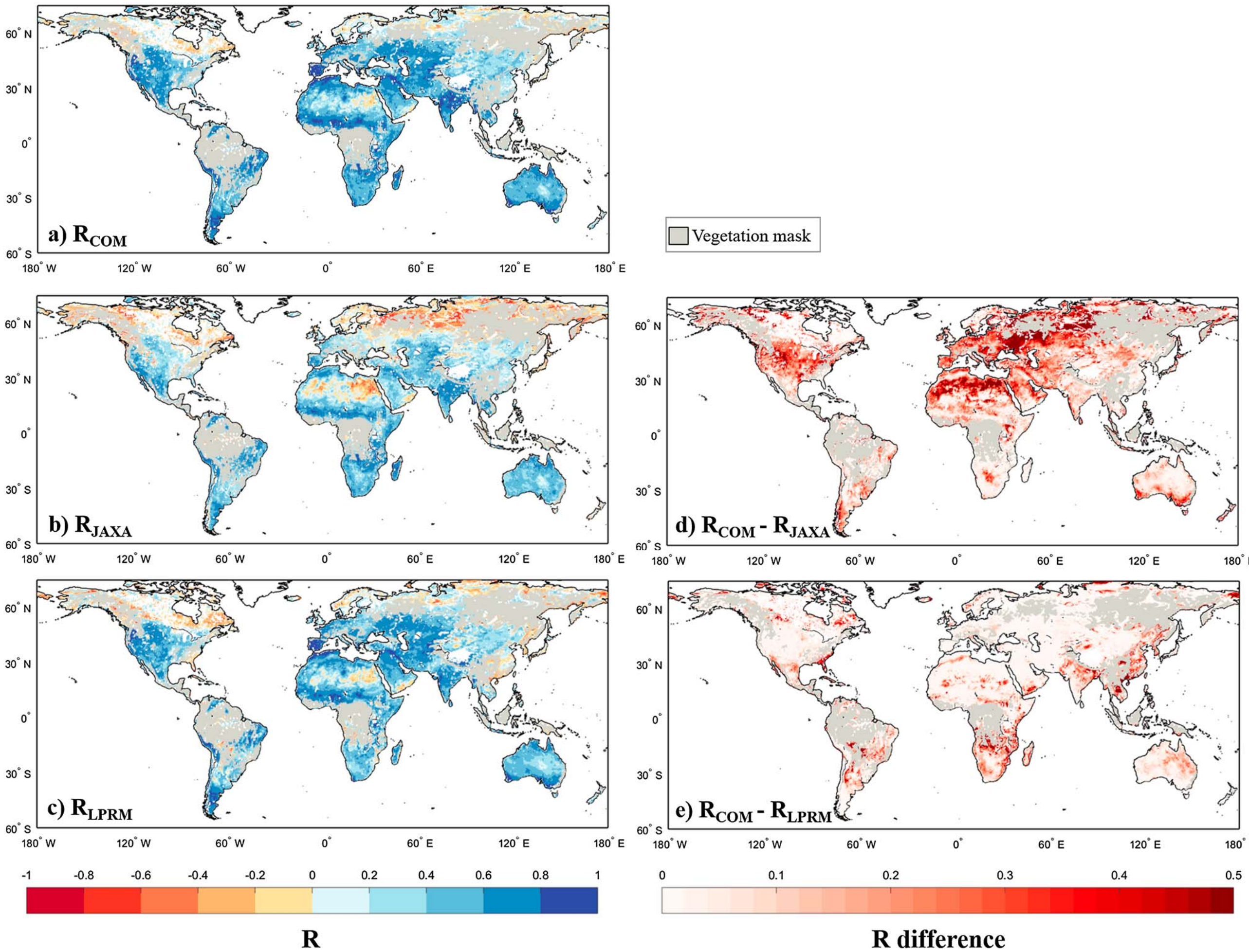

Figure 2. Spatial distribution of Pearson's correlation coefficients between the reference (ERA-Interim) and (a) the combined product (R_{COM}), (b) the JAXA product (R_{JAXA}), and (c) the LPRM product (R_{LPRM}). (d) The differences in between correlation coefficients of the combined and JAXA products (R_{COM} minus R_{JAXA}) and (e) the combined and LPRM products (R_{COM} minus R_{LPRM}).

should therefore be considered as a flexible tool that can be applied given a chosen reference data set. The analysis was repeated using a different reference product—The Modern-Era Retrospective Analysis for Research and Applications Land (MERRA-Land, ftp://goldsmr2.sci.gsfc.nasa.gov/data/s4pa//) [*Reichle et al.*, 2011] top soil layer soil moisture content—for a sensitivity analysis. It showed (somewhat) different weights but these differences simply reflect the relative differences (and similarities) of the chosen references. Combination results using MERRA-Land as the reference are summarized in the supporting information. Also presented in the supporting information are results based on cross validating the combination product against a different reference product. Even in cross validation the proposed temporal combination approach provides superior results compared to either of the parent products.

4.2. Evaluation Against In Situ Soil Moisture

The global maps of correlation coefficients (Figure 2) show an improved match for the combined product compared to the two individual remotely sensed soil moisture products. Of interest is how the combination approach compares to an independent validation data set. In order to achieve this goal, the two remotely sensed soil moisture products (JAXA and LPRM) and the combination were evaluated through the set of ground-based observations from the 159 stations. Figure 3 presents the evaluation results.

The rationale of the scatterplot (Figure 3a) is that stations that fall below the 1:1 line (red line) indicate locations where the performance of the combined product is better than the parent product. The dashed

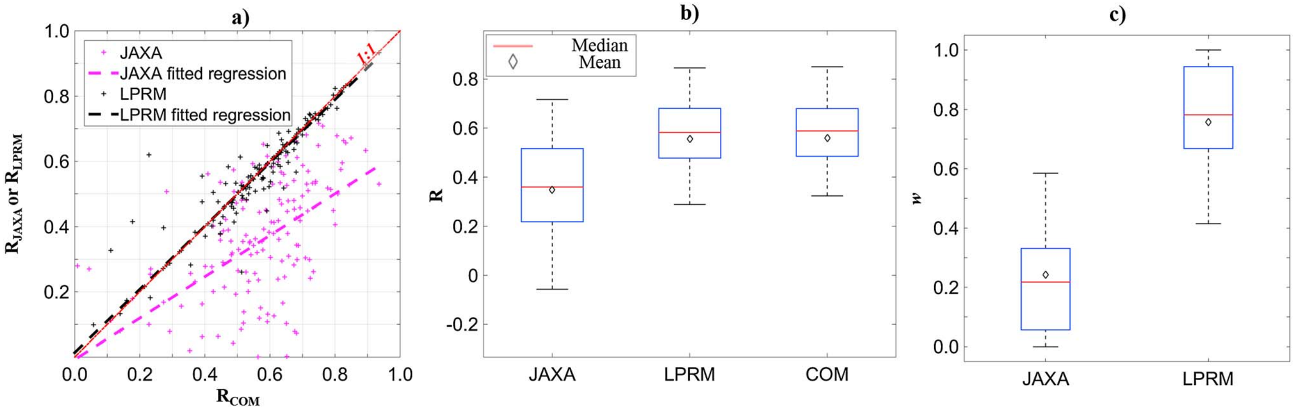

Figure 3. Results for evaluating improvements in correlation coefficients through combinations. (a) Scatter plot showing correlation coefficients of the JAXA and LPRM products (R_{JAXA} and R_{LPRM} on *y* axis, respectively) against correlation coefficients of the combined product (R_{COM} on *x* axis). (b) Boxplots for three sets of correlation coefficients for the JAXA, LPRM, and combined products against the reference. (c) Boxplot for weighting factors (*w*) from all in situ stations.

lines are fitted linear regressions for JAXA (magenta) and LPRM (black) and present the overall performance of the combined product versus the parent products. For both products it can be seen that the combination is generally better than either product when considered over all the validation ground stations. In Figure 3b, the mean R_{JAXA} is 0.35 and the mean R_{LPRM} is 0.56 over the in situ stations, and after combining the two AMSR2 products at each location, the mean R_{COM} is calculated as 0.56. The average improvements compared to the LPRM product are marginal but this is most likely due to the uneven distribution of the selected in situ stations. As shown in Figure S1, they are mostly distributed over the USA and the northern Europe where the LPRM product shows better performances than the JAXA product (Figure 1). If we had sufficient ground data in regions where the JAXA product shows better performance, such as the southeastern U.S., northern India, and the southeastern Asia, more balanced results would be expected. The mean weights applied to each product further support this finding. When using the ERA-Interim as the reference, the mean weight for JAXA product over the grid cells with in situ stations is 0.24 (Figure 3c), whereas its global mean weight is 0.35. In addition, over the U.S. (30°N–50°N, 70°W–125°W), the regional mean weight is 0.26 for the JAXA product. This shows that the JAXA performance is generally worse in the areas well sampled by the in situ data. More improvements are evident in the ascending data where the LPRM product has relatively lower quality than the descending data [*De Jeu et al.*, 2008]. The results from the ascending data are presented and summarized in the supporting information.

The points above the 1:1 line in Figure 3a represent locations where the correlation with the validation data is degraded after the combination. This is a result of significant differences between the ERA-Interim data and the in situ data at these locations. In general, however, under both the calibration and the validation settings, the correlations for the combined product are improved compared to both the AMSR2 products.

5. Conclusions

In this study, a correlation-based combination approach was developed which maximizes the temporal correlation coefficient of soil moisture retrievals. This method was applied to two remotely sensed soil moisture products from the AMSR2 sensor over a 2 year study period. Based on the method developed here, the JAXA and LPRM soil moisture products were combined into a single product that showed superior results against the chosen reference soil moisture data set after applying the optimal weighting factors (Figure 2). The spatial distribution of optimal weighting factors provides information on the relative strengths of the JAXA and LPRM products at the global scale. These weighting factors provide an important step forward in terms of how best to combine soil moisture products and improve over taking a simple average of the two products [*Liu et al.*, 2011]. The performance of the combined product was validated against in situ observations from the ISMN. The combined product showed a significant improvement compared to the JAXA product and marginal improvements compared to the LPRM product. An important factor to consider is the unevenly distributed in situ stations for the evaluation due to the ISMN coverage.

The actual weighting factors presented depend on the choice of reference data (ERA-Interim in this study) and different results would be obtained if a different reference data set was chosen. Sensitivity testing with MERRA-Land demonstrated that the method continues to perform well even with a different reference data set choice. The main contribution of this work is to provide a method that can be used to improve soil moisture products compared to any choice of reference data set. And of particular relevance for soil moisture, the new method focuses on temporal correlations which have not previously considered in combination approaches. The comparison of the combined product using in situ stations showed that improvements in correlations were also obtained when considered in a validation setting. The uneven distribution of in situ stations due to the ISMN coverage led to small but consistent improvements for the combined product over LPRM and larger improvements for JAXA; a different set of in situ stations would lead to different results.

Even though the new correlation-based combination approach has been demonstrated to operate robustly, there are a number of future extensions that could provide even better combined products. First, as demonstrated with the MERRA-Land analyses, it is useful to test different reference data sets to understand the sensitivities in the combined product. Second, the linear rescaling method [*Draper et al.*, 2009] was used in this study to only adjust the mean and standard deviation of satellite soil moisture data sets against the reference. It may be worth investigating in future work whether other rescaling methods (e.g., Cumulative Distribution Function matching [*Brocca et al.*, 2011; *Liu et al.*, 2011]) could lead to further improvements to the combined satellite product. The demonstration of the concept here has used just two parent data sets but there is no limit to the number of products that could be combined. In the context of soil moisture this is an exciting area of future research due to the number of satellite-based soil moisture products from different remote sensing techniques or different retrieval algorithms that are being developed. Any combined product would be expected to reflect the varying strengths of these techniques and algorithms. Another area for potential development is time-varying weights as well as the spatial weighting developed in this paper. Dynamic weights would take account of the time-varying performances of different soil moisture products. If weights can be updated in close to real time, such a development could be particularly useful for operational flood forecasting or other forecast problems.

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