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# Spatial Disaggregation of Coarse Soil Moisture Data by Using High-Resolution Remotely Sensed Vegetation Products

Seokhyeon Kim, Keerthana Balakrishnan, Yi Liu, Fiona Johnson, and Ashish Sharma

***Abstract*— A novel approach is presented to spatially disaggregate coarse soil moisture (SM) by only using remotely sensed vegetation index. The approach is based on the conditional relationship of vegetation with time-aggregated SM, allowing the coarse-scale SM to be disaggregated to the spatial resolution of the vegetation product. The method was applied to satellite-derived SM over January 2010–December 2011, using the high-resolution normalized difference vegetation index (NDVI). The results were evaluated against ground measurements during the two-year period over the contiguous United States and Spain, and also compared with an existing disaggregation method that also requires land surface temperature observations. It is shown that the proposed approach can provide fine-resolution SM with reasonable spatial variability.**

***Index Terms*— Climate change initiative (CCI), disaggregation, downscaling, moderate resolution imaging spectroradiometer (MODIS), normalized difference vegetation index (NDVI), soil moisture (SM).**

## I. Introduction

SOIL moisture (SM) is important because of its interactions with the hydrological cycle, atmospheric conditions, vegetation, and temperature [1]. It is therefore vital to obtain information on SM at both reasonable spatial and temporal resolutions. While ground-based measurements are a common source of soil moisture information, they tend to be sparsely located in space and only available for limited temporal periods. As a result, most parts of the world are still ungauged or poorly gauged [2]. To overcome the issue, satellite remote sensing SM products based on active and passive microwave have been investigated as alternatives to ground-based measurements, with advantages of availability at the global scale in near real time even under cloud cover and at nighttime. However, the direct use of satellite SM products has been limited by their coarse spatial resolution ($>100$ km$^2$) and uncertainties resulting from the complex SM retrieval procedures [3]. Current research is focusing on both these problems; first to reduce the uncertainties [4] and to downscale the satellite microwave measurements to a finer spatial resolution appropriate for regional SM assessments [5].

Compared to microwave sensors, optical/thermal sensors can provide observations at a relatively high spatial resolution. The tradeoff is that the optical/thermal sensors are affected by atmosphere conditions such as clouds [6]. This suggests that data collected by optical or thermal sensors may be useful in spatially disaggregating the coarse microwave SM products. Disaggregation methods develop relationships between SM estimated from the microwave sensors and land surface temperature (LST) and appropriately selected vegetation indices (VI) which are available at finer spatial resolutions. For example, a SM disaggregation method was recently proposed that used the vegetation temperature condition index (VTCI) as a soil moisture proxy. The method spatially distributes coarse SM values (0.25°) to fine values (0.05°), which are linearly proportional to the VTCI at 0.05° resolution [7], [8].

However, these methods require the vegetation and LST data at both coarse fine scales to be available at the same time as the SM data. This presents a problem as there are many missing values in LST data sets from optical/thermal infrared sensors due to cloud masks and thus the disaggregated SM products tend to be discontinuous. For example, it is just around 45% annual mean percentage of the contiguous United States (CONUS) domain for which satellite land surface temperature data is available [9]. In this letter, the temporal interaction of SM with vegetation proxies at a higher spatial resolution is considered and a simple SM disaggregation model is developed to provide a continuous time series of SM with a persistence structure closer to what is observed.

Two case studies have been used to validate the proposed method. First, using the new method, coarse SM at a spatial resolution of 0.25° (approximately 25 km, hereafter referred to as "coarse") is disaggregated to fine SM at 0.05° (approximately 5 km, hereafter referred to as "fine") over the CONUS for a two-year study period from January 2010 to December 2011. The results were evaluated against *in situ* SM measurements from ground stations distributed over the CONUS. The method was also applied to the REMEDHUS network in Spain for a direct comparison with [8] by applying the same SM data, study period and area. Importantly, due to

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the density of the REMEDHUS network the disaggregated SM can be evaluated on its ability to reproduce the spatial variation at the fine spatial scale.

## II. Data and Processin

### A. Satellite Soil Moisture

The European Space Agency Climate Change Initiative (ESA CCI) SM has been generated using four passive and two active microwave spaceborne instruments covering 36 years from 1978 to 2014 [10]. It consists of three products: active, passive, and active-passive merged data which provide daily surface SM at a spatial resolution of 0.25°. Among them, the merged data (version 02.2) was used in this letter which has comprehensively been validated at the global scale, and also used in [8].

### B. Ground Soil Moisture Networks Over Study Areas

The primary study area was selected as the CONUS (24.25° N–49.50° N, 66.75° W–125° W). It covers a wide range of climate and land cover types which allows the general applicability of the proposed method to be assessed. The four dominant climate zones are cold in the northern areas, arid in the western regions, temperate in the central and middle Atlantic coast regions, and tropical in the southern Florida [11]. There is also an extensive network of *in situ* SM stations for evaluating the disaggregated SM.

Spatially dense networks are necessary to validate spatial variability of disaggregated SM at a subpixel scale. The second study area over the REMEDHUS network covers a flat spatial domain (41° N–41.75° N, 5° W–5.75° W). The land cover mainly consists of croplands and shrub lands and the climate is classified as semiarid continental Mediterranean. The network consists of more than 20 stations within 1300 km$^2$ and has frequently been used for validating disaggregated remotely sensed SM data [12], [13] including [8].

The ground SM measurements were obtained from the International Soil Moisture Network (ISMN) [2]. The ISMN measurements were filtered to ensure quality and minimize systematic differences between remotely sensed SM at satellite footprint scale and *in situ* SM at point scale. *In situ* SM from the shallowest soil layer ($<$10 cm) was used after applying the standard quality control flags [14]. Data from the Snow Telemetry and Atmospheric Radiation Measurement networks were not used as their primary purposes are snow and radiation observation, respectively. The timestamp of the CCI SM data in coordinated universal time was used to select the closest hourly ground soil moisture measurements. If there is more than one station in a fine grid cell, the measurements were averaged on daily basis. Only stations with at least 100 observations coincident with the coarse SM data and with positive temporal correlations were used. The distribution of the selected stations for each study area (177 for the CONUS and 17 for the REMEDHUS) is shown in Fig. 1.

### C. MODIS Vegetation Index

The Moderate Resolution Imaging Spectroradiometer derived 16-day composite Normalized Difference Vegetation Index (NDVI, MOD13Q1) [15] was used for this letter. As it consists of $10° \times 10°$ tiles in the sinusoidal projection, they were reprojected and resampled to both coarse (0.25°) and fine scales (0.05°) using the reprojection tool [16]. Only quality assured data with a pixel-level QA code of "lower quality" or better was used. For the fine scale product, only regions over coarse grid cells where an *in situ* station exists and the eight coarse grid cells surrounding it (i.e., $3 \times 3$ coarse grid cells where $15 \times 15$ fine grid cells coexist for each group of stations) were processed due to the large data requirements.

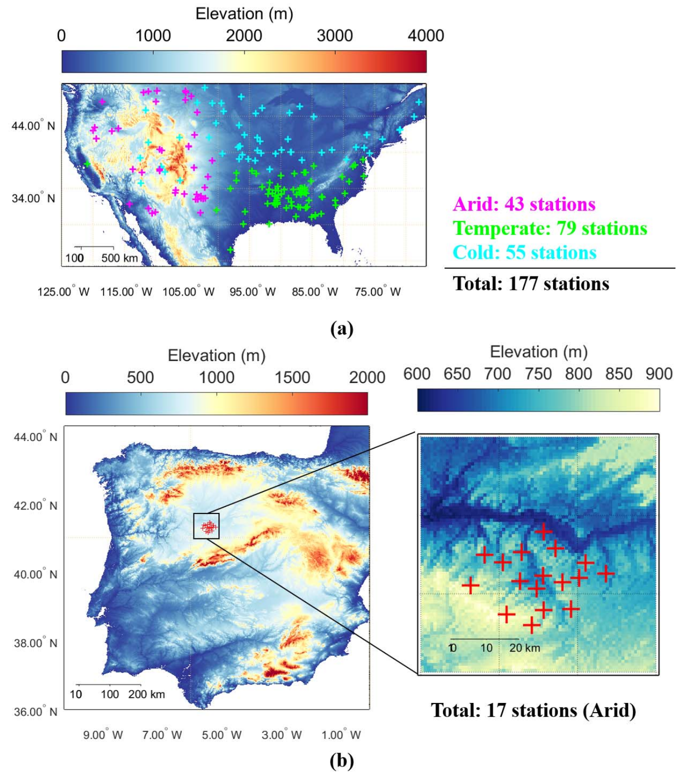


Fig. 1. Locations of ground stations (red crosses) used for validation. (a) 177 stations over the CONUS. (b) 17 stations over the REMEDHUS network in Spain. Each location is classified into the climate zones by the updated world map of the Koppen–Geiger climate classification.

After applying the pixel-level QA code, some gaps are created. These gaps negatively affect the disaggregation process and hence a three-dimensional (3-D) gap-filling method [17] was adopted. This is a Penalized Least-Square regression based on 3-D Discrete Cosine Transform (DCT-PLS) which solely relies on a smoothing parameter $s$ (the higher the $s$, the smoother the result). In this letter, the 16-day composite NDVI products over the study period were simultaneously filled by the DCT-PLS method using $s$ of $10^{-6}$ [18]. The gap-filled NDVI maps were assumed to represent the middle of the composite periods and linearly interpolated to daily time scale. However, it should be noted that these preprocessing steps for the NDVI data will introduce additional uncertainty in the disaggregated SM estimates.

## III. Methodology

### A. Proposed Disaggregation Method

The rationale behind the proposed disaggregation method is that the disaggregated data should smoothly transition from

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one-time step to the next due to the SM interacting with regional vegetation conditions. To start with, a simple linear relationship was formed to characterize coarse NDVI and temporally aggregated coarse SM within a past $n$-day window at each location as shown

$$\overline{SM}_{I,J,t} = L_{I,J} \cdot NDVI_{I,J,t} + C_{I,J} \quad (1)$$

where $L_{I,J}$ is a slope estimated by linear regression at a coarse grid cell of which spatial indices are $I$ (row) and $J$ (column), respectively, $C_{I,J}$ is an intercept and $\overline{SM}_{I,J,t}$ is an exponentially weighted temporal average of SM over the past $n$ days prior to time $k = t$ as defined

$$\overline{SM}_{I,J,t} = \left(\sum_{k=t-n+1}^{t} \alpha_{I,J}^{k-t} \cdot SM_{I,J,k}\right) / \left(\sum_{k=t-n+1}^{t} \alpha_{I,J}^{k-t}\right) \quad (2)$$

where $\alpha_{I,J}$(0–1) is a decay coefficient which reflects local properties together with temporal window size $n$ days. Namely, (1) statistically matches two time series by linearly scaling NDVI with the $L_{I,J}$ and $C_{I,J}$, and temporally aggregating/smoothing SM with the $n$-day window and $\alpha_{I,J}$. Given that a pair of SM and NDVI time series is available at a coarse grid cell, optimal coefficients can be obtained by maximizing the coefficient of determination ($R^2$) of (1).

A finite difference between the aggregated soil moisture across lagged time steps enables simplification as shown in (3), where $\Delta NDVI_{I,J,t}$ is the temporal difference in NDVI between $k = t$ and $k = t - 1$. Note that, the intercept $C_{I,J}$ is deleted in this case

$$\overline{SM}_{I,J,t} = \overline{SM}_{I,J,t-1} + L_{I,J} \cdot \Delta NDVI_{I,J,t}. \quad (3)$$

The key hypothesis of the proposed disaggregation method is that it is also applicable the coarse data-derived parameters ($L_{I,J}$, $\alpha_{I,J}$ and $n$) and (2) and (3) are also applicable at subgrids at the fine spatial resolution. Therefore, (2) and (3) are rearranged in terms of SM and NDVI at the fine spatial resolution as

$$SM_{i,j,t} = \left\{\overline{SM}_{i,j,t-1} + L_{I,J} \cdot \Delta NDVI_{i,j,t}\right\} \cdot \sum_{k=t-n+1}^{t} \alpha_{I,J}^{k-t} - \sum_{k=t-n+1}^{t-1} \alpha_{I,J}^{k-t} \cdot SM_{i,j,k} \quad (4)$$

where $SM_{i,j,t}$ and $NDVI_{i,j,t}$ are disaggregated SM and NDVI at a subgrid cell ($i$, $j$) and time $t$. When aggregated, fine scale SM also needs to match the coarse scale value. For this, a rescaling step is adopted as (5) to ensure consistency across both scales [19], and therefore quick responses in the daily coarse SM after rainfall are directly propagated into the all subgrids in proportion to the initially estimated SM values at all subgrids by (4)

$$SM'_{i,j,t} = \left(SM_{i,j,t} - \sum_{i,j} SM_{i,j,t}/p\right) + SM_{\boldsymbol{I},\boldsymbol{J},t} \quad (5)$$

where $SM'_{i,j,t}$ is corrected fine scale SM and $p$ is the total number of subgrid cells within a coarse grid cell, which is 25 (5 × 5) in case of 0.25° to 0.05°.

Because the disaggregation by (4) requires a window of length $n$ days for the calculations, there is a warm-up period prior to the study period until first $n$-day data is available. Therefore, additional $n$-day data was added before the study period and the actual length of soil moisture and NDVI data is thus $n+730$ days in this work. For these initial days, the coarse SM is disaggregated to the fine scale using the ratio of the fine scale and coarse-scale NDVI on that day. The warm-up period was not considered in validation.

There are sometimes breaks in the time series of the CCI SM due to freeze-up and swath patterns of the instruments. These missing values within the $n$-day window produce large variability in the estimated mean SM. To test this, 95% confidence limits on the mean SM are calculated using a two-sided $t$-test considering number of available data in the $n$-day window. A small number of observations or a large standard deviation of SM values within the window increases the width of the confidence limits. When the width is more than ±0.2, the SM values are regarded as too variable and the coarse SM is disaggregated to the fine scale using the same method as the warm-up period disaggregation. The value of 0.2 is based on the threshold used for masking unreliable SM values under dense vegetation [20].

### *B. Summary of VTCI-Based Disaggregation Approach*

The VTCI represents a joint relationship between LST, VI, and SM. Various VI could be used, but here only NDVI was considered. When pairs of LST ($x$-axis) and VI data ($y$-axis) at the coarse spatial scale are plotted, it generally forms a triangular or trapezoidal shape if it uses data from a large enough area to represent the entire range of SM and NDVI [21]. This is called the LST/NDVI feature space where a VTCI (0–1) is calculated using a pair of LST and NDVI data at a subgrid cell ($i$, $j$, $t$).

After calculating all VTCI across all $i$ and $j$ at time $t$, coarse $SM_{I,J,t}$ is simply disaggregated in proportional to the fine VTCIs. Thus, high spatial coverage for the LST data is required to effectively implement this method. A higher coverage threshold could improve the disaggregation quality but also lead to larger gaps in time series of the disaggregated SM [8] that the proposed method in this letter addresses.

### *C. Evaluation Strategy*

For both study areas, all SM estimates were evaluated against *in situ* measurements using temporal correlation ($R$), root mean square error (RMSE), bias and unbiased RMSE (ubRMSE).

For the REMEDHUS area, the disaggregation results were directly compared with [8] in terms of the four metrics, and spatial variability of disaggregated SM was evaluated as well. Correlations and separation distances were calculated for all possible pairs of station locations. The relationship of correlations with distance could then be checked for each product at the fine scale.

TABLE I
STATISTICS OF OPTIMAL PARAMETERS FOR EACH STUDY AREA

| Study Area | CC | #Stan. | Par. [a] | Med. | 25th | 75th |
|---|---|---|---|---|---|---|
| CONUS (177 stations) | Arid | 43 | α | 1.00 | 1.00 | 1.00 |
| | | | *n* | 295 | 240 | 327 |
| | | | *L* | 0.12 | 0.06 | 0.20 |
| | | | $R^2$ | 0.40 | 0.22 | 0.56 |
| | Tem. | 79 | α | 1.00 | 0.97 | 1.00 |
| | | | *n* | 194 | 157 | 244 |
| | | | *L* | 0.07 | 0.04 | 0.11 |
| | | | $R^2$ | 0.20 | 0.07 | 0.44 |
| | Cold | 55 | α | 1.00 | 0.93 | 1.00 |
| | | | *n* | 254 | 202 | 326 |
| | | | *L* | 0.04 | 0.02 | 0.09 |
| | | | $R^2$ | 0.25 | 0.11 | 0.47 |
| REMEDHUS (17 stations) | Arid | 17 | α | 0.98 | 0.98 | 0.98 |
| | | | *n* | 152 | 149 | 159 |
| | | | *L* | 0.50 | 0.38 | 0.52 |
| | | | $R^2$ | 0.69 | 0.66 | 0.71 |

[a] Constraints for parameters: $0 \leq \alpha \leq 1$, $2 \leq n \leq 365$ (integer), and $0 \leq L \leq 1$
CC = climate classification, Tem. = temperate, Par. = parameter, Med. = median, OO$^{th}$ = OO% percentile, #Stan. = number of stations

## IV. RESULTS AND DISCUSSION

### A. Parameter Optimization Results

For optimizing the parameters in (4), one-year data of SM and NDVI before the study period was additionally used for considering the warm-up period. Table I shows the optimization results for each climate zone. All parameters ($\alpha$, $n$, and $L$) over the REMEDHUS area are reasonably stable and have high $R^2$. However, there is a much larger range of parameters and $R^2$ in the climate zones over the CONUS. It was found that $R^2$ is higher in the arid region than temperate and cold, and parameters vary as per the climate zones over the CONUS. Long windows were generally necessary for sufficiently smoothing the highly variable CCI SM to match the slowly varying NDVI. In detail, the longest $n$ values are required for the arid regions followed by cold regions and finally temperate regions. The arid regions were found to have generally larger $L$ values than the cold and temperate regions.

### B. Results of the CONUS

As shown in the box plots in Fig. 2, the disaggregated SM are compared to the CCI SM in terms of the four metrics against all ground stations over the CONUS by the three climate zones (i.e., arid, temperate and cold). The CCI SM shows the best performance in the arid regions, the cold regions come second and the temperate, third. This sequence in performance by the climate zones directly propagates into the disaggregated SM with a slight performance degradation compare to the CCI SM. As the proposed SM disaggregation method only uses the NDVI product, the performance degradation is closely related with the quality and applied preprocessing of the NDVI product. Regarding this, to obtain better disaggregation results, it is necessary to conduct further investigations on the use of other VI products and associated preprocessing steps such as gap filling, temporal interpolation, and quality assurance [19], [22].

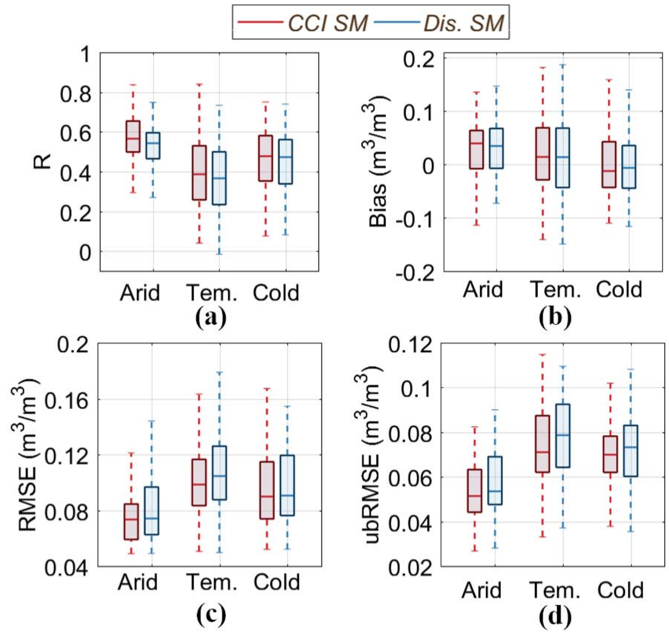


Fig. 2. Box plots by three climate zones showing distributions of (a) *R*, (b) bias, (c) RMSE, and (d) ubRMSE of CCI SM (0.25°) and disaggregated SM (0.05°) against *in situ* SM from 177 ground stations over the CONUS (43 stations for arid region, 79 for temperate and 55 for cold).

TABLE II
DISAGGREGATION RESULTS FOR REMEDHUS AREA

| Metric | R | Bias (m$^3$/m$^3$) | RMSE (m$^3$/m$^3$) | ubRMSE (m$^3$/m$^3$) |
|---|---|---|---|---|
| CCI SM (0.25°) | 0.58±0.13 | 0.06±0.08 | 0.11±0.05 | 0.06±0.01 |
| Dis. SM (0.05°) | 0.49±0.14 | 0.06±0.09 | 0.11±0.04 | 0.05±0.02 |

*The results in the metrics are slightly different from Peng et al. (2015) due to the QC flags to the ground measurements and the temporal coverage of the disaggregated SM between the two approaches

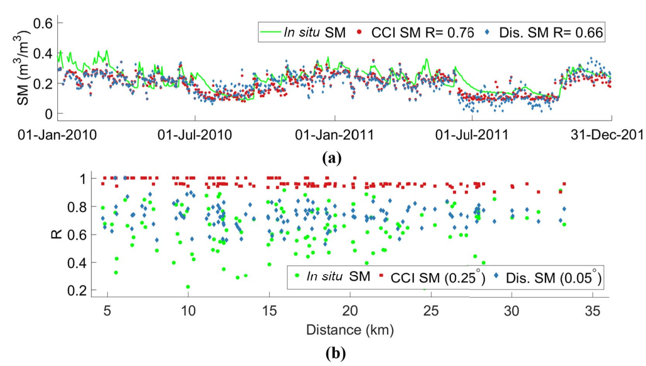


Fig. 3. Time series of in *in situ* (green), CCI (red), and disaggregated SM (blue) at (a) canizal station in the REMEDHUS network and (b) representation of spatial variability in *in situ* (green diamonds), CCI, and disaggregated SM over the REMEDHUS network.

### C. Results of the REMEDHUS

The proposed disaggregation approach provides similar performances in terms of the four metrics (Table II). This is in line with the results of the CONUS and means that the proposed SM-NDVI relation can replace LST information used in the latter approach. In addition, the temporal behavior of disaggregated SM is explicitly modeled in the proposed approach as shown in Fig. 3(a) compared to the time series of disaggregated SM in [8].

More importantly, Fig. 3(b) shows representation of spatial variability of *in situ*, CCI and disaggregated SM using the correlations of all possible pairs of station locations (i.e., 136 in this case) ($y$-axis) with distance ($x$-axis, km). Whereas the CCI SM has almost identical $R$ over the pairs, the disaggregated SM correctly captures the spatial variability of the *in situ* SM.

## V. Conclusion

In this letter, the coarse data-derived SM-NDVI relation is proposed for spatially disaggregates coarse SM. The SM-NDVI relation is based on the optimal statistical matching of the scaled NDVI and smoothed CCI SM. The disaggregation results support the hypothesis that the SM-NDVI relation can replace the LST information in SM disaggregation. Accordingly, when LST data is unavailable or of poor quality, the proposed method provides a good alternative to existing approaches using LST data. Importantly, the proposed approach can provide continuous time series of SM at the fine spatial resolution without losing the temporal variability of coarse SM. It also can correctly represent spatial variability in the disaggregated SM.

However, the work presented here is a proof-of-concept study to demonstrate the feasibility of the proposed method and there are a few future opportunities that could lead to better results. The uncertainty in the disaggregated product could be assessed using improved SM products [23] and different VI such as Enhanced Vegetation Index and Leaf Area Index. Second, a simple gap-filling method [17] and linear interpolation were used in the NDVI data sets. The method can lead to poor or physically unrealistic results with when gaps are large [18]. It would be worth examining whether other gap filling and interpolation methods [19], [22] could lead to better disaggregation performances.

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