AGU PUBLICATIONS

Reviews of Geophysics

REVIEW ARTICLE

10.1002/2016RG000543

Key Points:
- Limitations of current downscaling methods and challenges ahead
- Need for intercomparison of different downscaling methods
- Opportunity for synthesis use of all data source for downscaling

Correspondence to:
J. Peng,
jian.peng@mpimet.mpg.de

Citation:
Peng, J., A. Loew, O. Merlin, and N. E. C. Verhoest (2017), A review of spatial downscaling of satellite remotely sensed soil moisture, *Rev. Geophys.*, *55*, 341–366, doi:10.1002/2016RG000543.

Received 5 OCT 2016
Accepted 20 MAR 2017
Accepted article online 22 MAR 2017
Published online 18 APR 2017

A review of spatial downscaling of satellite remotely sensed soil moisture

Jian Peng[1], Alexander Loew[1,2], Olivier Merlin[3], and Niko E. C. Verhoest[4]

[1]Max Planck Institute for Meteorology, Hamburg, Germany, [2]Department of Geography, Ludwig-Maximilians Universität München, Munich, Germany, [3]Centre d'Etudes Spatiales de la Biosphère, Toulouse, France, [4]Laboratory of Hydrology and Water Management, Ghent University, Ghent, Belgium

Abstract Satellite remote sensing technology has been widely used to estimate surface soil moisture. Numerous efforts have been devoted to develop global soil moisture products. However, these global soil moisture products, normally retrieved from microwave remote sensing data, are typically not suitable for regional hydrological and agricultural applications such as irrigation management and flood predictions, due to their coarse spatial resolution. Therefore, various downscaling methods have been proposed to improve the coarse resolution soil moisture products. The purpose of this paper is to review existing methods for downscaling satellite remotely sensed soil moisture. These methods are assessed and compared in terms of their advantages and limitations. This review also provides the accuracy level of these methods based on published validation studies. In the final part, problems and future trends associated with these methods are analyzed.

1. Introduction

Soil moisture (SM) is a key state variable in the climate system, which controls the exchange of water, energy, and carbon fluxes between the land surface and the atmosphere [*Ochsner et al.*, 2013; *Robock et al.*, 2000; *Wagner et al.*, 2007; *Western and Blöschl*, 1999; *Western et al.*, 2002]. It plays important roles in various processes and feedback loops within the Earth system [*Seneviratne et al.*, 2010]. As a result, the soil moisture data sets are essential for a wide range of applications in hydrology [e.g., *Pauwels et al.*, 2002; *Robinson et al.*, 2008; *Western et al.*, 2004], meteorology [e.g., *Dai et al.*, 2004; *Koster et al.*, 2004; *Loew et al.*, 2013], climatology [e.g., *Anderson et al.*, 2007; *Hollinger and Isard*, 1994; *Mintz and Serafini*, 1992], and water resource management [e.g., *Bastiaanssen et al.*, 2000; *Dobriyal et al.*, 2012; *Engman*, 1991]. The soil moisture is usually defined as the total amount of water within the unsaturated zone [*Hillel*, 1998]. In practice, it is often separated into surface soil moisture corresponding to water in the upper soil and the root zone soil moisture that is available to plants (Figure 1) [*Seneviratne et al.*, 2010]. Soil moisture can be expressed in different units, such as gravimetric unit (g/cm^3) that is independent of soil characteristics [e.g., *Ulaby et al.*, 1979]. It can also be expressed as the function of the field capacity and the wilting point, which are dependent on soil types [e.g., *Givi et al.*, 2004]. The most common is the volumetric unit (m^3/m^3 or vol %), which is expressed as the ratio of water volume to soil volume [e.g., *Robock et al.*, 2000].

A number of techniques have been developed to measure soil moisture with ground instruments, which include gravimetric methods [e.g., *Robock et al.*, 2000; *Vinnikov and Yeserkepova*, 1991], time domain reflectometry [e.g., *Robinson et al.*, 2003; *Topp and Reynolds*, 1998], capacitance sensors [e.g., *Bogena et al.*, 2007; *Dean et al.*, 1987], neutron probes [e.g., *Hollinger and Isard*, 1994], electrical resistivity measurements [e.g., *Samouëlian et al.*, 2005; *Zhou et al.*, 2001], heat pulse sensors [e.g., *Valente et al.*, 2006], and fiber optic sensors [e.g., *Garrido et al.*, 1999]. For more details on these methods, the reader is referred to, e.g., *Robock et al.* [2000], *Walker et al.* [2004], *Robinson et al.* [2008], *Dobriyal et al.* [2012], and *Vereecken et al.* [2014]. With these techniques, spatially and temporally highly resolved measurements of soil moisture can be obtained at the point scale. These techniques have the advantages of easy installation, relative maturity, and the ability to measure soil moisture at different soil depths. The measurements from these techniques are normally recognized as the "ground truth." Significant efforts have been made to establish long-term operational soil moisture measurement networks [*Crow et al.*, 2012] with ground instruments. The in situ soil moisture observations from these networks have also been unified into a common database [*Dorigo et al.*, 2011; *Robock et al.*, 2000]. However, these point measurements are not representative for the neighboring areas due to the large spatial heterogeneity of soil moisture over a range of scales [e.g., *Collow et al.*, 2012; *Crow et al.*, 2012; *Loew*, 2008;

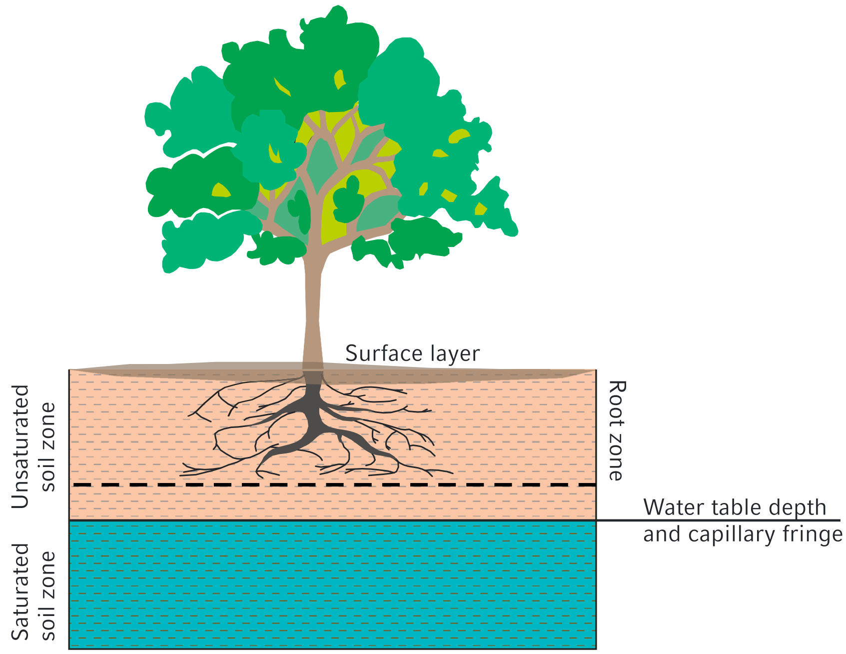

Figure 1. Schematic diagram of unsaturated and saturated soil zones.

Njoku et al., 2003; *Vinnikov et al.*, 1996; *Zreda et al.*, 2012]. The spatial variability of surface soil moisture is due to the complex interactions between various environmental variables, which include soil texture and structure, topographic features, land cover patterns, and meteorological forcing (Figure 2) [*Brocca et al.*, 2007; *Crow et al.*, 2012; *Mohanty and Skaggs*, 2001; *Vereecken et al.*, 2008]. Recently, *Vereecken et al.* [2014] reviewed the roles of these factors in the presence of soil moisture spatial variability at the field scale. They found that these factors are generally difficult to be isolated and measured and the impact of these factors on soil moisture variability varies significantly over time and space. In addition, the temporal stability of soil moisture is determined by the combined effects of the same factors [*Vanderlinden et al.*, 2012]. It should be noted that, although the absolute value of soil moisture between neighboring sites can have high variability, the temporal dynamic of soil moisture is often highly related, which implies that the soil moisture dynamics should be compared between data sets based on different estimation methods [*Seneviratne et al.*, 2010]. Therefore, the spatial characteristics of the in situ soil moisture networks are not ideal to construct spatially distributed soil moisture products, although in situ soil moisture can be

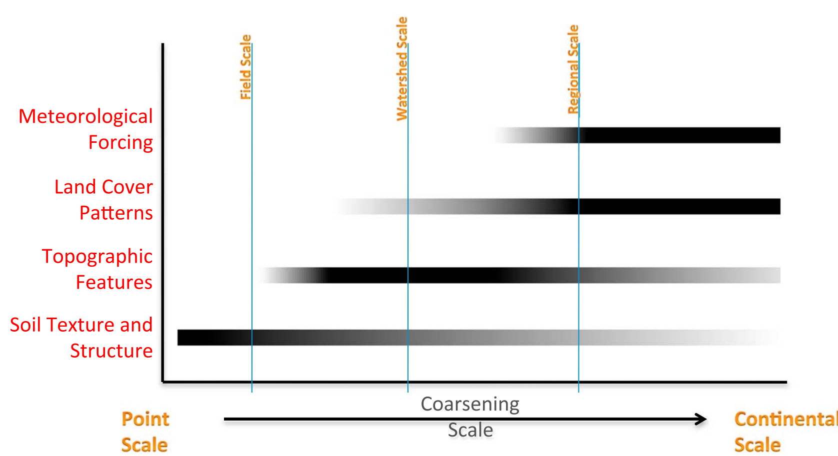

Figure 2. The dominant physical controls on spatial variability of soil moisture as a function of scale (figure modified from *Jana* [2010] and reprinted from *Crow et al.* [2012]).

extrapolated to larger scales via geostatistical techniques [e.g., *Bárdossy and Lehmann*, 1998; *Qiu et al.*, 2001]. In addition, the extrapolation of such point-scale measurements to large spatial scale is usually complex and time-consuming, especially over the land surface with high spatial heterogeneity [*Greifeneder et al.*, 2016; *Qin et al.*, 2013]. There are even many areas where dense soil moisture observational networks are not established yet. Thus, it is still challenging to quantify spatially and temporally distributed soil moisture at regional and global scales with the above-mentioned ground instruments, although the emergence of new soil moisture measurement technologies such as the COsmic-ray Soil Moisture Observing System (COSMOS) [*Desilets et al.*, 2010; *Zreda et al.*, 2008], the Global Positioning System (GPS) [*Larson et al.*, 2008], and the fiber optic Distributed Temperature Sensing (DTS) systems [*Sayde et al.*, 2010] shows significant potentials.

This problem is progressively solved with the development of remote sensing techniques, which can be used to obtain soil moisture from regional to global scales and at a temporal resolution of days. Satellite microwave observations from active and passive sensors are best suitable for the retrieval of soil moisture [e.g., *de Jeu et al.*, 2008; *Mohanty et al.*, 2017; *Schmugge et al.*, 2002]. Microwave remote sensing cannot directly measure soil moisture but makes use of the direct relationship between soil dielectric constant and water content. Active microwave remote sensing techniques measure the energy reflected from the land surface after transmitting a pulse of microwave energy, while passive microwave sensors measure the self-emission of the land surface [e.g., *Schmugge et al.*, 2002; *Wigneron et al.*, 2003]. Compared to ground instruments, the main limitation of remote sensing techniques is that only the surface soil moisture (the top 5 cm of the soil column) can be estimated [e.g., *Collow et al.*, 2012; *Crow et al.*, 2012; *Kerr*, 2007; *Wagner et al.*, 2007]. It is still challenging to estimate soil moisture at the root zone depth with remote sensing methods, although the superficial measurements from satellite can be vertically extrapolated to constrain root zone soil moisture estimates with the use of land data assimilation techniques [*Reichle et al.*, 2008]. Nevertheless, various approaches have been developed to retrieve soil moisture from measurements obtained from different active and passive sensors such as Advanced Microwave Scanning Radiometer–EOS (AMSR-E) for the Earth observing system [*Njoku et al.*, 2003], the advanced scatterometer (ASCAT) [*Bartalis et al.*, 2007], the Soil Moisture and Ocean Salinity (SMOS) [*Kerr et al.*, 2010], the recently launched Soil Moisture Active Passive (SMAP) mission [*Entekhabi et al.*, 2010], and Sentinel-1 satellite by European Space Agency [*Wagner et al.*, 2009]. Excellent reviews on the estimation of soil moisture from remote sensing data especially with microwave observations are provided by, e.g., *Wigneron et al.* [2003], *Wagner et al.* [2007], and *Petropoulos et al.* [2015]. Several global microwave soil moisture products have been produced, such as the AMSR-E Land Parameter Retrieval Model (LPRM) [*Owe et al.*, 2008], the ASCAT [*Naeimi et al.*, 2009], the SMOS [*Jacquette et al.*, 2010; *Kerr et al.*, 2001], and the European Space Agency's Climate Change Initiative (ESA CCI) soil moisture products [*Liu et al.*, 2011; *Wagner et al.*, 2012]. These products have been validated against extensive field campaigns and are widely used for a range of applications such as drought monitoring and climate model evaluation [e.g., *AghaKouchak et al.*, 2015; *Albergel et al.*, 2012; *Brocca et al.*, 2011; *Dorigo et al.*, 2015; *Jackson et al.*, 2012, 2010; *Loew et al.*, 2013; *Martínez-Fernández et al.*, 2016; *Peng et al.*, 2015a; *Sanchez et al.*, 2012; *Wagner et al.*, 2013].

As the above-mentioned soil moisture products have spatial resolutions, which are in the order of tens of kilometers, a spatial downscaling to several kilometers or even tens of meters is required for many regional hydrological and agricultural applications. The downscaled soil moisture can also help to solve the problem of scale mismatch between in situ measurements and satellite soil moisture retrievals for validation applications [*Malbéteau et al.*, 2016]. Within this context, various methods have been proposed to downscale soil moisture by accounting for the impact of numerous environmental variables. The idea behind these methods is to establish either a statistical correlation or a physically based model between coarse-scale soil moisture and fine-scale auxiliary variables. These methods differ in (1) the type of input data (radar data, optical/thermal data, topography, and soil depth) and (2) the characteristics of the scaling model (physical and statistical).

The aim of this paper is to provide a comprehensive review on the downscaling methods for satellite remote sensing-based soil moisture. The assumptions, advantages, and drawbacks associated with each method are discussed. Particular attention is given to the evaluation of these methods against in situ measurements. This paper also highlights the uncertainties and limitations associated with the reviewed methods. The review paper is supposed to assist the development of high spatial resolution soil moisture product, from which

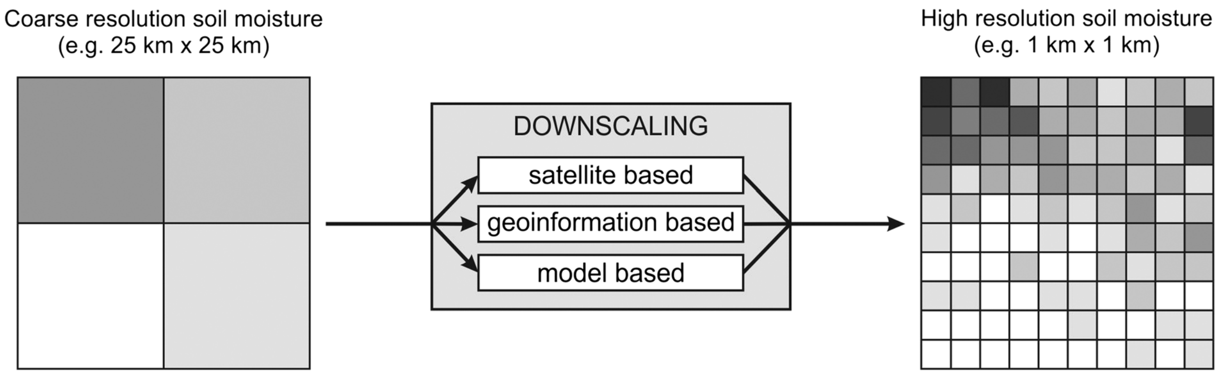

Figure 3. Flowchart of soil moisture downscaling methods.

the regional applications in hydrology, meteorology, climatology, and water resource management would benefit significantly.

2. Downscaling Methods

This section presents different downscaling methods for soil moisture, which are broadly classified into the following three major groups: (1) satellite-based methods, (2) methods using geoinformation data, and (3) model-based methods (Figure 3). Within each group, the downscaling methods are further detailed if appropriate.

2.1. Satellite-Based Methods

2.1.1. Active and Passive Microwave Data Fusion Methods

Both passive and active microwave observations have been widely explored to estimate soil moisture for several decades [e.g., *de Jeu et al.*, 2008; *Petropoulos et al.*, 2015; *Wagner et al.*, 2007]. The passive microwave radiometers can provide frequent observations but have rather coarse spatial resolutions. Active microwave sensors and especially synthetic aperture radars (SARs) are capable of providing much higher spatial resolutions than passive radiometers [e.g., *Loew et al.*, 2006; *Wagner et al.*, 2008; *Wigneron et al.*, 2003]. However, the retrieval of soil moisture from SAR is often difficult due to the combined effects of surface roughness, vegetation canopy structure, and water content on the backscattering coefficients of SAR [*Wagner et al.*, 2007]. Passive microwave observations as well as scatterometer data currently build the basis for globally available soil moisture data sets due to their better temporal sampling. Products derived from AMSR-E, ASCAT, SMOS, and SMAP satellites are therefore widely used. In order to take advantage of radiometer and radar observations, several algorithms such as a change detection method [*Njoku et al.*, 2002] and a Bayesian merging method [*Zhan et al.*, 2006] have been proposed to merge radiometer and radar data to provide high-resolution soil moisture data. Figure 4 illustrates the general framework for the fusion of SMAP radiometer with radar products. The letters C, F, and M represent coarse scale (36 km), fine scale (3 km), and medium scale (9 km) for the radiometer, radar, and combined product grid scale, respectively. Currently, there are three general groups of methods that have been proposed to fuse active and passive microwave data to derive soil moisture products with improved spatial resolutions:

1. Disaggregation of soil moisture product from passive sensor with backscatter data from an active sensor: *Njoku et al.* [2002] proposed a change detection method to retrieve soil moisture from passive and active L-band data collected during the Southern Great Plains Experiment in 1999. This method is based on the approximate linear relationship between backscatter data and soil moisture and assumes that the effects of vegetation and surface roughness are time-invariant. *Narayan et al.* [2006] applied the change detection method to retrieve high-resolution soil moisture by using L-band radiometer and radar observations made during the SMEX02 experiments. *Piles et al.* [2009] further tested the method by assuming simultaneous observations from an Observation System Simulation Experiment (OSSE) and showed that the active-passive disaggregation algorithm presented much more spatial details than the radiometer-only method (Figure 5). Furthermore, *Das et al.* [2011] improved the change detection algorithm and developed a new method that serves as the baseline algorithm for the SMAP combined active/passive soil

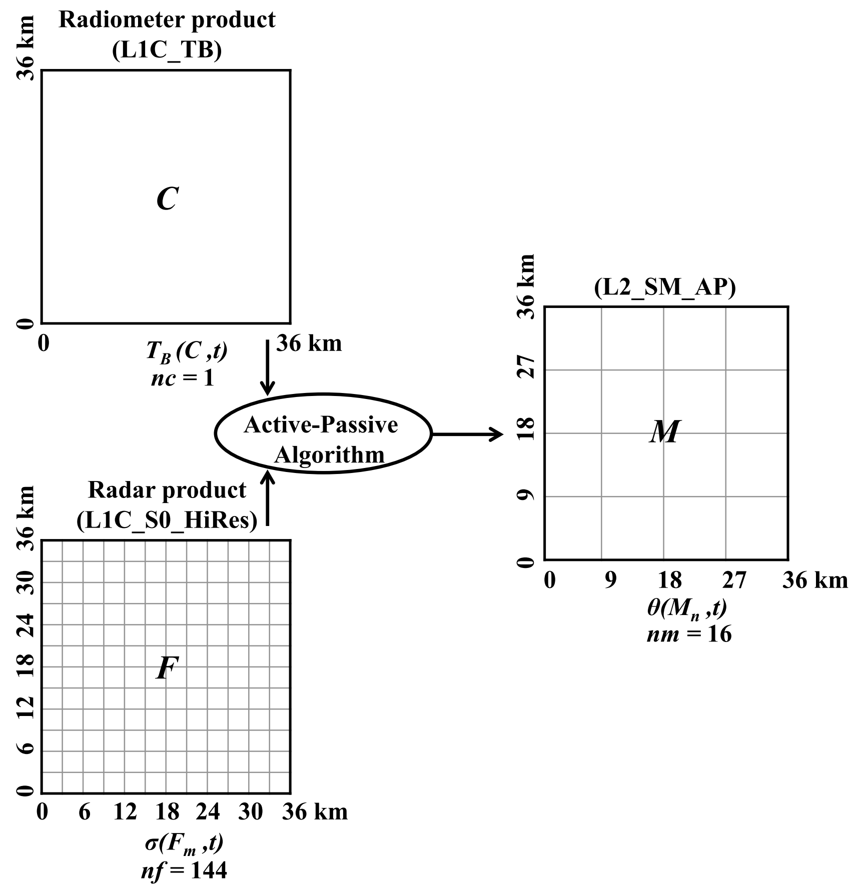

Figure 4. Flowchart of the fusion of SMAP radiometer (L1C_TB) and radar (L1C_S0_HiRes) into combined product (L2_SM_AP), where *nf* and *nm* are the number of grid cells of radar and combined product within one radiometer grid cell *nc*. T_B, σ, *and* θ represent brightness temperature, backscatter, and volumetric soil moisture, respectively (figure reprinted from *Das et al.* [2014]).

moisture product. Unlike the previous change detection methods, the baseline method does not require previous satellite overpass observations and provides an absolute soil moisture rather than relative soil moisture change. Except for the above methods, *Zhan et al.* [2006] demonstrated a statistical method that was based on Bayesian merging for soil moisture retrieval from hydros L-band radiometer and radar observations.

2. Disaggregation of brightness temperature from a passive sensor with backscatter data from an active sensor and subsequent inversion to soil moisture: in order to bypass the disadvantage of being highly dependent on the accuracy of the retrieved passive microwave soil moisture product as is the case in the previous method, a modified baseline method was proposed by *Das et al.* [2014]. In this method, the radar backscatter data were used to downscale the brightness temperature data first, from which the high-resolution soil moisture was then retrieved. However, this method requires the high-resolution ancillary data such as temperature and vegetation water content for the further retrieval of soil moisture.
3. Fusion of soil moisture products from a passive and an active sensor: *Montzka et al.* [2016] disaggregated the radiometer soil moisture product directly with radar soil moisture product and suggested that the direct fusion of active/passive soil moisture product was related to a simplified wavelet-based image enhancement method [*Aiazzi et al.*, 2002].

In general, the active/passive fusion method has great potential for improving the spatial resolution of soil moisture. The challenge is the inconsistent observation time of the current active/passive sensors on board the satellites and the low revisit rate of the radars. The launch of SMAP in January 2015 was supposed to solve this problem, with radiometer and SAR operating on a single observation system. Along with this mission,

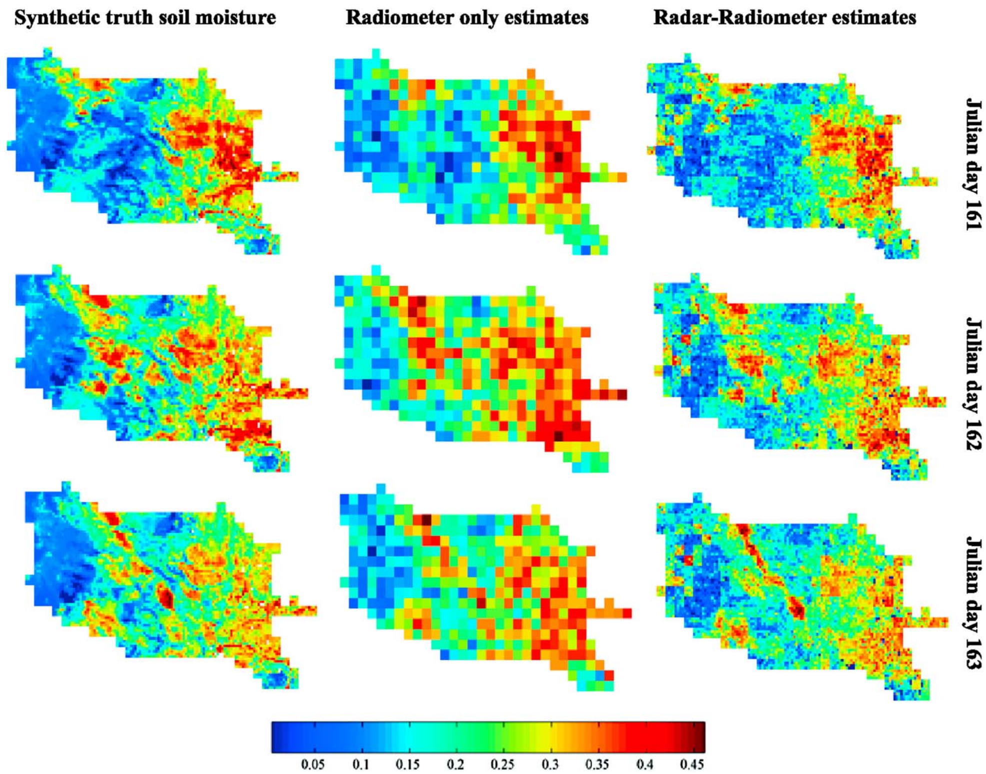

Figure 5. Comparisons between the high resolution (10 km) soil moisture estimate using active-passive method and low resolution (40 km) soil moisture obtained from radiometer and synthetic ground-truth soil moisture over three sample days. The unit of the color bar is m^3/m^3 (figure reprinted from *Piles et al.* [2009]).

many studies have investigated the performance of different active/passive fusion methods in support of SMAP [e.g., *Akbar and Moghaddam*, 2015; *Das et al.*, 2016; *Leroux et al.*, 2016; *Montzka et al.*, 2016; *van der Velde et al.*, 2015; *Wu et al.*, 2014, 2015]. Based on Monte Carlo simulation and optimization to retrieve soil moisture, Figure 6 shows the average soil moisture retrieval error for active, passive, and active-passive combined methods over corn, grass, and soybean land cover types. The results show that the active-passive combined method outperforms other methods especially for higher vegetation water content (VWC) over different land cover types [*Akbar and Moghaddam*, 2015]. However, the active radar that is deployed in SMAP stopped transmitting since July 2015. In order to continue the SMAP mission of

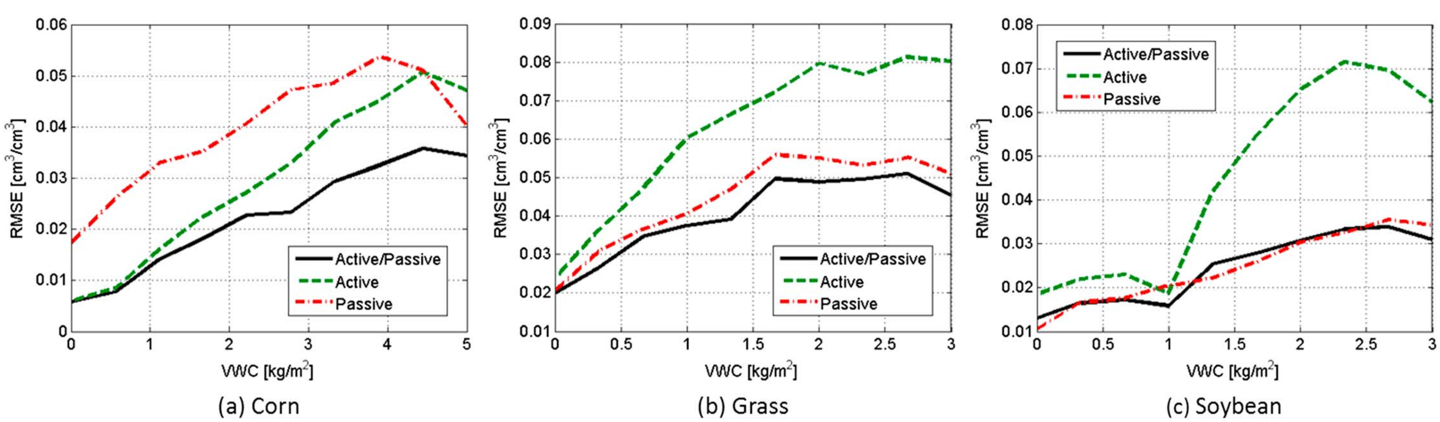

Figure 6. Average soil moisture retrieval error for active, passive, and active-passive combined methods for (a) corn, (b) grass, and (c) soybean over the range of vegetation water content (VWC) (figure reprinted from *Akbar and Moghaddam* [2015]).

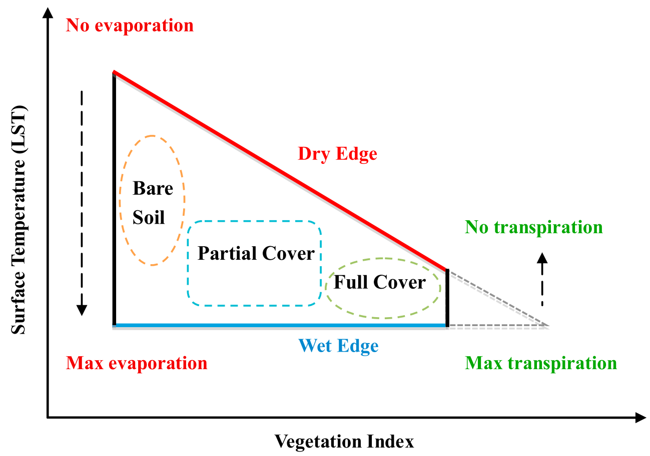

Figure 7. Conceptual diagram of the triangular feature space that is constructed by land surface temperature and vegetation index (figure adapted from *Peng et al.* [2013a]).

providing high spatial resolution soil moisture products, the possible solution is combining the brightness temperature observations with other active microwave data. The problem of large time lags between passive and active microwave observations still needs to be solved.

2.1.2. Optical/Thermal and Microwave Fusion Method

Compared to microwave remote sensing, optical and thermal remote sensing have the advantage of providing land surface parameters at higher spatial resolution. However, optical and thermal observations are affected by cloud coverage. A number of studies have attempted to downscale microwave soil moisture products with help of vegetation cover and surface temperature information as well as other surface parameters obtained from optical and/or thermal sensors. The general idea of these methods is to obtain a downscaling factor from high-resolution optical/thermal data. This downscaling factor is then used to improve the soil moisture spatial variability of the coarse resolution microwave soil moisture.

On the basis of the widely used surface temperature/vegetation index triangular feature space (Figure 7) [*Carlson*, 2007; *Petropoulos et al.*, 2009], an empirical polynomial fitting downscaling method was proposed by *Zhan et al.* [2002] and improved by *Chauhan et al.* [2003]. This method expresses the high-resolution soil moisture as a polynomial function of land surface temperature (LST), vegetation index, and surface albedo derived from optical/thermal data. The polynomial expression is first applied at coarse resolution to determine regression coefficients. The high-resolution soil moisture is then obtained through applying the polynomial expression with the coarse resolution regression coefficients, where the polynomial function described above is normally expressed as

$$\mathrm{SM} = \sum_{1=0}^{2}\sum_{j=0}^{2}\sum_{k=0}^{2} a_{\mathrm{ijk}}\mathrm{NDVI}^{i}T^{j}A^{k} \tag{1}$$

where SM is the soil moisture, T and NDVI are the normalized surface temperature and normalized difference vegetation index (NDVI) that are calculated based on the T/NDVI feature space [*Carlson et al.*, 1994], a_{ijk} is the regression coefficient, and A is the scaled surface albedo obtained from high-resolution optical/thermal sensors. *Piles et al.* [2011] further improved the polynomial fitting method by replacing the surface albedo with coarse resolution microwave brightness temperature in the polynomial expression. It was found that the bias between downscaled and in situ soil moisture was reduced. The polynomial fitting downscaling approach has been applied to downscale SMOS, AMSR-E soil moisture with high-resolution surface variables from Moderate Resolution Imaging Spectroradiometer (MODIS) or Meteosat Second Generation Spinning Enhanced Visible and Infrared Imager (MSG-SEVIRI) observations [e.g., *Choi and Hur*, 2012; *Peischl et al.*, 2012; *Piles et al.*, 2016, 2014; *Sánchez-Ruiz et al.*, 2014; *Zhao and Li*, 2013]. The polynomial fitting approaches are relatively simple and purely rely on satellite measurements. It is worth noting that these approaches are nonconservative, implying that the aggregated downscaled SM is not necessarily equal to the coarse resolution observation.

Merlin et al. [2008b] and *Merlin et al.* [2012] proposed the Disaggregation based on Physical And Theoretical scale CHange (DISPATCH, evaporation-based) method to relate the disaggregated soil moisture at high resolution (noted HR in the following) with observed soil moisture at coarse resolution (noted CR). Compared to the polynomial fitting approach, the evaporation-based method is more theoretically and physically based. The method is categorized as physical because it is based on the soil evaporation process to link optical and near-surface SM data. It is also qualified as theoretical because the scale change modeling relies on mathematical tools such as partial derivatives, Taylor series expansions, and projection techniques [*Merlin et al.*, 2005]. The development of the DISPATCH method can be found in *Merlin et al.* [2006a] and *Merlin et al.* [2008a], where soil temperature, evaporative fraction (EF), and evaporative efficiency (EE) as SM proxies were investigated. Among them, the surface EF is defined as the ratio of latent heat flux to the sum of latent and sensible heat fluxes, while the surface EE is the ratio of latent heat flux to potential latent heat flux. The reason why EF and EE were chosen as proxies of SM is that both ratios are generally constant during the day [e.g., *Crago and Brutsaert*, 1996; *Crago*, 1996; *Gentine et al.*, 2007; *Peng et al.*, 2013b; *Peng and Loew*, 2014; *Shuttleworth et al.*, 1989; *Sugita and Brutsaert*, 1991]. Moreover, they are more directly linked to SM [*Kustas et al.*, 1993] and less dependent on incoming radiation than evapotranspiration (ET) or land surface temperature [*Nishida et al.*, 2003]. The current version of DISPATCH [*Malbéteau et al.*, 2016; *Molero et al.*, 2016] is based on the downscaling relationship proposed by *Merlin et al.* [2008b], where the soil evaporative efficiency (SEE) was taken as SM proxy and was estimated from the feature space of land surface temperature and vegetation fractional cover at high resolution. The downscaling relationship is described as

$$\mathrm{SM_{HR}} = \mathrm{SM_{CR}} + \left(\frac{\partial \mathrm{SEE}}{\partial \mathrm{SM}}\right)_{\mathrm{CR}}^{-1} \times \left(\mathrm{SEE_{HR}} - \mathrm{SEE_{CR}}\right) \tag{2}$$

with $(\partial \mathrm{SEE}/\partial \mathrm{SM})_{\mathrm{CR}}^{-1}$ being the inverse of the derivative of an SEE model estimated at CR. The main sources of uncertainties when using DISPATCH are related to the modeling of SEE using two different information types: (1) the modeling of SEE as a function of LST and visible/near-infrared reflectances and (2) the modeling of SEE as a function of SM. Further improvements of DISPATCH need revising the modeling of temperature end-members [*Stefan et al.*, 2015], the topographic correction of LST including both elevation and illumination effects [*Malbéteau et al.*, 2017], and the modeling of SEE as a function of SM, soil properties, and atmospheric conditions [*Merlin et al.*, 2016].

Similar to the evaporation-based method, but even simpler downscaling method (UCLA) was proposed by *Kim and Hogue* [2012]. This method uses a linear relationship to connect soil wetness index [*Jiang and Islam*, 2003] with soil moisture. It can be described as

$$\mathrm{SM_{HR}} = \mathrm{SW_{HR}} \frac{\mathrm{SM_{CR}}}{\mathrm{SW_{CR}}} \tag{3}$$

where $\mathrm{SW_{CR}}$ stands for the soil wetness index that is calculated from the trapezoidal feature space of surface temperature and vegetation index [*Jiang and Islam*, 2003]. $\mathrm{SW_{CR}}$ is the SW at coarse spatial resolution. They also compared the UCLA method to the polynomial fitting approach from *Chauhan et al.* [2003] and the downscaling method from *Merlin et al.* [2008b] and found that both UCLA and the method from *Merlin et al.* [2008b] perform better than the polynomial fitting approach. Since the soil wetness index used in UCLA was originally used to retrieve evaporative fraction rather than for assessing soil moisture, *Peng et al.* [2016] replaced the soil wetness index in the UCLA method with the Vegetation Temperature Condition Index (VTCI), which is proposed by *Wan et al.* [2004]. *Peng et al.* [2015b] further optimized the estimation of VTCI and applied the method to downscale ESA CCI soil moisture with high-resolution MODIS and MSG-SEVIRI data (Figure 8). Both the UCLA method and Peng method highly depend on the accuracy of the soil moisture proxy either SW or VTCI. The type of method is expected to provide more accurate downscaled SM if the accuracy of soil moisture proxy can be highly improved similarly, with the use of high-resolution surface temperature and vegetation. Another soil moisture downscaling scheme was proposed by *Fang et al.* [2013] and *Fang and Lakshmi* [2014] based on the thermal inertia relationship between daily temperature change and daily average soil moisture. Instead of directly relating soil moisture to a high-resolution surface temperature and vegetation index, *Song et al.* [2014] first downscaled microwave brightness temperature with high-resolution surface temperature and NDVI. The high-resolution soil moisture was retrieved from the high-resolution brightness temperature with the single-channel algorithm (SCA) [*Jackson*, 1993] and the Qp model [*Shi et al.*, 2006]. In addition, *Srivastava et al.* [2013] combined the SMOS soil moisture and MODIS surface temperature to downscale the SMOS soil moisture through artificial intelligence techniques including support vector machines, artificial neural networks, and relevance vector machines. This is the first attempt to apply the artificial intelligence techniques for downscaling soil moisture.

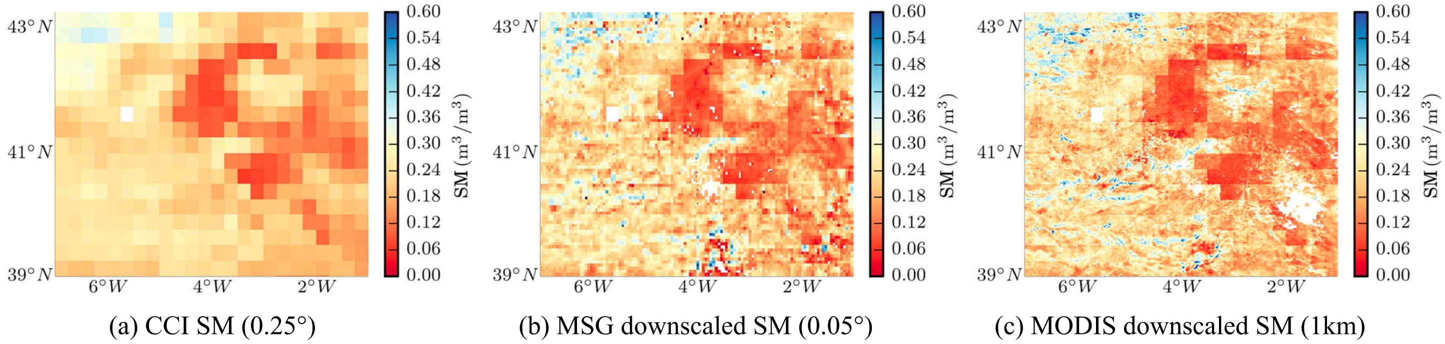

Figure 8. Spatial comparisons between (a) coarse CCI soil moisture and (b and c) downscaled CCI soil moisture based on MSG-SEVIRI and MODIS for 22 May 2010 (figure modified from *Peng et al.* [2015b]).

Most of the above-mentioned methods rely on the surface temperature/vegetation index feature space. However, one big difference between evaporation-based method and other methods is that the surface temperature/vegetation index feature space is applied at the pixel scale for evaporation-based methods and at the image scale for other methods. Such information is worth mentioning since the application of the feature space implicitly assumes that the meteorological forcing is uniform. Overall, the above methods fully make use of the high spatial resolution advantage of the thermal/optical data. The notable advantages of this type of methods are the multidata sources and long-term records of the optical/thermal data. However, this group of methods is only applicable under clear-sky conditions, due to the availability of optical/thermal data [*Djamai et al.*, 2016]. It can be seen from Figure 9 that the south-eastern region of the downscaled soil moisture is empty, which is due to the influence of clouds on MODIS observations [*Molero et al.*, 2016]. The accuracy of the downscaled soil moisture highly depends on the accuracy of the scaling factor that is used to represent soil moisture status at high resolution. For example, Figure 10 shows the downscaled soil moisture by using DISPATCH from SMOS and AMSR-E over the Yanco area on 22 November 2010. The downscaled soil moisture shows more similarities than original coarse SMOS and

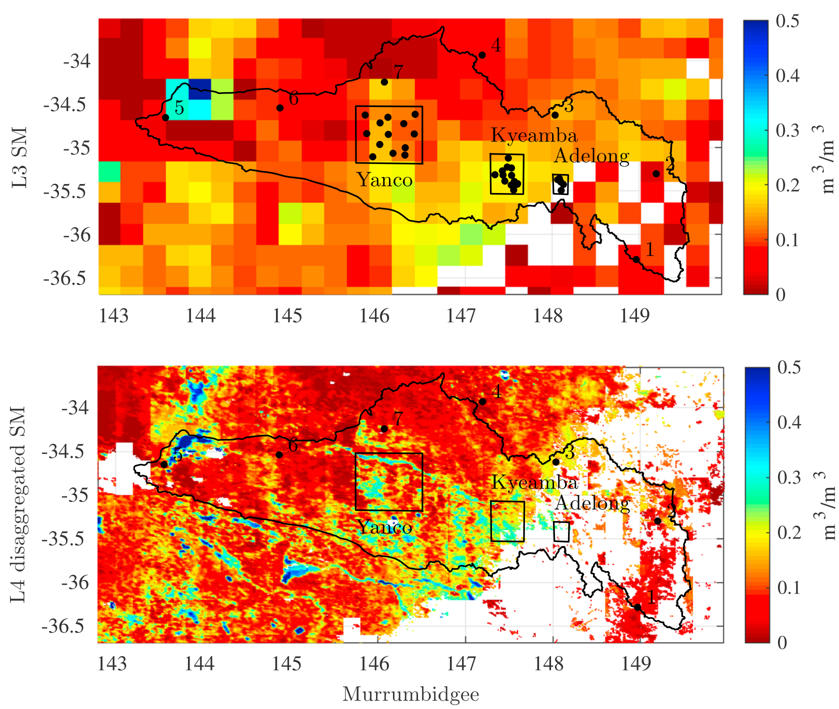

Figure 9. Maps of SMOS and downscaled soil moisture based on MODIS data over Murrumbidgee watershed (Australia) on 22 November 2010 (figure reprinted from *Molero et al.* [2016]).

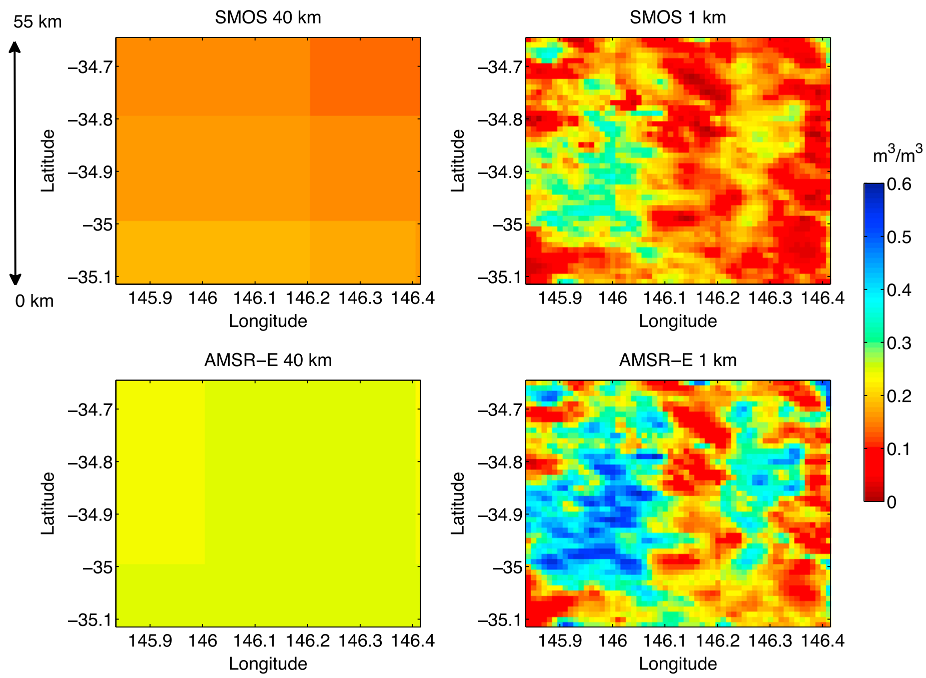

Figure 10. Downscaled 1 km spatial resolution soil moisture and original coarse SMOS and AMSR-E soil moisture over Yanco area (Australia) on 22 November 2010 (figure reprinted from *Malbéteau et al.* [2016]).

AMSR-E soil moisture, with correlation coefficient increasing from 0.27 to 0.96 after downscaling [*Malbéteau et al.*, 2016]. Compared to in situ measurements, the downscaled soil moisture also shows significant improvement for both SMOS and AMSR-E [*Malbéteau et al.*, 2016], implying the potential for obtaining high-resolution soil moisture with the use of all available soil moisture products such as AMSR-E, SMOS, SMAP, ASCAT, and ESA CCI.

2.2. Methods Using Geoinformation Data

Given that soil moisture is correlated with topographical, soil attribute, and vegetation characteristics [*Werbylo and Niemann*, 2014], these data could be used within the downscaling process. Topography has frequently been used as an ancillary source of information within downscaling approaches [e.g., *Busch et al.*, 2012; *Coleman and Niemann*, 2013; *Pellenq et al.*, 2003; *Ranney et al.*, 2015]. Unfortunately, the relationships between the catchment average or coarse-scale soil moisture values, topography-based attributes, and fine-scale soil moisture are generally established by using extensive in situ observations and have shown to be catchment-specific [*Busch et al.*, 2012], which clearly limits their applicability [*Werbylo and Niemann*, 2014]. Although these studies have shown the potential for downscaling soil moisture, to the authors' knowledge, no research has been reported in peer reviewed literature that apply these relationships to remotely sensed soil moisture so far.

2.3. Model-Based Methods

Models are often used in the downscaling approach. Two types of model can be discerned: models that describe statistics within or across scales (based on geostatistics, multifractals, or wavelets) or hydrological models that account for the different hydrologic processes within catchments. The following subsections briefly describe these different approaches.

2.3.1. Statistical Models

Different approaches exist to preserve statistics within or across scales. Many studies have been conducted on dense soil moisture observation networks or remotely sensed observations in order to describe the spatial statistics of the soil moisture field [e.g., *Famiglietti et al.*, 1999; *Grayson and Western*, 1998; *Peng et al.*, 2013b], to relate the spatial variability to the spatial average [*Grayson and Western*, 1998], or to reveal how statistics change across scales [*Crow and Wood*, 1999; *Famiglietti et al.*, 2008; *Rodriguez-Iturbe et al.*, 1995]. Based on these insights, downscaling algorithms have been suggested. For instance, *Kaheil et al.* [2008] make use of a geostatistical description of the spatial distribution of the soil moisture field in a coarse-scale image to model a soil moisture field at a finer scale. They further optimize the latter image based on in situ soil moisture observations and a support vector machine algorithm. Yet it may be argued that geostatistical techniques are less suited to account for the two-dimensional scale-dependent nonstationary of soil moisture fields. *Kaheil et al.* [2008] therefore suggest to make use of a wavelet-based multiresolution technique for downscaling. In such approach, the soil moisture field is decomposed into wavelet coefficients that are specific to the spatial scale and the location within the field and that allow for describing the typical (multi)fractal behavior of the soil moisture field; i.e., the statistical moments of the soil moisture field vary as a function of the scale considered but are related across scales through a scaling exponent [*Gupta and Waymire*, 1990]. Based on Polarimetric Scanning Radiometer (PSR)-based soil moisture estimates, *Kaheil et al.* [2008] found that, depending on the wetness condition, soil moisture shows simple or multifractal scaling. Yet a downscaling of remotely sensed soil moisture using the wavelet approach was not demonstrated. An alternative approach makes use of the fractal scaling properties of soil moisture fields. *Kim and Barros* [2002] suggest a fractal interpolation as downscaling approach and rely therefore on the assumptions that the scaling can be described by time-invariant fractals and that the fractal surface is uniquely determined by the power spectrum. This methodology was successfully applied by *Bindlish and Barros* [2002] to downscale Electronically Scanned Thinned Array Radiometer (ESTAR)-based soil moisture data at a resolution of 200 m to a higher resolution of 40 m. *Mascaro et al.* [2010, 2011] applied multifractal cascades to downscale soil moisture by means of a log-Poisson stochastic generator [*Deidda et al.*, 1999] that produces multifractal fields and found a good performance of the approach.

2.3.2. Involving a Land Surface Model

There are different ways in which a land surface model can be used in the downscaling of coarse-scale remote sensing observations. These range from optimizing hydrological or land surface model parameters based on the coarse-scale observations (this is often referred to as deterministic downscaling), statistical downscaling (in which the downscaling is performed based on regressions), to assimilating coarse-scale observations in land surface models.

2.3.2.1. Deterministic Downscaling

In deterministic downscaling, the fine-scale soil moisture is obtained from a hydrologic model that is optimized in such a way that the coarse-scale remotely sensed soil moisture is well approximated by the average of the corresponding subpixel soil moisture predictions. *Ines et al.* [2013] used a genetic algorithm approach [*Ines and Droogers*, 2002] to optimize the soil hydraulic parameters of a hydrologic model (i.e., the Soil Water Atmosphere Plant (SWAP) model [*Kroes et al.*, 2000; *Van Dam et al.*, 1997]), through minimizing the difference between the coarse-scale observed remotely sensed soil moisture and the average of the corresponding fine-scale resolution simulated soil moisture values. To further constrain the model optimization, *Shin and Mohanty* [2013] extended the objective function by including the deviation between Landsat TM-based evapotranspiration values, derived with the Simplified-Surface Energy Balance Index (S-SEBI) model [*Roerink et al.*, 2000], and the evapotranspiration estimated from the hydrological model. Based on field observations during the Southern Great Plains 1997 (SGP97) experiment [*Famiglietti et al.*, 1999], a good correspondence between the downscaled soil moisture estimates and the in situ observations was found.

2.3.2.2. Statistical Downscaling

In statistical downscaling, the land surface model is used as a basis for describing the relationship between the soil moisture of each individual fine-scale subpixel and that of the overlapping coarse-scale pixel. Through this statistical relationship, every coarse-scale soil moisture observation can be disaggregated to its finer scale. *Loew and Mauser* [2008] fitted for each fine-scale pixel a linear regression between its soil moisture content and that of the overlapping coarse-scale pixel in the assumption of a temporally stable relationship. As this relationship is obtained for each individual fine-scale pixel, it is dependent on site specific conditions such as land cover, soil texture, slope, aspect, height, and meteorological boundary conditions [*Loew and Mauser*, 2008]. *Verhoest et al.* [2015] also statistically related fine-scale soil moisture to the overlapping coarse-scale observation retrieved from radiometers. However, they recognized that often bias is found between soil moisture retrieved from remote sensing and that predicted by land surface models [*Koster et al.*, 2009]. Furthermore, this bias may differ depending on the soil moisture state (wet versus dry states may show different biases). To resolve this problem of nonconsistent bias, the bivariate relationship of remotely sensed soil moisture observations at one coarse-scale pixel and all corresponding fine-scale soil moisture values, as

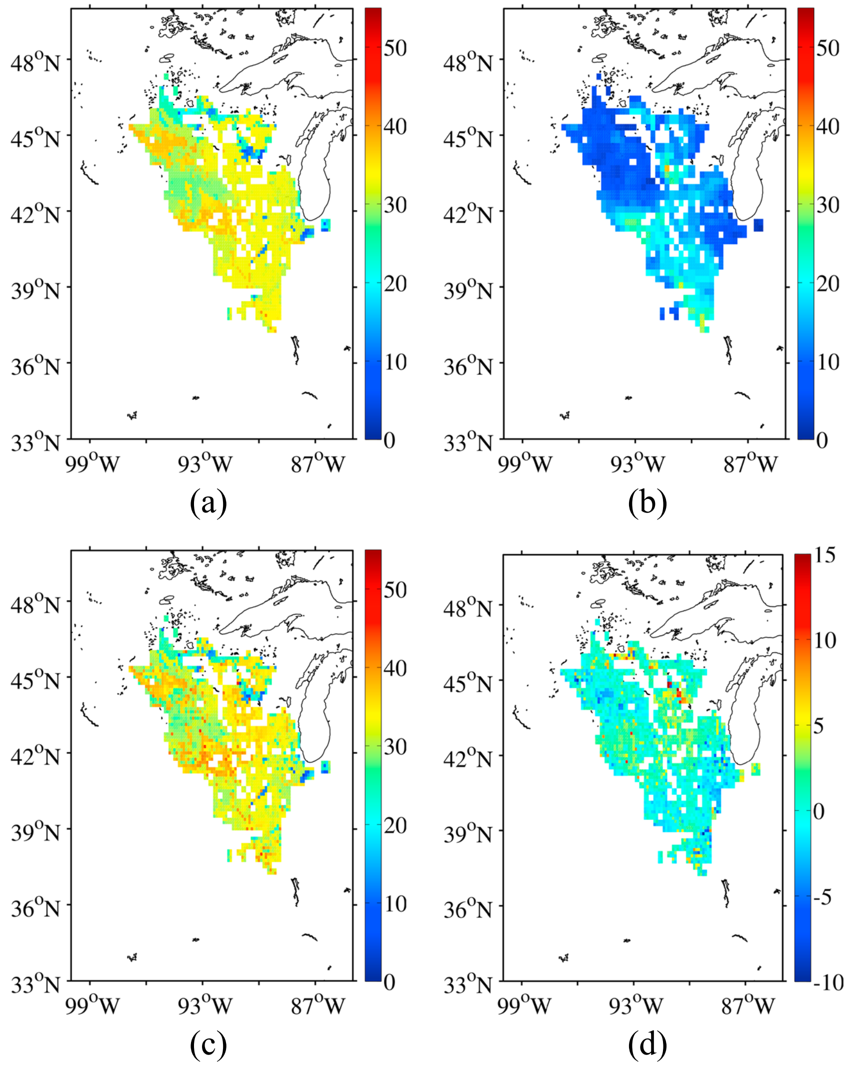

Figure 11. (a) VIC simulation of soil moisture at (b) high-resolution corresponding SMOS observations, (c) downscaled soil moisture map using the copula-based statistical downscaling approach, and (d) difference map, i.e., panel Figure 11c minus Figure 11a. All soil moisture contents are expressed as vol % (figure reprinted from *Verhoest et al.* [2015]).

obtained from a land surface model, was exploited. This bivariate distribution was described mathematically by means of a copula. Through conditioning the bivariate distribution to a remotely sensed coarse-scale soil moisture observation, a probability distribution is obtained that describes the subgrid variability of fine-scale soil moisture values, given the coarse-scale observation. In order to derive a downscaled soil moisture map, a cumulative distribution function (CDF) matching (or quantile mapping) of modeled soil moisture at the time of observation is performed toward the obtained conditional distribution function. This methodology differs from the classical CDF matching [*Drusch et al.*, 2005; *Reichle and Koster*, 2005] in that sense that the CDF to which the modeled soil moisture values are matched to obtain a downscaled product is not constant but depends on the value of the coarse-scale observation. Figure 11 shows the results of this methodology for SMOS-based soil moisture downscaled toward VIC-based high-resolution soil moisture.

2.3.2.3. Data Assimilation

Data assimilation aims at adjusting modeled states (e.g., soil moisture) based on in situ or remotely sensed observations. Many studies have been performed on this topic, but generally, the remotely sensed data are first downscaled to the resolution of the land surface model [*Merlin et al.*, 2006b; *Sahoo et al.*, 2013]. There are fewer studies available that assimilate coarse-scale observations into the model in order to update the fine-scale model states, which can then be considered as a downscaled soil moisture product. Such

Table 1. Summary of the Methods for Downscaling Soil Moisture

Section	Method	Source	Main Assumptions	Main Inputs	Advantages	Disadvantages
2.1.1	Change detection method	[*Narayan et al.*, 2006]	Linear relationship between backscatter data and soil moisture and the effects of vegetation and surface roughness are time-invariant.	Backscatter data from active microwave	Simplicity	Depends on the accuracy of soil moisture retrieved from passive microwave data
2.1.1	Baseline algorithm for SMAP	[*Das et al.*, 2011]	The effects of vegetation and surface roughness are time-invariant.	Backscatter data from active microwave	Provide absolute soil moisture content	Depends on the accuracy of soil moisture retrieved from passive microwave data
2.1.2	Polynomial fitting method	[*Chauhan et al.*, 2003]	Soil moisture is linked to surface temperature, vegetation index, and surface albedo.	Surface temperature, vegetation index, and surface albedo	Simplicity and without requirements of in situ measurements	Only applicable under clear-sky condition
2.1.2	DISPATCH	[*Molero et al.*, 2016]	Soil evaporation process is used as the proxy of soil moisture.	Surface temperature and vegetation index	Physical and theoretical based without requirements of in situ measurements	Only applicable under clear-sky condition and over partially covered vegetation
2.1.2	UCLA and Peng method	[*Kim and Hogue*, 2012]	Soil moisture index is used as a proxy of soil moisture.	Surface temperature and vegetation index	Simplicity and without requirements of in situ measurements	Depends on the accuracy of soil moisture index and only applicable under clear-sky condition
2.2	Based on geoinformation data	–	Soil moisture is correlated to surface properties (topography, vegetation, etc.).	Topography, land use maps, and remotely sensed soil moisture map	Simplicity	Requires much in situ data to derive statistical relationships of geophysical data and soil moisture
2.3.1	Geostatistical interpolation + support vector machines	[*Kaheil et al.*, 2008]	Soil moisture can be interpolated by using geostatistics.	Hydrologic model, in situ soil moisture, and remotely sensed soil moisture map	Simplicity	Requires in situ soil moisture data and a calibrated hydrologic model
2.3.1	Wavelets	[*Kaheil et al.*, 2008]	Soil moisture scaling can be described by wavelets.	Remotely sensed soil moisture map	Does not require in situ measurements	Complexity
2.3.1	Fractals	[*Kim and Barros*, 2002]	Soil moisture scaling is (multi-)fractal.	Remotely sensed soil moisture map	Does not require in situ measurements	Complexity
2.3.2.1	Deterministic downscaling	[*Ines et al.*, 2013]	Soil moisture distribution can well be described by a land surface model.	Land surface or hydrologic model, remotely sensed soil moisture maps, and ET map (not necessary)	Simplicity	Fully relies on modeled soil moisture
2.3.2.2	Statistical downscaling-linear regression	[*Loew and Mauser*, 2008]	Fine-scale and coarse-scale soil moisture are linearly related. This relation is stable in time.	Small-scale soil moisture time series (through hydrologic model) and corresponding remotely sensed soil moisture maps	Simplicity does not require in situ data; accounts for bias between model and remotely sensed observation	Relationship used may not be stable in time
2.3.2.2	Statistical downscaling-copulas	[*Verhoest et al.*, 2015]	Fine-scale and coarse-scale soil moisture are statistically dependent and can be described by a bivariate distribution (copula). Land surface model is able to capture spatial soil moisture patterns.	Land surface model and corresponding remotely sensed soil moisture maps	Does not require in situ data; accounts for bias between model and remotely sensed observation	Requires fitting of copulas

Table 1. (continued)

Section	Method	Source	Main Assumptions	Main Inputs	Advantages	Disadvantages
2.3.2.3	Data assimilation	[*Reichle et al.*, 2001]	Land surface model is able to capture spatial soil moisture patterns.	Land surface model	Accounts for the uncertainties in both observation and model prediction	Necessity to deal with scaling within the assimilation framework. Bias removal needs to be accounted for.

approach is often referred to as dynamical downscaling. One of the first examples, though with synthetic data, is reported by *Reichle et al.* [2001] in which a four-dimensional variational data assimilation approach is used to update fine-scale soil moisture predictions of the model based on brightness temperatures. In this approach, all remotely sensed observations during a time interval (i.e., the assimilation interval) are jointly assembled into a three-dimensional land surface model. A more frequently used assimilation approach is the ensemble Kalman filter. *Sahoo et al.* [2013] were among the first to apply dynamical downscaling to satellite-based soil moisture retrievals. In their approach, the innovations (i.e., differences between the observations and the ones predicted based on the model states) are calculated at the coarse-scale level and are mapped back to the fine-scale pixels through the Kalman gain that is related to the error cross correlations between the fine-scale variables and the coarse-scale observation variables [*Sahoo et al.*, 2013]. *Lievens et al.* [2015] applied a similar methodology, using SMOS observations, in which only the topsoil layer was updated through the ensemble Kalman filter, and found significant improvements in the soil moisture estimations through assimilating remotely sensed observations. It is important to state that in both studies, bias was removed within the data assimilation framework.

The above subsections describe the details of different downscaling methods from satellite observation-based to model-based. A brief summary of the above methods in terms of their assumptions, advantages, and disadvantages is given in Table 1.

3. Discussion

3.1. Evaluation of the Current Methods

Currently, there are still no effective ways for evaluating either the original remotely sensed soil moisture or the downscaled soil moisture outputs. Normally, the remotely sensed soil moisture products are validated directly against ground-based soil moisture observations. Numerous efforts have been made to unify different soil moisture measurement networks into a common database such as the International Soil Moisture Network (ISMN) [*Dorigo et al.*, 2011]. However, the spatial representativeness of the point-scale in situ measurements is not ideal for the evaluation of the coarse remotely sensed soil moisture products. This scale mismatch could introduce spatial sampling errors to the accuracy of the remotely sensed soil moisture. Taking advantage of intensive soil moisture measurements from small-scale networks, upscaling sparse ground-based soil moisture is one potential solution for validation of the coarse spatial resolution remotely sensed soil moisture products. *Crow et al.* [2012] summarized the existing soil moisture upscaling strategies for reducing the impacts of spatial sampling errors on the validation of remotely sensed soil moisture. They noted that a number of feasible upscaling methods already exist, but these methods require extensive in situ soil moisture observations and need to be validated independently before application.

Considering the validation of the downscaled soil moisture, little effort has been undertaken and the validation is mostly conducted through direct comparison with in situ measurements. Table 2 lists the published validation studies where downscaled soil moisture was compared to in situ measurements. To quantify the differences between the downscaled and the original soil moisture products, many studies also provide the evaluation results of the original soil moisture. Table 2 shows the references to the original study with description of the downscaled method and to the actual validation study and the

Table 2. A List of Published Studies on the Validation of Downscaled Soil Moisture Against In Situ Soil Moisture Measurements

Section	Method	Source	Validation	Study Area	Data Used	R(CR/HR)	RMSD (m^3/m^3) (CR/HR)	ubRMSD (m^3/m^3) (CR/HR)
2.1.1	Change detection method	[*Narayan et al.*, 2006]	[*Narayan and Lakshmi*, 2008]	Little Washita, Oklahoma, USA	AMSR-E, TMI, TRMM-PR	0.41–0.61/0.56–0.6	0.077–0.08/0.049–0.052	–
2.1.1	Baseline algorithm for SMAP	[*Das et al.*, 2011]	[*van der Velde et al.*, 2015]	Twente, Netherlands	AMSR-E, PALSAR	0.593/0.608 (1 km)	0.193/0.206(1 km)	–
2.1.1	Baseline algorithm for SMAP	[*Das et al.*, 2011]	[*van der Velde et al.*, 2015]	Twente, Netherlands	AMSR-E, PALSAR	0.593/0.6 (5 km)	0.193/0.203(5 km)	–
2.1.1	Baseline algorithm for SMAP	[*Das et al.*, 2011]	[*van der Velde et al.*, 2015]	Twente, Netherlands	AMSR-E, PALSAR	0.593/0.6 (10 km)	0.193/0.208(10 km)	–
2.1.1	Baseline algorithm for SMAP	[*Das et al.*, 2011]	[*Leroux et al.*, 2016]	Manitoba, Canada	PALS	0.61/0.74	0.09/0.084	0.072/0.061
2.1.1	Baseline algorithm for SMAP	[*Das et al.*, 2011]	[*Montzka et al.*, 2016]	Rur Catchment, Germany	PLMR2, F-SAR	–	0.0639–0.0701/0.0831–0.0940	–
2.1.2	Polynomial fitting method	[*Chauhan et al.*, 2003]	[*Choi and Hur*, 2012]	South Korea	AMSR-E, MODIS	0.127–0.725/0.348–0.658	0.131–0.179/0.059–0.171	–
2.1.2	Polynomial fitting method	[*Chauhan et al.*, 2003]	[*Zhao and Li*, 2013]	Iberian Peninsula, Spain	AMSR-E, SEVIRI	0.756/0.467	0.078/0.109	–
2.1.2	Polynomial fitting method	[*Chauhan et al.*, 2003]	[*Piles et al.*, 2014]	Iberian Peninsula, Spain	SMOS, MODIS	0.50–0.58/0.40–0.59	0.07–0.08/0.05–0.07	0.03/0.03-0.04
2.1.2	Polynomial fitting method	[*Chauhan et al.*, 2003]	[*Sánchez-Ruiz et al.*, 2014]	Iberian Peninsula, Spain	SMOS, MODIS	0.61–0.73	0.049–0.070	0.038-0.044
2.1.2	DISPATCH	[*Merlin et al.*, 2012]	[*Merlin et al.*, 2013]	Catalunya, Spain	SMOS, MODIS, ASTER, Landsat	0.59/0.58–0.67 (3 km)	0.12/0.11	–
2.1.2	DISPATCH	[*Merlin et al.*, 2012]	[*Merlin et al.*, 2013]	Catalunya, Spain	SMOS, MODIS, ASTER, Landsat	0.59/0.73–0.86 (100 m)	0.12/0.073–0.11	–
2.1.2	DISPATCH	[*Merlin et al.*, 2012]	[*Djamai et al.*, 2015]	Saskatchewan, Canada	SMOS, MODIS	0.3–0.52	0.03–0.05	–
2.1.2	DISPATCH	[*Merlin et al.*, 2013]	[*Malbéteau et al.*, 2016]	Southeastern Australia	SMOS, AMSR-E, MODIS, GTOPO30	0.7–0.833/0.714–0.775	0.084–0.117/0.068–0.092	–
2.1.2	DISPATCH	[*Merlin et al.*, 2013]	[*Molero et al.*, 2016]	Murrumbidgee, Australia; Little Washita, USA	SMOS, MODIS, GTOPO30	0.321–0.468/0.356–0.436	–	0.044-0.105/0.051-0.120
2.1.2	DISPATCH	[*Merlin et al.*, 2008b]	[*Kim and Hogue*, 2012]	Southern Arizona, USA	AMSR-E, MODIS	−0.08/0.34	0.049/0.048	–
2.1.2	UCLA method	[*Kim and Hogue*, 2012]	[*Kim and Hogue*, 2012]	Southern Arizona, USA	AMSR-E, MODIS	−0.08/0.27	0.049/0.051	–
2.1.2	Peng method	[*Peng et al.*, 2016]	[*Peng et al.*, 2016]	Southwestern China	ESA CCI SM, MODIS	0.843/0.746	0.062/0.078	–
2.1.2	Peng method	[*Peng et al.*, 2016]	[*Peng et al.*, 2015b]	Central Spain	ESA CCI SM, MODIS SEVIRI	0.594/0.58–0.617	0.079/0.072–0.076	0.041/0.04-0.042
2.1.2	Fang method	[*Fang et al.*, 2013]	[*Fang et al.*, 2013]	Oklahoma, USA	AMSR-E, MODIS, AVHRR	–	0.141–0.048/0.146-0.063	0.025-0.042/0.026-0.042
2.3.1	Fractals	[*Kim and Barros*, 2002]	[*Bindlish and Barros*, 2002]	Little Washita River Experimental Watershed, USA	SIR-C	–	0.0316/0.0279	–
2.3.2.2	Statistical downscaling-copulas	[*Verhoest et al.*, 2015]	[*Verhoest et al.*, 2015]	Upper Mississippi Basin, USA	SMOS	–	–	–
2.3.2.3	Data assimilation: ensemble Kalman filter	[*Sahoo et al.*, 2013]	[*Sahoo et al.*, 2013]	Little River Experimental Watershed, USA	AMSR-E	0.74–0.77	0.01–0.09	<0.03
2.3.2.3	Data assimilation: ensemble Kalman filter	[*Lievens et al.*, 2015]	[*Lievens et al.*, 2015]	Murray Darling Basin, Australia	SMOS	0.564/0.714	0.058/0.046	–

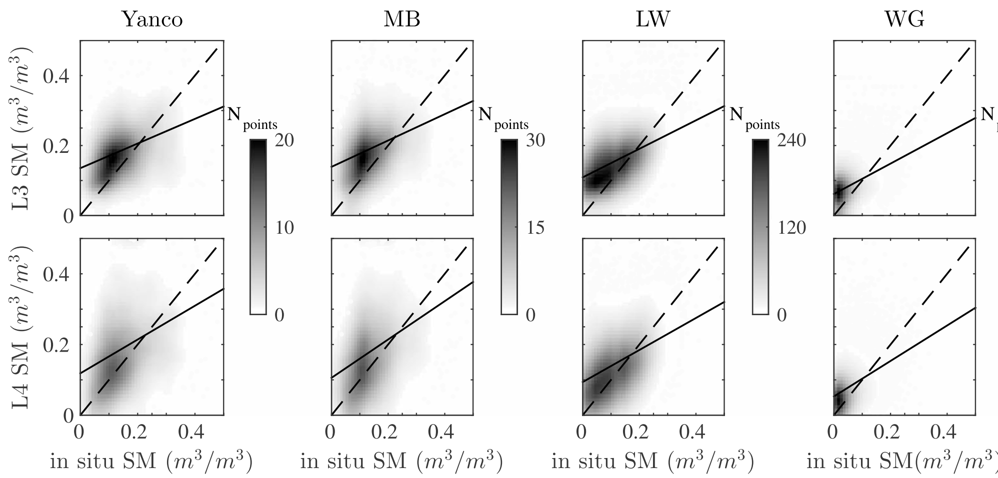

Figure 12. Scatterplots of (first row) original SMOS and (second row) downscaled SMOS soil moisture against in situ measurements over SMAP calibration/validation (Cal/Val) networks: the Murrumbidgee (MB), Little Washita (LW), and Walnut Gulch (WG). The solid line represents the linear regression line, while the dashed line corresponds to the 1:1 slope (figure reprinted from *Molero et al.* [2016]).

details on the study area as well as the main satellite inputs. Mainly due to the availability of the in situ measurements and the quality of the original coarse soil moisture, most of the validations were conducted in USA and Europe with only a few studies over Asia such as China and South Korea. For each validation, the statistical metrics including root-mean-square difference (RMSD), unbiased root-mean-square difference (ubRMSD), and correlation coefficient (R) are listed where available in Table 2. As an example, Figure 12 shows the validation results of SMOS and downscaled soil moisture over three SMAP calibration/validation (Cal/Val) networks: the Murrumbidgee (MB) in Australia [*Smith et al.*, 2012] and two U.S. Department of Agriculture networks: Little Washita (LW) in Oklahoma [*Cosh et al.*, 2006] and Walnut Gulch (WG) in Arizona [*Cosh et al.*, 2008]. These networks represent contrasted types of land cover, soil properties, spatial extent, and climate. A good agreement between SMOS, downscaled soil moisture, and the in situ measurements was found. In general, the results in Table 2 show that the accuracy of the downscaled soil moisture highly depends on the accuracy of the original soil moisture and surpasses the original coarse soil moisture for many studies, especially with active/passive fusion methods and the DISPATCH method. The degradation of the downscaled soil moisture might be caused by the quality of the downscaling method, the uncertainties of the input data, and scale mismatch issues. It should be noted that the statistical values of different methods listed in Table 2 are not comparable, because those validations were based on various satellite inputs and different number of stations in regions with very different soil moisture dynamics. To quantify the differences of the existing methods, downscaling with same inputs and validation against same in situ observations are needed. In addition, some validation studies such as *van der Velde et al.* [2015] and *Merlin et al.* [2013] also evaluated the downscaled soil moisture at different spatial resolutions, with the statistics results shown in Table 2. Figure 13 shows that the spatial variability of soil moisture is in agreement with the landscape heterogeneity, especially at the 1 km resolution compared to 5 km and 10 km. However, the higher resolution soil moisture does not always provide better accuracy [*van der Velde et al.*, 2015], which might be due to the surface heterogeneity and the remaining scale mismatch between downscaled and in situ soil moisture. Although the spatial resolution of the downscaled soil moisture is highly improved, the grid size of the downscaled soil moisture is still much bigger compared to point-scale measurements. Based on over 3600 in situ measurements collected during the SGP97, SGP99, SMEX02, and SMEX03 field campaigns, *Famiglietti et al.* [2008] generalized the spatial variability of soil moisture within spatial scales ranging from 2.5 m to 50 km. They found that the mean soil moisture variability increased from 0.036 cm^3/cm^3 within 2.5 m scale to 0.071 cm^3/cm^3 within 50 km scale. Due to the large spatial variability of soil moisture, the average value within 1 km^2 cannot certainly show better agreement with point measurements, compared to that of 5 km^2 or even larger extent. Nevertheless, the amiability of downscaled soil moisture at various spatial resolutions will facilitate different applications such as numerical weather prediction and hydrological modeling. Particularly, the precision agriculture will benefit

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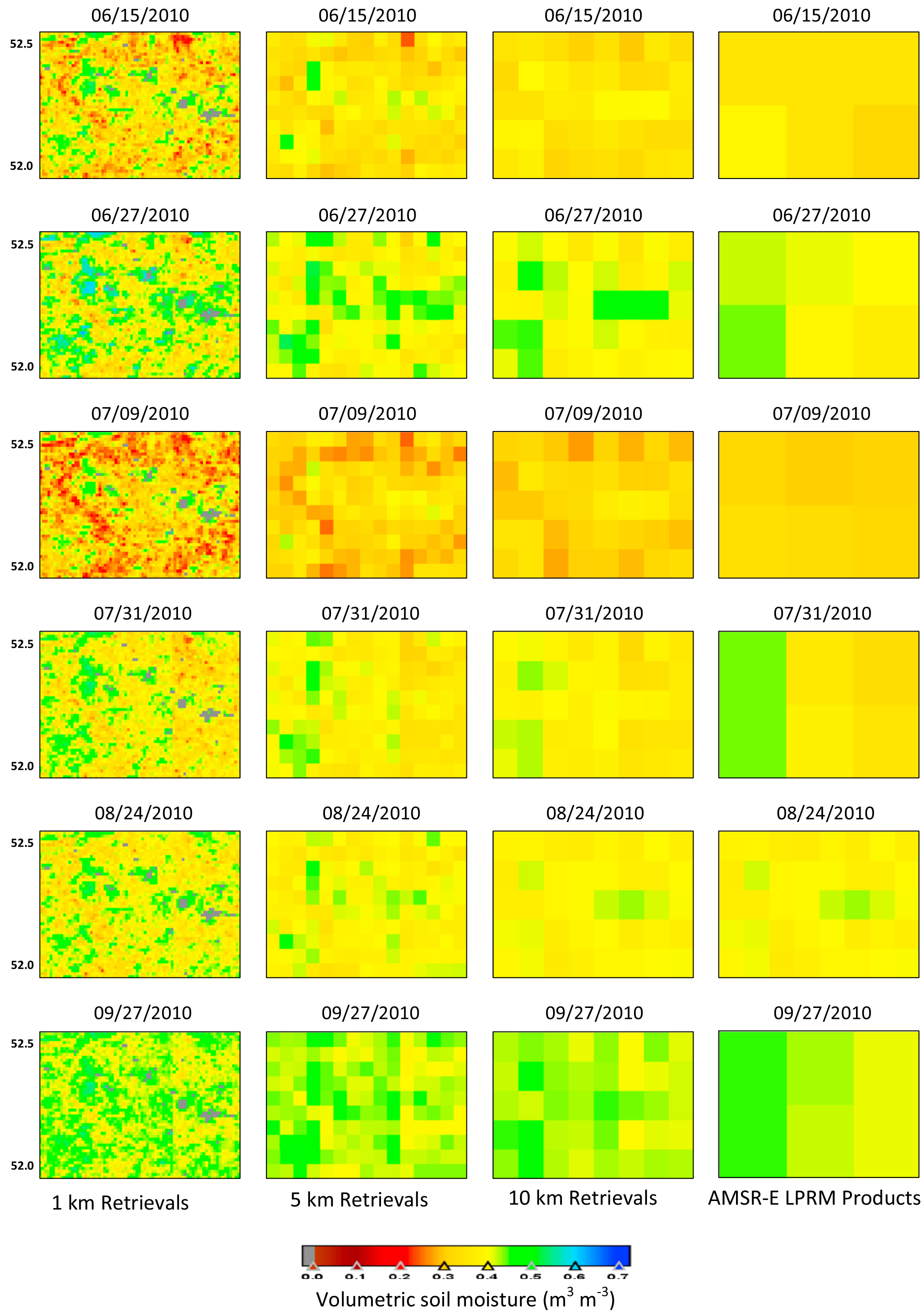

Figure 13. Maps of 25 km LPRM AMSR-E and downscaled 1 km, 5 km, and 10 km soil moisture over the Twente region, Netherlands (figure reprinted from *van der Velde et al.* [2015]).

significantly from soil moisture with the spatial resolution less than 100 m. In order to better evaluate the downscaled soil moisture, a consistent and robust validation strategy is still required. One possible direction is the selection of better performance metrics; *Merlin et al.* [2015] developed a new metric called GDOWN to assess the gain of downscaling compared to nondownscaling case. They noted that the new metric provides an assessment of error statistics relative to the nondownscaling case, which is different from the traditional metrics like RMSD. In addition, to ease the challenge of the scale mismatch between in situ and downscaled soil moisture, the upscaling of in situ measurements before validation should be strengthened in further validation studies. The spatial intercomparison with upscaled soil moisture or other variables such as landcover map would provide evaluation of the spatial variation of the downscaled soil moisture. In addition, another solution is to identify the representative in situ soil moisture station for the satellite footprints based on temporal and spatial statistical methods such as temporal stability analysis [e.g., *Vachaud et al.*, 1985; *Yee et al.*, 2016]. It is also possible that the spatial representativeness of the soil moisture observation is increased with new in situ measurement technologies. The newly developed COSMOS is one of them, which measures area-average soil moisture at spatial resolution higher than 500 m [*Desilets et al.*, 2010]. The cosmic ray probe measures the neutrons that are generated by cosmic rays at scale of hundreds of meters, whose density is inversely correlated with soil moisture [*Zreda et al.*, 2012]. The cosmic ray probes have been deployed mainly in the United States, Germany, and the UK. The soil moisture measured from one COSMOS site over the United States has been used to evaluate the ESA CCI soil moisture product [*Dorigo et al.*, 2015]. Due to the characteristic of area-average, the measurements from COSMOS have potential for validation of satellite-derived soil moisture products, especially the downscaled soil moisture. However, it should also be noted that the overall utility of COSMOS as a validation tool for satellite remote sensing estimates still has some inherent limitations. For example, the COSMOS also provides a vertically integrated value of soil moisture (from the surface into the root zone) and, depending on the soil and vegetation conditions, the "effective depth" of the vertically integrated value can vary. Further, the COSMOS water content is also impacted by water molecules in the vegetated surface within the sensor range.

3.2. Limitation of the Current Methods

In this section, the issues that cause the uncertainties of the downscaled soil moisture and the limitations of the existing downscaling methods are discussed.

3.2.1. Uncertainties of Remotely Sensed Products

There is a considerable amount of uncertainty in the remotely sensed products. Soil moisture products are not directly measured by microwave remote sensing but retrieved from radiative transfer models with the requirement of many other parameters such as vegetation properties and surface roughness [*Njoku and Entekhabi*, 1996]. The uncertainties in the determination of these parameters would add errors to the accuracy of the retrieved soil moisture. To obtain more accurate soil moisture products, improvements of the retrieval algorithms and in the accuracies of the input parameters are still made [*Petropoulos et al.*, 2015; *Wang and Qu*, 2009]. Several methods have also been proposed to characterize the retrieval errors, which can provide insights to the development of the retrievals. These methods include error propagation model [e.g., *Naeimi et al.*, 2009; *Parinussa et al.*, 2011], triple collocation method [e.g., *Draper et al.*, 2013; *Stoffelen*, 1998], and power spectrum analysis [*Su et al.*, 2014]. However, the results obtained from these methods are not comparable due to the use of different reference data and error metrics for defining the biases. In addition, there are significant differences between soil moisture products from different satellite missions due to different overpass time, retrieval algorithms, and distinctive error characteristics of each sensor [*Reichle et al.*, 2007; *Rüdiger et al.*, 2009; *Yilmaz et al.*, 2012]. *Su et al.* [2016] investigated the random error and systematic differences in nine passive and active microwave remote sensing soil moisture products and found that the error maps of the retrieved soil moisture are linked to the confounding effects of various factors such as vegetation index, land cover fraction, topographic variability, and local microclimatic conditions. However, quantification of the impacts of these factors on the spatial variability of retrieval errors is still unclear. Another factor that affects the accuracy of the downscaled soil moisture is the input satellite data of the downscaling method. Most of the aforementioned downscaling methods rely on the high-resolution optical/thermal inputs such as surface temperature, vegetation index, and surface albedo. However, different downscaling methods have different sensitivity on the uncertainties of these inputs. Existing downscaling evaluation studies rarely quantify the impacts of uncertainties of these inputs on the downscaled soil moisture.

3.2.2. Uncertainties Associated With the Downscaling Model

A range of different downscaling methods from satellite-based to geoinformation-based to model-based have been proposed and applied to improve the spatial resolution of soil moisture product. Each of these methods has its own advantages and disadvantages and has been applied successfully in different areas as shown in Table 1. The methods vary widely with different complexity and data requirements. Noted that each method has its applicability under certain purposes, and over different surface and climate conditions, none of the methods can be applied everywhere over the world without any calibration or improvements. For example, the active/passive fusion methods might not be suitable for areas with dense vegetation cover due to the strong effects of vegetation on soil moisture retrieval from microwave observations. With respect to optical/thermal-based downscaling methods, LST is linked to SM in the case of nonenergy limited conditions. Therefore, the optical/thermal-based downscaling methods rely on a strong atmospheric evaporative demand and are more adapted to arid and semiarid areas. In order to quantitatively evaluate and further improve each method, there is a need for performing a benchmarking of the downscaling algorithms based on constructed synthetic data sets with a rich variability in temporal and spatial heterogeneities and patterns of soil moisture. In addition, there are also opportunities to develop models and algorithms that assimilate multiple data sources into model simulations to generate high-resolution soil moisture data set.

3.2.3. Limitations in Scales

Many of the downscaling techniques rely on auxiliary data, being another remote sensing product or geoinformation. Because of this, the target scale is restricted to that of these auxiliary data. Optical data generally provide a higher spatial resolution, yet due to cloud cover, their use for downscaling is less robust. An alternative source of auxiliary data are models, as they may provide information at any desired scale. However, using this type of information imposes model errors on the downscaled products.

3.2.4. Limitations of the Satellite Coverage

All the downscaling methods that rely on the inputs from optical/thermal remote sensing data are affected by the presence of clouds. This limitation makes the application of these methods under nonclear-sky conditions impractical and unreliable. To obtain temporally and spatially continuous values, one possible solution for this type of methods is the interpolation of the satellite estimates temporally and spatially either before or after downscaling. Another direction is the combined use of observations from polar orbit and geostationary satellite [*Peng et al.*, 2015b; *Piles et al.*, 2016]. It will intergrade the high spatial resolution of polar orbit data and high temporal frequency of geostationary data (~15 min), which can add the chance of data availability at daily scale. Considering the active/passive fusion method, the data from microwave satellite are available over full sky conditions. However, the failure of the SMAP active sensor and the low temporal frequency of other existing SAR sensors make the application of this type of method challenging. The methods based on hydrological models are not affected by clouds and can provide temporally and spatially continuous values. Therefore, a gap filling method and a coupling with models should be strengthened in future studies.

3.2.5. Uncertainties of the In Situ Observations

In order to validate the downscaling methods, research-quality validation observations are required. While there are known limitations to the accuracy and representativeness of in situ observations, there is growing knowledge of the uncertainty between the sensors themselves. This is addressed in the recent article by *Cosh et al.* [2016], whereby various sensor brands and technologies have a dynamic range within the same soil and environmental conditions. Therefore, calibration must be applied to the soil moisture sensors before the development of unified reference data set for validation activities.

4. Conclusions and Outlook

Great progress has been made in the estimation of soil moisture from microwave remote sensing. To apply these retrieved soil moisture products for regional hydrological and agricultural research, various downscaling methods have been developed and evaluated to improve the spatial resolution of the microwave soil moisture products. This paper provides a comprehensive review of these downscaling methods and summarizes the associated assumptions, advantages, and disadvantages. Despite the progress that has been made in the past decades, limitations and uncertainties of these methods still need to be properly overcome in future studies.

1. The soil moisture products are needed at high spatial and temporal resolutions for regional agricultural applications. To obtain at least daily frequency, time extrapolation methods are required to avoid the impacts of clouds on optical/thermal observations and the low temporal resolution of active microwave data.
2. There is a need to develop downscale schemes that combine multiple data sources: (1) other finer scale remote sensing; (2) ancillary data such as topography, soils, and landcover; and (3) models. As such, the optimal approach consists of models and algorithms that assimilate multiple data sets into model simulations to generate high-resolution soil moisture, which would be the ultimate synthesis of information from various sources.
3. A consistent and robust validation strategy for the downscaled soil moisture is still missing. Effective performance metrics for the evaluation of the downscaled soil moisture at point scale still need to be

developed and evaluated. Evaluation of the spatial patterns of the downscaled soil moisture would be strengthened with the help of upscaling in situ soil moisture.

4. The accuracy of the downscaled soil moisture relies on the input satellite data and the downscaling method. On the one hand, improving the accuracy of the input data such as satellite-based coarse soil moisture is needed. On the other hand, the uncertainties of the downscaling method need to be quantified with the upscaled in situ soil moisture observations. Intercomparison of different downscaling methods based on constructed synthetic data sets with a rich variability in temporal and spatial heterogeneities and patterns of soil moisture will help to determine the applicability of each method for certain conditions.
5. The recently launched Sentinel-1 satellites by ESA provide SAR data in C-band, which would help to retrieve soil moisture at 1 km spatial resolution and 6 day temporal resolution [*Wagner et al.*, 2009]. With the increasing number of both satellite and in situ measurements, the improvement of the downscaling methods and the synergy with new satellite data become possible, allowing for the development of operational high-quality soil moisture product.

In summary, there is a need for synthesis use of all available data sources to generate high-accuracy soil moisture products. Future research in this area can lead to the generation of long-term, temporally continuous, and operational high spatial resolution soil moil moisture data sets.

Notation

AMSR-E	Advanced Microwave Scanning Radiometer–EOS
ASCAT	advanced scatterometer
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CDF	cumulative distribution function
COSMOS	COsmic-ray Soil Moisture Observing System
CR	coarse resolution
DISPATCH	Disaggregation based on Physical And Theoretical scale CHange
DTS	Distributed Temperature Sensing
EE	evaporative efficiency
EF	evaporative fraction
ESA CCI	European Space Agency's Climate Change Initiative
ESTAR	Electronically Scanned Thinned Array Radiometer
ET	evapotranspiration
GPS	Global Positioning System
HR	high resolution
ISMN	International Soil Moisture Network
LW	Little Washita
LPRM	Land Parameter Retrieval Model
LST	land surface temperature
MODIS	Moderate Resolution Imaging Spectroradiometer
MSG-SEVIRI	Meteosat Second Generation Spinning Enhanced Visible and Infrared Imager
MB	Murrumbidgee
NDVI	normalized difference vegetation index
OSSE	Observation System Simulation Experiment
PSR	Polarimetric Scanning Radiometer
R	correlation coefficient
RMSD	root-mean-square difference
S-SEBI	Simplified-Surface Energy Balance Index
SAR	synthetic aperture radars
SCA	single-channel algorithm
SEE	soil evaporative efficiency
SGP	Southern Great Plains
SM	soil moisture

SMAP	Soil Moisture Active Passive
SMOS	Soil Moisture and Ocean Salinity
SWAP	Soil Water Atmosphere Plant
ubRMSD	unbiased root-mean-square difference
VTCI	Vegetation Temperature Condition Index
VWC	vegetation water content
WG	Walnut Gulch

Acknowledgments
This work was supported by the by the Cluster of Excellence CliSAP (EXC177), University of Hamburg, funded through the German Science Foundation (DFG), the ESA CCI program (CMUG), and the Belgian Federal Science Policy through the HYDRAS+ project (SR/00/302). We are also grateful to the French Agence Nationale de la Recherche (MIXMOD-E project, ANR-13-JS06-0003-01) and the European Commission Horizon 2020 (REC project, grant agreement 645642) programs. There were no original data used in this paper; all the results presented can be found in the cited references. We would also like to thank the Editor Alan Robock, Editor-in-Chief, and three anonymous reviewers for their constructive comments that helped improve this paper.

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