Evaluation of soil moisture downscaling using a simple thermal based proxy – the REMEDHUS network (Spain) example

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Abstract

Soil moisture retrieved from satellite microwave remote sensing normally has spatial resolution in the order of tens of kilometers, which are too coarse for many regional hydrological applications such as agriculture monitoring and drought prediction. Therefore, various downscaling methods have been proposed to enhance the spatial resolution of satellite soil moisture products. The aim of this study is to investigate the validity and robustness of the simple Vegetation Temperature Condition Index (VTCI) downscaling scheme over a dense soil moisture observational network (REMEDHUS) in Spain. Firstly, the optimized VTCI was determined through sensitivity analyses of VTCI to surface temperature, vegetation index, cloud, topography and land cover heterogeneity, using data from MODIS and MSG SEVIRI. Then the downscaling scheme was applied to improve the spatial resolution of the European Space Agency's Water Cycle Multi-mission Observation Strategy and Climate Change Initiative (ESA CCI) soil moisture, which is a merged product based on both active and passive microwave observations. The results from direct validation against soil moisture observations, spatial pattern comparison, as well as seasonal and land use analyses show that the downscaling method can significantly improve the spatial details of CCI soil moisture while maintain the accuracy of CCI soil moisture. The accuracy level is comparable to other downscaling methods that were also validated against REMEDHUS network. Furthermore, slightly better performance of MSG SEVIRI over MODIS was observed, which suggests the high potential of applying geostationary satellite for downscaling soil moisture in the future. Overall, considering the simplicity, limited data requirements and comparable accuracy level to other complex methods, the VTCI downscaling method can facilitate relevant hydrological applications that require high spatial and temporal resolution soil moisture.

Keywords: Soil moisture; Downscaling; Essential climate variable; MODIS; MSG SEVIRI; REMEDHUS;

1. Introduction

Soil moisture (SM) is known to be an important state variable that determines the partitioning of surface net energy into latent and sensible heat fluxes, as well as the partitioning of precipitation into infiltration and runoff (e.g., Porporato et al., 2004; Vereecken et al., 2014). In the context of global climate change, accurate information of soil moisture is of great importance for advancing our understanding of the energy and mass exchanges between the atmosphere, hydrosphere and biosphere (Petropoulos et al., 2015; Seneviratne et al., 2010). In addition, soil moisture is important for numerous practical applications such as irrigation water management (Bastiaanssen et al., 2000), ecological modeling (Nemani et al., 2009), vegetation productivity estimation (Reichstein et al., 2003) and numerical weather prediction (Douville et al., 2000). However, quantifying the spatially and temporally distributed soil moisture properties is still challenging due to dynamic meteorological forcing and surface heterogeneity (Njoku et al., 2003; Loew, 2008). Traditionally, the ground-based measurements of soil moisture are interpolated to a large scale through geostatistical techniques such as kriging (Bárdossy and Lehmann, 1998; Qiu et al., 2001). Such method is however limited to areas where dense soil moisture observational networks are available.

The advent of satellite remote sensing over the past decades provides an opportunity to obtain soil moisture estimates at global and regional scales without the need of ground-based measurements. Tremendous efforts have been devoted to retrieve soil moisture with measurements from passive and active microwave remote sensing sensors/satellites, including the Advanced Microwave Scanning Radiometer E for the Earth observing system (AMSR-E), the Advanced Microwave Scanning Radiometer-2 (AMSR2), the Advanced Scatterometer (ASCAT), the Soil Moisture and Ocean Salinity (SMOS), and recently launched Soil Moisture Active Passive (SMAP) mission. Theoretical and experimental results suggest that both the passive and active sensors are reliable for estimating soil moisture from space (Owe et al., 2008; Petropoulos et al., 2015). The significant advantages of the microwave remote sensing techniques are that 1) dielectric constant measurement can be related directly to soil moisture; 2) soil moisture can be retrieved regardless of the atmospheric conditions (Hain et al., 2011; Loew et al., 2006). To date, several global microwave based soil moisture products are available, such as the ASCAT soil moisture product (Wagner et al., 1999; Naeimi et al., 2009), the AMSR-E and AMSR2 soil moisture products (Owe et al., 2008; Parinussa et al., 2014a), the SMOS soil moisture product (Kerr et al., 2001; Jacquette et al., 2010), as well as the European Space Agency's Water Cycle Multi-mission Observation Strategy and Climate Change Initiative (ESA CCI) soil moisture product. The CCI SM product is a merged product based on six microwave products (Liu et al., 2012; Liu et al., 2011; Wagner et al., 2012). These soil moisture products normally have spatial resolution on the order of tens on kilometers, which serves well for global scale applications. However, this spatial resolution is often too coarse for regional and local applications such as agriculture monitoring and drought prediction, which normally require a spatial resolution of 1-10 km (Crow et al., 2000; Piles et al., 2011).

Optical/thermal infrared (TIR) sensors can provide complementary information of soil moisture patterns at higher spatial resolutions (tens of meters to several kilometers) (Zhang et al., 2014). The surface reflectance observed by optical sensors can be used to explore the state of soil moisture indirectly through empirical spectral vegetation index (Gao et al., 2013; Lobell and Asner, 2002). The common method used by thermal infrared remote sensing to estimate soil moisture is by calculating thermal inertia (Qin et al., 2013; Verstraeten et al., 2006). Yet, the observations from optical/thermal infrared sensors are only available under clear sky conditions. To take the advantages of microwave and optical/TIR remote sensing, more and more studies try to develop synergistic techniques that use multi-sensors to estimate soil moisture at different spatial resolutions. These approaches have a wide range of complexity from empirical regression methods to physically based models (Fang and Lakshmi, 2014; Kim and Hogue, 2012; Merlin et al., 2009; Sahoo et al., 2013). A number of these methods are based on the relationship between land surface temperature and vegetation index. When the remote sensed surface temperature and vegetation index over heterogeneous areas are plotted, the shape of the scatterplot generally resembles a physically meaningful triangular or trapezoidal feature space, due to different sensitivity of surface temperature to soil moisture variations over bare soil and vegetation covered areas (Carlson et al., 1994; Peng et al., 2013b). Based on this feature space, several indexes such as Vegetation Temperature Condition Index (VTCI) (Wan et al., 2004) and Temperature Vegetation Dryness Index (TVDI) (Sandholt et al., 2002) have been widely used for assessing the status of soil moisture and monitoring drought condition (Patel et al., 2008; Karnieli et al., 2010; Mallick et al., 2009; Peng et al., 2013a). Similarly, Chauhan et al. (2003) proposed a soil moisture downscaling scheme that links the soil moisture with surface temperature, vegetation index and surface albedo through linear regression equation. Following this idea, some other studies have tried to improve the regression models by including other inputs such as brightness temperature and surface emissivity (Piles et al., 2014; Sobrino et al., 2012). Recently, Peng et al. (2016) proposed a new and simple method to improve the spatial resolution of microwave soil moisture with VTCI as the unique downscaling factor. They demonstrated the feasibility of the proposed method via validation against limited ground-based soil moisture measurements and spatial comparison with land cover map. However, to further investigate the robustness of the proposed method, Peng et al. (2016) suggested that more validation work against dense soil moisture observational networks is required.

Therefore, the present study focuses mainly on investigating the validity and robustness of this simple downscaling scheme through comparison with ground-based soil moisture measurements from a dense observational network (REMEDHUS) in Spain (Martínez-Fernández and Ceballos, 2003). The REMEDHUS site has already been widely used for validation of soil moisture estimates from remote sensing (Brocca et al., 2011; Ceballos et al., 2005; Sánchez et al., 2012). This study has two major objectives. First it explores and analyzes the sensitivity and robustness of VTCI on land surface temperature, vegetation index, clouds, terrain condition and heterogeneity of land cover and validates the accuracy of soil moisture downscaling using VTCI over the REMEDHUS site. Secondly it investigates the merit of using of geostationary satellite data for downscaling soil moisture. Normally the polar orbiting satellites such as Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR) are in general used for downscaling microwave soil moisture, while the geostationary satellite data are rarely applied. As geostationary observations can provide more cloud free observations due to their high temporal resolution, they have the potential of estimating the thermal inertia at higher frequencies (Fensholt et al., 2007; Shu et al., 2011; Stisen et al., 2008). Hain et al. (2011) successfully used ALEXI model together with thermal infrared observations from geostationary satellites to estimate soil moisture at a relatively high spatial resolution of 3 km. Parinussa et al. (2014b) further inter-compared the geostationary satellite-based soil moisture with microwave-based soil moisture products at various spatial scales over the Iberian Peninsula. They found that all these products agree well with ground-based observations. Thus, the results from both, polar orbit satellite (MODIS Terra/Aqua) as well as geostationary satellite (MSG SEVIRI) were used in the current study to downscale ESA CCI soil moisture product. To the best of our knowledge, this is also the first study to inter compare the performances of geostationary and orbit satellites for downscaling soil moisture.

2. Study area and REMEDHUS observation network

The current study is carried out in Spain, where a central area is selected for downscaling CCI SM due to its relatively flat characteristic (Figure 1). The land cover of this region is dominated by croplands and shrublands, and the mean elevation of the area is about 650 m above sea level. The region has a continental semiarid Mediterranean climate, which is characterized by dry and warm summers and cool to mild and wet winters (Castro et al., 2004; Ceballos et al., 2004). The REMEDHUS soil moisture observation network is in the central part of the study area and shown in Figure 1 as well. The network covers a 35 km x 35 km flat area (41.1°-41.5°N; 5.1°-5.7°W) with elevation ranging from 700 to 900 m above sea level. The average annual precipitation and air temperature are 385 mm and 12 °C respectively. The land use of the network is mainly rainfed cereals (78%), forest and pasture (13%), irrigated crops (5%), and vineyards (3%) (Sánchez et al., 2012). A total of 19 soil moisture stations and 4 automatic weather stations in the REMEDHUS network are used in this study. The soil moisture stations are equipped with capacitance probes that measure top layer (0-5cm) soil moisture at hourly intervals. The details of the 19 soil moisture stations used in our study are summarized in Table 1. The REMEDHUS network has been widely used for different applications such as parameterization of water balance models (Sánchez et al., 2010), calibration and validation of soil moisture product from remote sensing (Sánchez et al., 2012; Wagner et al., 2008), and especially evaluation of downscaled soil moisture products from SMOS and AMSR-E (Piles et al., 2014;

Sánchez-Ruiz et al., 2014; Zhao and Li, 2013). These studies presented more complex downscaling approaches than the one explored in this study. They provide a baseline to cross compare the downscaling results of this study with their results. Therefore, study period from January 1st 2010 to December 31st 2011 is chosen to be similar to the published studies and to make the inter-comparison more reasonable. The soil moisture measurements are obtained from the International Soil Moisture Network (ISMN, https://ismn.geo.tuwien.ac.at) (Dorigo et al., 2011; Dorigo et al., 2013).

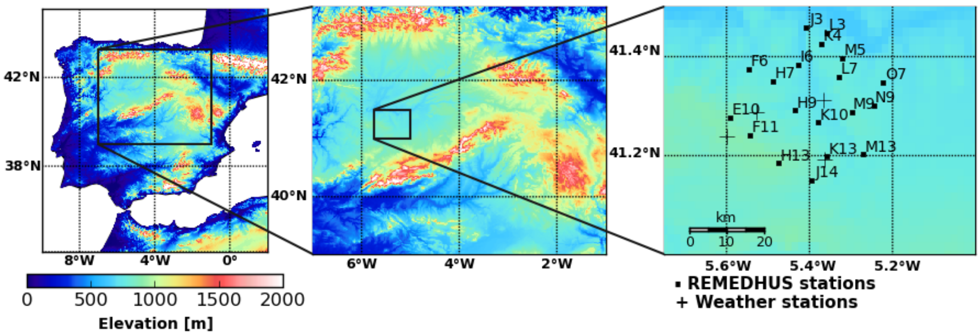


Figure 1: Quick view of the study area in central Spain and the location of the REMEDHUS observation network.

Table 1: Descriptions of the 19 soil moisture stations used in the study.

Station name	Short name	Land use	Elevation (m)	Latitude/ Longitude (°)
Las Tres Rayas	E10	Vineyard	870	41.28 / -5.59
Llanos de la Boveda	L7	Rainfed	790	41.36 / -5.33
El Tomillar	H7	Vineyard	755	41.35 / -5.49
Las Vacas	O7	Rainfed	770	41.35 / -5.22
El Coto	I6	Vineyard	720	41.38 / -5.43
Guarena	M13	Forest-Pasture	720	41.20 / -5.27
Canizal	K13	Rainfed	720	41.20 / -5.36
Las Arenas	F6	Vineyard	745	41.37 / -5.55
Las Brozas	L3	Vineyard	675	41.45 / -5.36
Las Victorias	K4	Vineyard	740	41.43 / -5.37
Las Bodegas	H13	Rainfed	900	41.18 / -5.48
Casa Periles	M5	Rainfed	750	41.40 / -5.32
La Cruz de Elias	M9	Rainfed	795	41.29 / -5.30
Concejo del Monte	N9	Rainfed	765	41.30 / -5.25
Guarrati	H9	Forest-Pasture	720	41.29 / -5.43
Paredinas	J3	Vineyard	665	41.46 / -5.41
Carretoro	K10	Rainfed	745	41.27 / -5.38
La Atalaya	J14	Rainfed	830	41.15 / -5.40
Zamarron	F11	Rainfed	855	41.24 / -5.54

3. Satellite data

Several satellite platforms with different temporal and spatial resolutions are used in this study. They provide different land surface products such as soil moisture, land surface temperature and vegetation indexes. Table 2 gives an overview of these satellite products used in our study.

Table 2: Descriptions of the satellite-based products used in this study.

Satellite product	Temporal resolution	Spatial resolution	Projection	Variable used
ESA CCI SM	Daily	0.25°	–	Soil moisture
MOD11C1 (Terra)	Daily	0.05°	Plate caree	Surface temperature
MYD11C1 (Aqua)	Daily	0.05°	Plate caree	Surface temperature
MYD11A1 (Aqua)	Daily	1 km	Sinusoidal	Surface temperature
MOD13C1 (Terra)	16-day composite	0.05°	Plate caree	EVI and NDVI
MCD15A3 (Aqua and Terra)	4-day composite	1 km	Sinusoidal	LAI and FPAR
LSA-SAF LST	15 minutes	4.8 km	Curvilinear	Surface temperature

3.1 ESA CCI soil moisture

The ESA CCI soil moisture is a unique multi-decadal (35 years from 1978 to 2013) satellite-based soil moisture dataset on a daily basis and at a spatial resolution of 0.25°, which has great potential for climate related studies and applications (Loew et al., 2013). The CCI SM was developed under the framework of ESA Water Cycle Multi-mission Observation Strategy and ESA Soil Moisture Climate Change Initiative (Hollmann et al., 2013). It was generated by merging four passive (SMMR, SSM/I, TMI, and AMSR-E) and two active (ERS AMI and ASCAT) microwave SM products together with a cumulative distribution function (CDF) matching technique. The detailed harmonization procedure is described in Liu et al. (2012; 2011). The first version of the CCI SM dataset (01.0) was published in 2012 covering the 32 years period from 1978 to 2010. To extend the temporal coverage to 2013, improve the gapping filling and processing algorithm, a new version of CCI SM product (02.1) was released recently. It contains three soil moisture products: active only, passive only, and merged active-passive product. A comprehensive validation of the merged active-passive product using 596 sites from 28 different observation networks worldwide was carried out by Dorigo et al. (2015). It was shown that the CCI SM product has a mean correlation coefficient (R) of 0.46 and an average unbiased root mean square deviation (ubRMSD) of 0.05 m^3/m^3 on daily timescales. Similarly, Albergel et al. (2013) provided an evaluation of CCI SM and two reanalysis soil moisture products using in-situ observations from five networks across the world. They concluded that the CCI SM product correlates well with in-situ observations with average R of 0.60. Furthermore, the trend of CCI SM highly agrees with the trends of precipitation, and vegetation vigor from various reanalysis products (Albergel et al., 2012; Dorigo et al., 2012; Peng et al., 2015). Therefore, the CCI merged soil moisture is selected in our study to explore the possibility and potential of downscaling to high spatial resolution with optical/thermal infrared data.

3.2 MODIS land surface temperature (LST) and vegetation index

The Moderate Resolution Imaging Spectroradiometer (MODIS) is the primary instrument in the NASA Earth Observing System (EOS) Terra and Aqua satellites, which were launched in December 1999 and May 2002 respectively. With 36 discrete spectral bands ranging from visible, near infrared, to thermal infrared, the MODIS has been widely used for land, ocean and atmosphere research (Salomonson et al., 1989; Huete et al., 2002). The Terra and Aqua satellites have different overpass times of 10:30 PM/10:30 AM for Terra, 1:30 PM/1:30 AM for Aqua in ascending/descending modes. The MODIS data from either Terra or Aqua have been used for downscaling soil moisture (e.g. Srivastava et al. (2013), Choi and Hur (2012)). The surface temperature normally has strong diurnal variation. Therefore, the surface temperature products provided by Terra and Aqua have different values due to different overpass time of Terra and Aqua. Since surface temperature is one of the most important inputs in downscaling methods, both MODIS/Terra and MODIS/Aqua are used to downscale soil moisture in this study. The MODIS products used in this study are Collection 5 MODIS land surface temperature and vegetation indexes (MOD11C1, MYD11C1, MYD11A1 MOD13C1, MCD15A3). Among them, MOD11C1 and MYD11C1 provide daily land surface temperature at 0.05 spatial resolution, while MYD11A1 provides daily surface temperature at 1 km resolution. MOD13C1 contains 16-day composite of Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI). MCD15A3 provides the combined (Terra and Aqua) MODIS Leaf Area Index (LAI) and Fraction of Photosynthetically Active Radiation absorbed by vegetation (FPAR) products every 4 days at 1 km resolution. The above products have all been validated against a wide range of in situ observations, and applied in many scientific studies (Coll et al., 2009; Fensholt et al., 2004; Tian et al., 2002).

3.3 MSG SEVIRI data

The Spinning Enhanced Visible and Infrared Imager (SEVIRI) is the main instrument on board Meteosat Second Generation (MSG) geostationary satellites (Schmetz et al., 2002). The SEVIRI has 12 separate channels from visible to thermal infrared and can provide observations at very high temporal resolution (every 15 min), which makes it possible to resolve the diurnal cycle of environmental variables such as land surface temperature (Peres and DaCamara, 2004). So far, geostationary satellite data has not been used for soil moisture downscaling. Compared to the polar orbit satellites, the geostationary satellites normally provide measurements with relatively low spatial resolution. As for SEVIRI, its spatial resolution is approximately 4.8 km with spatial sampling of 3 km for nadir view. But the major advantage of the SEVIRI over MODIS is the high temporal frequency (96 times per day), which can highly increase the possibility of obtaining cloud-free measurements. Furthermore, the downscaling approach used in this study can further benefit from the increased observation frequency through obtaining thermal inertial information from surface temperature diurnal cycle. The 15 min 4.8 km land surface temperature product generated by the Land Surface Analysis Satellite Applications Facility (LSA SAF, http://landsaf.meteo.pt) is used in this study.

It should be noted here that the satellite-based products used in this study have different data formats, spatial resolutions and projections. Therefore, a preprocessing is required to make them consistent in space. The surface temperature and vegetation indexes products from MODIS and SEVIRI are all resampled to a regular latitude / longitude grid with 0.05º spacing.

4. Methodology

The methodology used in this study includes a soil moisture downscaling scheme and evaluation strategies. The details are described in the following paragraphs.

4.1 Downscaling scheme

The soil moisture downscaling scheme used in this study was proposed by Peng et al. (2016). It uses VTCI as the only scaling factor to improve the soil moisture from coarse to high spatial resolution. The theoretical basis of this approach is that the VTCI can represent the status of soil moisture, and has been widely used for estimating soil moisture and monitoring drought condition (Petropoulos et al., 2009). The estimation of VTCI is based on the triangular or trapezoidal feature space that is constructed by land surface temperature and vegetation index (Figure 2) over the study area. It is calculated by rescaling the surface temperature of each pixel between two extreme surface temperature values for each vegetation index interval:

$$VTCI = \frac{T_{max} - T_s}{T_{max} - T_{min}} \tag{1}$$

where T_s is the observed surface temperature for a given pixel, T_{max} and T_{min} are the corresponding maximum and minimum surface temperatures that have the same vegetation index value as the given pixel. The assumption behind is that the variation of T_s between the two extreme T_s values reflects the changes of evapotranspiration and soil moisture (Peng and Loew, 2014). The maximum and minimum temperature values form the dry and wet edges in the triangular/trapezoidal feature space. The dry edge reflects the status of limited soil moisture and minimum evapotranspiration, while the wet edge reflects the condition of unlimited soil moisture and maximum evapotranspiration. To accurately estimate dry and wet edges, different approaches have been proposed such as Tang et al. (2010) and Long et al. (2012). Some of these methods are physically based, but increase the operational difficulty due to the requirements of ground-based measurements such as air temperature and wind speed.

To keep the simplicity of the downscaling method, we use a relatively simple method proposed by de Tomás et al. (2014) to determine dry and wet edges in this study. The calculation of dry edge is based on the linear regression between each vegetation index interval and corresponding maximum surface temperature within this interval (T_{max} = a + b*vegetation index), where a and b are the intercept and slope of the dry edge. Before performing the linear fit, the maximum surface temperature that are to the left (with lower vegetation index) and the maximum surface temperature less than mean minimum surface temperature are removed, to filter out the spurious dry points and outliers. The wet edge is the mean of the minimum surface temperature within the last five vegetation index intervals.

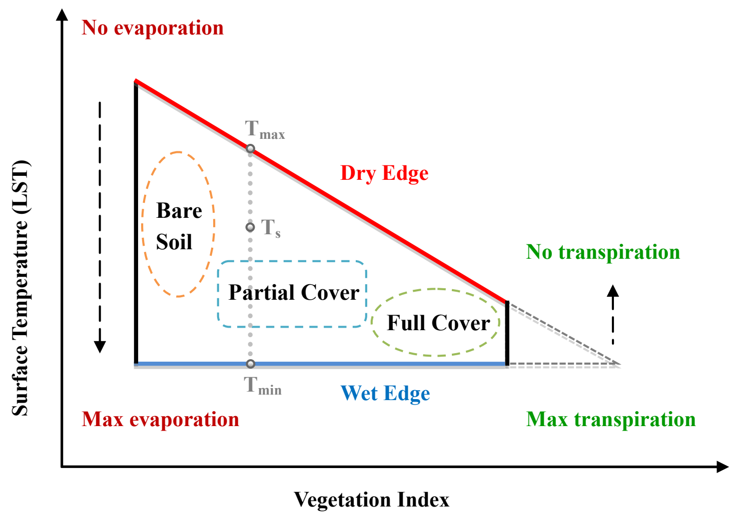


Figure 2: Conceptual diagram of the triangular/trapezoidal feature space that constructed by land surface temperature and vegetation index.

In order to downscale the coarse resolution CCI soil moisture, the spatially average VTCI ($\overline{VTCI}$) is then estimated for each CCI soil moisture grid box at 0.25° (CMG) as:

$$\overline{VTCI} = \frac{1}{n}\sum_{i=1}^{n} VTCI_i \tag{2}$$

where n is the number of 0.05° grids in the $\overline{SM}$ 0.25° grid. Based on the above results, the following equation is used to downscale the soil moisture:

$$SM = VTCI * \frac{\overline{SM}}{\overline{VTCI}} \tag{3}$$

where *SM* is the downscaled CCI soil moisture at 0.05° (CMG), $\overline{SM}$ is the actual CCI soil moisture at 0.25° (CMG), *VTCI* stands for the scaling factor at 0.05° (CMG).

Compared to other downscaling methods, this downscaling approach is very simple and requires only limited input data.

Since VTCI is the key variable in the downscaling scheme, it determines the accuracy of the downscaled soil moisture field. The performance of VTCI mainly depends on the accuracy of surface temperature and type of vegetation index. Furthermore, clouds, terrain and land cover heterogeneity might be also sources of the errors for the estimation of VTCI (de Tomás et al., 2014). Therefore, to optimize the performance of VTCI as the proxy of soil moisture, a sensitivity analysis of VTCI to five influential factors (surface temperature, vegetation index, cloud, topography and land cover heterogeneity) was conducted before downscaling soil moisture. The VTCI was firstly calculated with different settings (see Table 3). Then the estimated VTCI were compared with ground-based soil moisture measurements from the REMEDHUS network to investigate the influence of the five factors on the performance of VTCI. The details of these factors are listed below, and the combinations of these factors for estimating VTCI are shown in Table 3.

1. Surface temperature: The instantaneous surface temperature observed at the time of satellite overpass is typically used for constructing a triangular/trapezoidal feature space. To avoid the influence of uncertainty of instantaneous surface temperature and make use of thermal inertial information, the surface temperature difference has been used by many studies such as Stisen et al. (2008) and Wang et al. (2006). Therefore, the influence of different surface temperature on the VTCI was investigated using different temperature proxies: (1) daytime temperature from Terra MODIS (10:30 AM), (2) daytime nighttime temperature difference from Terra MODIS, (3) daytime temperature from Aqua MODIS (1:30 PM), (4) daytime nighttime temperature difference from Aqua MODIS, (5) instantaneous MSG SEVIRI temperature at 10:30 AM, (6) instantaneous MSG SEVIRI temperature at 1:30 PM, (7) MSG SEVIRI temperature difference between 8:00 AM and 12:00 AM, (8) MSG SEVIRI temperature difference between daily maximum and minimum temperature.

2. Vegetation index: The NDVI is originally used for the estimation of VTCI due to its simplicity. But the NDVI can suffer saturation problem at high levels of vegetation density (Carlson et al., 1990). Therefore, different vegetation indexes instead of NDVI such as EVI and LAI are also explored in the present study. To test the impact of different types of vegetation indexes on VTCI, the following vegetation indexes generated by MODIS are investigated: (1) NDVI, (2) EVI, (3) FPAR and (4) LAI.

3. Cloud: As clouds restrict optical/TIR remote sensing, only measurements under cloud free conditions are useable. Two cloud thresholds are tested to examine the influence of clouds on VTCI. They are 75% and 85%, which mean that 75% and 85% of the study area are cloud free. It should be noted here that the higher the threshold is, the less clear sky sample days remain.

4. Topography: The estimation of VTCI requires a relatively flat area, because the variation of surface temperature in the triangular/trapezoidal feature space is assumed to be caused by evaporative cooling effect rather than the variation of elevation. To examine the effects of topography on VTCI, the performances of non-masked terrain and masked terrain are both tested. In this study the masked terrain is based on removing the areas with 300 meters higher or lower elevation than average REMEDHUS elevation.

5. Land cover heterogeneity: In order to get the triangular/trapezoidal feature space, the study domain should cover a wide range of soil moisture and vegetation cover conditions. On the other hand, the study area also needs to be homogeneous in terms of vegetation type and surface roughness (Moran et al., 1994). The sensitivity of VTCI to land cover heterogeneity is evaluated at two conditions: (1) full land cover, (2) only cropland.

Finally, the optimized VTCI is calculated based on the sensitivity analysis results. The CCI soil moisture is then downscaled with the optimized VTCI.

Table 3: Different combinations of the five influential factors (surface temperature, vegetation index, cloud, topography and land cover heterogeneity) for the estimation of VTCI.

Acronym	Satellite			Surface temperature					Vegetation index				Cloud fraction		Elevation mask		Land cover	
	Terra	Aqua	MSG	10:30	13:30	12:00-8:00	day-night	max-min	NDVI	EVI	FPAR	LAI	75%	85%	No	Yes	Full	Cropland
NDVI_T_D	+			+					+				+		+		+	
NDVI_T_DN	+						+		+				+		+		+	
NDVI_A_D		+		+					+				+		+		+	
NDVI_A_DN		+					+		+				+		+		+	
FPAR_A_DN		+					+				+		+		+		+	
EVI_A_DN		+					+			+			+		+		+	
LAI_A_DN		+					+					+	+		+		+	
LAI_A_DN_cf85		+					+					+		+	+		+	
LAI_A_DN_elev		+					+					+	+			+	+	
LAI_DN_crop		+					+					+	+		+			+
NDVI_1030			+	+					+				+		+		+	
NDVI_1330			+		+				+				+		+		+	
NDVI_0812			+			+			+				+		+		+	
NDVI_tmintmax			+					+	+				+		+		+	
FPAR_tmintmax			+					+			+		+		+		+	
EVI_tmintmax			+					+		+			+		+		+	
LAI_tmintmax			+					+				+	+		+		+	
LAI_tmintmax _cf85			+					+				+		+	+		+	
LAI_tmintmax _elev			+					+				+	+			+	+	
LAI_tmintmax _crop			+					+				+	+		+			+

4.2 Evaluation strategies

Two metrics are used to evaluate the performance of the downscaled soil moisture. The first is direct comparison between satellite-based products including CCI SM and downscaled CCI SM, and measured soil moisture at each REMEDHUS station. In addition, the cross comparisons between the present results and reported results from published researches are summarized as well. In order to investigate the influence of land use on the downscaled soil moisture, the comparisons between satellite-based results and in situ measurements are performed per land use of the stations. These land use are rainfed, vineyard and forest-pasture. Furthermore, a seasonal analysis is also carried out to examine its influence on downscaled soil moisture. The study period is separated into four seasons to represent different dry/wet conditions and vegetation growth conditions. The four seasons are September/October/ November (autumn), December/January/February (winter), March/April/May (march), and June/July/August (summer) respectively. The widely used statistical metrics including correlation coefficient (R), mean bias error (BIAS), root mean square difference (RMSD), and unbiased RMSD (ubRMSD) are used in this study to quantify the differences between satellite-based products and in situ measurements (Entekhabi et al., 2010).

5 Results and discussion

5.1 Sensitivity analyses of the VTCI to surface temperature, vegetation index, cloud, topography and land cover heterogeneity

Figure 3 shows the box plots of R for the comparisons between in situ soil moisture measurements and VTCI estimated from different settings (Table 3) for all stations. For the effects of surface temperature, the use of surface temperature difference generally shows better results than the use of instantaneous surface temperature. However, for SEVIRI, the use of temperature difference between 8:00 AM and 12:00 AM does not improve VTCI compared to the use of instantaneous surface temperature at 10:30 AM and 1:30 PM. For Terra MODIS, the daytime nighttime temperature difference method performs slightly worse than the daytime method. As stated before, one advantage of temperature difference method is avoiding the uncertainty of instantaneous surface temperature. The similar performance between temperature difference method and instantaneous temperature method can be expected if the surface temperature product has high accuracy. Nevertheless, the improvements of VTCI are clearly observed when using maximum and minimum temperature difference for SEVIRI, as well as daytime nighttime temperature difference for Aqua MODIS. These results indicate the effectiveness of integrating the information of thermal inertial. From definition, the thermal inertial requires the maximum diurnal temperature difference, which is fully met by the SEVIRI. For Aqua MODIS, the observations at 1:30 AM and 1:30 PM are also close to the local maximum and minimum temperature. But in reality, the time of local maximum and minimum temperature change with seasons and locations. Therefore, the use of SEVIRI can give better performance than MODIS platforms due to the better integration of thermal inertial information. It should be also noted that Aqua has slightly better performance than Terra in terms of mean R. The reason is likely because the observation time (1:30 PM/1:30 AM) of Aqua is closer to the time of daily maximum and minimum surface temperature than those of Terra (10:30 PM/10:30 AM).

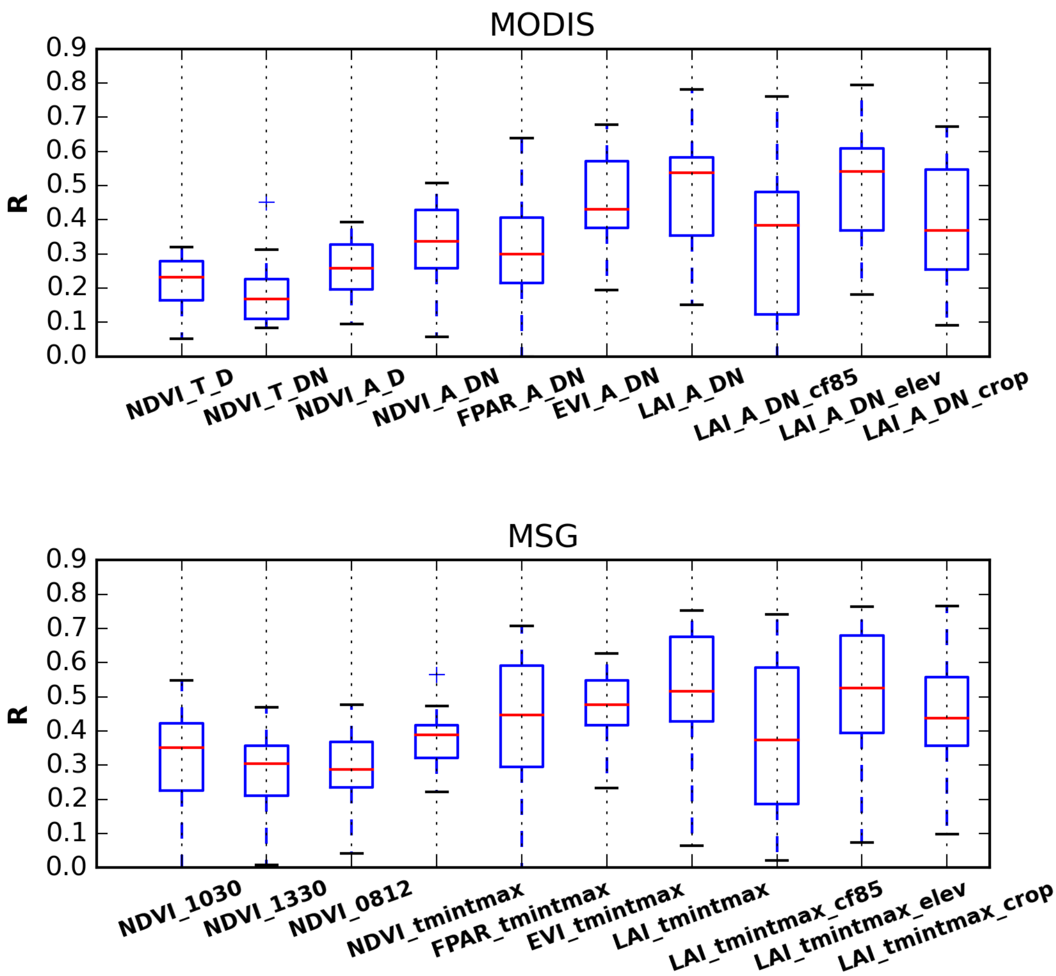


Figure 3: Sensitivity analyses of VTCI to different variables. The box plots show the R values of the comparisons between in situ soil moisture measurements and VTCI calculated from different configurations (Table 3) for all stations. The results for MODIS and SEVIRI are shown separately.

The change of VTCI when using different type of vegetation index is also shown in Figure 3. The LAI gives the best performance in terms of mean R for both SEVIRI and MODIS platforms, and then followed by EVI and FPAR. The NDVI gives relatively worse performance. It is because NDVI is only an indicator of surface greenness due to its sensitivity to effect of soil background. The other indexes are physical parameters and can better represent the reality of vegetation density, which leads to better performance of VTCI. To our knowledge, many studies have used one of these vegetation indexes to form the triangular/trapezoidal feature space, but none of them compare and quantify the difference of VTCI estimated from different types of vegetation indexes. The results suggest that LAI is the best proxy for vegetation cover among different vegetation indexes in the applications based on the triangular/trapezoidal feature space.

Regarding the influence of clouds, Figure 3 shows that the 85% cloud mask gives worse performance for VTCI than 75% cloud mask. In theory, the increase of the cloud mask threshold should lead to the improvement of the accuracy of VTCI. The opposite result obtained here is due to the sharply decreased sample days for 85% cloud mask. It should be noted that the totally clear sky in the study domain is rare in real conditions. The higher cloud mask threshold normally results in less sample days. To keep the balance between avoiding the influence of clouds and having more sample days, we use 75% cloud mask in this study.

Contrary to our expectations, the masked terrain performs quite similar to non-masked terrain method. It is because that the masked out pixels are normally located within the triangular/trapezoidal feature space (see green color points in Figure 5 f and g), which means the dry and wet edges keep almost the same for both methods. Therefore, the terrain has no strong impacts on VTCI in our study area. But for other study areas, the terrain effects still need to be investigated before the estimation of VTCI.

The use of full land cover types gives better performance of VTCI than the use of croplands. It suggests that although the use of croplands keeps the surface cover more homogeneous in terms of vegetation properties and surface roughness, the range of surface moisture conditions that are required for the estimation of VTCI decreases meanwhile. In arid or semiarid study areas such as our study area, only one vegetation type cannot represent a wide range of soil moisture that is required by the estimation of VCTI. For these kinds of study areas, the requirements of homogeneous surface cover and wide range of soil moisture conditions cannot be met at the same time. As shown in our results, for the estimation of VTCI, having a wide range of soil moisture is more important than keeping surface cover homogeneous in such areas.

Based on the above results, it can be seen that these factors have strong impacts on performance of VTCI. The optimal configurations in this study for the estimation of VTCI are using Aqua MODIS daytime nighttime temperature difference, SEVIRI maximum and minimum temperature difference, LAI, 75% cloud mask, non-masked terrain and full land cover types.

5.2 VTCI as a proxy of soil moisture

To further investigate the performance of VTCI as the proxy of soil moisture, the temporal evolution of station averaged LAI, surface temperature, VTCI and in situ soil moisture over REMEDHUS are presented in Figure 4. Meanwhile, the R between each parameter and soil moisture measurement is also shown. The LAI has similar seasonal trend as in situ measured soil moisture, but with very low R of 0.04 between them. Compared to LAI, a significantly negative correlation with R of -0.25/-0.57 for MODIS/SEVIRI between surface temperature and soil moisture are obtained. The results suggest that the surface temperature is more sensitive to soil moisture than the LAI. As expected, the VTCI, combining the information from both LAI and surface temperature, agrees well with soil moisture with R of 0.38/0.53 for MODIS/SEVIRI, which further demonstrating the effectiveness of VTCI as a proxy of soil moisture.

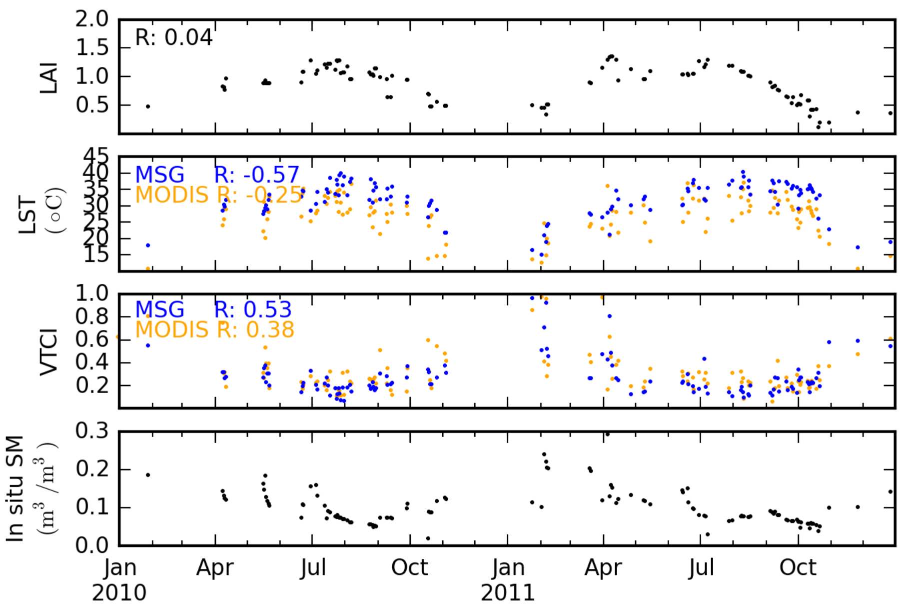
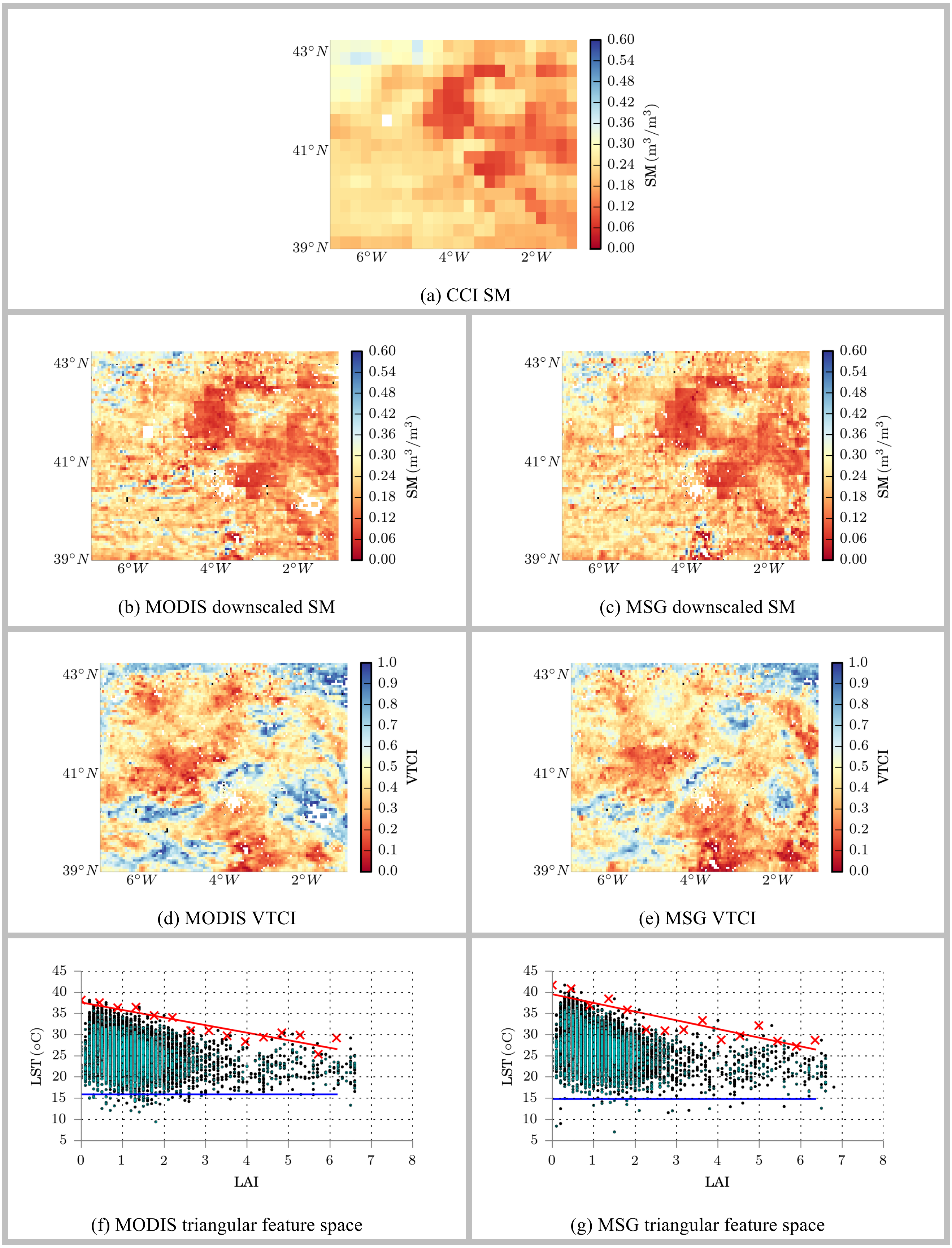


Figure 4: Time series of the station averaged LAI, surface temperature, VTCI and in situ soil moisture over REMEDHUS during the study period. The R values listed in the figure refer to the correlation coefficient with measured soil moisture.

5.3 Spatial patterns of the soil moisture estimates

On the basis of VTCI, the CCI SM is downscaled to high spatial resolution using the proposed method during the study time period. The spatial distributions of original CCI SM and downscaled soil moisture on May 22nd 2010 are shown in Figure 5. It can be clearly seen that the downscaled soil moisture (Figure 5 b and c) have quite similar spatial patterns as the original CCI SM. High soil moisture is typically presented in northwest and southwest, while low soil moisture appears in northeast and southeast. Meanwhile, the spatial details of the soil moisture are highly improved by the downscaling scheme. The downscaled soil moisture map (Figure 5 d) generated from MODIS also exhibits very similar patterns as that (Figure 5 e) from SEVIRI. It is due to the similar VTCI patterns calculated from MOIDS and SEVIRI. The similar shape of the triangular/trapezoidal feature space constructed from MODIS and SEVIRI can also be seen from Figure 5 f and g. These results suggest that the proposed downscaling scheme can capture the spatial pattern of original CCI soil moisture, and similar performance of downscaled soil moisture maps can be obtained from both MODIS and SEVIRI. The following section will further investigate the accuracy of the downscaled soil moisture and quantify the difference between estimates from MODIS and SEVIRI.



(a) CCI SM

(b) MODIS downscaled SM

(c) MSG downscaled SM

(d) MODIS VTCI

(e) MSG VTCI

(f) MODIS triangular feature space

(g) MSG triangular feature space

Figure 5: Spatial comparisons between coarse CCI soil moisture (a) and downscaled CCI soil moisture (b and c) based on MODIS and SEVIRI for May 22nd 2010. The corresponding VTCI (d and e) and triangular/trapezoidal feature space (f and g) are also shown. The green points in the triangular feature space indicate the pixels with elevation 300 meters higher or lower than average REMEDHUS elevation.

5.4 Validation of the soil moisture estimates against in situ soil moisture measurements

The validation results between original CCI SM and in situ soil moisture measurements at each station are shown in Figure 6, with mean R of 0.53±0.13, mean Bias of 0.07±0.08 m^3/m^3, mean RMSD of 0.11±0.04 m^3/m^3, and mean ubRMSD of 0.05±0.02 m^3/m^3. These values are consistent with the reported accuracy level of CCI SM from a recent validation study over Tibetan Plateau (Zeng et al., 2015), and are slightly better than the reported accuracy (mean R = 0.46, ubRMSD = 0.05 m^3/m^3) from the global validation of CCI SM by Dorigo et al. (2015). Regarding the validation results of downscaled soil moisture, the general accuracy level is similar to that of original CCI SM, with mean R of 0.42±0.17/0.48±0.15, BIAS of 0.06±0.09/0.06±0.08 m^3/m^3, RMSD of 0.12±0.05/011±0.04 m^3/m^3, and ubRMSD of 0.06±0.02/0.05±0.02 m^3/m^3 for MODIS and SEVIRI respectively. When compared to original CCI SM at each individual station, the downscaled soil moisture has clearly better performance at some stations such as H9P and M9R, while performs worse at stations like L3V and K4V. These results suggest that the downscaled soil moisture can maintain the accuracy of original CCI SM but cannot highly improve its accuracy. Similar results have been reported by many soil moisture downscaling studies (Choi and Hur, 2012; Sánchez-Ruiz et al., 2014; Zhao and Li, 2013), which suggest that the accuracy level of downscaled soil moisture highly depend on the original soil moisture. Besides, as expected, slightly better performance of SEVIRI over MODIS can be observed due to the better performance of VTCI from MSG, which demonstrates the potential of MSG for downscaling soil moisture.

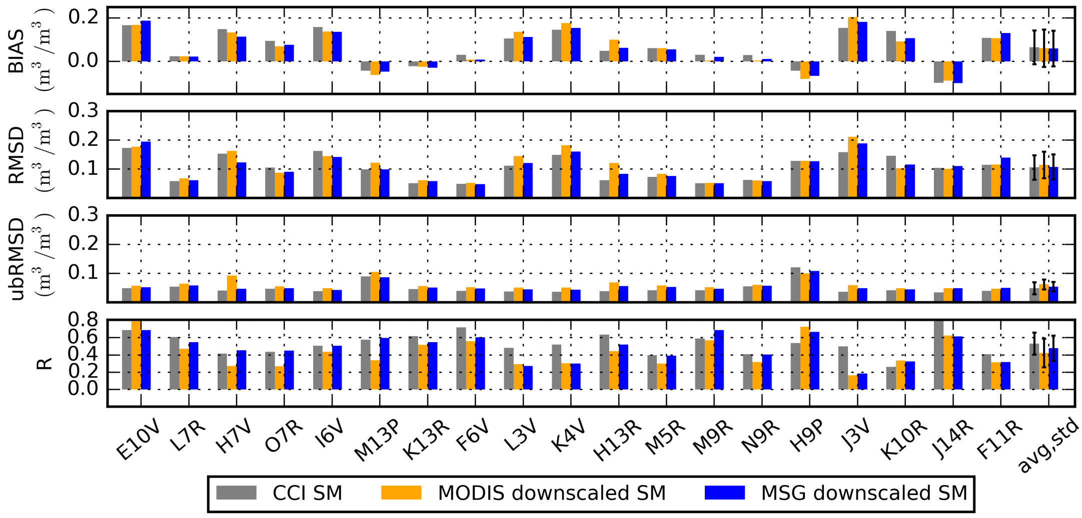


Figure 6: Bar plots for the comparisons between CCI soil moisture, downscaled soil moisture and in situ soil moisture at each station.

The temporal variations of downscaled soil moisture for individual station are also investigated here. The stations K13 and M13 are selected due to their representatives of wet and dry soil moisture conditions (Sánchez et al., 2012). Besides, the location of K13 is close to one weather station (Figure 1), which gives us the chance to investigate the connection between soil moisture and rainfall. Figure 7 displays the time series of the in situ soil moisture, CCI soil moisture, downscaled CCI soil moisture, as well as rainfall for stations K13 and M13 respectively. For dry station K13, the CCI soil moisture and downscaled soil moisture both agree well with in situ soil moisture. Regarding the wet station M13, the in situ soil moisture responds well to the rainfall, with high soil moisture occurring during the rainfall period in spring. But the CCI soil moisture and downscaled soil moisture seem to be insensitive to the rainfall, presenting relatively low value compared to in situ soil moisture during the rainfall period. The results here are similar to that reported by (Sánchez-Ruiz et al., 2014). They found that the downscaled SMOS soil moisture has limited response to rain events.

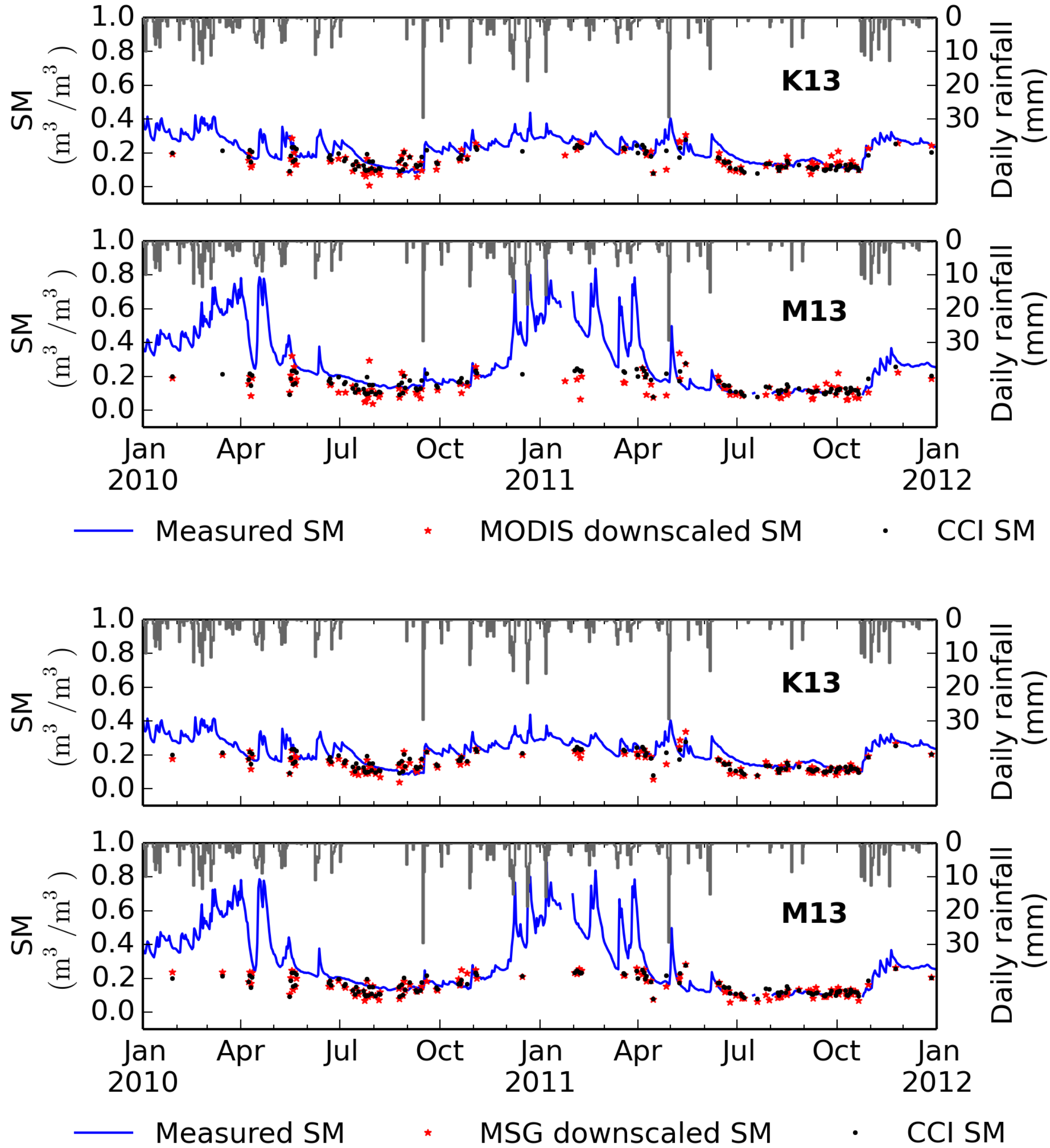


Figure 7: Time series of the in situ soil moisture, CCI soil moisture, downscaled CCI soil moisture, as well as rainfall for stations K13 and M13. The results from MODIS and SEVIRI are shown separately.

In addition to the validation at each individual station, the performance of different soil moisture results averaged at REMEDHUS network scale are also analyzed and summarized in Figure 8. Similar to the above results, both original CCI SM and downscaled soil moisture agree well with the averaged in situ soil moisture over network in terms of R, BIAS, RMSD and ubRMSD. But systematic overestimation of soil moisture from all of them can also be observed. It implies that the CCI SM has the problem of overestimating soil moisture, which needs to be further investigated. Overall, the above results suggest that the downscaled soil moisture can preserve the accuracy of coarse CCI SM, and meanwhile present more detailed spatial details. Since the proposed downscaling method highly depends on the original CCI soil moisture and VTCI, the accuracy of the downscaled soil moisture is expected to be improved if the VTCI can better represent the soil moisture.

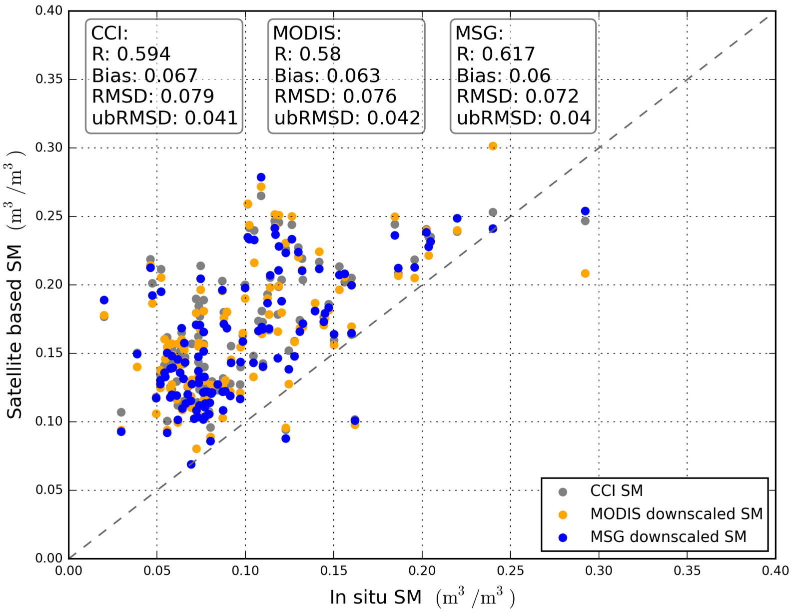


Figure 8: Scatter plots of the REMEDHUS network averaged estimates and soil moisture measurements. The corresponding comparison statistics are shown as well.

Furthermore, the above results are also compared with other published soil moisture downscaling studies. These studies apply different downscaling methods to downscale soil moisture product from SMOS and AMSR-E, using either MODIS or SEVIRI data as inputs. The results are all validated against the observations from REMEDHUS network, which makes them ideal for inter-comparison with our results. Table 4 lists the statistics of the comparison between downscaled and measured soil moisture from different studies. It can be seen that the R, BIAS, RMSD and ubRMSD of these published studies range respectively from 0.467 to 0.73, -0.026 to 0.108 m^3/m^3, 0.049 to 0.109 m^3/m^3, and 0.040 to 0.042 m^3/m^3. The corresponding statistics of the current study are within theses ranges, which imply that the results of current study are reasonable and satisfactory. Considering the simplicity, limited inputs, and acceptable accuracy, we conclude that the proposed downscaling method is feasible and effective for improving soil moisture from coarse to high spatial resolution.

Table 4: Summary of the errors statistics from other soil moisture downscaling studies using REMEDHUS observation for validation as well. The statistics of the current study are from the comparison of station averaged soil moisture.

Reference	**Soil moisture**	**Sensor**	**R**	**BIAS (m^3/m^3)**	**RMSD (m^3/m^3)**	**ubRMSD (m^3/m^3)**
Sánchez-Ruiz et al. (2014)	SMOS	MODIS	0.73	-0.026	0.049	0.042
Piles et al. (2014)	SMOS	MODIS	0.590	-0.010	0.050	0.040

Zhao and Li (2013)	AMSR-E	SEVIRI	0.467	0.108	0.109	–
Current study	CCI SM	MODIS SEVIRI	0.580 0.617	0.063 0.060	0.076 0.072	0.042 0.040

5.5 Seasonal and land use analyses of the soil moisture estimates

To investigate the performance of the downscaling method over different climatic and vegetation growth conditions, seasonal analysis has been performed based on the comparisons between network-averaged soil moisture estimates and in situ soil moisture observations for different seasons. Figure 9 shows the statistical results of the comparisons between CCI SM, downscaled soil moisture, and in situ soil moisture. It can be seen that the downscaled soil moisture especially from SEVIRI has similar performance as original CCI SM, with better performance in summer and winter in terms of R, BIAS, RMSD and ubRMSD values. The worse performance in spring might be due to flat temporal pattern of CCI SM (Figure 7). As discussed in section 5.4, it seems that CCI SM has limited response to rainfall, while the study area has frequent rainfall during spring. Compared to CCI soil moisture, the downscaled soil moisture from SEVIRI has slightly better performance in terms of R and BIAS. Similar to the previous results, the SEVIRI generally has slightly better performance than MODIS in terms of R, BIAS, RMSD and ubRMSD values.

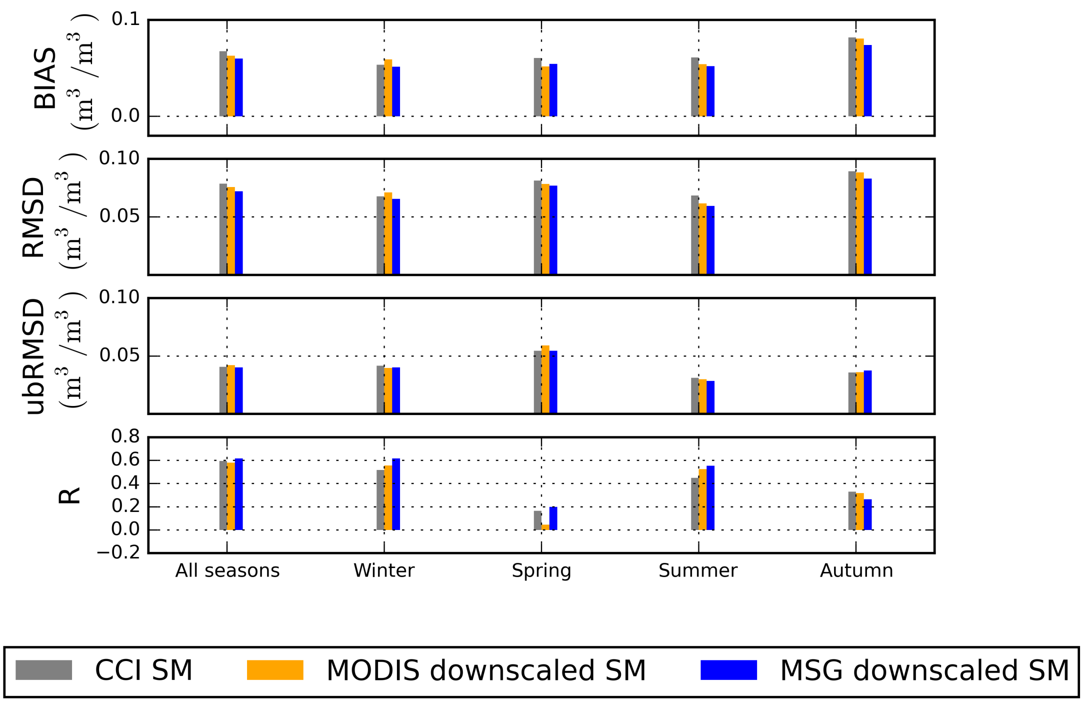


Figure 9: Bar plots for the comparisons between soils moisture estimates and in situ soil moisture over seasons.

The influence of land use on the downscaling scheme is also investigated and the results are summarized in Figure 10. The stations are divided into three land use groups: vineyard (7), rainfed (9) and forest-pasture (2). Figure 10 shows the performances of original CCI SM and downscaled SM over different land use categories. It can be seen that vineyard and rainfed have similar performance in terms of R and ubRMSD, while the forest-pasture presents relatively high R and ubRMSD that might be due to its limited number of stations. These results suggest that both CCI SM and downscaled soil moisture are not sensitive to the generally used land use. Furthermore, the results from MODIS and SEVIRI have similar performance, which further implies that the proposed method is independent on platforms. It has the potential to be used on different platforms and other regions.

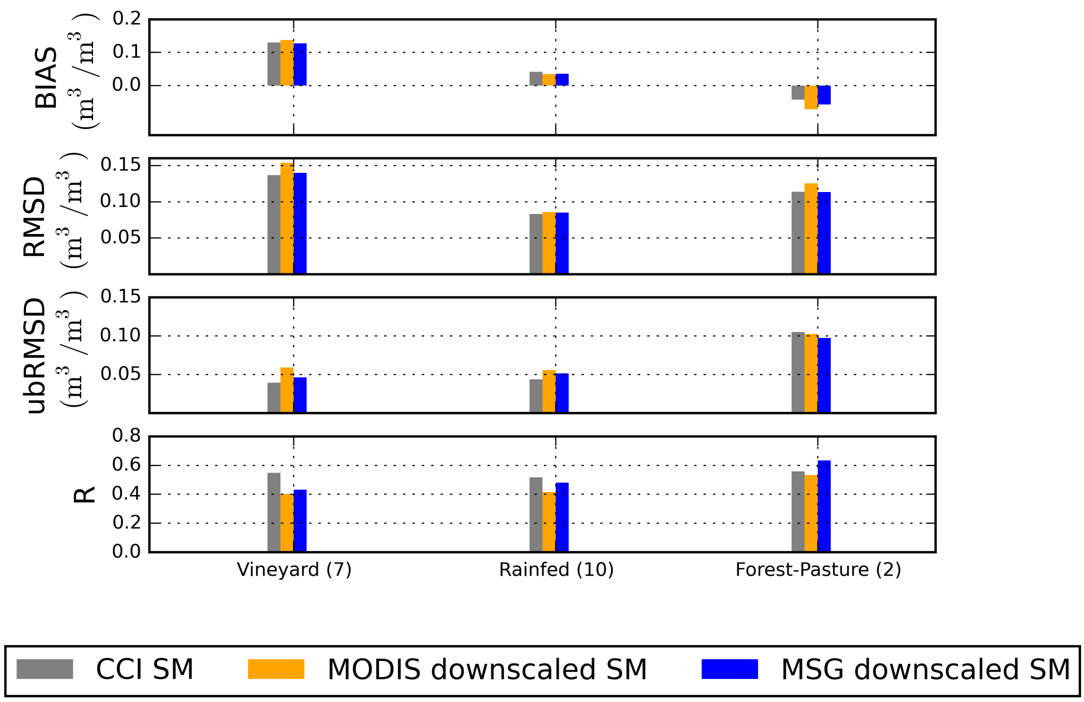


Figure 10: Bar plots for the comparisons between soils moisture estimates and in situ soil moisture per land use (vineyard, rainfed and forest-pasture).

5.6 Evaluation of downscaled soil moistrue at different spatial resolutions

Since MODIS has the advantage of providing measurements at high spatial resolution of 1 km, it gives us the opportunity to evaluate the downscaled soil moisture at different spatial resolutions. Figure 11 displays the spatial patterns of downscaled soil moisture at 1 km and 0.05°(CMG) on May 22nd 2010. It can be seen that these two maps have quite similar patterns, implying that the downscaling scheme can be applied at different spatial scales. To further evaluate the performance of downscaled soil moisture at different spatial resolutions, Figure 12 shows the bar plots of the comparisons between downscaled soil moisture from MODIS different spatial resolution MODIS and measured soil moisture at each station. In general, the downscaled soil moisture at 1 km has similar accuracy level as that at 0.05°, which suggests that the accuracy of CCI soil moisture can be preserved at higher spatial resolutions. Besides, the 1 km soil moisture has slightly better performance than 0.05° soil moisture in terms of mean R (0.465/0.44), RMSD (0.112/0.113 m^3/m^3), ubRMSD (0.055/0.058 m^3/m^3) values. It further suggests that finer spatial resolution datasets can improve the accuracy of downscaled soil moisture, which demonstrates the assumption proposed by Sánchez-Ruiz et al. (2014). In summary, the above results indicate that the downscaling scheme can be applied at different spatial resolutions. Taking advantage of high spatial resolution of MODIS datasets, combined use of MODIS and MSG datasets has the potential of providing downscaled soil moisture at high spatial and temporal resolutions.

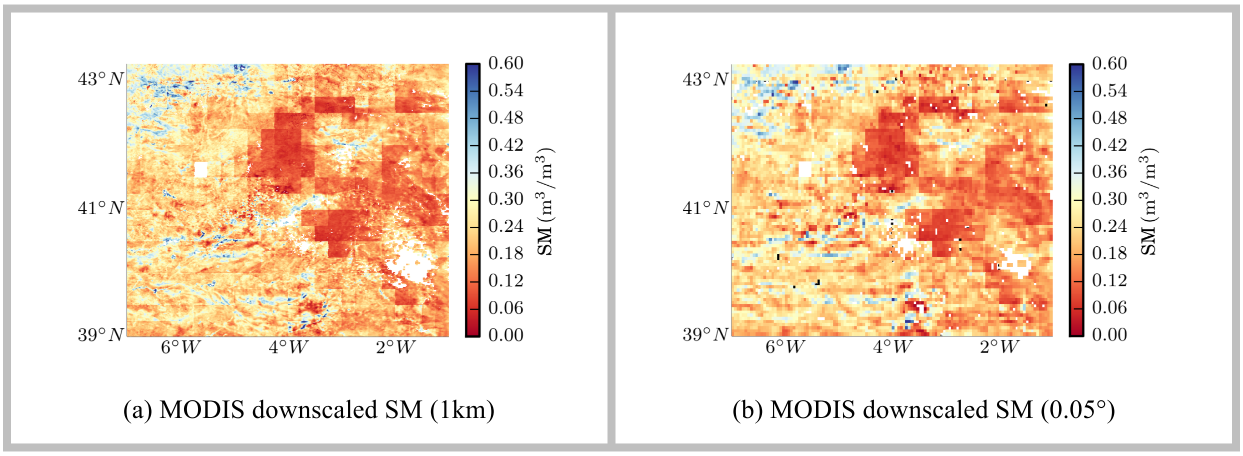


Figure 11: Spatial patterns of the downscaled soil moisture from MODIS at (a) 1 km and (b) 0.05° spatial resolutions.

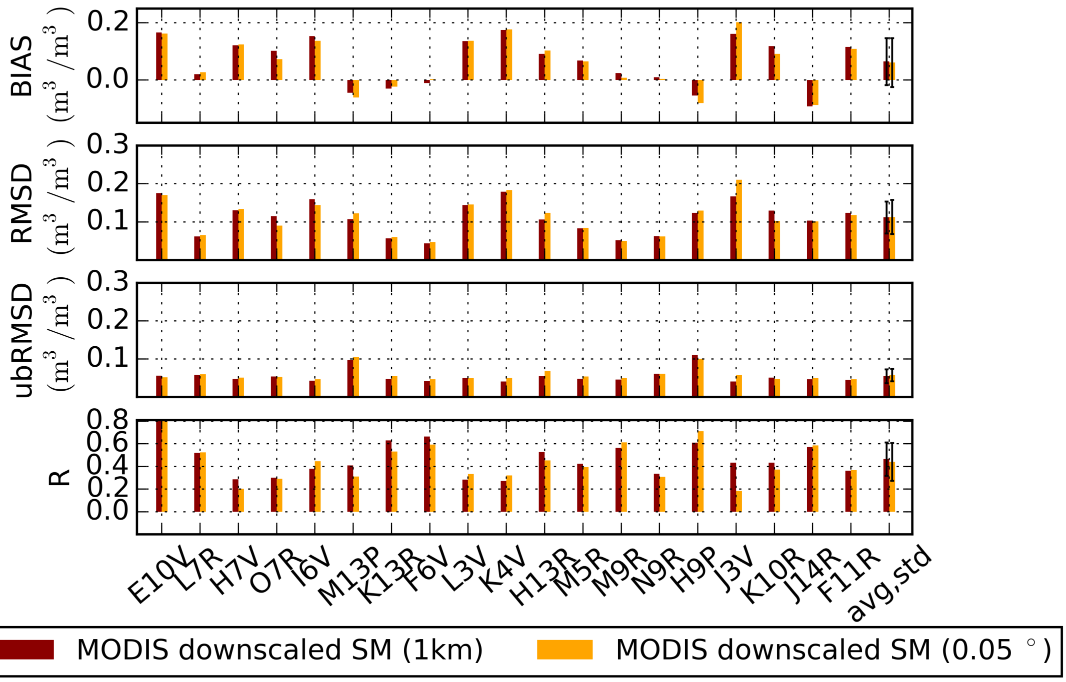


Figure 12: Bar plots for the comparisons between measured soil moistureand downscaled soil moisture at 1 km and 0.05° spatial resolutions.

6 Conclusions

In this study, a newly developed soil moisture downscaling method was applied to the ESA CCI soil moisture product and validated against the REMEDHUS soil moisture observation network in Spain. In general, agreement between the CCI soil moisture and the in situ soil moisture was observed with similar accuracy level to the published validation studies. But systematic overestimation of soil moisture was also observed for CCI SM from the network-averaged analysis. Before applying the downscaling scheme, the sensitivity analyses of the downscaling factor VTCI were conducted. The surface temperature difference method performs better than instantaneous surface temperature method due to the integrated information of thermal inertial. Besides, the VTCI performance also depends on the type of vegetation index. The LAI performs best for estimation of VTCI compared to NDVI, EVI and FPAR. After downscaling the CCI soil moisture from coarse to high spatial resolution, the soil moisture map can replicate the CCI soil moisture spatial patterns and show more spatial details. Comparisons with in situ soil moisture indicate that the downscaled soil moisture can maintain the accuracy of original CCI soil moisture. Further inter-comparisons with published soil moisture downscaling studies suggest that the accuracy level of the proposed method is comparable. Compared with those methods, the advantages of the proposed method are its simplicity, the fewer required inputs and comparable accuracy level.

In addition, the downscaled soil moisture from MSG SEVIRI performs better than that from MODIS, which is due to the better performance of corresponding VTCI from SEVIRI. It indicates the great potential of applying SEVIRI to downscale soil moisture. To take full advantages of the high temporal resolution of SEVIRI and high spatial resolution of MODIS, combined use of data from both platforms should be considered in soil moisture downscaling applications in the future.

In summary, the present study, together with the work by Peng et al. (2016) demonstrated the feasibility of downscaling soil moisture with the proposed method. The notable advantage of this approach is simplicity in terms of inputs requirement and implementation. Furthermore, the proposed method is independent on satellite platforms, implying that the downscaled soil moisture can be obtained at either very high spatial resolution (500 m for MODIS) or very high temporal resolution (every 15 minutes for SEVIRI). It has potential to facilitate regional hydrological related studies that require soil moisture information at different spatial and temporal scales. Application of the proposed method in other regions and comparison with other downscaling methods will be conducted in future studies.

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