Intercomparison of soil moisture retrievals from in-situ, ASAR and ECV SM datasets over different European sites

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Abstract
The availability of satellite-derived global surface soil moisture products during the last decade has opened up great opportunities to incorporate these observations into applications in hydrology, meteorology and climatic modelling. This study evaluates a new global soil moisture product developed under the framework of the European Space Agency (ESA) Climate Change Initiative (CCI), using finer spatial resolution Synthetic Aperture Radar (SAR) and ground-based measurements of soil moisture. The analysis is carried out over selected in-situ networks over Ireland, Spain, and Finland with the aim of assessing the temporal representativeness of the coarse scale CCI Essential Climate Variable (ECV) soil moisture product (ECV SM) in these different areas. A good agreement (correlation coefficient (R) values between 0.53 and 0.92) was observed between the three soil moisture datasets for the Irish and Spanish sites while a reasonable agreement (R values between 0.41 and 0.52) was observed between the SAR and ECV SM soil moisture datasets at the Finnish sites. Overall, the two different satellite derived products captured the soil moisture temporal variations well and were in good agreement with each other, highlighting the confidence of using the coarse scale ECV SM product to track soil moisture variability in time.

Keywords: Soil moisture; ASAR; Essential climate variable; In-situ; Temporal analysis.

1. Introduction

The amount of water stored in the soil is a key parameter for the energy and mass fluxes at the land surface-atmosphere boundary and is of fundamental importance to many agricultural, meteorological, biological and biogeochemical processes (Koster et al., 2004; Seneviratne et al., 2010; Bolten and Crow, 2012). Soil moisture dynamics are dependent on both meteorological conditions and soil physical characteristics and, as a result, exhibit large spatial and temporal variations between different areas, seasons, and years (Western and Blöschl, 1999; Schulte et al., 2005). The spatial and temporal coverage attainable by spaceborne remote sensing has demonstrated the capability to monitor soil moisture over large areas at regular time intervals, and several approaches for soil moisture retrieval have been developed using optical, thermal infrared (TIR), and microwave (MW) sensors over the last three decades (Barrett and Petropoulos, 2013; Petropoulos et al., 2015). Since the late 1970s, coarse resolution (25 - 50km) soil moisture products derived from past and present microwave radiometers (Advanced Microwave Scanning Radiometer (AMSR-E) (Njoku et al., 2003) and WindSat (Li et al., 2010)) and scatterometers (European Remote Sensing satellites (ERS) scatterometer (SCAT) (Wagner

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et al., 2003) & Meteorological Operational satellite (MetOp) Advanced Scatterometer (ASCAT) (Bartalis et al., 2007; Naeimi et al., 2009)) have been available on an operational basis. Data from the European Space Agency (ESA) Soil Moisture and Ocean Salinity (SMOS) (Kerr et al., 2012; Mecklenburg et al., 2012) and the National Aeronautics and Space Administration (NASA) Soil Moisture Active Passive (SMAP) (Entekhabi et al., 2010) dedicated soil moisture missions are strengthening this record of observations and further facilitating the study of long term soil moisture behaviour (please see Petropoulos et al. (2015) and Zeng et al. (2015) for further details of available satellite derived soil moisture products). With the availability of these products, it is necessary to validate them using independently derived soil moisture observations obtained through in-situ monitoring, models, or with different satellite sensors (van Doninck et al., 2012; Ochsner et al., 2013; Al-Yaari et al., 2014). In-situ validation has generally been achieved over small temporal and spatial scales but has been significantly advanced since the establishment of the Global Soil Moisture Data Bank (Robock et al., 2000) and the International Soil Moisture Network (ISMN) (Dorigo et al., 2011). For example, Albergel et al. (2013c) validated three global soil moisture products using a combination of 196 in-situ stations taken from five different soil moisture networks across the world. Similarly, Paulik et al. (2014) and Dorigo et al. (2015) used over 600 in-situ stations for validating ASCAT and ECV SM soil moisture products respectively. All these studies generally found good agreement between the satellite derived and in-situ observations.

The comparison of time series of soil moisture datasets acquired by different sources and representing different spatial scales is challenging however, due to the scale differences between products and/or observations (Crow et al., 2012). In-situ networks represent single point locations and usually cover only limited observation periods. Gruber et al. (2013) investigated the quality of over 1400 in-situ stations of the ISMN for representing soil moisture at satellite footprint scales (~25km) on a global basis using triple collocation and highlighted the need for a comprehensive characterisation of in-situ representativeness errors in addition to measurement errors when considering satellite-derived soil moisture – in-situ soil moisture intercomparisons. Consequently, the spatial and temporal resolution provided by synthetic aperture radar (SAR) data make them a promising additional data source for measuring seasonal and long-term variations in surface soil moisture content and characterising the errors of coarse scale soil moisture products. The Advanced Synthetic Aperture Radar (ASAR) instrument onboard the ENVISAT satellite was capable of providing global measurements at 1km and 150m spatial resolution every four to seven days, depending on the acquisition plan (Desnos et al., 2000). Although there are certain technical limitations in retrieving surface soil moisture from SAR data, significant progress has been made in recent years to the point that SAR data could be used not only as another validation source for coarse-scale soil moisture products but also for applications which require finer spatial resolution soil moisture data such as hydrological or runoff modelling (Dostálová et al., 2014; Pratola et al., 2014). Furthermore, the regular temporal coverage and higher spatial resolution of current C-band sensors such as Sentinel-1 will provide greater opportunities to characterise surface soil moisture within the large areas covered by coarse-scale product cells and help strengthen the understanding of such products. In this study, the capability of the coarse scale ECV SM product in representing the temporal variations in surface soil moisture content at finer scales is evaluated using both in-situ and ASAR-derived soil moisture observations in three different European countries, characterised by contrasting climate and vegetation conditions.

2. Materials and Methods

2.1 In-situ soil moisture observations

The Irish in-situ soil moisture measurements were collected at two grassland sites: Kilworth and Solohead, located in southern Ireland (see Figure 1) using Campbell Scientific CS616 water content reflectometers, installed horizontally at a depth of 5cm below the surface under the framework of the Aeon project (http://aeon.ucc.ie (last accessed 1st July 2015)). Measurements were recorded continuously at 30 minute intervals between 2007 and 2010 and are expressed as the soil water-filled pore space (WFPS). These values were subsequently converted to volumetric units (m^3m^{-3}) by multiplying by the associated soil porosity values. The network also measured precipitation and soil temperature and has been used predominantly for modelling N_2O fluxes from agricultural grasslands, but has also been used for the validation of soil moisture products (e.g. Pratola et al., 2014). The sites have a temperate maritime climate with annual precipitation of 900-1200mm and an annual average temperature of 10°C.

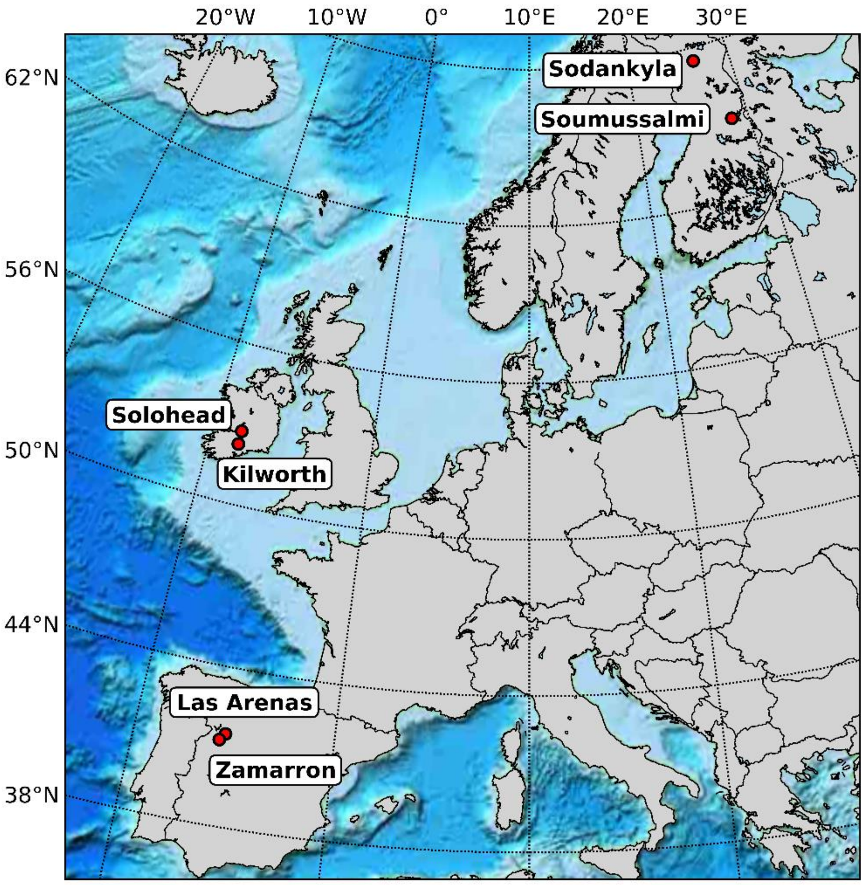

Figure 1: Test site locations (red dots) in Ireland, Spain, and Finland.

The Red de Medición de la Humedad del Suelo (REMEDHUS) soil moisture network (Martínez-Fernández and Ceballos, 2005) is located in the semi-arid region of the Duero basin (Zamora) in Spain. It has a continental Mediterranean climate with a mean annual temperature of 12°C and mean annual precipitation of 400mm. The land use is predominantly agricultural, with small areas of forest and pasture. The network comprises of 20 soil moisture monitoring stations, each using a Stevens Hydra probe sensor integrated over a depth of 0 - 5cm below the surface. The network has been used for several purposes, including calibration and validation campaigns in support of the SMOS mission (Sanchez et al., 2012), and the evaluation of different satellite derived soil moisture products (Ceballos et al., 2005; Wagner et al., 2008; Albergel et al., 2012).

The Sodankyla (Finnish Meteorological Institute (FMI)) and Soumussalmi (Geological Survey of Finland (GTK)) sites are located in northern Finland and have a boreal climate, with average summer temperatures of 12°-13°C and average winter temperatures of -12°C. Annual rainfall is 600 - 650mm and snow generally covers the soil surface from the beginning of November to the end of April. The predominant land cover type is forest. Table 1 details the main characteristics for each of the study sites. For the Spanish and Finnish sites, daily precipitation data from nearby meteorological stations were acquired through the European Climate Assessment & Dataset (Klein Tank et al., 2002)(Data available at http://www.ecad.eu). In-situ soil moisture datasets for Spain and Finland were retrieved from the ISMN (Dorigo et al., 2011; Dorigo et al., 2013) at https://ismn.geo.tuwien.ac.at/. At all sites, soil moisture values have been evaluated on a daily basis, by averaging the measurements recorded at 30 minute intervals from 00:00 to 23:30 of the same day as the ASAR and ECV SM acquisition.

Table 1. Study site characteristics

Site	Latitude	Longitude	Elevation (masl)	Land cover	Soil type
Kilworth	52°10' N	-8°14' E	51	Grassland	Sandy loam
Solohead	52°30' N	-8°12' E	98	Grassland	Loam
Zamarron	41°14' N	-5°32' E	855	Cropland	Sandy loam
Las Arenas	41°22' N	-5°32' E	745	Cropland	Sandy loam
Sodankyla	67°22' N	26°37' E	179	Forest	Sandy loam
Suomussalmi	64°54' N	28°41' E	220	Forest	Sandy loam

2.2 ECV soil moisture observations

The Essential Climate Variable Soil Moisture (ECV SM) product (Liu et al., 2011; Liu et al., 2012; Wagner et al., 2012) was initiated within the Water Cycle Multi-Mission Observation Strategy (WACMOS) project (see http://wacmos.itc.nl/) and is being continued and refined in the context of the ESA Climate Change Initiative (CCI) programme (http://www.esa-soilmoisture-cci.org/). It currently provides daily global surface soil moisture values (m^3m^{-3}) covering the period 1978 – 2013 at a 0.25 degree spatial resolution. To achieve this, the ECV SM product combines observations from multiple C-band scatterometers (ERS AMI and MetOp ASCAT) and multi-frequency radiometers (Advanced Microwave Scanning Radiometer (AMSR-E), Scanning Multichannel Microwave Radiometer (SMMR), Special Sensor Microwave Imager (SSM/I), Tropical Rainfall Measurement mission Microwave Imager (TRMM-TMI), and WindSat). The Water Retrieval Package (WARP) developed by TU Wien (Wagner et al., 1999a; Wagner et al., 1999b; Naeimi et al., 2009) is used to convert backscatter measurements to soil moisture values and the Land Parameter Retrieval Model (LPRM) developed jointly by VU University Amsterdam and the NASA Goddard Space Flight Center (Owe et al., 2001; De Jeu and Owe, 2003; Owe et al., 2008) is used to convert brightness temperatures to soil moisture respectively. The ECV SM product has been validated across different regions using in-situ, model and SAR-derived soil moisture datasets in previous studies (e.g. Albergel et al., 2013b; Loew et al., 2013; Dorigo et al., 2015; Pratola et al., 2014; Zeng et al., 2015) where good agreement between the datasets was generally found. For example, Zeng et al. (2015) found the ECV SM product to be highly related to in-situ data from two different soil moisture networks at the Tibetan Plateau, with the highest R values (0.70 - 0.85) and smallest *ubRMSD* values (0.034 – 0.042m^3m^{-3})

compared to six other satellite derived soil moisture products (AMSR-E (NASA product), AMSR-E (JAXA product), AMSR-E (LPRM product), AMSR-2, ASCAT, and SMOS). Similarly, Pratola et al. (2014) found strong correlations (R = 0.72 – 0.88) and associated low *ubRMSD* values (0.05 – 0.06) between ECV SM and SAR-derived soil moisture values across three grassland sites in Ireland.

2.3 ASAR soil moisture observations

The ENVISAT satellite was launched on 1st March 2002 by ESA and operated until 8th April 2012. The ASAR instrument onboard the satellite operated at C-band (5.3 GHz) and was capable of acquiring data in multiple modes (Image, Alternating Polarisation, Wave, ScanSAR (Wide Swath), and ScanSAR (Global Monitoring)) at various incidence angles and in several polarisations. This study focused on the use of Wide Swath (WS) mode data rather than Global Monitoring (GM) mode data due to its higher radiometric accuracy (0.6 dB compared to 1.2 dB) and also due to its higher native spatial resolution (150m compared to 1km). WS data have a 405km swath width and could potentially acquire 3 – 5 images a month. Acquisitions between 2005 and 2010 (see Figure 2) from both ascending and descending orbits were considered in VV polarisation. As WS mode data use ScanSAR technology to cover a much larger swath width, effects on the backscatter due to varying incidence angle and distance from the sensor are usually present in the scene. To limit the influence of the large incidence angle range (17° – 42°) and to ensure inter-comparability between the different data scenes, an angular normalisation to an incidence angle of 30° was applied to all scenes. The WS data were geometrically and radiometrically calibrated and resampled to a regular grid with a 15 arc-second sampling interval. Consequently, the ASAR WS data were aggregated to 1km spatial resolution, supporting the comparison with the ECV product and also improving the radiometric accuracy of the satellite data.

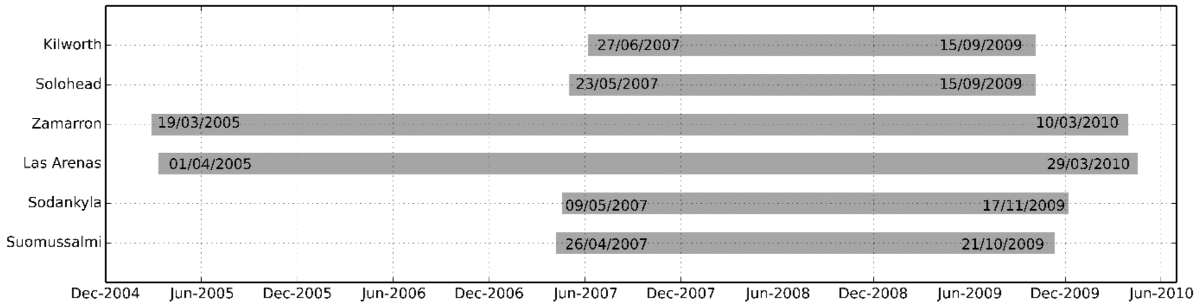

Figure 2. Temporal interval of study period for each of the study sites used in the dataset comparison.

There are different approaches to soil moisture estimation using SAR data (Barrett et al., 2009; Petropoulos et al., 2015) and in this study, soil moisture values were retrieved from the ASAR WS acquisitions by applying the TU Wien change detection algorithm (Wagner et al., 1999a; Wagner et al., 1999b). This technique was originally developed for ERS scatterometer and Advanced Scatterometer (ASCAT) data but has been successfully adapted to both ASAR WS and GM data (e.g. Pathe et al., 2009; Mladenova et al., 2010; Doubková et al., 2012; Peters et al., 2012; Dostálová et al., 2014; Zribi et al., 2014). The TU Wien change detection approach derives relative changes in surface soil moisture and indirectly accounts for surface roughness and vegetation by assuming changes in these parameters will generally occur at longer temporal scales than soil moisture changes. It is based on the assumption of a linear relationship between the surface soil moisture content and the backscatter coefficient and provides soil moisture values expressed in terms of the degree of saturation, whereby variations in a time series of soil moisture values are adjusted between the historically lowest (0% - dry soil) and highest (100% - saturated soil) values.

The retrieved soil moisture values were masked using the Corine Land Cover Map 2006 (EEA, 1995) in order to exclude pixels representing areas where the soil moisture values were unreliable (e.g. urban, water bodies, and snow and ice). Furthermore, and as demonstrated in Wagner et al. (2008), the temporal stability of soil moisture fields gives rise to an associated temporal stability in the backscatter signal. Strong correlations between local and regional backscatter is usually a good indicator of high sensitivity to soil moisture dynamics at the local scale (similarly, if the signal observed at the local scale correlates with the coarse scale measurement, then the local scale measurement is sensitive to the dynamics at the coarse scale). Areas where there are weak correlations are indicative of where either a) the backscatter response to soil moisture dynamics is dominated by noise and speckle, b) the backscatter characteristics are adversely influenced by factors such as dense vegetation or complex topography, inhibiting the retrieval of reliable soil moisture values, or c) the local-scale soil moisture dynamics are simply not representative of the coarse-scale dynamics. For each 1km x 1km ASAR pixel, the correlation between the time series of backscatter coefficients and the average of the backscattering over a 25km x 25km area encompassing the ASAR pixel was evaluated. A minimum threshold of $R^2 = 0.3$ was applied and only those ASAR acquisitions that covered the ECV cell size for more than 50% of the available pixels were selected. The average of the soil moisture values retrieved within the corresponding ECV cell for each ASAR acquisition is considered for the dataset intercomparison. In a final step, soil moisture values were converted to volumetric units (m^3m^{-3}) by multiplying by the associated soil porosity values, obtained from the Harmonised World Soil Database (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2009).

2.4 Characterisation of errors

In addition to large-scale differences, systematic differences between satellite derived and in-situ soil moisture observations make it difficult to have absolute agreement between the time series of these datasets (Brocca et al., 2013). As a result, satellite derived soil moisture products typically require scaling and/or filtering before being compared to in-situ soil moisture measurements. The cumulative distribution function (CDF) matching approach has been demonstrated with various satellite derived soil moisture datasets (e.g. Scanning Multichannel Microwave Radiometer (SMMR) (Reichle and Koster, 2004), TRMM (Tropical Rainfall Measuring Mission) Microwave Imager (TMI) (Drusch et al., 2005)), and combined SMMR, SSMI, TMI & AMSR-E datasets (Liu et al., 2009) and was used in this study to adjust the satellite derived soil moisture values to the same range and distribution as the in-situ measurements. Only ECV SM and in-situ soil moisture data corresponding to the ASAR WS acquisition dates have been considered in this study.

Different metrics are commonly used for the validation of soil moisture products. In this study, the correlation coefficient (R) was calculated to provide details of the temporal agreement between the different soil moisture datasets. In addition, the unbiased root mean square difference (*ubRMSD*) was calculated instead of the conventional *RMSD* in order to correct for biases in the mean of the satellite derived datasets (Albergel et al., 2013a), and is given by:

$$ubRMSD = \sqrt{\frac{1}{N}\sum_{N=1}^{N}\{[(sat_n - \overline{sat_n}) - (insitu_n - \overline{insitu_n})]^2\}} \quad (1)$$

where sat_n and $insitu_n$ represent the satellite derived and in-situ soil moisture measurements respectively, and the overbars represent averaged quantities.

In addition to the whole time series analysis, a seasonal comparison was also carried out to help evaluate the performance of ASAR and ECV SM soil moisture products in capturing the soil moisture dynamics. The time series data were analysed by season: winter (December, January, February), spring (March, April, May), summer (June, July, August), and autumn (September, October, November) and analysed with respect to the in-situ measurements which were taken as a reference.

3. Results and Discussion

3.1 Time series temporal analysis

The temporal evolution of the ECV SM scaled surface soil moisture estimates compared to the ASAR scaled estimates and in-situ observations from the Irish, Spanish, and Finish sites are displayed in Figures 3 - 5. In general, the satellite derived datasets and the in-situ observations were in good agreement. The Irish sites, to a large extent, displayed the same temporal pattern with highest soil moisture levels observed between December and March, although the dynamic ranges differ between the sites. Soils generally dry between March and July as a result of increased surface temperature, evapotranspiration and decreasing precipitation. The characteristically high soil moisture after snowmelt can be observed at both the Finnish sites (Figure 5) and is more pronounced for the Sodankyla site. The Soumussalmi site generally displayed higher soil moisture variability during the summer months, compared to Sodankyla.

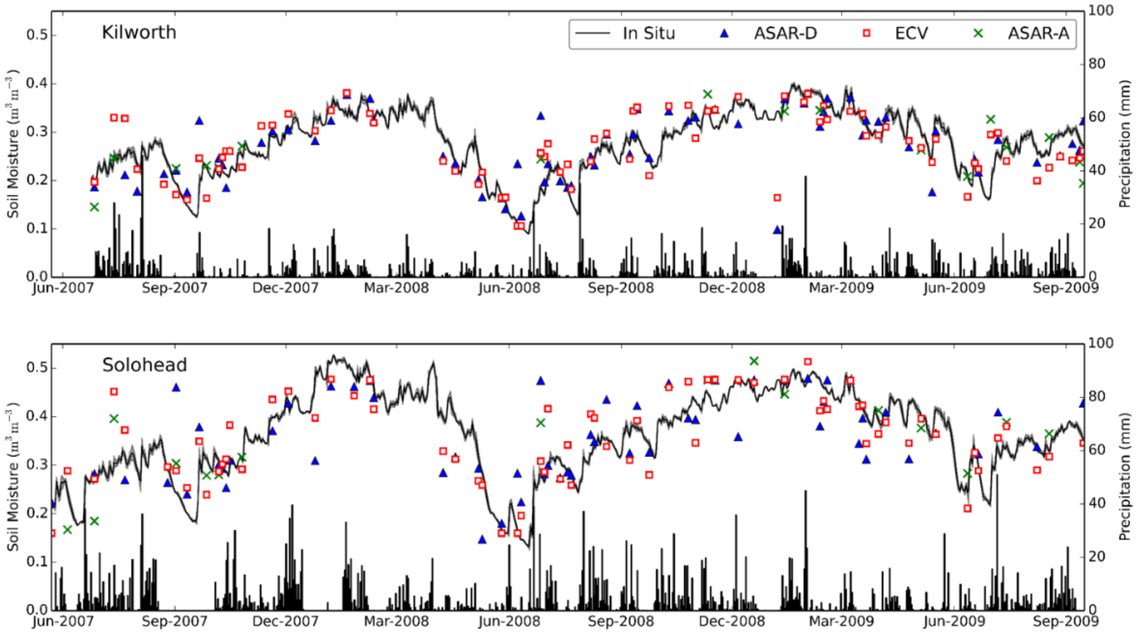

Figure 3: Time series of in-situ (continuous black line), ASAR (ascending (green cross) and descending (blue triangle) passes), and ECV (red square) soil moisture values for Kilworth and Solohead sites in Ireland. The daily accumulated precipitation is represented by vertical bars along the x-axis.

In Figure 3, the ability of the ECV SM and ASAR data to represent the soil moisture variability at Kilworth and Solohead is well represented. From Table 2, it can be observed that there is essentially no difference between the correlation coefficients for the ascending orbit (R = 0.71), descending orbit

(R = 0.71) or combined ascending and descending orbit (R = 0.70) ASAR acquisitions when compared to the in-situ measurements at the Kilworth site. When ascending and descending data were available for the same day, the average soil moisture value was taken. Although the number of ascending acquisitions is far fewer than descending, the results were still statistically significant (p < 0.01) and the unbiased RMSD (*ubRMSD*) values remained low (0.05). The correlations between the ECV SM and in-situ measurements were also high (R between 0.63 – 0.79) with strong correlations between the ASAR and ECV SM soil moisture values (R between 0.73 – 0.83). There is a larger difference at the Solohead site between the correlations for ascending (R = 0.87) and descending ASAR acquisitions (R = 0.71) with the in-situ measurements. Solohead is very wet site and a possible explanation for the difference between both passes could be due to the effects of diurnal solar heating cycles (van der Velde et al., 2012). Additionally, the ECV SM data displayed higher correlations (R between 0.84 and 0.85) with the in-situ measurements in comparison to the Kilworth site. As identified in Dorigo et al. (2015), sites which exhibit a pronounced annual soil moisture cycle and where this seasonality is suitably detected by the ECV SM product, usually result in high correlations between the ECV SM and in-situ data such as those obtained at the Irish sites.

Table 2. Comparison (correlation coefficient – *R*, and unbiased root mean square difference –*ubRMSD*) between ASAR derived soil moisture and in-situ soil moisture, ECV and in-situ, and ASAR and ECV at the six study sites. A represents ASAR ascending acquisitions, D represents ASAR descending acquisitions, and AD represents combined ASAR ascending and descending acquisitions (daily averages were calculated if there were ascending and descending passes on the same day).

			ASAR *vs* In-situ			ECV *vs* In-situ			ASAR *vs* ECV		
		n	*R*	*p*	*ubRMSD*	*R*	*p*	*ubRMSD*	*R*	*p*	*ubRMSD*
Kilworth	AD	85	0.70	<0.001	0.05	0.77	<0.001	0.04	0.81	<0.001	0.04
	A	17	0.71	0.001	0.05	0.63	0.007	0.05	0.73	<0.001	0.05
	D	68	0.71	<0.001	0.05	0.79	<0.001	0.04	0.83	<0.001	0.04
Solohead	AD	76	0.71	<0.001	0.07	0.85	<0.001	0.05	0.77	<0.001	0.06
	A	16	0.87	<0.001	0.04	0.84	<0.001	0.05	0.92	<0.001	0.03
	D	60	0.71	<0.001	0.07	0.85	<0.001	0.05	0.77	<0.001	0.06
Zamarron	AD	51	0.71	<0.001	0.03	0.86	<0.001	0.02	0.77	<0.001	0.02
	A	16	0.67	0.004	0.03	0.90	<0.001	0.02	0.79	<0.001	0.02
	D	32	0.63	<0.001	0.03	0.87	<0.001	0.02	0.71	<0.001	0.02
Las Arenas	AD	60	0.56	<0.001	0.07	0.64	<0.001	0.07	0.80	<0.001	0.05
	A	19	0.63	0.004	0.06	0.72	<0.001	0.05	0.69	0.001	0.05
	D	41	0.53	<0.001	0.08	0.66	<0.001	0.07	0.82	<0.001	0.05
Sodankyla	AD	121	-0.18	0.048	0.05	-0.24	0.008	0.05	0.52	<0.001	0.03
	A	73	-0.17	0.150	0.05	-0.24	0.041	0.05	0.55	<0.001	0.03
	D	48	-0.19	0.195	0.05	-0.25	0.086	0.05	0.47	<0.001	0.03
Suomussalmi	AD	101	-0.09	0.370	0.07	0.14	0.162	0.06	0.41	<0.001	0.05
	A	62	-0.15	0.244	0.07	0.30	0.018	0.05	0.28	0.027	0.05
	D	39	0.05	0.762	0.07	-0.11	0.505	0.07	0.95	<0.001	0.04

At the Spanish sites, the soil moisture is a lot less variable at Zamarron, compared to Las Arenas (see Figure 4). Interestingly, the ASAR and ECV SM datasets displayed a better overall agreement with the in-situ measurements at Zamarron, compared to Las Arenas, given the lower soil moisture variability (R = 0.71 compared to 0.56 for the ASAR – in-situ comparison, and R = 0.86 compared to 0.64 for the ECV – in-situ comparison). As expected, the Zamarron site had a much lower *ubRMSD* (0.02 – 0.03) compared to the Las Arenas site (0.05 – 0.08), as the area is much dryer and the soil moisture less variable in this region. At Las Arenas, the highest soil moisture values were observed between December and May for most years, with lowest values occurring between June and November. The trend is similar for Zamarron, although the overall range of soil moisture values were much lower. Similar to the Irish sites, the correlation between the ASAR and ECV SM soil moisture values was high for the Zamarron and Las Arenas sites, with R = 0.77 and 0.80 respectively. However, the correlations for ASAR against the in-situ measurements were generally weaker than for the ECV SM dataset, despite the scale gap between measurements being less pronounced. Similar findings were observed by Pathe et al. (2009) when comparing ASAR-GM derived soil moisture to ERS scatterometer and in-situ soil moisture measurements (Oklahoma MESONET. Zribi et al. (2014) also found similar results for ASAR-WS derived soil moisture (resampled to 1km resolution) and ERS/ASCAT products covering a semi-arid region in central Tunisia. Moreover, both of these studies demonstrated a strong correlation between coarse scale soil moisture products and the finer resolution ASAR derived soil moisture products (R > 0.8). This is an indication of the representativeness errors in the in-situ sites which were very likely to be larger than those of the ASAR data and supports the argument of using finer spatial resolution SAR data as another source for intercomparison.

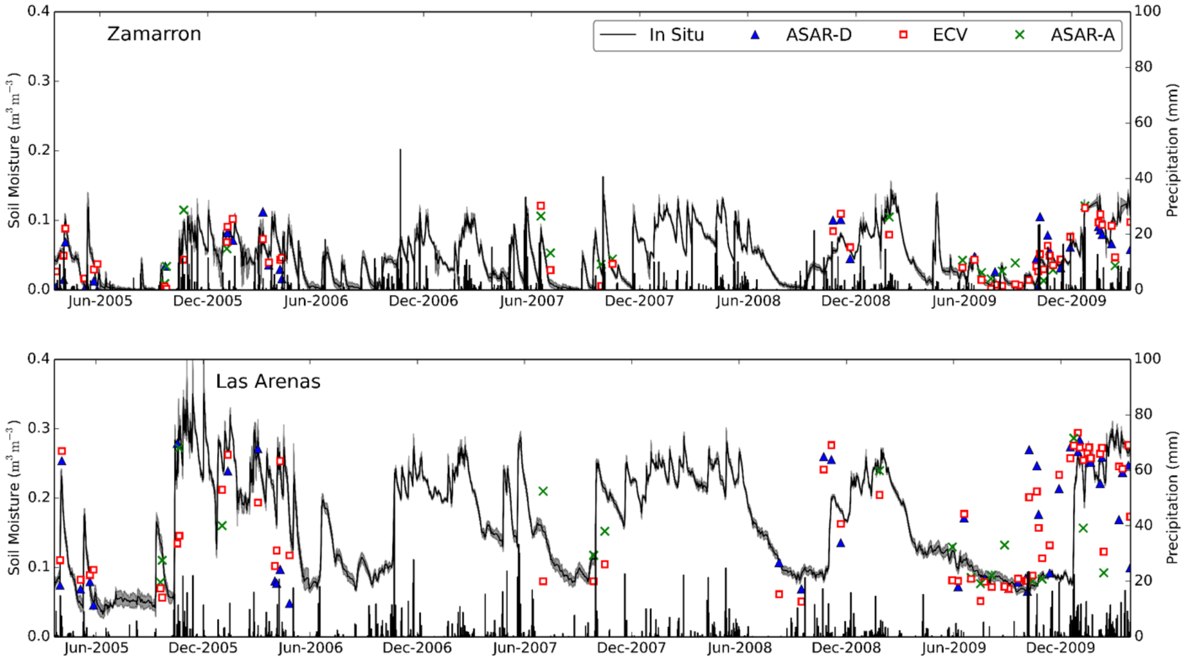

Figure 4: Time series of in-situ (continuous black line), ASAR (ascending (green cross) and descending (blue triangle) passes), and ECV (red square) soil moisture values for Zamarron and Las Arenas sites in Spain. The daily accumulated precipitation is represented by vertical bars along the x-axis.

The weakest correlations across all dataset comparisons occurred at the Finnish sites (Figure 5). There are several possible reasons for this poor performance. Firstly, the area contained within these ECV cells is dominated by forests. Dense vegetation cover attenuates the backscattered signal and decreases the sensitivity of the radar backscatter to soil moisture (Ulaby et al., 1986). Secondly, the GTK Soumussalmi in-situ soil moisture sensor is buried at a depth of 0.1m which may be considered beyond the depth at which the satellite is sensitive to surface soil moisture (generally only sensitive to top few centimetres of the soil surface at C-band). Despite this, the correlations were no better for the FMI Sodankyla in-situ sensor which is buried at a depth of 0.05m. Similar low correlations have been observed by Paulik et al. (2014) using ASCAT data and by Al-Yaari et al. (2014) for the northern latitudes. Conversely, Griesfeller et al. (2015) found relatively high correlations at stations (with soil sensors buried at a depth of 0.1m) located in Norway (ranging in latitude from 58°45' to 69°01') for both ASCAT (R ranging from 0.68 to 0.72) and AMSR-E (R ranging from 0.52 to 0.64) data. Despite this, the ASAR – ECV SM comparison at both Soumussalmi and Sodankyla displayed moderate agreement with *R* values of 0.41 and 0.51 respectively, indicating the two independently satellite derived datasets were in reasonable agreement with one another. A further possible explanation for the lower correlation values, in comparison to the Irish and Spanish sites, may be as a result of the increased presence of surface water bodies. Most soil moisture validation studies occur around the central latitudes and there is a need for further studies concentrating on the northern high latitudes, as indicated by our results and those of Al-Yaari et al. (2014) and Griesfeller et al. (2015), and in light of the rapid warming occuring in these regions in recent decades (Xu et al., 2013).

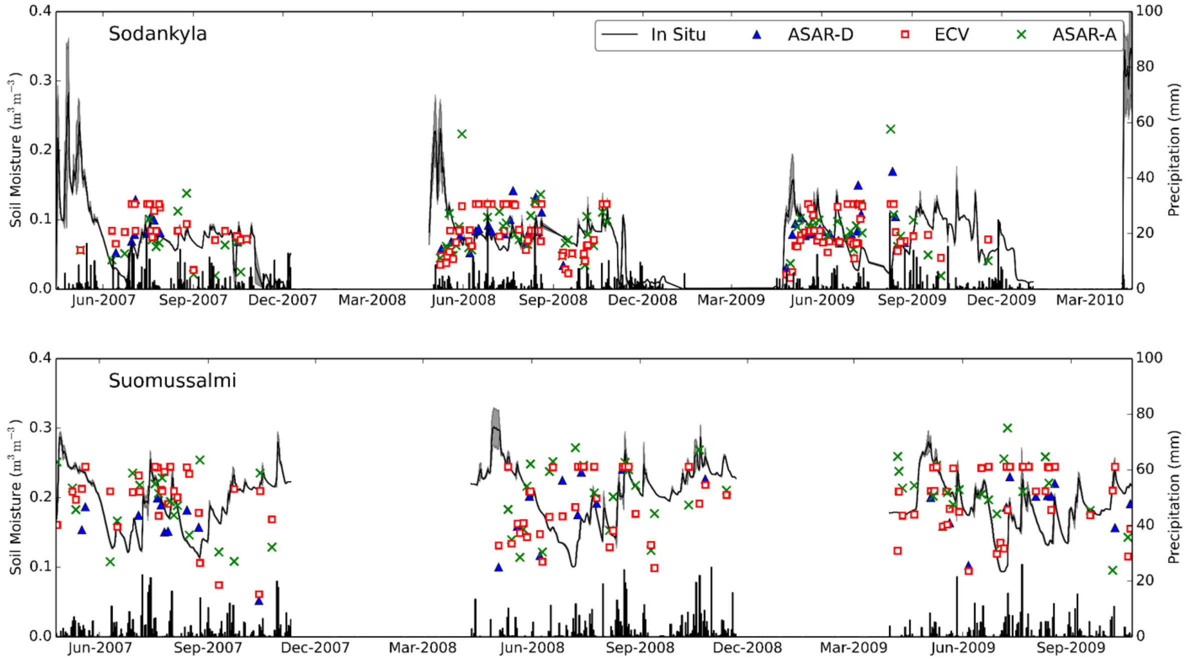

Figure 5: Time series of in-situ (continuous black line), ASAR (ascending (green cross) and descending (blue triangle) passes), and ECV (red square) soil moisture values for Sodankyla and Suomussalmi sites in Finland. The daily accumulated precipitation is represented by vertical bars along the x-axis. There are missing values between the months of December and April as the soil is frozen during this time period.

3.2 Seasonal analysis

Figure 6 displays four Taylor diagrams, illustrating the statistics from the comparison between ASAR and in-situ, and ECV and in-situ soil moisture measurements for the six different study sites on a seasonal basis. There was less agreement during winter acquisitions, where negative correlations were not displayed, and hence there were fewer symbols. Additionally, as the soil at the Finnish sites was frozen during the winter months, no values were included in the analysis. The ECV (red) and ASAR (blue) soil moisture values were less variable in spring, as demonstrated by their proximity to the dashed arc, representing a normalised standard deviation (SDV) value of one. The ECV values for Kilworth, Zamarron, and Las Arenas exhibited less variability than the in-situ measurements (SDV < 1). However, there was generally no tendency for the stations located in Ireland, Spain, and Finland, as symbols were present on either side of the dashed line for all seasons. Overall, the highest correlation values and lowest SDV values occurred in spring for the Irish and Spanish sites. This would suggest that the ECV SM and ASAR product have a reduced capability for capturing the driest and wettest soil conditions at these sites, occurring during summer and winter, respectively. The grassland vegetation also reaches maximum growth during the summer months which may reduce the quality of the soil moisture retrievals. In contrast, the Zamarron ECV SM and ASAR values displayed high correlations during summer and autumn, while the results for Las Arenas were more variable.

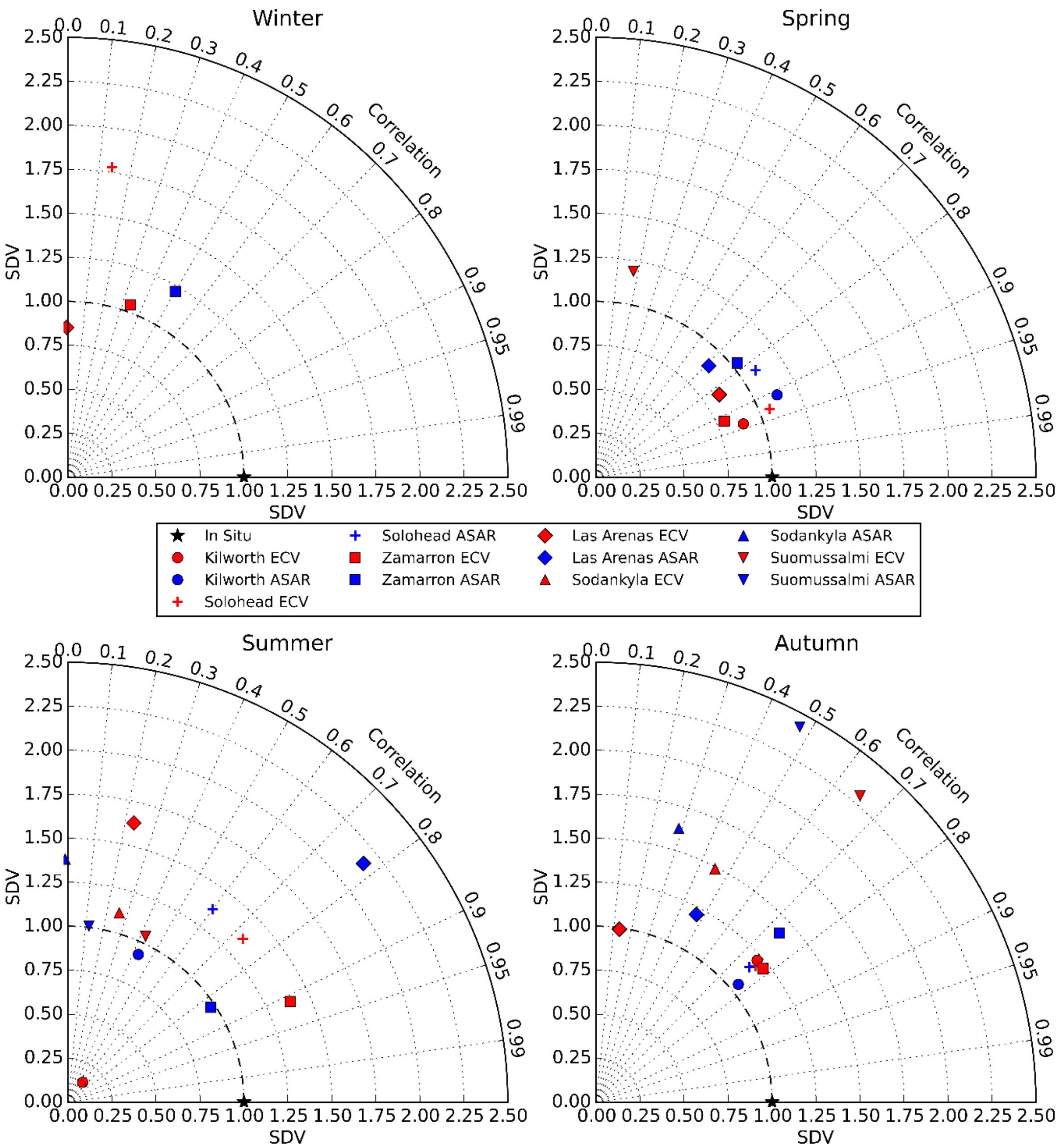

Figure 6. Taylor diagram illustrating the seasonal comparison metrics between ASAR and in-situ soil moisture (blue), and ECV and in-situ soil moisture (red) for the six study sites. The SDV represents the normalised standard deviation and is calculated as the ratio between satellite and in-situ standard deviations.

The poorest agreement generally occurred at the Finnish sites across spring and summer but was much improved during autumn. Nonetheless, they still represented weak to moderate correlations, where the ECV SM product outperformed the ASAR product. These poor results were likely due to the dense forest cover in these areas and also the reduced capability of the ASAR soil moisture retrieval algorithm for data acquired above 60° latitude. The challenges for deriving soil moisture in high latitudes has been documented by Bartsch et al. (2011) and further explored by Gouttevin et al. (2013) and Högström et al. (2014). The presence of permanenet open water surfaces within the ECV cell size may be an additional source of disagreement between the satellite derived and in-situ soil moisture values.

4. Conclusions

An intercomparison study of two satellite derived surface soil moisture products with in-situ measurements in three European countries has been presented in this chapter. The study focused on the ability of the satellite soil moisture datasets to capture the same relative temporal behaviour and this was compared to the in-situ soil moisture observations as a reference. The study demonstrated that the coarse scale ECV SM product was representative of the temporal soil moisture variations observed through finer scale ASAR-derived and in-situ soil moisture observations at the selected study sites. Strong correlations were observed over humid (Irish) and semi-arid (Spanish) sites, while weak correlations were observed over the boreal (Finnish) sites. Given the current large data volumes being generated by Sentinel-1A, and the significant increase when Sentinel-1B is launched in 2016, soil moisture change detection techniques such as the TU Wien approach adapted for ASAR data are likely to be applicable and improved for Sentinel-1 data (Hornacek et al., 2012). The benefits of using SAR data with a higher radiometric resolution has been demonstrated by Dostálová et al. (2014) and this new dataset could be used not only as another validation source for coarse-scale soil moisture products but also for applications which require finer spatial resolution soil moisture data such as hydrological or runoff modelling.

The ECV SM product uses multiple active and passive sensors; however, the future NASA Soil Moisture Active Passive (SMAP) mission (Entekhabi et al. 2010), a successor to the cancelled Hydrosphere State (HYDROS) mission (Entekhabi et al., 2004), will integrate L-band radar and radiometer measurements from a single platform to provide high-resolution and high-accuracy global maps of surface SMC every two to three days and may thereby overcome some of the limitations of using individual active or passive MW observations to determine soil moisture content. Further improvements in the ECV SM product such as eliminating the use of any ancillary data (e.g. soil texture maps (de Jeu et al., 2014) or rescaling to GLDAS-Noah land surface model) within the retrieval routine are highly desired by the scientific community (Loew et al., 2013). Incorporating additional sensors and improving their intercalibration will also lead to an improved product that will further strengthen our knowledge on observed soil moisture dynamics.

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