Evaluation of satellite soil moisture products over Norway using ground-based observations

A. Griesfeller[a], W. A. Lahoz[a], R. A. M. de Jeu[b], W. Dorigo[c], L. E. Haugen[d], T. M. Svendby[a], and W. Wagner[c]

[a]Norwegian Institute for Air Research (NILU), Postboks 100, 2027 Kjeller, Norway

[b]Department of Earth Sciences, Faculty of Earth and Life Sciences, VU University Amsterdam, Amsterdam, The Netherlands

[c]Department of Geodesy and Geo-Information, Vienna University of Technology, Vienna, Austria

[d]Norwegian Water Resources and Energy Directorate (NVE), Oslo, Norway

Corresponding author: W. A. Lahoz, wal@nilu.no, Norwegian Institute for Air Research (NILU), Postboks 100, 2027 Kjeller, Norway, +4763898257

Abstract.

In this study we evaluate satellite soil moisture products from the Advanced SCATterometer (ASCAT) and the Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E) over Norway using ground-based observations from the Norwegian Water Resources and Energy Directorate. The ASCAT data are produced using the change detection approach of Wagner et al. (1999), and the AMSR-E data are produced using the VUA-NASA algorithm (Owe et al., 2001, 2008). Although satellite and ground-based soil moisture data for Norway have been available for several years, hitherto, such an evaluation has not been performed. This is partly because satellite measurements of soil moisture over Norway are complicated owing to the presence of snow, ice, water bodies, orography, rocks, and a very high coastline-to-area ratio. This work extends the European areas over which satellite soil moisture is validated to the Nordic regions. Owing to the challenging conditions for soil moisture measurements over Norway, the work described in this paper provides a stringent test of the capabilities of satellite sensors to measure soil moisture remotely. We show that the satellite and in situ data agree well, with averaged correlation (R) values of 0.72 and 0.68 for

ASCAT descending and ascending data vs in situ data, and 0.64 and 0.52 for AMSR-E descending and ascending data vs in situ data for the summer/autumn season (1 June - 15 October), over a period of 3 years (2009-2011). This level of agreement indicates that, generally, the ASCAT and AMSR-E soil moisture products over Norway have high quality, and would be useful for various applications, including land surface monitoring, weather forecasting, hydrological modelling, and climate studies. The increasing emphasis on coupled approaches to study the Earth System, including the interactions between the land surface and the atmosphere, will benefit from the availability of validated and improved soil moisture satellite datasets, including those over the Nordic regions.

Keywords: cal-val, in situ, satellite, soil moisture

1 Introduction

Soil moisture plays an important role in land-atmosphere interactions (Seneviratne et al., 2010). It is classified as an essential climate variable (ECV) since 2010. By directly affecting plant growth and other organic processes it connects the water cycle to the carbon cycle. As soil moisture has a significant impact on the partitioning of water and heat fluxes (latent and sensible heat), it connects the hydrological cycle with the energy cycle (see, e.g., Lahoz and De Lannoy, 2014). Evaporation, through which soil moisture is a source of water for the atmosphere, is an important energy flux (Trenberth et al., 2009), and is connected to the surface skin and soil temperature. By returning 60% of the whole land precipitation back to the atmosphere (e.g., Oki and Kanae, 2006), it is also important for the continental water cycle. Soil moisture, temperature and their impacts on the water, energy and carbon cycles play a major role in climate-change projections (Seneviratne et al., 2010; IPCC, 2013). The state of the land surface, for example identified by the amount of soil moisture, has an impact on the land-atmosphere fluxes of CH_4 (e.g., Blodau, 2002; Tagesson et al., 2010) and of N_2O (e.g., Bouwman, 1998; Thompson et al., 2014), both of which are important greenhouse gases.

The use of observations from satellites has become a powerful tool to enhance our understanding of the role of soil moisture in the hydrological cycle in a number of areas, e.g., land-atmosphere processes (Miralles et al., 2012; Taylor et al., 2012); weather and runoff forecasts (Brocca et al., 2010; Bisselink et al., 2011); landslides (Brocca et al., 2012b); and rainfall products (Chen et al., 2012). Since 2000 several satellite missions measuring soil moisture have been launched: e.g., the Advanced Microwave Sounding Radiometer for EOS (AMSR-E) (Njoku and Chan, 2006), the Advanced SCATterometer (ASCAT) (Bartalis et al., 2007b), and the Soil Moisture Ocean Salinity (SMOS) (Kerr et al., 2010). The AMSR-2 mission (Imaoka et al., 2012) is continuing the soil moisture measurements from AMSR-E, which failed in late 2011. These missions include either passive or active microwave measurement techniques. More recently, the Soil Moisture Active Passive (SMAP) mission (Entekhabi et al., 2014) was launched on 30 January 2015.

Satellite observations provide information on soil moisture spatio-temporal variability, which is key to understanding processes linking the land surface and the atmosphere, and their impact on, e.g., climate change. This is a key motivation behind the setting up by the European Space Agency (ESA) of the climate change initiative (CCI) project for soil moisture (http://www.esa-soilmoisture-cci.org/). The objective of the soil moisture ESA CCI is to produce the most complete and most consistent global soil moisture data record based on active and passive microwave sensors from satellite platforms. Within this ESA CCI effort, there has been a first attempt to produce a multi-satellite product of surface soil moisture with global coverage at 25 km resolution and a daily time stamp for the period 1979-2010 (Liu et al., 2011, 2012).

For northern high latitudes, the vegetation in its terrestrial ecosystems is interactively controlled by temperature, soil moisture, light and availability of nutrients during the growing season (Barichivich et al., 2014, and references therein). Whereas temperature is the main climate constraint on plant growth in the cooler northern regions, in the southern boreal regions soil moisture becomes more important. The rapid warming at northern latitude regions in recent decades has resulted in a lengthening of the growing season, greater photosynthetic activity and enhanced carbon sequestration by the ecosystem. These changes are likely to intensify summer droughts, tree mortality and wildfires. A key concern is the release of carbon-bearing compounds (CH_4 and CO_2) from soil thawing at high northern latitudes associated with rapid warming of these regions, and which has been identified as a potential major climate change feedback (Hodgkins et al., 2014). These changes make it important to have information on the land surface (particularly, soil moisture and temperature) at high northern latitude regions. In particular, the availability of soil moisture measurements from several satellite platforms provides an opportunity to address issues associated with the effects of climate change at high northern latitudes, e.g., assessing multi-decadal links between increasing temperatures, snow cover, soil moisture variability and vegetation dynamics (see Barichivich et al., 2014, and references therein).

The remote measurements of soil moisture from satellite platforms require evaluation. This is commonly done using ground-based measurements of soil moisture that are independent from the satellite measurements. Several ground-based soil moisture datasets are used to evaluate satellite soil moisture data. A comprehensive data base of in situ soil moisture networks is found in the ISMN (International Soil Moisture Network) website, http://ismn.geo.tuwien.ac.at/ (Dorigo et al., 2011, 2013).

Evaluation of satellite soil moisture data using in situ networks assesses the spatial and temporal correlations between the satellite and in situ datasets. Other metrics such as bias and root mean square difference (RMSD) are also used. Examples include the evaluation of data from ASCAT Soil Water Index (SWI; see Section 3.2 for a discussion of SWI) using data from the SMOSMANIA in situ network (Albergel et al., 2009), the evaluation of ASCAT SWI using data from various in situ networks in the ISMN (Paulik et al., 2014), and the evaluation of ASCAT SWI and AMSR-E SWI using different in situ networks in Italy, France, Spain, and Luxembourg (Brocca et al., 2011). Data from the ISMN is being used to evaluate the satellite-derived soil moisture products from the ESA CCI for soil moisture (see, e.g., Dorigo et al., 2014).

Although evaluation of soil moisture satellite data has been done over many locations over the globe, to our knowledge this has not been done over Norway. This is because measurements of soil moisture are generally difficult or not possible over snow, ice, water bodies, orography and rocks, all present in Norway (see the discussion in Kerr et al., 2010). Most evaluation studies of soil moisture satellite data in Europe have been done at central and southern European latitudes for different climate regimes to those found in Norway. Soil moisture studies in northern regions outside Europe include Canada (e.g., Champagne et al., 2010). Similar to this study, where we use data from June until mid-October, to avoid periods with frozen ground or snow covered ground, Champagne et al. (2010) used only the period from May until October. Al-Yaari et al. (2014) evaluate soil moisture satellite data against land data assimilation estimates at the European Centre for Medium-Range Weather Forecasts (ECMWF) for biomes over the world. They find the northern high latitudes have the worst performance in terms of correlation (R), RMSD, and biases. The results of Al-Yaari et al. (2014) (see, e.g., their Fig. 6) indicate the need to evaluate soil moisture satellite data at northern high latitudes, including the Nordic regions.

Although to our knowledge satellite soil moisture data have not been evaluated hitherto over Norway, the performance of simulated soil moisture over Norway, in particular its spatio-temporal distribution, has been evaluated (Kristiansen et al., 2012). Tests of the sensitivity of screen-level (2 m) temperature forecasts to initial conditions in soil moisture and temperature indicate the importance of an accurate representation of the soil moisture field for Numerical Weather Prediction (NWP) forecasts. This provides a further reason for evaluation of satellite soil moisture over Norway.

In this paper we start to remedy the lack of comprehensive evaluation of remotely sensed soil moisture over northern regions, particularly over Europe, and present results of the evaluation of soil moisture data from ASCAT and AMSR-E over Norway using in situ data from the NVE (Norges vassdrags- og energidirektorat, the Norwegian Water Resources and Energy Directorate; http://www.nve.no/en/). This extends the European areas over which satellite soil moisture data are evaluated.

This paper is structured as follows. In Section 2 we describe the main soil moisture datasets used in this paper, namely ASCAT soil moisture data (produced using the change detection approach of Wagner et al., 1999) and AMSR-E soil moisture data (produced using the VUA-NASA algorithm described in Owe et al., 2001, 2008) and NVE in situ soil moisture data. The data treatment needed owing to the different spatio-temporal resolutions of the satellite and in situ soil moisture data is shown in Section 3, followed by results and discussion in Section 4, and conclusions in Section 5.

2 Data

2.1 The Advanced SCATterometer: ASCAT

The Advanced SCATterometer (ASCAT), an active real aperture radar backscatter instrument, was launched in October 2006 onboard EUMETSAT's MetOp-A satellite. The MetOp-A is in a sun-synchronous orbit, crossing the Equator at the local times of 09:30 (descending orbit) and 21:30 (ascending orbit). In this study, data from both the descending and ascending orbits are used – this follows the approach in Brocca et al. (2011) and, by increasing the amount of data analysed, helps provide more robust results. In September 2012, MetOp-B was launched with a new ASCAT instrument on board. In this study we use data from ASCAT on MetOp-A.

ASCAT operates in the C-band (5.255 GHz) using six vertically polarized antennas, which measure at six different azimuth angles (Wagner et al., 2007a; Albergel et al., 2009): at both sides of the platform looking 45° forward, sideways, and 45° backwards with respect to the satellite's flight direction. Measurements are thus performed on both sides of the satellite track, producing two 550 km wide swaths (Figa-Saldaña et al., 2002; Bartalis et al., 2007a, b, 2008). The spatial resolution of the level 2 (L2) gridded data (produced using the Discrete Global Grid, DGG) used in this paper is about 25 km.

Soil moisture from ASCAT (version W54) is derived using the change detection approach described by Wagner et al. (1999). The derived surface soil moisture, measured to a depth of approximately 0.5 cm to 2 cm, represents the degree of saturation from 0 % (dry) to 100 % (saturated). It is derived by scaling the normalized backscattering coefficients between the lowest / highest values corresponding to the driest / wettest soil conditions. The approach is based on the assumption that over a long period of time the highest observed reflectivity corresponds to the maximum soil moisture, and viceversa.

2.2 The Advanced Microwave Scanning Radiometer – Earth Observing System: AMSR-E

The Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E), a passive microwave sensor, was launched in May 2002 onboard NASA's Aqua satellite in a polar sun-synchronous orbit. In October 2011 it stopped producing data owing to a problem with its antenna. The AMSR-E crosses the Equator at the local times of 01:30 (descending orbit) and 13:30 (ascending orbit). In this study we use the data from the descending and ascending orbits. As indicated in Fig. 3 of Brocca et al. (2011), data from the two different orbits have similar quality when compared against in situ data. Furthermore, as for ASCAT, increasing the amount of data analysed helps provide more robust results. AMSR-E operates at an incidence angle of 55° in horizontal and vertical polarization. It measures brightness temperatures at six frequencies: 6.9, 10.7, 18.7, 23.8, 36.5, and 89 GHz (Njoku et al., 2003).

We use in this study the L2 data (in units of m^3m^{-3}) from the Land Parameter Retrieval Model (LPRM version 3) developed at the Vrije Universiteit Amsterdam (VUA) in collaboration with NASA (Owe et al., 2001, 2008). This method uses a radiative transfer model to retrieve soil moisture from the AMSR-E brightness temperatures. The LPRM generally uses only the 6.9 GHz for the soil moisture retrieval (when this retrieval is contaminated by RFI, Radio Frequency Interference, the 10.7 GHz brightness temperature is used) and uses the vertical polarized 36.5 GHz as input in the temperature algorithm, which is part of the LPRM. This 36.5 GHz approximation is fine for the nighttime (descending) images because there is not a strong temperature gradient, but during the daytime (ascending) the gradient can be large which would cause a mismatch. Therefore, in many studies the AMSR-E descending products are of better quality than the ascending products (e.g., Jackson et al., 2010). One exception, where the ascending products were better than the descending can be found in Brocca et al. (2011).

For the data used in this study, no RFI was detected over the study areas. The traditional spectral difference indices method (Njoku et al., 2005) was used to detect RFI and with this method no RFI signals were found for AMSR-E. Because ASCAT is a real aperture radar backscatter instrument it is not affected by RFI.

2.3 The In Situ Soil Moisture Network over Norway

Figure 1 shows the geographical locations of the six NVE in situ stations used in this study. Table 1 identifies the latitude, longitude and altitude for these six stations, as well as the wetland and open water fraction, and the topographic index of each station. These stations cover a broad range of geographical locations and features within Norway.

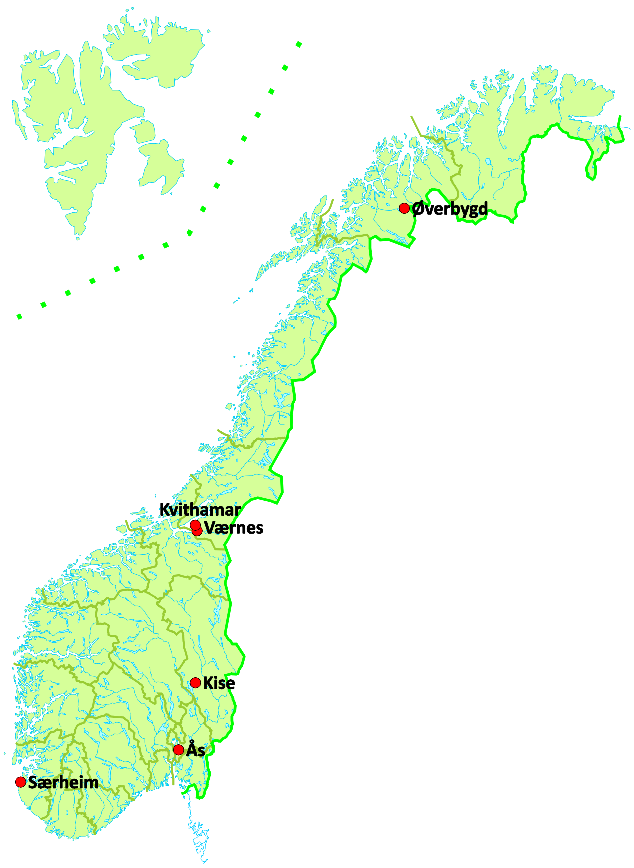

Fig. 1. Map of the six NVE in situ stations used in this study.

Table 1. In situ stations used in this study. The latitude, longitude and altitude (metres above sea level, masl) are shown together with the wetland fraction and the topographic index as well as information about the soil type.

station name	latitude	longitude	altitude	wetland fraction	topogr. index	soil type
Øverbygd	69.02° N	19.35° E	83 masl	5 %	21 %	sand
Kvithamar	63.49° N	10.88° E	70 masl	48 %	8 %	silty clay
Værnes	63.45° N	10.97° E	90 masl	6 %	9 %	sand
Kise	60.77° N	10.81° E	130 masl	17 %	7 %	silty sand
Ås	59.66° N	10.77° E	80 masl	1 %	2 %	clay
Særheim	58.76° N	5.65° E	90 masl	32 %	4 %	silty sand

The wetland fraction information in Table 1 (provided as an advisory flag with the ASCAT data) describes the coverage of inundated and wetland areas from 0 % (no water) to 100 % (lake). It is derived from a combined analysis of the Global Lakes and Wetlands Database (GLWD) Level 3 product from 2004 and the Global Self-consistent, Hierarchical, High-resolution Shoreline Database GSHHS (v1.5, 2004). The topographic index information in Table 1 (provided as an advisory flag with the ASCAT data) is derived from GTOPO30 data and is defined as the standard deviation of the elevation normalized between 0 % (flat) and 100 % (vertical). Table 1 also gives information on the soil type, as determined by NVE.

The information on the wetland and open water fraction and the topographic index in Table 1 reflects that Norway has extremely heterogeneous terrain. A comparison of soil moisture and in situ data over Southern France by Draper et al. (2011) excluded pixels with steep mountainous terrain (defined as having a topographic index greater than 15 %), and pixels with open water (defined as having a wetland fraction greater than 5 %). This was done due to the expected lower quality of ASCAT soil moisture for such conditions. If this approach were used in our study, only the in situ station at Ås would qualify from the sites listed in Table 1.

The in situ measurements are done using "PR2 Profile Probes" (http://www.delta-t.co.uk/product-display.asp?id=PR2%20Product&div=Soil%20Science). They measure soil moisture at six depths: 10, 20, 30, 40, 60 and 100 cm. For this study we use the measurements performed at 10 cm, as they are the in situ measurement nearest to the land surface.

3 Data preparation

3.1 Spatio-temporal issues

In situ observations have relatively high spatio-temporal resolution (order of centimetres and minutes, respectively) but only have local coverage, which may lead to poor representativeness for a large area (Crow et al., 2012; Gruber et al., 2013). In this paper we use for the comparison with satellite data from ASCAT and AMSR-E the satellite grid points closest to the ground-based stations. The maximum distance between satellite grid points and the ground-based stations is less than 6 km for ASCAT and less than 1° in both latitude and longitude for AMSR-E (this is less than 111 km in latitude and less than 57 km in longitude at the latitudes of Norway). The reason for choosing this larger grid for AMSR-E is that otherwise there are only a few coincidences at a number of stations (less than 50 coincident measurements at Kvithamar and Værnes; only for Øverbygd was there a sufficient number of coincidences, which we establish as more than 50) and no coincidences at other stations (Kise, Særheim and Ås), For these stations several soil moisture measurements were missing because they exceeded the 5 % water body limit associated with open water which means if an AMSR-E pixel contains more than 5% water, then the data are flagged. A finer grid, e.g., 0.25° as available for AMSR-E (Njoku et al., 2003), would mean too few in situ stations would be available for AMSR-E evaluation. The reason for not choosing 1° for ASCAT as well is that, generally, the smaller spatial separation (6 km) ameliorates problems arising from spatial variability within a satellite pixel when comparing in situ and satellite data, and that with this value there are enough ASCAT coincident measurements to compute robust statistics (191 number of pairs on average for the different stations, see Table 3 below).

A fair treatment of ASCAT and AMSR-E requires application of a spatial filter to the AMSR-E data (e.g., applying the AMSR-E averaging kernel matrix – see Rodgers, 2000) until it reaches the same spatial resolution as ASCAT. This has not been hitherto done and is beyond the scope of this work. Nevertheless this does not impact our results as we do not compare ASCAT and AMSR-E directly. It is not the goal of this paper to select the best satellite data for representing soil moisture over Norway; rather, we wish to assess how well the data from ASCAT and AMSR-E represent soil moisture over Norway.

3.2 Conversion of satellite data

The procedure described in this section to convert satellite soil moisture data to match the characteristics of in situ soil moisture data is standard, and has been used in many studies to evaluate soil moisture data (e.g., Brocca et al., 2013; Draper et al., 2013; Leroux et al., 2014; Su et al., 2013).

As mentioned in Section 2.1, the ASCAT soil moisture product is provided as degree of saturation from 0 % (dry) to 100 % (saturated). For comparison with volumetric in situ data we use the minimum and maximum observed in situ values to convert the ASCAT data to volumetric soil moisture values (in units of m^3m^{-3}). This conversion is done using Eq. (1), where SSM (indicating surface soil moisture) denotes original ASCAT measurements, I denotes in situ measurements and SSM_{vol} is ASCAT volumetric soil moisture:

$$SSM_{vol} = I_{min} + \frac{I_{max} - I_{min}}{SSM_{max} - SSM} \times (SSM - SSM_{min}) \quad (1)$$

Only days where both satellite and in situ datasets are available are used to determine the minimum and maximum values. Furthermore, as in Draper et al. (2011), the 1^{st} and 99^{th} percentiles are applied instead of the actual minimum and maximum in situ values to minimize the likelihood of using outliers as lower / upper boundaries. The use of the 1^{st} and 99^{th} percentiles is not applied to the AMSR-E dataset, as this dataset is already in volumetric units.

The in situ measurements have a measurement depth of 10 cm, which is deeper in the ground than the ASCAT and AMSR-E satellites can measure (these satellites typically measure at most to a depth of a few cm). A way to (partly) overcome this is to apply to the satellite data the exponential filter first described by Wagner et al. (1999). This filter is used to estimate the root-zone soil moisture (specified as SWI, and given in units of m^3m^{-3}):

$$SWI(t_n) = \frac{\sum_i^n SSM(t_i)\, e^{-\frac{t_n - t_i}{T}}}{\sum_i^n e^{-\frac{t_n - t_i}{T}}} \qquad \text{for } t_i \leq t_n \quad (2)$$

where $SWI(t_n)$ is the result of applying the exponential filter, $SSM(t_i)$ is the surface soil moisture given in m^3m^{-3} and estimated from the satellite at time t_i, and T is a characteristic time scale (in days) of soil moisture variability, estimated off-line. This extends the satellite measurements from ASCAT and AMSR-E to soil depths matching those of the NVE stations. We apply just one filter for ASCAT and for AMSR-E, without accounting for differences between the NVE stations. Tests indicate that this has no significant effect on the results.

We apply a filter with a characteristic time scale T of three days for ASCAT and two days for AMSR-E, including at time t all measurements in the period $[t-4T, t]$. We only calculate the modified soil moisture if at least two coincident satellite and in situ measurements are available in a period of $4T$+1 days; for ASCAT this is 13 days and for AMSR-E this is 9 days. The three parameters involved in defining the exponential filter, namely, the characteristic time scale, the factor used to define the time period over which the filter is applied (13 and 9 days in this case), and the minimum number of measurements used, are selected by requiring that the correlation between the modified satellite data and the in situ data be a maximum. Partially following Paulik et al. (2014), we tested other characteristic time scales (T values between 1 day and 5 days); according to Paulik et al. (2014), a higher T value typically represents a deeper soil layer. With T=3 days for ASCAT and T=2 days for AMSR-E we found the best results for the satellite products. This is consistent with ASCAT (0.5-2 cm) penetrating deeper into the soil than AMSR-E (several mm).We thus decided not to use other T values for each satellite instrument, and used these fixed values for T for all stations and for both ascending and descending satellite data.

Systematic differences between satellite and in situ soil moisture data make it difficult to have good absolute agreement between time series of these datasets. These differences, typically reflected in differences between dataset climatologies, can arise because of uncertainties affecting both data sources (Koster et al., 2009; Entekhabi et al., 2010), and differences in the spatial extent of satellite and in situ data in the horizontal (relatively fine vs relatively coarse scales), and the vertical (depth of penetration of the soil). Furthermore, owing to the well-known scaling properties of soil moisture (Vachaud et al., 1985; Brocca et al., 2012a), in situ measurements can capture the large-scale temporal dynamics of which satellite data are representative. For these reasons, satellite soil moisture data are often scaled and/or filtered before comparison to in situ soil moisture data.

After applying the filter of Wagner et al. (1999), the ASCAT and AMSR-E data are normalized using the mean and standard deviation of the in situ data (Brocca et al., 2011; Al-Yaari et al., 2014):

$$SWI_{norm} = (SWI_{vol} - SWI_{mean}) \times \frac{I_{std}}{SWI_{std}} + I_{mean} \qquad (3)$$

with SWI_{norm} the normalized SWI for the satellite data, SWI_{vol} the volumetric SWI, and SWI_{mean}, SWI_{std}, and I_{mean} and I_{std} the mean and standard deviation of the SWI satellite data and the in situ data, respectively.

After the transformation in Eq. (3), the satellite data have the same mean and standard deviation as the in situ data. This reduces the study to assessing the behaviour of satellite soil moisture anomalies (in other words, the dynamical behaviour of the satellite soil moisture dataset) with respect to the in situ climatology (in this case, calculated for the summer and autumn during the period 2009-2011). As we are interested in whether the satellite soil moisture data capture the same relative behaviour as the in situ soil moisture data, this approach is suitable for our needs.

Seasonal variations can suppress soil moisture anomalies which proceed with a much weaker magnitude, and thus can dominate the correlation and increase it unrealistically (Scipal et al., 2008). To avoid the influence of these seasonal effects, soil moisture anomalies are computed in the same way as Albergel et al. (2009; 2012, 2013b) and Brocca et al. (2011): A five-weeks sliding window with at least five measurements in it is used to calculate the anomaly in the in situ and satellite soil moisture fields. The difference from the mean is scaled to the standard deviation in this sliding window. For each satellite / in situ soil moisture field at day *t*, and for a period of (t – 17: t + 17) days, corresponding to five weeks, the dimensionless anomaly $SWI_{anom}(t)$ is defined:

$$SWI_{anom}(t) = \frac{SWI\ (t) - \overline{SWI\ (t-17:t+17)}}{\sigma\ [SWI(t-17:t+17)]} \quad (4)$$

with the overbar indicating the mean and σ the standard deviation for this 5 week period. According to Eq. (4) the anomaly is not calculated for the first 17 days and the last 17 days of the four and a half month observation period for each year.

Additional to the correlation between the satellite SWI data and the in situ data (computed for both the absolute soil moisture data and the anomalies), the unbiased root mean square difference (ubRMSD) is used to compare the satellite SWI data and the in situ data for the absolute soil moisture data (i.e., not the dimensionless anomalies calculated using Eq. (4)):

$$ubRMSD = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\{[(SWI_n - \overline{SWI_n}) - (I_n - \overline{I_n})]^2\}} \quad (5)$$

with SWI_n the SWI given from Eq. (3), and I_n the in situ data; the overbars represent averaged quantities. This scaling affects the RMSD, so for this reason the RMSD metric is not presented here. The ubRMSD metric always corrects for bias, and this is why it is used in this study. The ubRMSD has been used in other studies as well, e.g., Albergel et al. (2013a) or Dorigo et al. (2014).

In this paper we describe soil moisture using the SWI formulation. An alternative description of soil moisture is provided by surface soil moisture (SSM). Brocca et al. (2011) described the difference between using SSM and SWI data for various regions across Europe. They showed that for the SWI the averaged correlations between satellite and in situ data are higher than the averaged correlations for SSM.

4 Results and discussion

We evaluate the satellite data only for the summer / autumn season (1 June - 15 October, 2009 - 2011), to minimize the influence from ice or snow. With this choice we also limit the number of coincidences, but enough coincidences remain (191 and 187 for ASCAT descending and ascending orbits and 293 and 333 for AMSR-E for descending and ascending orbits) to get robust information about the correlations and the ubRMSD between the in situ and satellite data. The study uses both ascending and descending data from ASCAT and AMSR-E. Exceptions include Kvithamar, where there are only coincidences with AMSR-E.

In this study we only use the correlations which are statistically significant. To identify them we use the p-value, a measure of the correlation significance. We only use data for which the p-value is less than the significance level of 5%, which means the correlation is not likely to be a coincidence (see, e.g., Albergel et al., 2010; 2012).

To evaluate the ASCAT data (both descending and ascending), five NVE stations (Øverbygd, Værnes, Kise, Ås, and Særheim – see Table 1) have sufficient coincidences (p-value < 0.05) to allow for a robust computation of statistics. The same number is found for AMSR-E descending data, but for a different set of stations: Øverbygd, Kvithamar, Værnes, Kise, and Ås (see Table 1). For the AMSR-E ascending orbits, all six stations have sufficient coincidences (this number is more than 50 for each station). Kvithamar and Værnes are located in the same AMSR- E VUA pixel, so the satellite measurements are the same for these two stations; however, note that the in situ measurements at these two stations are different. Note that we discard data, which are treated as outliers. We did this following the approach of Albergel et al. (2012), in which data suspected of being outliers (from a first visual quality check) are removed.

Prior to comparing the transformed AMSR-E and ASCAT satellite data (see Section 3.2 for details of the transformation procedure), with the NVE in situ soil data, we compare the variability of the soil moisture datasets without application of Eq. (3) (expressed as SWI to account for the different depths of penetration of the soil by the satellite and in situ data) for the summer / autumn season over the years 2009 - 2011 by means of a Taylor diagram (Taylor, 2001). For the NVE stations matched with AMSR-E and ASCAT satellite data (see above) we find that the AMSR-E data have less variability than the NVE data - the normalized standard deviation is less than 1, and that the ASCAT data have a variability ranging around that of the NVE data – the normalized standard deviations range from 0.8 to 1.2 (Fig. 2). One factor for these differences might be the different footprints of the satellites and the different coincidence criteria used. For AMSR-E, the descending data tend to have less variability than the ascending data; for ASCAT, the variability for the descending and ascending data is similar.

Table 2 shows the value of the standard deviation of the satellite data normalized against the in situ data (shown as the normalized standard deviation in Fig. 2). The correlations between the satellite (ASCAT and AMSR-E) and in situ datasets are shown in Table 3.

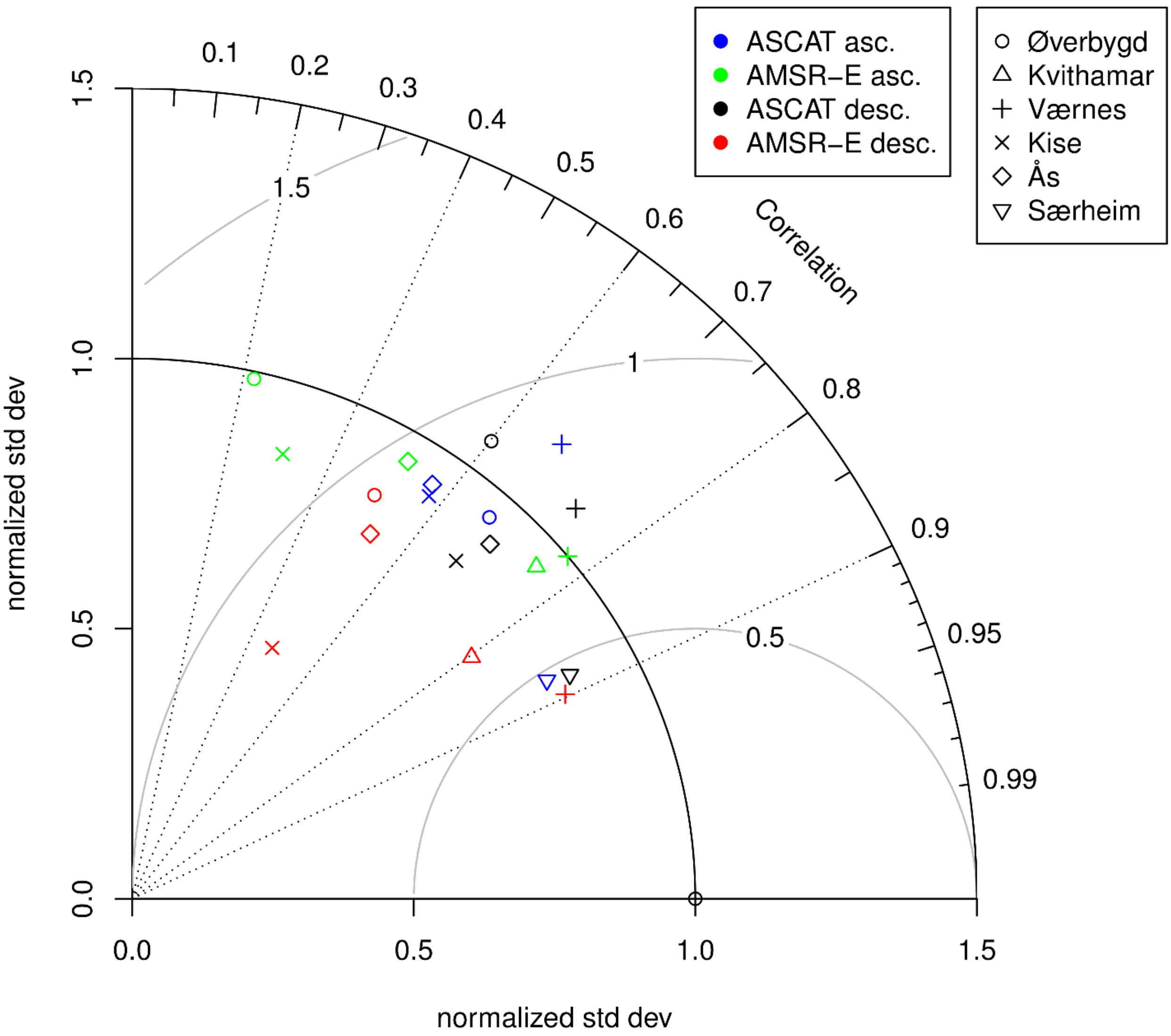

Fig. 2. Taylor diagram illustrating the statistics between in situ and ASCAT ascending data (blue), ASCAT descending data (black), AMSR-E ascending data (green), and AMSR-E descending data (red). The different symbols identify the different in situ stations.

Table 2. Normalized standard deviation (standard deviation of the satellite data divided by the standard deviation of the in situ data) for ASCAT and AMSR-E satellite data. Identified as normalized std.

name of station	normalized std ASCAT descending	normalized std ASCAT ascending	normalized std AMSR-E descending	normalized std AMSR-E ascending
Øverbygd	1.06	0.95	0.86	0.99
Kvithamar	-	-	0.75	0.95
Værnes	1.07	1.13	0.86	1.00
Kise	0.85	0.91	0.53	0.87
Ås	0.91	0.93	0.80	0.95
Særheim	0.88	0.84	-	-

For the remainder of the paper, we consider the comparisons between the satellite and in situ datasets where the former have been normalized to have the same mean and standard deviation as the latter (see Eq. (3)). Tables 3 and 4 show the results for all data for the summer / autumn season, where the coincidences are between the dataset pairs AMSR-E / in situ and ASCAT / in situ; Table 5 summarizes the results of the cross comparison, where coincidences for all three datasets (ASCAT, AMSR-E and in situ) exist. Looking at these triplets is a way to confirm our comparison from the pair coincidences and to show the robustness of the results.

Figures 3 to 8 show the time series of the modified values of ASCAT and AMSR-E soil moisture data at the location of the NVE stations, and the in situ soil moisture data at the NVE stations (see Table 1 for a list of the NVE stations used in this study). These figures show all the coincidences between the satellite data (ASCAT and AMSR-E) and the in situ data, regardless of whether there is a coincidence for all three datasets. Note that for these figures the range of the y-axis is not uniform. For these figures we merge the data for the periods 1 June – 15 October for each year of the time period considered (2009-2011), omitting the periods in between.

Table 3. Correlation (R) between ASCAT SWI data and in situ data, and number of pairs in which in situ data over Norway and coincident ASCAT SWI data are available for the summer / autumn period (1 June - 15 October, 2009 - 2011). The different columns indicate, left to right: correlation for the absolute soil moisture data of the descending (ascending in the brackets) orbit; number of coincidence days used to compute the correlation for the absolute soil moisture data for the descending (ascending in the brackets) orbit; correlation for the anomalies for the descending (ascending in the brackets) orbit; number of coincidence days used to compute the correlation for the anomalies for the descending (ascending in the brackets) orbit; and ubRMSD (unbiased root mean square difference, units of m^3m^{-3}) computed for the absolute soil moisture data, i.e., not the anomaly for the descending (ascending in the brackets) orbit.

name of station	correlation	number of pairs	correlation; anomaly	number of pairs; anomaly	ubRMSD
Øverbygd	0.60 (0.67)	290 (275)	0.48 (0.48)	265 (251)	0.03 (0.03)
Værnes	0.74 (0.68)	206 (202)	0.68 (0.49)	163 (156)	0.05 (0.05)
Kise	0.68 (0.58)	182 (182)	0.64 (0.56)	137 (137)	0.07 (0.08)
Ås	0.70 (0.57)	180 (182)	0.47 (0.14)	135 (138)	0.07 (0.08)
Særheim	0.88 (0.88)	96 (94)	0.50 (0.37)	60 (58)	0.06 (0.04)
Average	**0.72 (0.68)**	**191 (187)**	**0.55 (0.41)**	**152 (148)**	**0.06 (0.06)**

Table 4. As Table 3 but for AMSR-E data.

name of station	correlation	number of pairs	correlation; anomaly	number of pairs; anomaly	ubRMSD
Øverbygd	0.50 (0.22)	330 (370)	0.45 (0.12)	285 (291)	0.03 (0.03)
Kvithamar	0.80 (0.76)	258 (253)	0.60 (0.22)	202 (200)	0.05 (0.05)
Værnes	0.90 (0.77)	372 (378)	0.62 (0.22)	301 (302)	0.03 (0.04)
Kise	0.47 (0.31)	383 (375)	0.42 (0.23)	302 (300)	0.08 (0.10)
Ås	0.53 (0.52)	120 (386)	0.26 (0.23)	69 (303)	0.08 (0.09)
Average	**0.64 (0.52)**	**293 (352)**	**0.47 (0.20)**	**232 (279)**	**0.05 (0.06)**

Table 5. Correlation (R) between satellite SWI data and in situ data, and number of pairs in which in situ data over Norway, and coincident satellite SWI are available. The different columns indicate, left to right: correlation for the absolute soil moisture data; number of coincidence days used to compute the correlation for the absolute soil moisture data; correlation for the anomalies; number of coincidence days used to compute the correlation for the anomalies; and ubRMSD (unbiased root mean square difference, units of m^3m^{-3}) computed for the absolute soil moisture data. Scenarios A, B, and C correspond to, respectively, ASCAT SWI vs in situ data, AMSR-E SWI vs in situ data, and ASCAT SWI vs AMSR-E SWI data for the descending (ascending in brackets) orbit each. Scenarios A-C concern instances when there are coincidences involving all three datasets, and thus differ from the situations documented in Tables 3-4.

name of station	correlation			number of pairs	correlation; anomaly			number of pairs, anomaly	ubRMSD		
	A	B	C		A	B	C		A	B	C
Øverbygd	0.61 (0.67)	0.58 (0.40)	0.61 (0.30)	279 (268)	0.48 (0.08)	0.44 (0.48)	0.37 (0.12)	261 (249)	0.03 (0.03)	0.03 (0.04)	0.03 (0.04)
Værnes	0.76 (0.67)	0.91 (0.79)	0.74 (0.65)	199 (192)	0.68 (0.43)	0.72 (0.19)	0.47 (0.32)	162 (153)	0.04 (0.06)	0.03 (0.04)	0.04 (0.06)
Kise	0.73 (0.60)	0.51 (0.34)	0.36 (0.36)	170 (167)	0.66 (0.58)	0.43 (0.37)	0.53 (0.51)	135 (132)	0.06 (0.09)	0.08 (0.10)	0.07 (0.09)
Ås	- (0.57)	- (0.56)	- (0.61)	- (170)	- (0.15)	- (0.23)	- (0.38)	- (137)	- (0.08)	- (0.09)	- (0.08)
Average	**0.70 (0.63)**	**0.67 (0.52)**	**0.57 (0.48)**	**216 (199)**	**0.61 (0.31)**	**0.53 (0.32)**	**0.46 (0.33)**	**186 (168)**	**0.04 (0.07)**	**0.05 (0.07)**	**0.05 (0.07)**

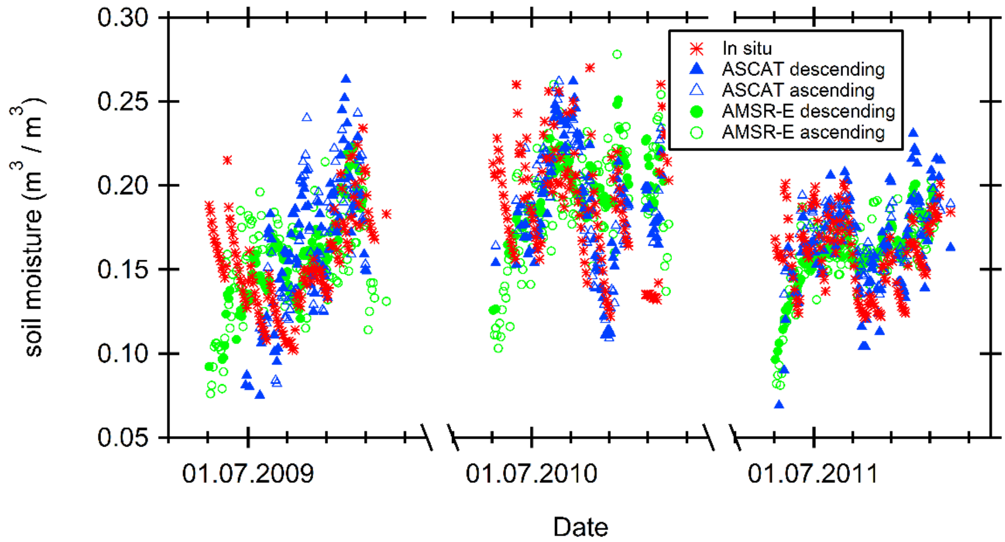

Fig. 3. Time series of filtered and normalized ASCAT, AMSR-E and in situ data over Øverbygd, units of m^3m^{-3}. The in situ data are shown by the red stars, the ASCAT data as blue triangles, and the AMSR-E data as green dots. The measurements are done between 1 June and 15 October, in the years 2009 to 2011.

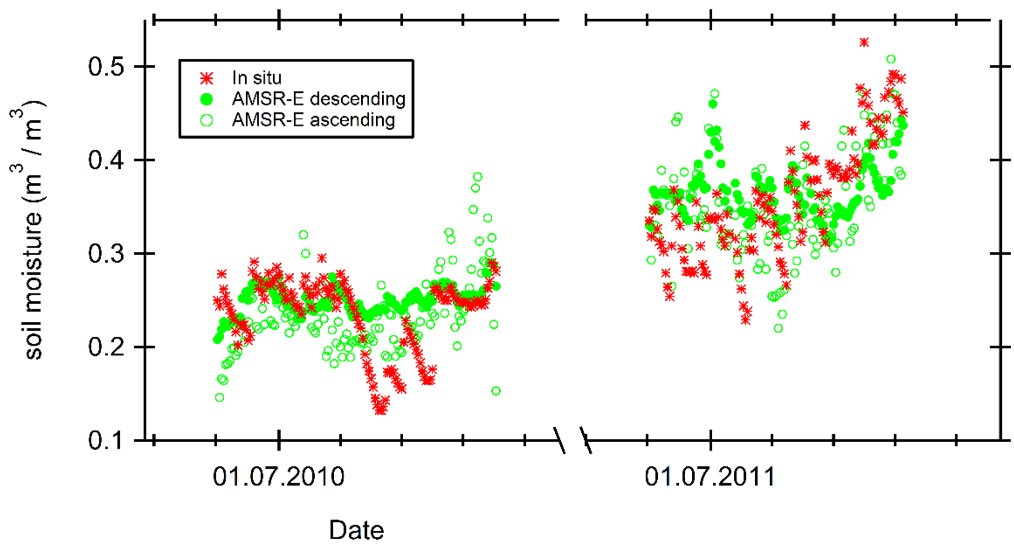

Fig. 4. Time series of filtered and normalized AMSR-E and in situ data over Kvithamar, units of m^3m^{-3}. The in situ data are shown by the red stars, and the AMSR-E data as green dots. The measurements are done between 1 June and 15 October, in the years 2010 to 2011 (there are no in situ data in Kvithamar for 2009).

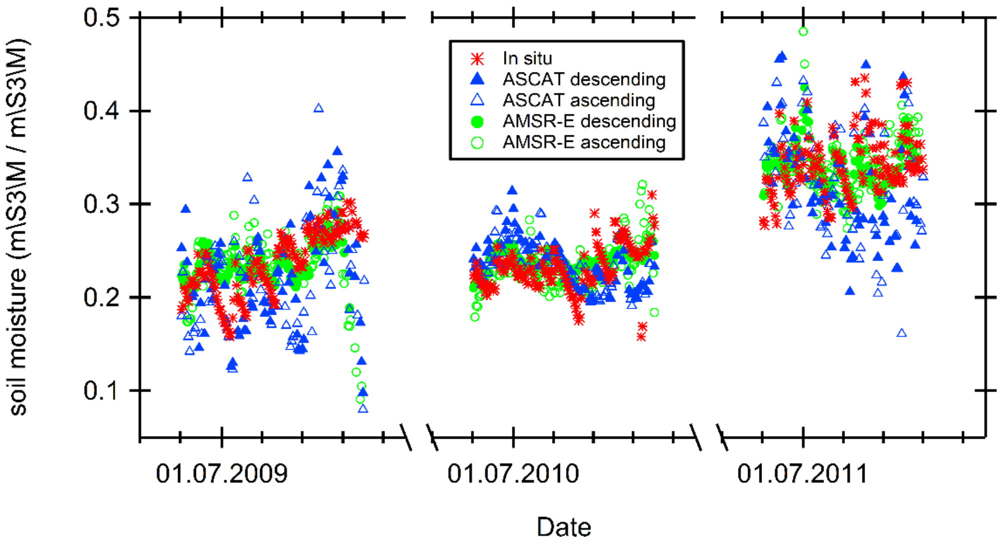

Fig. 5. Same as Figure 3 but for Værnes.

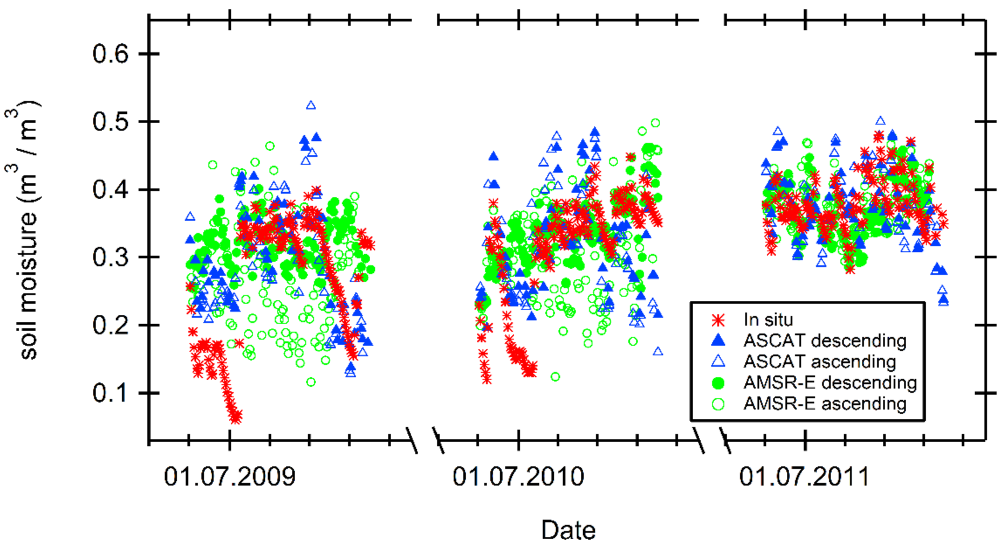

Fig. 6. Same as Figure 3 but for Kise.

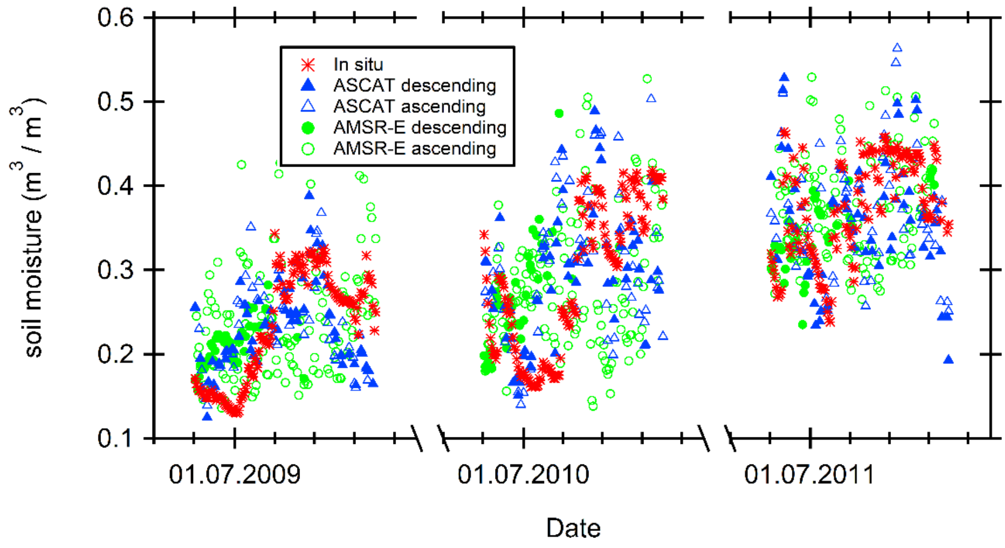

Fig. 7. Same as Figure 3 but for Ås.

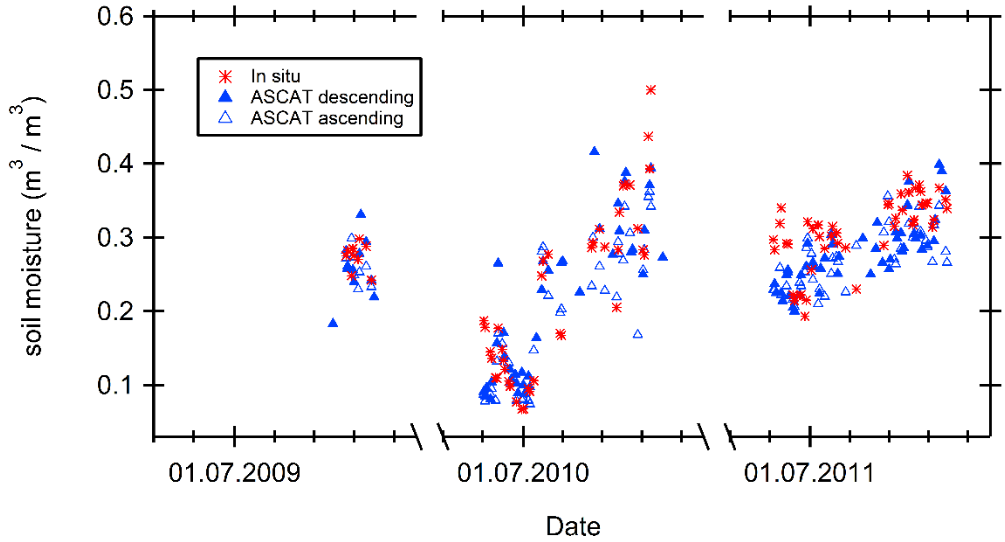

Fig. 8. Time series of filtered and normalized ASCAT and in situ data over Særheim, units of m^3m^{-3}. The in situ data are shown by the red stars and the ASCAT data as blue triangles. The measurements are done between 1 June and 15 October, in the years 2009 to 2011.

The results of this study can be summarized as follows:

- The variability of the soil moisture datasets for the summer / autumn period considered is compared: The AMSR-E data tend to have less variability than the in situ data, and the ASCAT data tend to have a variability ranging around that of the situ data.

- For the absolute soil moisture data values for the summer / autumn period considered, the averaged correlation (R) with in situ data for ASCAT (0.72 for descending orbit and 0.68 for ascending orbit) and AMSR-E (0.64 for descending orbit and 0.52 for ascending orbit) found for Norway is relatively high, indicating reasonably good agreement between the modified satellite dataset and the in situ dataset. Other studies have compared similar numbers of stations as well as comparable time periods. Comparisons of ASCAT soil moisture data with in situ data over southwest France (see, e.g., Albergel et al., 2009) have similar correlations, but these studies used an older ASCAT dataset, which has larger errors than the ASCAT data used in this study. Thus, the level of agreement between the ASCAT and in situ data for Norway, although encouraging, is not directly comparable to that found from earlier studies comparing satellite data and in situ data from other areas of the globe. Compared to other studies that used near real time data provided by EUMETSAT (e.g. Albergel et al., 2012), the correlations found in this study are higher. Another study by Paulik et al. (2014) found very small correlations for ASCAT vs in situ measurements in Finland. Even when removing measurements where the soil could still be frozen, the correlation found by Paulik et al. is 0.27, thus much lower than found in this study.
- For AMSR-E, other studies comparing its data to in situ data, have generally found higher correlations than reported here, even when only evaluating the SSM (surface soil moisture), and not the SWI (see, e.g., Wagner et al., 2007b; Gruhier et al., 2010). These higher correlations could be due to our study using a relatively large grid of 1° for AMSR-E around the in situ stations; this relatively large grid is used because, otherwise, there are only a few coincidences at some stations and no coincidences at other stations.
- For Værnes, Kise and Ås the correlations for ASCAT / in situ are higher for the data from the descending orbit, for Særheim, they are the same, and for Øverbygd the correlations for the ascending data are higher.
- Similar to ASCAT the correlations for the AMSR-E / in situ data from the descending orbits are higher than for the data from the ascending orbits for all stations. This is expected, because during daytime the temperature gradient can be large which would cause a mismatch, as described in Section 2.2. The lowest correlation is found for Kise.

This low correlation might be explained by a problem with AMSR-E measurements over wet soils, as Kise is on a peninsula in Lake Mjøsa, the largest lake in Norway.

- The correlations for the anomalies are as expected smaller for all stations for ASCAT / in situ as well as for AMSR-E / in situ both descending and ascending than for the absolute data because of the removal of the seasonal variation.
- For the cross comparison between modified ASCAT SWI and ASMR-E SWI, and in situ soil moisture measurements (involving three stations for both ascending and descending orbits), the correlations for ASCAT / in situ and AMSR-E / in situ are comparable to the measurements taking all summer and autumn data into account. On average, they have similar values for the whole period: 0.70 for ASCAT / in situ and 0.67 for AMSR-E / in situ. The correlation for the AMSR-E / ASCAT comparison (0.57) is on average lower than for the individual satellite comparisons with in situ data. This might be because the satellite data are selected to match the in situ data, not the other satellite data. For the cross comparison of the anomalies the average correlations are 0.61 (ASCAT / in situ), 0.53 (AMSR-E / in situ), and 0.46 (AMSR-E / ASCAT).
- The ubRMSD ranges between 0.03 m^3m^{-3} and 0.08 m^3m^{-3} for all comparisons (ASCAT / in situ and AMSR-E / in situ). The ubRMSD is larger for the southern stations Kise, Ås and Særheim. These are also the stations with the smallest number of coincident measurements, so this might be a reason for the larger ubRMSD.
- There is no influence of soil type (sand, clay) or latitude (the stations considered range from 58.76° to 69.02°) on the results in this study (see Table 1). Large wetland fractions at the in situ stations do not influence the data: both Kvithamar and Særheim have high correlations, although these two stations also have relatively large wetland fractions (48% and 32%, respectively), and the stations with low wetland fractions have similar high correlations. The topographic index of the in situ station might have an influence on the data: Øverbygd (topographic index 21%) has relatively low correlation with both ASCAT and AMSR-E data. For the comparison with ASCAT data it has the lowest correlation for all stations, but it is the only station with a large topographic index. The

influence of the topographic index should be investigated by using data from more stations with a large topographic index.

- We are not interested in a direct comparison between ASCAT and AMSR-E, rather with their comparison against NVE data. Furthermore, without applying the averaging kernel matrix, it would be difficult to perform a fair comparison. We do not have a clear explanation for the fact that the best results for ASCAT and AMSR-E are not obtained for the same stations. A factor could be the different spatial resolutions.

5 Conclusions

We investigate soil moisture measurements over Norway from two satellite instruments, ASCAT and AMSR-E. Both data sets are modified and then compared with ground-based in situ measurements from NVE, the Norwegian Water Authority. The satellite data are modified in the following way. We convert the ASCAT data to volumetric soil moisture values, then run an exponential filter to estimate the root-zone soil moisture because of the different measurement depths of the satellite data and the in situ data. After applying this filter, the satellite data are normalized using the mean and standard deviation of the in situ data, and finally, to avoid undue influence from the seasonal variations, we calculate the anomalies.

The results in this paper show that ASCAT and AMSR-E soil moisture products over Norway generally have satisfactory quality. It is shown that there is no influence of soil type, latitude or wetland fractions at the in situ station. Only the topographic index appears to have an influence on the correlations (R), but as there is only one station with a relatively large topographic index (Øverbygd – the others considered have a relatively small topographic index); further investigation is needed to address this point.

We conclude that ASCAT and AMSR-E soil moisture products over Norway are useful for various applications that rely on well-characterized global soil moisture datasets from satellites. These applications include: estimating precipitation (see, e.g., Brocca et al., 2013, 2014); land surface monitoring of flood / drought conditions (see, e.g., Kerr et al., 2010);

land surface monitoring of ecosystem changes associated with climate change (Barichivich et al., 2014, and references therein); weather forecasting using better land surface estimates and better fluxes between the land and atmosphere – soil moisture has been shown by a number of studies to have a significant impact on weather forecast skill at the short and medium range (Beljaars et al., 1996; Drusch and Viterbo, 2007; van den Hurk et al., 2008) and at the seasonal range (Koster et al., 2004, 2011; Weisheimer et al., 2011); and hydrological modelling, where soil moisture datasets are used to evaluate models (see, e.g., Lahoz and De Lannoy, 2014, and references therein).

To improve the fidelity of satellite remote sensing over Norway, there are a number of things that could addressed. There is only a limited amount of stations over Norway, so to get more robust information, more data would be useful. Also the time period could be extended to obtain more information. The errors of the data (especially the in situ data) are not well characterized, so this could be improved as well in a future study. Future work could also include assimilation of the satellite soil moisture data (from ASCAT, AMSR-E and other satellite platforms such as SMOS) into a land surface model, and comparison against independent in situ soil moisture data, to investigate in further detail the quality of the satellite data and the in situ data, and extend soil moisture information in the horizontal (by gridding) and in the vertical (by providing information on the root zone).

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