

Sensitivity of spaceborne radar to near-surface soil moisture in grasslands across southern Ireland

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The amount of water stored in the soil is a key parameter for the energy and mass fluxes at the land surface and is of fundamental importance to many agricultural, meteorological, biological and biogeochemical processes. This study investigates the potential of retrieving surface soil moisture in grassland areas from a time series of 68 ENVISAT Advanced Synthetic Aperture Radar (ASAR) Wide Swath Mode (WSM) scenes, acquired between 2007 and 2009, using an empirical regression approach. WSM data enables larger areas to be observed with a higher temporal sampling capability, compared to Image Mode (IM) data, and provide an appropriate spatial resolution for regional applications. As expected, the radar backscatter signal was found to increase with increasing soil moisture. Inter-seasonal analysis showed that the VV (Vertical transmit-Vertical receive) polarisation radar signal is more sensitive to surface soil moisture during the spring and autumn months, where average signal increases of about 4dB corresponding to relative soil moisture increases of ~40% were obtained. Results also display significant ($p < 0.05$) correlations between the HH (Horizontal transmit – Horizontal receive) polarisation signal and surface soil moisture, with r^2 values ranging from 0.67 – 0.86 for some of the test sites. Overall, the results suggest that the use of an empirical linear relationship approach is a good approximation of the relationship between ASAR WSM backscatter coefficients and surface soil moisture over grassland areas.

Keywords: Radar, soil moisture, grasslands, empirical regressions, *in situ* measurements

1. Introduction

Measurements of surface soil moisture are needed to improve the understanding of local and regional water cycles, ecosystem dynamics and, through its control on evaporation and plant transpiration, the many processes that link the water, energy and carbon cycles (Teuling and Troch 2005, Brocca *et al.* 2010). Furthermore, a thorough understanding of soil moisture behaviour would facilitate effective flood and drought forecasting, improved weather prediction and to a larger extent, global climate change research (Entekhabi *et al.* 1996).

Soil moisture dynamics is dependent on both meteorological conditions and soil physical characteristics and, as a result, exhibits large spatial and temporal variations between different areas, seasons and years (Schulte *et al.* 2005). The spatial and temporal coverage attainable by spaceborne Synthetic Aperture Radars (SARs) makes them a promising approach for measuring short-term, seasonal and long-term variations

in surface soil moisture (Baghdadi *et al.* 2008). In the past 30 years, several different approaches to derive soil moisture from spaceborne active microwave measurements have been investigated (Barrett *et al.* 2009). The most common techniques employed are empirical/semi-empirical (e.g. Dubois *et al.* (1995), Wickel *et al.* (2001), Oh *et al.* (2002), Zribi and Dechambre (2002)) and theoretical models (e.g. Fung *et al.* (1992), Altese *et al.* (1996), Song *et al.* (2009)) to determine the relationship between the radar signal and volumetric soil moisture. The main advantage of empirical backscatter models over theoretical models is that many natural surfaces do not fall into the validity ranges of the theoretical models and the number of input parameters required usually makes the model's implementation extremely complex (Walker and Houser 2004).

For multi-temporal soil moisture monitoring, the spatial coverage and temporal resolution of fine-scale SAR observations can be relatively low, usually due to either sensor limitations (e.g. satellite repeat cycle) or user conflicts in the case of multi-mode SAR sensors (e.g. ASAR, PALSAR, RADARSAT) (Van der Velde *et al.* 2008). The medium resolution ASAR Wide Swath mode (Desnos *et al.* 2000) on the other hand, has a wider swath (405 km) than higher resolution modes (e.g. Image mode) and provides shorter revisit intervals (3 - 5 days compared to 35 days for Image mode). The focus of this study was to investigate the influence of surface soil moisture on backscatter signatures from VV (Vertical transmit-Vertical receive) and HH (Horizontal transmit – Horizontal receive) polarisation medium resolution ASAR WSM data in seven grassland study sites in the south of Ireland. The study concentrated on grassland, as almost 80% of the agricultural area of Ireland (4.4 million hectares) is devoted to grass (Teagasc 2010). This represents approximately 50% of the total land area of Ireland (6.9 million hectares).

2. Description of Study Sites

The research was carried out in seven homogeneous grassland (permanent pasture) sites located in the south of Ireland namely, Ballinhassig, Carraig na bhFear, Clonakilty, Donoughmore, Kilworth, Pallaskenry and Solohead. All seven sites are typically low lying (ranging from a minimum altitude of 15m to a maximum 104m above sea level) and relatively flat (slope < 6°) with a loamy soil texture. Figure 1 shows the geographic location of each of the study sites (marked by yellow triangles) and three Met Éireann (Irish Meteorological Service) stations (red circles). The area has a temperate climate and generally high relative humidity, averaging ~90% throughout the year. Annual precipitation recorded at each of the study sites is given in table 1. Due to a suspected instrument fault, no value is included for Carraig na bhFear in 2009. Overall, 2009 was the wetter year in which November is notable for the high rainfall recorded across all stations. An increasing annual precipitation is observed, considering the long-term annual average rainfall (1961-1990) recorded for three nearby Met Éireann climatological stations (1207mm, 935mm and 926mm for Cork Airport, Roches Point, and Shannon Airport respectively).

Figure 1.

Table 1.

3. Data and Methods

3.1 Ground Measurements

Campbell Scientific CS616 water content reflectometers (Campbell Scientific 2004), installed at a depth of 5cm below surface at each of the study sites under the framework of the Aeon project (<http://aeon.ucc.ie/>), were used for the continuous measurement of soil moisture content. Measurements were recorded at 30 minute intervals from a single point at each study site and are expressed in volumetric water content (m^3/m^3). The CS616 sensor is a frequency domain reflectometer (FDR) that uses high frequency pulses travelling back and forth along a 30cm two-rod probe installed horizontally into the ground to estimate the permittivity of the soil. The sensors were calibrated using soil moisture measurements obtained through gravimetric sampling and have an accuracy of $\pm 2.5\%$ and a probe-to-probe variability of $\pm 1.5\%$. Precipitation and soil temperature were also recorded at each of the test sites at 30 minute intervals. The surface soil moisture at the time of image acquisition (both VV and HH polarisations) displayed in figure 2, shows that, for both years, between November and April, levels approach near saturation and gradually decrease to a minimum in June. However, between June and November 2008 there was a steady increase in the surface soil moisture while it remained relatively uniform for the same period in 2009, with a sudden large increase in October 2009. The values vary between study sites but all display, more or less, the same general trend in increases and decreases. The large spikes in the Ballinhassig dataset around April 2009 may have been caused from a localised buildup of surface water.

Figure 2.

An analysis of the time-series plots of measured soil moisture reveals distinct soil moisture phases, similar to those observed by Illston *et al.* (2004). The November to March period generally has the highest soil moisture levels, as a result of inactive vegetation and minimal evapotranspiration. Soils dry between March and July as a result of increasing surface temperature, evapotranspiration and decreasing precipitation. Soil evaporation decreases from July to November due to decreased sun angles in addition to vegetation biomass decreases and precipitation increases, which results in increasing soil moisture levels.

3.2 SAR data Acquisition and Processing

ENVISAT was launched on the 1st March 2002 by the European Space Agency (ESA) and operated successfully until the end of its mission on 8th April 2012. The onboard Advanced Synthetic Aperture Radar (ASAR) instrument, operating at C-band (5.3

GHz), was capable of operating in multiple modes (Stripmap- Image and Wave modes; and ScanSAR-Alternating polarisation, Wide Swath, and Global Monitoring modes) at various incidence angles in several polarisations. The satellite passes the descending node at ~11:00 am UTC and the ascending node at ~22:00 pm UTC. In this research, the emphasis is on the Wide Swath mode data. Sixty-eight ASAR WSM data acquisitions were acquired over the study sites between 11th Nov 2007 and 4th Dec 2009. The SAR data were delivered as ASA_WSM_1P data products from the European Space Agency (ESA) and processed and calibrated using SARscape® software within an ENVI® environment. The dataset consists of 7 scenes in HH polarisation (3 ascending and 4 descending) and 61 scenes in VV polarisation (8 ascending and 53 descending) (see Appendix 1). Both HH and VV datasets were analysed separately.

Auxiliary orbit and calibration information for each image was used to generate the most accurate output backscattering coefficients (σ^0). The most recent external calibration files (XCA) along with precise satellite orbital data (VOR) provided by the DORIS (Doppler Orbitography and Radiopositioning Integrated by Satellite) instrument onboard ENVISAT were used. The WSM data were multi-looked by a factor of 3 in azimuth and 7 in range to produce 21-look images (quasi-square pixels of 150m x 150m) and no further speckle filtering was carried out. Since WSM data use ScanSAR technology to cover a much larger swath-width, effects on the backscatter due to the varying incidence angle and distance from the sensor are present in the scene. Previous studies have found that low to medium incidence angles are best for soil moisture estimation (Srivastava *et al.* 2003, Baghdadi *et al.* 2006). To limit the influence of the large incidence angle (17°-42°) range and to ensure inter-comparability between the different data scenes, an angular normalisation to an incidence angle of 30° was applied based on a modified cosine model (Ulaby and Dobson, 1989). The images were subsequently geometrically and radiometrically calibrated. A 90m SRTM (Shuttle Radar Topography Mission) digital elevation model was used to geocode the images into the Irish National Grid projection using a Range-Doppler approach. Polygons of 5x5 pixels centred on the study site location were used to calculate the mean backscattering coefficient at each study area for all acquisition dates. Finally, mean backscatter values were then converted to decibel (dB) units (σ^0) for analysis with ground measurements.

3.3 Methodology

Vegetation cover attenuates the backscattered signal and therefore decreases the sensitivity of the radar backscatter to soil moisture (Ulaby *et al.* 1986). Some studies (e.g. Loew *et al.* (2006), Zribi *et al.* (2005), and Van Doninck *et al.* (2012)) have presented methodologies to correct backscatter measurements for these effects. However, it has been found in various studies that sparse or low vegetation cover has little influence on the backscattered signal and can generally be neglected. For example, Dobson *et al.* (1992) found that a grass cover (average height of 40cm) had little influence on ERS-1 (VV polarisation) backscattering coefficients, attenuating the signal by less than 0.2 dB. As all the study sites were cultivated with relatively short grass (average height < 30cm), the influence of the vegetation cover is not considered in this study. Similarly, for each of the test sites, the surface roughness was assumed to be

constant throughout the study period, as in Wagner and Scipal (2000), Baup *et al.* (2007), and Van der Velde *et al.* (2008). Under these assumptions, the backscatter coefficient can be considered to be linearly related to the soil moisture (Ulaby *et al.* 1982, Cognard *et al.* 1995, Quesney *et al.* 2000). Regression analysis was performed to investigate the relationship between *in situ* soil moisture measurements and backscatter coefficients in both VV and HH polarisations. All statistical analyses were performed using PASW/SPSS ® 17 software.

4. Results and Discussion

4.1 Backscatter Signature Analysis

Soil moisture variations usually follow precipitation trends, however they are difficult to determine or predict due to the complex interactions between the different factors affecting the moisture content of a soil (e.g. topography, vegetation cover, soil type) (Hawley *et al.* 1983, Famiglietti *et al.* 1999, Daly and Porporato 2005, Tromp-van Meerveld and McDonnell 2006). Daily precipitation data from November 2007 to November 2009 show that in general the wettest months are December and January with the driest being May and June (figure 3). This is largely in agreement with the *in situ* soil moisture measurements shown in figure 2.

Overall, no discernible association between precipitation and the multi-temporal backscatter signatures is evident from the data. On some acquisition dates, it appears that rainfall was associated with an increase in backscatter. However, on other dates, the amount of rainfall seemed to have little or no influence on the backscatter. Strong temporal variations in the observed backscatter across all sites are observed in figure 3, with many abrupt increases (spikes) occurring throughout the year. This behaviour stabilised to some degree from about April 2009 to October 2009. November 2009 is notable for the high rainfall recorded across all study sites (except Carraig na bhFear due to a suspected instrument fault) and the considerable increase in the backscatter during this period (figure 3).

Figure 3.

4.2 Regression Analysis

A regression analysis was performed for each polarisation separately. In the VV polarisation dataset, the backscatter and soil moisture relationship was initially investigated for each study site using the two-year dataset as a whole, and was subsequently divided into investigating the inter-annual and inter-seasonal relationships. Due to the low number of acquisitions, a comparable analysis could not be performed for the HH dataset (acquisition dates ranging from 27th June 2008 – 4th December 2009). Linear regression functions of the form $\sigma^0 = B_0 + B_1.m_v$ were computed, where σ^0 is the mean backscatter coefficient (dB), B_0 is the intercept, B_1 is the slope of the regression equation and m_v is the volumetric soil moisture (%). The slope is used as an indicator of the sensitivity of σ^0 to m_v . The significance of the linear relationship

between the soil moisture measurements and the backscattering coefficient was tested using Fisher's F test for $\alpha = 0.05$ significance level. The P-value (two-tailed) calculated from the F test is shown for each analysis (in table 2 and in each plot of figure 4, figure 5 and figure 6).

The relationship between the σ^0 measured in HH polarisation and volumetric soil moisture for each study site was calculated and is displayed in figure 4. The regression equation for each site is shown along with the 95% confidence limits of the regression line, denoted by dashed lines. The radar backscatter clearly increases with increasing soil moisture at the majority of sites. Significant positive correlations ($p < 0.05$) were observed for five out of the seven study sites, with Donoughmore and Ballinhassig displaying non-significant positive correlations. The slope of the relationship varies from one site to another, ranging from 0.06 (Donoughmore) to 0.13 (Kilworth).

Figure 4.

The relationship between the σ^0 measured in VV polarisation and volumetric soil moisture for each study site is displayed in table 2. Generally weak to moderate significant positive relationships are observed for each site. To understand the inter-annual and seasonal variability of soil moisture during the study period the yearly and seasonal soil moisture and backscatter relationships were calculated. The inter-annual variations in VV polarisation backscatter as a function of volumetric soil moisture for each test site are plotted in figure 5 for 2008 and figure 6 for 2009. Across all sites, the backscatter coefficient for 2008 varied from approximately -12 to -4dB for a variation in soil moisture from about 17 to 70%. In 2009, the σ^0 variation is approximately -12 to -6dB for soil moisture ranging from 17 to 82%. The regression equations for 2008 (figure 5) show low correlations and dispersions are high for all study sites. The highest significant correlations were observed for the Donoughmore ($r^2 = 0.47$, $p < 0.001$) and Solohead ($r^2 = 0.31$, $p = 0.002$) sites. The 2009 coefficients of determination are generally stronger, ranging from 0.26 to 0.68. The highest significant correlations were observed for the Clonakilty ($r^2 = 0.68$, $p < 0.001$) and Kilworth ($r^2 = 0.53$, $p < 0.001$) sites. The Donoughmore ($r^2 = 0.39$, $p = 0.001$) and Solohead ($r^2 = 0.45$, $p < 0.001$) sites displayed similar relationships to their respective 2008 datasets. The individual slopes (i.e. radar sensitivity to soil moisture) corresponding to the two sites are approximately the same for both years.

Table 2.

Figure 5.

Figure 6.

The coefficients of determination observed in this study were lower than those found in previous investigations using ERS-1/2 (Image mode, VV polarisation) SAR data (e.g. Cognard *et al.* (1995), Weimann *et al.* (1998), Moeremans and Dautrebande (2000), Quesney *et al.* (2000), Shoshany *et al.* (2000), Le Hegarat-Mascle *et al.* (2002), Haider *et al.* (2004)). Furthermore, the slopes of the regression equations derived in this study were much lower, though the intercept values are within the variation of those reported in previous studies (~-10 to -14). For example, Le Hegarat-Mascle *et al.* (2002) found a slope of 0.33-0.34 and Weimann *et al.* (1998) a slope of 0.55. However, Kong and Dorling (2008) found a similar coefficient of determination ($r^2 = 0.46$) and slope ($B_1=0.12$) for a grasslands site in the UK, as did Van der Velde *et al.* (2008) who derived a coefficient of determination of $r^2 = 0.43$ and slope $B_1 = 0.16$ for a grasslands site in Tibet, both using ASAR WSM VV datasets. The correlations and slopes of the regression lines using HH polarisation (figure 4) were generally higher than those observed for the VV polarisation dataset (figure 5 and 6). Although the HH polarisation dataset contains considerably fewer samples, this observation is consistent with Le Morvan *et al.* (2008) who found the sensitivity of soil moisture to radar backscatter at HH polarisation to be marginally higher than that from VV polarisation.

The seasonal variations in backscatter as a function of soil moisture at each of the test sites for 2008 and 2009 were also investigated. The seasons are classed as per the meteorological season for the Northern hemisphere, i.e. winter begins on the 1st December, spring on 1st March, summer on 1st June, and autumn on 1st September. Statistics related to the seasonal regression functions are given in table 3. The coefficients describing the relationships are different from one site to another and also from one year to the next. A large number of the regressions display poor correlations between the soil moisture and radar signal. Six seasonal datasets for 2008 display significant positive correlations (r^2 ranging from 0.38 to 0.60) while thirteen datasets in 2009 display significant positive correlations (r^2 ranging from 0.39 to 0.99). The sensitivity of σ^0 to m_v also varies for each of these datasets, ranging from 0.05 to 0.13dB/% for 2008 and 0.04 to 0.17dB/% for 2009.

Given the large fluctuations in soil moisture throughout the year, it was hypothesised that a seasonal analysis could provide improved results, as opposed to analysing the observations for the year as a whole. For example, Hupet and Vanclooster (2002) found surface soil moisture variability to increase strongly during the vegetative growth period (due to evapotranspiration and water uptake by plants). Similarly, Illston *et al.* (2004) found lower soil moisture variability during the winter and spring than during summer and autumn for a dataset of 58 sites over a six year time-period in Oklahoma. Consequently, the winter (wetter) datasets would be considered to theoretically provide the best results. This was not observed to be the case in this study, as only one winter dataset displayed a significant positive correlation - Clonakilty in 2009. An analysis of temperature recordings for up to five hours before each winter-time image acquisition revealed no instances of the soil temperature dropping below 0°C (frozen soils) which might have provided a possible explanation for the observed low correlations.

Table 3.

The spring datasets comprised the majority of significant correlations (four in 2008 and four in 2009). The Solohead, Kilworth and Ballinhassig sites all displayed significant correlations during both 2008 and 2009. The autumn datasets displayed the highest coefficients of determination, with an r^2 of 0.60 in 2008 (Donoughmore) and r^2 ranging from 0.78 to 0.99 in 2009. The slopes of the autumn 2009 relationships are relatively consistent for the Pallaskenry, Kilworth and Clonakilty sites (ranging from 0.12 – 0.16) and for the Solohead, Carraig na bhFear and Ballinhassig sites (ranging from 0.04 – 0.08).

The spatial variability of the soil moisture is likely to be due to differences in radiation effects, gains due to precipitation, losses due to evapotranspiration, runoff and drainage, and heterogeneities in soil and vegetation characteristics (Brocca *et al.* 2007). The observed variation in backscatter as a function of soil moisture was likely to have been caused by several factors. In terms of image calibration, the influence of speckle can cause pixel values to vary randomly. In this study, the influence of speckle was considered to be low as an appropriate preprocessing was carried out with a suitable number of looks. Similarly, the low coefficients of determination observed between the backscatter and soil moisture time-series does not necessarily point to an alternative and dominating influence (e.g. surface roughness or vegetation), but might be due to the scaling problem (Pathe *et al.* 2009). The spatial scale at which the backscatter and soil moisture relationship is determined is of critical importance (Zribi *et al.* 2005). At larger scales, the sub-pixel heterogeneity (in terms of vegetation, surface roughness and moisture) can invariably lead to errors in the estimated soil moisture values. In this study, discrete soil moisture measurements were compared to backscatter values corresponding to an area of 375m x 375m. The increased scale increases soil moisture variability as the spatial heterogeneities in factors such as topography, vegetation and surface roughness also become larger.

5. Conclusions

The aim of this study was to assess the relationship between ASAR WSM backscatter and variations in surface soil moisture at several test sites located in the south of Ireland over a two year period. Empirical regressions were formulated using ASAR WSM data (acquired in HH and VV polarisation) and *in situ* measurements of soil moisture. The need for measurements of other surface parameters such as surface roughness and vegetation is removed using this approach. For dominantly vertical-oriented vegetation cover (e.g. grasslands), the use of HH polarisation is considered best for soil moisture estimation. The default mode for ASAR WSM acquisitions is VV polarisation so it was not possible to acquire a larger HH polarisation dataset for this study. Nonetheless, the HH polarisation images (seven in total) acquired during summer and winter months displayed strong significant correlations between σ^0 and m_v for five out of the seven test sites. Similarly, several of the test sites displayed significant correlations in VV polarisation for images acquired throughout 2008 and 2009 respectively. The seasonal analysis of the VV polarisation data showed that the radar signal is more sensitive to surface soil moisture during the spring and autumn months, with average backscatter increases of about 1dB per 10% increase in soil moisture.

It must be noted that the derived regression equations are only valid for the given sensor wavelength (C-band) and are site-specific (low lying grassland) where a negligible influence of vegetation and surface roughness was assumed. While many studies have operated on the premise of negligible surface roughness change and vegetation contributions, further research in this area is required to understand the biases and temporal error introduced by neglecting these effects. The high seasonal and inter-annual variability observed in this dataset highlights the importance of formulating algorithms that are successful from one year to the next. In order to determine a true model of the backscatter-soil moisture relationship for a particular area, and for a robust validation of the assumptions of the empirical approach, it would be necessary to have uniform, continuous and prolonged observations at a larger number of well-distributed monitoring stations. For example, the temporal stability concept, introduced by Vachaud *et al.* (1985) reduces the need for a large ground-based soil moisture measurement network by identifying a few single (well-distributed) *in situ* stations whose soil moisture measurements are representative of the mean soil moisture over an area (i.e. display similar absolute values and temporal trends) where various studies (e.g. Cosh *et al.* 2006, Wagner *et al.* 2008) have demonstrated that time invariant relationships can be used to predict soil moisture from backscatter measurements across different spatial scales.

Although some of the reported correlations were low, there was still an evident positive relationship between the observed soil moisture values and the normalised radar backscatter. Considering the uncertainties involved, the reported regressions are encouraging and demonstrate the potential of simple empirical models for retrieving surface soil moisture from WSM data.

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References

- ALTESE, E., BOLOGNANI, O., MANCINI, M., and TROCH, P. A., 1996, Retrieving soil moisture over bare soil from ERS 1 synthetic aperture radar data: Sensitivity analysis based on a theoretical surface scattering model and field data. *Water Resources Research*, **32**, pp. 653–661.
- BAGHDADI, N., CERDAN, O., ZRIBI, M., AUZET, V., DARBOUX, F., HAJJ, M. E., and KHEIR, R. B., 2008, Operational performance of current synthetic aperture radar sensors in mapping soil surface characteristics in agricultural environments: application to hydrological and erosion modelling. *Hydrological Processes*, **22**, pp. 9–20.
- BAGHDADI, N., HOLAH, N., and ZRIBI, M., 2006, Soil moisture estimation using multiincidence and multipolarization ASAR data. *International Journal of Remote Sensing*, **27**, pp. 1907–1920.
- BARRETT, B., DWYER, E., and WHELAN, P., 2009, Soil moisture retrieval from active spaceborne microwave observations: An evaluation of current techniques. *Remote Sensing*, **1**, pp. 210–242.
- BAUP, F., MOUGIN, E., DE ROSNAY, P., TIMOUK, F., and CHÊNERIE, I., 2007, Surface soil moisture estimation over the AMMA Sahelian site in Mali using ENVISAT/ASAR data. *Remote Sensing of Environment*, **109**, pp. 473–481.
- BROCCA, L., MELONE, F., MORAMARCO, T., and MORBIDELLI, R., 2010, Spatial-temporal variability of soil moisture and its estimation across scales. *Water Resources Research*, **46**, pp. W02516.
- BROCCA, L., MORBIDELLI, R., MELONE, F., and MORAMARCO, T., 2007, Soil moisture spatial variability in experimental areas of central Italy. *Journal of Hydrology*, **333**, pp. 356–373.
- CAMPBELL SCIENTIFIC, 2004, *Instruction Manual: CS616 and CS625 Water Content Reflectometers*, (Logan, Utah: Campbell Scientific), Available at: <http://www.campbellsci.com/documents/manuals/cs616.pdf> (last accessed 7th December 2010).
- COGNARD, A., LOUMAGNE, C., NORMAND, M., OLIVIER, P., OTTLÉ, C., VIDAL-MADJAR, D., LOUAHALA, S., and VIDAL, A., 1995, Evaluation of the ERS 1/synthetic aperture radar capacity to estimate surface soil moisture: Two-year results over the Naizin watershed. *Water Resources Research*, **31**, pp. 975–982.
- COSH, M. H., JACKSON, T. J., STARKS, P., and HEATHMAN, G., 2006, Temporal stability of surface soil moisture in the Little Washita River watershed and its applications in satellite soil moisture product validation. *Journal of Hydrology*, **323**, pp. 168–177.
- DALY, E., and PORPORATO, A., 2005, A review of soil moisture dynamics: from rainfall infiltration to ecosystem response. *Environmental engineering science*, **22**, pp. 9–24.
- DESNOS, Y., BUCK, C., GUIJARRO, J., SUCHAIL, J., TORRES, R., and ATTEMA, E., 2000, ASAR-Envisat's Advanced Synthetic Aperture Radar. *ESA BULLETIN*, **102**, pp. 91–100.
- DOBSON, M., PIERCE, L., SARABANDI, K., ULABY, F., and SHARIK, T., 1992, Preliminary analysis of ERS-1 SAR for forest ecosystem studies. *IEEE Transactions on Geoscience and Remote Sensing*, **30**, pp. 203–211.
- DUBOIS, P. C., VAN ZYL, J., and ENGMAN, T., 1995, Measuring soil moisture with imaging radars. *IEEE Transactions on Geoscience and Remote Sensing*, **33**, pp. 915–926.
- ENTEKHABI, D., RODRIGUEZ-ITURBE, I., and CASTELLI, F., 1996, Mutual interaction of soil moisture state and atmospheric processes. *Journal of Hydrology*, **184**, pp. 3–17.
- FAMIGLIETTI, J., DEVEREAUX, J., LAYMON, C., TSEGAYE, T., HOUSER, P., JACKSON, T., GRAHAM, S., RODELL, M., and VAN OEVELEN, P., 1999, Ground-based investigation of soil moisture variability within remote sensing footprints during the Southern Great Plains 1997 (SGP 97) Hydrology Experiment. *Water Resources Research*, **35**, pp. 1839–1851.
- FUNG, A. K., LI, Z., and CHEN, K. S., 1992, Backscattering from a randomly rough dielectric surface. *IEEE Transactions on Geoscience and Remote Sensing*, **30**, pp. 356–369.
- HAIDER, S., SAID, S., KOTHYARI, U., and ARORA, M., 2004, Soil moisture estimation using ERS 2 SAR data: a case study in the Solani River catchment/Estimation de l'humidité du sol grâce à des données ERS-2 SAR: étude de cas dans le bassin de la rivière Solani. *Hydrological Sciences Journal*, **49**, pp. 323–334.
- HAWLEY, M., JACKSON, T., and MCCUEN, R., 1983, Surface soil moisture variation on small agricultural watersheds. *Journal of Hydrology*, **62**, pp. 179–200.
- HUPET, F., and VANCLOOSTER, M., 2002, Intraseasonal dynamics of soil moisture variability within a small agricultural maize cropped field. *Journal of Hydrology*, **261**, pp. 86–101.

- ILLSTON, B., BASARA, J., and CRAWFORD, K., 2004, Seasonal to interannual variations of soil moisture measured in Oklahoma. *International Journal of Climatology*, **24**, pp. 1883–1896.
- KONG, X., and DORLING, S. R., 2008, Near-surface soil moisture retrieval from ASAR Wide Swath imagery using a Principal Component Analysis. *International Journal of Remote Sensing*, **29**, pp. 2925–2942.
- LE HEGARAT-MASCLE, S., ZRIBI, M., ALEM, F., WEISSE, A., and LOUMAGNE, C., 2002, Soil moisture estimation from ERS/SAR data: toward an operational methodology. *IEEE Transactions on Geoscience and Remote Sensing*, **40**, pp. 2647–2658.
- LE MORVAN, A., ZRIBI, M., BAGHDADI, N., and CHANZY, A., 2008, Soil moisture profile effect on radar signal measurement. *Sensors*, **8**, pp. 256–270.
- LOEW, A., LUDWIG, R., and MAUSER, W., 2006, Derivation of surface soil moisture from ENVISAT ASAR wide swath and image mode data in agricultural areas. *IEEE Transactions on Geoscience and Remote Sensing*, **44**, pp. 889–899.
- MOEREMANS, B., and DAUTREBANDE, S., 2000, Soil moisture evaluation by means of multi-temporal ERS SAR PRI images and interferometric coherence. *Journal of Hydrology*, **234**, pp. 162–169.
- OH, Y., SARABANDI, K., and ULABY, F. T., 2002, Semi-empirical model of the ensemble-averaged differential Mueller matrix for microwave backscattering from bare soil surfaces. *IEEE Transactions on Geoscience and Remote Sensing*, **40**, pp. 1348–1355.
- PATHE, C., WAGNER, W., SABEL, D., DOUBKOVA, M., and BASARA, J. B., 2009, Using ENVISAT ASAR Global Mode Data for Surface Soil Moisture Retrieval over Oklahoma, USA. *IEEE Transactions on Geoscience and Remote Sensing*, **47**, pp. 468–480.
- QUESNEY, A., LE HEGARAT-MASCLE, S., TACONET, O., VIDAL-MADJAR, D., WIGNERON, J., LOUMAGNE, C., and NORMAND, M., 2000, Estimation of watershed soil moisture index from ERS/SAR data. *Remote Sensing of Environment*, **72**, pp. 290–303.
- SCHULTE, R., DIAMOND, J., FINKELE, K., HOLDEN, N., and BRERETON, A., 2005, Predicting the soil moisture conditions of Irish grasslands. *Irish Journal of Agricultural and Food Research*, **44**, pp. 95–110.
- SHOSHANY, M., SVORAY, T., CURRAN, P. J., FOODY, G. M., and PEREVOLOTSKY, A., 2000, The relationship between ERS-2 SAR backscatter and soil moisture: generalization from a humid to semi-arid transect. *International Journal of Remote Sensing*, **21**, pp. 2337–2343.
- SONG, K., ZHOU, X., and FAN, Y., 2009, Empirically adopted IEM for retrieval of soil moisture from radar backscattering coefficients. *IEEE Transactions on Geoscience and Remote Sensing*, **47**, pp. 1662–1672.
- SRIVASTAVA, H. S., PATEL, P., MANCHANDA, M. L., and ADIGA, S., 2003, Use of multiincidence angle RADARSAT-1 SAR data to incorporate the effect of surface roughness in soil moisture estimation. *IEEE Transactions on Geoscience and Remote Sensing*, **41**, pp. 1638–1640.
- TEAGASC, 2010, Agriculture in Ireland. Available at: <http://www.teagasc.ie/agrifood/> (last accessed 8th February 2011).
- TEULING, A., and TROCH, P., 2005, Improved understanding of soil moisture variability dynamics. *Geophysical Research Letters*, **32**, pp. L05404.
- TROMP-VAN MEERVELD, H., and MCDONNELL, J., 2006, On the interrelations between topography, soil depth, soil moisture, transpiration rates and species distribution at the hillslope scale. *Advances in Water Resources*, **29**, pp. 293–310.
- ULABY, F., MOORE, R., and FUNG, A., 1982, *Microwave Remote Sensing: Active and Passive Radar Remote Sensing and Surface Scattering and Emission Theory*, Volume II (Reading, Massachusetts: Addison-Wesley).
- ULABY, F. T., MOORE, R. K., and FUNG, A. K., 1986, *Microwave Remote Sensing: Active and Passive. Volume Scattering and Emission Theory, Advanced Systems and Applications*, Volume III (Dedham, Massachusetts: Artech House).
- ULABY F. T. and DOBSON, C., 1989, *Handbook of Radar Scattering Statistics for Terrain*. Artech House.
- VACHAUD, G., BALABANIS, A., and VAUCLIN, P., 1985, Temporal Stability of Spatially Measured Soil Water Probability Density Function. *Soil Science Society of America Journal*, **49**, pp. 822.
- VAN DER VELDE, R., SU, Z., and MA, Y., 2008, Impact of Soil Moisture Dynamics on ASAR s o Signatures and Its Spatial Variability Observed over the Tibetan Plateau. *Sensors*, **8**, pp. 5479–5491.
- VAN DONINCK, J., PETERS, J., LIEVENS, H., DE BAETS, B. & VERHOEST, N. 2012. Accounting for seasonality in a soil moisture change detection algorithm for ASAR Wide Swath time series. *Hydrology and Earth System Sciences*, **16**, pp. 773–786.

- WAGNER, W., and SCIPAL, K., 2000, Large-scale soil moisture mapping in western Africa using the ERS scatterometer. *IEEE Transactions on Geoscience and Remote Sensing*, **38**, pp. 1777–1782.
- WAGNER, W., PATHE, C., DOUBKOVA, M., SABEL, D., BARTSCH, A., HASENAUER, S., BLÖSCHL, G., SCIPAL, K., MARTÍNEZ-FERNÁNDEZ, J., and LÖW, A., 2008, Temporal Stability of Soil Moisture and Radar Backscatter Observed by the Advanced Synthetic Aperture Radar (ASAR). *Sensors*, **8**, pp. 1174–1197.
- WALKER, J. P., and HOUSER, P. R., 2004, Requirements of a global near-surface soil moisture satellite mission: accuracy, repeat time, and spatial resolution. *Advances in Water Resources*, **27**, pp. 785–801.
- WEIMANN, A., VON SCHONERMARK, M., SCHUMANN, A., JORN, P., and GUNTHER, R., 1998, Soil moisture estimation with ERS-1 SAR data in the East-German loess soil area. *International Journal of Remote Sensing*, **19**, pp. 237–243.
- WICKEL, A., JACKSON, T., and WOOD, E., 2001, Multitemporal monitoring of soil moisture with RADARSAT SAR during the 1997 Southern Great Plains hydrology experiment. *International Journal of Remote Sensing*, **22**, pp. 1571–1583.
- ZRIBI, M., BAGHDADI, N., HOLAH, N., and FAFIN, O., 2005, New methodology for soil surface moisture estimation and its application to ENVISAT-ASAR multi-incidence data inversion. *Remote Sensing of Environment*, **96**, pp. 485–496.
- ZRIBI, M., and DECHAMBRE, M., 2002, A New Empirical Model to Retrieve Soil Moisture and Roughness from C-band Radar Data. *Remote Sensing of Environment*, **84**, pp. 42–52.

Appendix 1.

A.1: ASAR WSM acquisition characteristics. Study sites: P = Pallaskenry, S = Solohead, K = Kilworth, D = Donoughmore, C = Clonakilty, B = Ballinhassig. 'All' indicates that every site was covered by the image swath coverage.

#	Date	Time	Polarisation	Orbit	Track	Frame	Study Site
1	11 th Nov2007	10:42:24	VV	29793	180	2591	Not P
2	20 th Nov2007	10:59:21	VV	29922	309	2560	All
3	7 th Jan2008	10:50:47	VV	30609	495	2574	All
4	20 th Jan2008	10:42:22	VV	30795	180	2590	Not P
5	26 th Jan2008	10:53:39	VV	30881	266	2563	All
6	29 th Jan2008	10:59:21	VV	30924	309	2560	All
7	1 st Feb 2008	11:04:27	VV	30967	352	2550	Not K
8	8 th Feb2008	10:45:05	VV	31067	452	2569	All
9	17 th Mar2008	10:50:49	VV	31611	495	2566	All
10	18 th Apr2008	10:45:11	VV	32069	452	2589	All
11	21 st Apr2008	10:50:47	VV	32112	495	2565	All
12	4 th May2008	10:42:15	VV	32298	180	2570	Not P
13	7 th May2008	10:47:57	VV	32341	223	2567	All
14	10 th May2008	10:53:39	VV	32384	266	2563	All
15	23 rd May2008	10:45:06	VV	32570	452	2569	All
16	26 th May2008	10:50:48	VV	32613	495	2565	All
17	11 th Jun2008	10:47:58	VV	32842	223	2567	All
18	27 th Jun2008	22:07:14	HH	33078	459	1000	All
19	30 th Jun2008	10:50:49	VV	33114	495	2565	All
20	13 th Jul2008	10:42:17	VV	33300	180	2570	Not P
21	16 th Jul2008	10:47:59	VV	33343	223	2567	All
22	7 th Aug2008	10:56:32	VV	33658	37	2562	All
23	21 st Sep2008	22:04:59	VV	34309	187	1036	All
24	24 th Sep2008	10:48:10	VV	34345	223	2580	All
25	10 th Oct 2008	10:44:56	VV	34574	452	2569	All
26	13 th Oct 2008	10:50:38	VV	34617	495	2565	All
27	11 th Nov 2008	22:01:57	VV	35039	416	1038	Not P, C, B, D
28	17 th Nov 2008	10:50:38	VV	35118	495	2569	All
29	3 rd Dec 2008	10:48:21	VV	35347	223	2590	Not P
30	6 th Dec 2008	10:52:26	VV	35390	266	2563	All
31	12 th Dec 2008	11:03:39	VV	35476	352	2551	Not K
32	28 th Dec 2008	11:01:08	VV	35705	080	2558	All
33	7 th Jan 2009	10:47:06	VV	35848	223	2567	All
34	10 th Jan 2009	10:53:34	VV	35891	266	2572	All
35	10 th Jan 2009	22:16:11	HH	35898	273	1028	All
36	13 th Jan 2009	11:00:10	HH	35934	309	2560	All
37	13 th Jan 2009	22:22:54	HH	35941	316	1025	Not C, B
38	16 th Jan 2009	11:05:51	VV	35977	352	2556	Not K
39	1 st Feb 2009	11:02:59	VV	36206	80	2558	All
40	8 th Feb 2009	10:43:05	VV	36305	180	2570	Not P

41	11 th Feb 2009	10:49:06	VV	36349	223	2589	All
42	14 th Feb 2009	10:54:29	VV	35392	266	2563	All
43	17 th Feb 2009	11:00:11	VV	36435	309	2560	All
44	5 th Mar 2009	10:56:19	VV	36664	37	2562	All
45	8 th Mar 2009	11:02:01	VV	36707	80	2558	All
46	18 th Mar 2009	10:47:46	VV	36850	223	2567	All
47	21 st Mar 2009	10:53:28	VV	36893	266	2563	All
48	27 th Mar 2009	11:04:52	VV	36979	352	2556	Not K
49	31 st Mar 2009	22:02:13	VV	37043	416	1058	Not C, B, D, P
50	6 th April 2009	10:50:37	VV	37122	495	2565	All
51	12 th April 2009	11:01:58	VV	37208	80	2558	All
52	25 th April 2009	10:54:31	VV	37394	266	2567	All
53	5 th May 2009	22:01:57	VV	37544	416	1038	Not C, B, D, P
54	11 th May 2009	22:13:19	VV	37630	1	1028	All
55	12 th June 2009	22:07:40	VV	38088	459	1033	All
56	18 th June 2009	10:56:20	VV	38167	37	2562	All
57	21 st June 2009	11:02:02	VV	38210	80	2558	All
58	1 st July 2009	22:10:11	VV	38360	230	1007	Not P, S
59	4 th July 2009	22:16:14	VV	38403	273	1029	All
60	7 th July 2009	10:59:09	HH	38439	309	2559	All
61	8 th Aug 2009	10:54:30	VV	38897	266	2563	All
62	15 th Sept 2009	10:59:13	VV	39441	309	2566	All
63	1 st Oct 2009	10:56:14	VV	39670	37	2561	All
64	2 nd Nov 2009	10:50:33	VV	40128	495	2565	All
65	15 th Nov 2009	10:42:21	VV	40314	180	2596	Not P, S
66	18 th Nov 2009	10:47:41	VV	40357	223	2566	All
67	4 th Dec 2009	10:44:48	HH	40586	452	2588	All
68	4 th Dec 2009	22:07:33	HH	40593	459	1036	All

Tables

Table 1. Annual precipitation recorded at each study site.

Site	Coordinates	Precipitation (mm)	
		2008	2009
Pallaskenry	Lat. 52°39'N, Long. -8°51' E	1147.9	1099.2
Solohead	Lat. 52°30'N, Long. -8°12' E	1405.0	1403.2
Kilworth	Lat. 52°10'N, Long. -8°14' E	772.3	1124.4
Donoughmore	Lat. 51°59'N, Long. -8°44' E	1578.6	1763.4
Carraig na bhFear	Lat. 51°58'N, Long. -8°27' E	824.4	-
Ballinhassig	Lat. 51°48'N, Long. -8°32' E	1019.6	1343.3
Clonakilty	Lat. 51°37'N, Long. -8°50' E	528.4	623.2

Table 2. Backscatter and soil moisture regression statistics for the combined 2008 and 2009 VV polarisation dataset. r^2 is the coefficient of determination, B_1 is the slope of the regression equation and n is the number of samples used to calculate the regressions.

Site	r^2	Sig.	n	B_0	B_1
Pallaskenry	0.19	0.002	50	-11.542	0.04
Solohead	0.25	<0.001	59	-13.418	0.06
Kilworth	0.21	<0.001	57	-11.791	0.06
Donoughmore	0.40	<0.001	57	-13.982	0.11
Carraig na bhFear	0.14	0.006	54	-11.563	0.04
Ballinhassig	0.33	<0.001	58	-11.214	0.04
Clonakilty	0.17	<0.001	58	-11.907	0.06

Table 3. Inter-seasonal vv polarisation backscatter and soil moisture regression statistics. r^2 is the coefficient of determination, B_1 is the slope of the regression equation and n is the number of samples used to calculate the regressions.

Site	Season	r^2		B_1		N	
		2008	2009	2008	2009	2008	2009
Pallaskenry	Winter	0.45*	0.08	-0.15	0.13	8	8
	Spring	0.26	0.12	0.05	0.04	7	9
	Summer	0.41	0.40	0.18	-0.12	4	5
	Autumn	0.006	0.99***	-0.02	0.12	6	4
Solohead	Winter	0.07	0.19	0.19	-0.31	10	8
	Spring	0.56**	0.61***	0.09	0.15	8	11
	Summer	0.003	0.74*	-0.002	0.08	5	5
	Autumn	0.006	0.81*	-0.014	0.07	8	4
Kilworth	Winter	0.04	0.07	0.13	0.84	8	7
	Spring	0.47*	0.78***	0.10	0.16	8	10
	Summer	0.002	0.04	-0.006	-0.02	5	6
	Autumn	0.06	0.92*	-0.06	0.15	8	5
Donoughmore	Winter	0.05	0.34	0.08	0.24	10	8
	Spring	0.44*	0.33	0.12	0.12	8	9
	Summer	0.12	0.16	0.03	0.05	5	6
	Autumn	0.60**	0.42	0.13	0.09	7	4
Carraig na bhFear	Winter	0.009	0.81	-0.05	0.19	10	3
	Spring	0.38	0.07	0.10	0.03	8	9
	Summer	0.61	0.31	0.097	0.10	5	6
	Autumn	0.04	0.78**	-0.03	0.08	8	5
Ballinhassig	Winter	0.24	0.11	0.05	-0.07	10	8
	Spring	0.38*	0.39*	0.05	0.04	8	9
	Summer	0.01	0.55*	-0.01	0.06	5	6
	Autumn	0.004	0.85**	0.009	0.04	7	5
Clonakilty	Winter	0.07	0.49*	0.14	0.17	10	8
	Spring	0.05	0.50**	0.045	0.08	8	9
	Summer	0.50	0.28	-0.20	-0.02	5	6
	Autumn	0.005	0.88**	0.017	0.16	7	5

* Significant at the 0.1 level

** Significant at the 0.05 level

*** Significant at the 0.01 level

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Figure 1. Field site locations in the south of Ireland (marked by yellow triangles) overlaid on ASAR WSM image subset. Red circles denote nearby Met Éireann climatological stations; from North, Shannon airport, Cork airport and Roches Point.

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Figure 3. Daily precipitation values (mm) (left y-axis) from 08/11/2007 to 30/12/2009 for each of the seven study sites along with the mean backscattering coefficient (dB) for each image acquisition (blue line, right y-axis).

Figure 4. Sensitivity of the HH polarisation backscattering coefficients to surface soil moisture at each test site. Each point corresponds to the mean backscattering coefficient in dB for the different acquisition dates. The continuous line represents the regression line, calculated using the equation $\sigma^0 = B_0 + B_1 m_v$, where B_0 is the intercept, B_1 is the slope and m_v is the volumetric soil moisture content. The dashed lines demarcate the 95% confidence intervals.

Figure 5. Sensitivity of the VV polarisation backscattering coefficients to surface soil moisture at each test site during 2008. Each point corresponds to the mean backscattering coefficient in dB for the different acquisition dates. The continuous line represents the regression equation $\sigma^0 = B_0 + B_1 m_v$, where σ^0 is the backscattering coefficient, B_0 is the intercept, B_1 is the slope and m_v is the volumetric soil moisture content. The dashed lines represent the 95% confidence intervals.

Figure 6. Sensitivity of the VV polarisation backscattering coefficients to surface soil moisture at each test site during 2009. Each point corresponds to the mean backscattering coefficient in dB for the different acquisition dates. The continuous line represents the regression equation $\sigma^0 = B_0 + B_1 m_v$, where σ^0 is the backscattering coefficient, B_0 is the intercept, B_1 is the slope and m_v is the volumetric soil moisture content. The dashed lines represent the 95% confidence intervals.

Figure 1

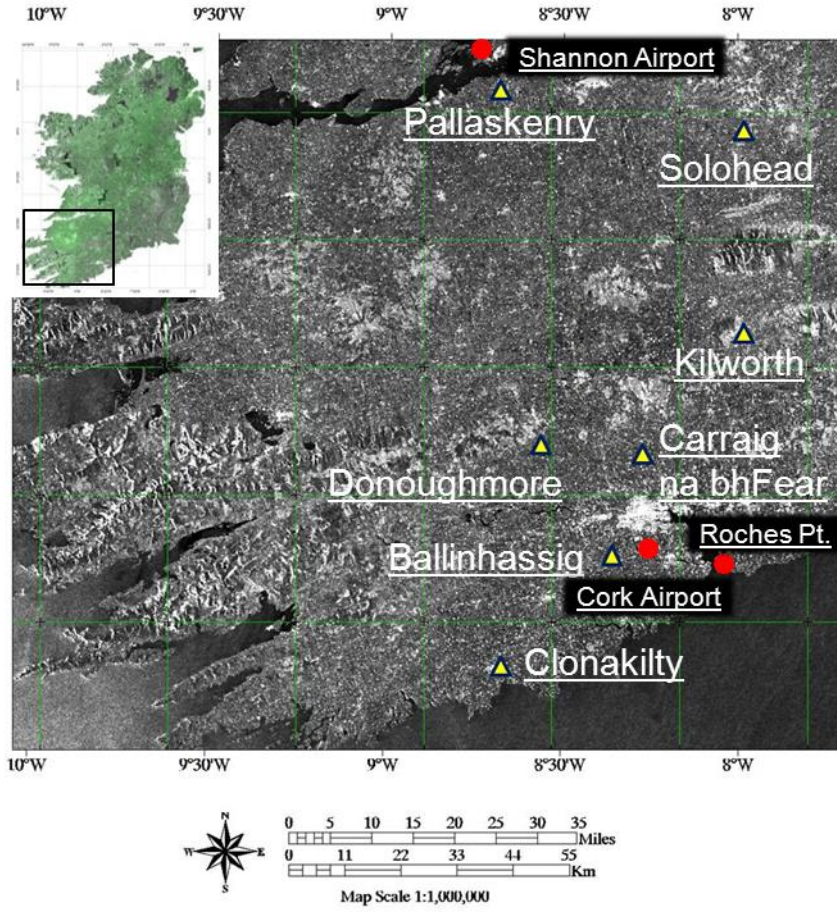


Figure 2

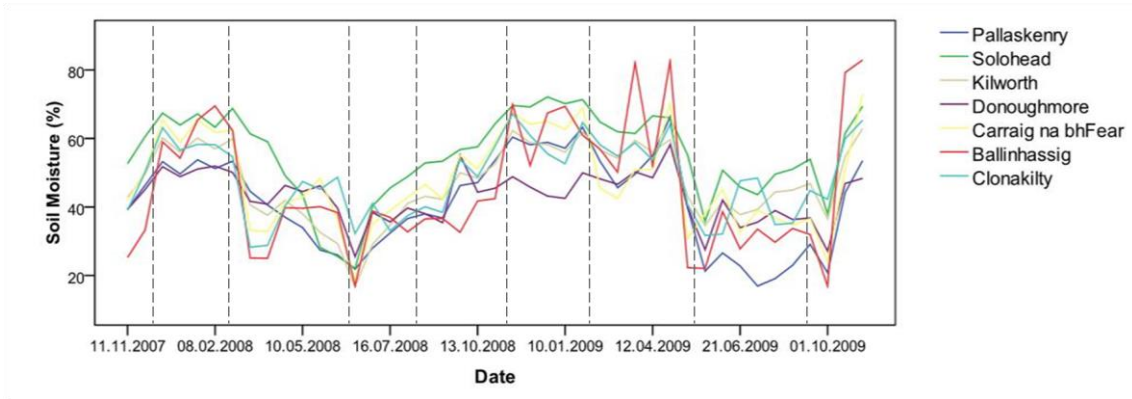


Figure 3

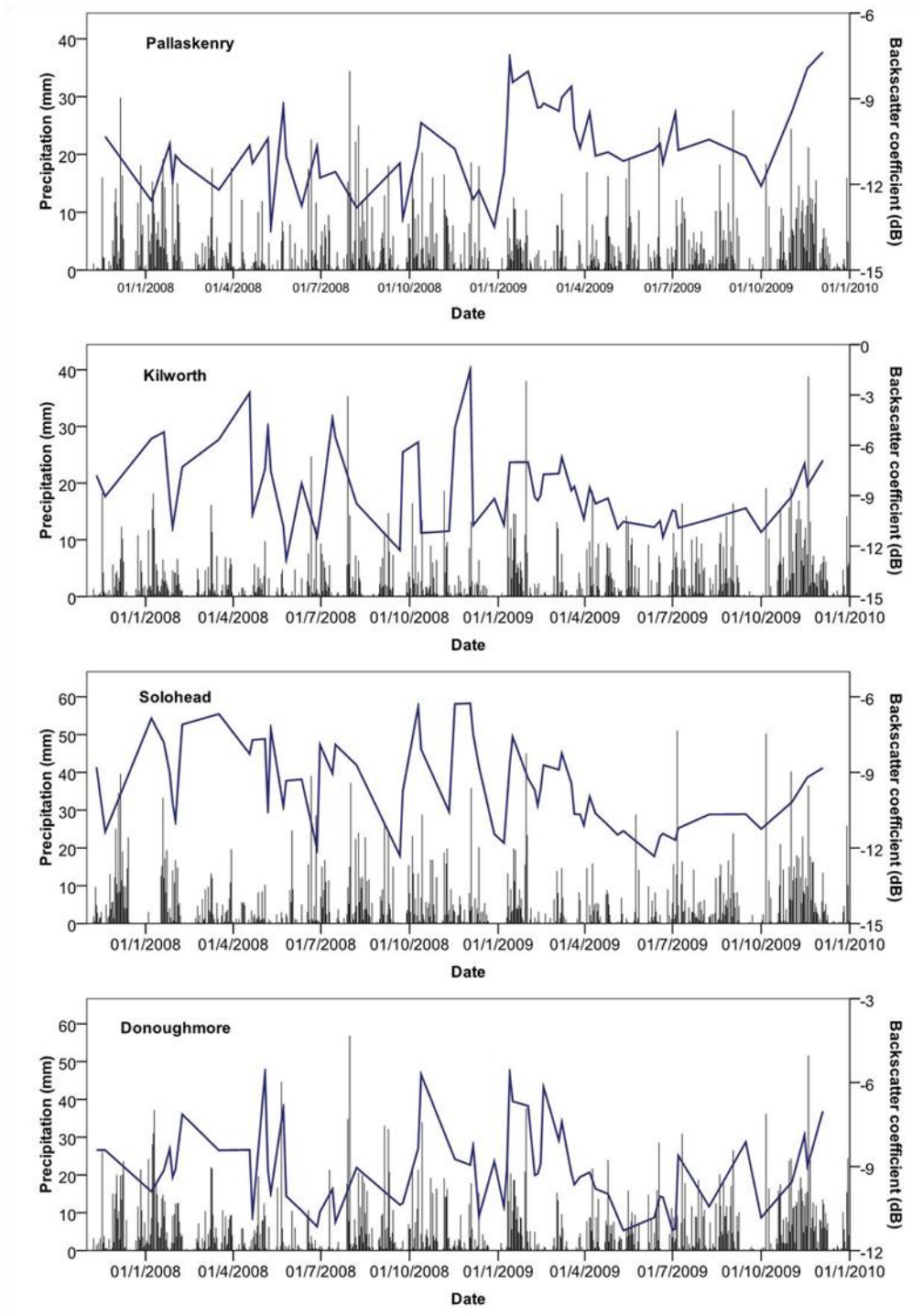


Figure 3 (cont)

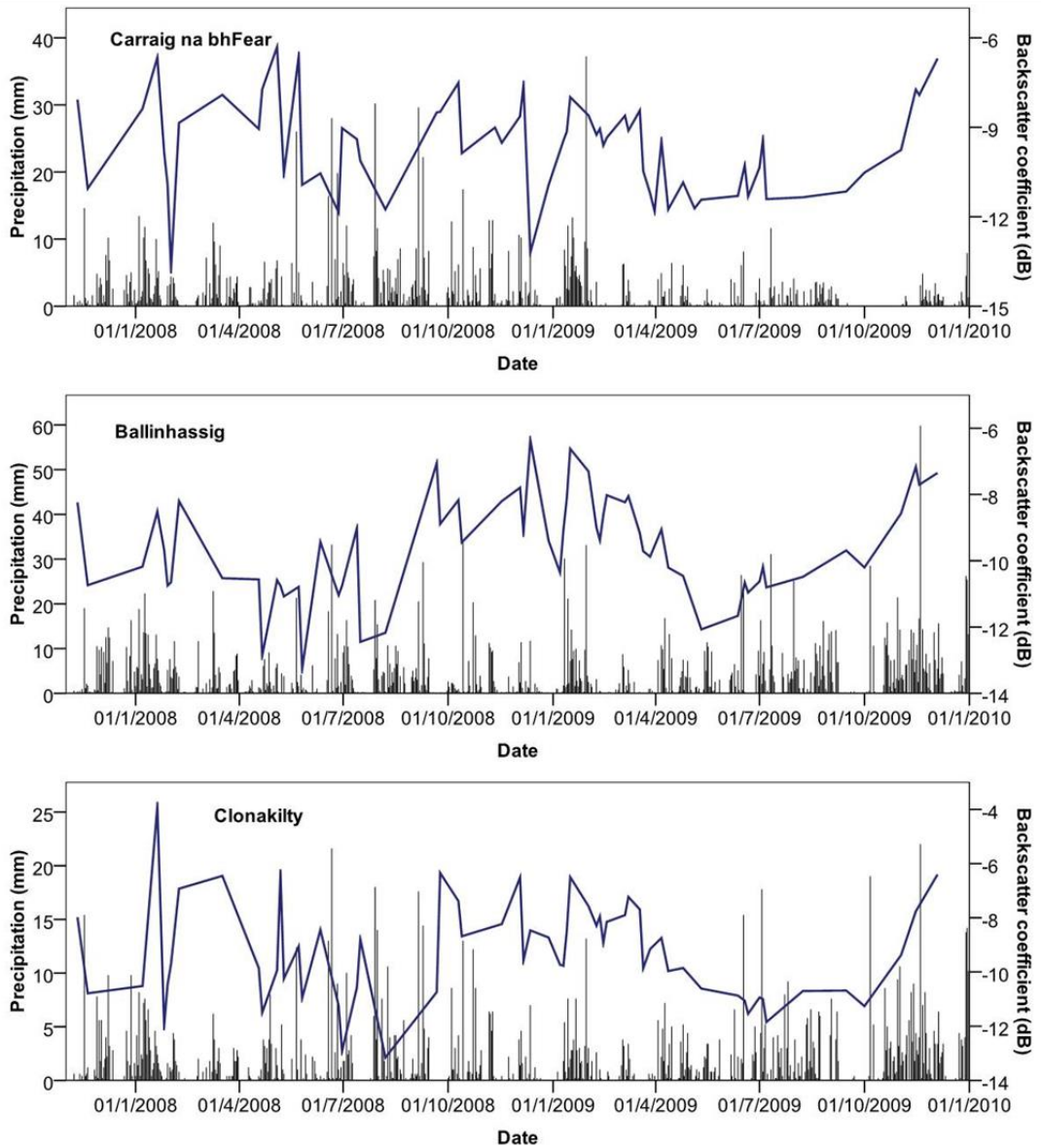


Figure 4

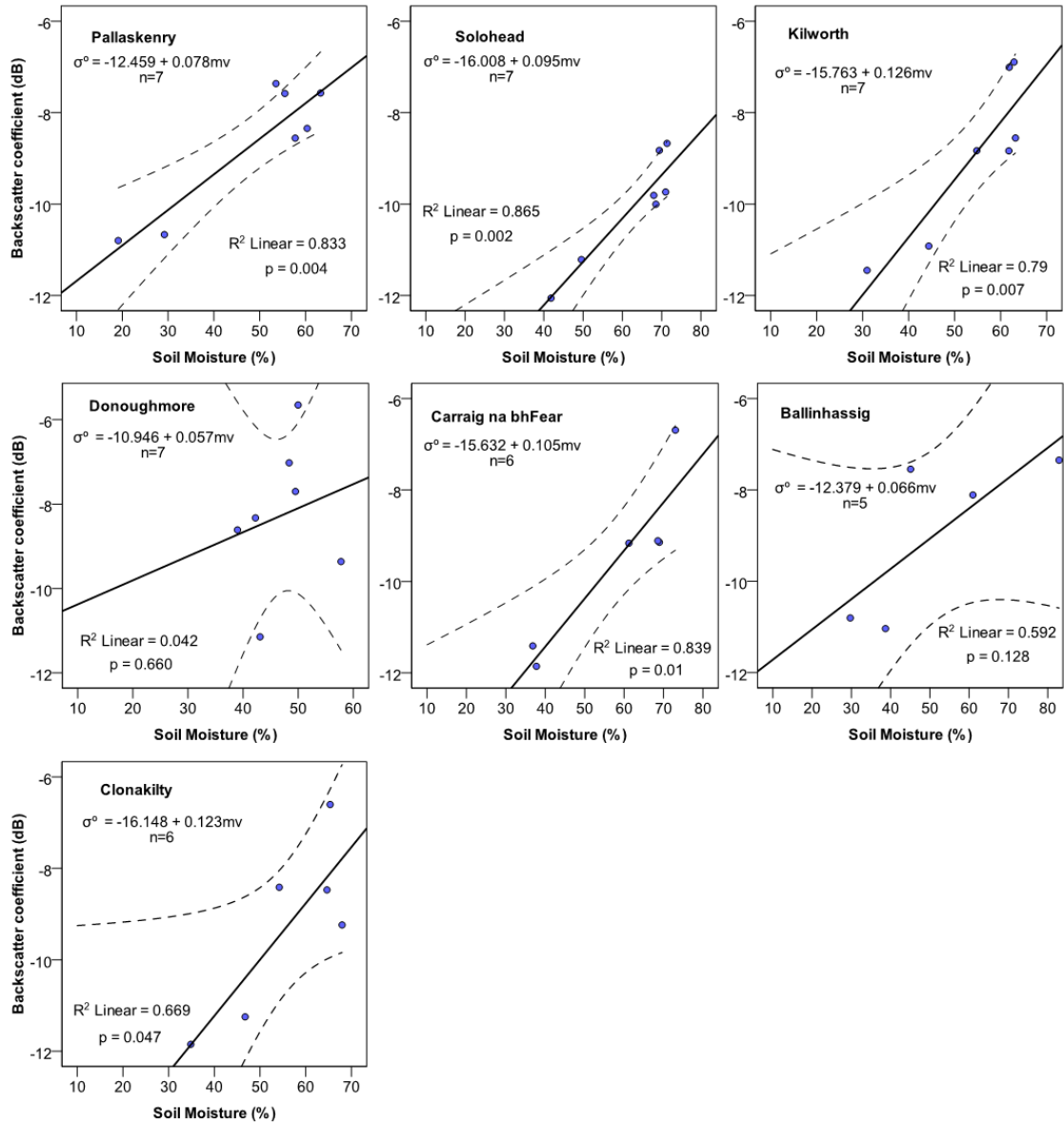


Figure 5

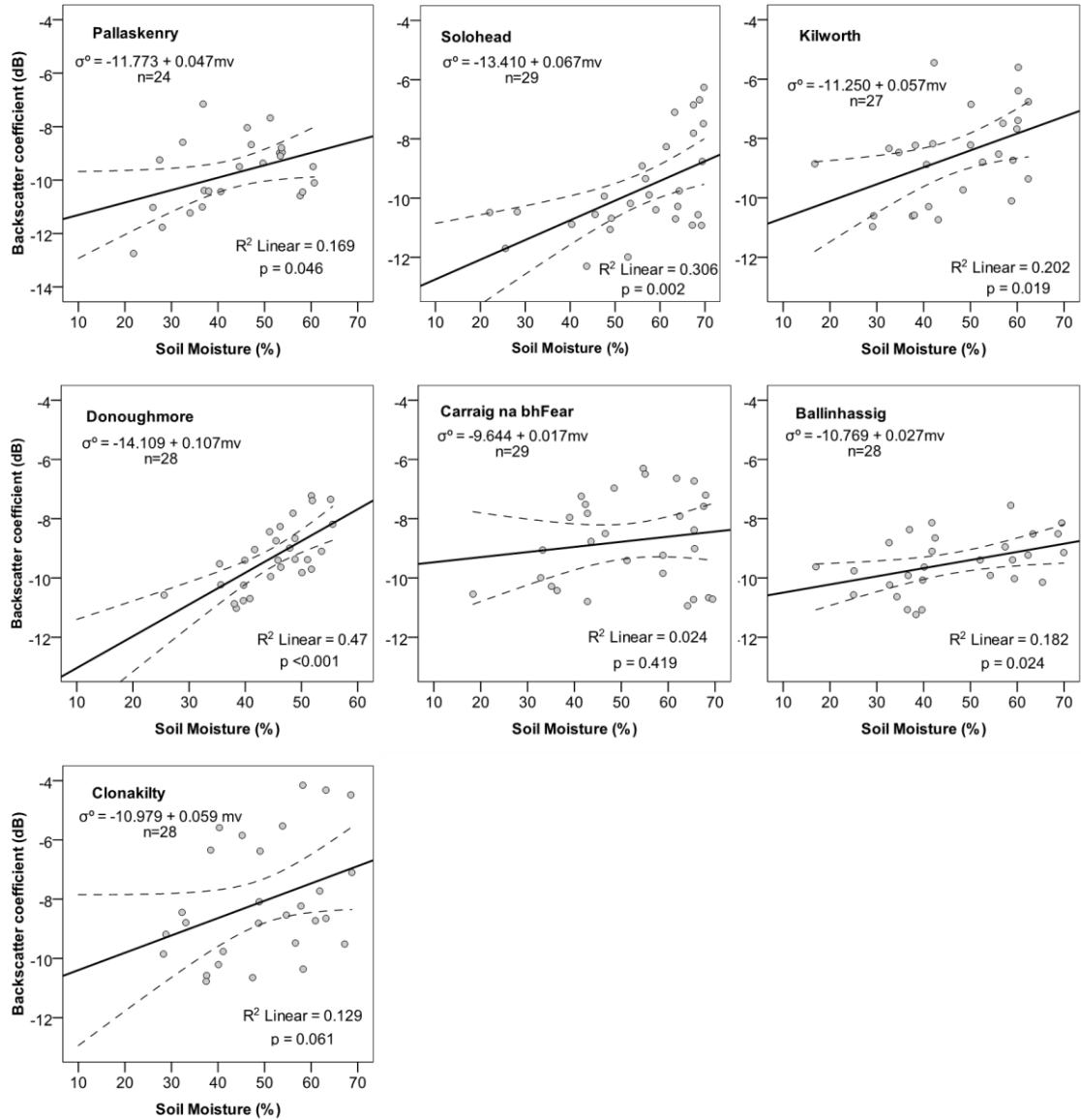


Figure 6

